Statistical and Numerical Integrated Approach for Detecting Onset of Prefabricated Bridge Component Connection Deterioration

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STATISTICAL AND NUMERICAL INTEGRATED APPROACH
FOR DETECTING ONSET OF PREFABRICATED BRIDGE COMPONENT CONNECTION DETERIORATION

by

Cem Mansiz

A Thesis
Submitted to the
Faculty of the Graduate College
in partial fulfillment of the
requirements for the
Degree of Master of Science in Engineering (Civil)
Department of Civil and Construction Engineering
Advisor: Dr. Upul Attanayake, Ph.D., P.E.

Western Michigan University
Kalamazoo, Michigan
August 2012
WE HEREBY APPROVE THE THESIS SUBMITTED BY

CEM MANSIZ

ENTITLED STATISTICAL AND NUMERICAL INTEGRATED APPROACH
FOR DETECTING ONSET OF PREFABRICATED BRIDGE
COMPONENT CONNECTION DETERIORATION

AS PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE

DEGREE OF Master of Science in Engineering (Civil)

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Bridges are the substantial part of the transportation infrastructure. Most recent report shows that of the 605,086 bridges in the United States, 67,526 (11%) are deemed structurally deficient, and 76,363 (13%) are declared functionally obsolete (FHWA, 2011). Deck is the shelter of a bridge that is subjected to severe loads due to exposure and traffic. Importance of detecting deck deterioration is further highlighted with the introduction of accelerated bridge construction (ABC) where prefabricated components are brought to the site, assembled, and connected using field cast joints. However, durability performance of field cast connections is not encouraging. Hence, continuous monitoring of structural integrity of bridges built using prefabricated components is vital to detect onset of deterioration. The thesis focuses on developing a tool based on statistical model(s) to present the structural health monitoring data in a meaningful and easily understood format and combining the statistical model(s) and detailed numerical model for damage detection is examined to simulate possible joint failure.
ACKNOWLEDGMENTS

First and foremost I wish to thank to my advisor, Dr. Upul Attanayake, for his excellent guidance, patience and understanding as well as his friendship throughout this study. I would also like to thank to Dr. Haluk Aktan for valuable advice, continuous guidance and encouragement. His technical knowledge has greatly influenced my research. I am sure it would have not been possible without their help.

I would also like to thank to the member of my committee, Dr. Osama Abudayyeh for guiding my research and provide feedback.

Last but not least, I would like to thank to my family Necdet Mansiz, Firdes Mansiz, Bilge Serdar and Ezgi Kirdok for their continuous support, patience and encouragement throughout my study.

Cem Mansiz
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CHAPTER I

INTRODUCTION

Bridges are the substantial part of the transportation infrastructure. Most recent report shows that of the 605,086 bridges in the United States, 67,526 (11%) are deemed structurally deficient, and 76,363 (13%) are declared functionally obsolete (FHWA, 2011). Therefore, one in four bridges in the United States is structurally deficient as of 2011. Use of precast components not only in rehabilitation projects but also for new construction has gained popularity in which road closures have high costs and cause major inconvenience to the public since the higher quality of precast components and fast construction speed.

Existing bridges are inspected biannually and outcomes are being kept in each bridge’s record (AASHTO, 1994). In addition, Issa et al. (1995) investigated field performance of prefabricated components. Inspections are based on visual evaluation. However, visual inspections are unreliable to detect invisible damage or distress (Chase, 2003). In recent years, sensor technology has been introduced to the bridges for condition assessment. Sensor technology gains popularity because of its low cost and reliability.

Structural monitoring would provide information on structure behavior and component interaction at any stage such as construction; in-service; and before, during and after rehabilitation of a bridge. Deck is the shelter of a bridge that is subjected to sever loads due to exposure and traffic. Deck deteriorates much faster
than the rest of the structure. Average service life of a bridge is 42 years; however, average service life of a cast-in-place concrete deck is 20-25 years (Ralls, 2005). This data shows the importance of developing effective and efficient maintenance and repair activities to extend the service life of the deck. Importance of detecting deck deterioration is further highlighted with the introduction of accelerated bridge construction (ABC) where prefabricated components are brought to the site, assembled, and connected using field cast joints. Though it is expected to have a longer service life with the use of prefabricated components, durability performance of field cast connections is not encouraging. Hence, continuous monitoring of structural integrity of bridges built using prefabricated components is vital to detect onset of deterioration. Detecting onset of deterioration is important to initiate efficient and effective maintenance and repair activities to extend bridge service life, thus eliminate costly repairs or replacements.

However, the percentage of bridges that require attention or repair remains same for years (FHWA 2008, BTS 2007 and FHWA 2011). The lack of technologies for structural health monitoring application is not the main problem. The focal problem is analyze the collected data accurately and continuously to extract useful information. Furthermore, it is vital to provide clear and usable output to users rather than inundating them with massive amounts of disjointed data (Lee, 2007).
1.1 Objective of the Study

The objective of this study is to develop a tool based on statistical model(s) to present the structural health monitoring data in a meaningful and easily understood format to detect onset of prefabricated bridge component connection deterioration.

1.2 Scope of the Study

The scope of the study is limited to using vibrating wire strain gage data from a full-depth deck panel system. Further, deterioration signatures are developed using refined finite element (FE) model of a bridge superstructure with full-depth deck panels. The FE model is validated using load test data and selected thermal gradient profiles.

4 tasks were defined to accomplish the research objective. The tasks are,

- state-of-the-art literature was collected and reviewed,
- statistical models were reviewed and sensor data was analyzed,
- numerical model was developed to simulate deterioration behavior,
- statistical models were tested using simulation results.

Overview of the study can be seen in Figure 1-1.
Figure 1-1. Overall schematic of SHM system
CHAPTER II

STATE-OF-THE-ART LITERATURE REVIEW

2.1 Literature Review on Structural Health Monitoring

Structural health monitoring implementations are improving with the technology and reduced cost of sensing. However, dealing with a large amount of data and extracting valuable information from huge data sets still requires significant research. Collected data sets would be used not only for decision making on maintenance but also recommendations for future designs when proper problem investigation techniques are implemented. Brownjohn et al. (2004) states that damage identification is a key to find the root of the problem in civil infrastructure.

According to Rytter (1993), damage assessment can be divided to 4 levels. These are damage detection, damage localization, damage quantification and prediction of remaining service life. However, environmental conditions may be misinterpreted as damage due to change in behavior and cause false alarm. Therefore, implementation of sensitive structural health monitoring system without false alarms is crucial for damage detection.

Shourky et al. (2009) present a health monitoring system installed on a concrete deck on steel girders bridge. The health monitoring system includes more than 700 sensors which record the response of main elements under various loading conditions. Data are recorded in every 20 min over 4 years and used for long term monitoring. Geokon vibrating wire strain gages are installed that are capable of...
collecting temperature data as well as strain using thermistor. Then, stresses in concrete deck, stresses at bridge ends are obtained in addition to the temperature profiles. Moreover, internal forces of diaphragm and tilting of steel girders are also monitored. Instead of detailed statistical analysis, authors used daily maximum and minimum points for monitoring and compared theoretical calculations with the readings coming from sensor data. Results show that although one of the abutments is in good conditions which satisfy theoretical calculations, other abutment shows a different behavior than expected because it was designed as unrestrained support. However, calculations show that it is partially restrained. Consequently, authors underline that thermal changes in bridge have great impact on the behavior of the total system.

Zhang and Aktan (1997) present an implementation of finite element modeling (FEM) to structural health monitoring. 2-D and 3-D finite element models are created by using design drawings. Impact and forced vibration tests are performed on Cross-Country Bridge in Ohio. Test results are compared initially to obtain frequency data. Once the repeatability of frequency data is confirmed, the results are used to calibrate 2-D and 3-D models. Considering simplicity of modeling and the level of accuracy yielded, 2D model was selected for further studies.

Cardini and DeWolf (2008) present an approach to use strain data for long-term structural monitoring without dealing with huge data set. Long-term structural health monitoring system is installed to series of bridges throughout the State of Connecticut to collect data during normal traffic. The key element in the monitoring
system is that strain gages trigger the system when a heavy truck passed the bridge, which means critical load condition for the bridges. This approach reduces the amount of data significantly. Therefore, it greatly simplifies analyses of the data. Then, results are compared with the finite element and show good correlation. Consequently, warning system is created. Peak values and neutral axis is determined. If there is a change in neutral axis, shift would indicate potential problem either in bridge deck or girder.

Fang and Kim (2008) present data analysis and vibration measurement on two newly constructed bridges in California instrumented for long-term health monitoring. Bridges are 3 span box-girder bridges and instrumented with strain gages, pressure sensors, displacement sensors, accelerometers. Data is collected every 10 minutes and modal parameters are obtained. The data is used to validate a finite element model of the bridge.

Issa et.al (2004) developed a long-term structural health monitoring systems for full-scale precast bridge decks and rehabilitated precast concrete beams to identify changes in the condition of components due to sustained load, traffic load and environmental conditions. Two VWSGs that were placed on the top surface of the bridge and five VWSGs that were embedded in the deck are used to evaluate the structural performance of the segments of the bridge. Load test is performed during the static service loads, overloads, and ultimate loads before and after applying the low cycle fatigues loading. The collected data reflects that components perform
well without any sign of cracks or debonding; however, details of analysis results are not present in the paper.

### 2.2 Literature Review on Vibrating Wire Strain Gauge – Working Principles

Vibrating Wire Strain Gages (VWSGs) are used to measure long-term strains in structures such as foundations, piles, bridges, etc. Two end blocks of steel wire which is tensioned are embedded directly in concrete structure. VWSGs should have stiffness much less than concrete because stiffness of the gages should not affect the reading by adding extra stiffness to the system. When structure is exposed to loading, two end blocks start to move relatively, thus changing the strain in steel wire. Then, tension is monitored by plucking the wire and measuring its resonant frequency of vibration whereby an electromagnetic coil (Geokon, 2000). Although the required time to finish the pluck/read operation is less than one second for a single sensor, it may take several seconds to read all of the gages when numerous sensors are multiplexed to a single data acquisition system. Therefore, VWSGs are not suitable tool for high speed measurements such as dynamic readings (Aktan et al., 2003).

Although calculation of strain seems very basic, thermal-induced effects in the vibrating data should be taken into account because difference between the coefficients of thermal expansion of the VWSG and concrete create differential elongation or shortening (Nield et al., 2005). Therefore, readings coming from VWSGs should be corrected by considering degree of restraint.
VWSGs should be welded, bolted or bonded to the material on which strain readings need to be monitored. Most of the strain gages convert change in resistance or change in voltage to strain measurement. Therefore, undesirable reading errors can occur due to usage of lead wires, long cables, solder which create additional resistance to the measurement system. However, VWSGs can compensate these kinds of reading errors because readings are based on frequency measurement. In addition, Vibrating Wire Strain Gages are very stable and shown very small deviations throughout its lifetime (Aktan et al., 2003).

Consequently, VWSGs are convenient and robust measurement tools to monitor strain changes in structures.

### 2.3 Literature Review on Statistical Models

Okosha et al. (2010) present an automated finite element updating approach using strain data for the lifetime reliability assessment of bridges. In order to compute the lifetime component reliabilities for the bridge, statistical distributions are generated by assuming probability density function of moment capacities of girders follow log-normal distribution. In addition, they also used finite element model as a link between the SHM and reliability analysis.

Samanta and Al-Balushi (2003) present an artificial neural network based fault diagnostics of rolling element bearings using time domain features. Their study focuses on condition monitoring and diagnostics of rotating machinery. Time domain vibrations signals are collected with normal and defective bearings and
used as inputs to the artificial neural network. They had successive results on monitoring of machine condition.

Methodology of the 3 statistical approaches that are selected as potential solution for detecting onset of prefabricated bridge component connection deterioration are presented in this section.

2.3.1 Literature Review on Probability Distributions

Brief information, shape of the functions, effect of parameters and their formulas for each distribution type are presented in this section. Detailed explanations on following distribution types can be found in Johnson et al. (1994), Kenney and Keeping (1951) and Evans et al. (2000).

2.3.1.1 Normal Distribution

The normal distribution is the most common statistical distribution since normality can be seen in many situations from many areas. Normal distribution is applicable if the data histogram follows a bell-shaped curve about its mean. The peak of the distribution is located at the mean ($\mu$) value and the standard deviation ($\sigma$) determines the spread in the data. Probability density function for different mean and standard deviation can be seen in Figure 2-1 and Figure 2-2.
Figure 2-1. Normal distribution probability density functions for different mean

Figure 2-2. Normal distribution probability density functions for different standard deviation

Mean: $\mu$

Standard deviation: $\sigma$

Probability density function: $PDF(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right)$
2.3.1.2 Normal Distribution with Box-Cox Transformation

If the data is not following normal distribution; then following transformation can be used. The main objective is to minimize standard deviation of transformed data set when lambda, $\lambda$, value is determined.

$$Y^t(x) = \frac{Y^{\lambda}(x) - 1}{\lambda G^{\lambda-1}} \text{ if } \lambda \neq 0$$

$$Y^t(x) = Gln(Y(x)) \text{ if } \lambda = 0$$

where $Y^t(x)$ is the transformed data set, $G$ is the geometric mean of the all data. After the Box-Cox transformation is applied, normal distribution can be applied.

2.3.1.3 Log-normal Distribution

The distribution fits best if the logarithm of the data follows normal distribution. It is generally used for reliability analysis and in financial applications. The log-normal distribution is a special case of 3-parameter log-normal distribution where the threshold parameter ($\lambda$) is 0. Probability density function for different scale and shape parameter can be seen in Figure 2-3 and Figure 2-4.
Figure 2-3. Log-normal distribution probability density functions for different scale parameters

Scale parameter: $\mu$  
Shape parameter: $\sigma$  
Mean: $\exp(\mu + 0.5\sigma^2)$  
Standard deviation: $\sqrt{\exp(2\mu + \sigma^2)(\exp(\sigma^2) - 1)}$
Probability density function: \( PDF(x) = \frac{1}{\sigma x \sqrt{2\pi}} \exp\left(\frac{-(\ln(x)-\mu)^2}{2\sigma^2}\right) \)

### 2.3.1.4 3-parameter Log-normal Distribution

This distribution type is same with log-normal distribution except an extra threshold parameter. Effect of threshold parameter can be seen in Figure 2-5.

![Distribution Plot](image)

**Figure 2-5.** 3-parameter log-normal distribution probability density functions for different threshold parameters

Scale parameter: \( \mu \)

Shape parameter: \( \sigma \)

Threshold parameter: \( \lambda \)

Mean: \( \exp(\mu + 0.5\sigma^2) \)

Standard deviation: \( \sqrt{\exp(2\mu + \sigma^2)(\exp(\sigma^2) - 1)} \)

Probability density function: \( PDF(x) = \frac{1}{\sigma(x-\lambda)\sqrt{2\pi}} \exp\left(\frac{-(\ln(x-\lambda)-\mu)^2}{2\sigma^2}\right) \)
2.3.1.5 Exponential Distribution

The 1-parameter exponential distribution is defined only by its scale parameter. This distribution type most often used to model the behavior of units that have a constant failure rate. The type of distribution function can be seen in Figure 2-6 for different scale parameters.

