Assessment of SHM Data Integrity by Statistical Pattern Recognition Techniques

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Abstract

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Farah Deeba

For implementing a successful structural health monitoring (SHM) system, it is important to develop strategies for ensuring the reliability of the sensor data and detecting any changes such as damage in a structure. The primary objective of damage detection is to ascertain with confidence if damage is present or not within a structure of interest. In SHM, various types of sensors are installed in structure. The responses from these installed sensors are generally acceleration, strain, or environmental data. Any kind of changes in structural integrity affects the characteristics of strain and vibration data. So analyses of these SHM data projects the new changes or anomalies in structure enabling one to detect damage or gradual change in the structure's properties. The objective of this thesis is to apply statistical pattern recognition techniques to assess the integrity of SHM, i.e. sensor data. Also the current study represents some sensitivity analysis to establish a good statistics to show how sensitive is this method to extracted damage features and based on this sensitivity one decides up to what extent and for which cases this method should be chosen as damage detection technique. Previous studies in statistical pattern recognition hardly involved any real life data from an existing structure. With a view to fill up this gap two real life structures have been chosen for the current work. Here the proposed methodologies have been applied to detect structural damage and to detect malfunctioning sensors if there is any.

To all the members of my sweet family whom

I missed a lot while accomplishing this thesis.

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Chapter 1 Introduction

1.1 General

The very moment the structures are built and open to operation, it is expected that the structure will face damages and will eventually degrade as time pass on. Damages in the structures can be for many reasons like loading, aging, environmental changes, misuse, natural disasters like excessive rain, flood, snow, earthquakes and storms. Hence damage assessment or monitoring of structural health is an important part of civil and structural engineering. The primary goal of any damage assessment technique is to figure out whether there is any damage and if so, to determine the vicinity and extent of damage. In general context, damage assessment can be defined at four levels (Rytter, 1993).

They are,

1. To detect whether there is damage
2. To determine the location of damage
3. To quantify the extent of damage
4. To carry out prognosis such as safety evaluation and remaining life prediction

An effective and reliable damage assessment methodology will be a valuable tool for timely determination of damage and deterioration state of structural members. The information produced by a damage assessment process can play a vital role in the development of economical repair and retrofit programs.

Visual inspection is the most common method of Structural Health Monitoring (SHM) and damage detection. These typical routine condition assessments are carried out after overloading, accidents, or when codes or use modes change. For large and complex structure this method is somehow difficult and to some extent costly due to problems of accessibility and the time required. Generally the inspection process is useful in finding signs of damage such as cracks, spalls, chemical deterioration, and corrosion when these become visible or the deterioration takes its course. The relation between such visible signs of damage and the corresponding ‘‘condition’’ or ‘‘reliability’’ of the structure is often very difficult to establish (Catbas and Aktan, 2002). Discovery of deterioration before or at its onset is important for cost-effective management (Shickert, 1995). Visual inspection for being subjective the diagnosis results vary. These limitations of visual inspection paved the way for some other methods of SHM demanding more accuracy and reliability. In recent years some indirect damage detection methodologies have earned the appreciation of researchers and engineers.

Among the new and emerging methodologies of condition assessment, one is assessing the structural damage condition by using dynamic characteristics or properties of structures. Dynamic attributes like frequency, mode shape and damping ratio change as the health condition of structure changes i.e. generally goes from good condition to bad condition. Exploiting these criteria for damage assessment got an upper hand in Structural Health Monitoring (SHM) because of its reliability and accuracy.

There are some basic steps which are more or less same for all traditional damage assessment methods. It starts with mathematical model development of the structures. Next step is to use this model to develop the understanding of structural behaviour and to establish comprehensive relationship between specific member damage conditions and changes in the structural response.

However identification of member damage from the response of the damaged structure is an inverse process, where causes are traced from effects.

1.2 Damage Detection Methods

Almost all damage detection methods for in-service structural components are non destructive. Many non-destructive technologies which can successfully characterize the in situ properties of construction materials, even through covers and other obstruction, have been developed (Shickert, 1995). Canadian Institute of NDE describes non-destructive Examination (NDE), also referred to as NDT (non-destructive testing) and NDI (non-destructive inspection), as a family of specialized technical inspection methods which provide information about the condition of materials and components without destroying them (CINDE, 2008). Though conventional NDE methods are tools for performance assessment, their scope can extend to almost all types of engineering, especially structural, aerospace and marine engineering.

Some conventional NDE methods are briefly described below along with Vibration Based Damage Identification (VBDI) techniques which are also a type of NDE method.

1.2.1Visual Inspection

Visual inspection is the predominant non-destructive evaluation (NDE) technique used in bridge inspections. However, since implementation of the National Bridge Inspection Standards in the US in 1971, a comprehensive study of the reliability of visual inspection has cast some doubt on this method as it relates to highway bridge inspections. Factors that appeared to affect the accuracy of visual inspection results include visual acuity and color vision; light intensity, inspector qualification and experience; and perceptions of maintenance, complexity, and accessibility. The damage might be the spalling of concrete, steel corrosion and cracking in reinforced concrete structures, loosening of bolts, and crack in weld. The part of the structure to be inspected must be accessible. This sometimes becomes impossible for large and complex structures. For underwater and space structures, the inspectors need to be geared and equipped properly. To reach the ordinarily inaccessible structural elements to examine, sometimes it may be necessary to use robotics technology and special transportation means.

1.2.2 Periodic Inspection

Periodic inspections are primarily visual inspections done at a specified time interval. Also sometimes sensors are used for intermittent structural response delivery to the central monitoring system for periodic remote monitoring. It could be weekly, monthly or yearly; even it could be for a particular time in a day taking only the crucial periods in account. Periodic Structural Health Monitoring is conducted to investigate any detrimental change that might occur in a structure or in a repair that has been made to the structure. By monitoring the behavior of the structure periodically changes in the structure can be detected and these changes may be used as an indication of damage or deterioration.

The inspection procedure should be designed to detect damage, deterioration, or signs of distress to avert any premature failure of the structure and to identify any future maintenance or repair requirements. The periodic inspection should assure that all critical members and connections are fit for service until the next scheduled inspection. Critical members and connections are those structural elements whose failure would render the structure inoperable. Fitness for service means that the material and fabrication quality are at an appropriate level considering risks and consequences of failure. To be effective, the periodic inspection should be a systematic and complete examination of the entire structure with particular attention given to the critical locations. It should be done while the structure is in use.

If the periodic inspection indicates that a structure may be distressed, a more detailed inspection and evaluation may be necessary. This detailed inspection may require non-destructive and/or destructive testing. The information obtained from the inspections and tests will then be used to perform a structural evaluation and make a recommendation for future action.

1.2.3 Continuous Monitoring

Continuous monitoring is essential for structures those are crucial in terms of size, economic issues and human safety. Generally for large infrastructure of a country the government implement the 24 hours monitoring to provide proper safety to public life and ensure damage detection at the onset of damage. At the beginning, to set the monitoring system might seem a bit expensive; but considering its beneficial effect during the whole life cycle of the infrastructure its fixing cost is very much reasonable. Generally this type of monitoring indicates monitoring by sensors like strain gauges, Fiber Optical sensors, Temperature gauges, accelometers etc. These sensors collect data from existing in service structures and temporarily store them onsite data acquisition system after filtering. Then these data are transferred to an off-site location to be stored, analyzed and diagnosis the concerned structural health condition. This transfer of data can be made through cables or without cables i.e. by wireless system. In the most sophisticated of these types of SHM applications, field data are transmitted remotely to the engineer's office for real-time monitoring and interpretation. If there is any doubt about the structural integrity for those structures who are exposed to extreme weather condition such as severe earth quakes, hurricanes etc. then continuous monitoring is a must for them.

1.2.4 Liquid Penetration Testing (LPT)

LPT is an advanced type of visual inspection. It is relatively simple and it can detect flaws in all type of materials. The flaw should be open to the surface and this requirement is a drawback to this method. Some fluid materials such as petroleum or watery substances dyed with color are inserted into the surface and they seep deep into the material. A white developer material is placed on the surface. The penetrated liquid strains the developer if there is any flaw. It is clearly not applicable for the determination of the strength of the material. This method is highly sensitive and needs prior knowledge of the location of the damage.

1.2.5 Magnetic Particle Testing (MT)

MT is applicable to metal substances only. A magnetic field is propagated by electrical equipment. Unlike Penetration Testing, the flaws do not have to be open to the surface, but it must be close to it. So, prior knowledge of the damage is still required. MT works best for flaws which are elongated rather than round. Magnetic field is generated inside the specimen or structural component to be tested. Distribution of magnetic particles such as iron over the magnetized area indicates flaw patterns. This method is not suitable for concrete and wood, two other major building materials of conventional structures. Circular type damage is not suitable for MT, adding to its disadvantages further. Assessment of strength is not possible by the analyzing the formation of the magnetic particles.

1.2.6 Radiographic Testing (RT)

Usefulness of RT depends on the density and thickness of the testing component. The denser and thicker materials will absorb more radiation. Therefore if a component such as column has some crack inside it, cracked area will absorb less radiation than the rest of the column from the radiator. The pattern on film capturing the radiation will indicate the location and extent of the flaws. However two dimensional views sometimes hide additional defects in a structural component.

1.2.7 Ultrasonic Testing (UT)

Ultrasonic testing uses transmission of mechanical vibration created by sophisticated equipment to identify both linear and non-linear damage. Any material that can act as a medium of transmission of mechanical vibration can be tested with this method. The propagated wave is reflected by a damaged area because of its different acoustic nature. Reflected waves are converted to electric energy and being received by a cathode ray tube (CRT) as signals. The pattern of the signals shows the location and extent of the damage. Again, prior knowledge of the damage is needed in this method. This method is expensive too.

1.2.8 Eddy Current Testing

The Eddy Current Method is usable only on electrically conductive materials. A magnetic field is created by electrified coil around the component. Fluctuating magnetic field induces an eddy current. The damaged portion resists the flow of eddy current. This can be identified by voltmeter reading. The equipment is small, but only a small area can be tested at a time. Prior knowledge of damage is required in this method, too.

1.2.9 Static Load Test

In static load test method, some loads of significant magnitude are placed at some critical locations of the segment to be tested. The displacements and deformations at some relevant locations are measured by sensors attached to those places. If structure is weakened, obvious deviation from the normal state can be observed from the test.

Usually this test is done after some possible occurrence of damage in part of the structure. This test is useful in determining the reduced strength of whole structure due to the presence of damage. However, like visual inspection this test cannot be used for the prior warning of occurrence of damage or the reduction of strength. Another drawback of this method is that the structure may have to be evacuated for the test. The cost of instrumentation and time involvement are other disadvantages of the test.

1.2.10 Vibration Based Damage Identification (VBDI)

VBDI depends on the change of dynamic characteristics of the structures. These characteristics are natural frequencies, mode shapes and damping properties. These characteristics directly depend on material properties, geometry and support condition which contributes to the stiffness and also the distribution of mass. Both stiffness and mass matrices together determine frequencies and mode shapes of a structure. Damage can cause change to any of these dynamic characteristics. Therefore, the VBDI method uses any change to dynamic or modal parameters of structures to identify, locate and detect the severity of the damage. The damage identification process also includes precise modeling of structure and calculation of damage detection algorithm, which necessitates computer programming. In addition, very accurate determination of modal parameters is a prerequisite to good diagnosis of the structure.

1.3 Structural Health Condition Assessment of Bridges

Bridges are very costly infrastructures. The capital cost and maintenance expenses for bridges hold the lion share in total transportation budget. The capital cost being very high, generally bridges are designed for a considerable long service life that ranges from 70 to 100 years. During this service period the bridges need to be monitored to ensure desired performance and structural safety. Each year government has to shoulder a heavy maintenance cost for the transportation infrastructures. Only the discovery of deterioration before or at its onset can help to achieve a cost-effective management (Enright & Frangopol, 2000). Hence the importance of SHM draws attention.

Health Monitoring reduces the chance for catastrophic failure, maintenance cost and down time for rehabilitation. According to Mufti (Mufti, 2001) , more than 40% of the bridges in service in Canada are 30 years old. Therefore now many of these bridges really need diagnosis, rehabilitation and even partial reconstruction to be structurally safe enough for the existing loading condition. Another similar survey conducted by Chase and Washer found that about 33% of the in service bridges in United States of America are deficient (Chase & Washer, 1997). Their health condition is yet to be determined by any instrumental and scientific approach. A study funded by the Federal Highway Administration (FHWA) concluded that visual inspections are labor and cost intensive activities (Dubin & Yanev, 2001), and always subjective and the degree of reliability is also low (Phares, 2001). So in the context of structural operational safety, to meet funding limitations the application of continuous, automatic and low-cost SHM has become highly important (Ping, 2008). Also for rehabilitation and maintenance purposes the need for SHM is increasing day by day.

1.4 Motivation

Many authors have shown that it is desirable to instrument a highway bridge and measure its vibration response to traffic excitation for the purpose of long-term structural health monitoring (SHM) (Chen et al. 2009). Within last two decades, long-term SHM of bridges has been increased dramatically due to the following factors (Farrar & Doebling, 1997) :

1. Aging of bridge infrastructures
2. Bridge failures
3. Realization of the ineffectiveness of visual inspection
4. Technology development

Long-term SHM has several practical advantages over other bridge structural condition assessment methods: (a) it does not interrupt traffic; (b) it captures the in situ dynamic behavior of the bridge undergoing its normal service; (c) it can be performed continuously, scheduled periodically, or triggered automatically; and (d) it requires no special experimental arrangements or heavy shaker/hammers. However, during such measurements, the excitation loads are neither controllable nor (easily) measurable. Thus, to extract the structural properties of the bridge from the vibration data, system identification is performed based only on the measured time histories of bridge responses (system output) without knowledge or measurements of traffic excitations (system input). To facilitate such output-only identification of structural properties, models or assumptions on the stochastic characteristics of the input must be established a priori; otherwise, there can be various combinations of bridge structural properties and excitation loads that might have resulted in the same measured vibration response.

Several output-only identification techniques have been developed. These include the natural excitation technique (Caicedo et al. 2004); (James et al. 1996); (Shen et al. 2003), the frequency domain decomposition (Brincker et al. 2001); (Feng et al. 2004), the subspace decomposition (Peeters et al. 2001), the random decrement technique (Asmussen & Brincker, 1996); (Feng & Kim, 1998), and various types of autoregressive-moving-average model fitting techniques (Garibaldi et al. 1998); (Huang, 2001); (Jensenet al. 1992).

For VBDI method damage assessment algorithms use a validated baseline model which is very often a finite element model (Zang et al, 2001). Baseline dynamic response of an structure is established first. The difference between the baseline response and the response of the damaged specimen will be used as an indicator of damage occurrence and damage identification algorithms will be employed to detect the damage location and severity. Despite having lots of attractive features, model based methods encounter some difficulties in practice. Local structural nonlinearities can pose great problem for this method while baseline modal parameters are obtained by mathematical modeling of linear vibrating system. Furthermore the accuracy of modeling is not guaranteed. For example, damping factor, while affecting the structural response significantly, is very difficult to model accurately (Zou et al. 2000). In general, for model-based methods, a complicated model updating procedure via correlated experimental and numerical analysis has to be taken first to establish the baseline (Bagchi, 2005). Complex damage detection algorithms, uncertainties in noise measurement, incomplete modal vectors and difficulties in simulating environmental factors are some factors that sometimes discourage this method (Humar et al. 2006).

On the other hand, data driven method of structural health monitoring is a direct approach of assessing the structural health condition. Installed sensors measuring strains and vibration of a structure produce signals that always respond to the change of environmental and operational conditions. Each group of signals can be considered a pattern which has some relation to the structural and ambient condition (Sohn et al. 2000). According to Sohn et al (2000), if the effect of ambient condition to the pattern is normalized, they should be clearly identical or close to one another for similar vibration effect as long as structural vibration property remains same. However it is assumed that change in physical properties, mainly stiffness, should be reflected on the processed signal blocks or patterns. Based on this assumption, various methods of damage detection by pattern recognition have been developed. Pattern recognition is aimed for machine learning process, ability of a computer to identify and classify them to make a decision. Since this method is arguably the newest of all global damage detection methods, much more research needed to develop methodologies to detect local damages with severity of the structures.

There are two approaches of pattern recognition in structural health monitoring.

1. Statistical approach
2. Neural Networking

Pattern recognition method incorporates the techniques of signal acquisition from sensors installed on the structure, and then processing of signals, constructing models of training data for classification, then identification and discrimination of the testing data and making decision accordingly

1.5 Thesis Objectives

1. To assess the structural condition of the Confederation bridge using SHM data.

2. Detect malfunctioning sensors using statistical pattern recognition process.

3. Sensitivity analysis of ARX model in detecting malfunctioning sensor and assessing structural health.

4. Assessing the health condition of Portage Creek Bridge using Outlier analysis and finite element static analysis.

1.6 Why statistical pattern recognition technique:

Some damage detection techniques require finite element modeling of the structure. For vibration based damage detection the signal should be completely noise free, but in real life cases it is impossible to get fully de-noised data. Statistical pattern recognition techniques eliminate out these problems. No physical modeling of the concerned structure is necessary for structural pattern recognition technique. Statistical Pattern Recognition technique also has high potential in assessing structural conditions, especially when the data is noisy and susceptible to environmental disturbances.

1.7 Thesis Organization

This thesis is organized in six chapters. The first chapter is giving an introduction about various damage detection techniques and also presents the motivation and objectives of this thesis. Discussion on the reviewed literature on damage detection techniques related to the proposed research fields and also proposed research areas are presented in the second chapter i.e. Literature Review. The third chapter describes about the installed monitoring system of Confederation Bridge and Portage Creek Bridge, two data sources of this thesis. Third chapter also explains the methodologies used all through this thesis work. Chapter four demonstrates the statistical pattern recognition scheme (Auto Regressive Exogenous) on Confederation Bridge SHM data. Chapter five shows sensitivity analysis for the proposed damage detection scheme using Portage Creek Bridge SHM data. In the same chapter Outlier analysis was performed for bridge health monitoring which was compared with a finite element analysis result to assess bridge health condition. The last chapter provides conclusion and summary of all the thesis work. It discusses the findings of the proposed work and based on the findings and limitations of this work the scope for further research has been mentioned.

Chapter 2 Literature Review

2.1 General

In this chapter, relevant literature has been reviewed for the purpose of understanding the field of thesis and identifying the scope of work. The review covers materials on statistical pattern recognition technique as a means of structural damage detection and assessing the integrity of SHM data. In addition to that other relevant areas are briefly explained.

2.2 Statistical Pattern Recognition as Damage Detection Technique

Recently, statistical pattern recognition paradigm has been considered as one of the damage detection techniques based on vibration data of structures. Farrar et al. 1999 have identified and discussed generally the various components of damage detection of structures by statistical pattern recognition technique.

Statistical model development deals with the methods for extracting features that are sensitive to damage to identify the damaged state and its location in the structure. The technique to be used to construct for a statistical model depends on the availability of the data at damaged state. When data are available for both undamaged and damaged states of the structure, the statistical modeling falls into the general classification referred to as *supervised learning*. If data for damaged state are not available, the process is called u*nsupervised learning.* In u*nsupervised learning* by modeling of the extracted features, classes representing undamaged and damaged states are constructed.

In general, damage assessment can be defined at four levels (Rytter.A, 1993) as mentioned in chapter 1. The statistical models are used to identify damage to fit any of these levels in a quantifiable manner. Experimental structural dynamic techniques can be used to address the first two levels. Analytical models are usually needed to identify damage at level 3 and 4 unless examples of data are available from the system (or a similar system) when it exhibits varying damage levels.

Sohn et al 2000 proposed a process of structural health monitoring using a statistical pattern recognition paradigm. They applied a method called a statistical process control technique to diagnose damage in a concrete column as the test article was progressively damaged. Autoregressive (AR) model was selected for time series modeling. Coefficients of AR model were selected as the damage sensitive features for the subsequent control chart analysis. A unique aspect of this study is the combination of various projection techniques such as principal component analysis, linear and quadratic discriminant operators with the statistical process control. The process successfully diagnosed the damage stages in the column.

Sohn et al. 2003 incorporated extreme value statistics in the pattern recognition method. When the structure undergoes structural degradation, it is expected that the prediction errors by time series model will increase for the damage case. Based on this premise, a damage classifier is constructed using a sequential hypothesis testing technique called the *sequential probability ratio* test (SPRT). The sequential test assumes a Gaussian distribution of the sample data sets is often used. This assumption, however, might impose potentially misleading behaviour on the extreme values of the data, i.e., those points in the tails of the distribution. To overcome this difficulty, the performance of the SPRT was improved by integrating extreme values statistics to it. The method was verified on a three-story laboratory test specimen and it could successfully differentiate between various damage stages.

(Taha & Lucero, 2005) proposed a method to improve pattern recognition and damage detection by supplementing Intelligent Structural Health Monitoring (ISHM) with fuzzy sets. They utilized Bayesian updating to demarcate levels of damage into fuzzy sets accommodating the uncertainty of ambiguous damage states. By using data simulated from finite element analysis of a pre-stressed concrete bridge, the proposed technique successfully detected damage.

(Nair & Kiremidjian, 2006) (Mita & Qian, 2006) proposed two algorithms for detection of damage with its location. In their first algorithm they used AR model for feature extraction of the vibration data and metric in the AR coefficient spaces was used for damage localization. In the second model a Gaussian Mixture Model (GMM) was used to model the feature vector. For damage detection the gap statistics which determined the optimal number of mixtures, GMM was used. Damage correlation was used to damage localization. For damage extent, the Euclidean metric between the centers of the Gaussian mixtures of the damaged and undamaged data were used. The techniques were practically exemplified on a physical model of 4-story frame structure in laboratory.

(Mita & Qian, 2006) proposed two methods for determination of damage localization and extent of damage. The first one was based on statistical pattern recognition using the Parzen-window method. The other method one was free-forward back-propagation neural network. They performed some series of vibration test on a model of 5-story shear-frame structure. The degree and extent of damage was successfully determined.

2.3 Pattern Recognition by Statistical Methods

Fugate et al. (2001) have proposed a generalized approach for SHM by statistical pattern recognition.

2.3.1. Operational Evaluation

Operational evaluation defines damage for the system being monitored and also the operational and environmental conditions under which the system structure function.

2.3.2 Data Acquisition

Data Acquisition involves selection of the types of sensors and location where they should be placed, determination of optimal number of sensors to be used and setup of data acquisition, storage or transmission hardware. Vibration response can be only obtained by ambient excitation.

2.3.3 Data Cleansing

The non-structural conditions such as civil loading or climate conditions always vary with time. Therefore it is needed to normalize the data to make them compatible to analyze for damage detection. In the case of varying environmental and operational conditions, normalized data can be compared at similar times of an environmental or operational conditions, normalized data can be compared at similar times of an environmental or operational cycle. Sources that affect the variation of data and the structured monitored are to be identified and minimized. For those variability sources which can be eliminated, they should be made available to be statically quantified. Signals are usually gathered continuously. Strain data is significantly influenced by temperature and external loading. Data needs to be corrected for all of these external noises on the signals. There are various ways to de-noise data. Some of them are described below in nutshell.

2.3.4 De-noising

De-noising is a process of signal recovery from noisy data. This problem is easy to understand by looking at the following simple example, shown in figure 2.1, where a slow sine wave is corrupted by white noise. The general de-noising procedure involves three steps. The basic version of the procedure follows the steps given below.

Decompose: Choose a wavelet, choose a level N. Compute the wavelet decomposition of the signal, s, at level N.

Threshold Detail Coefficients: For each level from 1 to N, select a threshold and apply soft thresholding to the detailed coefficients.

Reconstruct: Compute the wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

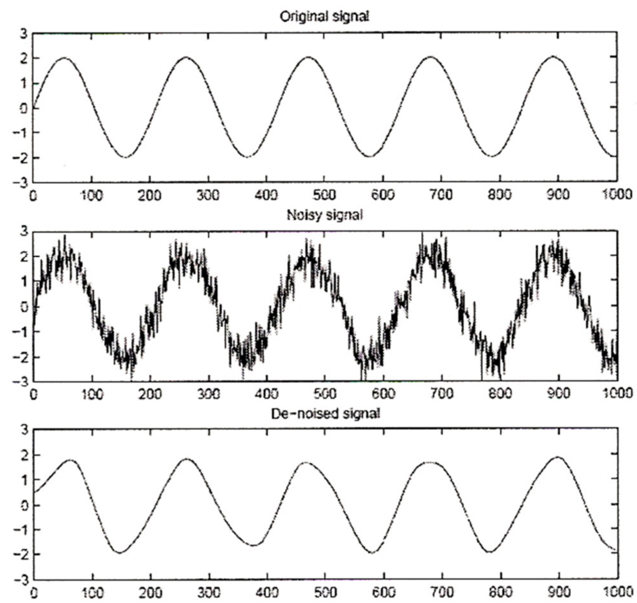


Figure 2.1Denoising of signal block (Islam, 2009)

2.3.5 Filter

A filter is usually needed to perform frequency dependent alteration of a data sequence. For example, a filter could be applied to remove noise above 30 Hz from a data sequence sampled at 100 Hz. A more rigorous specification might call for a specific amount of passband ripple, stopband attenuation, or transition width. A very precise specification could ask to achieve the performance goals with the minimum filter order, or it could call for an arbitrary magnitude shape, or it might require an FIR filter. Filter design is the process of creating the filter coefficients to meet specific filtering requirements. Filter implementation involves choosing and applying a particular filter structure to those coefficients. Only after both design and implementation have been performed can data be filtered. To meet the specifications with more rigid constraints like linear phase or arbitrary filter shape, FIR (finite impulse response) and direct IIR (Infinite impulse response) filter design routines are followed. The primary advantage of IlR filters over FIR filters is that they typically meet a given set of specifications with a much lower filter order than a corresponding FIR filter. Although IIR filters have nonlinear phase, data

processing within MATLAB software is commonly performed 'offline," that is, the entire data sequence is available prior to filtering. This allows for a non causal, zero. Phase filtering approach (via the "filtfilt" function), which eliminates the nonlinear phase distortion of an IIR filter. The classical IIR filters, such as, Butterworth approximate the ideal "brick wall" filter in different ways. Roy et al 1997 have explored the implications of the low-pass Butterworth filter on the characteristics of correlation analyses. It has also proposed that knowing the filter response, it is possible to reconstruct the original signal spectrum and to allow comparisons between data collected with different instruments The autocorrelation function also is affected by filtering which increases the value of the coefficients in the first lags, resulting in an overestimation of the integral length scale of coherent structures, These important effects add to those related to size and shape differences in electromagnetic current meters sensors and must be taken into account in comparative studies.

2.3.6 Data Normalization

The data normalization procedure begins by assuming that a "pool" of signals is acquired from various unknown operational and environmental conditions, but from a known structural condition of the system. The ability of this procedure to normalize the data is directly dependent on this pool being representative of data measured in as many varying environmental and operational conditions as possible. The collection of this time series is called "the reference database". All the signals are standardized prior to any subsequent analyses such that:

$$\hat{x} = \frac{x - \mu_x}{\sigma_x} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(2.1)$$

Where $\hat{x}$ is the standardized signal of x, and μ_x and σ_x are the mean and standard deviation of x, respectively.

2.3.7 Feature Extraction

It is the process of identifying damage-sensitive properties derived from the measured vibration response that allows one to distinguish between the undamaged and damage structure. Silva et al 2007 deals with the application of a two-step auto-regressive and auto-regressive with exogenous inputs (AR-ARX) model for linear prediction of damage diagnosis in structural system. This damage detection algorithm is based on the monitoring of residual error as damage-sensitive indexes, obtained through vibration response measurements.

The basic input-output configuration of ARX model is shown in figure 2.2. Assuming unit sampling interval, there is an input quantity or signal u(t) and output quantity or signal y(t) , t=1,2………….. n. Assuming that the signals are related by a linear system, input-output relationship can be written as

$$y(t)= G(q)u(t)+v(t)\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.2)$$

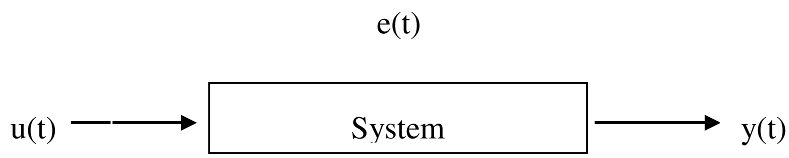


Figure 2.2 Basic input-output configuration of ARX model

Where q is the shift operator and G(q) is the transfer function of the deterministic part of the system(t) is the disturbance of the system which can be described as filtered white noise.

$$V(t)=H(q)e(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(2.3)$$

Where e(t) is white noise with variance and H(q) is the transfer function of the stochastic part of the system. Where e(t) is white noise with variance and H (q) is the transferfunction of the stochastic part of the system. Equations (2.2) and (2.3) together, give a time-domain description of the system,

$$y(t)= G(q) + H(q)\, e(t)\ldots\ldots\ldots\ldots\ldots\ldots (2.4)$$

A commonly used parametric model is the ARX model that corresponds to

$$G(q) = q - nk\frac{B(q)}{A(q)};\ H(q) = \frac{1}{A(q)} \ldots\ldots\ldots..(2.5)$$

The number nk is the number of delays from input to output. Where A(q) and B(q) are polynomials in the shift operator q -1

$$B(q) = \begin{bmatrix} b_{11} & b_{12} & \ldots. & \ldots. \\ b_{21}q^{-1} & b_{22}q^{-1} & \ldots. & \ldots. \\ \ldots. & \ldots. & \ldots. & \ldots. \\ b_{nb1}q^{-nb+1} & b_{nb2}q^{-nb+1} & \ldots. & b_{nbnu}q^{-nb+1} \end{bmatrix}$$

Here, B(q) is an nb x nu matrix where numbers na and nb are the orders of their respective polynomials, and nu is the number of input variables. For the SISO (Single Input Single Output) model, nu = The general structure of the SISO or MISO (Multiple Input Single Output) ARX models is given by

$$A(q)y(t) = B(q)u(t - nk) + e(t) \ldots\ldots\ldots\ldots\ldots\ldots.(2.6)$$

One of the simplest models in the system identification literature is the ARX model, Where AR refers to the Auto-Regressive part A(q) y(t) and X to the extra input B(q) u (t) part. Eq. (2.7) can also be written explicitly for a first-order model with a delay of two sampling times as,

$$y(t) = -\alpha_1 y(t\text{-}1) + b_{11}u_1(t-2) + b_{12}u_1(t-2) + \ldots\ldots\ldots\ldots + b_{1n}u_n(t-2) + e(t)\ldots\ldots..(2.7)$$

Given a description and having observed the input-output quantities u; y, the errors or residuals e(t) in Eq. (2.8) can be computed as

$$e(t) = H^{-1}(q)[y(t) - G(q)u(t)] \dots \dots \dots \dots \dots \dots \dots \dots (2.8)$$

These residuals are, for given observations y and u, functions of G and These in turn are parametrized by the polynomial in Eq. (2.9). The most common parametric identification method is to determine the estimates of G and H by minimizing

$$V_n(G, H) = \sum_{t=1}^{n} e^{2(t)} \dots \dots \dots \dots .. (2.9)$$

That is

$$\left[\hat{G}_n \, \hat{H}_n\right] = \arg\min \sum_{t=1}^{n} e^{2(t)} \dots \dots \dots \dots \dots \dots (2.10)$$

This is a prediction error method. The identification method for the ARX model is the LS(Least Square) method, which is a special case for the prediction error method. The LS method is the most efficient polynomial estimation method because this method solves linear regression equations analytically.

For linear models, model estimation can be done using time-domain data, and then model validation can be done using frequency domain data. For nonlinear models, only time-domain data can be used for both estimation and validation. Measured and simulated model output pattern matching can be computed using the following equation:

$$Best\ fit = (1 - \frac{|y - \hat{y}|}{|y - \bar{y}|}) \times 100 \dots \dots \dots \dots \dots \dots .. (2.11)$$

In this equation, y is the measured output, $\hat{y}$ is the simulated or predicted model output, $\bar{y}$ is the mean of y. 100% corresponds to a perfect fit, and 0% indicates that the fit is no better than guessing the output to be a constant ($\hat{y} = \bar{y}$). Because of the definition of Best Fit, it is possible for this value to be negative. A negative best fit is worse than 0% and can occur for the following reasons: The estimation algorithm failed to converge. The model was not estimated by minimizing $|y - \hat{y}|$. Best Fit can be negative when you minimized I-step-ahead prediction during the estimation, but validate using the simulated output $\hat{y}$. The validation data set was not pre-processed in the same way as the estimation data set. (Matlab 2009b help files).

2.3.8 Statistical Model Development

It is concerned with the implementation of the algorithms that analyze distribution of the extracted features in an effort to determine the damage state of the structure. The appropriate algorithm to use will depend on the ability to perform supervised and unsupervised learning. Supervised learning refers to the case where examples of data from damaged and undamaged structures are available. Unsupervised learning refers to the case where data is only available from the undamaged structure.

2.4 Summary

From the literature review it has been found that identification of damage by statistical pattern recognition is still not at fully developed stage. It is found that structural damage affects the dynamic properties of a structure, causing a change in the vibration signals i.e. strain and acceleration time histories. Damage detection can be performed using time series analysis of vibration signals measured from a structure before and after damage. The references cited in this review propose different techniques of statistical pattern recognition for extracting damage sensitive features from vibration response of laboratory based simple structure. Most of research studies done so far dealt with model frame structures. Current situation demands more researches in this field which will involve real life structures. Therefore statistical pattern recognition method seems very promising field of research. In this thesis, statistical pattern recognition techniques are applied for damage detection of real structure like the Confederation Bridge and Portage Creek Bridge.

Chapter 3 Methodology

3.1 General

This thesis is divided into two parts. In the first part, vibration data are collected from 34 sensors of Confederation Bridge. These data were obtained from ISIS Canada Research Network, a Canadian Network of Centres of Excellence (NCE). Then Statistical pattern recognition technique was applied to these vibration data to detect any damage in structure and at the same time detecting malfunctioning sensor.

In the 2^{nd} part of this thesis sensitivity analysis has been done on pattern recognition technique by ARX model. For this sensitivity analysis strain data were collected from ISIS website (ISIS Canada Database) for Portage Creek Bridge. In addition to the sensitivity analysis a finite element model was developed for pier-2 of Portage Creek Bridge. A static analysis was conducted with this model. The strains found from static analysis were matched with the strain data from real life strain gauges. While matching the static analysis data with the real data, some structural changes had been made in the model. Based on what kind of structural changes had been made and to what extent the changes were made; the structural condition of that bridge was assessed.

3.2 A Brief Overview on Installed SHM System of Confederation Bridge

Being the world's largest bridge crossing ice laden water, it took three-and-a-half years for complete construction. This beautiful gigantic superstructure links Canada's eastern islands; i.e. Prince Edward Island and New Brunswick. In 1993 this fixed link construction began and the huge construction work was completed in 1997.

Figure 3.1 Aerial photo of Confederation Bridge, New Brunswick (Courtesy Strait Crossing Bridge Ltd.)

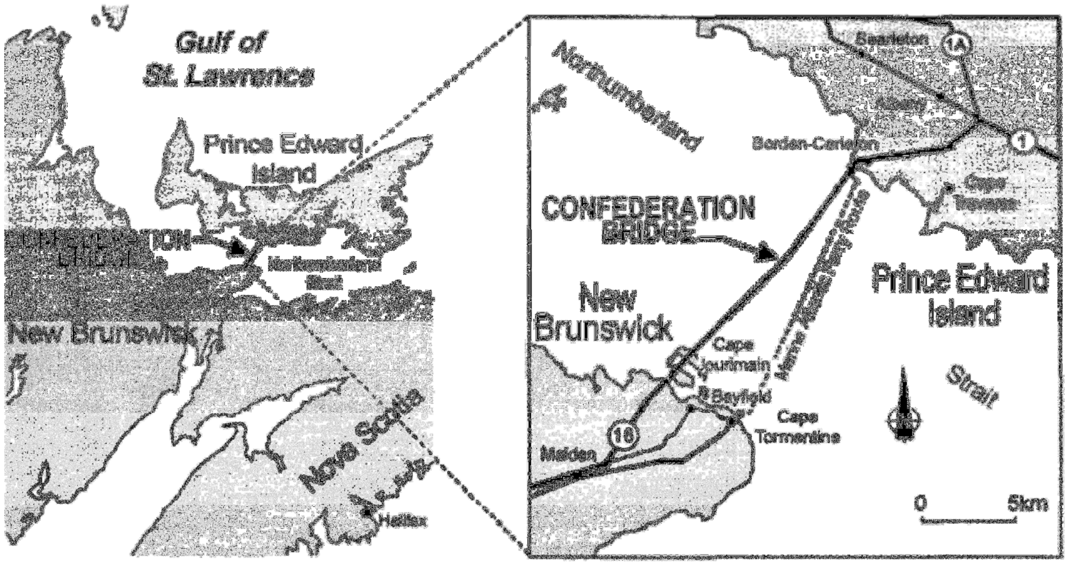


Figure 3.2 Location of Confederation Bridge (Becker et al. 1998)

It was designed for a service life of 100 years, twice the service life of typical bridges. This curved bridge is 12.9 km long, with major part consisting of 43 spans, each 250 meters in length and 2 end spans are 165 m each. The total width of the bridge is 12 meters providing an 11 meter roadway with considerable wide shoulders on both sides. This is a multi-span post-tensioned concrete box girder structure. The Confederation Bridge consists of two approach bridges at its ends and a main bridge between them. The approach bridge at the Prince Edward Island end has 7piers and a length 555 m. The New Brunswick end has 14 piers and a length of 1275 m. The Bridge has a typical clearance of 28 meters above sea level with the exception of 49 meters high middle span allowing navigation through it (Langley et al. 1995) the middle span Both the approach bridges and the main bridge were built of precast concrete segments which were assembled using post-tensioned tendons.

A special structural system is used to prevent progressive collapse of the bridge, ensuring that a collapse of any span would not lead to other spans collapsing. It consists of a series of rigid portal frames connected by simply supported girders. Every second span is constructed as a portal frame. All other spans are constructed using drop-in girders. There are a total of 21 portal frames in the bridge.

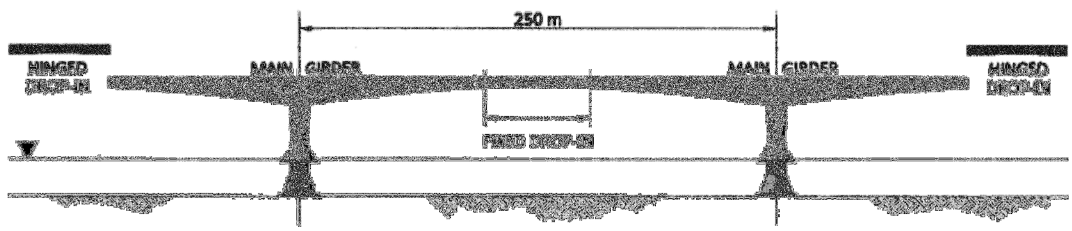


Figure 3.3 Typical Portal Frame (Butcher, 2009)

The superstructure is a single-cell post-tensioned concrete box girder with a depth of 4.5 meters at mid-span to 14.5 meters at the pier location (Tadros, 1997).

This project was one of the most costly projects of Canadian government and consequently one of the most extensively instrumented bridges in the world. Confederation Bridge was an excellent candidate for a full SHM program for several reasons (Cheung et al. 1997):

- The bridge has a very high design life (100 years)
- Heavy storms with wind in excess of 100 km/hr and presence of ice in the strait for four months in each winter.
- Advance the knowledge in modeling and analysis techniques and design of the long-span bridges.
- SHM data and research results will be valuable for design, construction and maintenance of other long-span complex bridges.

- SHM knowledge gained from this bridge will contribute to set new design guidelines and industry standards for long-span bridges all over the world.

To verify some safety and serviceability assumptions this SHM can be used.

Health monitoring of Confederation Bridge started in June 1997. The instrumentation used in this bridge was designed by Public Works and Government Services, Canada.

Using SHM technologies in the Confederation Bridge project provides information about the health of the bridge due to dynamic loads, ice forces, short- and long-term deformations, thermal effects, and corrosion. This is a two-stage method for health assessment which looks at both the overall and a detailed structural health assessment based on the natural frequencies of the vibrations of the bridge.

3.2.1 Sensor Details

The instrumentation of Confederation Bridge is installed over three spans of the main bridge, between piers P30 and P33 as shown in Figure 3.4. For monitoring and measuring of dynamic effects due to traffic, wind, ice and seismic loads a network of 76 accelerometers is used. Since the completion of the bridge thermocouples are mounted on six locations to measure the thermal variation and effects. Also corrosion is a great concern here and it should not go unmonitored. 29 corrosion probes were wrapped around the reinforcement and then embedded in the concrete for corrosion monitoring (Butcher, 2009). Table 3.1 is presenting all the sensor details installed in the monitored section of Confederation Bridge.

Table 3.1 Sensor details of Confederation Bridge

Type	Number	Location
Electric foil strain gauges	-	At the girders and the Piers 31, 32
Thermocouples	6	4 on the girder and 2 at top of the Piers
Accelerometer (dynamic effect)	76	42 in the girders and 34 in the piers
Bi-axial tilt meter (ice pressure)	2	On piers no. 31, and 32
Corrosion probes	29	At the Pier no. 34

ISIS Canada define SHM with the definition given below-

“A non-destructive in-situ structural evaluation method that uses any of several types of sensors which are attached to, or embedded in, a structure. These sensors obtain various types of data (either continuously or periodically), which are then collected, analyzed and stored for future analysis and reference. The data can be used to assess the safety, integrity, strength, or performance of the structure, and to identify damage at its onset.” (ISIS Canada, 2004)

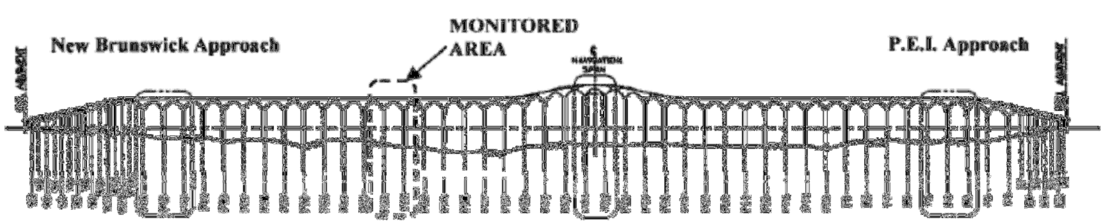


Figure 3.4 Location of monitored section in the Confederation Bridge

The overall structural health assessment is based on the natural frequencies of the vibrations of the bridge. Since the bridge is designed to behave purely elastically under expected traffic loads, wind, and ice forces, the natural frequencies of vibrations of the bridge, determined from recorded vibrations due to such loads, must be almost constant with time (Butcher, 2009).

The health assessment procedure consists of two stages, overall (or global) and a detailed (or local) structural health assessment. The overall assessment is based on the results of the measured vibrations as recorded by the dynamic instrumentation. The detailed or local assessment is based on the measurements of all effects.

3.2.2 Data from Monitored Structure

In this study, signal data blocks were taken from 34 vibration wire strain gauges. These gauges are installed in piers 31 and 32. The signals produced here are unidirectional. The data used in this thesis covers a period between August, 2003 and January, 2004.

The Caltrans (California Department of Transportation) recommended that any approach should include enough modes of vibration to achieve a total mass participation not less than 90% for a given bridge. To capture a sufficient number of modes that gives mass participation more than 95%, it is required to collect data up to 16 Hz. For this case the data sampling rate was 124Hz.

The data blocks were collected for different days of the above mentioned period. The days were chosen arbitrarily and for each day only ten minutes data are available.

3.2.3 Data Processing

The approaches followed in this study to process the data are as follows –

Data files were combined chronologically according to the time period for which particular analysis is done. For example: If the analysis is done for the time frame November/03 to January/04 then signal blocks only from these period were joined together chronologically. For each second there are 124 data available. So average of 124 data was taken as second data. For analysis average second data was used.

