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Short and Long-Term Structural Health Monitoring of Highway Bridges

Navid Zolghadri

Utah State University

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SHORT AND LONG-TERM STRUCTURAL HEALTH MONITORING OF HIGHWAY BRIDGES

by

Navid Zolghadri

A dissertation submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Civil and Environmental Engineering

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2017
ABSTRACT

Short- and Long-Term Structural Health Monitoring
of Highway Bridges

by

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Utah State University, 2017

Major Professor: Dr. Marvin Halling
Department: Civil and Environmental Engineering

Structural Health Monitoring (SHM) is a promising tool for condition assessment of bridge structures. SHM of bridges can be performed in long or short-term. A few aspects of short- and long-term monitoring of highway bridges are addressed in this research.

Without quantifying environmental effects, applying vibration-based damage detection techniques may result in false damage identification. As part of a long-term monitoring project, the effect of temperature on vibrational characteristics of two continuously monitored bridges are studied. Variability of the identified natural frequencies from ambient vibration is investigated. Different statistical models are tested and the most accurate model is selected to remove the effect of temperature from the identified frequencies. After removing temperature effects, different damage scenarios are simulated on calibrated finite-element models. Comparing the effect of simulated damages on natural frequencies showed what levels of damage could be detected with this method.
Evaluating traffic loads can be helpful to different areas including bridge design and assessment, pavement design and maintenance, fatigue analysis, economic studies and enforcement of legal weight limits. In this study, feasibility of using a single-span bridge as a weigh-in-motion tool to quantify the gross vehicle weights (GVW) of trucks is studied. As part of a short-term monitoring project, this bridge was subjected to four sets of high speed, live-load tests. Measured strain data are used to implement bridge weigh-in-motion (B-WIM) algorithms and calculate the corresponding velocities and GVWs. A comparison is made between calculated and static weights, and furthermore, between supposed speeds and estimated speeds of the trucks.

Vibration-based techniques that use finite-element (FE) model updating for SHM of bridges are common for infrastructure applications. This study presents the application of both static and dynamic-based FE model updating of a full scale bridge. Both dynamic and live-load testing were conducted on a bridge and vibration, strain, and deflections were measured at different locations. A FE model is calibrated using different error functions. This model could capture both global and local response of the structure and the performance of the updated model is validated with part of the collected measurements that were not included in the calibration process.
PUBLIC ABSTRACT

Short- and Long-term Structural Health Monitoring
of Highway Bridges

Navid Zolghadri

Structural Health Monitoring (SHM) is a promising tool for condition assessment of bridge structures. SHM of bridges can be performed for different purposes in long or short-term. A few aspects of short- and long-term monitoring of highway bridges are addressed in this research.

Without quantifying environmental effects, applying vibration-based damage detection techniques may result in false damage identification. As part of a long-term monitoring project, the effect of temperature on vibrational characteristics of two continuously monitored bridges are studied. Natural frequencies of the structures are identified from ambient vibration data using the Natural Excitation Technique (NExT) along with the Eigen System Realization (ERA) algorithm. Variability of identified natural frequencies is investigated based on statistical properties of identified frequencies. Different statistical models are tested and the most accurate model is selected to remove the effect of temperature from the identified frequencies. After removing temperature effects, different damage cases are simulated on calibrated finite-element models. Comparing the effect of simulated damages on natural frequencies showed what levels of damage could be detected with this method.
Evaluating traffic loads can be helpful to different areas including bridge design and assessment, pavement design and maintenance, fatigue analysis, economic studies and enforcement of legal weight limits. In this study, feasibility of using a single-span bridge as a weigh-in-motion tool to quantify the gross vehicle weights (GVW) of trucks is studied. As part of a short-term monitoring project, this bridge was subjected to four sets of high speed, live-load tests. Measured strain data are used to implement bridge weigh-in-motion (B-WIM) algorithms and calculate the corresponding velocities and GVWs. A comparison is made between calculated and static weights, and furthermore, between supposed speeds and estimated speeds of the trucks.

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Navid Zolghadri
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CHAPTER 1
INTRODUCTION

1.1 Background and Motivation

Bridges, amid different types of civil infrastructure, play a key role in the transportation infrastructure which has a considerable impact on long-term economic growth and productivity. Deterioration and maintenance of existing bridges have become a great concern in the United States as bridge structures are aging and approaching their intended design lives rapidly. The average age of the bridges is 42 years and FHWA investigation shows that more than 30% of existing bridges have exceeded their 50-year design lives (American Society of Civil Engineers report card 2013). This concern is not limited to the US and even other countries, for instance, Canada (Intelligent Sensing for Innovative Structures Canada, 2000) and Japan (Fujino and Siringoringo 2011), are encountering similar challenges for managing their infrastructure.

The increase of aging bridges has required more investments for bridge maintenance, repair, and rehabilitation. The total estimated cost to rehabilitate deficient bridges in the US has risen from $71 billion in 2009 to $76 billion in 2013 (American Society of Civil Engineers report card 2013). If bridge maintenance is not managed properly, this increasing cost may escalate over the upcoming years.

In addition, bridge failures, such as Silver Bridge collapse in 1967, or more recently, I-35W collapse in Minneapolis, have raised concerns for better management approaches and nation-wide strategies for replacement and repair of deficient bridges with limited available funding (Hao 2010).
As a result of Silver Bridge collapse, National Bridge Inspection program was initiated to improve the safety of bridges. This program has mandated all the states to inspect all highway bridges periodically (NBIS 1996).

On-site visual inspection by qualified trained inspector has been traditionally practiced as a tool for bridge condition assessment; however, this type of inspection has different shortcomings: (1) only observable damages can be detected and the accuracy is very limited; (2) results are subjective and depend on inspectors experience and judgment; and (3) it is a time and cost inefficient method and continuous inspection is not feasible. As a result, there is a constant concern of the occurrence of serious damages between inspection periods.

The subjectivity of visual inspection was highlighted by Phares et al. (2004) in a study that 100 experienced inspectors independently inspected the same bridge. While each component of the bridge, such as deck, substructure, and superstructure, is rated on a 0-9 scale, the study reported that 95% of condition rating by inspectors would vary within two points. This variation clearly proved the subjective nature of visual inspections which makes it less reliable.

In the past decades, structural health monitoring (SHM) has emerged as a great tool to evaluate structural conditions continuously and periodically. Since collecting data has become more affordable in different areas (Khalilikhah et al. 2015; Sharifi et al. 2015a; Sharifi et al. 2015b) and in the area of bridge monitoring, SHM has become more affordable and consequently more common (Moser et al. 2013). SHM is defined as
implementation of a strategy to detect possible damages at the earliest possible stage and assess the remaining life of structures. In addition to detecting damages, knowing the current condition and load capacity of in-service structures may be of great value to the bridge owners (such as state DOT’s, or other agencies).

Damage in a structure is defined as any changes in material properties, boundary conditions, and system integrity. Damage may occur due to natural catastrophic events, such as earthquakes, man-made hazards, such as explosions, or under service load conditions in the form of aging, traffic growth, progressive deterioration, and environmental effects. One of the benefits of SHM systems is the possibility of continuous evaluation of structural condition without personal judgements and instant detection of the occurrence of any damage under service loads or right after any catastrophic events.

Damage detection is classified into four different levels: (1) the presence of damage (2) location of damage (3) type of damage (4) damage extent. Different methods provide information at different levels. There are many damage detection methods for detecting damage at different levels. Vibration-based damage detection methods are one of the most common methods that are based on the premise that the dynamic properties of a structure change in the presence of damage. Dynamic characteristics of structures can be measured by measuring vibration response of a structure and it is assumed that damage causes only a loss of stiffness in one or more elements of the structure but not a loss of mass. An extensive review of vibration-based damage identification methods has been provided by Doebling et al. (1996 and 1998) and Sohn et al. (2004).
Non-Destructive Testing (NDT) techniques, which are effective techniques for structural health monitoring of bridges and detecting damages, can be categorized into two major approaches: local and global. The first approach (local) includes the methods that are intended to provide information from a small region of structural elements such as acoustic emission technique, ultrasonic, and infrared thermography. The second approach (global) comprises the methods that provide global information about the structural condition based on the measurements from various sensors.

In addition to global and local classification, SHM of bridges can be divided into two categories: short-term and long-term. There has been significant allocation of funding to the research community to investigate and monitor bridges for short and long-term purposes. One of the recent efforts for investigating long-term monitoring of bridges was the Long-Term Bridge Performance Program (LTBP) which was initiated by Federal Highway Administration (FHWA) with $25.5 investment.

Long-term monitoring usually consists of collecting ambient vibration and environmental data to evaluate structural condition over long periods of time. For instance, with long-term monitoring, changes or abnormalities in structural behavior can be detected without human interactions, or environmental effects on the performance of the structure can be quantified (Karbhari and Ansari 2009; Farrar and Worden 2012).

Short-term monitoring consists of live-load and dynamic testing. Data is only collected over a relatively short period of time when these field tests are taking place. The collected measurements can provide information about structural performance such as load
and moment distributions, stress/strain levels, and serviceability issues. In addition, the collected data will provide valuable insights for future designs, and improve qualitative assessments of the bridge structures with different load tests.

1.2 Objective and Scope

This research addresses both short and long-term structural health monitoring of bridges. The results of this research contribute to the performance assessment of bridge structures with structural health monitoring and field testing. As previously stated, there are different purposes for collecting short and long-term data from bridge structures. The focus of this research is in these areas: (1) quantifying the range of environmental effects on structural properties of bridge structures based upon long-term ambient vibration and temperature measurements; (2) evaluate the truck loads a bridge experiences with developing bridge weigh-in-motion (B-WIM) techniques based on collected data from live-load testing of a bridge; (3) improving condition assessment through finite-element model updating with using combination of both dynamic and live-load data.

Environmental variation effects structural properties and needs to be quantified for evaluating structural conditions. These variations, such as temperature, may mask changes in the identified structural properties, such as natural frequencies, because of damage. In this research, in order to achieve the goal of damage detection through vibration measurements, environmental effects are quantified on two different bridges.

B-WIM techniques are good tools for quantifying the traffic load without interrupting traffic and have the potential to provide valuable information for designing
bridges and reducing maintenance costs. The simplified method that is proposed and
verified in this research may quantify the existing traffic passing over a bridge at a full
highway speed without using axle detectors.

Finite-element model updating can be used to estimate structural parameters and
assess bridge performance. The improved model updating technique with using both static
and dynamic measurements offers a better model to identify the global behavior and load
capacity of bridge structural elements.

1.3 Organization of Dissertation

This dissertation is divided into five main chapters (Fig. 1). The first chapter
provides background and overview of this research. The next three chapters are 3 separate
manuscripts and are formatted to be submitted to peer-reviewed journals. These three
chapters include the major contributions of this research. Finally, Chapter 5, summarizes
all the findings and brings together the final conclusions discussed in the first four chapters.
Additionally, Chapter 5 explains the possible future direction of the research areas that are
discussed in the other chapters.
Fig. 1. Organization of dissertation
CHAPTER 2
EFFECTS OF TEMPERATURE VARIATIONS ON NATURAL FREQUENCIES AND VIBRATION-BASED DAMAGE DETECTION OF BRIDGE STRUCTURES

Abstract

Vibration-based structural health monitoring is a promising approach for condition assessment of bridge structures. This approach relies upon the change of the identified modal parameters as damage sensitive features. However, changes of environmental conditions, such as temperature, usually effect the identified modal parameters more significantly than changes in structural properties. In order to employ vibration-based damage detection techniques effectively, evaluating the environmental effects is essential. For quantifying these effects, two continuously monitored bridges are studied in this paper. These bridges are subjected to a fairly wide range of temperature and the results from both of the bridges showed a strong correlation between measured temperatures and identified natural frequencies. Then, different statistical models were thoroughly investigated to find the most appropriate model that represents the relationship between temperature and natural frequencies. The input variables were carefully selected and these models were validated with randomly selected data. Subsequently, these models allowed for removing the effects of temperature from the identified frequencies. Then, different damage scenarios were simulated on calibrated finite-element models of the bridges. As a result, the range of possible damage that can be detected after removing the effect of temperature from the identified natural frequencies was quantified.
2.1 Introduction

According to the current status of infrastructure reported by the American Society of Civil Engineer (ASCE), the necessity of improving maintenance and management approaches has been evidently obvious. In the latest report of ASCE that was published in 2013 (ASCE 2013), bridges are graded as “C+” and more than 24.9% of the in-service bridges are classified as “structurally deficient”, meaning that they require significant rehabilitation and maintenances, or “functionally obsolete”, meaning that they are not capable of handling current traffic demand.

Visual inspection has been the dominant practiced method for evaluating bridge condition. However, in the past decades, vibration-based structural health monitoring has been widely investigated since it has emerged as a tool for assessing structural condition less subjectively (Doebling et al. 1998; H. Sohn et al. 2003; Hsieh, Halling, and Barr 2006).

One of the major objectives of vibration-based structural health monitoring technique is detecting possible damage in the monitored structures at early stages. This objective can be achieved by collecting ambient vibration, extracting modal parameters, and detecting abnormalities in the continuously measured modal parameters (Salawu, O. S. 1997; Abdel Wahab and De Roeck 1999; Dutta and Talukdar 2004; Farrar and Worden 2007; Magalhães, Cunha, and Caetano 2012; Seo, Hu, and Lee 2015; Zolghadri et al. 2016a).

Extracted modal parameters are potentially appropriate damage-sensitive features since they are well correlated to physical properties and stiffness of a structure. These
parameters can be used for condition assessment of a structure effectively. However, monitoring different in-service structures, such as bridges, has shown that the changes in modal parameters are not merely effected by the changes in structural properties, but also by variations in environmental and operational conditions (Hoon Sohn et al. 1999; Brownjohn 2007; Xu and Zhishen Wu 2007; Liu and DeWolf 2007; Yuen and Kuok 2010; Moaveni and Behmanesh 2012; Nandan and Singh 2014a, 2014b). The damaging effects of environment has been also investigated in other areas (for example see Khalilikhah and Heaslip 2016a; Khalilikhah and Heaslip 2016b; Javid et al 2014).

The extent of these effects on the extracted modal parameters may be large enough to conceal the influence of any on-going structural deterioration or possible occurring damage. For example, monitoring Alamosa Canyon Bridge at two-hour increments during a 24-hour period showed that the variation of the first three natural frequencies were 4.7%, 6.6%, and 5.0% respectively (Cornwell et al. 1999; Farrar et al. 1997). In another study, collecting data from Z24 bridge for one year depicted that the change of the first four measured natural frequencies could reach 18% (Peeters and De Roeck 2001). Consequently, quantifying environmental effects for detecting changes in structural properties from measured modal parameters is necessary and inevitable.

Environmental and operational effects consist of wind, humidity, rainfall, solar radiation, traffic loads, and temperature. Among different environmental effects, temperature is the most frequently considered environmental factor for short and medium-span studied highway bridges (Peeters and De Roeck 2001; Sohn et al. 1999; Xia et al. 2012; Zhou and Yi 2014). However, for long-span bridges, such as the bridge studied by
Laory et al. 2014, the effect of wind and traffic can be more critical. Comparing different environmental and operational factors on that bridge, which was a 642 m long suspension bridge with main span of 335 m, showed the effect of traffic loads, and wind was more significant.

Investigating other modal parameters, damping ratios and mode shapes, have not shown any consistent conclusion regarding the effect of temperature (X. He 2008; Moser and Moaveni 2011). In addition, the damping ratios are less sensitive to damages and there are relatively high errors involved when they are extracted from ambient measurements. Therefore, they are seldom included between modal parameters as a damage-sensitive feature.

Different methods can be used for investigating the relationship between temperature and natural frequencies. One of the possible methods is to accurately model the physical changes that effect the frequencies. For example, Nandan and Singh (2014) simulated the variation of vibration properties of a concrete box girder bridge with regards to the change of modulus of elasticity and thermal pre-stress. Although this method is appealing for understanding the physics behind this phenomenon, it is generally not practical in the area of SHM of bridges. For bridge SHM to be successful, a very complex model needs to be developed and yet the effectiveness of this method is not guaranteed. As a result, black-box models have been proposed instead of trying to use complex and costly models (Hua et al. 2007; Laory et al. 2014; Moser and Moaveni 2011; Peeters and De Roeck 2001). This approach relies upon a large number of observations that can
successfully establish a model to map inputs (temperature measurements) to the outputs (identified modal properties).

In a few of the mentioned studies, machine-learning models such as neural networks or support vector machine techniques have been investigated. These methods can successfully map the inputs to the outputs, but coupling the inputs in a method such as neural networks is difficult to understand and may not have physical interpretations.

Also, using “static” regression models to correlate the instant temperature measurements to the measured frequencies has been extensively investigated in the current available literature. However, identified modal parameters may lag behind the temperature changes because of the thermal inertia effect. Therefore, “dynamic” models that take temporal correlation into consideration intuitively provide more accurate predictions.

This study presents the effect of temperature on identified natural frequencies of two different bridges. These bridges have been instrumented for long-term monitoring purposes and vibration and environmental measurements have been collected periodically. Since these bridges are subjected to a fairly wide range of temperature, they are appropriate for the investigation of environmental effects. The natural frequencies of these bridge were identified using structural identification and preliminary investigation shows the correlation between identified natural frequencies and recorded temperature. This correlation has been modeled with different statistical modeling techniques. The process of modeling including both “static” and “dynamic” methods and selecting appropriate variables for each model are discussed in detail. The non-linear autoregressive method with
exogenous inputs (NARX) is a strong tool to map inputs to the outputs and has not been investigated before in this context. This technique includes both lagged inputs and outputs and this paper explains the effectivity of this technique and its ability to provide a model for interpretation of the effects of temperature on natural frequency. Lastly, the investigated models are used to specify the damage levels that can be detected after removing temperature effects from the measured identified natural frequencies of the bridges.

2.2 Description of Bridges and Long-term Monitoring Systems

2.2.1 Perry Bridge

The Perry Bridge, shown in Fig. 2, is a simple-span bridge located 2.41 km west of Perry, Utah. This bridge is 24.89 m long and 13.40 m wide with a 0.53 m wide parapet on each side. The 12.34 m wide traveling surface consists of two travelling lanes that are 3.66 m wide and two shoulders on the east and the west side that are 3.42 m and 1.6 m wide respectively (Fig. 2). The superstructure of this bridge consist of 5 pre-cast pre-stressed Type IV AASHTO girders and the abutments were designed as integral abutments. The reinforced concrete deck is 20.32 m thick and the minimum compressive strength of the deck was specified 24.2 MPa. The deck is covered with a moisture barrier membrane and an asphalt overlay with varying thickness from 76 mm to 89 mm.

This bridge is instrumented with a long-term monitoring system consists of various types of sensors. The proper locations and types of instrumentation were specified after performing several live-load and dynamic field tests. More details about the live-load and dynamic tests can be found in (Petroff et al. 2011). The final long-term instrumentation includes foil and vibrating wire strain gauges, velocity transducers, thermocouples,
tiltmeters, and hydrotracker impedance sensors. In addition, a weather station has been placed next to the bridge that is equipped with sensors that record wind direction, wind speed, radiation, humidity, and air temperature. In this study, the collected vibration measurements from velocity transducers and recorded temperature by thermocouples at various locations are mainly used for further analysis. To analyze temperature effects, 31 thermocouples have been installed on the superstructure and a weather station have been placed next to the bridge. Ten of the superstructure thermocouples are placed in the deck and providing the temperature profile along the depth of the deck, 15 thermocouples are mounted on the webs of the girders, 5 thermocouples are underneath the girders and 1 air temperature is at the weather station next to the bridge. For measuring vibrations of the bridge, three velocity transducers have been mounted in protective boxes underneath the deck. Fig. 3 and Fig. 4 show the exact locations of the mounted velocity transducers and thermocouples.

Fig. 2. Perry Bridge
Fig. 3. Plan view of the Perry Bridge

The velocity transducers are measuring the ambient vibrations from mostly traffic load and environmental sources. These dynamic responses are recorded every hour for 3 minutes at the sampling frequency of 100 Hz. Each data set includes (3*60*100=18000) samples. Environmental data that mainly consists of temperature measurements are sampled every 3 minutes. In order to alleviate the effects of instantaneous errors in temperature measurements, the average of 5 measurements is calculated and stored every 15 minutes.

2.2.2 Sacramento Bridge

The Sacramento Bridge (Fig. 5) is located about 32 km south of Sacramento, California and carries two Interstate-5 (I-5) southbound lanes over Lambert road. The
bridge was constructed in 1975 as a cast-in-place, pre-stressed, continuous box-girder bridge.

![Cross-sectional view with monitoring details](image)

**Fig. 4.** Cross-sectional view with monitoring details (in meters): (a) Section A-A (b) Section B-B (C) Section C-C

This bridge is 78.7 m long and consists of two equal 39.35 m long spans. The total width of the deck is 12.8 m with clear road width of 12.2 m and two barrier railings that each of them is 0.3 m wide. The deck was constructed as a reinforced concrete slab with
the thickness of 203 mm and overhangs the box-girder cells a distance of 0.92 m. The bottom flange of the box girder is 152 mm thick at 0.3 m from the pier and increases to 254 mm at the pier. The bridge has an $8^\circ$ skew with each supporting abutment and the bent caps.

There are three diaphragms; two 203 mm thick diaphragms located at each mid span and an intermediate diaphragm at the bent cap with the thickness of 1.83 m. These diaphragms follow the same $8^\circ$ skew as the abutments.

The concrete in the deck and girders has a specified 28-day compressive strength of 24.2 MPa. The reinforcing steel is grade 60 in the girders and is grade 50 in the deck.