Figure 2-6. Exponential distribution probability density functions for different scale parameters

Scale parameter: $\theta$

Mean: $\theta$

Standard deviation: $\theta$

Probability density function: $PDF(x) = \frac{1}{\theta} \exp\left(\frac{-x}{\theta}\right)$
2.3.1.6 2-parameter Exponential Distribution

The distribution is defined not only by its shape but also its threshold parameter. The threshold parameter shifts the curve to right if it is positive as shown in Figure 2-7.

![Distribution Plot](image)

Figure 2-7. 2-parameter exponential distribution probability density functions for different threshold parameters

Scale parameter: $\theta$

Mean: $\theta + \lambda$

Threshold parameter: $\lambda$

Standard deviation: $\theta$

Probability density function: $PDF(x) = \frac{1}{\theta} \exp \left( \frac{\lambda-x}{\theta} \right)$
2.3.1.7 Weibull Distribution

This distribution type is widely used in engineering applications. The advantage of this distribution type is that distribution can take various shapes to fit the data. Weibull distribution depends on scale and shape parameters and special case of 3-parameter Weibull when the threshold parameter is 0. Effect of the shape and scale parameter can be seen in Figure 2-8 and Figure 2-9.

![Distribution Plot](image1)

**Figure 2-8.** Weibull distribution probability density functions for different shape parameters

![Distribution Plot](image2)

**Figure 2-9.** Weibull distribution probability density functions for different scale parameters

Scale parameter: $\alpha$

Shape parameter: $\beta$
Mean: \( \alpha \Gamma \left( 1 + \frac{1}{\beta} \right) \)

Standard deviation: \( \sqrt{\frac{\alpha^2 \left( \Gamma \left( 1 + \frac{2}{\beta} \right) - \Gamma^2 \left( 1 + \frac{1}{\beta} \right) \right)}{}} \)

Probability density function: \( PDF(x) = \frac{\beta}{\alpha^\beta} (x)^{\beta-1} \exp \left( - \left( \frac{x}{\alpha} \right)^\beta \right) \)

### 2.3.1.8 3-parameter Weibull Distribution

Distribution is same as Weibull distribution except threshold parameter. The threshold parameter does not have any effect on the shape or peak of the function. Threshold parameter only shifts the curve right if the value is positive as can be seen in Figure 2-10.

![Distribution Plot](image)

**Figure 2-10.** 3-parameter Weibull distribution probability density functions for different threshold parameters

Scale parameter: \( \alpha \)

Shape parameter: \( \beta \)

Threshold parameter: \( \lambda \)
Mean: $a \Gamma \left(1 + \frac{1}{\beta}\right) + \lambda$

Standard deviation: $\sqrt{a^2 \left( \Gamma \left(1 + \frac{2}{\beta}\right) - \Gamma^2 \left(1 + \frac{1}{\beta}\right) \right)}$

Probability density function: $PDF(x) = \frac{\beta}{\alpha^\beta} (x - \lambda)^{\beta-1} \exp \left( - \frac{x-\lambda}{\alpha} \right)^\beta$

2.3.1.9 **Largest Extreme Value Distribution**

The distribution is used when the distribution skewed right. The location and scale parameters determine the function as shown in the Figure 2-11 and Figure 2-12.

Figure 2-11. Largest extreme value distribution probability density functions for different location parameters
Figure 2-12. Largest extreme value distribution probability density functions for different scale parameters

Location parameter: $\mu$

Scale parameter: $\sigma$

Constant: $\gamma$

Mean: $\mu + \gamma \sigma$

Standard deviation: $\frac{\pi^2 \sigma^2}{6}$

Probability density function: $PDF(x) = \frac{1}{\sigma} \exp \left( \frac{x-\mu}{\sigma} \right) \exp \left\{ -\exp \left( \frac{x-\mu}{\sigma} \right) \right\}$

2.3.1.10 Smallest Extreme Value Distribution

If $x$ is largest extreme value; then $-x$ is the smallest extreme value. Therefore, instead of right skew this distribution type fits if the data skewed left.
2.3.1.11 Gamma Distribution

This distribution type is commonly used for positively skewed data in reliability survival studies and used in reliability survival studies. Effect of scale and shape parameters can be seen in Figure 2-13 and Figure 2-14.

Figure 2-13. Gamma distribution probability density functions for different shape parameters

Figure 2-14. Gamma distribution probability density functions for different scale parameters

Scale parameter: $\beta$
Shape parameter: $\alpha$

Mean: $\beta \alpha$

Standard deviation: $\beta^2 \alpha$

Probability density function: 

$$PDF(x) = \frac{1}{\Gamma(a)\beta^a} x^{a-1} \exp\left(-\frac{x}{\beta}\right)$$

### 2.3.1.12 3-parameter Gamma Distribution

The distribution is similar to that of Gamma distribution except threshold parameter. Effect of threshold parameter can be seen in Figure 2-15.

![Distribution Plot](image)

*Figure 2-15. 3-parameter gamma distribution probability density functions for different threshold parameters*

Scale parameter: $\beta$

Shape parameter: $\alpha$

Threshold parameter: $\lambda$
Mean: $\beta \alpha + \lambda$

Standard deviation: $\beta^2 \alpha$

Probability density function: $PDF(x) = \frac{1}{\Gamma(\alpha) \beta^\alpha} (x - \lambda)^{\alpha-1} \exp\left(-\frac{x-\lambda}{\beta}\right)$

2.3.1.13 Logistic Distribution

The distribution is widely used as a growth curve and to model binary response. It is described by its location and scale parameters. The distribution type does not have any shape parameter which means shape of the function always same. The shape looks similar to shape of the normal distribution but the logistic distribution has longer tails. Effect of location and scale parameters can be seen in Figure 2-16 and Figure 2-17.

![Distribution Plot](image)

Figure 2-16. Logistic distribution probability density functions for different scale parameters
Location parameter: $\mu$

Scale parameter: $\sigma$

Mean: $\mu$

Standard deviation: $\sigma \sqrt{\frac{\pi^2}{3}}$

Probability density function: $PDF(x) = \frac{\frac{1}{\sigma} \exp\left(\frac{x-\mu}{\sigma}\right)}{(1+\exp\left(\frac{x-\mu}{\sigma}\right))^2}$

2.3.1.14 Loglogistic Distribution

The distribution fits best if the logarithm of the data follows logistic distribution. It is known as the Fisk distribution. Effect of location and shape parameter can be seen in Figure 2-18 and Figure 2-19.
Figure 2-18. Loglogistic distribution probability density functions for different location parameters

Location parameter: $\mu$

Scale parameter: $\sigma$

Mean: $\exp(\mu)\Gamma(1 + \sigma)\Gamma(1 - \sigma)$
Standard deviation: \( \sqrt{ \exp(2\mu)(\Gamma(1 + 2\sigma)\Gamma(1 - 2\sigma) - \Gamma^2(1 + 2\sigma)\Gamma^2(1 - 2\sigma))} \)

Probability density function: \( PDF(x) = \frac{\frac{1}{\sigma} \exp\left(\frac{\ln(x)-\mu}{\sigma}\right)}{(1+\exp\left(\frac{\ln(x)-\mu}{\sigma}\right))^2} \)

2.3.1.15 3-parameter Loglogistic Distribution

The loglogistic distribution is described by its location, scale and threshold parameter. Shape parameter is not defined for loglogistic distributions similar to logistic distribution. The threshold parameter shifts the curve as shown in Figure 2-20.

![Loglogistic distribution probability density functions for different threshold parameters](image)

**Figure 2-20.** Loglogistic distribution probability density functions for different threshold parameters

Location parameter: \( \mu \)

Scale parameter: \( \sigma \)

Threshold parameter: \( \lambda \)

Mean: \( \exp(\mu) \Gamma(1 + \sigma)\Gamma(1 - \sigma) + \lambda \)
Standard deviation: \( \sqrt{\exp(2\mu)(\Gamma(1 + 2\sigma)\Gamma(1 - 2\sigma) - \Gamma^2(1 + 2\sigma)\Gamma^2(1 - 2\sigma)} \)

Probability density function: \( PDF(x) = \frac{1}{\pi(x-\bar{x})} \exp\left(\frac{\ln(x-\bar{x})-\mu}{\sigma}\right) \left(1+\exp\left(\frac{\ln(x-\bar{x})-\mu}{\sigma}\right)\right)^2 \)

2.3.2 Literature Review on Tolerance Interval Identification

This approach can be expressed as:

Let \( X_1, X_2, X_3, \ldots X_n \) be a random sample of size \( n \) from some continuous distribution with distribution function \( F(x, \theta) \).

Let \( L(X_1, X_2, X_3, \ldots X_n) < U(X_1, X_2, X_3, \ldots X_n) \) where \( L \) is the lower bound of the interval, \( U \) is the upper bound of the interval based on the sample such that for any given \( 0 < \gamma < 1 \) and \( 0 < P < 1 \) where \( \gamma \) is the confidence level for the interval and \( P \) is the proportion of the population which will be included.

Then mathematical expression of this statement is \( Pr \left( F(U(X_1, X_2, X_3, \ldots X_n)) - F(L(X_1, X_2, X_3, \ldots X_n)) \geq P \right) = \gamma \). Therefore, \( L \) and \( U \) is closed interval which enclose at least \( P*100 \) percent of the data with a confidence of \( \gamma \).

2.3.2.1 The Normal Method:

Howe’s approximation would be used in order to compute two-sided tolerance intervals for a normal distribution (Howe, 1969) as follows.

Tolerance interval is expresses as \([\bar{x} - k * s, \bar{x} + k * s]\) where \( \bar{x} \) is the mean, \( s \) is the standard deviation and \( k \) is the values that can be obtained from following equation.
\[ k = Z_{(1-P)/2} \sqrt{\frac{(n - 1)(1 + \frac{1}{n})}{\chi^2_{n-1,\gamma}} \left( 1 + \frac{(n - 3) - \chi^2_{n-1,\gamma}}{2 \cdot (n + 1)^2} \right)} \]

Where \( n \) is the sample size, \( Z_p \) is the \((1-P)\)th percentile of the standards normal distribution. \( \chi^2_{n-1,\gamma} \) is the \((1-\gamma)\)th percentile of the chi-square distribution with \( n-1 \) degrees of freedom.

### 2.3.2.2 The Nonparametric Method (Distribution Free Method):

Let the tolerance interval be the \([X_r, X_{(n-s+1)}]\) based on the sample where \( X_r \) is the \( r \)th smallest number in the sample and \( X_{(n-s+1)} \) is the \( s \)th largest number in the sample such that for any given \( 0 < \gamma < 1 \) and \( 0 < P < 1 \) where \( \gamma \) is the confidence level for the interval and \( P \) is the proportion of the population which will be included.

\[ r + s = m \]

\[ m = n + 1 - t \text{ where } n \text{ is the sample size} \]

\( t \) is the maximum integer value that satisfies \( I_p(t, n + 1 - t) \leq 1 - \gamma \)

Then achieved confidence level is calculated as \( 1 - I_p(t, n + 1 - t) \) from following formula

\[ I_p(t, n + 1 - t) = \int_0^P \frac{\Gamma(t + (n + 1 - t))}{\Gamma(t)\Gamma(b + 1 - t)} P^{t-1}(1 - P)^{(n-t)} dP \]

which is also known as cumulative distribution function (c.d.f.) of the beta distribution where \( \Gamma(x) \) is the gamma function.
2.3.3 Literature Review on Artificial Neural Networks

Brains are composed of two main parts which are neurons and glial and the most important part of the brain could be considered as neurons (Kandel, 2000). Neurons are sending the signals to other neurons by using axons by means of specialized junctions called synapses. An axon can make connections with other several thousand cells. And one of the most crucial properties is that synapses are dynamically modifiable. Therefore, synapses have mechanism for learning and memory by changing strength which is known as activity dependent modification (Shepherd, 2004).

An artificial neural network was inspired by human brain. The most basic model of neuron was developed by Warren McCulloch and Walter Pitts. The model can be seen in Figure 2-21 similar to brain model. However, this model was considered static because weights are stable during processing which is not a proper representation of brain because changing strengths (weights) are the most crucial part of the learning process. Then, basic model was improved by several people from many different areas.
Using artificial neural networks is a state-of-the-art approach. The beauty of using artificial neural network is that all behavior of the data can be represented within a unified environment which is directly built by an experimental data using the self-organizing capability of neural network.

### 2.3.3.1 Neural Network Architecture and Components

Neural network is composed of several components similar to brain neurons to transfer and receive data. In order to understand the behavior of the network, multiple-input neuron model can be investigated as shown in Figure 2-22. $p_1, p_2, p_3, ..., p_R$ are individual inputs where $R$ is the input matrix size. The individual inputs are each weighted by $w_{1,1}, w_{1,2}, w_{1,3}, ..., w_{1,R}$. In addition, $b$ is bias. Then, neuron is summed with the weighted inputs and bias.
Then, $n$ can be calculated as

$$n = w_{1,1} \times p_1 + w_{1,2} \times p_2 + w_{1,3} \times p_3 + \cdots + w_{1,R} \times p_R + b$$

Then, output of the neuron can be calculated as

$$a = f(w_{1,1} \times p_1 + w_{1,2} \times p_2 + w_{1,3} \times p_3 + \cdots + w_{1,R} \times p_R + b)$$

where $f$ is the transfer function in layers. There are approximately 9 transfer functions which are hard limit, symmetrical hard limit, linear, saturating linear, symmetric saturating linear, log-sigmoid, hyperbolic tangent sigmoid, positive linear and competitive functions that are available in the literature (Hagan et al., 1996). However, the log-sigmoid, the hyperbolic tangent sigmoid and the positive linear transfer functions are more often used than others.

Log-sigmoid and hyperbolic tangent sigmoid functions are most commonly used transfer function in neural networks. This function takes the input function which may have any value between $-\infty$ and $+\infty$ and converts the output into the range between 0 and 1. The expression is as follows (Figure 2-23). The log-sigmoid
function is differentiable which makes it most commonly used transfer function for multilayer networks that are trained by using backpropagation (Hagan et al., 1996).

\[
a(n) = \frac{1}{1 + e^{-n}}
\]

The linear function with bias is also widely used. The function is as follows (Figure 2-24).

\[
a(n) = w * p + b
\]

Alternatively, multilayer networks may use the tan-sigmoid transfer function (Figure 2-25).

\[
a(n) = \frac{e^n - e^{-n}}{e^n + e^{-n}}
\]
The idea of single neuron with multiple inputs is explained above. Even though one neuron uses multiple inputs it may not be sufficient for analysis. Therefore, more neurons are needed in parallel called as layer similar to human brain. The concept is same except number of neurons. The single layer network with multiple neurons and multiple inputs can be seen in Figure 2-26.

