An Enhanced Bridge Weigh-in-motion Methodology and A Bayesian Framework for Predicting Extreme Traffic Load Effects of Bridges

Yang Yu

Louisiana State University and Agricultural and Mechanical College, josephyangyu@gmail.com

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AN ENHANCED BRIDGE WEIGH-IN-MOTION METHODOLOGY AND A BAYESIAN FRAMEWORK FOR PREDICTING EXTREME TRAFFIC LOAD EFFECTS OF BRIDGES

A Dissertation

Submitted to the Graduate Faculty of
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Department of Civil & Environmental Engineering

by

Yang Yu
B.S., Hunan University, 2014
December 2017
To my parents
ACKNOWLEDGEMENTS

I would like to express my utmost gratitude to my advisor, Prof. Steve C.S. Cai. I could not have imagined the completion of this dissertation without his consistent supports, valuable suggestions, and endless encouragements on both research and life during my Ph.D. study at LSU. It has truly been a great pleasure working with such a professional and admirable scholar.

I would also like to express my sincere appreciation to the rest of my committee members: Prof. Ayman Okeil, Prof. Michele Barbato, Prof. Aly-Mousaad Aly, and Prof. Richard Ng, for the useful courses they offered and helpful suggestions on my research. My special thanks go to Prof. Lu Deng of Hunan University for his recommendation and valuable guidance on both my research and career.

I would like to thank my fellow members of Prof. Cai’s group for always lending a helping hand in times of need and for all the fun we had in the past three and a half years.

The financial support for this research provided by the Louisiana Transportation and Research Center (LTRC) is fully acknowledged.

Last but not least, I would like to thank my family, especially my parents, for the consistent love, faith, and patience they have given me throughout my life. This journey would not have been possible without their spiritual supports.
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ABSTRACT

In the past few decades, the rapid growth of traffic volume and weight, and the aging of transportation infrastructures have raised serious concerns over transportation safety. Under these circumstances, vehicle overweight enforcement and bridge condition assessment through structural health monitoring (SHM) have become critical to the protection of the safety of the public and transportation infrastructures. The main objectives of this dissertation are to: (1) develop an enhanced bridge weigh-in-motion (BWIM) methodology that can be integrated into the SHM system for overweight enforcement and monitoring traffic loading; (2) present a Bayesian framework to predict the extreme traffic load effects (LEs) of bridges and assess the implication of the growing traffic on bridge safety.

Firstly, an enhanced BWIM methodology is developed. A comprehensive review on the BWIM technology is first presented. Then, a novel axle detection method using wavelet transformation of the bridge global response is proposed. Simulation results demonstrate that the proposed axle detection method can accurately identify vehicle axles, except for cases with rough road surface profiles or relatively high measurement noises. Furthermore, a two-dimensional nothing-on-road (NOR) BWIM algorithm that is able to identify the transverse position (TP) and axle weight of vehicles using only weighing sensors is proposed. Results from numerical and experimental studies show that the proposed algorithm can accurately identify the vehicle’s TP under various conditions and significantly improve the identification accuracy of vehicle weight compared with the traditional Moses’s algorithm.

Secondly, a Bayesian framework for predicting extreme traffic LEs of bridges is presented. The Bayesian method offers a natural framework for uncertainty quantification in parameter estimation and thus can provide more reliable predictions compared with conventional methods. A framework for bridge condition assessment that utilizes the predicted traffic LEs is proposed and a case study on the condition assessment of an instrumented field bridge is presented to demonstrate the proposed methodology. Moreover, the non-stationary Bayesian method is adopted to predict the maximum traffic LEs during the lifetime of bridges subject to different types of traffic growth and the influence of the traffic growth on the bridge safety is investigated.
CHAPTER 1. INTRODUCTION

This dissertation consists of seven chapters. All chapters, except for the introduction (Chapter 1) and conclusions (Chapter 7), are based on papers that have been accepted, are under review, or are to be submitted to peer-reviewed journals, and are constructed using the technical paper format that is approved by the Graduate School of Louisiana State University. The technical paper format is intended to facilitate and encourage technical publications. Therefore, each chapter is relatively independent. For this reason, some important information may be repeated in some chapters for the completeness of each chapter. All chapters document the research results of the Ph.D. candidate under the direction of the candidate’s advisor as well as the dissertation committee members.

This introductory chapter gives a general background of the present research and simply discusses what have been achieved in the present research. More detailed information can be found in each individual chapter. In this chapter, a brief introduction on bridge condition assessment through structural health monitoring (SHM) is first presented to show how SHM can facilitate the bridge condition assessment. Secondly, the bridge weigh-in-motion (BWIM) technology, which can be integrated into SHM systems, is briefly introduced to demonstrate the applications of BWIM technology highlighting its use in bridge condition assessment. Finally, the common methods used for the prediction of extreme traffic load effects (LEs) of bridges, which provides important information for bridge condition assessment through SHM, are presented.

1.1 Bridge Condition Assessment through Structural Health Monitoring

The objective of bridge condition assessment is to evaluate the capacity and performance of the bridge, and check if the bridge can safely carry its operational loading. The damage of the structure can occur due to natural causes such as the deterioration of material and natural hazards or due to human factors such as vehicle and vessel impacts. Structural health monitoring (SHM) uses the monitored bridge response to detect sudden or progressive damages of the structure and can provide valuable information for bridge condition assessment. In the past few decades, bridge condition assessment through SHM has received much attention from researchers. SHM methods are usually classified into the following four levels (Rytter 1993):

Level 1: identify the presence of the damage.

Level 2: identify the presence and location of the damage.

Level 3: identify the damage presence and location, and quantify of the level of damage.

Level 4: identify the damage presence and location, quantify of the level of damage, and predict the remaining life of structures.

When structural damage occurs, the structural properties also change correspondingly. Therefore, the core of SHM is to find a damage index that is sensitive to the changes in structural properties. Previous research has developed various damage detection strategies. Generally
speaking, the damage detection methods can be classified into two types, i.e., response-based methods and model-based methods.

1.1.1 Response-based Methods

- Natural Frequency-based Methods

  The natural frequency of structures is sensitive to structural damages since it is related to the stiffness and mass of the structure. The shift of natural frequency may indicate the presence of structural damage. Also, the natural frequency of the structures can be easily measured. Thus, the change of natural frequencies is an attractive damage index to indicate the presence of structure damage (Carden and Fanning 2004). Furthermore, it was shown that the ratio of the change of frequency in two modes is a function of the damage location and thus the measurement of a pair of frequencies yield a locus of potential damage locations (Adams et al. 1978; Cawley and Adams 1979). To identify the location of the damage, the loci of different pairs of modes are superimposed and the damage location can be identified as the intersection of the curves (Cawley and Adams 1979). Nevertheless, there are many limitations to natural frequency-based methods. For example, it is not sensitive to local damages (Kong 2013). Some researchers have found that the shift of natural frequency was not significant even though significant loss of stiffness had occurred in real structures (Law et al. 1995). Moreover, it was reported that the variation of natural frequency due to ambient vibrations and environmental effects could reach ten percent, which makes it difficult to distinguish the cause of the change in the natural frequency (Carden and Fanning 2004). For these reasons, the greatest success of using natural frequency-based methods for damage detection is still in laboratory tests using simple structures with single damage locations (Fan and Qiao 2010).

- Mode Shape-based Methods

  In the past, different methods have been developed to extract the mode shapes from the measured bridge responses (Ewins 1984). The mode shape-based methods are based on the assumption that the mode shapes of the structure change as a result of structural damage. Thus, the damage can be detected by comparing the mode shapes of the intact and damaged structures (Gandomi et al. 2008). Two indices have been developed to measure the similarity of mode shapes including the modal assurance criterion (MAC) (Allemang and Brown 1982) and the coordinate modal assurance criterion (COMAC) (Lieven and Ewins 1988). The MAC measures the overall similarity of mode shapes. The value of MAC varies from 0 to 1 with 0 being entirely dissimilar and 1 being perfect match (Carden and Fanning 2004). A reduction of the MAC indicates the presence of damage. The COMAC is the measure of similarity of mode shapes at a point. A low value of COMAC at a point indicates the difference of the mode shapes at the point and can thus provide information on the potential damage locations (Fan and Qiao 2010). The mode shape-based methods are more sensitive to local damages than the frequency-based methods since the mode shapes contain the location information. Nevertheless, the mode shape-based methods depend on the accurate measurement of mode shapes (Carden and Fanning 2004). The main difficulties lie in a large number of sensors required (Fan and Qiao 2010), sensitivity to measurement noise (Kong 2013), and the expansion techniques to obtain the mode shapes from incomplete measurements (Shi et al. 2000).
In addition to the direct comparison of mode shapes, the change of mode shape curvature is considered to be more sensitive to the location of the damage and it is usually more pronounced than the change of displacement of mode shapes (Pandey et al. 1991; Wahab and De Roeck 1999). The curvature can be calculated using the displacement of the mode shapes. The method based on the change of mode shape curvature has been shown to be effective in detecting local damages (Byung Hwan Oh 1998). However, at higher modes, the difference in mode shape curvatures may not be caused by structural damages (Kong 2013). Usually, only the first few modes are used to extract the curvatures for damage detection. Besides, the mode shape curvature is the derivative of mode shape displacement and thus it relies even more on the accurate measurement of mode shapes (Carden and Fanning 2004).

1.1.2 Model-based Methods

Model-based methods use a numerical model of the structures to identify structural damages. Initially, the numerical model is calibrated using the baseline measurement to reflect the structural behavior at the healthy state. Then, the model is updated to reproduce the measured response of the structure and the comparison of the updated model and the initially calibrated model can provide information on the damage location and extent (Mottershead and Friswell 1993). Usually, the finite element (FE) model of the structure is constructed and FE model updating is conducted to calibrate the model to reflect the structural behavior (Kim and Park 2004). The model updating involves minimizing an objective function with respect to the parameters that represent the structural properties. There have been many studies on model updating and different optimization methods were used. The main advantage of the model-based methods is that the identification of the damage location and extent is straightforward (Fritzen 2010). However, it heavily relies on a detailed and accurate model of the structure which may be difficult to obtain. Furthermore, one common problem of model updating is that there are multiple solutions. Therefore, though a solution can be obtained through optimizing the objective function, the obtained solution still may not correspond to the actual damage case. In this case, a visual inspection will be helpful to identify whether the identified damage is a false positive.

1.2 Bridge Weigh-in-motion Technology

Overloaded trucks pose serious threats to the safety of the public and transportation systems. Vehicle overloading causes accelerated degradation of highway infrastructures (Jacob and Beaumelle 2010). For highway bridges, overloaded trucks lead to fatigue damages or even cause the collapse of bridges in some extreme cases. Moreover, overloaded vehicles have higher risks of causing traffic accidents due to the reduced maneuverability. Due to these reasons, vehicle overweight enforcement becomes critical to the protection of the safety of the public and highway infrastructures. The traditional method of enforcement is to use static scales to weigh highways trucks as shown in Figure 1-1. However, this causes the interruption of the traffic and decreases the efficiency of the transportation system. In order to overcome these limitations, weigh-in-motion (WIM) technology has been developed to measure the weight of vehicles while they are in motion. WIM technology provides an efficient method for overweight enforcement (Richardson et al. 2014). Furthermore, WIM can also be used to implement toll-by-weight and collect traffic information for traffic planning and design.
Generally speaking, WIM can be classified into two types including the pavement-based WIM and bridge WIM (BWIM). The pavement-based WIM uses devices installed on the road surface such as bending plates, piezoelectric sensors to directly measure the axle force of the vehicle when the vehicle axle contacts the device. The technology adopted by pavement-based WIM systems is relatively simple. However, since the device is installed on the road surface, it is intrusive to the pavement and has poor durability due to the direct exposure to the heavy traffic. Thus, its installation and maintenance usually requires traffic closures. Furthermore, the axle force measured by the pavement-based WIM is not the static weight of the axle since the axle force is a time-varying force. Therefore, the errors of estimated vehicle weight could be significant especially when the dynamic effect is pronounced (Yu et al. 2016).

Figure 1-1 A typical weigh station on the highway

The concept of BWIM was first proposed by Moses (Moses 1979) in 1979. BWIM uses an instrumented bridge as the weighing scale to estimate the vehicle weight. The BWIM has many advantages over the pavement-based WIM. Firstly, the BWIM uses sensors installed underneath the bridge. Thus, the BWIM has better durability and its installation does not interrupt the traffic. Furthermore, the measurement period of BWIM is usually significantly longer, which allows the dynamic effect to be filtered out and the static weight of the vehicle to be obtained. In addition, the BWIM also has the advantages of being non-intrusive and portable, making it an ideal replacement for pavement-based WIM. Figure 1-2 shows the framework of BWIM systems and their applications. A detailed review on BWIM algorithms and instrumentations is presented in Chapter 2. The applications of BWIM technology are briefly introduced here:

Figure 1-2 Framework of BWIM and its applications

- **Overweight Enforcement**

  The traditional method for overweight enforcement uses static scales aided with visual pre-selection to weigh highway trucks. However, the use of static scales is time-consuming and
Infeasible for transportation systems with heavy truck traffic (Haugen et al. 2016). The WIM technology is able to identify the truck weight without interrupting the traffic, which makes it an ideal tool for overweight enforcement. Nevertheless, the use for direct enforcement requires very accurate estimation of vehicle weight. As a prerequisite of direct enforcement, the error of the identified vehicle weight should be less than 5% for 95% of the results (Lydon et al. 2016). For pavement-based WIM, the accuracy is affected by many factors including the quality of system installation, usage and maintenance, vehicle speed and acceleration, road surface condition, tire friction and weather conditions, which makes it difficult to satisfy the requirements of direct enforcement (Hang et al. 2013). Instead, pavement-based WIM can be used for effective pre-selection of overloaded trucks (Karim et al. 2014). As shown in Figure 1-3, the truck is first weighed on the highway as it travels at its normal speed using pavement WIM sensors. The estimated weight of truck is then compared with a preset threshold determined based on the distribution of the measured vehicle weight (Han et al. 2012). If the estimated weight exceeds the threshold, then the truck may be overloaded and needs to bypass the inspection station to be weighed by the static scale. Otherwise, the truck can proceed without inspection.

Figure 1-3 Pre-selection of overloaded trucks using pavement-based WIM (Jacob and Beaumelle 2010)

The BWIM is potentially more accurate than the pavement-WIM since it has longer measurement periods. The BWIM can be used for direct enforcement provided that the selected bridge meets certain requirements such as a relatively short span length and good surface condition. In addition, another advantage of BWIM for overweight enforcement is that it is invisible to truck drivers. In practice, BWIM has been used for the pre-selection of overloaded vehicles. However, the application for direct enforcement is still rare.

- **Toll-by-weight**

In some countries such as China, the toll rate is calculated based on the truck weight and thus the accurate estimation of truck weight is critical to the implementation of the toll-by-weight method (Hang et al. 2013). The static weighing has good accuracy but is not suitable considering the large volume of trucks that need weighing. Instead, pavement-based WIM has frequently been used for the toll-by-weight method. Figure 1-4 shows the setup of a WIM-based
toll booth. Typically, bending plate or piezoelectric cable WIM scales are used due to the low costs. However, their accuracy is relatively low. Sometimes, multiple weighing is needed, leading to congestions at the toll station. BWIM, on the other hand, is potentially more suitable for the toll-by-weight method since it is more accurate than the pavement-based WIM. However, it does require a bridge suitable for BWIM implementation, which, to some degree, limits the application of BWIM for the implementation of the toll-by-weight method.

![Figure 1-4 A typical WIM-based toll booth (Hang et al. 2013)](image)

In addition to the above two applications, the BWIM can also be used to simply monitor the traffic. The obtained traffic data can be used for traffic planning and the design of pavement and bridges, which does not necessarily require very high accuracy of the system (COST 323 2002).

- **Application of BWIM in SHM**

  A well-calibrated BWIM system should be able to accurately identify the vehicle weight. However, if the bridge structure has suffered damage, then the calibration can no longer reflect the actual behavior of the bridge, which will result in identification errors of the vehicle weights. Cantero and González (2014) proposed a Level 1 damage-detection method using the relative difference of GVW identified from the BWIM and pavement-based WIM as the damage indicator, $E_{BWIM}$, as shown in Figure 1-5. It was noted that even if the bridge is intact, there still exist errors of GVW identified in both systems due to factors other than the damage such as measurement noise. Thus, the $E_{BWIM}$ is averaged over a large sample of trucks to compensate for the dispersion of individual trucks. Simulation study was conducted to test the effectiveness the proposed method. In their study, 1,000 trucks were simulated for each day and the daily average $E_{BWIM}$ was calculated as shown in Figure 1-6. The monthly $E_{BWIM}$ was used to detect the presence of global and local damages that were modeled as the loss of stiffness. It was found that the proposed damage indicator is sensitive to both global and local damages and that the proposed method is robust in detection damages since it is applicable for different road profiles and it allows for the intrinsic errors in WIM systems themselves.

  Cantero et al. (2015) proposed a Level 1 damage detection method using the concept of virtual axle (VA). When identifying the axle weight in BWIM, the vehicle was assumed to have a weightless axle in addition to its existing axles as shown in Figure 1-7. This additional axle is
termed “virtual axle”. It was shown that if there is no change in the influence line of the structure, i.e., the structure is intact, the BWIM will estimate the weight of the VA to be zero. Otherwise, the estimated weight of the VA will be different than zero, which indicates the presence of structural damage. Based on this, a damage index named VA* is defined to reflect the weight of the VA relative to the GVW identified without the VA. The VA* is averaged over a large number of trucks to reduce the influence of errors due to the noise and dynamic effects. The simulation results indicate that the proposed method is able to detect small local damages. However, it should be noted that the proposed method is only applicable to statically indeterminate bridges with relatively short span lengths.

Carey et al. (2013) investigated the possibility of using moving force identification method for damage detection of bridges. They found that the axle force history is sensitive to the structural damage as can be seen from Figure 1-8. However, different vehicles have different
properties, which results in different axle forces that are not comparable. To address this issue, the mean axle force of a large number of vehicles with the same axle configuration is used as the damage indicator. The results show that the proposed method can successfully detect local damages and has the potential to provide possible locations of damage.

Gonzalez and Karoumi (2015) proposed a model-free damage detection method using BWIM and machine learning method. The proposed method utilizes the vehicle information identified from the BWIM system as input to an artificial neural network (ANN) that is able to predict the deck acceleration. Since the ANN is trained to predict the behavior of the structure at its healthy state, the difference between the predicted acceleration and measured acceleration can indicate possible damages of the structure. The framework of the proposed method is shown in Figure 1-9.
Bridge Condition Assessment

Bridge load rating is a common practice used to assess the in-service condition of bridges. Bridges are typically rated every two to five years depending on their conditions. The AASHTO load and resistance factor rating (LRFR) specification (AASHTO 2011) defines the rating factor as:

\[
RF = \frac{C - \gamma_{DL} DL - \gamma_{DW} DW}{\gamma_{LL} LL (1 + IM)}
\]  

(1-1)

where \( C \) is the capacity of the member; \( DL \) and \( DW \) are the deal loads due to structural components and wearing surfaces, respectively; \( \gamma_{DL} \) and \( \gamma_{DW} \) are the corresponding dead load factors; \( LL \) is the live load; \( IM \) is the impact factor; and \( \gamma_{LL} \) is the live load factor. The rating factor reflects the safety reserve of the structure. A rating factor larger than one indicates that the bridge has the capacity to carry the live load. Otherwise, the bridge is considered to be vulnerable and needs to be posted. In order to be consistent to the LRFD design specification (AASHTO 2012), the live load factor is generally chosen to be 1.75. However, the factor of 1.75 may be overly conservative for some bridges since the design codes need to cover a wide range of bridges and there exist significant uncertainties.

The BWIM system is able to collect specific traffic data at the bridge site and thus significantly reduce the uncertainties of live load for condition assessment. The collected site-specific traffic data can be used to calibrate live load factors specific for the bridge under assessment, which can help avoid unnecessary load posting and increase the efficiency of the transportation system. Zhao et al. (2012) used the data collected by pavement-based WIM and BWIM systems in Alabama to calibrate the statewide live load factors. They found that the live load factor specified by the LRFR is overly conservative for the economic assessment of bridges. Accordingly, they suggest that the ALDOT adopt the state-specific live load factors to improve the load rating especially when the LRFR specified load factor results in the bridge to be posted. In addition, they also found that different traffic direction and seasonal variation do not have a significant effect on the live load factor. Similar works have also been conducted by Pelphrey et al. 2008).

1.3 Prediction of Extreme Traffic Load Effects of Bridges

Accurate evaluation of extreme traffic load effects (LEs) provides important information for the condition assessment of bridges. Due to the limited monitoring duration, the maximum traffic LEs during the lifetime of bridge structures need to be extrapolated using statistic-based methods. Previously, different methods have been proposed to model and predict the extreme traffic LEs. O’Brien et al. (2015) presented a comprehensive review on the various prediction methods for extreme traffic LEs. The commonly adopted methods include the block maxima method, the peak-over-threshold method, and the level crossing method based on the Rice formula. A brief review of these methods is presented below.

- **Block Maxima Method**

  The block maxima (BM) method divides the observation into non-overlapping time intervals (blocks) of an equal length and the maximum value in each block is extracted. Based on
the extreme value theory (Fisher and Tippett 1928), if the block maxima are independent and identically distributed (i.i.d.), then the block maxima data will converge to the generalized extreme value (GEV) distribution whose CDF is expressed as:

\[
G(x) = \exp \left\{ - \left[ 1 + k \left( \frac{x - \mu}{\sigma} \right) \right]^{-1/k} \right\}
\]

where \( k \) is the shape parameter; \( \sigma \) is the scale parameter; and \( \mu \) is the location parameter. The GEV distribution contains three types of extreme value distributions depending on the value of the shape parameter: (i) when \( k > 0 \), \( G(x) \) corresponds to the heavy-tailed (Fréchet) distribution; (ii) when \( k < 0 \), \( G(x) \) corresponds to the short-tailed (Weibull) distribution; and (iii) when \( k = 0 \), \( G(x) \) corresponds to the light-tailed (Gumbel) distribution.

In extreme value analysis, the future extreme is predicted by computing the return level corresponding to a certain return period. Under the i.i.d. assumption, the return level corresponding to a certain return period has an equal probability of exceedance in any block. Therefore, the return level can be calculated as the quantile of the GEV distribution:

\[
x_{RL} = \mu + \frac{\sigma}{k} \left\{ -\ln \left( 1 - \frac{t}{T} \right) \right\}^{-k} - 1
\]

where \( t \) is the block length and \( T \) is the return period and \( x_{RL} \) is the return level corresponding to the return period \( T \).

- **Peak-over-threshold Method**

One problem of the BM method is that it does not fully utilize the data since if several extreme events exist in one block, only the one with maximum LE is considered. The peak-over-threshold (POT) method, on the other hand, makes better use of data by using all observations exceeding a certain threshold, \( \mu \). Based on the Pickands-Balkema-de Haan theorem (Pickands 1975), the excess of a sequence of i.i.d. random variables over a significantly high threshold \( Z_i = X_i - \mu \) where \( \mu \) is the threshold, converges to the generalized Pareto (GP) distribution whose CDF is expressed as:

\[
F(z) = \begin{cases} 
1 - [1 + k \left( \frac{z}{\sigma} \right)]^{-1/k}, & k \neq 0 \\
1 - \exp \left( -\frac{z}{\sigma} \right), & k = 0 
\end{cases}
\]

where \( \sigma \) is the scale parameter; and \( k \) is the shape parameter. When the shape parameter \( k = 0 \), \( F(z) \) corresponds to the exponential distribution. The support of the GP distribution is: (1) for \( k \geq 0 \), \( 0 < z < \infty \); (2) for \( k < 0 \), \( 0 < z < -\sigma / k \). For the POT method, the choice of the threshold is an important issue. If the threshold is set too high, the number of excess may not be sufficient to provide a reliable estimate of the parameters. If the threshold is set too low, the data may not converge to the GP distribution. In order to find the optimal threshold, the common method is to
use a goodness-of-fit test, such as the Kolmogorov-Smirnov (KS) test (Crespo-minguilh and Casas 1997) and Cramér-von Mises test (Zhou et al. 2016), to select the threshold that provides the best fit. After the threshold is selected, the GP parameters need to be estimated. The available methods include the maximum likelihood method, the method of moments, and the method of probability weighted moments. To calculate the return level, the quantile of the GP distribution is given as (Hosking and Wallis 1987):

\[
x(F) = \begin{cases} 
\mu - \frac{\sigma}{k} \left(1 - (1 - F)^k\right), & k \neq 0 \\
\mu - \sigma \log (1 - F), & k = 0
\end{cases}
\] (1-5)

● Level Crossing Method based on the Rice Formula

Ditlevsen and Madsen (1994) showed that the traffic LEs of long span bridges can be assumed as a stationary Gaussian process. Therefore, under this assumption, the mean up-crossing rate for a threshold level, \(x > 0\), can be described by the Rice’s formula as:

\[
v^*(x) = \frac{1}{2\pi} \frac{\hat{\sigma}}{\sigma} \exp\left(-\frac{(x - \hat{m})^2}{2\sigma^2}\right)
\] (1-6)

where \(\hat{m}\) is the expected value of \(x\), \(\sigma\) and \(\hat{\sigma}\) is the standard deviation of \(x\) and \(\hat{x}\). To model the extreme traffic LE, the upper tail of the up-crossing rate histogram is fitted to the Rice formula as shown in Figure 1-10. The optimal threshold \(x_0\) can be determined by using the Kolmogorov test (Cremona 2001).

![Figure 1-10 Fitting the up-crossing rate histogram to the Rice formula (Cremona 2001)](image-url)
\[ y = \ln[v(x)] = a_0 + a_1 + a_2x^2 \]  
\[ a_0 = \ln(v_0) - \frac{m^2}{2\sigma^2} \]  
\[ a_1 = \frac{m}{\sigma^2} \]  
\[ a_2 = -\frac{1}{2\sigma^2} \]

Based on the definition of return period, the relationship between the return level \( x_{rl} \) and the return period \( T \) can be derived as:

\[ Tv^+ (x) = T \cdot \frac{1}{2\pi\sigma} \exp\left(-\frac{(x_{rl} - m)^2}{2\sigma^2}\right) = 1 \]  

which leads to:

\[ x_{rl} = m \pm \sigma \sqrt{-2\log\left(\frac{2\pi\sigma}{T\hat{\sigma}}\right)} \]

### 1.4 Overview of the Dissertation

This dissertation aims to: (1) develop an enhanced BWIM methodology using SHM; (2) present a Bayesian framework for predicting extreme traffic LEs of bridges and assess the implication of the growing traffic on bridge safety. In the first part of this dissertation (Chapters 2 to 4), an enhanced nothing-on-road (NOR) BWIM methodology based on a novel axle detection method and an improved two-dimensional (2D) BWIM algorithm is developed. The enhanced BWIM methodology can be integrated into SHM systems for overweight enforcement and monitoring traffic loading. In the second part of this dissertation (Chapters 5 and 6), a Bayesian framework to predict the extreme traffic LEs of bridges is presented. The prediction methodology can be applied for both stationary and non-stationary traffic conditions. The predicted extreme traffic LEs can be used for bridge condition assessment. Case studies using both field monitored bridge responses and simulated traffic LEs are conducted to demonstrate the prediction methodology, and the influence of the traffic growth on the safety of bridges is investigated. It should be noted that the two parts of this dissertation are not independent because the purpose of both the enhanced BWIM methodology and the Bayesian framework for predicting extreme traffic LEs is to facilitate bridge condition assessment by providing critical information of the traffic loading on bridges. A brief summary of the contents presented in the following chapters of this dissertation is provided as follows:

To form and sharpen the research visions and identify the remaining issues, Chapter 2 presents a comprehensive review on the BWIM technology. The existing BWIM algorithms including the Moses’s algorithm, the orthotropic BWIM algorithm, the influence area method, the reaction force method, and the moving force identification algorithms are reviewed in details.
The advantages and disadvantages of each algorithm are discussed. Then, the instrumentation of BWIM systems is introduced focusing on the use and installation of sensors, and strategies for axle detections. Finally, a summary of findings is given based on the existing research and the remaining issues of the BWIM technology are identified, which serves as the motivation for the development of the enhanced BWIM methodology that will be presented in Chapters 3 and 4.

Chapter 3 proposes a new axle detection method using wavelet analysis of the global response of bridges. Traditional BWIM systems use axle detectors placed on the road surface to identify vehicle axles. However, the axle detectors have poor durability due to the direct exposure to the traffic. To resolve this issue, an alternative strategy of axle detection for NOR BWIM systems is proposed in this chapter. The proposed method uses wavelet transformation to extract the axle information from the bridge global response. A brief introduction on the wavelet theory is first given. Numerical simulations are then conducted on a multi-girder bridge with different trucks traveling at different speeds. A parametric study is carried out to investigate the effect of several factors including the sampling frequency, road surface condition and measurement noise on the identification accuracy. The simulation results demonstrate that the proposed axle detection method can accurately identify vehicle axles, except for cases where the road surface condition is poor or the measurement noises exceed certain levels.

Chapter 4 proposes a novel 2D NOR BWIM algorithm that is able to identify the vehicle’s transverse position (TP) and axle weights using only weighing sensors. Previous research has shown that ignoring the TP of vehicles may lead to significant identification errors of vehicle weight for the BWIM systems. However, the traditional method to identify the vehicle’s exact TP requires using axle detectors on the road surface. In order to achieve the NOR BWIM, a novel BWIM algorithm is proposed to identify the vehicle’s transverse position (TP) and axle weights using only weighing sensors. Numerical simulations are conducted using three-dimensional vehicle and bridge coupled analysis and a parametric study is carried out to examine the effects of the road surface condition, the vehicle speed, the vehicle width, and different measurement stations on the identification accuracy. The results show that the proposed algorithm can successfully identify the vehicle’s TP and that the identification of vehicle weight is significantly improved after considering the vehicle’s TP. The proposed algorithm is then verified by a field study.

The enhanced BWIM methodology is developed using the new axle detection method proposed in Chapter 3 and the novel NOR BWIM algorithm proposed in Chapter 4. The developed BWIM methodology is based on the 2D Moses’s algorithm enhanced by novel methods to identify the longitudinal and transverse positions of the vehicle using only weighing sensors, which allows the complete function of BWIM to be realized using only weighing sensors that are readily available in many SHM systems. This is considered as a significant advantage over the existing BWIM systems which typically require axle detection sensors in addition to the weighing sensors.

Chapter 5 presents a Bayesian framework to predict the extreme traffic LEs of bridges. Accurate prediction of extreme traffic LEs during the remaining life of bridges is critical to the reliable condition assessment of bridges. However, most of the previous prediction methods did not consider the epistemic uncertainty of distribution parameters, which could lead to
underestimation of predicted LEs especially when only limited observation period is available. The Bayesian method is able to quantify the uncertainties inherent in the parameters and incorporates these uncertainties into the prediction. In this chapter, the Bayesian method is introduced for the prediction of extreme traffic LEs and a framework for bridge condition assessment making use of the predicted LEs is proposed. A case study on the condition assessment of the new I-10 Twin Span Bridge is presented to demonstrate the proposed methodology.

Chapter 6 extends the Bayesian framework for predicting extreme traffic LEs to account for the traffic growth. The past decades have witnessed considerable growth of the road traffic as results of economic developments and technological advances. Nevertheless, most previous studies assumed that the traffic is a stationary process in order to extrapolate the extreme traffic LEs of bridges. In order to provide more accurate evaluation of extreme traffic LEs, the Bayesian framework for predicting extreme traffic LEs of bridges subject to growing traffic is presented. Long-term traffic LEs are simulated using Monte Carlo simulation and influence line analysis considering three types of traffic growth including the growth of the truck volume, the proportion of heavy vehicles, and the truck weight. The non-stationary Bayesian method is applied to predict the maximum traffic LEs during the lifetime of bridges. The influence of the traffic growth on the bridge safety is studied. The obtained results provide references for the decision making on regulation changes and bridge management.

Finally, Chapter 7 presents a summary of findings of this dissertation and proposes recommendations for the future research.

1.5 References


CHAPTER 2. REVIEW ON BRIDGE WEIGH-IN-MOTION TECHNOLOGY*

2.1 Introduction

Vehicle overloading has become a common issue that has raised serious concerns worldwide (Fu and Hag-Elsafi 2000). Overweight trucks can lead to serious damages and accelerate the degradation of road infrastructures. The most common issue is the fatigue problems of bridge components, which can significantly shorten the service life of bridges (Wardhana and Hadipriono 2003; Biezma and Schanack 2007). In some extreme cases, the weight of the overloaded truck may even exceed the load-carrying capacity of the bridge and directly cause the bridge to collapse. Moreover, overloaded trucks have higher risks of being involved in traffic accidents (Jacob and Beaumelle 2010). In light of these concerns, overweight truck enforcement has become increasingly important for the protection and maintenance of modern transportation systems.

The common techniques used to weigh highway trucks include static weighing techniques and weigh-in-motion (WIM) techniques. While static weighing can be very accurate, it is costly and time-consuming to implement, and therefore it is impractical for transportation systems with heavy truck traffic. To overcome the limitations of static weighing, pavement-based WIM technologies have been developed since the 1960’s (Richardson 2014). Pavement-based WIM systems use devices installed on the road to weigh highway vehicles under normal traffic conditions. The common devices used for pavement-based WIM systems include bending plates, load cells, capacitance mats, and strip sensors.