For the training of ARX model, time histories are taken from earlier months. The testing data are chosen from the last month of considered time frame. For example; if the analysis is done for the period of November/03 to January/04, reference data blocks for model training are chosen from November, 03 and December, 03 while test data blocks are selected from January,04.

Once the above mentioned tasks are done then both reference (training) blocks and testing data blocks are processed by de-noising and normalization following the methods proposed in literature review chapter. All data are normalized using equation 2.1 which removes the mean from each data series. AR-ARX are zero mean Gaussian process. The above normalization approximates the monitoring data to have such characteristics.

3.2.4 Damage Identification Approach by Pattern Comparison

The basic concept of this approach was first proposed by Sohn et al. 2000. It is logical to assume that the patterns in data at a certain state, either steady or agitated, taken at various points of time of the structure will not vary significantly if the structure does not change significantly. Conversely if the structure has undergone a significant change, it should reflect in the pattern of data in a given state. In order to observe the variation of structure by studying the pattern of signals or data blocks, it is necessary to nominate certain block as reference data block with which patterns of the other data series or blocks are compared. Usually the reference data blocks for particular conditions are taken from earlier time of the observation of the structure and other data blocks are called test blocks. The time series model (ARX model for this study) particularly developed for reference block is defined as reference model. As structure undergoes change over time, usually degradation, so will the pattern of data series change. Therefore the pattern of later time data blocks will not match closely with that of reference block (earlier time blocks).

ARX (Auto Regressive Exogenous) time series analysis finds the best fit match (in percentage) between the reference and testing signal blocks. Depending on this best fit variation structural health is diagnosed. If the sensors signal patterns from different period, for the same condition i.e. steady or agitated, are not giving good match then there might be any or both of the following reasons-

1. Loss in monitored structure's integrity
2. Presence of malfunctioning sensor(s)

This study mainly focused on detecting malfunctioning sensor using ARX model. Sequential search and Binary search methods were applied in detecting faulty sensor. Also some sensitivity analyses have been done.

3.2.5 Detection of Defective Sensor by ARX model and Application of Binary and Sequential Search Method

Binary and sequential search methods are commonly used in computer science. The concept has been used in the study for defective sensor detection. Before explaining the total approach, definition of the two methods are described in the next two subsection

3.2.5.1 Sequential Search

Linear search is a search algorithm, also known as sequential search that is suitable for searching a list of data for a particular value. It operates by checking every element of a list one at a time in sequence until a match is found. The best case is that the value is equal to the first element tested, in which case only 1 comparison is needed. The worst case is that the value is not in the list (or it appears only once at the end of the list), in which case n comparisons are needed. The simplicity of the linear search means that if just a few elements are to be searched it is less trouble than more complex methods that require preparation such as sorting the list to be searched or more complex data structures, especially when entries may be subject to frequent revision. Another possibility is when certain values are much more likely to be searched for than others and it can be arranged that such values will be amongst the first considered in the list. (Kunth, 1997).

3.2.5.2 Binary Search

Binary search is an algorithm for locating the position of an element in a sorted list by checking the middle, eliminating half of the list from consideration, and then performing the search on the remaining half. If the middle element is equal to the sought value, then the position has been found; otherwise the upper half or lower half is chosen for searched based on whether the element is greater than or less than the middle element. The method reduces the number of elements needed to be checked by a factor of two each time, and finds the target value. (Kunth, 1997)

3.2.5.3 General Steps Followed for the Search Methods

In this study, for the Confederation Bridge, data from 34 vibration wire strain gauges were harvested. Then these data were divided into training and input groups. One strain gauge data has been selected as target and remaining sensors data as input data to create a representative set of model by proper training. These models are created to produce the data pattern at a particular period of time with respect to the corresponding input at that time. In Figure 3.5 it is shown that time series data are first pre-processed by de-noising and normalization method. Then 33 sensors data are used to get simulated output with the help of ARX model which is trained by similar sensors data of earlier months. It is assumed that earlier month's data are from undamaged structure. Comparing the measured and simulated output pattern by sequential or binary search method faulty sensor is detected. In this thesis several case studies have been done for both of the methods.

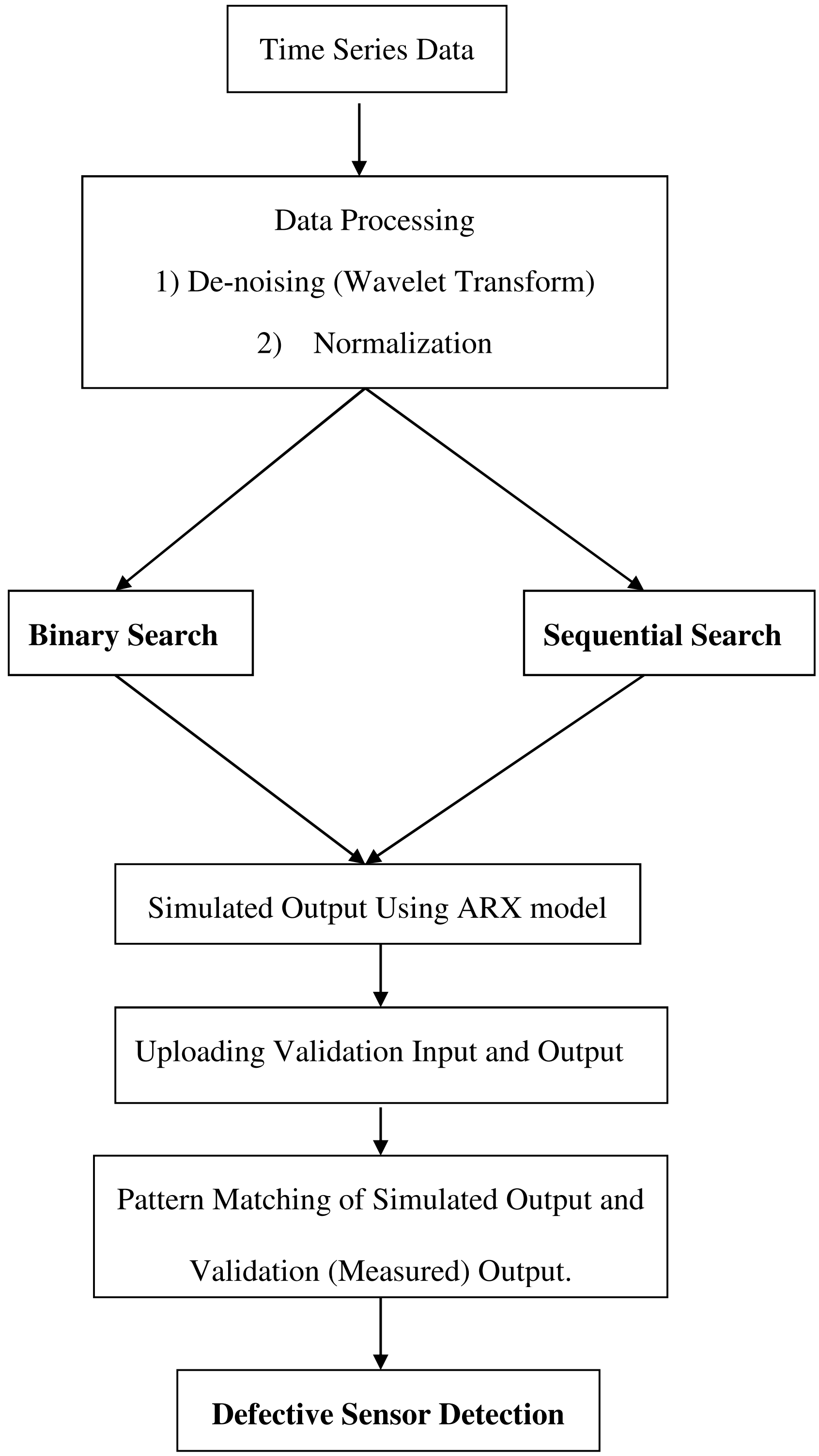


Figure 3.5 Flow chart showing the steps of the search methods

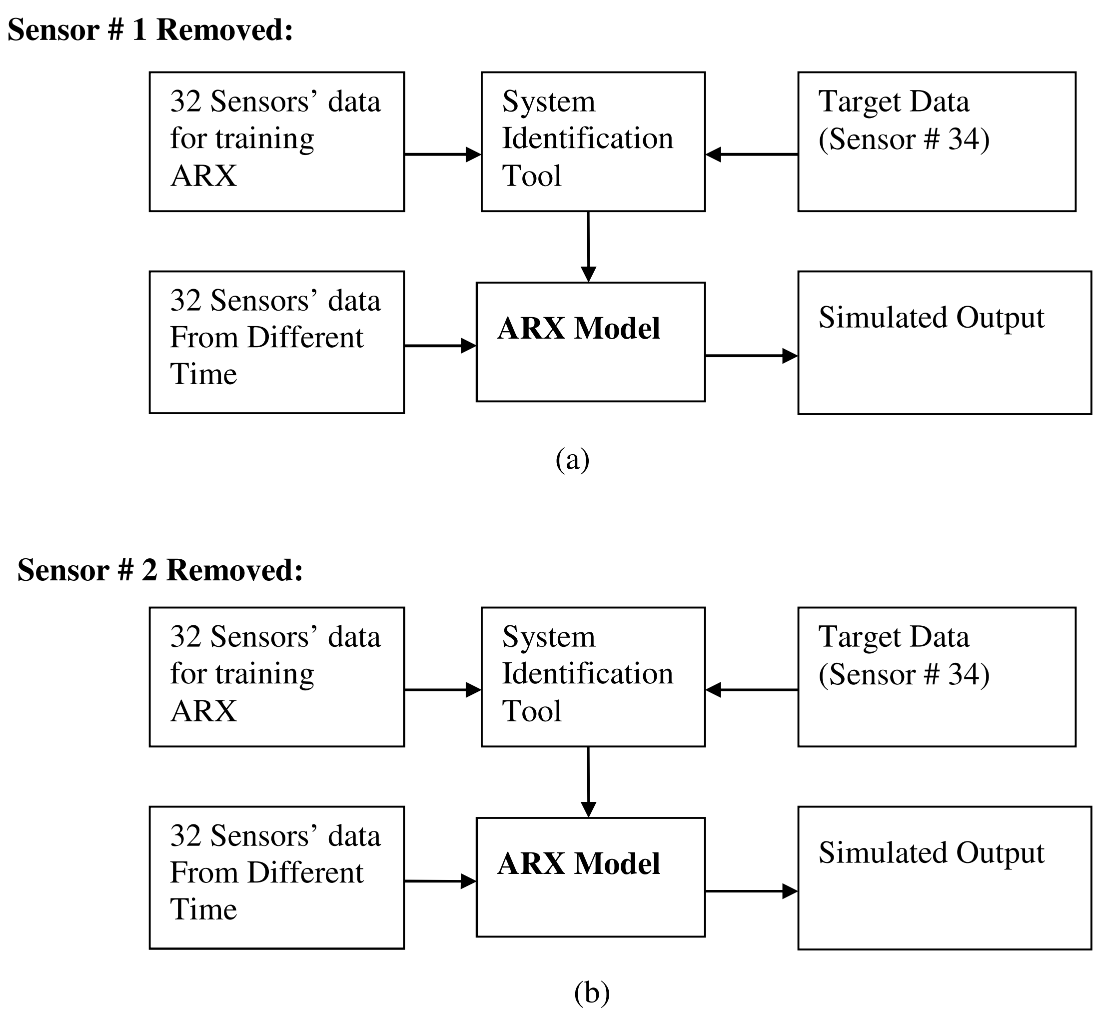
The general steps of search techniques are given below-

1. Strain data from various sensors at the Confederation Bridge are first uploaded to MATLAB workspace.
2. As there are 34 sensors in total, 33 of them are imported as input data and one sensor data is imported as output data. Then the ARX tool is used to build the model. These data are collected from the presumably undamaged condition of the structure.
3. Again data from 33 sensors are imported as input data and one sensor data is imported as measured output data. This output data is used for validation. These data are collected from unknown condition of structure.

Finally using the ARX model the simulated output is produced and compared to the measured output.

For better understanding of the methodology the 1st case of sequential search method (Section 4.3, Case I) is explained in nutshell. To build the ARX model to produce the data pattern for a particular period of time, November, December/2003 data blocks were used. Sensor 34 was fixed as target sensor, assuming that it is in good working condition all through the period of analysis. For sequential search method 33 models have been trained. Each time one sensor is removed from 33 sensors and used for training the model. Then corresponding sensors' data for a different time, January/2004, but similar environmental and operational condition, has been used as input to get 33 simulated outputs. In the Figure 3.6 (a) it is shown that sensor 34 is used as target and for training the 1st model sensor 1 is removed from 33 sensors. Then corresponding sensors' data of different time are used to get the 1st simulated output. In the Figure 3.6 (b) it is shown that sensor 34 is used as target and for training the 2nd model sensor 2 is removed from 33 sensors. Then corresponding sensors' data of different time are used to get the 2nd

simulated output. The rest 31 simulated outputs are obtained through the same process. Each simulated output pattern is compared with corresponding measured output shown in Figure 3.7. The highest best fit would indicate that the excluded sensor is responsible for the change in data pattern. For instance if removal of sensor 15 from training data and input data cause highest best fit for simulated and measured data, then it is indicating



sensor 15 is defective.

Figure 3.6 Schematic diagrams for identifying defective sensor by ARX model with sequential search method. (a) simulated output when sensor 1 is removed from training and actual data. (b) simulated output when sensor 2 is removed from training and actual data.

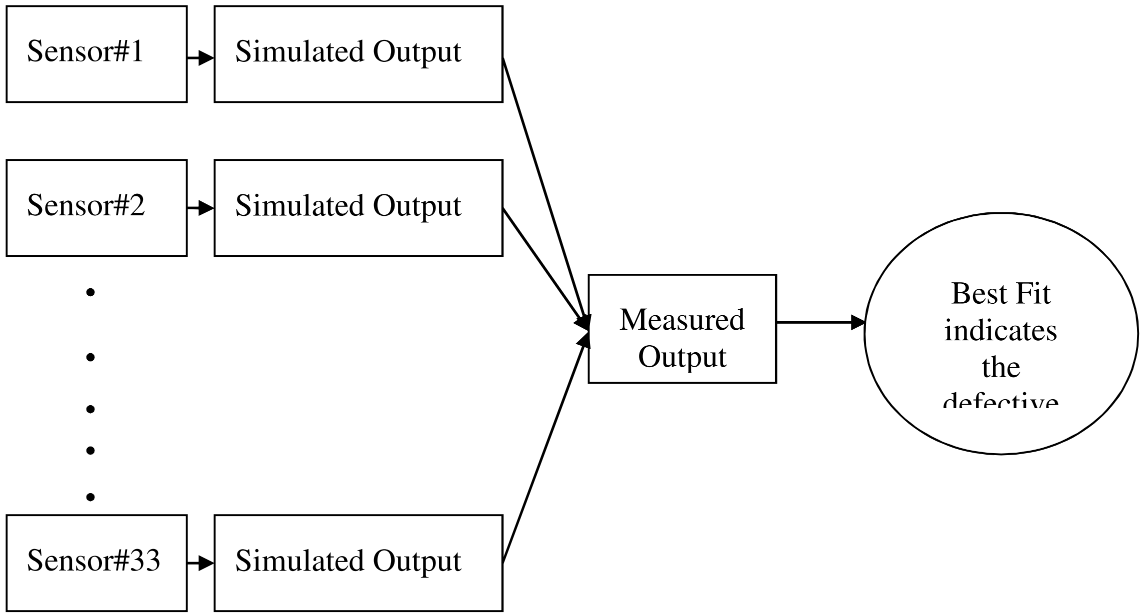


Figure 3.7 Schematic diagrams for comparing all simulated output with measured output. The highest best fit would indicate that the excluded sensor is responsible for the change in data pattern

In 1st case of Binary Search method (Details in Section 4.4, Case I) first 28 sensors are divided into two groups and for each group sensor 30 is fixed as target sensor. To build ARX model August to November/2003 data has been fed to ARX tool. December/2003 data, for similar environmental and operational conditions, has been used to produce simulated Output and at the same time to provide the system the measured output to compare with simulated one. In the same way, the second 14 sensors' data had been analyzed to get simulated output. Each simulated output pattern is compared with the corresponding measured output pattern. The best fit indicates a defective sensor is in the other group. For instance, Figure 4.4 and Figure 4.5 are showing that the best fit value of measured and simulated output of the 2nd group of sensors is higher than that of the 1st group. So the defective sensor is in 1st group. Then the 1st group is again divided into two groups of seven sensors. Then, the sequential search method was applied to the defective sensor group. In this way the defective sensor was identified. When the group size reduces to 4 sensors (preferably 5 sensors) rather than applying binary method one should apply sequential search method; because a group of less than 4 sensors has too small data to apply binary search method. So if we divide the following seven sensors into two groups to apply Binary Search technique, one group will have only three sensors' data which is quite inadequate to build a reasonable statistical model for analysis. Figure 3.8 is showing the schematic diagram of the above mentioned case.

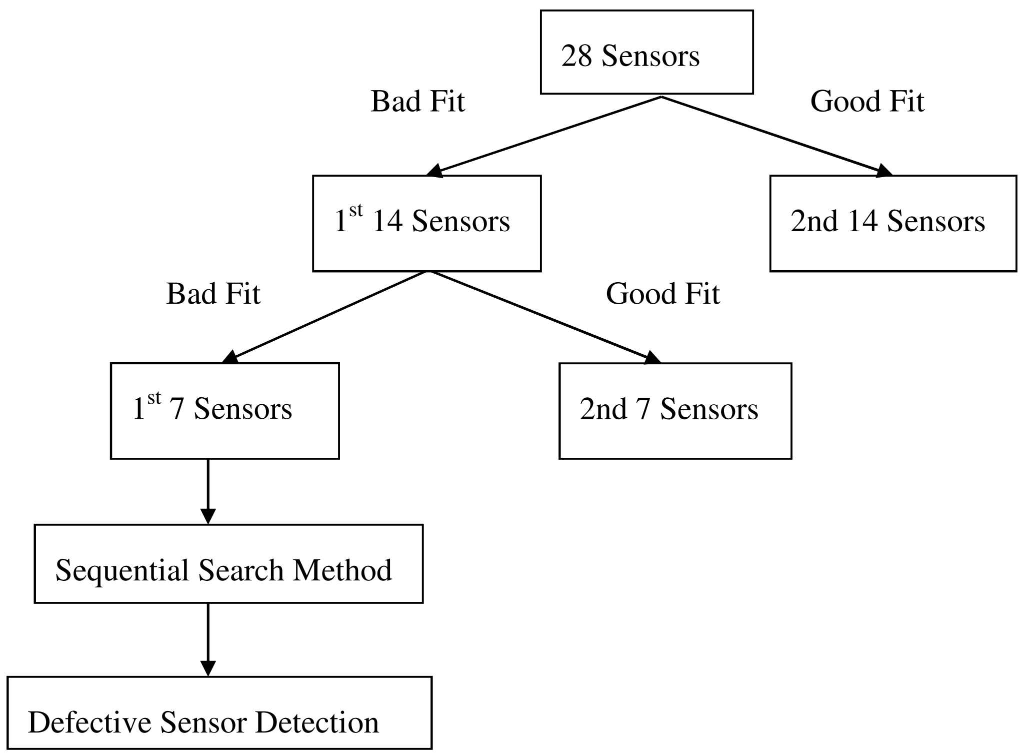


Figure 3.8 Schematic diagram for identifying defective sensor by ARX model with binary search method.

3.2.5.4 Sensitivity Analysis

Sensitivity analysis is used to determine how "sensitive" a model is to changes in the value of the parameters of the model and to changes in the structure of the model. By showing how the model behaviour responds to changes in parameter values, sensitivity analysis is a useful tool in model building as well as in model evaluation. Sensitivity analysis helps to build confidence in the model by studying the uncertainties that are often associated with parameters in models (Breierova et al.1996). In this study, parameter sensitivity has been focused. Parameter sensitivity is usually performed as a series of tests in which the modeller sets different parameter values to see how a change in the parameter causes a change in the dynamic behaviour of the stocks. Many parameters in system dynamics models represent quantities that are very difficult, or even impossible to measure to a great deal of accuracy in the real world. Sensitivity analysis allows the modeller to determine what level of accuracy is necessary for a parameter to make the model sufficiently useful and valid. If the test reveal that the model is insensitive, then it may be possible to use an estimate rather than a value with greater precision. Sensitivity analysis can also indicate which parameter values are responsible to use in the model.

In Chapter-4 several case studies have been performed on SHM data of Confederation Bridge in order to get a well perception of the sensitivity of applied damage detection method.

3.3 A Brief Overview on Installed SHM System of Portage Creek Bridge

The Portage Creek Bridge located in British Columbia (BC), Canada (Figure 3.9) has been used as one of the SHM data sources for the current thesis. The Ministry of Transportation in BC designed the Portage Creek Bridge, as shown in Figure 3.10 and Figure 3.11. Located in the city of Victoria, British Columbia, the bridge crosses Interurban road and Colquitz River at McKenzie Avenue.

Figure 3.9 Portage Creek Bridge in Victoria, British Columbia (Huffman et al. 2006)

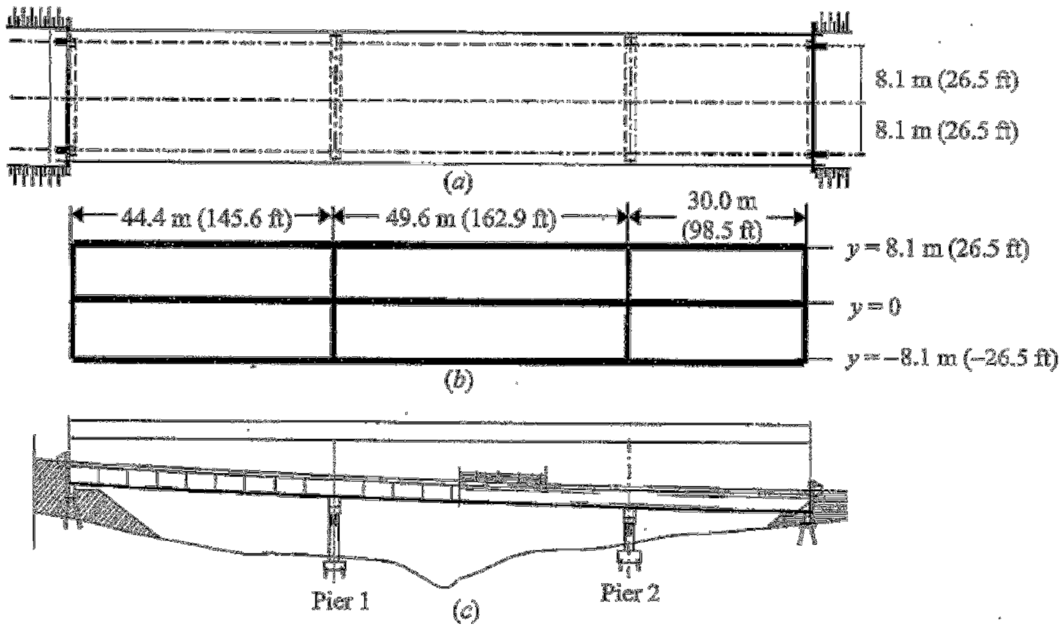


Figure 3.10 Plan and elevation of Portage Creek Bridge (Huffman et al. 2006)

The bridge is described as a 124m (407 ft) long, three-span structure with a reinforced concrete deck supported on two reinforced concrete piers, and abutments on H piles. The deck has a roadway width of 16.2m (53 ft) with two 1.98m sidewalks and aluminum railings. There are eight bi-directional electrical strain gauge rosettes on each column, four long gauge fiber optic sensors on each column and one 3-D accelerometer on top of the pier cap of each column. An elevation view of the instrumented pier No.2 is shown in Figure 3.11 with sensor locations.

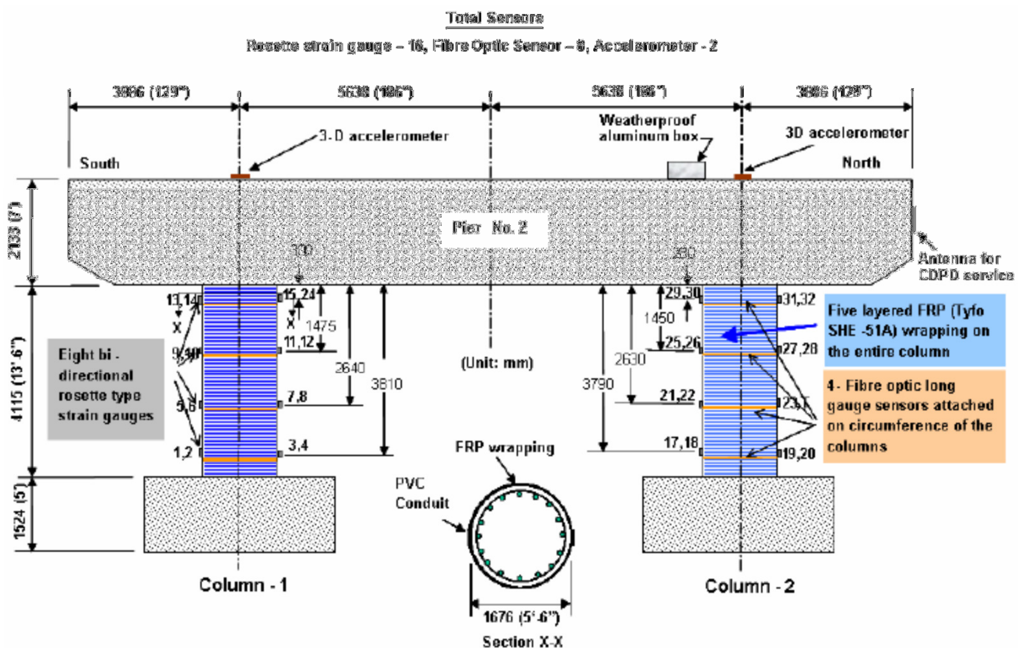


Figure 3.11 Sensor locations on Pier-2 columns of the Portage Creek Bridge (Huffman et al. 2006)

3.3.1 Damage Identification Approach for Portage Creek Bridge

In Chapter-5 of this study, SHM data from this bridge had been used for damage detection purpose using Statistical Pattern Recognition method. Chapter-5 consists of two parts. In first part the signals used, were produced in every minute from eight bi-directional strain gauges installed at column-2 (C2) of pier-2 of this bridge. And the 2nd part of the same chapter deals with the SHM data from column-1 of pier-2 of the same bridge. Each bi-directional strain gauge produces two data series, one for horizontal movement and another for vertical movement.

In the 1st part of concerning chapter some sensitivity analysis had been done to determine the feasibility of Statistical pattern recognition for damage detection. Both Binary and sequential methods were applied for sensitivity analysis.

In the 2nd part of Chapter-5, Outlier analysis has been performed as a means of statistical pattern recognition to assess structural condition. Outlier analysis is suitable for automated continuous system monitoring. It can be applied to the selected features to investigate the existence of damage in the structure. When the system experiences abnormal conditions, the mean and variance of the extracted features are expected to change. SHM data from the sensors installed in column 1 was used for outlier analysis. X bar control charts were employed to monitor the changes of the selected feature's mean and to identify samples that are inconsistent with the past data sets.

Application of the S control chart, which measures the variability of the structure over time, to the current test structure is presented in Fugate et al 2000. Several variations of the control charts can be found in Montgomery, 1997.

To monitor the mean variation of the features, they are first arranged in subgroups of size p. τ_{ij} is the jth feature from the ith subgroup. The subgroup size p is often taken to be 4 or 5 (Montgomery, 1997). If p is chosen too large, a drift present in individual subgroup mean may be obscured, or averaged-out. An additional reason for the using subgroups, as opposed to individual observations, is that the distribution of the subgroup mean values can be reasonably approximated by a normal distribution as a result of central limit theorem.

Next, the subgroup mean Type equation here.$\overline{X}_i$ and standard deviation S_t of the features are computed for each subgroup ($i = 1,,,, ,q$, where q is the number of subgroups):

$\overline{X}_i = mean(\tau_{ij})$, and

$S_i = std(\tau_{ij})$

Here, the mean and standard deviation are with respect to p observations in each subgroup. Finally, an X-bar control chart is constructed by drawing a centerline (CL) at the subgroup mean and two additional horizontal lines corresponding to the upper and lower control limits, UCL and LCL, respectively versus subgroup numbers (or with respect to time).

The centerline and two control limits are defined as follows:

$$UCL, LCL = CL \pm Z_{\alpha/2} \frac{S}{\sqrt{n}} \quad \textbf{(3.1)}$$

and

$$CL = mean(\overline{X_i})$$

Here mean is calculated with respect to all sub groups. i.e., *i=1,2,…..,q.* $Z_{\alpha/2}$ is the percentage point of the normal distribution zero mean and unit variance such that

$$p[z \geq Z_{\alpha/s}] = \alpha/2$$

The variance S^2 = mean (S_i^2). If the system experienced damage, this would likely be indicated by an unusual number of subgroup means outside the control limits; a charted value outside the control limits is referred to as an *outlier* in this thesis. The monitoring of damage occurrence is performed by plotting $\overline{X}$ values obtained from the new data set along with the previously constructed control limits.

In Chapter 5, once X-bar control chart was done then a Finite element model was built to perform a simple static analysis and then co-relating the results of static analysis with the X-bar control chart analysis in order to assess the structural condition.

Chapter 4 Health Monitoring for PEI Bridge Using Statistical Pattern Recognition

4.1 General

In this chapter SHM data i.e. sensor data have been collected from Prince Edward Island Bridge and Statistical Pattern Recognition technique is applied on these data to assess structural health condition and to detect if sensors are working properly. ARX tool in MATLAB R2009b was used for the pattern recognition purpose. In order to evaluate the feasibility of the proposed approach as damage detection technique sensitivity analysis has been performed.

4.2 Identifying unknown defective sensor (Sequential search method)

Case 1

There are total 34 sensors. Sensor#34 has been used as the target sensor. ARX model was built in MATLAB R2009b using November and December, 2003 data. Validation data was chosen from January, 2004. It is supposed that all the sensors were in good condition for the months of November and December, 2003. Each time one sensor is removed from input data to see that removal of which sensor is giving the best fit.

Table 4.1Results for sequential search method, Case 1 (Unknown Defective Sensor)

Eliminated	Best fit	Eliminated	Best fit
1	71.49	18	63.17
2	70.57	19	70.73
3	76.37**	20	71.76
4	69.12	21	72.05
5	72.68	22	75.71
6	74.28	23	71.06
7	72.10	24	71.96
8	70.55	25	73.96
9	72.52	26	70.54
10	71.34	27	67.98
11	68.52	28	72.13
12	69.79	29	69.15
13	69.27	30	66.84
14	73.54	31	69.24
15	67.97	32	74.66
16	71.89	33	71.12
17	72.35	Note: ** Max Best Fit (%)	

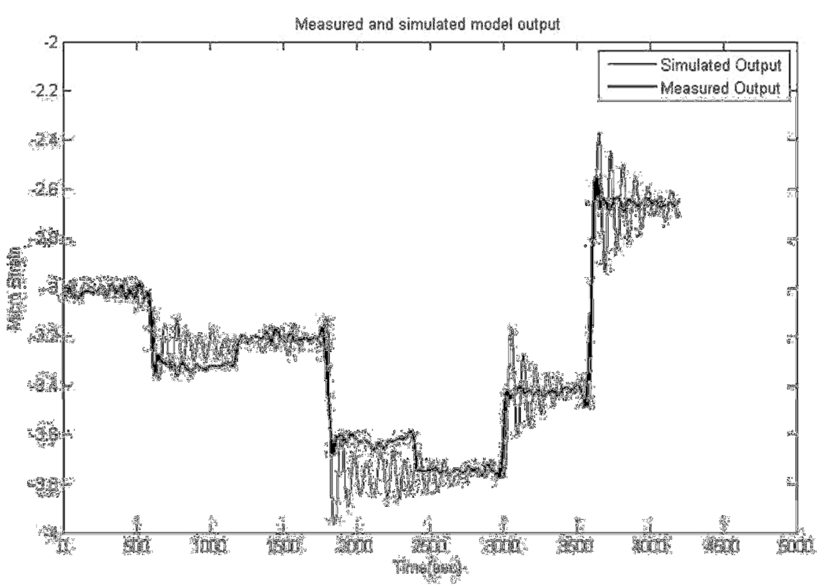


Figure 4.1 Measured and Simulated Output of January 2004, sensor #1 removed

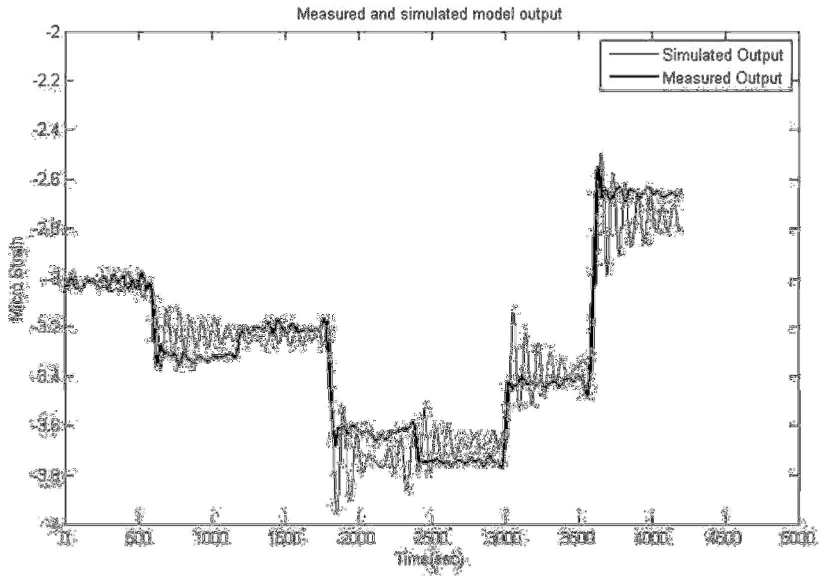


Figure 4.2 Measured and Simulated Output of January 2004, sensor #12 removed

Figure 4.1 and Figure 4.2 are showing the measured and simulated output pattern matching while sensor #1 and sensor #12 were removed, respectively. Table 4.1 shows that when sensor 3 was removed the best fit was maximum (76.37%). It could mean that sensor 3 data is erroneous, i.e. sensor 3 is a malfunctioning sensor. But the entire table shows that the range of best fit varies from around 60% to 80%. So the variation is not too much among the results, which indicates all the sensors are functioning properly.

Case 2

To verify the above analysis, another ARX model has been built with different time period. For this analysis simulated output has been produced by feeding all the 33 sensors data for the months from August to December, 2003. January, 2004 data was used as validation data. Sensor 34 data was taken as target data. It is supposed that all the sensors were in good condition in the period of August to December, 2003. For each run one sensor is removed and the best fit is recorded to see which sensor removal gives the highest best fit.

Table 4.2 Results for sequential search method, Case 2 (Unknown Defective Sensor)

Eliminated	Best fit	Eliminated	Best fit
1	12.15	18	55.08
2	21.1	19	25.72
3	67.48**	20	22.86
4	21.21	21	21.42
5	20.90	22	21.16
6	19.76	23	21.63
7	24.38	24	22.37
8	21.37	25	20.61
9	49.26	26	48.64
10	55.14	27	63.09
11	24.49	28	27.08
12	48.36	29	8.795
13	32.48	30	19.76
14	21.04	31	26.79
15	22.00	32	53.29
16	21.15	33	21.36
17	25.48	Note: ** Max Best Fit (%)	

Table 4.2 is showing a wide range (10%~70%) of best fit percentage. The time period here, includes the data from August to December, 2003 and January, 2004. So here some data are from summer, some are from fall and some are from winter. Eventually the data pattern for sensors varies significantly specially from fall to winter because of mainly drastic temperature change, wind and snow loading. It is hard for the ARX Model to recognize a very specific pattern based on these assorted type time series pattern. When too many different data patterns come together it makes the modeling cumbersome. This

resulted in low best fit percentage ranging from 20% to 30% for most of the runs. The ARX model which was built based on the data from August to December produced a simulated output that has very low matching with the measured or validated output which is basically from winter period January, 2004.

In second case the removal of sensors# 3, 9,10,12,13,18,26,27 and 32 gave comparatively higher best fit. The first reason could be all of the nine sensors are defective. But it is unlikely that nine sensors will go out of order just in one month i.e. in January, 2004. So besides defective sensors, there might be another reason for what the removal of those sensors gave higher matching. The reason could be the "time period" considered for analysis. The data pattern changes significantly from fall to winter. For sensors the signal pattern varied a lot over this period because of temperature, weather and traffic changes. So the ARX model which was built based on the data from August to December i.e. mostly for fall period produced a simulated output that has very low matching with the measured or validated output which was taken from winter period January, 2004.

For the first case all the best fit was higher because the concerned time period covers mainly data from the months which have pretty much similar weather condition. So the loading condition does not differ too much. The data fed to ARX tool for the first case study was from the months of November, December, 2003 and January, 2004 which were consecutive. So while November and December data were used building the ARX model, the given January sensor data produced a simulated output which is pretty much close to the measured output. It implies that by this period the sensors do not experience too much pattern variation. Hence the ARX Model could recognize the data pattern more specifically and with better accuracy.

Case 3

To see the seasonal effect or the effect of time span on the results another analysis is done. This time the model was built with the data from months August, September, October, November, 2003 and validation data was from December, 2003. It is supposed that for the months from August to November all the sensors were in good condition. Like the other two cases mentioned before this time also, for each run, one sensor is removed from the sensor group at a time and sensor 34 is used as target sensor. The best fits (%) are given on Table 4.3.

Table 4.3 Results for sequential search method, Case 3 (Unknown Defective Sensor)

Eliminated	Best fit	Eliminated	Best fit
1	35.99	18	35.11
2	51.33	19	38.66
3	58.84**	20	54.94
4	53.95	21	51.75
5	51.29	22	52.7
6	52.1	23	50.52
7	48.48	24	49.09
8	40.91	25	54.14
9	38.44	26	51.37
10	40.42	27	46.15
11	57.29	28	41.54
12	39.78	29	48.19
13	55.10	30	49.18
14	38.25	31	40.4
15	51.42	32	54.03
16	51.37	33	56.63
17	48.71	Note: ** Max Best Fit (%)	

Table 4.3 shows that the best fit ranges from 35% to 60%. Most of them fall in a range of 40% to 60%. Unlike the analysis for the time span August to January (Case-2), there is no abrupt change in the best fits in this case. For this period the data patterns do not vary too much because the modeling does not include the winter data along with the fall data. Mostly all of the time series data were taken from fall, 2003 and a few were from summer, 2003 to build the model and the model was validated with December, 2003 data. So the best fit range does not vary widely unlike the 2nd case. The following graph is showing the results for the three cases.

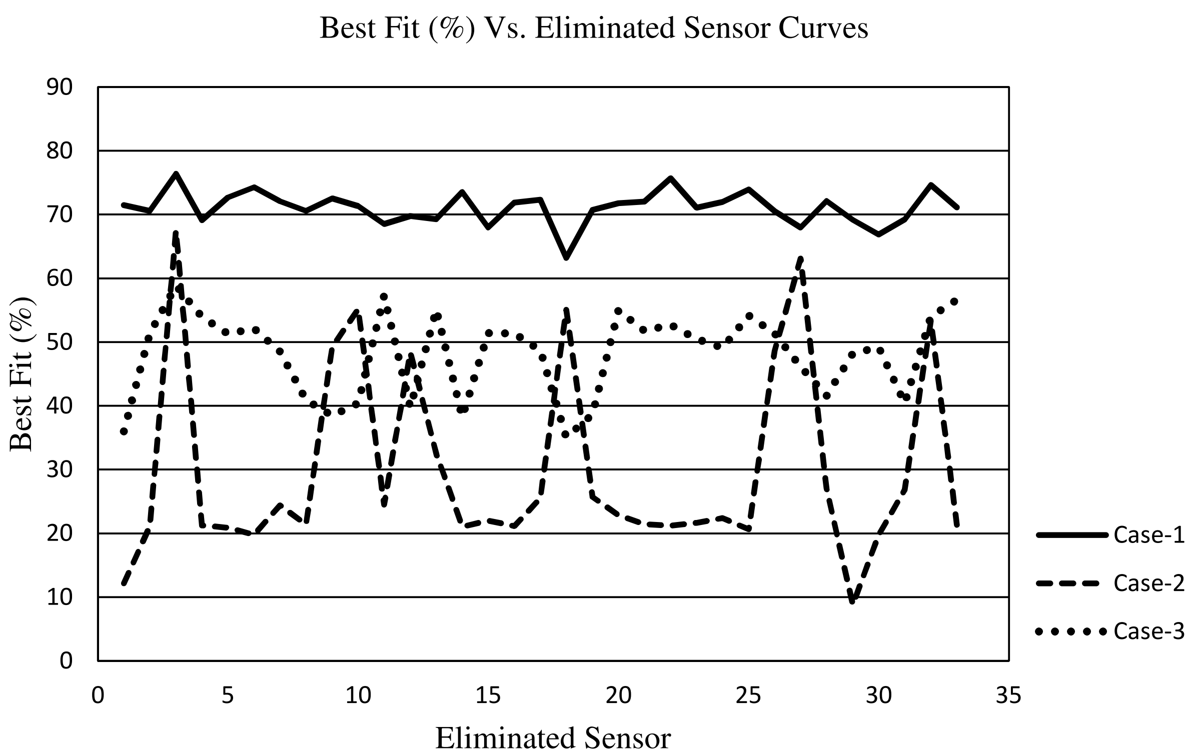


Figure 4.3 Best Fit (%) Vs. Eliminated Sensor Curves for three different cases.

From Figure 4.3 it's clear that all the results in Case-1 are high and close enough to conclude that none of the sensors is out of order. There is no significant difference among the best fit results, which indicates that all sensors are functioning properly. For the 2nd case the results showing higher variation because of the inclusion of data from various seasons. And in the 3rd case the results ranges in a reasonable width showing that sensors are in good condition. But in all of the above cases elimination of sensor 3 gave the highest pattern match. So some practical tests could be conducted to see if sensor 3 has indeed malfunctioned.

4.3 Identifying a sensor known to be defective (Sequential Search Method)

To test the feasibility of ARX model as a reliable damage detection method sensitivity analysis is a must which shows how sensitive is the model is, to any kind of arbitrary change in the concerned parameters. Hence some cases are presented below as sensitivity analysis.

Case 1

Here it is assumed that all the sensors are in good condition for the months of November and December, 2003. For this analysis sensor#15 has been made defective artificially for January, 2004 by replacing the sensor readings by random numbers that does not follow any specific pattern. Sensor #34 is taken as the target. Now each time, while building the model, one sensor is taken out from the 33 sensors and the program was run for each sensor combination to see which run gives the highest best fit. Table 4.4 is showing the results below.

Table 4.4 Results for sequential search method, Case 1 (Defective Sensor#15)

Eliminated	Best fit	Eliminated	Best fit (%)
1	-83.51	18	60.67
2	66.74	19	46.43
3	-47.07	20	66.73
4	-247.6	21	72.79
5	65.46	22	-234
6	-237.7	23	69.09
7	69.12	24	65.54
8	56.91	25	-54.43
9	26.7	26	43.69
10	67.15	27	-236.8
11	-264.8	28	61.74
12	-177.1	29	61.18
13	-318.5	30	71.15
14	71.93	31	-43
*15	80.2**	32	66.68
16	-47.56	33	61.36
17	65.75	Note: * Defective sensor ** Max Best Fit (%)	

When sensor 1 is removed it gave negative best fit. When sensor 15 is removed the best fit is highest. So the ARX Model could detect the defective sensor.

Case 2

Again the same analysis is done with different time period. Now the 34 sensors are divided in 3 arbitrary groups. In each group one sensor is made defective by selecting random data and one sensor is fixed as target. The model is built with August, September, October and November, 2003 data and for validation December, 2003 data is used. The groups are in Table 4.5

Table 4.5 Three random group of sensors (Sequential search method Case 2).

