Final Report

Movable Bridge Maintenance Monitoring

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The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the State of Florida Department of Transportation.

UNIT CONVERSION TABLE

To convert from	To	Multiply by
inch	centimeter	2.54
square inch	square centimeter	6.4516
kip	kiloNewton (kN)	4.44747
kip/sq.in.	(ksi) kN/sq.m (kPa)	6,894.28
kip-foot	kN-meter	1.3556
btu	joule	1,055
btu/hr	watt	0.2931
degrees Fahrenheit – 32	degrees Celcius	0.5555
lb/cu.in.	kg./cu.m	27,680
Btu/sq.ft./min.	watt/sq.in.	0.122

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16. Abstract

Movable bridges have particular maintenance issues, which cost considerably more than those of fixed bridges, mostly because of the complex interaction of the mechanical, electrical and structural components. In order to track maintenance and operational performance, a comprehensive monitoring system was implemented on Sunrise Bridge (Ft. Lauderdale) to track the behavior and condition of several critical mechanical, electrical and structural components. In this project, a number of statistical analysis and machine learning-based methods were developed and employed to track the operation of the mechanical components. After the completion of the previous phases of the project, the bridge was scheduled for painting; however, the monitoring system was significantly damaged during the preparation, sandblasting and painting despite the considerable efforts of FDOT personnel to protect the system. The research team focused on repairing the monitoring system, which was affected by the painting operation, collecting and analyzing more data and preparing the system for FDOT. In this phase, the monitoring system was maintained. Details of the field work conducted to repair the damaged monitoring system are presented. Then, analysis of data that were collected after the monitoring system was repaired is presented for different mechanical components. The baseline response and the thresholds for acceptable behavior were established. During this phase of the project, unanticipated behaviors were observed for two components (one at the span locks and one at the gearbox) at two different times. These findings indicating the unanticipated behavior using the monitoring system are also corroborated with the independent maintenance reports. These changes in behavior required maintenance work at the span lock and gearbox as noted in the maintenance logs. Finally, recommendations are provided based on the findings and experiences from this project.

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Finally, several other graduate and undergraduate students were involved in this project from the very beginning for different aspects of the studies from field work to data analysis. Many of these students were listed in the authorship or acknowledgments previously. In this phase, we would also like to acknowledge the contribution of Dr. Kirk Grimmelsman and Mr. Travis Henriques for the analysis of the data as well as the development of this report. All of these research assistants made important contributions to the development work presented in this report, and they are greatly appreciated.

PREFACE

The report describes and presents the background, methodology, and results of a research project conducted by University of Central Florida researchers and funded by the Florida Department of Transportation.

EXECUTIVE SUMMARY

The report describes and presents the background, methodology, and results of a research project conducted by University of Central Florida researchers and funded by the Florida Department of Transportation. The objective of this one-year project was to keep the monitoring system operational to expand FDOT's understanding of the bridge machinery behavior and maintenance practices. In addition, this system and findings can be employed for demonstration during discussion at national and international workshops and meetings with industry and practicing engineers. The project was extended to achieve the following objectives, which are summarized as follows:

- Maintain existing electrical/mechanical monitoring system and continue with data collection.
- Review maintenance logs on a monthly basis and identify relevant maintenance events.
- Correlate relevant events (date/time) with collected data to identify, if possible, a reflection of maintenance activity.
- Compare correlated data before and after events and indicate the trend on the different parameters being monitored (vibration, temperature, noise, etc.).

Movable bridges have particular maintenance issues, which cost considerably more than those for fixed bridges, mostly because of the complex interaction of the mechanical, electrical and structural components. In order to track maintenance and operational performance, a comprehensive monitoring system was implemented on Sunrise Bridge (Ft. Lauderdale) to track the behavior and condition of several critical mechanical, electrical and structural components. In this project, a number of statistical analysis and machine learning-based methods were developed and employed to track the operation of the mechanical components. After the completion of the previous phases of the project, the bridge was already scheduled for painting; however, the monitoring system was significantly damaged during the preparation, sandblasting and painting despite the considerable efforts of FDOT personnel to protect the system. The research team focused on repairing the monitoring system, which was affected by the painting operation, collecting and analyzing more data and preparing the system for FDOT. In this phase, the

monitoring system was maintained. Details of the field work conducted to repair the damaged monitoring system are presented. Then, analysis of data that were collected after the monitoring system was repaired is presented for different mechanical components. The baseline response and the thresholds for acceptable behavior were established. During this phase of the project, unanticipated behaviors were observed for two components (one at the span locks and one at the gearbox) at two different times. The findings from the monitoring system indicating unanticipated behavior are also corroborated with the independent maintenance reports. These changes in behavior required maintenance work at the span lock and gearbox as noted in the maintenance logs. Finally, recommendations are provided based on the findings and experiences from this project.

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CHAPTER 1. INTRODUCTION

1. INTRODUCTION

1.1. Background

Obtaining reliable and timely assessments of bridge condition, performance and safety throughout increasingly longer service lives represents a considerable challenge for bridge owners, engineers and the Federal Highway Administration (FHWA). The ability to quantitatively characterize existing bridges may lead to more cost-effective and efficient maintenance management decisions, and more robust evaluations of structural safety. Presently, the long-term performance and condition of most bridges are evaluated on the basis of biennial visual inspection data. Visual inspection data are inherently qualitative and are subject to other important limitations that can hamper their effectiveness for assessing bridge performance and safety. A study by the FHWA on the reliability of visual inspection (Phares et al., 2004) revealed many of the uncertainties associated with this assessment approach. Structural Health Monitoring (SHM) is an emerging approach that has gained significant attention because it promises to enable more quantitative, reliable and timely assessments of bridge condition and performance than are possible using only visual inspection data.

The Florida Department of Transportation (FDOT) is responsible for one of the largest populations of movable bridges in the U.S., and as a result, has decided to investigate the efficacy of SHM systems for evaluating and tracking the long-term performance of these complex structures in the context of Bridge Maintenance Monitoring. The westbound span of the two parallel spans on Sunrise Boulevard in Ft. Lauderdale was selected to serve as the test-bed for this research. A comprehensive monitoring system was designed and installed on this representative movable bridge to monitor the long-term performance of both its mechanical systems and structural components to track any problems, to establish thresholds, and to compare findings with maintenance actions. A number of studies have been performed over the past few years using the measurement data collected from the instrumented mechanical systems and structural components. This report presents the current status of the research program, the monitoring system and the results of the studies that were performed using the measurement data.

1.2. Issues Related to Movable Bridges

Movable bridges are unique structures from the perspective that they represent the integration of conventional structural components with mechanical systems and electrical power and control systems. These structures are also different from most highway bridges in that they actively facilitate the flow of both vehicular and waterborne traffic. The operation of a movable bridge, and hence its serviceability, can be disrupted or completely compromised by performance problems and failures with any of the mechanical and electrical systems or the structural components. Movable bridges are advantageous in that the vertical clearance requirement for these structures is minimal; however, there are several drawbacks associated with this bridge type. Firstly, movable bridges are located over navigable waterways that are often situated in coastal areas. Coastal areas represent especially harsh environments for bridges, and this increases the risk of corrosion damage to the different bridge components. Secondly, the repetitive movements associated with opening and closing of the structure leads to wearing and deterioration of the bridge's various mechanical systems. The repeated motions involved in opening and closing of the bridge can also lead to large stress cycles and stress reversals, which in turn can lead to fatigue problems. Maintenance and performance monitoring of movable bridges is often more essential and justified than for fixed bridges given their dual service role and the potential for deterioration and other problems with the integrated systems that are essential for ensuring their operation and safety.

1.3. Design of the Monitoring System and Instrumentation

Although monitoring of structural components is usually the only concern for fixed bridges, a properly designed monitoring system for a movable bridge should consider all of the critical electrical, mechanical and structural systems and their components. These components include electrical motors, gearboxes, drive shafts, open gears, rack and pinions, trunnions, live load shoes, span locks, main girders, floor beams and stingers. The most common problems associated with these components were investigated to serve as the starting point for the design of the monitoring system. A series of meetings and field visits with bridge engineers, FDOT officials and consultants were also conducted to solicit their perspectives on the final design of the monitoring system. The hardware and software components of the implemented monitoring system were designed to track the behavior of these components, detect problems and plan for corrective actions.

The final design for the bridge monitoring system incorporated two separate and synchronized data acquisition (DAQ) systems that are used to record measurement data from the sensors located to either side of the separate span leaves. The design of the system, market search and equipment purchases were completed in 2007-2008. The two DAQ systems were connected and synchronized wirelessly. The final instrumentation scheme for the bridge incorporated an array of different sensor types. These included accelerometers, strain gages, tiltmeters, pressure gages, strain rosettes, amp meters, infrared temperature sensors, microphones, environmental sensors, and cameras. The system installation was completed in 2008. It should be mentioned that, based on the findings of this research, the instrumentation plan used for the bridge can be optimized and significantly reduced for future installations of monitoring systems on similar bridges.

1.4. Findings from the Previous Project

The findings from the first phase of this project have been presented in a prior final report (Catbas et al. 2010, Gul et al. 2011). This section briefly summarizes the results obtained from the second phase of the project. In the second phase of the project, the statistics of the responses from various mechanical components were examined. These components included the gearbox, electrical motor, and the rack and pinion system. The efficacy of the monitoring methods and analysis techniques that were developed in the first phase of the project were investigated throughout the second phase of the project. Moreover, throughout the second phase of this study the efficiency of the proposed methods and techniques, which were developed in the first phase, were investigated. Artificial neural network, image processing techniques, and cross correlation analysis methods are implemented for processing the data from mechanical and structural components. Finally, at the end of the previous report, a study was conducted to explore the correlation of monitoring data with maintenance activities performed on the bridge by maintenance contractors. For that reason, the maintenance activities were extracted and classified from the maintenance reports provided by the contractors with the permission of FDOT. Successful results have been found related to span lock as well as gearbox in terms of showing good correlation with contractor work. The details of these are presented in the two project reports described above.

The finding from the monitoring system that correlated with maintenance activities was a span lock issue identified by the maintenance crew during weekly inspection on June 19, 2011. The monitoring data shows that the problem initiation day was several days earlier than June 19, 2011. This reveals the fact that the SHM system could identify the malfunction associated with the span lock in a timely manner.

The second interesting finding is related to gearbox, which is another critical element of movable bridge. This case was related to the gearbox shaft seal replacement on June 28, 2011. In this case, the effect of maintenance was also evaluated with the help of monitoring data. In this case as well as the first one, the malfunctions were detected successfully using the monitoring system. This shows the efficiency of implemented SHM system.

1.5. Objectives of the Extension Project

The objective of this one-year project was to keep the monitoring system operational to expand FDOT's understanding of the bridge machinery behavior and maintenance practices. In addition, this system and its findings can be employed for demonstration during discussions at national and international workshops and meetings with industry and practicing engineers. The project was extended to achieve the following objectives, which are summarized as follows:

- Maintain existing electrical/mechanical monitoring system and continue with data collection.
- Review maintenance logs on a monthly basis and identify relevant maintenance events.
- Correlate relevant events (date/time) with collected data to identify, if possible, a reflection of maintenance activity.
- Compare correlated data before and after the event and indicate the trend on the different parameters been monitored (vibration, temperature, noise, etc.).

The monitoring system was maintained during this phase of the project. The system experienced operational problems on several occasions due to hardware and software issues, which may be attributed to old computer systems, damage experienced during the sand-blasting and painting, needs for better protection of the system and cables from maintenance personnel activities, burnt fuses, hard-disk problems, etc. and also due to some unknown causes. When these issues were encountered, the PI and his research team repaired and fixed the problems within the allowed scope and budget of the extended project. FDOT requires that all work activities would take place within the bascule piers on components such as gearboxes, live load shoes, electrical motors, trunnions, and open gears (racks). No equipment or MOT would be provided during this extension.

For this project, the data have been collected continuously and the results from data collected previously have already been reported in prior reports. The data collected during the extension are analyzed and presented in this report along with the relevant previous data. The functionality of the movable bridge is directly affected by performance of its mechanical components. On-going condition monitoring of these critical elements is also a primary objective for the bridge monitoring system. A framework has been proposed and developed for continuous condition monitoring of the bridge's mechanical components. In addition, results obtained from the monitoring of mechanical systems are compared with maintenance activities to assess the maintenance effectiveness and to match problems that are observed by maintenance personnel. As mentioned earlier, continuous safety assessment of the movable bridge is a primary objective for the bridge monitoring system.

The performance of structural components of the movable bridge should be monitored over time in order to avoid any unexpected failure or damage. In light of this requirement, a novel damage detection algorithm is proposed for long-term monitoring of structural components.

CHAPTER 2. STATUS OF MONITORING SYSTEM

2. INTRODUCTION

The technical issues encountered during the extension are discussed in the following sections. The current status of the monitoring system is discussed, and the field visits for maintenance and repair of the monitoring system are described. Possible improvements to the bridge monitoring system that could improve its future performance and reliability are also discussed as the monitoring system in place was designed and implemented in 2007 and 2008, and the system is still running with the same computers, data acquisition system and software.

2.1. Status of the Monitoring System at the End of the Previous Project

The primary causes of performance issues with the bridge monitoring system were generally related to a combination of hardware and software problems. These problems are summarized and described below.

- Data acquisition hardware and computer

One issue that has disrupted the operation of the bridge monitoring system more than any other problem has been interruptions in the wireless communications link between the hardware systems installed on the east and west sides of the bridge. The disconnections of wireless communication link have been traced to several issues including maintenance, network issues, and interruptions with the AT&T service.

Another hardware issue that has contributed to performance problems with the monitoring system is the performance of the computers used to interface and control the data acquisition hardware on the east and west sides of the bridge. These computers have been running continuously in a harsh operating environment since the first day of the project. As a result, the performance and reliability of the computer hard drives has decreased with age. Issues with the computer hard drives occurred twice during the extended project and were noted in the monthly reports. The hard drive issue was mitigated by replacing the existing drives with new units. The monitoring system has been operating properly since the computer hard drives were replaced; however, there is a high possibility that this issue will occur again in the future. Replacement of the computer systems used in the monitoring system with more advanced systems is advised to ensure that the system will be operated continuously.

- Software improvements needed

The software programs that are being used in the SHM project, including LabVIEW and other software codes, should also be upgraded. Upgrading the codes and software with the last available versions will help the entire SHM system to operate more efficiently. In fact, since the software has not been upgraded since its installation, it may directly affect the speed of the data collection and the entire performance of the data acquisition system.

2.2. Field Visits to Repair the System

One of the objectives for the extended project was to maintain the monitoring system in its operational condition. In order to satisfy this requirement, the monitoring system's performance was evaluated during the extended project. Four individual field visits were conducted during the extension period in order to repair issues that impacted the performance of the monitoring system. The field visits were conducted to address different problems that included both hardware and software issues as described above. The following provides a brief explanation for each field visit including the purpose, action taken, and date. Additional details of these field visits were provided in the monthly project reports that were submitted to the FDOT.

1. Field Visit 1 (March 16, 2012): The first visit was conducted several months after the end of previous project. The objectives of this visit were to investigate the reason why the SHM system could notbe accessed from UCF campus. The Internet connection was identified as the problem and fixed with the help from AT&T technicians.

2. Field Visit 2 (April 19, 2012): There was another issue happening at the East SHM system as the monitoring data could not be collected since the beginning of April, 2012. With the support from our former team member Dr. Ricardo Zaurin, the problem was DAQ system issue. Another field trip was carried out on April 19, 2012 to inspect the East SHM system and bring the DAQ system back to UCF campus for further evaluation and repairs.

3. Field Visit 3 (May 7, 2012): The East DAQ system removed from the bridge on the last visit was investigated, and the reason the system stopped running was due to some broken fuses in the power box of the DAQ chassis. Broken fuses were replaced and the system was tested for two days before reinstalling the system on the bridge on May 7, 2012.

4. Field Visit 4 (June 7, 2012): The systems on both East and West leaf stopped working around May 23 and we could not download any data. A new visit was conducted on June 7 to check the systems on site. After doing some preliminary investigation, it was

determined that both systems had hard-drive issues. As a result, the computers were removed to UCF campus for more in-depth evaluation.

5. Field Visit 5 (July 20, 2012): The broken computers removed from the bridge were inspected by UCF computer technicians and it was realized that the functionality problem was because the hard drives had failed. Technicians decided to replace the broken hard drives with new hard drives of the same model to minimize incompatibility with other computer hardware and software. Because of discontinued model of hard drives, two replaced ones were only ordered on the first week of July. After installing new hard drives and testing software compatibility, both computers were brought back to bridge on July 20, 2012 and they were reinstalled.

6. Field Visit 6 (July 22, 2012): The computer at the East leaf stopped just two days after the previous visit. The field visit was conducted on July 22, and it was seen that the auto-reboot function in the East side computer did not work after power off. The investigation had revealed that the CMOS battery had run down. These type of batteries were changed for the both computers at East and West sides to bring them back to normal status.

7. Field Visit 7 (December 20, 2012): Because of unidentified reasons, some accelerometers attached to motors and gear boxes had not given reasonable data. The main objectives of this field trip were to fix and/or replace those malfunctioning sensors. During the trip, it is shown that two accelerometers were detached and one was cut out of its cable. All of accelerometers were replaced by installing a new shortcut directly connecting to DAQ system.

8. Field Visit 8 (May 28, 2013): For couple of months after March, 2013, the SHM systems in the both sides had been crashing frequently; and the data downloading rate was extremely slow. Due to above reasons, a field trip was implemented to investigate the problems in the both SHM systems. The preliminary inspection revealed the very slow Internet quality as well as computer speed. Upon further checking, the both computers were taken back to campus one more time and they were reinstalled. Moreover, the internet equipments such as modems, wireless routers were rebooted to refresh the internet connection.

9. Field Visit 9 (June 7, 2013): The computers were inspected, cleaned, and fixed by UCF computer technicians. After that, the computers were brought back to bridge on June 7, 2013. Although no serious issues were discovered at this time, the obsolete computers as well as old Internet equipments may be the main issue for slowing system. It also shown that the speed of the system was improved after restarting Internet modems and wireless routers.

10. Field Visit 10 (August 9, 2013): The SHM system at East leaf was stopped working around July 17, 2013 as the monitoring data could not be collected. The objectives of the trips were to investigate the happen and fix the system if it can be. Having experience from last failure of the DAQ system, some fuses were brought in case they needed to be replaced. The problem was as same as the happening on May 7, 2012, a fuse was broken causing the system to be stopped working. The broken fuse was replaced, and the system was returned to normal operating. Figure 1 shows one the visit to Sunrise Bridge.

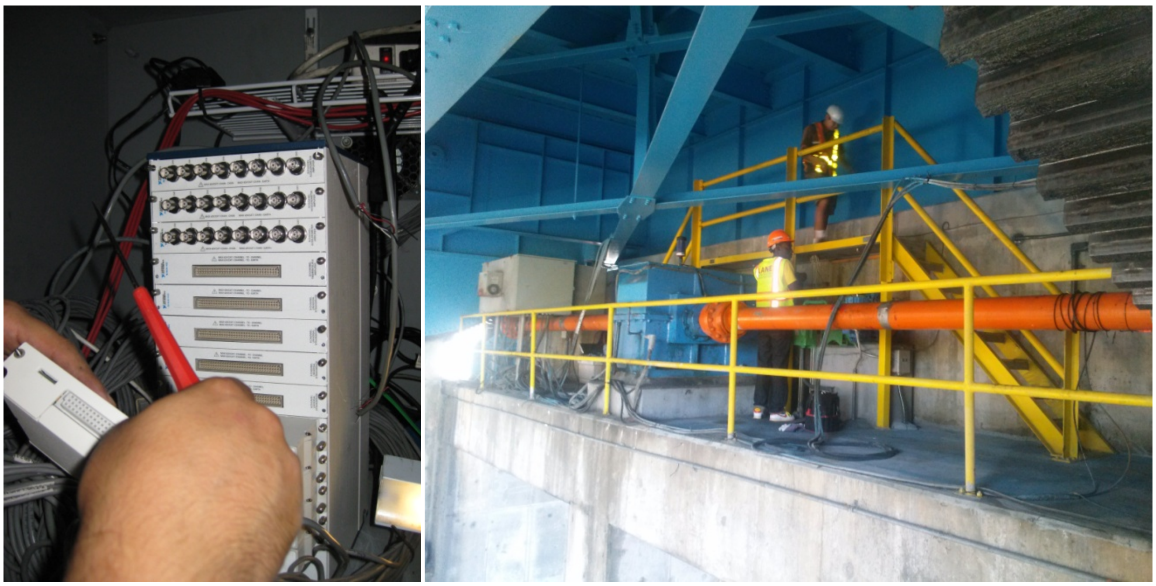

Figure 1-Picture from the field visit for fixing DAQ system and replacing malfunctioned sensors

2.3. *Current status of the monitoring system*

The movable bridge was instrumented with a total of 160 sensors (more than 200 channels) located on both the East and West leafs for performance monitoring of mechanical and structural components. Mechanical components on each side are being monitored during opening condition, while the structural data is collected for vehicle loads. The SHM system is operating on each leaf and data is being recorded regularly. The current status of sensors employed for the system is summarized in two separate tables (Table 3.1 and Table 3.2) in Chapter 3 of this report. Currently, the status of the entire SHM system is satisfactory and the system operates without any functionality issue. However, as was discussed in the previous section, the computer systems and software should be upgraded to ensure that the system will continue to operate reliably in the future.

