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ARTIFICIAL NEURAL NETWORKS FOR WIRELESS STRUCTURAL CONTROL

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To my Mom; to my Dad.

Thank you.

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(The names are put in alphabetical order.)

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This thesis is dedicated to my family—my Mom, my Dad, and my little sister.

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ABSTRACT

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We live in an age when people desire taller buildings and longer bridges. These increasing demands of more flexible structures challenge civil engineers to ensure structural safety in the state where they are more prone to extreme dynamic loading, such as earthquakes. Extensive wiring required in traditional structural control applications may be expensive and inconvenient, especially for large scale structures. To improve the scalability, wireless sensors offer a promising alternative. However, the presence of time delay and data loss in a wireless sensor network can potentially reduce the performance of the control system. Here an artificial neural network is proposed to improve the performance of a wireless sensor network based control system. The proposed technique is named as Neural Network Wireless Correction Function (NNWCF). By applying this strategy, a wireless structural control can be utilized without experiencing major performance degradation due to the wireless characteristics.

Keywords: structural control, artificial neural network, wireless sensor network

1. INTRODUCTION

Keeping structures safe during their lifetime becomes more challenging as demands for more flexible civil structures (taller buildings and longer bridges) increase with societal expectations. Flexible structures tend to be prone to extreme dynamic loading, such as earthquakes, due to the relatively small amount of inherent damping present in the structures [1]. In the last decades, control techniques have been employed in numerous applications to protect structures from extreme loading. However, extensive wiring is required in traditional applications of the structural control systems. The cabling and installation demands are expensive and inconvenient, especially for large scale structures.

To improve the scalability of structural control systems, wireless sensors offer a promising alternative. Nevertheless, some challenges presented in wireless sensor networks including the presence of time delay and data loss in data transmission. The presence of time delay and data loss can potentially reduce the performance of a control system.

Here an artificial neural network is proposed to improve the performance of a wireless sensor network based control system. The proposed technique is named as Neural Network Wireless Correction Function (NNWCF). One example where NNWCF can be employed is in structural control systems, in which NNWCF can improve the performance of a wireless structural control. By applying this strategy, a wireless structural control can be utilized without experiencing major performance degradation due to the wireless characteristics.

1.1 Control System to Mitigate Seismic Hazards in Civil Structures

We live in an age when people desire taller buildings and longer bridges. These tendencies are often seen in big cities where land is inadequate to provide sufficient capacity for the growing population.

In traditional structural engineering, structures are designed based on static loads applied to them. Although, in most cases, dynamic loading also plays a significant role in the structures' performance. Large vibrations in a structure can be caused by severe environmental loading (e.g. earthquakes or strong winds) and may endanger safety to its occupants and damage nonstructural components, equipment, or valuable building content.

There are several ways to control structural vibrations due to dynamic loading. The traditional approach is by modifying the structural properties, such as stiffness, mass, or damping properties. Other approach is by employing a control technique to the structure. This technique can be implemented by generating a force to the structure that will counter the excitation experienced by the structure. This counter force can be produced by a passive or an active system. This strategy will allow the system to adapt its dynamic behavior regarding to a particular dynamic excitation due to the external loading.

The control system attributes its roots to concept in aerospace engineering due to necessity in aerospace engineering to problems like tracking or pointing. The civil engineering profession is gaining greater acceptance of this technology. One main difference between the application of the systems in the two different fields is the environment at conditions. In most aerospace engineering problems, the object under control is intended to float in open space. Meanwhile, most civil engineering objects, such as buildings and bridges, are anchored to a fixed boundary condition. Therefore, it is stable from the start. Additionally, civil engineering design is replete with uncertainties that arise from variable load [2] that may introduce another challenge in adopting the control system to civil engineering applications.

Early in the development of control systems, researchers classified them into two groups: passive and active. The difference between those two control systems is in the presence of an energy supply, feedback, and control computer to run the system.

In the passive system, the control device does not require any external power, sensors, or computer. The system itself has been tuned or designed so that it can respond by itself to any dynamic excitation that shakes the structure. However, the passive control system is usually only suitable for one (or a few) dominant frequency of external dynamic loading. Therefore, in the case where a random dynamic force is applied to the structure, it may not always yield a desirable performance. Also, the responses in a poorly designed system might get worse with the application of the passive damper since the control system fundamentally changes the dynamic properties of the structure (mass, stiffness, or damping).

The idea of making the control system adaptable to any dynamic loading that the structure might be subjected to led to the development of active control system. Three principal components in active control systems that are not found in passive control are sensors, an energy supply, and a control computer. The energy supply provides a mean to generate force to change the dynamic properties of the structures depending on the loading. To determine the forces to apply that are appropriate for the dynamic responses of the structure, the control computer is there to perform the computational tasks. Sensors are used to determine the responses and compute the control action. A suitable algorithm must be designed to provide the control force for the desired performance. By connecting all these, an active controller can be implemented.