Group	Sensors	Defective Sensor	Target Sensor
1	1,2,3,7,8,11,12,15,22,31	22	1
2	4,5,6,9,10,13,14,17,19,21,29,30	21	6
3	16,18,20,23,24,25,26,27,28,32,33,34	25	26

Each group from Table 4.5 is analyzed separately. In each group for each run one sensor is removed from reference and input data. For every case the simulated and measured output pattern matching was recorded.

Table 4.6 Results of three random sensor group analyses.

GROUP 1		GROUP 2		GROUP 3	
ELIMINATED SENSOR	BEST FIT (%)	ELIMINATED SENSOR	BEST FIT (%)	ELIMINATED SENSOR	BEST FIT (%)
2	22.82	4	-19.35	16	10.23
3	-79.73	5	-1039	18	-329.6
7	26.34	9	-14.84	20	-56.75
8	26.67	10	-1193	23	-1257
11	21.37	13	-1310	24	15.25
12	15.68	14	-1050	* 25	26.47**
15	35.21	17	-516.2	27	-24.15
*22	51.31**	19	19.39	28	-552.3
31	27.5	*21	22.85**	32	12.47
Note: * Defective sensor **Max Best fit (%)		29	-409.7	33	-980.6
		30	-261.1	34	20.08

Table 4.6 shows that for each group the removal of known defective sensor gave highest best fit. So for any combination of sensors the ARX method is reliable to detect a defective sensor.

4.4 Binary Search Method (Identifying Unknown Defective sensor)

While applying the binary search method the sensors were arbitrarily divided into two groups. The case studies are given below-

Case 1

In this case first 28 sensors were divided into two groups of 14 sensors. To train ARX model sensor 30 was fixed as target and input data were taken from the months of August to November, 2003. Measured Output from December, 2003 was used to find the best fit. Figure 4.4 and Figure 4.5 show that measured and simulated model output of 2nd 14 sensors fit better than the 1st 14 sensors (-12.13%, 13.99% respectively). Therefore malfunctioning sensors are located in first 14 sensors group.

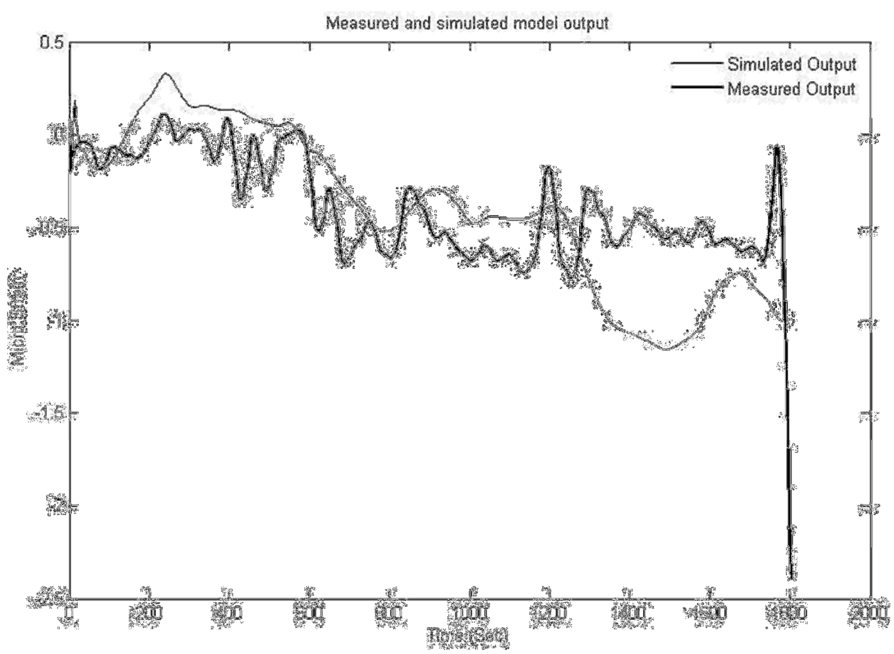


Figure 4.4 Measured and Simulated Output of Dec 2003, 1st 14 sensors

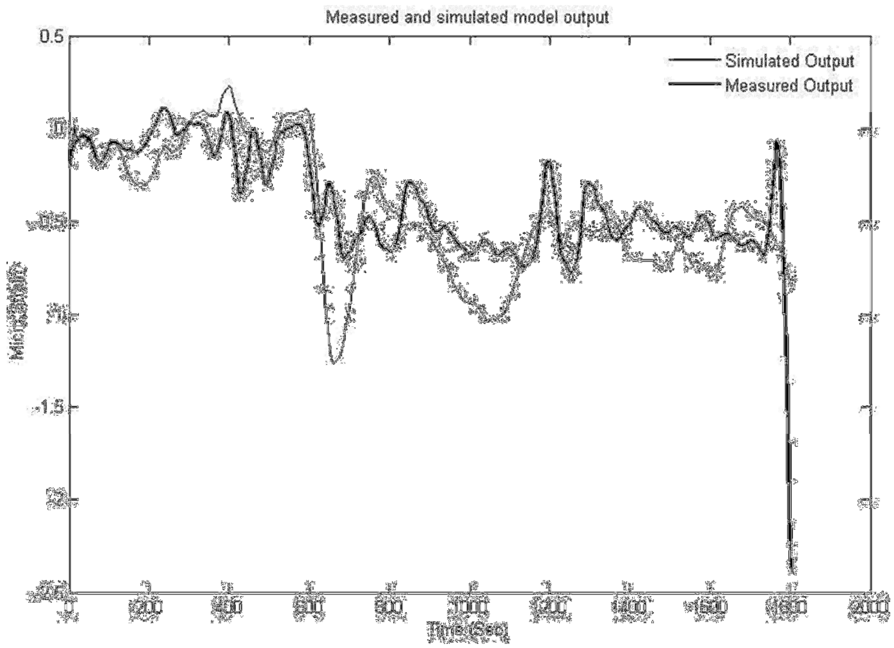


Figure 4.5 Measured and Simulated Output of Dec 2003, 2nd 14 sensors

Then first 14 sensors were then divided into two groups of 7 sensors. The best fits found are -53.7% and 40.23% respectively. Then for the first group (consists of sensor#1 to #7) sequential search method was applied to find the defective sensor. The results for sequential search method are shown in Table 4.7

Table 4.7 Results of Sequential search method for minimum Best fit group (Sensor#1~7)

Eliminated sensor	Best fit (%)
1	-134
2	-53.34
3	11.69
4	-66.17
5	-52.28
6	-56.97
7	-32.92

From the table it is observed that removal of sensor 3 produces the highest best fit among all the 7 sensors. So sensor#3 is could be labelled as the potentially malfunctioning one.

Same observation was made when a purely sequential search method (i.e., without any groups) was applied earlier.

Case 2

In this case the two groups of sensors are shown in Table 4.8

Table 4.8 Two random groups of sensor (Case 2)

Group	Sensor No.
1	1,2,3,4,9,10,11,12,17,18,19,20,25,26,27
2	5,6,7,8,13,14,15,16,,21,22,23,24,,28,29,30

To train the ARX model sensor 33 was fixed as target and input data were from the months of August to November, 2003. Measured Output from December, 2003 was used to find the best fit. For the first group the best fit found is 13.83% (Figure 4.6) and for the 2nd group the best fit was 70.44% (Figure 4.7).

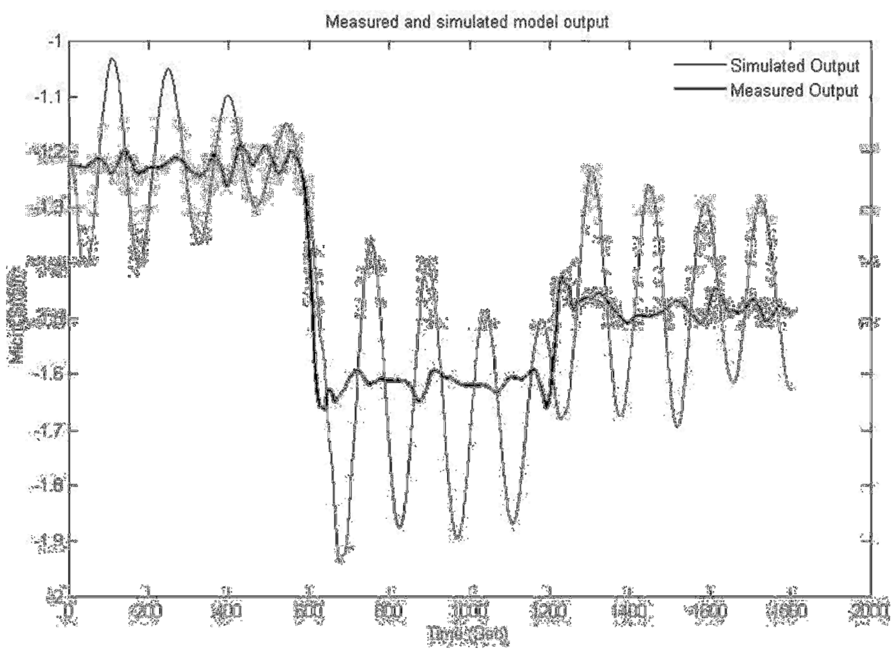


Figure 4.6 Measured and Simulated Output of Dec 2003, 1st group of sensors.

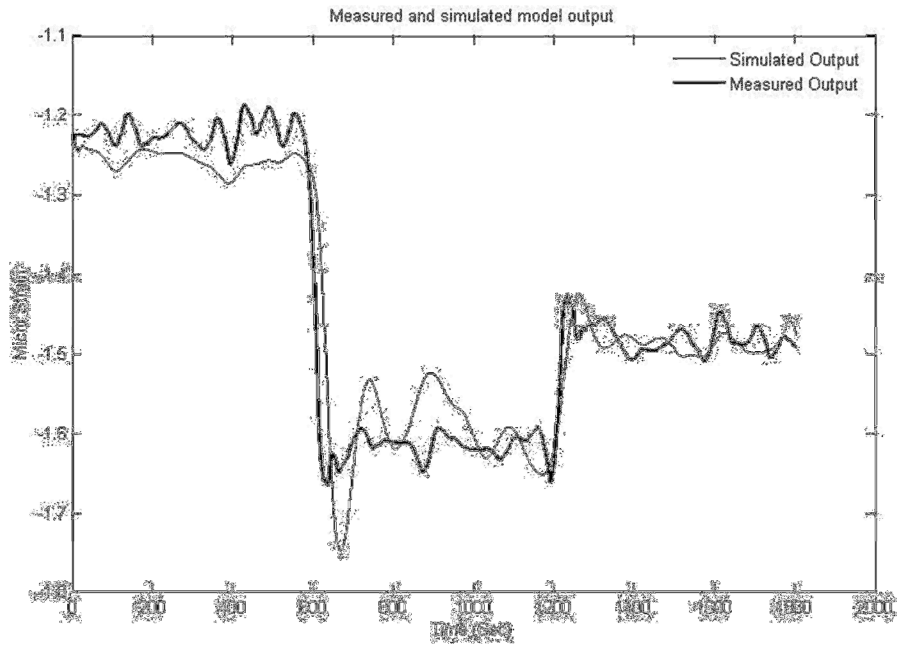


Figure 4.7 Measured and Simulated Output of Dec 2003, 2nd group of sensors.

Then first 15 sensors were divided into two groups of 8 and 7 sensors respectively. The best fits found for 1st group is 32.05% and for 2nd group is 42.19%. Then the first group (consists of sensors 1 to 8) was divided into two groups of 4 sensors and the best fits found were -16.97% and 53.97% respectively. After that for the first group (consists of sensor1 to 4) sequential search method was applied to find the defective sensor. The results for sequential search method are presented in Table 4.9

Table 4.9 Results of Sequential search method for minimum Best fit group (Sensor#1~4)

Eliminated Sensor	**Best Fit(%)**
1	44.5
2	57.1
3	65.67
4	56.72

From the table it is observed that removal of sensor 3 gives the highest best fit among all the 4 sensors, which conforms to the previous observation.

4.5 Sensor malfunctioning Vs. Structural damages:

From sensor data analyses we try to figure out if there is any problem with the structural integrity or the sensors are malfunctioning. If there is any local damage in a structure that will affect the pattern of the sensors attached with that particular part of structure. In damaged state all attached sensors will record time series which is different from undamaged state. Combination of time series from a group of sensors gives one combined pattern for that particular period. This combined pattern is matched with that of another time. If the pattern matching percentage is too small compared to other time results, then one can say; there are some anomalies in the structure or sensor malfunctioning might cause this anomaly.

If the pattern anomaly is caused just because one sensor, it is more likely that particular sensor is malfunctioning. But if the matching percentage is not good because of more than one sensor, it is assumed that some changes have been occurred in the concerned structure. These physical changes reflect in the modal properties like frequency of structure which affects the regular time series data of the sensors. So under this circumstances more than one sensor will reflect the newly changed structural properties which will give a different combined pattern leading lower match with the previous pattern. So from the SHM data analysis if it is found that more than one sensor is showing data pattern variation; it is more likely that the structure is undergoing some physical changes.

4.6 Summary

Statistical Pattern Recognition by ARX model has been conducted on the vibration data from Confederation Bridge. Both methods based on the Sequential and Binary search techniques give similar results. Sensor# 3 was found defective. In all the cases, done for the sensitivity analysis, the defective sensors were detected. But it is recommended to follow another pattern recognition method like Neural Network to verify the results obtained from ARX method. After analyzing the SHM data it can be concluded that this bridge was not experiencing any major structural problem for the period for which the analysis had been made.

Chapter 5 Portage Creek Bridge Monitoring

5.1General

In this chapter sensitivity analysis has been done on SHM data collected from Portage Creek Bridge, Victoria, BC. Previously for this bridge some works have been done with statistical pattern recognition but in limited scale. Statistical Pattern Recognition methods were earlier used by (Islam, 2009) to explore the possibility of detecting structural damage and defective sensor. In this chapter the work of (Islam, 2009) is continued and extended by exploring many different ways of constructing the ARX model and conducting a detailed sensitivity study. Here sensitivity analysis has been done in order to establish a reliable and good amount of statistics to evaluate the feasibility of the damage detection method.

(Noman, 2008) performed outlier analysis to detect the damage state of Portage Creek Bridge as data for known damaged state of this structure were not available. He used control chart analysis for Outlier Analysis. In this study, X-bar control chart analysis is performed and a Finite element analysis is done to compare the results from control chart analysis.

5.2 Sensitivity Analysis

For sensitivity analysis, data from the following sensors were used-

Table 5.1 Sensors on column 2 of pier-2 of the Portage Creek Bridge

Sensor notation (Huffman et al, 2006)	**Sensor notation** (current study)	**Sensor notation** (Huffman et al, 2006)	**Sensor notation** (current study)
Sensor# 17	1_1	Sensor# 18	1_2
Sensor# 19	2_1	Sensor# 20	2_2
Sensor# 21	3_1	Sensor# 22	3_2
Sensor# 23	4_1	Sensor# 24	4_2
Sensor# 25	5_1	Sensor# 26	5_2
Sensor# 27	6_1	Sensor# 28	6_2
Sensor# 29	7_1	Sensor# 30	7_2
Sensor# 31	8_1	Sensor# 32	8_2

Table 5.1 is presenting the sensors` notation for the analysis in the current study. Location of the above mentioned sensors are shown in Figure 3.11.

So from eight strain gauges sixteen output signals are obtained. Along with these sixteen signal blocks, another data block from a temperature gauge was used for analysis. Frequency of data collected is 32 Hz. The monitoring data was available from the ISIS Canada Research Network. The webpage for Portage Creek Bridge real time monitoring is hosted by a centralized SHM system of ISIS Canada website. The data available from the bridge site covers a period between 2004 and 2006. A user can pick up and access individual sensor's data from the sensors list. The approaches followed in this study to process the data are:

1. Time interval between points, number of data points, data channels to query are selected.
2. Data points are saved as comma separated values.
3. Data collected in every second are converted into minute data and then again minute data are converted into hourly data, micro strain/hr.
4. For the training, time data are taken in the month of December/05, January/06 and February/06 data. Total number of data points in a segment for each strain gauge sensor is 1738. Out of 2160 data points, only 1738 are valid and the rest are removed from data sets.
5. The testing data are taken from the month of March/06 because of the presence of peaks or novel events in that period.

5.2.1 Data Processing

SHM data used for this thesis were processed by denoising and normalization, in the same way as data from Confederation Bridge were processed.

5.2.2 Detection of a known defective sensor using Binary Search technique

Here several case studies have been done. Binary search method was applied to identify a known defective sensor. In total six different case studies will be presenting for sensitivity analysis. In the first three cases the target sensor was fixed but different sensors were made defective in three different cases. In next three cases the malfunctioning sensor was fixed but different target sensors were used in three different cases. Time period for all the cases was chosen the same i.e. December, 2005, January, February, 2006 data were used to build the ARX model and March, 2006 data were used to produce the simulated output and provide the system the measured output.

5.2.2.1 Detection of faulty sensor (sensor# 5_1 is fixed as target sensor in all cases)

Case1

In this case the concerning sensors were divided into two groups. Sensor# 5_2 was made defective by putting random data that does not follow specific pattern in its data block. The Best fits found after the Auto Regressive analysis are shown in Table 5.2

Table 5.2 Binary search method, Case 1(Sensor#5_1 is fixed as target)

Group Number	Sensor Number	Best fit (%)
1	1_1,1_2, 2_1, 2_2, 3_1, 3_2, 4_1, 4_2	2.813
2	5_2, 6_1, 6_2, 7_1, 7_2, 8_1, 8_2, 9_1	0.7598

Figure 5.1and Figure 5.2 are presenting the best fit analysis curves for the two groups mentioned above.

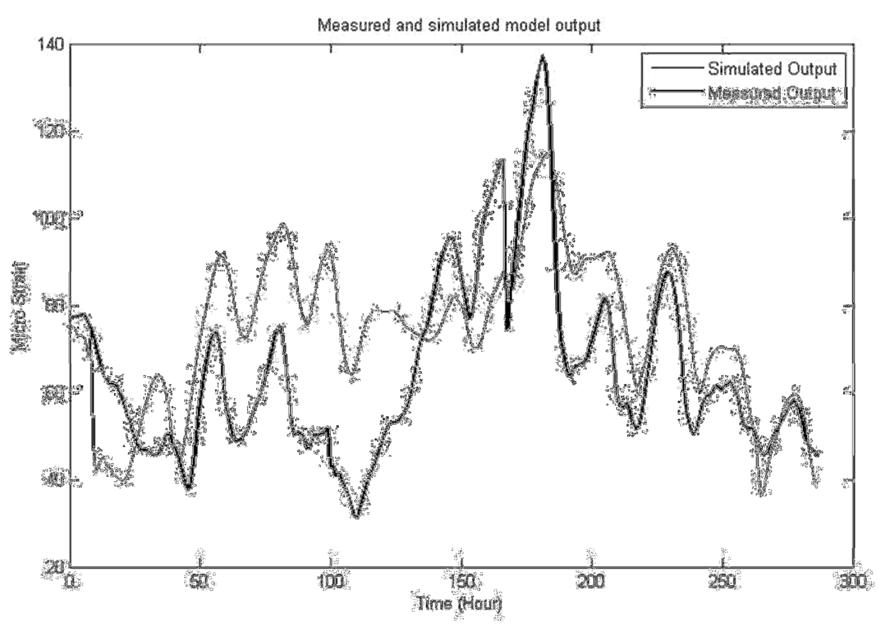


Figure 5.1 Measured and simulated output of group-1

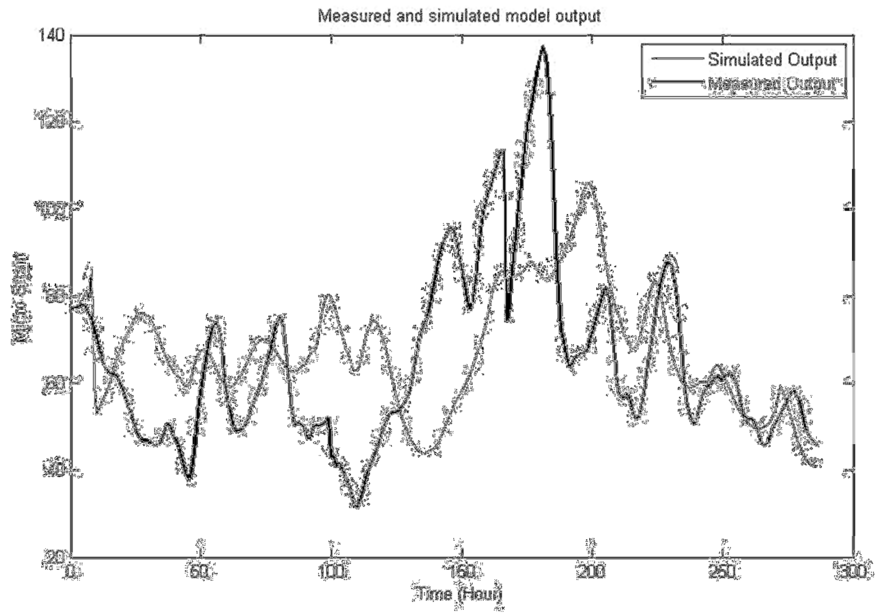


Figure 5.2 Measured and simulated output of group-2

As best fit is less for group-2, defective sensor belongs to this group. So this group was divided into another 2 groups and the Best fits found are in Table 5.3.

Table 5.3 Results of Binary search for group 2

Group Number	Sensor Number	Best fit (%)
1	5_2, 6_1, 6_2, 7_1,	2.431
2	7_2, 8_1, 8_2, 9_1	8.117

As group 1 has less best fit, Sequential search technique was applied for group 1 and results are in Table 5.4.

Table 5.4 Sequential search method for minimum best fit group.

Eliminated	Best fit (%)
5_2	33.91
6_1	-20.43
6_2	-11.57
7_1	2.433

Figure 5.3 and Figure 5.4 are showing the best fit (Sensor #5_2) and worst best fit (Sensor#6_1) respectively. The elimination of sensor# 5_2 showed highest pattern matching. So sensor# 5_2 was detected as defective sensor.

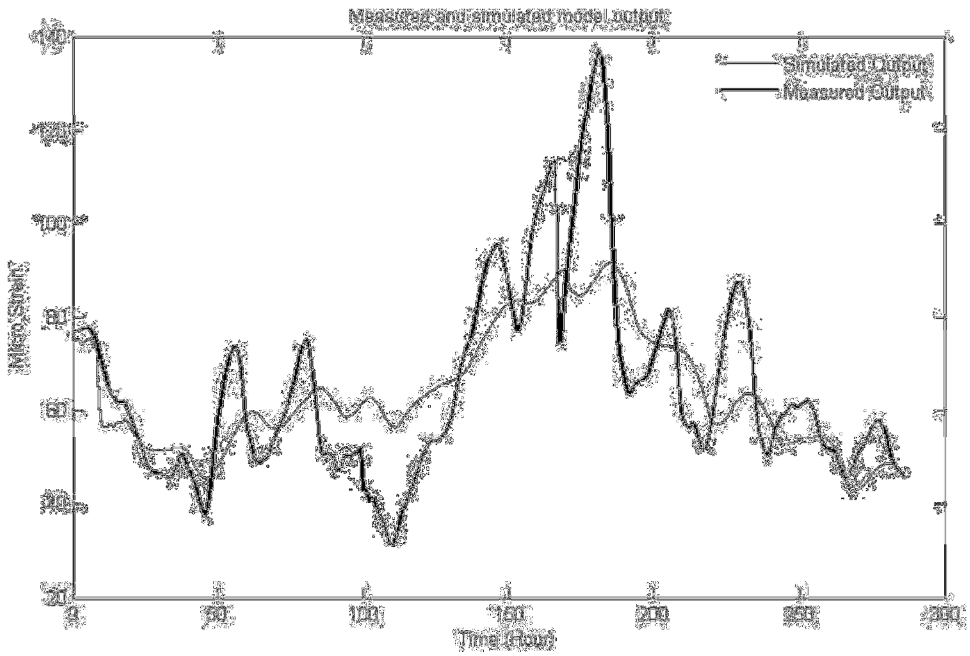


Figure 5.3 Measured and simulated output, sensor# 5_2 removed

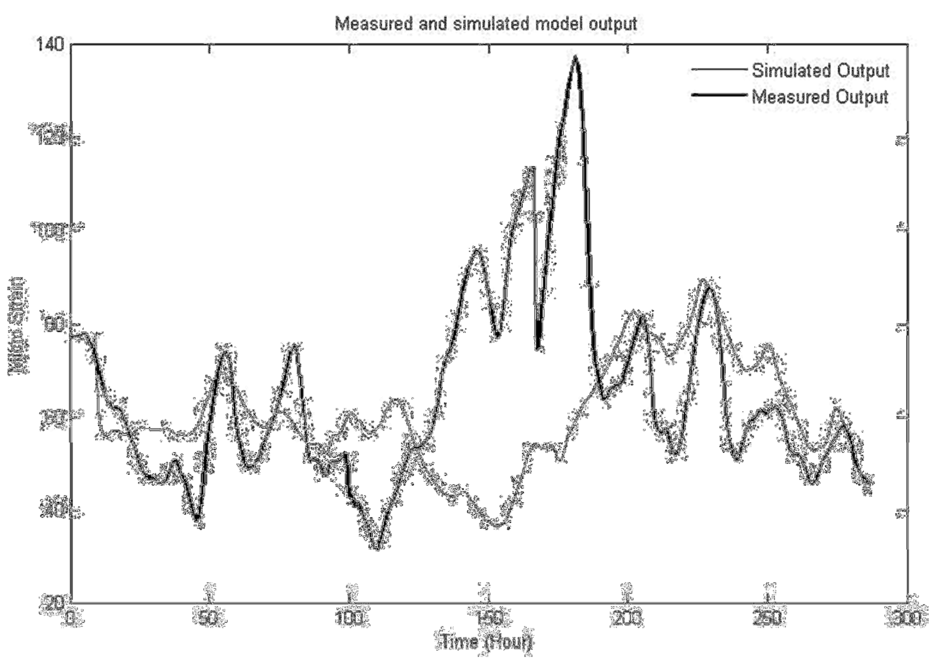


Figure 5.4 Measured and simulated output, sensor# 6_1 removed

Case 2

In this case the concerning sensors were divided into two groups. Sensor# 2_1 was made defective by putting random data that does not follow specific pattern in its data block. The Best fits found after the Auto Regressive analysis is shown in Table 5.5.

Table 5.5 Binary search method, Case 2(Sensor#5_1 is fixed as target)

Group Number	Sensor Number	Best fit (%)
1	1_1,1_2, 2_1, 2_2, 3_1, 3_2, 4_1, 4_2	14.74
2	5_2, 6_1, 6_2, 7_1, 7_2, 8_1, 8_2, 9_1	52.59

As best fit is less for group-1, defective sensor belongs to this group. So this group was divided into another 2 groups and the Best fits found are in Table 5.6

Table 5.6 Results of Binary search for group 1

Group Number	Sensor Number	Best fit (%)
1	1_1,1_2, 2_1, 2_2	-22.87
2	3_1, 3_2, 4_1, 4_2	24.95

Then sequential search technique was applied for group-1 and results are as in Table 5.7

Table 5.7 Sequential search method for minimum best fit group.

Eliminated Sensor	Best fit (%)
1_1	-30.69
1_2	-115.9
2_1	-26.25
2_2	-86.84

The elimination of sensor# 2_1 showed highest pattern matching. So sensor# 2_1 was detected as defective sensor. All the figures are provided in Appendix.

Case 3

In this case the concerning sensors were divided into two groups. Sensor# 8_2 was made defective by putting random data, that does not follow specific pattern, in its data block. The Best fits found after the Auto Regressive analysis are shown in Table 5.8

Table 5.8 Binary search method, Case 3(Sensor#5_1 is fixed as target)

Group Number	**Sensor Number**	**Best fit (%)**
1	1_1, 2_1, 3_1, 4_1, 6_1,7_1,8_1,9_1	53.55
2	1_2, 2_2, 3_2,4_2,5_2, 6_2, 7_2, 8_2	0.9113

As best fit is less for group-2, defective sensor belongs to this group. So this group was divided into another 2 groups and the Best fits found are in Table 5.9.

Table 5.9 Results of Binary search for group 2

Group Number	**Sensor Number**	**Best fit (%)**
1	1_2, 2_2, 3_2,4_2	16.22
2	5_2, 6_2, 7_2, 8_2	-9.536

Then sequential search technique was applied for group-2 and results are in Table 5.10

Table 5.10 Sequential search method for minimum best fit group.

Eliminated Sensor	**Best fit (%)**
5_2	36.16
6_2	-92.38
7_2	-95.86
8_2	48.32

The elimination of sensor# 8_2 showed highest pattern matching. So sensor# 8_2 was detected as defective sensor. All the figures are provided in Appendix.

5.2.2.2 Detection of faulty sensor (sensor# 6_2 was fixed as defective sensor in all cases)

Case 1

In this case the concerning sensors were divided into two groups. Sensor# 6_2 was made defective by putting random data that does not follow specific pattern in its data block. Sensor#1_1 data were used as measured output. The Best fits found after the Auto Regressive analysis are shown in Table 5.11

Table 5.11 Binary search method, Case 1(Sensor#6_2 is fixed as defective)

Group Number	Sensor Number	Best fit (%)
1	1_2, 2_1, 2_2, 3_1, 3_2, 4_1, 4_2, 5_1	38.94
2	5_2, 6_1, 6_2, 7_1, 7_2, 8_1, 8_2, 9_1	-42.07

Figure 5.5 and Figure 5.6 are presenting the best fit analysis curves for Table 5.11

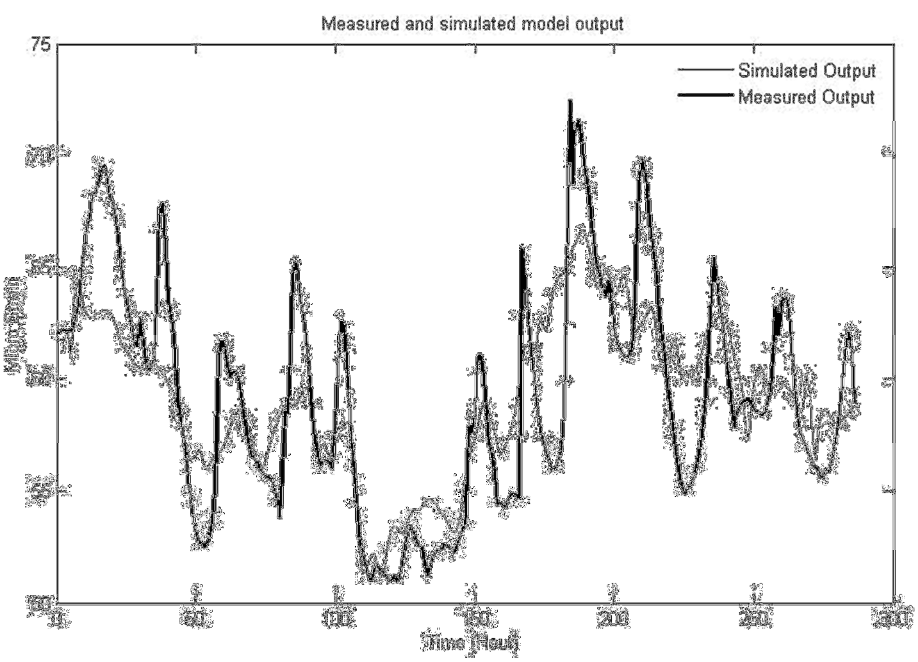


Figure 5.5 Measured and simulated output of group_1

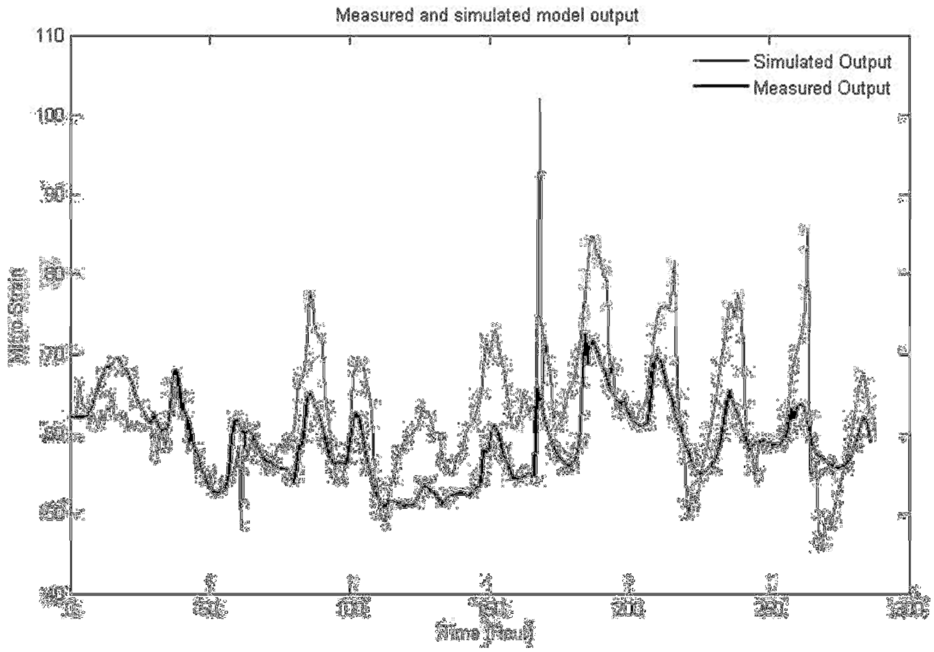


Figure 5.6 Measured and simulated output of group_2

As the best fit is less for group-2, defective sensor is supposed to be in this group. So this group was divided into another 2 groups and the best fits found are in Table 5.12

Table 5.12 Results of Binary search for group 2

Group Number	Sensor Number	Best fit (%)
1	5_2, 6_1, 6_2, 7_1	-147.4
2	7_2, 8_1, 8_2,9_1	16.92

Then sequential search technique was applied for group-1 and results are in Table 5.13

Table 5.13 Sequential search method for minimum best fit group.

Eliminated Sensor	Best fit (%)
5_2	-472.1
6_1	-23.19
6_2	1.687
7_1	-15.12

Figure 5.7 and Figure 5.8 Figure 5.4 are showing the worst fit (Sensor #5_2) and best fit (Sensor#6_2) respectively. The elimination of sensor #6_2 showed highest pattern matching. So sensor# 6_2 was detected as defective sensor.

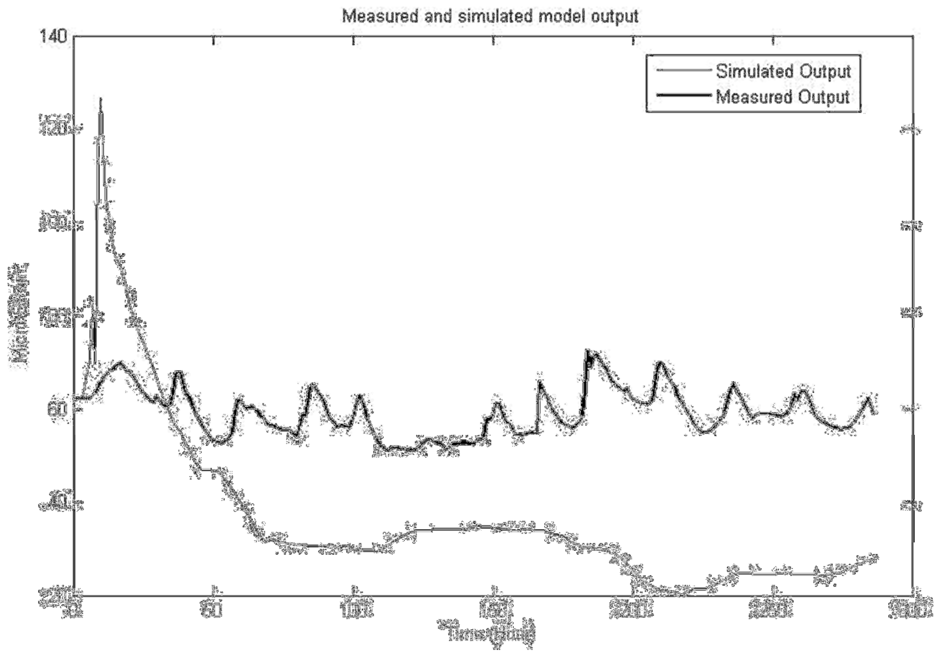


Figure 5.7 Measured and simulated output, sensor# 5_2 removed

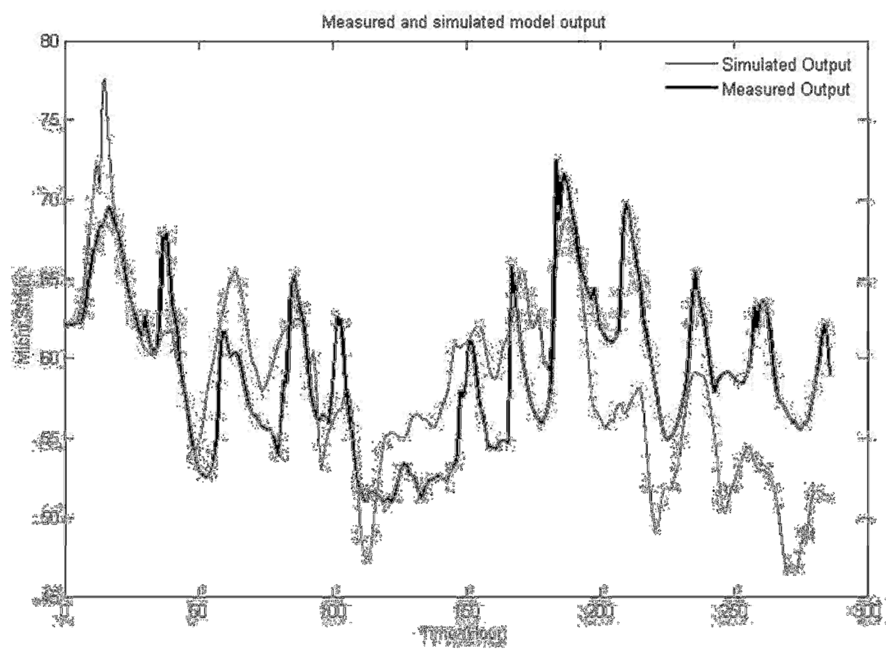


Figure 5.8 Measured and simulated output, sensor# 6_2 removed

Case 2

In this case the concerning sensors were divided into two groups. Sensor# 6_2 was made defective by putting random data, that does not follow specific pattern, in its data block. Sensor#3_2 data were used as measured output The Best fits found after the Auto Regressive analysis are shown in Table 5.14

Table 5.14 Binary search method, Case 2(Sensor#6_2 is fixed as defective)

Group Number	**Sensor Number**	**Best fit (%)**
1	1_1,1_2, 2_1, 2_2, 3_1, 4_1, 4_2, 5_1	29.96
2	5_2, 6_1, 6_2, 7_1, 7_2, 8_1, 8_2, 9_1	-38.3

As best fit is less for group-2, defective sensor belongs to this group. So this group was divided into another 2 groups and the Best fits found are in Table 5.15.

Table 5.15 Results of Binary search for group 2

Group Number	Sensor Number	Best fit (%)
1	5_2, 6_1, 6_2, 7_1	2.332
2	7_2, 8_1, 8_2, 9_1	29.89

Then sequential search technique was applied for group-1 and results are in Table 5.16

Table 5.16 Sequential search method for minimum best fit group.

Eliminated Sensor	**Best fit (%)**
5_2	-67.06
6_1	-34.51
6_2	4.88
7_1	-69.47

The elimination of sensor #6_2 showed highest pattern matching. So sensor# 6_2 was detected as defective sensor. All the figures are provided in Appendix.

Case 3

In this case the concerning sensors were divided into two groups. Sensor# 6_2 was made defective by putting random data, that does not follow specific pattern, in its data block. Sensor#7_1 data were used as measured output The Best fits found after the Auto Regressive analysis are shown in Table 5.17

Table 5.17 Binary search method, Case 3(Sensor#6_2 is fixed as defective)

Group Number	Sensor Number	Best fit (%)
1	1_1,1_2, 2_1, 2_2, 3_1, 3_2, 4_1, 4_2	3.905
2	5_1, 5_2, 6_1, 6_2, 7_2, 8_1, 8_2, 9_1	-2.305

As best fit is less for group-2, defective sensor belongs to this group. So this group was divided into another 2 groups and the Best fits found are in Table 5.18

Table 5.18 Results of Binary search for group 2

Group Number	Sensor Number	Best fit (%)
1	5_1, 5_2, 6_1, 6_2	-39.98
2	7_2, 8_1, 8_2, 9_1	22.44

Then sequential search technique was applied for group-1 and results are as follows-

Table 5.19 Sequential search method for minimum best fit group.

Eliminated Sensor	**Best fit (%)**
5_1	-174.6
5_2	-26.88
6_1	-47.43
6_2	1.723

The elimination of sensor #6_2 showed highest pattern matching. So sensor# 6_2 was detected as defective sensor. All the figures are provided in Appendix.

5.3 Outlier Analysis for Damage Detection

For this study nine random data blocks were taken that include heavy vehicle loads for gauges S_1_1_C1 (direction 1 of strain gauge 1 in column 1) S_1_2_C1 (direction 2 of strain gauge 1 in column 1). Each block has sampling frequency 32Hz and duration of 8 seconds. Analysis of these signal blocks will not only provide information on the structural behaviour of the bridge over time under live loads, but also determine if all the gauges are working properly and find out the faulty one if there is any. Since the change of behavioural patterns is expected be similar for all gauges if they are all functioning properly. The magnitude and signs (+/-) may vary among the data series but relative values in test blocks as compared to the reference blocks of particular strain should not differ significantly from the corresponding values of other strains under observation.

5.3.1 Feature Extraction

As any data block in this study is essentially a time series, time series analysis is adopted for the purpose of feature extraction and also residual error determination for the use in pattern comparison technique. All data are analyzed with AR(*p*) process. The Variation of AR process is mainly dependent on AR coefficients $Ø_{xj}$. Hence, $Ø_{xj}$ *is* considered as structural degradation feature or damage sensitive feature. For the calculation of the AR coefficients, Yule-Walker methods were applied using statistical process control software called ISTM2000. Since AR process is zero mean method, in order to attain nearly this property of the series, from the live loaded and accelerometer data their respective means are subtracted. Every observation is mean corrected before applying the AR process.

5.3.2 Damage Identification by Statistical Model Development

Statistical model development has been implemented through appropriate algorithm to analyze the distribution of extracted features to determine the damage state of the structure. As there is no damaged case known for this bridge, control chart analysis, as a means of unsupervised technique, is applied to the calculated and selected damage sensitive features.

The signal blocks (strains) of strain gauge S_1_1_C1 and S_1_2_C1 are used for creating the pools of features, which are AR coefficients. There are 132 signal blocks for gauge S_1_1_C1 and 40 signal blocks for gauge S_1_2_C1. For the process control analysis according to Nair & Kiremidjian, 2006 the first three AR coefficients give most robust damage indication. So the first three coefficients of the AR analysis of strain blocks are taken. The mean and standard deviation of the first quarter of the arranged features are taken as basic mean and standard deviation.

Here X-bar control charts are employed to monitor the changes of the selected feature over time. Subgroup of 4 features is considered here. The subgroup size is taken as 4 according to the suggestion of Montgomery (1997). The results for three AR coefficients of strain readings of S_1_1_C1 and S_2_1_C1 are shown through Figure 5.9 to Figure 5.14.