The layer has weight matrix, bias values and output of a. This approach can be summarized by using matrix. The input, \( p \), the weight, \( W \), the bias, \( b \), and the output, \( a \), values can be written in matrix for as follows.

\[
p = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_R \end{bmatrix}, \quad W = \begin{bmatrix} W_{1,1} & \cdots & W_{1,R} \\ \vdots & \ddots & \vdots \\ W_{S,1} & \cdots & W_{S,R} \end{bmatrix}, \quad b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_S \end{bmatrix}, \quad a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_S \end{bmatrix}
\]

The matrix representation of Figure 2-26 can be seen in Figure 2-27.
Moreover, single layer networks are not powerful when they compared to multi-layer networks (Hagan et al., 1996). Multi-layer networks can be composed of several layers and the last one called as output layer which produces the final output and the other layers are called as hidden layers. Multi-layer networks can have several hidden layers and only one output layer. Each layer has the weight
matrix, $W$, the bias matrix, $b$, and the output matrix, $a$. The input matrix at the initial hidden layer is called as input weight (IW) and all other inputs are called as layer weight (LW). Moreover, the number of layer is affixed using superscript not to confuse the IW, LW and output matrices. An example of multi-layer network with 3 layers can be seen in Figure 2-28. The first and second layers are the hidden layers whereas the third one is the output layer. For example, a two layer network which has a sigmoid transfer function at the first layer and a linear second layer can be used for any function.

Figure 2-28. Multi-layer network (Matlab User’s Guide, 2000)

The most crucial property of neural networks is its self-organization and learning capability. Rumelhart et al. (1986) states that there are two different types of learning mechanism, supervised and unsupervised. In unsupervised learning, network does not know what needs to be learned by means of output. Learning process composed of discovering the similarities and regularities among input parameters. On the other hand, backpropagation provides supervised in neural networks. The supervised learning is performed by generalized delta rule invented
by Rumelhart. Although there many changes and new algorithms are implemented to improve accuracy and speed of iterations, the idea behind the backpropagation remains unchanged. For backpropagation of neural network, each step requires modification of weights after determination of error associated with each unit. A cycle is a process of training of one unit and consequent modification of connection strength. A set of cycles is called epoch which means one complete period for each training case. This process may be repeated up to several thousand times, thereby requiring several thousand epochs up to certain error level. The adjustment of strengths of connections can be summarized as follows.

$$\Delta W = \eta \cdot \delta \cdot p$$

Where $\eta$ is a learning constant known as the learning rate and $\delta$ is the gradient of the total error with respect to the net input at unit. $\delta$ can be determined from the difference between expected activations, $t$ and computed activations, $a = f(W \cdot p + b)$. Then,

$$\delta = (t - a) \cdot F'(W \cdot p + b)$$

where $F'$ is a derivative function. Recall that the log-sigmoid function is differentiable which makes it most commonly used transfer function for multilayer networks that are trained by using backpropagation. The reason is that they can easily used in networks that are using backpropagation. Although expected values of function are known at the output unit, there is no way to know expected
activations at the hidden units a priori. The following equation is an estimate for hidden layer units to calculate error.

\[
\delta = \left( \sum_{k=1}^{M} \delta_k \cdot W \right) \cdot F'(W \cdot p + b)
\]

The method explained above is the simplest approach for the error calculation; however, it is still used by many methods. Advanced methods of backpropagation problems can be found in Jesús et al. (2007).
CHAPTER III

KNOWLEDGE DISCOVERY THROUGH STATISTICAL ANALYSIS OF WV SENSOR DATA

3.1 Objective and Approach

The objectives of this section are to (1) display instrumentation details, data collection and filtering steps of SHM system, (2) present 3 statistical approaches that can be used for SHM, and (3) display data analysis for each model using sensor data.

Results of SHM were demonstrated using the data coming from a full depth deck panel system, The Parkview Bridge.

First, distribution identification method is discussed using 15 different statistical models that can be used to define confidence limits. Next, tolerance intervals are discussed. The main focus is to find an answer to “what percentage of the reading we want to cover” and “how high we want our confidence in the interval itself to be”. Then, artificial neural network is discussed by proving detailed literature summary.

It is vital to provide clear and usable output to users rather than inundating them with massive amounts of disjointed data. Total of 6 different sensors were selected for the statistical analysis. Statistical analysis was performed for 2 longitudinal and 4 transverse joint sensors. One of the longitudinal sensors (N-12-C) is over pier and other (N-7-C) is at the midspan. Four different midspan transverse joint sensors
between panels were used. These sensors are N-7-B, N-8-E, 16-N-B, N-17-E and location of the sensors can be seen in Figure 3-2. Following approaches will be shown for one sensor which is longitudinal north panel sensor over pier 2 (N-12-C). The analysis for each approach and each sensor can be found in APPENDIX B.

3.2 Overview

The bridge that is selected for data for this study is the Parkview Bridge. The bridge is located in Kalamazoo, Michigan. The bridge carries the Parkview Avenue over US-131. The bridge was designed with four spans and three traffic lanes, with all its major bridge elements including substructure prefabricated off site. The superstructure is composed of 7 Type III AASHTO girders and 48, 9-inch thick precast reinforced concrete deck panels. These panels are labeled as North and South. Once the North and South panels were installed on-site, the transverse continuity between north and south panels were established using a reinforced concrete cast-in-place longitudinal closure pour. The deck was post-tensioned after grouting the transverse joints between panels and the closure. Then the shear pockets and the haunches were grouted to establish the connection between girders and the deck panels. A waterproofing membrane was placed over the deck and a 1-1/2 inch asphalt wearing surface was placed. Figure 3-1 illustrates the various prefabricated elements of the bridge including multi-section abutments, single segment pier columns, single section pier caps, pre-stressed concrete I-girders, and post-tensioned full-depth deck panels.
3.3 Structural Health Monitoring System

3.3.1 Instrumentation

Geokon Vibrating-Wire Strain Gauges (sensors) Model VCE-4200 with built-in thermocouples installed in the bridge deck panels. In addition, 2 Geokon MICRO-10 Data Loggers Model Number 8020-1-1, 12 Geokon Multiplexers Model 8032-16-1S, 2 modems, a remote computer workstation in a laboratory with communication software, and necessary wiring for communication and data transfer are used to monitor bridge (Abudayyeh 2010).

Monitoring was started in December 2008. Data was stored on data logger every 10 minute increments for each 184 sensors. Then, data loggers were connected weekly to download and archive data for analysis by using telephone lines.

184 Vibrating Wire Strain Gauges (Sensors) are placed to the critical locations and four different types of behavior are monitored by using four groups of sensors to effectively monitor the bridge performance under varying load conditions.
• Group 1 – Longitudinal stresses at mid spans and over the piers,

• Group 2 – Transverse stresses at mid spans,

• Group 3 -- Stresses at joints between panels (parallel-to-edge), and

• Group 4 -- Stress at both sides of the cast-in-place closure between North and South panels (Abudayyeh 2010).

Figure 3-2 shows the locations and labels of all the sensors in the panels. The construction details in terms of the plans and specifications for the design and installation of the selected instrumentation are provided in (Abudayyeh 2010).

3.3.2 Data Collection and Filtering

3.3.2.1 Data Reduction

The bridge behavior is monitored using Vibrating Wire Strain Gauges. Bridge construction was started on April 15, 2008 and opened to traffic September 8, 2008. Data collection was started in December 2008 due to lack of telephone lines at bridge site. Hence, the data from first four months could not be collected. Therefore, stress changes which are drastic at initial stages could not be monitored. These changes can be as attributed to creep, shrinkage, elastic shortening of post-tension, losses due to stressing sequence of post-tension strands and all other losses at initial stages.

Data was downloaded at 10 minute interval for 3 years starting from December 2008. Dynamic behavior of the bridge was investigated using data of two different
sensors which were transformed to the frequency domain using FFT method. Details of this process can be found in Abudayyeh et al. (2012). Results show that data did not contain any high frequency components which mean sensors are not capable of capturing dynamic stresses. Therefore, it can be concluded that the change in strain is due to thermal.
Figure 3-2. Sensor layout
3.4 Application of Distribution Identification Method in Health Monitoring

First, stress readings collected at 10 min interval were plotted. Figure 3-3 shows that stress values are significantly affected by seasonal variations. In addition, data variation shows that there was significant decrease between 1\textsuperscript{st} year and 2\textsuperscript{nd} year as well as 2\textsuperscript{nd} year and 3\textsuperscript{rd} year.

![Figure 3-3. Stress variations for 3 years](image)

Data set was divided to 3 subgroups for each year and basic statistical analysis was performed to determine change in behavior during time. Statistical software Minitab 16 was used to interpret statistical outcomes shown in Figure 3-4, Figure 3-5 and Figure 3-6.
Figure 3-4. Statistical summary for 1st year

Figure 3-5. Statistical summary for 2nd year
In order to compare change between years; mean, median and highest stress values were compared since mean could not be used as only evidence for these data sets. Mean values were -1886.3 psi, -2096.7 psi and -2108.6 psi for the first 3 years, respectively. Moreover, median values were -1965.4 psi, -2132.1 psi, -2100.7 psi and highest stress values for each year were -2568.0 psi, -2708.8 psi and -2818.8. Therefore, results that are obtained from Figure 3-4, Figure 3-5 and Figure 3-6 as well as Figure 3-3 show that change between 2\textsuperscript{nd} and 3\textsuperscript{rd} year was very small compared to 1\textsuperscript{st} and 2\textsuperscript{nd} year. The main reason for the changes is can be listed as creep and shrinkage. Several studies show that stress change due to creep and shrinkage are highly active at early ages especially for the first 100 days as shown in Figure 3-7 and Figure 3-8.
Unfortunately, the first 4 months data is not available due the reasons explained above. Therefore, initial losses and drastic stress changes due to creep and shrinkage could not be monitored. Hence, 3rd year data can be used for damage detection data analysis as it can be assumed that data will follow same pattern without changing stress due to creep and shrinkage after 2.5 years.
Generating confidence interval for collected data is widely used approach in statistics and reliability engineering analysis. The confidence interval depends on a variety of parameters. Many practical applications and analysis are based on a 95% confidence interval. First, Anderson-Darling normality test was performed by using Minitab 16. Although central limit theorem states data sets with sufficiently large values of sample size follow approximately normal distribution, Figure 3-9 shows that data is not following normal distribution because A-squared value is not sufficiently small and p-value is not sufficiently large enough. Therefore, proper distribution type needs to be determined to establish confidence limits to check whether new data sets are in the limit or not.

![Summary for 3rd Year](image)

**Figure 3-9. Normality test for 3rd year**

Describing the correct distribution is crucial to identify confidence interval. Minitab 16 provides a tool for distribution identification which helps user to select the distribution that best fits. 15 parametric distribution families are available in the
literature. Based on plots and goodness-of-fit tests, distribution type would be identified. Figure 3-9 shows distribution analysis for the data set coming from N-12-C. Distribution identification analysis for other sensor can be found in APPENDIX B. There are two parameters to check the quality of the distribution in addition to the probability plot. Anderson-Darling test measures how well data follow the specific distribution. If the Anderson-Darling (AD) value is small, distribution type would fit to the data. If the p-value is smaller than 0.05 or 0.10 (significance level), test concludes that distribution is not fitting to the data set. The values of p-value for the Anderson-Darling test could not be obtained for each distribution since it is not present mathematically for certain distribution types. It is usually correct to compare them using AD and p-value to decide distribution type. On the other hand, if the values are close to each other, one of them could be chosen based on practical knowledge. Another measure is probability plot to determine distribution type. The middle line is expected percentile according to distribution based on likelihood parameters estimates. The lower and upper bounds for the confidence interval is represented at the left and right line. Therefore, if the points follow middle line which reinforce the goodness of the distribution can be considered distribution is correct. 15 different types of distributions were used to investigate data which are normal, normal with Box-Cox transformation, lognormal, 3-parameter lognormal, exponential, 2-parameter exponential, Weibull, 3-parameter Weibull, smallest extreme value, largest extreme value, gamma, 3-parameter gamma, logistic, log-logistic and 3-parameter log-logistic. Results can be seen in Figure 3-10, Figure 3-11, Figure 3-12 and Figure 3-13.
Figure 3-10. Distribution determination for normal, normal with Box-Cox transformation, lognormal, 3-parameter lognormal

Figure 3-11. Distribution determination for exponential, 2-parameter exponential, Weibull, 3-parameter Weibull
Figure 3-12. Distribution determination for smallest extreme value, largest extreme value, gamma, 3-parameter gamma.

Figure 3-13. Distribution determination for log-logistic and 3-parameter log-logistic.
Although 3-parameter Weibull provides the best AD and p-value, it is unattainable to say data follows the distribution. Therefore, none of the distribution types available in the literature can be applicable to the data set obtained from sensors.

Another conclusion is that seasonal changes have high influence on the data set shown in Figure 3-3 because stress values alter by changing season. In addition, Figure 3-4, Figure 3-5, and Figure 3-6 show local peaks can be seen in the histograms which reinforce the effect of seasonal variations. Therefore, model should be implemented which includes temperature effects as input to predict the behavior of the stress variations. Linear regression is performed which can be seen in Figure 3-14. Stress values are highly correlated with the temperature. R-square value is 96.1% which indicates main reason for the change in the stress and strain values are due to temperature. Therefore, stress values can be estimated by following equation for the sensor N-12-C. Linear regression analysis for other sensor can be found in APPENDIX B.

\[ \sigma = -1865.0 - 21.44 \]

* \( \sigma \) is stress in psi and \( T \) is the temperature in °C.

In addition, Figure 3-14 provides 95% confidence limits for the data to detect possible problems from future reading. However, residuals should be investigated carefully to determine the confidence interval shown in Figure 3-15. Residual means the difference between the sample and estimated function values. The standardized residual can be obtained by dividing residual of the sample to the standard deviation of the residuals to scale the residuals. The limit of standardized residual would be considered ±2 for 95% confidence interval. Standardized
residuals fits in Figure 3-15 shows standardized residuals are slightly more than ±2 limit.

Generating of confidence interval to examine future data is an effective way as long as the assumptions being made are true. One of the most important assumptions is that residuals are normally distributed when the confidence interval is used; however, histogram in Figure 3-15 reveals that residuals are following bimodal distribution instead of normal distribution. Therefore, assumption is not valid and using of confidence interval is not reasonable.
Another approach would be using tolerance intervals instead of confidence intervals. Focus of confidence intervals is population parameter, mean or the variance. Nonetheless, most of engineering applications require attention on the likelihood that a certain percentage of the measurements will be in the limit or not (Levine et al., 2001). According to book definition, tolerance interval is an interval.
that includes at least a certain proportion of the measurements with a stated confidence. Therefore, there are two input values which are “what percentage of the reading we want to cover” and “how high we want our confidence in the interval itself to be”. For instance, if the inputs are 95% and 90% for the confidence and proportion respectively, at least 90% of the future measurement will be in the limit with 95% confidence. This approach is more reliable than creating confidence interval because interval’s size will approach to population’s probability with increased sample when tolerance interval is used; on the other hand, confidence interval’s size will approach to zero width because size depends on sampling error (Vardeman, 1992).