CHAPTER 3. LONG-TERM STATISTICAL ANALYSIS

3. LONG-TERM STATISTICAL ANALYSIS OF MECHANICAL COMPONENTS

3.1. Introduction

In this chapter, the data that were collected from mechanical components of the bridge are analyzed using statistical methods. Having various types of sensors installed on mechanical and structural components turns data processing into a comprehensive task. The measurement data for the different mechanical components that was recorded during the prior phase of the project were processed and analyzed to establish a baseline description of performance for each individual component. The measurement data recorded from the current phase are processed with the same procedures and are subsequently compared to the previous results in order to monitor the performance of the components. In fact, any variations from the developed baselines can be considered as indicative of a change or damage to the monitored components.

3.2. Analysis results for the data collected during the extension project

Measurement data was collected from the critical mechanical components over the time period from 9/1/2009 to 6/15/2013. The extension project covered the time period from 1/1/2012 until 6/15/2013. The data that was collected during this extension project (1/1/2012 to 6/15/2013) are analyzed statistically in time and plotted against the previous results in order to identify any possible changes. The statistical parameters that are extracted include maximum, minimum, standard deviation and root mean squares (RMS) of the measured responses. These parameters are then compared with those extracted during the previous phase of the project to monitor and track the performance of different mechanical components. The locations of the different mechanical components that are monitored are illustrated in Figure 2.

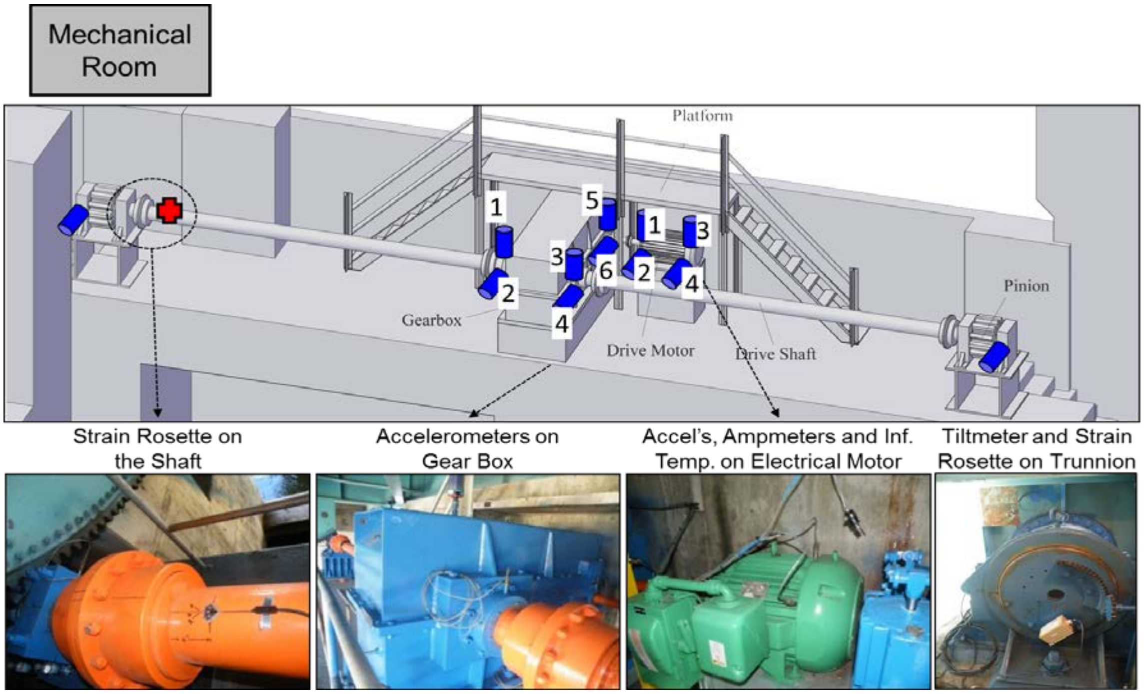

Figure 2-Mechanical components and their corresponding sensor location

3.3. Gearbox

The gearboxes contain the assembly that transmits the torque generated by the motor to the shafts (Figure 3). When the gearboxes experience deterioration or lack of lubrication, some change in the vibration and sound characteristics during the bridge operation should be noted. Abnormal vibration is an indicator of wear in the gears. Oil viscosity is also an important parameter for proper functioning of the gearbox. Considering these issues, the monitoring system included accelerometers to measure the vibration of the gearbox during bridge opening/closing events. Furthermore, microphones were also installed in the vicinity of the gearbox to determine its acoustic signature for opening/closing events. The vibration and acoustic signatures associated with a bridge opening/closing event are shown in Figure 3 and Figure 4, respectively.

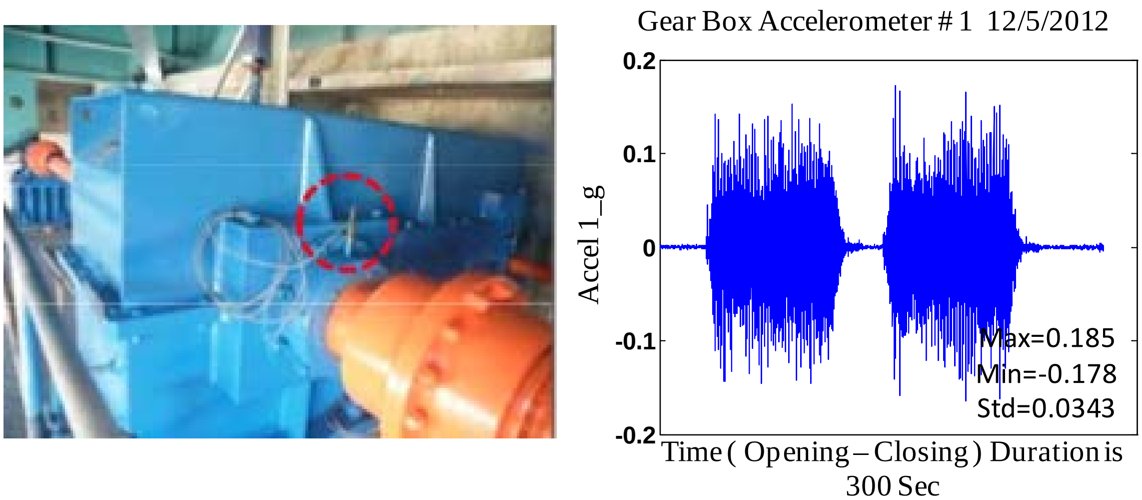

Figure 3-Gearbox acceleration and sample data

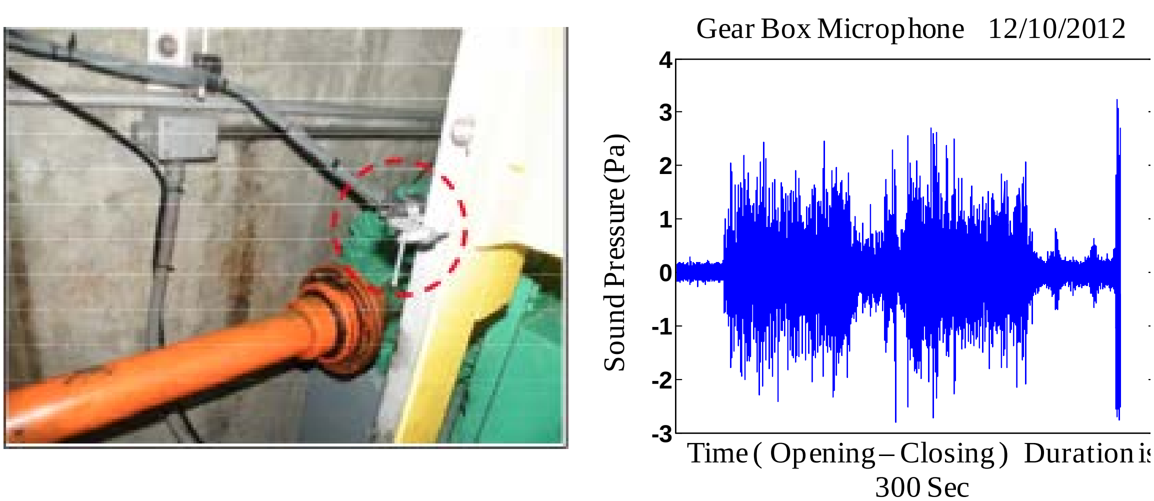

Figure 4-Gearbox microphone and sample data

The new data recorded from the gearbox accelerometer were analyzed statistically and are plotted along with previous measurement data in Figure 5. The 30 largest and the 30 smallest acceleration values were extracted for both the opening and closing events that occurred each day and are shown at the top of this figure. The standard deviation and root mean squares of the accelerations are also calculated and stored for each individual opening and closing of the movable bridge, and these are also shown in the top of Figure 5. The bottom of Figure 5 shows the histograms of maximum and minimum acceleration values.

It is clear from Figure 5 that the average vibration level is nearly constant over time with the exception of one anomaly. The anomaly occurred between 4/11/2010 and 5/18/2011 and is characterized by a dramatic jump in the measured vibration level. The root cause of this abrupt jump is investigated in conjunction with the maintenance reports for the bridge in Chapter 5. With the exception of this one anomaly, the gearbox was and is performing at an ordinary vibration level. This indicates that the gearbox has been maintained properly over the past few years.

The statistical results from the gearbox microphone are presented in Figure 6. The results indicate that the measured responses have not exceeded the baseline results. The results also exhibit good consistency with the acceleration data.

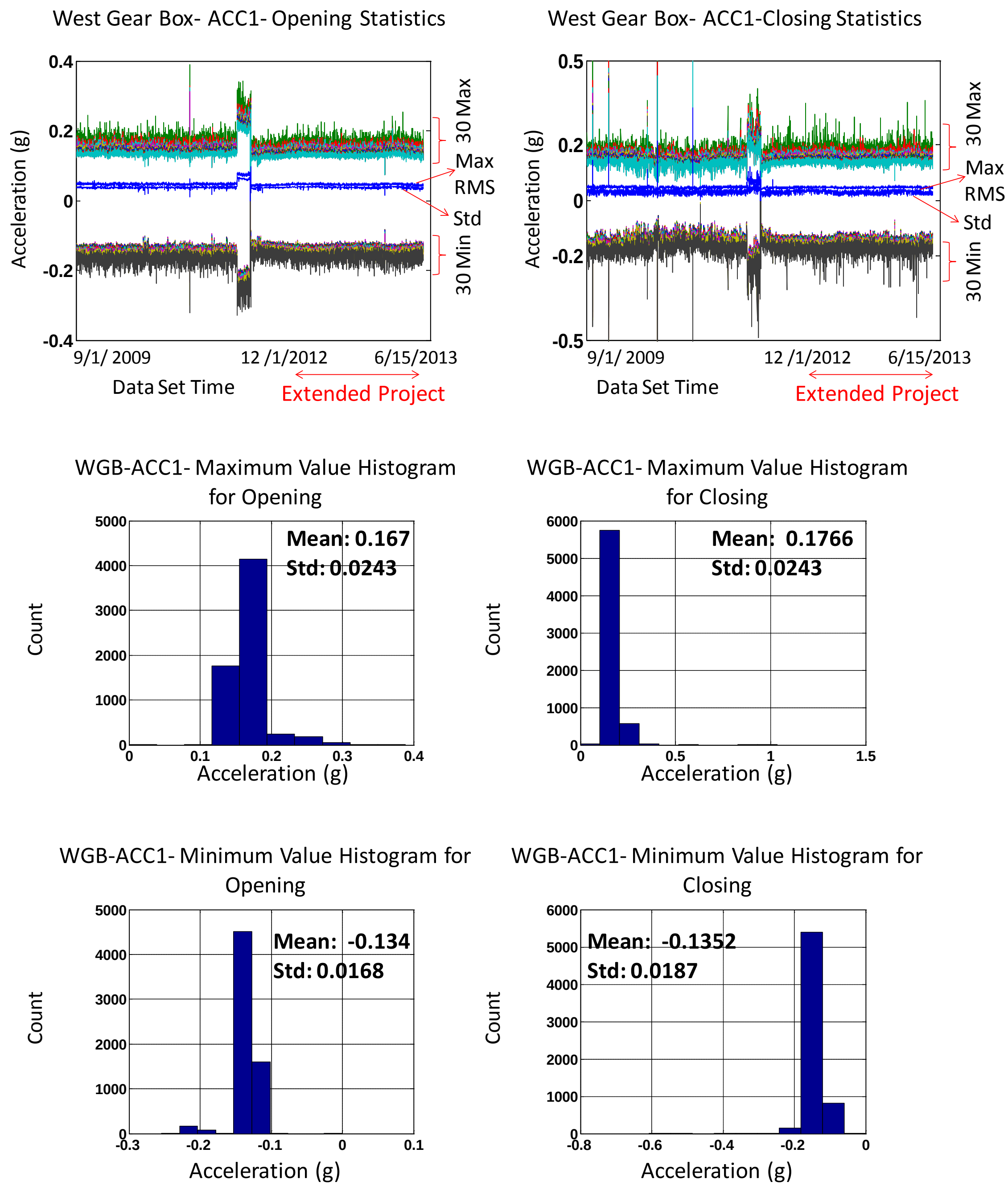

Figure 5- West gearbox acceleration statistics for opening and closing (max,min and standard) and acceleration maximum and minimum value histograms

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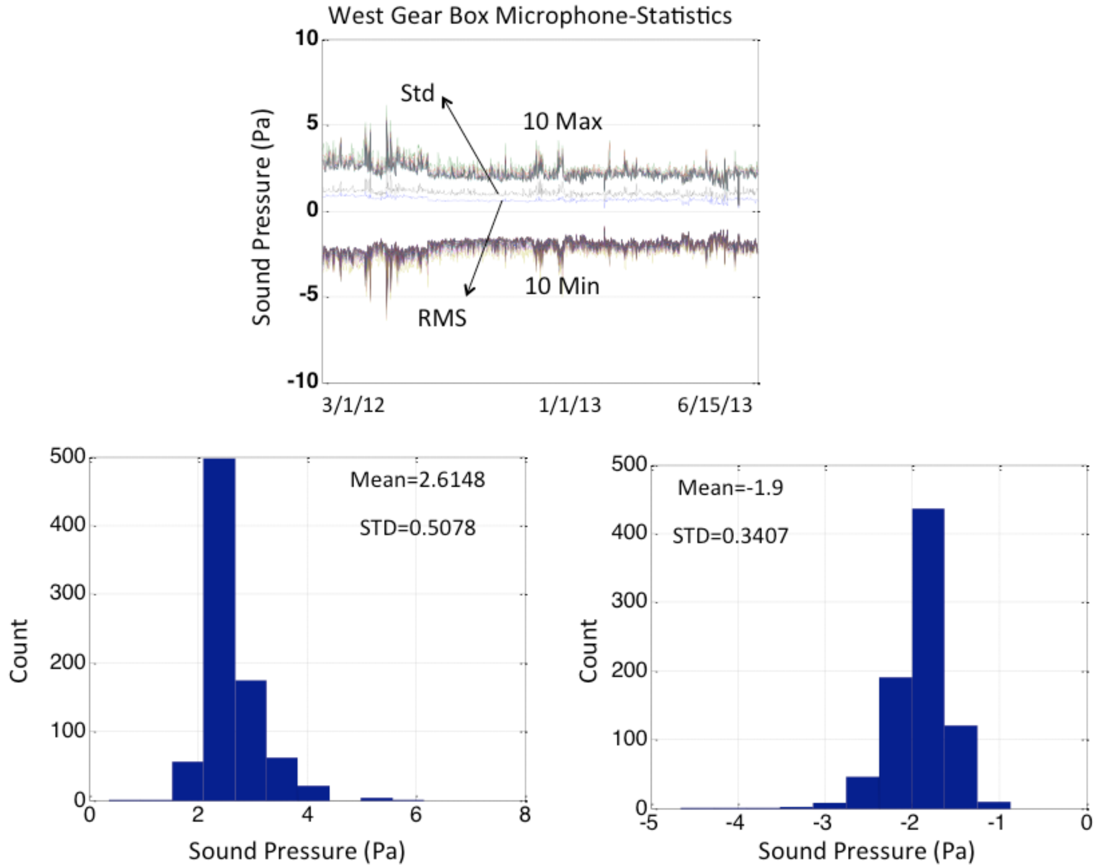


Figure 6- West gearbox microphone statistics for opening and closing (max,min, and standard) and accelerometer maximum and minimum value histogram

3.1.Electrical Motor

The electrical motors generate the torque required for the opening and closing of the bridge. Some of the indicators for improper functioning of the electrical motors are high amperage, high temperature, high vibration level and high revolution speed. Therefore, it was decided that the monitoring system would include ampmeters to measure the amperage levels for each one of the electric motor phases (Figure 7), accelerometers to measure the vibration on the motor during the bridge openings and closings (Figure 8), and infrared temperature sensors to monitor the temperature of the electrical motor (Figure 9).

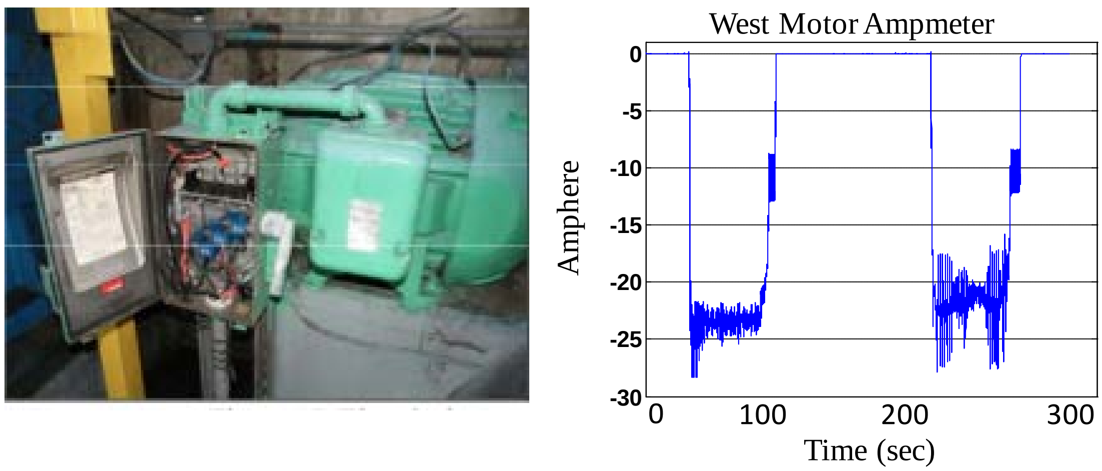


Figure 7-Electrical motor amp meter and sample data

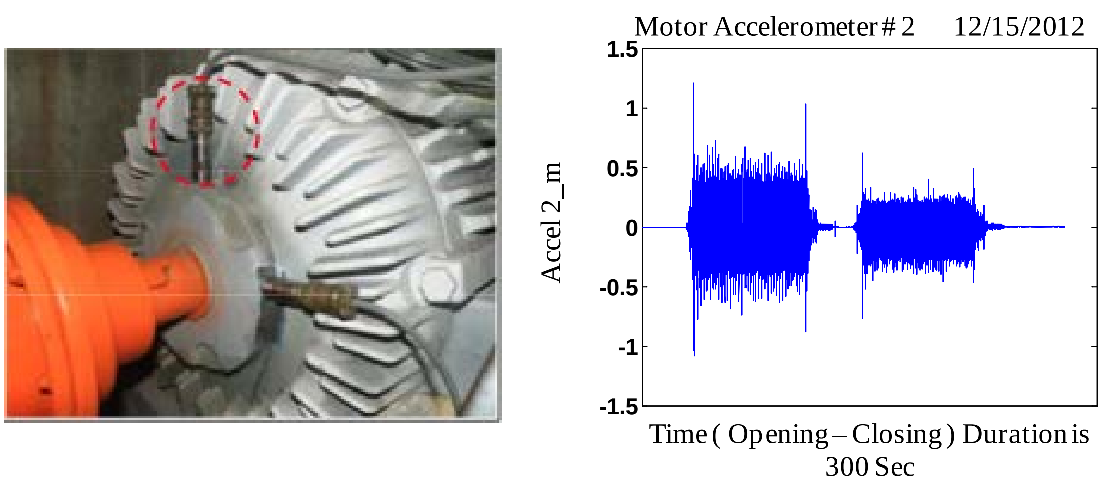


Figure 8-Electrical motor accelerometer and sample data

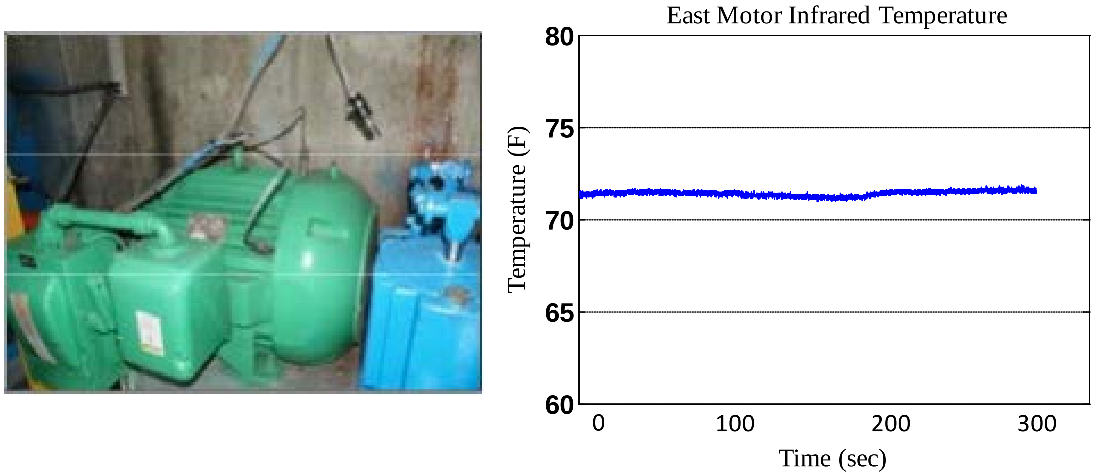


Figure 9-Electrical motor infrared temperature sensor and sample data

In order to monitor the vibration level of the motor, the 30 highest and 30 smallest acceleration values were extracted separately from the bridge opening and closing events that occurred during each day. In addition, the standard deviation and root mean squares are calculated and stored for each individual opening and closing of the movable bridge. Moreover, the histogram for maximum and minimum values are extracted and presented in Figure 10.