Moses (1979) first proposed the concept of bridge weigh-in-motion (BWIM). Unlike the pavement-based WIM techniques, the BWIM techniques use an instrumented bridge as the weighing scale to estimate the vehicle weights. In Moses’s algorithm, the axle weight is predicted by minimizing the difference between the measured bridge response and the predicted bridge response which is computed using the influence line concept. Moses’s algorithm has been used to establish the basic framework for modern commercial BWIM systems. In the 1980’s, Peters (1984) developed the AXWAY system in Australia. Later, Peters (1986) developed a more effective system known as the CULWAY which uses a culvert as the weighing scale. The reason for using a culvert rather than a bridge is that the dynamic effects caused by the interaction between the vehicle and the culvert can be more quickly dampened out by the surrounding soil. In Europe, the COST 323 action (COST 323 2002) and WAVE project (WAVE 2001) were carried out in the late 1990’s. These projects brought significant improvements to the accuracy of the BWIM techniques and led to the development of a well-known commercial BWIM system known as the SiWIM system. In recent years, much effort has been made to continuously improve the accuracy of the existing algorithms and to develop novel algorithms to extend the applicability of BWIM technologies. Lydon et al. (2015) provided a general review on the BWIM theory and critical issues emerged during the current practice along with detailed case

studies of BWIM applications. The review presented herein will focus more on the technical aspects of the BWIM technology including the fundamental methodologies and the field implementation of BWIM systems.

BWIM systems have several advantages over the pavement-based WIM systems. Firstly, BWIM systems are more durable than pavement-based WIM systems since most sensors in BWIM systems are installed under the bridge, which avoids the direct exposure of sensors to the traffic. Additionally, the installation of BWIM systems is easy and safe as it can be done without interrupting traffic. Furthermore, BWIM systems are more accurate than pavement-based WIM systems. This is because the contact time between vehicle wheels and pavement-based WIM sensors, usually at a few milliseconds, is not sufficient to record a complete cycle of the axle force oscillation. This could easily result in under- or overestimation of the axle weights since the dynamic axle force may significantly deviate from the static weight, especially under a rough surface profile (O’Brien et al. 1999). BWIM systems, on the other hand, record the complete time history of the bridge response, based on which a complete cycle of the varying axle force can usually be obtained. This enables a more accurate calculation of axle weights through proper post-processing. All these advantages have made BWIM systems a superior tool for overweight truck enforcement.

This paper is intended to present a comprehensive review on the BWIM technologies. The BWIM algorithms, which are classified into the static algorithms and the dynamic algorithms, are first reviewed in detail, and different algorithms are compared. Then, the typical instrumentation for a BWIM system is introduced focusing on the sensors for strain measurements and techniques for axle detections. Finally, conclusions are drawn based on the recent advances and suggestions are provided for future research in the field of BWIM technologies.

### 2.2 Bridge Weigh-in-motion Algorithms

Generally speaking, BWIM algorithms can be divided into two broad categories, i.e., the static algorithms that aim at obtaining the static axle weight, and the dynamic algorithms that seek to obtain the time history of axle forces. The static algorithms include the Moses’s algorithm, the influence area method, the reaction force method, and the orthotropic BWIM algorithm. The dynamic algorithms are also known as the moving force identification (MFI) methods.

#### 2.2.1 Moses’s Algorithm

Moses (1979) proposed the first BWIM algorithm for a beam-slab bridge. For this type of bridges, the measured bending moment at time step $k$ can be obtained by summing the individual bending moment of each girder:

$$M_k^{m} = \sum_i^G ES_i \epsilon_i$$  \hspace{1cm} (2-1)
where \( G \) is the total number of girders; \( E \) is the modulus of elasticity; \( S_i \) is the section modulus of the \( i \)th girder; and \( \varepsilon_i \) is the measured strain in the \( i \)th girder. Meanwhile, the predicted bending moment at time step \( k \) can be obtained using the influence line concept as:

\[
M_k^p = \sum_{i=1}^{N} A_i I_{i,(k-C_i)}
\]

(2-2)

\[
C_i = \frac{D_i f}{v}
\]

(2-3)

where \( N \) is the number of axles; \( A_i \) is the weight of the \( i \)th axle; \( I_{i,(k-C_i)} \) is the influence ordinate at the position of the \( i \)th axle; \( D_i \) is the distance between the first axle and \( i \)th axle; \( C_i \) is the number of scans corresponding to \( D_i \); \( f \) is the sampling frequency of the BWIM system; and \( v \) is the vehicle speed which is assumed to be a constant as the vehicle travels on the bridge. The error function for the total number of step \( T \) is defined as:

\[
E = \sum_{k=1}^{T} (M_k^p - M_k^m)^2
\]

(2-4)

To minimize the error function, the least-squares method is used. The partial derivative with respect to the axle weight is set to zero:

\[
\frac{\partial E}{\partial A_j} = 2 \sum_{k=1}^{T} (M_k^p - M_k^m) \frac{\partial (M_k^p - M_k^m)}{\partial A_j} = 0
\]

(2-5)

which leads to the following equation upon rearrangement and substitution:

\[
\sum_{k=1}^{T} \sum_{i=1}^{N} A_i I_{i,(k-C_i)} I_{j,(k-C_j)} = \sum_{k=1}^{T} M_k^m I_{j,(k-C_j)}
\]

(2-6)

Define:

\[
F = [F_{ij}] = \sum_{k=1}^{T} I_{i,(k-C_i)} I_{j,(k-C_j)}
\]

(2-7)

\[
M = [M_{ij}] = \sum_{k=1}^{T} M_k^m I_{j,(k-C_j)}
\]

(2-8)

Eq. (2-6) can then be written in a matrix form as:

\[
FA = M
\]

(2-9)
Thus, the axle weight and gross vehicle weight (GVW) can be calculated as:

\[ A = F^{-1}M \]  
\[ GVW = \sum_{i=1}^{N} A_i \]  

**Accuracy of the Moses’s Algorithm**

The accuracy of the Moses’s algorithm is affected by several factors. The three most significant factors include the dynamic effect of moving vehicles, the transverse position of vehicles, and the condition of the final system equations. First of all, the dynamic effect caused by the moving vehicles reduces the accuracy of the Moses’s algorithm. This is because the Moses’s algorithm determines the axle weights through minimizing the difference between the measured and predicted bridge responses. However, the dynamic effect causes the measured response to deviate from the predicted response obtained using the static influence line and thus reduces the accuracy of the identified axle weights. From this perspective, the Moses’s algorithm usually requires that the bridge surface and approach span be in good conditions if a satisfactory accuracy is desired. Furthermore, the transverse position of the vehicle may also affect the accuracy of the Moses’s algorithm. While the transverse position of the vehicle is not considered in the original Moses’s algorithm, some researchers have found that ignoring the transverse position of the vehicle within the lane will still have an influence on the accuracy. Also, another issue associated with bridges having more than one lane is that there might be multiple vehicles present on the bridge, which makes the identification of individual axle weight very difficult. Accordingly, some researchers proposed two-dimensional (2D) BWIM algorithms on the basis of the Moses’s algorithm to address this issue. Quilligan (2003) proposed a 2D BWIM algorithm as an extension to the Moses’s algorithm. In the 2D algorithm, the influence surface concept is used instead of the influence line. The influence surface represents the load effect caused by a unit concentrated load at position \((x,y)\) and the axle weights can be found by following the same minimization routine as used in the Moses’s algorithm. Theoretically, this would be an ideal solution to account for the effect of the transverse position of vehicles. However, the disadvantage of this algorithm is that it requires an accurate finite-element (FE) model of the bridge, which comes at the cost of complex calculations as well as time-consuming calibrations. Alternatively, some researchers proposed other methods that modified the original Moses’s algorithm without involving the use of influence surface. Znidaric et al. (2012) proposed a sensor strip method as an enhancement to the original Moses’s algorithm. The idea is to separate sensors into groups for each lane, and instead of summing the strains into one value at each time step, the strains are summed within each group to provide extra information on the load distribution of traffic which increases the solvability of the system equations using linear methods. Zhao et al. (2014) proposed a modified 2D Moses’s algorithm. The proposed algorithm considered the spatial behavior of the bridge by incorporating the transverse distribution of the wheel loads on different girders to predict the bridge responses.
Another common problem encountered when implementing the Moses’s algorithm is that the derived system equations are usually ill-conditioned, especially for rough road surface (Rowley et al. 2008) and vehicles with closely spaced axles (O’Brien et al. 2009). In this case, the solution of the axle weights using the least-squares method would be sensitive to the measurement noise. This problem can be resolved by applying the Tikhonov regularization technique (Tikhonov and Arsenin 1977) to provide bounds to the solution. An additional penalty term multiplied by a regularization parameter is added into the original minimization formulation to improve the condition of the original system. The regularization technique was reported to significantly improve the accuracy of the identified axle weights; however, as the vehicle dynamics becomes more noticeable, the convergence of the regularized solution becomes slower (O’Brien et al. 2009).

In addition, it should be mentioned that the accuracy of a WIM system is usually defined in a statistical way by the closeness of a measured value to an accepted reference value, typically within a 95% confidence interval (COST 2002). The readers can refer to COST 323 (COST 2002) for details on the target accuracy levels for different purposes.

Calibration of Influence Lines for BWIM Systems

For the Moses’s algorithm, the accuracy of the influence line is critical for the BWIM system to achieve an accurate identification. When Moses (1979) first proposed the BWIM concept, the theoretical influence line of a simply-supported beam was adopted. However, the theoretical influence line could not accurately predict the real behavior of the bridge. To reduce the errors caused by the difference between the theoretical and true influence lines, Žnidaric and Baumgartner (1998) proposed an improved theoretical influence line by adjusting the support conditions and smoothing the peaks to reach better consistency with the real situation. McNulty and O’Brien (2003) proposed a point-by-point graphical method to generate the influence line. However, this method has to be executed manually, which means that its accuracy relies on the skill of the operator. O’Brien et al. (2006) presented a method to generate the influence line from direct measurements. By using the least-squares method, the error function defined in Eq. (2-4) is minimized with respect to the influence ordinate while the axle weights of the calibration vehicle are already known and thus the measured response of a load effect is converted into the influence line of that effect. This method was verified by field tests and was successfully applied in a BWIM system developed by Zhao et al. (2015). However, it should be mentioned that this method generates the influence line by connecting discrete points instead of producing a smooth curve. In order to generate a continuous influence line, some researchers adopted a polynomial function to describe the influence line and the optimal coefficients of the polynomial function are determined by minimizing the error function (Yamaguchi et al. 2009). Ieng (2015) pointed out that the method proposed by O’Brien et al. (2006) is sensitive to perturbations and revised the method on a probabilistic basis utilizing the maximum likelihood estimation principle. The revised method takes advantage of more signals in the estimation of the influence line and thus reduces the error caused by the noise in a specific signal.
2.2.2 Orthotropic BWIM Algorithm

In the WAVE project (2001), the free-of-axle-detector (FAD) algorithm was initially developed for orthotropic deck bridges since axle detectors were not allowed on the deck surface in order to maintain the waterproofing of the deck. The idea of the FAD algorithm is to identify the vehicle speed and the axle spacing through sensors installed underneath the bridge where the measured signal shows a sharp peak corresponding to each axle passing. For orthotropic deck bridges, the longitudinal stiffeners are usually supported by transverse cross-beams and the supported span is usually short enough so that the strain of the longitudinal stiffeners will show a peak response corresponding to the axle passage, making them suitable for the FAD algorithm. However, it was also realized that axle detection using the FAD algorithm would be less accurate than that using traditional axle detectors. Therefore, a new identification algorithm, known as the orthotropic BWIM algorithm, was proposed (WAVE 2001). This algorithm adopts an optimization routine using the conjugate direction methods to minimize the objective function in the form of Eq. (2-4) and thus finds the best solution of all vehicle parameters including the vehicle speed, axle spacing, and axle weights. The identified parameters from the FAD algorithm, including the vehicle speed and the axle spacing, are used as inputs into the optimization procedure, and thus the new algorithm is less sensitive to the errors in the initially identified values of vehicle speed and axle spacing. However, if the objective function is non-convex, there will be multiple solutions for the vehicle parameters. This would require constraints being applied during the optimization procedure. In the WAVE project (2001), it was found that the vehicle speed cannot exceed five percent of its initial value for the proposed algorithm.

It should be mentioned that the Moses’s algorithm could still be applicable to the orthotropic bridges with some additional post-processing procedures. Xiao et al. (2006) instrumented the longitudinal ribs on an orthotropic box-girder bridge. The response of the longitudinal ribs can be divided into a girder component, i.e., the flexural stress due to the rib acting as the part of the upper flange of the box girder to support the vehicle weight, and a rib component, i.e., the local stress due to the rib acting as a continuous beam to support the wheel load. In the axle weight calculation, the girder component is first separated from the rib component. Then the Moses’s algorithm is applied using the rib component to obtain the axle weights.

From the review of the above algorithms, it can be seen that the identification of axle weights through the static BWIM algorithms is essentially a mathematic optimization problem that seeks to minimize the error function which reflects the difference between the measured bridge response and the bridge response reconstructed using the vehicle parameters. In this sense, any optimization method that is capable of minimizing the error function of the form given by Eq. (2-4) can be used for the BWIM algorithms. In fact, some researchers have proposed using different optimization methods to identify the parameters of vehicles moving on the bridge. Jiang et al. (2004) and Au et al. (2004) proposed a multi-stage optimization scheme based on the genetic algorithm for the vehicle parameter identification using the acceleration responses of the bridge. Law et al. (2006) proposed an optimization method that makes use of the response sensitivity to indirectly identify the vehicle parameters. Deng and Cai (2009) applied the genetic algorithm to identify vehicle parameters in a full-scale three-dimensional (3D) vehicle-bridge system using different responses of the bridge. They found that the vehicle mass can be identified with very
good accuracy while some parameters, such as damping, are difficult to identify due to the measurement noise. Pan and Yu (2014) adopted the firefly algorithm as the optimization scheme to identify the constant moving forces. In addition to optimization methods, Kim et al. (2009) developed a BWIM algorithm based on the artificial neural networks (ANN). The algorithm is formed by two neural networks, i.e., one for the GVW calculation using the signal from the weighing sensors, and the other for the axle weight calculation using the signal from the FAD sensors. The training data were acquired from an adjacent pavement-based WIM station. Field tests found that the developed BWIM algorithm based on the ANN shows similar accuracy with the traditional BWIM algorithm using the influence line concept. Since the proposed ANN algorithm does not require any knowledge of the bridge behavior, it could serve as a potential tool to address the issues faced by the traditional BWIM algorithms, such as the application on long-span bridges and bridges with a rough road surface, and the identification of multiple vehicles.

2.2.3 Influence Area Method

Ojio and Yamada (2002) proposed a method to calculate vehicle weights based on the principle that the area under the response curve can be expressed as the product of the GVW and the area under the influence line, i.e., the influence area. This can be shown by:

\[ A = \int_{-\infty}^{+\infty} \sum_{n=1}^{N} P_n \times IL(x - X_n) dx = \sum_{n=1}^{N} P_n \int_{-\infty}^{+\infty} IL(x) dx = GVW \times \int_{-\infty}^{+\infty} IL(x) dx \]  

where \( A \) is the influence area; \( N \) is the number of axles of the vehicle; \( P_n \) is the axle weight of the \( n \)th axle; \( IL(x) \) is the function of the influence line; \( x \) is the position of the first axle; and \( X_n \) is the distance from the first axle to the \( n \)th axle. The area under the response curve can be obtained by numerically integrating the response of the bridge. Thus, with a calibration vehicle of a known weight, the weight of another vehicle with unknown weight can be obtained by:

\[ GVW = A \frac{GVW_c}{A_c} \]  

where \( GVW \) is the gross vehicle weight of the unknown vehicle; \( A \) is the area under the response curve for the vehicle with the unknown weight; \( A_c \) is the area under the response curve for the calibration truck; and \( GVW_c \) is the gross vehicle weight of the calibration truck. While the implementation of this algorithm is easy and does not require axle detections, one obvious disadvantage is that identifying the weight of individual axles becomes very difficult. Thus, this method is more suitable for cases where the axle weights of the vehicle are not of interest (Cardini and DeWolf 2009).

2.2.4 Reaction Force Method

Ojio and Yamada (2005) proposed a method where the measured reaction force at the support is used to calculate the axle weights. This method utilizes the influence line of the reaction force of a simply-supported bridge. An important feature of such an influence line is that
a sharp edge appears at the beginning of the influence line since the maximum value of the reaction influence line occurs as the unit load first presents on the bridge. The edge can be assumed to be solely contributed by the axle load since it is generated in a very short time. Thus, the axle weights can be calculated from the height of the edge.

The reaction force method is simple and easy to implement. Furthermore, an edge will appear in the signal as each axle of the vehicle enters the bridge and thus it can also be used for the purpose of axle detection. However, this method has not been extensively applied in practice due to the following drawbacks: (1) the reaction force method uses only the peak strain of the response instead of the entire time history of the response and thus the dynamic effect of the axle forces is not accounted for, which, in turn, causes errors in the identified axle weights; (2) the reaction forces are difficult to measure in practice; (3) the method is only applicable to right-angled bridges.

2.2.5 Moving Force Identification

The moving force identification (MFI) method seeks to obtain the complete time history of the vehicle axle forces when a vehicle passes the bridge. The MFI method has the potential to be very accurate in the identification of static axle weights since the complete history of the time-varying forces will allow the dynamic effects of the vehicle to be identified and removed when calculating the static axle weights. The MFI theory has been developed since the 1990’s when several classic MFI methods were proposed including the interpretive method (IM), the time domain method (TDM) and the frequency-time domain method (FTDM):

- **Interpretive Methods**

  O’Connor and Chan (1988) proposed an interpretive method in which the beam is modeled as an assembly of lumped masses interconnected by massless elastic beam elements. The identification process is treated as an inverse problem to the predictive analysis for the beam in which the dynamic responses of the beam are derived as:

  \[
  \{Y\} = [Y_A]\{P\} - [Y_f][\Delta m]\{\dot{Y}\} - [Y_f][C]\{\ddot{Y}\} \tag{2-14}
  \]

  \[
  \{M\} = [M_A]\{P\} - [M_f][\Delta m]\{\dot{Y}\} - [M_f][C]\{\ddot{Y}\} \tag{2-15}
  \]

  where \(\{Y\}\), \(\{\dot{Y}\}\), \(\{\ddot{Y}\}\) and \(\{M\}\) are the vectors for the nodal displacements, velocities, accelerations and bending moments, respectively; \(\{P\}\) is the vector of axle loads; \(\Delta m\) is the diagonal matrix of lumped mass; \([C]\) is the damping matrix; \([Y_A]\) and \([M_A]\) are the matrices in which the \(i\)th column representing the nodal displacements and bending moments caused by a unit load acting at the position of the \(i\)th axle load, respectively; \([Y_f]\) and \([M_f]\) are the nodal displacement matrix and the bending moment matrix, respectively, with their \(i\)th column representing the corresponding response, i.e., displacement or bending moment, caused by a unit load acting at the \(i\)th node. It can be seen from Eq. (2-14) and Eq. (2-15) that once \(\{Y\}\) or \(\{M\}\) is known at any instant, \(\dot{Y}\) and \(\ddot{Y}\) or \(\dot{M}\) and \(\dddot{M}\) can be obtained by using a numerical
differentiation method. Then Eq. (2-14) or Eq. (2-15) becomes an over-determined set of linear simultaneous equations where \( \{P\} \) can be solved using the least-squares method. For the purpose of discussion, this method is referred to as the Interpretive Method I (IMI).

Chan et al. (1999) proposed another interpretive method which uses the Euler’s beam theory instead of the beam-element model. The equation of motion of the Euler-Bernoulli beam can be written as:

\[
\rho \frac{\partial^2 v(x,t)}{\partial t^2} + C \frac{\partial v(x,t)}{\partial t} + EI \frac{\partial^4 v(x,t)}{\partial x^4} = \delta(x-ct)P(t) \tag{2-16}
\]

where \( \rho \) is the mass per unit length; \( v(x,t) \) is the deflection of the beam at position \( x \) and time \( t \); \( C \) is the damping coefficient; \( E \) is the Young’s modulus; \( I \) is the moment of inertia of the cross-section; \( \delta(x-ct) \) is the Dirac delta function; and \( P(t) \) is the axle force moving at a constant speed of \( c \). Using the modal superposition technique, the solution of Eq. (2-16) can be expressed as:

\[
v(x,t) = \sum_{n=1}^{\infty} \frac{n\pi x}{L} q_n(t) \tag{2-17}
\]

where \( q_n(t) \) is the modal displacements for the \( n \)th mode. Substituting Eq. (2-17) into Eq. (2-16) gives:

\[
\ddot{q}_n(t) + 2\xi_n \omega_n \dot{q}_n(t) + \omega_n^2 q_n(t) = \frac{2P(t)}{\rho L} \sin \frac{n\pi x}{L}, \quad (n = 1, 2, ..., \infty) \tag{2-18}
\]

where \( \omega_n \) is the natural frequency for the \( n \)th mode; \( \xi_n \) is the damping ratio for the \( n \)th mode; and \( \pi \) is the distance between the moving force and the left end of the beam, assuming that the force \( P \) is moving from the left to the right. If there are \( k \) moving forces, Eq. (2-18) can be written in matrix form as:

\[
\begin{bmatrix}
\ddot{q}_1 \\
\ddot{q}_2 \\
\vdots \\
\ddot{q}_n \\
\end{bmatrix} + \begin{bmatrix}
2\xi_1 \omega_1 \dot{q}_1 \\
2\xi_2 \omega_2 \dot{q}_2 \\
\vdots \\
2\xi_n \omega_n \dot{q}_n \\
\end{bmatrix} + \begin{bmatrix}
\omega_1^2 q_1 \\
\omega_2^2 q_2 \\
\vdots \\
\omega_n^2 q_n \\
\end{bmatrix} = \begin{bmatrix}
\frac{2P_1(t)}{\rho L} \sin \frac{\pi (ct - \hat{x}_1)}{L} \\
\frac{2P_2(t)}{\rho L} \sin \frac{2\pi (ct - \hat{x}_2)}{L} \\
\vdots \\
\frac{2P_k(t)}{\rho L} \sin \frac{n\pi (ct - \hat{x}_k)}{L} \\
\end{bmatrix} \tag{2-19}
\]
where \( \hat{x}_1 \) is the distance between the \( k \)th axle load and the first axle load.

To obtain the time history of the axle forces, the measured response is first transferred to the modal displacement. Then, the numerical differentiation method is used to obtain the modal velocity and acceleration from the modal displacement. Therefore, Eq. (2-19) again becomes an over-determined set of linear equations where the axle load \( \bar{P}_k \) can be solved using the least-squares method. For the purpose of discussion, this method is referred to as the Interpretive Method II (IMII).

● **Time Domain Method**

Law et al. (1997) developed a system identification method based on the modal superposition principle. In their method, the dynamic deflection can be obtained by solving Eq. (2-16) in the time domain using the convolution integral:

\[
v(x,t) = \sum_{n=1}^{\infty} \frac{2}{\rho L \omega_n'} \sin \left( \frac{n\pi ct}{L} \right) \int_0^t e^{-\xi \omega_n (t - \tau)} \sin \left( \omega' (t - \tau) \right) \sin \left( \frac{n\pi c \tau}{L} \right) P(\tau) d\tau
\]

(2-20)

where \( \omega_n' \) is the damped natural frequency and is equal to \( \omega_n \sqrt{1 - \xi_n^2} \). Since the axle force \( P(t) \) and the deflection \( v(x,t) \) can be treated as step functions in a small time interval, Eq. (2-20) can be written in discrete terms and rearranged into a set of linear equations from which \( P(t) \) can be solved by using the least-squares method in the time domain.

● **Frequency-time Domain Method**

Law and Chan (1999) proposed the frequency-time domain method where Eq. (2-16) is solved in the frequency domain to identify the axle forces. The Fourier transformation of the deflection \( v(x,t) \) can be expressed as:

\[
V(x, \omega) = \sum_{n=1}^{\infty} \frac{2}{\rho L} \sin \left( \frac{n\pi x}{L} \right) H_n(\omega) P(\omega)
\]

(2-21)

\[
H_n(\omega) = \frac{1}{\omega_n^2 - \omega^2 + i2\xi \omega_n \omega}
\]

(2-22)

\[
P_n(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} p_n(t) e^{-i\omega \tau} dt
\]

(2-23)

\[
p_n(t) = P(t) \sin \left( \frac{n\pi ct}{L} \right)
\]

(2-24)

where \( H_n(\omega) \) is the frequency response function of the \( n \)th mode and \( P_n(\omega) \) is the Fourier transformation of the modal force \( p_n(t) \).
Similarly, the real and imaginary parts of $P(\omega)$ can be obtained by solving a set of simultaneous equations in the frequency domain. Then, the time history of the axle force $P(t)$ can be found by performing the inverse Fourier transformation.

It can be seen that for the above MFI methods, the problem eventually becomes solving the linear algebraic equation of the form:

$$Ax = b$$

(2-25)

where $A$ is an $m$-by-$n$ matrix. In the case of MFI problems, $m$ is larger than $n$ and the over-determined set of system equations can be solved by using the least-squares method, leading to:

$$x = A^+ b = [(A^T A)^{-1} A^T] b$$

(2-26)

where $A^+$ denotes the pseudo-inverse (PI) of the matrix $A$ and $x$ is called the PI solution. In order to be able to obtain this PI solution, $A$ needs to have a full rank. However, it was found that sometimes there exists linear dependency in $A$, which would increase the error of the PI solution (O’Connor and Chan 1988). To overcome this problem, the singular value decomposition (SVD) technique can be used to calculate $A^+$. In fact, it has been shown by some studies that using the SVD can significantly improve the accuracy of the identified force history, especially for the FTDM (Yu and Chan 2002; Yu and Chan 2003; Yu and Chan 2007). However, it was still found that the identified results are sensitive to noise and exhibit large fluctuations since the nature of the inverse problem is ill-conditioned. In this case, regularization is necessary to provide bounds to the solution. Many researchers adopted the Tikhonov regularization method and found that the regularization is very effective in reducing the effect of noise on the identification accuracy (Law and Zhu 2000; Zhu and Law 2000; Law and Fang 2001; Zhu and Law 2002a; Law et al. 2004; Deng and Cai 2010). Nevertheless, this method requires finding the optimal regularization parameter using methods such as cross-validation (Golub et al. 1979) and the L-curve method (Hansen 1992), which is usually time-consuming. To resolve this issue, Pinkaew (2006) proposed a regularization method using the updated static component (USC) technique and found that the identification accuracy by using the USC technique is not sensitive to the regularization parameter and that the identification using the USC technique actually provides a better accuracy than the conventional regularization method (Pinkaew 2006; Pinkaew and Asnachinda 2007; Asnachinda et al. 2008).

Following the development of the classic MFI theories, some comparative studies have been conducted to investigate the effectiveness of the four methods under different conditions and the sensitivity of each method to the errors in the vehicle-bridge parameters and the measurement parameters (Chan et al. 2000a; Chan et al. 2001a; Chan et al. 2001b; Zhu and Law 2002b; Yu and Chan 2007). Furthermore, much effort has also been made to improve the accuracy and to extend the applicability of existing MFI algorithms. Zhu and Law (1999) extended the IMII to a continuous bridge which is modeled as a multi-span Timoshenko beam. Chan et al. (2000b) and Chan and Yung (2000) applied the TDM and the IMI in the moving force identification on pre-stressed concrete bridges considering the pre-stressing effect in the beam model. Zhu and Law (2000) extended the TDM to a bridge deck that is modeled as an
orthotropic plate and introduced the Tikhonov regularization to provide bounds to the identified force. Zhu and Law (2001) used the exact solution of the mode shapes considering the rigid support condition for the IMII, which eliminates the modeling errors from the assumed mode shapes. Also, they adopted the generalized orthogonal function to obtain the derivatives of the bridge modal response so as to reduce the errors due to the measurement noise. Zhu and Law (2003) revised the way that the system matrices are calculated in the TDM, which improved the computation efficiency of the method. Zhu and Law (2006) applied the TDM on a multi-span bridge deck that is modeled as an Euler-Bernoulli beam with elastic restraints at the supports. Chan and Ashebo (2006) proposed identifying moving forces on continuous bridges using the TDM by considering the response of only one of the spans. Asnachinda et al. (2008) presented a method to identify multiple vehicles on a continuous bridge based on the FE method where the bridge is modeled as a continuous Euler-Bernoulli beam. Dowling et al. (2012) adopted the Cross Entropy optimization method to infer the material properties required to form the mass and stiffness matrices and thus solved the issue of FE model calibration for the MFI algorithm.

Meanwhile, some novel MFI algorithms have been proposed. Law and Fang (2001) developed a new method for the MFI based on the state-space formulation and dynamic programming which inherently provide bounds to the ill-conditioned force. Law et al. (2004) presented an MFI method based on the FE method and the improved system condensation technique. The error caused by the modal truncation is thus eliminated by expressing the measured displacements as shape functions. Law et al. (2008) introduced a new MFI method based on the wavelet decomposition and FE method. This method requires no assumption on the initial condition of the system. Deng and Cai (2010 and 2011) proposed a new identification method based on the superposition principle and influence surface and adopted a 3D FE model for the bridge used in their studies. Wu and Law (2010) presented a stochastic identification algorithm that can deal with complex random excitation forces with large uncertainties and system parameters with small uncertainties. The algorithm is formed based on the established statistical relationship between the random excitation forces and the structural responses which are assumed to be Gaussian and are represented by the Karhunen-Loève expansion.

Despite the fact that the MFI methods have the potential to be very accurate and ideal for direct enforcement, there are still many challenges to implement the MFI algorithms in the modern commercial BWIM systems. Firstly, the MFI is computationally expensive and thus it may be difficult to achieve the real-time identification of axle weights. Furthermore, most of the previous studies on the MFI are still based on overly simplified bridge models such as simple beams and plates. However, in practice, 3D bridge models must be adopted in order to accurately reflect the behavior of the bridge. The Moses’s algorithm, on the other hand, is simple to implement. As long as certain requirements are met, the accuracy of the Moses’s algorithm can satisfy the requirements for direct enforcement, which makes the Moses’s algorithm the optimal choice for modern commercial BWIM systems. Other static algorithms have distinctive limitations and are thus not suitable for direct enforcement, but they can provide alternatives when the Moses’s algorithm is not suitable.
2.3 Instrumentation of BWIM Systems

An on-site BWIM system usually consists of a data acquisition system, a communication system, a power supply system, and sensors. As an example, Figure 2-1 shows the components of the SiWIM system, a commercially available BWIM system that was originally developed within the framework of the WAVE project (2001) and has been continuously improved and updated over the years. The data collected from the on-site system are processed with software using BWIM algorithms. The results are then presented in a graphic user interface (GUI) that is designed for users to visualize the real-time monitoring data. The following sections will introduce the typical instrumentation of BWIM systems including the types of sensors used in a BWIM system and their installation locations.

Figure 2-1 Components of a SiWIM system: (1) FAD sensors; (2) spider; (3) weighing sensors; (4) cabinet and panel; (5) batteries; (6) solar panels; (7) solar panel installation; (8) antenna; (9) camera; (10) PDA (From Zhao et al. (2014))

2.3.1 Strain Measurement

In a modern BWIM system, the sensors can be divided into two main categories, i.e., the weighing sensors and the axle detecting sensors. Weighing sensors usually measure the global bending strain of the bridge due to the vehicle loading which serves as the main input for the calculation of axle weights, i.e., the measured strain in a certain girder \( \varepsilon_i \) in Eq. (2-1). It should be noted that although the MFI methods allow the displacement and the acceleration responses to be used for axle load identifications as shown in some previous studies (Zhu and Law 2000; Yu and Chan 2003; Deng and Cai 2011), they are challenging to implement and responses such as
displacements are difficult to measure in practice. Therefore, strain responses are the best available information for modern commercial BWIM systems and the selection of an appropriate type of sensors for strain measurements becomes important to ensure the accuracy of the measurement and reliable operation of the system. Common types of sensors used for strain measurements include foil strain gauges, vibrating wire strain gauges, and Fiber Bragg Grating (FBG) sensors. In this section, the applicability of these sensors for BWIM systems will be discussed.

- **Foil Strain Gauges**

  Foil strain gauges have been commonly used for strain measurements. When the measured material is strained, the foil will deform and cause the electrical resistance to change. This change is calibrated to reflect the equivalent change in strain. Foil strain gauges can be attached to the surface of the structural components. They are cheap and have acceptable accuracy, which makes them suitable for experimental tests and short-term measurements. However, they are not suitable for long-term field measurements as in the case of BWIM systems due to their poor durability and susceptibility to electromagnetic interferences and environmental changes.

- **Vibrating Wire Strain Gauges**

  Vibrating wire strain gauges can either be embedded in concrete or mounted on the surface of structural components. It works based on the principle that the change in strain will cause a change of the tension in the wire, which leads to the variation in the resonant frequency of the wire. Vibrating wire strain gauges have good durability, and their installation requires little surface preparation. However, the vibrating wire strain gauge has a low scanning rate, which makes it difficult to record the dynamic response of the bridge if the vehicle travels at a high speed.

- **Fiber Optic Sensors**

  Fiber optic sensors, especially FBG sensors, have become increasingly popular in the field of structural health monitoring. FBG sensors use the relationship between the change of the wavelength in the reflected spectrum and the strain induced by forces or temperature changes to measure the strain. FBG sensors have the following advantages when compared to conventional strain gauges: (1) FBG sensors are immune to electromagnetic interferences, which eliminates the noise from external sources to a certain degree; (2) FBG sensors have good durability, which makes them suitable for long-term measurements; (3) FBG sensors have small sizes and can be multiplexed, which allows easy installation of multiple sensors on large structures. These advantages have made FBG sensors an excellent candidate for BWIM applications. Recent studies have also found that using FBG-based sensors improved the accuracy of the BWIM system overall (Lydon et al. 2014, Lydon et al. 2015).