In brief, tolerance intervals would be used to handle a range of values for a measurement’s characteristics that expected to cover a specified proportion of future readings. In addition, lower and upper limit would be formed such that future readings can be compared with the past values. There are two options available which are determination of tolerance interval by using Normal Method and Nonparametric (Distribution Free) method in the literature. If the data set shows the normal distribution or close to normal distribution, then Normal Method is the best for the set without any limit on the sample size. However, The Normal Method could not be considered robust when the data show significant deviation from normality (Elison, 1964). If the data is not normal, then The Nonparametric Method which is widely known as Distribution Free Method can be used. Distribution free method only requires that the data should be continuous. In addition, this approach needs to be used with large sample size.
Minitab 16 was used to calculate tolerance interval and 3\textsuperscript{rd} year data was used due to reasons explained above. 95\% confidence was requested for the at least 95\% of the population as shown in Figure 3-16. Then, 95\% confidence was requested for the at least 90\% of the population from past data can be seen in Figure 3-17. There are no specific value for confidence and proportion available in the literature; then, values close to 100\% were used in this approach.

Whereas upper and lower limits are -2626.1 psi and -1591.0 psi for The Normal Method, The Distribution Free Method gives -2620.2 psi and -1643.5 psi for the 95\% confidence and 95\% coverage as shown in Figure 3-16.

On the other hand, upper and lower limits are -2542.9 psi and -1674.25 psi for The Normal Method, The Distribution Free Method gives -2552.1 psi and -1702.9 psi for the 95\% confidence and 90\% coverage as shown in Figure 3-17. Interval is becoming narrow with decreased population as expected since the tail side has lower frequency than the middle; therefore, probability of including data that are at the tail side is becoming smaller with the decreased proportion of the population. In addition, it was proved that data is not following normality; therefore, The Distribution Free Method could be considered more reliable and accurate.
Although tolerance interval boundaries are obtained, boundaries are too wide to obtain proper information. Good data will be in the limit with certain confidence; however, data with problem may be in the limit as well. The reason is that as shown
in Application of Distribution Identification Method temperature has major effect on the stress and strain readings. As can be seen in Figure 3-14, stress values are low at the lower temperature and high at the high temperatures because girders and deck panels are trying to expand. On the other hand, an integral abutment from both ends restraints the movement which causes secondary stresses. Therefore, user may obtain higher stresses due to possible deterioration during low temperature seasons. However, user will not be able to understand that data is not safe and readings have potential problems up to bridge reaches higher temperatures and higher stresses as well. Hence, temperature induced models can be considered more reliable to detect possible deterioration problems. Nevertheless, linear regression approach does not offer using distribution free methods. One possible solution is that using combination of these two by dividing the data set to smaller intervals in certain temperature limit; tolerance interval can be used for each specific period. Temperature increment is selected as 5°C from -15°C to +40°C which are the minimum and maximum limit taken from sensors during 3rd year. All the tolerance intervals can be seen in APPENDIX A.

A significant result is that intervals for high and low temperature values are following distribution type very close to normal distribution which can be seen in Figure 3-20 and Figure 3-21. On the other hand, the intervals for +5°C to +20°C show the distribution different than normal as shown in Figure 3-18 and Figure 3-19. The reason is that temperature values for low and high temperatures belong to specific season such as winter or summer. It is not likely to have very low and high temperature readings during fall and spring season. Nevertheless, middle range values such as +10°C could be from summer, fall, winter or spring. Therefore,
seasonal changes have impact on the data as well as temperature. The main reason is stresses are not due to uniform temperature changes. The stress changes are mainly caused by temperature gradient throughout the depth which will be discussed in Thermal Gradient Load in detail. Creating tolerance interval charts for each season and each temperature interval for every sensor is not an easy process both for user and developer. In addition, creating these intervals for each season will not give crucial improvement compared to effort that will be given.

Consequently, the tolerance interval is adequate and easy method to detect potential problems easily. Each chart can be used for specific temperature and checked the future reading.
Figure 3-18. Tolerance interval plot for the data between +5°C to +10°C

Figure 3-19. Tolerance interval plot for the data between +10°C to +15°C
Figure 3-20. Tolerance interval plot for the data between +25°C to +30°C

Figure 3-21. Tolerance interval plot for the data between +30°C to +35°C
3.6 Application of Neural Networks in Health Monitoring

Neural networks are good at fitting functions. Advantages make the neural network best tool to estimate future values of stress readings coming from vibrating wire strain gages. Neural network function fitting tool was used in the analysis to predict and estimate future values. In fitting problems, the main goal is create a map between a data set of numeric inputs and numeric targets. In structural health monitoring, inputs may not be easily obtained for many applications; however, previous analysis results show that stress readings are highly affected by temperature changes. Therefore, input-output relationship can be determined by using neural networks. Neural network fitting function in Matlab helps for creating and training a network. Then, the performance of the network was evaluated by using mean square error and regression analysis.

A two layer network was used (hidden and output layer) with neurons using sigmoid transform function in hidden layer and linear output neurons. This layout can fit to multi-dimensional mapping problems if the data is consistent and enough neurons are used (Matlab, 2011).

In order to start to use the neural network, network should be configured by initializing the weights and biases after data is collected. Then, network needs to be trained and network should be validated. Only data set collected from 3rd year data were used when training and validating the network. Data set collected from sensors was used to train, validate and test the accuracy of the model. Therefore, 3 subsets are needed to obtain proper network. The first and the most important subset is the training set which is used for calculating the gradient and updating the weights and biases. The second subset is validation subset which is a kind of
retraining procedure by collecting error during the training process. Although the validation error is decreasing during training with the decreasing error of training in general, when the network starts to overfit the data; then, validation errors become large which stops the training and saves weights and biases at the minimum of the validation set error. Thus, this increasing error from validation set is a signal to end iterations for converging to minimum error with best fit. The last set which is the test set is not used in training. Therefore, test data set does not have any effect on the training, thereby providing an independent measure of network performance during and after training. In most of the cases 70% of the data is used to train data and rest is divided into two (15% each) and used for validation and test (Mathworks, 2000). The effect of division of the data was checked for the sensor N-12-C as shown in Figure 3-22, Figure 3-23, Figure 3-24 and Figure 3-25. Therefore, the division is not have any significant influence on the results; then, the recommended value was decided to use for further analysis which is 70% for training, 15% for validation and 15% for testing.

The last step before start to training is initializing weights and bias values. Although it requires random hand input, Matlab R2011b automatically assign weights with the configure command. On the other hand, user can define the initial weights by using the init.

After weights and bias are initialized, network is ready to train. There are many training algorithms which use gradient based methods for training as explained above for backpropagation calculation. Levenberg-Marquardt is the most famous training algorithm. Moreover, Bayesian Regularization, BFGS Quasi-Newton
Resilient Backpropagation are the other famous training algorithms available in the literature.

Levenberg-Marquardt optimization was used in the analysis because it has the fastest backpropagation algorithm and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms (Matlab, 2011).

The standard network that is used for function fitting with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer is used. The minimum number of hidden layer needs to be defined. The accuracy is increasing with the increasing number of hidden layers; however, increasing number of hidden layers would increase the epoch number that cause increase in the analysis time. Although there is not a strict and optimum number for number of hidden layers, value of 10 is used in many applications. In this analysis, 10 and 20 were assigned as number of hidden layers and the difference between them were monitored. The difference between them is not significantly different compared to an extra analysis effort can be seen in Figure 3-26. R values are same for training and validation and R values of testing is slightly lower in the network with 10 hidden layers. Mean square values are slightly low in the network with 20 hidden layer; however, the values are consistent enough and 10 hidden layers were decided to use can be seen in Figure 3-27.
Figure 3-22. Training of network with 80% for training, 15% for validation and 5% for testing

Figure 3-23. Training of network with 70% for training, 15% for validation and 15% for testing

Figure 3-24. Training of network with 60% for training, 25% for validation and 25% for testing

Figure 3-25. Training of network with 50% for training, 25% for validation and 25% for testing
Temperature values are assigned to input whereas stress values are outputs. Although epoch (iteration) number is changing for each training for same data set, approximately 249 epochs was used and analysis time was 8 min. Training process and performance can be seen in Figure 3-28.
There are 4 regression plots in Figure 3-29 for the best and last epoch. The plots show the network outputs with respect to targets for training, validation, test and the all data sets. Data needs to fall along a 45 degree line if there is a perfect relation. Falling along 45 degree indicates network outputs are equal to the targets which means network learned what it needs to learn. Network would be retrained in order to obtain more accurate results. Retraining process is a changing initial weights and bias values.
Figure 3-29. Regression plot for the best epoch

Figure 3-30 shows the error histogram which is created by using the differences between targets and outputs. It is an indication of model accuracy. If the error values are significant or outlier are dominating the histogram, which would be a sign for potential problem in the data set or in the structure. Most of the errors are between -60 and +70 psi which can be considered reasonable. In addition, there are substantial outliers present in the data set.
Consequently, neural networks are explained above is practically feasible for structural health monitoring. When 3 methods are compared, the best results with minimum error are obtained by using the neural networks. It is proven that artificial neural networks are a promising tool for system identification. In addition, analysis results are also reinforcing the practical feasibility of the neural network approach for structural health monitoring.

The Matlab algorithm of proposed neural network method can be found in APPENDIX D. In addition, same method could be used for each sensor that needs to be checked. User should only define the data as explained in the algorithm.
In conclusion, different three methods are explained for structural health monitoring and possible damage detection by using statistical methods. Advantages and disadvantages can be summarized as follows.

First, distribution determination types of statistical methods are tried to implement to analyze data. The key advantage of using first method is that implementation of methods are simple compared to others. In addition, these distribution types are widely used and accuracy of implementation is proven for years. Moreover, in order to apply these distribution types and create some certain confidence, users can create or write their own algorithms or there are commercially available software can be found in market for inexpensive prices or free. The main disadvantage is that stress data is not following any of the distributions available in the literature. This makes it unachievable to create the confidence level and predictions for future.

The second method is that generating tolerance interval. Tolerance interval is an interval that includes at least a certain proportion of the measurements with a stated confidence. Therefore, the likelihood that a certain percentage of the measurements would be analyzed to check whether readings are in the limit or not. The core advantage of using tolerance interval is that tolerance intervals allow to use normal and nonparametric models which is known as distribution free methods. Therefore, the method can overcome the distribution problem when the data is not following any distributions. In addition, the tolerance intervals are more appropriate for the engineering applications because it dealing with the complete data set instead of some specific values of data set as mean and variance. However, the major drawback is input output relationship would not be embedded into model. Linear regression analysis shows that there is an obvious correlation between temperature
and stress readings. Therefore, creating a model by disregarding this behavior can cause misinterpretation of analysis. In order to overcome this problem, simple solution is proposed which is dividing the data into smaller subsets. The recorded minimum temperature value is around -15°C and maximum is near to +40°C. 5°C increment size was decided to use and data set was divided into subsets. Then tolerance intervals are obtained for both normal and distribution free methods. The drawback of using this method is that it requires effort by user to create tolerance interval for each interment and each sensor.

The third method is using artificial neural networks to define representative function for data obtained from past. The neural network has the ability to detect pattern and create relationship between temperature and stress changes with its learning process. Moreover, artificial neural network can simulate all behavior of the data within a unified environment which is directly built by an experimental data using the self-organizing capability of neural network. The main drawback is its black box nature and greater computational burden.
CHAPTER IV

NUMERICAL SIMULATION OF FULL-DEPTH DECK PANEL CONNECTION FAILURE

4.1 Objective and Approach

The objectives of this section are to (1) present design details of the Parkview Bridge superstructure, (2) display and discuss the finite element (FE) modeling of components and their interactions, (3) show model calibration using sensor data, and (4) elaborate upon the simulation of identified distress types to develop stress/strain contours. The analysis results, in conjunction with sensor data, are used to identify signatures of potential performance issues of the full-depth deck panel system.

4.2 Bridge Configuration and Details

The twenty three degree (23°) skew Parkview Bridge has four spans with seven simply supported PC-I Type III girders (Figure 4-1). Expansion is allowed only at piers 1 and 3. Fixed bearings are used at the abutments and pier 2. One inch nominal diameter dowel bars are used to prevent backwall sliding over the abutment stems, making them integral abutments (Figure 4-2). In addition, staggered threaded inserts are provided between girder webs and the backwall allowing shear transfer. Concrete diaphragms are used to encase beam ends over the piers, but asphalt felt with roofing tar/asphalt is used to debond beam ends (Figure 4-3). Joints between beam ends over the piers are filled with concrete to form the diaphragms.
Furthermore, the pier diaphragm detail allows girder ends to translate along the girder longitudinal axis (provided that the expansion bearings are used) and to rotate about a horizontal axis perpendicular to the girder’s longitudinal axis. However, the beam ends over the abutments are not debonded using asphalt felt. ASTM A709 grade 36 structural steel sections (MC 18 × 42.7) are used as intermediate diaphragms for span 2 and 3 (Figure 4-4).

Deck width is made up of two full-depth panels, referred as north and south panels, which are connected using a 2 ft wide cast-in-place closure pour (Figure 4-5). Once the panels are placed and leveled, transverse joints between panels were grouted, and the longitudinal joint was formed with cast-in-place concrete. The full-depth deck panel assembly was post-tensioned in the longitudinal direction using tendons placed through 14 ducts. The haunches and deck shear connector pockets were grouted after the longitudinal post-tension application. Finally, bridge construction was completed by placing a waterproofing membrane, a 1.5 in. asphalt wearing surface, and safety barriers.

Initial post-tension force applied at each location was 182.8 kips. The spacing between post-tension ducts is shown in Figure 4-5. The post-tension tendon size, tendon length, stressing force, stressing end, and stressing sequence are shown in Table 4-1.
### Table 4-1. Post-tension Details

<table>
<thead>
<tr>
<th>PT Designation</th>
<th>Tendon Size</th>
<th>Tendon Length</th>
<th>Stressing Force (kips)</th>
<th>Stressing End</th>
<th>Stressing Sequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT A</td>
<td>6</td>
</tr>
<tr>
<td>L2</td>
<td>4×0.6&quot;</td>
<td>245’-6 3/4&quot;</td>
<td>182.8</td>
<td>ABUT B</td>
<td>14</td>
</tr>
<tr>
<td>L3</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT A</td>
<td>1</td>
</tr>
<tr>
<td>L4</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT B</td>
<td>8</td>
</tr>
<tr>
<td>L5</td>
<td>4×0.6&quot;</td>
<td>245’-6 3/4&quot;</td>
<td>182.8</td>
<td>ABUT A</td>
<td>5</td>
</tr>
<tr>
<td>L6</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT B</td>
<td>11</td>
</tr>
<tr>
<td>L7</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT A</td>
<td>3</td>
</tr>
<tr>
<td>L8</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT B</td>
<td>10</td>
</tr>
<tr>
<td>L9</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT B</td>
<td>12</td>
</tr>
<tr>
<td>L10</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT A</td>
<td>4</td>
</tr>
<tr>
<td>L11</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT B</td>
<td>9</td>
</tr>
<tr>
<td>L12</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT A</td>
<td>2</td>
</tr>
<tr>
<td>L13</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT B</td>
<td>13</td>
</tr>
<tr>
<td>L14</td>
<td>4×0.6&quot;</td>
<td>245’-6 1/4&quot;</td>
<td>182.8</td>
<td>ABUT A</td>
<td>7</td>
</tr>
</tbody>
</table>
Figure 4-1. Parkview Bridge elevation
Figure 4-2. Backwall-abutment connection details
Figure 4-3. Pier-diaphragm-beam end connection details

Figure 4-4. Intermediate diaphragm details
Figure 4-5. Deck panel and post-tension layout
4.3 Material Properties

Table 4-2 shows the material properties used in the model.