There was no significant change observed in the vibration level of the motor. In fact, the motor vibration level has been bounded in a constant range throughout the monitoring process. Some interesting results have been identified by evaluating the monitoring data from the motor along with the maintenance actions extracted from the maintenance reports. Those results are presented separately in Chapter 5 of this report.

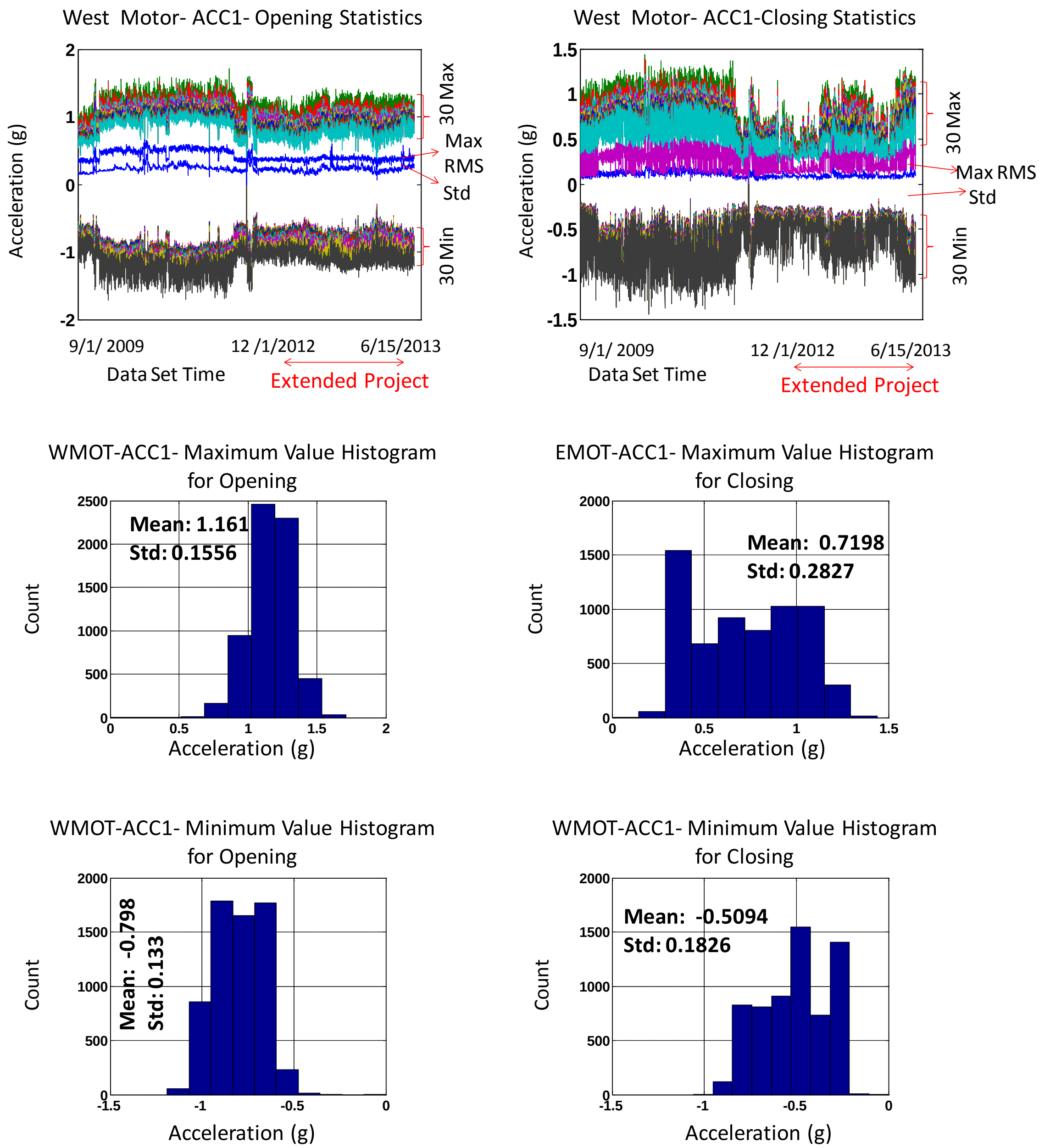


Figure 10-West Motor accelerometer statistics for opening and closing (max, min, and standard) and accelerometer maximum and minimum value histograms

3.2. Open Gear and Rack and Pinion

The open gears are the main gears, which are part of the leaf main girder and receive the torque from the rack and pinion assembly. Corrosion due to lack of lubrication, excessive strain, out-of-plane rotation and misalignment are common problems for open gears. Another concern is loading sequence problems, which mean that the drive shafts begin rotation in delayed sequence. This has an adverse effect on the condition of the open gears, usually by causing impact loading. Routine maintenance is required on the gear teeth. If the gear teeth are not kept lubricated at all times, wear and corrosion due to grinding of the rack and the pinion will occur.

To monitor the condition and maintenance needs of the open gears and rack and pinions, accelerometers were installed at the base of the rack and pinion to monitor its vibrations (Figure 11). A video camera was also installed facing the open gear (Figure 12) to allow the use of computer vision algorithms for detecting corroded and/or non-lubricated areas as discussed in the previous report.

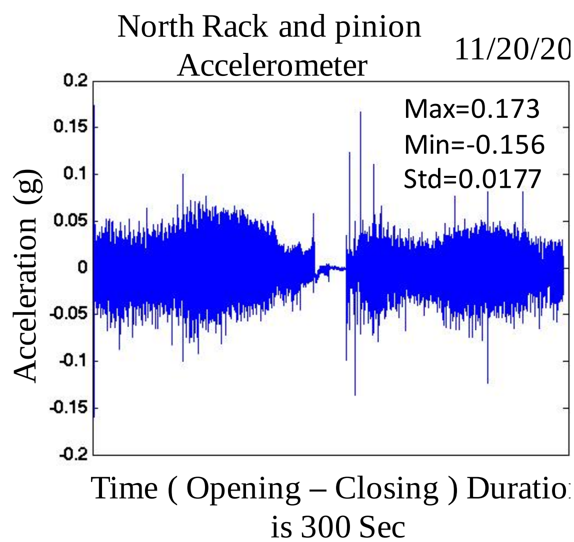


Figure 11- Rack and Pinion accelerometer and sample data

In the Figure 13, a two-month window of video clip data on September and October 2012 was analyzed and described. As stated above, the LI values were determined daily in the two-month window and LI values show that those never drop to a lower threshold level except the two days on September 4, 2012 and October 14, 2012. The images in both days was re-checked visually, and it is seen that the grease chunks are lacking on September 4; however, the lubrication level on the 14th of October is not that low. The issue on October 14 was finally discovered because of rainy condition that cause the video clip much less brightness than usual, and the low quality of images on that day affected to the result of the algorithm (LI value).

Figure 12- Open gear and video camera

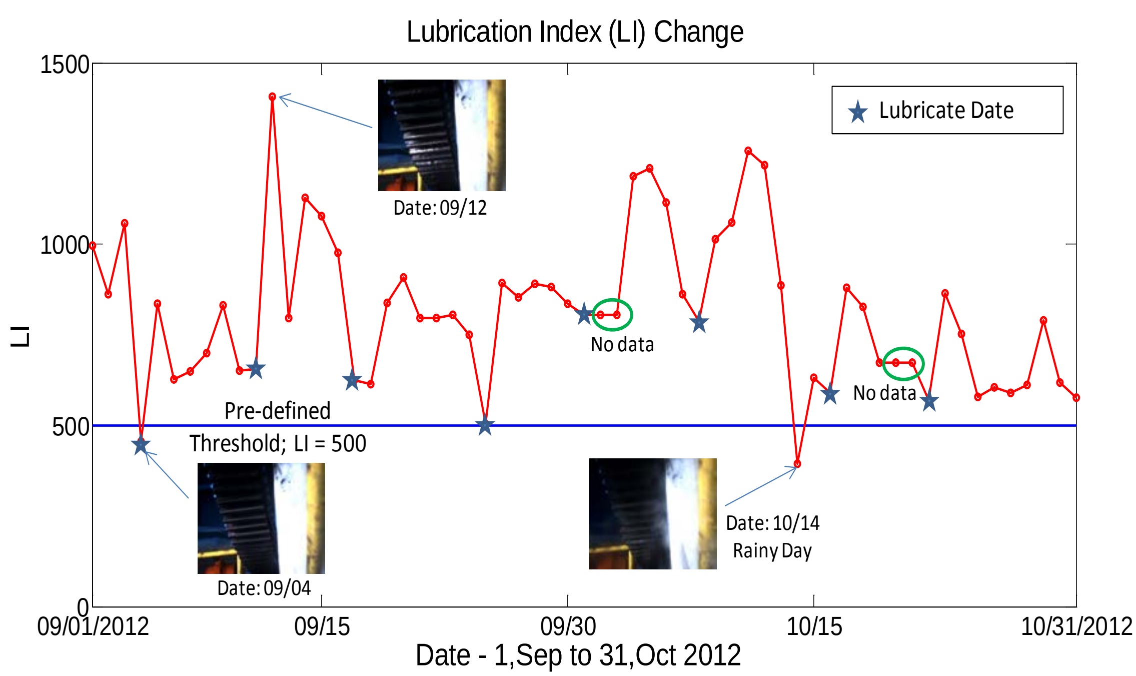


Figure 13- Monitoring and tracking lubrication index (LI) over long-term

Moreover, this report correlates the LI values with the maintenance data in order to study the effectiveness of the lubrication along with maintenance actions.. The LI graph can give the bridge owners another way to check the quality of lubrication instead of depending on the maintenance reports issued by the contractors. By synchronizing the lubricating dates given the maintenance reports with the LI graph, it is seen that the LI values increased significantly after the lubricating days and gradually decreased until the next lubricating days as part of field maintenance. Based on the trend of the LI graph, the bridge owners can determine not only the lubrication status on open gears but also the schedule and lubrication work quality of the maintenance personnel.

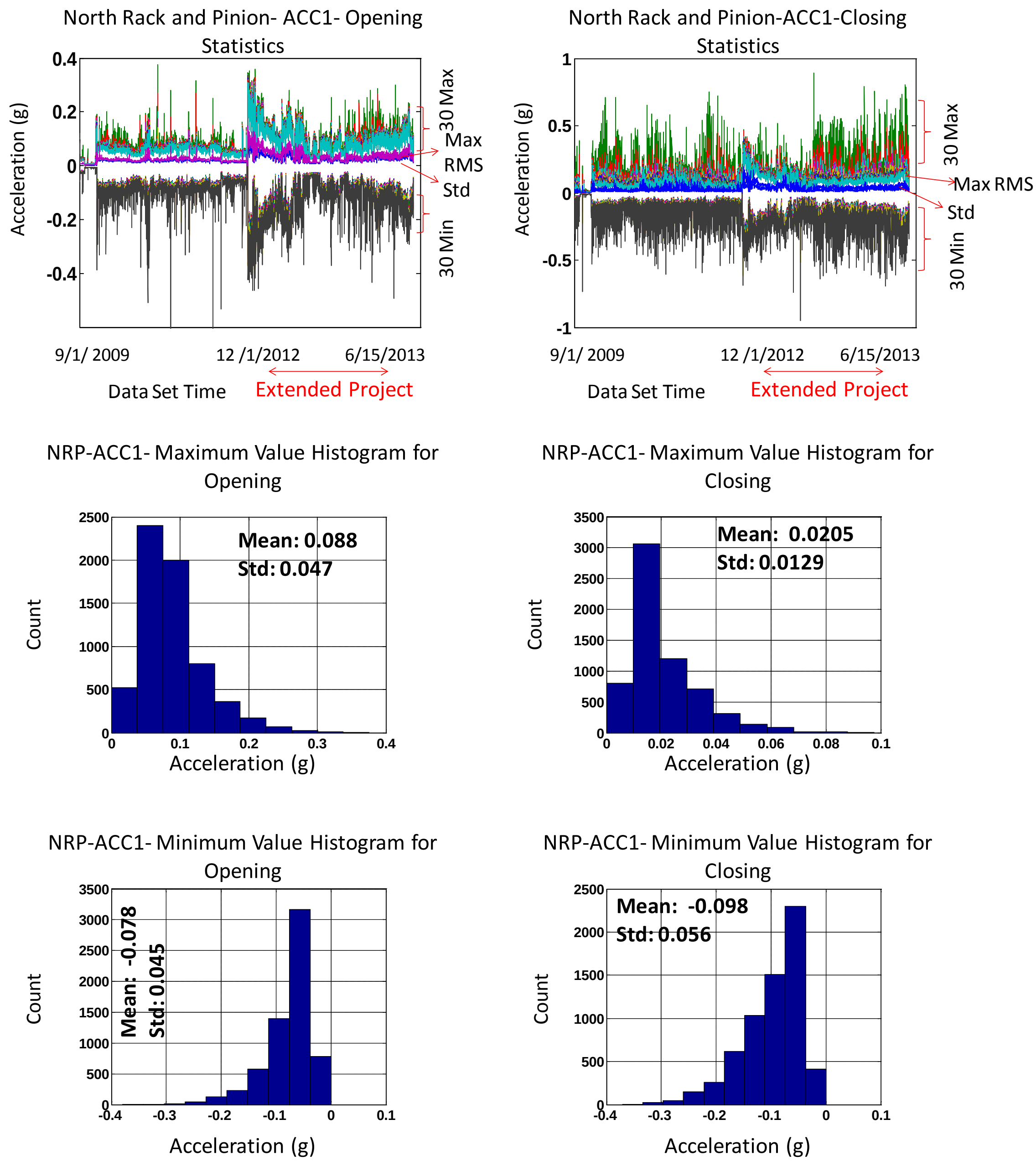


Figure 14- North Rack and pinion accelerometer statistics for opening and closing (max,min and standard) and accelerometer maximum and minimum value histograms

3.3. Bridge Balance

The shaft is the connecting element between the gearbox and rack pinion, and it is responsible for transmitting the required power for opening and closing operations. Its condition is directly related to the structural integrity and proper functioning of the movable bridge. Any unanticipated distress on the shaft will indicate either degradation of the shaft, motor, gears, rack, or overloading of the bridge during operation.

The drive shafts can be monitored for the total torque, friction of the system, as well as for the center of weight, by means of a balance test, which is a common method for detecting changes in the opening/closing operational characteristics. During the test, torsional strain measurements are collected using strain gage rosettes mounted on the shaft (Figure 15).

Figure 15-Strain rosette on the drive shaft

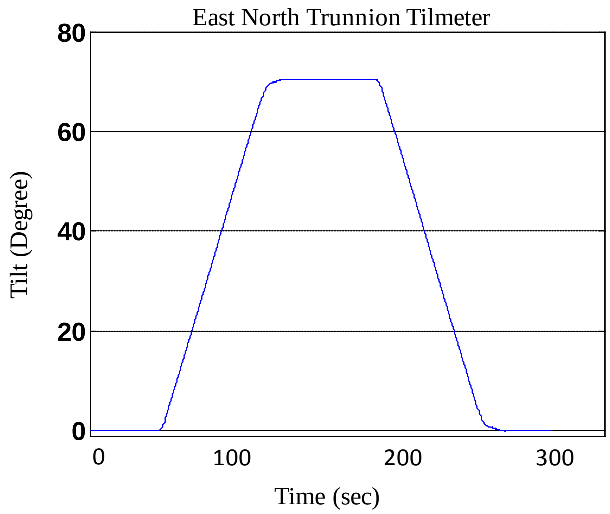


Figure 16- Trunnion tiltmeter and sample data

The torque on the drive shafts can be determined from these torsional strain measurements using the procedure presented by Malvern et al. (1982), which is discussed in detail in the previous report. In addition, tilt data is recorded by tiltmeters installed on trunnions as shown in Figure 16.

To monitor the shafts continuously, the monitoring system included strain rosettes at both shafts on each leaf. The instrumentation of both shafts enables their performance to be compared as an indicator of shaft condition/deterioration. The implemented monitoring system is capable of performing a balance test for each opening/closing operation. This continuous monitoring offers numerous advantages. Tracking of the torque and friction number with time can help to apply corrective/preventive maintenance on time, establish power/imbalance relationships and prevent failures of motor, shaft, gearbox and trunnion. Savings in technical labor and repairs are anticipated benefits of the system.

In this report, the opening and closing operation data collected from 3/15/12 to 6/15/13 from the West leaf was analyzed to obtain friction numbers. The friction trends are presented in Figure 17. From this figure, a steady trend in the friction number can be seen during this period.

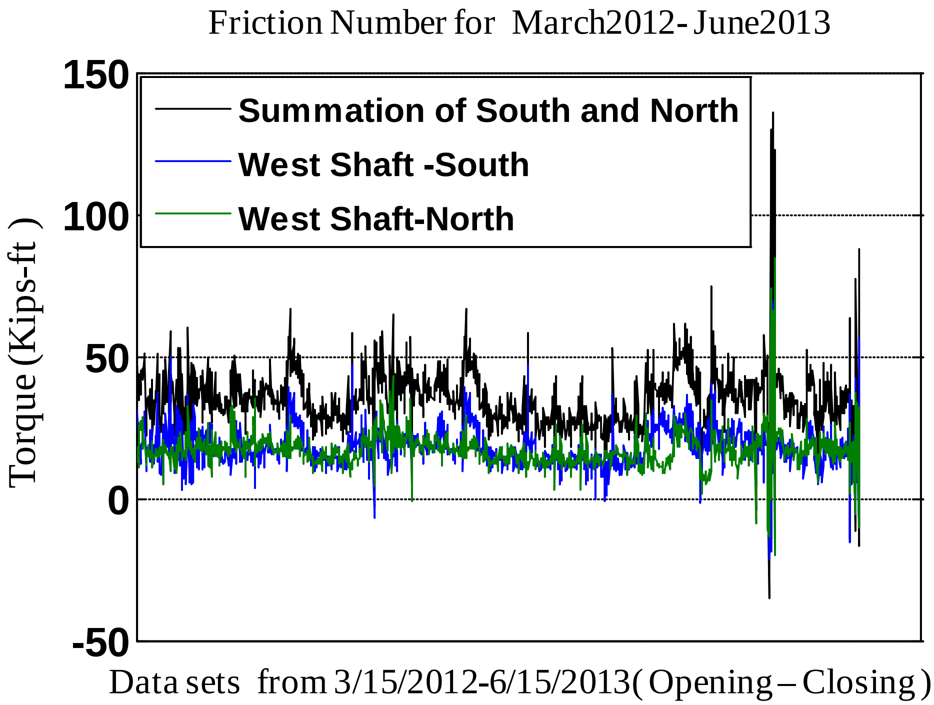


Figure 17-Friction and temperature trends over long-term

List of available sensors for mechanical components: Two individual tables were prepared to present the available sensors and their performance ranges. This information is presented separately for each leaf. Table 1 shows all sensors installed on the West leaf mechanical components along with their performance ranges while Table 2 presents the same information for the East leaf.