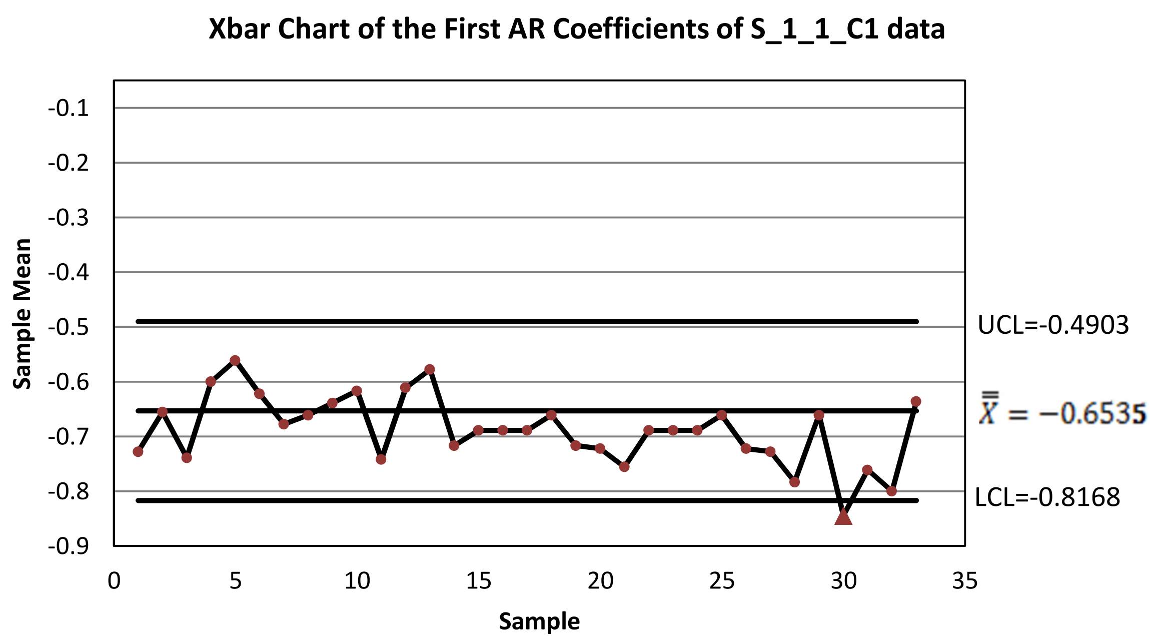


Figure 5.9 Outlier analysis of the first AR Coefficients of strain readings of S_1_1_C1.Pool size=132, Subgroup size=4

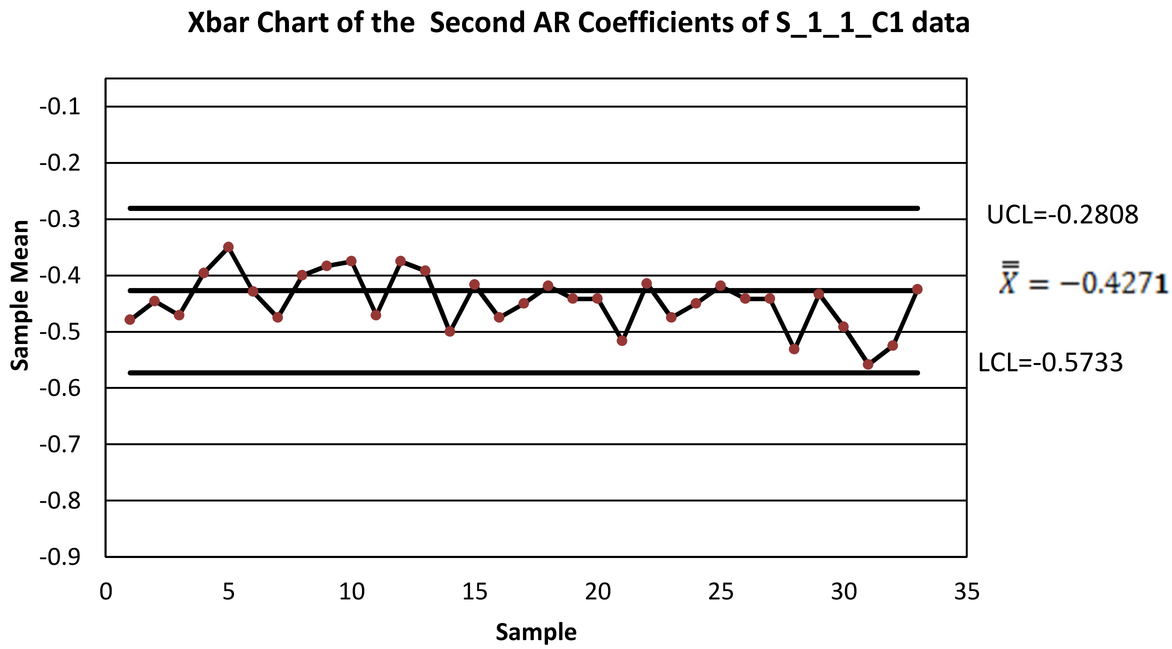


Figure 5.10 Outlier analysis of the second AR Coefficients of strain readings of S_1_1_C1.Pool size=132, Subgroup size=4

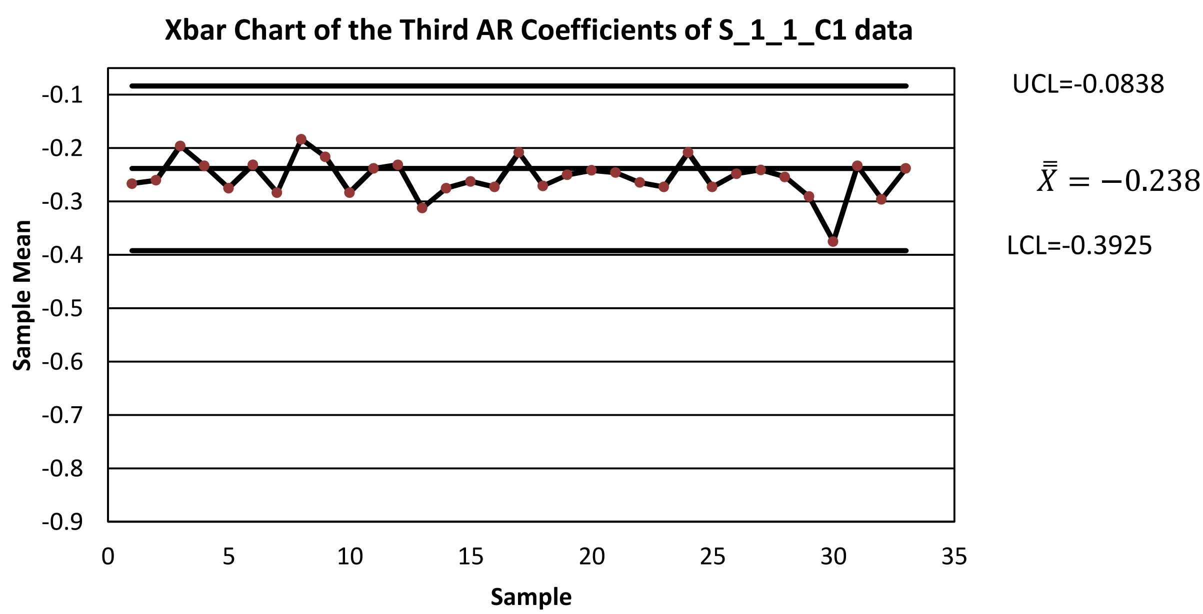


Figure 5.11 Outlier analysis of the third AR Coefficients of strain readings of S_1_1_C1.Pool size=132, Subgroup size=4

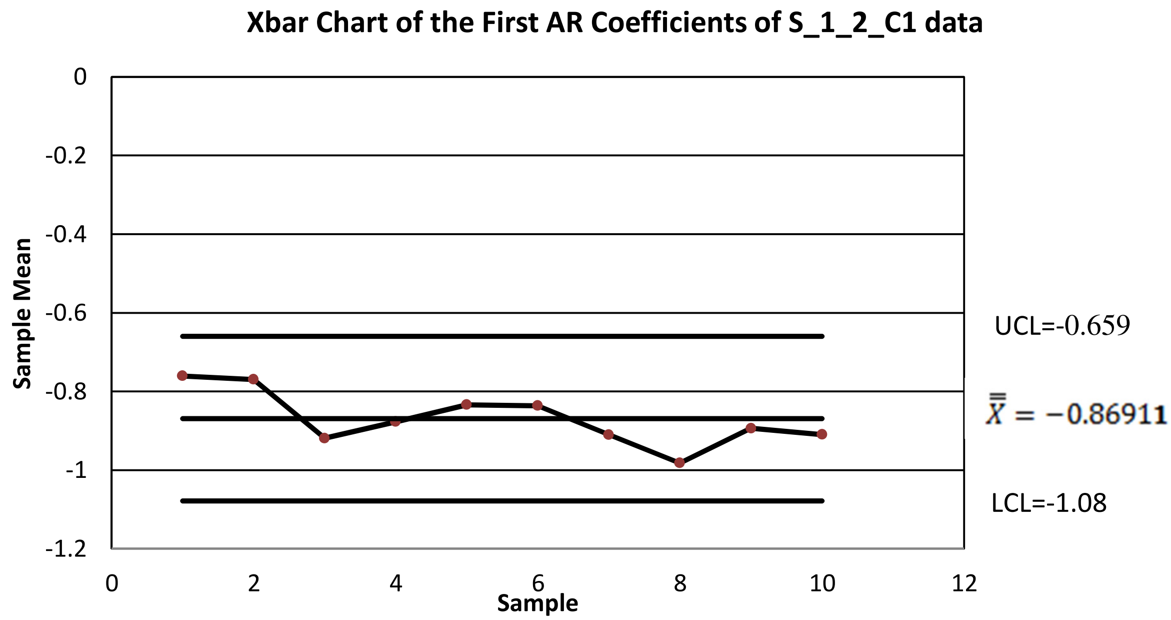


Figure 5.12 Outlier analysis of the first AR Coefficients of strain readings of S_1_1_C1. Pool size=40, Subgroup size=4

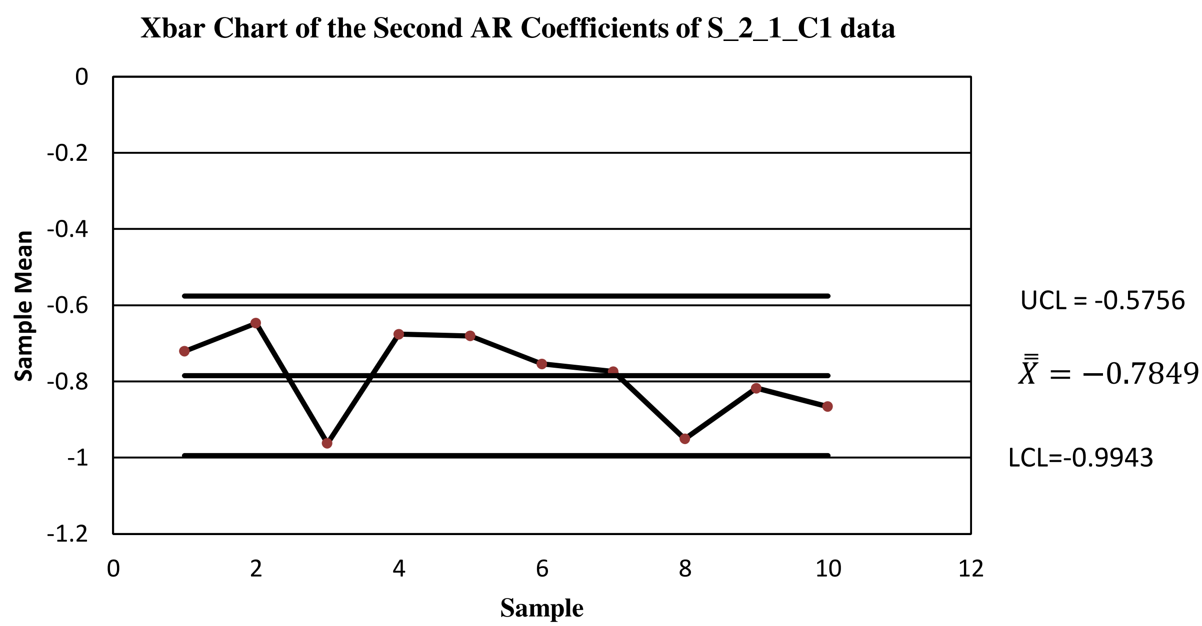


Figure 5.13 Outlier analysis of the second AR Coefficients of strain readings of S_1_2_C1. Pool size=40, Subgroup size=4

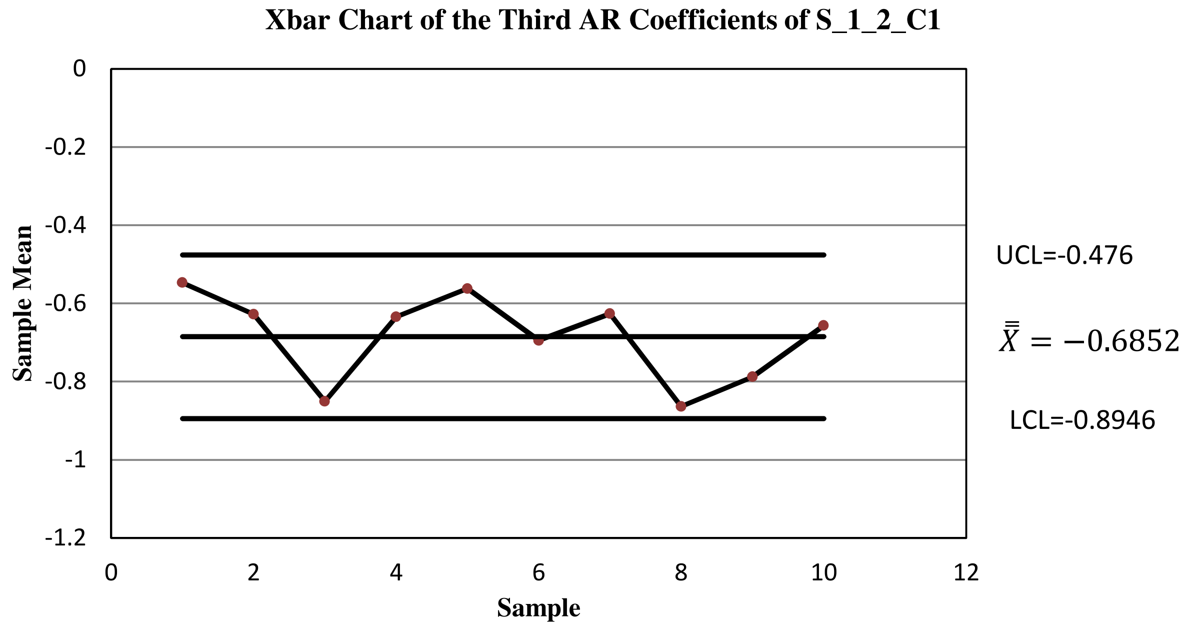


Figure 5.14 Outlier analysis of the third AR Coefficients of strain readings of S_1_2_C1. Pool size=40, Subgroup size=4

5.3.3 Results of damage Identification by Statistical modeling:

Examining the control charts in Figure 5.9 to Figure 5.11, only 1 outlier of total 132 (0.75%) subgroups of the first 3 AR coefficients of Strain S_1_1_C1 is detected and no outlier is found for S_1_2_C1. However slight downward tendency of the features is noticeable.

In an earlier study by (Sohn et al 2000) on a concrete column in a laboratory test, at very mild damaged state, statistical modeling showed 6.25% and significant damage 29.17% outliers of total subgroups. Comparing their results, it can be concluded that the structure considered in the present study is not damaged and which is expected for a bridge of this age. However the increased tendency of features getting closer to the limits at the third or fourth quarters of the chart (towards the end of the monitoring period) indicates that the structure is undergoing some small degradation towards the end of the monitoring period.

It was observed from the data blocks that for each sensor there was random increment in strain readings in each year than previous year. Here only the data blocks for S_1_2_C1 (vertical direction strain data for sensor 1 for column 1 of pier_2) are discussed with respect to finite element model (FEM) and AR coefficients. The average strain values of S_1_2_C1 for different summer periods are shown in Table 5.20.

Table 5.20 Average strain values (micro strain) for S_1_2_C1 in summer period of different years

Time period	**Average Strain Values (micro strain)**
Summer 2003	400.75
Summer 2004	520.69
Summer 2006	651.178

One Finite Element Model (Figure 5.15) has been developed considering structural modulus of elasticity E=2e+7KN/m2.

This FE model of pier_2 of Portage Creek Bridge has been developed to run a simple static analysis to show the structural change over time. In this model half of the deck system weight (as there are two piers) and pier self weight has been applied as 3 concentrated load on pier-2 which is 2379 KN each. For vehicle loading CL1-W Truck loading (Canadian Highway Bridge Design Code) was applied as two concentrated load on either side of the axle and this loading was applied on both lane. The wheel load is 312.5 KN. But the load was increased to 500 KN applying an impact factor 1.6 to take the dynamic impact into consideration. A lateral load of 2000KN was applied which represents both EQ and wind pressure load together.

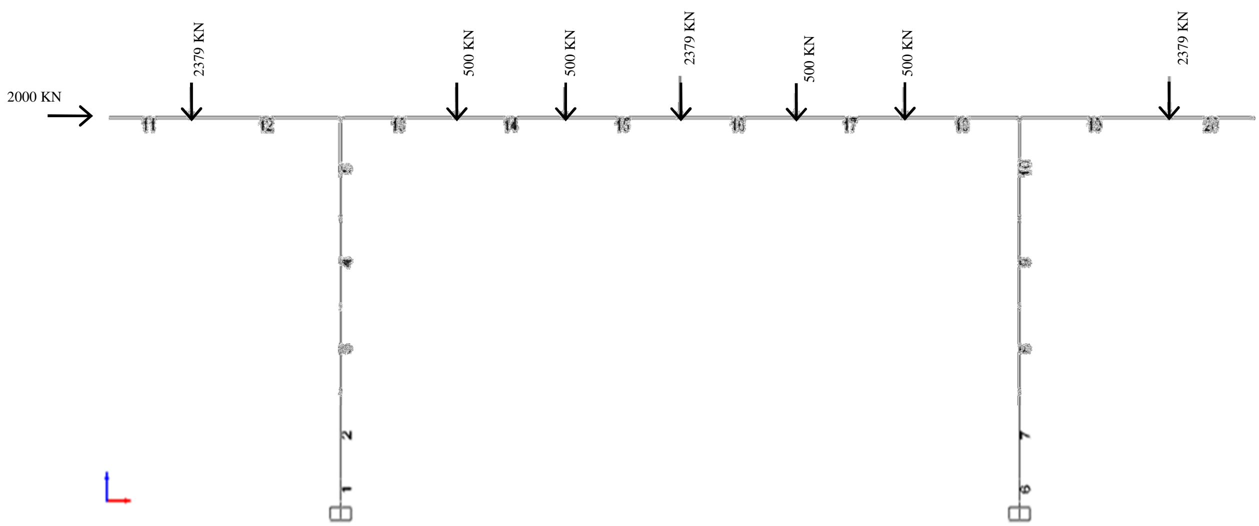


Figure 5.15 Finite element model for Pier 2 of Portage Creek Bridge

In the FE model the loading condition and the structural stiffness were adjusted to get a strain value of 400 micro strain which is average strain value for summer 2003. Rather than simulating the actual real loading condition the model was adjusted to get the particular strain because it is almost impossible to simulate real environmental conditions for those particular time when strains were recorded. Assuming no increment in traffic for the concerned years and taking the temperature corrections into considerations; the stiffness of the structures were changed to get the strains for the following years. After starting with an E=2e+7 KN/m2, structural stiffness was reduced 23% and 38% to get the strains 520.69 (Summer 2004) and 651.178(Summer 2006) micro strain respectively. The reduction in stiffness is indicating gradual degradation of the bridge.

The first three AR coefficients were plotted for the data blocks of S_1_2_C1 (Figure 5.12 to Figure 5.14). The curves are showing a slight downward tendency. So correlating the FE model to AR coefficients graph, it can be concluded that the downward tendency in the graphs refers to structural deterioration.

But stiffness reduction in the FE model was over calculated because only concrete stiffness was considered as structural stiffness. If both steel and concrete stiffness are considered then the stiffness reduction percentage will be reasonably less than what is calculated now. Also, for the time period; summer, 2003 to summer, 2006 it was assumed that there was no increment in traffic which is not the case is real life. It was nearly difficult to simulate the actual change in traffic from time to time due to the information lack. Also the environmental variation over this time period was considered to remain the same. If all the conditions could have been simulated properly then the reduction of the structural stiffness would be really small to match the slow degradation curve from outlier analysis.

5.4 Summary

The sensitivity analysis performed here implies that for any combination of sensors Auto Regressive Exogenous method gives satisfactory results. So using ARX tool as damage detection technique or to detect malfunctioning sensor can reduce the frequency of expensive and time consuming tests done for structural damage detection purpose. The outlier analysis showed no major structural problem in the concerned structure. But the curves from the outlier analysis showed slight downward tendency indicating slow gradual degradation. The finite element analysis also showed structural degradation but the degradation rate was a bit more than X-bar control chart analysis. The reason might be that only concrete stiffness was considered as total structural stiffness. If both the concrete and steel stiffness has been considered certainly the structural degradation rate will be lower than what was calculated showing better similarity with Control chart analysis.

Chapter 6 Summary and Conclusion

6.1 Summary

In fact there is no sensor that can directly measure damage and there never will be. However, SHM cannot go without sensing. Sensors acquire data from structures which reflect the structural dynamic properties. Damage in structure affects its dynamic properties, causing a change in the vibration signals, i.e. strain and acceleration time histories. So assessment of structural integrity can be performed by analyzing the time series produced by installed sensor.

In this current study, SHM data, i.e. sensor data were taken from two real life structures. One is Confederation Bridge linking Canada's eastern islands; i.e. Prince Edward Island and New Brunswick and the other structure is the Portage Creek Bridge, Victoria, BC.

6.1.2 Confederation Bridge Monitoring

For the Confederation Bridge, the SHM data were collected from 34 strain gauges that are installed on pier 31 and 32 of this structure. These are all acceleration data. Prior to analysis they were processed by de-noising and normalization. Once the data are processed, then a Statistical Pattern Recognition technique like ARX model was applied on them. The regression algorithm used in the ARX (Auto Regressive Xeogeneous) tool finds the best fit among signal blocks taken from different periods. Thus, by recognizing the pattern matching through best fit percentage, ARX tool helps engineers to take a decision about a particular structure's health.

First, the Sequential search method was used for indentifying defective sensors. Three different case studies were done. While doing so, along with determining defective sensors, seasonal effects on the proposed diagnostic method were also watched. In first case, all the model building data were chosen from months that have similar weather conditions. As a result, the best fits found for pattern matching were higher and within a close range. In 2nd case, the chosen SHM data for model building covers a considerable long period comprising some summer, some fall and some winter data. As three seasons are combined together, the data model became cumbersome. As a result, the simulated and measured outputs did not have a very high match. In third case only summer and fall data were used to build the ARX model and December data were used to produce the simulated output and find the best fit. For last case, the best fit percentages were higher than the second case because the data were from seasons of similar weather condition. But in all cases, removal of sensor# 3 gave highest best fit which implies sensor# 3 is malfunctioning. Some physical test can be conducted to cross check the analysis results.

If one sensor is found responsible, it is more likely that the sensor is not functioning properly. On the other hand, if a group of sensors is found to be responsible, it is likely that the structural or load condition has been changed. In that case, further analysis of the SHM and structural systems would be necessary. In the absence of unusual patterns, the relationships would be simply updated with the new data and compared with the initial pattern of relationship to determine the rate of gradual change in the pattern which would indicate the rate of deterioration in the structure.

To verify the strength of this damage detection method, some sensitivity analysis had been done. For sensitivity analysis, in each case study, one known defective sensor was introduced in the sensor group and the sequential method was applied to see if the ARX model could detect the faulty one. All the case studies gave satisfactory results and detected the malfunctioning sensors.

Last but not the least; binary search method was applied to detect defective sensors. Two case studies were done and in both cases sensor# 3 was found defective. So the results are similar as sequential search method. As binary search method is faster than sequential search method, it should be considered in practical implementation of the proposed methods.

6.1.3 Portage Creek Bridge Monitoring

In the second part of this thesis, SHM data from Portage Creek Bridge had been used for health monitoring. Statistical pattern recognition by the ARX model was applied to detect a known malfunctioning sensor. All the case studies were for sensitivity analysis purpose. For first three cases, one sensor was fixed as target and defective sensors were different for each case. For next three cases, one sensor was fixed as defective and different target sensors were chosen arbitrarily. In all the cases, defective sensors were detected. So, the sensitivity analysis concludes that it's a very robust method to detect damage.

Finally, Outlier analysis was performed for column-1 sensor data of Portage Creek Bridge. All data blocks have been processed for the features that were sensitive to damage of the structures. For this purpose, Auto Regressive model has been adopted for all blocks and the coefficients of AR models have been considered the damage sensitive features. Then the first four features of all data blocks of a particular measurement type, (for example, S_1_1_C1), have been arranged in order of time to make feature pools. Each pool has been then analyzed for statistical modeling to classify damage. In this case, outlier detection which is appropriate form unsupervised condition has been unitized. X-bar charts have been generated for every feature pool of a measurement type. From the result of X-bars, a decision has been made of damage condition of structure. For horizontal strain blocks (S_1_1_C1) only 1 outlier of total 132 (0.75%) subgroups of the first 3 AR coefficients was detected and for vertical strain data (S_1_2_C1) among 40 subgroups of the first three AR coefficients no outlier was found. Comparing these results with Sohn et al 2000, we can consider our structure still in a safe condition which is expected for a bridge of this age. The curves for first 3 AR coefficients (Figure 5.17 to Figure 5.22) show slight downward tendency which indicates gradual degradation over time at a low pace.

To verify the results from outlier analysis one finite element model of pier-2 of Portage Creek Bridge was built and some static analysis was done. The finite element analysis also shows gradual degradation of structure at a slow rate which confirms the results from outlier analysis.

6.2 Conclusion

- Based on all the case studies it can be concluded that there is no major damage or structural change in the Confederation Bridge. Most of the concerned strain gauges are working properly with a few anomalies.
- The ARX model with proposed sequential search technique or binary search technique can be successfully used in identifying defective sensors or changes in the behavior of structure.
- If one sensor among a group of sensors shows anomaly in pattern, it is more likely that particular sensor has functional problem and if more than one sensor are found responsible then it is likely that the structural or load condition has been changed.
- Structural damage detection by statistical pattern recognition methods has been applied on the Portage Creek Bridge. The sensitivity analysis for Portage Creek Bridge showed that ARX model is well enough to detect defective sensor for any combination of sensors.
- The AR process has been applied from derived data blocks to extract the AR coefficients which are then statistically modeled for damage classification by X-bars. From the X-bars of strain readings, percentages of outliers found are not so high to indicate any damage in the structure or prominent structural degradation, if any. However, a few cases suggest that the structure may be getting slightly degraded towards the end of the period considered, though it is still adequately safe.

- To verify the results from outlier analysis one finite element analysis was done which shows a slow degradation of structure over years.
- The process of damage detection by statistical methods can be performed by entirely automated system without intermediate manual intervention. It can greatly save time, money and increase accuracy. This can be done by developing and integrating software tools for data acquisition and cleansing, scanning the entire data for relevant and interesting features, then performing feature extraction and modeling for damage classification and finally making the decision. Entire system can be integrated through a computer network with the implementation of the applications on it. A research on integrated automated statistical pattern recognition system is a possible scope for future research.

6.3 Limitations and Future Works

- For the statistical pattern recognition by ARX model it is assumed only one sensor to be defective. But in reality more than one sensor can be out of order at the same time. So future work can be conducted considering a group of sensors defective.
- In sequential search technique removal of some sensors gave very close best fits. So it is not very practical to consider only one sensor as defective rather than considering all of them. After that physical tests should be performed to verify the analysis results.

- Though ARX model gives faster results, only ARX model should not be enough to conclude any diagnosis system. It should be verified by other methods of statistical pattern recognition such as Neural Network.
- Further pattern recognition works should be done on the SHM data of same season but from different years.
- Availability of continuous monitoring data for Confederation Bridge was another limitation of this thesis.
- For the Finite Element model only static analysis was done. Future work is needed to conduct dynamic analysis and compare the results.
- For Finite Element model only concrete stiffness was considered as structural stiffness. Further study is needed considering both concrete and steel stiffness.

6.4 Main contributions of this thesis

Even though few works have been done before on statistical pattern recognition technique, but this method is yet to be explored to its very full extent, capacity and validity.

The current study is important for

- Establishing the validity of algorithm.
- To assess the effect of seasonal variation
- Sensitivity analysis
- Relating physical component with the Pattern Recognition results.

To validate the algorithm several case studies were done. Some case studies were performed to show the effect of seasonal variation on the pattern recognition results. Sensitivity analysis was performed to know how sensitive the method is to different parameter changes. Finally finite element model was built to relate the physical components of structure to the pattern recognition results.

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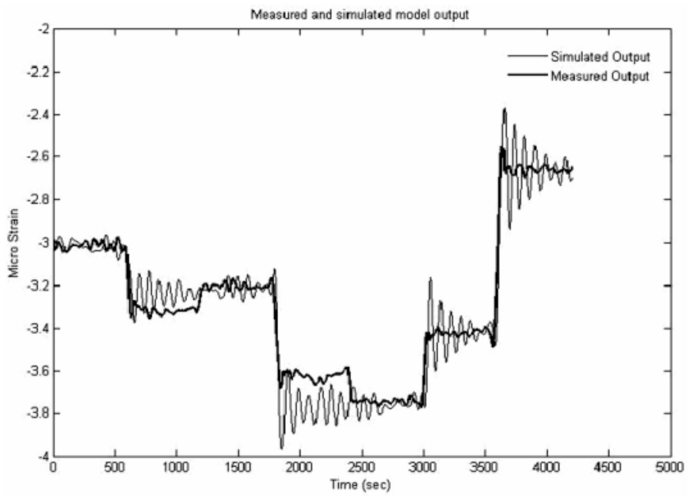
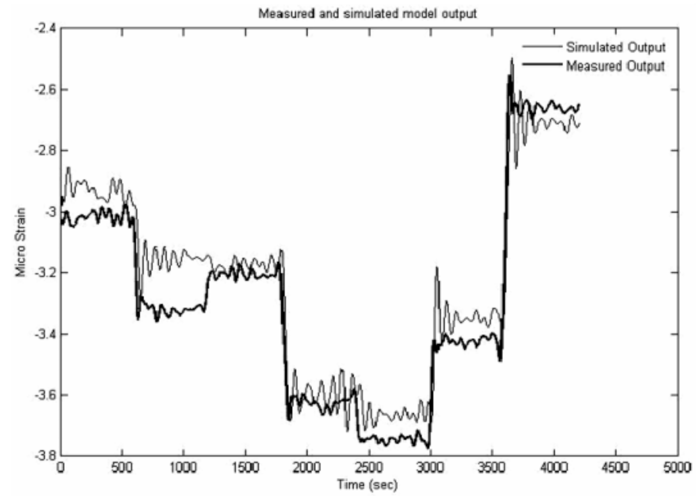
Appendices

Appendix A

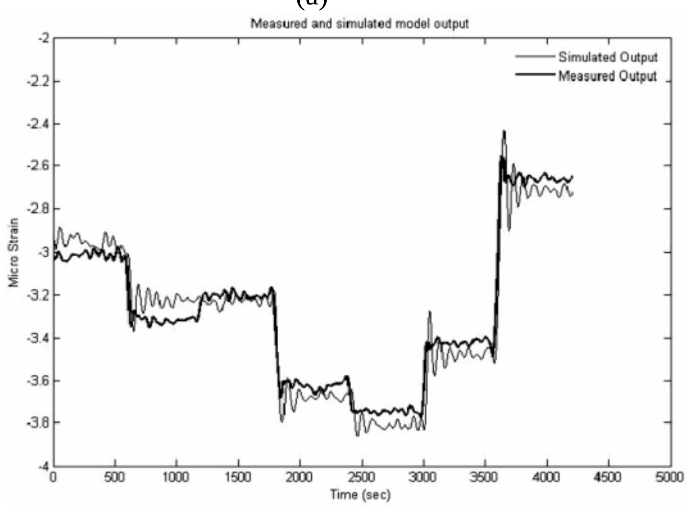
Graphical Outputs of unknown defective sensor detection for Confederation Bridge by Sequential Search Method. The details are described in Chapter 4, section 4.2, Case 1



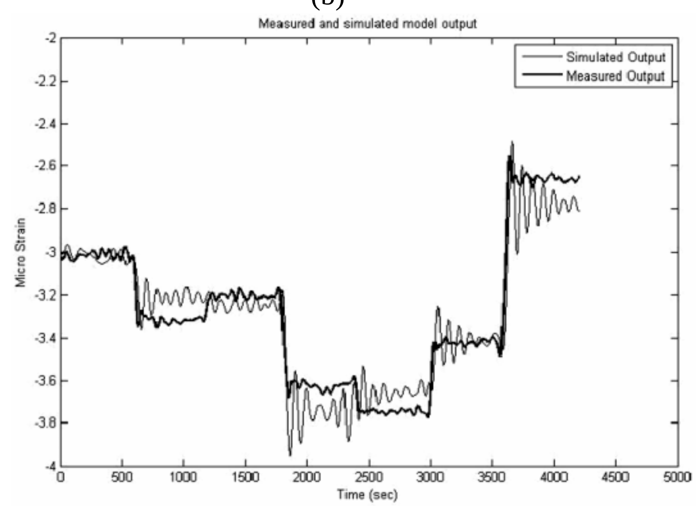
(a)



(b)

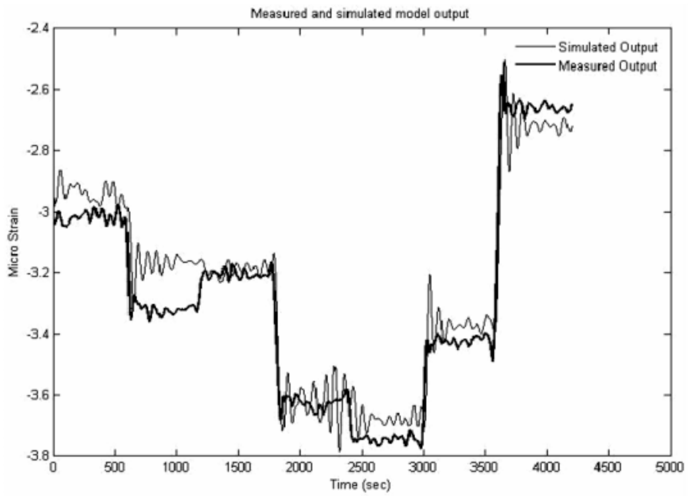


(c)

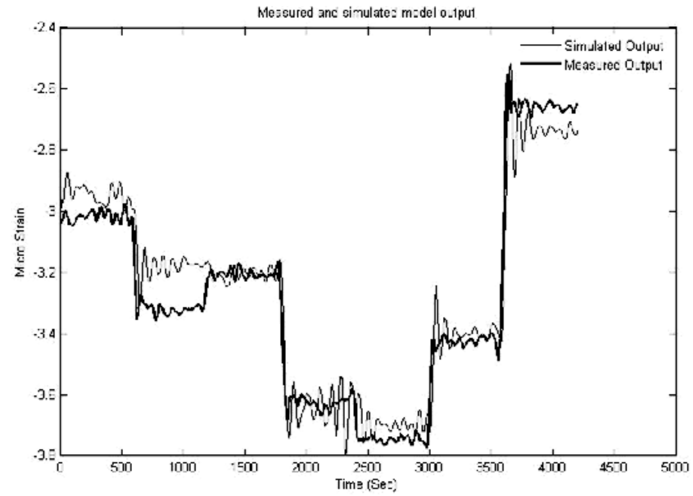


(d)

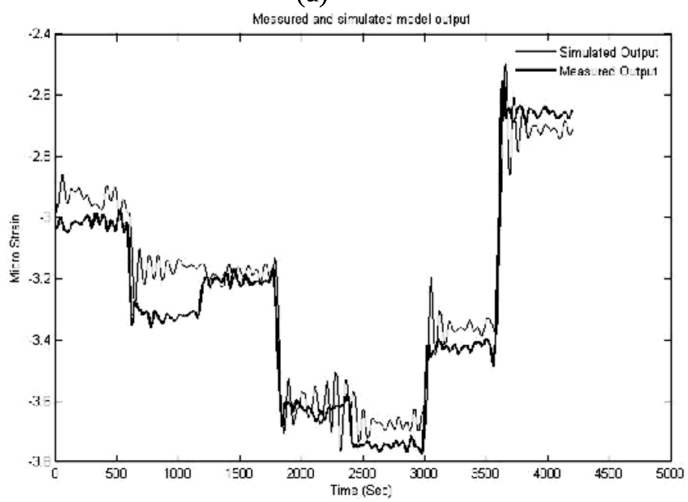
Figure A.1 Measured and Simulated Output of January 2004, (a) sensor# 1 removed, (b)) sensor# 2 removed, (c) sensor# 3 removed, (d)) sensor# 4 removed.



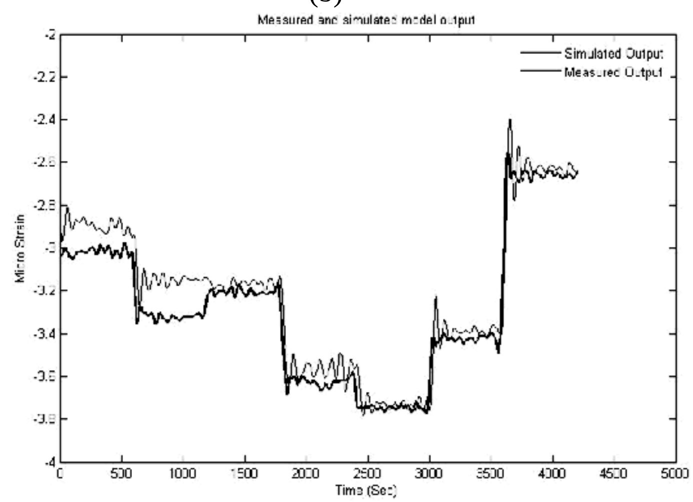
(a)



(b)



(c)



(d)

Figure A.2 Measured and Simulated Output of January 2004, (a) sensor# 5 removed, (b)) sensor# 6 removed, (c) sensor# 7 removed, (d)) sensor# 8 removed.

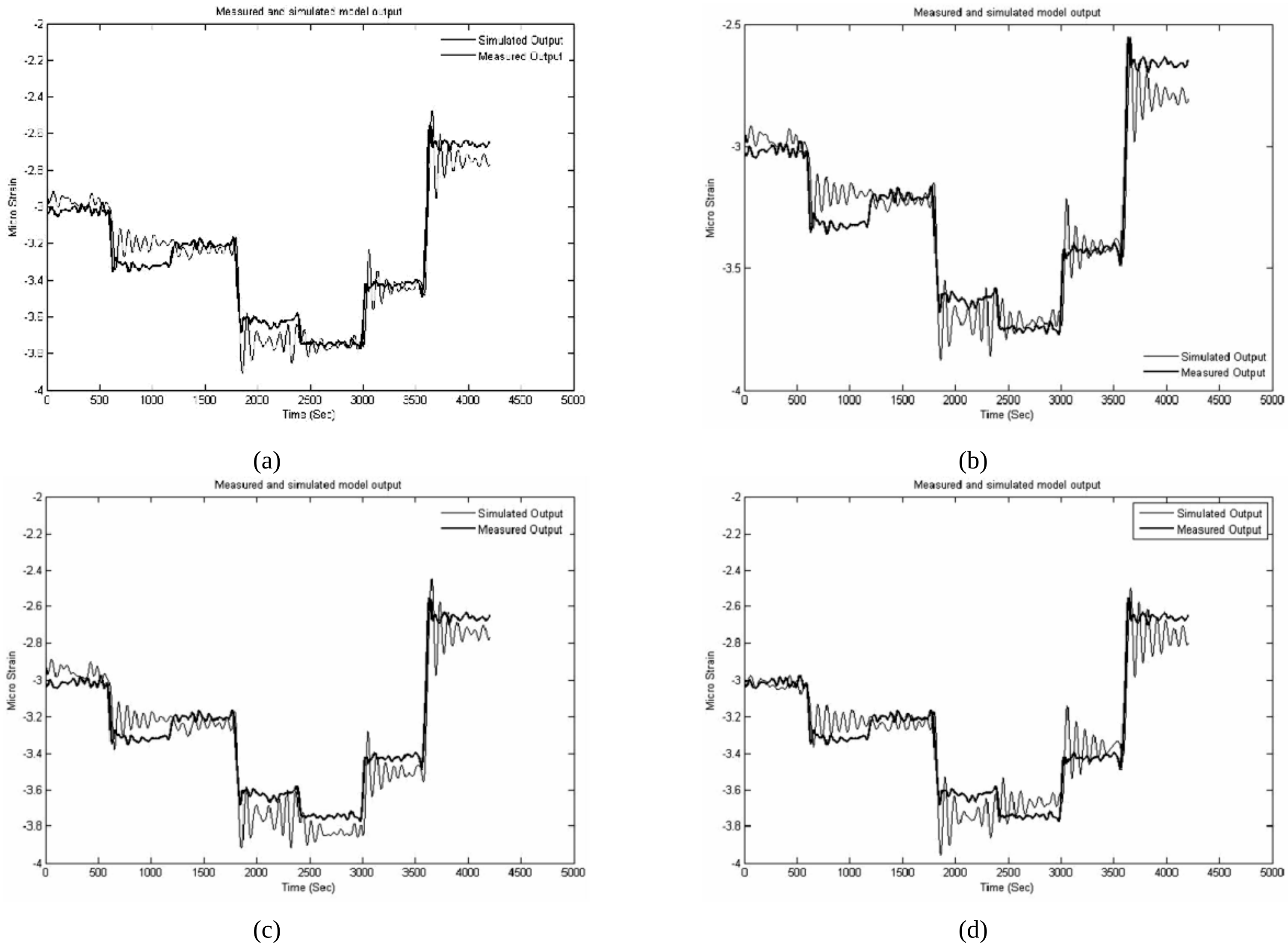
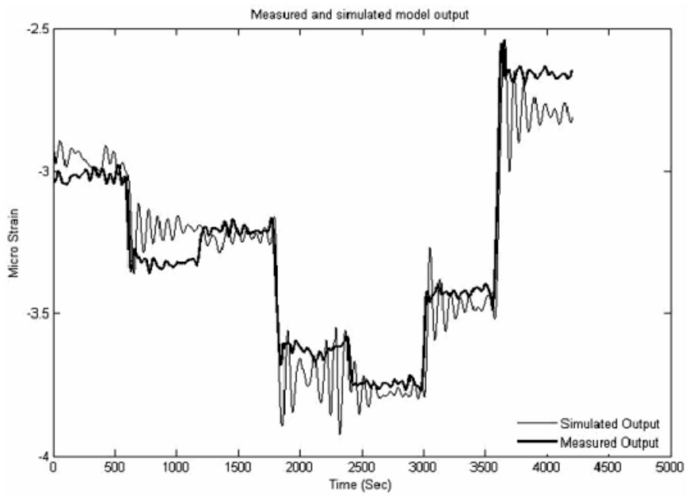
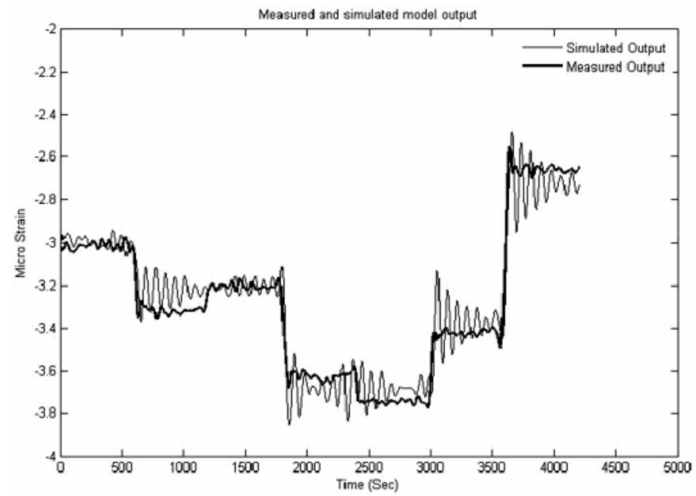


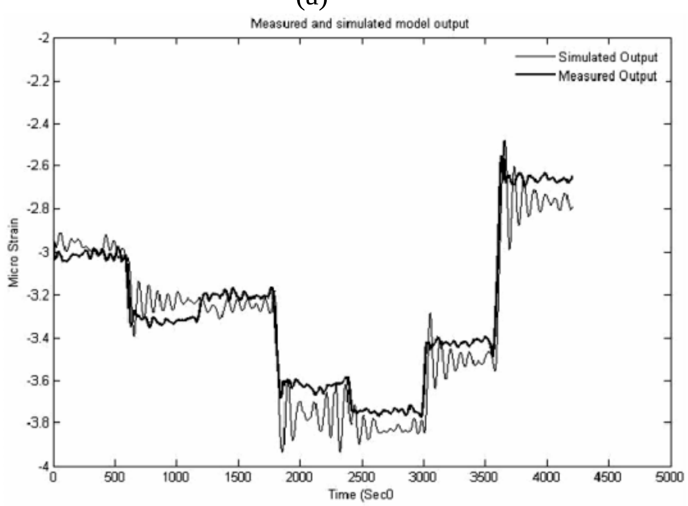
Figure A.3 Measured and Simulated Output of January 2004, (a) sensor# 9 removed, (b)) sensor# 10 removed, (c) sensor# 11 removed, (d)) sensor# 12 removed.