### 2.3.2 Axle Detection

In a modern BWIM system, axle-detecting sensors are used to identify the presence of vehicle axles from which the speed and axle spacing of the vehicle can be calculated. Axle detection is an indispensable part of the BWIM system since the identified vehicle speed and axle spacing of the vehicle will directly affect the results of the axle weight calculation. The
traditional instruments for axle detection include tape switches and pneumatic tubes. Moses (1979) pointed out that tape switches are easier to be incorporated into the system while the pneumatic tubes require a pressure sensing device to produce the signal of axle passage. The identification of vehicle speed and axle spacing using traditional axle detectors is actually quite simple. Usually, two parallel axle detectors are placed on the road surface where the spacing between the two detectors is measured as an input into the system. In some cases where the transverse location of the vehicle needs to be determined, a third detector is placed diagonally with a known angle corresponding to the other two detectors. Nevertheless, the installation of axle detectors on the pavement usually requires lane closure and the poor durability of sensors also diminishes the advantage of the BWIM systems over the pavement-based WIM systems.

To overcome the problems of the traditional axle detection, the FAD algorithm was first proposed in the WAVE project (2001). The basic idea of the FAD algorithm is to use FAD sensors to replace traditional axle detectors on the road surface. The FAD sensors measure the local strain responses and thus they pick up a sharp peak upon each axle passage above the sensor location. Typically, two FAD sensors are installed at different longitudinal locations on each lane with a known distance. Figure 2-2 shows some typical signals of the FAD sensors, which were recorded when a five-axle truck passed through the bridge (Zhao et al. 2014). It can be seen that each FAD sensor picked up five peaks corresponding to the five axles. However, it should be mentioned that clear peaks in the strain signal might not occur if the wheel load is directly applied over the beam (Lydon et al. 2015). In practice, a correlation function is usually used to calculate the vehicle speed. The correlation function is defined as:

$$Corr(t) = \int_{-\infty}^{+\infty} f(\tau)g(t+\tau)d\tau$$

(2-27)

where $f(t)$ and $g(t)$ are the signals of the FAD sensors at two longitudinal locations, respectively. To calculate the vehicle speed, the time taken by the vehicle to pass the known distance between the two sensors is needed. From Eq. (2-27), it can be seen that the correlation function will reach the maximum value when $f(t)$ and $g(t+\tau)$ both reach the maxima, i.e., picking up the peak corresponding to the same vehicle axle. Since the time difference between $f(t)$ and $g(t+\tau)$ is $t$, the time difference $t_0$ that gives the maximum value of the correlation function is the time taken by the same vehicle axle to pass the known distance between the two FAD sensors and then the vehicle speed can be easily calculated by using the known distance and the time difference $t_0$. Once the vehicle speed is known, the axle spacing can be obtained by using the time difference between the peaks in the FAD signals (Kalin et al. 2006).

Although the FAD algorithm resolves the durability problem of the traditional axle detectors, it still requires additional sensors, i.e., the FAD sensors, only for the purpose of axle detection. Furthermore, the FAD algorithm imposes certain restrictions upon the span length and superstructure thickness of the selected bridge. Namely, the FAD algorithm is not applicable to all types of bridges. As a general rule of thumb, the bridges suitable for the FAD algorithm should have the following: (1) a short span or relatively longer span but with transverse supports, i.e., secondary members such as transverse cross-beams or stiffeners, to divide the bridge into sub-spans because longer spans will have joint contributions of several axles that make it
difficult to distinguish individual axles; (2) a thin superstructure because a thick superstructure will “smear” the peaks induced by the vehicle axles; (3) a smooth road surface and approach span since a rough surface condition will cause significant dynamic effects which impose additional peaks into the signal (WAVE 2001; Kalin et al. 2006). The types of bridges that have already been identified as suitable for the FAD algorithm include orthotropic deck bridges, short integral bridges with thin slabs (usually six to twelve meters long with the slab thickness between forty to sixty centimeters), and beam-slab bridges with secondary members (WAVE 2001).

![Graph showing FAD signals](image)

Figure 2-2 Typical FAD signals of a five-axle truck crossing (From Zhao et al. (2014))

Recently, the concept of a nothing-on-road (NOR) BWIM system was proposed. The goal of the NOR BWIM system is to free the use of axle detectors on the road surface. While the FAD algorithm is one application of the NOR BWIM, a more effective way is to directly employ the global strain signal obtained from the weighing sensors to identify the vehicle speed and axle spacing. This will be a very attractive feature for future commercial BWIM systems since it reduces the number of sensors required and thus the cost of the system, making the installation even easier. Besides, it does not impose any restriction on the selection of bridges, which helps extend the application of BWIM technologies. However, direct identification from the global strain signal is very difficult since it usually does not have a sharp peak upon each axle passage. Nevertheless, it has been shown by some researchers that the identification can be achieved through proper signal processing techniques such as a wavelet-based analysis, which are suitable to treat non-stationary signals. Dunne et al. (2005) first proposed using wavelet transformation to identify closely-spaced axles from the FAD signals. Chatterjee et al. (2006) conducted field testing on a culvert and adopted the wavelet transformation to analyze the strain signal obtained from vehicle crossing. The results show that the wavelet techniques can help identify closely-spaced axles within a tandem or tridem group which could not be directly identified from the FAD signal and reveal the potential of using the wavelet techniques to identify vehicle axles.
from the strain signal of weighing sensors. Yu et al. (2015) proposed a vehicle axle identification method based on the wavelet transformation of the global signal. The numerical results showed that this method could provide accurate identification of vehicle axles using only the weighing sensors.

In addition, some other methods for axle detections have also been reported. Some researchers found that crack openings on the bottom of the concrete slabs are sensitive to axle loads and thus they measured the changes in the widths of existing cracks to detect the vehicle axles (Matui and El-Hakim 1989; Lechner et al. 2010). However, this method cannot be generalized since it is only applicable to bridges with crack openings. Wall et al. (2009) adopted an approach where the change of slope induced by the axle passage is used for the axle identification. In an ideal setting, the passage of each axle will have a corresponding impulse in the second derivative of the strain signal. However, in practice, this approach requires the strain signal to have evident slope discontinuities; in other words, the strain signal must show a certain level of sensitivity to the vehicle axles. Also, as these slope discontinuities are only subtle changes, this approach may no longer be feasible once the measurement noise is introduced in practice. O’Brien et al. (2012) proposed a novel axle detection strategy using shear strain sensors based on the assumption that each axle passage will induce a sudden change of the shear strain. Preliminary FE analyses were carried out on a beam-slab bridge, and the interface of the web and the flange was recommended for the sensor locations. Further work was planned in order to assess the feasibility of this novel axle detection method. With the recent advances in the image processing technologies, the identification of the vehicle axle configuration has been made possible through proper image analysis algorithms and thus a vision-based system utilizing a roadside camera was proposed by some researchers as a potential tool for the axle detection (Caprani et al. 2013; Ojio et al. 2016).

2.3.3 Installation Location of Sensors

The sensor installation locations should account for several factors including the function of sensors, types of bridges, strain levels, sensitivity to strain variations, etc. In this section, the sensor installation locations will be discussed with respect to the two most important factors, i.e., the function of sensors and types of bridges chosen for installation. In addition, a case study with specific sensor layouts on a typical beam-slab bridge is also presented.

Function of Sensors

Weighing sensors measure the global bending strain caused by vehicle loads and thus they are usually installed at locations of the most pronounced responses, e.g., the mid-span of the bridge. Nevertheless, it is interesting to note that other installation locations have also been reported for weighing sensors. For example, in the reaction force method proposed by Ojio and Yamada (2005), the weighing sensors were attached to the end vertical stiffeners above the supports of a steel plate girder bridge to measure the strain for the bearing. For complex bridge structures, the locations of weighing sensors can be determined by a preliminary FE analysis. As for axle-detecting sensors, both the traditional axle detection and the FAD algorithm require two parallel lines of sensors to be installed at a known distance. However, the differences are the following: (1) the traditional axle-detecting sensors are installed on the road surface while the FAD sensors are installed underneath the bridge; (2) the traditional axle-detecting sensors can be
installed at almost any location on the bridge; however, the selection of the installation locations for the FAD sensors depends on the shape of the influence line since the influence line at the location of installation needs to present a sharp peak in order for the axle identification.

- **Type of Bridges**

The sensitivity of strain responses to axle loads differs between different bridge types and different measurement locations on a certain bridge, thus the specific plan of sensor layouts for each bridge should be determined on a case-by-case basis. Nevertheless, based on the existing BWIM practices, the general schemes of sensor layouts for some typical bridges are summarized and shown in Table 2-1. It should be mentioned that the reason for requiring only one line of axle-detecting sensors in orthotropic deck bridges is that the installed weighing sensors also pick up sharp peaks corresponding to the axle passage, namely, the weighing sensors in this case also serve the purpose of axle detection.

In addition, Brown (2011) studied the influence of different installation schemes of FAD sensors on the accuracy of axle detections including the longitudinal and transverse locations, and installation angles. Based on the signals obtained from a T-beam reinforced concrete bridge, it was concluded that FAD sensors should be orientated longitudinally and installed close to the beginning or the end of the bridge span, ideally directly below the wheel path, in order to obtain a clear signal with sharp peaks. The reason for choosing the beginning or the end of the bridge span is that the bridge is stiffer at these locations, and thus more definite peaks can be produced. The dynamic effects at these stiffer locations are also less pronounced, which leads to a cleaner signal. Furthermore, the study also shows that, compared to longitudinally orientated sensors, transversely orientated sensors provide poor signals for axle detection. Besides, it was also found that weighing sensors do not have to be installed exactly at the mid-span since any location near the mid-span can provide an adequate strain level for weighing purposes.

<table>
<thead>
<tr>
<th>Type of bridges</th>
<th>Location of weighing sensors</th>
<th>Location of axle-detecting sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Orthotropic deck bridges</td>
<td>Bottom of longitudinal stiffener</td>
<td>One line of sensors at a section away from the mid-span</td>
</tr>
<tr>
<td>Integral slab bridges</td>
<td>Mid-span</td>
<td>Bottom of the slab</td>
</tr>
<tr>
<td>Beam-slab bridges</td>
<td>Bottom of the girder</td>
<td></td>
</tr>
</tbody>
</table>

- **Case Study**

In order to give a better illustration on the sensor installation of the BWIM system, a case study is presented here. The case study is chosen from a recent BWIM practice conducted by Zhao et al. (2014) in Alabama. The instrumented bridge is a three-span simply-supported concrete multi-girder bridge. The three spans have an equal length of 12.8 m, and the first span was chosen for the installation of the BWIM system. The reasons for selecting this bridge are as
follows: (1) the bridge has a short span and thin superstructure, suggesting that it is suitable for the implementation of the FAD algorithm; (2) the short span has higher natural frequencies to avoid matching the natural and pseudo frequencies of the vehicle and thus reduces the dynamic effect of the moving vehicles; (3) the bridge has a smooth approach and a good surface condition, which again helps minimize the dynamic effect.

For the sensor installations, a total of four weighing sensors were installed in a parallel manner underneath the girders (one for each girder), and a total of four FAD sensors were mounted beneath the concrete slab (two for each lane). The specific sensor layouts are presented in Figure 2-3. It should be noted that the sensors are not installed exactly at the mid-span because of the diaphragm.

![Figure 2-3 Sensor layouts of a typical BWIM system (unit in cm) (From Zhao et al. (2014))](attachment://Figure_2-3.png)
2.3.4 Data Acquisition and Storage

In a BWIM system, the collection of raw data from the sensors is achieved through an on-site data acquisition system. The sensors communicate with the data acquisition system by wired or wireless connections. The core of a data acquisition system is a well-designed algorithm of data sampling and recording. Based on the Nyquist-Shannon sampling theorem, it is suggested that the sampling frequency for the data collection be at least twice the maximum vibration frequency of interest so as to prevent the folding and aliasing problems when digitizing the data (Paultre et al. 1995). In practice, the sampling frequency may be higher and an anti-aliasing filter may be necessary as well. However, the sampling frequency should not be too high as this will result in a huge volume of data being stored. Nevertheless, in terms of long-term monitoring, the amount of produced data will still be enormous. This problem can be resolved by establishing an event-triggering mechanism, i.e., the strain data will only be recorded and stored when a critical event, which is defined as a truck with a certain weight that is larger than the minimum weight of interest passes through the bridge. This can be done by setting a lower limit for the sensor and the value of the lower limit is determined by the maximum response caused by the load corresponding to the minimum truck weight. In this case, only those critical events under which the bridge responses equal or exceed the lower limit will be recorded, and thus the amount of stored data will be significantly reduced.

2.4 Conclusions

This paper presents a comprehensive review on the state of the art bridge weigh-in-motion technologies from two important perspectives, i.e., the BWIM algorithms and instrumentation of BWIM systems. On the basis of recent developments achieved in the field, the following conclusions can be drawn and remarks can be made:

(1) The BWIM technique has significant advantages over the pavement-based WIM technique. BWIM systems are more durable, and their installations are also easier and safer. Moreover, BWIM systems are potentially more accurate than pavement-based WIM systems;

(2) The static BWIM algorithms include the Moses’s algorithm, the influence area method, the reaction force method, and the orthotropic BWIM algorithm. Although the accuracy of the Moses’s algorithm depends on several factors, it is straightforward and relatively simple to implement. The influence area method can be used to estimate the gross vehicle weight; however, it is difficult to identify the weight of individual axles. The reaction force method is simple to implement; however, some drawbacks have limited its extensive applications. The orthotropic BWIM algorithm employs a different optimization scheme and can serve as an alternative to the Moses’s algorithm in some cases;

(3) The moving force identification methods, i.e., the dynamic BWIM algorithms, have the potential to be very accurate. However, they also have distinctive drawbacks when compared to the static BWIM algorithms, including expensive computation and requiring detailed FE model of the bridge. Besides, most of the current MFI theories are still based
on simple bridge models. These disadvantages have made it difficult to implement the MFI algorithms in modern commercial BWIM systems;

(4) In a modern BWIM system, weighing sensors are used to measure the global strain responses of the bridge. Of all the candidates for weighing sensors, FBG sensors are considered the most suitable for the BWIM application since FBG sensors have many advantages over the traditional strain gauges such as the ease of installation, capability of multiplexing, good durability, and electromagnetic immunity;

(5) The traditional axle detectors have been gradually replaced by the FAD sensors in the modern BWIM systems. The FAD algorithm utilizes the sharp peaks in the local strain responses measured by FAD sensors to identify the axle presence. Nevertheless, a more effective approach to achieve the NOR BWIM is to identify vehicle axles from the signals of weighing sensors through the use of well-chosen signal processing techniques. The implementation of such an axle identification scheme would further simplify the installation and reduce the cost of BWIM systems.

Through the review of the recent developments of BWIM technologies, the following issues are identified and corresponding suggestions for the future research are tentatively proposed:

(a) The application of BWIM techniques on long bridges has rarely been studied. This is because: (1) the possibility of multiple-vehicle presence, which is difficult to identify, increases in long bridges; (2) longer bridges have lower natural frequencies that are more likely to match the vehicle frequencies and thus increase the dynamic effect; (3) the speed of the vehicle is more likely to change during the crossing on long bridges; (4) it is easier to identify closely-spaced axles in shorter bridges (WAVE 2001). To overcome these difficulties and achieve the implementation of BWIM systems on long bridges, future research may refer to unconventional methods such as a neural network as a possible alternative to the traditional BWIM algorithms whose accuracies are susceptible to the occurrence of multiple vehicle presence and significant dynamic effects caused by either a rough road surface or the frequency matching between the vehicle and bridge;

(b) Even though the MFI methods have the potential to be very accurate, it is still not fully ready to be implemented in the modern commercial BWIM systems. This is because: (1) the MFI algorithms are computationally demanding, which makes it difficult to achieve the real-time identification of vehicle parameters; (2) the MFI algorithms require an accurate FE model of the bridge that is usually difficult to obtain; (3) most of the proposed MFI algorithms are still based on simple 2D beam models that may not be able to accurately represent the real behavior of bridges. Nevertheless, the MFI is still considered to be a very promising algorithm for future commercial BWIM systems. Thus, future research should focus on employing optimization and condensation methods to reduce the calculation efforts and extending the current MFI theories to 3D bridge models;

(c) Although the current practice of the FAD algorithm has been proven to be successful on certain types of bridges, it still requires additional FAD sensors to identify the vehicle
axles and the algorithm also imposes restrictions on the selection of bridges, which limit its applications. Naturally, a more advanced method of achieving the NOR BWIM is to identify all vehicle parameters from the weighing sensors. This will be considered as a very attractive feature in the future development of commercial BWIM systems. Nevertheless, current studies on this topic are still limited and are based on simple bridge models. More research should be conducted to explore the effectiveness of identifying vehicle speed and axle spacing from the strain signals of weighing sensors and to extend the identification algorithm to more complex bridge structures;

(d) The information extracted from BWIM systems can also be used for the purpose of structural health monitoring (SHM) or vice versa. There have been some recent investigations on the use of BWIM systems for damage detection (Carey et al. 2013; Cantero and González 2015; Cantero et al. 2015; Zhu and Law 2015) and determination of dynamic amplification factors (O’Brien et al. 2013; Zhao and Uddin 2014). In the future, more research can be focused on incorporating BWIM technologies into the SHM systems to further extend their applications and reduce the cost of SHM systems.

2.5 References


CHAPTER 3. VEHICLE AXLE IDENTIFICATION USING WAVELET ANALYSIS OF BRIDGE GLOBAL RESPONSES*

3.1 Introduction

Bridge weigh-in-motion (BWIM) is a recently developed technology that aims at identifying vehicle weights using an instrumented bridge as the weighing scale. Compared to the traditional pavement-based WIM techniques, the BWIM technique has several advantages: (1) A BWIM system is more durable than a pavement-based WIM system since most sensors are not directly exposed to traffic; (2) the installation of a BWIM system is easy and safe as it can be done without interrupting the traffic; (3) a BWIM system is potentially more accurate than a pavement-based WIM system since it records the complete time history of the bridge response (O’Brien et al. 1999). These advantages have made the BWIM systems a cost-effective alternative to the pavement-based WIM systems and a potential tool for truck overweight enforcement.

Axle detection is an indispensable part of the BWIM systems. In traditional BWIM systems, the sensors can be classified into two types, i.e., the weighing sensors and axle detectors. The weighing sensors measure the bridge global responses, usually in terms of bending strains, due to the vehicle loading and thus they are usually installed at locations of most pronounced responses, e.g., the mid-span of the bridge. Axle detectors are typically placed on the road surface to identify the vehicle speed and axle spacing which are then used as inputs to the BWIM algorithm to calculate axle weights (Moses 1979). While the method using axle detectors is very accurate, the durability of the detectors becomes a concern. In an effort to address this concern, a free-of-axle-detector (FAD) algorithm was developed in the WAVE project (WAVE 2001). The concept of the FAD algorithm is to replace the traditional axle detectors on the road surface by placing the FAD sensors underneath the bridge to measure the bridge local responses. An important feature of the FAD sensors is that they show a sharp peak when an axle is present above the sensor location. The application of the FAD algorithm eliminates the use of axle detectors that have poor durability. However, it still requires the FAD sensors solely for the purpose of identifying the vehicle velocity and axle spacing. Also, the FAD algorithm is not applicable to all types of bridges as it imposes certain restrictions, such as thin superstructure, short span, etc. (WAVE 2001).

Recently, the concept of a nothing-on-road (NOR) BWIM system was proposed (WAVE 2001). The goal of the NOR BWIM is to free the use of axle detectors as well as FAD sensors and to directly employ the strain signal obtained from weighing sensors to identify the vehicle speed and axle spacing. This will be a very attractive feature for commercial BWIM systems since it reduces the number of sensors and thus the cost of the system, making the installation even easier. However, the strain signal of weighing sensors corresponds to the global response of the bridge, which means that a direct identification from the signal would be very difficult.

Therefore, a proper signal processing technique needs to be employed to extract the axle information from the strain signal.

Wavelet analysis is a recently developed technique that provides a powerful tool to solve many difficult engineering problems. This exciting new method has been applied to many fields such as signal processing, data compression, computer graphics, etc. Nevertheless, the study on the use of wavelet analysis in the identification of vehicle axles has been very limited. Dunne et al. (2005) first proposed using wavelet transformation to identify closely-spaced axles from the FAD signals. Chatterjee et al. (2006) conducted a further study to explore the possibility of using wavelet transformation of the strain signal to identify the vehicle axles. In their study, a numerical simulation was carried out on a simply supported beam and field testing was conducted on a short box culvert. The results showed that wavelet analysis is able to identify the vehicle velocity and axle spacing with a reasonable accuracy. However, the beam model seems overly simple to accurately represent the behavior of the bridge. Moreover, the box culvert used in their study is a very simple structure and it has been reported that for these types of structures, the dynamic effect caused by a vehicle is basically negligible (Quilligan 2003). Besides, in their field test, the obtained strain signals already have relatively sharp peaks corresponding to some axles due to the fact that the instrumented superstructure is very thin. Thus, the identification was actually achieved through the wavelet analysis of bridge local responses rather than the global responses.

The objective of this paper is to employ the wavelet technique to identify vehicle axles from the signals of weighing sensors, i.e., the bridge global responses, which give no direct information with respect to the vehicle axles. A brief introduction on the wavelet theory is first given. Numerical simulations are then carried out on a multi-girder bridge with different trucks traveling at different speeds and a continuous wavelet transformation is then used to extract the information of vehicle axles from the bridge global responses. A parametric study is finally conducted to investigate the effect of several parameters including the sampling frequency, road surface condition and measurement noise on the identification accuracy.

3.2 Wavelet Theory

Fourier analysis allows the frequency information being extracted from the signal presented in the time domain. However, the time information is lost during the Fourier transformation (FT), i.e., it gives no information on the time occurrence of certain frequency components of the signal. In this sense, Fourier analysis is only suitable for stationary signals or cases where the time information is not of interest. To overcome this drawback, short-time Fourier analysis (STFT) was proposed (Gabor 1946). The idea of the STFT is to divide the signal into many intervals and the signal in each small interval is assumed to be stationary. In this case, FT can be carried out at each time interval and a time-frequency representation of the signal can be obtained. However, the STFT is still not the perfect solution to analyze non-stationary signals since it has a fixed resolution, i.e., a satisfactory resolution with respect to both time and frequency cannot be achieved at the same time. Wavelet transformation was then developed on this basis to provide a multi-resolution analysis of the signal. The purpose of the wavelet transformation is to expand the signal in terms of wavelets which are generated from the transformations, including dilations and translations, of the wavelet function, i.e., a compactly
supported function that is also known as the mother wavelet. An important feature of the wavelet transformation is that the width of the window can be changed to adapt to different frequency components of the signal. Therefore, wavelet analysis is very effective in analyzing non-stationary signals.

The continuous wavelet transformation (CWT) of a signal is defined as:

\[
W_\psi(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(t)\psi\left(\frac{t-b}{a}\right)dt
\] (3-1)

where \(a\) is the scaling factor; \(b\) is the shifting factor; \(s(t)\) is the signal as a function of time; and \(\psi(t)\) is the so-called mother wavelet that must satisfy the following criterion:

\[
\int_{-\infty}^{\infty} \left| \hat{\psi}(\omega) \right|^2 d\omega < \infty
\] (3-2)

where \(\hat{\psi}(\omega)\) is the Fourier transformation of \(\psi(t)\). This is known as the admissibility condition which implies \(\hat{\psi}(0) = 0\). If we define \(\psi_{a,b}(t)\) as:

\[
\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right)
\] (3-3)

then Eq. (3-1) can be rewritten as the inner product of the signal \(s(t)\) and \(\psi_{a,b}(t)\) as:

\[
W_\psi(a, b) = \int_{-\infty}^{\infty} s(t)\psi_{a,b}(t)dt
\] (3-4)

In terms of the application in the identification of vehicle axles, the presence or absence of a vehicle axle will cause a sudden change of the slope of the strain signal. While this abrupt change is very difficult to directly observe, a wavelet analysis may be able to amplify these slope discontinuities in the form of sharp peaks in the transformed signal. In the present study, the Morlet wavelet is used to conduct the CWT after comparing the performance with several alternatives such as the reverse biorthogonal wavelets and Daubechies wavelets. The Morlet wavelet can be considered as a modulated Gaussian wave formation. It has a good locality property in both the time and frequency domains. Technically, the Morlet wavelet is complex-valued. However, in many applications, only the real part is used. The complex version is more well-known as the Gabor wavelet. A figure representation of the Morlet wavelet used in this study is shown in Figure 3-1 and the wavelet function is given as:

\[
\psi(t) = e^{-\frac{t^2}{2}} \cos(5t)
\] (3-5)
3.3 Numerical Simulations

3.3.1 Bridge Model

In the present study, a simply-supported multi-girder concrete bridge was adopted for the simulation. As a good representative of highway bridges, the selected bridge was designed according to AASHTO standard specification (AASHTO 2002) and the bridge span length is 24.38 meters (80 ft). The bridge has a uniform cross-section consisting of five identical I-girders and three diaphragms located at the two ends and middle. The cross-section of the bridge is shown in Figure 3-2. The bridge was modeled with the ANSYS software using solid elements (with three translational degrees-of-freedom at each node) to predict the fundamental dynamic characteristics including the natural frequencies and mode shapes. Figure 3-3 shows the finite element model of the bridge. The fundamental frequency of the bridge was found to be 3.46 Hz.
3.3.2 Vehicle Model

In this study, four typical highway trucks with different axle configurations as listed in Table 3-1 were employed. In the numerical simulation, the truck was modeled using spring-dashpot systems. The vehicle bodies (tractor and trailer) were represented by rigid bodies with mass and three DOFs, i.e., the vertical displacement, pitching rotation, and rolling rotation. The connection between the tractor and trailer is modeled as a pinned connection, i.e., the tractor and trailer have equal vertical displacement at the connection. Each wheel was represented by a lumped mass with one DOF, i.e., the vertical displacement. An analytical model of Truck 2 is shown in Figure 3-4.

Table 3-1 Axle configurations of truck models

<table>
<thead>
<tr>
<th>Truck Number</th>
<th>Number of axles</th>
<th>Axle spacing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>First to second</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Second to third</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Third to fourth</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Fourth to fifth</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>6.25</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>4.27</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>4.94</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>8.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>N.A.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.40</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>N.A.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>N.A.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>N.A.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5.00</td>
</tr>
</tbody>
</table>
3.3.3 Vehicle-bridge Interaction

The interaction between the bridge and vehicle can be solved by either an iterative procedure (Broquet et al., 2004) or a coupled approach (Deng and Cai, 2010). In this study, the coupled approach was used. The equations of motion for the vehicle and bridge can be written in matrix forms as:

\[
[M_v] \{ \ddot{d}_v \} + [C_v] \{ \dot{d}_v \} + [K_v] \{ d_v \} = \{ F_v \} + \{ F_G \} = [M_b] \{ \ddot{d}_b \} + [C_b] \{ \dot{d}_b \} + [K_b] \{ d_b \} = \{ F_b \}
\] (3-6)
(3-7)

where \([M_v], [C_v], [K_v]\) = the mass, damping, and stiffness matrices of the vehicle, respectively; \([M_b], [C_b], [K_b]\) = the mass, damping, and stiffness matrices of the bridge, respectively; \(\{d_v\}\) and \(\{d_b\}\) = the displacement vector of the vehicle and bridge, respectively; \(\{F_G\}\) = the gravity force vector of the vehicle; and \(\{F_v\}\) and \(\{F_b\}\) = the wheel-road contact force vectors acting on the vehicle and bridge, respectively, and they can be expressed as:

\[
\{ F_v \} = -\{ F_b \} = [K_l] \{ \Delta_l \} + [C_l] \{ \dot{\Delta}_l \}
\] (3-8)

where \([K_l]\) and \([C_l]\) = coefficients of the vehicle lower spring and damper, respectively; \(\Delta_l\) is the deformation of the lower spring of the vehicle which can be obtained from the displacement relationship:

\[
Z_a = Z_b + \Delta_l + r(x)
\] (3-9)

where \(Z_a\) is the vehicle axle suspension displacement; \(Z_b\) is displacement of the bridge at the wheel-road contact point; and \(r(x)\) is the road surface elevation as a function of the vehicle position.

Based on the interaction force relationship and displacement relationship at the contact points, namely, Eq. (3-8) and Eq. (3-9), the two equations of motion for the vehicle and bridge can be combined into one coupled equation:
\[
\begin{bmatrix}
M_b & K_b + K_{b-b} & K_{b-v} & d_b \\
C_{v-b} & C_v & F_{b-r} & \{F_{b-r}\}
\end{bmatrix}
\begin{bmatrix}
\ddot{d}_b \\
\ddot{d}_v
\end{bmatrix} = \begin{bmatrix}
M_v & 0 \\
0 & \omega_i^2
\end{bmatrix}
\begin{bmatrix}
\dot{d}_b \\
\dot{d}_v
\end{bmatrix} + \begin{bmatrix}
C_{b-b} & C_{b-v} \\
K_{b-b} & K_{b-v}
\end{bmatrix}
\begin{bmatrix}
\dot{d}_b \\
\dot{d}_v
\end{bmatrix} + \begin{bmatrix}
\Phi_b^T F_{b-r} \\
\Phi_v^T F_{b-r}
\end{bmatrix} = \begin{bmatrix}
F_{b-r} \\
F_{v-r} + F_G
\end{bmatrix}
\]

(3-10)

where \( C_{b-b}, C_{b-v}, C_{v-b}, K_{b-b}, K_{b-v}, K_{v-b}, F_{b-r}, \) and \( F_{b-r} \) are the interaction terms caused by the contact forces. As the vehicle moves across the bridge, the positions of contact points change and so do the contact forces. Thus, the interaction terms are time-dependent terms and will change as the vehicle moves across the bridge.

In order to reduce the size of the matrices and save calculation efforts, the modal superposition technique was adopted and the bridge displacement vector \( \{d_b\} \) in Eq. (3-10) can therefore be expressed as:

\[
\{d_b\} = \left[ \{\Phi_1\}, \{\Phi_2\}, \ldots, \{\Phi_m\} \right] \{\xi_1, \xi_2, \ldots, \xi_m\} = [\Phi_b] \{\xi_b\}
\]

(3-11)

where \( m \) = the total number of modes considered for the bridge; \( \{\Phi_i\} \) and \( \xi_i \) = the \( i \)th mode shape of the bridge and the \( i \)th generalized modal coordinate, respectively. If each mode shape is normalized such that \( \{\Phi_i\}^T [M_b] \{\Phi_i\} = 1 \) and \( \{\Phi_i\}^T [K_b] \{\Phi_i\} = \omega_i^2 \) and the damping matrix \( [C_b] \) in Eq. (3-7) is assumed to be equal to \( 2\omega_i\eta_i[M_b] \), where \( \omega_i \) and \( \eta_i \) = the natural circular frequency and the percentage of the critical damping of the \( i \)th mode of the bridge, respectively, then Eq. (3-10) can be simplified as:

\[
\begin{bmatrix}
I & 2\omega_i\eta_i I + \Phi_b^T C_{b-b} \Phi_b & \Phi_b^T C_{b-v} \\
M_v & \omega_i^2 I + \Phi_b^T K_{b-b} \Phi_b & \Phi_b^T K_{b-v} \\
0 & K_{v-b} \Phi_b & K_v
\end{bmatrix}
\begin{bmatrix}
\dot{d}_b \\
\dot{d}_v \\
\dot{d}_v
\end{bmatrix} = \begin{bmatrix}
\Phi_b^T F_{b-r} \\
\Phi_v^T F_{b-r}
\end{bmatrix} = \begin{bmatrix}
F_{b-r} \\
F_{v-r} + F_G
\end{bmatrix}
\]

(3-12)

The coupled Eq. (3-12) contains only the modal properties of the bridge and the mechanical parameters of the vehicles. As a result, the complexity of solving the coupled equations was significantly reduced. A computer program was developed in the MATLAB environment to solve Eq. (3-12) in the time domain using the fourth-order Runge-Kutta method.

After obtaining the displacement responses of the bridge \( \{d_b\} \), the strain responses can be obtained through:

\[
\{\varepsilon\} = [B] \{d_b\}
\]

(3-13)

where \([B]\) = the strain-displacement relationship matrix assembled with the x, y, and z derivatives of the element shape functions. The \([B]\) matrix depends on the type of finite elements employed and can be derived following the standard finite element formulation procedure.
3.3.4 Simulation Results

In the numerical simulation, each of the four highway trucks are set to cross the bridge at three constant speeds, i.e., 10 m/s, 20 m/s and 30 m/s in lane 2 and Figure 3-5 shows the transverse position of the vehicle on the bridge. In a commercial BWIM system, five weighing sensors would be installed underneath the five girders at the mid-span to measure the global responses of the bridge, i.e., longitudinal strain responses, and at least four FAD sensors (two for each lane) would be installed underneath the bridge slab to identify the vehicle axles. In this study, as an attempt to achieve the NOR BWIM without FAD sensors, the strain signal of the weighing sensor installed on the girder directly beneath the vehicle trajectory, i.e., Girder 4, is used for the axle identification.