Table 1-List of sensors and their performance ranges for the mechanical components installed on the west side of leaf

West										
	Measurement	Sensor ID	Last Month			This Month			Amplitude	Note
			Good	Problem	Not Working	Good	Problem	Not Working		
Gear Box										
	Accelerometer 1	W-GB-ACC-1	x			x			0.10 / -0.10	There is not any significant change
	Accelerometer 2	W-GB-ACC-2	x			x			0.08 / -0.08	There is not any significant change
	Accelerometer 3	W-GB-ACC-3	x			x			0.13 / -0.13	There is not any significant change
	Accelerometer 4	W-GB-ACC-4	x			x			0.08 / -0.08	There is not any significant change
	Accelerometer 5	W-GB-ACC-5	x			x			0.18 / -0.18	There is not any significant change
	Accelerometer 6	W-GB-ACC-6			x			x	0.10 / -0.10	N/A
	Microphone	W-GB-MIC-1	x			x			1.7 / -1.7	There is not any significant change
Motor										
	Accelerometer 1	W-MOT-ACC-1	x			x			0.45/-0.45	There is not any significant change
	Accelerometer 2	W-MOT-ACC-2	x			x			0.5 / -0.5	There is not any significant change
	Accelerometer 3	W-MOT-ACC-3	x			x			1.2/-1.2	There is not any significant change
	Accelerometer 4	W-MOT-ACC-4	x			x			1.1 / -1.1	There is not any significant change
	Infrared Temp	W-BRK-IT2			x			x	70-80 degree	N/A
Rack and Pinion, and open Gear										
	N Accelerometer	WN-RP-ACC-1	x			x			0.06 / -0.06	There is not any significant change
	S Accelerometer	WS-RP-ACC-1	x			x			0.04 / -0.04	There is not any significant change
	Camera		x			x			N/A	There is not any significant change
Shaft										
	N Rosettes 1	WN-SHFT-SR-1	x			x			Values used to determine friction value	There is not any significant change
	N Rosettes 2	WN-SHFT-SR-2	x			x				There is not any significant change
	S Rosettes 1	WS-SHFT-SR-1	x			x				There is not any significant change
	S Rosettes 2	WS-SHFT-SR-2	x			x				There is not any significant change

Table 2- List of sensors and their performance ranges for the mechanical components installed on the east side leaf

East										
	Measurement	Sensor ID	Last Month			This Month			Amplitude	Note
			Good	Problem	Not Working	Good	Problem	Not Working		
Gear Box										
	Accelerometer 1	E-GB-ACC-1	x			x			0.15 / -0.15	There is not any significant change
	Accelerometer 2	E-GB-ACC-2	x			x			0.15 / -0.15	There is not any significant change
	Accelerometer 3	E-GB-ACC-3	x			x			0.12 / -0.12	There is not any significant change
	Accelerometer 4	E-GB-ACC-4	x			x			0.12 / -0.12	There is not any significant change
	Accelerometer 5	E-GB-ACC-5	x			x			0.25 / -0.25	There is not any significant change
	Accelerometer 6	E-GB-ACC-6	x			x			0.10 / -0.10	There is not any significant change
	Microphone	E-GB-MIC-1	x			x			1.5 / -1.5	There is not any significant change
Motor										
	Accelerometer 1	E-MOT-ACC-1	x			x			0.42 / -0.42	There is not any significant change
	Accelerometer 2	E-MOT-ACC-2	x			x			0.51 / -0.51	There is not any significant change
	Accelerometer 3	E-MOT-ACC-3	x			x			1.3 / -1.3	There is not any significant change
	Accelerometer 4	E-MOT-ACC-4	x			x			1.3 / -1.3	There is not any significant change
	Infrared Temp	E-BRK-IT2			x			x	N/A	N/A
Rack and Pinion										
	N Accelerometer	EN-RP-ACC-1	x			x			0.023 / -0.023	There is not any significant change
	S Accelerometer	ES-RP-ACC-1	x			x			0.03/ -0.03	There is not any significant change
Shaft										
	N Rosettes 1	EN-SHFT-SR-1	x			x			Values used to determine friction value:	There is not any significant change
	N Rosettes 2	EN-SHFT-SR-2	x			x				There is not any significant change
	S Rosettes 1	ES-SHFT-SR-1	x			x				There is not any significant change
	S Rosettes 2	ES-SHFT-SR-2	x			x				There is not any significant change

3.4. Slow speed structural data

The temperature can be considered as a special type of load that induces on a structure. Previous reports have shown that the strain values caused by temperature gradients are even higher than strain induced by vehicle traffic at some particular locations. Observing the temperature strains can help researchers understand the daily strain cycles at monitoring locations by mean of the temperature differential cycles and the correlations between them. In long-term monitoring, the changing of relationship between temperature strains and ambient temperature is considered as a possible clue of damage happening in the structures. To obtain the temperature and strains on the bridge, vibrating wire gages were installed on different components and the data collected from those sensors can be seen in Figure 18.

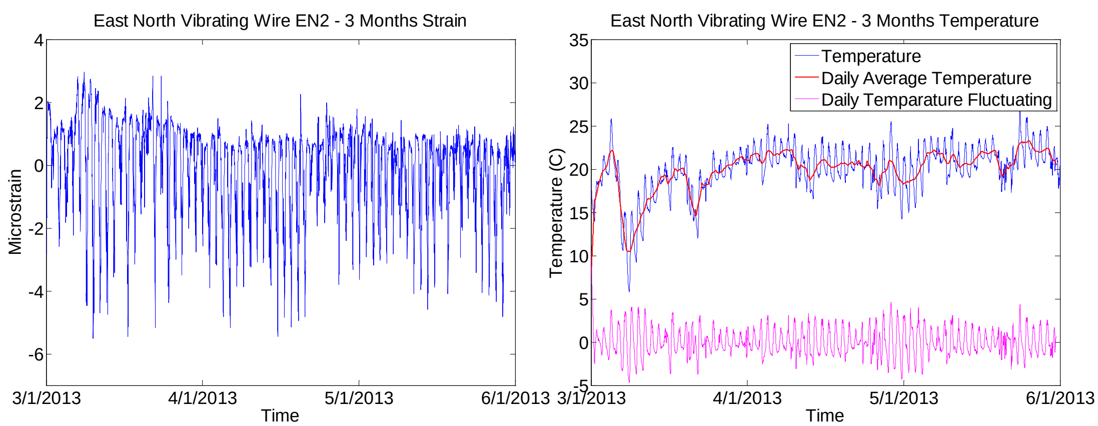


Figure 18-EN2 vibrating wire three-month window strain and temperature data

By ploting both temperature and strain values on the same graph as in Figure 19, it is observed that the strain range of vibrating wire EN2 at East North location is around 6 microstrain while the temperature differential is approximately 9°C during the three month period from March to June, 2013.

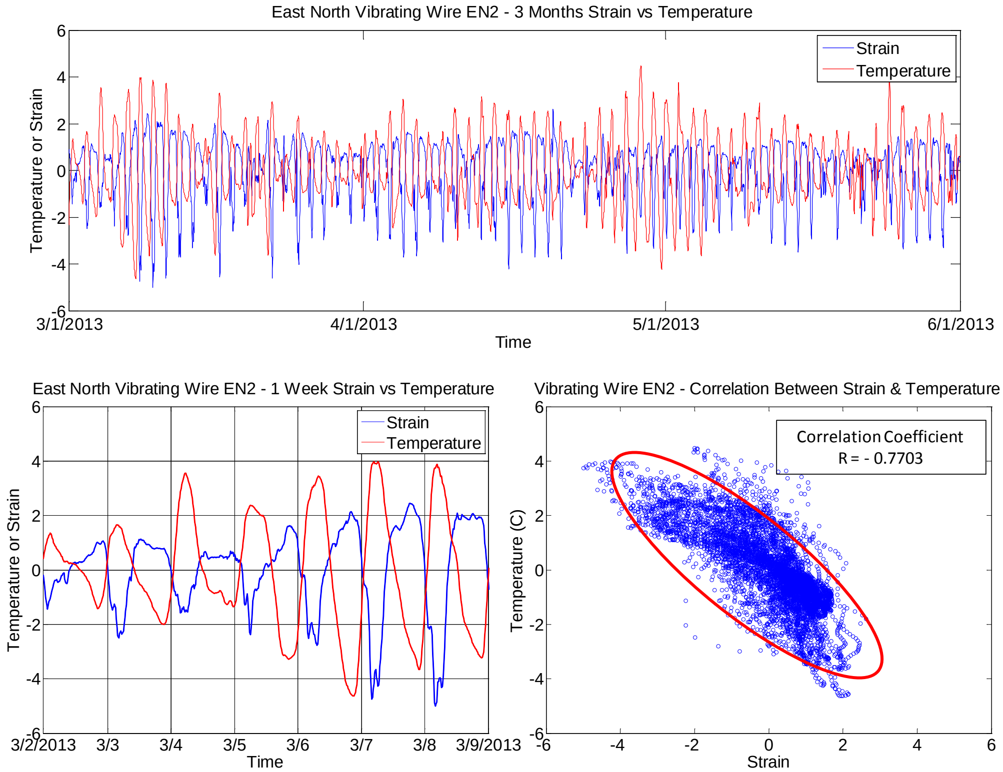


Figure 19-Correlation between strain and temperature data of EN2 sensor

The negative correlation between the ambient temperature and the strain data can be clearly seen on one-week window as well as on the scatter graph. The correlation coefficient value R in this case is determined as -0.7703 value. For the West leaf data, the WS3 sensor at West South area is selected and the data for three-month window is presented in Figure 20.

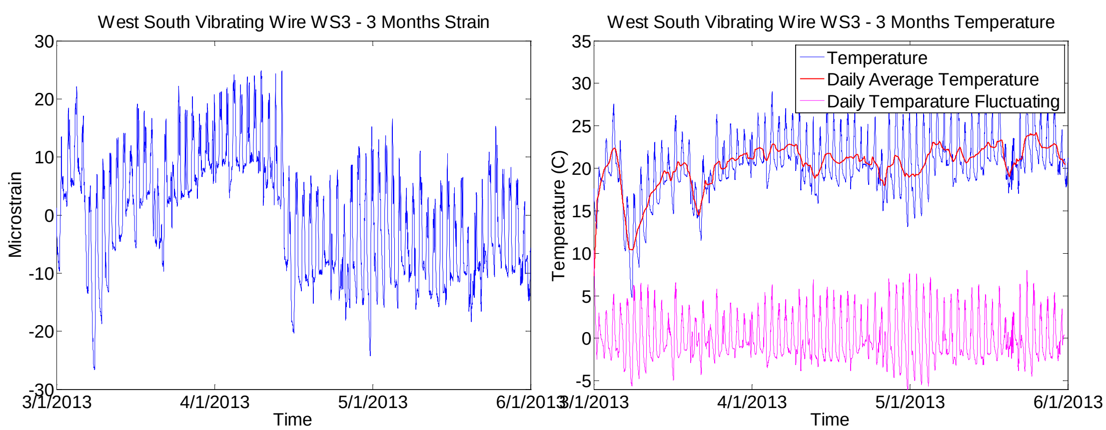


Figure 20-WS3 vibrating wire 3 months-window strain and temperature data

After analyzing the data, the results show that the strain range of WS3 sensor is nearly 40 microstrain and higher than the one obtained from EN2 sensor in the same period. The correlation between temperature and strain is determined as well and it is seen that there is high correlation between temperature and strain. This conclusion can be proved by visually checking in one-week window data presentation as well as the high value of the correlation coefficient R as 0.8746 value.

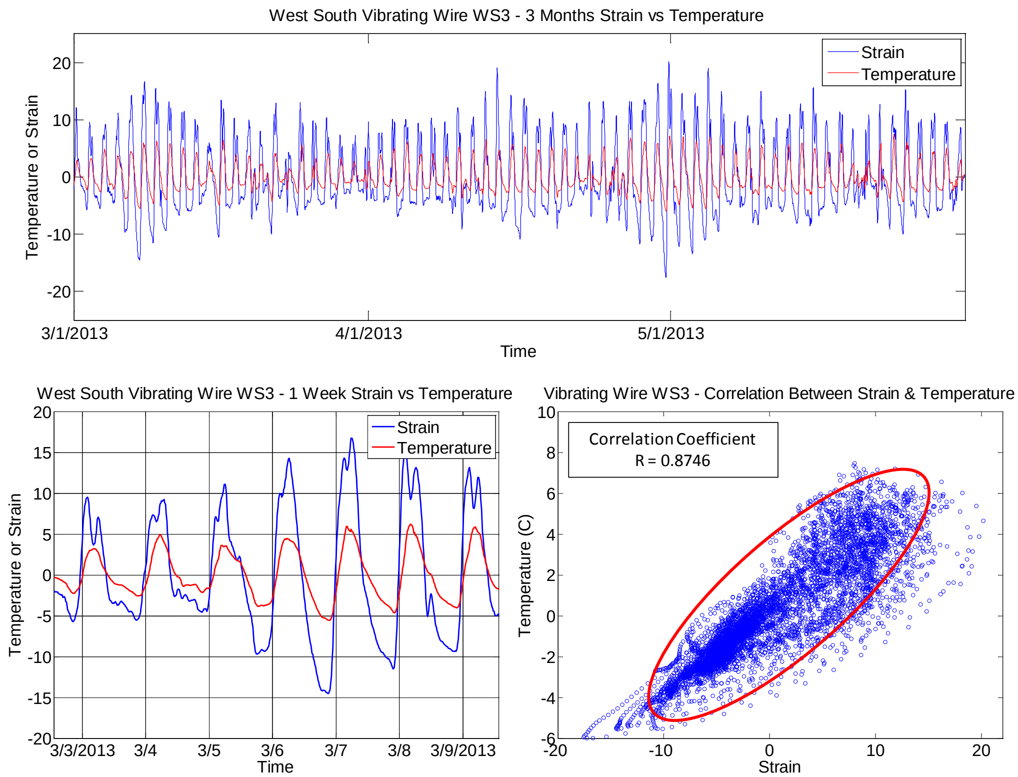


Figure 21-Correlation between strain and temperature data WS3 sensor

CHAPTER 4. LONG-TERM MONITORING OF STRUCTURAL COMPONENTS USING ADVANCED NON-PARAMETRIC TECHNIQUES

4. MONITORING OF STRUCTURAL COMPONENTS USING ADVANCED NON-PARAMETRIC ALGORITHMS

4.1. Introduction

The structural framing system for the bridge includes the main girders, the floor beams and the stringers. These components are constructed from both rolled and built-up steel sections with welded plates. Corrosion is one of the main concerns for the bridge girders, floor beams, and stringers, especially at exposed surfaces. Corrosion leads to section loss and reduced capacity. Any misalignment, bending, or deformation in these components can also cause increased strain on the structure. Deformation or thermal effects can cause misalignment of the girders, leading to a malfunction in the bridge operation. The selected sensor layout provides the distribution of stresses on the girders and is expected to provide information regarding damage and deterioration for preventive maintenance purposes. Figure 22 shows the main structural components of the Sunrise Boulevard Bridge.

Figure 22-Structural components of Sunrise Boulevard Bridge

After several discussions and careful investigations, it was decided that the instrumentation plan of the main girders would include different sensors at critical components of the bridge to track possible issues, to evaluate maintenance actions and determine needs for maintenance by analyzing the data coming from the monitoring system. Corresponding sample data and analysis methodologies are presented in the following sections of this report.

4.2. Data Interpretation Approaches

Having access to reliable sensors and cost-effective data acquisition capabilities, the next challenge for long-term monitoring of infrastructures is interpreting the tremendous amounts of data collected from complex civil structures. There are several data-driven techniques available for damage detection purposes; however, these techniques are selected based on the type of application and also with respect to their advantages and drawbacks. Civil infrastructures are large and complex systems. Consequently, they require a significant number of sensors to monitor their behavior. Installing a large number of sensors on a civil structure will definitely generate a large amount of measurement data; however, the data are not automatically meaningful for detecting damage without the implementation of higher level data analysis approaches.

Previous studies indicate that only a few of the available data-driven damage detection techniques remain effective when applied to civil structures. Moving Principal Component Analysis (MPCA), Moving Cross Correlation Analysis (MCCA) and Robust Regression Analysis (RRA) have been selected as three of the most reliable data-driven algorithms (based on the comparative studies conducted on 10 different data-driven algorithms). This chapter first summarizes each of these algorithms. A new data-driven approach is also introduced. The so called MPCA-SVM algorithm has been developed to overcome disadvantages associated with the MPCA, MCCA and RRA approaches. Finally, the efficiency of these algorithms is explored using the data collected from Sunrise Movable Bridge.

4.2.1. Principal Component Analysis (PCA)

PCA is the dimensionality reduction technique that transfers the data from original space, variable space, to the fewer dimension space referred to as principal component space. In other words, the intention of this transformation is to transfer a number of possibly correlated variables into the smaller number of uncorrelated variables called principal components. PCA projection provides the opportunity to remove redundancy in information and also undesirable measurements such as noise. The first few principal components usually retain the most variance of the data, and as a result, are commonly considered as appropriate representatives of the original data. The rest of this section is devoted to discussion of the PCA method. The steps involved in PCA analysis are explained in more detail in the following sections. The concept of principal component analysis and the projection procedure are exhibited in Figure 23.

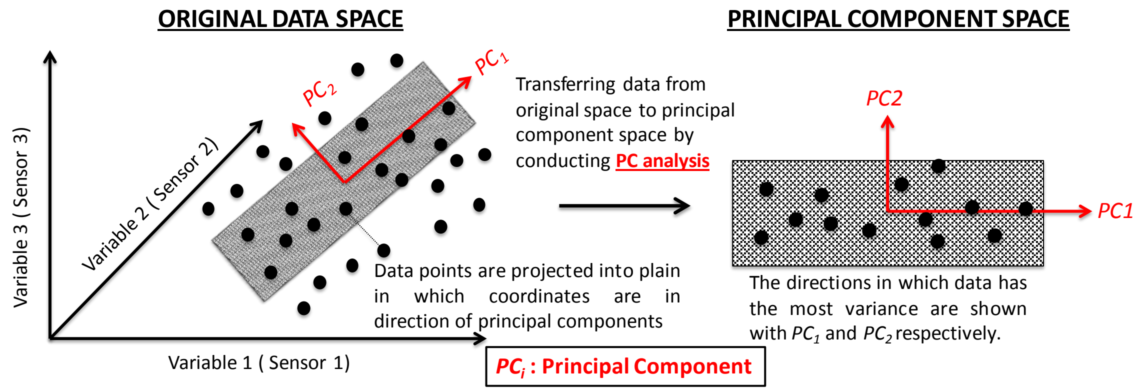


Figure 23-Schematic demonstration of Principal Component Analysis

4.2.2. Moving Principal Component Analysis (MPCA)

There are two principal deficiencies coupled with traditional PCA algorithm for SHM application; in particular, long-term monitoring of civil infrastructure in which the main challenge is dealing with the large-size type of matrix. The primary reason is that as the matrix becomes bigger in terms of size, the time that is required for computing the covariance matrix increases. The second problematic issue is that there is a delay in detecting an abnormal behavior in time series using PCA. Especially for long-term monitoring and in particular, for large civil structures, as the number of measurements increases, the effect of new points in the covariance matrix is lower and lower due to the fact that they are averaged by the total number of points. Considering these two main drawbacks associated with PCA, a modified version of this algorithm has been developed. The so-called moving principal component analysis (MPCA), in which the covariance matrix is calculated inside of a fixed-size moving window, has been proposed (Posenato et al. 2008) as an alternative approach.

4.2.3. Moving Cross Correlation Analysis (MCCA)

The second algorithm that was investigated in this study is the Moving Cross Correlation Analysis (MCCA). MCCA is an enhanced version of Cross Correlation Analysis (CCA) algorithm. The CCA algorithm was recently proposed as robust damage detection algorithm (Catbas et al. 2012). The implementation of this algorithm is summarized by the flowchart shown in Figure 24.

In order to conduct MCCA, the cross correlation coefficient of the strain data at one location with all other locations is calculated within a moving window from the following equation:

$$\rho_{ij}(t) = \frac{\sum_{k=1}^{n}(S_i(t_k)-\mu_i)(S_j(t_k)-\mu_j)}{\sqrt{\sum_{k=1}^{n}(S_i(t_k)-\mu_i)^2}\sqrt{\sum_{k}^{n}(S_j(t_k)-\mu_j)^2}} \tag{4.1}$$

where ρ_{ij} is the correlation between the sensors i and j, n is the total number of time observations during the monitoring duration, $S_i(t_k)$ and $S_j(t_k)$ are the values from the sensors i and j at time t_k, and μ_i, μ_j are the mean values of the data from the sensors i and j.

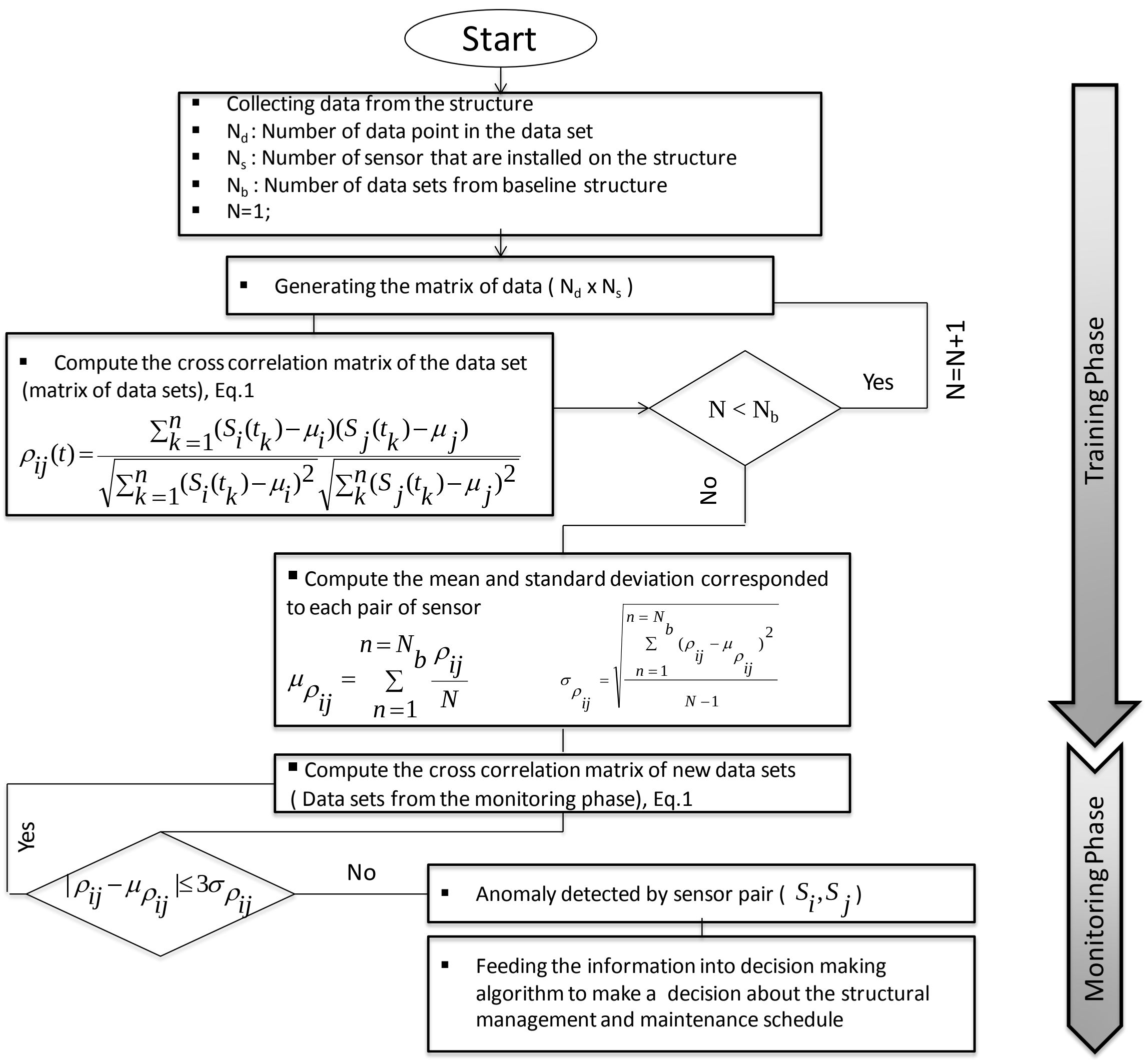


Figure 24- Application of CCA algorithm to long term monitoring of structures

4.2.4. Robust Regression Analysis (RRA)

Traditional regression methods are based on a least squares estimation, and as a result, they are sensitive to outliers. One of the main drawbacks associated with least squares estimation is that each data point is weighted equally for analysis. Robust regression analysis (RRA) was developed in order to overcome this disadvantage by considering different weights for different data points. The individual data points are weighted based on their distance from a regression line. Hence, after several trials, the weights that are assigned to the points with more distance from regression line are reduced. In this way the points, which are farthest away from other points, are assigned with less weights and eventually their effects are diminished.