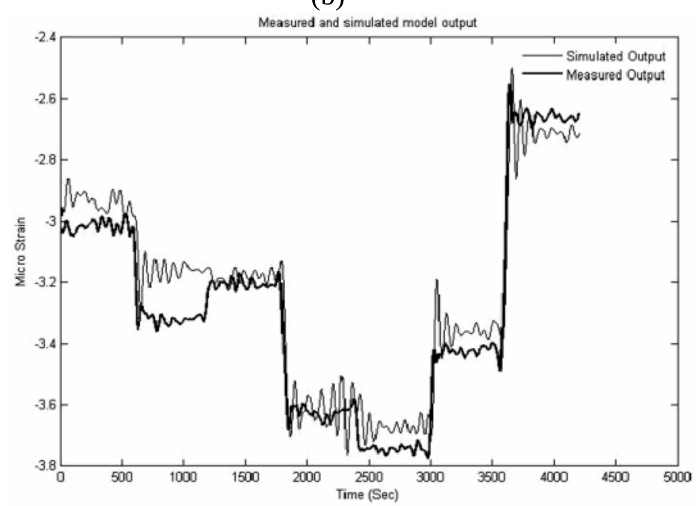
(a)



(b)

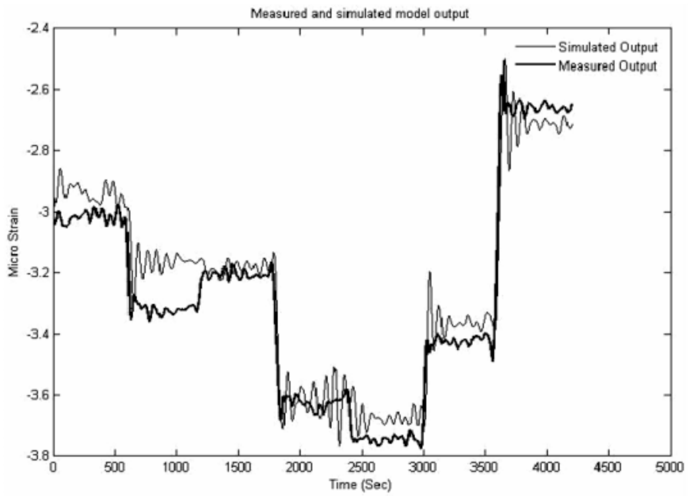


(c)

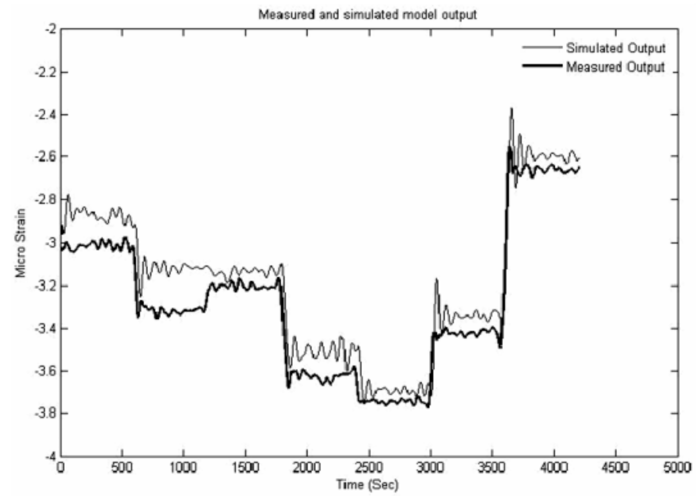


(d)

Figure A.4 Measured and Simulated Output of January 2004, (a) sensor# 13 removed, (b)) sensor# 14 removed, (c) sensor# 15 removed, (d)) sensor# 16 removed.



(a)



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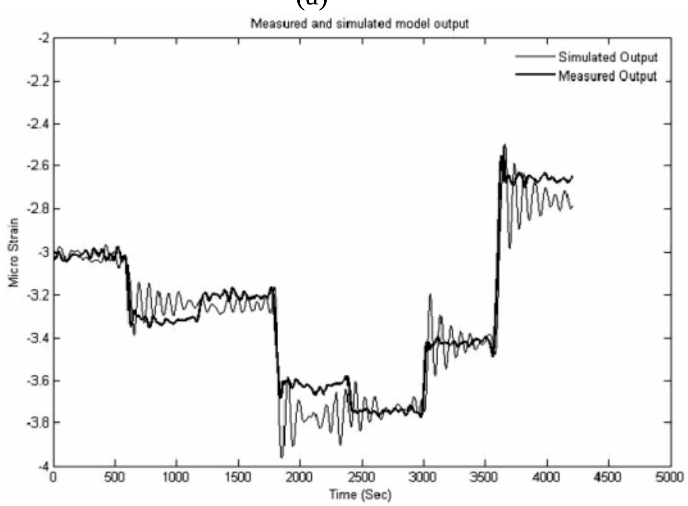
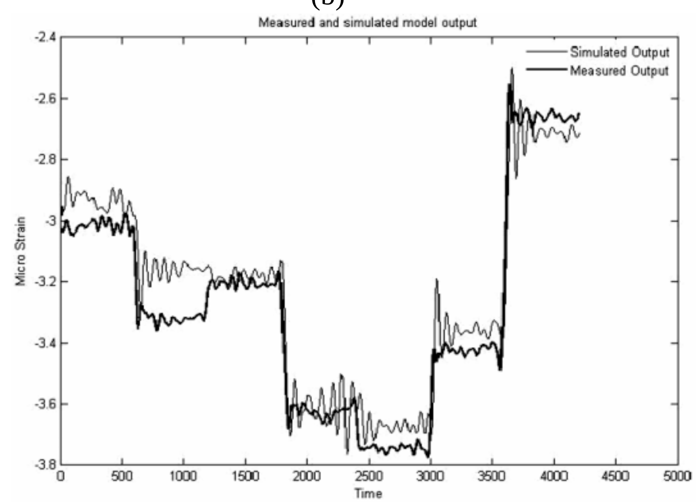
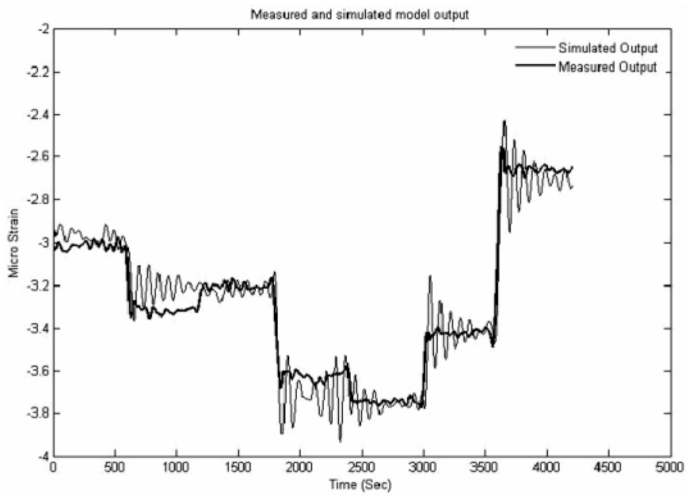


(c)

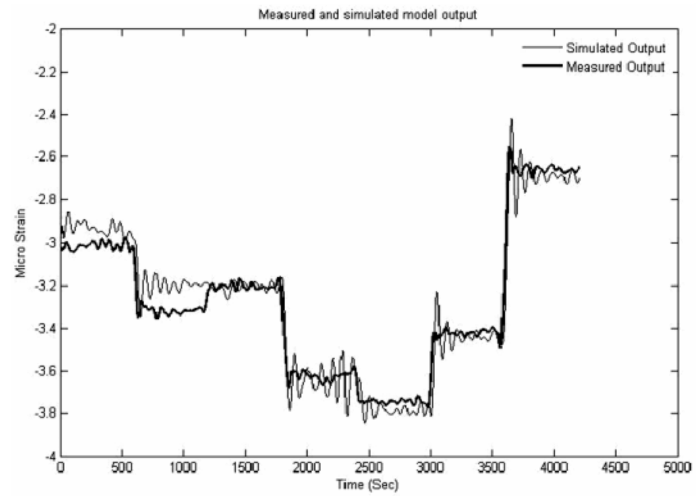


(d)

Figure A.5 Measured and Simulated Output of January 2004, (a) sensor# 17 removed, (b)) sensor# 18 removed, (c) sensor# 19 removed, (d)) sensor# 20 removed.



(a)



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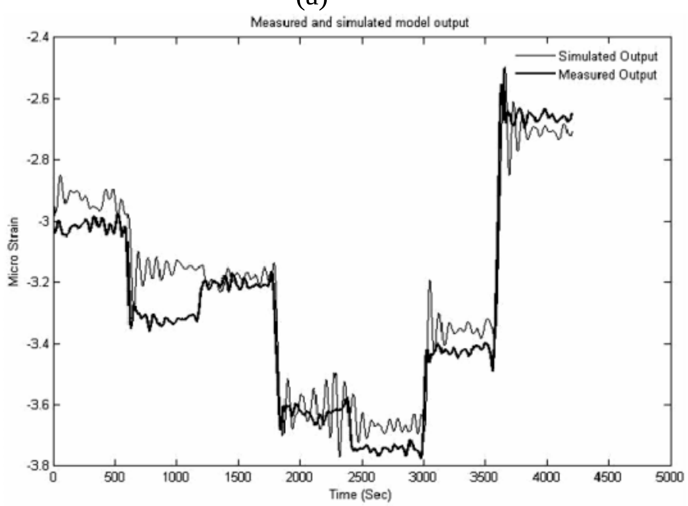
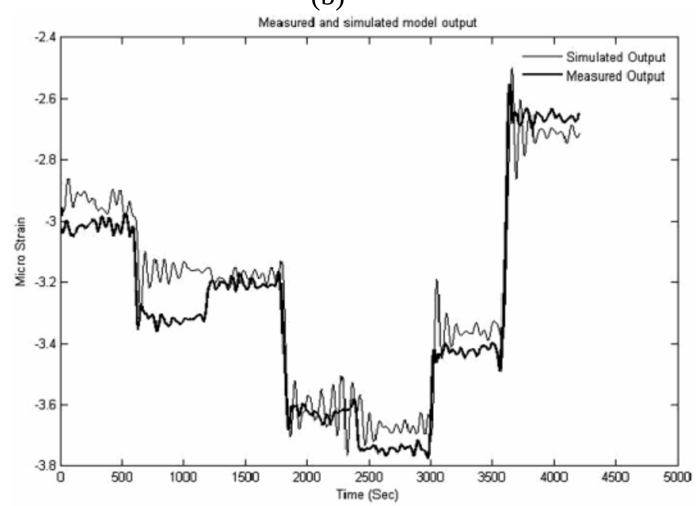
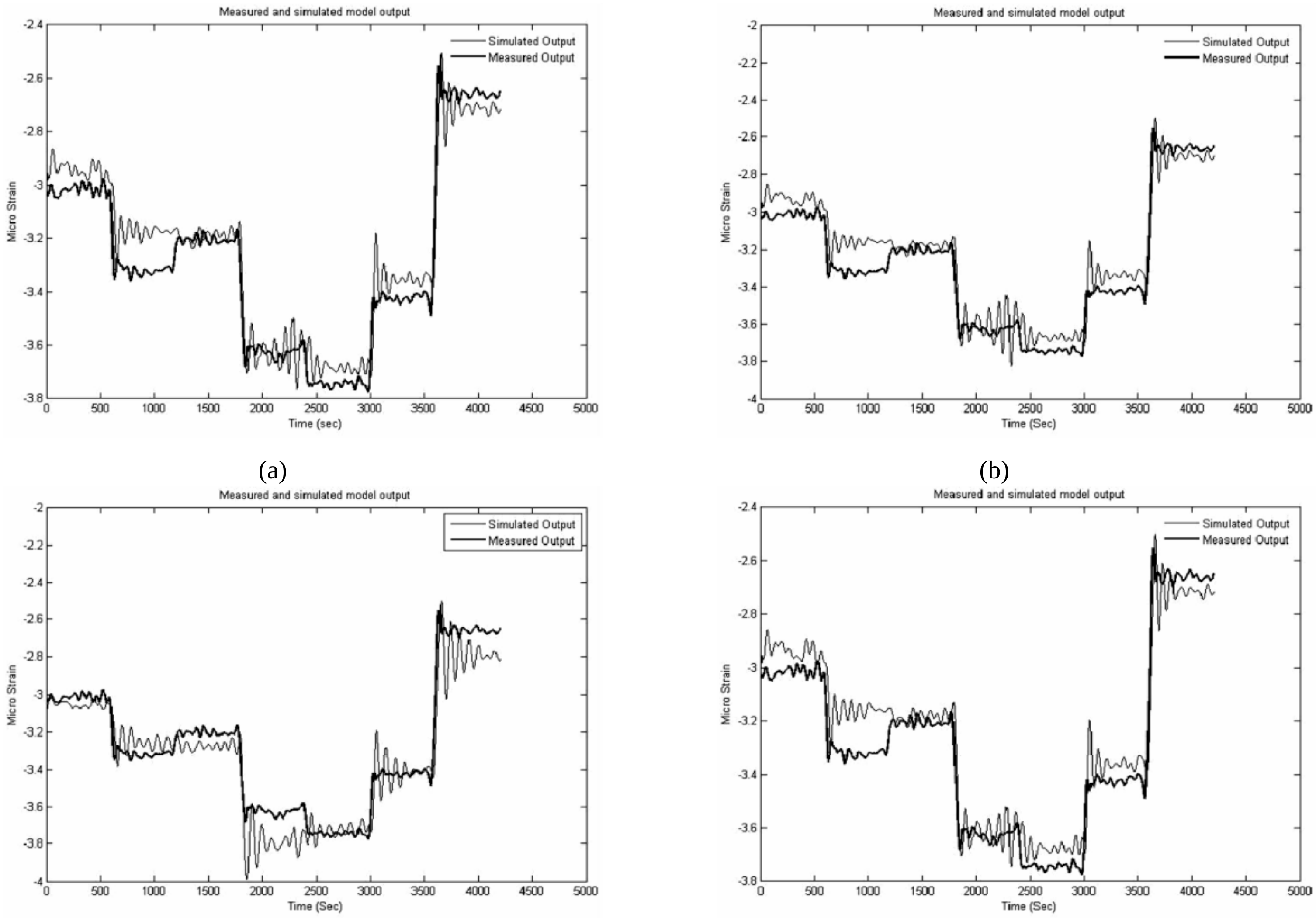


(c)



(d)

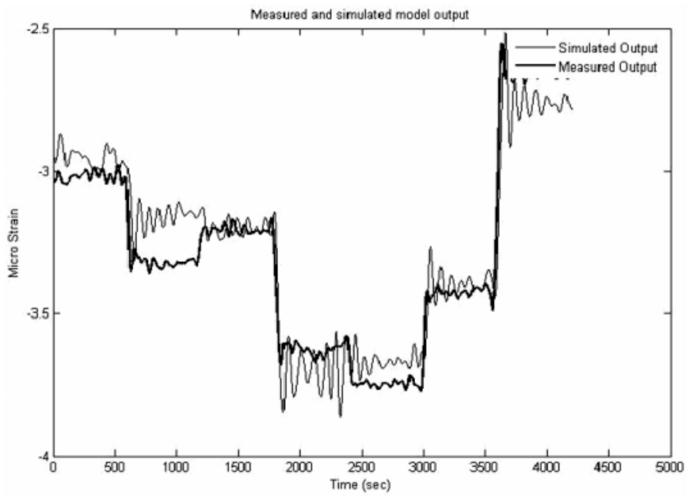
Figure A.6 Measured and Simulated Output of January 2004, (a) sensor# 21 removed, (b)) sensor# 22 removed, (c) sensor# 23 removed, (d)) sensor# 24 removed.



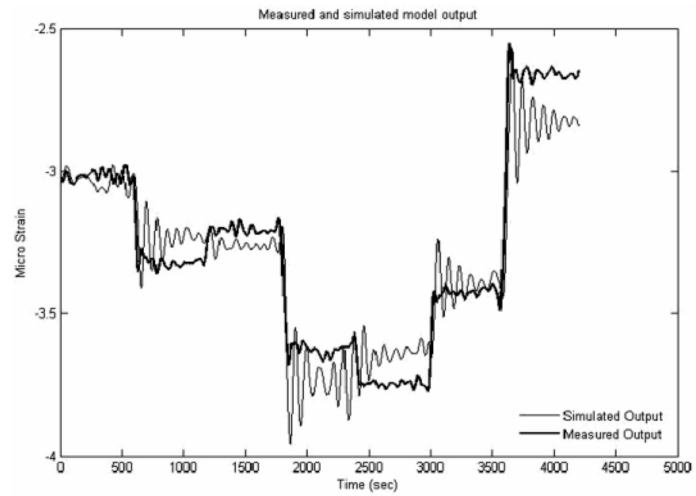
(a) (b)

(c) (d)

Figure A.7 Measured and Simulated Output of January 2004, (a) sensor# 25 removed, (b)) sensor# 26 removed, (c) sensor# 27 removed, (d)) sensor# 28 removed.



(a)



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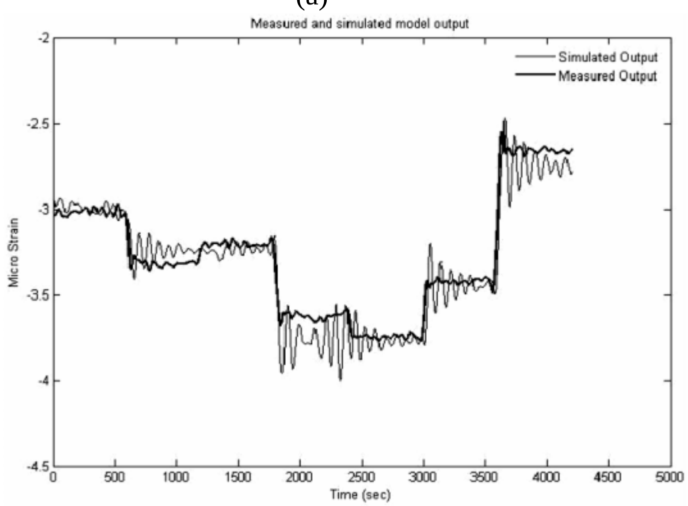

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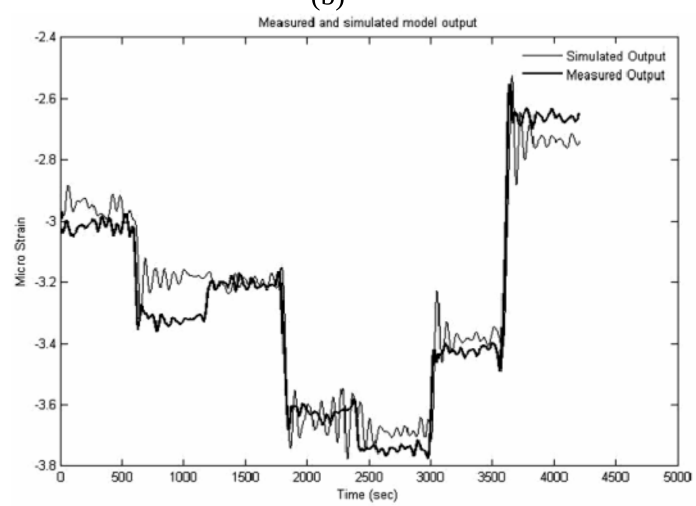
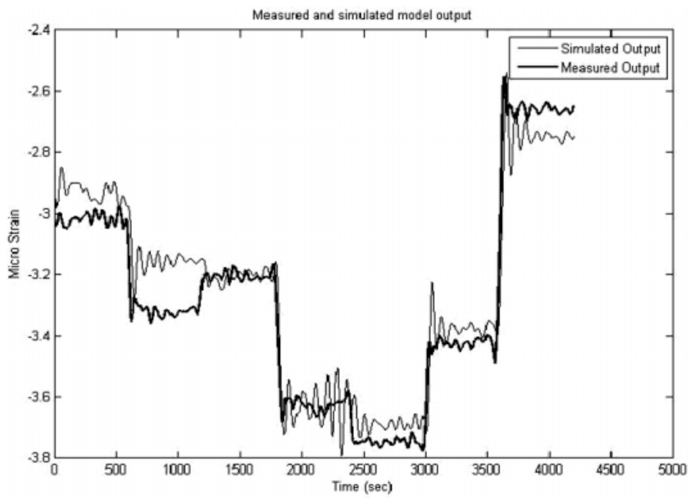


(d)

Figure A.8 Measured and Simulated Output of January 2004, (a) sensor# 29 removed, (b)) sensor# 30 removed, (c) sensor# 31 removed, (d)) sensor# 32 removed.

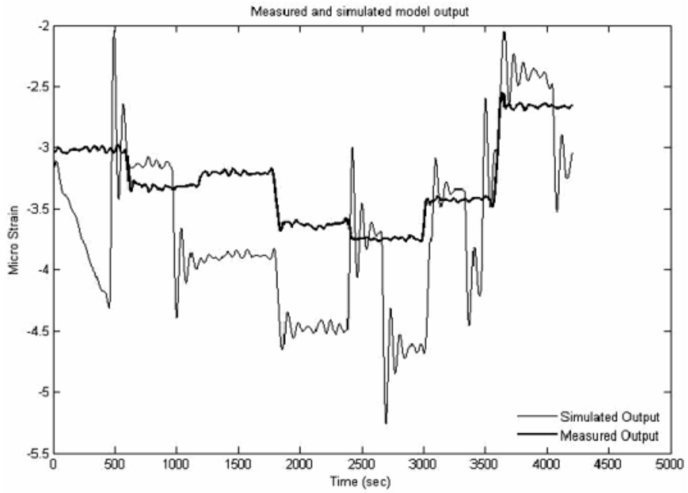


(a)

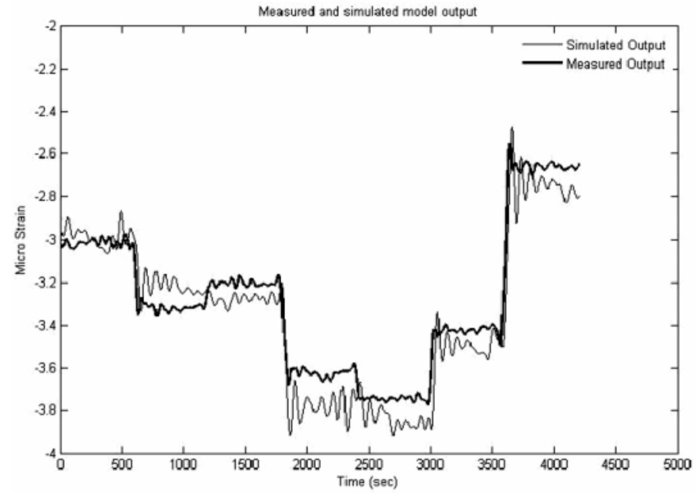
Figure A.9 Measured and Simulated Output of January 2004, (a) sensor# 33 removed.

Appendix B

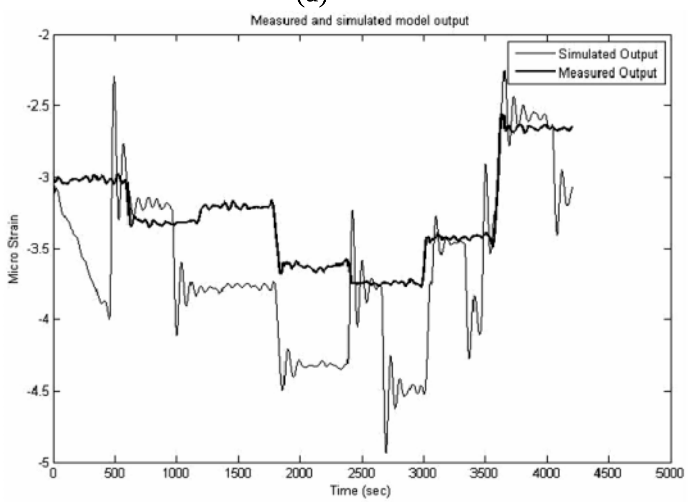
Graphical Outputs of known defective sensor detection for Confederation Bridge by Sequential Search Method. The details are described in Chapter 4, section 4.3, Case 1



(a)



(b)



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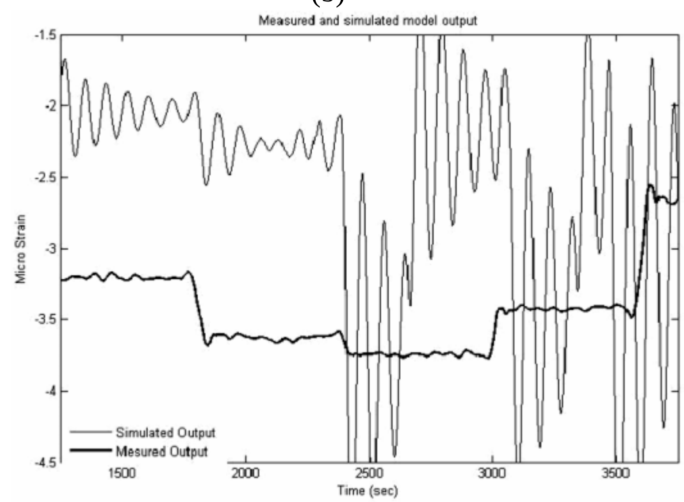
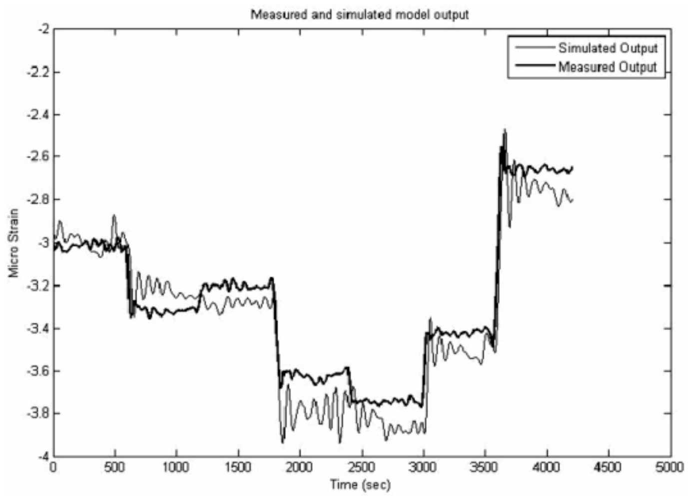
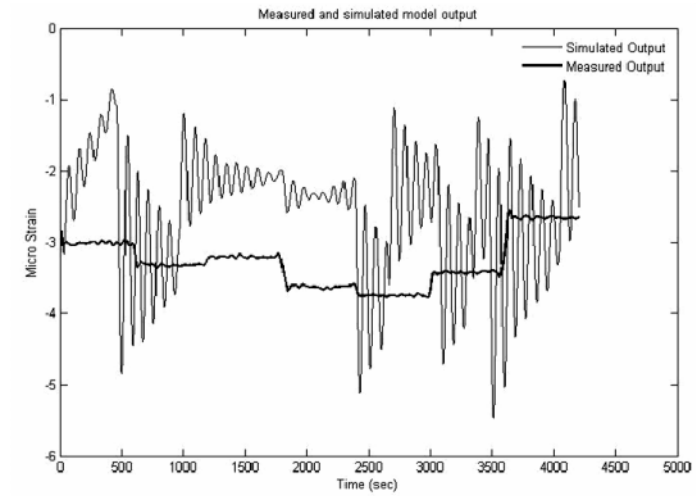


(d)

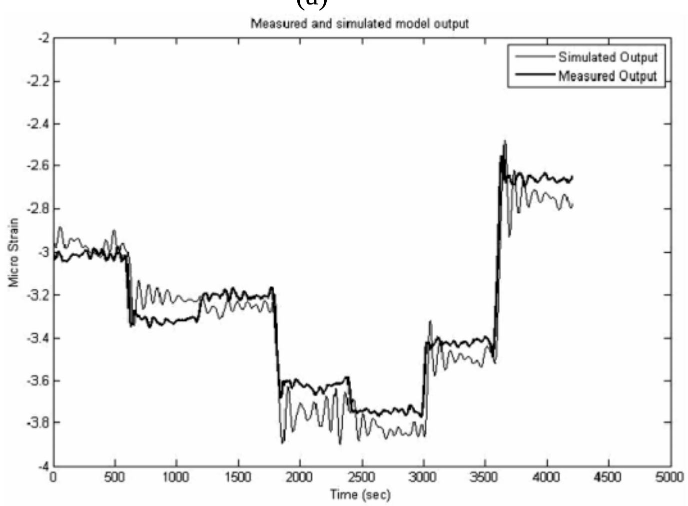
Figure B.1 Measured and Simulated Output of January 2004, (a) sensor# 1 removed, (b)) sensor# 2 removed, (c) sensor# 3 removed, (d)) sensor# 4 removed.



(a)



(b)



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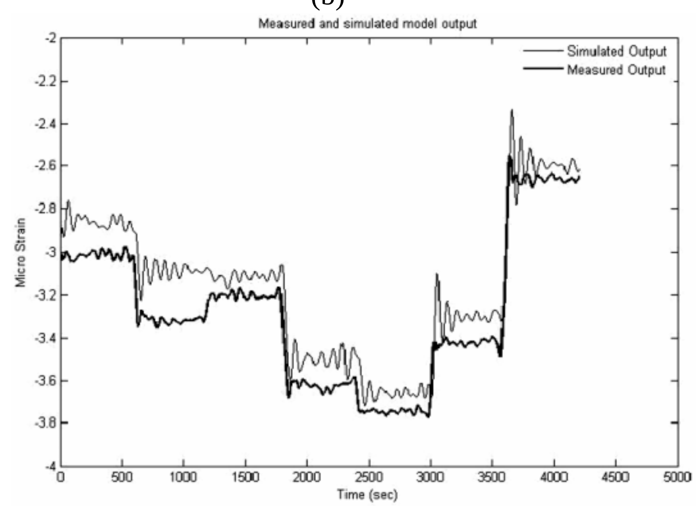
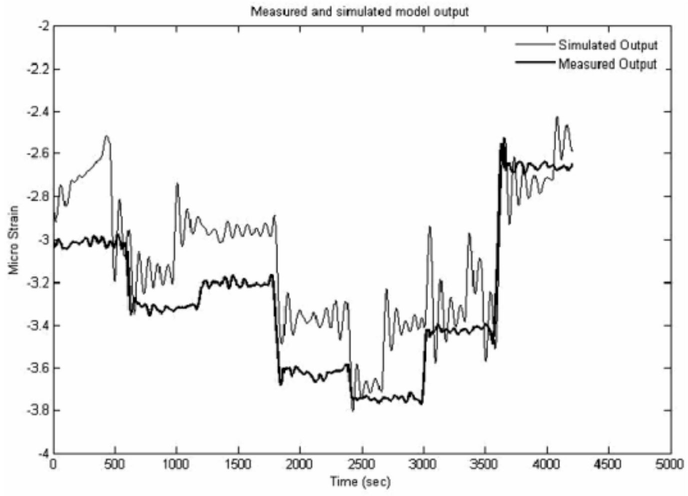
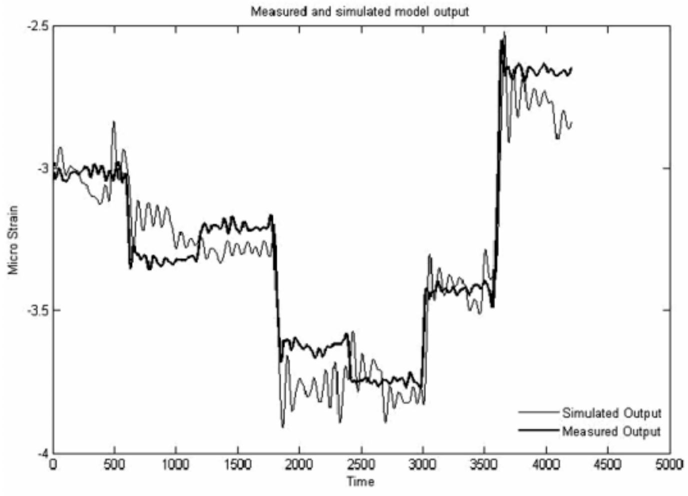


(d)

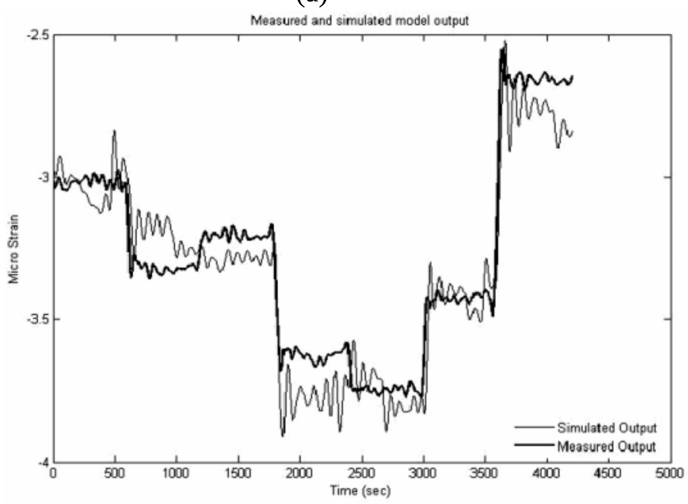
Figure B.2 Measured and Simulated Output of January 2004, (a) sensor# 5 removed, (b)) sensor# 6 removed, (c) sensor# 7 removed, (d)) sensor# 8 removed.



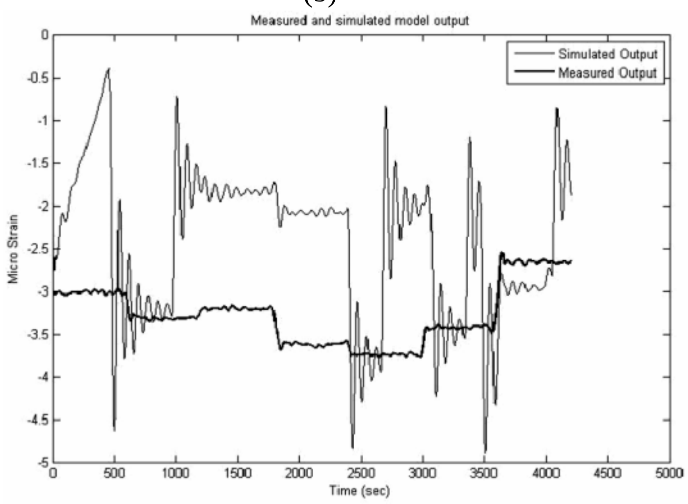
(a)



(b)

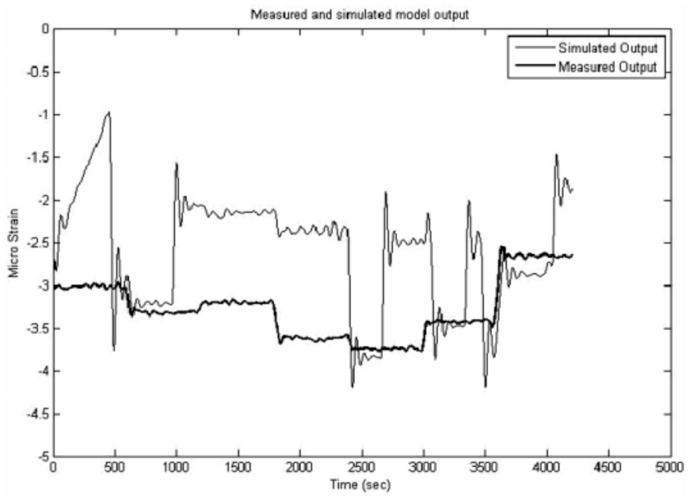


(c)

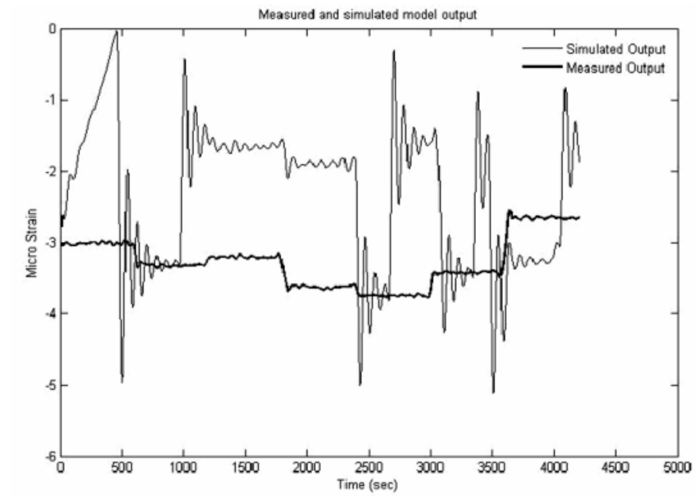


(d)

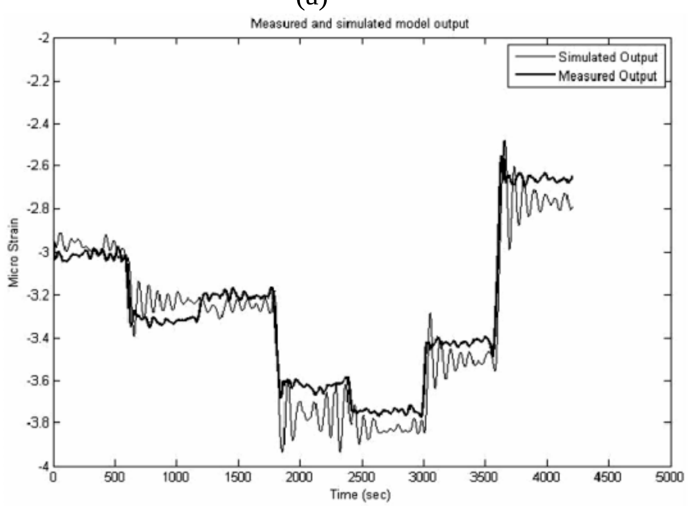
Figure B.3 Measured and Simulated Output of January 2004, (a) sensor# 9 removed, (b)) sensor# 10 removed, (c) sensor# 11 removed, (d)) sensor# 12 removed.



(a)



(b)



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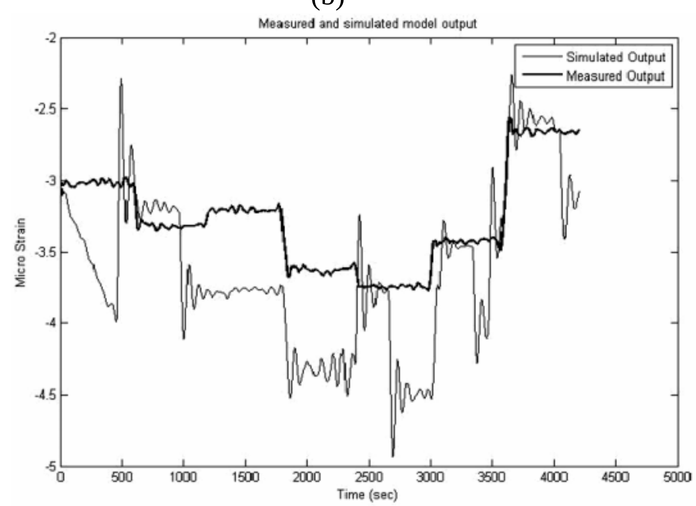
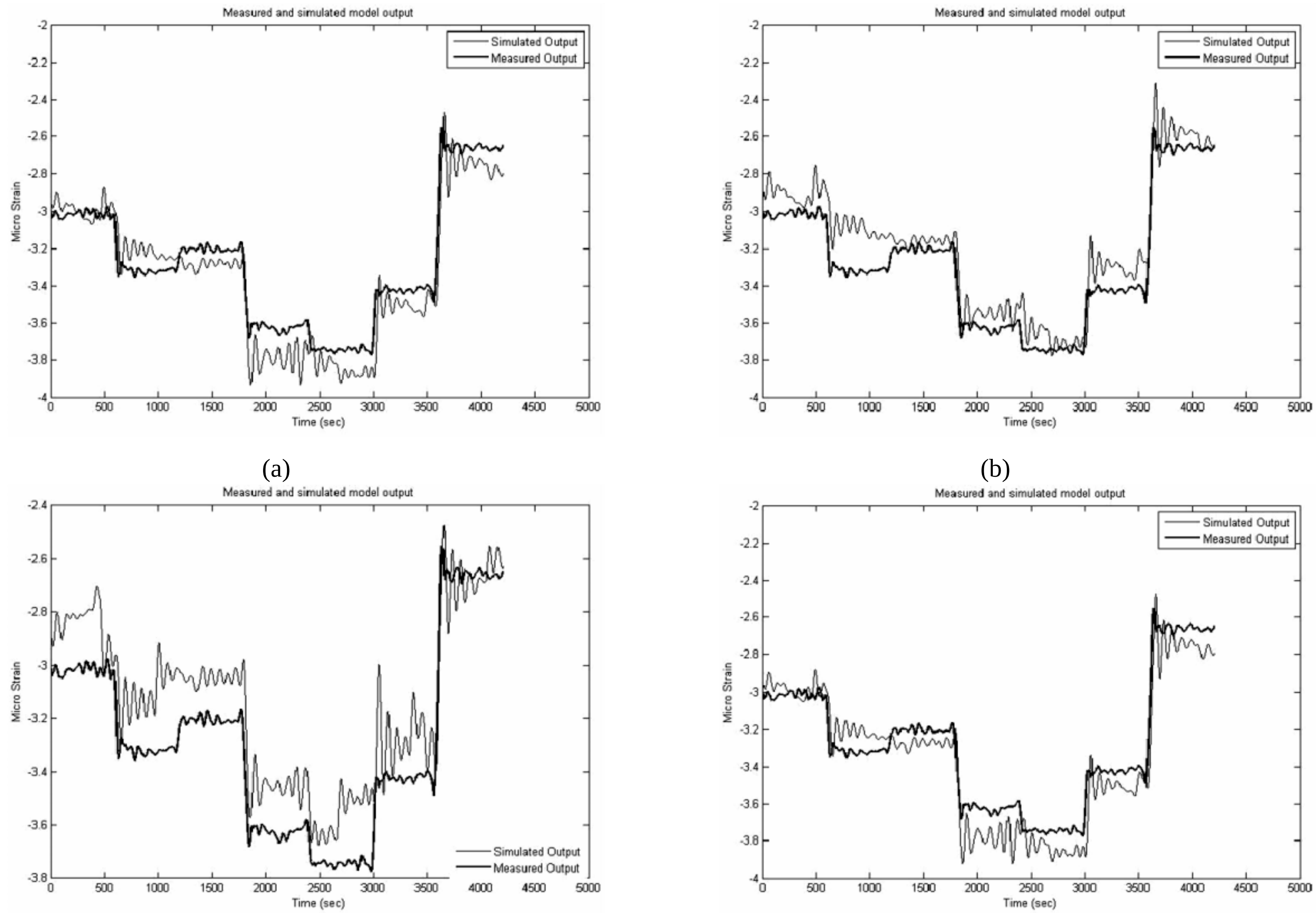


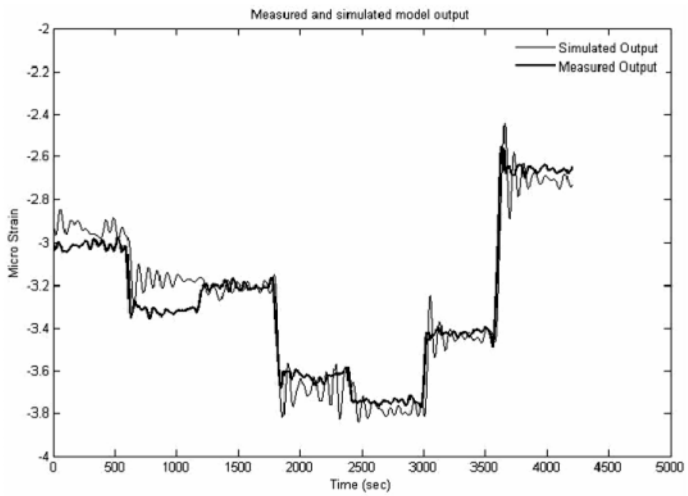
(d)

Figure B.4 Measured and Simulated Output of January 2004, (a) sensor# 13 removed, (b)) sensor# 14 removed, (c) sensor# 15 removed, (d)) sensor# 16 removed.