![Figure 3-5 Transverse position of the vehicle on the bridge](image)

Figure 3-6 shows the typical time histories of the strain response of Girder 4 corresponding to Trucks 2 and 4 traveling at 20 m/s and 10 m/s under a smooth road surface, respectively. A sampling frequency of 200 Hz is used. From the strain response histories, it can be seen that there is no obvious information on the presence of vehicle axles. This is understandable since the longitudinal strain responses of girders are the global responses of the bridge and they are not sensitive to the presence of axle loads. Nevertheless, as discussed before, the details of the original strain signals still contain the information of vehicle axles. Therefore, a CWT is conducted on the strain signals and the results are presented in Figure 3-6. The plotted wavelet coefficients are chosen at the scale of 14. As can be seen, the transformed signals have several pronounced peaks. These sharp peaks correspond to vehicle axles entering or exiting the bridge. For the three-axle truck, i.e., Truck 2, the first three peaks correspond to the three axles entering the bridge and the last three peaks correspond to the three axles exiting the bridge. Again, the same feature was also observed for the transformed signal for Truck 4, i.e., the five-axle truck.

Since the span length of the bridge is already known, the vehicle speed can be calculated from the time difference between each vehicle axle entering and exiting the bridge. Once the vehicle speed is known, the time difference between vehicle axles can be used to obtain the axle spacing of the truck. For the signals shown in Figure 3-6, the velocity and two axle spacings of Truck 2 were calculated as 19.85 m/s, 4.22 m and 4.27 m, respectively, and the velocity and four axle spacings of Truck 4 were calculated as 9.92 m/s, 7.96 m, 4.94 m, 1.99 m and 4.94 m,
respectively. Compared to the true values given in Table 3-1, the identified results are found to be very accurate.

The identification results for all considered cases are tabulated in Table 3-2. To better examine the accuracy of identification, the identification error is defined as:

\[
\text{Identification Error} = \left| \frac{P_{iden} - P_{true}}{P_{true}} \right| \times 100\% \tag{3-14}
\]

where \(P_{iden}\) and \(P_{true}\) are the identified parameter and the true parameter, respectively. Using this definition, the identification errors were calculated and the results are given in Table 3-3.

Figure 3-6 Typical strain signals and corresponding wavelet transformations at scale of 14: (a) Truck 2 (3-axle) traveling at 20 m/s; (b) Truck 4 (5-axle) traveling at 10 m/s
Table 3-2 Identified results using wavelet transformation

<table>
<thead>
<tr>
<th>Truck number</th>
<th>Number of axles</th>
<th>Velocity (m/s)</th>
<th>Axle spacing First to second (m)</th>
<th>Axle spacing Second to third (m)</th>
<th>Axle spacing Third to fourth (m)</th>
<th>Axle spacing fourth to fifth (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>9.93</td>
<td>6.21</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>9.92</td>
<td>4.24</td>
<td>4.22</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>9.93</td>
<td>4.86</td>
<td>1.42</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>9.92</td>
<td>7.96</td>
<td>4.94</td>
<td>1.99</td>
<td>4.94</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>19.85</td>
<td>6.21</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>19.85</td>
<td>4.22</td>
<td>4.27</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>19.85</td>
<td>4.67</td>
<td>1.64</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>19.89</td>
<td>7.96</td>
<td>5.07</td>
<td>1.94</td>
<td>4.92</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>29.92</td>
<td>6.28</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>29.92</td>
<td>4.19</td>
<td>4.34</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>29.86</td>
<td>6.19</td>
<td>2.76</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>29.88</td>
<td>7.92</td>
<td>4.48</td>
<td>2.39</td>
<td>4.78</td>
</tr>
</tbody>
</table>

Table 3-3 Identification errors using wavelet transformation

<table>
<thead>
<tr>
<th>Truck number</th>
<th>Number of axles</th>
<th>Vehicle speed (m/s)</th>
<th>Velocity</th>
<th>Axle spacing First to second</th>
<th>Axle spacing Second to third</th>
<th>Axle spacing Third to forth</th>
<th>Axle spacing fourth to fifth</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>10</td>
<td>0.70</td>
<td>0.64</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>10</td>
<td>0.70</td>
<td>0.64</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>10</td>
<td>0.70</td>
<td>1.62</td>
<td>1.43</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>10</td>
<td>0.80</td>
<td>0.50</td>
<td>1.20</td>
<td>0.50</td>
<td>1.20</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>20</td>
<td>0.70</td>
<td>0.64</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>20</td>
<td>0.75</td>
<td>1.17</td>
<td>0.00</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>20</td>
<td>0.75</td>
<td>5.47</td>
<td>17.1</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>20</td>
<td>0.55</td>
<td>0.50</td>
<td>1.40</td>
<td>3.00</td>
<td>1.60</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>30</td>
<td>0.27</td>
<td>0.48</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>30</td>
<td>0.27</td>
<td>1.87</td>
<td>1.64</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>30</td>
<td>0.47</td>
<td>25.3</td>
<td>97.1</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>30</td>
<td>0.40</td>
<td>1.00</td>
<td>10.4</td>
<td>19.5</td>
<td>4.40</td>
</tr>
</tbody>
</table>

From Table 3-3, it can be seen that a satisfactory accuracy was achieved with most errors well below two percent. However, it was found that there are several cases with large identification errors and that these large errors seem to occur at high vehicle speeds. For example, for Truck 3 traveling at 30 m/s, the maximum error of axle spacing reaches 97.1 percent, indicating a failure of identification. The reason for these large errors is that some high-frequency information of the signal is lost due to the relatively low sampling frequency as the vehicle travels at a high speed. It will be shown in the next section that once the sampling frequency is increased, these errors will considerably decrease.

The successful axle identification using bridge global responses has significant implications since the vehicle speed and axle spacing can be identified using only the weighing sensors. In the real application, the use of this advanced axle detection technique will reduce the
number of sensors to be installed and thus the cost of BWIM systems. Furthermore, since the identification principle of this technique does not impose any restrictions on bridge types as in the case of FAD applications, it could potentially help extend the application of the BWIM technology to different types of bridges.

3.4 Parametric Study

3.4.1 Effect of Sampling Frequency

As mentioned earlier, some large errors occurred due to the relatively low sampling frequency. To investigate the effect of sampling frequency on the identification accuracy, two sampling frequencies, i.e., 200 Hz and 500 Hz, are used to record the strain response for Truck 3 traveling at 30 m/s. Figure 3-7 shows the transformed signals under the two sampling frequencies. It should be mentioned that with the increase of sampling frequency, the scale of wavelet coefficients used for identification is reduced to 4.

From Figure 3-7, it can be clearly seen that the peaks in the transformed signal corresponding to the sampling frequency of 500 Hz are much sharper than the one corresponding to the sampling frequency of 200 Hz. As a result, the identified vehicle speed and the two axle spacings using the sampling frequency of 500 Hz changed to 30.25 m/s, 4.95 m and 1.42 m, respectively, and corresponding identification errors for the two axle spacings were reduced from 25.3% and 97.1% to 0.20% and 1.43%, respectively. For other cases with relatively large errors, it was also found that increasing the sampling frequency considerably reduced the identification errors.

![Wavelet transformations of signals for Truck 3 traveling at 30 m/s: (a) sampling frequency of 200 Hz; (b) sampling frequency of 500 Hz](image)

Figure 3-7 Wavelet transformations of signals for Truck 3 traveling at 30 m/s: (a) sampling frequency of 200 Hz; (b) sampling frequency of 500 Hz

Essentially, increasing the sampling frequency sharpens the peaks in the transformed signal, which, in turn, increases the accuracy of identification. However, higher sampling frequency would also substantially increase the amount of data and its processing time.
Therefore, an appropriate sampling frequency should be determined based on the maximum vehicle speed of interest. In addition, this example also demonstrates that the wavelet analysis is capable of identifying closely-spaced axles which can be difficult sometimes for the FAD techniques (Chatterjee et al. 2006).

### 3.4.2 Effect of Road Surface Condition

A road profile is usually represented by a zero-mean stationary stochastic process that can be expressed by a power spectral density (PSD) function. In this study, a modified PSD function (Wang and Huang 1992) was used:

\[
\varphi(n) = \varphi(n_0) \left( \frac{n}{n_0} \right)^{-2} \quad (n_1 < n < n_2)
\]  

(3-15)

where \(n\) is the spatial frequency (cycle/m); \(n_0\) is the discontinuity frequency of 0.5\(\pi\) (cycle/m); \(\varphi(n_0)\) is the roughness coefficient (m\(^3\)/cycle); and \(n_1\) and \(n_2\) are the lower and upper cut-off frequencies, respectively. The International Organization for Standardization (ISO 1995) classified the road surface condition into several categories depending on different values of roughness coefficients. In the present study, according to ISO specifications (ISO 1995), the roughness coefficients of \(5 \times 10^{-6}\), \(20 \times 10^{-6}\), \(80 \times 10^{-6}\), and \(256 \times 10^{-6}\) m\(^3\)/cycle were used for very good, good, average, and poor road surface conditions, respectively.

The road surface elevation can then be generated by an inverse Fourier transformation as:

\[
r(x) = \sum_{k=1}^{N} \sqrt{2\varphi(n_k)\Delta n} \cos(2\pi n_k x + \theta_k)
\]

(3-16)

where \(\theta_k\) is the random phase angle uniformly distributed between 0 and 2\(\pi\); \(n_k\) is the wave number (cycle/m); \(N\) is the number of frequencies between \(n_1\) and \(n_2\); and \(\Delta n\) is the frequency interval between \(n_1\) and \(n_2\).

In order to examine the effect of road surface roughness on the identification accuracy, Truck 2 is set to travel at 20 m/s under four different surface conditions, i.e., very good, good, average, and poor road surface conditions and the sampling frequency is chosen to be 500 Hz. The wavelet transformations of the strain signals at the scale of 4 are presented in Figure 3-8. It can be seen that as the road roughness increases, the peaks used to identify the axles become less pronounced as there appears to have many other “noise” peaks. These other “noise” peaks are caused by the dynamic effect of the vehicle-bridge interaction. As the road surface condition worsens, these “noise” peaks become more pronounced, making the identification more difficult. Nevertheless, under very good and good surface conditions, the identification is still effective, as the identification errors were calculated to be below one percent. However, as road surface condition further deteriorates, the identification becomes infeasible since it is difficult to distinguish the peaks due to vehicle axles from other “noise” peaks caused by the dynamic effect.
In some previous studies on the bridge dynamic behaviors (e.g., Calçada et al. 2005, Ashebo et al. 2007), a low-pass filter was often employed to remove the dynamic effect of the response. However, in the case of axle identifications using wavelet analysis, low-pass filtering is not a solution, since the high frequency components of the signal contain the useful information used to identify the vehicle axles. Namely, low-pass filtering will also filter out the useful information. Nonetheless, it should be pointed out that, a smooth road condition is a prerequisite to achieve a satisfactory identification accuracy for most existing BWIM technologies such as those using Moses’s algorithm (Moses 1979, WAVE 2001). Therefore, the fact that the axle identification using wavelet analysis is limited to good bridge surface conditions does not really impede the implementation of modern commercial BWIM systems whose basic framework is the Moses’s algorithm (Moses 1979). Naturally, a new methodology that can work well under rough road surface conditions, and at the same time can eliminate the axle detection sensors, is very desirable.

### 3.4.3 Effect of Measurement Noise

While the presented identified results above can be very accurate for good road surface conditions, they are obtained in the ideal situation. In real practice, the obtained signals are usually contaminated by measurement noises induced by the environmental changes and electric devices used for data acquisition. Thus, it is necessary to examine the effect of measurement noise on the identification accuracy. For this purpose, different levels of Gaussian white noise are added to the original strain signal obtained when Truck 2 travels at 20 m/s under sampling frequencies of 500 Hz and 200 Hz. As mentioned before, the scale of the wavelet coefficients for the two frequencies are 4 and 14, respectively. Figure 3-9 shows the wavelet transformations of the original signal and polluted signals under four different signal-to-noise ratios (SNR) of 100, 50, 20 and 10.
From Figure 3-9 (a), it can be seen that under the sampling frequency of 500 Hz, the peaks induced by the vehicle axles quickly get submerged by the noise as the noise level increases, making the identification impossible. This suggests that the identification method is sensitive to the measurement noise. The main reason for this is that the information of vehicle axles is reflected by very delicate changes in the original signal. Therefore, it becomes very difficult to separate this information from the measurement noises even through de-noising techniques that allow the preservation of certain features of the original signal, such as median filter and wavelet de-noising.

Figure 3-9 Wavelet transformations of signals under different levels of noise: (a) sampling frequency of 500 Hz; (b) sampling frequency of 200 Hz

Nevertheless, it was also noticed from Figure 3-9 (b) that as the sampling frequency decreases to 200 Hz, the peaks induced by the vehicle axles tend to get submerged more slowly than the previous case, i.e., the identification becomes less susceptible to the noise under a lower sampling frequency. This is because while the scale of the noise remains the same, the scale of...
the peaks increased due to the lower sampling frequency. From this perspective, increasing the sampling frequency, though it sharpens the peaks induced by the vehicle axles, it does not necessarily increase the identification accuracy. Therefore, the choice of an optimal sampling frequency should take into consideration the maximum vehicle speed of interest as well as the level of noise.

### 3.5 Conclusions

This paper presents a vehicle axle identification method using bridge global responses. The identification is achieved using a continuous wavelet transformation. Numerical simulations were conducted using three-dimensional vehicle and bridge models and the effect of several parameters including sampling frequency, road surface condition and measurement noise on the identification accuracy were investigated and discussed. Based on the results obtained, the following conclusions can be drawn:

1. Vehicle axle identifications can be achieved through a wavelet analysis of bridge global responses. This approach has obvious advantages over existing axle identification methods in that it requires fewer sensors and it does not impose any additional restrictions on the basis of the Moses’s algorithm (Moses 1979);

2. The sampling frequency of the data acquisition system has significant influence on the identification accuracy. A higher sampling frequency leads to sharper peaks in the transformed signal, which in turn, increases the identification accuracy, especially in cases where vehicles travel at relatively higher speeds;

3. Road surface condition also affects the accuracy of the axle identification in that road surface roughness causes additional peaks in the transformed signal due to the vehicle-bridge interaction, and once these peaks overcome the peaks induced by the vehicle axles, the identification of vehicle axles becomes very difficult;

4. The proposed identification method is susceptible to measurement noises. This is inevitable since the information on vehicle axles is reflected by very delicate changes in the original signal. Nevertheless, it has been shown that reducing the sampling frequency increases the scale of the peaks induced by the vehicle axles and thus makes the identification less susceptible to the measurement noise.

While the proposed method in this paper provides a promising tool for the axle identification of BWIM systems, limitations and conditions are also recognized and noted. Future work will be conducted to experimentally verify this method and relevant algorithms will be designed to enable automatic identification of vehicle axles in the BWIM systems.

### 3.6 References


CHAPTER 4. NOTHING-ON-ROAD BRIDGE WEIGH-IN-MOTION CONSIDERING THE TRANSVERSE POSITION OF THE VEHICLE

4.1 Introduction

Overloaded trucks pose serious threats to the safety of the public and transportation systems as they cause accelerated degradation of highway infrastructures and increase the risk of traffic accidents (Jacob and Beaumelle 2010). Over the past few decades, weigh-in-motion (WIM) technology has been developed to provide an efficient tool for overweight enforcement as it is able to measure the vehicle’s weight while it is traveling at its operation speed. Bridge weigh-in-motion (BWIM) is a type of WIM technology that uses the bridge as a weighing platform to measure the vehicle weights. The BWIM system has many advantages over the pavement-based WIM system (Yu et al. 2016). Theoretically, the BWIM can achieve more accurate identification than the pavement-based WIM since the BWIM uses longer measurement period to identify the axle weights rather than the time-varying axle forces measured at a time instant by the pavement-based WIM. Furthermore, the BWIM system is installed underneath the bridge, which does not interrupt road traffic and also improves the durability and portability of the system. These advantages made the BWIM an ideal tool for traffic monitoring and truck overweight enforcement (Jacob and Beaumelle 2010). The development of BWIM technologies can be found in some recent reviews (O’Brien et al. 2008; Yu et al. 2016; Lydon et al. 2016; Zhu and Law 2016; Žnidarič et al. 2016).

The concept of BWIM was first proposed by Moses (Moses 1979), treating the bridge as a one-dimensional (1D) beam structure. In other words, the transverse position (TP) of the vehicle was not considered. However, some studies found that ignoring the vehicle’s TP on the bridge could lead to significant errors in the identified vehicle weights (Quilligan 2003; WAVE 2001). In order to account for the effect of the vehicle’s TP, some researchers proposed two-dimensional (2D) BWIM algorithms (Moses and Ghosn 1983; Deng and Cai 2011; Quilligan 2003; Zhao et al. 2014). The 2D algorithms considered the 2D behavior of the bridge due to the effect of different TPs of the vehicle. The results showed that the 2D algorithms improved the identification accuracy compared with the 1D Moses’s algorithm. Nevertheless, the implementation of 2D BWIM algorithms requires the knowledge of the vehicle’s TP. Traditionally, the vehicle’s TP can be identified along with the axle spacing and vehicle speed using axle detectors on the road surface (Quilligan 2003; Zhou et al. 2015). However, having any sort of sensors on the road surface would diminish the advantage of BWIM systems over pavement-based WIM systems.

Recently, the concept of nothing-on-road (NOR) BWIM has received much attention from researchers. The NOR BWIM aims at removing the traditional axle detectors from the road surface in order to enhance the portability and durability of the BWIM system, which will further facilitate the installation and maintenance of BWIM systems. The main difficulty of NOR BWIM lies in the accurate identification of the vehicle’s longitudinal position without using traditional axle detectors. In the past decade, many studies have been conducted to develop alternative strategies of axle detection. The free-of-axle-detector (FAD) algorithm was first proposed in WAVE (WAVE 2001) to identify the vehicle axles using the sensitivity of bridge local responses to axle loads. The FAD algorithm later became in commercial BWIM systems (Kalin et al. 2006). However, the FAD algorithm is not suitable for certain types of bridges and
is susceptible to the transverse position of wheels (Chatterjee et al. 2006; Lydon et al. 2016). O’Brien et al. (2012) explored the feasibility of using the measurement of shear strains for axle detection, which was recently verified in a field study by Bao et al. (2016). Yu et al. (2015) applied wavelet analysis to identify the vehicle speed and axle spacings using only the weighing sensor. Ojio et al. (2016) developed a contactless BWIM (cBWIM) system which uses high-speed cameras to detect vehicle axles and measure the bridge deflection. He et al. (2017) proposed a novel method of axle detection based on the concept of the virtual simply-supported beam. In the recent project BridgeMon, an improved FAD algorithm that features signal processing, axle reconstruction and peak amplification was developed to overcome existing problems of the FAD algorithm such as low signal to noise ratio and varying lateral positions of vehicles (Žnidarič et al. 2016). In addition, the project BridgeMon also achieved improvements on the calibration of influence line and the correction of temperature and velocity effects in BWIM systems. Nevertheless, there are very few studies on the identification of the vehicle’s exact TP in the NOR BWIM.

The objective of the present study is to develop a NOR BWIM algorithm that is able to identify the vehicle’s TP and axle weights using only weighing sensors. The identification methodology is first introduced and numerical simulations are carried out on a beam-slab bridge using highway trucks of different axle configurations to validate the effectiveness of the proposed algorithm. Then, a parametric study is conducted to examine the effects of the road surface condition, the vehicle speed, the vehicle width, and different measurement stations on the identification accuracy. Finally, a field study is presented to verify the proposed algorithm in practice.

4.2 Identification Methodology

In the Moses’s algorithm (Moses 1979), the vehicle weight is identified by minimizing an error function with respect to the axle weights using the least-squares method. The error function is defined as the squared difference between the predicated and the measured total responses of the beam-slab bridge:

$$E = \sum_{k=1}^{T} \left( \sum_{i=1}^{n} M_{i,k}^p - \sum_{i=1}^{n} M_{i,k}^m \right)^2$$

where $n$ is the number of girder; $T$ is the number of scans; $M_{i,k}^m$ is the measured bending moment for the $i$th girder at time instant $k$; and $M_{i,k}^p$ is the predicted bending moment for the $i$th girder at time instant $k$ and can be calculated using the influence line concept:

$$M_{i,k}^p = \sum_{j}^{N} A_j \times IL_{i,j,k}$$

where $A_j$ is the axle weight of the $j$th axle; $N$ is the number of axles of the vehicle; and $IL_{i,j,k}$ is the influence line ordinate for the $i$th girder corresponding to the position of the $j$th axle at time instant $k$. Essentially, the bridge was treated as a 1D beam and the TP of the vehicle was not considered. The error function given by Eq. (4-1) is not suitable for the identification of the
vehicle’s TP in that the total response of the bridge is not very sensitive to the TP of the vehicle. Nevertheless, the response of an individual girder is sensitive to the vehicle’s TP.

Generally speaking, for a bridge with \( n \) parallel measurement stations in the transverse direction, the error function for the \( m \)th measurement station can be expressed as:

\[
E_m = \sum_{k=1}^{T} (M_{m,k}^p - M_{m,k}^m)^2
\]  

(4-3)

where \( M_{m,k}^p \) can be more accurately calculated using the influence surface concept than the influence line concept in Eq. (4-2) as:

\[
M_{m,k}^p = \sum_{j}^{N} A_j \times IS_{m,j,k}(TP)
\]  

(4-4)

where \( IS_{m,j,k}(TP) \) is the influence surface ordinate for the \( m \)th measurement station corresponding to the transverse position of the vehicle at \( TP \) and the longitudinal position of \( j \)th axle at time instant \( k \). Essentially, \( M_{m,k}^p \) becomes a function of both the axle weights and the TP when the influence surface concept is adopted.

To identify the TP of the vehicle, a series of values for the TP covering all possible positions where the vehicle may be present is first assumed and for each assumed TP, the measured response of the \( m \)th station is used to identify a set of axle weights corresponding to this TP by using the least-squares method to minimize Eq. (4-3), i.e., the \( m \)th measurement station can be thought of as the weighing station in the proposed algorithm. Due to the response sensitivity of the weighing station to the TP of the vehicle, the obtained sets of axle weights will vary with different assumed TPs. Mathematically, the different sets of axle weights obtained are all solutions to the least-squares problem, i.e., all solutions can reproduce the measured response for the weighing station. However, only the solution corresponding to the true TP of the vehicle has physical meanings. In other words, only the set of axle weights identified at the true TP can reproduce the measured responses for all other measurement stations. Thus, if the assumed TP of the vehicle is not the true one, the set of axle weights identified from the weighing station will be either over- or underestimated and thus cannot simultaneously reproduce the measured responses for all other measurement stations, based on which the following error function can be defined:

\[
E = \sum_{i=1}^{n-1} \sum_{k=1}^{T} (M_{i,k}^m - M_{i,k}^p)^2
\]  

(4-5)

where \( n \) is the number of measurement stations; \( M_{i,k}^m \) and \( M_{i,k}^p \) are the measured and the predicted responses for the \( i \)th non-weighing station at time instant \( k \), respectively; and \( i=1,...,m-1, m+1,...n \) (totally \( n-1 \)), i.e., the error of the \( m \)th measurement station (the weighing station) is excluded here. By substituting all solutions into Eq. (4-5), the value of the error function for each assumed TP can be calculated and the true TP of the vehicle will be the one that minimizes Eq. (4-5). The reason for not considering the error of the \( m \)th measurement station, i.e., the weighing station, in Eq. (4-5) is that although the measured and the predicted responses should match for
the weighing station for all possible TPs, there still exist small errors caused by factors other than the vehicle’s TP such as the dynamic effect and the measurement noise. Therefore, the error of the weighing station is excluded from Eq. (4-5) in order to reduce the unintended errors. In addition, it should be mentioned that that the vehicle speed and axle spacing are assumed to be known for the identification of vehicle weight in this study since the main objective of this study is the identification of the vehicle’s TP and its application to improve the identification accuracy of vehicle weight in BWIM systems.

4.3 Numerical Simulation

4.3.1 Vehicle Model

In the present study, three typical highway trucks with different numbers of axles are adopted. Table 4-1 lists the axle configurations of these trucks. The width of all trucks is set as 2.5 m. In the simulation, the truck is modeled as spring-dashpot systems. The vehicle body (tractor or trailer) is represented by a rigid body with a mass and three degrees of freedom (DOFs), i.e., the vertical displacement, the pitching rotation, and the rolling rotation. The connection between the tractor and the trailer is modeled as a pinned connection, i.e., the tractor and the trailer have equal vertical displacement at the connection. Each wheel is represented by a lumped mass with one DOF, i.e., the vertical displacement. For example, the analytical model of Truck 2 is shown in Figure 4-1 where \( Z_V \) and \( Z_a \) represent the vertical displacement of the vehicle body and the tire, respectively; \( \theta_V \) represents the pitching rotation of the vehicle body; \( \phi_V \) represents the rolling rotation of the vehicle body; \( K_u \) and \( K_l \) represent the stiffness of the suspension system and the tire, respectively; \( C_u \) and \( C_l \) represent the damping of the suspension system and the tire, respectively.

Table 4-1 Axle configurations of adopted highway trucks

<table>
<thead>
<tr>
<th>Truck Number</th>
<th>Number of axles</th>
<th>Axle spacing (m)</th>
<th>Axle weight (kN)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1st to 2nd</td>
<td>2nd to 3rd</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>5.65</td>
<td>N.A.</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>4.27</td>
<td>4.27</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>8.00</td>
<td>5.00</td>
</tr>
</tbody>
</table>

4.3.2 Bridge Model

In the numerical study, a simply supported beam-slab bridge is adopted. As a good representative of highway bridges, the selected bridge was designed according to the AASHTO standard specification (AASHTO 2002) and is 24.38-m long and 10.67-m wide. The bridge consists of five identical I-girders and three diaphragms located at the two ends and the mid-span of the bridge. Figure 4-2 shows the cross section of the bridge. The bridge is modeled with the ANSYS software using solid elements (with three translational DOFs at each node) to predict the dynamic characteristics including the natural frequencies and mode shapes. The finite element (FE) model of the bridge is shown in Figure 4-3. Modal analysis shows that the bridge has a fundamental frequency of 3.46 Hz corresponding to the first bending mode.
Figure 4-1 Analytical model of Truck 2: (a) Back view; (b) Side view

Figure 4-2 Cross section of the bridge used in the simulation

Figure 4-3 Finite element model of the bridge used in the simulation
4.3.3 Vehicle-bridge Interaction

In the present study, a coupled approach is used to solve the vehicle-bridge interaction problem (Deng and Cai 2010). The equations of motion for the vehicle and bridge can be written in matrix forms as:

\[
\begin{bmatrix} M_v \end{bmatrix} \{ \ddot{d}_v \} + \begin{bmatrix} C_v \end{bmatrix} \{ \dot{d}_v \} + \begin{bmatrix} K_v \end{bmatrix} \{ d_v \} = \{ F_G \} + \{ F_v \} \tag{4-6}
\]

\[
\begin{bmatrix} M_b \end{bmatrix} \{ \ddot{d}_b \} + \begin{bmatrix} C_b \end{bmatrix} \{ \dot{d}_b \} + \begin{bmatrix} K_b \end{bmatrix} \{ d_b \} = \{ F_b \} \tag{4-7}
\]

where \([M_v]\), \([C_v]\), and \([K_v]\) are the mass, damping, and stiffness matrices of the vehicle, respectively; \([M_b]\), \([C_b]\), and \([K_b]\) are the mass, damping, and stiffness matrices of the bridge, respectively; \(\{d_v\}\) and \(\{d_b\}\) are the displacement vector of the vehicle and bridge, respectively; \(\{F_G\}\) are the gravity force vector of the vehicle; and \(\{F_v\}\) and \(\{F_b\}\) are the wheel-road contact force vectors acting on the vehicle and bridge, respectively.

Based on the displacement relationship and interaction force relationship at the contact points, the two equations of motion above can be combined into a coupled equation:

\[
\begin{bmatrix} M_b & M_v \\ M_v \end{bmatrix} \begin{bmatrix} \ddot{d}_b \\ \ddot{d}_v \end{bmatrix} + \begin{bmatrix} C_b + C_{b-v} & C_{b-v} \\ C_{v-b} & C_v \end{bmatrix} \begin{bmatrix} \dot{d}_b \\ \dot{d}_v \end{bmatrix} + \begin{bmatrix} K_b + K_{b-v} & K_{b-v} \\ K_{v-b} & K_v \end{bmatrix} \begin{bmatrix} d_b \\ d_v \end{bmatrix} = \begin{bmatrix} F_{b-v} \\ F_v + F_G \end{bmatrix} \tag{4-8}
\]

where \(C_{b-v}\), \(C_{v-b}\), \(K_{b-v}\), \(K_{v-b}\), \(F_{b-v}\), and \(F_{v}\) are the interaction-related terms caused by the contact forces. As the vehicle travels through the bridge, the positions of contact points change and so do the contact forces. Therefore, the interaction-related terms are time-dependent terms which will change as the vehicle moves across the bridge.

In order to reduce the size of the matrices and save calculation efforts, the modal superposition technique is adopted and thus the bridge displacement vector \(\{d_b\}\) in Eq. (4-8) can be expressed as:

\[
\{ d_b \} = \{ \Phi_1 \} \{ \Phi_2 \} \ldots \{ \Phi_m \} \{ \xi_1 \ \xi_2 \ldots \xi_m \}^T = [\Phi_b] [\xi_b] \tag{4-9}
\]

where \(m\) is the total number of modes considered for the bridge; \(\{\Phi_i\}\) and \(\xi_i\) are the \(i\)th mode shape of the bridge and the \(i\)th generalized modal coordinate, respectively. If each mode shape is normalized such that \(\{\Phi_i\}^T [M_b] \{\Phi_i\} = 1\) and \(\{\Phi_i\}^T [K_b] \{\Phi_i\} = \omega_i^2\), and the damping matrix \([C_b]\) in Eq. (4-7) is assumed to be equal to \(2\omega_i \eta_i [M_b]\) where \(\omega_i\) and \(\eta_i\) are the natural circular frequency and the percentage of the critical damping of the \(i\)th mode of the bridge, respectively, then Eq. (4-8) can be simplified as:
\[
\begin{bmatrix}
I \\
M_r
\end{bmatrix}\begin{bmatrix}
\ddot{d}_b \\
\ddot{\xi}_b
\end{bmatrix} + \begin{bmatrix}
2\omega_i\eta_iI + \Phi_b^T C_{b-b} \Phi_b & \Phi_b^T C_{b-v} \\
C_{v-b} \Phi_b & C_v
\end{bmatrix}\begin{bmatrix}
\ddot{\xi}_b \\
\ddot{d}_v
\end{bmatrix} = \begin{bmatrix}
\Phi_b^T F_{b-r} \\
F_{v-r} + F_G
\end{bmatrix}
\]

(4-10)

The coupled Eq. (4-10) contains only the mechanical parameters of vehicles and the modal properties of the bridge. Consequently, the computation cost of solving the coupled equations was considerably reduced. A computer program was developed in the MATLAB environment to solve Eq. (4-10) in the time domain using the fourth-order Runge-Kutta method. After obtaining the displacement responses of the bridge \( \{d_b\} \), the strain responses can then be calculated by:

\[
\{\varepsilon\} = [B]\{d_b\}
\]

(4-11)

where \([B]\) is the strain-displacement relationship matrix assembled with the x, y, and z derivatives of the element shape functions. For more details on the vehicle-bridge interaction and its validation, readers can refer to Shi (2006).

### 4.3.4 Calibration of the Influence Surface

In the numerical study, five measurement stations (S1, S2, S3, S4, and S5) are selected at the bottom of the five girders (G1, G2, G3, G4, and G5) at the mid-span of the bridge. The longitudinal strains at these measurement stations were recorded. Figure 4-4 shows the locations of the measurement stations. The vehicle’s TP is defined as the distance from the right wheels of the vehicle to the right end of the bridge’s cross section as illustrated in Figure 4-4. In order to generate the influence surface, Truck 2 is used as the calibration truck. A series of TPs ranging from 0.6096 m to 7.62 m with an interval of 0.1524 m is considered in the calibration. These positions cover all cases of the vehicle traveling within the two traffic lanes and bridge shoulders as shown in Figure 4-4. For each TP, Truck 2 is set to pass the bridge and the bridge response obtained from the simulation is used to extract the influence line corresponding to that TP using the method proposed by O’Brien et al. (2006). The influence ordinates at positions in-between these TPs were obtained using linear interpolations. Figure 4-5 shows the contour plots of the numerically calibrated influence surface for S2 and S5. It can be seen that the maximum value of the influence surface occurs around positions where the axle load is directly applied above the location of the measurement station.
Figure 4-4 Location of the measurement stations and traffic lanes

Figure 4-5 Contour plots of numerically calibrated influence surfaces: (a) S2; (b) S5 (unit: microstrain)
4.3.5 Simulation Results

Numerical simulations were conducted on the simply supported beam-slab bridge. For the selected bridge, thirty mode shapes were considered based on a sensitivity study. Seven loading cases were considered with each case corresponding to the vehicle traveling at a different TP based on the location of traffic lanes. As shown in Figure 4-4, two traffic lanes, each with a width of 3.67 m, were designed for the bridge. The first three loading cases correspond to the vehicle traveling at the center of Lane 1, the vehicle’s right wheel traveling at the right side of Lane 1, and the vehicle’s left wheel traveling at the left side of the Lane 1. The second three cases correspond to the same vehicle layout as the first three cases but in Lane 2. Case 7 corresponds to a special case where the vehicle travels at the center of the bridge. Table 4-2 summarizes the description of the seven loading cases. In the following study, the vehicle is set to travel at a constant speed of 10 m/s under a smooth road surface profile unless otherwise specified in the parametric study.