A 1.83 m thick bent cap supports the bridge and a 1.07 m wide bent column supports the bent cap at midspan. In the transverse direction, this column has a varying width that starts with 3.66 m at the ground and follows a 14:1 slope from the bottom towards the superstructure. A foundation of 5.48 m by 3.66 m with the thickness of 1.07 m supports the column and 24 cast-in-drilled-hole concrete piles that are designed for 623 kN load support the foundation. These piles are 406 mm in diameter.

Integral abutments with attached wing balls support the ends of this box-girder bridge. These abutments are 46 mm thick and are supported by a reinforced pile cap which is 1.22 m wide, 0.46 m thick, and 12.96 m long. Seven cast cast-in-drilled-hole concrete piles with 406.4 mm diameter, which are designed for 623 kN load, support each pile cap. More details can be found in Barr et al. (2012).
A long-term structural health monitoring system, similar to Perry Bridge SHM system, has been installed on the Sacramento Bridge. This long-term SHM system includes various sensor types that measure bridge properties and environmental conditions periodically. The total number of sensors that have been installed on the bridge is 71, but in this study the collected data from 4 velocity transducers and 44 thermocouples have been separated for further analysis. There are also 7 other temperature measurements, 4 temperature measurements from vibrating wire strain gauges and 3 from tilt meters. In total, 51 sets of temperature measurements are included in this study. The velocity transducer signals are sampled at a rate of 50 Hz and the measurements were collected every hour for 6 minutes. The number of records per collection was 18000. The longitudinal locations of the sensors are shown in Fig. 5 and the transverse and vertical (depth) locations can be found in Fig. 6.

Fig. 5. Sacramento Bridge
2.3 Modal Identification

Using controlled excitation for identification of dynamic properties is very difficult and usually impossible to achieve. Closing bridges for isolating operational forces like traffic can also be very costly. As a result, output-only system identification techniques that use ambient excitation are generally preferred for extracting modal parameters. Using wireless sensors for system identification has also been studied in Zolghadri et al. (2014).

The first step in a successful modal identification is to understand the properties of the signals and systems. To identify the range of structures’ natural frequencies in this study, Frequency Domain Decomposition (FDD) method was applied to identify the natural frequencies.
Fig. 7. Cross-sectional view of Sacramento Bridge with monitoring details (in meters)
This method is an extension of the peak picking method in which modal parameters are estimated through singular value decomposition (SVD) of the inputs power spectral density (PSD) matrix (Brincker et al. 2000) (Equation 1).

\[ G_{yy}(jw) = H(jw)G_{xx}(jw)H^T(jw) \]  

Equation 1

Where \( G_{xx} \) is the PSD matrix of the inputs, \( G_{yy} \) is the PSD matrix of the system outputs, and \( H(jw) \) is the Frequency Response Functions (FRFs). Superscript “\(^T\)” denotes transpose and “\(^-\)” denotes complex conjugate.

When the input is white noise (\( G_{xx}(jw) = C \)) and the structure is lightly damped, the results of this method are exact. By assuming that the structure is lightly damped, the contribution of different modes at a particular frequency is limited to one or two.

Taking the singular value decomposition of the spectral matrix (Equation 2)

\[ G_{yy}(jw) = U_i S_i U_i^H \]  

Equation 2

Where \( U_i \) is a unitary matrix holding the singular vectors \( U_{ij} \), \( S_i \) is a diagonal matrix holding the scalar singular values \( S_{ij} \). Basically, the SVD decomposed the PSD matrix into single degree-of-freedom functions.

Fig. 8 shows the FDD analysis of Perry and Sacramento Bridge respectively. For Perry Bridge, records from January 1\(^{st}\), 2015 and for Sacramento Bridge, records from October 1\(^{st}\), 2015 are presented.
For long-term modal identification of these bridges, an automated system identification method should be implemented. Among different modal identification methods, stochastic subspace identification (SSI) and the Eigensystem Realization Algorithm (ERA) are two of the most common methodologies and in this study ERA has been selected for further analysis. For this method, the structure is assumed to behave linearly, time-invariant and the force is uncorrelated with the response.
The first step in applying ERA is to obtain the structure’s response that has the same characteristics of a free vibration response. When the free response of the structure is not directly available, there are a few estimation techniques that can provide the free response of the structure such as Natural Excitation Technique (NExT). This method has been developed and applied successfully for modal identification of a wind turbine (James III et al. 1993). It has been shown that the cross-correlation functions between the vectors of recorded velocities and an appropriately selected reference (velocity vector) have the same characteristics of a free vibration response of the structure.

There are two available methods for calculating cross-correlation functions, the direct method and the FFT-based method. The direct method uses time domain data without any requirement to switch from the time-domain to frequency-domain. However, when longer records of data are analyzed, it is more computationally efficient to use the FFT-based method. In this method, cross-spectral density functions of the recorded signals are first calculated and then the Inverse Fourier Transform is applied to obtain Impulse Response (Fig. 9).

Selecting the data records that can be used for calculating cross-correlations can affect the final results significantly. Signal-to-noise ratio (SNR) and stationarity of the records play important roles to successfully apply system identification. The signal-to-noise ratios of the sensors were generally high enough according to the previously performed testing.
Fig. 9. Sample of calculated Impulse Response from one of the velocity transducers on Sacramento Bridge

To investigate the stationary status of the recorded signals, the mean and standard deviation of the measurements were calculated based on 500-point long windows with 50% overlap. The relative consistency of these properties, shown in Fig. 10, indicates the sufficient stationarity of the records. If a measurement was found to not be entirely stationary, ERA could still be applied to the stationary portion of the record.

Fig. 10. Piece-wise mean and standard deviation of the records: (a) Perry Bridge (b) Sacramento Bridge
Since the FFT-based method was used for estimating cross-correlation functions, the quality of the final results depends on sampling frequency of the data, the length of the records, and the number of points and overlapping ratio for applying the FFT.

The sampling frequency determines the identified frequency range based on the Nyquist criterion. Considering the limitation of the data acquisition system, the sampling frequency was set to be 100 Hz and 50 Hz for Perry and Sacramento Bridges respectively.

For noisy data, longer records for modal identification and final cross-correlation will produce smoother results.

After proper calculations of cross-correlation functions, the ERA realization can be applied to obtain the state-space model of the structure. The first step in applying ERA is forming the Hankel matrix represented by $H(k)$ in Equation 3.

$$H(k) = \begin{bmatrix}
Y(k + 1) & Y(k + 2) & \cdots & Y(k + m) \\
Y(k + 2) & Y(k + 3) & \cdots & Y(k + m + 1) \\
\vdots & \ddots & \vdots & \vdots \\
Y(k + n) & Y(k + n + 1) & \cdots & Y(k + m + n)
\end{bmatrix}$$

Equation 3

The number of rows and columns of the Hankel matrix are specified based on the number of expected frequencies from the structure. The number of rows depends on the available number of points in the cross-correlation functions. The number of columns has been suggested to be at least four times the number of expected modes (Caicedo 2011).
Then, the singular value decomposition of $H(0)$ will provide $R, \Sigma$, and $S$ based on Equation 4. $R$ and $S$ are orthonormal matrices that are $m \times m$ and $n \times n$ respectively. $\Sigma$ is an $m \times n$ matrix which has this form (Equation 5).

$$\text{SVD } [H(0)] = R \Sigma S^T$$ \hspace{1cm} \text{Equation 4}

$$\Sigma = \begin{bmatrix} \Sigma_n & 0 \\ 0 & 0 \end{bmatrix}$$ \hspace{1cm} \text{Equation 5}

$\Sigma_n$ is an $n$ by $n$ matrix and $n$ is the number of poles (order of the system). The diagonal terms of $\Sigma$ are usually not absolutely zero because of the presence of noise in the data. The minimum realization of the system will be obtained by eliminating smaller singular values.

One solution for the state matrix $A$ and $C$ is based on Equation 6 and Equation 7:

$$A = \Sigma_n^{-1/2} R^T H(1) S_n^{-1/2}$$ \hspace{1cm} \text{Equation 6}

$$C = \text{the first } m \text{ rows of } R_n \Sigma_n^{-1/2}$$ \hspace{1cm} \text{Equation 7}

$A$ and $C$, along with $B$ and $D$, are state-space matrices that represent a discrete-time system, described in Equation 8, while $x(k)$ is the state vector, $u$ is the input vector, and $y$ is the system outputs.

$$x(k + 1) = Ax(k) + Bu(k)$$ \hspace{1cm} \text{Equation 8}

$$y(k) = Cx(k) + Du(k)$$
The eigenvalues of $A$ are complex conjugate pairs that correspond to the modes of vibrations. The complex conjugates are also known as poles of the system, and natural frequencies and damping ratios of the system can be calculated from them.

In the application of ERA, a system order must be determined for the model to be realized. If the determined system order is not high enough, some observable modes will remain undetected. On the other hand, if the system order is too high, non-physical models may be falsely identified. Determining the actual model order for structures can be flawed and subsequently, using stabilization diagram has been proposed as an effective tool to identify the model orders by repeating the identification with different numbers of poles. Stable identified parameters are selected as the final structural modal parameters. These stable parameters were derived based on the stepwise comparison of each order with the previous one. The model order was varied from 2-70 in this study and criteria for choosing stable poles are that the frequencies match to within 1%, that the damping ratios match to within 25%, and that the Modal Assurance Criterion (MAC) values are in the range of 0.95 to 1.0. In addition, modes with damping ratios that exceed 5% were excluded. If these criteria have been met for 10 consecutive steps, the mode was flagged stable and stored for further analysis.

2.4 Seasonal Variation of the Identified Modal Parameters

Modal identification was completed for each set of measurements where dynamic data were successfully collected from the dataloggers. There are cases that dynamic data were not completely collected because of communication problems or other technical issues. For the Perry Bridge, there are 15,251 available collections between 11/01/2014
and 07/31/2016. For the Sacramento Bridge, there are 1550 collections between 09/16/2015 and 01/30/2016. Sacramento Bridge encountered significant data acquisition problems and nearly half of the collections were missed.

**Fig. 11.** Sample of Stabilization Diagram for Identifying Natural Frequencies of the Perry Bridge

Further, in this section, more details of identified modal properties and the statistics of the collected dynamic and environmental data from the Perry and Sacramento Bridges are presented.

2.4.1 Perry Bridge

During the test period, the maximum recorded bridge and ambient temperature were 45.5 °C and 38.5 °C. The minimum temperatures were -21.4 °C and -17.5 °C,
respectively. With these changes in temperature, some frequencies varied by as much as 22%.

The pattern of seasonal temperature variation and identified natural frequencies are shown in Fig. 12 and Fig. 13. This pattern depicts how temperature is an important factor for causing variations in identified frequencies. Generally, it can be understood from Fig. 12 and Fig. 13 that higher temperatures result in lower identified frequencies. To investigate these seasonal changes, statistics of modal frequencies, air temperature, and bridge temperature are presented in Table 1. The bridge temperatures in this table include all the thermocouples mounted on the girders and in the deck of the bridge.

It is worth noting that the statistics of Table 1 showed that the standard deviation of identified frequencies is lower during warmer months such as July. Fig. 14 shows this comparison between the first week of July and first week of December in the year 2015. The standard deviation of the identified frequencies during the first week of July (Fig. 14a) is 0.138 while during the first week of December (Fig. 14b) it is 0.287.

It is also worth noting that there are two instantaneous changes detected in the identified frequencies on March 10th, 2016 and June 14th, 2016. These changes could be seen in Fig. 13, but it was more clear when the mean values of identified frequencies in Table 1 are compared at different months. The mean value of identified frequencies of the first mode in April 2016 is 7.26 Hz which is 7% higher than 6.81 Hz in April 2015 while the average temperature is very close. This variation was mainly because of the construction works that started taking place on this bridge during that time. This
construction work included the hydro-demolition of parts of the parapets of the bridge which caused this increase in the identified frequencies. This change will be discussed later in the paper.

To investigate the correlation between temperature and frequencies, the identified natural frequencies of the Perry Bridge are plotted versus the recorded air temperature in Fig. 15. It is more evident that the lower temperature result in higher identified natural frequencies. Mode 5 shows more scatter than the other modes and this can be because of larger uncertainties in the identification of that mode.

2.4.2 Sacramento Bridge

Between 09/16/2015 and 01/30/2016, the minimum recorded temperature on the Sacramento Bridge was -0.45 ºC on December 31st. This temperature was recorded at TC22 that is located in the deck of the bridge and occurred when air temperature was at its minimum 2.05 ºC. The variation in temperature has caused frequencies to vary up to 25%. On the other hand, the maximum temperature recorded on this bridge was 45.6 ºC at TC32
Fig. 12. Seasonal variation of the air temperature of the Perry Bridge between 11/01/2015 and 07/31/2016

Fig. 13. Seasonal variation of the natural frequencies of the Perry Bridge between 11/01/2015 and 07/31/2016
Table 1. Statistics of temperature and identified frequencies of Perry Bridge between January 1st, 2015 and July 31st, 2016 (every three month)

<table>
<thead>
<tr>
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<td>Month</td>
<td>1</td>
<td>4</td>
<td>7</td>
<td>11</td>
<td>1</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>Mode 1</td>
<td>Mean</td>
<td>7.38</td>
<td>6.81</td>
<td>6.04</td>
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<tr>
<td></td>
<td>St.D.</td>
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<td>0.54</td>
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<td>0.57</td>
<td>0.79</td>
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<tr>
<td></td>
<td>Min</td>
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<td>4.87</td>
<td>5.97</td>
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<tr>
<td>Mode 2</td>
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<td>10.84</td>
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on September 21\textsuperscript{st}. The highest air temperature recorded at this bridge was 31.4 °C. The annual change of temperature and natural frequencies are presented in Fig. 16 and Fig. 17. These figures show that temperature effects identified frequencies. To study the seasonal changes of these variations more carefully, statistics of modal frequencies, air temperature, and bridge temperature are depicted in Table 2. The bridge temperature in this table is the average of all the thermocouples mounted on the girders and deck of the bridge.

2.5 Modeling Temperature-Natural Frequency Relationship

Statistical modeling and analysis have been used in different areas to study the impact of different variables on different phenomena (Sharifi et al. 2015c; Sharifi et al. 2016; Soltani-Sobh et al. 2016b; Soltani-Sobh et al. 2016c; Javid and Nejat 2017; Salari and Javid 2016; Salari and Javid 2017). In this section, the procedure for establishing models to correlate the temperature and natural frequencies is explained. The available data was split into two, a training set and a validation set. These are explained in more detail later in the validation
section. Because of the change in the structure of the Perry Bridge in March 2016, only the data that was collected before March 1st, 2016 was used.

**Fig. 15.** Identified natural frequencies (Mode 1 to 5) of the Perry Bridge versus air temperature (TC31)
To quantify the goodness-of-fit of different models, there are several available statistical metrics that can be used. One of the most common metrics is the coefficient of determination, usually known as $R^2$. This metric can be calculated from Equation 9.

$$R^2 = 1 - \frac{SSE}{SST}$$  \hspace{1cm} \text{Equation 9}

In which, $SSE$ is the regression sum of squares, $SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$, and $SST$ is total sum of squares, $SST = \sum_{i=1}^{n} (y_i - \bar{y})^2$.

The problem with $R^2$ is that it always improves with increasing model complexity and cannot measure the over-fitting of models.

As an alternative, Akaike’s Information Criteria (AIC) can be used to compare a large number of models with different numbers of variables and parameters. This metric includes a penalty for the number of parameters and can be calculated from Equation 10:

$$AIC = n \cdot \ln \left( \frac{SSE}{n} \right) + 2 \cdot K$$  \hspace{1cm} \text{Equation 10}

Where $n$ is the number of data points (observations), and $K$ is the number of parameters in the model. A low AIC indicates an improved fit.

Both of the AIC and $R^2$ metrics are compared for selecting appropriate models.
Fig. 16. Seasonal variation of the air temperature of the Sacramento Bridge between 09/16/2015 and 01/31/2016

Fig. 17. Seasonal variation of the natural frequencies of the Sacramento Bridge between 09/16/2015 and 01/31/2016
Table 2. Statistics of temperature and identified frequencies of Sacramento Bridge between September 19th, 2015 and January 31st, 2016

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Fig. 18. Identified natural frequencies (Mode 1 to 5) of Sacramento Bridge versus air temperature (TC22)

2.5.1 Multiple Linear Regression (MLR)

The simplest available method to establish a model between input variables and response of a system is the multiple linear regression (MLR). This statistical model can estimate the relationship between input variables and the response and then, it can be used
to predict future values of the output based on the inputs. In this study, identified natural frequencies are the output and different temperature measurements at various locations are the input variables. Using this model, defined by Equation 11, natural frequencies of the structures are assumed to be a linear combination of the selected measured temperatures.

\[ y^n = \beta_0^n + \sum_{i=1}^{m} X_i^n \beta_i^n + e^n \]  
Equation 11

In this equation, \( y \) is the measured frequencies and \( n \) is the mode number. \( \beta_i \) is the coefficient of the model associated with the \( i \)th input variables. \( X \) represents temperature measurements while \( m \) is the number of input variables (for example \( X_1 \) can be air temperature and \( X_2 \) can be the recorded temperature by TC1). \( e \) is the random error with zero mean. The unknown coefficients of \( \beta_i \) are estimated from the collected data using the least-square method. If the number of data points that have been selected for training the model is assumed to be \( N_T \), then for each mode, \( y \) has \( N_T \) Rows, \( X \) is a \( N_T \times (m+1) \) matrix, \( \beta \) has \((m+1) \) rows and \( e \) has \( N_T \) rows.

**Input Variable Selection**

The desired outcome is to have the MLR model characterize the relationship between the natural frequencies and temperature measurements. However, the co-dependency between temperature measurements at various locations can cause unnecessary complexity in the model. Therefore, to have a simple and accurate model, the input variables of the regression models have to be selected appropriately. Fig. 19 shows the similarities between a subsets of temperature measurements on Perry and Sacramento...
Bridge. These measurements are similar and using all of them as inputs to the model provides redundant information.

The total number of collected temperatures on Perry Bridge was 31, including air temperature. Out of the 30 bridge thermocouples, 6 of them (TC12, 13, 18, 25, 26, and 29) were found to be erroneous and eliminated from analysis. The rest of the 26 thermocouples were analyzed to select the best inputs.

The Sacramento Bridge is instrumented with 51 thermocouples. It was observed that 5 of the thermocouples on this bridge were dysfunctional and, therefore, excluded from the available data. The remaining 46 were kept for further analysis. As stated previously, the thermocouple underneath girder 2 was assumed to be the closest measurement to air temperature and used as air temperature.

The correlation coefficient of each pair of thermocouples was calculated for both bridges to quantify the resemblance between measured temperatures by different thermocouples (Fig. 20). It is worth noting that the values are symmetric across the main diagonal and all the diagonal values are 1 since the measurements are compared against themselves. The values of correlation coefficients show high correlation between different groups of temperature at various locations. For example, on the Perry Bridge (Fig. 20a), TC1 to TC5 that measure temperatures underneath Girder 1 (G1) through Girder 5 (G5) had a correlation coefficient ranging from 99.3% to 99.6%. The correlation coefficients of the thermocouples located in the deck of the Perry Bridge (TC21, TC22, TC23, TC24, TC27, TC28, and TC30) are between 99.4% and 100%. Air Temperature has a high
correlation with TC1 to TC5 (94.8-96.5 %), but lower correlation with Deck thermocouples (75- 80%). Given the high correlation between temperature measurements, the redundancy of the information is obvious and the number of sensors included in the MLR model was reduced.

**Fig. 19.** Similarities between temperature measurements (a) Perry Bridge (b) Sacramento Bridge
On the Sacramento Bridge (Fig. 20b), the similar high correlation coefficients can be found between temperature measurements. For instance, all the correlation coefficients between TC 22 to 30, which are placed in the deck of the bridge, are above 98.5%.

This high correlation allows for grouping the measurements based on the correlation coefficients values and only one sensor can represent that group and be included in the final models.

Principal Component Analysis (PCA) is another appropriate method to simply reduce the dimensions of variables and only include the variables that account for most of the variance in a set of observed data. Singular value decomposition (SVD) of the matrix included all temperature measurements and is the key part to obtain a transformed set of variables. The relatively large singular values determine the number of independent variables.

PCA of the Perry Bridge temperature measurements (Fig. 21a) shows that the first 6 singular values are relatively large and the first 2 are much larger than the rest. PCA of the temperature measurements from the Sacramento Bridge (Fig. 21b) shows that the first 2 singular values are substantially larger than the rest of the singular values.

Summing up the results from the correlation coefficients and PCA analysis, 3 temperature measurements were selected for the Perry Bridge and Sacramento Bridge. The use 4th, 5th, and 6th temperature measurements were also investigated for modeling the Perry Bridge as PCA suggested, but the goodness-of-fit metrics showed that including the extra variables does not significantly improve the modeling results. For the Perry Bridge TC31
(air temperature), TC4, and TC14 were selected, and for Sacramento Bridge, TC 20 (representing air temperature) TC 22, and TC 43 were selected.

Fig. 20. Correlation coefficients between all the pairs of temperature measurements (a) Perry Bridge (b) Sacramento Bridge
Fig. 21. Singular Values from PCA of temperature measurements (a) Perry Bridge (b) Sacramento Bridge

Temperature Gradients Effects

As part of the investigation of different temperature effects, temperature gradient is a phenomenon that may show an impact on identified frequencies. The gradient profile and
the recorded temperatures from the regarding sensors are plotted in Fig. 22. This figure shows the evolution of the gradient profile during a day. When the top surface is hotter than the web, it is referred to as positive, and when the top surface is colder than the webs it is defined as negative thermal gradient.