<table>
<thead>
<tr>
<th>Description</th>
<th>Density (lb/ft³)</th>
<th>Strength (psi)</th>
<th>Modulus of elasticity (ksi)</th>
<th>Poisson’s ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deck Panel</td>
<td>150</td>
<td>8,000</td>
<td>5,000</td>
<td>0.2</td>
</tr>
<tr>
<td>Haunch</td>
<td>150</td>
<td>8,000</td>
<td>5,000</td>
<td>0.2</td>
</tr>
<tr>
<td>I-beam at release</td>
<td>150</td>
<td>5,700</td>
<td>4,303</td>
<td>0.2</td>
</tr>
<tr>
<td>I-beam at service</td>
<td>150</td>
<td>7,000</td>
<td>4,769</td>
<td>0.2</td>
</tr>
<tr>
<td>Prestress strands (0.6” ø, 270 ksi low relaxation)</td>
<td>491</td>
<td>270,000</td>
<td>28,500</td>
<td>0.3</td>
</tr>
<tr>
<td>Post-tension tendons (0.6” ø, 270 ksi low relaxation)</td>
<td>491</td>
<td>270,000</td>
<td>28,500</td>
<td>0.3</td>
</tr>
<tr>
<td>Grout</td>
<td></td>
<td>8,000</td>
<td>5,000</td>
<td></td>
</tr>
<tr>
<td>CIP closure</td>
<td>150</td>
<td>6,000</td>
<td>4,415</td>
<td>0.2</td>
</tr>
<tr>
<td>Intermediate diaphragm</td>
<td>491</td>
<td>60,000</td>
<td>29,000</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Thermal expansion coefficient (AASHTO LRFD 2007):

Concrete and grout materials = $6 \times 10^{-6}$ (in/in/°F)

Steel = $6.5 \times 10^{-6}$ (in/in/°F)
4.4 Analysis Loads

The load types used in the analysis include the bridge self-weight, the trucks used for load testing, and thermal gradient. As discussed in Chapter 5, live load effect is not captured by the sensors. Further, the static truck load testing data presented in Abudayyeh (2010) shows that the bridge is very stiff, and the live load has a negligible effect on the structure response to loading.

4.4.1 Self-weight

Material densities and component geometries are used to introduce the self-weight of bridge components, except the asphalt wearing surface, diaphragms, and barriers. The weight of the asphalt wearing surface is applied as a uniformly distributed load. Barrier load is applied as a uniformly distributed strip load along the deck edge.

4.4.2 Truck Loads

The FE model calibration under static loads is performed using load test data. Four single-direction and six bi-directional load scenarios are considered. Two types of trucks were used in load testing (Figure 4-6).

![Type I truck for single-directional testing](image1) ![Type II truck for bi-directional testing](image2)

*Figure 4-6. Truck types used for load testing*

Trucks were placed to develop ten loading scenarios (Table 4-3). The truck positions are shown in Figure 4-7. Trucks were placed to maximize the span
moments of the loaded spans. Dimensional details of the Truck I and Truck II are illustrated in Figure 4-8 and Figure 4-9, respectively. Axle weights given in Table 4-4 were measured in field.

According to Yap (1989) tire contact area and pressure distribution can be changed due to the state of loading and tire production methods. Therefore, tire contact pressure distribution may differ even within the same type of tire produced by same company. Due to difficulty in knowing the exact pressure distribution, it was decided to use the tire pressure distribution and the patch dimension of 20 in.×10 in. specified in the AASHTO (2010).

Table 4-3. Load Testing Scenarios

<table>
<thead>
<tr>
<th>Testing Scenario</th>
<th>Truck Type 1 Location (Single-Directional – 1 Truck)</th>
<th>Truck Type II Location (Bi-Directional – 2 Trucks)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>47</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>42</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>49</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>40</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>45,44</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>47,42</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>49,40</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td>51,38</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td>47,40</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td>45,33</td>
</tr>
</tbody>
</table>

Figure 4-7. Truck positions
Figure 4-8. Truck type I truck configuration

Figure 4-9. Truck type II configuration

Table 4-4. Axle Weight of Type I and II Trucks

<table>
<thead>
<tr>
<th>Axle #</th>
<th>Single Directional Truck Type 1 Weights (lbs)</th>
<th>Bi-Directional Truck Type 1 Weights (lbs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Front Axle</td>
<td>9,640</td>
<td>17,850 18,350</td>
</tr>
<tr>
<td>#2 Axle</td>
<td>35,540</td>
<td>18,050 18,600</td>
</tr>
<tr>
<td>#3 Axle</td>
<td></td>
<td>17,800 18,250</td>
</tr>
<tr>
<td>#4 Axle</td>
<td>34,580</td>
<td>-</td>
</tr>
<tr>
<td>#5 Axle</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>Gross Weight</td>
<td>79,760</td>
<td>53,700 55,200</td>
</tr>
</tbody>
</table>
4.4.3 Thermal Gradient Load

The thermal gradient profiles specified in AASHTO (2010) are defined for design purposes. The analysis performed in this project is to understand the structural performance; hence, the use of thermal gradient profile through the depth of bridge superstructure, at the time of interest, is important. This is a great challenge as there were no temperature sensors placed through the cross-section depth. Extensive literature review was performed and various recommendations were reviewed in order to identify thermal gradient profile representatives of a day in summer and a day in winter. Priestly (1976) proposed that vertical temperature gradient, during a period that the deck heats up follows a fifth-degree parabola (Figure 4-10). The example presented by Priestly (1976) is a box-girder in which the temperature reaches ambient value at a depth of 47.24 in. along the web during an early afternoon of a hot summer day.

![Temperature profile proposed by Priestly (1976)](image)

Based on a set of data collected over a period of 18 hours from the I-35W St. Anthony Falls Bridge, French et al. (2009) developed thermal gradients through the
depth at midnight, 6 a.m., noon and 6 p.m. (Figure 4-11). The data collected at noon closely represents the fifth-order model presented by Priestly (1976). The profile at 6 p.m. closely represents a second-order curve.

Vibrating wire gages embedded in the deck panels contain thermistors and records strains as well as temperature. Within a limited area, vibrating wire gages are attached to top and bottom reinforcements of the deck panels. However, bottom layer sensors are not available above the girders. Literature recommended the fifth and second-order thermal profiles for concrete girders to represent thermal gradient profile at noon and 6 p.m. during a summer day. Hence, the fifth and second-order thermal profiles that were calibrated with the measured temperature at the depth of vibrating wire gages were used for thermal gradient load at noon and 6:00 p.m. for the girders and the deck above the girders (Figure 4-12). On the other hand, the temperature records from top and bottom thermistors were used for the rest of the
deck (Figure 4-13). Even though different temperature profiles were used to represent temperature distribution within concrete elements, a constant temperature was assigned to the top surface of the entire deck. There are no reliable models to represent temperature profile during winter. Hence, temperature and stress data recorded during summer were used for model calibration.
4.5 Finite Element Modeling

Altair HyperMesh version 10 (Altair 2010) is used as the finite element pre/post-processor while Abaqus version 6.10 (Simulia 2010) is used as the solver. The finite element model consists of full-depth deck panels, PC-I girders, prestress strands, post-tension tendons, diaphragms, shear keys and haunch. Concrete components are modeled by using, incompatible mode, 8-node linear brick elements (C3D8I). The behavior of incompatible mode elements is similar to quadratic elements with lower computational demand compared to quadratic elements. Their disadvantage is the sensitivity to element distortion, which may result in stiffer elements. The element types listed in the following table are used in the model. In addition to the individual components models, component interaction models is vital to understanding the structural system behavior and implications of potential issues on structural durability such as debonding at panel joints or at the haunch. The boundary interaction between the components is modeled by contact
options in Abaqus. A detailed discussion of contact analysis options, their use, and selection and verification is given in Romkema et al. (2010).

<table>
<thead>
<tr>
<th>Components</th>
<th>Element Types</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deck Panel</td>
<td>C3D8I</td>
<td>8-node linear brick element</td>
</tr>
<tr>
<td>Haunch</td>
<td>C3D8I</td>
<td>8-node linear brick element</td>
</tr>
<tr>
<td>I-beam</td>
<td>C3D8I, C3D6</td>
<td>8-node linear brick element, 6-node linear triangular prism</td>
</tr>
<tr>
<td>Prestress strands</td>
<td>T3D2</td>
<td>2-node linear 3-D truss</td>
</tr>
<tr>
<td>Post-tension tendons</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grout</td>
<td>C3D8I</td>
<td>8-node linear brick element</td>
</tr>
<tr>
<td>Intermediate diaphragm</td>
<td>B31</td>
<td>2-node linear beam</td>
</tr>
<tr>
<td>End diaphragm</td>
<td>MPC, Beam</td>
<td>Rigid Beam Element</td>
</tr>
</tbody>
</table>

### 4.5.1 PC-I Girder

Simply supported PC-I girder models with prestressing strands are developed representing girder geometries and prestressing strand profiles for each span. The girder models are verified against the camber calculated from basic relations given in the PCI Bridge Design Manual (PCI 2003). Further, the girder cambers are compared against those stated in the bridge plans.

Girder end stresses are not needed in this particular study. Hence, strands are lumped into groups. They are modeled in groups maintaining the strand eccentricity by considering the total cross-section area of strands (Table 4-6) and debonded lengths (Table 4-7) that matches the camber and stresses under self-weight and prestressing forces. The C3D8I and C3D6 elements represent girder geometry.
while T3D2 elements represent the strands. Moreover, the FE mesh configuration is developed by limiting the maximum aspect ratio to 5 for more than 90 percent of the elements used in girder models (Figure 4-14). Material properties are assigned as per Table 4-2. The girder design details and FE models are shown in Figure 4-14, Figure 4-15 and Figure 4-16.
Table 4-6. Strand Locations and Total Number of Strands

<table>
<thead>
<tr>
<th>Span</th>
<th>Midspan</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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Table 4-7. Strand Debond Length

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<th>Debonded length (ft)</th>
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<td>2 and 3</td>
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<td>2</td>
<td>20</td>
</tr>
<tr>
<td>2 and 3</td>
<td>2</td>
<td>2</td>
<td>10</td>
</tr>
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<td>2 and 3</td>
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</tr>
<tr>
<td>2 and 3</td>
<td>3</td>
<td>2</td>
<td>5</td>
</tr>
</tbody>
</table>

Section view

Isometric view

Figure 4-14. General views of PC-I girder FE models
Figure 4-15. Span 1 and span 2 and 3 end section girders details and FE models
Span 2 and 3 girder details (mid section)

Span 4 girder details

Span 2 and 3 FE model (mid section)

Span 4 FE model

Figure 4-16. Span 2 and 3 mid section and span 4 girders details and FE models
4.5.2 Girder End Boundary Conditions

Movement is allowed over pier 1 and 3 while fixed bearings are used over pier 3 (Figure 4-1). Girder movement is allowed in the direction of the girder centerline by providing a slotted sole plate based on bearing details provided in Figure 4-17 and Table 4-8. Note that elastomeric pads are not used over the abutments. Further, dowels are used to connect the backwall to the abutment developing integral abutment details (Figure 4-18). As per the design plans, the shear moduli of plain elastomeric bearings and laminated elastomeric bearings are 200 psi (+/− 30 psi) and 100 psi (+/− 15 psi), respectively. Elastomeric bearing design is based on a maximum pressure of 500 psi under dead load and 800 psi under combined dead and live loads.
Plan view of a bearing

Section C-C

Section D-D

Figure 4-17. Bearing details
Table 4-8. Elastomeric Pad and Shim Dimensions

<table>
<thead>
<tr>
<th></th>
<th>Span 1</th>
<th>Span 2</th>
<th>Span 3</th>
<th>Span 4</th>
</tr>
</thead>
<tbody>
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<td>2</td>
<td>2.5</td>
<td>2.5</td>
</tr>
<tr>
<td>(Q) Parallel to beam (in.)</td>
<td>12</td>
<td>8</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>(W) Perpendicular to beam (in.)</td>
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<td>19</td>
<td>19</td>
<td>19</td>
</tr>
<tr>
<td>GG (in.)</td>
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<td>0.25</td>
<td>0.25</td>
</tr>
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<td>4@0.37”</td>
<td>4@0.37”</td>
</tr>
<tr>
<td>Shims</td>
<td>-</td>
<td>4@0.1046”</td>
<td>5@0.1046”</td>
<td>5@0.1046”</td>
</tr>
</tbody>
</table>

Figure 4-18. Abutment and backwall connection details
4.5.3 Full-Depth Deck Panels, Joints, and Haunch

The 9 in., full-depth deck panels are designed to span over the girders. The deck panels are modeled having node lines along the post-tensioning duct locations to accommodate post-tensioning tendons depicted in Figure 4-5. The typical deck panel joint detail, described in the plans, is simplified in the model since its effect on the global structural response is negligible. Simplified flat contact, 2 in. wide joint detail represents grouted joints between deck panels (Figure 4-19).

Furthermore, haunch thickness changes as detailed in the plans, but a 2 in. uniformly thick haunch is incorporated into the model (Figure 4-20). The element type of C3D8I is selected for all of the deck panels, joints, and haunch in this model.

(a) Typical joint detail  (b) FE deck panel model with a panel joint

Figure 4-19. Typical joint details and FE representation
4.5.4 End and Intermediate Diaphragms

The intermediate diaphragms are modeled using beam element, which has an equal cross-section and moment of inertia to the MC 18x42.7 steel section. For end diaphragms, instead of using solid elements, rigid elements are used. Ends of the rigid elements are connected to the beam as shown in Figure 4-21. The rigid element configuration, shown in Figure 4-21, is selected to avoid potential over-constrained problems. Concrete fill material shown in Figure 4-21 is defined at the pier location between girder ends by using C3D8I elements.
4.5.5 Bridge Model

During the construction, prestress I-beams were erected and shim packs were installed on top of the girders. Deck panels were placed on top of the shim packs allowing horizontal movement of the panels. Subsequently, deck panel joints were grouted and the CIP closure concrete was placed. After CIP and grout joints reached 3500 psi, post-tensioning tendons were installed and stressed. Finally, haunch and shear pockets were grouted. This process allowed compressing only the deck panel system without creating any secondary stresses on rest of the components.

The FE model represents the entire bridge superstructure. Abaqus version 6.10 allows removing and adding elements during analysis. This option in abaqus was implemented to model the construction process by first removing elements from the full bridge models and adding them back on gradually. First, surfaces were generated. Then, the self-weight of the haunch and deck panels was calculated. Then, the haunch was removed, and the self-weight of haunch and deck panels was applied to the top of the beam. At the same time, tendons in I-beam and deck panels
were stressed to induce prestress and post-tension effects. During this particular analysis step, deck panels were supported on temporary supports such that there was no load transfer between the deck panels and the I-beams. Afterwards, the haunch was added to the structure, and uniform load and temporary boundary conditions were removed. Consequently, the complete superstructure model was developed without inducing secondary stresses.