A damage detection algorithm was designed based on robust regression analysis (Posenato et al. 2010). Like the other two algorithms, RRA is also started by dividing data into two categories referred as training and monitoring phase. In the training phase, all pairs of sensors with a correlation that exceeds a predefined threshold are selected. In the following step, regression lines are established between individual pair of sensors. Afterward, confidence intervals are developed for each individual pair of sensors based on the error between real value of the sensor and the estimation of regression line. During the final monitoring phase, this error (difference between real value and estimation from regression line) is computed and considered as a damage index. A change/damage is reported once the error in any of the pairs exceeds the confidence interval. A summary of the above-mentioned procedures is presented in Figure 25.

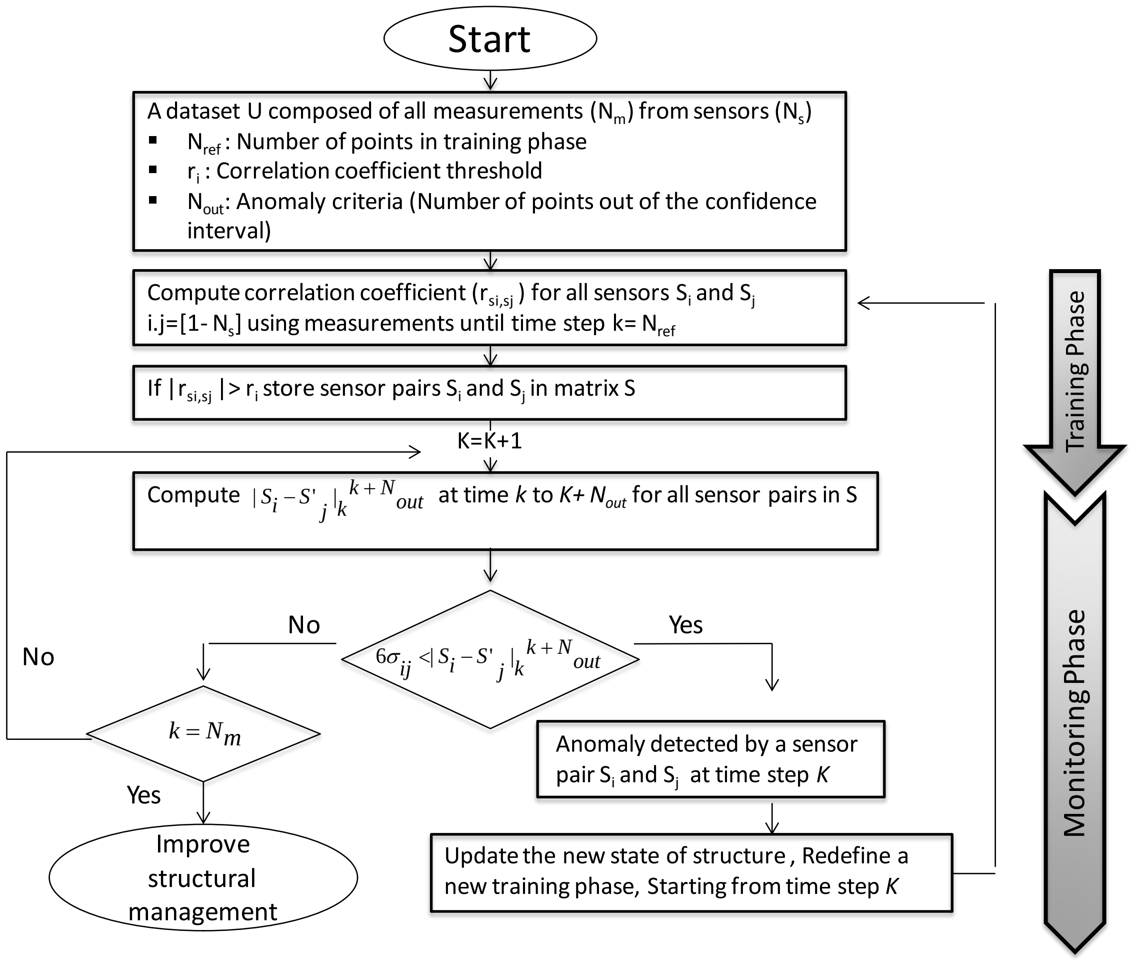


Figure 25-Application of RRA algorithm to long term monitoring of structures

4.2.5. Combined Algorithm - MPCA and Support Vector Machine(SVM)

As mentioned previously, there is a significant drawback associated with the MPCA algorithm. Delays in detection that occur with this approach makes MPCA less effective for monitoring of critical structures in which timely detection of deterioration and damage is paramount. Therefore, in this study, a new combined algorithm is proposed in order to decrease the delays in the detection of changes in performance. The procedures required for implementing MPCA-SVMs are summarized in Figure 26.

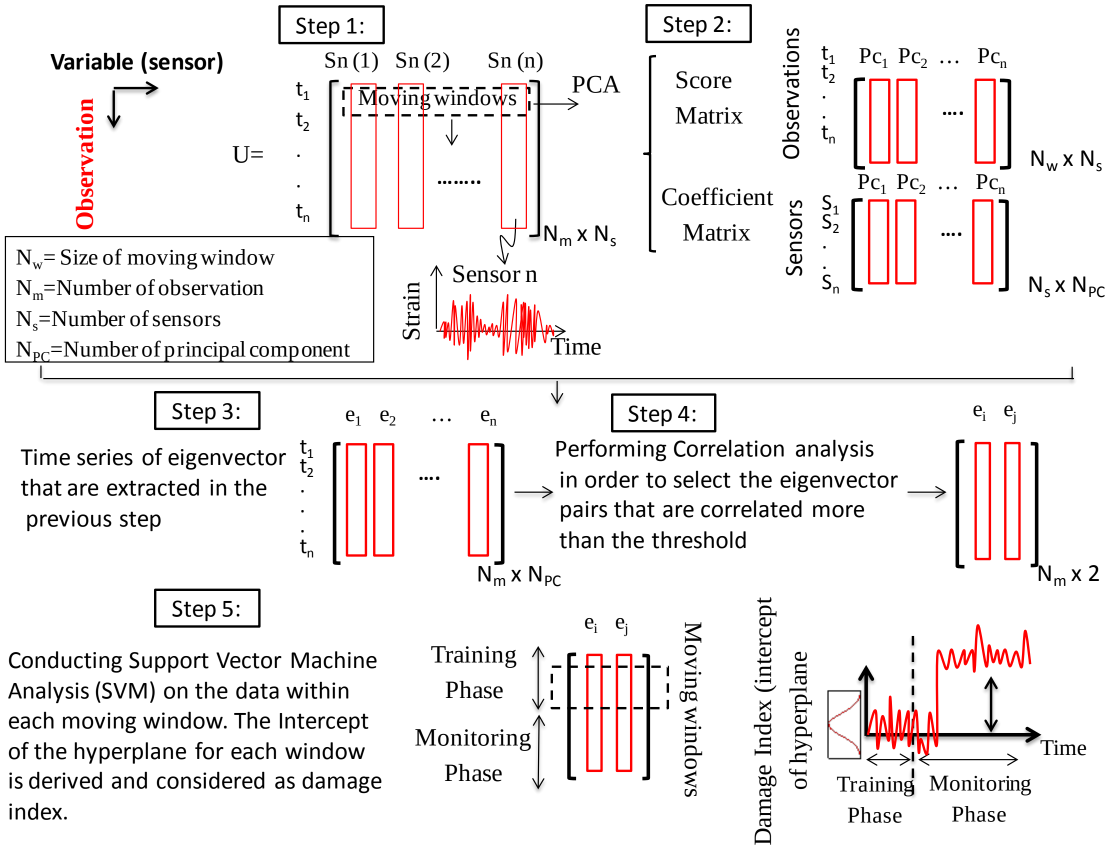


Figure 26-Summary of the procedure for MPCA_SVM damage detection algorithm

4.3. *Part I: Laboratory Study with a Four Span Bridge*

4.3.1. Structural Configuration

Several experiments were performed in the laboratory using a bridge model structure (UCF 4-span Bridge Model) to compare the capabilities of the MPCA, MCCA, RRA and MPCA-SVMs algorithms. Three common damage scenarios were simulated using the model for this evaluation. These scenarios were designed based on feedback obtained from bridge engineers from four different state Departments of Transportation. For this study, two global damage scenarios (boundary alterations) and a local damage (lack of local connectivity) were selected and simulated with the laboratory bridge model.

The laboratory model structure consists of two 120 cm approach (end) spans and two 304.8 cm main spans. The model has a 3.18 mm thick, 121.92 cm wide steel deck that is supported by two steel HSS 25x25x3 girders spaced 60.96 cm from each other. Figure 4.5 shows the configuration of the 4-span bridge model. A unique feature of this laboratory structure is the ability to simulate and test variety of damage scenarios that are commonly observed in bridge structures (Zaurin and Catbas 2010). It should be noted that although the structure is not a scaled down model of a specific bridge, its responses are representative of typical values for medium-span bridges. Radio controlled vehicles (15.7 kg) were crawled over the deck of the bridge model to simulate traffic loads on the structure as shown in Figure 27.

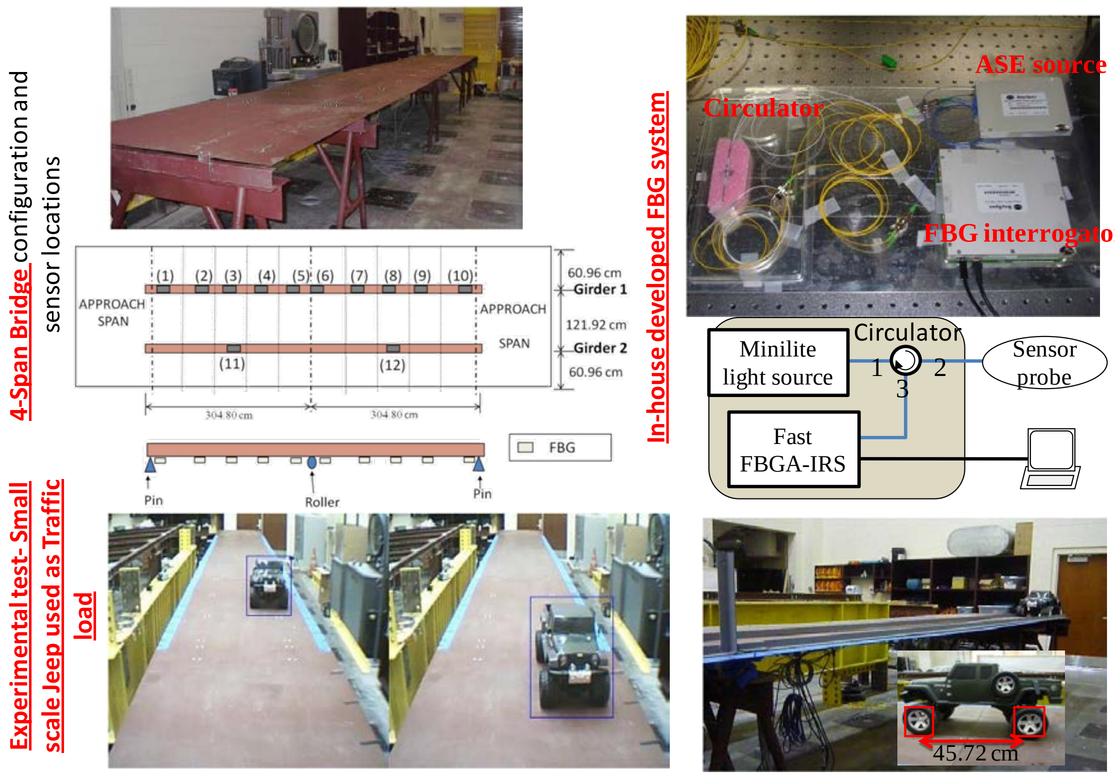


Figure 27- Experimental test conducted on the 4-span bridge using Fiber Optic Sensor and radio controlled vehicle

4.3.2. Implemented Damage Scenarios

The ability to shift the boundary conditions for the bridge model from roller to fixed supports and to simulate a lack of local connectivity provides an opportunity to evaluate the capabilities of various damage detection algorithms in terms of both local and global detectability characteristics. Three representative damage scenarios that included both local and global effects were introduced to the 4-span bridge model and the bridge responses due to simulated traffic loads were measured with fiber Bragg grating (FBG) sensors. The simulated damage scenarios are illustrated in Figure 28.

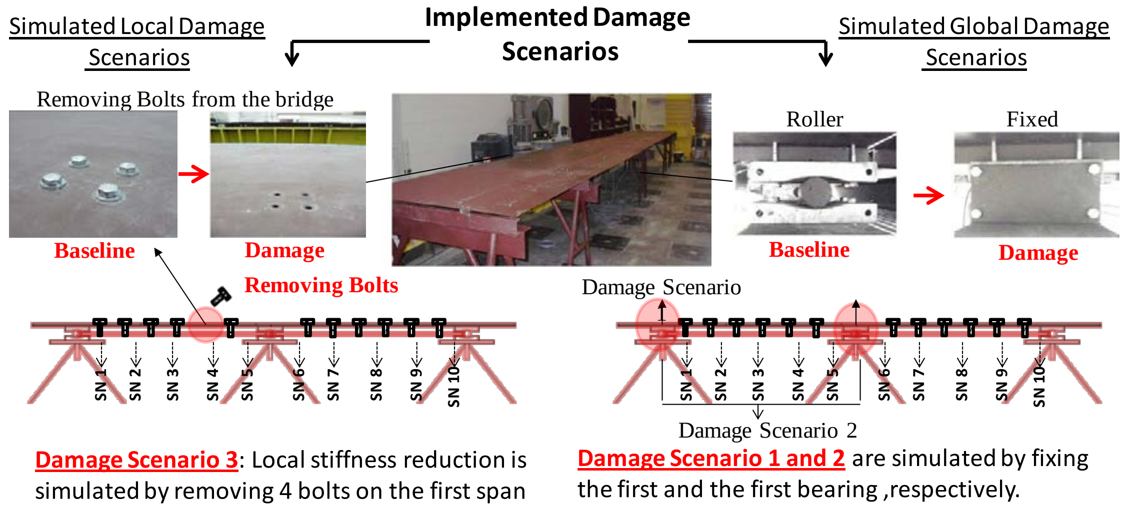


Figure 28- Implemented damage scenarios on four span bridge

In this section the results from the lab study are presented in a comparative fashion. Selective results from different damage scenarios are illustrated in Figure 29.

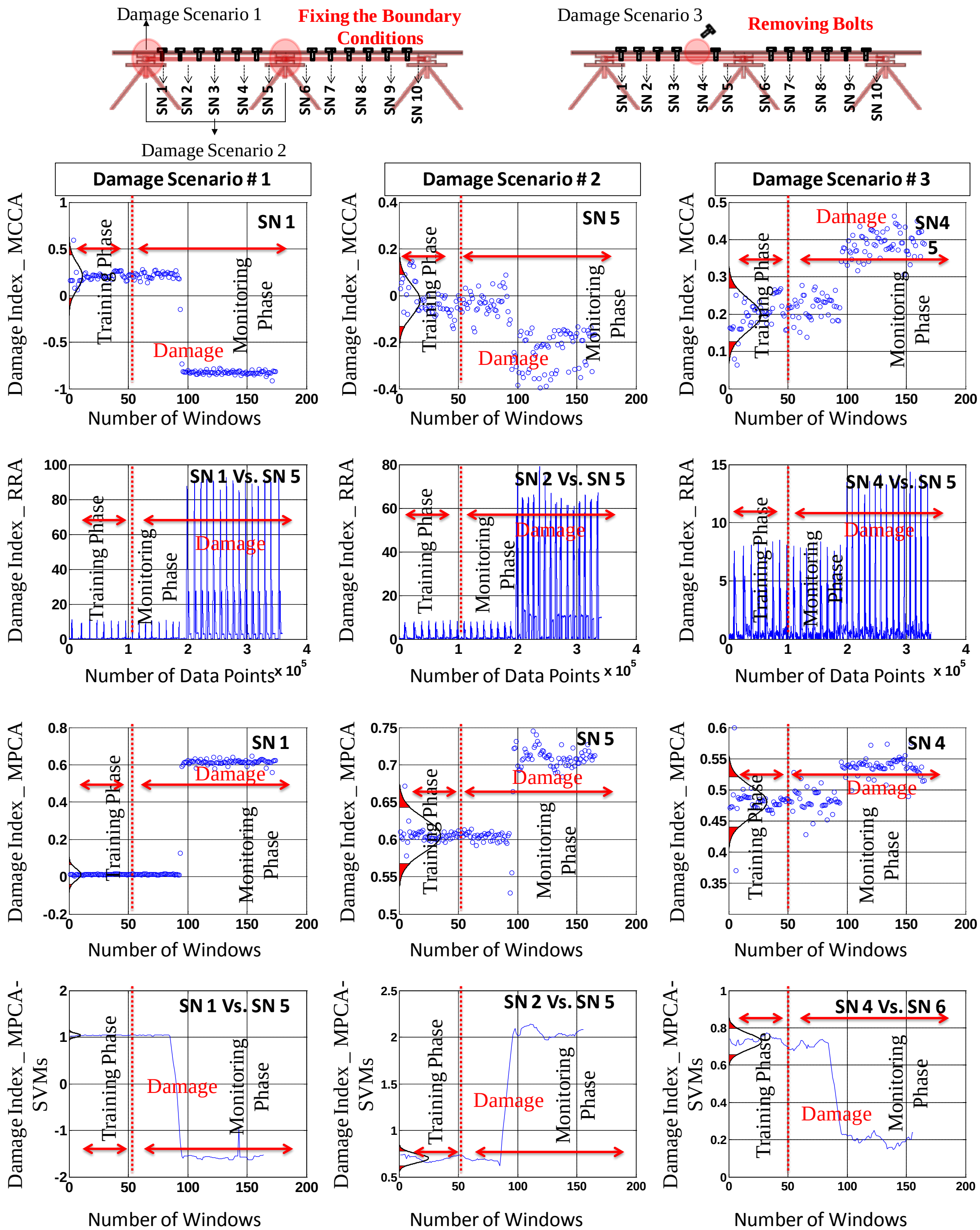


Figure 29- Selected results from the laboratory study for different non-parametric algorithms

4.4. *Part II: Application of Non-Parametric Techniques for Continuous Monitoring of a Real-Life Structure (Sunrise Boulevard Bridge)*

In order to investigate the efficacy of the MPCA, MCCA, RRA and MPCA-SVM algorithms for long-term monitoring of civil infrastructures, strain measurements from Sunrise Boulevard Bridge, as illustrated in Figure 30, were analyzed using each of these algorithms. The strain data were measured using dynamic strain gages (Hitec weldable) at 12 individual locations along the bottom flange of the main girders. The data were recorded with a 250 Hz sampling frequency. Figure 30 illustrates the locations of the strain gages and their corresponding nomenclatures. For example, WN refers to West North and ES refers to East South.

The measurement data recorded during three prescheduled time slots (morning and early and late afternoons), corresponding to the peak hours of operation a in a 24-h period, were selected for the analysis. The data were collected continuously for 5 minutes during each time slot. Field tests were also conducted to establish thresholds for conditions that are critical for the maintenance and operation of the bridge. These conditions will be referred as “damage”. In collaboration with FDOT engineers, some of the most common structural maintenance problems were identified and subsequently implemented on the movable bridge to simulate damaged conditions. These damage scenarios are further discussed in the following.

Figure 30-Sensor locations for structural components of Sunrise Boulevard Bridge

4.4.1. Implemented Damage Scenarios

Critical issues that create maintenance problems on the bridge are discussed and simulated on the Sunrise Boulevard Bridge. These problems were identified from a detailed investigation of the bridge inspection reports and interviews with the bridge engineers. The two main structural damage scenarios for this study included a live load shoe (LLS) shim removal and span lock (SL) shim removal. A combined damage scenario was also applied to the structure. First, the West South LLS shims were removed (Case-1), then the West South SL shims were removed for the combined damage scenario (Case-2). Finally the

LLS shims were installed again to observe the effect of only the SL shim removal on the structure (Case-3). The LLS are the support locations of the main girders when the bridge is in closed position (Figure 31). For the Sunrise Blvd. Bridge, the LLS is located forward of the trunnions. Cracking and wear are rarely seen on the live load shoe, but operational problems, such as loss of contact, are of concern. If misaligned or improperly balanced, the bridge may not fully sit on the LLS. In that case, the dead load and traffic loads are transferred to the gears and shafts, and damages these mechanical assemblies. Small gaps can also lead the girders to pound on the live load shoes, which results in further misalignment, additional stresses, fatigue damage, and excessive wear.