**Fig. 22.** Variation of Gradient Profile Graphed Every 3 hours

To have a measure for the intensity of thermal gradients, three effective gradients have been defined as follows (Equation 12, Equation 13, and Equation 14):

\[
\text{Effective Gradient 1} = \sum_{i=1}^{N} |T_{Ci} - T_{C_{mean}}| \\
\text{Effective Gradient 2} = \sum_{i=1}^{N} |T_{Ci} - T_{C_{min}}|
\]

*Equation 12*
\[
\text{Effective Gradient 3} = |T_{C_{\text{max}}} - T_{C_{\text{min}}}|
\]

Equation 14

In which, \( N_{\text{Grad}} \), is the number of thermocouples included in the gradient analysis.

The correlation coefficients between these effective gradients and identified natural frequencies of the fourth mode of Perry Bridge shows there is not a strong correlation between these thermal gradients and natural frequencies, and therefore, they were not included in the final models.

To investigate the option of using only air temperature (in the case that there are no thermocouples mounted on the bridge elements) for each model, two cases are presented. In the first case, such as MLR 1, air temperature was the only input to the model. In the second case, such as MLR 2, three temperature measurements were the inputs to the model.

The goodness-of-fit metrics, in their entirety, are presented in Table 3 and Table 4. Fig. 24-Fig. 27 show the comparison of the training data sets using different models to predict the natural frequencies with temperature. The figure on the left side is the first and the figure on the right is the second case of each model.

2.5.2 Bi-Linear

From the observed data, it was understood that the change of frequencies are behaving more non-linearly when the temperature approaches the freezing point. Therefore, bi-linear regression models, which have also been utilized for this relationship by other researchers, was a good option for obtaining a better fitting model without adding any
Fig. 23. Correlation between Identified Frequencies and 3 Separate Effective Gradients of (a) Perry Bridge (b) Sacramento Bridge
Fig. 24. Correlation between identified and predicted natural frequency of mode 1 modeled by MLR (a) Perry Bridge (b) Sacramento Bridge

complexity. For this regression model, the dividing line for frequency groups was assigned to 3 °C. The frequencies with corresponding air temperature less than 3 °C were modeled with one MLR, while any others were modeled with a separate MLR. One of the reason for this bi-linear behavior is the contribution of asphalt overlay to the stiffness of the deck.
since the material property of asphalt changes more significantly in lower temperature (Keshavarzi and Kim 2016).

Fig. 25. Correlation between identified and predicted natural frequency modeled by Bi-linear regression (a) Perry Bridge (Mode 3) (b) Sacramento Bridge (Mode 5)

It was observed that in Bi-Linear models, the difference between using only air temperature and 3 temperature measurements was not as considerable as MLR models for
Perry Bridge. Using Bi-Linear model with only air temperature (Bi-Linear 1), the goodness-of-fit was improved significantly compared with MLR 1.

Since the air temperature on Sacramento Bridge was seldom below 3 °C often during the period of monitoring, the difference between Bi-Linear and MLR models was very small. This model only shows a considerable improvement when the bridge experiences lower temperature more often.

2.5.3 Linear ARX model

Autoregressive models with exogenous inputs (ARX) is one of the common methods that has shown good results for modeling of natural frequencies vs. temperature (Sohn et al. 1999). This model is represented by Equation 15.

\[ y(k) + a_1 y(k-1) + \cdots + a_{na} y(k-na) = b_1 u(k) + b_2 u(k-1) + \cdots + b_{nu} u(k-nk-nu) + e(k) \]  

Equation 15

Where \( na \) is the autoregressive order, \( nu \) is the exogenous order, and \( nk \) is the pure time delay between input and output. The model orders were selected based on the minimum values of the AIC criteria. The selected model had \( na=3, \ nb=2, \) and \( nk=0 \).

The goodness-of-fit metrics of the ARX models showed that they did not perform well compared to the Bi-Linear models for Perry Bridge which experienced lower temperatures more often. For the Sacramento Bridge, ARX models yielded better results than MLR and Bi-linear models. Since the frequencies change more non-linearly when temperature approaches freezing point, the ARX models do not perform well for the bridges in areas with lower temperature.
2.5.4 NARX Model

Nonlinear Autoregressive Model with Exogenous Inputs (NARX) was developed in 1981 to represent a wide class of nonlinear systems (Equation 16):

\[ y(k) = F[y(k - 1), \ldots, y(k - n_y), u_1(k - 1), \ldots, u_1(k - n_u), u_m(k - 1), \ldots, u_m(k - n_u_m)] + e(k) \]

Equation 16

In Equation 16, the output at time \( k \), \( y(k) \), can be represented as a non-linear function, \( F \), of the previous system inputs, \( u(k - 1), u(k - 2), \ldots \), system outputs, \( y(k - 1), y(k - 2), \ldots \), and noise sequences, \( e(k) \); \( n_y, n_u_1, \ldots, n_u_m \), and \( n_e \) are the maximum lags for the system outputs, \( m \) inputs, and noise respectively. NARX has been able to simulate complex input-output relationship (Billings 2013).

In order to detect model structure the Error Reduction Ratio (ERR) algorithm was applied. The details of this algorithm can be found in Billings (2013). This analysis determines which nonlinear terms should be involved in the model by computing the potential contribution of each candidate (model term) to the system output. Different models have shown that the ERR technique is more powerful than simpler techniques like correlation functions for NARX models.

Using the NARX model, R² values increased (and AIC values decreased) significantly compared to the other models. This model provided a better fit for both bridges. The main reason is the ability of this method to model non-linear behavior of identified frequencies around freezing temperature. However, this model is
computationally less efficient, and requires investigation with more terms than other methods.

Fig. 26. Correlation between identified and predicted natural frequency of mode 2 modeled by ARX (a) Perry Bridge (b) Sacramento Bridge

2.6 Model Validation Based on Randomly Selected Data Subset

The performance of a model cannot be merely evaluated by the data that were used in fitting a model. The common method that is usually practiced is to split the data into a
training set and a validation set. In this study, 75% of the data was assigned for training and 25% for validation. The results of this validation are presented only for the NARX method which provided the best fit according to the goodness-of-fit metrics. The NARX models were validated and the results are shown for the validation data set in Fig. 28 (Perry Bridge) and Fig. 29 (Sacramento Bridge).

![Correlation plots](image-url)

**Fig. 27.** Correlation between identified and predicted natural frequency of mode 4 modeled by NARX (a) Perry Bridge (b) Sacramento Bridge
2.7 Analysis of Damage Detection

After modeling the effect of temperature on identified natural frequencies of the Perry and Sacramento Bridge and finding the most accurate model, it is valuable to investigate the types of structural changes or possible damages that can be detected with continuous identification of natural frequencies and recording temperature.

**Table 3.** Comparison of the goodness-of-fits of different models of the Perry Bridge

<table>
<thead>
<tr>
<th>Model</th>
<th>Goodness of fit</th>
<th>Mode 1</th>
<th>Mode 2</th>
<th>Mode 3</th>
<th>Mode 4</th>
<th>Mode 5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MLR 1</strong></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.673</td>
<td>0.594</td>
<td>0.704</td>
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</tr>
<tr>
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<td>-10220</td>
<td>-14071</td>
<td>-15385</td>
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<td></td>
</tr>
<tr>
<td><strong>MLR 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.696</td>
<td>0.614</td>
<td>0.731</td>
<td>0.769</td>
<td>0.396</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.696</td>
<td>0.615</td>
<td>0.731</td>
<td>0.769</td>
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</tr>
<tr>
<td><strong>Bi Linear 2</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.696</td>
<td>0.615</td>
<td>0.731</td>
<td>0.769</td>
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<tr>
<td><strong>ARX 1</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.688</td>
<td>0.608</td>
<td>0.722</td>
<td>0.759</td>
<td>0.392</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.709</td>
<td>0.625</td>
<td>0.745</td>
<td>0.783</td>
<td>0.403</td>
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<td></td>
</tr>
<tr>
<td>R²</td>
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<td>0.731</td>
<td>0.769</td>
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</tr>
<tr>
<td>R²</td>
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<td>0.627</td>
<td>0.748</td>
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<td>-10823</td>
<td>-15128</td>
<td>-16580</td>
<td>-2663</td>
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</tr>
</tbody>
</table>

For these bridges various damage scenarios were simulated in a finite-element model created in SAP2000. The changes in the first 5 natural frequencies were extracted and compared to the level of the change in the identified natural frequencies. This SAP2000 model was initially calibrated based on the available modal properties.
Table 4. Comparison of the goodness-of-fits of different models of the Sacramento Bridge

<table>
<thead>
<tr>
<th>Model</th>
<th>Goodness of fit</th>
<th>Mode</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R^2</td>
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<td></td>
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</tr>
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<td>MLR 1</td>
<td>0.684</td>
<td>0.650</td>
<td>0.381</td>
<td>0.654</td>
<td>0.708</td>
<td></td>
<td></td>
</tr>
<tr>
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</tr>
<tr>
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<td>0.523</td>
<td>0.710</td>
<td>0.770</td>
<td></td>
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</tr>
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</tr>
<tr>
<td>Bi Linear 1</td>
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<td>0.381</td>
<td>0.654</td>
<td>0.708</td>
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<td>Bi Linear 2</td>
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<td>0.635</td>
<td>0.711</td>
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<td></td>
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<tr>
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<td>-4867</td>
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</tr>
<tr>
<td>ARX 1</td>
<td>0.742</td>
<td>0.709</td>
<td>0.486</td>
<td>0.709</td>
<td>0.770</td>
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<td>ARX 2</td>
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<td>0.772</td>
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<td>-7936</td>
<td>-4940</td>
<td>-5463</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Five damage scenarios were simulated on these bridges. These damage scenarios were based on deck deterioration of the bridges and the overall degradation of the bridge structures because of aging and operational factors. Damage cases are as follows: 1-reduction of the deck stiffness by 10%, 2-reduction of deck stiffness by 20%, 3-overal reduction of stiffness in all the members by 5%, 4-overal reduction of stiffness in all the members by 10%, and 5-overal reduction of stiffness in all the member by 20%.

The bridge condition based on the fitted model is assumed to be a baseline condition for any future assessments. When the level of damage on the identified natural frequencies...
is higher than the possible level of environmental effects, then this approach can successfully detect damage.

Fig. 28. Validation with 25% randomly selected data from NARX model for the Perry Bridge
Fig. 29. Validation with 25% randomly selected data from NARX model for the Sacramento Bridge

This approach can be applied to any bridge as far as the accuracy of predicted natural frequencies with regards to environmental variations has been quantified.
For the Perry Bridge, data from the beginning of January 2016 were used to evaluate damage detection and the result is presented in Fig. 30. On the left side of the figure, the percentage of change in the identified natural frequencies after removing the temperature effects with NARX model are presented. The bridge is assumed to be in a healthy condition up to that time and the changes in these frequencies are assumed to be caused by other uncertainties such as modal identification and other operational factors that were not considered in this study. On the right side, different lines representing different levels of damage are plotted. This figure shows that damage case 1 cannot be detected with this approach since the level of change that the 10% reduction in deck stiffness causes is always lower than the level of uncertainties represented by the residuals of the identified versus predicated frequencies. On the other hand, the approximated level of change in damage case 4 is considerably above the level of uncertainties in the identified natural frequencies and; therefore, can always be detected with this approach.

For the Sacramento Bridge, 500 data points were randomly selected from the available data. Although Mode 3 of the Sacramento Bridge did not show large residuals after removing temperature effects and apparently was able to detect all types of damages, this mode did not represent removal of temperature effects appropriately. The identified frequencies of this mode did not change with temperature and remained fairly constant during the period the data was collected. Thus, the effect of damage on the actual bridge may not certainly be detected with this mode although FE results showed the potential of using it for detecting all different damage cases.
2.8 Summary and Conclusion

The effects of temperature on modal frequencies were investigated for two bridges. Data was collected on the Perry, Utah, USA Bridge for 21 months, and on the Sacramento, California, USA Bridge for 5 months.

The modal properties of these bridges were calculated from the ambient vibration measurements that were collected hourly from velocity transducers. For an automated extraction of the modal properties, the Natural Excitation Technique (NExT) method along with Eigensystem Realization Algorithm (ERA) was applied.

The pattern of identified natural frequencies from the Perry Bridge during a 21-month, and from the Sacramento Bridge showed the variability of identified modal parameters exceeded 20%.

Three different models were used to correlate temperature to natural frequencies of different modes; Multiple Linear Regression (MLR), Autoregressive model with exogenous inputs (ARX), and Nonlinear ARX model. In this study, 75% of the data sets were randomly selected for training the models and 25% were used for cross validation. The goodness-of-fit metrics were compared for different models and NARX resulted the best fit model. According to the comparison of the goodness-of-fit metrics, if only air temperature is available, using more complex models like NARX can result in a much better fitting models. If, in addition to air temperature, there is another direct temperature measurement from members of the bridge, ARX and MARX models are similarly appropriate. However, if there are more than 3 available temperature measurements from
different locations of the bridge, using more complex models like ARX or NARX, do not improve the goodness-of-fit significantly.

Fig. 30. Comparison of damage levels for different damage cases for the Perry Bridge.
Fig. 31. Comparison of damage levels for different damage cases for the Sacramento Bridge

After finding the most accurate model, the temperature effects were removed from the identified frequencies and the level of damage that can be potentially detected with this
method was evaluated by simulating different damage cases through finite-element modeling of both bridges.
CHAPTER 3

FIELD VERIFICATION OF BRIDGE WEIGH-IN-MOTION TECHNIQUES

Abstract

This study addresses the feasibility of using a single-span bridge as a weigh-in-motion (WIM) tool to quantify the gross vehicle weights (GVW) of trucks inexpensively with a small number of sensors and without using axle detectors. Four pre-weighed trucks with different axle configurations travelled over a bridge at three different speeds and on two separate lanes. This field testing was performed on an interstate, without any lane closures. Measured strain data were used to implement bridge weigh-in-motion (B-WIM) algorithms and calculate the corresponding velocities and GVWs. A comparison was made between calculated and actual measured static weights, as well as the calculated and specified speeds of the trucks. In addition to field testing, a finite-element (FE) model of the tested bridge was created and calibrated based on the measured strains at different locations. This calibrated FE model enabled the acquisition of the influence values for the bridge at any location (influence surface). Ten different points were selected to calculate the influence surface values and a comparison was made between calculated strains from the influence surface and the actual response of the bridge recorded by strain gauges. The comparison showed that the updated FE model was capable of providing the influence surface values at different locations. The validated influence surfaces were then used to simulate the passing of common types of trucks with various weights and axle configurations over the bridge. The measured GVWs based on simulated strain
measurements provided by the FE model and validated influence surfaces verified the applied method (Zolghadri et al. 2016a).

3.1 Introduction

The increasing cost of maintenance and renewal of bridges, and infrastructure generally, has become a looming crisis in the United States. In order to evaluate the safety and the proper method for strengthening different bridges (Soltani-Sobh et al. 2015; Soltani-Sobh et al. 2016a; Kazem et al. 2015; Tabrizi et al. 2015), policy makers need to have accurate information about the actual loads acting on bridges (traffic), and the structural elements’ resistance to these applied loads. Weigh-in-motion (WIM) systems have the potential to provide valuable information for bridge and pavement design and to lower maintenance costs.

There are two general WIM categories: traditional in-pavement systems, and Bridge Weigh-in-Motion (B-WIM) systems. In-pavement systems use sensors on the road surface and the theory behind them is to relate a measurable property from the sensors to the applied loads, i.e. vehicle weights (Jacob and Feypell-de La Beaumelle 2010). The major disadvantage of in-pavement WIM systems is the cost of installation due to required road closures and long-term maintenance of the embedded sensors while the accuracy are not considerably high in some cases (Kim et al. 1996; Bushman and Pratt 1998). The B-WIM concept was first developed by Moses (1979) to measure axle weights. B-WIM is relatively inexpensive and cost effective for long-term measurements. However, detecting individual axles and determining axle spacing are some of the major challenges for a B-WIM system. In Moses’s study, the number of axles and velocity of a vehicle were assumed
to be measured through on-pavement pneumatic tubes. Moses’s original algorithm was extended by using calibration trucks and testing different bridges (Moses and Ghosn 1983; Moses et al. 1985; Ghosn and Xu 1988; Snyder 1992; Quilligan et al. 2002; Rowley et al. 2009; González et al. (2012); Zhao et al. 2014). In addition to pneumatic road tubes, tape switches that are also placed on the road surface have been used for detecting truck velocities and axle configurations. Axle detection and velocity identification were essential to the calculation of GVWs using Moses’ principle (O’Brien et al. 1999). Some other projects have been carried out in Australia and Europe to improve the performance of WIM systems such as AXWAY, WAVE, COST323, 4th Framework Wave and 5th Framework TOP TRIAL. (Peters 1984; Jacob and O’Brien 2005). A Free-of-Axle detector (FAD) system was first introduced through the WAVE project (Žnidarič et al. 2002). In Alabama, two proprietary B-WIM systems known as SiWIM, owned by ALDOT were examined (Brown 2011). SiWIM uses strain gauges for axle detection and accuracy of GVWs are highly reliant on the accuracy of number of axles and velocities.

The major focus of the study discussed in this paper is inexpensive calculation of the GVWs of the vehicles passing over a bridge at a full highway speed without using axle detectors. Therefore, the number of axles and axle spacing are assumed to be unknown for calculating the GVWs. Recorded strains on the bottom flange of the girders at two separate cross sections were used for the calculations. Two different sets of sensors were evaluated for the accuracy of measuring GVWs with smaller number of sensors. Smaller number of sensors implies lower cost of installation and maintenance particularly for possible long-term implementations. Field testing and finite-element (FE) modeling were both utilized.
Field testing was performed with four known trucks driven on a single-span concrete girder bridge on Interstate-15. These trucks were used to evaluate the accuracy of the calculated speeds and weights compared to the conducted speed and static weights measured on a static scale. Two of the four trucks were selected to have the same weight but different axle configurations. This was used to ensure the accuracy of GVW calculations were independent of axle configurations and the method is applicable to different cases. A SAP2000 FE model was created using Open Application Programing Interface (OAPI) through Excel. This model was updated based on the measured field data. The OAPI link allowed for automatic update of FE model parameters for optimization for the purpose of model calibration. The comparison between the FE results and field data was performed to show the accuracy of the calibrated model. Since the OAPI link enables repeated execution of the FE model, various truck loads were also evaluated with the FE model. The influence surface was derived based on a single load moving along the bridge in the FE model. In order to assess the calculated influence surface, a comparison was made between calculated strains based on the influence surface values and the measured field strains. Then, this validated FE model was used to examine common types of trucks with various weights and axle configurations.

3.2 Field Testing

3.2.1 Bridge Description

The bridge selected for this B-WIM study is located in Perry, Utah with Utah Department of Transportation (UDOT) structure number 1F 205. It was designed as a two-lane bridge that carries northbound traffic on Interstate-15 (I-15) over Cannery Street. This
single-span bridge has a 24.9 m clear span length from abutment to abutment. This span length is suitable for B-WIM purposes due to the low probability of multiple trucks on the bridge simultaneously. Additionally, single-span bridges are less complicated for modeling and analysis. The width of the bridge is 13.40 m with two 3.66 m traveling lanes, a 3.42 m shoulder on the east side, a 1.6 m shoulder on the west side and a 0.53 m wide parapet on each side. The bridge is a pre-cast, pre-stressed, concrete girder bridge that was designed and constructed using integral abutments. All five girders are AASHTO Type IV and have a 2.69 m center-to-center spacing with the centerline of the first girder located 1.32 m from the edge of the bridge. There is a 7.6 to 8.9 cm thick asphalt overlay covering the 20.3 cm reinforced concrete deck. This bridge is located 1.8 km north of a port-of-entry station where all trucks are instructed to pass over an in-pavement WIM which allows for further WIM studies. Fig. 32 shows the plan view of the bridge with two travelling lanes and the position of the girders. The girders have been identified by G1 through G5 from east to west. According to the size of the bridge, the probability of having two trucks on the bridge behind each other at the same time is very low. This was seen during the field testing as well.

3.2.2 Instrumentation

The bridge was instrumented with long-term (permanent) and short-term (temporary) sensors. Permanent sensors were installed on the bridge as part of a long-term installation. These sensors were Temporary sensors were installed to collect the data for this specific field study. Although there were a large quantity of sensors to record various types of data, for both short-term and long-term instrumentation, only 6 Hitec foil strain
gauges, as part of the Permanent system, and ten BDI strain transducers, as part of the Temporary system, were used in the data analysis. Hitec foil gauges consist of a full Wheatstone bridge with four 350 ohm foil gauges.

Fig. 32. Plan view with monitoring details (in meters)
The model used in this study has Teflon ribbon stress relief between the sensor and the cable transition. BDI strain transducers consist of a full Wheatstone bridge with four 350 ohm foil gauge that can measure strain up to 4000 micro strain. Fig. 32 and Fig. 33 show the longitudinal and transverse sensor positions on the bridge. Two sectional locations were selected to place the strain gauges longitudinally along the bridge. Strain sensors were attached on the bottom flange of each of the girders where the maximum strains take place. Due to data acquisition limitations, the sampling frequency for all instrumentation was set to 100 Hz.
3.2.3 Truck Loads

Four different trucks were used in this field testing: 1) Light Superdump (LS), 2) Heavy Superdump (HS), 3) Single Belly (SB), and 4) Double Belly (DB). Each truck was instructed to traverse the bridge at 3 different speeds on each lane (Right (R) and Left (L)), and each run was repeated 3 times. Therefore there were $4 \times 3 \times 2 \times 3 = 72$ events in this field test. All of the trucks were weighed using a static scale before the experiment. Fig. 34, Fig. 35, Fig. 36, and Fig. 37 show each truck’s axle weights, spacing, and total Gross Vehicle Weight (GVW).