<table>
<thead>
<tr>
<th>Case Number</th>
<th>Traveling Lane</th>
<th>Transverse position (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Lane 1</td>
<td>1.676</td>
</tr>
<tr>
<td>2</td>
<td>Lane 1</td>
<td>2.286</td>
</tr>
<tr>
<td>3</td>
<td>Lane 1</td>
<td>2.896</td>
</tr>
<tr>
<td>4</td>
<td>Lane 2</td>
<td>5.334</td>
</tr>
<tr>
<td>5</td>
<td>Lane 2</td>
<td>5.944</td>
</tr>
<tr>
<td>6</td>
<td>Lane 2</td>
<td>6.553</td>
</tr>
<tr>
<td>7</td>
<td>Lane 1 and Lane 2</td>
<td>4.115</td>
</tr>
</tbody>
</table>

To identify the TP of the vehicle, the measurement station of the largest response is first used to calculate the set of axle weights for an assumed TP. Then, the obtained set of axle weights are used to predict the responses for other measurement stations using the calibrated influence surface and the results are substituted into Eq. (4-5) to calculate the value of the error function at the assumed TP. The same procedure is repeated for all possible TPs and the one that gives the minimum value of the error function is identified as the true TP of the vehicle. For example, Figure 4-6 shows the variation of the error function with the possible TPs for Case 2 with Truck 3 and Case 4 with Truck 1. It can be seen that the minimum value of the error function is achieved at a specific TP. In Figure 4-6 (a) and (b), the two TPs that minimize the error function are 2.286 m and 5.334 m, respectively, corresponding to the true TPs of the vehicle for the two cases. It should be noted that the reason for not plotting all possible TPs in Figure 4-6 is that the values of the error function at positions far away from the true TP is so large that plotting them in the figure would make it difficult to visually identify the minimum value of the error function.

To better illustrate the identification principle, Figure 4-7 plots the simulated responses and the reconstructed responses obtained using the axle weights identified at different TPs of different measurement stations under Case 2 with Truck 3. Only the responses corresponding to the true TP and two other assumed TPs are plotted for visualization purposes. For Case 2, Girder 5 had the largest response. Therefore, S5 was selected as the weighing station. It can be seen
from Figure 4-7 (e) that the reconstructed responses corresponding to different TPs uniformly match the simulated response very well for S5, i.e., the weighing station. However, this is not the case for other measurement stations. As can be seen from Figure 4-7, the degree of match between the simulated and reconstructed responses gradually decreases as the location of the measurement station gets further away from S5 with the exception of the reconstructed responses obtained using the axle weights identified at the true TP. This is because if the assumed TP is not the true one, the axle weights will either be over- or underestimated depending on the assumed TP in order to match the simulated response of S5, which in turn causes a mismatch between the simulated and reconstructed responses for other measurement stations. In other words, only the axle weights identified at the true TP will be able to achieve a good match between the simulated and reconstructed responses for all measurement stations.

![Graphs showing variation of the error function with respect to possible TPs](image)

**Figure 4-6** Variation of the error function with respect to the possible TPs of the vehicle: (a) Case 2 with Truck 3; (b) Case 4 with Truck 1
Figure 4-7 Simulated and reconstructed bridge responses of different measurement stations for Case 2 with Truck 3: (a) S1; (b) S2; (c) S3; (d) S4; (e) S5

The proposed algorithm was implemented for all seven loading cases using the three highway trucks. The identification results are given in Table 4-3 with the identified values of vehicle weights rounded to one decimal place. To better examine the identification accuracy, the identification error is defined as:

\[
\text{Identification Error} = \left| \frac{P_{\text{id}} - P_{\text{true}}}{P_{\text{true}}} \right| \times 100\% 
\]

where \(P_{\text{id}}\) and \(P_{\text{true}}\) are the identified parameter and the true parameter, respectively. Using this definition, the identification errors of the vehicle’s TP, axle weights and gross vehicle weight (GVW) were calculated and the results are given in Table 4-4. It should be mentioned that the errors were calculated using the identified values before the rounding. In order to compare the
identification accuracy between the proposed algorithm and the 1D Moses’s algorithm, the
identification was also conducted using the 1D Moses’s algorithm and the identification errors
are also given in Table 4-4. It should be noted that for the 1D Moses’s algorithm, the axle
weights are identified using the total response of the bridge and in this case, the influence lines
under the vehicle traveling at the center of the bridge were used to predict the total response of
the bridge.

<table>
<thead>
<tr>
<th>Case Number</th>
<th>Truck Number</th>
<th>Identified TP of the vehicle (m)</th>
<th>Identified vehicle weights (kN)</th>
<th>Gvw</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>First axle</td>
<td>Second axle</td>
<td>Third axle</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1.676</td>
<td>125.9</td>
<td>145.9</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1.676</td>
<td>35.5</td>
<td>141.9</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1.676</td>
<td>125.8</td>
<td>178.3</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>2.286</td>
<td>125.9</td>
<td>145.9</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2.286</td>
<td>35.5</td>
<td>141.9</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2.286</td>
<td>125.8</td>
<td>178.6</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>2.896</td>
<td>125.9</td>
<td>145.9</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2.896</td>
<td>35.6</td>
<td>141.9</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2.896</td>
<td>125.8</td>
<td>179.2</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>5.334</td>
<td>125.9</td>
<td>145.9</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>5.334</td>
<td>35.6</td>
<td>141.9</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>5.334</td>
<td>125.8</td>
<td>179.2</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>5.944</td>
<td>125.9</td>
<td>145.9</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>5.944</td>
<td>35.5</td>
<td>141.9</td>
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<td>3</td>
<td>5.944</td>
<td>125.8</td>
<td>178.6</td>
</tr>
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<td>1</td>
<td>6.553</td>
<td>125.9</td>
<td>145.9</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>6.553</td>
<td>35.5</td>
<td>141.9</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>6.553</td>
<td>125.8</td>
<td>178.3</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>4.115</td>
<td>126.0</td>
<td>146.0</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>4.115</td>
<td>35.5</td>
<td>142.0</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>4.115</td>
<td>125.6</td>
<td>179.8</td>
</tr>
</tbody>
</table>
Table 4-4 Comparison of identification errors between the Moses’s algorithm and the proposed algorithm

<table>
<thead>
<tr>
<th>Case Number</th>
<th>Truck Number</th>
<th>Moses’s algorithm (%)</th>
<th>Proposed algorithm (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1st axle</td>
<td>2nd axle</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>4.12</td>
<td>5.39</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>19.5</td>
<td>2.19</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>3.86</td>
<td>5.55</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>2.71</td>
<td>3.85</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>10.4</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2.20</td>
<td>4.09</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1.73</td>
<td>2.09</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>9.34</td>
<td>1.54</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1.09</td>
<td>2.71</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0.05</td>
<td>1.01</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>6.72</td>
<td>2.98</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.53</td>
<td>1.40</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>0.52</td>
<td>2.72</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>7.42</td>
<td>2.43</td>
</tr>
<tr>
<td></td>
<td>3</td>
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<td></td>
<td>2</td>
<td>18.5</td>
<td>4.63</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2.16</td>
<td>4.35</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>0.24</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.10</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.78</td>
<td>0.91</td>
</tr>
</tbody>
</table>
From Table 4-4, it can be seen that the proposed algorithm successfully identified the true TPs of the vehicle for all cases. For the axle weights and GVW, most errors are within one percent, indicating a very accurate identification. Slightly larger errors were observed for the third and fourth axles of Truck 3. This is because the third and fourth axles of Truck 3 are closely spaced at a distance of two meters and it has been found that accurately identifying the weights of closely spaced axles is very difficult (O’Brien et al. 2009; WAVE 2001). Actually, closely spaced axles forming an axle group are usually identified as a single axle in practice. In the case of the 1D Moses’s algorithm, the identification errors of axle weights and GVW seem to be related with the TP of the vehicle. The errors appear to decrease as the TP gets closer to the center of the bridge, i.e., the TP corresponding to which the influence lines were selected to predict the total response of the bridge. As a matter of fact, accurate identification of axle weights and GVW was achieved using the 1D Moses’s algorithm for Case 7 in which the vehicle was located at the center of the bridge. Nevertheless, the identification errors using the 1D Moses’s algorithm are generally much higher than those using the proposed algorithm. This suggests that the TP of the vehicle has a significant influence on the identification accuracy. In addition, it is noted that in practice, the influence lines are calibrated for each lane and the influence lines corresponding to a certain lane are used to identify the weight of the vehicles traveling in that lane. In the present study, the traffic lane can also be assumed to be located in the middle of the bridge and Case 7 was used to calibrate the influence line of the middle lane for the 1D Moses algorithm. Cases 3 and 4 can be seen as cases where the vehicle travels within the middle lane but with the left/right wheels on the left/right edge of the lane. By comparing the identification errors obtained using the 1D Moses’s algorithm and the proposed algorithm for Cases 3 and 4 given in Table 4-4, it can be seen that even when the vehicle is traveling within the traffic lane for which the influence lines are calibrated, the proposed algorithm still has better accuracy than the 1D Moses algorithm. From this perspective, the vehicle’s TP should be considered in order to achieve more accurate identification of vehicle weights. Therefore, a BWIM algorithm that is able to identify the vehicle’s TP such as the proposed one will be able to improve the identification accuracy compared with the 1D Moses’s algorithm in practice.

4.4 Parametric Study

4.4.1 Effect of Road Surface Condition

A road surface profile can be represented by a zero-mean stationary stochastic process that can be expressed through a power spectral density (PSD) function. In the present study, a modified PSD function (Wang and Huang 1992) was used:

\[ \varphi(n) = \varphi(n_0) \left( \frac{n}{n_0} \right)^{-2} \quad (n_1 < n < n_2) \]  \hspace{1cm} (4-13)

where \( n \) is the spatial frequency (cycle/m); \( n_0 \) is the discontinuity frequency of 0.5\( \pi \) (cycle/m); \( \varphi(n_0) \) is the roughness coefficient (m\(^3\)/cycle); and \( n_1 \) and \( n_2 \) are the lower and upper cut-off frequencies, respectively. The International Organization for Standardization (ISO) categorized the road surface condition into several levels depending on different values of the roughness coefficients (ISO 1995). In the present study, based on the ISO specifications (ISO 1995), the
roughness coefficients of $5 \times 10^{-6}$, $20 \times 10^{-6}$, $80 \times 10^{-6}$, and $256 \times 10^{-6}$ m$^3$/cycle were used for very good, good, average, and poor road surface conditions, respectively.

The road surface elevation can be generated by an inverse Fourier transformation as:

$$r(x) = \sum_{k=1}^{N} \sqrt{2\varphi(n_k)\Delta n} \cos(2\pi n_k x + \theta_k)$$

(4-14)

where $\theta_k$ is the random phase angle uniformly distributed between 0 and $2\pi$; $n_k$ is the wave number (cycle/m); $N$ is the number of frequencies between $n_1$ and $n_2$; and $\Delta n$ is the frequency interval between $n_1$ and $n_2$. In order to examine the effect of the road surface condition on the identification accuracy, Truck 3 was set to travel under four different road surface conditions, i.e., very good, good, average, and poor conditions and the identification was conducted under Case 5. The identification errors are summarized in Table 4-5. It can be seen that although the identification of the GVW remains accurate, the identification errors of axle weights increases significantly as the road surface condition worsens. This is because the dynamic effect of the vehicle was induced by the road surface roughness, which causes the simulated response to deviate from the predicted response obtained using the influence surface, resulting in larger identification errors. In fact, the accurate identification of axle weights under rough surface conditions remains a challenging issue to modern commercial BWIM systems. Usually, a good road surface condition is the prerequisite of achieving satisfactory identification accuracy (Yu et al. 2016). Nevertheless, the vehicle’s TP was successfully identified regardless of the road surface conditions used, implying that the proposed algorithm is robust in identifying the TP of the vehicle.

<table>
<thead>
<tr>
<th>Road surface condition</th>
<th>TP (%)</th>
<th>Axle weights (%)</th>
<th>GFW (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>First axle</td>
<td>Second axle</td>
</tr>
<tr>
<td>Identification errors using unfiltered responses</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Smooth</td>
<td>0.00</td>
<td>0.38</td>
<td>0.60</td>
</tr>
<tr>
<td>Very good</td>
<td>0.00</td>
<td>1.71</td>
<td>4.33</td>
</tr>
<tr>
<td>Good</td>
<td>0.00</td>
<td>2.46</td>
<td>7.30</td>
</tr>
<tr>
<td>Average</td>
<td>0.00</td>
<td>3.94</td>
<td>13.23</td>
</tr>
<tr>
<td>Poor</td>
<td>0.00</td>
<td>6.30</td>
<td>22.58</td>
</tr>
<tr>
<td>Identification errors using filtered responses</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Smooth</td>
<td>0.00</td>
<td>0.16</td>
<td>1.47</td>
</tr>
<tr>
<td>Very good</td>
<td>0.00</td>
<td>0.78</td>
<td>1.10</td>
</tr>
<tr>
<td>Good</td>
<td>0.00</td>
<td>0.80</td>
<td>1.33</td>
</tr>
<tr>
<td>Average</td>
<td>0.00</td>
<td>0.83</td>
<td>1.79</td>
</tr>
<tr>
<td>Poor</td>
<td>0.00</td>
<td>0.87</td>
<td>2.47</td>
</tr>
</tbody>
</table>

In order to reduce the influence of the road roughness, a low-pass filter can be applied to remove the dynamic effect. Based on trial and error, a cut-off frequency of 1.5 Hz was chosen for the low-pass filter as this frequency can effectively remove the dynamic components of the
response and leave the static components intact. The identification errors using filtered responses are also given in Table 4-5 and it was found that the identification accuracy was considerably improved after the application of the low-pass filter. In addition, it is interesting to note that the identification errors for the third and fourth axles under the smooth surface condition actually increased after the filtering. This is probably because the low-pass filtering blurred the distinction between the effects of the closely spaced axles (WAVE 2001), which are reflected in the high-frequency components of the response. For this reason, it was suggested that the low-pass filtering only be used for bridges with high fundamental frequencies (WAVE 2001). Nevertheless, the low-pass filter is able to improve the identification accuracy overall in the present study.

Additionally, it is conceivable that the measurement noise will also have an impact on the identification accuracy and the effect of the measurement noise is, to some degree, similar to that of the road surface roughness in a way that they all cause deviations to the measured static response. Similarly, a low-pass filter can be used to remove the high-frequency noise and thus improve the identification accuracy. For the sake of simplicity, the effect of the measurement noise on the identification accuracy is not further discussed here.

4.4.2 Effect of Vehicle Speed

In order to determine the effect of the vehicle speed on the identification accuracy, Truck 2 was set to travel at six different speeds ranging from 5 m/s to 30 m/s with an interval of 5 m/s. The identification was conducted under Case 2. The identification errors are given in Table 4-6. It can be seen that the TP of the vehicle was successfully identified for all considered speeds and that most identification errors for axle weights and GVW are within one percent. Moreover, vehicle traveling at speeds higher than 10 m/s appears to cause slightly larger errors in the identified axle weights. This is because higher speeds induced the dynamic effect of the vehicle while this effect is basically negligible for the vehicle traveling at lower speeds. However, the dynamic effect does not necessarily become more evident as the vehicle speed increases. In fact, the largest errors occur at the vehicle speed of 15 m/s. A possible explanation for this is that the excitation frequency of the vehicle at this speed approached the fundamental frequency of the bridge, which led to the resonant vibration of the bridge. The excitation frequency of the vehicle may be calculated using the following equation (Shi et al. 2008):

\[
f_{ex} = \frac{v}{L_v} \quad (n = 1, 2, 3, \ldots)
\]

where \(v\) is the vehicle speed; \(L_v\) is the vehicle’s axle spacing which is uniformly 4.27 m for Truck 2; and \(f_{ex}\) is the excitation frequency of the vehicle. When the vehicle speed is 15 m/s, the excitation frequency is calculated to be 3.51 Hz, which is very close to the fundamental frequency of the bridge of 3.46 Hz. Therefore, the larger identification errors at this speed may be contributed to the stronger dynamic effect caused by the resonance. Nevertheless, accurate identification was achieved for various vehicle speeds, indicating that the vehicle speed does not have a significant influence on the identification accuracy.
### 4.4.3 Effect of Vehicle Width

In the present study, the truck used to calibrate the influence surface has a width of 2.5 m. However, the vehicle width varies between different vehicles in practice and it is conceivable that this variation will result in identification errors. Nevertheless, it has been found that the variation of the width of commercial trucks is very small. The survey by Berard and Bouroin (1998) showed that the mean width of heavy trucks is 2.52 m with approximately ninety percent of the widths falling within the range from 2.5 m to 2.6 m. Furthermore, according to the latest Federal Size Regulations for Commercial Motor Vehicles (Federal Highway Administration 2015), the maximum width of commercial trucks is established at 2.6 m.

To examine the effect of the vehicle width on the identification accuracy, a series of vehicle widths ranging from 2.3 m to 2.7 m with an interval of 0.1 m was set for Truck 2. The identification was conducted under Case 6 and the identification errors are summarized in Table 4-7. It can be seen that the TP of the vehicle was successfully identified except for vehicle widths of 2.3 m and 2.7 m where a negligible error of 0.02% was obtained. The variation of identification errors of axle weights and GVW with respect to the vehicle width is plotted in Figure 4-8. It can be observed that the identification errors increase as the vehicle width deviates from 2.5 m, i.e., the original vehicle width that was used in the calibration of the influence surface. Nevertheless, even with the varying vehicle width, the identification of axle weights and GVW was still accurate with the maximum error within four percent. This suggests that the vehicle width will not have a significant effect on the identification accuracy in practice.

### Table 4-6 Identification errors for Case 2 with Truck 2 traveling at different vehicle speeds

<table>
<thead>
<tr>
<th>Vehicle speed (m/s)</th>
<th>TP (%)</th>
<th>Axle weights (%)</th>
<th>GVV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>First axle</td>
<td>Second axle</td>
</tr>
<tr>
<td>5</td>
<td>0.00</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>10</td>
<td>0.00</td>
<td>0.11</td>
<td>0.05</td>
</tr>
<tr>
<td>15</td>
<td>0.00</td>
<td>1.56</td>
<td>0.66</td>
</tr>
<tr>
<td>20</td>
<td>0.00</td>
<td>0.38</td>
<td>0.15</td>
</tr>
<tr>
<td>25</td>
<td>0.00</td>
<td>1.01</td>
<td>0.46</td>
</tr>
<tr>
<td>30</td>
<td>0.00</td>
<td>0.37</td>
<td>0.19</td>
</tr>
</tbody>
</table>

### Table 4-7 Identification errors for Case 6 with Truck 2 using different vehicle widths

<table>
<thead>
<tr>
<th>Vehicle width (m)</th>
<th>TP (%)</th>
<th>Axle weights (%)</th>
<th>GVW (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.3</td>
<td>0.02</td>
<td>2.37</td>
<td>0.91</td>
</tr>
<tr>
<td>2.4</td>
<td>0.00</td>
<td>0.53</td>
<td>0.26</td>
</tr>
<tr>
<td>2.5</td>
<td>0.00</td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>2.6</td>
<td>0.00</td>
<td>0.10</td>
<td>0.19</td>
</tr>
<tr>
<td>2.7</td>
<td>0.02</td>
<td>3.41</td>
<td>0.68</td>
</tr>
</tbody>
</table>

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4.4.4 Effect of Different Measurement Stations

In previous identifications, the measurement station of the largest response was selected as the weighing station while other stations were used to identify the TP. In order to investigate the effect of using different measurement stations as the weighing station, Truck 2 was set to run under Case 1 and the identification was conducted using each measurement station as the weighting station. In this case, S5 had the largest response while the responses of S3 and S4 were smaller than that of S5 but close. The responses of S1 and S2 were noticeably smaller than those of other measurement stations. Table 4-8 lists the identification errors obtained using different weighing stations. It can be seen that the TP of the vehicle was successfully identified regardless of the weighing stations selected and that accurate identification of axle weights and GVW was achieved with the maximum error within one percent. Nevertheless, the identification of axle weights and GVW seems more accurate when S3, S4 and S5, i.e., measurement stations underneath the traveling lane, were respectively selected as the weighing station. To a certain degree, this implies that using measurement stations of smaller responses as the weighing station may lead to larger identification errors of axle weights and GVW. As a general rule of thumb, the measurement station of the largest response is preferred for the selection of the weighing station in order to facilitate the implementation in practice.

Table 4-8 Identification errors for Case 1 with Truck 2 using different weighing stations

| Weighing stations | TP (%) | Axle weights (%) | | |
|-------------------|--------|-----------------| | |
|                   |        | First axle     | Second axle | Third axle | GVW (%) |
| S1                | 0.00   | 0.69           | 0.30        | 0.18       | 0.02    |
| S2                | 0.00   | 0.32           | 0.14        | 0.09       | 0.01    |
| S3                | 0.00   | 0.03           | 0.01        | 0.00       | 0.00    |
| S4                | 0.00   | 0.04           | 0.02        | 0.01       | 0.00    |
| S5                | 0.00   | 0.08           | 0.04        | 0.02       | 0.00    |
4.5 Verification by a Field Study

4.5.1 Tested Bridge

In order to verify the effectiveness of the proposed algorithm in practice, the proposed algorithm was demonstrated using a previously conducted field test. The field test was conducted on a beam-slab bridge in 2006. The tested bridge is located over Cypress Bayou in District 61, on LA 408 East, Louisiana. The bridge has three simply supported spans and all three spans have an identical length of 16.764 m (55 ft) with zero skew angles as shown in Figure 4-9. The bridge consists of seven AASHTO Type-II prestressed concrete girders with a center-to-center spacing of 2.13 m (7 ft). The girders are supported by rubber bearings at both ends of the bridge. For each span, three intermediate diaphragms are located at the mid-span and the two ends of the bridge, separated from the bridge deck. The cross section and the lane arrangement of the bridge are shown in Figure 4-10.

![Longitudinal profile of the tested bridge](image)

Figure 4-9 Longitudinal profile of the tested bridge

![Cross section and lane arrangement of the tested bridge](image)

Figure 4-10 Cross section and lane arrangement of the tested bridge

The third span of the bridge was instrumented. Seven strain gauges were installed at the bottom of the seven girders to measure the longitudinal strains. These strain gages were installed 0.305 m (1 ft) away from the mid-span of the bridge in order to avoid stress concentrations caused by the diaphragms placed at the mid-span. Therefore, a total of seven measurement
stations (S1, S2, S3, S4, S5, S6, and S7) were selected corresponding to the seven girders G1, G2, G3, G4, G5, G6, and G7.

4.5.2 Test Vehicle

In the field test, a dump truck with a single front axle and a rear two-axle group was used as the test vehicle. The static loads for the first, second, and third axles of the test truck are 80.0 kN, 95.6 kN, and 95.6 kN, respectively. The axle spacing between the first axle and the center of the rear axle group is 6.25 m, and the distance between the two rear axles is 1.2 m. The width of the test vehicle is 2.41 m. In the weighing of highway trucks, it is a common practice to treat a group of closely-spaced axles such as a tandem and a tridem group as one equivalent axle. This is because the weight of an axle group is often of more interests than the individual axles within it and combining closely-spaced axles does not affect the identification results of the GVW. Therefore, the two rear axles of the test truck are replaced by one equivalent axle in order to simply the identification in this study.

4.5.3 Field Calibration of Influence Surface

Six testing cases (three static and three dynamic tests) were considered in the field testing. A brief description of the testing cases is given in Table 4-9. Detailed testing setups can be found in Araujo (2009). The first three cases correspond to the static testing with three different TPs of the vehicle. The responses obtained from these three cases were used to calibrate the influence surface as the dynamic effect was very small during the static testing. For each TP, the corresponding influence line was calculated from the measured bridge response using the method proposed by O’Brien et al. (2006). Previous experimental studies found that a cubic spline function is suitable for the interpolation of influence ordinates at positions in-between the measured TPs in field calibrations (Quilligan 2003; WAVE 2001). Therefore, a spline interpolation was adopted in the current study to form a continuous influence surface using the field calibrated influence lines obtained at different TPs.

<table>
<thead>
<tr>
<th>Case number</th>
<th>Testing type</th>
<th>Traveling Lane</th>
<th>Transverse position (m)</th>
<th>Planned truck speed (m/s [mph])</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>Static</td>
<td>Shoulder</td>
<td>0.914 (36 inch)</td>
<td>2.24 (5)</td>
</tr>
<tr>
<td>Case 2</td>
<td>Static</td>
<td>Lane 1</td>
<td>4.420 (174 inch)</td>
<td>2.24 (5)</td>
</tr>
<tr>
<td>Case 3</td>
<td>Static</td>
<td>Lane 2</td>
<td>7.798 (307 inch)</td>
<td>2.24 (5)</td>
</tr>
<tr>
<td>Case 4</td>
<td>Dynamic</td>
<td>Lane 1</td>
<td>4.420 (174 inch)</td>
<td>13.41 (30)</td>
</tr>
<tr>
<td>Case 5</td>
<td>Dynamic</td>
<td>Lane 1</td>
<td>4.420 (174 inch)</td>
<td>17.88 (40)</td>
</tr>
<tr>
<td>Case 6</td>
<td>Dynamic</td>
<td>Lane 2</td>
<td>7.798 (307 inch)</td>
<td>17.21 (38.5)</td>
</tr>
</tbody>
</table>

4.5.4 Identification Results

The proposed algorithm was used to identify the TP and axle weights of the test truck for all considered cases. Based on the proposed algorithm, the measurement station with the largest response is used as the weighing station and only the measurement from the weighing station will be used as the input for the calculation of axle weights and GVW. For Case 2, Case 4 and Case 5, S5 had the largest response and thus S5 was selected as the weighing station. Similarly,
S3 was selected as the weighing station for Case 3 and Case 6 while S7 was selected as the weighing station for Case 1. Based on the proposed algorithm, the measurement stations other than the weighing station will be used to identify the vehicle’s TP. Nevertheless, it was found that in each case, the response of the station furthest from the test vehicle is so small that significant variations were observed in the response. Thus, the furthest measurement station from the test truck was not used for the identification in order to reduce the effect of measurement errors. In addition, the measured axle spacing and the planned truck speed for each testing case were used for the calculation of the vehicle weight. It should be noted that the actual traveling speed of the test truck during the field test may vary from the planned speed, which could lead to a certain degree of errors in the identified vehicle weight.

Figure 4-11 shows the variation of the error function with respect to the possible TPs of the vehicle for Case 4. It can be seen that the error function is minimized when the vehicle’s TP is approximately 4.6 m. The identification results and corresponding errors are shown in Table 4-10. It can be seen that the identification errors for the first three cases, i.e., the static testing cases, are basically negligible as expected. For the dynamic testing cases, it was observed that the identification errors of the TP are approximately within four percent while the errors of axle weights and GVW for most cases are within four percent as well. In fact, the only case where the error of axle weights and GVW exceeded four percent is Case 6. This is probably because the actual truck speed in Case 6 was not well controlled according to the record. Nevertheless, the identification accuracy achieved using the proposed algorithm is acceptable in practice.

In addition, another approach to examine the identification accuracy is to reconstruct the bridge response using the identified TP and axle weights of the vehicle and compare it with the measured response. Figure 4-12 shows the comparison between the measured response and the reconstructed response of the weighing station for Case 4 and Case 6. It can be seen that a good match between the measured and reconstructed responses is achieved.
### Table 4-10 Identification results and corresponding errors in the field study

<table>
<thead>
<tr>
<th>Case Number</th>
<th>Transverse position Value (m)</th>
<th>Error (%)</th>
<th>First axle Value (kN)</th>
<th>Error (%)</th>
<th>Second axle Value (kN)</th>
<th>Error (%)</th>
<th>GVW Value (kN)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>0.914</td>
<td>0.00</td>
<td>79.8</td>
<td>0.25</td>
<td>191.4</td>
<td>0.08</td>
<td>271.1</td>
<td>0.02</td>
</tr>
<tr>
<td>Case 2</td>
<td>4.420</td>
<td>0.00</td>
<td>79.7</td>
<td>0.33</td>
<td>191.4</td>
<td>0.10</td>
<td>271.1</td>
<td>0.03</td>
</tr>
<tr>
<td>Case 3</td>
<td>7.798</td>
<td>0.00</td>
<td>79.8</td>
<td>0.25</td>
<td>191.3</td>
<td>0.07</td>
<td>271.1</td>
<td>0.02</td>
</tr>
<tr>
<td>Case 4</td>
<td>4.597</td>
<td>4.02</td>
<td>81.7</td>
<td>2.11</td>
<td>185.6</td>
<td>2.92</td>
<td>267.3</td>
<td>1.44</td>
</tr>
<tr>
<td>Case 5</td>
<td>4.343</td>
<td>1.72</td>
<td>77.0</td>
<td>3.71</td>
<td>191.3</td>
<td>0.07</td>
<td>268.3</td>
<td>1.05</td>
</tr>
<tr>
<td>Case 6</td>
<td>7.798</td>
<td>0.00</td>
<td>68.2</td>
<td>14.7</td>
<td>185.8</td>
<td>2.81</td>
<td>254.0</td>
<td>6.33</td>
</tr>
</tbody>
</table>

Figure 4-12 Comparison between the measured and reconstructed bridge responses of the weighing station: (a) S5 of Case 4; (b) S3 of Case 6
4.6 Conclusions

This paper proposed a novel NOR BWIM algorithm considering the transverse position (TP) of the vehicle. In the proposed algorithm, the identification of the vehicle’s TP and axle weights is achieved using only weighing sensors, which enhances the portability and reduces the cost of NOR BWIM systems. Numerical simulations were conducted using three-dimensional vehicle and bridge models while the TP and the axle weights of different vehicles were identified using the proposed algorithm. Parametric study was conducted to examine the effects of the road surface condition, the vehicle speed, the vehicle width, and different measurement stations on the identification accuracy. Finally, the proposed algorithm was verified by a field study. Based on the results obtained, the following conclusions can be drawn:

(1) Numerical results showed that the proposed algorithm can accurately identify the TP and the axle weights of vehicles and that considering the vehicle’s TP can significantly improve the identification accuracy of axle weights compared with the 1D Moses’s algorithm;

(2) Successful identification of the vehicle’s TP was achieved regardless of the different road surface conditions used. However, the identification accuracy of axle weights decreases significantly as the road surface condition becomes worse. In this case, a low-pass filter can be applied to effectively improve the identification accuracy of axle weights;

(3) Vehicle speed does not have a significant influence on the identification accuracy. Nevertheless, vehicle traveling at certain speeds may induce the resonant vibration of the bridge, which leads to larger identification errors of axle weights;

(4) Although the variation of the vehicle width has certain effects on the identification accuracy, the actual variation of vehicle width is quite small and the influence of the vehicle width on the identification accuracy is negligible in practice;

(5) Using measurement stations of smaller responses as weighing stations may result in larger identification errors of axle weights. It is thus suggested that the measurement station of the largest response be selected as the weighing station in practice;

The proposed NOR BWIM algorithm is suitable for the application in modern commercial BWIM systems to improve the identification accuracy due its simplicity and robustness. In addition, it is noted that the identification of multiple-vehicle presence is still one of the main challenges faced by BWIM technology. For the proposed algorithm, the TP of each vehicle needs to be identified when there are multiple vehicles present on the bridge. Future works will focus on using the proposed algorithm to identify different cases of multiple-vehicle presence, such as side-by-side, staggered, and following truck patterns, and investigating the effect of actual traffic on the effectiveness of the proposed algorithm.

4.7 References


CHAPTER 5. PREDICTION OF EXTREME TRAFFIC LOAD EFFECTS OF BRIDGES UNDER THE BAYESIAN FRAMEWORK AND APPLICATION TO BRIDGE CONDITION ASSESSMENT

5.1 Introduction

Bridges are important components of the transportation system. For in-service bridges, the reduction of resistance caused by the deterioration of materials and the increase of traffic intensity due to the economic growth have raised serious concerns over their safety. According to ASCE’s 2017 infrastructure report card (ASCE 2017), the average age of bridges in the U.S. is 43 years old, and many bridges have approached their design lifespan of 50 years, requiring major rehabilitation or retirement. Meanwhile, based on the recent USDOT report “Beyond Traffic: 2045” (US Department of Transportation 2016), the freight volume will increase by more than 40 percent by 2045, posing great challenges on the existing transportation infrastructures, many of which were not designed to meet the increasing demands. In light of these concerns and challenges, the condition assessment of in-service bridges has received increasing attention in recent years. Bridge condition assessment through structural health monitoring (SHM) can provide real-time information on the performance and health condition of bridges, allowing bridge owners to make well-informed decisions for bridge maintenance and management. In the past decades, numerous studies have been conducted on the condition assessment of bridges and different assessment strategies were proposed (Aktan et al. 1997; Frangopol et al. 2008; Ni et al. 2012; Xia et al. 2017). Generally speaking, a bridge can be considered safe if it has the capacity to withstand the expected loading during its design life. However, the duration of monitoring period is usually short compared with the typical rating period and design life of bridges. Therefore, in order to evaluate the safety condition of existing bridges during their remaining life, a statistic-based method is needed to predict the extreme traffic load effects (LEs) of bridges based on the monitoring data.