Case-1 is the creation of a gap (around 1/8” up to 3/16”) between the West South LLS and resting support pads, which corresponds to non-fully seated LLS (Figure 31). This will cause misalignment and problems for proper opening and closing of the leaves. Moreover, because of the inadequate support conditions, bouncing may occur in the girders, creating additional stresses due to impact, as well as stress redistribution, possibly subjecting the structure to different internal forces.

In double leaf bascule bridges, Span Locks (SL) are used to connect the tip ends of two cantilever bascule leaves; therefore, both leaves are forced to deflect equally (Figure 31). This ensures compatibility of the deck deflections from the opposing span leaves under traffic loads. The span locks typically consist of two main components: the receiver and the rectangular lock bar.

Figure 31 -Implemented damage scenarios on the Sunrise Bridge

4.4.2. Results from the Real-Life Study

The results for the MPCA, MCCA, RRA, MPCA-SVM algorithms are summarized in Figure 32 through Figure 34. The results are quite interesting since three out of four algorithms are found to be ineffective for the real-life application of civil infrastructure monitoring. In the earlier study, MPCA, MCCA and RRA were identified as the most reliable algorithms for civil infrastructure monitoring. It was also shown that these algorithms are quite effective for detecting the abnormal behaviors using the laboratory model structure. However, when evaluating the long-term monitoring data available from the movable bridge, only the MPCA-SVM approach remained effective. It was already discussed in the first part of the study that MPCA-SVM has several advantages in comparison to others in terms of detectability, time to detection and also immunity to noise. This was also observed to be the case for the measured data.

It is understood that the damage indices derived based on MPCA, MCCA and RRA are not sensitive enough to detect the critical induced damages that are implemented on a real-life structure. Figure 32 through Figure 34 indicate that the damage index computed based on the proposed algorithm is dramatically altered in response to data from a damaged structure. Moreover, after the structure was repaired by replacing the shim in the LLS, the damage index from MPCA-SVM was shifted back to the level it was at before the damage was induced. This is a significant observation since it reveals that the damage index from MPCA-SVM can be directly linked to the condition of the structure.

The fact that MPCA, MCCA and RRA could not detect the abnormal behavior from the real-life data does not mean that these algorithms are entirely ineffective for any applications. In fact, these algorithms express reliable performance based on the earlier study and also the first part of the current study. However, the results derived in this section show that MPCA, MCCA and RRA are not reliable enough for this given real-life applications. The damage indices that are derived based on these algorithms need to be improved in such way that they are more sensitive to any type of change/ damage. On the other hand, MPCA-SVM is shown to be a quite reliable damage detection algorithm for interpreting both laboratory and real-world data. Although this algorithm was able to detect all different damage scenarios from both the laboratory and the field, it still needs improvement in terms of computational time. A principal concern regarding long-term data processing with MPCA-SVM is the required computational time for the analysis.

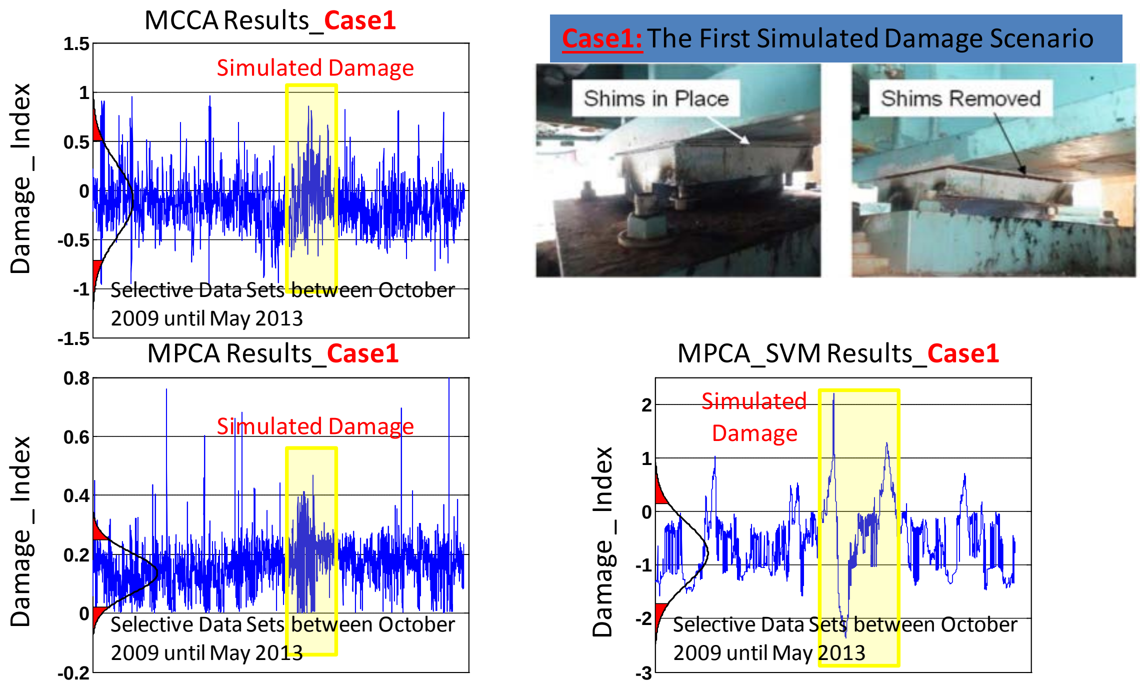


Figure 32- Results for damage Scenario 1

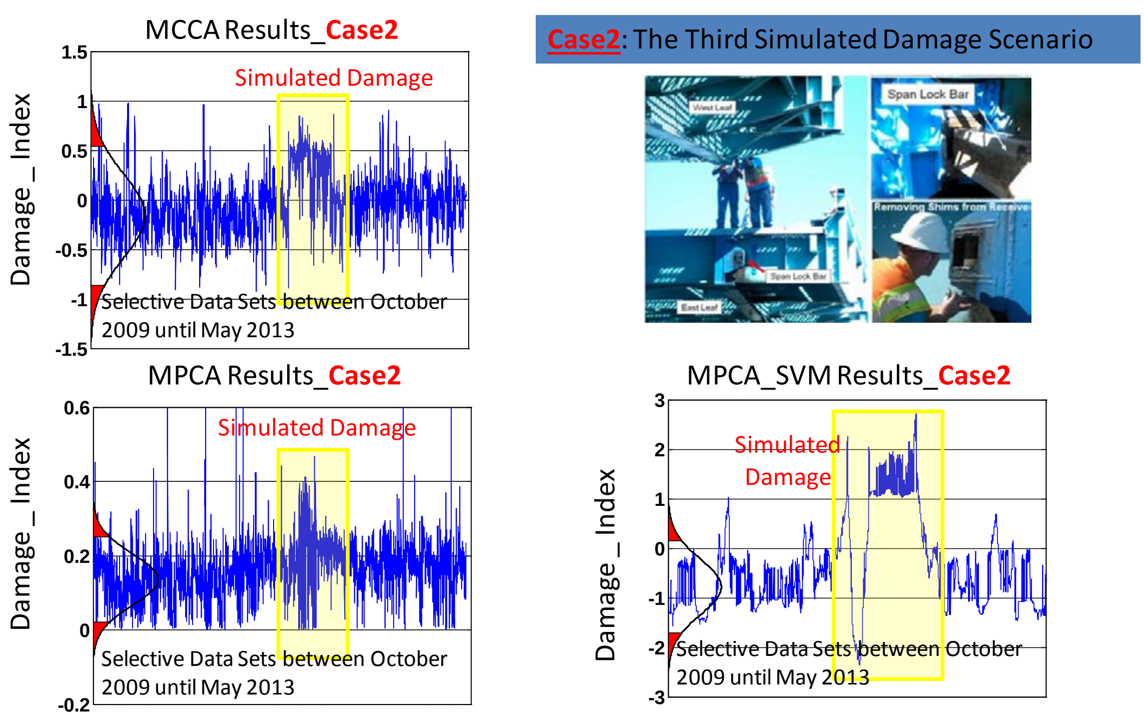


Figure 33- Results for damage scenario 2

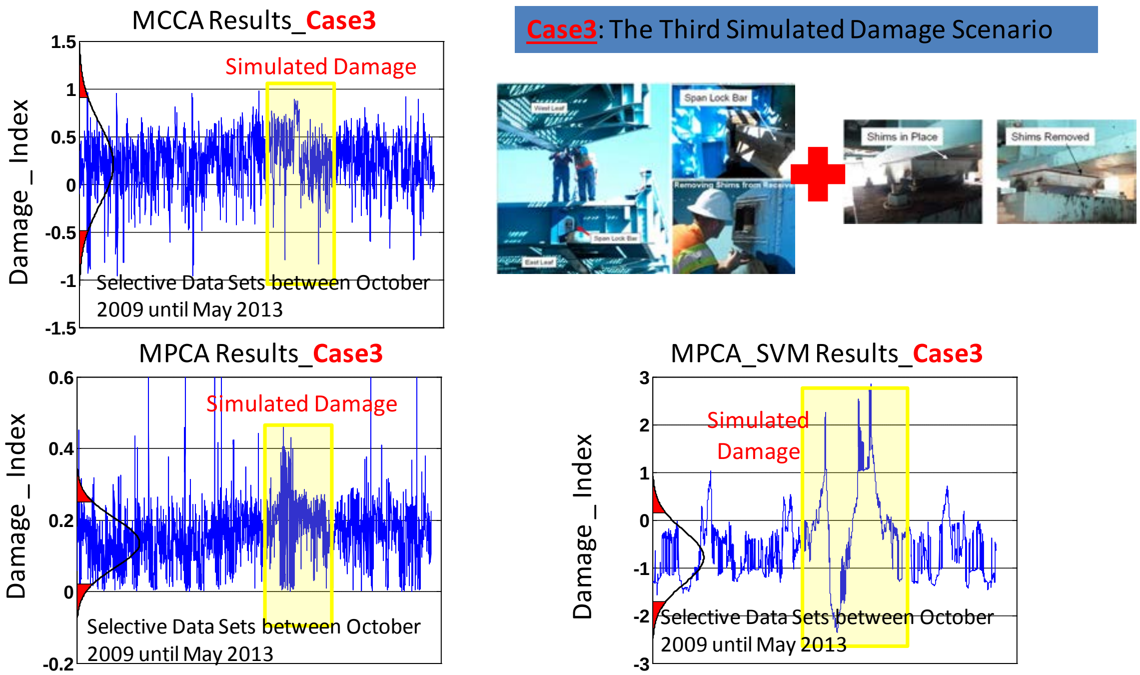


Figure 34- Results for damage scenario 3

CHAPTER 5. LONG-TERM MONITORING OF MECHANICAL COMPONENTS USING ADVANCED NON-PARAMETRIC TECHNIQUES

5. MONITORING OF MECHANICAL COMPONENTS USING ADVANCED NON-PARAMETRIC ALGORITHMS

5.1. Introduction

One of the primary objectives of this study was to collect data that would serve two purposes: to better understand the operational environment for a movable bridge, and to establish criteria for system-wide monitoring of a bridge population. Long-term monitoring of the bridge was conducted to determine the operating conditions of the various critical structural, mechanical and electrical components. The following mechanisms were to be monitored for a sufficiently long period of time: the opening and closing of the leaves, and activation of mechanical and electrical components. Monitoring serves to increase the understanding of the normal behavior of the bridge and the causes of abnormal behaviors. In this chapter, the application of the methodologies discussed in the previous chapter will be presented for the mechanical components.

Two main objectives are defined in this chapter. The first objective was to explore the Moving Principal Component Analysis (MPCA) algorithm for detecting malfunctions in the gearbox and rack and pinion system. As mentioned previously, the most likely causes of machinery malfunctions were identified as being due to lack of lubrications and a loss of bolts. These scenarios were induced on two of the critical mechanical components of the Sunrise Boulevard movable bridge while data was collected by the SHM system. This data was used to validate the MPCA algorithm.

In the second part of this chapter, an analysis of the maintenance reports is conducted in order to compare and correlate the monitoring data with the maintenance records. The objective of this section is to propose and evaluate a framework for long-term condition assessment of the machinery components including the gearbox and the electrical motors. A new framework is proposed for continuous operational monitoring of the critical machinery components in a movable bridge.

5.2. *Part I: Application of MPCA for Malfunction Detection*

5.2.1. Mechanical Alteration and Simulated Damage

5.2.1.1 Gearbox Oil Removal

The gearbox, also called the transmission, uses gears to provide speed and torque conversion from a rotating power source to another device. The gearbox is equipped to provide the necessary amount of oil to the various gear meshes and bearings, thereby resulting in smooth and trouble free operation. The gearbox should be regularly checked for any leaks to see if the gearbox has adequate oil. In this project, the oil in the gearbox was partially removed to provide data corresponding to such an undesirable condition. Figure 35 shows the removal of the oil from the gearbox. Only 25% of the oil was removed, and the effect of the oil reduction was monitored by six accelerometers attached to the gearbox during a few openings of the bridge spans.

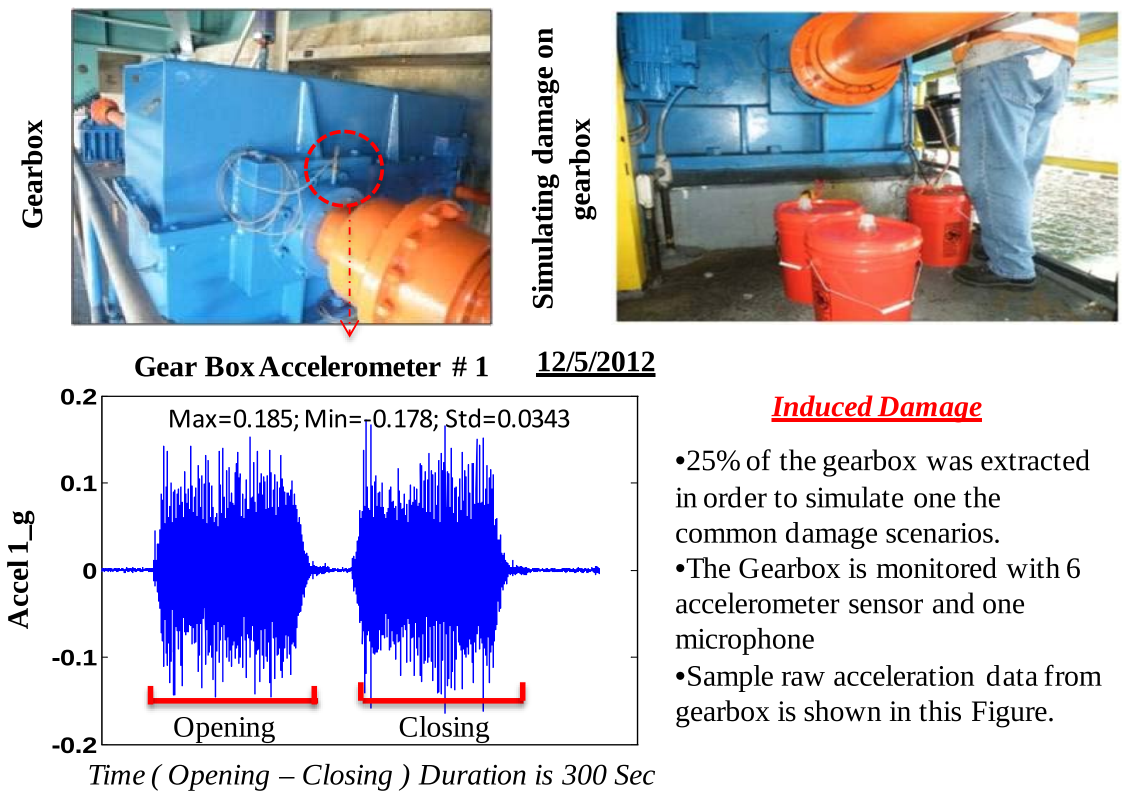


Figure 35- Removal of the oil from the gearbox and raw acceleration data from gearbox

5.2.1.2 Rack and Pinion Bolt Removal

The rack and pinion system is located between the shaft and the open gear; therefore, it can be considered a transmission zone for opening and closing operation forces. Therefore, it should be free from defects to ensure safe operation of the bridge. Here, the removal of bolts was the simulated damage scenario, and the effect of the absence of these bolts was monitored by one horizontal accelerometer. Figure 36 shows the Rack and Pinion with the removal of the bolts.

5.2.2. Application of MPCA for Fault Detection in Mechanical Components

The application of MPCA for anomaly detection of machinery components of the movable bridge is investigated and described in the following section. A matrix of raw data is generated that includes data sets from both healthy and damaged conditions. Data sets are analyzed from before, during and after the damage was induced on the machinery components. A moving window was identified based on average length of implemented opening data sets. The procedure for conducting MPCA was discussed in detail throughout the previous chapter. The results from this analysis are summarized as follows for the individual components.

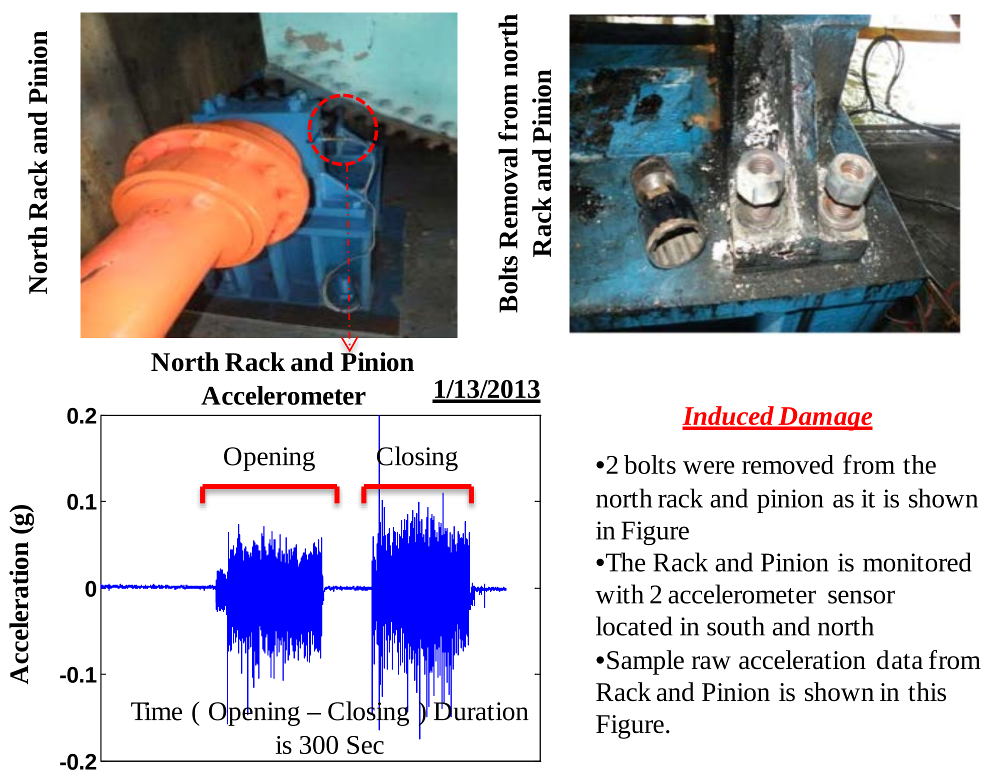


Figure 36- Bolts removal from the south rack and pinion and raw acceleration data from the deck rack and pinion

5.2.2.1 Detection of Abnormal Behavior in the Gearbox

As explained earlier, one of the most common sources of damage to the gearbox is lack of oil. In light of this fact, 25% of oil was extracted from a gearbox at the Sunrise Boulevard Bridge in order to study the efficacy of the MPCA algorithm for anomaly detection. A matrix of raw data generated including selective data sets before September 21, 2009 (day in which damage was simulated) on September 21, 2009 and finally selective data sets from 2009 to 2012. The damage indices calculated by the MPCA algorithm are presented in Figure 37 for each individual accelerometer. The damage indices are sensitive enough to detect the simulated damage. In fact, extraction of oil on September 21, 2009 caused an abrupt jump in the damage index computed by the MPCA. A confidence interval was established based on the data from the baseline condition (healthy stage), and as a result any variation from that is considered as a change/damage. The MPCA can be regarded as a reliable technique for gearbox condition monitoring.

It is obvious from Figure 37 that the damage index was confined within the confidence interval prior to damage for all accelerometer sensors. However, once the moving window included the damage data sets, the principal component values showed a dramatic change that is observable in all 4 of the considered sensors. Therefore, the change in the vibration level was caused by the extraction of oil from the gearbox. This is detectable from the eigenvector values shown in Figure 37.

If the computed damage index exceeds the established threshold, the gearbox should be subject to maintenance actions that will move the index back to its normal range. Once the moving window passes the data sets from the damage phase, the damage index shifts back to the range in which it was fluctuating during healthy condition.