Fig. 34. Truck Light Superdump (LS) Layout

Fig. 35. Truck Heavy Superdump (HS) Layout
Since some of the temporary sensors were located in the same locations as the permanent sensors, they were used to verify the data collected on the Permanent system.
Fig. 38 shows data segments from two sensors at the same location when truck DB traversed the bridge on the right lane in run 12. SG7 is a strain transducer used temporarily for this field testing and PSG3 is a permanent gauge utilized for long-term monitoring. Both of the gauges were located on the bottom flange of Girder 2 at section B-B as shown in Fig. 32. These two co-located strain sensors are attached to different data acquisition systems. Since the time stamps were different by a fraction of a second, the data from PSG3 were zero padded in the beginning for alignment of timing of the data. The comparison shows a good agreement.

In order to study the effect of axle spacing on the GVW determination, two of the trucks, HS and SB, were chosen to have the same weight while having different axle spacing. Multiple speeds were used to determine the impact of vehicle velocity on the strain response. The trucks traveled in each lane in order to observe the lateral strain distribution and to be able to calibrate the FE model later having loads in both lanes.

Fig. 39 shows recorded strains at different girders at longitudinal section B-B when the same truck passed the bridge in the right and in the left lane. According to the positioning of lanes on the girders of the bridge, strain distributions are not symmetrical when trucks pass in the different lanes. For instance, as shown in Fig. 39, measured strains in Girder 1 are smaller when truck HS travels in the right lane at 72 km/h compared to the measured strain in Girder 5 when the same truck travels in the left lane at the same speed. Because of the non-symmetrical lane placement, separate analyses are required for each lane in spite of having a symmetrical girder layouts on the structure of the bridge. Considering the asphalt overlay and the depth of the girder, the change of strain peaks with
regards to different speeds of trucks passing over the bridge was low. Therefore, a separate calibration and analysis for different speeds was not necessary.

Fig. 38. Comparison of recorded data between two co-located strain gauges

Fig. 39. Strain comparison of truck passing in left and right lane
3.3 Finite Element Modeling

Since the number of trucks which could be used to study the B-WIM algorithms and bridge responses was limited, a finite-element (FE) model was created in SAP2000 and used to conduct further analyses. In order to have flexibility in creating, analyzing, and updating the model, SAP2000 Open Application Programming Interface (OAPI) was used to build a model of the bridge. The OAPI was compatible with major programming languages. In this study, the Visual Basic (VBA) code was used to command SAP2000 through Excel including creating and analyzing the bridge model. This feature enabled the exchange of data between SAP2000 and Excel and alleviated the problem of running a model with variable inputs and outputs.

All of the requirements for creating the model were imported from Excel sheets and included: material and tendon properties, object coordinates, solid element properties, boundary conditions, load cases, and assigned loads. Then, the model was analyzed based on various truck locations which were defined with different load patterns and the outputs were exported to Excel for each load pattern (truck front axle location).

The FE model was assembled using solid elements for all of the components including the girders, deck and parapets. The solid elements are eight-node objects, each having six quadrilateral faces with 8 joints and allowing three degrees of translational freedom at each joint. The solid elements were created by extruding area objects to 305 mm thickness. Solid elements increase the accuracy of modeling, however they add significantly to the complexity of the model and increase the analysis runtime.
As recommended in SAP2000 literature (CSi Analysis Reference Manual), aspect ratios close to unity provide the best results and should be kept below four. The transverse and vertical solid element size was between 203 mm and 254 mm. Therefore, longitudinal mesh size of 152 mm, 305 mm, 457 mm and 610 mm were created to have the aspect ratios in the acceptable range and simultaneously allow a convenient allocation of truck loads. The outputs deviated less than 0.01% when mesh size varied from 305 mm to 152.4 mm. Despite the fact that finer mesh produces more accurate results, the cost of model complexity and runtime compared to the gained precision, lead to the decision to utilize 305 mm as the longitudinal mesh size for this model. Fig. 40 shows the 3D view of the FE Model.

![FE model](image)

**Fig. 40.** FE model

SAP2000 does not directly provide strain as an output, hence the strain was calculated from the stress outputs. The stress was averaged at the points where strains were measured during the field test. The model stresses were then divided by the modulus of elasticity to obtain the FE strains. In the updating process, just the set of data from the SB truck was used to calibrate the model. All of the field results from the other three trucks, the LS, HS, and DB were used to validate the previously updated and calibrated model.
The model was updated based on minimizing the square of the errors (least-squares) between recorded strains in the live-load test $S^{LL}$ and the FE models outputs $S^{FE}$ at different locations $x$. The parameter that is being updated is represented by $E$ in Equation 17.

$$e(E, x) = S^{LL}(E, x) - S^{FE}(E, x)$$  \hspace{1cm} \text{Equation 17}$$

Scalar objective error function $J$ is defined in Equation 18 and minimized through bounded optimization.

$$J(E) = [e(E, x)]^T [e(E, x)]$$  \hspace{1cm} \text{Equation 18}$$

The recorded strains used were at both section A-A and section B-B at the bottom flange of the five different girders.

Longitudinal springs were used in a preliminary investigation of boundary conditions. Since the study indicated that the minimum of cost function $J$ was achieved with very high springs’ stiffnesses, boundary conditions were set as fixed-fixed. This was expected as the studied bridge has integral abutments. Therefore, the boundary conditions were kept as fixed-fixed while the material properties (concrete modulus of elasticity) of the various bridge components were adjusted through Excel in each analysis. This process was done by changing the modulus of elasticity by 690 Mpa (50 ksi) increments. The minimum $J$, which implied the best match between the FE output and the field measurements, was found with the final material properties shown in Table 5.
Table 5. Final material properties in the FE model

<table>
<thead>
<tr>
<th>Material Name</th>
<th>Modulus of Elasticity (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Girders</td>
<td>27560 [Updated]</td>
</tr>
<tr>
<td>Parapet</td>
<td>24800</td>
</tr>
<tr>
<td>Diaphragm</td>
<td>27560 [Updated]</td>
</tr>
<tr>
<td>Pre-stressed strands</td>
<td>196365</td>
</tr>
</tbody>
</table>

Fig. 41 shows the comparison of the strain at different girders for the FE model and the live-load data. This comparison is for the truck used to update the model (SB) for both the right and the left lanes. In order to directly compare the field recorded strains in the time domain to the strains from the FE model, the field recorded time domain strains were converted to the spatial domain based on the assumed speed of the truck. From this comparison, the FE model was updated. Then, the FE model was verified by using the data sets from the other three known trucks used for live-load testing. Fig. 42 shows the comparison of the data for the other three trucks which were not used in the training (updating) of the model, but only in its verification. The comparison showed good agreement between the FE results and collected data. The average discrepancies between the data from the other trucks were no more than %6 and the FE model verified that the model had been calibrated sufficiently to give consistent results.

3.4 Velocity Identification

Determining the vehicle velocity is one of the first steps in B-WIM. The conversion of the recorded data versus time to data versus location of a vehicle on a bridge is only
possible after velocity has been determined. When Moses (1979) started developing the B-WIM algorithm, tape switches were set up to measure velocity. This system was designed to let metallic strips contact when a vehicle tire passes over the strip. These strips have been used to identify velocity and axle spacing in many past field tests. However, in an effort to reduce costs and increase simplicity, practical B-WIM systems employ “Nothing-on-the-road” (NOR) techniques. These techniques require that no sensors be mounted in or on the pavement. In this study, cross correlation functions were found to be the best method to identify velocities since the tested bridge was a single span and strains at two different longitudinal sections were measured (Fig. 43). More details about velocity identification can be found in Zolghadri et al. (2013). It has been shown that a correlation function between two recorded signals at two different longitudinal sections of a bridge is well correlated to velocity (Kalin et al. 2006).

The correlation function is calculated from Equation 19. Although both signals do not match, the value of \( t \), at which the maximum value of the correlation function occurs, corresponds to the time difference and therefore velocity of a vehicle travelling over a bridge.

\[
r_{sasb}[t] = \sum_{n=-\infty}^{\infty} S_a[n] S_b[n - t] \quad t = 0, \pm 1, \pm 2, \pm 3, \ldots \quad \text{Equation 19}
\]

In Equation 19 \( S_a \) and \( S_b \) are measured strain signals at two different sections and \( r_{sasb} \) is the correlation between \( S_a \) and \( S_b \).
Fig. 41. Comparison of the calibrated FE data and collected field measurements Truck SB passing (a) Right Lane (b) Left Lane
(a)
Fig. 42. Comparison of the calibrated FE data and collected field measurements on left and right lane for Truck (a) HS (b) DB (c) LS
Fig. 43. Measured strains at two different longitudinal sections (A-A and B-B)

Different sensors were selected to calculate the cross-correlation between the two points. When a truck passes a bridge in the right lane, Girder 2 carries a majority of the load and has the largest signal-to-noise ratio, thus sensors at Girder 2 were used to calculate the velocity. For trucks in left lane, sensors attached to Girder 4 were selected for the same reason. This is also the process to identify what lane a vehicle travels through. In this research, the sensors were at 30% (0.3L) and 60% (0.6L) of the span which is in agreement with the former recommendation and the distance between the sensors was 7.32 m. Given the distance between two sensors and calculated cross-correlation function between two strain signals, Equation 20 is used to estimate the velocity. The calculation of this equation was preformed using MATLAB.

\[ v = CF \times \frac{L_{ab}}{t (\text{Max} \ r_{SaSb})} \]

Equation 20

In this equation, \( L_{ab} \) is the distance between two sections, and \( t (\text{Max} \ r_{SaSb}) \) is the time index where the maximum of cross-correlation happens. Since four different trucks
with different axle configurations were used to measure the velocity, it is concluded that
the estimated velocity based on correlation function can be calibrated to identify velocities
for different axle weights and spacing configurations. CF is a calibration factor which is
used to improve the velocity estimation. CF was calculated by minimizing the differences
between the measured and specified velocities for truck “SB.” CF was calculated as 0.84
based on test results and all the other velocity identifications were based on applying this
calculated CF.

Table 6. Calculated velocity comparison at different specified speeds

<table>
<thead>
<tr>
<th>Specified Speed (km/h)</th>
<th>72.42</th>
<th>96.56</th>
<th>120.70</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truck Type</td>
<td>Mean Value of Estimated Speed</td>
<td>Avg. Error</td>
<td>Mean Value of Estimated Speed</td>
</tr>
<tr>
<td>SB</td>
<td>78.90</td>
<td>8.95</td>
<td>92.51</td>
</tr>
<tr>
<td>HS</td>
<td>81.35</td>
<td>12.34</td>
<td>105.27</td>
</tr>
<tr>
<td>LS</td>
<td>80.56</td>
<td>11.24</td>
<td>103.10</td>
</tr>
<tr>
<td>DB</td>
<td>72.21</td>
<td>3.50</td>
<td>84.41</td>
</tr>
<tr>
<td>Overall</td>
<td>72.21</td>
<td>3.50</td>
<td>84.41</td>
</tr>
</tbody>
</table>

Table 6 shows the comparison between calculated and specified speeds at three
different predetermined speeds. In fact, the drivers of the trucks were instructed to drive
across the bridge using three different speeds. It should be noted that considerable error is
possible in the “specified” velocity that was requested of each truck driver, and the actual
velocity as the truck crossed the bridge. Calculated speeds for truck “DB” were larger for
the two higher predetermined speeds. Since truck “DB” was longer than the length of the
bridge, measured speeds are less accurate. Higher sampling frequency would certainly
increase the accuracy of this method. For this study, the sampling frequency was limited due to the data acquisition system utilized.

Table 7 shows the average error for the calculated speeds compared to the specified speed for different trucks in the right and the left lanes. The errors are relatively higher when trucks travelled in the left lane compared to the right lane. The higher errors can be explained by the location of the girders to the lanes. Namely, the location of Girder 2 to the right lane, compared to the location of Girder 4 to the left lane.

**Table 7.** Calculated speed comparison for right and left lane

<table>
<thead>
<tr>
<th>Truck Type</th>
<th>Avg. Error (%)</th>
<th>Left Lane</th>
<th>Right Lane</th>
</tr>
</thead>
<tbody>
<tr>
<td>SB</td>
<td>17.11</td>
<td>15.08</td>
<td></td>
</tr>
<tr>
<td>HS</td>
<td>14.47</td>
<td>10.70</td>
<td></td>
</tr>
<tr>
<td>LS</td>
<td>17.74</td>
<td>9.34</td>
<td></td>
</tr>
<tr>
<td>DB</td>
<td>18.48</td>
<td>15.83</td>
<td></td>
</tr>
</tbody>
</table>

3.5 Gross Vehicle Weight (GVW) Identification

The first method used for calculating the weights based on strains was obtained based on the Moses algorithm (Moses 1979). This method solves the equations for individual axle weights based on minimizing the errors between measured and theoretical strains. It utilizes a theoretical influence line. In this algorithm, number of axles, axle spacings, and velocity of a vehicle were assumed to be known. Moreover, a theoretical constant to correlate between moments and strains was assumed. Using Moses algorithm for a simply supported span simplifies the calculations and is therefore recommended. Žnidarič et al. (2002) showed that bridges with 8 – 30 m span lengths provide GVW more
precisely. Since the bridge in the current project has a 24.4 m span length, the accuracy of determining GVW was investigated. Zhao et al. (2014) calculated different influence lines for different girders and estimated individual axle weights after determining vehicle speed and axle spacing via strain sensors (Free-of-Axle Detector) mounted under the deck.

In this research, the number of axles and axle spacing is assumed to be undetermined from the strain signals, hence minimizing the error to estimate individual axle weights is not feasible. For determining GVW without knowing number of axles and axle spacing, Ojio and Yamada (2002) described a method to correlate the area under a strain signal with GVW. The area under the strain signal should be determined in the spatial domain. After converting the time domain to the spatial domain, or position on the bridge, Equation 21 can be used to calculate the GVW of an unknown truck by using a calibration truck, GVW\text{cal}.

\[
\text{GVW} = \frac{A \times \text{GVW}_{\text{cal}}}{A_{\text{cal}}}
\]  

Equation 21

\(A\) and \(A_{\text{cal}}\) are the areas under the measured strain in the spatial domain for the unknown and calibrated trucks, respectively (strain vs. front-axle location). The calculated vehicle velocity was assumed to be constant along the bridge and the front-axle location was calculated by multiplying the time with the constant velocity. Trapezoidal and Simpson are two common numerical integration methods which can be used to calculate the area under the strain graphs. Although the calculation is easier for the Trapezoidal method, Simpson integration shows less error for higher order functions. Therefore, the Simpson integration method was used in this study. There were two different approaches
for calculating the area: 1) calculate the summation of the area under the recorded strains beneath all five girders or 2) calculate the area based on which lane the truck passed through. When the truck passes in the left lane, most of the load is carried by Girder 3 and 4. When a truck passes in the right lane the loads are mainly carried by Girder 2 and 3. In the second approach the summation of the area under strain signals of the corresponding two girders were calculated. It is obvious that the second approach requires less computation and is therefore faster to implement. Fig. 44 shows the measured strains at the 5 girders and the calculated area is the summation of the area under each strain signal. In order to determine the calibration coefficient, $\text{GVW}_{\text{cal}} / A_{\text{cal}}$, one of trucks, “SB” was selected to be used as the calibration truck. Truck SB was selected as the calibration vehicle because it had the most consistent area of the four vehicles. The calibration coefficients are shown in Table 8 and Table 9; Note that run 9 was omitted from the coefficient calculations as it was determined to be erroneous. The other three trucks were used to verify and evaluate the accuracy of the calculations.

Using only the calibration coefficient calculated from the SB, the proposed B-WIM technique was tested by calculating the GVW of the LS, HS and DB trucks using only the recorded strain measurements. These calculations were then compared to the actual GVWs as determined using a static scale. Method 1, using all five girders, and method 2, using just two girders, were evaluated. Table 10 shows the comparison of the two approaches to calculate the area under the strain signals. The errors for the two approaches are fairly similar; yet, the second approach requires 40% less calculations. Therefore, it is the recommended approach for calculating GVWs.
Fig. 44. Measured strains at Section B-B (0.6 L), Girders 1 to 5 (area = summation of the area under each measured strain)

The ratio of GVW to the area under strain measurements was also calculated for the other trucks and is shown in Table 7. Area 1 represents the method when strain measurements of all the five girders were integrated and area 2 represents the method when only strain of two girders were considered. Note that these additional coefficients were not used in evaluating the B-WIM technique as presented above, but to show that this coefficient is essentially constant for different truck weights and axle configurations.

In some algorithms, B-WIM accuracy relies upon adjusting and optimizing the correct influence line or surface of a bridge. Therefore, different methods have been proposed to derive such an influence line or surface of a bridge. Moses (1979) used the theoretical influence line. Obviously, the theoretical influence line could result in enormous errors in the calculations. As mentioned in the introduction, OBrien et al. (2006) described a mathematical method to calculate the influence line from on-site measurements by
passing pre-weighed trucks. Instead of using a single influence line, Quilligan et al. (2002) used an algorithm which searched across the influence surface of each sensor. In a recent study, Zhao et al. (2014) presented a modified 2-D algorithm to calculate a calibrated influence line for separate girders of a bridge by considering the load distribution on each girder.

3.6 Influence Surface

In this study, rather than using a calibration truck to solve the mathematical equations to acquire an influence line, the data was used to calibrate an FE model. The FE model was then used to calculate the influence surface of the tested bridge. In this respect, there was no need to solve equations based on the number of axles, axle spacing or axle weights. The influence surface for a desired point location can be determined using field measurements from a sensor at that same location.

Table 8. Calculating GVWcal / Acal for selected truck (SB) on right lane

<table>
<thead>
<tr>
<th>Run</th>
<th>Area 1 (G1-G5)</th>
<th>Area 2 (G2 &amp; G3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>33130</td>
<td>24930</td>
</tr>
<tr>
<td>3</td>
<td>31270</td>
<td>23660</td>
</tr>
<tr>
<td>11</td>
<td>34100</td>
<td>25830</td>
</tr>
<tr>
<td>12</td>
<td>34010</td>
<td>26160</td>
</tr>
<tr>
<td>13</td>
<td>29460</td>
<td>22120</td>
</tr>
<tr>
<td>14</td>
<td>34460</td>
<td>25780</td>
</tr>
<tr>
<td>15</td>
<td>34100</td>
<td>25930</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>GVW/Mean</td>
<td>2.07</td>
<td>2.73</td>
</tr>
</tbody>
</table>
Table 9. Calculating GVWcal / Acal for selected truck (SB) on left lane

<table>
<thead>
<tr>
<th>Run</th>
<th>Area 1 (G1-G5)</th>
<th>Area 2 (G3 &amp; G4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>31260</td>
<td>19720</td>
</tr>
<tr>
<td>6</td>
<td>31540</td>
<td>19250</td>
</tr>
<tr>
<td>7</td>
<td>29970</td>
<td>18300</td>
</tr>
<tr>
<td>8</td>
<td>31640</td>
<td>19640</td>
</tr>
<tr>
<td>10</td>
<td>30800</td>
<td>19500</td>
</tr>
<tr>
<td>16</td>
<td>27800</td>
<td>16690</td>
</tr>
<tr>
<td>17</td>
<td>32080</td>
<td>19190</td>
</tr>
<tr>
<td>18</td>
<td>31180</td>
<td>19070</td>
</tr>
<tr>
<td>Mean</td>
<td>30950</td>
<td>19010</td>
</tr>
</tbody>
</table>

Table 10. Calculated area and GVW

<table>
<thead>
<tr>
<th>Truck</th>
<th>Lane</th>
<th>Static Weight</th>
<th>Avg. Area 1 (G1-G5)</th>
<th>Avg. GVW 1 (KN)</th>
<th>Error 1 (%)</th>
<th>Avg. Area 2 (G3 &amp; G4)</th>
<th>GVW 2 (KN)</th>
<th>Error 2 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HS</td>
<td>R</td>
<td>302.6</td>
<td>33490</td>
<td>307.7</td>
<td>2.99</td>
<td>25070</td>
<td>304.4</td>
<td>3.38</td>
</tr>
<tr>
<td>HS</td>
<td>L</td>
<td>302.6</td>
<td>31420</td>
<td>307.1</td>
<td>9.98</td>
<td>20300</td>
<td>323.1</td>
<td>12.65</td>
</tr>
<tr>
<td>LS</td>
<td>R</td>
<td>193.4</td>
<td>22160</td>
<td>203.6</td>
<td>13.14</td>
<td>15810</td>
<td>192.1</td>
<td>8.61</td>
</tr>
<tr>
<td>LS</td>
<td>L</td>
<td>193.4</td>
<td>18850</td>
<td>184.3</td>
<td>9.00</td>
<td>11600</td>
<td>184.5</td>
<td>8.78</td>
</tr>
<tr>
<td>DB</td>
<td>R</td>
<td>565.8</td>
<td>63390</td>
<td>582.4</td>
<td>5.47</td>
<td>46890</td>
<td>569.4</td>
<td>4.07</td>
</tr>
<tr>
<td>DB</td>
<td>L</td>
<td>565.8</td>
<td>58860</td>
<td>575.4</td>
<td>4.97</td>
<td>37320</td>
<td>593.9</td>
<td>7.50</td>
</tr>
<tr>
<td>Avg. Error (%)</td>
<td></td>
<td>7.59</td>
<td>7.50</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Additionally, using the calibrated FE model enables one to calculate the influence surface at any point of the bridge without the need of a large quantity of sensors. The biggest challenge is the large number of possible load patterns in the FE model which is impossible to completely define. In the current study, there were more than 2400 load patterns used. Since the SAP2000 model was run by OAPI through Excel, all the load
patterns were defined automatically. The updated SAP2000 model was then loaded with a unit load at 305 mm increments on the surface of the bridge and the strains were calculated at the girders at sections A-A and B-B, which correspond to the locations of the strain gauges from the field test, and exported to Excel. These strains were used to calculate the influence surface for all ten strain gauge locations. Therefore, the theoretical strains derived from the influence surface can be compared with the collected strains from the four known trucks passing over the bridge. To increase the precision of the influence surface, a finer mesh could be used on the FE model. However, due to the length of the bridge used in this study, 305 mm was a reasonable value. Fig. 45 shows the calculated influence surface at Girder 2, Section B-B. To verify the influence surface, calculated strains obtained from the influence surface were compared with the strains obtained from the field test. The agreement between calculated strains using the influence surface, FE output, and field measured strains demonstrates the accuracy of using an adjusted model to calibrate the influence surface (Fig. 46).