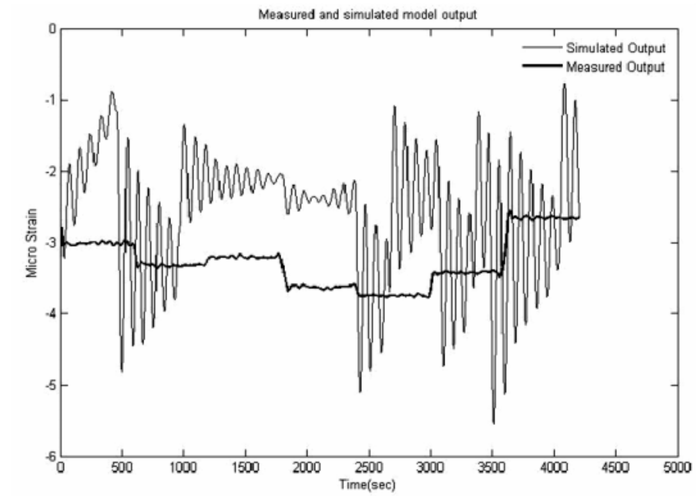


(a) (b) (c) (d)

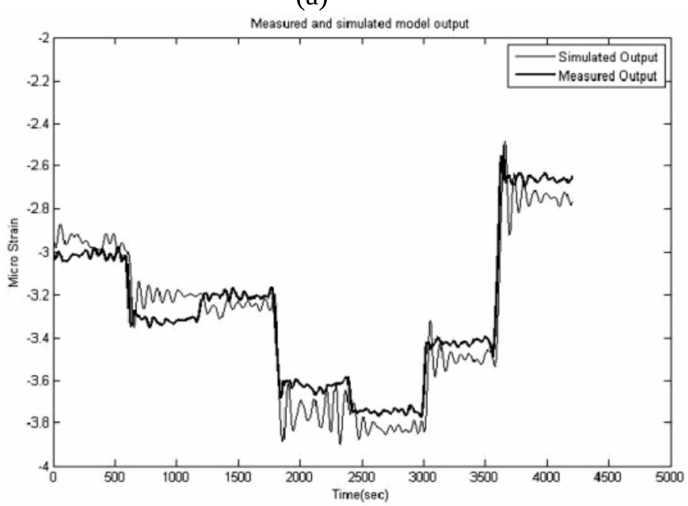
Figure B.5 Measured and Simulated Output of January 2004, (a) sensor# 17 removed, (b)) sensor# 18 removed, (c) sensor# 19 removed, (d)) sensor# 20 removed.



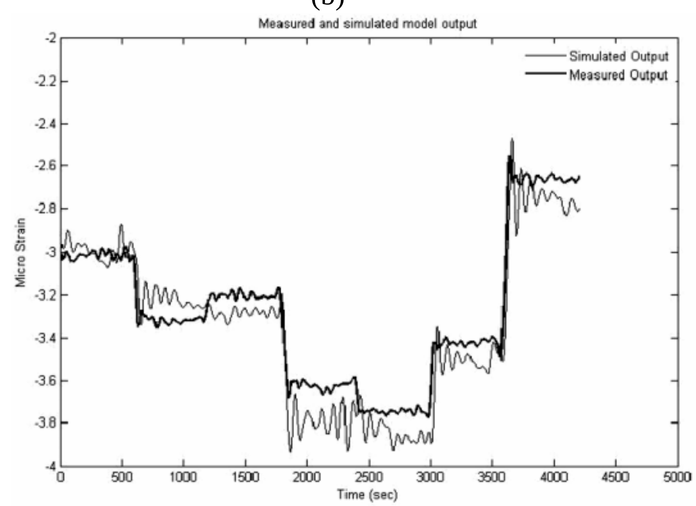
(a)



(b)

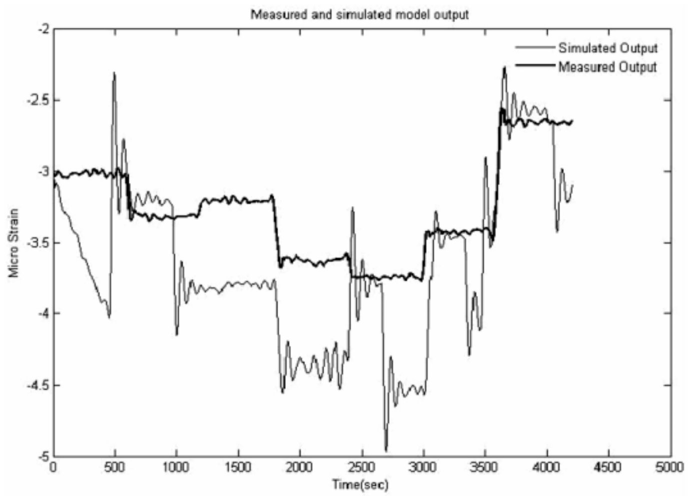


(c)

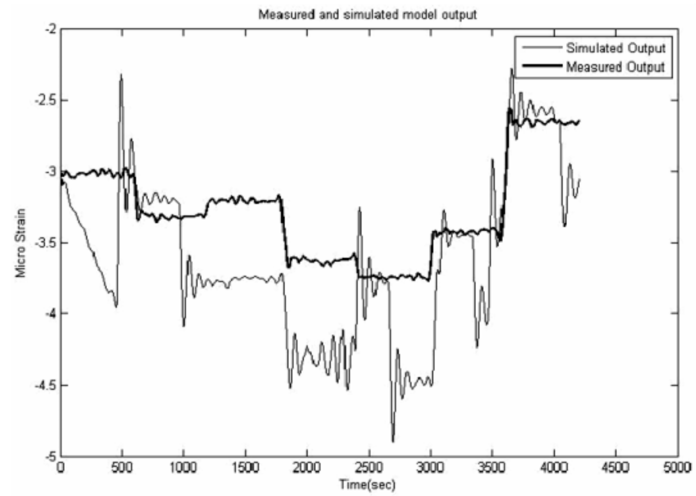


(d)

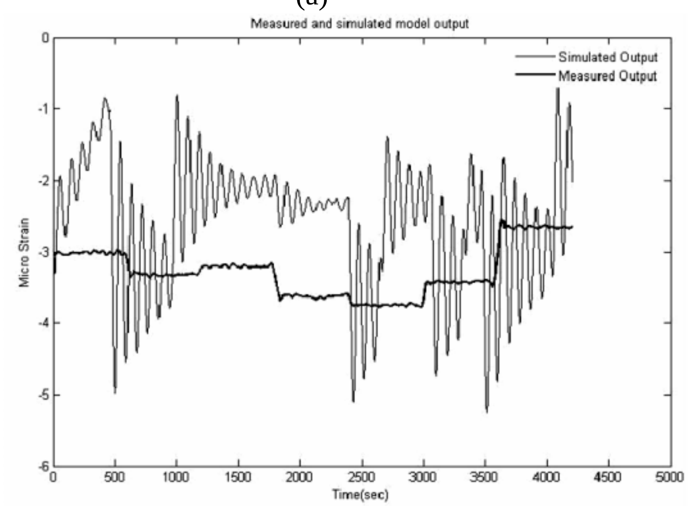
Figure B.6 Measured and Simulated Output of January 2004, (a) sensor# 21 removed, (b)) sensor# 22 removed, (c) sensor# 23 removed, (d)) sensor# 24 removed.



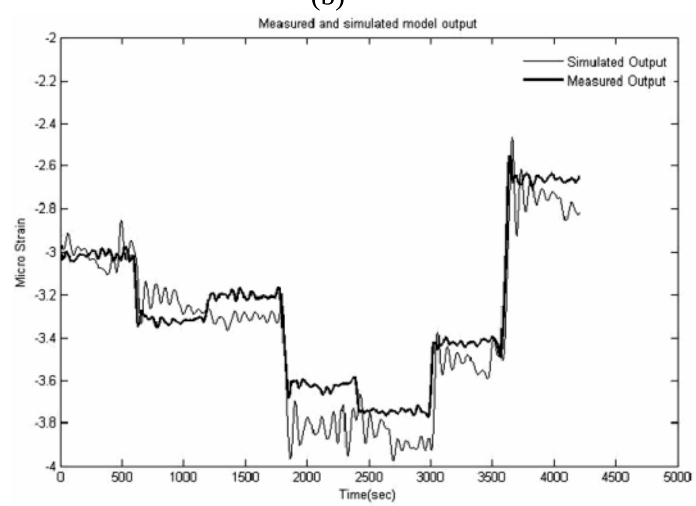
(a)



(b)

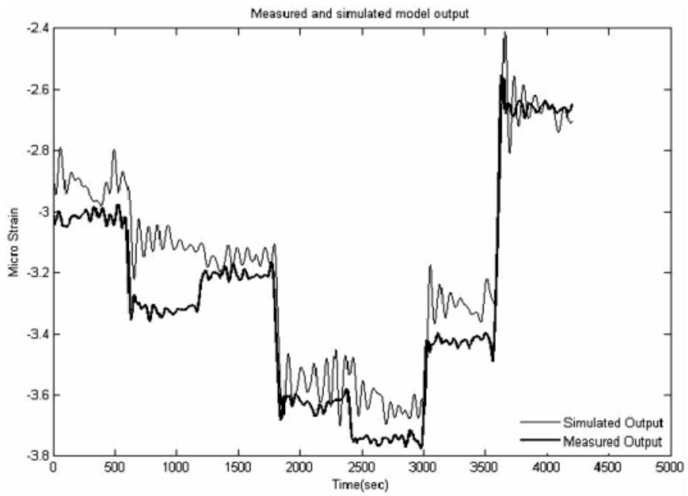


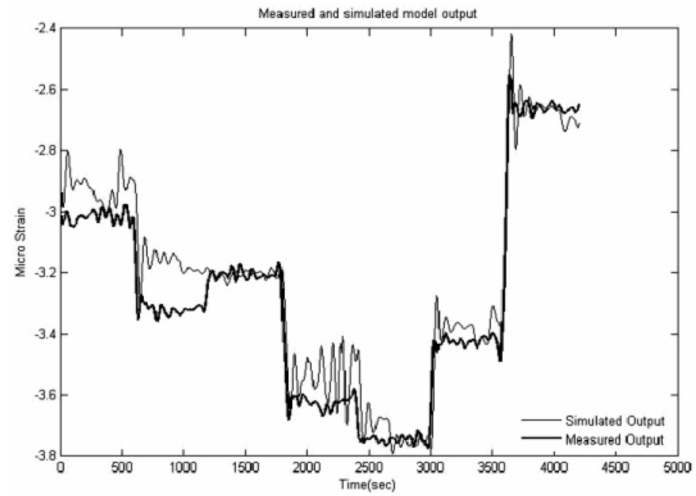
(c)



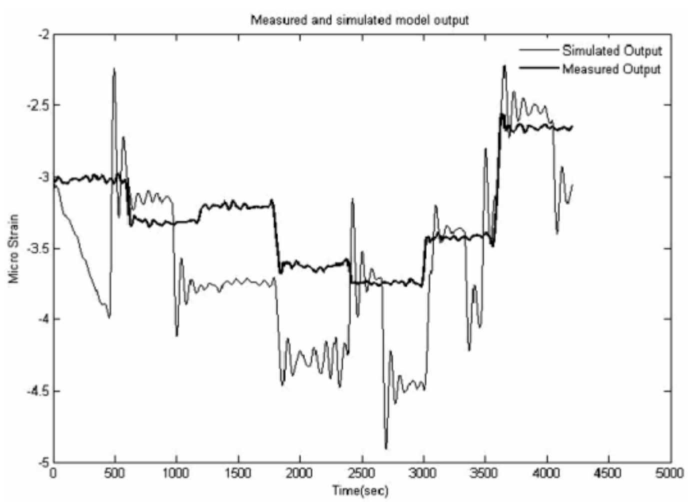
(d)

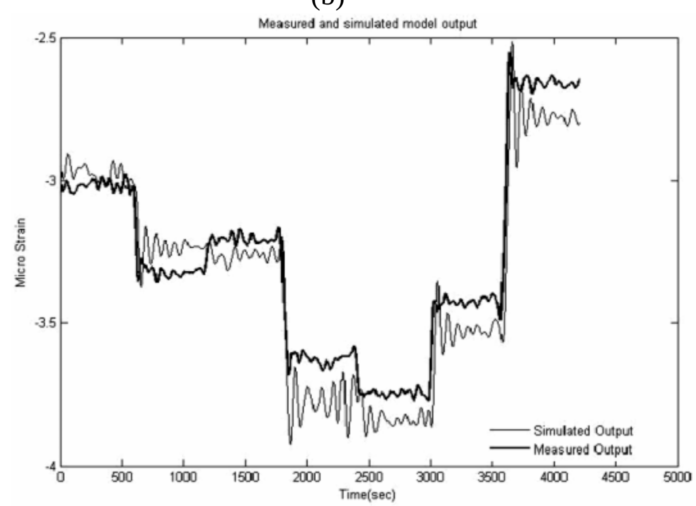
Figure B.7 Measured and Simulated Output of January 2004, (a) sensor# 25 removed, (b)) sensor# 26 removed, (c) sensor# 27 removed, (d)) sensor# 28 removed.





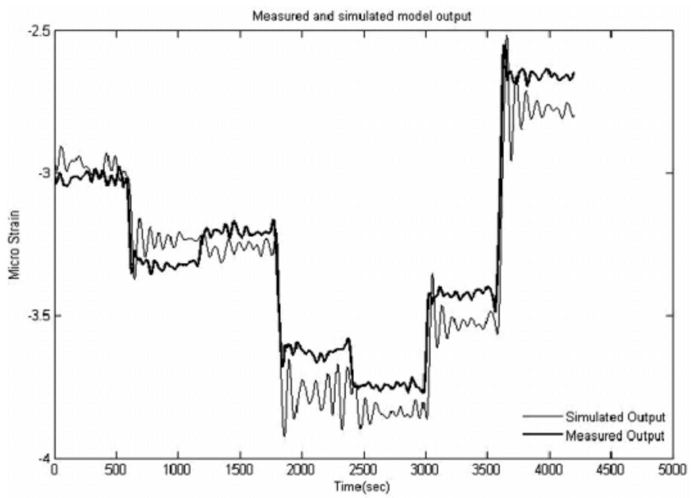
(b)





(c) (d)

Figure B.8 Measured and Simulated Output of January 2004, (a) sensor# 29 removed, (b)) sensor# 30 removed, (c) sensor# 31 removed, (d)) sensor# 32 removed.



(a)

Figure B.9 Measured and Simulated Output of January 2004, (a) sensor# 33 removed.

Appendix C

Graphical Outputs of known defective sensor detection for Confederation Bridge by Sequential Search Method. The details are described in Chapter 4, section 4.3, Case 2

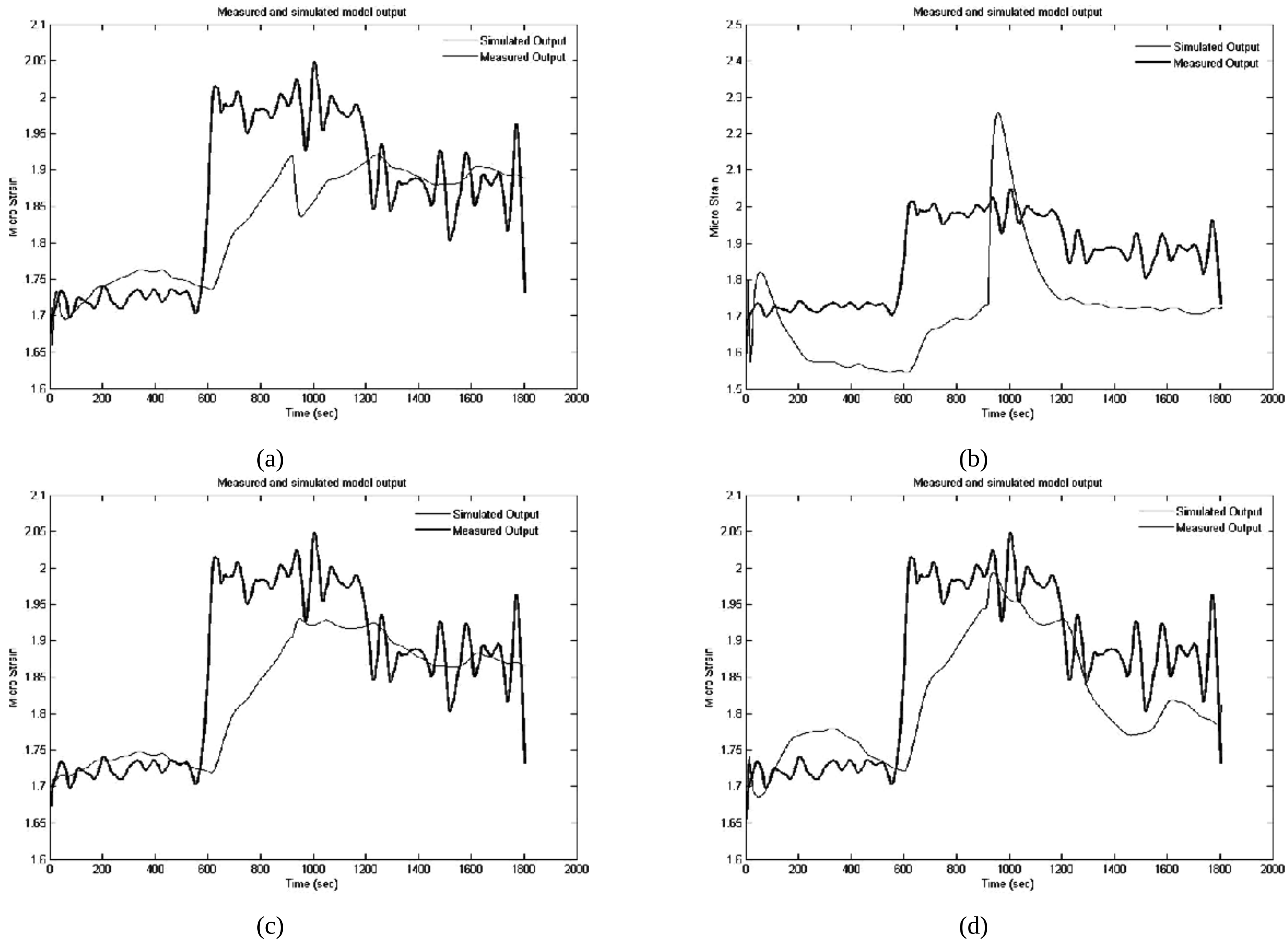
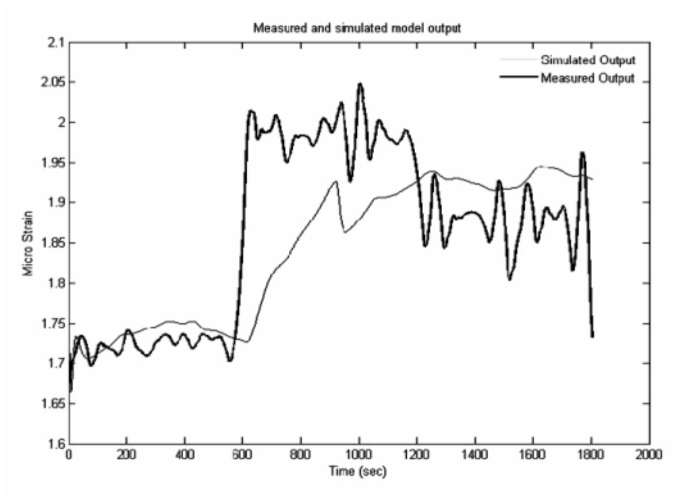
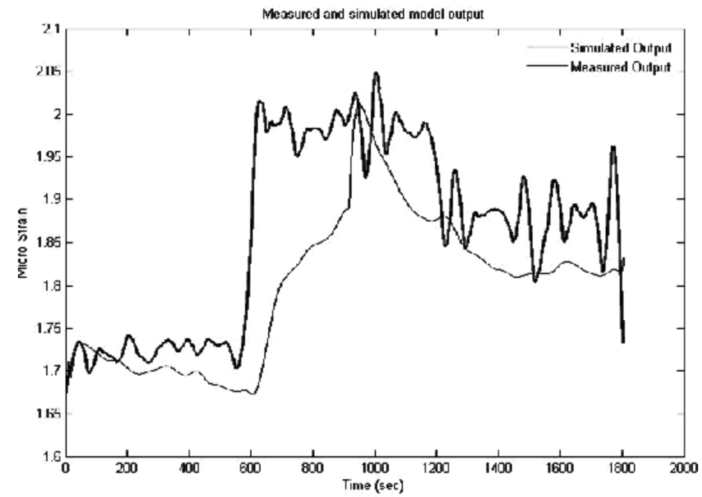


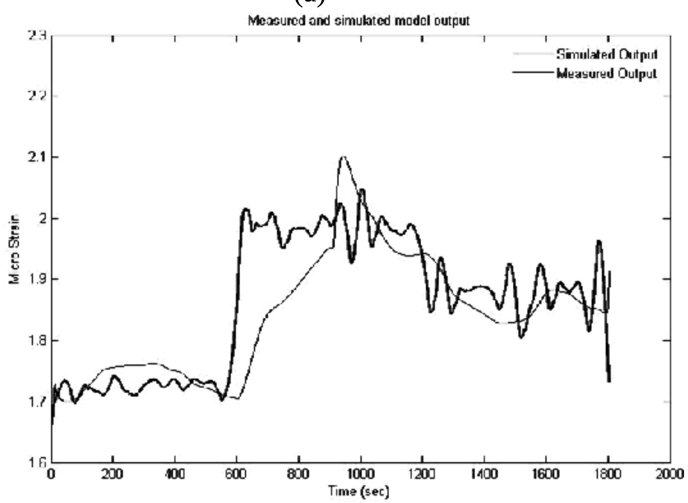
Figure C.1 Measured and Simulated output of December 2003, (a) sensor# 2 removed, (b) sensor# 3 removed, (c) sensor# 7 removed, (d) sensor# 8 removed.



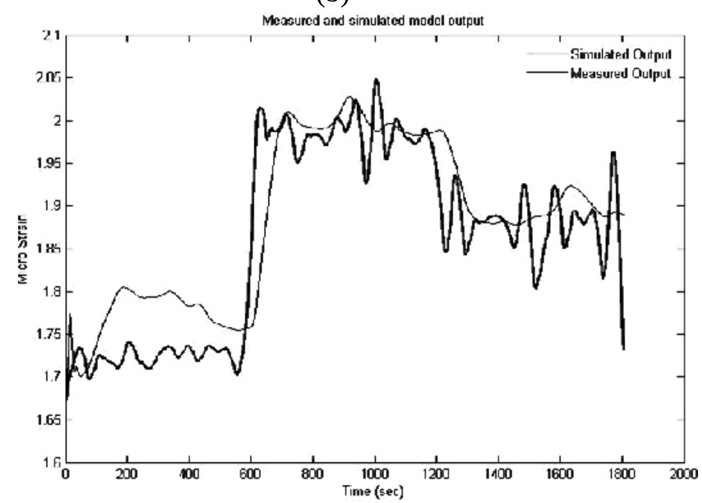
(a)



(b)

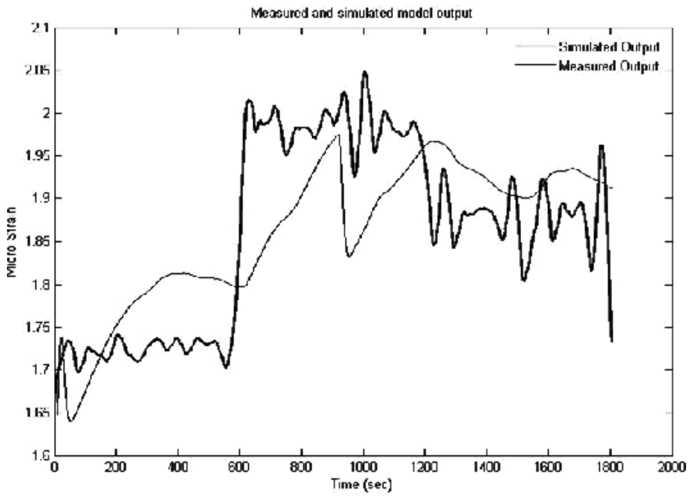


(c)



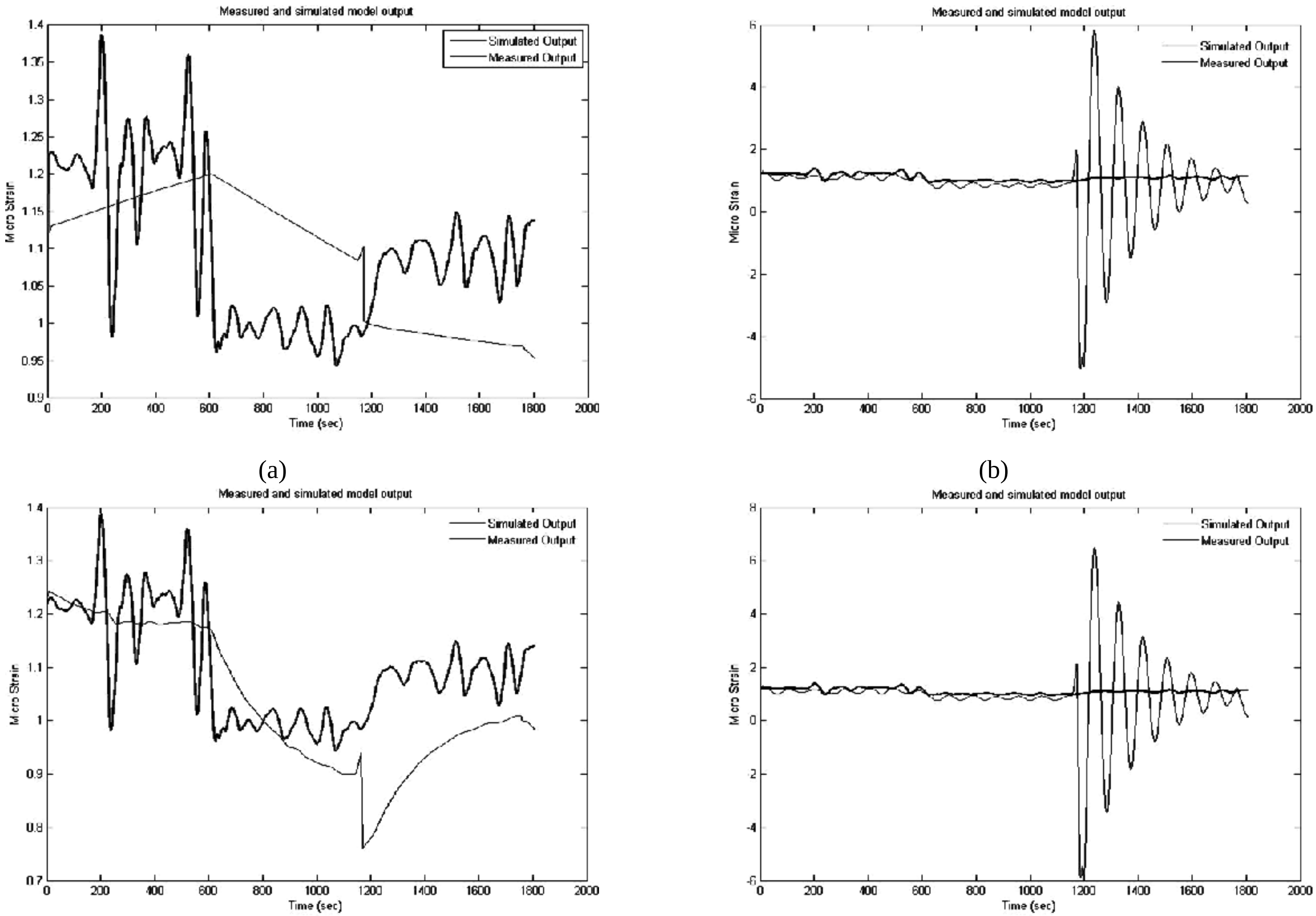
(d)

Figure C.2 Measured and Simulated output of December 2003, (a) sensor# 11 removed, (b) sensor# 12 removed, (c) sensor# 15removed, (d) sensor# 22 removed.



(a)

Figure C.3 Measured and Simulated output of December 2003, (a) sensor# 31 removed



(a) (b) (c) (d)

Figure C.4 Measured and Simulated output of December 2003, (a) sensor# 4removed, (b) sensor# 5 removed, (c) sensor# 9 removed, (d) sensor# 10 removed.

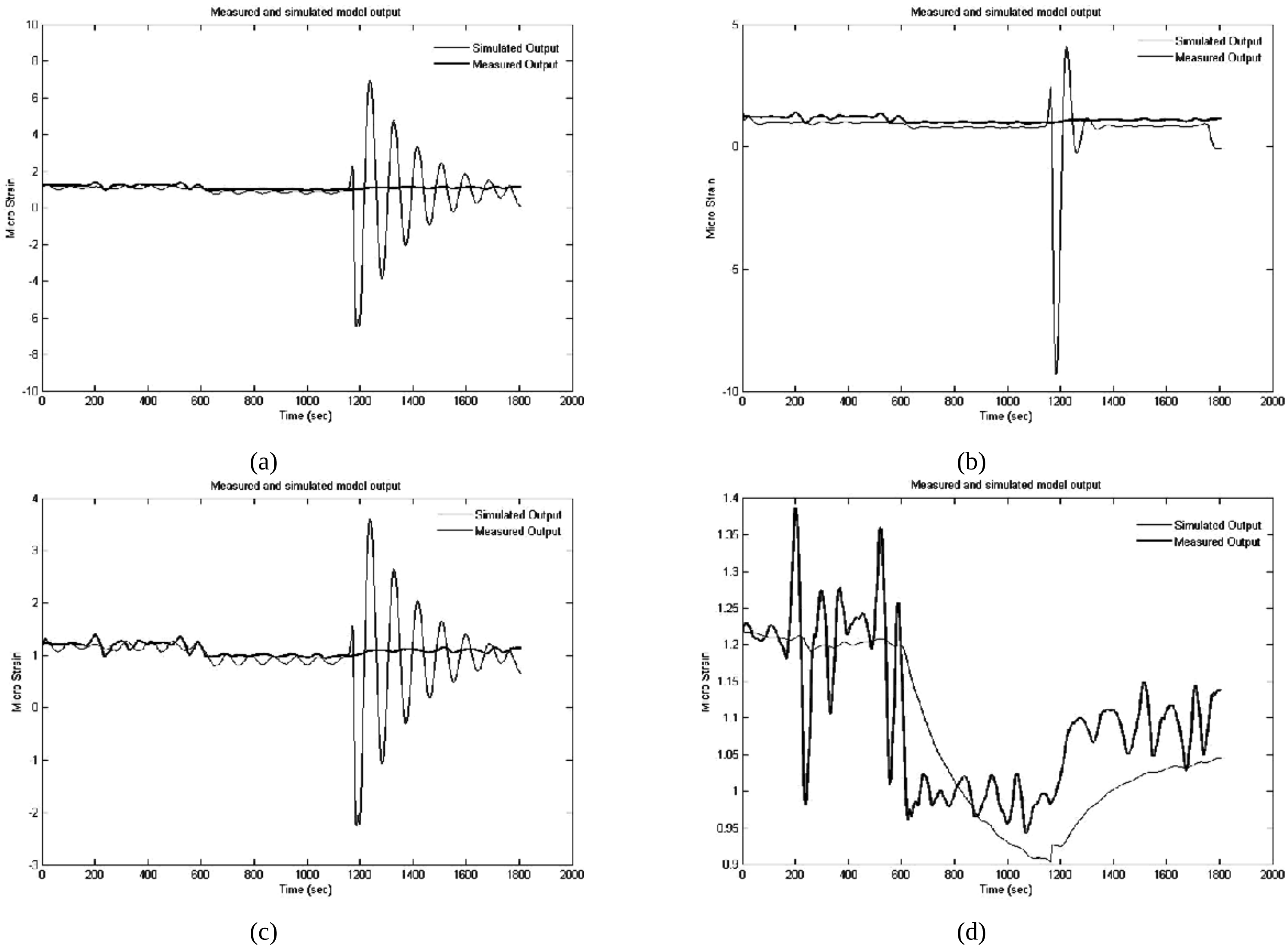
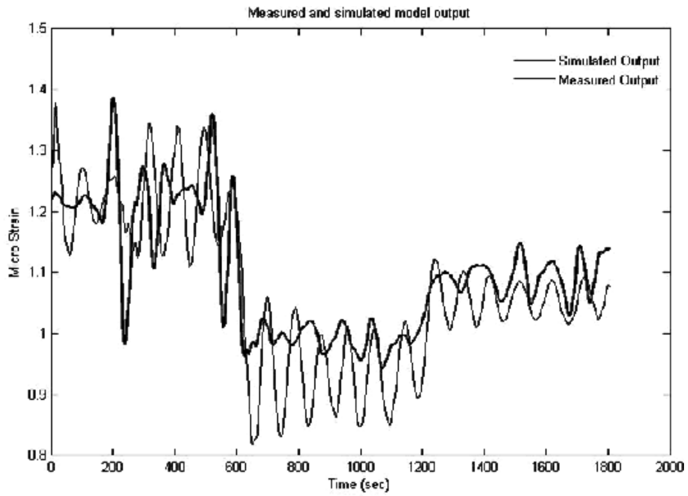
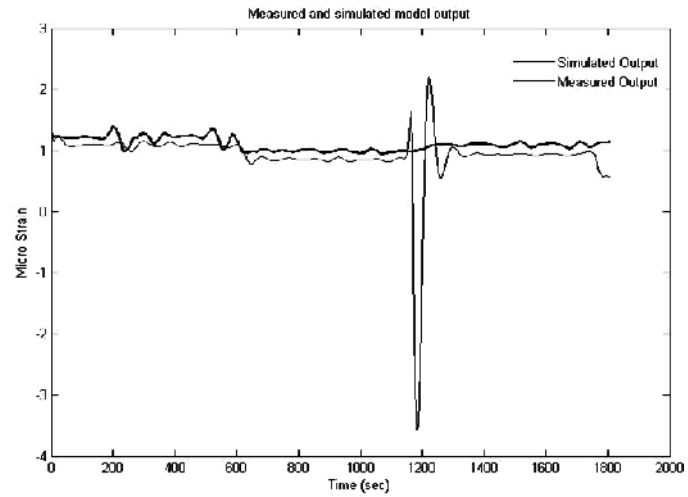


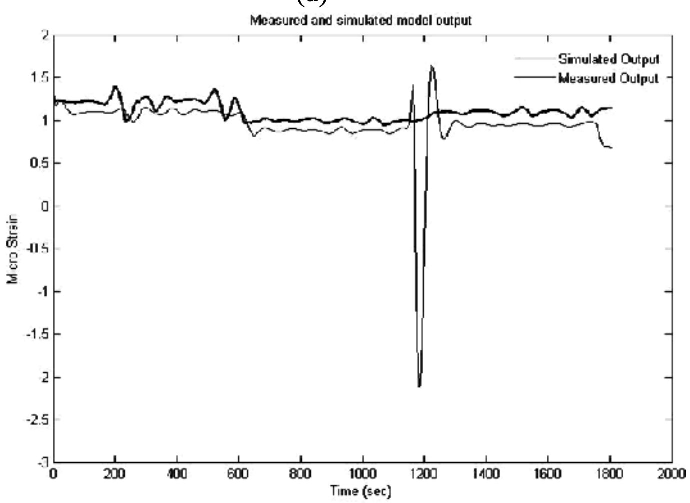
Figure C.5 Measured and Simulated output of December 2003, (a) sensor# 13 removed, (b) sensor# 14 removed, (c) sensor# 17 removed, (d) sensor# 19 removed.



(a)



(b)



(c)

Figure C.6 Measured and Simulated output of December 2003, (a) sensor# 21 removed, (b) sensor# 29 removed, (c) sensor# 30 removed.

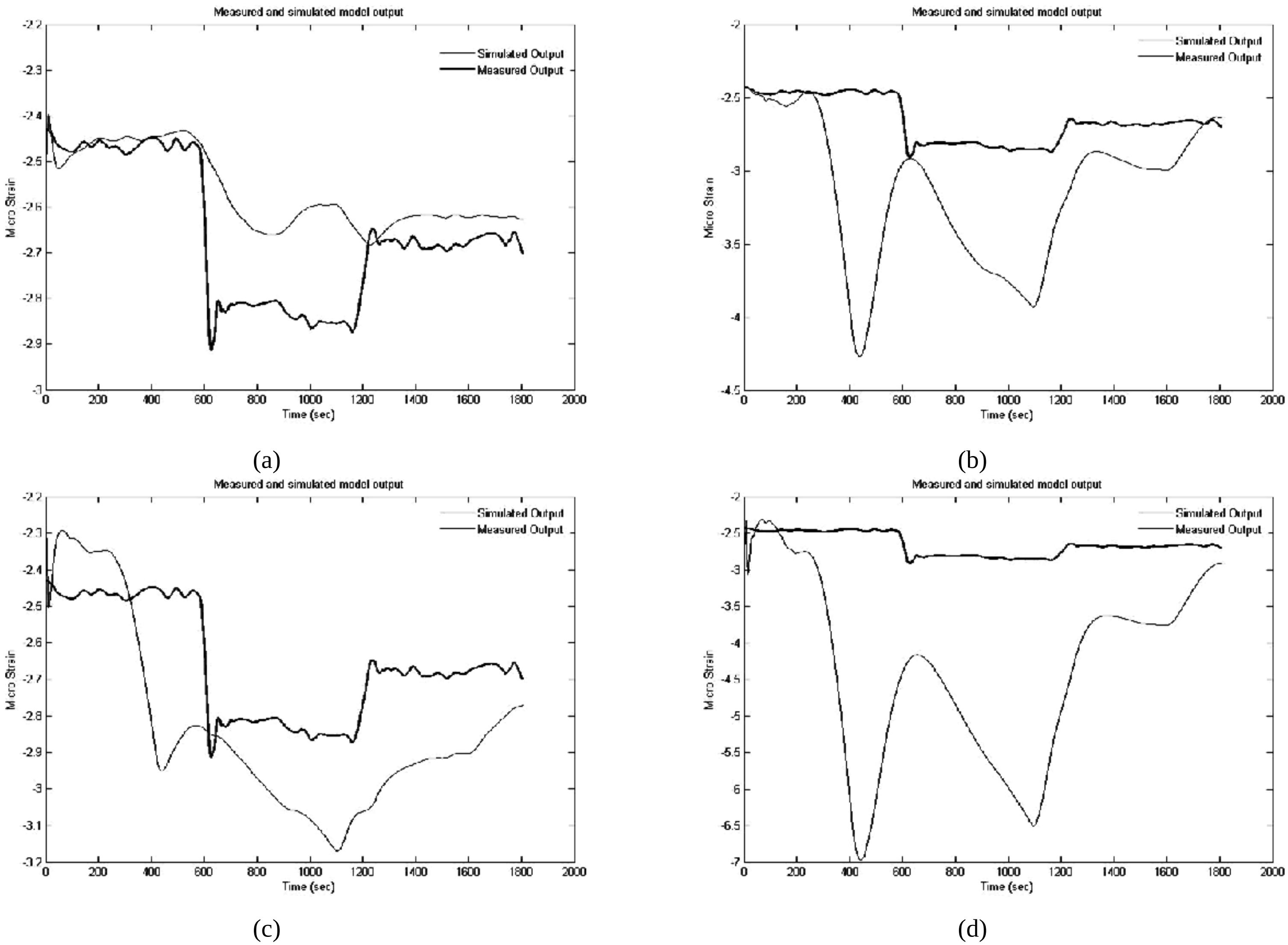
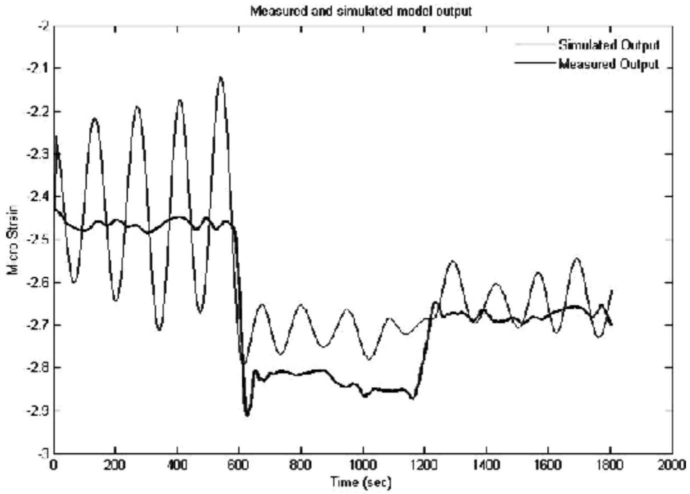
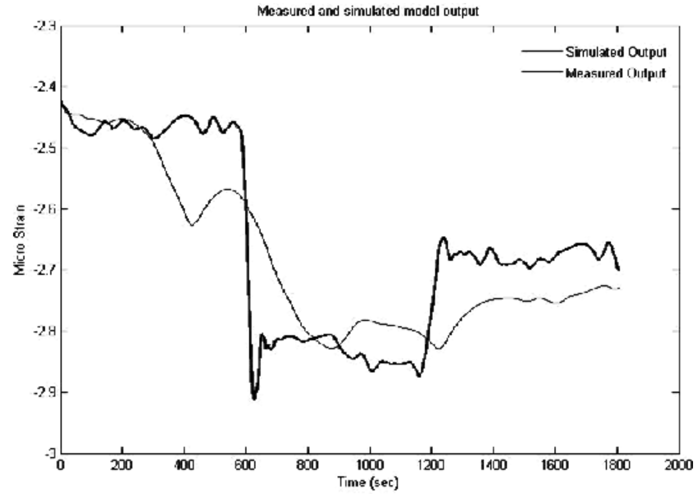


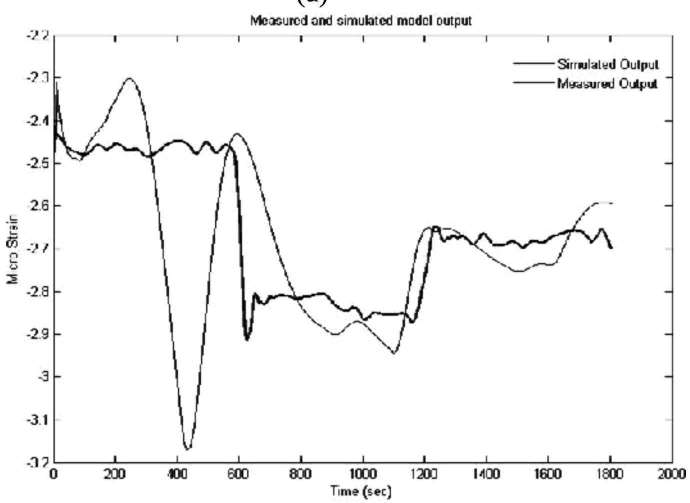
Figure C.7 Measured and Simulated output of December 2003, (a) sensor# 16 removed, (b) sensor# 18 removed, (c) sensor# 20 removed, (d) sensor# 23 removed.