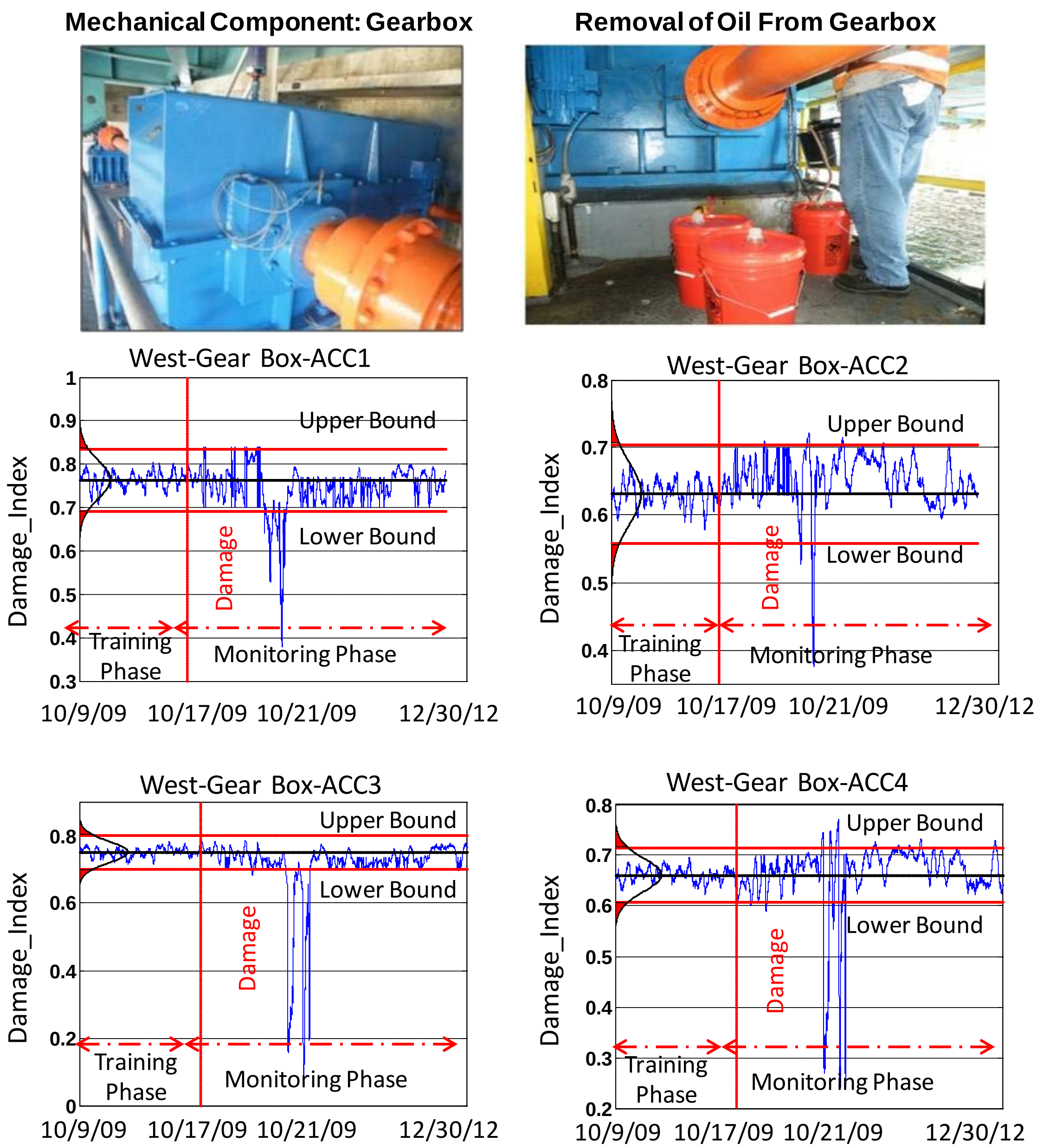


Figure 37-Results of MPCA application for gearbox malfunction detection

5.2.2.2 Detection of Abnormal Behavior in Rack and Pinion System

As shown in Figure 38 a representative damage scenario that was selected for the rack and pinion was to remove bolts from the system. Two bolts were removed from the north rack and pinion in order to simulate this common scenario. The results are illustrated in Figure 38 individually for north and south rack and pinion systems. It is obvious from the results that the damage index for the north rack and pinion exhibits an abrupt jump during the damage, while there is not any significant variation for the other system. The principal component values did not exceed the confidence interval for the south rack and pinion system, which indicates it was undamaged. The north rack and pinion system, where two bolts were removed, shows a dramatic change during the damage phase. The same index for the north rack and pinion system is bounded within the developed confidence interval before the damage and after it was repaired. Therefore, the MPCA can also be considered as an effective technique for damage detection of the rack and pinion systems.

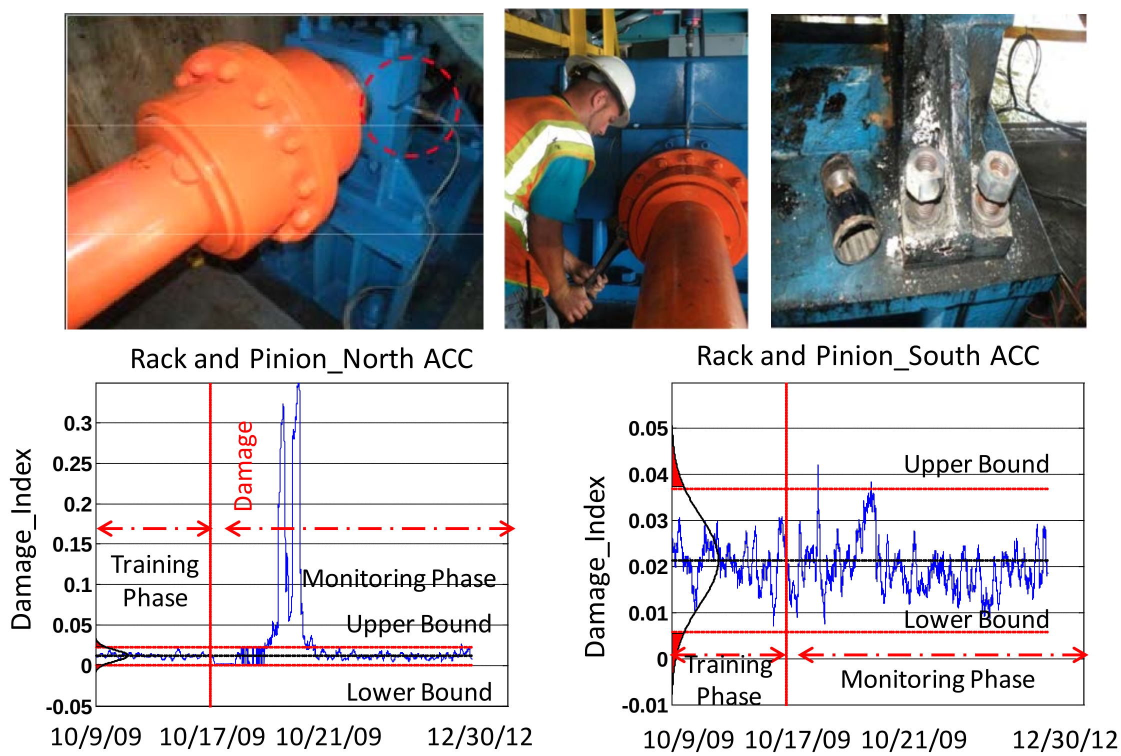


Figure 38- Results of MPCA application for rack and pinion malfunction detection

5.3. *Part II: Application of the MPCA for Long-Term Monitoring of Machinery Components*

5.3.1. A New Framework for Continuous Long-Term Assessment of Machinery Components

The application of the MPCA for abnormal behavior detection of machinery components was discussed in the previous section. It was observed that the MPCA is effective for both gearbox and rack and pinion fault detection. However, in terms of long-term condition monitoring of machinery components, compiling the raw data from all openings over years results in a very large data matrix which is quite time consuming to analyze. In fact, it is not practical to continuously monitor the gearbox or rack and pinion systems with the procedure that was discussed in the previous section. Therefore, the MPCA algorithm requires some modification to render it practical for continuous monitoring. A new approach is proposed in order to make the existing algorithm more appropriate for long-term monitoring applications. The steps described in the following sections are proposed to generate the main data matrix. It should be noted that after the main data matrix is formed, the rest of the procedure is the same as explained in the previous chapter.

Four individual statistical features including maximum vibration (average of the ten largest values to avoid outliers) and minimum vibration (average of the ten minimum values to avoid outliers), standard deviation of opening data sets, and finally root mean square of signals are extracted from raw acceleration data. These features can be expressed as follows:

$$Feature1\ (Max) = \frac{\sum_{i=1}^{10} Sort(\text{Opening data}, '\mathit{descend}')(i)}{10} \tag{5.1}$$

$$Feature2\ (Min) = \frac{\sum_{i=1}^{10} Sort(\text{Opening data}, '\mathit{ascend}')(i)}{10} \tag{5.2}$$

$$Feature3\ (Stdev) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{5.3}$$

$$Feature4\ (Rms) = \sqrt{\frac{1}{N}({x^2}_1 + {x^2}_2 + \ldots + {x^2}_n)} \tag{5.4}$$

The main data matrix is assembled by a continuous statistical analysis of opening data sets collected from the machinery components. Subsequently, the MPCA algorithm is applied to this matrix to extract the damage index. This process is illustrated in Figure 39, which divides the algorithm into two distinct stages: the training phase and the monitoring phase. Throughout the training phase, the algorithm develops a confidence interval for the baseline condition. In other words, a threshold is established based on the data (eigenvector values) from the healthy state. In the first step, the raw acceleration data was collected from opening phase of movable bridge. Afterward, four of the aforementioned statistical features were extracted and stored over a long period of time.

The main matrix is generated by assigning the time series of each individual feature to a column. The next step is to define the size of appropriate window, which is supposed to move forward along the time dimension. The PCA analysis is performed for each window of data during the training phase and subsequently the eigenvalues and eigenvectors are stored. The next critical step is to establish a confidence interval or a threshold for healthy state based on the eigenvector values from training period. Any variations to the threshold or the confidence interval observed in the monitoring phase are considered to indicate changes or damage. These steps are illustrated by the flowchart shown in Figure 39.

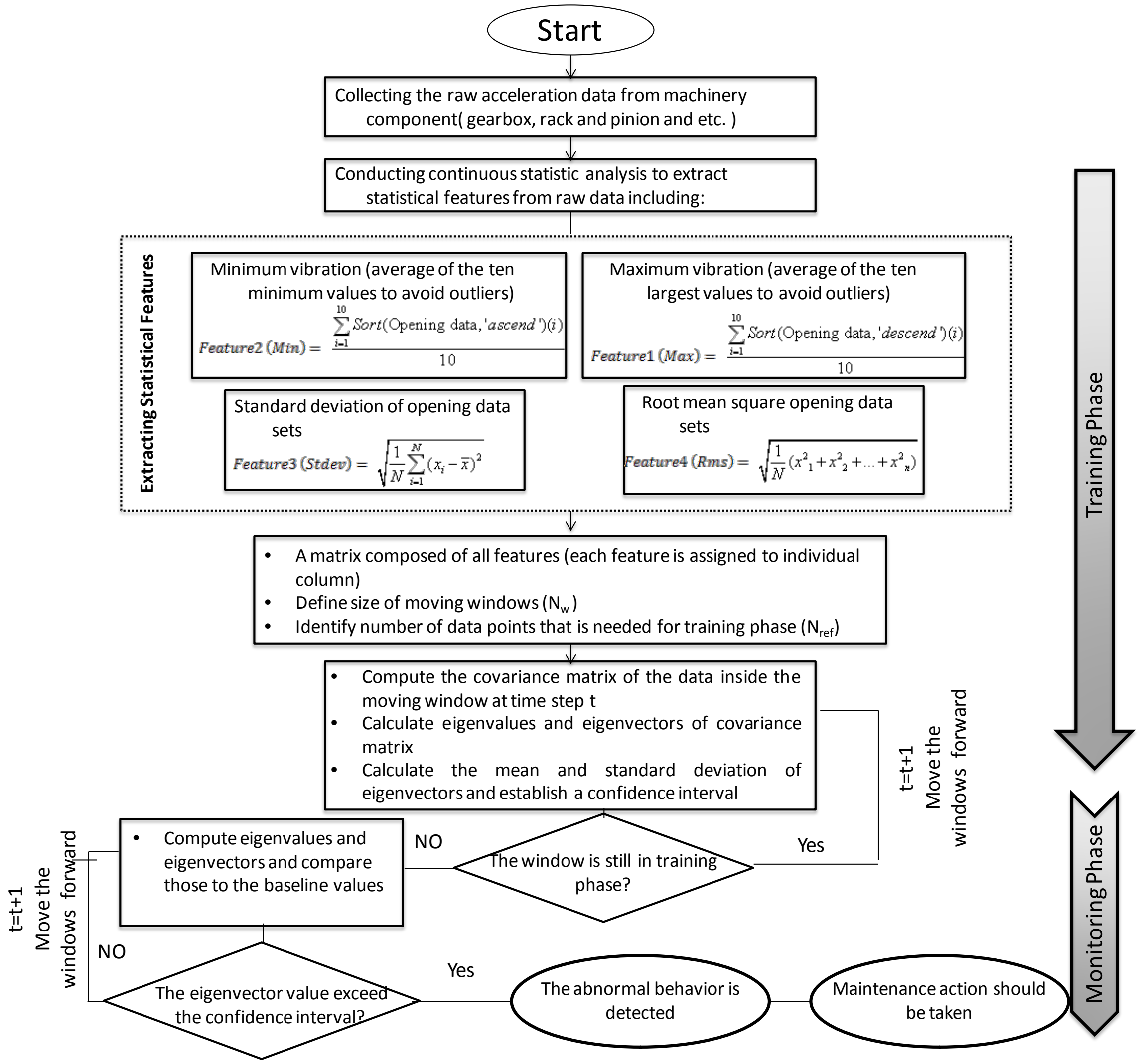


Figure 39-The proposed algorithm for continuous long-term condition assessment of machinery components

5.3.2. Long-term Condition Assessment of the Gearbox

5.3.2.1 Analysis of Maintenance Reports

In order to compare and correlate monitoring data and maintenance records, it is important to develop a numerical scheme for the maintenance actions. A preliminary study is conducted by evaluating the available maintenance and inspection reports from September 2009 to May 2013 that were obtained from the engineers and the maintenance personnel of the Sunrise Bridge. A total of 17 reports spanning over almost 4 years were analyzed to have a good understanding of the maintenance schedule and procedures at the Sunrise Blvd. bridge. The most critical actions were identified and categorized through inspection of the maintenance reports for each of the machinery components. In the following sections, the results of principal component analysis for the gearbox and motor are discussed in more detail. The eigenvectors (from both motor and gearbox) are also correlated with maintenance actions.

5.3.2.2 Correlation of Eigenvector and Gearbox Maintenance Actions

Time series of eigenvector values is calculated according to the procedure explained in section 5.3. The results for the gearbox are shown in Figure 40 in which the time series of statistical features are plotted against the time history of eigenvectors for each individual gearbox accelerometer. As observed from Figure 40, all the calculated eigenvectors demonstrate the abnormal behavior between May 2, 2011 and March 5, 2012. In other words, all eigenvectors are consistent with each other in terms of normal conditions and abnormal behavior. As a result, the eigenvector correspondent to the third accelerometer (Acc3) was selected as the most informative one and subsequently was studied in more detail along with maintenance reports. The results are demonstrated in Figure 41.

The idea was to investigate the correlation of eigenvector values and the maintenance actions extracted from maintenance reports. It is concluded that the variations in eigenvector values show good consistency with the major maintenance actions applied to the gearbox component over the past 4 years. In effect, it is shown that time series of eigenvectors is an appropriate index for the purpose of gearbox (in general, machinery components) condition assessment. Any variations in the values of this index can be correlated to a major action occurring to the gearbox.

In order to automate the process of machinery condition assessment for the movable bridge, a confidence interval was established based on the value of index during the period of October 9, 2009 and January 5, 2010 (training phase). The values of the index are confined within the confidence interval between October 9, 2009 and May 1, 2011 except for a few points, which were due to the issues with the gearbox component during this timeframe.

It is obvious from Figure 41 that the index values exceeded the confidence interval on January 13, 2010. The abnormal behavior continued until January 18, 2010 when the index values shifted back to the normal condition. This anomaly in behavior was further investigated through the maintenance report where it was realized that on January 18, 2010 the gear reducer break was replaced by FDOT maintenance personnel. The ID that is assigned to this action is A, and it is shown in Figure 41.

It should be noted that the bridge maintenance personnel were not able to detect this issue until January 18, 2010, which was almost 5 days after the abnormal gearbox behavior began. The SHM system was able to identify and detect this malfunction immediately after it occurred. Indeed, this malfunction could result in a major problem and the timely detection of this kind of gearbox issue is very critical for the continuous operation of the entire movable bridge.

After the gear reducer brake was replaced, the gearbox operated in a normal range until April 24, 2010 at which time the index started fluctuating again. Inspection of the maintenance reports indicated that on May 2, 2011 the input shaft seal had been replaced for the gearbox. The input shaft seal for the west gearbox had a major issues that began around April 24, 2010 and because of that the index exceeded the confidence interval. However, similar to the first issue, it was detected almost 1 year after the occurrence, which could result in a major problem as well.

After replacing the input shaft seal for the west gearbox, the index changed back again to the normal range for a short period of time. However, on June 17, 2011(6 weeks) the index again went beyond the developed confidence interval.

Analysis of maintenance reports for the Sunrise Blvd. Bridge indicated that on June 28, 2011 the output shaft seal was replaced for the west gearbox. After changing the input shaft seal on May 2, 2011, this time (June 28, 2011) the output shaft seal had a major issue and accordingly it was replaced by a new one. The SHM system was able to detect this issue on June 17, 2011, which is almost 10 days ahead of maintenance personnel. This timely detection highlights the advantage of implementing the SHM system for condition assessment of critical components. Having output shaft seal replaced, the index changed back to the normal condition again. However, after a short period of normal operation, the gearbox experienced another major issue, which caused a dramatic alteration in the value of the condition index. This time the problem was not due to the gearbox, but instead the motor which is connected directly to it had an operational issue. There are several notes in the report from September 21, 2011until September 27, 2011 related to the motor’s abnormal behavior. There were some serious problem associated with the motor including bearing and brake issues. As it is clearly noticed from Figure 41, these functionality issues in the motor resulted in operational abnormality in the gearbox during that period.

Finally on March 5, 2012 the gearbox brakes were replaced by new ones allowing the condition index to change back to the normal range. After this point the gearbox operated in normal condition for more than one year (until June 15, 2013) and the index continued bounded within the confidence interval, meaning that there were not any critical issues related to the gearbox.

5.3.2.3 *Correlation of Eigenvector and Motor Maintenance Actions*

The second most important mechanical component of a movable bridge is the electrical motor, which is directly linked to the gearbox. This means that any malfunction behavior of either of these components can directly influence the other one as well. Therefore, the results related to motor components are also presented here in order to not only evaluate the efficiency of the framework for motor condition assuagement but also to verify the gearbox findings. The results for moving principal components analysis of the motor are demonstrated in Figure 42 for each accelerometer individually. As it is clear from Figure 42, both eigenvectors demonstrate some abnormal behavior between May 2, 2011 and March 5, 2012 which is exactly the same period that gearbox expressed some malfunction issues.

This good consistency between eigenvector of motor and gearbox and their meaningful correlation with maintenance actions reveal the fact that the proposed condition assessment framework is an appropriate one for long term performance monitoring of machinery components.

Since both eigenvectors are conveying the same information and in order to avoid redundancy, only the eigenvector from the second accelerometer on motor is selected to be studied in accordance with maintenance actions. These results are shown in Figure 43. After investigating the maintenance reports, the variations of the condition index were found to be very meaningful. The variation started around May 2, 2011 in which the gearbox started facing some operational issues. This variation continued until September 28, 2011 when the motor was replaced due to major malfunction issues. Similar to gearbox case, all the abnormal behaviors were detected timely by the SHM system. This can prove the efficiency of both SHM system and the proposed condition assessment framework. Therefore, considering both gearbox and motor, eigenvector values can be used for condition assessment and in general fault detection of machinery components.