Since the number of trucks in field testing is always limited, this FEM was used to verify that the simplified approach was independent of truck configurations. Therefore, the calibrated influence surface values of the bridge at different locations were used to provide simulated strains when different trucks travel over the bridge in the right and in the left lanes. These examined trucks are used for implementing bridge weight restrictions (posting loads) and the configurations can be found in NCHRP Report 575 (NCHRP 2007). Ten percent white Gaussian noise was added to the simulated strain measurements provided by the calibrated influence surface values with “awgn” command in MATLAB. In addition,
these simulations verified that this simplified technique with limited number of strain measurements was independent of truck configuration and can be implemented effectively (Fig. 47).

Fig. 45. Influence surface values at Girder 2, Section B-B (0.6 L)

3.7 Summary and Conclusion

Field testing and finite-element modeling were both used to evaluate the feasibility of using a single-span bridge in Utah to calculate gross vehicle weights (GVWs) and quantify the traffic using bridge weigh-in-motion (B-WIM) algorithms. A SAP2000 finite element (FE) model was created and analyzed through Open Application Programming Interface (OAPI) by Excel VBA. For other data analysis MATLAB was chosen to program and implement the algorithms.
Findings are as follows:

1- GVWs were calculated with two different approaches for calculating the area under strain signals. The errors in GVW estimation were within 15% for both approaches. Using strain values of only two girders is proposed because the computational effort is 40% of the five girder approach. This approach was computationally more efficient while the average error for both approaches are identical. Furthermore, the ratios of GVW to calculated area were nearly constant for different trucks which had different weights and axle configurations. Therefore, this method is appropriate for quantifying the GVWs of trucks with differing axle configurations travelling over this bridge. The errors in the calculated GVWs of different trucks showed the high level of accuracy for these implemented B-WIM algorithms.
Fig. 47. Comparison of actual and estimated GVWs for various truck configurations

2- Using correlation functions to calculate vehicle velocities were shown to be effective for single-span bridges. Comparison of measured velocities with specified velocities showed the average errors were below 15%. The majority of the error comes from driver variability and collecting data at too slow of sampling rate.

3- The influence surface of the bridge was acquired based on the calibrated FE model instead of using static truck load testing and solving mathematical equations. The results were verified by comparing the field strain measurements and calculated strains using influence surface values. The maximum difference between these two strains was 9% which shows a good match between the FE output and the field measurements. After calibrating the FE model with the field measurements, influence surface values can be calculated at any desired location, while influence line or surface values can only be derived at sensor points by solving equations based on field testing. Moreover, for each axle configuration different equations
need to be derived and solved. The only difficulty with using the FE model was the large quantity of load patterns which are nearly impossible to define manually. Using interface programs allows the definition of load patterns to be automatic. In this study Excel was used to define more than 2400 load patterns, run the SAP2000 FE models and calculate the influence surface values at ten different points. The validated influence surfaces were then used to verify that the simplified approach was independent of truck configuration.
CHAPTER 4

CONDITION ASSESSMENT OF A FULL-SCALE BRIDGE STRUCTURE WITH
FINITE-ELEMENT MODEL UPDATING USING DYNAMIC AND STATIC
MEASUREMENTS

Abstract

Vibration-based damage identification methods are classified into two major
categories: Non-Model-Based (NMB) and Model-Based (MB) techniques. NMB
techniques evaluate structural conditions without using a finite-element (FE) model while
MB techniques use an FE modal updating method. The NMB approaches generally require
a large network of sensors while they are not capable of simply detecting the type and
extent of damage that may be present. The MB techniques includes calibrating the mass,
stiffness, and damping matrices based on experimentally collected measurements.

This paper presents an improved FE model updating method, as a MB technique,
to evaluate structural condition of a full-scale bridge. In this method, both static and
dynamic measurements are used to enhance FE model updating of a simple-span bridge.
This improved updated model provides better knowledge of the structural condition on
both local and global levels.

Static measurements include strains and deflections at various locations while
dynamic data consist of several measured frequency response functions (FRFs) with
forced-vibration dynamic testing. Instead of using FRFs to extract natural frequencies and
mode shapes, the FRFs themselves are used as part of the objective function. FRFs are computer in an efficient way by using decomposition of different modes.

Normalization is necessary when a combination of different types of measurements are included in the final objective function. In this study, instead of initial values, standard deviations of the measurements are selected as normalization terms. Using standard deviation avoids having larger errors when initial values are close to zero.

In order to evaluate the performance and quality of the calibrated (updated) model, 70% of the collected measurements are employed for calibration and 30% for validation of the calibration procedure.

4.1 Introduction

Condition assessment of deteriorated bridges is one of the major concerns of federal, state, and local agencies that need to make necessary decisions and take essential steps for repairing, upgrading, or replacing structurally deficient or functionally obsolete bridges.

While visual inspection has been practiced for many years, more recently, the application of Structural health monitoring (SHM) and different types of load tests have been proposed as a great tool for evaluating the performance of bridge structures, and generally infrastructure. SHM systems provide non-subjective details about the behavior of structures and the necessity of replacement or rehabilitations.

In the past decades, vibration-based methods in SHM that rely on modal properties and dynamic characteristics of structures have been studied extensively. Vibration-based
damage identification methods are able to detect abnormalities in structural parameters based upon the collected dynamic measurements. These methods are classified into two major categories: Non-Model-Based (NMB) and Model-Based (MB) techniques (Farrar and Worden 2007).

NMB techniques evaluate structural condition and detect damages by comparing two different sets of collected data at two different states without using a finite-element (FE) models. This approach is computationally efficient; however, it has these following shortcomings: (1) type and extent of damage cannot be quantified easily. (2) a large network of sensors is commonly needed to locate possible damages precisely (Talebinejad et al. 2011).

Since monitoring a structure is always constrained with regards to the available resources and funding, employing MB techniques is desired in many cases. In addition, the number of components that can be instrumented and the amount of data that can be collected are always limited; therefore, utilizing MB techniques may improve the effectivity of condition assessment of bridge structures through structural health monitoring.

FE modeling, as an inexpensive MB method, is intended to simulate the response of the structure subjected to various loads. FE models have become highly sophisticated with advancements in computational resources (Babazadeh et al. 2015). However, different field tests, such as live-load and dynamic tests, usually show a considerable discrepancy
between analytical FE outputs and experimental measurements, and in some cases, these discrepancies may lead to a misunderstanding of the behavior of the structure.

There are different reasons for the discrepancies between FE model and measured data. For instance, using inaccurate damping ratios, uncertainties in modeling of joints and boundary conditions, difficulties in modeling complex nonlinearity, incorrect values of material properties, and measurement errors in collected experimental data (Mottershead and Friswell 1993; Babazadeh et al. 2016). These discrepancies may not allow the FE model to represent the behavior of the structure as expected.

The main goal of FE model updating is to minimize an objective function that quantifies the error between the analytical response and the experimentally measured results. This error function will be minimized by calibrating selected unknown parameters. The selection of these parameters depends on field observations and engineering judgements (Sanayei et al. 2015). In order to avoid acquiring meaningless parameters, appropriate constraints needs to be assigned to some or all of the parameters.

FE model updating techniques can generally be divided into two categories: direct and iterative techniques. Direct methods provide the result of model updating in a single step by updating mass and stiffness matrices. The problem with this technique is that mass and stiffness may not have physical meanings, or in other words, the associated mass and stiffness matrices may not turn out being symmetric and positive definite. Iterative methods require a number of iterations to reduce error functions, but the final results (matrices) are structurally meaningful (symmetric and positive definite).
A comparison of these two categories can be found in an investigation by Arora (2011). First, a direct method was used to update a model in two steps. In the first step, the analytical mass matrix was updated based on the orthogonality constraint and then in the second step, stiffness matrix was updated to satisfy the equation of motion. Response function method (RFM), which is a common iterative method, was additionally investigated and compared with the direct approach. RFM is an iterative method that uses measured FRFs directly. The iterative approach was found more accurate for predicting FRFs using numerical and experimental data.

Garcia-Palencia and Santini-Bell (2013) proposed a two-step algorithm to identify stiffness, mass, and viscous damping via model updating. In the first step only mass and stiffness were updated while damping matrix was kept constant. And then in the second step, the damping matrix was updated based on changing unknown modal damping ratios. The proposed algorithm was based on the difference between experimental and theoretical FRFs and was validated with applying the method on the UCF Benchmark Structure.

Sipple and Sanayei (2014) applied numerical sensitivities to solve the inverse problem of finite element model updating. This method was applied to a simulated example of a six-bay truss in which damage was successfully detected.

There is an extensive research available on using model updating techniques for dynamic or static purposes separately. A review of structural model updating techniques and a complete comparison of the direct methods and iterative methods can be found in
(Sehgal and Kumar 2015). However, simultaneous use of both dynamic and static measurements has not been investigated on full-scale bridge structures adequately.

In this research, a combination of static and dynamic measurements are used to calibrate a FE model in order to obtain a model that can represent the behavior of a full-scale bridge structure, on both local and global levels, more accurately.

This bridge was subjected to both dynamic and live-load field tests simultaneously. The dynamic test was a forced-vibration test with an electro-magnetic shaker that could excite the bridge structure with chirp signals. The live-load test included instructing a truck to travel the bridge in different load paths.

Instead of using FRFs to extract natural frequencies and mode shapes, the FRFs themselves, along with static measurements, were used as part of the different objective functions. FRFs represent the dynamic behavior of the structure appropriately. Static measurements included strains and deflections at various spots. Although the available data were selected in a way to minimize the contribution of noisy measurements, errors in the measurements are not the subject of this study.

When the objective function consists of different types of measurements, normalization is necessary so that results are not dependent to any chosen units. Standard deviations of the measurements were selected as normalization terms in this research. Instead of using conventional analytical sensitivity method, numerical sensitivity was adopted for parameter estimation. The data included in the calibration process was 70% of
the collected measurements. The remaining 30% of the measurements were used to validate
the performance and evaluate the quality of the calibrated (updated) model.

4.2 Bridge Description

The Icy Springs Bridge was constructed in 1965 as a single-span bridge and was
replaced in November 2013 after 48 years of service (Fig. 48). This bridge was 15.54 m
long with the overall width of 6.10 m. The superstructure of the bridge consisted of three
double-tee girders with the total length of 16.31 m from end to end. The width of the
exterior and interior flanges were 2.13 m and 1.83 m respectively and the thickness of them
was 15 cm. The webs of the girders were tapered from 13 cm wide at the bottom to 18 cm
wide at their intersections with the flanges and were measured 56 cm tall for all the girders.
The distance between the centerline of the webs of the exterior girders and the outside
dges was measured 61 cm on both sides. The deck of the bridge was cast with the girders
and was reinforced with one 13-mm rebar at 10cm on center longitudinally and with two
13-mm rebars at 10cm on center along transverse direction. There were sixteen 11-mm
seven-wire prestressing strands in each girder web. Twelve of the strands were harped and
4 of them were straight strands. More details about the bridge structure and girder
reinforcement can be found in Pettigrew (2014).

4.3 Field Testing of the Icy Springs Bridge

Before the Icy Springs Bridge was replaced, it was subjected to field testing that
can provide valuable insights about the deterioration of the pre-stressed concrete bridges.
The field testing of this bridge included both dynamic- and live-load tests which are
described in the following sections:
4.3.1 Dynamic Testing

For the dynamic testing of the Icy Springs Bridge, an APS Dynamics 400 Series Long-Stroke vertical shaker was used. This shaker is capable of producing 444 KN force per stroke. Eight L-4 velocity transducers were installed on the bridge as shown in Fig. 49. There were 4 velocity transducers on each side of the bridge spaced at 3.11 m. The data acquisition unit consisted of an APS 145 dynamic amplifier and a Data Physics 24-channel Signal Analyzer that made measurements with Signal Calc 730 software. The shaker and sensors setup are shown in Fig. 49.

Fig. 48. Icy Spring Bridge before and after replacement
The shaker was moved to two different locations, as shown in Fig. 51. For each location, 20 tests were run at location 1, and 10 tests were run at location 2. The first few runs were to examine the measurements on-site. Out of these 30 tests, 4 tests were finally selected for further analysis, 2 from each location. The dynamic load tests were chirp signals from 2-52 Hz. The responses were collected from all the eight velocity transducers at 240 Hz for each test. There were 8 sets of FRF measurements for each test, resulting in a total of 32 FRFs.

**Coherence Metric**

Coherence function is a data quality metric that shows how well the output signal is related to the measured input signal. Coherence is a function of frequency and varies from 0 to 1. When there is noise over a frequency range, the coherence values will be smaller than 1 and more noise will result in the coherence function to be closer to 0. In this study, the coherence threshold for accepting the FRF values in a frequency range was specified as 0.9 and all the FRF measurements that were used for any further analysis were
filtered based on this threshold. Fig. 50 shows a sample of measured FRF and the corresponding coherence function. The horizontal red line on the coherence plot is the 0.9 threshold. H1,2 represents FRF measurement from velocity transducer (VT) 1, when the shaker (excitation source) was placed at location 2.

![Graph 1: FRF vs Frequency](image1)

![Graph 2: Coherence vs Frequency](image2)

**Fig. 50.** Coherence threshold for selecting usable FRF

### 4.3.2 Live-load Testing

Prior to performing the live-load test on the Icy Springs Bridge, the bridge was instrumented with strain transducers and deflectometers. The sensors and data acquisition system were part of a semi-wireless system provided by Bridge Diagnostic Inc. (BDI). The data were sampled at 100 Hz for the static load-test. The instruments were installed at mid-span or 0.5L (section A-A) and quarter span or 0.25L (section B-B). The plan and cross-sectional view of the bridge (Fig. 51 and Fig. 52) show the longitudinal, transverse, and
vertical locations of the sensors. For shear studies, a section at twice of the height of the girders (2H) were also instrumented with strain gauges (Torres 2014). The data from these sensors were not used in this study, and thus, those sensors were not included in the instrumentation layout.

**Fig. 51.** Plan view of the Icy Springs Bridge with shakers and velocity transducer layout

For the static load-test, a dump truck was instructed to drive slowly along 4 different load paths shown in Fig. 53. The axle weights were 81 KN, 97, and 96.5 KN with axle spacing of 5.03 and 1.4 m respectively. The total length of the truck was 6.43m and total weight was 274 KN. It is worth noting that the bridge was posted for 35.6 KN which was determined very conservatively by the inspector(s).
Recorded Strain measurements by different sensors at mid-span from load case 2 (LC 2) are compared in Fig. 54. The recorded strain from SG 4 surpassed 400 micro-strain which is a relatively high value. In Fig. 55, strain measurements from a single sensor (SG 3) were compared for different load cases (LC 1-4). This figure also shows the maximum recorded strain for all the load cases were above 300 micro-strain. Smaller values of strain measurements are usually contaminated with higher level of errors according to a fairly larger noise-to-signal ratios. Therefore, strain measurements below 30 micro-strain were decided to be removed for further analysis. The removal of those measurements only included approximately 25% of the data since large portion of the measurements was fairly higher than 30 micro-strain in many cases.

**Fig. 52.** Cross-sectional view of the Icy Springs Bridge with sensors locations
4.4 Error Functions (EFs) for Parameter Estimation

The first step in the parameter estimation is defining error functions (EFs). EFs quantify the residuals between measured experimental data and the analytical outputs of the numerical models. The structure can be loaded statically while strains, displacements, and rotations being measured at certain locations, or can be excited dynamically while modal parameters or FRFs are being measured. Therefore, EFs are divided into two static-based and modal-based categories (Sanayei et al. 2015).

Various static-based and modal-based EFs can be defined as functions of different specified unknown parameters. For instance, flexural rigidity (EI), or axial rigidity (EA), or mass density (ρ) can be determined as unknown parameters. Then, these unknown parameters are estimated based on the global minimum of the defined EFs. Three different EFs are determined in this study which are explained in 4.4.1 to 3. The first two of these EFs are static-based and the third one is modal-based.
Fig. 54. Strain measurements at mid-span/0.5L (LC 2)

Fig. 55. Strain measurements of SG 3 (LC 1-4)

4.4.1 Strain-based EF

This error function, which was developed by Sanayei and Saletnik (1996), measures the residuals between measured and analytical strain values at certain locations.
In Equation 22, $[\varepsilon]$ is the experimental strain, $[B]$ is the matrix that maps nodal displacements to strains in the direction along the member, $[K(p)]$ is the stiffness matrix, and $[F]$ represent the applied loads.

### 4.4.2 Deflection-based EF

This error function was developed by Sanayei et al. (1997) and measures the residuals between measured and analytical displacement (or deflection).

$$[e_s(p)] = [K(p)]^{-1}[F] - [U]$$  \hspace{1cm} \text{Equation 23}

In Equation 23, $[U]$ represents the experimental deflection measurements.

### 4.4.3 FRF-based EF

There are three forms of the FRF, known as receptance/compliance, mobility, and acclerance/intertance. Since velocity was measured as the response in this study, mobility FRFs are used in the calculations. This form of FRF calculation has been proposed by Sipple and Sanayei (2014) and since no matrix inversion is required, it is an efficient form of FRF calculation.

$$H_{a,b} = \frac{V_{a}(w)}{F_{b}(w)} = 20 \times \log_{10} \sum_{i=1}^{q} -\frac{jw(\phi_{ai}(p)\hat{\phi}_{bi}(p))}{w^2 + 2jw\Omega_i(p)\xi_i(p) + w^2 n_i(p)}$$  \hspace{1cm} \text{Equation 24}

In Equation 24, $a$ is the point where the response is measured and $b$ is the point where excitation is applied. $V(w)$ is the velocity and $F(w)$ is the excitation while $w$ is the desired frequency range. $\Omega_i$, $\xi_i$ and $\hat{\phi}_i$ are the natural frequencies, damping ratios, and
mass-normalized mode shapes of mode \( i \). \( q \) is a subset of the total degrees of freedom. And \( p \) represents the parameters that are selected to be updated.

The error function (Equation 25), is defined as the difference between the analytical (subscript \( \text{ana} \)) and experimental (subscript \( \text{exp} \)) FRF measurements.

\[
[e(p, w)] = [H_{\text{ana}}(P, w)] - [H_{\text{exp}}(P, w)]
\quad \text{Equation 25}
\]

4.4.4 Multi-response EF

When different types of error functions are included in the updating process, stacking has been shown to be an effective way of combining various measurements in the forms of different error functions. The stacked error function is presented in Equation 26:

\[
e_{\text{stack}}(p) = \begin{bmatrix}
[e_1(p)] \\
[e_2(p)] \\
\vdots \\
[e_n(p)]
\end{bmatrix}
\quad \text{Equation 26}
\]

Where \( n \) is the desired number of error functions that are involved in the updating procedure.

4.5 Parameter Estimation

The parameter estimation procedure is the search for minimizing the objective function, \( J(p) \), which is the Euclidean norm of the above error functions (Equation 27).

Parameters \( P \) in Equation 27, are used in a normalized form, meaning that each parameter is divided by its initial value. As a result, the final values of each parameter are reported in ratios.
\[ J(p) = \sum_{i=1}^{NL}(e_i(p))^T W(e_i(p)) \]

Equation 27

One of the necessary tasks, that expedites the convergence of the optimization, is grouping the parameters. Groups may represent a meaningful selection of parameters. This grouping can be performed based on the engineering judgements and available as-built construction documents. This bridge consisted of 3 double-tee girders; therefore, 3 modulus of elasticity and mass density were selected for each girders. Since the deck was cast with the web of the girders, the modulus of elasticity of the deck was assumed to be the same value. The other parameter that was selected to be updated was the boundary condition that was modeled with springs. This will be discussed in 4.7.1.

4.6 Normalization of Multi-response Objective Function

When different types of measurements are involved in the objective function, they need to be normalized in order to become unit-less. Otherwise, the objective function will be dependent to the units of the measurements and the estimated parameters based on the minimum of the objective function will be different (Equation 28).

\[ J(p) = \sum_{i=1}^{NL}(e_i(p))^T W(e_i(p)) \]

Equation 28

Initial values has been frequently used to normalize the contribution of different types of measurements based on initial values. However, this method causes problems when the initial values are close to zero. This specifically happens when small strain measurements included in the calibration data. Although small strain measurements were removed from the calibration data in this research, it was still preferred to use the reciprocal of the variance of the measurements as normalization factor. This will prevent the objective
function from being dominated with only one type of measurement regardless of the initial values in the case no filtering is applied to the data.