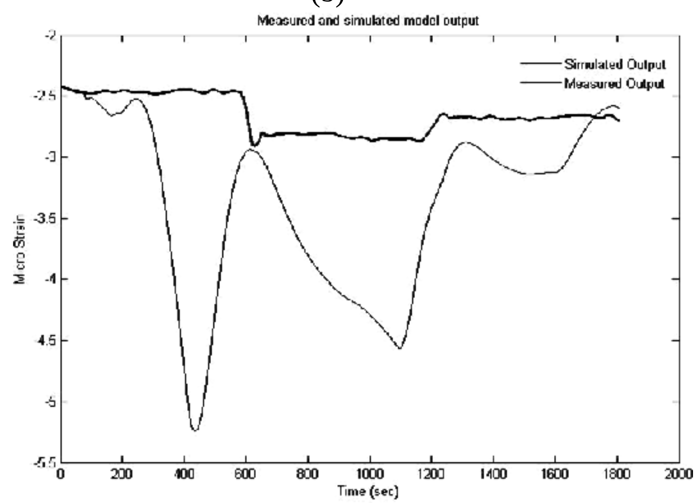
(a)



(b)

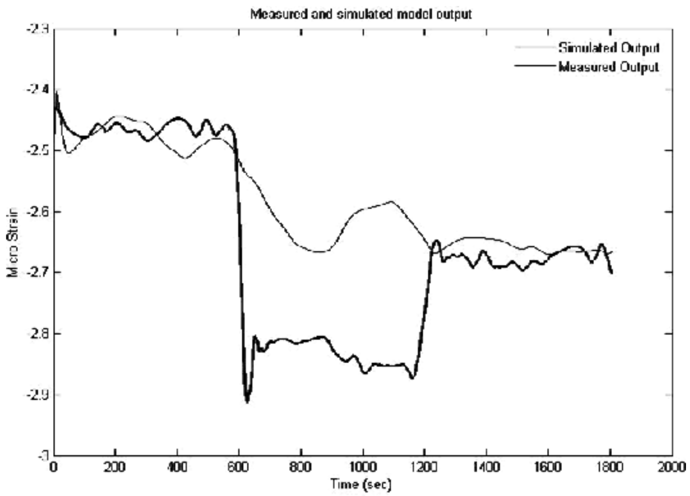


(c)

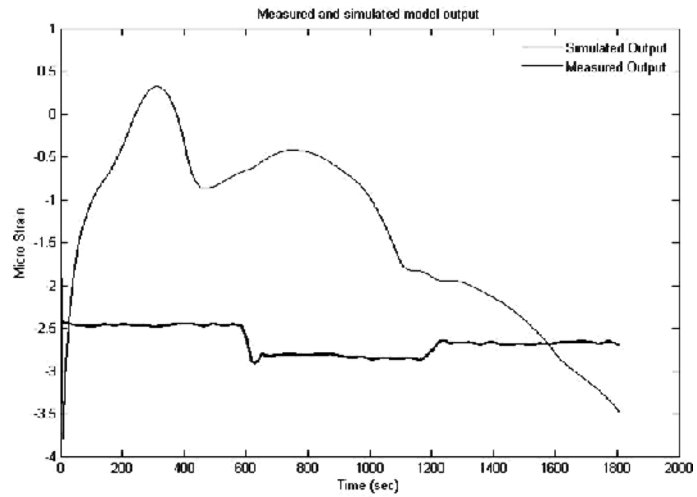


(d)

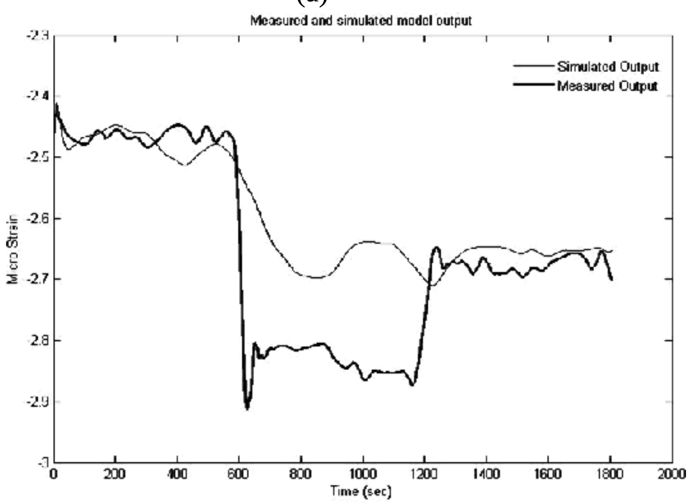
Figure C.8 Measured and Simulated output of December 2003, (a) sensor# 24 removed, (b) sensor# 25 removed, (c) sensor# 27 removed, (d) sensor# 28 removed.



(a)



(b)

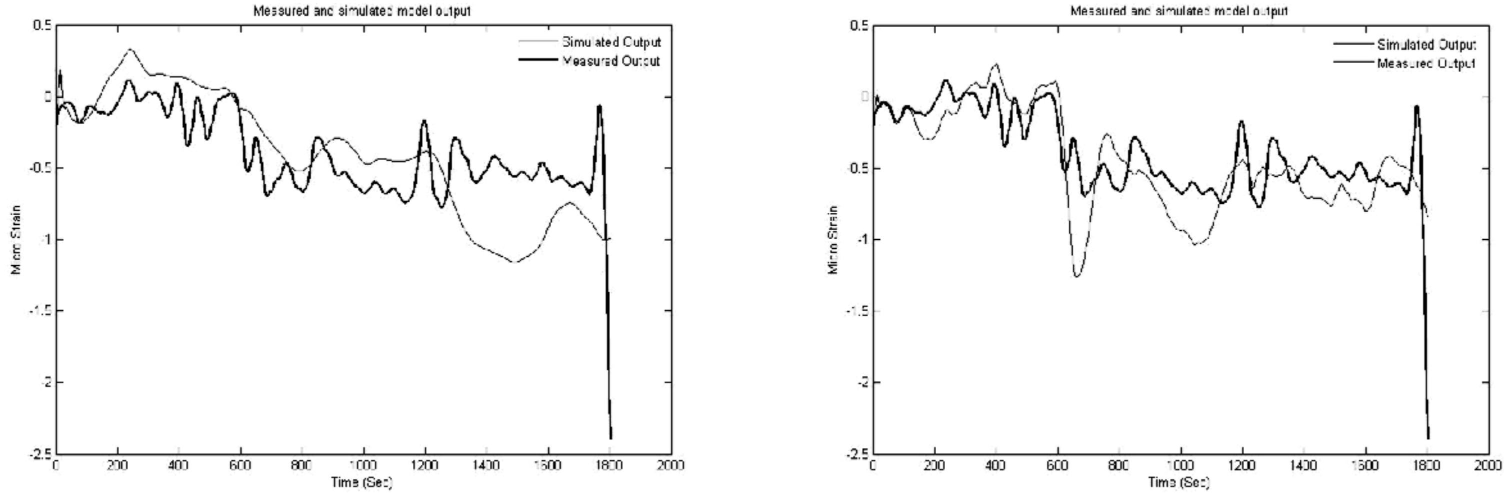


(c)

Figure C.9 Measured and Simulated output of December 2003, (a) sensor# 32 removed, (b) sensor# 33 removed, (c) sensor# 34 removed.

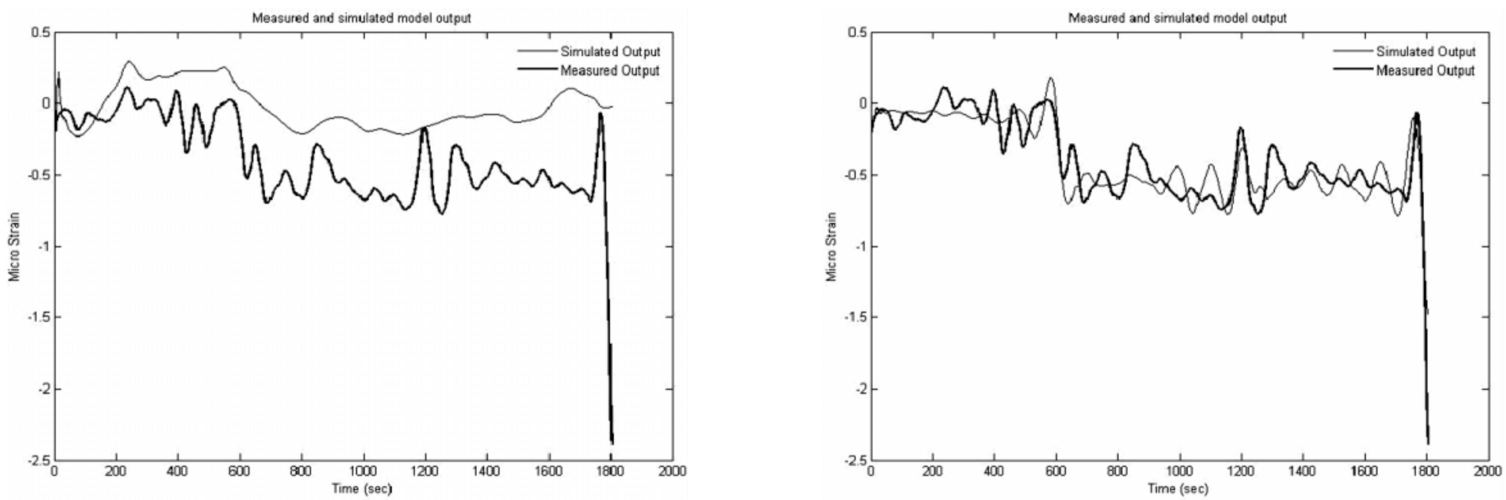
Appendix D

Graphical Outputs of known defective sensor detection for Confederation Bridge by Binary Search Method. The details are described in Chapter 4, section 4.4, Case 1



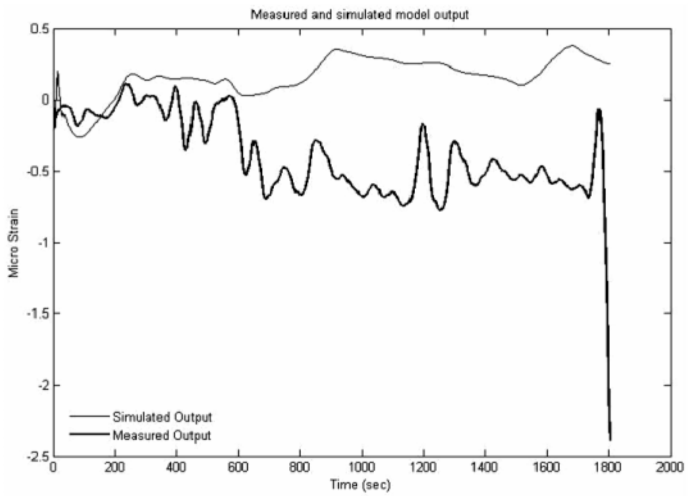
(a) (b)

Figure D.1 Measured and Simulated output of December 2003, (a) Group_1, (b) Group_2

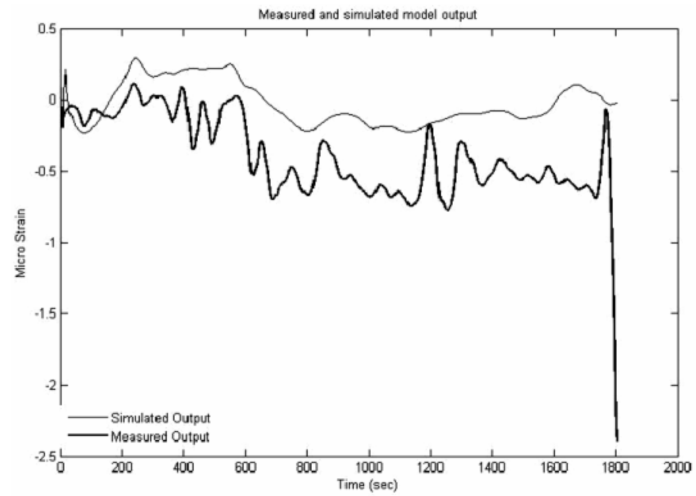


(a) (b)

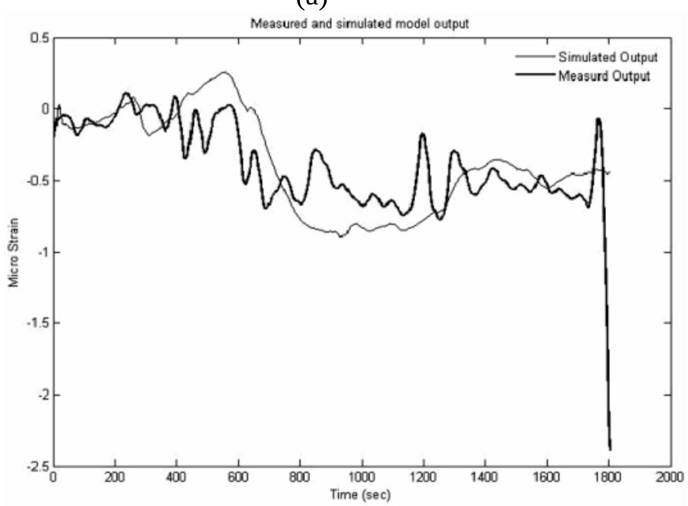
Figure D.2 Measured and Simulated output of December 2003, (a) 1st subgroup of group_1, (b) 2nd subgroup of group_1.



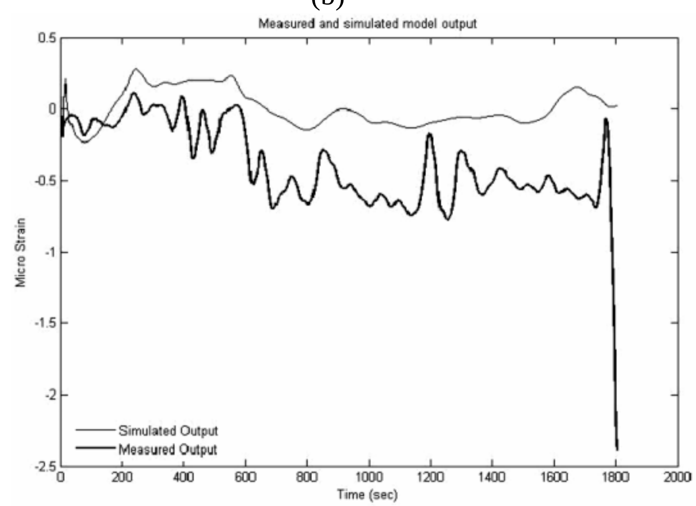
(a)



(b)

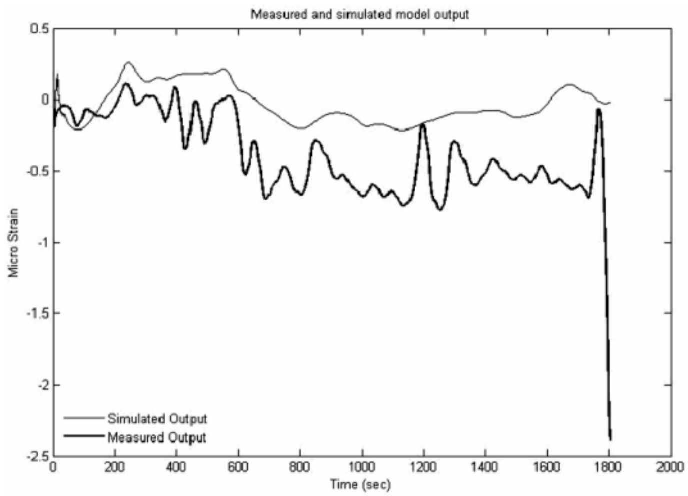


(c)

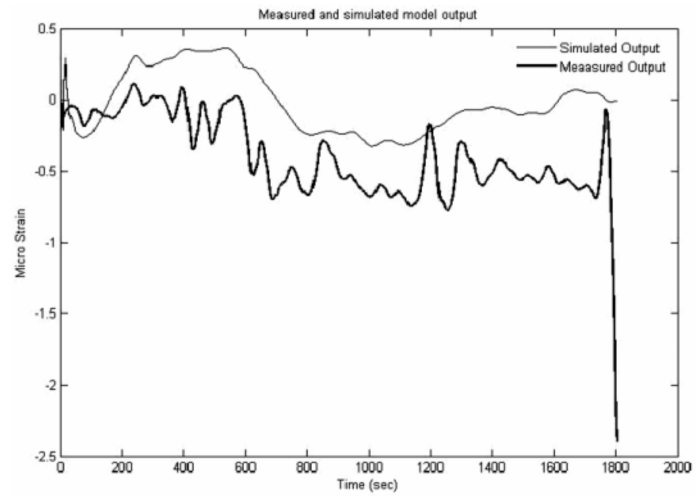


(d)

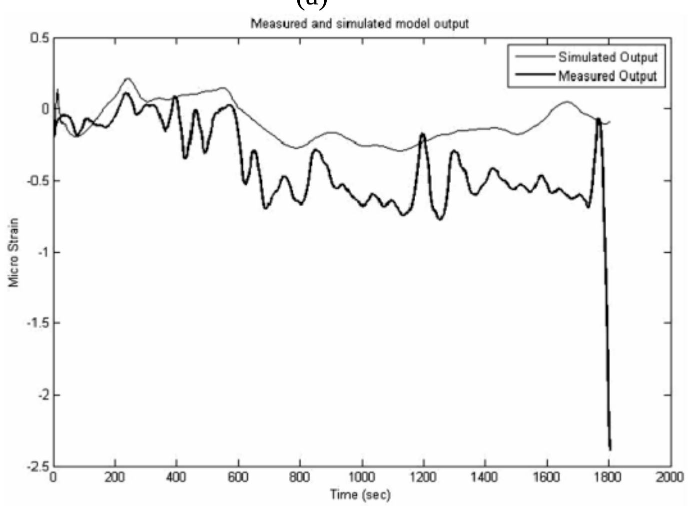
Figure D.3 Measured and Simulated output of December 2003 in Sequential Search Method (a) sensor# 1 eliminated, (b) sensor# 2 eliminated, (c) sensor# 3 eliminated, (d) sensor# 4eliminated.



(a)



(b)

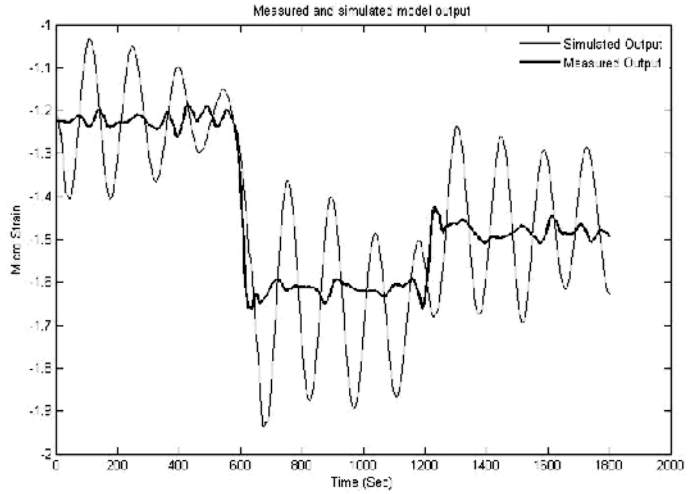


(c)

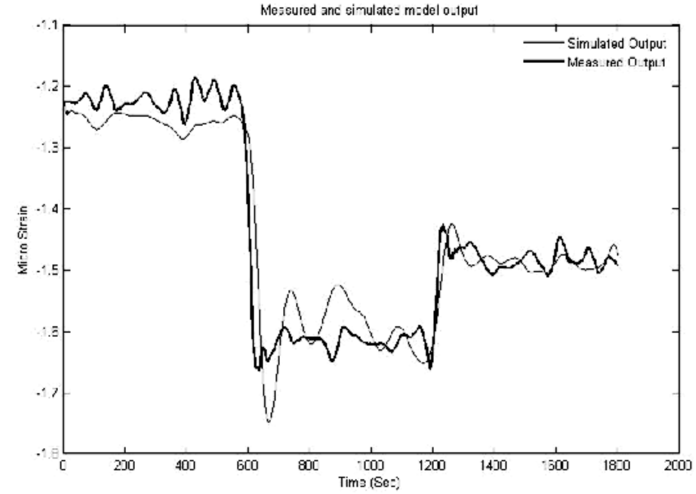
Figure D.3 Measured and Simulated output of December 2003 in Sequential Search Method (a) sensor# 5 eliminated, (b) sensor# 6 eliminated, (c) sensor# 7 eliminated

Appendix E

Graphical Outputs of known defective sensor detection for Confederation Bridge by Binary Search Method. The details are described in Chapter 4, section 4.4, Case 2

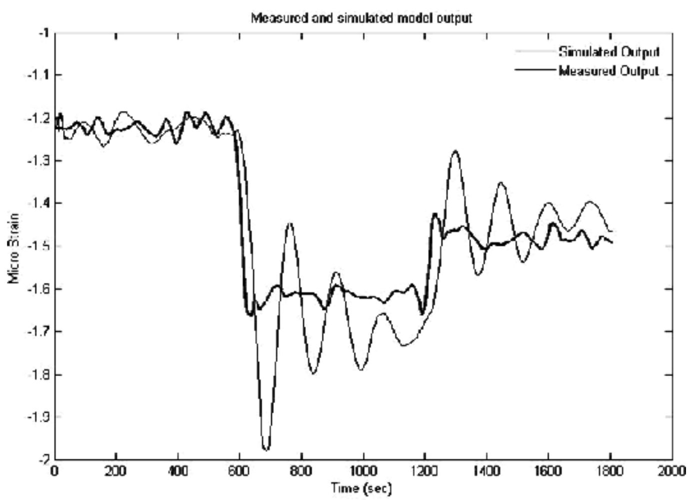


(a)

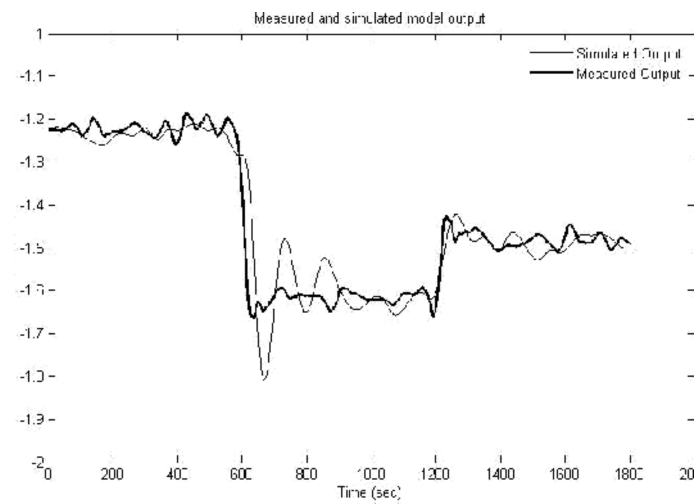


(b)

Figure E.1 Measured and Simulated output of December 2003, (a) Group_1, (b) Group_2

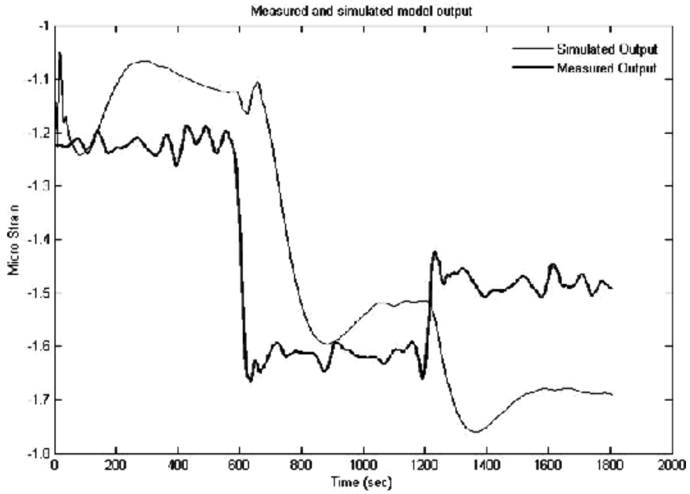


(a)

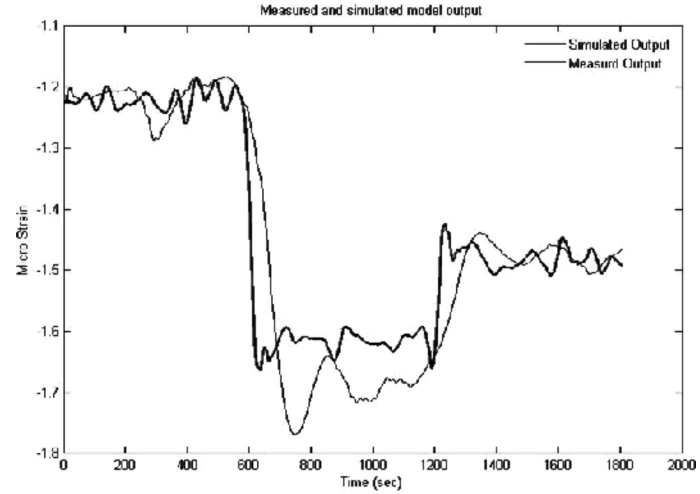


(b)

Figure E.2 Measured and Simulated output of December 2003, (a) 1st subgroup of group_1, (b) 2nd subgroup of group_1.



(a)



(b)

Figure E.3 Measured and Simulated output of December 2003, (a) 1st subgroup of group1_1, (b) 2nd subgroup of group1_1.

(c)

(d)

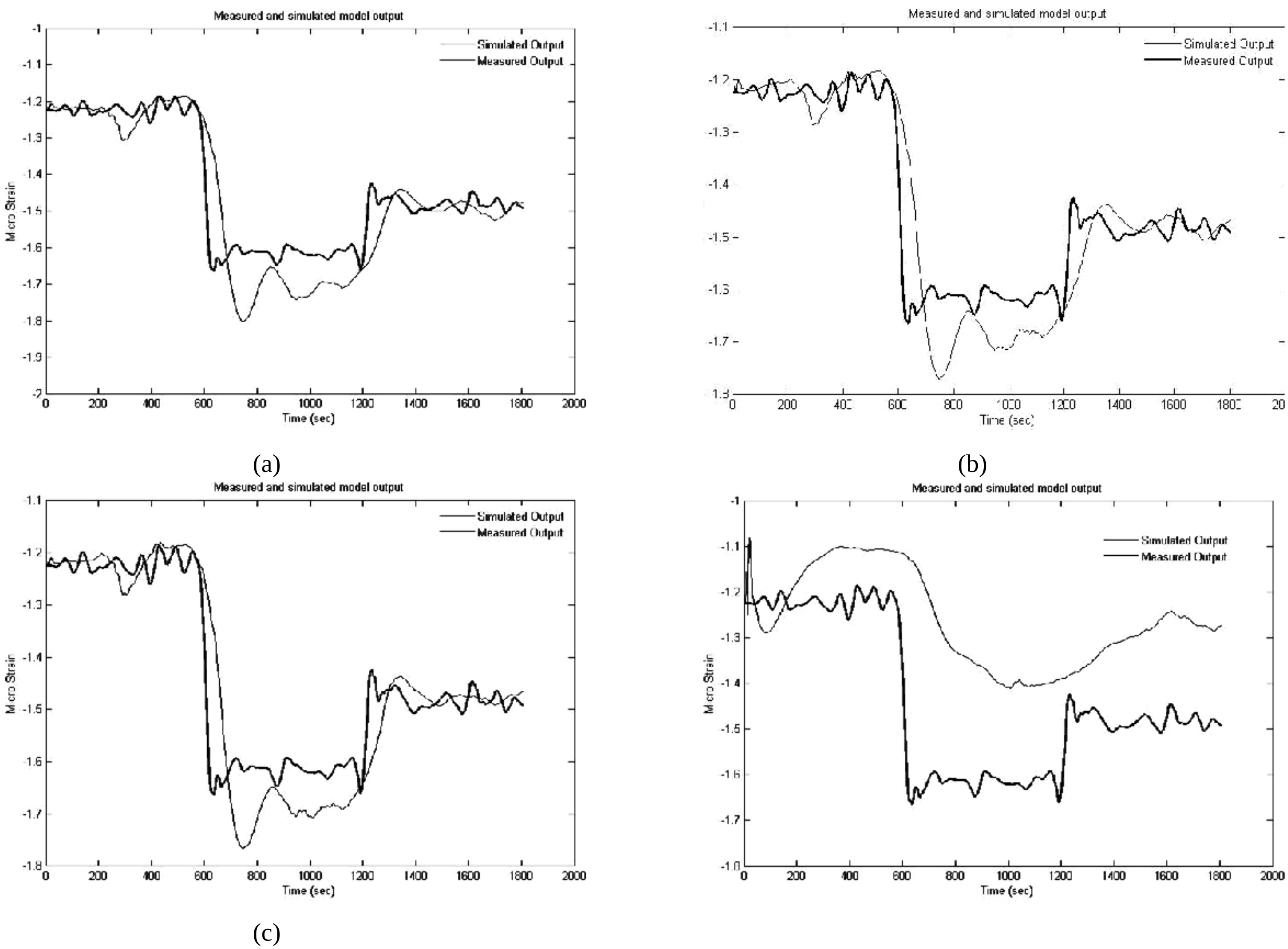
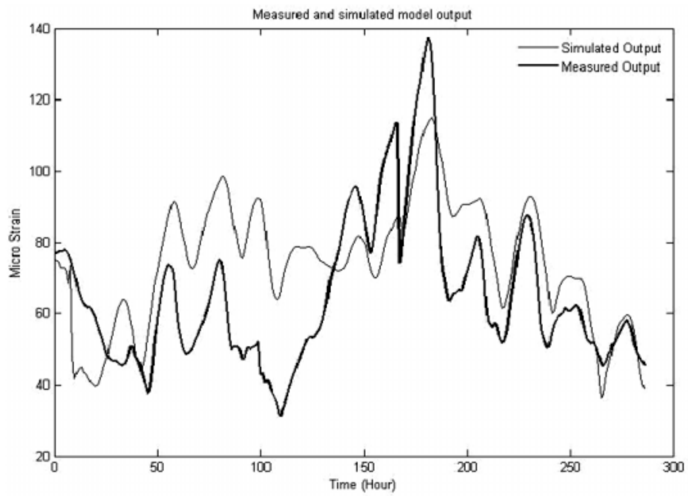


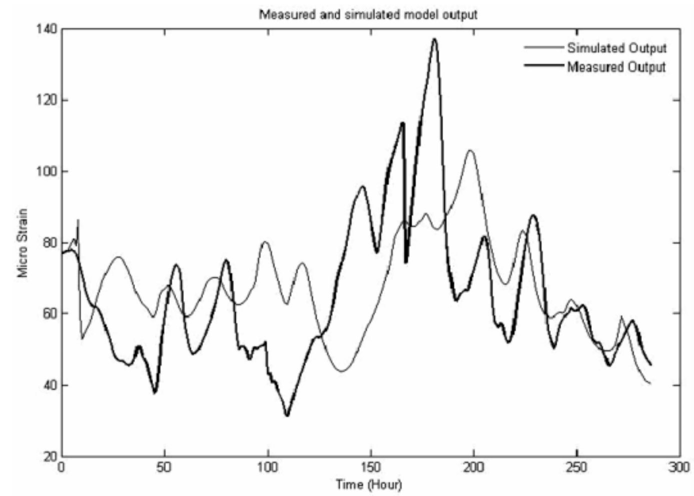
Figure E.4 Measured and Simulated output of December 2003 in Sequential Search Method (a) sensor# 1 eliminated, (b) sensor# 2 eliminated, (c) sensor# 3 eliminated, (d) sensor# 4eliminated.

Appendix F

Graphical Outputs of known defective sensor detection for Portage Creek Bridge by Binary Search Method. The details are described in Chapter 5, section 5.2.2.1, Case 1

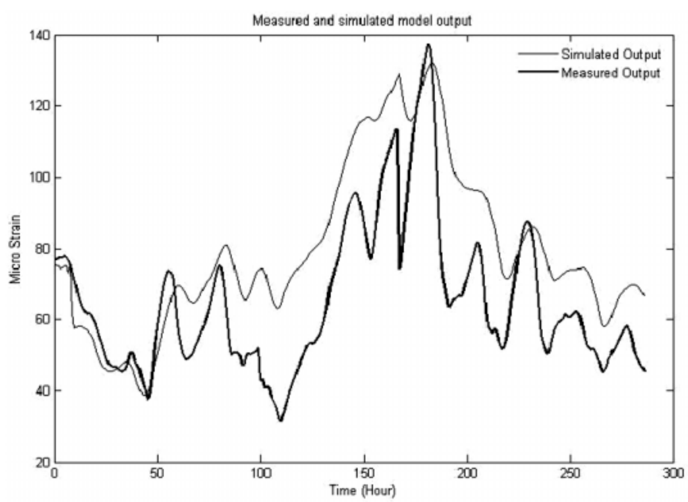


(a)

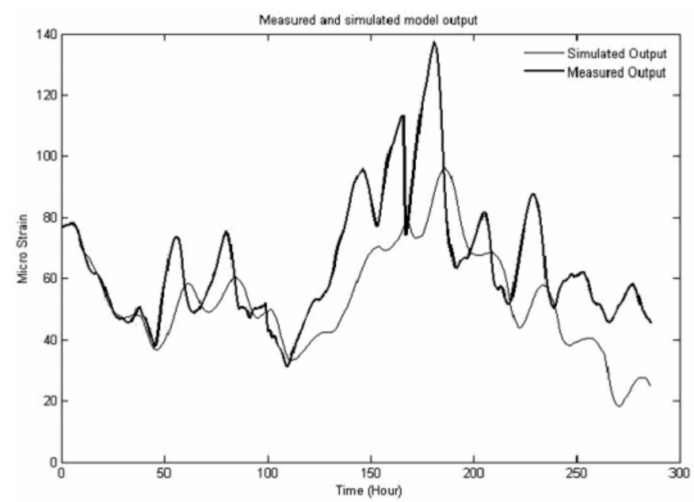


(b)

Figure F.1 Measured and Simulated output of March 2006, (a) Group_1, (b) Group_2

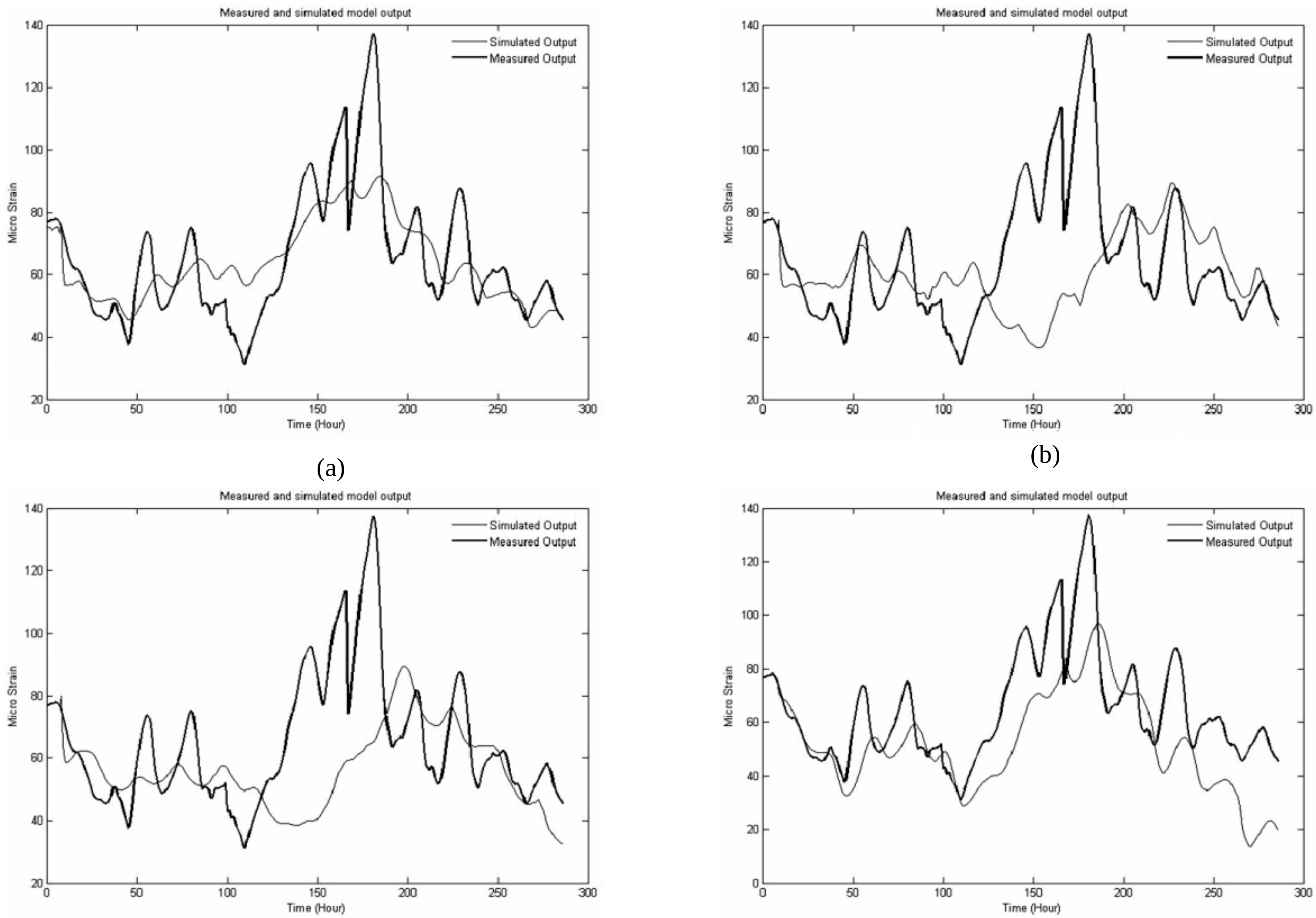


(a)



(b)

Figure F.2 Measured and Simulated output of March 2006, (a) 1st subgroup of group_2, (b) 2nd subgroup of group_2.



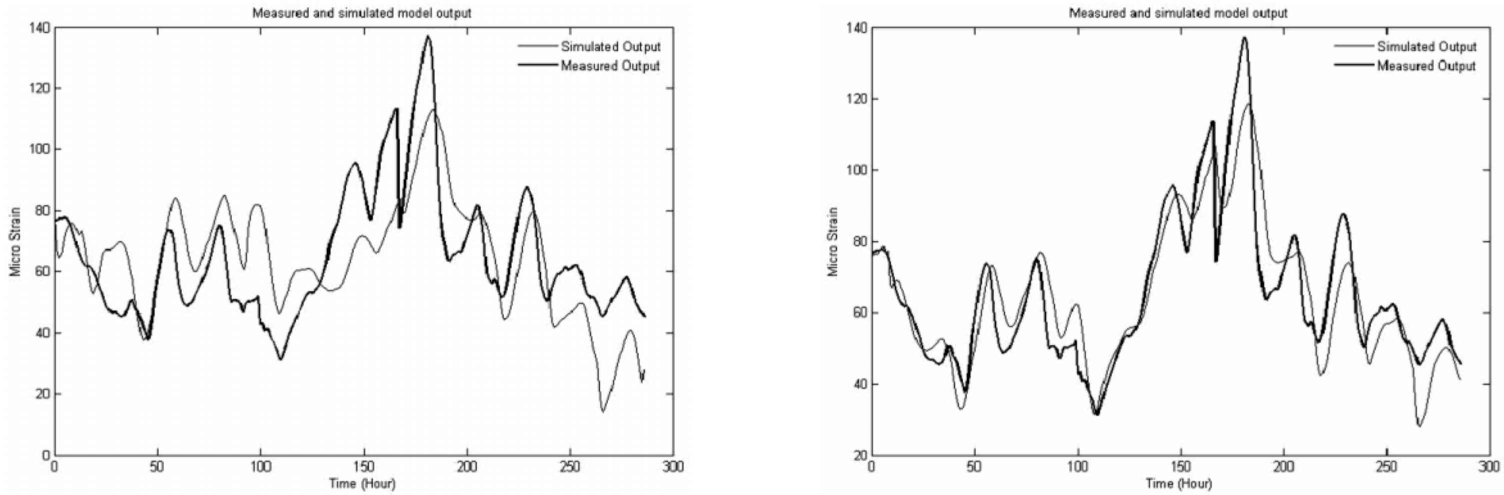
(a) (b)

(c) (d)

Figure F.3 Measured and Simulated output of March 2006 in Sequential Search Method (a) sensor# 5_2 eliminated, (b) sensor# 6_1 eliminated, (c) sensor# 6_2 eliminated, (d) sensor# 7_1eliminated.