Previously, different methods have been developed for the modeling and prediction of the extreme traffic LEs of bridges. Some researchers fitted the upper tail of the maximum traffic LEs to a normal distribution and extrapolated the future extreme LEs using the normal probability paper (Nowak 1993; Nowak and Hong 1991). Some other researchers assumed that the bridge traffic LE is a stationary Gaussian process and adopted the level crossing method based on the Rice formula to predict the extreme traffic LEs (Chen et al. 2015; Cremona 2001). Or perhaps more commonly, many researchers conducted extreme value analysis based on either the block maxima (Caprani et al. 2008; Xia et al. 2016) or the peak-over-threshold method (Crespo-minguilh and Casas 1997; Zhou et al. 2016) to predict the extremes traffic LEs. A comprehensive review on the various prediction methods for bridge traffic LEs was presented by O’Brien et al. (2015). However, most of the previous studies did not consider the uncertainty of distribution parameters during the modeling and prediction of extreme traffic LEs. The conventional approach is to fit the observed extreme LEs to some probabilistic distribution and use the point estimate of the distribution parameters to extrapolate the LE. In fact, there are two types of uncertainty when modeling the extreme traffic LEs, i.e., the aleatory and epistemic uncertainties (Catbas et al. 2008). Aleatory uncertainty reflects the inherent randomness of the natural process while the epistemic uncertainty is caused by the lack of knowledge such as
limited data and modeling errors. Most prediction methods only recognize the aleatory uncertainty, assuming the distribution parameters to be deterministic. However, in reality, the amount of monitoring data is limited and thus the epistemic uncertainty could be significant when a probabilistic distribution is used to model the data. This uncertainty, if ignored, could lead to significant underestimations of predicted traffic LEs. Hence, in order to provide more reliable predictions, the epistemic uncertainties need to be accounted for.

The Bayesian method offers a natural framework for the uncertainty quantification and prediction. A direct outcome from the Bayesian inference is the posterior distribution, i.e., the uncertainty is formally introduced under the Bayesian framework. Furthermore, the Bayesian method incorporates the uncertainty into the prediction of future outcomes through the use of the posterior predictive distribution and thus gives more reliable predictions. One difficulty in implementing the Bayesian method is the high cost of computation. Nevertheless, with the advances in computer technologies and powerful simulation techniques such as the Markov Chain Monte Carlo (MCMC) algorithms, the Bayesian method has increased in popularity in modern statistics. The Bayesian method has been applied for the prediction of future extremes in fields such as hydrology and climatology (Cheng et al. 2014; Lima and Lall 2009). However, there are very few studies on using the Bayesian method for the prediction of bridge traffic LEs. O’Brien et al. (2015) adopted the Bayesian method in a comparative study and it was found that the Bayesian method showed inconsistent prediction performances for different bridge span lengths and types of LE. However, only partial uncertainties of the distribution parameters were considered in their study.

The objective of this study is to systematically introduce the Bayesian method for the prediction of extreme traffic LEs of bridges. Firstly, the theories of extreme value analysis and Bayesian inference are introduced. Then, a framework for bridge condition assessment is proposed making use of the predicted traffic LEs. A case study on the condition assessment of the new I-10 Twin Span Bridge is presented to demonstrate the proposed methodology.

5.2 Bayesian Method for Extreme Value Analysis

5.2.1 Extreme Value Analysis

- Modeling of Extremes using Extreme Value Theory

For a sequence of independent and identically distributed (i.i.d.) random variables $(X_1, X_2, ..., X_n)$ whose cumulative distribution function (CDF) is $F(x)$, let $M_n = \text{Max}(X_1, X_2, ..., X_n)$. Then, the CDF of $M_n$ can be expressed as:

$$F_{M_n}(x) = P(M_n < x) = P(X_1 < x, X_2 < x, ..., X_n < x) = F^n(x)$$  \hspace{1cm} (5-1)

Based on the Fisher-Tippett-Gnedenko theorem (Fisher and Tippett 1928), if there exists a sequence of real numbers $(a_n, b_n)$ with $a_n > 0$ such that

$$\lim_{n \to \infty} P\left(\frac{M_n - b_n}{a_n} < x\right) = G(x)$$  \hspace{1cm} (5-2)
where \( G(x) \) is a non-degenerate distribution function, then \( G(x) \) must be in the form of the generalized extreme value (GEV) distribution whose CDF can be written as:

\[
G(x) = \exp \left\{ - \left[ 1 + k \left( \frac{x - \mu}{\sigma} \right) \right]^{-1/k} \right\}
\]  

(5-3)

where \( k \) is the shape parameter; \( \sigma \) is the scale parameter; and \( \mu \) is the location parameter. The GEV distribution contains three types of extreme value distributions depending on the value of the shape parameter: (i) when \( k > 0 \), \( G(x) \) corresponds to the heavy-tailed (Fréchet) distribution; (ii) when \( k < 0 \), \( G(x) \) corresponds to the short-tailed (Weibull) distribution; and (iii) when \( k = 0 \), \( G(x) \) corresponds to the light-tailed (Gumbel) distribution.

In order to model the extreme traffic LEs using the extreme value theory, the maximum traffic LEs are assumed to be i.i.d. The maximum traffic LEs are obtained using the block maxima method where the observation is divided into non-overlapping time intervals (blocks) of equal length and then the maximum traffic LE in each block is extracted. Based on the extreme value theory, the block maxima will converge to the GEV distribution.

### Prediction of Future Extremes

In extreme value analysis, the future extreme is predicted by computing the return level corresponding to a certain return period. Under the i.i.d. assumption, the return level corresponding to a certain return period has an equal probability of exceedance in any block. Therefore, the return level can be calculated as the quantile of the GEV distribution:

\[
xRL = \mu + \frac{\sigma}{k} \times \left[ \ln \left( 1 - \frac{t}{T} \right) \right]^{-k}
\]  

(5-4)

where \( t \) is the block length and \( T \) is the return period. The reliability of the prediction is affected by the block length because the return level is usually obtained at the tail region of the distribution where the distribution is typically less accurate. For example, if the block length is chosen as one day, then the 50-year return level corresponds to approximately 0.9999452 quantile of the distribution of the daily maximum LE, which would require very high precision of the daily maximum LE distribution. From this perspective, increasing the block length will make the prediction more reliable. Meanwhile, the data sample size should also be considered when choosing the block length as an overly large block length would render the effective data size too small. Besides, the reliability of long-term predictions needs to be taken into consideration during the decision making process.

For a conventional extreme value analysis, the block maxima data is first fitted to the GEV distribution and the point estimates of the distribution parameters are obtained using the maximum likelihood estimation (MLE). Then, the prediction can be made by computing the return levels using Eq. (5-4).
5.2.2 Bayesian Inference

Based on the Bayes theorem, the posterior distribution of the parameters to be inferred can be written as:

\[
p(\theta | x) = \frac{L(\theta | x) p(\theta)}{\int L(\theta | x) p(\theta) d\theta}
\]

(5-5)

where \( \theta \) is the parameters to be inferred; \( p(\theta | x) \) is the posterior distribution; \( x \) is the data; \( p(\theta) \) is the prior distribution of the parameters; and \( L(\theta | x) \) is the likelihood function that can be expressed as:

\[
L(\theta | x) = \prod_{i=1}^{N_t} p(x_i | \theta)
\]

(5-6)

where \( x_i \) is the value for the \( i \)th observation and \( N_t \) is the number of observations.

- Choice of Prior Distribution

In Bayesian statistics, the prior distribution represents the prior knowledge of the parameters and it is independent from the existing observations. Generally speaking, the prior distribution can be classified into two types, i.e., the informative prior and the non-informative prior. The informative prior is specified based on the prior knowledge that is usually obtained from the previous studies and the knowledge of experts. A well-specified informative prior can help reduce the uncertainty of parameters and lead to more efficient MCMC sampling. Nevertheless, the prior knowledge may be difficult to express in terms of probability distributions and it often contains a certain degree of subjectivity. The non-informative prior, on the other hand, is adopted when little or no prior knowledge of the parameters is known. The non-informative prior usually features a flat distribution to represent the lack of knowledge. For example, a uniform distribution with a wide support or a normal distribution with a large variance is commonly used as the non-informative prior. In addition, it is noted that there exist conjugate priors for some distribution families. The use of conjugate priors is convenient as it avoids using the MCMC sampling. However, the conjugate prior is not available for the GEV distribution (Renard et al. 2012).

In the present study, it is very difficult to elicit informative priors because the traffic LEs of bridges are highly site-specific due to the different traffic characteristics and bridge behaviors. Therefore, the non-informative prior is selected as the prior distribution. Three independent uniform distributions with wide supports are specified as the prior distribution as:

\[
p(\theta) = p(k) p(\sigma) p(\mu)
\]

(5-7)

where \( p(k) \), \( p(\sigma) \), and \( p(\mu) \) are the prior distributions for the shape, scale, and location parameters, respectively. It should be noted that although the prior distributions are independent
for each parameter, the obtained posterior distributions for each parameter will be dependent after the inference.

- **Markov Chain Monte Carlo (MCMC) Sampling**

  The denominator in Eq. (5-5) is a multi-dimensional integral that depends only on the data and its evaluation is often difficult. Nevertheless, the evaluation of this integral is usually not necessary since it can be treated as a normalizing constant and the posterior distribution can be written as:

  \[ p(\theta | x) \propto L(\theta | x) p(\theta) \]  

  (5-8)

  The Markov Chain Monte Carlo (MCMC) sampling can be used to directly sample from the posterior distribution using Eq. (5-8). In this study, the Metropolis-within-Gibbs (MG) sampler is adopted. The sampling procedures are described as follows:

  1. Assigning initial values to the parameters: \( \theta^{(0)} = [k^{(0)}, \sigma^{(0)}, \mu^{(0)}]^T \) where \( k \), \( \sigma \), and \( \mu \) are the shape, scale, and location parameters of the GEV distribution, respectively;

  2. For \( i = 1:N \) (N=the number of iterations), first generate a candidate value for the shape parameter, \( k^* \), from the normal proposal distribution conditional on \( k^{(i-1)} \), i.e., \( k^* \sim f(k^* | k^{(i-1)}) = N(k^{(i-1)}, s_k) \) where \( s_k \) is the scale of the proposal distribution. Then, calculate the acceptance ratio for \( k^* \) as:

  \[ \tau = \frac{f(k^* | \sigma^{(i-1)}, \mu^{(i-1)}, x)}{f(k^{(i-1)} | \sigma^{(i-1)}, \mu^{(i-1)}, x)} \]  

  (5-9)

  where \( f(k | \sigma^{(i-1)}, \mu^{(i-1)}, x) \) is the unnormalized full conditional distribution of the shape parameter that is expressed as the product between the likelihood function and the prior distribution of the shape parameter as:

  \[ f(k | \sigma^{(i-1)}, \mu^{(i-1)}, x) = L(k | x, \sigma^{(i-1)}, \mu^{(i-1)}) = \prod_{i=1}^{N} p(x_i, \sigma^{(i-1)}, \mu^{(i-1)} | k)p(k) \]  

  (5-10)

  Then, sample \( u \) from the uniform distribution \( U(0,1) \); if \( u < \min(1, \tau) \), accept \( k^* \), i.e., \( k^{(i)} = k^* \); otherwise, reject \( k^* \), i.e., \( k^{(i)} = k^{(i-1)} \);

  3. Generate a candidate value for the scale parameter, \( \sigma^* \), from the normal proposal distribution conditional on \( \sigma^{(i-1)} \), i.e., \( \sigma^* \sim f(\sigma^* | \sigma^{(i-1)}) = N(\sigma^{(i-1)}, s_\sigma) \) where \( s_\sigma \) is the scale of the proposal distribution. Then, calculate the acceptance ratio for \( \sigma^* \) as:

  \[ \tau = \frac{f(\sigma^* | k^{(i)}, \mu^{(i-1)}, x)}{f(\sigma^{(i-1)} | k^{(i)}, \mu^{(i-1)}, x)} \]  

  (5-11)

  Similarly, \( f(\sigma | k^{(i)}, \mu^{(i-1)}, x) \) is the unnormalized full conditional distribution of the scale parameter that is expressed as:
\[
 f(\sigma | k^{(i)}, \mu^{(i-1)}, x) = \prod_{i=1}^{N_i} p\left(x_i, k^{(i)}, \mu^{(i-1)} | \sigma\right) p(\sigma)
 \]

Then, sample \( u \) from the uniform distribution \( U(0,1) \); if \( u < \min(1, \tau) \), accept \( \sigma^* \), i.e., \( \sigma^{(i)} = \sigma^* \); otherwise, reject \( \sigma^* \), i.e., \( \sigma^{(i)} = \sigma^{(i-1)} \).

4. Generate a candidate value for the location parameter, \( \mu^* \), from the normal proposal distribution conditional on \( \mu^{(i-1)} \), i.e., \( \mu^* \sim f(\mu^* | \mu^{(i-1)}) = N(\mu^{(i-1)}, s^2_\mu) \) where \( s^2_\mu \) is the scale of the proposal distribution. Then, calculate the acceptance ratio for \( \mu^* \) as:

\[
 \tau = \frac{f(\mu^* | k^{(i)}, \sigma^{(i)}, x)}{f(\mu^{(i-1)} | k^{(i)}, \sigma^{(i)}, x)}
\]

Similarly, \( f(\mu | k^{(i)}, \sigma^{(i)}, x) \) is the unnormalized full conditional distribution of the location parameter that is expressed as:

\[
 f(\mu | k^{(i)}, \sigma^{(i)}, x) = \prod_{i=1}^{N_i} p\left(x_i, k^{(i)}, \sigma^{(i)} | \mu\right) p(\mu)
 \]

Then, sample \( u \) from the uniform distribution \( U(0,1) \); if \( u < \min(1, \tau) \), accept \( \mu^* \), i.e., \( \mu^{(i)} = \mu^* \); otherwise, reject \( \mu^* \), i.e., \( \mu^{(i)} = \mu^{(i-1)} \).

5. Repeat step 2 to 4 until \( i \) reaches \( N \).

Following the above procedures, the parameter values generated by the MG sampler will asymptotically converge to the target distribution after a sufficient number of iterations. Nevertheless, the initial portion of the Markov Chain may not be a true realization from the target distribution because initial values of parameters have a significant influence on the initial portion. Therefore, in order to minimize the influence of the initial values, the initial portion of the Markov Chain is usually discarded and only the stabilized portion of the chain is used as the realization from the target distribution. The discarded portion is known as the burn-in period. Furthermore, the scale of the proposal distribution is a critical parameter that affects the sampling efficiency. On the one hand, if the scale is too small, then almost all proposed values will be accepted and the chain will move very slowly. On the other hand, if the scale is too large, then most proposed values will be rejected and the chain will hardly move at all. Both cases will cause the chain to mix poorly, leading to inefficient sampling. Thus, in order to achieve efficient sampling, the MG sampler needs to be tuned to obtain the optimal acceptance rate. For one-dimensional normal proposal distribution, the optimal acceptance rate was found to be approximately 0.44 (Rosenthal 2011).

**Posterior Predictive Distribution**

The ultimate goal of the extreme value analysis is the prediction of future extremes. In Bayesian statistics, the posterior predictive distribution is defined as:
\[ p(y \mid x) = \int p(y, \theta \mid x)d\theta \]  

(5-15)

where \( y \) is the future outcome to be predicted. Since the future outcome is independent from the existing observations, the posterior predictive distribution can be rewritten based on the Bayes rule as:

\[ p(y \mid x) = \int p(y \mid \theta)p(\theta \mid x)d\theta \]  

(5-16)

where \( p(y \mid \theta) \) is the GEV distribution and \( p(\theta \mid x) \) is the posterior distribution. Essentially, the posterior predictive distribution accounts for the parameter uncertainties by integrating the GEV distribution over all possible values of parameters specified by the posterior distribution. In fact, if the parameters are considered deterministic, then Eq. (5-16) becomes:

\[ p(y \mid x) = p(y \mid \theta) \]  

(5-17)

which is simply the case of the conventional method where point estimates of the parameters are adopted. Therefore, compared with the conventional method, the Bayesian method is able to incorporate the uncertainties inherent in the parameters into the prediction and provides more reliable estimate of future outcomes.

In practice, the integration in Eq. (5-16) does not need to be performed analytically given a sample of the posterior distribution. The procedures described below can be followed to sample from the posterior predictive distribution as:

1. For \( i=1:N \) (\( N=\)sample size of the posterior distribution), generate a sample of size \( m \) from the GEV distribution given the parameters \( \theta^{(i)} \) from the posterior distribution, i.e., sample \( y_1^{(i)}, y_2^{(i)}, \ldots, y_m^{(i)} \) from \( p(y \mid \theta^{(i)}) \);

2. Repeat step 1 until \( i \) reaches \( N \) and the obtained sample with the size of \( N \times m \) will be a realization from the posterior distribution.

### 5.3 Framework for Bridge Condition Assessment

The objective of bridge condition assessment is to evaluate the capacity of the bridge and check if the bridge can safely carry the operational loading. In order to achieve this objective, a framework presented in Figure 5-1 is proposed to assess the bridge condition in this study. First, the bridge responses at critical locations are measured by the sensors. For bridge condition assessment, strain responses are probably the most important data since they reflect the safety reserve of structural components (Ni et al. 2012). Then, the maximum traffic LEs of the bridge are extracted from the sensor measurement upon signal processing and the future extreme traffic LEs are predicted using the Bayesian method described earlier. Finally, the measured and predicted maximum traffic LEs are compared with the response envelops to determine the condition of the bridge.
In the proposed framework, two response envelops are developed to evaluate the bridge condition at two levels. The first response envelop reflects the live load (LL) capacity that the bridge is designed to sustain and is thus named the design LL capacity envelop. This design LL capacity envelop should not be exceeded by the traffic LEs of the bridge. Otherwise, the bridge will be severely damaged or even collapse conceptually. In this case, the bridge is considered unsafe and actions should be taken to repair and strengthen the bridge. Nevertheless, the design LL capacity of the bridge is usually considerably larger than the measured traffic LEs under the normal operational loading. This is because the design LL capacity is determined under the ultimate loading condition and bridge design codes are inevitably conservative due to the simplifications made during the design process and the requirement of covering a wide range of bridges. Therefore, it is difficult to evaluate the expected bridge performance under the normal operational loading by comparing the bridge traffic LEs with the design LL capacity envelop.

In order to check the in-service performance of the bridge, the service performance envelop is developed by applying the design LL on a three-dimensional (3D) finite element (FE) model of the bridge. The 3D FE model of the bridge can more accurately reflect the bridge behavior because it is specific to the bridge under assessment and it models the actual distribution of the LL by considering the system behavior of the bridge. The FE model is calibrated using the measured LEs to establish the baseline state of the bridge. Conceptually, if the field bridge is the same as the FE model (i.e., no damage compared with the baseline state) and the operational loading is the same as the design LL, the measured traffic LEs should be the same as those predicted by the FE model. In other words, the service performance envelop establishes the baseline performance of the bridge under the normal design service traffic load. Thus, if the traffic LE of the bridge is within the service performance envelop, we can conclude that the bridge is performing normally. On the other hand, if the traffic LE of the bridge exceeds the service performance envelop, it could indicate one of the following issues: (1) there exist structural damages compared with the baseline state of the bridge; (2) the operational loading level is higher than the design service LL; (3) both of the above issues. In any of these three cases, the bridge is overstressed conceptually and an inspection is recommended to determine whether a repair or strengthening is necessary.
Figure 5-1 Proposed framework for bridge condition assessment
5.4 Case Study

5.4.1 Bridge Description

The bridge selected for the case study is the new I-10 Twin Span Bridge (TSB) located in southern Louisiana. Being a vital part of the Interstate 10, the new TSB crosses Lake Pontchartrain connecting Slidell and New Orleans. The new I-10 TSB as shown in Figure 5-2 (a) was built after the original spans suffered extensive damages from Hurricane Katrina in 2005. The strong storm surge brought by the hurricane lifted many precast segments off their piers as shown in Figure 5-2 (b). Although the original TSB was repaired shortly after the catastrophic hurricane, the original bridge was deemed too vulnerable to future storm surges and it was decided that a new bridge with a higher capacity to withstand extreme events such as hurricanes needs to be built to replace the existing bridge. The construction of the new I-10 TSB started in 2006 and was completed in 2011.

![Figure 5-2 The I-10 Twin Span Bridge in Louisiana: (a) the new I-10 TSB; (b) the original I-10 TSB damaged by Hurricane Katrina.](image)

The new TSB, constructed entirely using high performance concrete, is approximately 8.7 km long and consists of two parallel spans, i.e., the Westbound and the Eastbound, each with three 3.66 m traffic lanes and two 3.66 m shoulders on two sides, allowing for a fifty percent increase of traffic volume. The bridge has an elevation of 9.14 m, 6.40 m higher than the original span, and a high-rise span of 24.38 m for navigations. The superstructures of the bridge include units of continuous concrete spans and a three-span continuous steel-concrete composite bridge deck for the high-rise span. Each span consists of six identical girders with an equal spacing of 3.28 m. A structural health monitoring (SHM) system was installed on the two spans supported by the M19 pier of the Eastbound, the pier south of the marine traffic underpass, to monitor the strain response of the bridge. Figure 5-3 shows the location and sensor layouts of the instrumented spans.
Figure 5-3 Instrumentation of the I-10 Twin Span Bridge; (a) longitudinal profile of instrumented spans; (b) sensor layout of the steel span at the mid-span (with traffic flow); (c) sensor layout of the concrete span at the mid-span (with traffic flow); (d) M19 pier
5.4.2 Analysis of Monitoring Data

Figure 5-4 (a) shows the sample time history of the measured strain response of S4 for one day from 0:00 to 24:00. The measured strain response of the bridge consists of temperature-induced and traffic-induced components. The variation of the temperature results in material deformations and causes the strain to vary slowly with time. The effect of traffic is more transient and thus causes peaks in the strain response as shown in Figure 5-4 (a). While the temperature-induced strain could be significant, its contribution to the stress is significantly reduced because the expansion joints allow the free longitudinal movement of the bridge. The traffic loading causes the bridge to bend and thus the traffic-induced strain is the main contribution to the stress. In order to obtain the stress of the bridge, the traffic-induced strain needs to be extracted from the measured strain response. This can be done by using the multi-resolution wavelet decomposition. Through wavelet decomposition, the signal is decomposed at multiple levels of resolutions. At each level, the signal is divided into approximation coefficients and detail coefficients. The approximation coefficients correspond to the low-frequency part of the signal which contains the temperature-induced strain. The traffic-induced strain can be obtained by subtracting the measured strain response with the temperature-induced strain.

![Wavelet Decomposition](image)

Figure 5-4 Sample time history of strain response of S4: (a) measured strain response and temperature-induced strain of one day; (b) traffic-induced strain of one day.

In this study, the Symlets wavelet is used and the temperature-induced strain is successfully separated from the measured strain response at 14-level decomposition as shown in Figure 5-4 (a). Figure 5-4 (b) shows the traffic-induced strain response extracted as the difference between the measured and temperature-induced strains. It can be seen that the peaks are more concentrated at daytimes from 8:00 to 18:00 time period when the traffic is denser.
5.4.3 Prediction of Extreme Traffic LEs

The daily maximum traffic LEs are obtained from sixty-five days of monitoring data and the Bayesian method is used to predict the future maximum traffic LEs. For demonstration purposes, the prediction of the maximum traffic LEs of S4 is used as an example to illustrate the prediction procedures. Figure 5-5 shows the normalized histogram for the daily maxima of positive traffic-induced strains of S4 and the corresponding GEV fit. The MLE estimates of the shape, scale, and location parameters are obtained as -0.077, 15.91, and 102.93, respectively.

![Normalized histogram of daily maximum traffic LEs of S4 and the corresponding GEV fit](image)

Figure 5-5 Normalized histogram of daily maximum traffic LEs of S4 and the corresponding GEV fit

Under the Bayesian framework, each distribution parameter is treated as a random variable and the posterior distribution of parameters can be obtained using the MCMC sampling. In this study, the MG sampler was first tuned to obtain the optimal acceptance rate and then 100,000 iterations were performed to ensure the prediction accuracy. Figure 5-6 shows the trace plots of parameters. It can be seen that the chain converged very quickly and that the chain mixed well. The burn-in period was chosen as 1,000. Figure 5-7 shows the marginal posterior distributions using the kernel density estimation (KDE) and a significant uncertainty of the parameters is observed. This is expected because of a relatively small sample size. Compared with the conventional method, the Bayesian method is able to quantify the uncertainties of parameters in terms of posterior distributions. In fact, it can be seen from Figure 5-7 that the modes of the marginal posterior distributions of the shape, scale, and location parameters are roughly estimated as -0.08, 16, and 103, respectively, which are very close to the MLE estimates. This is because the uniform prior distribution is adopted and the posterior distribution is essentially the normalized likelihood function. Furthermore, the uncertainty of return levels can be subsequently quantified using the obtained posterior distribution of parameters. For each set of GEV parameters obtained using the MG sampler, the corresponding $T$-year return level is calculated using Eq. (5-4) and thus the distribution of the $T$-year return levels can be obtained. Figure 5-8 shows the distributions of the 5-year and 75-year return levels of the traffic LEs of S4 using the KDE. It can be seen that the distribution of the 75-year return level has longer tails than that of the 5-year return level, indicating that extreme loading events are more likely to occur for longer return periods. The distribution of return levels can be used for the reliability assessment of the bridge.
Figure 5-6 Trace plots of GEV parameters: (a) shape parameter; (b) scale parameter; (c) location parameter.

Figure 5-7 Marginal posterior distributions of the GEV distribution parameters: (a) shape parameter; (b) scale parameter; (c) location parameter
Finally, following the previously described procedures, the posterior predictive distribution is obtained to predict the future maximum traffic LEs. Figure 5-9 shows the predictive distribution using the KDE as well as the fitted GEV distribution. It can be seen that the predictive distribution has a wider spread than the fitted GEV distribution. This is because the uncertainties inherent in the parameters were included in the predictive distribution. Based on the i.i.d. assumption, the Bayesian estimate of the future maximum traffic LEs are obtained by evaluating the quantiles of the predictive distribution. Figure 5-10 plots the variation of the...
predicted maximum traffic LEs of S4 with respect to the return period obtained using both the Bayesian and conventional methods. From Figure 5-10, it can be seen that the predicted maximum traffic LEs using the Bayesian method are significantly higher than those using the conventional method and that the difference between the two increases as the return period increases. This is because there exist significant uncertainties of parameters as observed from Figure 5-7. In this case, ignoring these uncertainties may lead to a significant underestimation of the predicted traffic LEs and from this perspective, the Bayesian method is able to provide more reliable predictions than the conventional method.

The same procedures are conducted for the measured strains at each sensor of the two instrumented spans. The predicted maximum traffic-induced strains are transferred to stresses by multiplying the modulus of elasticity of materials assuming that the bridge is operating in the elastic stage. Table 5-1 and Table 5-2 summarize the predicted maximum stresses for the steel and concrete spans in 5 years (the typical rating period) and 75 years (the design life). These values will later be used for the condition assessment of the bridge.

### Table 5-1 Predicted maximum stresses of the steel span using Bayesian method

<table>
<thead>
<tr>
<th>Sensor Number</th>
<th>5-year maximum stresses (MPa)</th>
<th>75-year maximum stress (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Positive</td>
<td>Negative</td>
</tr>
<tr>
<td>S1</td>
<td>48.86</td>
<td>-13.13</td>
</tr>
<tr>
<td>S2</td>
<td>64.36</td>
<td>-21.85</td>
</tr>
<tr>
<td>S3</td>
<td>46.88</td>
<td>-19.43</td>
</tr>
<tr>
<td>S4</td>
<td>46.01</td>
<td>-17.97</td>
</tr>
<tr>
<td>S5</td>
<td>27.44</td>
<td>-11.37</td>
</tr>
<tr>
<td>S6</td>
<td>25.72</td>
<td>-10.90</td>
</tr>
<tr>
<td>S7</td>
<td>21.24</td>
<td>-9.17</td>
</tr>
<tr>
<td>S8</td>
<td>25.84</td>
<td>-10.99</td>
</tr>
<tr>
<td>S9</td>
<td>18.02</td>
<td>-8.64</td>
</tr>
<tr>
<td>S10</td>
<td>23.74</td>
<td>-10.38</td>
</tr>
<tr>
<td>S11</td>
<td>37.32</td>
<td>-11.95</td>
</tr>
<tr>
<td>S12</td>
<td>37.05</td>
<td>-13.75</td>
</tr>
</tbody>
</table>
Table 5-2 Predicted maximum stresses of the concrete span using Bayesian method

<table>
<thead>
<tr>
<th>Sensor Number</th>
<th>5-year maximum stresses (MPa)</th>
<th>75-year maximum stress (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Positive</td>
<td>Negative</td>
</tr>
<tr>
<td>C1</td>
<td>3.96</td>
<td>-0.71</td>
</tr>
<tr>
<td>C2</td>
<td>3.49</td>
<td>-0.67</td>
</tr>
<tr>
<td>C3</td>
<td>2.67</td>
<td>-0.67</td>
</tr>
<tr>
<td>C4</td>
<td>2.33</td>
<td>-0.64</td>
</tr>
<tr>
<td>C5</td>
<td>2.28</td>
<td>-0.67</td>
</tr>
<tr>
<td>C6</td>
<td>3.02</td>
<td>-0.75</td>
</tr>
</tbody>
</table>

Figure 5-11 plots the variation of the measured and predicted maximum stresses with respect to the sensor location. It can be seen that the measured stresses generally decrease as the sensor number increases. This is because most heavy trucks travel on the slow lane (Lane 3 as shown in Figure 5-3) and the girders close to the slow lane experience higher LEs. Moreover, it was observed that the maximum positive and negative stresses of the steel span have a similar trend of variation while this is not the case for the concrete span. The reason for this is that the maximum positive and negative stresses of the steel span are mostly caused by the same truck events and thus they have similar shapes of distribution. However, the maximum positive and negative stresses of the concrete span are usually caused by different truck events. Figure 5-12 shows the maximum positive and negative stresses of the concrete span during one day recorded by sensor C2. Comparing Figure 5-12 (a) with (b) reveals that the maximum positive and negative stresses do not necessarily originate from the same truck event for the concrete span. In fact, although the concrete span was designed to be continuous, the negative stress induced by the truck before it enters the instrumented span is rather small. Instead, the free vibration of the bridge is the main cause of negative stresses for the concrete span. This is probably because the natural frequency of the concrete span, which is identified to be about 3 Hz, is close to the typical frequencies of highway trucks. The matching of frequencies could lead to quasi-resonance and cause significant vibrations of the bridge (Deng et al. 2015). In addition, the occurrence of the free vibration also requires the absence of heavy trucks on the span. Therefore, the causes of positive and negative stresses are different for the concrete span, leading to different trends of variation.

Furthermore, it can be seen from Figure 5-11 that the predicted maximum stresses of exterior girders tend to increase faster with the increase of the return period than those of interior girders. This is because the maximum traffic LE distributions of exterior girders have longer upper tails. For example, Figure 5-13 shows the distribution of the maximum traffic LEs for S2 on an exterior girder and S5 on an interior girder. It can be seen that the distribution for S2 is obviously right skewed with a long upper tail while the distribution for S5 is left skewed with a much shorter upper tail. For the GEV distribution, the tail behavior is governed by the shape parameter. A larger shape parameter results in a longer upper tail and thus higher return levels. The marginal posterior distributions of shape parameters for S2 and S5 are shown in Figure 5-14. It can be seen that the shape parameters of S2 are mostly positive while the shape parameters of S5 are negative. Consequently, the increasing rate of the predicted maximum stresses of exterior girders is higher than that of interior girders for this bridge.
Figure 5-11 Variation of measured and predicted maximum stresses with respect to sensor locations: (a) steel span; (b) concrete span.
Figure 5-12 Maximum positive and negative stresses of the concrete span of one day recorded by sensor C2: (a) maximum positive stress; (b) maximum negative stress

Figure 5-13 Distribution of daily maximum traffic LEs: (a) S2 on an exterior girder; (b) S5 on an interior girder.

Figure 5-14 Marginal posterior distributions of shape parameters: (a) S2 on an exterior girder; (b) S5 on an interior girder.
In fact, the upper tail of the maximum traffic LE distributions of exterior girders is caused by cases where trucks were traveling on or close to the shoulder. These cases produce significantly higher traffic LEs in exterior girders but their occurrences are less frequent than trucks traveling within traffic lanes, which causes the distribution to be right skewed with heavy upper tails. This also indicates that the daily maximum traffic LEs of some sensors are not identically distributed. In other words, the distribution of daily maximum traffic LE is a mixed distribution. Caprani et al. (2008) adopted the composite distribution statistics (CDS) approach to account for the mixture of loading events. In the CDS approach, the maximum traffic LEs are classified based on their event types and the maximum traffic LEs of each event type are fitted to the GEV distribution. The composite distribution is then formulated based on the GEV distributions of each event type. However, it is very difficult to always identify the event types in practice (Zhou 2013) and collect sufficient data for some extreme event types. Therefore, it may not be practical to use the CDS approach in reality. The Bayesian method can be seen as a compromise between the CDS approach and the conventional approach in that although it does not classify data based on event types, it recognizes and considers the uncertainties in distribution parameters and thus provides more reliable predictions than the conventional method.

It should be mentioned that the prediction of the future maximum stresses were made based on only sixty-five daily maximum stresses and thus the accuracy of the prediction for longer return periods such as 75 years needs to be taken into consideration when using the prediction results. Conceptually, when more data becomes available in the future, it should be included to update the prediction. In this case, the uncertainties of parameters will be reduced and the posterior distribution will become more concentrated. Consequently, the prediction using the Bayesian method will approach that using the conventional method. Nevertheless, as more data is obtained, the block length should also be increased to obtain more reliable predictions as discussed earlier. Thus, there will always exist certain levels of uncertainties that need to be accounted for using the Bayesian method.