The optimization technique to obtain the minimum of the objective function was a constrained nonlinear minimization which can be implemented with MATLAB function, \textit{fmincon}. This function is available in the MATLAB Optimization Toolbox. In addition to the use of \textit{fmincon}, multiple start points were used to guarantee that the final result was the global minimum.

4.7 Finite-Element Model

The ultimate goal of model updating is minimizing the objective function that quantifies the residuals between analytical outputs of the FE model and the experimental measurements from the field tests. For this purpose, the selected parameters of a FE model need to be adjusted so that the output of FE model matches with the measured experimental data. SAP2000, as an advanced FE modeling software, can communicate with other numerical programming languages through Open Application Programming Interface (OAPI). OAPI makes it possible to solve this optimization problem with available advanced optimization techniques in MATLAB toolboxes in conjunction with the FE modeling capabilities of SAP2000.

A finite-element (FE) model of the bridge was created using SAP2000 (Fig. 56). Selected parameters, including modulus of elasticity, mass density, and boundary conditions, were set initially based on the ordinary properties of the concrete and the sensitivity analysis of the boundary condition that is explained in details in 4.7.1.
Three cases were defined for updating the FE model: For Case 1, strain-based and deflection-based EFs were included; For Case 2, FRF-based EFs were included; and for Cases 3 all the strain, deflection, and FRF-based EFs were included in the final objective function. It is worth noting that mass density values were only updated in Case 2 and Case 3 where dynamic properties were involved.

It is always recommended to verify the updating process by separating the data into two parts: one part is used for updating the model; and another part for validating the updated model. Therefore, collected data from approximately 30% of the measurements were excluded from the error functions initially. The excluded measurements from static and dynamic load-test data included 7 FRFs, data from SG 3, 6, 7 and 11, and D5.

4.7.1 Boundary Condition Study

Boundary conditions always effect the behavior of FE models significantly. As Fig. 57 shows, large cracks were observed on both ends of the bridge that could change the fixity of the bridge structure.
As a result, a study was conducted to determine the sensitivity of the natural frequencies to boundary conditions. The stiffness of the assigned springs on the boundaries of the FE model were incrementally increased and the natural frequencies were extracted by modal analysis. Fig. 58 shows how the natural frequencies vary from a pinned-pinned condition through partially fixed, and fixed-fixed condition.

Fig. 57. Cracks effecting the boundary condition of the bridge
The initial values, assigned to the modulus of elasticity, $E$, and mass per unit volume, $\rho$, were 20 GPa and 2400 kg/m$^3$ respectively. $K_x$ was initially valued with 100000 N/cm. The concrete was assumed to be isotropic in this model.

4.8 FE Model Updating Results

The results of the model calibration are shown in Table 11. The normalized values of the moduli of elasticity, mass per unit volume, and springs stiffness with regards to their initial values are represented. N/A denotes “not applied” because in Case 1 mass parameters could not be estimated. Case 2, in which FRF functions were used in EFs, shows higher values for $K_x$ and the calibrated model was stiffer than Case 1 when static-load test data were used. Fig. 59 shows the comparison of experimental strain measurements and FE strain outputs for different updating cases. The values of the strains also shows that the FE model updated with only FRF measurements (Case 2) were stiffer.

![Fig. 58. Change of natural frequencies with boundary condition](image-url)
(had smaller strain values) than the other cases and this was mostly the result of stiffer boundary condition for Case 2 while moduli of elasticity values were only 4.8% different in average. This shows the recorded strains and deflections may be more affected with local deteriorations which resulted in lower stiffness for the bridge structure. The experimental natural frequencies and FE outputs of Case 2 and Case 3 are compared in Table 12. These values show the partial fixity in the boundary conditions which may not be idealized with either pinned-pinned or fixed-fixed condition.

For comparing FRFs, FDAC has been proposed to consider FRFs directly (Pascual et al., 1996). $\Omega_e$ is the frequency at which $\{q_a\}$ was measured experimentally; $q_p$ is the frequency at which $\{q_p\}$ was calculated from the FEM (Equation 29). FDAC is equivalent to the MAC values that quantify the match between mode shapes.

**Table 11. Parameter Estimates**

<table>
<thead>
<tr>
<th>Updated Parameters</th>
<th>$E1$</th>
<th>$E2$</th>
<th>$E3$</th>
<th>$\rho_1$</th>
<th>$\rho_2$</th>
<th>$\rho_3$</th>
<th>$K_x$</th>
</tr>
</thead>
<tbody>
<tr>
<td>FE Case 1</td>
<td>0.82</td>
<td>0.78</td>
<td>0.81</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>1.12</td>
</tr>
<tr>
<td>FE Case 2</td>
<td>0.85</td>
<td>0.82</td>
<td>0.86</td>
<td>0.79</td>
<td>0.79</td>
<td>0.8</td>
<td>1.31</td>
</tr>
<tr>
<td>FE Case 3</td>
<td>0.83</td>
<td>0.81</td>
<td>0.84</td>
<td>0.76</td>
<td>0.76</td>
<td>0.77</td>
<td>1.29</td>
</tr>
</tbody>
</table>

$$FDAC(\Omega_p, \Omega_e)_l = \frac{|q_p(q_p)^T a(q_e)|^2}{(q_p(q_p)^T q_p(q_p))(q_a(q_e)^T q_a(q_e))}$$  

**Equation 29**

The comparison between one of the excluded FRFs from calibration data ($\vec{H}_{2,2}$) and the analytical FRFs from FE Case 2 and Case 3 was performed and the diagonal values of
FDAC are plotted in Fig. 60. This figure showed a good agreement while the minimum values of FDAC was 0.97.

![Figure 59. Comparison of FE outputs and experimental strain measurements](image)

**Table 12.** Comparison of the experimental and analytical natural frequencies

<table>
<thead>
<tr>
<th>Mode Number</th>
<th>Experimental</th>
<th>FEM (Pinned-Pinned)</th>
<th>FEM (Fixed-Fixed)</th>
<th>FE Case 2</th>
<th>FE Case 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.11</td>
<td>4.01</td>
<td>8.73</td>
<td>6.81</td>
<td>6.21</td>
</tr>
<tr>
<td>2</td>
<td>7.76</td>
<td>5.38</td>
<td>9.30</td>
<td>8.01</td>
<td>7.07</td>
</tr>
<tr>
<td>4</td>
<td>18.52</td>
<td>15.77</td>
<td>20.78</td>
<td>19.12</td>
<td>18.50</td>
</tr>
<tr>
<td>5</td>
<td>19.35</td>
<td>16.88</td>
<td>23.44</td>
<td>19.48</td>
<td>19.28</td>
</tr>
<tr>
<td>6</td>
<td>19.76</td>
<td>19.10</td>
<td>23.83</td>
<td>20.34</td>
<td>19.69</td>
</tr>
</tbody>
</table>
4.9 Summary and Conclusion

In this study, a multi-response approach for parameter estimation of a full-scale bridge was investigated. This bridge was subjected to both static and dynamic load tests. Measured data included strain measurements, deflections, and frequency response functions (FRFs). The strain measurements below 30 micro-strain were removed to minimize the noise ratio in the calibration data. For FRFs, coherence functions were used to judge the quality of the measurements and the smaller values than 0.9 were removed for improving the outcomes of model calibration.

Different error functions (EFs) were discussed in details and these EFs were then used to calibrate a full-scale bridge FE model. This research illustrated the feasibility of
using different EFs, particularly multi-response EF, for better calibration of a full-scale bridge FE model. The results of the FE model calibration can be translated to meaningful stiffness and mass values which can help bridge owners make necessary decisions according to the non-subject condition assessment of the bridge.

Three different cases were discussed for calibrating the finite-element (FE) model. Case 1 only included static-based EFs, Case 2 included FRF-based EF, and Case 3 was the combination of Case 1 and 2 and included a multi-response EF. These cases wanted to show the comparison when different EFs are used for model calibration.

Selecting the parameters is a key step for successful FE model calibration. More parameters can be estimated when different types of measurements are included. In this research, 7 parameters included 3 moduli of elasticity, 3 mass density, and 1 spring stiffness were selected. Instead of using initial experimental measurements for normalization, the reciprocal of the variance of the measurements were used. This will help avoid the dominance of one of the measurements in the objective functions in the case initial values are small.

Different comparisons between experimental and analytical FRF and strain values were made for each case. The analytical FRFs were computed efficiently with using a decomposed formation of the FRF functions. The calibration results were validated when the excluded data for only validation was compared for different cases. Comparing FRFs in Case 2 and Case 3 showed a better agreement in lower frequencies. In Case 2, using FRF-based EF, resulted in a stiffer model which provided smaller values for analytical
strain values and higher natural frequencies. The local deterioration of the structure at measured strain locations could be the reason for this discrepancy.
CHAPTER 5

CONCLUDING REMARKS AND FUTURE WORK

Since chapters 2, 3, and 4 have their own separate conclusions, this chapter is only trying to provide overall contributions with regards to the scope of this research. Additionally, the possible future work and directions for improving the outcomes is discussed.

5.1 Summary and Overall Contributions

This research contributed to different aspects of short- and long-term structural health monitoring of highway bridges.

The effect of temperature on dynamic properties of different bridges were presented as part of long-term monitoring of two bridges. Different statistical models were investigated and the most accurate model was selected to remove the effect of temperature from identified natural frequencies. Then, the feasibility of detecting damages after removing the effect of temperature was illustrated and showed what type of damage could be detected.

B-WIM is an inexpensive method for evaluating traffic loads. Doing a live-load test on a bridge allowed for field verification of different B-WIM approaches. The results showed how to estimate traffic load with only few strain gauges mounted at different sections.
Condition assessment of a bridge can be improved through finite-element (FE) model calibration using different types of measurements. The feasibility and the results of a successful FE model calibration were presented on a full-scale bridge that was subjected to both dynamic and static load tests.

5.2 Directions for Future Research

The data that have been collected from different bridges in the LTBP lab are very valuable and can be exploited much more for future research. These are a few potential directions that future research can be aiming at:

5.2.1 Uncertainty of Identified Modal Parameters

There are different sources of uncertainties when modal properties of a bridge are estimated from ambient vibration. For instance, amplitude of excitation, length of recorded response, and selected model orders may effect the results of modal identification.

5.2.2 Computer Vision Systems for Bridge Weigh-in-Motion

The multi-presence of trucks when using B-WIM techniques for evaluating traffic loads is always an issue. Computer-vision systems have been developed significantly and become more sophisticated in the past decades. Employing this technology for detecting the multi-presence of trucks will benefit B-WIM techniques. In addition, computer vision system can help detect the axle configuration of the trucks traveling over the bridge.

5.2.3 Real-time FEM Updating with Different Objective Functions

Finite-element model (FEM) updating can translate the collected data, such as strain, deflection, tilt, vibration, and etc., to stiffness and mass properties of the structure.
If this process is totally automated, the change of collected data in real-time will be correlated to the properties that engineers can use to understand the current condition of the structures compared with the initial values when the structure was constructed.
REFERENCES


Pascual R, Golinval JC, Razeto M. (1997). A frequency domain correlation technique for model correlation and updating.15th International Modal Analysis Conference (IMAC XV), Orlando,


APPENDICES
A.1. Sampling

Campbell Scientific dataloggers are used for measuring output signals from the sensors. Dataloggers are coded to sample different sensors. Scan rate in the codes specifies how fast the measurements are scanned and then sampled and stored in different tables. Dataloggers are assigned a static IP address when the network was set up, therefore, it is possible to connect to them remotely and collect the recorded data.

A.1.1 Perry (Utah) Bridge

Perry Bridge has 3 different dataloggers, CR5000, CR3000, and CR1000. CR5000 has 4, CR3000 has 3, and CR1000 has 2 separate tables that data are stored in.

Table names and a brief sampling description of Perry Bridge dataloggers are as below:

**Perry_CR5000_Dyn_1Hr**: Dynamic Data - Sampled every 1 hour for 3 minutes at 100 Hz - Scan: 10 m sec

**Perry_CR5000_SD_15Min**: Slow Data - Averaged every 15 minutes continuously - Scan: 10 m sec

**Perry_CR5000_RF_24Hr**: Rainflow Histogram, Calculated every 24 hours - Scan: 10 m sec
Perry_CR5000_AV_15Min: Sampled every 15 minutes continuously - Scan: 10 m sec

Perry_CR3000_SD_15: Vibrating Wire Slow Data - Averaged every 15 minutes continuously - Scan: 10 m sec

Perry_CR3000_VWDynamic: Vibrating Wire Dynamic Data - Sampled every 1 hour for 3 minutes at 100 Hz - Scan: 10 m sec

Perry_CR3000_VWStatic: Vibrating Wire Static Data - Sampled continuously at 1 Hz - Scan: 10 m sec

Perry_CR1000_IRS_15Min: Road Sensor - Sampled every 15 minutes continuously - Scan: 3 min

Perry_CR1000_SD_15Min: Slow Data - Averaged every 15 minutes continuously - Scan: 3 min

A.1.2 Sacramento (California) Bridge

Sacramento Bridge has 2 different dataloggers, CR5000 and CR1000. CR5000 has 3, and CR1000 has 1 separate table(s) that data are stored in.

Dataloggers on Sacramento (California) Bridge had stopped communicating on January 19th, 2015. This problem was not solvable remotely and according to lack of funding the travel to Sacramento was not possible for researchers at Utah State University. In September 2015, the funding was provided from another resource and after an on-site inspection by researchers from Utah State University the following problem was detected:
the internal battery of CR5000 was damaged because of aging issue and it had been draining the whole current from external charging power. To resolve this issue, batteries were disconnected and a power module was replaced in the data acquisition box to provide the energy to the dataloggers.

Table names and sampling descriptions of the Sacramento Bridge dataloggers are:

**Sacramento_CR5000_Dyn_1Hr:** Dynamic Data - Sampled every 1 hour for 6 minutes at 50 Hz - Scan: 20 m sec

**Sacramento_CR5000_RF_24Hr:** Rainflow Histogram, Calculated every 24 hours - Scan: 20 m sec

**Sacramento_CR5000_SD_15Min:** Slow Data - Averaged every 15 minutes continuously - Scan: 20 m sec

**Sacramento_CR1000_SDAvg_15:** Slow Data - Averaged every 15 minutes continuously - Scan: 3 min

It should to be noted that the sampling rate is different from the scan rate of the measurements on the dataloggers. Dataloggers may scan a measurement every second, but those scanned measurements will not be sampled or those measurements may be sampled over a minute, then averaged, and then, only one single sample will be recorded. For instance, thermocouples on Perry Bridge are scanned every 3 minutes, but they are sampled every 15 minutes after averaging 5 scanned measurements.
Appendix B includes a sample of wiring diagrams that shows which sensor is connected to what channel on a datalogger. A sample of tables that include all the information about Dataloggers and associated tables can be found in Appendix C.

The data that are sampled and recorded by dataloggers need to be transferred and collected through a computer. Internet connections can be used to collect the recorded data from Campbell Scientific dataloggers in certain time intervals with regards to their assigned IP addresses.

LoggerNet (Fig. A.1.) is a software that is developed by Campbell Scientific Inc. to establish an internet connection to dataloggers using their static IP addresses. After a successful connection is established, LoggerNet demands the datalogger to transfer the data. The transferred data is collected and saved according to the record numbers. More details about LoggerNet and its capabilities can be found in the manual provided by Campbell Scientific group.

Fig. A.1. LoggerNet Window
LoggerNet needs to be customized for each bridge to properly collect the data. Since dynamic data are sampled every hour for 3 minutes, LoggerNet has been set to collect the data at 10 minutes past the hour every hour. It takes the datalogger between 10 to 15 minutes to collect the dynamic measurements while static measurements are collected in a few seconds after the collection process starts. The data collected every hour is appended to the end of the created files from previous collections. Sometimes the connection to dataloggers might be impossible. In this case, LoggerNet will attempt 3 times every minute. If the connection cannot be established, the next collection will try to collect the missing data records from previous collections.

The files that include high frequency dynamic measurements grow large rapidly. Therefore, it is usually better to move the files after a few collections and start writing the data on a newly created file. Based on the size of the collected data, it has been decided to move and create a new file every 24 hour period. This process has been automated with MATLAB and will be discussed additionally in the Data Storage session.

If any data file gets too large that even MATLAB cannot handle it, then Campbell Sci. split program can be used to break down a huge DAT file into smaller files.

These are the instructions to use the Campbell Sci. split program:

(1) These information must be known from the “DAT File” that will be split:

   a. Start/End time for the DAT File information
b. The number of total columns in the DAT File (date stamps and Record Number both count)

c. The decimal places wanted to be saved for each column

Fig. A.2. Campbell Scientific Split Program Window

(2) A Par File must be created for each DAT File (if data inside each DAT File differ) by the user for the command prompt (Fig. A.2. and Fig. A.3.):
Fig. A.3. PAR file for splitting DAT files

a. Open the Split Program

b. In the Input File(s) Tab place the number of total columns from the DAT File in the Select Field as shown below (21 columns = “1..21”). Notice the 1 is followed by (2) periods, then, the number of total columns.

c. In the Output File Tab, the number entered in step 2b should appear in the Report Heading Table that can be updated. The Decimal and Width Fields in the Report and Heading Table need to be filled in for the values that the DAT Files have stored. The Width field is how many characters, punctuation, or numbers are saved for each column. The Decimal Field determines where the decimal place is located within the Width field that was designated. In the example below, the first column is for the date stamp (letters and numbers are present so Decimal input is NOT required). The second column is for the record number (all record numbers are integers so the Decimal input is set to zero). The third through the eighth columns in
the example were strain gauge measurements (measured in micro-strain). The DAT File showed the strain gauge measurements to have 6 decimal places (it is important to know that the decimal places can be hidden or not showing in the DAT file. by right clicking in the view pro program, you can sometimes adjust how many decimal places are shown). The rest of the columns were for Velocity Transducers which had up to 9 decimal places. Obviously, these inputs depend on the data that was recorded by the datalogger in the DAT File. These values must be adjusted for your needs and the files that are to be split. It is recommended to use this par file in small trials to verify the output before using a par file in large command prompt programs.

d. Save this PAR file in the desired location (this location will be used in the command prompt coding)

(3) Create a text file for the Command Prompt Code

d. You must know:

i. Split Program’s location on your computer

ii. PAR file(s) location(s) on your computer – Created in Step 2

iii. DAT file(s) location(s) on your computer – File that you are splitting

iv. Name and location of text file(s) you want to create
e. In the text file, each line should read:

"Split_Program_Location.exe"  "Par_File_Location.par"/R

"DAT_File_Location.dat"  "Text_File_Name_and_Location.txt"/0/[NaN]

1[Start_Year]:1[Start_Day_of_Year]:, 1[End_Year]:1[End_Day_of_Year]::

A.2 Data Archiving

The next step after data collection is archiving the collected data. Archiving collected data is crucial in different aspects: (1) security and safekeeping (2) accessibility. First, collected measurements need to be stored and secured to guarantee they are not going to be deleted or lost in the case of any accidents. Second, archived data shall be accessible and simply retrievable. The first aspect is being discussed in more details in Data Storage session. The second aspect is divided into two subsections, Data Retrieval and Data Visualization. Data retrieval explains how data can be retrieved in different ways with regards to the storage process. Data visualization discusses different ways of plotting and examining data visually.

A.3 Data Storage

To choose a reliable and appropriate form of storage for archiving, the size of the data and the required capacity to store the collected data have to be specified. Future expansion of the storage needs to be considered to specify an appropriate available capacity. This consideration is vital when for example a cloud storage with limited available space might be used. In addition, speed and performance of data retrieval play an important role for choosing the appropriate form. Data visualization is considerably affected with the
speed of data retrieval. Last, the cost of the storage needs to be evaluated before any plan is chosen.

Making more than one copy of the collected data is necessary in order to have a secure archive. Therefore, if one copy becomes corrupted or has any unexpected problem, there are other copies to recover the data. In addition to automatic data collection, the process of copying and transferring collected data should preferably be automated. Thus, archiving will be more accurate and convenient.

Using different storage platforms for different copies may reduce the risk of losing data significantly. If one platform fails in the case of any unexpected error, the other in-service platforms will be available to recover the data. In the last few years, cloud storage has been offered in addition to internal and external hard drives. Cloud storage system is built from thousands of storage devices that are clustered by network to provide storage services for their users. These developed cloud storage services are one of the benefits of faster network connections and capable of providing storage services at a lower cost with more reliability and security.

Cloud storage is currently being offered by many providers like Dropbox, Box, Google Drive, Microsoft OneDrive, and etc. These providers propose different features such as sharing and accessing options, technology of syncing, collaboration possibilities, and mobile supports at a wide range of costs. The available services and the associated costs are changing rapidly by time. Since moving from one system to another system may
pose a serious risk of corrupting or losing some parts of data, it would be preferred not to switch between systems in a short period when one service is selected for archiving.

In this study, three different platforms have been used to keep the data secured and safe. First, the collected data are being saved on an internal hard drive of a computer. Then, two copies are made from the original files, one on Google Drive and one on an external hard drive. There are two types of copies on Google Drive. One copy is the original collected files and another copy is made temporarily for preprocessing data. A MATLAB code, which is run with Windows Task Scheduler, has been used to automatically copy and transfer the collected data.

Considering the size of the collected static and dynamic data and required time to load the data, it has been decided to copy and move data every 24 hour period. Therefore, Windows Task Scheduler has been set to open MATLAB every night at 11:45 pm, runs an assigned code for copying and moving collected data files and then closes MATLAB (Fig. A.4.).