4.5.6 Soil-Structure Interaction Modeling

Bridges with integral abutments are a type of bridge in which deck is connected monolithically with the abutment wall with a moment-resisting connection. In addition, steel or concrete piles are used to carry vertical load beneath the abutment in general. Although this abutment type becomes one of the most popular abutment types due to its cost advantage, secondary stresses under thermal expansion and contraction should be investigated well. The stress reading coming from sensors show that thermal changes have the major influence on the structure.
Hence, secondary stresses are highly active in this type of bridge type due to reaction of the soil. Uniform and gradient thermal changes, settlements of substructure, post tensioning may cause these secondary stresses because of the restraint coming from continuous superstructure by backfill (Burke, 1990). In order to find the reaction of the soil abutment should be modeled considering the soil behind the abutment walls and next to the foundation piles. However, this soil behavior is nonlinear due to nonlinear behavior of soil during compaction and depends on both wall translation and wall rotation. Modeling of soil-structure interaction is quite difficult because it needs iterative analysis in which soil reaction should be modified manually depending on the deformation level behind the abutment wall and pile. Iterative analysis of soil-structure interaction which is known as equivalent linear approach is time consuming and not accurate (Faraji et al., 2001). Faraji et al. (2001) proposed a model for integral abutment bridges to evaluate substructure and superstructure under earthquake. A 3D finite element model of bridge was modeled using nonlinear springs by considering force deflection relations based on National Cooperative Highways Research Program (NCHRP, 1991) design manual for the abutment walls and American Petroleum Institute (API) (1993) design curves for the piles.
Hence, modeling the bridge disregarding soil-structure interaction may affect the accuracy of the model where precise results are needed. The FE analysis results can be improved by modeling soil-structure interaction using nonlinear springs with compete model; however, required modeling efforts and increase in analysis time do not justify the potential outcome since complete finite element model with abutment and piles in addition to the model which uses contact modeling in several areas would increase the analysis time tremendously. Hence, separate 3D model pile-abutment slice was decided to model of the interaction instead of modeling complete bridge as shown in Error! Not a valid bookmark self-reference.

First, abutment slice is modeled for left and right side of the bridge. For the wall C3D8I brick elements are used for concrete wall with 23 degree skew. Three dimensional first order B31 beam element is used to model HP piles. B31 is a Timoshenko beam which allows transverse shear deformation which makes it usable for slender beams (Abaqus, 2010). SPRING1 type of spring element is used since SPRING1 elements are used between a node and ground, acting in a fixed direction. In addition, end points of piles are assumed fixed.

Total of 16 nonlinear springs are used for 4 layers for the abutment. The behavior of the soil is defined by using National Cooperative Highways Research Program (NCHRP, 1991) design manual. Duncan and Clough (1991) proposed a method by considering the wall movement to calculate coefficient of lateral earth pressure $K$ as shown in Figure 4-24.

The horizontal normal stress can be found by using following equation.

$$\sigma_n' = K \cdot \sigma_z' \text{ where } \sigma_z' = \gamma \cdot z$$
where $\sigma_z'$ is the vertical effective normal stress, $K$ is the coefficient of lateral earth pressure from Figure 4-24, $\gamma$ is the dry density of the soil and $z$ is the depth of soil. Then, following formula is used to calculate lateral force-deflection curve for a node that spring was defined.

$$F = K \ast \sigma_z' \ast w \ast h$$

where $F$ is the force, $w$ is the width of tributary area and $h$ is the height as shown in Figure 4-23. Several assumptions have been made. First, soil type behind the wall was assumed dense sand. Dry density, $\gamma$, of the sand was assumed 125 lb/ft$^3$ and angle of internal friction was assumed 45 degree. In addition, soil behavior behind the abutment wall and next to the pile is assumed uncoupled nonlinear Winkler springs wherein the deflection or stress at one level does not affect the other levels. Additionally, the intensity of pressure due to soil depends on the relative abutment displacement towards backfill. Duncan and Clough (1991) represent this behavior using finite element analysis as a ratio of wall movement to wall height ($\Delta/H$). The earth pressure coefficient, $K$, would change according to $\Delta/H$ as shown in Figure 4-24. Assuming a small displacement of the abutment, the $K$ value could be assumed linear and secant slope of the curve could be used to obtain linear $K$ value (Dicleli and Erhan, 2010). Same approach was used to determine $K$ for Parkview Bridge and $K_o = 0.29$ at $\Delta/H = 0.000$ and $K_o = 1.89$ at $\Delta/H = 0.001$. Then, $K$ can be assumed 1600 * $\Delta/H$ for small displacement calculations. Although this approach is not effecting the results significantly, small displacement assumption should be validated after the analysis because if the displacement values are not small; then $\Delta$ will be high and it may mislead the results.
Then, force-deflection properties are defined for each layer of nonlinear springs behind abutment wall. On the other hand, force-deflection relationship should be implemented for the springs that are adjacent to HP piles. 6 nonlinear springs were
defined for each pile to model the nonlinear soil pressure-deflection behavior. An American Petroleum Institute (1993) design guideline provides a soil pressure-deflection calculation method for given depth. According to design guideline soil resistance pressure-deflection can be expressed as follows:

\[ P = A \cdot p_u \cdot \tanh \left( \frac{k \cdot H}{A \cdot p_u} \cdot \gamma \right) \]

where \( A \) is the factor to account for cyclic or static loading condition. For static condition \( A \) is 0.9. \( p_u \) is the ultimate bearing capacity at depth \( H \). \( p_u \) is the smaller of \( (C_1 \cdot H + C_2 \cdot D) \cdot \gamma \cdot H \) or \( C_3 \cdot D \cdot \gamma \cdot H \). In addition, \( k \) is the modulus of subgrade reaction as a function of angle of internal friction. Coefficients and \( k \) can be found in API (1993) design manual.

Spreadsheet program is used to determine force deflection relationship of pile springs. After all the spring properties are defined; then, displacement controlled analysis has been made by giving +0.5 in and -0.5 in lateral displacement. Then, reaction forces are monitored and recorded. Obtained force-deflection values have been assigned to the full model by using same spring properties.

**4.5.7 Contact Surface Modeling**

The bridge has a 23 degree skew. Girders are placed parallel to the bridge’s longitudinal axis, and their ends are perpendicular to its longitudinal axis. Deck panels are placed parallel to pier or abutment axes. Because of these reasons, two different mesh configurations were developed for the girders and deck panels. Furthermore, a refined mesh configuration is used for deck panels to maintain their maximum aspect ratio of less than five. Five is considered to be the critical aspect
ratio for stress analysis since we are interested in deck panel stresses under the aforementioned loads.

Interaction between dissimilar meshes can be established using contact interaction. Abaqus allows three different types of contact analysis which are general contacts, contact elements and contact pairs. According to Romkema (2010), the contact pair option requires a surface to be created at each interface but will yield more accurate results; hence, interaction between two dissimilar meshes was defined by using contact pair option in Abaqus. Details of this modeling process can be found in Romkema et al. (2010) and Simulia (2010). Master and slave surfaces were generated between the beam and haunch and haunch and deck panels (Figure 4-25).

![Figure 4-25. Contact surfaces](image)

### 4.5.8 FE Model Calibration

#### 4.5.8.1 Calibration with Load Test Data

Three sensor groups were monitored during load testing. As stated previously, data was collected during all 10 loading scenarios. The three sensor groups are: (1) all C sensors embedded in the north panels and located closed to the closure joint; (b) A sensors embedded in south panels and located over the piers; and (c) F sensors embedded in south panels and located at the mid-span of spans 2 and 3 (Figure 4-26). These three sensor groups are labeled as North C, South A, and South F,
respectively for the purpose of comparison with FE results. The measured stress from sensors during each of the 10 loading scenarios was compared with the FE results. Figure 4-27 is an example of the comparison of stresses measured using North C, A, and F sensors and the FE analysis results for loading scenario 1.

FE analysis results correlate well with sensor data except in scenarios 2 and 9. During these two loading scenarios, several C and F sensors show tensile stresses of up to 40 psi, while they are expected to be under compressive stresses. As seen from the Figure 4-27, the change in stress under static truck load is very small. Accuracy of the Vibrating Wire Sensors embedded in concrete is at ± 0.5%. Initial readings of the sensors, before placing the trucks, were about -2000 psi; therefore, a ±10 psi deviation would be within the resolution accuracy and not discernible. Hence, most of the load testing data lies within the noise level of the sensors, an indication of the negligible impact of live load on stresses that develop in the deck panels.

For joint durability, thermal loads play a significant role, and further analysis was required to calibrate the model under temperature loads. Other scenarios can be found in APPENDIX C.
Figure 4-26. Sensor locations and deck layout
Figure 4-27. Comparison of load test data and FE analysis results – Scenario 1
4.5.8.2 Calibration with Thermal Loads

A parametric analysis was conducted evaluating various mesh configurations, temperature profiles, and boundary conditions. As per the abutment design details, girder ends are encased with a cast-in-place concrete backwall which is connected to the abutment wall through a single layer of dowels. Note that, in this bridge, the girder ends are not constrained from rotation. Therefore, only horizontal shear and vertical forces are transferred from the bridge superstructure to the abutment. Backfill and the piles provide some restraint to bridge movement. As shown in the sensor data shows good correlation. Note that the data shown in Figure 4-28 represent the change in stress from noon to 6 p.m.

In addition, a slight change in temperature profile changes the stresses developed in the deck. The temperature profiles, discussed in section 4.4.3, are for a section without an asphalt wearing surface. Presence of an asphalt cover affects the surface temperature (Fouad 2007). However, due to unavailability of temperature profiles for bridge decks with asphalt wearing surface, the temperature profiles and values given in section 4.4.3 were used for further analysis.

According to the design details, bridge superstructure is restrained for vertical, lateral, and transverse directions at pier 2. Expansion bearings are used at pier 1 and 3 which do not prevent uplift of girders. Hence, analysis was performed by allowing uplift and longitudinal translation at pier 1 and 3 while maintaining pin supports at pier 2 and the abutments. The results are identical to the stresses calculated from the model without uplift (Figure 4-28). Hence, further analysis was
performed using the model without uplift at pier 1 and 3 which drastically reduced the analysis time.

The differences observed in analysis results and sensor data can be attributed to the difference in actual temperature variation within the deck and the temperature profiles used in the analysis and potential movements at the abutments.
Figure 4-28. Change in longitudinal stress from noon to 6 p.m. under thermal load
4.5.9 Bridge Deck Stresses at the End of Construction

After model was calibrated, the bridge deck stresses at the end of construction were calculated through a construction process simulation. Stress contours were developed under self-weight and post-tension (Figure 4-29). Tensile stresses were developed at the edge of the deck panel over the abutments and located in between the post-tension ducts. Bridge deck top surface longitudinal stress variation, between two post-tension ducts, under self-weight and post-tension is shown in Figure 4-30. As shown in Figure 4-30, all the deck panel joints are in compression and the values are around -400 psi, as expected from the design.

![Deck panel stress at the end of construction under self-weight and post-tension (psi)](image)

Figure 4-29. Deck panel stress at the end of construction under self-weight and post-tension (psi)
4.5.10 Modeling Panel Joint Defects

The long-term durability and serviceability of full-depth deck system is questionable as deterioration starts at the transverse joints between deck panels. Most of the durability problems are associated with construction quality control and quality assurance issues related to panel joint grout and grouting procedures (Sneed 2010). After careful consideration of the design details and performance of existing full-depth deck panel systems, in terms of durability, the weakest link in the Parkview Bridge is identified as the transverse joints between deck panels. Hence, it was decided to simulate only the debonding of transverse deck panel joints and develop deterioration prediction models.

As discussed previously, the impact of traffic load is insignificant and not considered in deterioration modeling. Due to lack of models representing temperature variation through the deck during an entire 24-hr cycle, discrete loading was applied simulating stress variation between noon and 6 p.m. As
presented in Section 4.4.3, change in thermal gradient from noon to 6 p.m. in a summer day was used. The analysis yielded only one data point a day. Analysis did not include creep and shrinkage as their impact on stress variation is minimum within such a short period of 6 hours in a precast system.

Deterioration of joint between panel 7 and 8 on the north span (i.e., 7N and 8N in Figure 4-26) was considered. Considering the worst case scenario, joint separation was simulated. Abaqus version 6.10 allows changing material properties between analysis steps. This option was used and grout modulus of elasticity was changed to a very small value so that there was no load transfer across the joint. Post-tension strands were continued through the joint, irrespective of the joint condition. Stress variation in panel 7N and 8N without and with deterioration is shown in Figure 4-31 and Figure 4-32, respectively. Stresses shown in the figures are due to change in temperature from noon to 6 p.m. When there is no deterioration at the joint, panel 7N and 8N behave monolithically while the deck panels remain compressed (note that the negative values presented in the figures represent compression). On the other hand, panels start to show tensile stresses as monolithic behavior between panels is lost due to deterioration at the joint (Figure 4-32).
Figure 4-31. Deck panel transverse stress at 6 p.m. - without joint deterioration (psi)

Figure 4-32. Deck panel transverse stress at 6 p.m. - with joint deterioration (psi)
4.6 Deterioration Signatures through Numerical Analysis

Two different models, with and without deterioration, were analyzed following the procedure discussed in Section 4.5.10 to monitor the behavior of the structure under thermal loads. According to load test data and the analysis of sensor data, the dominant load is thermal. Hence, the FE analysis was performed under thermal gradient. The temperature data collected from embedded sensors was used for this purpose. VWSG readings and FE results comparison table and chart for the sensor N-7-B and N-8-E can be found in Table 4-9 and Figure 4-33, respectively. Variation of the data comparison shows same behavior; however, there are small difference between readings and analysis results. Direct comparison of stresses from sensors and FE analysis was not meaningful because the FE model did not include shrinkage, creep and other parameters that might have contributed to the sensor readings. Sensor readings expected to same for N-7-B and N-8-E; however, there is shift between them which reinforce the inadequacy of direct comparison. The most elementary approach would be shifting the analysis results to the readings which will be calibration constant for each sensor.
Table 4-9. Comparison Table for VW Readings and FE Results

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>N-7-B - VW Reading (psi)</th>
<th>N-8-E - VW Reading (psi)</th>
<th>N-7-B - FE Analysis (psi)</th>
<th>N-8-E - FE Analysis (psi)</th>
</tr>
</thead>
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</tr>
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<td>-1416.2</td>
<td>-1250.1</td>
<td>-1271.1</td>
</tr>
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</table>

Figure 4-33. Stress variation for 7 days

Calibration constant was determined by taking the difference between August 1 - noon reading and corresponding analysis result for the sensors N-7-B and N-8-E
first reading. Finite element model was calibrated using temperature data collected during a period of 7 days and stress data collected from vibrating wire sensors during the same period by adding calibration constant to shift the curves as shown in Figure 4-34. Finite element results and sensor data correlate well. This proves that the FE model is capable of representing bridge superstructure response under thermal gradient.