5.4.4 Bridge Condition Assessment

Using the measured and predicted traffic LEs, the condition of the bridge is assessed using the proposed framework. First, the design LL capacity envelops are developed. The bridge under assessment was designed according to the AASHTO LRFD specification (AASHTO 2012). The design LL is specified as the HL-93 including a design truck or design tandem and design lane load. The design LL is distributed to the girders using the distribution factors. For the bridge under assessment, the design calculation shows that the exterior girder controls and the factored live load moments are given in Table 5-3. The section properties were also calculated and listed in Table 5-3. Assuming that the bridge is perfectly designed, the design LL capacity for stress can be evaluated as:

\[ \sigma = \frac{M}{S} \quad (5-18) \]

where \( M \) is the design LL moment and \( S \) is the section modulus. Using Eq. (5-18), the design LL capacities of the steel and concrete spans are calculated and given in Table 5-3. It should be noted that for the concrete span, the uncracked cross-section was used to calculate the section
modulus $S$. This is justified for two reasons. First, the calculated lower design LL stress capacity $\sigma$ tends to be conservative in the safety condition assessment later. Second, the prestressed girders have most likely not been cracked in the current service condition.

In order to obtain the service performance envelops, the FE models were constructed according to the bridge design plans using the ANSYS FE package. For the steel span, the concrete deck was modeled using solid elements and the steel girders were modeled using shell elements. The full-composite action between the concrete deck and steel girders was assumed. The K-shaped cross frames at the supports and intermediate locations were modeled using 3D beam elements with defined cross-sections. The concrete span is modeled entirely using solid elements. Figure 5-15 shows the FE models of the bridge. The FE models were preliminarily calibrated using the natural frequencies identified from the measured strain responses. Figure 5-16 shows the amplitude spectra of the traffic-induced strain responses of one day. It can be seen that three frequencies can be identified for the steel span while only one frequency can be identified for the concrete span. To calibrate the FE models, the elastic moduli of materials are adjusted to match the identified natural frequencies. Table 5-4 shows the as-design and calibrated values of the elastic moduli. The calibrated parameters can serve as better indicators of the bridge behavior than the as-design parameters. Nevertheless, it should be mentioned that a more refined calibration of FE models could be conducted if a load test using known trucks were carried out, which was not available due to the busy traffic of this bridge. Using the calibrated FE models, one or multiple design lanes were positioned at different locations on the bridge to find the most unfavorable loading cases and the multiple presence factors were applied to account for the probability of simultaneous occurrence. For the steel span, three design lanes were found to control for both interior and exterior girders. For the concrete span, three design lanes and two design lanes were found to control for the interior and exterior girders, respectively. The obtained design LL capacity envelops and service performance envelops for the steel and concrete spans are summarized in Table 5-5 and Table 5-6, respectively, along with the measured maximum stresses. It can be seen that the service performance envelops are significantly smaller than the design LL capacity envelops. This is because the FE models more closely modeled the distribution of LL to better reflect the bridge behavior.
Figure 5-15 FE models of the bridge: (a) steel span; (b) concrete span.

Figure 5-16 Amplitude spectra of strain responses: (a) steel span; (b) concrete span

Table 5-4 Calibration parameters of the bridge FE model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>As-design value (MPa)</th>
<th>Calibrated value (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steel Span</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elastic modulus of concrete deck</td>
<td>34169</td>
<td>38500</td>
</tr>
<tr>
<td>Elastic modulus of steel girders</td>
<td>204774</td>
<td>201000</td>
</tr>
<tr>
<td>Concrete Span</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elastic modulus of concrete deck</td>
<td>34169</td>
<td>41300</td>
</tr>
<tr>
<td>Elastic modulus of concrete girders</td>
<td>41145</td>
<td>47400</td>
</tr>
</tbody>
</table>
Table 5-5 Measured maximum stresses and response envelops of the steel span

<table>
<thead>
<tr>
<th>Sensor Number</th>
<th>Measured maximum stress (MPa)</th>
<th>Service performance envelop (MPa)</th>
<th>Design LL capacity envelop (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Positive</td>
<td>Negative</td>
<td>Positive</td>
</tr>
<tr>
<td>S1</td>
<td>17.63</td>
<td>-8.06</td>
<td>70.58</td>
</tr>
<tr>
<td>S2</td>
<td>33.07</td>
<td>-13.87</td>
<td>72.63</td>
</tr>
<tr>
<td>S3</td>
<td>31.34</td>
<td>-11.75</td>
<td>62.52</td>
</tr>
<tr>
<td>S4</td>
<td>33.05</td>
<td>-12.29</td>
<td>64.68</td>
</tr>
<tr>
<td>S5</td>
<td>25.31</td>
<td>-9.47</td>
<td>54.59</td>
</tr>
<tr>
<td>S6</td>
<td>23.57</td>
<td>-9.20</td>
<td>56.61</td>
</tr>
<tr>
<td>S7</td>
<td>18.57</td>
<td>-7.24</td>
<td>56.61</td>
</tr>
<tr>
<td>S8</td>
<td>22.57</td>
<td>-9.56</td>
<td>54.59</td>
</tr>
<tr>
<td>S9</td>
<td>13.22</td>
<td>-6.42</td>
<td>64.68</td>
</tr>
<tr>
<td>S10</td>
<td>18.27</td>
<td>-8.03</td>
<td>62.52</td>
</tr>
<tr>
<td>S11</td>
<td>20.99</td>
<td>-9.49</td>
<td>72.63</td>
</tr>
<tr>
<td>S12</td>
<td>23.17</td>
<td>-10.79</td>
<td>70.58</td>
</tr>
</tbody>
</table>

Table 5-6 Measured maximum stresses and response envelops of the concrete span

<table>
<thead>
<tr>
<th>Sensor Number</th>
<th>Measured maximum stress (MPa)</th>
<th>Service performance envelop (MPa)</th>
<th>Design LL capacity envelop (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Positive</td>
<td>Negative</td>
<td>Positive</td>
</tr>
<tr>
<td>C1</td>
<td>2.09</td>
<td>-0.649</td>
<td>6.88</td>
</tr>
<tr>
<td>C2</td>
<td>2.73</td>
<td>-0.551</td>
<td>5.90</td>
</tr>
<tr>
<td>C3</td>
<td>2.00</td>
<td>-0.549</td>
<td>4.93</td>
</tr>
<tr>
<td>C4</td>
<td>1.17</td>
<td>-0.263</td>
<td>4.93</td>
</tr>
<tr>
<td>C5</td>
<td>1.86</td>
<td>-0.446</td>
<td>5.90</td>
</tr>
<tr>
<td>C6</td>
<td>1.65</td>
<td>-0.476</td>
<td>6.88</td>
</tr>
</tbody>
</table>

In order to assess the current condition of the bridge, Figure 5-17 plots the measured maximum stresses and response envelops for the steel and concrete spans. It can be seen that the measured maximum stresses of both spans are below the service performance envelops and design LL capacity envelops, indicating that the bridge is currently safe and performing normally. Also, it is observed that the bridge has considerable safety reserve under the current condition. Furthermore, in order to assess the future condition of the bridge, the predicted maximum stresses and response envelops are plotted in Figure 5-18 and Fig. 5-19 for the steel and concrete spans, respectively. It can be seen from Figur 18 (a) and Fig. 8-19 (a) that the 5-year maximum stresses of both spans are generally below the response envelops, indicating that the bridge will be safe and performing normally in the next five years. For the 75-year condition, it is observed from Figure 5-18 (b) and Figure 5-19 (b) that although the design LL capacity is able to envelop the maximum stresses of all sensors, the maximum stresses of certain sensors exceed the service performance envelops, suggesting that the bridge may be overstressed in the future. These sensors are installed on the exterior girders under the shoulder close to the slow lane for both spans and the interior girder under the slow lane for the steel span. In practice, these girders also experience the largest traffic LEs due to their close vicinity to the heavy truck traffic.
Nevertheless, it can be seen that the bridge still has sufficient safety reserves in 75 years from the design perspective.

Figure 5-17 Assessment of current condition: (a) steel span; (b) concrete span.
Figure 5-18 Assessment of future condition for the steel span: (a) 5-year; (b) 75-year
5.5 Conclusions

In this study, the Bayesian method was introduced for the prediction of extreme traffic LEs of bridges. The detailed estimation procedures were presented. The Bayesian method
provides a systematic framework of uncertainty quantifications for extreme value analysis. Compared to the conventional method, the Bayesian method is able to quantify the uncertainties of parameters in terms of posterior distributions and incorporate the uncertainties into the prediction through the posterior predictive distribution. The prediction results are intended for the application of bridge condition assessment for which a framework was proposed to evaluate the bridge condition at two different levels.

A case study featuring the I-10 Twin Span Bridge was presented to demonstrate the proposed methodology. The monitored strain response was first processed using the wavelet decomposition to extract the traffic LEs and then the Bayesian method was adopted to predict the future maximum traffic LEs of the bridge. The prediction results show that the predicted maximum traffic LEs obtained using the Bayesian method are significantly higher than those obtained using the conventional method. The difference is caused by the uncertainties inherent in the parameters. Furthermore, it is found that the variation trend of the maximum positive and negative stresses with the transverse location of sensors is similar for the steel span but different for the concrete span. Also, the maximum stresses of exterior girders generally increase faster with the increase of return period than those of interior girders due to the different tail behaviors between the maximum traffic LE distributions of exterior and interior girders. Finally, the condition assessment of the bridge was conducted using the proposed framework. The design LL capacity envelopes and service performance envelopes were developed based on the design calculation and the FE modeling of the bridge. The condition assessment results show that the bridge is performing normally under the current condition and that the bridge will be safe during its remaining life from the design perspective except that certain girders close to the slow lane may be overstressed in the future (75-year return period).

In addition, it is noted that the traffic was assumed to be stationary in this study. While this assumption may hold for a relatively short period of time, the nature of traffic is non-stationary and it usually increases over time due to economic developments and technological advances (O’Connor and O’Brien 2005). For this reason, the prediction for shorter return periods by assuming stationary traffic will be more reliable than that for longer return periods. The Bayesian method to account for non-stationary traffic LEs will be future studies of the writers. Also, while the measured LL stress will automatically reflect both the effect of traffic and structural property changes, the capacity envelopes used in the performance assessment should reflect these variations as time goes.

5.6 References


from a mixture of loading events on short to medium span bridges.” *Structural Safety*, 30(5), 394–404.


CHAPTER 6. PREDICTION OF MAXIMUM TRAFFIC LOAD EFFECTS OF BRIDGES SUBJECT TO TRAFFIC GROWTH USING NON-STATIONARY BAYESIAN METHOD

6.1 Introduction

With the increasing economy and technological development, the road traffic is experiencing a substantial growth over the past decades. The U.S. Department of Transportation (USDOT 2016) predicts that the freight volume in the U.S. will increase by more than 40 percent by 2045. Correspondingly, the growth of traffic volume has led to regulation changes to raise the truck weight limit to meet the increasing demands. According to the SAFE (Safe, Flexible and Efficient) Trucking Act (SAFE 2015) that was recently introduced to the U.S. Congress, the federal truck weight limit may be increased from 36.3 t (80,000 lbs) to 41.3 t (91,000 lbs). Under these circumstances, assessment of the impacts of growing traffic on the safety of transportation infrastructures becomes critical especially when considering that the live load models of many bridge codes did not account for the traffic growth (Getachew 2003; Nowak 1993). Furthermore, the aging of highway bridges has also raised concerns on transportation safety. According to the 2017 Infrastructure Report Card by ASCE (ASCE 2017), 9.1% of the bridges in the U.S. were rated structurally deficient and the average age of bridges in the U.S. has reached 43 years old. In light of these concerns, bridge management, especially the condition assessment to determine if rehabilitation or replacement of the bridge is necessary, becomes essential from both the safety and economic standpoints.

In the past, statistical methods have been used to predict the characteristic value of the maximum traffic load effect (LE) during the design life or the remaining life of bridges that can be used for bridge design and condition assessment. Nowak and Hong (1991) fitted the upper tail of the maximum LEs to a normal distribution and extrapolated the LEs using normal probability paper. Crespo-minguilh and Casas (1997) adopted the peak-over-threshold (POT) method and extrapolated the maximum lifetime traffic LEs using the generalized Pareto distribution. Cremona (2001) fitted the Rice formula to the level crossing rate of traffic LEs and extrapolated the LEs under the hypothesis that the bridge traffic LE is a stationary Gaussian process. Chen et al. (2015) proposed a new method for determining the optimal threshold of tail fitting for the Rice formula. Caprani et al. (2008) recognized that different load events have different distributions and proposed a composite distribution statistic (CDS) approach for block maxima method using the generalized extreme value (GEV) distribution. Zhou et al. (2016) extended the CDS approach to the POT method to consider the mixture of load events. Xia et al. (2016) fitted the maximum traffic LEs recorded during relatively short periods to the Gumbel distribution and used the fitted distribution to extrapolate long-term extreme traffic LEs. A review on the various prediction methods of extreme traffic LEs was presented by O’Brien et al. (2015). In most previous studies, the traffic is assumed as a stationary process in order to extrapolate the traffic LE. However, in reality, the nature of traffic is non-stationary as it tends to gradually grow over time. Thus, it becomes necessary to consider the traffic growth in the assessment of traffic LEs of bridges. Nevertheless, the effect of non-stationary traffic was rarely addressed in previous studies. O’Brien et al. (2014) adopted the non-stationary GEV distribution to model the extreme traffic LEs of short-span bridges subject to growing traffic volumes and reported a modest increase of characteristic maximum traffic LEs under growing traffic volume compared with
those under the stationary traffic. Leahy et al. (2016) studied the effect of traffic growth on the characteristic maximum LEs and found that the growth of truck weight has more significant impact on the characteristic maximum traffic LEs than the growth of truck volume. However, only limited cases of traffic growth and non-stationary models were considered in these studies.

While modeling non-stationary traffic LEs, the parameters of non-stationary models are typically estimated by using the maximum likelihood (ML) method. Numerical methods is usually used to obtain the ML estimates due to the complexity of the likelihood function and sometimes the ML method was reported to have convergence problems that lead to results that are not physically feasible (Adlouni et al. 2007; Katz et al. 2002). Furthermore, the ML method does not consider the epistemic uncertainties of parameters which could be significant when the sample size is not sufficiently large. The Bayesian method offers a natural framework for uncertainty quantification in parameter estimation and prediction. Under the Bayesian framework, the uncertainty is formally introduced using the posterior distribution and incorporated into the prediction by the use of the predictive distribution, which gives more reliable predictions. Recently, the application of Bayesian method has become increasingly popular with advances in computation power and simulation techniques such as Markov Chain Monte Carlo (MCMC) (Cheng et al. 2014; Lima and Lall 2009). However, the Bayesian method was still rarely used in the prediction of extreme traffic LEs of bridges (O’Brien et al. 2015).

This paper presents a Bayesian framework for predicting extreme traffic LEs of bridges subject to growing traffic and investigates the influence of traffic growth on the safety of bridges. Firstly, the Bayesian framework for non-stationary extreme value analysis is described. Then, Monte Carlo simulation and influence line analysis are conducted to simulate long-term traffic LEs considering three types of traffic growth including the growth of the truck volume, the truck weight, and the proportion of heavy trucks. The non-stationary Bayesian method is used to predict the maximum traffic LEs during the lifetime of the bridge and the effect of the growing traffic on bridge safety is discussed based on the prediction results. Finally, the influence of the block size and the observation period on the prediction results is examined.

6.2 Non-stationary Extreme Value Analysis under the Bayesian Framework

6.2.1 Stationary Extreme Value Analysis

Based on the extreme value theory (Fisher and Tippett 1928), for a sequence of independent and identically distributed (i.i.d.) random variables \((X_1, X_2, ..., X_n)\), if there exists a sequence of real numbers \((a_n, b_n)\) with \(a_n > 0\) such that

\[
\lim_{n \to \infty} P\left( \frac{M_n - b_n}{a_n} < x \right) = F(x)
\]  

(6-1)

where \(M_n = \text{Max}(X_1, X_2, ..., X_n)\) and \(F(x)\) is a non-degenerate distribution function, then \(F(x)\) must be in the form of the generalized extreme value (GEV) distribution whose cumulative distribution function (CDF) can be expressed as:
where $\xi$ is the shape parameter; $\sigma$ is the scale parameter; and $\mu$ is the location parameter. The GEV distribution contains three types of extreme value distributions depending on the value of the shape parameter: (i) when $k > 0$, $F(x)$ corresponds to the heavy-tailed (Fréchet) distribution; (ii) when $k < 0$, $F(x)$ corresponds to the short-tailed (Weibull) distribution; and (iii) when $k = 0$, $F(x)$ corresponds to the light-tailed (Gumbel) distribution.

To model the extreme traffic LEs using the extreme value theory, the block maxima series, such as daily or weekly maximum traffic LEs, is derived by dividing the observation of traffic LEs into non-overlapping time intervals (blocks) of equal lengths and extracting the maximum LE in each block. Based on the extreme value theory, the block maxima will converge to the GEV distribution provided that the occurrences of traffic loading events are independent and that the traffic is a stationary process. The prediction of the maximum traffic LE during a certain period of time (return period) is achieved by computing the return level corresponding to the return period. Under the i.i.d. assumption, the return level corresponding to a certain return period has an equal probability of exceedance in any block. Therefore, the return level can be evaluated as the quantile of the GEV distribution as:

$$x_{RL} = \mu + \frac{\sigma}{\xi} \left[ -\ln \left( 1 - \frac{t}{T} \right) \right]^{\frac{1}{\xi}} - 1$$

where $x_{RL}$ is the return level or the predicted maximum traffic LE during return period $T$; and $t$ is the block size.

### 6.2.2 Non-stationary Extreme Value Analysis

Considering that the traffic varies with time, the maximum traffic LEs are no longer identically distributed. Hence, the non-stationary GEV distribution is adopted to model the non-stationary extreme traffic LEs:

$$F(x, t) = \exp\left\{ -\left[ 1 + \xi(t) \left( \frac{x - \mu(t)}{\sigma(t)} \right) \right]^{1/\xi(t)} \right\}$$

The non-stationary form of the GEV distribution considers the distribution parameters to be time-dependent. The parameters can be modeled either using parametric (Katz et al. 2002) or non-parametric method (Hall and Tajvidi 2000). Furthermore, it is important to note that the probability of exceedance will vary with time under the non-stationary context. In this case, in order to predict the maximum traffic LEs, the analytical relationships between the return level

$$ln\left( \frac{1}{F(x, t)} \right) = \xi(t) \frac{x - \mu(t)}{\sigma(t)}$$

...
and return period need to be derived. Generally speaking, there are two definitions of the return period:

**Definition (1):** The return period is defined as the time period during which the expected number of exceedance is one. The number of exceedance in a \( T \)-year return period can be expressed as:

\[
N = \sum_{t=1}^{T} I(M_t)
\]  

(6-5)

where \( M_t \) is the maximum observation in the \( t \)th year and \( I(M_t) \) is an indicator variable whose probability mass function (PMF) can be expressed as:

\[
P[I(M_t)] = \begin{cases} 
1 - F(RL,t), & I(M_t > RL) = 1 \\
F(RL,t), & I(M_t < RL) = 0 
\end{cases}
\]  

(6-6)

By setting the expected number of exceedance to one, the relationship between the return level and return period under **Definition (1)** can be obtained as:

\[
E(N) = \sum_{t=1}^{T} [1 - F(RL,t)] = 1
\]  

(6-7)

**Definition (2):** The return period is defined as the expected waiting time for the first exceedance over the return level. The waiting time \( T_w \) for the first exceedance follows a non-homogeneous geometric distribution (Mandelbaum et al. 2007) and its PMF can be expressed as:

\[
P(T_w = t) = \prod_{i=1}^{t-1} F(RL,i), \quad t = 1, \ldots, \infty
\]  

(6-8)

The expected value of the waiting time can be computed as:

\[
E(T_w) = \sum_{t=1}^{\infty} \prod_{i=1}^{t-1} F(RL,i)
\]  

(6-9)

By simplifying Eq. (6-9) and setting the expected waiting time to be the return period \( T \), the relationship between the return level and return period under **Definition (2)** can be derived as:

\[
1 + \sum_{i=1}^{\infty} F(RL,i) = T
\]  

(6-10)

Although the solution of Eq. (6-10) is not straightforward, the bound of the return period can be obtained as (Cooley 2013):
where $L$ is a positive integer. The width of the bound of return period depends on the value of $L$. By selecting a sufficiently large $L$, Eq. (6-11) can be solved numerically to obtain the return level.

### 6.2.3 Bayesian Inference

In this study, the parameters of the non-stationary GEV model are estimated using Bayesian inference. Based on the Bayes theorem, the posterior distribution of the parameters to be estimated can be expressed as:

$$
p(\theta | x) = \frac{L(\theta | x) p(\theta)}{\int L(\theta | x) p(\theta) d\theta}$$

where $\theta$ is the parameters to be estimated; $p(\theta | x)$ is the posterior distribution; $x$ is the data; $p(\theta)$ is the prior distribution of the parameters; and $L(\theta | x)$ is the likelihood function that is calculated as:

$$L(\theta | x) = \prod_{i=1}^{N_t} p(x_i | \theta)$$

where $x_i$ is the value for the $i$th observation and $N_t$ is the number of observations. In Bayesian statistics, the prior distribution represents the prior knowledge of the parameters and it is independent from the existing observations. Generally speaking, the prior distribution can be classified into two types, i.e., the informative prior and the non-informative prior. In the present study, the difficulty to elicit informative priors originates from the highly site-specific traffic characteristics and bridge behaviors. Therefore, the non-informative prior is adopted and uniform distributions with wide supports are specified as the prior distribution.

- **Markov Chain Monte Carlo (MCMC) sampling**

  The multi-dimensional integral in Eq. (6-12) is a normalizing constant and thus the posterior distribution can be written as:

  $$p(\theta | x) \propto L(\theta | x) p(\theta)$$

  The Markov Chain Monte Carlo (MCMC) method can be used to sample from the posterior distribution using Eq. (6-14). In this study, the Metropolis-within-Gibbs (MG) sampler is adopted. The sampling procedures are described as follows:

  1. Assign initial values to the parameters $\theta^{(0)}$

  2. For $i=1:N$ ($N$ is the number of iterations) and $m=1:n$ ($n$ is the number of parameters), first generate a candidate value for the $m$th parameter $\theta_{m}^{*}$ from the normal proposal distribution conditional on $\theta_{m}^{(i-1)}$, and the acceptance ratio for $\theta_{m}^{*}$ is computed as:
\[
\tau = \frac{f(\theta^*_m | \theta^{(i)}_1, \theta^{(i)}_{m-1}, \theta^{(i-1)}_{m-1}, \theta^{(i-1)}_n, \mathbf{x})}{f(\theta^{(i-1)}_m | \theta^{(i-1)}_1, \theta^{(i-1)}_{m-1}, \theta^{(i-1)}_{m-1}, \theta^{(i-1)}_n, \mathbf{x})} \tag{6-15}
\]

where \( f(\theta^*_m | \theta^{(i)}_1, \theta^{(i)}_{m-1}, \theta^{(i-1)}_{m-1}, \theta^{(i-1)}_n, \mathbf{x}) \) is the unnormalized full conditional distribution that is evaluated as:

\[
f(\theta^*_m | \theta^{(i)}_1, \theta^{(i)}_{m-1}, \theta^{(i-1)}_{m-1}, \theta^{(i-1)}_n, \mathbf{x}) = \prod_{i=1}^N p(x_i | \theta^{(i)}_1, \theta^{(i)}_{m-1}, \theta^{(i-1)}_{m-1}, \theta^{(i-1)}_n, \theta^*_m) p(\theta^*_m) \tag{6-16}
\]

Then, sample \( u \) from the uniform distribution \( U(0,1) \); if \( u < \min(1, \tau) \), accept \( \theta^*_m \); otherwise, reject \( \theta^*_m \).

3. Repeat step 2 until \( i \) reaches \( N \).

It is noted that the initial portion of the Markov Chain may not be a true realization from the target distribution because the initial values of parameters have a significant influence on the initial portion. For this reason, the initial portion of the Markov Chain is usually discarded and only the stabilized portion of the chain is used. Furthermore, the sampling efficiency of the MG sampler is mainly affected by the scale of the proposal distribution. In this study, the MG sampler is first tuned to obtain the optimal acceptance rate in order to achieve efficient sampling (Rosenthal 2011).

- **Posterior predictive distribution**

In Bayesian statistics, the prediction of future observations is achieved using the posterior predictive distribution that is defined as:

\[
p(y | \mathbf{x}) = \int p(y | \theta) p(\theta | \mathbf{x}) d\theta \tag{6-17}
\]

where \( p(y | \theta) \) is the assumed distribution of the data and \( p(\theta | \mathbf{x}) \) is the posterior distribution. Essentially, the posterior predictive distribution incorporates the parameter uncertainties into the prediction by integrating the assumed distribution of data over all possible values of parameters specified by the posterior distribution. As a matter of fact, the ML method is a special case of the Bayesian method with \( \theta \) being deterministic, which leads to the loss of parameter uncertainties in the prediction.

In this study, since the extreme traffic LEs is non-stationary, the predictive distribution is a function of time. The following procedures are adopted to predict the maximum traffic LEs:

1. For \( t=1:L \) (\( L \) is the positive integer in Eq. (6-11)), generate a sample of the predictive distribution for time \( t \) given the sample of the posterior distribution of size \( N \), i.e., \( y^{(i)}_t \sim p(y | \theta^{(i)}_t) \) for \( i = 1:N \) where \( p(y | \theta, t) \) is the non-stationary GEV distribution given in Eq. (6-4);

2. Substitute the prediction distributions obtained in Step 1 into Eq. (6-7) and Eq. (6-11) to numerically solve for the return level corresponding to the return period \( T \).
6.3 Simulation of Traffic Load Effects of Bridges

6.3.1 Simulation of Random Traffic Flow

In this study, Monte Carlo simulation is used to generate the random traffic flows. The traffic data collected at a weigh-in-motion (WIM) site located in Louisiana is used to extract the statistical characteristics of traffic. The WIM data was collected on a two-lane state highway with one-way traffic for over a year and more than 100,000 vehicles were recorded. To ensure the quality of the WIM data for traffic simulation, the WIM data was first cleaned to remove light passenger vehicles and erroneous vehicle records (Feng 2016). After the cleaning, a total of 77,171 trucks were recorded. For each vehicle, the traveling lane, the time stamp, the number of axles, the gross vehicle weight (GVW), the vehicle speed, the axle spacing, and the axle weights were recorded. Based on the WIM data, the statistical characteristics of the traffic parameters were obtained separately for each lane. The percentage of truck volume of the passing lane and the slow lane was found to be 19.1% and 80.9%, respectively.

To simulate the random traffic flow, two lanes of traffic in the same direction are generated. The traveling lane of the vehicle is generated using a binomial distribution given the percentage of traffic in the passing lane and the slow lane. For each lane, the number of axles and GVW of the vehicle are generated using a non-parametric bivariate distribution (O’Brien and Enright 2011). Figure 6-1 shows the empirical distribution of the GVW from the WIM data.

![Empirical distribution of GVW from the WIM data](image)

The vehicles are classified into different types based on the number of axles. For each vehicle type, the proportion of the GVW carried by each axle is generated using the empirical distribution of that vehicle type. The correlation of axle weights between adjacent and non-adjacent axles is considered. The axle spacings of the vehicle are simulated using a method similar to that described by Enright and O’Brien (2013). The maximum axle spacing of the vehicle is believed to be closely related to its GVW and vehicle type. Thus, the maximum axle spacing is generated using the conditional distribution of the maximum axle spacing given the GVW and the vehicle type. The second, third and fourth largest spacings are considered.
independent from the GVW and are simulated using bi-modal normal distributions given the vehicle type. For the fifth largest and subsequent spacings, a single distribution is adopted as they are usually small and of similar magnitudes. The generated axle spacings are ranked in a descending order and the position of each ranked axle spacing is then assigned using the empirical distribution of the position of the axle spacing of that ranked order given the vehicle type.

O’Brien and Caprani (2005) proposed a flow-dependent approach to model vehicle headways that is defined as the time between the first axles of successive vehicles reaching the same location on road. For headways less than 4 seconds, the headway is assumed to depend on the hourly flow rate and piecewise quadratic curves are fitted to the empirical CDF for each flow rate. For headways larger than 4 seconds, an exponential distribution is used to simulate the headway. Nevertheless, the proposed approach can only model headways for flow rate up to the maximum observed one. In the present study, since the flow rate of the generated traffic may exceed the maximum observed flow rate under the growing traffic volume, an alternative approach is proposed to model the vehicle headway and speed considering the dependence of headway on the flow rate and the correlation between the speeds of successive vehicles. The procedures are described below:

1. The vehicle is assigned to an hour of the day using a multinomial distribution based on the percentage of truck volume of each hour of a day obtained from the WIM data as shown in Figure 6-2;

2. The position (time stamp) of the vehicle within the assigned hour is randomly assigned using a uniform distribution and the speed of the vehicle is generated from the empirical distribution of the given traveling lane;

3. For vehicles with headway less than 4 seconds, the headway and difference of speeds between successive vehicles are resampled using the empirical bivariate distribution of headway and speed difference for the given traveling lane.

Figure 6-2 Percentage of trucks in each hour of a day from the WIM data
In this study, three types of traffic growth are considered including the growth of the truck volume, the truck weight, and the proportion of heavy trucks. The considered cases include 11 cases featuring in different types of growth at different annual growth rates (AGRs) and a reference case where stationary traffic is assumed. Table 6-1 summarizes the description of the cases considered in this study. For each type of growth, a day-by-day growth model, where the daily growth rate is calculated as the AGR divided by 250 days (number of working days per year), is adopted (Lu et al. 2017; O’Brien et al. 2014). For each case, 20 years of traffic were simulated and ten simulations were conducted to account for the random sampling variability.

For cases with the growth of truck volume and the proportion of heavy vehicles, constant AGR is assumed. The growth of traffic volume was accounted for by increasing the average daily truck traffic (ADTT). The initial ADTT is assumed to be 1,000 and three different AGRs, i.e., 2%, 4%, and 6%, were considered. The growth of the proportion of heavy vehicles was simulated by increasing the proportion of trucks with six or more axles. Similarly, three different AGRs, i.e., 4%, 6% and 8%, were considered. Compared with the above two types of growth, the growth of truck weight is more difficult to predict. This is because: (1) there is a lack of long-term truck weight data; (2) there is an explicit limit of truck weight that is subject to regulation changes. Nevertheless, it is expected that when the truck weight limit is raised, the truck weight will increase correspondingly and the growth will tend to gradually slow down as the truck weight approaches the weight limit. In order to model this trend of variation, the exponential decay model was adopted to simulate the AGR of truck weight. Figure 6-3 shows the variation of the AGR with time of the three cases considered for weight growth and the resulting annual average GVW. In addition, two cases where the truck weight is assumed to grow at constant AGRs of 0.5% and 1% are also considered. It is noted that realistically, the truck weight is unlikely to increase at a constant rate due to the weight limit. Nevertheless, the two cases are considered in this study for comparison purposes.

### Table 6-1 Cases of traffic growth considered in this study

<table>
<thead>
<tr>
<th>Case number</th>
<th>Type of growth</th>
<th>AGR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>Truck volume</td>
<td>2</td>
</tr>
<tr>
<td>Case 2</td>
<td>Truck volume</td>
<td>4</td>
</tr>
<tr>
<td>Case 3</td>
<td>Truck volume</td>
<td>6</td>
</tr>
<tr>
<td>Case 4</td>
<td>Proportion of heavy trucks</td>
<td>4</td>
</tr>
<tr>
<td>Case 5</td>
<td>Proportion of heavy trucks</td>
<td>6</td>
</tr>
<tr>
<td>Case 6</td>
<td>Proportion of heavy trucks</td>
<td>8</td>
</tr>
<tr>
<td>Case 7</td>
<td>Truck weight</td>
<td>0.5</td>
</tr>
<tr>
<td>Case 8</td>
<td>Truck weight</td>
<td>1</td>
</tr>
<tr>
<td>Case 9</td>
<td>Truck weight</td>
<td>$1 \times \exp(-0.115t)$</td>
</tr>
<tr>
<td>Case 10</td>
<td>Truck weight</td>
<td>$2 \times \exp(-0.15t)$</td>
</tr>
<tr>
<td>Case 11</td>
<td>Truck weight</td>
<td>$3 \times \exp(-0.17t)$</td>
</tr>
<tr>
<td>Case 12</td>
<td>No growth</td>
<td>N.A.</td>
</tr>
</tbody>
</table>

Note: $t$ is in years
6.3.2 Traffic Load Effect Calculation

In order to calculate the LEs induced by the traffic, an influence line analysis is conducted where the simulated traffic flow is set to pass over a selected bridge in the time step of 0.02 s. The bridge selected in this study is a simply supported beam-slab bridge. The bridge is 24-m long and 11-m wide with two lanes of traffic in the same direction. Figure 6-4 shows the cross-section and lane positions of the bridge where Lane 1 and Lane 2 are the passing lane and the slow lane, respectively. The girder influence lines of the longitudinal strains at the mid-span are extracted using the finite element model of the bridge that was modeled using solid elements in ANSYS. The strain response of Girder 5 is adopted for the following analysis since Girder 5 experiences the largest traffic LEs. Figure 6-5 shows a sample time-history of the simulated traffic LEs for one day with ADTT of 2,000. It can be seen that the peaks are more concentrated during the time period from 7:00 to 16:00, which is consistent with Figure 6-2. In this study, the block size for the maximum traffic LE is selected as 25 days unless specified otherwise. Figure 6-6 shows the flow chart for the simulation of traffic LEs.
Figure 6-5 Sample time-history of simulated traffic LEs for one day with ADTT of 2,000

```
Start
Vehicle number i=1

Generate vehicle information
Assign traveling lane
Generate number of axles and GVW
Distribute GVW to individual axles
Generate axle spacings

Generate flow information
Generate vehicle time stamp
Generate vehicle speed
Adjust vehicle headway and speed

i=i+1

i>ADTT?
T
F

End
```
6.4 Prediction of Extreme Traffic Load Effects

6.4.1 Model Selection

In order to model the non-stationary extreme traffic LEs, the parameters of the non-stationary GEV distribution are modeled as functions of time and a variety of models can be constructed to incorporate different trends of variation. In this case, model selection needs to be conducted to select the optimal model to describe the non-stationary extreme traffic LEs. The likelihood ratio test has been widely used for this purpose. However, the likelihood ratio test can only be used to compare nested models. In Bayesian statistics, the Bayes factor is used to compare the likelihood between two models and it does not require the two models to be nested. Nevertheless, the Bayes factor is sensitive to the choice of prior distributions and the evaluation of the marginal likelihood is usually computationally demanding (Kass and Raftery 1995). Alternatively, the Bayesian Information Criterion (BIC) can provide a reasonably good approximation to the log of the Bayes factor when the reference prior is used and the sample size is relatively large compared to the number of model parameters. The BIC of a given model is defined as:

$$BIC = -2 \ln L(\hat{\theta} \mid x) + k \ln(n)$$  \hspace{1cm} (6-18)$$

where $x$ is the observed data; $n$ is the number of observed data; $k$ is the number of model parameters; $\hat{\theta}$ is the ML estimate of the model parameters. For model selection, the BIC of each model is calculated and the model with the lowest BIC is preferred. The difference of BICs
between two models reflects the evidence of favoring one model over the other. Table 6-2 gives the strength of evidence against the model of higher BIC.