This nomenclature was used to easily specify which bridge the archived data files have been collected from and at what time they have been copied and moved. This code can be run manually at any other time if necessary and the name will clearly show when it was run. Then, a report will be automatically generated and saved after each time this program is run. A sample of an automatically generated report after the process of copying and moving is included in Appendix D.
Different files that have been collected during a 24 hour period is copied in a folder which is named with this pattern:

“Bridge Name_Year_Month.Day_Hour.Minute.Second”.

A.4 Data Retrieval and Preprocess

If all the collected data are archived appropriately in a specific format, they can simply and quickly be retrieved in different ways. Data retrieval is basically the process to call back and read the data that have been archived in different formats like TXT or DAT files in a very short period of time. The speed and performance of retrieving data effects the smoothness of any further process such as preprocessing and data visualization. The other consideration was to provide automatically generated reports than can be Emailed to the supervisors and capable of sending alerts and warnings in the case of emergencies.
To be able to retrieve the data rapidly, DAT files need to be preprocessed. Preprocessing is the process of reading data from the original collected format and save them in a format that can be retrieved simply and quickly. “.mat” format has been selected which is a binary MATLAB file that store workspace variables.

In addition to collected measurements, bridges information are all included when any piece of data is inverted to “.mat” files. Bridge information are read from tables in Excel sheets that needs to have a special format to be properly loaded to MATLAB. Different tables include different information. The first table includes bridge basic information like selected bridge names, alternative names like Perry Bridge or Utah Bridge, location and exact address. The second table include the bridge notes that is updated with each field trip. The third table shows all the details about the wiring of the sensors to the channels of the associated dataloggers. The fourth table shows all the details about different sensors and measurements. These details include what is the measurement name, what sensor the measurement is made from, what is the type measurement (temperature, velocity, etc.), what is the unit of the measurements, the sensors location, associated dataloggers for each measurement, the name of the DAT file that measurements are originally collected from, the sampling intervals, the gauge factors and manufacturers details. To describe the sensors location, X, Y, and Z coordinates are described in both numerical and descriptive formats. The numerical format shows the coordinates according to an origin (like X=576 inch, Y=105 inch, Z=-54 inch) while the descriptive format shows the section that have been agreed on (like X=0.6L, Y=Girder 1, Z=Bottom Flange). Including all these
information in the “.mat” files with the measurements help retrieve all the information when any data is being retrieved at any time.

Retrieving data in different ways enables researchers to evaluate and control the data collection and archiving process regularly. There are various properties that may be specified by the users to retrieve the data. For instance, Bridge name, time interval, record number, recorded file names, datalogger, measurement name, sensor name, sensor location, and many other properties. The written functions needs to be capable of retrieving the required data with any specified properties. In addition, the prepared functions has the capability to detect errors in any inserted inputs and make suggestions to correct them. For example, if the time interval is not valid or there was no recorded data in that period, a message shows how the interval needs to be corrected. Or if a measurement name that does not exist is inserted as an input, the functions will suggest what sensors are available according to other specified properties.

After reading correct inputs, the users will have the options to plot the data, save the data in any directory, save the plotted figure in different formats.

The elapsed time for loading a month of data from Perry (Utah) Bridge is 226 seconds and from the Sacramento (California) Bridge is 162 seconds. This includes both the dynamic and static data that have been collected from each bridge and inverted into “.mat” files by the described preprocess. The major cause of the difference in the elapsed time is the sampling rate of the dynamic data which is 50 Hz on Sacramento Bridge and 100 Hz on Perry Bridge.
Generating reports automatically is another benefit of developing an organized data archive with constant formatting and pre-processing. An example of one of these reports can be found in Appendix E. This report shows all the information about the DAT files that have been copied and moved in the data storage process. The other report, that is automatically generated after the data is pre-processed, shows all the details of the collected measurements on a single day. A sample of this report is presented in Appendix F.

Collected data in real time can be visualized in LoggerNet with Real-Time Monitor and Control Software (RTMC). This program provides graphical screens showing real-time data. Different form of displays can be chosen with its large library of components including alarms, switches, status bars, charts, and gauges. A component that needs to be monitored in real-time can be selected and the data value needs to be specified from available collected data. Fig. A.5. shows a sample that include temperature measurements collected from Perry (Utah) bridge in real-time. After each collection this data will be updated. The length of the time that data is being shown in this window can be customized. As it is shown in Fig. A.5, collected temperature data in the last 6 hours is being shown.
Fig. A.5. RTMC window showing collected data in real-time

In addition to real-time monitoring of the recently collected, past data may need to be visualized and examined.

Different function have been prepare to retrieve and plot the data. Figure 17 through 19 show different group plots. Data can be plotted individually on a single graph. Plotting different sensors on top of each other help to examine different data from various sensors simultaneously. In a case that various data overlap considerably, plotting data on top of each other may not be clear, therefore, sub-plotting can be helpful.
Fig. A.6. Plotting a single data record

Fig. A.6. Plotting recorded data from few sensors on a single figure
Fig. A.7. Sub-plotting recorded data from few sensors under each other
APPENDIX B

A Sample Row of Tables Containing the Measurement Details

<table>
<thead>
<tr>
<th>Idx</th>
<th>Measurement Name (Alias)</th>
<th>Sensor Name</th>
<th>Measuring</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>VT_UD_G1_2_06L</td>
<td>VT_UD_G1_2_06L</td>
<td>Velocity</td>
<td>in/sec</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>576</td>
<td>105</td>
<td>0</td>
<td>0.6L</td>
<td>Girder 1-2</td>
<td>Under Deck</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>DataLogger</th>
<th>Sensor Field Name</th>
<th>Sensor Type</th>
<th>Table Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR5000</td>
<td>VT 1</td>
<td>Velocity Transducer</td>
<td>Perry_CR5000_Dyn_1Hr</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sampling Description</th>
<th>Destination Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dynamic Data - Sampled every 1 hour for 3 minutes at 100 Hz - Scan:10 m sec</td>
<td>VT_UD_G1_2_06L</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Gage Factors</th>
<th>Measurement Description</th>
<th>Sensor Model</th>
</tr>
</thead>
</table>
Multiplier=$1/(276.99*0.0254*1000)$; offset=0

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mark/Sercel</td>
<td>0.05 Hz</td>
</tr>
</tbody>
</table>

Velocity Transducer, Under Deck Mount, Between Girder 1 & 2, 0.6L

Mark L-4 1.0 Hz Seismometer
### CR1000 Wiring Diagram

<table>
<thead>
<tr>
<th>No.</th>
<th>Function</th>
<th>GND</th>
<th>Color</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Wind A.T.</td>
<td>1H</td>
<td>Blk</td>
<td>AM25T</td>
</tr>
<tr>
<td>2</td>
<td>Wind A.T.</td>
<td>1L</td>
<td>Blk</td>
<td>AM25T</td>
</tr>
<tr>
<td>3</td>
<td>RH</td>
<td>2H</td>
<td>Rd</td>
<td>AM25T</td>
</tr>
<tr>
<td>4</td>
<td>RH</td>
<td>2L</td>
<td>Rd</td>
<td>AM25T</td>
</tr>
<tr>
<td>5</td>
<td>Radiation</td>
<td>3H</td>
<td>Ylw</td>
<td>AM25T</td>
</tr>
<tr>
<td>6</td>
<td>Radiation</td>
<td>3L</td>
<td>Ylw</td>
<td>AM25T</td>
</tr>
<tr>
<td>7</td>
<td>Rain Det.</td>
<td>4H</td>
<td>Blk</td>
<td>AM25T</td>
</tr>
<tr>
<td>8</td>
<td>Rain Det.</td>
<td>4L</td>
<td>Blk</td>
<td>AM25T</td>
</tr>
</tbody>
</table>

### Table

<table>
<thead>
<tr>
<th>No.</th>
<th>Function</th>
<th>GND</th>
<th>Color</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>Type T. Thermo</td>
<td>5H</td>
<td>Blk</td>
<td>AM25T</td>
</tr>
<tr>
<td>10</td>
<td>Type T. Thermo</td>
<td>5L</td>
<td>Blk</td>
<td>AM25T</td>
</tr>
<tr>
<td>11</td>
<td>Tilt Jump</td>
<td>6H</td>
<td>Rd</td>
<td>AM25T</td>
</tr>
<tr>
<td>12</td>
<td>Tilt Jump</td>
<td>6L</td>
<td>Rd</td>
<td>AM25T</td>
</tr>
</tbody>
</table>

### Additional Notes

- **White**: (2) IRS 21
- **Brown**: (1) AM 16/32B
- **Gry**: (1) HMP45
- **Red**: (2) IRS 21
- **Green**: (1) AVW 200
- **Black**: (1) AVW 200
- **Yellow**: (1) AVW 200
- **Blue**: (1) AVW 200
- **White**: (1) AVW 200
- **Crimson**: (1) AVW 200

---

**APPENDIX C**

**A Sample of Wiring Diagram Tables**
APPENDIX D

A Sample of Tables Containing Dataloggers Details

<table>
<thead>
<tr>
<th>Data Logger</th>
<th>IP/Port Address</th>
<th>Pak Bus Address</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perry_CR5000</td>
<td>166.154.3.4:3001</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>File Names (Tables)</th>
<th>Sampling Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perry_CR5000_Dyn_1Hr</td>
<td>Dynamic Data - Sampled every 1 hour for 3 minutes at 100 Hz - Scan:10 msec</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Column Number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Column Name</td>
<td></td>
<td></td>
<td>VT_UD_G1_2_06L</td>
<td>VT_UD_G1_2_03L</td>
<td>VT_UD_G4_5_06L</td>
<td>SG_G5_B F_06L</td>
</tr>
<tr>
<td>Regarding Sensor</td>
<td></td>
<td></td>
<td>VT_UD_G1_2_06L</td>
<td>VT_UD_G1_2_03L</td>
<td>VT_UD_G4_5_06L</td>
<td>SG_G5_B F_06L</td>
</tr>
<tr>
<td>Measuring</td>
<td></td>
<td></td>
<td>Velocity</td>
<td>Velocity</td>
<td>Velocity</td>
<td>Strain</td>
</tr>
<tr>
<td>Unit</td>
<td></td>
<td></td>
<td>Time</td>
<td>integer</td>
<td>in/sec</td>
<td>in/sec</td>
</tr>
<tr>
<td>Type (String/Number)</td>
<td>%s</td>
<td>%f</td>
<td>%f</td>
<td>%f</td>
<td>%f</td>
<td>%f</td>
</tr>
</tbody>
</table>
APPENDIX E

A Sample of Automatically Generated Reports for Copying and Moving Collected Data in a 24-Hour Period

"Perry Bridge"

Copying and Moving Collected Files Daily

Inputs:

Copy Dat Files Flag=1
Move Dat Files Flag=1
Zip Copied Dat Files Flag=0

Source Folder (where the recorded Dat files are located at):

"D:\Current Records\Perry Bridge"

Copy Destination Directory (where files will be copied to):

"D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\LoggerNet Original Files"
Copy Destination Directory2 (where files will be copied to):

"D:\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\LoggerNet Original Files"

Copy Destination Directory3 (where files will be copied to):

"H:\External Hard Drive"

Move Destination Directory (where files will be moved to):

"D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Temporary Moved Files"

Inputs (End)

******************************************************************

Copying recorded Dat files to 3 destinations:

Copying Dat files

From: "D:\Current Records\Perry Bridge"

To: "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\LoggerNet Original Files\Perry_2015_10_16_23_45_30"
"Perry_CR1000_IRS_15Min.dat" has been copied.

"Perry_CR1000_SD_15Min.dat" has been copied.

"Perry_CR3000_SD_15.dat" has been copied.

"Perry_CR3000_VWDynamic.dat" has been copied.

"Perry_CR3000_VWStatic.dat" has been copied.

"Perry_CR5000_AV_15Min.dat" has been copied.

"Perry_CR5000_Dyn_1Hr.dat" has been copied.

"Perry_CR5000_RF_24Hr.dat" has been copied.

"Perry_CR5000_SD_15Min.dat" has been copied.

Copying Dat files

From: "D:\Current Records\Perry Bridge"

To:  "D:\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\LoggerNet Original Files\Perry_2015_10_16_23_45_30"

"Perry_CR1000_IRS_15Min.dat" has been copied.

"Perry_CR1000_SD_15Min.dat" has been copied.
"Perry_CR3000_SD_15.dat" has been copied.

"Perry_CR3000_VWDynamic.dat" has been copied.

"Perry_CR3000_VWStatic.dat" has been copied.

"Perry_CR5000_AV_15Min.dat" has been copied.

"Perry_CR5000_Dyn_1Hr.dat" has been copied.

"Perry_CR5000_RF_24Hr.dat" has been copied.

"Perry_CR5000_SD_15Min.dat" has been copied.

Copying Dat files

From: "D:\Current Records\Perry Bridge"

To:  "H:\External Hard Drive\Perry_2015_10_16_23_45_30"

"Perry_CR1000_IRS_15Min.dat" has been copied.

"Perry_CR1000_SD_15Min.dat" has been copied.

"Perry_CR3000_SD_15.dat" has been copied.

"Perry_CR3000_VWDynamic.dat" has been copied.

"Perry_CR3000_VWStatic.dat" has been copied.

"Perry_CR5000_AV_15Min.dat" has been copied.
"Perry_CR5000_Dyn_1Hr.dat" has been copied.

"Perry_CR5000_RF_24Hr.dat" has been copied.

"Perry_CR5000_SD_15Min.dat" has been copied.

Copying recorded Dat files has been done successfully.

******************************************************************

Moving recorded Dat files:

From: "D:\Current Records\Perry Bridge"

To: "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Temporary Moved Files\Perry_2015_10_16_23_45_30"

"Perry_CR1000_IRS_15Min.dat" has been moved.

"Perry_CR1000_SD_15Min.dat" has been moved.

"Perry_CR3000_SD_15.dat" has been moved.

"Perry_CR3000_VWDynamic.dat" has been moved.

"Perry_CR3000_VWStatic.dat" has been moved.
"Perry_CR5000_AV_15Min.dat" has been moved.

"Perry_CR5000_Dyn_1Hr.dat" has been moved.

"Perry_CR5000_RF_24Hr.dat" has been moved.

"Perry_CR5000_SD_15Min.dat" has been moved.

Moving recorded Dat files has been done successfully.

******************************************************************
This Process was performed by Navid Zolghadri (navidz@aggiemail.usu.edu).
Time: "October 16, 2015  23:45:39"
******************************************************************
APPENDIX F

A Sample of Automatically Generated Reports Including the Details of the Copied and Moved “.dat” Files

This is part of a report that is automatically generated after the copied and moved originally DAT files are preprocessed. Instead of opening files separately and scrutinizing what data have been included and collected in different DAT files in a directory, this report simply shows all the information about all the DAT files in directory. Since these reports are too long to fit in this report, a shortened version of one of the reports has been included in this appendix. This report shows the details of all the collected data from different “.dat” files in a folder named "Perry_2015_01_07_11_49_04". There are different flags in this code to control the pre-process and the output options. For instance, “ReplaceNaNFlag” lets the users to replace not-a-number (NaN) values between collected measurements. Datalogger puts “NaN” when it skips a measurement or a sensors output exceeds voltage limits of the datalogger. Another example is “ReadBridgeInfoFromExcelFile Flag” that allows users to include available bridge information from a specially formatted Excel sheet.

Here is the report:

******************************************************************
"Perry Bridge"
******************************************************************

Pre-Processing
Start Time: "January 11, 2015 16:50:12"

******************************************************************

Inputs:

Name of the folder includes under-process dat files:

"Perry_2015_01_07_11_49_04"

SaveAfterPreProcess Flag = 1

ReplaceNaN Flag = 1

ReadBridgeInfoFromExcelFile Flag = 1

MatlabDestinationFolder (where the matlab variables will be saved):

"D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files"

PreProcessed Directory (where the pre-processed folder will be moved to):

"D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files"

ExcelInfoFileName (Excel file name which includes all the information for current recorded data):
"Perry Details_2014_12_20"

ExcelFileDir (where the Excel file includes bridge info is located):

"D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Long-Term Documents\Long-Term Details In Excel"

NHeader = 4

DefaultColumnNumbers = 150

Input (End)

******************************************************************
******************************************************************

Excel file "Perry Details_2014_12_20" which includes the regarding bridge information has been copied:

From: "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Long-Term Documents\Long-Term Details In Excel"

To: "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Temporary Moved Files\Perry_2015_01_07_11_49_04"
Under-process folder "Perry_2015_01_07_11_49_04" has been moved:

From: "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Temporary Moved Files"

To: "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files"

Separating dat files inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04" into daily Matlab variables:

Under-Process Folder: "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04"

There is(are) 9 dat file(s) inside this folder.

Separated daily variables will be saved to "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files".
Separating file "Perry.CR1000.IRS.15Min.dat" from "D:\Google Drive\USULTBP Lab\USULTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04" into daily Matlab variables:

Under-Process File Name: "Perry.CR1000.IRS.15Min.dat"

This file is from "D:\Google Drive\USULTBP Lab\USULTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04".

Default Number of Columns: 150 Number of header rows: 4 SaveFlag: 1
ReplaceNaNFlag: 1

Save Flag = 1 means data will be saved into separate daily variables at "D:\Google Drive\USULTBP Lab\USULTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files".

ReplaceNaN Flag = 1 means NaN values will be replaced when daily files are saved.
Bridge Info is collected from Excel file "Perry Details_2014_12_20.xlsx".

"Perry Details_2014_12_20.xlsx" inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Database\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Proccessed Files\Perry_2015_01_07_11_49_04", which has special format, is being converted to a matlab variable.

Number of Columns=18 has been determined from Excel file "Perry Details_2014_12_20.xlsx".

Bridge Info.DataLoggerFiles column 4 specified FormatString for reading data.

File includes collected data between: "2015-01-06 17:15:00" and "2015-01-07 11:00:00".

File includes 72 row(s) and 18 column(s) of data.

This file includes some cell values at column 8 which are not numbers and cannot not be included in the sensors data.

This file includes some cell values at column 10 which are not numbers and cannot not be included in the sensors data.

This file includes some cell values at column 16 which are not numbers and cannot not be included in the sensors data.

This file includes some cell values at column 18 which are not numbers and cannot not be included in the sensors data.
File includes data from 2 day(s).

******************************************************************

Daily data inside file "Perry_CR1000_IRS_15Min.dat":

************************************************************************

Date Number 1: "2015_01_06"

Start Time:   "2015-01-06 17:15:00"

End Time:     "2015-01-06 23:45:00"

Number of Rows:  27

************************************************************************

Collection Hours Details:

Data was collected in 7 different hour(s).

-----------------------------------------------------------------------------------

<table>
<thead>
<tr>
<th>Hours</th>
<th>Start</th>
<th>End</th>
<th>Interval</th>
<th>Number of Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>17</td>
<td>17:15:000</td>
<td>17:45:000</td>
<td>00:15:000</td>
<td>3</td>
</tr>
</tbody>
</table>

-----------------------------------------------------------------------------------
Checking for NaN Vaues:

WARNING: There is more than 5 NaN.

Saving separated data:

Daily variables from file "Perry_CR1000_IRS_15Min.dat" inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Proccessed Files\Perry_2015_01_07_11_49_04" will be saved into "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files".
"D2015_01_06.mat" is already existed inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files" and will be updated.

Data from file "Perry_CR1000_IRS_15Min.dat" has NOT been written into "D2015_01_06" before. Therefore, it will be added to the next row.

Existing NaN values will be replaced by spline interpolation.

WARNING: Column 6 (8 in dat file) is all NaN and cannot be replaced. Check these data out.

Some parts have been removed from here for condensation.

DailyData from file "Perry_CR1000_IRS_15Min.dat" has been saved successfully into "D2015_01_06".

BridgeInfo has been added into "D2015_01_06".

******************************************************************

Date Number 2: "2015_01_07"

Start Time:   "2015-01-07 00:00:00"

End Time:     "2015-01-07 11:00:00"
Number of Rows: 45

*****************************************
Collection Hours Details:

Data was collected in 12 different hour(s).

---------------------------------------------------------------------------------------------------

<table>
<thead>
<tr>
<th>Hours</th>
<th>Start</th>
<th>End</th>
<th>Interval</th>
<th>Number of Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>00</td>
<td>00:00:00.000</td>
<td>00:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
</tbody>
</table>

Some parts have been removed from here for condensation.

*****************************************
Checking for NaN Values:

WARNING: There is more than 5 NaN.

*****************************************

Saving separated data:
Daily variables from file "Perry_CR1000_IRS_15Min.dat" inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04" will be saved into "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files".

"D2015_01_07.mat" is already existed inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files" and will be updated.

Data from file "Perry_CR1000_IRS_15Min.dat" has been already written into "D2015_01_07" and will be updated.

Checking for NaN Values:

WARNING: There is more than 5 NaN.

Existing NaN values will be replaced by spline interpolation.

WARNING: Column 6(8 in dat file) is all NaN and cannot be replaced. Check these data out.

Some parts have been removed from here for condensation.

DailyData have been sorted and same data rows have been removed from DailyData variable.

This file information on "D2015_01_07.mat" are updated as below:
Start Time(updated): "2015-01-07 00:00:00"

End Time(updated): "2015-01-07 23:45:00"

Number of Rows(updated): 96

*********************************
Collection Hours Details(updated):

Data was collected in 24 different hour(s).

---------------------------------------------------------------------------------------------------

Hours **** Start **** End **** Interval **** Number of Records

---------------------------------------------------------------------------------------------------

00 **** 00:00:00.000 **** 00:45:00.000 **** 00:15:00.000 **** 4

Some parts have been removed from here for condensation.