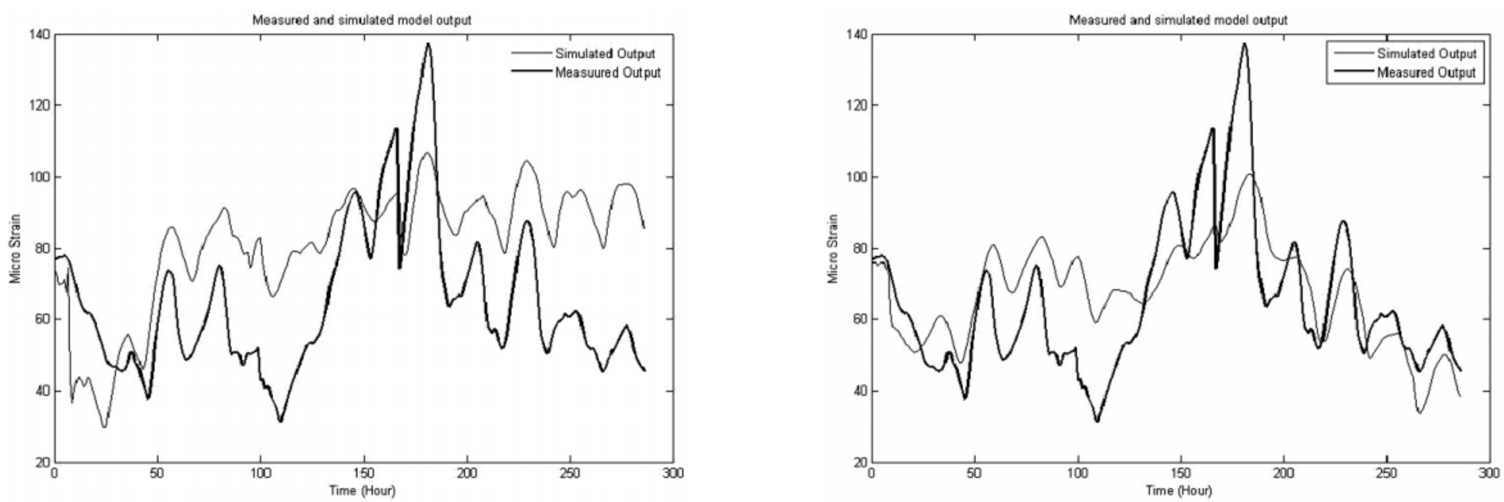
Appendix G

Graphical Outputs of known defective sensor detection for Portage Creek Bridge by Binary Search Method. The details are described in Chapter 5, section 5.2.2.1, Case 2



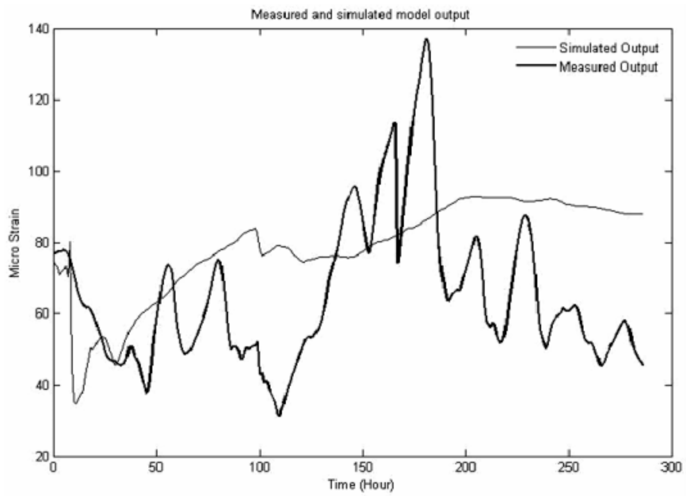
(a) (b)

Figure G.1 Measured and Simulated output of March 2006, (a) Group_1, (b) Group_2

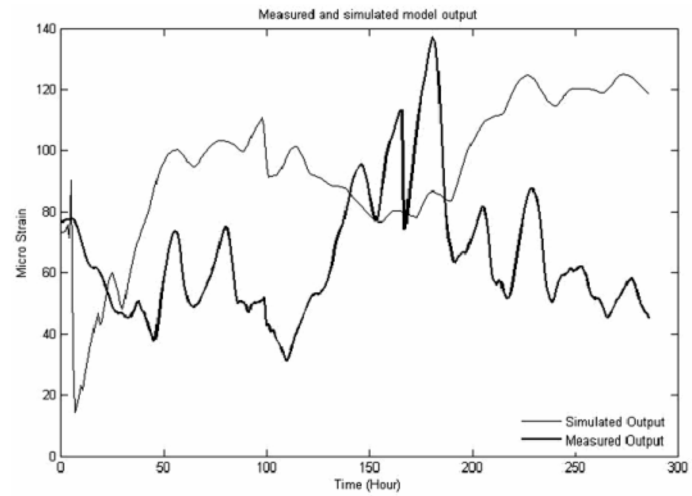


(a) (b)

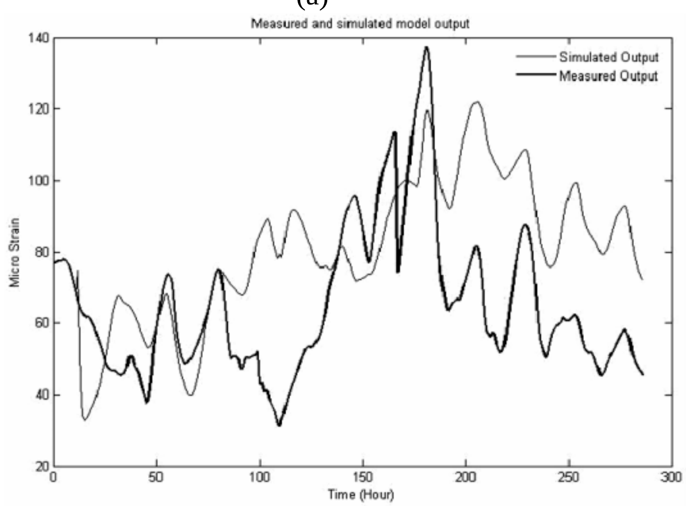
Figure G.2 Measured and Simulated output of March 2006, (a) 1st subgroup of group_1, (b) 2^{nd} subgroup of group_1.



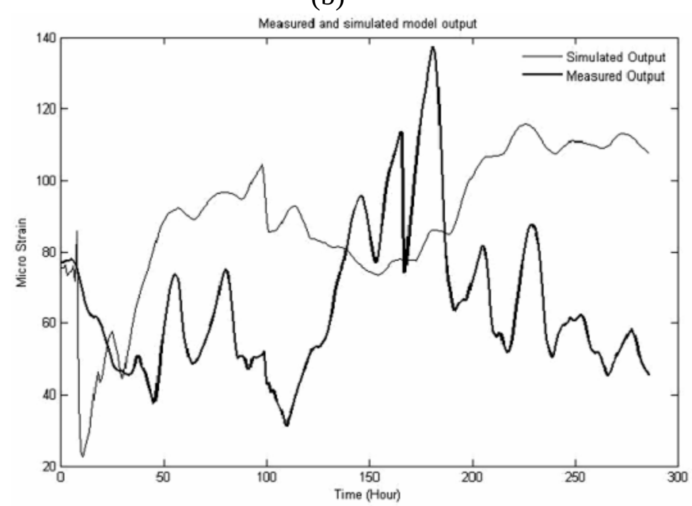
(a)



(b)



(c)

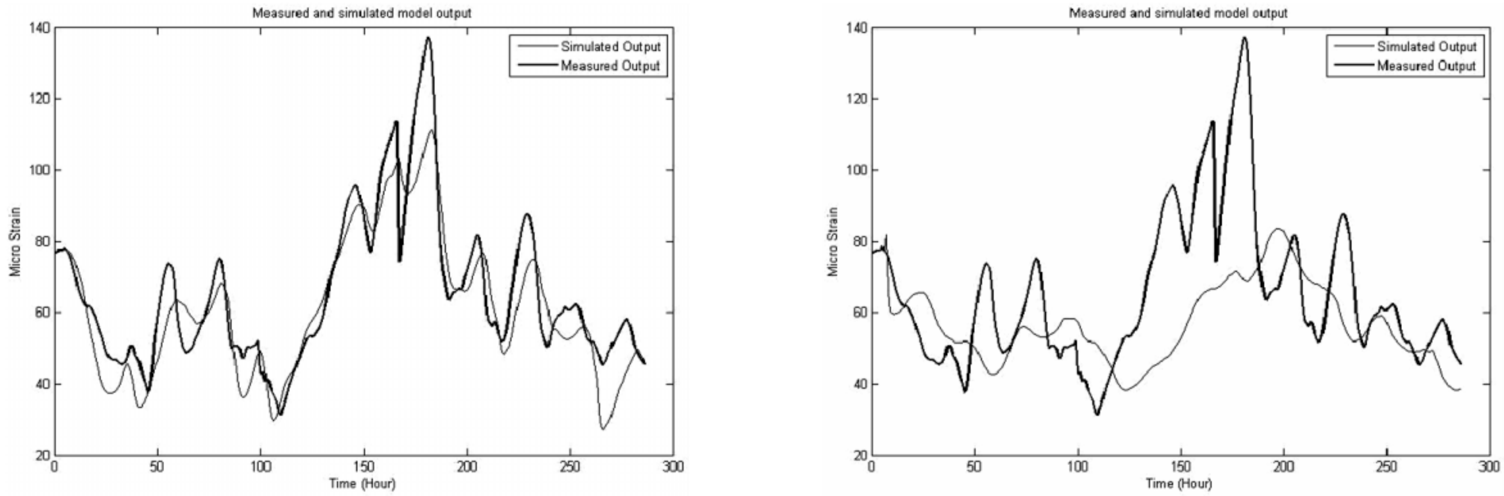


(d)

Figure G.3 Measured and Simulated output of March 2006 in Sequential Search Method (a) sensor# 1_1 eliminated, (b) sensor# 1_2 eliminated, (c) sensor# 2_1 eliminated, (d) sensor# 2_2eliminated.

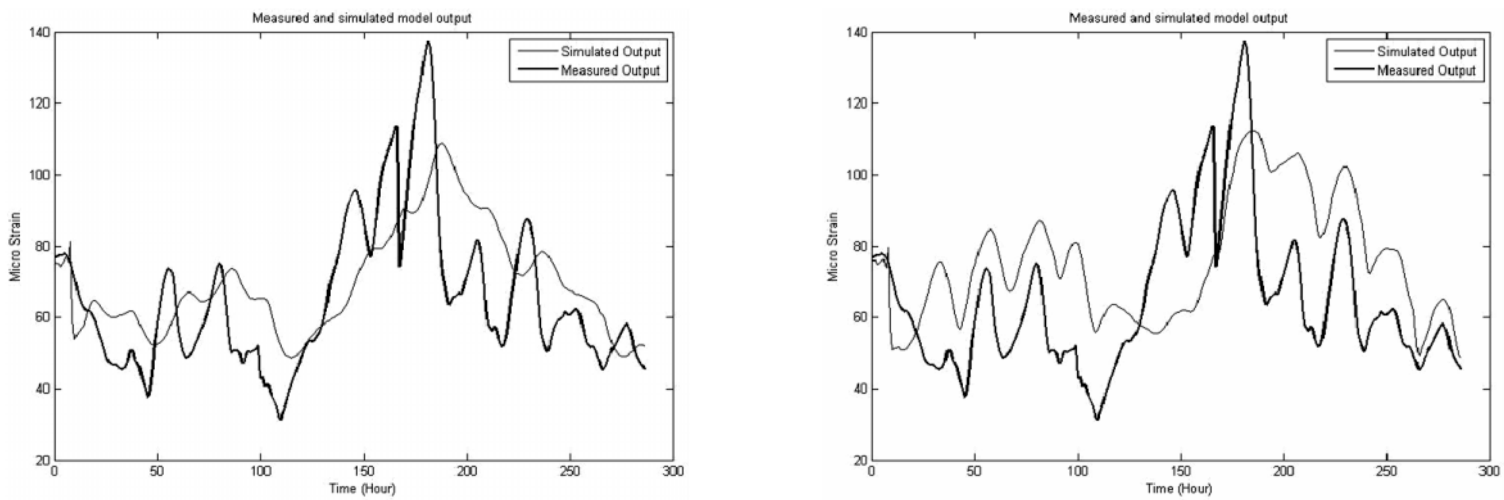
Appendix H

Graphical Outputs of known defective sensor detection for Portage Creek Bridge by Binary Search Method. The details are described in Chapter 5, section 5.2.2.1, Case 3



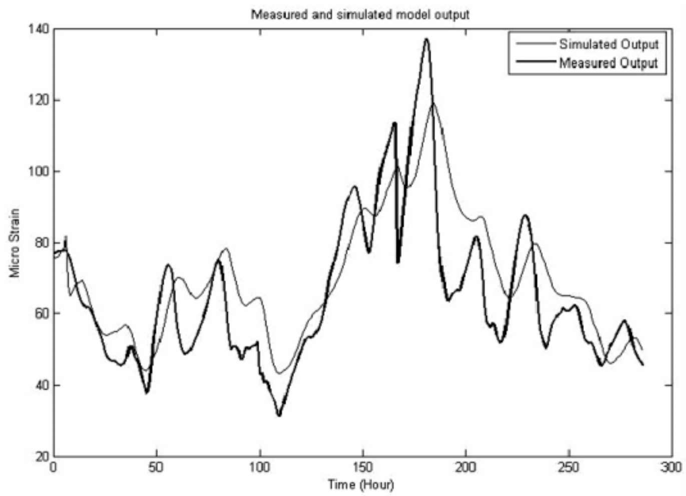
(a) (b)

Figure H.1 Measured and Simulated output of March 2006, (a) Group_1, (b) Group_2

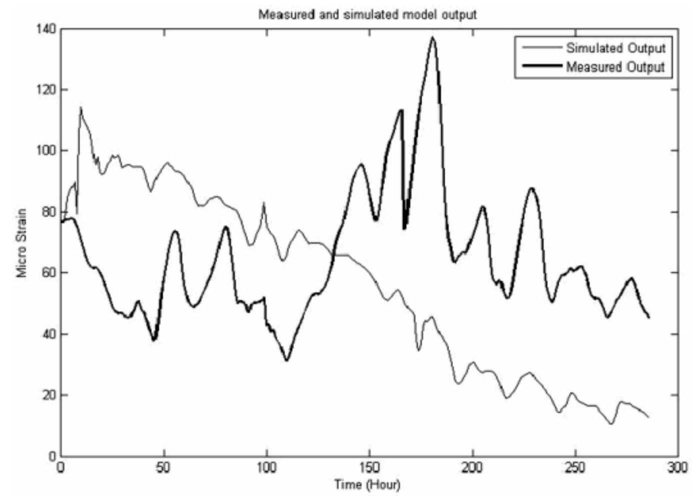


(a) (b)

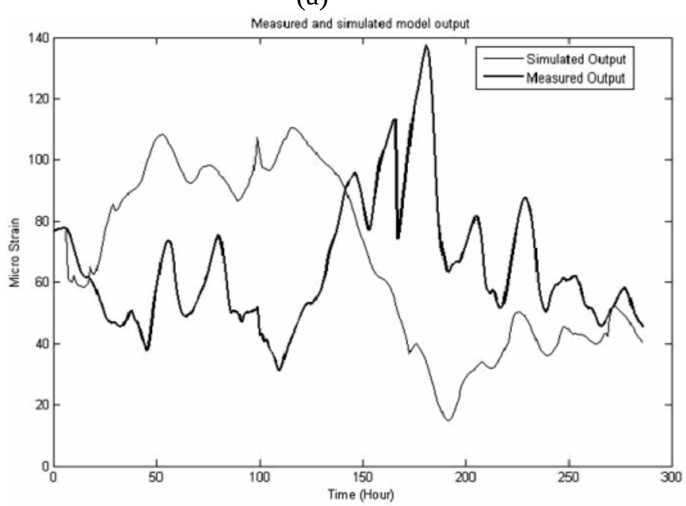
Figure H.2 Measured and Simulated output of March 2006, (a) 1st subgroup of group_2, (b) 2^{nd} subgroup of group_2.



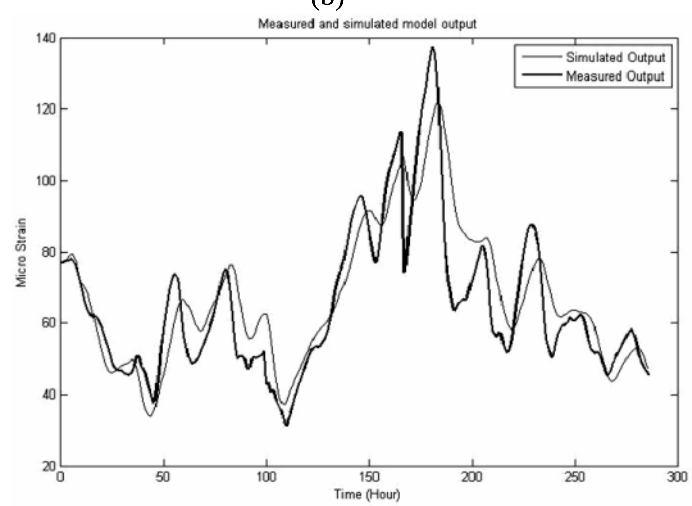
(a)



(b)



(c)

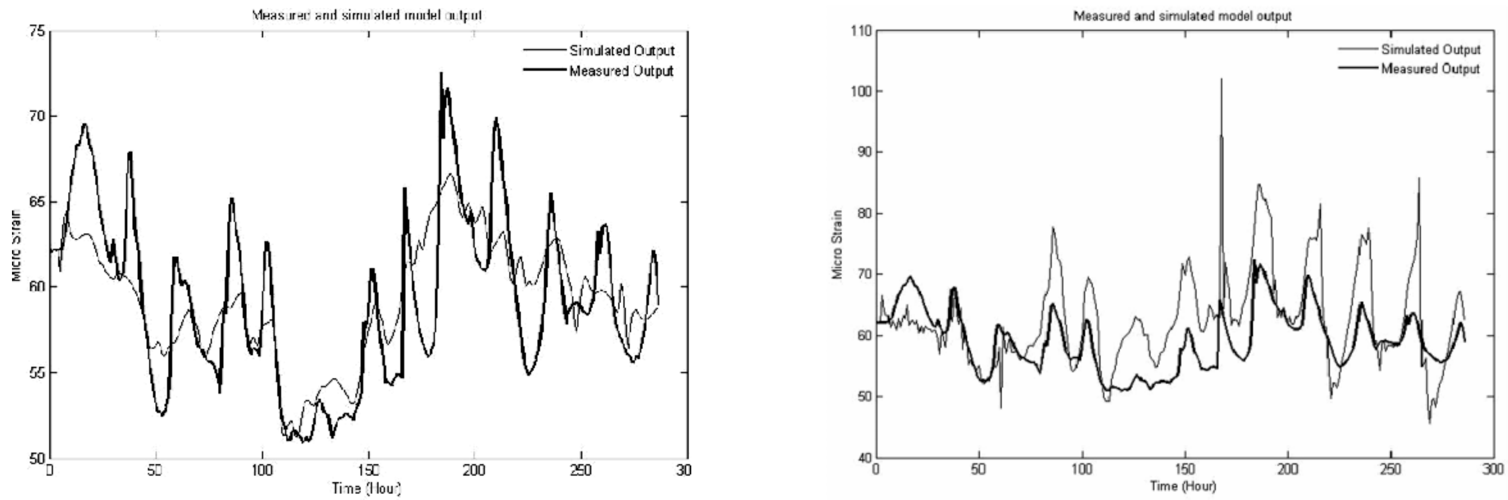


(d)

Figure H.3 Measured and Simulated output of March 2006 in Sequential Search Method (a) sensor# 5_2 eliminated, (b) sensor# 6_2 eliminated, (c) sensor# 7_2 eliminated, (d) sensor# 8_2eliminated.

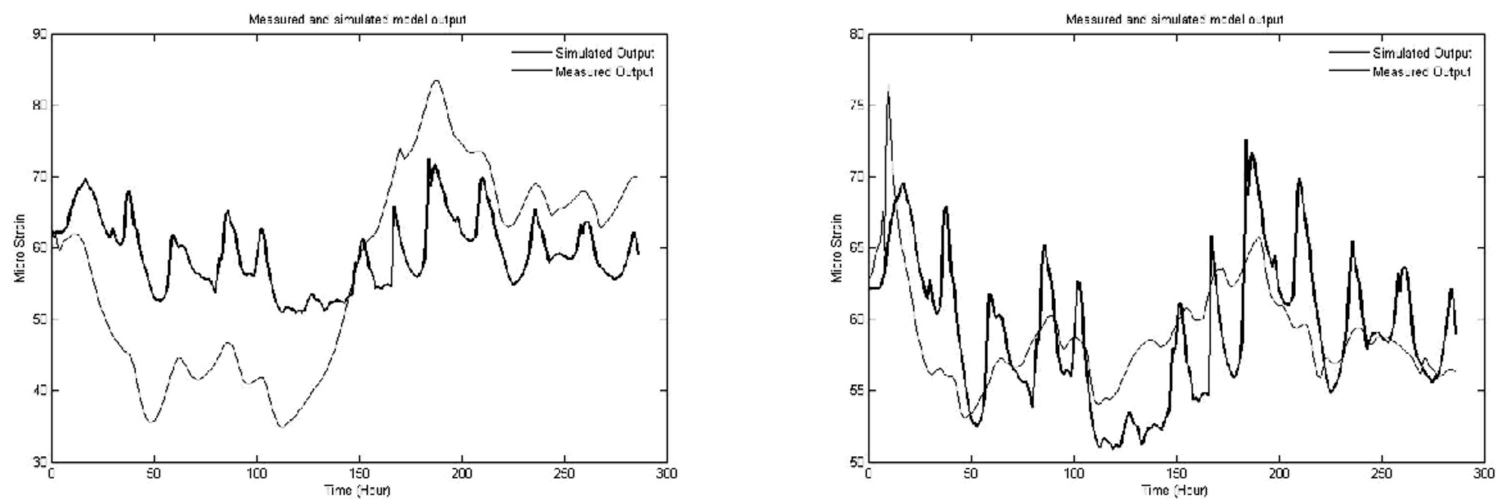
Appendix I

Graphical Outputs of known defective sensor detection for Portage Creek Bridge by Binary Search Method. The details are described in Chapter 5, section 5.2.2.2, Case 1



(a) (b)

Figure I.1 Measured and Simulated output of March 2006, (a) Group_1, (b) Group_2



(a) (b)

Figure I.2 Measured and Simulated output of March 2006, (a) 1st subgroup of group_2, (b) 2nd subgroup of group_2.

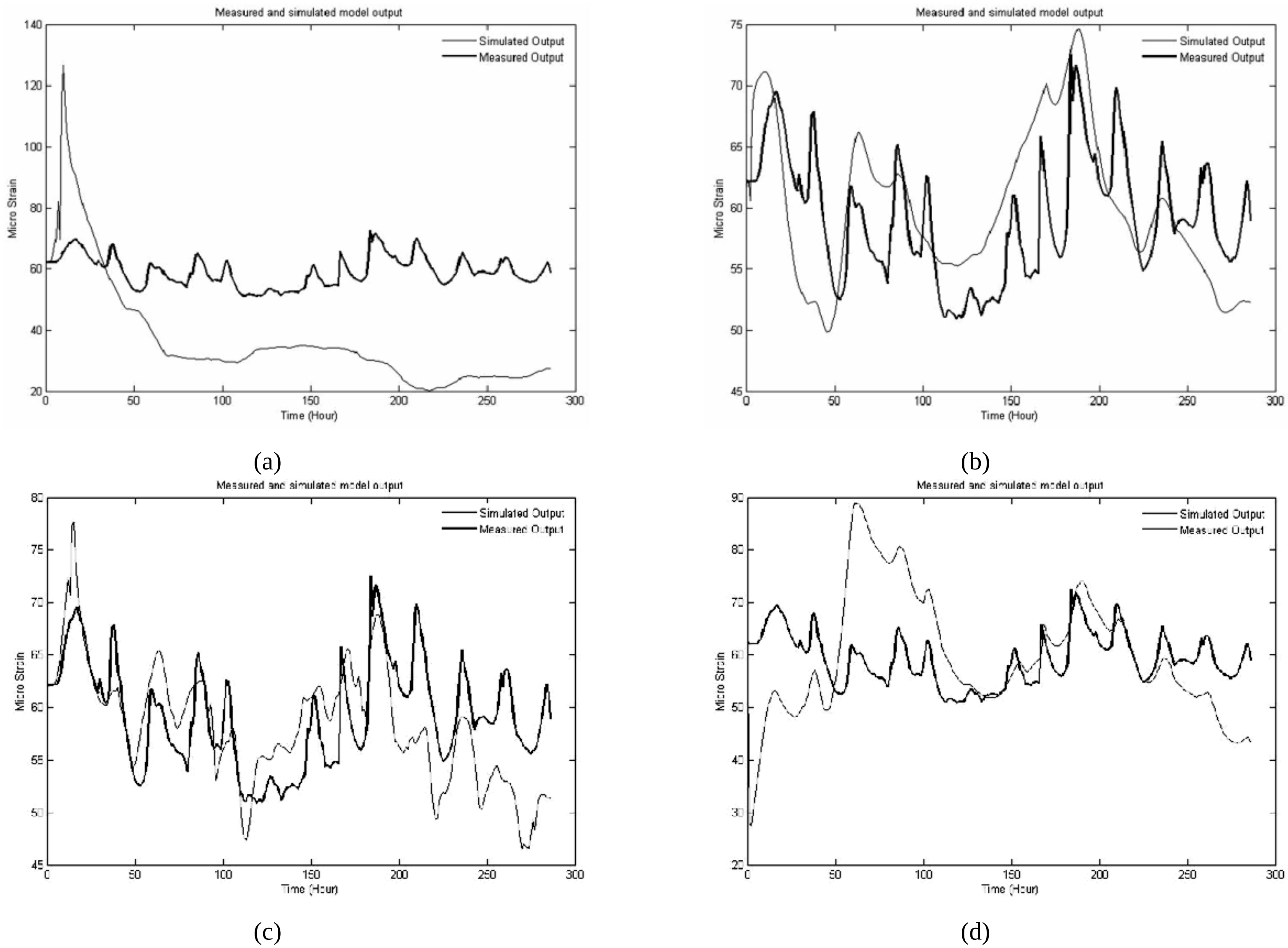
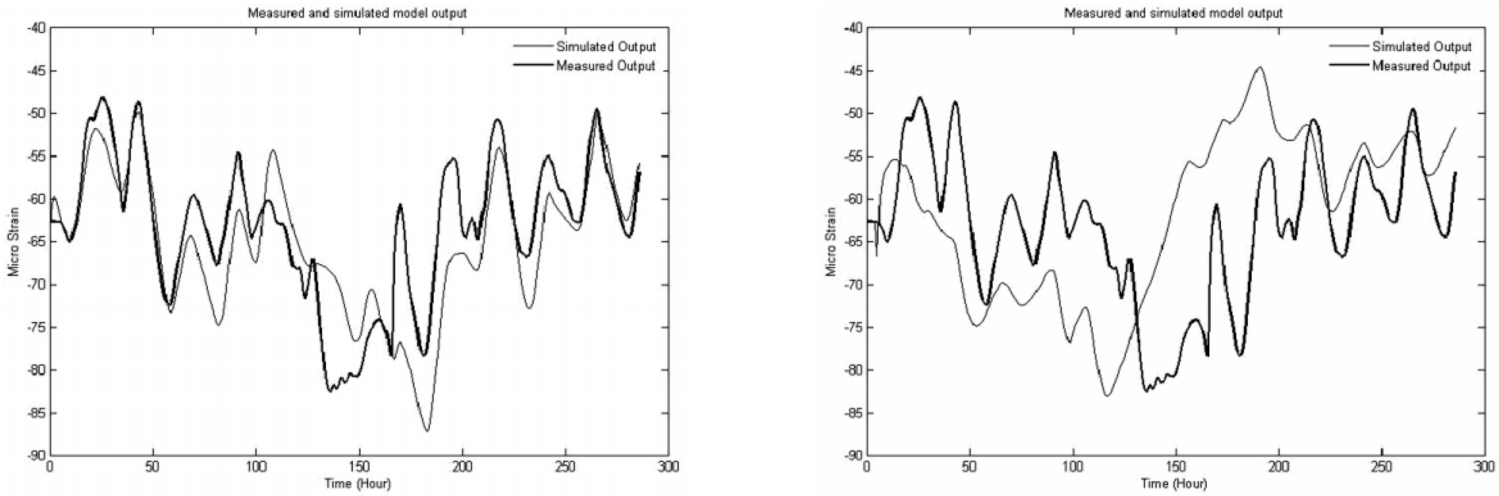


Figure I.3 Measured and Simulated output of March 2006 in Sequential Search Method (a) sensor# 5_2 eliminated, (b) sensor# 6_1 eliminated, (c) sensor# 6_2 eliminated, (d) sensor# 7_1eliminated.

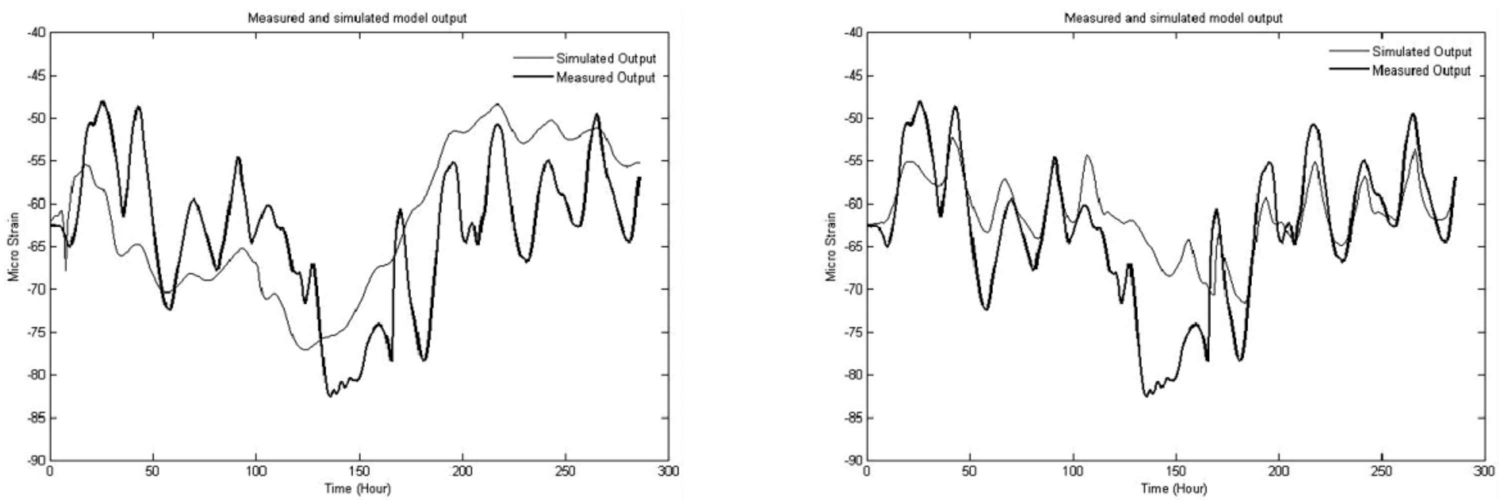
Appendix J

Graphical Outputs of known defective sensor detection for Portage Creek Bridge by Binary Search Method. The details are described in Chapter 5, section 5.2.2.2, Case 2



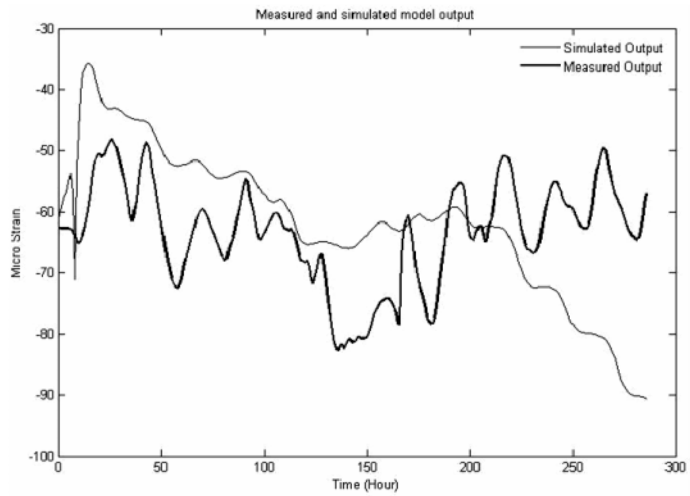
(a) (b)

Figure J.1 Measured and Simulated output of March 2006, (a) Group_1, (b) Group_2

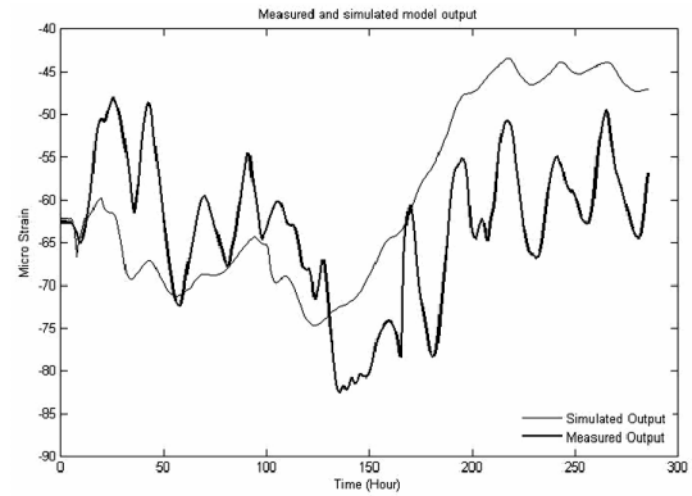


(a) (b)

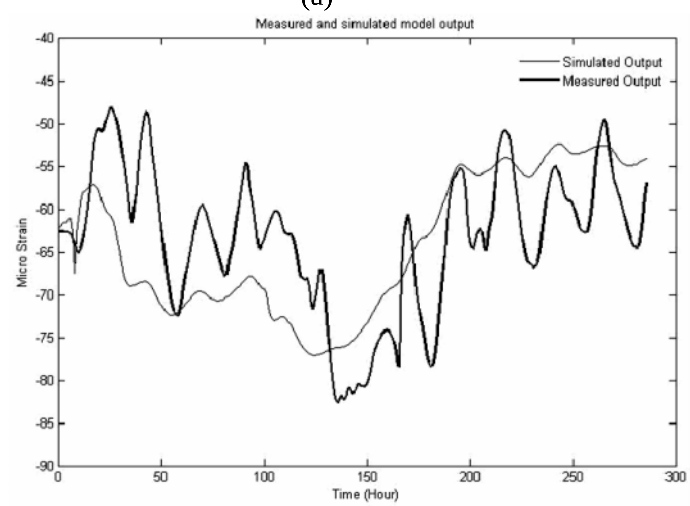
Figure J.2 Measured and Simulated output of March 2006, (a) 1st subgroup of group_2, (b) 2nd subgroup of group_2.



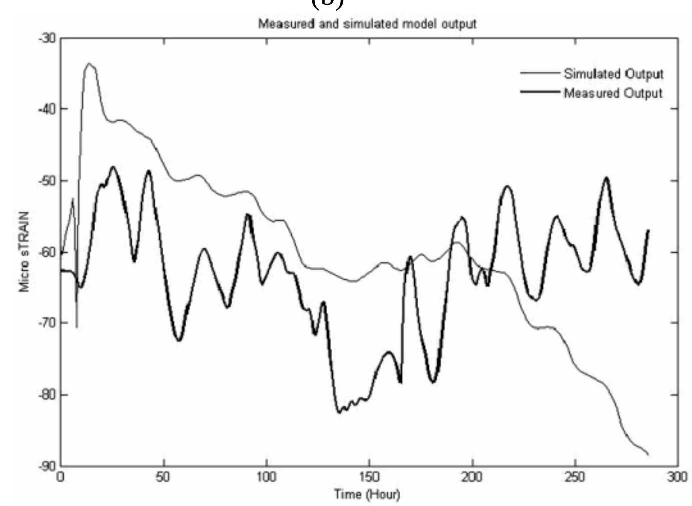
(a)



(b)



(c)

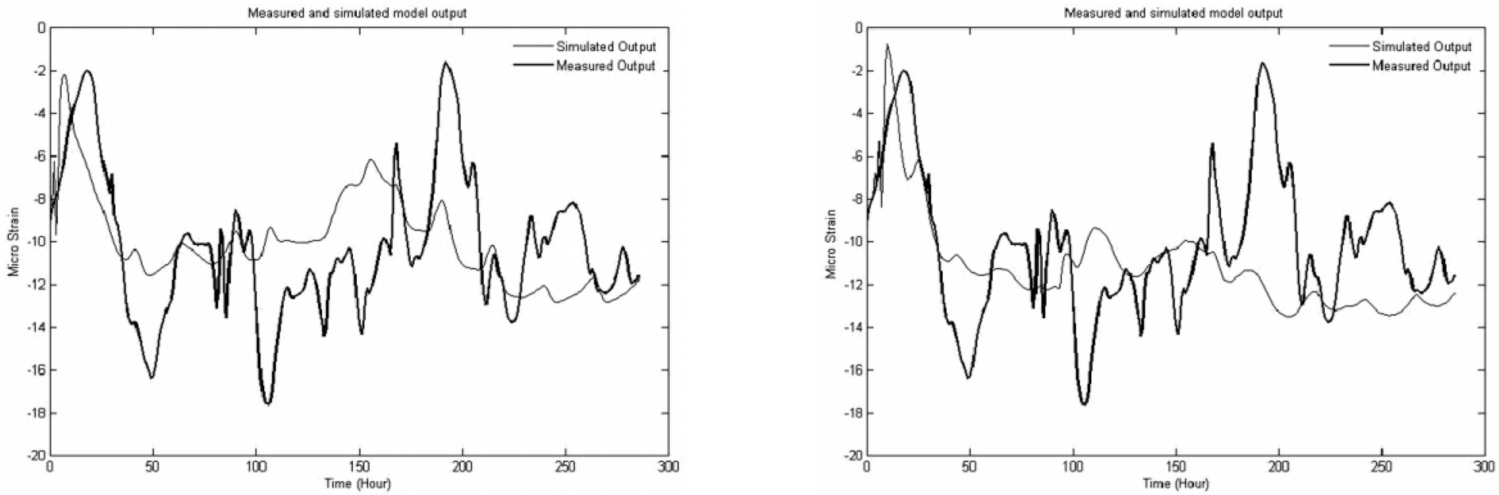


(d)

Figure J.3 Measured and Simulated output of March 2006 in Sequential Search Method (a) sensor# 5_2 eliminated, (b) sensor# 6_1 eliminated, (c) sensor# 6_2 eliminated, (d) sensor# 7_1eliminated.

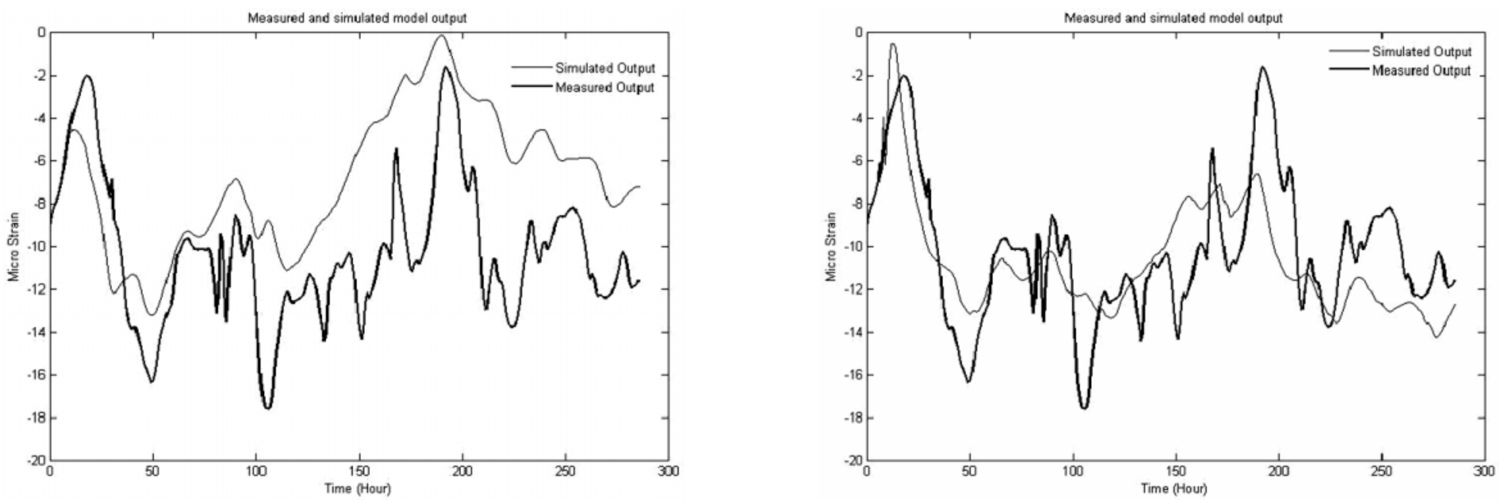
Appendix K

Graphical Outputs of known defective sensor detection for Portage Creek Bridge by Binary Search Method. The details are described in Chapter 5, section 5.2.2.2, Case 3



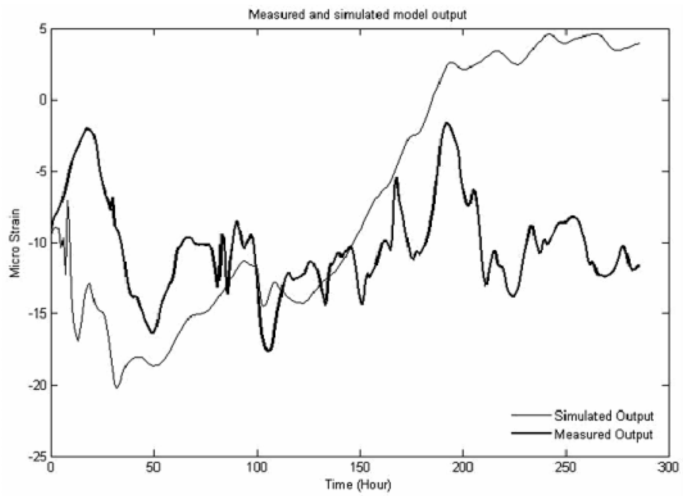
(a) (b)

Figure K.1 Measured and Simulated output of March 2006, (a) Group_1, (b) Group_2

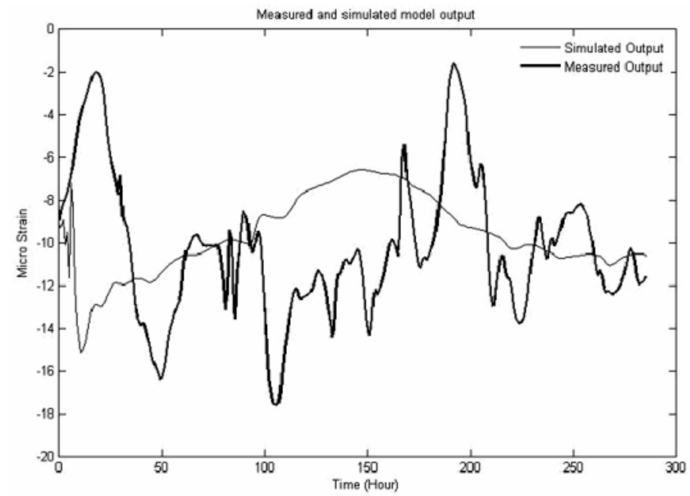


(a) (b)

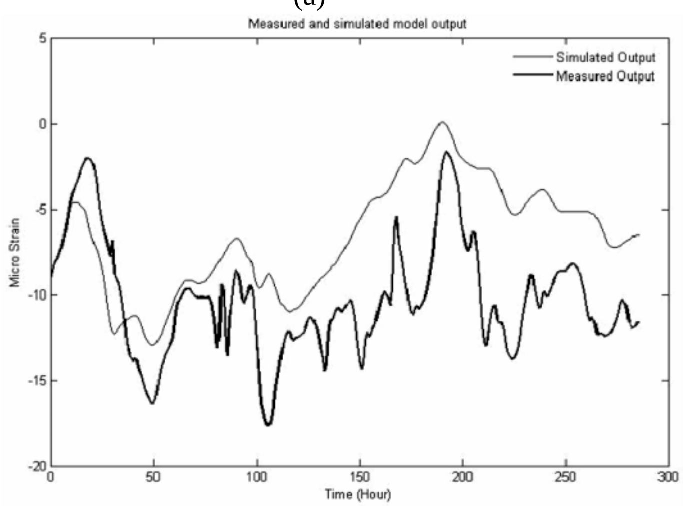
Figure K.2 Measured and Simulated output of March 2006, (a) 1st subgroup of group_2, (b) 2nd subgroup of group_2.



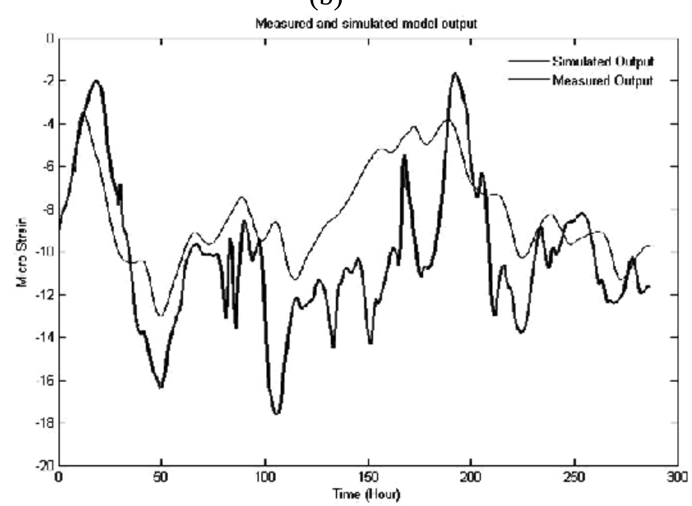
(a)



(b)



(c)



(d)

Figure K.3 Measured and Simulated output of March 2006 in Sequential Search Method (a) sensor# 5_1 eliminated, (b) sensor# 5_2 eliminated, (c) sensor# 6_1 eliminated, (d) sensor# 6_2eliminated.