Table 6-2 Strength of evidence against the model of higher BIC (Kass and Raftery 1995)

<table>
<thead>
<tr>
<th>BIC&lt;sub&gt;i&lt;/sub&gt;-BIC&lt;sub&gt;min&lt;/sub&gt;</th>
<th>Evidence against Model &lt;sub&gt;i&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-2</td>
<td>Not worth more than a bare mention</td>
</tr>
<tr>
<td>2-6</td>
<td>Positive</td>
</tr>
<tr>
<td>6-10</td>
<td>Strong</td>
</tr>
<tr>
<td>&gt;10</td>
<td>Very strong</td>
</tr>
</tbody>
</table>

In this study, two types of models for the non-stationary GEV distribution are considered. For the first type of models, the GEV parameters are modeled as polynomial functions of the time <i>t</i> as:

\[
\xi(t) = \xi_0 + \xi_1 t + \xi_2 t^2 \\
\ln[\sigma(t)] = \sigma_0 + \sigma_1 t + \sigma_2 t^2 \\
\mu(t) = \mu_0 + \mu_1 t + \mu_2 t^2
\]  

(6-19)

where \(\xi_i, \sigma_i, \) and \(\mu_i (i=1,2,3)\) are the polynomial coefficients. The logarithm of the scale parameter is taken to ensure that the scale parameter is positive. For each GEV parameter, up to quadratic trends of variation are considered, which leads to a total of nine possible coefficients and 27 permutations of these coefficients. For the second type of models, the GEV parameters are modeled as power functions of time as:

\[
\xi(t) = \xi_0 + t^{\delta_1} \\
\ln[\sigma(t)] = \sigma_0 + t^{\sigma_1} \\
\mu = \mu_0 + t^{\mu_1}
\]  

(6-20)

where \(\xi_1, \sigma_1, \) and \(\mu_1\) are the coefficients of power for the three parameters. Nevertheless, it was found that the MG sampler cannot achieve convergence when the shape or the scale parameter is modeled as power function. It should be noted that this convergence failure is not simply a numerical issue. Rather, it implies that the parameters \(\xi_1\) and \(\sigma_1\) are not identifiable from the data. Therefore, for the second type of model, only the trend in the location parameter is considered.

For each candidate model, the MG sampler is first used to sample from the posterior distribution. Since the uniform prior was adopted, the posterior distribution is essentially the normalized likelihood function and thus the ML estimates of coefficients can be obtained as the modes of the posterior distribution. The BIC of each model is then calculated and the model with the lowest value of BIC is selected. For the illustration purposes, Case 10 is used as an example to demonstrate the model selection. Table 6-3 summarizes the candidate models considered and the corresponding parameters and BIC. A total of 28 candidate models were considered. Models 1 to 27 correspond to the first type of models with different permutations of polynomial coefficients while Model 28 corresponds to the second type of model with the location parameter modeled using the power function.
### Table 6-3 Model selection results for Case 10

<table>
<thead>
<tr>
<th>Model number</th>
<th>$\hat{\xi}_0$</th>
<th>$\hat{\xi}_1$</th>
<th>$\hat{\xi}_2$</th>
<th>$\hat{\sigma}_0$</th>
<th>$\hat{\sigma}_1$</th>
<th>$\hat{\sigma}_2$</th>
<th>$\hat{\mu}_0$</th>
<th>$\hat{\mu}_1$</th>
<th>$\hat{\mu}_2$</th>
<th>BIC</th>
<th>BIC - BIC_{min}</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.139</td>
<td>N.A.</td>
<td>N.A.</td>
<td>9.15</td>
<td>N.A.</td>
<td>N.A.</td>
<td>103.79</td>
<td>N.A.</td>
<td>N.A.</td>
<td>1498.5</td>
<td>32.8</td>
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<tr>
<td>2</td>
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<td>N.A.</td>
<td>N.A.</td>
<td>97.60</td>
<td>0.062</td>
<td>N.A.</td>
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<td>N.A.</td>
<td>8.02</td>
<td>N.A.</td>
<td>N.A.</td>
<td>94.49</td>
<td>0.158</td>
<td>-5.0E-04</td>
<td>1468.7</td>
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</tr>
<tr>
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<td>N.A.</td>
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</tr>
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<td>2.9E-03</td>
<td>-1.4E-05</td>
<td>94.11</td>
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<td><strong>93.76</strong></td>
<td><strong>0.514</strong></td>
<td>N.A.</td>
<td><strong>1465.7</strong></td>
<td><strong>0.0</strong></td>
</tr>
</tbody>
</table>

Note: when the trend in the scale parameter is considered, the log-transformed parameters were used.
From Table 6-3, it can be seen that Model 28 has the lowest BIC and that the evidence against other models is at least “positive” according to Table 6-2. Therefore, Model 28 was selected as the optimal model for Case 10. Figure 6-7 shows the trace plots and marginal posterior distributions of the four coefficients of Model 28 using kernel density estimation (KDE). From Figure 6-7 (a), it can be observed that the chains have converged quickly and mixed well.

Figure 6-7 Trace plots and marginal posterior distributions of coefficients of Model 28 for Case 10: (a) trace plots; (b) marginal posterior distributions
From Figure 6-7 (b), it can be seen that the distribution of the power coefficient $\mu_i$ is left-skewed and that the values of $\mu_i$ are less than one. This suggests that the location parameter is increasing more and more slowly with time as a result of the exponential decay of the AGR of the truck weight. Furthermore, it can be seen from Table 6-3 that the ML estimates of the linear and quadratic coefficients of the shape and scale parameters are generally close to zero, which implies that the shape and scale parameters do not vary significantly with time. In addition, it was found that the model with the second lowest BIC is Model 3 with constant shape and scale parameters and a quadratically varying location parameter. The negative ML estimate of the quadratic coefficient of the location parameter also confirms that the growth rate of the location parameter is decreasing with time.

For each case, the same procedures were conducted and the selected models are listed in Table 6-4. It can be seen that for cases where a constant AGR is assumed, the model with constant shape and scale parameters and a linearly varying location parameter is selected. This implies that the traffic LEs are increasing at a steady rate under a constant AGR. For cases where the growth is exponentially decaying, the model with constant shape and scale parameters and location parameter modeled using power function is selected. Moreover, also given in Table 6-4 are the average differences of BIC between the selected model and the stationary model for the ten simulations of each case. It can be seen that for cases where a constant AGR is assumed, the model with constant shape and scale parameters and a linearly varying location parameter is selected. This implies that the traffic LEs are increasing at a steady rate under a constant AGR.

Table 6-4 Selected models for each case and corresponding evidence against the stationary model

<table>
<thead>
<tr>
<th>Case Number</th>
<th>Selected model</th>
<th>BIC_{selected}−BIC_{stationary}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t$</td>
<td>-0.99</td>
</tr>
<tr>
<td>Case 2</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t$</td>
<td>4.80</td>
</tr>
<tr>
<td>Case 3</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t$</td>
<td>16.19</td>
</tr>
<tr>
<td>Case 4</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t$</td>
<td>2.93</td>
</tr>
<tr>
<td>Case 5</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t$</td>
<td>8.77</td>
</tr>
<tr>
<td>Case 6</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t$</td>
<td>20.85</td>
</tr>
<tr>
<td>Case 7</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t$</td>
<td>15.60</td>
</tr>
<tr>
<td>Case 8</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t$</td>
<td>56.53</td>
</tr>
<tr>
<td>Case 9</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t^{\mu}$</td>
<td>11.01</td>
</tr>
<tr>
<td>Case 10</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t^{\mu}$</td>
<td>30.81</td>
</tr>
<tr>
<td>Case 11</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu(t) = \mu_0 + \mu t^{\mu}$</td>
<td>54.16</td>
</tr>
<tr>
<td>Case 12</td>
<td>$\xi = \xi_0$; $\sigma = \sigma_0$; $\mu = \mu_0$</td>
<td>0</td>
</tr>
</tbody>
</table>
6.4.2 Prediction Results

After the model is selected, the predictive distributions for different return periods are obtained and the maximum traffic LEs for return periods from 1 to 75 years are predicted using the aforementioned procedures. Figure 6-9 shows the predictive distributions of 20-year, 50-year, and 75-year of Case 4 using KDE. From Figure 6-9, the right shift of the predictive distributions is observed as the return period increases, reflecting the increase of extreme LEs over time. Figure 6-10 plots the variation of the predicted maximum traffic LEs with the return period for Case 1, Case 4, Case 7, and Case 9. The maximum traffic LEs shown in Figure 6-10 are the average of the ten simulations of each case. The maximum traffic LEs were predicted using two methods, i.e., the conventional method and the non-stationary Bayesian method. The conventional method uses the stationary GEV model with ML estimates of parameters to predict the extreme LEs. From Figure 6-10, it can be seen that the maximum traffic LEs predicted using the non-stationary Bayesian method are generally higher than those obtained using the stationary method and the difference becomes larger as the return period increases, which indicates that the stationary assumption of traffic could lead to significant underestimation of predicted maximum traffic LEs for longer return periods. Furthermore, it was found that the maximum traffic LEs predicted using Definition 1 of the return period is slightly smaller than those predicted using Definition 2. From the design perspective, Definition 2 where the return period is defined as the expected waiting time for the first exceedance leads to more conservative assessment of the traffic LEs and is in better accordance with the design purpose. Thus, the maximum traffic LEs predicted using Definition 2 are adopted for the following analysis.
Table 6-5 summarizes the 20-year and 75-year (typical lifetime of bridges) maximum extremes of traffic LEs predicted using the non-stationary Bayesian method for all considered cases. In order to better examine the effects of traffic growth, the percentage increase of the predicted maximum traffic LE under growing traffic relative to that under stationary traffic is calculated as:
\[ \text{Increase of } LEs = \frac{LE_{ns} - LE_s}{LE_s} \times 100\% \]  

(6-21)

where \( LE_{ns} \) is the predicted maximum traffic LEs under the non-stationary traffic and \( LE_s \) is the predicted maximum traffic LEs under stationary traffic obtained from Case 12. From Table 6-5, it can be seen that the traffic growth causes different levels of increase of predicted maximum traffic LEs depending on the type of growth and the growth rate. Among the three types of growth, the growth of truck weight was found to have the most significant influence on the predicted maximum traffic LEs. For cases with a constant AGR of truck weight (Cases 7 and 8), considerable increases of predicted maximum traffic LEs at the 75-year return period were observed. Under the AGR of truck weight of one percent (Case 8), the 75-year maximum traffic LE increased by 54.7 percent relative to the stationary traffic. For cases where the AGR of truck weight was modeled to exponentially decay (Cases 9 to 11), while the increase of traffic LEs is less significant compared with former cases, there are still noticeable percentage increases of the predicted maximum traffic LEs at both 20-year and 75-year return periods. Furthermore, it was found that the growth of traffic volume and the proportion of heavy trucks (Cases 1 to 6) have similar effects on the predicted maximum traffic LEs. For these cases, an insignificant increase of predicted maximum traffic LEs was observed at 20-year return period and the increase of predicted maximum traffic LEs at 75-year return period is generally moderate. In addition, it is noted that for Cases 3 and 6, significant percentage increase of LEs at 75-year return period was observed. Nevertheless, the AGRs considered for the two cases are relatively larger and are less likely to maintain in reality.

Table 6-5 Predicted maximum traffic LEs of each case and corresponding percentage increases

<table>
<thead>
<tr>
<th>Case Number</th>
<th>Predicted maximum traffic LE (( \mu_e ))</th>
<th>Percentage increase of LEs relative to stationarity (%)</th>
<th>20-year</th>
<th>75-year</th>
<th>20-year</th>
<th>75-year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>128.50</td>
<td>145.68</td>
<td>1.98</td>
<td>10.77</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 2</td>
<td>128.83</td>
<td>150.88</td>
<td>2.24</td>
<td>14.73</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 3</td>
<td>129.20</td>
<td>158.11</td>
<td>2.53</td>
<td>20.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 4</td>
<td>130.05</td>
<td>150.47</td>
<td>3.21</td>
<td>14.42</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 5</td>
<td>130.81</td>
<td>156.29</td>
<td>3.81</td>
<td>18.84</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 6</td>
<td>131.17</td>
<td>164.97</td>
<td>4.09</td>
<td>25.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 7</td>
<td>134.39</td>
<td>165.88</td>
<td>6.65</td>
<td>26.13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 8</td>
<td>145.55</td>
<td>203.47</td>
<td>15.51</td>
<td>54.72</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 9</td>
<td>135.04</td>
<td>148.98</td>
<td>7.17</td>
<td>13.28</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 10</td>
<td>141.40</td>
<td>162.55</td>
<td>12.21</td>
<td>23.60</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 11</td>
<td>149.83</td>
<td>178.63</td>
<td>18.90</td>
<td>35.83</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 12</td>
<td>126.01</td>
<td>131.51</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In reality, the growth of traffic volume is the most common type of traffic growth due to the economic development. However, the growth of traffic volume generally does not lead to significant increase of extreme traffic LEs of bridges as can be seen from Table 6-5. On the other hand, the growth of the proportion of heavy trucks (many of which are permit trucks) and truck weight is mainly subject to regulation changes. Thus, the decision making on regulation changes should consider the implications of the corresponding traffic growth on the safety of bridges.
particularly, it is suggested that caution be exercised when changing the regulation to allow a higher truck weight limit as it is expected to cause a significant increase of the maximum traffic LEs, which will accelerate the degradation and eventually reduce the normal service life of bridges. One possible option to reduce the impacts brought by raising the truck weight limit is to require extra axles be equipped for trucks with increased weight limit, which is actually similar to the growth of the proportion of heavy trucks since many heavy trucks are permit trucks that are overloaded. In this case, the increase of traffic LEs due to the growth of truck weight may be alleviated to some degree.

6.4.3 Parametric Study

In order to examine the influence of the block size and the observation period on the prediction results, a parametric study based on Case 4 is conducted. Ten simulations of 50 years of traffic LEs under the AGR of the proportion of heavy trucks of four percent are performed. Six block sizes ranging from 5 days to 30 days and five observation periods from 10 years to 50 years are considered. Figure 6-11 plots the variation of the predicted maximum traffic LEs with the block size and the observation period. It can be seen that: (1) the predicted maximum traffic LEs do not change significantly with the increase of block size except for the observation period of 10 years at 75-year return period; (2) the predicted maximum traffic LEs tend to slowly decrease as the observation period becomes longer.

Figure 6-11 Variation of predicted maximum traffic LEs with the block size and observation period for Case 4: (a) 20-year return period; (b) 75-year return period

Figure 6-12 shows the variation of the marginal posterior distributions with the block size for the data duration of 30 years of one simulation. It can be seen that as the block size increases, the marginal posterior distributions of the shape and scale parameters shift to the left while the marginal posterior distributions of $\mu_0$ and $\mu_1$ shift to the right. Furthermore, it can be seen that the marginal posterior distributions become increasingly flat as the block size increases, which suggests that the uncertainty of the parameters increases with the increase of the block size for a given observation period. In this case, if only the modes of the posterior distribution, i.e., the ML estimates of parameters, are used to predict the traffic LEs, the reliability of the prediction will
decrease as the block size increases. The Bayesian method, on the other hand, is able to incorporate the quantified uncertainties of parameters into the prediction and thus provide more reliable predictions of the traffic LEs. As a result, the prediction of traffic LEs will tend to increase as the uncertainty of parameters becomes larger. However, this trend is canceled out by the effect of the decreasing shape parameter with the increase of the block size. Therefore, the predicted traffic LEs remain relatively unchanged with the increase of the block size. It is noted that for the observation period of 10 years, the predicted maximum traffic LEs show noticeable growth with the increase of the block size. This is probably because the uncertainty of parameters is too large due to the small data sample size. In addition, it was found that for a given block size, the marginal posterior distributions do not shift significantly as the observation period changes. Nevertheless, the uncertainty of parameters still reduces with the increase of the observation period. Therefore, the predicted maximum traffic LEs appear to slowly decrease with the increase of the observation period as shown in Figure 6-12. It should be noted that the variation trends shown here are valid only if the observation period is sufficiently long so that extreme loading events will be able to occur during the observation.

Figure 6-12 Variation of marginal posterior distributions with block size for observation period of 30 years: (a) shape parameter; (b) scale parameter; (c) $\mu_0$; (d) $\mu_1$
6.5 Conclusions

In this paper, a Bayesian framework for predicting extreme traffic LEs of bridges subject to non-stationary traffic was presented and the impact of traffic growth on bridge safety was examined. Long term traffic LEs considering different types of traffic growth were simulated using Monte Carlo simulation and influence line analysis. The non-stationary Bayesian method was applied to predict the extreme traffic LEs using the simulated traffic LEs. Based on the results obtained, the following conclusions can be drawn:

1) For the non-stationary GEV distribution, the shape and scale parameters do not vary significantly with time under the traffic growth while the location parameter tends to increase linearly with time when a constant AGR of the traffic is assumed. Nevertheless, when the AGR gradually decreases with time, modeling the location parameter using a power function can better capture the variation of extreme traffic LEs over time;

2) The growth of truck weight results in a significant increase of the maximum lifetime traffic LEs of bridges even at a relatively small or gradually decreasing AGR of truck weight while the growth of truck volume and proportion of heavy trucks tends to cause a relatively moderate increase of the maximum lifetime traffic LEs;

3) For the non-stationary Bayesian method, the block size does not have a significant impact on the prediction results while the predicted maximum traffic LEs tend to gradually decrease with the increase of the observation period provided that the observation period is sufficiently long.

The results presented in this study emphasize the importance to consider the growth of traffic in the prediction of the maximum traffic LEs of bridges. For bridge design, the development of live load models should consider the possible traffic variations in order to ensure the safety of the bridge during its design life. For bridge management, the consideration of traffic growth in the prediction of the maximum traffic LEs during the remaining life of bridges helps provide more accurate assessment of the bridge safety condition. In addition, the decision making on regulation changes should take into account the potential impacts of the corresponding traffic growth on the safety of bridges. Specifically, when the truck weight limit needs to be raised, it is suggested that some measures such as equipping extra axles for heavy trucks be adopted to reduce the impact brought by the weight increase.

Future study will incorporate the non-stationary traffic LE model presented in this study and a resistance model considering the deterioration of materials into a time variant reliability study in order to more accurately estimate the remaining life of bridges.

6.6 References


CHAPTER 7. CONCLUSIONS AND RECOMMENDATIONS

In this dissertation, an enhanced BWIM methodology using SHM was developed and a Bayesian framework for predicting extreme traffic LEs of bridges was presented. Firstly, a comprehensive review on the BWIM technology was conducted to identify remaining gaps in the current BWIM technology, which led to the subsequent development of the enhanced BWIM methodology. The enhanced BWIM methodology developed in this study includes two parts: (1) a new axle detection method that is able to identify vehicle axles using the global response of bridges; (2) a novel NOR BWIM algorithm that is able to identify the vehicle’s transverse position (TP) and axle weight using only weighing sensors. The enhanced BWIM methodology can be achieved using only weighing sensors that are typically available in many SHM systems. Secondly, a Bayesian framework for predicting extreme traffic LEs of bridges, which can be applied for both stationary and non-stationary traffic conditions, was presented and the influence of the growing traffic on bridge safety was investigated. The prediction methodology was first applied for the condition assessment of the new I-10 Twin Span Bridge and then employed to study the influence of the traffic growth on the bridge safety. Both the enhanced BWIM methodology and the Bayesian framework for predicting extreme traffic LEs can facilitate the bridge condition assessment through SHM by providing critical information of the traffic loading on bridges. In this chapter, a summary of findings of this dissertation and the recommendations for the future research are provided.

7.1 Development of an Enhanced BWIM Methodology

A state-of-the-art review on the BWIM technology was conducted from two perspectives, i.e., the BWIM algorithms and the instrumentation of BWIM systems. The main findings of the review are given as:

- The BWIM technique has significant advantages over the pavement-based WIM technique. BWIM systems are more durable, and their installations are also easier and safer. Moreover, BWIM systems are potentially more accurate than pavement-based WIM systems.

- The static BWIM algorithms include the Moses’s algorithm, the influence area method, the reaction force method, and the orthotropic BWIM algorithm. Although the accuracy of the Moses’s algorithm depends on several factors, it is straightforward and relatively simple to implement. The influence area method can be used to estimate the gross vehicle weight; however, it has the difficulty of identifying the weight of individual axles. The reaction force method is simple to implement; however, some drawbacks have limited its extensive applications. The orthotropic BWIM algorithm employs a different optimization scheme and can serve as an alternative to the Moses’s algorithm in some cases. The dynamic BWIM algorithms, also known as the moving force identification (MFI) methods, have the potential to be very accurate. However, they are computationally expensive and require well-calibrated FE model of the bridge.

A new axle detection method was proposed in the present study. The vehicle axle information is extracted using continuous wavelet transformation of the global response of
bridges. Numerical simulations were conducted using three-dimensional vehicle and bridge models, and the effect of several parameters including sampling frequency, road surface condition, and measurement noise on the identification accuracy were investigated. Based on the results obtained, the following conclusions are drawn:

- Vehicle axle identifications can be achieved through a wavelet analysis of the bridge global responses. This approach has obvious advantages over existing axle identification methods in that it requires fewer sensors and it does not impose any additional restrictions on the basis of the Moses’s algorithm.

- The sampling frequency of the data acquisition system has significant influence on the identification accuracy. A higher sampling frequency leads to sharper peaks in the transformed signal, which in turn, increases the identification accuracy, especially in cases where vehicles travel at relatively higher speeds.

- Road surface condition also affects the accuracy of the axle identification in that road surface roughness causes additional peaks in the transformed signal due to the vehicle-bridge interaction, and once these peaks overcome the peaks induced by the vehicle axles, the identification of vehicle axles becomes very difficult.

- The proposed identification method is susceptible to measurement noises. This is inevitable since the information on vehicle axles is reflected by very delicate changes in the original signal. Nevertheless, it has been shown that reducing the sampling frequency increases the scale of the peaks induced by the vehicle axles and thus makes the identification less susceptible to the measurement noise.

A novel NOR BWIM algorithm considering the TP of the vehicle was proposed. The proposed algorithm is able to identify the vehicle’s TP and axle weights using only weighing sensors, which enhances the portability and reduces the cost of the NOR BWIM systems. Numerical simulations were conducted using three-dimensional vehicle and bridge models. A parametric study was conducted to examine the effects of the road surface condition, vehicle speed, vehicle width, and different measurement stations on the identification accuracy. Finally, the proposed algorithm was verified by a field study. Based on the results obtained, the following conclusions can be drawn:

- Numerical results showed that the proposed algorithm can accurately identify the TP and the axle weights of vehicles and that considering the vehicle’s TP can significantly improve the identification accuracy of axle weights compared with the 1D Moses’s algorithm.

- Successful identification of the vehicle’s TP was achieved regardless of the different road surface conditions used. However, the identification accuracy of axle weights decreases significantly as the road surface condition becomes worse. In this case, a low-pass filter can be applied to effectively improve the identification accuracy of axle weights.
Vehicle speed does not have a significant influence on the identification accuracy. Nevertheless, vehicles traveling at certain speeds may induce the resonant vibration of the bridge, which leads to larger identification errors of axle weights.

Although the variation of the vehicle width has certain effects on the identification accuracy, the actual variation of vehicle width is quite small and the influence of the vehicle width on the identification accuracy is negligible in practice.

Using measurement stations of smaller responses as weighing stations may result in larger identification errors of axle weights. It is thus suggested that the measurement station of the largest response be selected as the weighing station in practice.

### 7.2 Predicting Extreme Traffic Load Effects of Bridges under a Bayesian Framework

In this study, the Bayesian framework for predicting extreme traffic LEs of bridges was presented. The detailed prediction procedures were introduced. The Bayesian method provides a systematic framework of uncertainty quantifications for extreme value analysis. Compared to the conventional method, the Bayesian method is able to quantify the uncertainties of parameters in terms of posterior distributions and incorporate the uncertainties into the prediction through the posterior predictive distribution. The prediction results are intended for the application in bridge condition assessment. As such, a framework was proposed to evaluate the bridge condition at two different levels.

A case study featuring the I-10 Twin Span Bridge was presented to demonstrate the proposed methodology. The monitored strain response was first processed using the wavelet decomposition to extract the traffic LEs and then the Bayesian method was adopted to predict the future maximum traffic LEs of the bridge. The prediction results show that the predicted maximum traffic LEs obtained using the Bayesian method are significantly higher than those obtained using the conventional method. The difference is caused by the uncertainties inherent in the parameters. Furthermore, it is found that the variation trend of the maximum positive and negative stresses with the transverse location of sensors is similar for the steel span but different for the concrete span. Also, the maximum stresses of exterior girders generally increase faster with the increase of return period than those of interior girders due to the different tail behaviors between the maximum traffic LE distributions of exterior and interior girders. Finally, the condition assessment of the bridge was conducted using the proposed framework. The design LL capacity envelopes and service performance envelopes were developed based on the design calculation and the FE modeling of the bridge. The condition assessment results show that the bridge is performing normally under the current condition and that the bridge will be safe during its remaining life from the design perspective except that certain girders close to the slow lane may be overstressed in the future (75-year return period).

Due to the economic developments and technological advances, the road traffic is experiencing substantial growth in both the volume and weight. Therefore, in this study, a Bayesian framework for predicting extreme traffic LEs of bridges subject to non-stationary traffic was presented and the influence of the traffic growth on bridge safety was investigated. Long term traffic LEs considering different types of traffic growth were simulated using Monte Carlo methods.
Carlo simulation and influence line analysis. The non-stationary Bayesian method was applied to predict the extreme traffic LEs using the simulated traffic LEs. Based on the results obtained, the following conclusions are drawn:

- For the non-stationary GEV distribution, the shape and scale parameters do not vary significantly with time under the traffic growth while the location parameter tends to increase linearly with time when a constant AGR of the traffic is assumed. Nevertheless, when the AGR gradually decreases with time, modeling the location parameter using a power function can better capture the variation of extreme traffic LEs over time;

- The growth of truck weight results in a significant increase of the maximum lifetime traffic LEs of bridges even at a relatively small or gradually decreasing AGR of truck weight while the growth of truck volume and proportion of heavy trucks tends to cause a relatively moderate increase of the maximum lifetime traffic LEs;

- For the non-stationary Bayesian method, the block size does not have a significant impact on the prediction results while the predicted maximum traffic LEs tend to gradually decrease with the increase of the observation period provided that the observation period is sufficiently long.

The results presented in this study highlight the importance to consider the growth of traffic when predicting the maximum traffic LEs of bridges. For bridge design, the development of live load models should consider the possible traffic variations in order to ensure the safety of the bridge during its design life. For bridge management, the consideration of traffic growth in the prediction of the maximum traffic LEs during the remaining life of bridges helps provide more accurate assessment of the bridge safety condition. In addition, the decision making on regulation changes should take into account the potential impacts of the corresponding traffic growth on the safety of bridges. Specifically, when the truck weight limit needs to be raised, it is suggested that some measures such as equipping extra axles for heavy trucks be adopted to reduce the impact brought by the weight increase.

7.3 Recommendations for Future Research

Identification of multiple-vehicle presence is still one of the main challenges faced by the BWIM technology. The challenge for the identification of multiple-vehicle presence mainly lies in the difficulty of differentiating between different patterns including side-by-side, staggered, and following trucks. In this case, a 2D BWIM algorithm is needed and the TP of each vehicle needs to be identified. Besides, the axle detection is also challenging since it is difficult to differentiate between the response peaks induced by each vehicle. The 2D BWIM algorithm proposed in the present study has the potential to address the problem of multiple-vehicle presence especially for patterns of side-by-side and staggered vehicles since the proposed algorithm is able to identify vehicles’ TPs. Future works may extend the proposed algorithm to identify different cases of multiple-vehicle presence and investigating the effect of actual traffic on the effectiveness of the developed BWIM methodology.
Although several NOR axle detection methods are available, they all use bridge response to indirectly identify the vehicle axles, which increases the chances of error, e.g., the failure to identify closely-spaced axles and mixed response peaks from axles of multiple vehicles. In order to increasing the reliability of detection, future study can consider using the direct method, i.e., visual identification of vehicle axles. More specifically, image processing techniques can be applied to extract the vehicle information including the number of vehicles and the axle configurations. Moreover, the video recorded by the camera can be used to identify the position of each vehicle at any time instant during the crossing event. In this case, the BWIM algorithm can be extended to identify cases where vehicles change speed and traveling lane. This will also help improve the applicability of the BWIM technology on long-span bridges since vehicles changing speed and traveling lane frequently occur on long-span bridges. In addition, visual identification can help differentiate between different patterns of multiple-vehicle presence especially for the pattern of following vehicles, which will improve the robustness of the BWIM technology.

In this study, the enhanced BWIM methodology was validated using a previously conducted load test. However, the original purpose of the load test was not designed to verify the proposed BWIM algorithms. As a result, the data acquired from the testing may not be perfectly suitable for the implementation of the enhanced BWIM methodology. For example, only three TPs of the vehicle were considered in the testing while the field calibration of the influence surface usually requires more TPs. Moreover, the load test was conducted under a relatively low sampling frequency, which prevented the application of the proposed axle detection method in the validation. In the future, a full-scale experiment with well-defined vehicle information, such as speed, location, axle spacing, weight, etc., is desired to validate the enhanced BWIM methodology. The experiment should include more refined calibration of the influence surface and use instrumentations with sufficiently high sampling frequency to test the effectiveness of the proposed axle detection method.

In the present study, the prediction of extreme traffic LEs is based on the block maxima (BM) method using the GEV distribution. Alternatively, the peak-over-threshold (POT) method using the generalized Pareto distribution is also widely adopted in extreme value analysis. Research in other disciplines has shown that the POT method is as effective as the BM method and may even perform better in some cases. Therefore, a future study can apply the Bayesian framework to predict the extreme traffic LEs using both the BM and POT methods. Under the Bayesian framework, the probabilities of competing models can be explicitly computed and a multi-model prediction can be realized using Bayesian model averaging, which allows the advantage of both methods to be fully exploited.

The statistical characteristics of the maximum traffic LEs may be different for different bridge span length since longer span bridges have higher probability of multiple-vehicle presence which is an important contribution to extreme traffic LEs. For future works, it would be interesting to conduct a parametric study to examine the effect of the bridge span length on the predicted extreme traffic LEs. Moreover, only the prediction of the bending strain (moment) was considered in the present study. However, bridge design also needs to consider other types of LE (e.g., displacement and shear). Thus, it is suggested that different types of LE be included in the future study.
The Bayesian method is able to quantify the uncertainty of predicted extreme traffic LEs by providing the distribution of the predicted extreme LEs instead of merely a point estimate, which can be used for the reliability analysis of bridges. In future studies, a time variant reliability study incorporating the non-stationary traffic LE model considering the traffic growth and a resistance model considering the deterioration of materials is desired. Such a framework can be used to more realistically estimate the remaining life of bridges, which could shed light on the development of live load models in bridge codes and decision making of bridge management such as the optimal maintenance schedule.

While the measured LL stress will automatically reflect both the effect of traffic and structural property changes, the capacity envelopes used in the performance assessment should reflect these variations as time goes.
APPENDIX: PERMISSIONS

From: PermissionsUK <PermissionsUK@sagepub.com>
Sent: Monday, October 16, 2017 12:06 PM
To: Yang Yu
Subject: RE: Permission Request

Dear Yang Yu,

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Mr. Yang Yu was born in 1992 in Hunan Province, People’s Republic of China. He received his Bachelor of Science degree from the College of Civil Engineering at Hunan University, People’s Republic of China, in June 2014. He anticipates graduating with his Ph.D. degree in December 2017.

Mr. Yu has worked as a Graduate Research Assistant at Louisiana State University since August 2014. During his Ph.D. study, he has been involved in several research areas such as bridge condition assessment, structural health monitoring, and structural dynamics. He has 19 publications during his research period.