23 **** 23:00:00.000 **** 23:45:00.000 **** 00:15:00.000 **** 4

---------------------------------------------------------------------------------------------------

DailyData from file "Perry_CR1000_IRS_15Min.dat" has been saved successfully into "D2015_01_07".
BridgeInfo has been added into "D2015_01_07".

******************************************************************
******************************************************************

Separating file "Perry_CR1000_IRS_15Min.dat" from "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Database\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04" into daily Matlab variables has been done successfully.

******************************************************************
Under-Process File Number: 2

******************************************************************

Separating file "Perry_CR1000_SD_15Min.dat" from "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Database\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04" into daily Matlab variables:

******************************************************************
Under-Process File Name: "Perry_CR1000_SD_15Min.dat"
This file is from "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04".

Default Number of Columns: 150 Number of header rows: 4 SaveFlag: 1 ReplaceNaNFlag: 1

Save Flag = 1 means data will be saved into separate daily variables at "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files".

ReplaceNaN Flag = 1 means NaN values will be replaced when daily files are saved.

Bridge Info is collected from Excel file "Perry Details_2014_12_20.xlsx".

"Perry Details_2014_12_20.xlsx" inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04", which has special format, is being converted to a matlab variable.

Number of Columns=49 has been determined from Excel file "Perry Details_2014_12_20.xlsx".

Bridge Info.DataLoggerFiles column 4 specified FormatString for reading data.
File includes collected data between: "2015-01-06 17:15:00" and "2015-01-07 11:00:00".

File includes 72 row(s) and 49 column(s) of data.

File includes data from 2 day(s).

******************************************************************
Daily data inside file "Perry_CR1000_SD_15Min.dat":
******************************************************************

Date Number 1: "2015_01_06"

Start Time: "2015-01-06 17:15:00"

End Time: "2015-01-06 23:45:00"

Number of Rows: 27

Collection Hours Details:

Data was collected in 7 different hour(s).
<table>
<thead>
<tr>
<th>Hours</th>
<th>Start</th>
<th>End</th>
<th>Interval</th>
<th>Number of Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>17</td>
<td>17:15:00.000</td>
<td>17:45:00.000</td>
<td>00:15:00.000</td>
<td>3</td>
</tr>
<tr>
<td>18</td>
<td>18:00:00.000</td>
<td>18:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>19</td>
<td>19:00:00.000</td>
<td>19:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>20</td>
<td>20:00:00.000</td>
<td>20:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
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<tr>
<td>21</td>
<td>21:00:00.000</td>
<td>21:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>22</td>
<td>22:00:00.000</td>
<td>22:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>23</td>
<td>23:00:00.000</td>
<td>23:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
</tbody>
</table>

Checking for NaN Values:

There is no NaN.

Saving separated data:
Daily variables from file "Perry_CR1000_SD_15Min.dat" inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Database\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04" will be saved into "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Database\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files".

"D2015_01_06.mat" is already existed inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Database\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files" and will be updated.

Data from file "Perry_CR1000_SD_15Min.dat" has NOT been written into "D2015_01_06" before. Therefore, it will be added to the next row.

DailyData from file "Perry_CR1000_SD_15Min.dat" has been saved successfully into "D2015_01_06".

BridgeInfo has been added into "D2015_01_06".

Some parts have been removed from here for condensation.

Under-Process File Number: 3

**********************************************************

Separating file "Perry_CR3000_SD_15.dat" from "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Database\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04" into daily Matlab variables:
Under-Process File Name: "Perry_CR3000_SD_15.dat"

This file is from "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04".

Default Number of Columns: 150       Number of header rows: 4       SaveFlag: 1       ReplaceNaNFlag: 1

Save Flag = 1 means data will be saved into separate daily variables at "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files".

ReplaceNaN Flag = 1 means NaN values will be replaced when daily files are saved.

Bridge Info is collected from Excel file "Perry Details_2014_12_20.xlsx".

"Perry Details_2014_12_20.xlsx" inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04", which has special format, is being converted to a matlab variable.
Number of Columns=10 has been determined from Excel file "Perry Details_2014_12_20.xlsx".

Bridge Info.DataLoggerFiles column 4 specified FormatString for reading data.

File includes collected data between: "2015-01-06 17:15:00" and "2015-01-07 11:00:00".

File includes 72 row(s) and 10 column(s) of data.

File includes data from 2 day(s).

******************************************************************
Daily data inside file "Perry_CR3000_SD_15.dat":
******************************************************************

Date Number 1: "2015_01_06"
Start Time:   "2015-01-06 17:15:00"
End Time:     "2015-01-06 23:45:00"
Number of Rows:  27

Collection Hours Details:
Data was collected in 7 different hour(s).

<table>
<thead>
<tr>
<th>Hours</th>
<th>Start</th>
<th>End</th>
<th>Interval</th>
<th>Number of Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>17</td>
<td>17:15:00.000</td>
<td>17:45:00.000</td>
<td>00:15:00.000</td>
<td>3</td>
</tr>
<tr>
<td>23</td>
<td>23:00:00.000</td>
<td>23:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
</tbody>
</table>

Some parts have been removed from here for condensation.

Checking for NaN Values:

There is no NaN.

Saving separated data:

Daily variables from file "Perry_CR3000_SD_15.dat" inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04" will be
saved into "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files".

"D2015_01_06.mat" is already existed inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files" and will be updated.

Data from file "Perry_CR3000_SD_15.dat" has NOT been written into "D2015_01_06" before. Therefore, it will be added to the next row.

DailyData from file "Perry_CR3000_SD_15.dat" has been saved successfully into "D2015_01_06".

BridgeInfo has been added into "D2015_01_06".

******************************************************************
Date Number 2:  "2015_01_07"

Start Time:     "2015-01-07 00:00:00"

End Time:       "2015-01-07 11:00:00"

Number of Rows: 45

******************************************************************

Collection Hours Details:
Data was collected in 12 different hour(s).

<table>
<thead>
<tr>
<th>Hours</th>
<th>Start</th>
<th>End</th>
<th>Interval</th>
<th>Number of Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>00</td>
<td>00:00:00.000</td>
<td>00:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>11</td>
<td>11:00:00.000</td>
<td>11:00:00.000</td>
<td>00:00:00.000</td>
<td>1</td>
</tr>
</tbody>
</table>

Some parts have been removed from here for condensation.

Checking for NaN values:

There is no NaN.

Saving separated data:

Daily variables from file "Perry_CR3000_SD_15.dat" inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Processed Files\Perry_2015_01_07_11_49_04" will be
saved into "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files".

"D2015_01_07.mat" is already existed inside folder "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Matlab Daily Files" and will be updated.

Data from file "Perry_CR3000_SD_15.dat" has been already written into "D2015_01_07" and will be updated.

Checking for NaN Values:

There is no NaN.

DailyData have been sorted and same data rows have been removed from DailyData variable.

This file information on "D2015_01_07.mat" are updated as below:

Start Time(updated):   "2015-01-07 00:00:00"

End Time(updated):     "2015-01-07 23:45:00"

Number of Rows(updated):  94

*******************************************************************************

Collection Hours Details(updated):
Data was collected in 24 different hour(s).

<table>
<thead>
<tr>
<th>Hours</th>
<th>Start</th>
<th>End</th>
<th>Interval</th>
<th>Number of Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>00</td>
<td>00:00:00.000</td>
<td>00:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>15</td>
<td>15:00:00.000</td>
<td>15:45:00.000</td>
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</tr>
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<td>16</td>
<td>16:00:00.000</td>
<td>16:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>17</td>
<td>17:00:00.000</td>
<td>17:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
</tbody>
</table>

Some parts have been removed from here for condensation.

DailyData from file "Perry_CR3000_SD_15.dat" has been saved successfully into "D2015_01_07".

BridgeInfo has been added into "D2015_01_07".

Separating file "Perry_CR3000_SD_15.dat" from "D:\Google Drive\USU LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data..."
Records\Pre-Processed Files\Perry_2015_01_07_11_49_04" into daily Matlab variables has been done successfully.

******************************************************************
Some parts have been removed from here.
******************************************************************

Coded by: Navid Zolghadri (navidz@aggiemail.usu.edu)

******************************************************************
This process was performed by Navid Zolghadri (navidz@aggiemail.usu.edu).

End Time: "January 11, 2015   16:58:33"

******************************************************************
A Sample of Automatically Generated Reports Including the Details of All the Measurements on a Single Day

This report shows the details of all the data that have been collected on a single day (January 11, 2015) from Perry Bridge. This report has been reduced in size to fit in this report better.

Here is the report:

*****************************************
Daily Report
"Perry Bridge"

January 11, 2015 (2015_01_11)

*****************************************

Data was collected from 9 file(s):

File 1: "Perry_CR1000_IRS_15Min.dat"

Folder 1: "D:\Google Drive\US U LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Proccessed Files\Perry_2015_01_11_14_40_52"

Folder 2: "D:\Google Drive\US U LTBP Lab\USU LTBP Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Proccessed Files\Perry_2015_01_11_23_45_07"

Some parts have been removed from here for condensation.
File 9: "Perry_CR5000_SD_15Min.dat"

Folder 1: "D:\Google Drive\US ULTB Lab\US ULTB Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Proccessed Files\Perry_2015_01_11_14_40_52"

Folder 2: "D:\Google Drive\US ULTB Lab\US ULTB Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Proccessed Files\Perry_2015_01_11_23_45_07"

Folder 3: "D:\Google Drive\US ULTB Lab\US ULTB Lab Bridge Data Base\Perry Bridge\Long-Term Data Recordings\Data Records\Pre-Proccessed Files\Perry_2015_01_12_23_45_06"

************************************************************************

File 1: "Perry_CR1000_IRS_15Min.dat"

************************************************************************

****************************     Measurement Details
***************************

"Perry_CR1000_IRS_15Min.dat" included 16 measurement(s).

Measurements:

Regarding DataLogger: Perry_CR1000

Sampling Description: Road Sensor - Sampled every 15 minutes continuously - Scan:3 minute

Regarding Measurements:
<table>
<thead>
<tr>
<th>Col</th>
<th>Column Name</th>
<th>Regarding Sensor</th>
<th>Measuring</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Time Stamp</td>
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<td>Time Date</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Record</td>
<td>NA</td>
<td>NA</td>
<td>Integer</td>
</tr>
<tr>
<td>3</td>
<td>InterntalT_1</td>
<td>Road Sensor (1)</td>
<td>Temperature</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>SaltConc_1</td>
<td>Road Sensor (1)</td>
<td>Salt Concentration</td>
<td>%</td>
</tr>
<tr>
<td>5</td>
<td>FreezTemp_1</td>
<td>Road Sensor (1)</td>
<td>Freezing</td>
<td>Temperature</td>
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<tr>
<td>6</td>
<td>WaterFilm_1</td>
<td>Road Sensor (1)</td>
<td>Water Film</td>
<td>mm</td>
</tr>
<tr>
<td>7</td>
<td>ConditionID_1</td>
<td>Road Sensor (1)</td>
<td>Condition ID</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>ConditionIDtxt_1</td>
<td>Road Sensor (1)</td>
<td>Condition ID</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>ErrorID_1</td>
<td>Road Sensor (1)</td>
<td>Error ID</td>
<td>Number</td>
</tr>
<tr>
<td>10</td>
<td>ErrorIDtxt_1</td>
<td>Road Sensor (1)</td>
<td>Error ID</td>
<td>Text</td>
</tr>
<tr>
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<td>Road Sensor (2)</td>
<td>Temperature</td>
<td></td>
</tr>
<tr>
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<td>Salt Concentration</td>
<td>%</td>
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<td>Freezing</td>
<td>Temperature</td>
</tr>
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<td>Road Sensor (2)</td>
<td>Water Film</td>
<td>mm</td>
</tr>
<tr>
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<td>Road Sensor (2)</td>
<td>Condition ID</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>ConditionIDtxt_2</td>
<td>Road Sensor (2)</td>
<td>Condition ID</td>
<td>Text</td>
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</tbody>
</table>
"Perry_CR1000_IRS_15Min.dat" included data between "2015-01-11 00:00:00" and "2015-01-11 23:45:00".

Hours of Collection:

Data was collected in 24 different hour(s).

<table>
<thead>
<tr>
<th>Hours</th>
<th>Start</th>
<th>End</th>
<th>Interval</th>
<th>Number of Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>00</td>
<td>00:00:00.000</td>
<td>00:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>01</td>
<td>01:00:00.000</td>
<td>01:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>22</td>
<td>22:00:00.000</td>
<td>22:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>23</td>
<td>23:00:00.000</td>
<td>23:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
</tbody>
</table>

Some parts have been removed from here for condensation.
Some parts have been removed from here for condensation.

File 7: "Perry_CR5000_Dyn_1Hr.dat"

************************************************************************
****************************     Measurement Details
***************************
************************************************************************

"Perry_CR5000_Dyn_1Hr.dat" included 9 measurement(s).

Measurements:

Regarding DataLogger: Perry_CR5000

Sampling Description: Dynamic Data - Sampled every 1 hour for 3 minutes at 100 Hz - Scan: 10 msec

Regarding Measurements:

<table>
<thead>
<tr>
<th>Col</th>
<th>Column Name</th>
<th>Regarding Sensor</th>
<th>Measuring</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Time Stamp</td>
<td>NA</td>
<td>Time</td>
<td>Date</td>
</tr>
<tr>
<td>2</td>
<td>Record</td>
<td>NA</td>
<td>NA</td>
<td>Integer</td>
</tr>
<tr>
<td>3</td>
<td>VT_UD_G1_2_06L</td>
<td>VT_UD_G1_2_06L</td>
<td>Velocity</td>
<td>in/sec</td>
</tr>
<tr>
<td>4</td>
<td>VT_UD_G1_2_03L</td>
<td>VT_UD_G1_2_03L</td>
<td>Velocity</td>
<td>in/sec</td>
</tr>
<tr>
<td>5</td>
<td>VT_UD_G4_5_06L</td>
<td>VT_UD_G4_5_06L</td>
<td>Velocity</td>
<td>in/sec</td>
</tr>
<tr>
<td>Strain</td>
<td>Sample 1</td>
<td>Sample 2</td>
<td>Strain</td>
<td>Sample 1</td>
</tr>
<tr>
<td>--------</td>
<td>----------</td>
<td>----------</td>
<td>--------</td>
<td>----------</td>
</tr>
<tr>
<td>6</td>
<td>SG_G5_BF_06L</td>
<td>SG_G5_BF_06L</td>
<td>Strain</td>
<td>Micro</td>
</tr>
<tr>
<td>7</td>
<td>SG_G4_BF_06L</td>
<td>SG_G4_BF_06L</td>
<td>Strain</td>
<td>Micro</td>
</tr>
<tr>
<td>8</td>
<td>SG_G3_BF_06L</td>
<td>SG_G3_BF_06L</td>
<td>Strain</td>
<td>Micro</td>
</tr>
<tr>
<td>9</td>
<td>SG_G2_BF_06L</td>
<td>SG_G2_BF_06L</td>
<td>Strain</td>
<td>Micro</td>
</tr>
<tr>
<td>10</td>
<td>SG_G1_BF_06L</td>
<td>SG_G1_BF_06L</td>
<td>Strain</td>
<td>Micro</td>
</tr>
<tr>
<td>11</td>
<td>SG_G1_BF_03L</td>
<td>SG_G1_BF_03L</td>
<td>Strain</td>
<td>Micro</td>
</tr>
</tbody>
</table>

--------------------------------------------

************************************************************************
****************************     Collection Details
****************************

"Perry_CR5000_Dyn_1Hr.dat" included data between "2015-01-11 00:00:00" and "2015-01-11 23:02:59.99".

Hours of Collection:

Data was collected in 24 different hour(s).

--------------------------------------------

Hours **** Start **** End **** Interval **** Number of Records
--------------------------------------------

00 **** 00:00:00.000 **** 00:02:59.990 **** 00:00:00.010 **** 18000
Some parts have been removed from here for condensation.

<table>
<thead>
<tr>
<th>Time</th>
<th>Sampled Value</th>
<th>Time</th>
<th>Sampled Value</th>
<th>Time</th>
<th>Sampled Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>01:00:00.000</td>
<td>02</td>
<td>02:02:59.990</td>
<td>03</td>
<td>00:00:00.010</td>
</tr>
<tr>
<td></td>
<td>18000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

File 9: "Perry_CR5000_SD_15Min.dat"

"Perry_CR5000_SD_15Min.dat" included 10 measurement(s).

Measurements:

Regarding DataLogger: Perry_CR5000

Sampling Description: Slow Data - Averaged every 15 minutes continuously - Scan:10 msec

Regarding Measurements:

<table>
<thead>
<tr>
<th>Col</th>
<th>Column Name</th>
<th>Regarding Sensor</th>
<th>Measuring</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Time Stamp</td>
<td>NA</td>
<td>Time</td>
</tr>
<tr>
<td>---</td>
<td>------------</td>
<td>----</td>
<td>------</td>
</tr>
<tr>
<td>1</td>
<td>and Hour</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>2</td>
<td>Record</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>3</td>
<td>SG_G5_BF_06L_Avg</td>
<td>SG_G5_BF_06L</td>
<td>Strain</td>
</tr>
<tr>
<td>4</td>
<td>SG_G4_BF_06L_Avg</td>
<td>SG_G4_BF_06L</td>
<td>Strain</td>
</tr>
<tr>
<td>5</td>
<td>SG_G3_BF_06L_Avg</td>
<td>SG_G3_BF_06L</td>
<td>Strain</td>
</tr>
<tr>
<td>6</td>
<td>SG_G2_BF_06L_Avg</td>
<td>SG_G2_BF_06L</td>
<td>Strain</td>
</tr>
<tr>
<td>7</td>
<td>SG_G1_BF_06L_Avg</td>
<td>SG_G1_BF_06L</td>
<td>Strain</td>
</tr>
<tr>
<td>8</td>
<td>SG_G1_BF_03L_Avg</td>
<td>SG_G1_BF_03L</td>
<td>Strain</td>
</tr>
<tr>
<td>9</td>
<td>TM_SA_G2_Avg</td>
<td>TM_SA_G2</td>
<td>Tilt</td>
</tr>
<tr>
<td>10</td>
<td>TM_SA_Wall_Avg</td>
<td>TM_SA_Wall</td>
<td>Tilt</td>
</tr>
<tr>
<td>11</td>
<td>TM_NA_G2_Avg</td>
<td>TM_NA_G2</td>
<td>Tilt</td>
</tr>
<tr>
<td>12</td>
<td>TM_NA_Wall_Avg</td>
<td>TM_NA_Wall</td>
<td>Tilt</td>
</tr>
</tbody>
</table>

************************************************************************

****************************     C o l l e c t i o n  D e t a i l s
****************************
"Perry_CR5000_SD_15Min.dat" included data between "2015-01-11 00:00:00" and "2015-01-11 23:45:00".

Hours of Collection:

Data was collected in 24 different hour(s).

<table>
<thead>
<tr>
<th>Hours</th>
<th>Start</th>
<th>End</th>
<th>Interval</th>
<th>Number of Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>00</td>
<td>00:00:00.000</td>
<td>00:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
<tr>
<td>23</td>
<td>23:00:00.000</td>
<td>23:45:00.000</td>
<td>00:15:00.000</td>
<td>4</td>
</tr>
</tbody>
</table>

Some parts have been removed from here for condensation.

Coded by: Navid Zolghadri (navidz@aggiemail.usu.edu)

This process was performed by Navid Zolghadri (navidz@aggiemail.usu.edu).

End Time: "January 15, 2015 08:58:33"
CURRICULUM VITAE

NAVID ZOLGHADRI

(DECEMBER 2016)

Education

Doctor of Philosophy, Civil (Structural) Engineering  2016
Utah State University

Masters of Science, Civil (Structural) Engineering   2011
Sharif University of Technology

Bachelors of Science, Civil Engineering    2009
Amirkabir University of Technology (Tehran Polytechnic)

Publications

- Zolghadri, N., Halling, M., Barr, P. (2016) Long-term Bridge Performance Program (LTBP), Continuous Data Collection of Utah and California Pilot Bridges. Report submitted to Center for Advanced Infrastructure and Transportation (CAIT) at Rutgers
- Zolghadri, N., Halling, M., Barr, P. (2016) Effects of temperature variations on structural vibration properties of bridge structures (In progress)
Presentations/Posters

- Structures Congress 2016. “Effects of temperature variations on structural vibration properties and finite element model updating”
- Transportation Research Board (TRB) 2016. “Effect of temperature changes on vibration characteristics of bridge structures”
- University of Connecticut Bridge Weigh-in-Motion (B-WIM) Workshop 2015. “Field Verification of B-WIM Techniques”
- Transportation Research Board (TRB) 2014. “A Field Test for Verification of WIM Techniques on a Single-Span Bridge”
- Structures Congress 2014. “Comparison of Wireless and Wired Structural System Identification”
- Utah Department of Transportation (UDOT) Annual Conference 2014. “Dynamic Testing and Modal Analysis of a Concrete Bridge”
- Structures Congress 2013. “Identification of Truck Types Using Strain Sensors Include Co-located Strain Gauges”

Memberships/Contributions

- American Society of Civil Engineers (ASCE)
- Structural Engineering Institute (SEI) Committee - Methods of Monitoring Structural Performance (Friend)
- Transportation Research Board (TRB)
  1. Committee AFF40 - Field Testing and Nondestructive Evaluation (NDE) of Transportation Structures (Friend)
  2. Subcommittee AFF40(1) - Non-destructive Evaluation of Structures (Friend)
  3. Join Subcommittee – Structural Health Monitoring (Friend)