![Figure 4-34. Calibrated stress variation for 7 days](image)

Once calibration factors were introduced, a very good correlation was observed between the transverse stresses calculated along the joint between panel 7 and panel 8. Therefore, stress change from sensor readings and finite element results between two different phases can be assumed same due to constant calibration factor. This assumption is crucial to evaluate behavior of deterioration by using numerical analysis outcomes. In addition, very high stress fluctuations were observed when joint deterioration was simulated in the FE model. Transverse stress variations between north panel 7 and 8 along the panel joint with and without deterioration can be seen in Figure 4-35.
Figure 4-35. Transverse stress variation along the panel joint.
CHAPTER V

A COMBINED STATISTICAL AND NUMERICAL APPROACH FOR DETERIORATION PREDICTION

5.1 Objective and Approach

The objectives of this section are to (1) present data for healthy and unhealthy structure from calibrated model, (2) display and discuss strength of the statistical models used for two different sensors. The first sensor was selected from deterioration location whereas the second was selected from one of the longitudinal sensors in the panel far from problem location.

5.2 Data Selection

Once numerical model has been calibrated, stress change due to deterioration can be predicted. Two different sensor readings and their numerical deterioration prediction will be used to detect potential deterioration between north panel 7 and 8. The transverse joint sensor at panel joint location (N-7-B) was used. In addition, although longitudinal sensor N-7-C is not at the potential deterioration location its values were also used to determine capability of possible determination detection.

First, sensor readings and predicted deterioration values were created for 5 days by using the approach discussed in previous section for the sensors N-7-B and N-7-C as shown in Table 5-1 and Table 5-2.
Table 5-1. Five Days Readings and Predictions for N-7-B

<table>
<thead>
<tr>
<th>Date</th>
<th>Time</th>
<th>Temperature</th>
<th>N-7-B VW Reading (psi)</th>
<th>N-7-B Prediction (psi)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-Aug</td>
<td>Noon</td>
<td>26.404</td>
<td>-1554</td>
<td>-506</td>
</tr>
<tr>
<td></td>
<td>6:00 PM</td>
<td>33.795</td>
<td>-1623</td>
<td>-440</td>
</tr>
<tr>
<td>2-Aug</td>
<td>Noon</td>
<td>28.224</td>
<td>-1562</td>
<td>-441</td>
</tr>
<tr>
<td></td>
<td>6:00 PM</td>
<td>34.643</td>
<td>-1643</td>
<td>-398</td>
</tr>
<tr>
<td>3-Aug</td>
<td>Noon</td>
<td>27.363</td>
<td>-1574</td>
<td>-490</td>
</tr>
<tr>
<td></td>
<td>6:00 PM</td>
<td>34.076</td>
<td>-1628</td>
<td>-412</td>
</tr>
<tr>
<td>4-Aug</td>
<td>Noon</td>
<td>27.028</td>
<td>-1532</td>
<td>-493</td>
</tr>
<tr>
<td></td>
<td>6:00 PM</td>
<td>32.967</td>
<td>-1631</td>
<td>-616</td>
</tr>
<tr>
<td>5-Aug</td>
<td>Noon</td>
<td>25.761</td>
<td>-1530</td>
<td>-455</td>
</tr>
<tr>
<td></td>
<td>6:00 PM</td>
<td>32.352</td>
<td>-1623</td>
<td>-433</td>
</tr>
</tbody>
</table>

Table 5-2. Five Days Readings and Predictions for N-7-C

<table>
<thead>
<tr>
<th>Date</th>
<th>Time</th>
<th>Temperature</th>
<th>N-7-C VW Reading (psi)</th>
<th>N-7-C Prediction (psi)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-Aug</td>
<td>Noon</td>
<td>25.761</td>
<td>-2593</td>
<td>-2657</td>
</tr>
<tr>
<td></td>
<td>6:00 PM</td>
<td>32.831</td>
<td>-2812</td>
<td>-2888</td>
</tr>
<tr>
<td>2-Aug</td>
<td>Noon</td>
<td>27.624</td>
<td>-2630</td>
<td>-2699</td>
</tr>
<tr>
<td></td>
<td>6:00 PM</td>
<td>33.518</td>
<td>-2834</td>
<td>-2915</td>
</tr>
<tr>
<td>3-Aug</td>
<td>Noon</td>
<td>26.799</td>
<td>-2603</td>
<td>-2669</td>
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<tr>
<td></td>
<td>6:00 PM</td>
<td>33.089</td>
<td>-2809</td>
<td>-2888</td>
</tr>
<tr>
<td>4-Aug</td>
<td>Noon</td>
<td>25.761</td>
<td>-2590</td>
<td>-2654</td>
</tr>
<tr>
<td></td>
<td>6:00 PM</td>
<td>27.983</td>
<td>-2666</td>
<td>-2732</td>
</tr>
<tr>
<td>5-Aug</td>
<td>Noon</td>
<td>26.674</td>
<td>-2589</td>
<td>-2655</td>
</tr>
<tr>
<td></td>
<td>6:00 PM</td>
<td>32.291</td>
<td>-2804</td>
<td>-2881</td>
</tr>
</tbody>
</table>

5.3 Distribution Identification for Deterioration Detection

Application of statistical models is discussed in this section to detect potential deterioration problems. First approach was using the distribution determination to decide confidence limits for the data set. Minitab 16 was used for both data set coming from the sensor N-7-B which is at the problem location and N-7-C.
However, proper distribution type from 15 distribution types could not obtained due to reasons explained in Section 3.4.

5.4 Tolerance Interval for Deterioration Detection

5.4.1 Tolerance interval for the sensor at problem location (N-7-B)

The second approach is to use tolerance interval instead of confidence interval. It is known that temperature and seasonal effects are the governing stress originators in the deck. Although tolerance interval is promising tool for engineering applications, it does not include input-output relationship which needs to be involved. Therefore, tolerance interval with 5°C increments were used to determine possible deterioration for the sensor N-7-B (Figure 5-1 and Figure 5-2).
Figure 5-1. Tolerance interval plot for N-7-B the data between +25°C to +30°C

Figure 5-2. Tolerance interval plot for N-7-B the data between +30°C to +35°C
The stress predictions for deteriorated joint are not in the limit whereas the readings without any defect fall within the limit for N-7-B. Hence, tolerance intervals can be used to identify problems for the sensors which are at the problem locations.

5.4.2 Tolerance interval for the longitudinal sensor in the panel (N-7-C)

The sensor N-7-C was selected because it is a longitudinal sensor in the panel but not close to the potential problem location. The tolerance intervals for two different arrays can be seen in Figure 5-3 and Figure 5-4. When the values in Table 5-2 are compared to upper and lower limits it is very hard to decide deterioration even in the worst case deterioration scenario.

In conclusion, potential damage or deterioration problem can be obtained if the sensor is embedded to location that has problems. In addition, tolerance interval can be considered promising tool for statistical analysis of deterioration detection.
Figure 5-3. Tolerance interval plot for N-7-C the data between +25°C to +30°C

Figure 5-4. Tolerance interval plot for N-7-C the data between +30°C to +35°C
5.5 Neural Network for Deterioration Detection

5.5.1 Neural Network for the sensor at problem location (N-7-B)

Neural network fitting was used to detect damage. Third year data was used to train, validate and test the network. Once network was trained, 5 days data with and without deterioration problems were used to check damage detection capability of the neural network for the sensor N-7-B.

70% of the data was used to train data and half of the unused data was used to validate whereas other half was used to test. In addition, 10 hidden layers were used. Then, results are obtained as in Figure 5-5 for training validation and testing.

![Figure 5-5. Neural network for N-7-B](image)

R which is the correlation coefficient values equal to 1 means perfect correlation between input and output is achieved. The R values for training, validation and testing were obtained 96.7%, 96.6% and 96.6%, respectively. Hence, almost perfect network was created successfully with high correlation between input and output. Then, the 5 days data sets in Table 5-1 with and without problems were tested. The test for the real sensor data without any problem gives R as 96.4% which means high correlation as shown in Figure 5-6. Therefore, there is no problem detected during testing of data.

![Figure 5-6. Testing result for healthy joint](image)

On the other hand, same test performed for data with predicted stresses (Figure 5-7). Test result gives negative R which means there is no relationship between test
data set and past sensor readings. In addition, mean square error shows drastic change when deterioration predictions are implemented due to enormous error values between model and prediction values.

![Figure 5-7. Testing result for deteriorated joint](image)

Therefore, neural networks can easily detect the changes in readings due to potential problems. The performance of the network is validated and neural networks are the tool that can be used for future applications.

### 5.5.2 Neural Network for the longitudinal sensor in the panel (N-7-C)

Exactly same approach is used for the sensor N-7-C. The objective is to check the potential of the neural networks to detect possible deterioration problems from the location that is not close to problem location. Neural network is trained and almost perfect correlation was obtained (Figure 5-8).

![Figure 5-8. Neural network for N-7-C](image)

Then, sensor readings from healthy joint without any problems were tested. Figure 5-9 shows there is almost perfect correlation between the model and readings.
Moreover, analysis was performed for the predicted data for potential problems as shown in Figure 5-10. Figure 5-9 and Figure 5-10 show that R values are almost same and insignificant change in means square values. Hence, it can be concluded that problem could not be monitored by using the sensor from the longitudinal sensor which is not at the problem location.

Figure 5-9. Testing result from the sensor N-7-C for healthy joint

Figure 5-10. Testing result from the sensor N-7-C for deteriorated joint
CHAPTER VI

SUMMARY, CONCLUSION AND RECOMMENDATIONS

6.1 Summary and Conclusion

Use of precast components not only in rehabilitation projects but also for new construction has gained popularity in which road closures have high costs and cause major inconvenience to the public since the higher quality of precast components and fast construction speed. It is expected to have a longer service life with the use of prefabricated components; durability performance of field cast connections is not encouraging. Hence, continuous monitoring of structural integrity of bridges built using prefabricated components is vital to detect onset of deterioration.

This study focuses on different deterioration detection approaches based on statistical data analysis in the context of Structural Health Monitoring. The thesis can mainly be summarized in four parts. First, state-of-the-art literature was collected and reviewed. Then, possible statistical analysis methods are investigated to detect deterioration and prefabricated full-depth deck panel and implemented sensor network are discussed. Next, detailed numerical simulation of full-depth deck panel connection failure is discussed. Finally, combination of statistical model(s) and numerical model for damage detection is examined to simulate possible joint failure.

Statistical analysis methods to detect possible deterioration in the bridge were evaluated. Three different methods are presented for statistical detection of possible damage. Only 3rd year data was used in the analyses because the effect of the creep, shrinkage and other stresses may highly active during first few years of bridge life.
Approach I was the identification of data distribution by using 15 different statistical models that can be used to define confidence limits. Even though the implementation of these methods is simple, none of the models was capable of representing sensor data distribution. However, the benefits from this method can be obtained when future data is added. It is expected that data will follow one specific distribution with larger data sets.

Approach II was the creating of tolerance intervals. The main advantage of using a tolerance interval is that it allows using normal and nonparametric models, which is known as the distribution free method. This approach is useful when there is no specific distribution of data that fits into any of the existing mathematical models. Furthermore, the tolerance intervals are more appropriate for the engineering applications because it deals with the entire data set instead of some specific values of a data set such as mean and variance. Linear regression analysis illustrates that there is an apparent relationship between temperature and stress readings. On the other hand, the major weakness of this method is that the input and output relationship would not be embedded into model. This drawback is unraveled by using subsets of data. Using of subsets helps to narrow limits. The recorded minimum temperature value is around -15°C and maximum is near to +40°C. Increment size of 5°C was selected and the data set was divided into 11 subsets. Then tolerance intervals are obtained for both normal and distribution free methods.

Approach III was to use the artificial neural networks. The neural network has the ability to detect patterns and create relationships between temperature and stress variation. This is accomplished through its learning process. Moreover, artificial
neural network can simulate the behavior represented by a set of data within a unified environment, which is directly built by an experimental data set using the self-organizing capability of neural network.

Since the vibrating wire sensor data was acquired from a brand new bridge, developing deterioration prediction models required simulation results. Hence, a detailed finite element model was developed and the model was first calibrated using load test data. However, due to the dominance of thermal loads, it was required to calibrate the FE model using stresses developed in the structural system under thermal loads. This was a challenge due to lack of thermocouples along the depth of bridge superstructure cross-section to document the temperature profile. A model was identified from literature that is capable of representing the thermal gradient profile at 12 p.m. and 6 p.m. in a summer day. The FE analysis of bridge superstructure was performed using these thermal gradient profiles. Sensor data was used to calibrate the model. The FE model results and sensor readings were correlated well. Using the calibrated model, debonding of a joint between two deck panels was simulated and a deterioration prediction model was developed combining FE results and sensor data.

When the prediction model was obtained, statistical models were tested for two different types of sensors. One of the sensors was selected from problem location. Representative distribution type could not be obtained to determine confidence levels. Then, predefined tolerance interval charts were used for certain temperature value. Sensor readings without any deterioration were in the limits; however,
prediction values for deteriorated joint fell outside the tolerance limits. Then, artificial neural network was tested and performance of the neural was admirable.

In conclusion, the proposed methods are very promising for deterioration detection. Therefore, these methods can be used for a variety of structures under different locations and it can be used as damage detection tool for future analysis.

6.2 Recommendations for Further Studies

This study focuses on different damage detection methods based on statistical data analysis in the context of Structural Health Monitoring using sensor network data and detailed finite element analyses. While temperature models for bridge design are available in design specifications, the structural performance assessment requires thermal profile models for a specific bridge configuration and for a specific time of a day in a specific season. Once a structure-specific thermal model is developed, the deterioration prediction model presented in this report will require further verification, fine-tuning, and analysis to identify potential weak zones, in terms of durability. Fine-tuning of the deterioration prediction models require identification of the exact location of sensors and conducting a sensitivity analysis to evaluate the impact of sensor location and orientation on the accuracy of the model. Therefore, it is recommended to establish a long-term, continuous monitoring program with additional sensors to monitor thermal profile of the bridge superstructure or a parallel study to develop thermal profiles.

Both finite element and sensor analysis results show that stresses changes are triggered due to temperature change. The impact of truck load on stress is negligible for this specific type of bridge which has integral abutments. However, most of
designs of bridges are based truck loads. It is recommended to design integral abutments after detailed analysis under thermal loading.

As finite element is promising tool for simulation, detailed finite element model could be developed before the instrumentation and possible deterioration scenarios can be tested to optimize sensor number. Analysis results show that sensors can detect the changes if they are at the problem location. Otherwise, recognition of possible determination is not expected. Therefore, instrumentation should be performed for each critical joint after detailed finite element analysis.

In addition, automated software can be implemented to detect problems. Software may include 3 methods and compare results. Moreover, only 3rd year data was used and when the new data is tested models can be improved automatically with the software.
REFERENCES


PCI. (2003). Precast Prestressed Bridge Design Manual, Precast/Prestressed Concrete Institute, 175 W. Jackson Boulevard, Chicago, IL 60604.