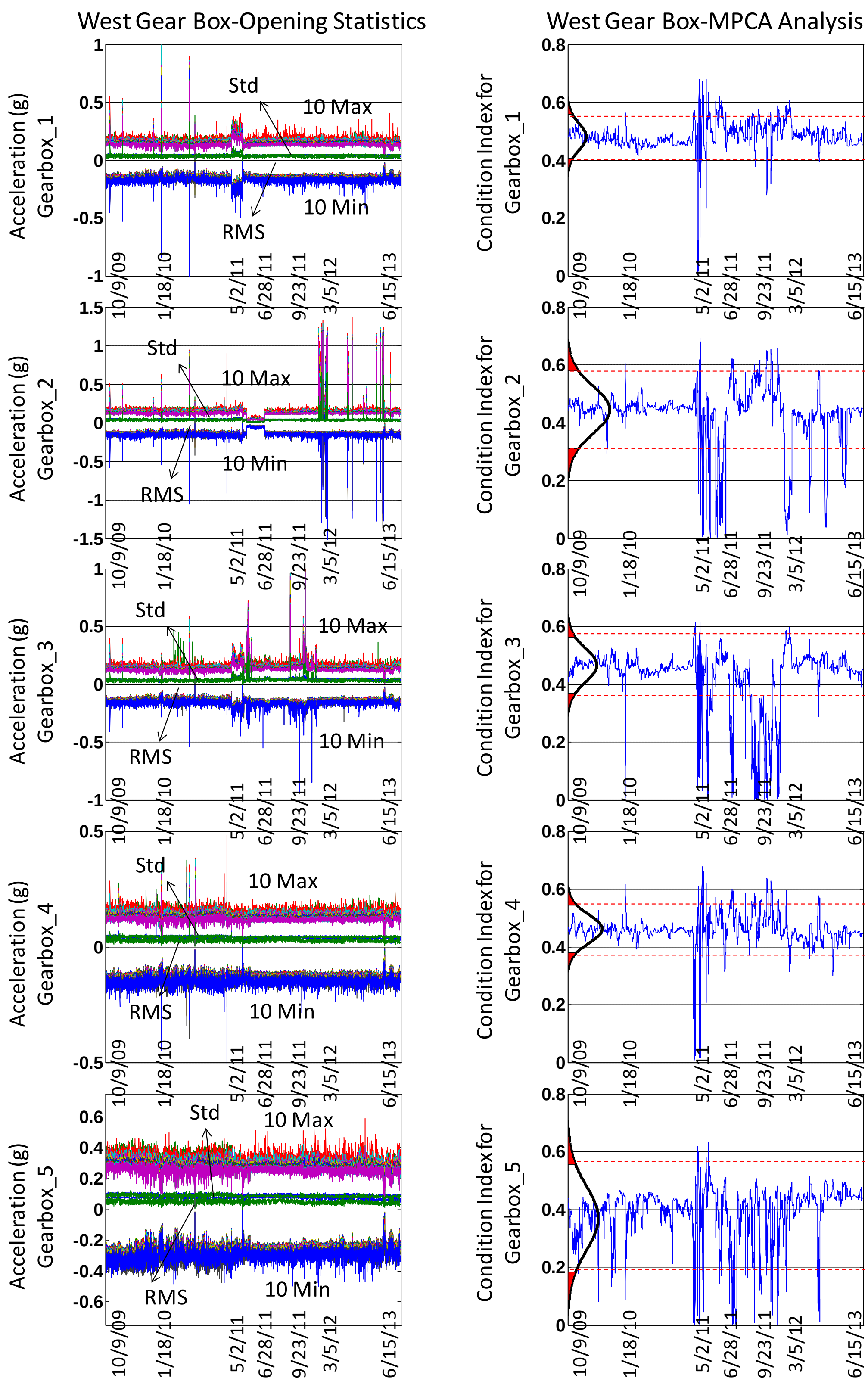
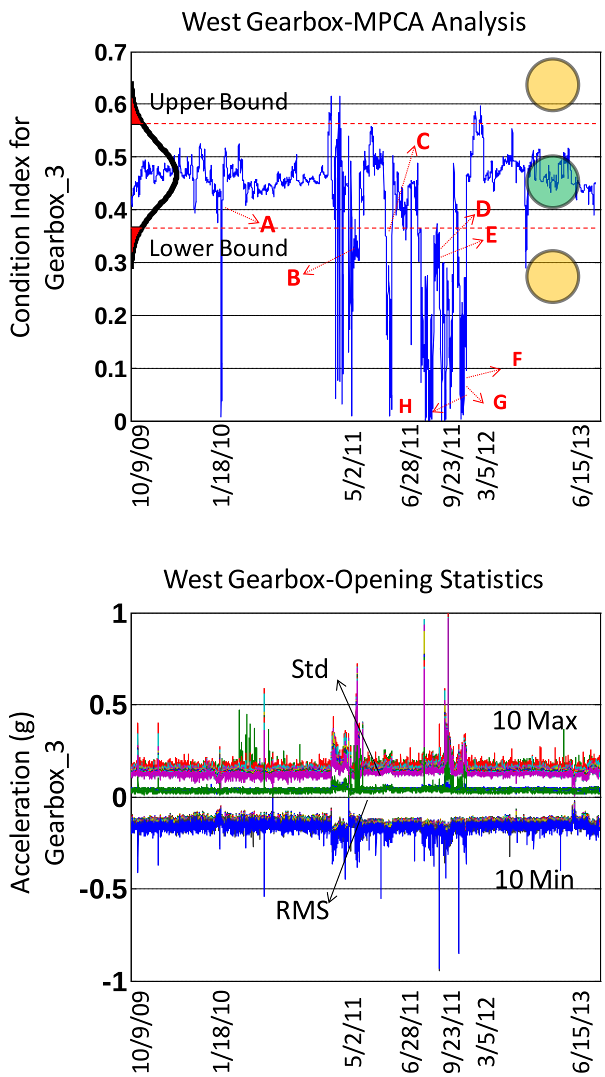

West Gear Box-Opening Statistics
West Gear Box-MPCA Analysis
Acceleration (g) Gearbox_1
Acceleration (g) Gearbox_2
Acceleration (g) Gearbox_3
Acceleration (g) Gearbox_4
Acceleration (g) Gearbox_5
Condition Index for Gearbox_1
Condition Index for Gearbox_2
Condition Index for Gearbox_3
Condition Index for Gearbox_4
Condition Index for Gearbox_5
Std
10 Max
10 Min
RMS
10/9/09
1/18/10
5/2/11
6/28/11
9/23/11
3/5/12
6/15/13

Figure 40- Long-term condition assessment of the gearbox using MPCA algorithm



Point ID	Date	Maintenance Action
A	1/18/2010	Replace **Gear Reducer Break** as Needed
B	5/2/2011	Replace West Span Gear Box **Input Shaft Seal**
C	6/28/2011	Replace **output shaft seal** on West Gearbox
D	9/21/2011	Check F.A. Span Motor for **Motor Replacement**
E	9/23/2011	Check F.A. Span Motor for **Motor Replacement**
F	9/26/2011	**Removed Brake** on F.A. Span Motor
G	9/27/2011	F.A. Span **Motor Bearing trouble shoot**
H	9/28/2011	The Motor was **Repaired**
I	3/5/2012	Replace **Gearboxes Breaks**

❖Major Maintenance Activities are Extracted from the Maintenance Reports Submitted by FDOT Personnel

Figure 41- Correlation of the gearbox eigenvector with the maintenance actions

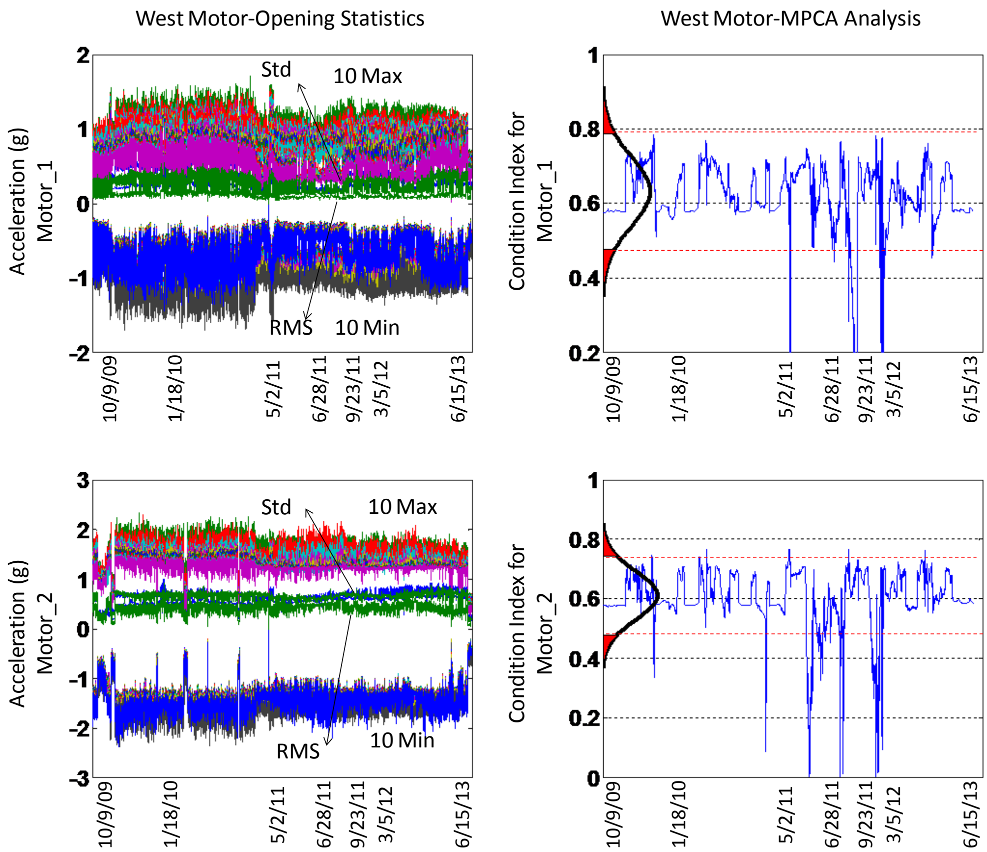
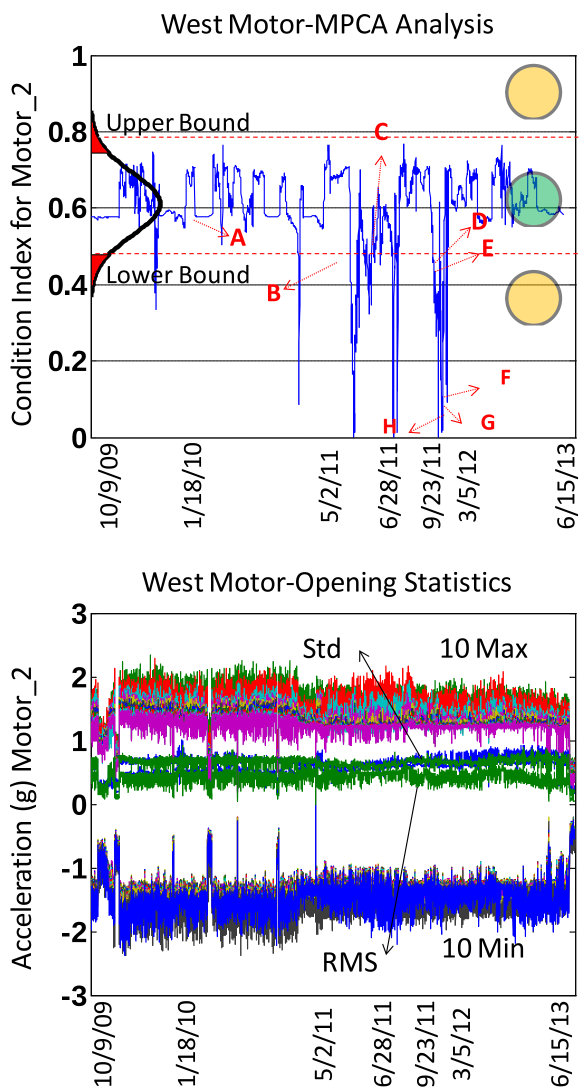


Figure 42-long-term condition assessment of the motor using MPCA algorithm



Point ID	Date	Maintenance Action
A	1/18/2010	Replace **Gear Reducer Break** as Needed
B	5/2/2011	Replace West Span Gear Box **Input Shaft Seal**
C	6/28/2011	Replace **output shaft seal** on West Gearbox
D	9/21/2011	Check F.A. Span Motor for **Motor Replacement**
E	9/23/2011	Check F.A. Span Motor for **Motor Replacement**
F	9/26/2011	**Removed Brake** on F.A. Span Motor
G	9/27/2011	F.A. Span **Motor Bearing trouble shoot**
H	9/28/2011	The Motor was **Repaired**
I	3/5/2012	Replace **Gearboxes Breaks**

❖Major Maintenance Activities are Extracted from the Maintenance Reports Submitted by FDOT Personnel

Figure 43-Study of the correlation of the motor eigenvector with the maintenance actions

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. General Review

A comprehensive bridge monitoring system was implemented on a movable bridge in order to monitor the long-term performance of both mechanical and structural components of the movable bridge. During the initial phases of the study the monitoring system was designed and implemented on the Sunrise Bridge. The findings from the first phases of this project have been presented in two prior final reports (Catbas et al. 2010, Gul et al. 2011) where detailed information about the issues related to the movable bridge are presented along with the instrumentation plan, approaches and methods to detect changes and track maintenance procedures are provided. This report briefly summarizes the results obtained from a one-year extension phase of the project. The main objectives of this project are as follows:

- Data collection and measurements during the extension period and comparison with the data that was collected earlier.
- Maintenance of the monitoring system including data acquisition system and sensors during the extension project.
- Replacement of critical monitoring components.
- Comparing the SHM data with the actions extracted from maintenance reports in order to study the efficiency of SHM system.

In this phase of the project, the mechanical components of the monitoring system were maintained as part of the objectives and scope of this project. FDOT limited to the project to activities within the bascule piers on components such as gearboxes, live load shoes, electrical motors, trunnions, and open gears (racks). As part of the maintenance, no equipment or MOT was to be requested during this extension. The monitoring system today operates well and provides useful data for research and engineering purposes. The researchers visited the bridge several times in order to maintain and repair the problems such as hardware and software issues. The list of visits was presented in this report.

The data from the monitoring system were employed to fine-tune specific methods and algorithms for the mechanical as well as the structural components of a bascule bridge. A very practical and fast approach is to utilize descriptive statistics, and track statistical data from various mechanical components. These mechanical components included the gearbox, electrical motor, and the rack and pinion system. The efficacy of the monitoring methods and analysis techniques that were developed in the first phase of the project were investigated throughout this phase of the project.

The data was collected after the installation of the monitoring system, and as a result, long-term data is available from both mechanical and structural components. In addition, there were different tests conducted on the bridge including a truck test as well as inducing artificial damage scenarios to establish operational limits and thresholds. As mentioned earlier, the data that was collected during the extension phase was compared with the data that had been collected during the previous phases. The intension is to detect any abnormal behaviors in any mechanical or structural components in a timely manner in order to take immediate action in the case of emergency. Another important goal of this extension was to comparatively analyze the monitoring data along with the maintenance actions, which were extracted from the maintenance reports. The idea was to study the efficiency of monitoring system in addition to establishing baseline for critical components (mostly mechanical) in order to automatically monitor those over a long period of time.

6.2. Conclusions and Findings

Through the previous phases of this project, unique data analysis techniques were developed and employed in order to analyze and track the data from different mechanical and structural components. The results were reported monthly as well as in previous final reports. For instance, cross correlation analysis was employed in order to monitor the performance of structural components and the results for this algorithm were presented in the previous FDOT report. However, in this report, more advanced and recent machine learning techniques were considered and implemented for the sake of monitoring different components. In this context, Robust Regression Analysis (RRA), Moving Cross Correlation Analysis (MCCA) and Moving Principal Component Analysis (MPCA) were the three selected methods utilized in this study to process the mechanical as well as structural data. These techniques were selected from the literature based on their promising results from applications in various fields of science and engineering. However, in addition to the above-mentioned algorithms, a newly developed damage detection algorithm was employed for the purpose of monitoring the safety of the critical components.

It was shown that this algorithm has advantages over the previous ones in terms of detectability and time to detection. The efficiency of this algorithm was tested using the data from normal operational condition as well as the data captured during the time that artificial damage was induced on the Sunrise Bridge. In Chapter 4 of this report, it was demonstrated that the new algorithm (MPCA-SVM) is a reliable algorithm for detecting abnormal behavior of structural components. In fact, while the RRA, MCCA and MPCA algorithms were not capable of detecting artificially induced damage in structural components; this damage was identified and detected by the MPCA-SVM. Long-term data was processed by the MPCA-SVM algorithm and is presented in the same chapter.

These algorithms were first compared their ability by using data collected from experimental structures in which several common damage scenarios were simulated. The results indicated that all four algorithms showed promising ability in terms of detectability;

however, with respect to time to detection, RRA and MPCA-SVM outperformed other ones. The computational efficiency is another important criteria, which has to be considered in particular when it comes to long-term monitoring of civil structures and where one is dealing with large amounts of data.

After verifying the algorithms with the data from an experimental structure in the UCF Structures Laboratory, the algorithms were also evaluated using the data collected from the Sunrise Bridge. Selective data sets from 2009 until 2013 were analyzed using the MPCA, MCCA and MPCA-SVM. The data from damaged structures were also included in order to evaluate the efficiency of different algorithms in terms of detectability. It is shown that the damage index that is driven based on MPCA-SVM is sensitive to changes in the data. In this case, the change was due to the simulated damage. Similarly, changes in data due to lack of maintenance, retrofit, new material etc. can be detected using this method and algorithm.

Chapter 5 of this report is devoted to discussion of a proposed non-parametric based (statistical change detection) framework for automated condition monitoring/assessment of mechanical components of the Sunrise Bridge. In fact, for the assessment of the mechanical components, three data analysis techniques were employed. The first method was the image-based analysis for open gear in which the edge detection based computer vision technique was used to identify whether the open gear was lubricated properly or not. The results of the open gear image analysis show that the lubrication index is effective enough for the purpose of open gear monitoring., The index increases after lubrication and decreases when the open gear does not have a proper lubrication condition.

Another technique was to track the statistical responses of mechanical components during the opening and closing phases. Throughout Chapter 3 of this report, statistical responses were presented individually for each critical mechanical component. For instance, long-term statistical response of the west gearbox is illustrated and these statistical responses were further studied in Chapter 5 in order to investigate the correlation of maintenance actions and monitoring data.

A non-parametric damage detection algorithm was developed and implemented for monitoring the status of mechanical components. This framework was presented in Chapter 5 of this report. The algorithm is based on the Moving Principal Component Analysis (MPCA). Statistical features were extracted from acceleration data (Motor and Gearbox) and then damage indices were derived based on MPCA analysis. These indices were tracked and monitor over time to make sure that the component was operating within acceptable limits. In order to verify the efficiency of the framework, the long-term data from the gearbox and motor were fed into the algorithm separately and the extracted damage indices were compared with the maintenance actions from maintenance reports. Investigating the extracted damage indices along with the maintenance actions revealed the fact that the proposed framework using the non-parametric method is effective for condition monitoring of critical components such as the Motor and Gearbox. A confidence interval was developed based on the value of the damage index during normal operation. It was observed that the damage index value exceeded the confidence interval during the times that the Gearbox or Motor were experiencing critical issues. It is shown that the damage index introduced in this approach is directly influenced by critical maintenance actions. The results for the gearbox were shown in the report and all the extracted damage indices were demonstrated abnormal behavior between May 2, 2011 and March 5, 2012. Another observation was that all eigenvectors are consistent with each other in terms of normal conditions and abnormal behavior.

While studying the monitoring data with the maintenance actions, it is obvious that the established index values exceeded the confidence interval on January 13, 2010. The abnormal behavior continued until January 13, 2010 when the index values shifted back to the normal condition. This anomaly in behavior was further investigated from the maintenance report, where it is realized that the gear reducer break was replaced by maintenance contractor personnel on January 13, 2010.

Another issue related to the input shaft seal caused fluctuation in damage index on April 24, 2010. After fixing this issue, the output shaft seal also had an issue, which resulted in fluctuation of the damage index. It is also understood that the performance of the motor, which is directly connected to the gearbox has significant influence on the performance of this component. For instance, there are several notes in the maintenance report from September 21, 2011 until September 27, 2011 related to motor's abnormal behavior. There are some serious problems associated with the motor including bearing and brake issues. As it is clearly noticed, these functionality issues in the motor result in operational abnormality in the gearbox during that period. The motor was investigated as a critical component in Chapter 5. The results were demonstrated for the duration of May 2, 2011 to March 5, 2012 where data showed some abnormal behavior, from the same time that the gearbox exhibited the malfunction. This can be considered as additional evidence of the efficiency of the proposed framework.

6.3. Recommendations

There are a number of recommendations that can be presented based on the understanding from this project, as well as from the previous research studies on the movable bridge. The recommendations are very parallel to the observations and recommendations presented in previous reports and other publications. These recommendations can be summarized as follows:

Monitoring of a movable bridge provides an excellent opportunity to increase safety and reliability and to reduce maintenance costs. The current system proved to detect changes and problems effectively as exemplified for the live load shoes, span locks, gearboxes, open gears, bridge friction, etc. The system behavior is now well established with baselines and thresholds. In this phase, a number of new approaches such as Robust Regression Analysis (RRA), Moving Cross Correlation Analysis (MCCA), Moving

Principal Component Analysis (MPCA), or combined Moving Principal Component Analysis-Support Vector Machine (MPCA-SVM) are presented and employed for laboratory and real life applications. Future monitoring applications are recommended to utilize this information.

The current monitoring system was developed to explore different sensors using the available technology in 2007-2008. It is possible to design and develop a more compact data acquisition system and use this compact system for future applications. Several commercial data acquisition systems and card providers can now supply smaller and more cost effective systems.

The research team developed National Instruments Labview codes for collecting data from the extensive monitoring system. These codes along with the National Instruments data acquisition systems can be renewed and improved, which would improve the regular operation of the monitoring system. As per FDOT recommendation, the researchers did not update and/or revise the existing programs; however, it is recommended that newer versions of software should be utilized. In addition, the data acquisition computers should be checked over time since these computers and necessary hardware/software need to be updated.

The operation of the bridge with the maintenance personnel and other maintenance such as bridge sandblasting and painting may induce damage to sensors and cables. Such applications should be coordinated in such a way that the damage to the monitoring system, sensors and cables are minimized. Another critical recommendation is that power to the data acquisition system should be dedicated power since using the same power for other bridge operations and maintenance applications may induce interruptions and possibly damage to the monitoring systems. Use of uninterruptible power supply can be a solution to a certain extent.

For detecting structural problems as exemplified in this and previous reports, at minimum, live load shoe locations are to be instrumented. Similarly, the number of vibration sensors at the electrical motors and gearboxes can be reduced to two and three, respectively. This exploratory study required the use of a large number of sensors; however, a much reduced sensor count could be sufficient to obtain the most critical information. In addition, with the advances in sensors, more sensitive sensors can be employed for applications such as vibration, sound and temperature measurements.

CHAPTER 7. REFERENCES

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