APPENDIX A

Tolerance Interval Plot for -15°C to -10°C
95% Tolerance Interval
At Least 95% of Population Covered

Statistics
N  717
Mean -1569.250
StDev  35.999

Normal
Lower -1643.077
Upper -1495.423

Nonparametric
Lower -1631.500
Upper -1496.350

Normality Test
AD  4.972
P-Value < 0.005

Tolerance Interval Plot for -10°C to -5°C
95% Tolerance Interval
At Least 95% of Population Covered

Statistics
N  3548
Mean -1699.733
StDev  45.244

Normal
Lower -1790.192
Upper -1609.274

Nonparametric
Lower -1776.400
Upper -1609.150

Normality Test
AD  13.653
P-Value < 0.005
Tolerance Interval Plot for -5°C to 0°C
95% Tolerance Interval
At Least 95% of Population Covered

Statistics
N 5396
Mean -1620.009
StDev 58.871

Normal
Lower -1938.063
Upper -1763.155

Nonparametric
Lower -1937.550
Upper -1718.400

Normality Test
AD 36.455
P-Value < 0.005

Tolerance Interval Plot for 0°C to +5°C
95% Tolerance Interval
At Least 95% of Population Covered

Statistics
N 8130
Mean -1934.462
StDev 58.792

Normal
Lower -2051.828
Upper -1817.897

Nonparametric
Lower -2041.359
Upper -1824.800

Normality Test
AD 27.542
P-Value < 0.005
Tolerance Interval Plot for +35°C to +40°C
95% Tolerance Interval
At Least 95% of Population Covered

Normal
Nonparametric

Normal Probability Plot

Statistics
N 426
Mean -2707.786
SD 41.302

Normal
Lower -2792.771
Upper -2622.800

Nonparametric
Lower -2810.500
Upper -2524.150

Normality Test
AD 1.867
P-Value < 0.005
APPENDIX B

A. Analysis for the sensor N-7-C

i. Distribution identification
ii. **Linear regression**
iii. **Tolerance interval**

**Tolerance Interval Plot for -15°C to -10°C (N-7-C)**

95% Tolerance Interval
At Least 95% of Population Covered

- **Statistics**
  - N: 871
  - Mean: -1886.436
  - StDev: 45.134
- Normal
  - Lower: -1898.595
  - Upper: -1714.277
- Nonparametric
  - Lower: -1887.750
  - Upper: -1713.600
- Normality Test
  - AD: 8.184
  - P-Value: < 0.005

**Normal Probability Plot**

**Tolerance Interval Plot for -10°C to -5°C (N-7-C)**

95% Tolerance Interval
At Least 95% of Population Covered

- **Statistics**
  - N: 5035
  - Mean: -1911.986
  - StDev: 48.595
- Normal
  - Lower: -2046.829
  - Upper: -1855.142
- Nonparametric
  - Lower: -2033.800
  - Upper: -1847.600
- Normality Test
  - AD: 19.726
  - P-Value: < 0.005

**Normal Probability Plot**
iv. **Neural Network**

![Tolerance Interval Plot for +35°C to +40°C (N-7-C)](image)

<table>
<thead>
<tr>
<th>Statistics</th>
<th></th>
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<tbody>
<tr>
<td>N</td>
<td>604</td>
</tr>
<tr>
<td>Mean</td>
<td>-2941.284</td>
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<tr>
<td>StdDev</td>
<td>40.391</td>
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<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Lower</td>
<td>-3024.471</td>
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<tr>
<td>Upper</td>
<td>-2818.097</td>
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<table>
<thead>
<tr>
<th>Nonparametric</th>
<th></th>
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</thead>
<tbody>
<tr>
<td>Lower</td>
<td>-3036.950</td>
</tr>
<tr>
<td>Upper</td>
<td>-2854.700</td>
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<table>
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<th>Normality Test</th>
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<tbody>
<tr>
<td>AD</td>
<td>1.559</td>
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<tr>
<td>P-Value</td>
<td>&lt; 0.005</td>
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### Results

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<tr>
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<th>Samples</th>
<th>MSE</th>
<th>R</th>
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</thead>
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<td>37720</td>
<td>2055.88776e-0</td>
<td>9.85310e-1</td>
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<tr>
<td><strong>Validation</strong></td>
<td>8083</td>
<td>2033.27168e-0</td>
<td>9.85661e-1</td>
</tr>
<tr>
<td><strong>Testing</strong></td>
<td>8083</td>
<td>2056.70996e-0</td>
<td>9.85268e-1</td>
</tr>
</tbody>
</table>
Best Validation Performance is 2033.2717 at epoch 16

- Training: R=0.98531
- Validation: R=0.98566
- Test: R=0.98527
- All: R=0.98536
B. Analysis for the sensor N-7-B

i. Distribution identification
ii. Linear regression
iii. **Tolerance interval**

![Tolerance Interval Plot for -15°C to -10°C (N-7-B)](image)

- **95% Tolerance Interval**
- **At Least 95% of Population Covered**

**Statistics**
- \( N = 798 \)
- \( \text{Mean} = -1057.329 \)
- \( \text{StDev} = 23.793 \)
- Normal
  - Lower: -1116.005
  - Upper: -1018.633
- Nonparametric
  - Lower: -1129.750
  - Upper: -1027.100
- Normality Test
  - \( A.D = 17.249 \)
  - P-Value < 0.005
iv. **Neural Network**

![Results Table]

<table>
<thead>
<tr>
<th></th>
<th>Samples</th>
<th>MSE</th>
<th>R</th>
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<tbody>
<tr>
<td>Training</td>
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<td>9.64389e-1</td>
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<td>Validation</td>
<td>7312</td>
<td>1141.60278e-0</td>
<td>9.64605e-1</td>
</tr>
<tr>
<td>Testing:</td>
<td>7312</td>
<td>1153.36172e-0</td>
<td>9.64242e-1</td>
</tr>
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</table>

![Graph]

*Best Validation Performance is 1141.6028 at epoch 11*
C. Analysis for the sensor N-8-E

i. Distribution identification
ii. Linear regression

Probability Plot for N-8-E (stress (psi))

Goodness of Fit Test
Logistic
AC = 604.733
P-value < 0.001
Logistic
AC = 518.329
P-value < 0.005
3-Parameter Logistic
AC = 570.025
P-value = *

Fitted Line Plot
Stress (psi) (N-8-E) = -1068 - 11.12 Temperature (°C) (N-8-E)

S = 38.1501
R-Sq = 92.9%
R-Sq(adj) = 92.9%
iii. Tolerance interval

![Tolerance Interval Plot for -15°C to -10°C (N-8-E)](image1)

- **Statistics**
  - N: 919
  - Mean: -848.879
  - StDev: 34.314

- **Normal**
  - Lower: -918.866
  - Upper: -778.893

- **Nonparametric**
  - Lower: -910.500
  - Upper: -773.930

- **Normality Test**
  - AD: 2.054
  - P-Value < 0.005

![Tolerance Interval Plot for -10°C to -5°C (N-8-E)](image2)

- **Statistics**
  - N: 4821
  - Mean: -922.840
  - StDev: 33.503

- **Normal**
  - Lower: -999.632
  - Upper: -856.049

- **Nonparametric**
  - Lower: -984.850
  - Upper: -833.000

- **Normality Test**
  - AD: 11.833
  - P-Value < 0.005
Tolerance Interval Plot for -5°C to 0°C (N-8-E)
95% Tolerance Interval
At Least 95% of Population Covered

Normal:
Nonparametric:

Normal Probability Plot

Tolerance Interval Plot for 0°C to +5°C (N-8-E)
95% Tolerance Interval
At Least 95% of Population Covered

Normal:
Nonparametric:

Normal Probability Plot

Statistics
N 8313
Mean -979.124
StdDev 32.326

Normal
Lower -1043.306
Upper -914.943

Nonparametric
Lower -1083.050
Upper -915.390

Normality Test
AD 7.956
P-Value < 0.005

Statistics
N 8451
Mean -1027.628
StdDev 34.426

Normal
Lower -1102.957
Upper -942.299

Nonparametric
Lower -1166.500
Upper -960.150

Normality Test
AD 7.661
P-Value < 0.005
### Tolerance Interval Plot for +15°C to +20°C (N-8-E)

**95% Tolerance Interval**

At Least 95% of Population Covered

#### Statistics

<p>| | |</p>
<table>
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<tbody>
<tr>
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</tr>
<tr>
<td><strong>Mean</strong></td>
<td>-1210.610</td>
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<tr>
<td><strong>StDev</strong></td>
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#### Normal

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<tbody>
<tr>
<td><strong>Lower</strong></td>
<td>-1297.285</td>
</tr>
<tr>
<td><strong>Upper</strong></td>
<td>-1173.935</td>
</tr>
</tbody>
</table>

#### Nonparametric

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<td><strong>Lower</strong></td>
<td>-1289.900</td>
</tr>
<tr>
<td><strong>Upper</strong></td>
<td>-1199.050</td>
</tr>
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</table>

#### Normality Test

| AD  | 10.063 |
| P-Value | < 0.005 |

### Tolerance Interval Plot for +20°C to +25°C (N-8-E)

**95% Tolerance Interval**

At Least 95% of Population Covered

#### Statistics

<p>| | |</p>
<table>
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<tr>
<td><strong>Mean</strong></td>
<td>-1270.343</td>
</tr>
<tr>
<td><strong>StDev</strong></td>
<td>43.890</td>
</tr>
</tbody>
</table>

#### Normal

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<table>
<thead>
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<tbody>
<tr>
<td><strong>Lower</strong></td>
<td>-1357.763</td>
</tr>
<tr>
<td><strong>Upper</strong></td>
<td>-1182.924</td>
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</table>

#### Nonparametric

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<table>
<thead>
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<tbody>
<tr>
<td><strong>Lower</strong></td>
<td>-1336.000</td>
</tr>
<tr>
<td><strong>Upper</strong></td>
<td>-1166.600</td>
</tr>
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#### Normality Test

| AD  | 72.761 |
| P-Value | < 0.005 |
Tolerance Interval Plot for +25°C to +30°C (N-8-E)
95% Tolerance Interval
At Least 95% of Population Covered

Statistics
N 5005
Mean -1365.070
StDev 46.081

Normal
Lower -1400.908
Upper -1217.232

Nonparametric
Lower -1375.800
Upper -1210.000

Normality Test
AD 76.916
P-Value < 0.005

Tolerance Interval Plot for +30°C to +35°C (N-8-E)
95% Tolerance Interval
At Least 95% of Population Covered

Statistics
N 2753
Mean -1348.511
StDev 46.970

Normal
Lower -1434.679
Upper -1246.343

Nonparametric
Lower -1412.950
Upper -1246.800

Normality Test
AD 34.711
P-Value < 0.005
iv. **Neural Network**

<table>
<thead>
<tr>
<th>Samples</th>
<th>MSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training:</td>
<td>38220</td>
<td>1329.89736e-0</td>
</tr>
<tr>
<td>Validation:</td>
<td>8190</td>
<td>1305.92479e-0</td>
</tr>
<tr>
<td>Testing:</td>
<td>8190</td>
<td>1312.41982e-0</td>
</tr>
</tbody>
</table>
Best Validation Performance is 1305.9248 at epoch 48

Training: R=0.96717

Validation: R=0.96789

Test: R=0.96728

All: R=0.96729
D. Analysis for the sensor N-15-B

i. Distribution identification
ii. Linear regression
iii. Tolerance interval
iv. **Neural Network**

![Results Table]

**Best Validation Performance is 889.2845 at epoch 9**

![Graph of Mean Squared Error over Epochs]
E. Analysis for the sensor N-16-E

i. Distribution identification
ii. Linear regression
iii. **Tolerance interval**

**Tolerance Interval Plot for -15°C to -10°C (N=16-E)**

95% Tolerance Interval
At Least 95% of Population Covered

Statistics

<p>| | |</p>
<table>
<thead>
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</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>901</td>
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<tr>
<td>Mean</td>
<td>-880.690</td>
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<tr>
<td>StDev</td>
<td>36.908</td>
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Normal

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<tbody>
<tr>
<td>Lower</td>
<td>-955.998</td>
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<tr>
<td>Upper</td>
<td>-805.383</td>
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</table>

Nonparametric

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<table>
<thead>
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</thead>
<tbody>
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<td>Lower</td>
<td>-964.200</td>
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<tr>
<td>Upper</td>
<td>-807.050</td>
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Normality Test

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<tbody>
<tr>
<td>AD</td>
<td>3.935</td>
</tr>
<tr>
<td>P-Value</td>
<td>&lt; 0.005</td>
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</tbody>
</table>

**Tolerance Interval Plot for -10°C to -5°C (N=16-E)**

95% Tolerance Interval
At Least 95% of Population Covered

Statistics

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<table>
<thead>
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</tr>
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<tbody>
<tr>
<td>N</td>
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<td>Mean</td>
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<tr>
<td>StDev</td>
<td>36.854</td>
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Normal

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower</td>
<td>-1038.800</td>
</tr>
<tr>
<td>Upper</td>
<td>-891.819</td>
</tr>
</tbody>
</table>

Nonparametric

<p>| | |</p>
<table>
<thead>
<tr>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower</td>
<td>-1034.450</td>
</tr>
<tr>
<td>Upper</td>
<td>-890.500</td>
</tr>
</tbody>
</table>

Normality Test

<p>| | |</p>
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<tbody>
<tr>
<td>AD</td>
<td>6.576</td>
</tr>
<tr>
<td>P-Value</td>
<td>&lt; 0.005</td>
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</table>
iv. **Neural Network**

<table>
<thead>
<tr>
<th>Samples</th>
<th>MSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training:</td>
<td>38218</td>
<td>1429.32416e-0</td>
</tr>
<tr>
<td>Validation:</td>
<td>8189</td>
<td>1459.63489e-0</td>
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<tr>
<td>Testing:</td>
<td>8189</td>
<td>1459.64618e-0</td>
</tr>
</tbody>
</table>
APPENDIX C

Figure C-1. Comparison of load test data and FE analysis results – Scenario 2
Figure C-2. Comparison of load test data and FE analysis results – Scenario 3
Figure C-3. Comparison of load test data and FE analysis results – Scenario 4
Figure C-4. Comparison of load test data and FE analysis results – Scenario 5
Figure C-5. Comparison of load test data and FE analysis results – Scenario 6
Figure C-6. Comparison of load test data and FE analysis results – Scenario 7
Figure C-7. Comparison of load test data and FE analysis results – Scenario 8
Figure C-8. Comparison of load test data and FE analysis results – Scenario 9
Figure B-9. Comparison of load test data and FE analysis results – Scenario 10
APPENDIX D

% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by Cem Mansiz
% Created Wed Jun 06 22:24:12 EDT 2012
%
% This script assumes these variables are defined:
% % Temperature - input data.
% % Stress - target data.

inputs = Temperature;
targets = Stress;

% Create a Fitting Network
hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% For help on training function 'trainlm' type: help trainlm
% For a list of all training functions type: help nntrain
net.trainFcn = 'trainlm'; % Levenberg-Marquardt

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse'; % Mean squared error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ... 
'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,inputs,targets);

% Test the Network
outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs)
% Recalculate Training, Validation and Test Performance
trainTargets = targets .* tr.trainMask{1};
valTargets = targets .* tr.valMask{1};
testTargets = targets .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,outputs)
valPerformance = perform(net,valTargets,outputs)
testPerformance = perform(net,testTargets,outputs)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotfit(net,inputs,targets)
%figure, plotregression(targets,outputs)
%figure, ploterrhist(errors)