The rapid development of new technologies in the control world led to many other types of control strategies. Since the requirement of external power in the active controller during natural hazards sometimes results in cost issue, semi-active control is being explored. The semi-active approach can adapt the properties of the control device due to the loading nature, but not by inserting mechanical energy to the system, as an active system controls the structural motion. The semi-active control has mechanical properties which have the ability to vary dynamically based on the dynamic responses and control inputs.

Another control approach is developed by combining the use of passive and active control systems. This implementation is named a hybrid control strategy. This strategy has been gaining interest from either industry and academics.

Some writings document the first suggestions for using control techniques in structural engineering applications in the 1960s [3]. Since then, researchers and engineers in the structural engineering community have employed this technology in different approaches, though all those aim for one common goal: to reduce the dynamic excitation experienced by civil structures. As control systems have become a very useful tool for structural engineers, this field is still developing with new research and implementations being considered frequently.

1.2 Wireless Sensor Networks to Improve Scalability of Structural Control Systems

In structural control systems, communication must take place to provide a link between sensors, actuators, and controllers. While wires have been a popular choice to connect those three components of the structural control system, the cost and the complexity of installation of the system increases as larger control systems are examined. For instance, in an actual building, the deployment of cables may create conflicts with the building's architectural or mechanical components. Moreover, physical damage may also occur to wires during its operation.

On the other hand, wireless sensor network offers flexibility in installation and it also avoids a significant increment in the cost when larger structure is investigated [4–6]. Also, they are relatively free from the risk of mechanical damage during its service time, as long as all electrical components can be guaranteed to work. Nevertheless, the presence of time-delay [7–9], data loss [10,11], and sensor failure [12,13] during the data transmission are potential drawbacks of this system, and thus appropriate design choices need to be made. A benchmark model was initiated to provide a standard system that would enable study of such issues [14].

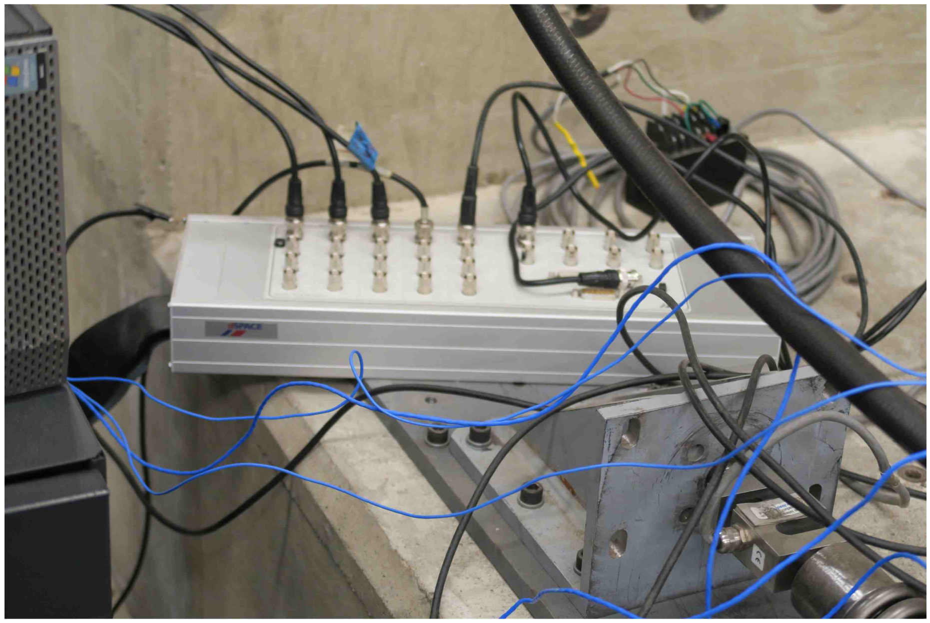


Figure 1.1. Wires may cause inconvenience for installation and maintenance

Various studies have been conducted to address these concerns and even integrate them using co-design approaches. The purpose of this research is to consider the use of intelligent systems, specifically artificial neural network, to accommodate the presence of time delay, data loss, and sensor failure in the system.

1.3 Introduction to Artificial Neural Networks

1.3.1 Nature-Inspired Design

Humans are curious creatures. We, perhaps, are the only animals that make efforts to understand the question: how does nature work? This existential thought inspires us to gain an understanding of the complex operation of nature.

As we understand how nature works, it inspires us to mimic nature's functions to make our life easier. Humans, perhaps, have had a desire to fly since we saw birds for the first time. Many of our tales also are filled with the characters of avian humanoids, such as Hermes or the Garuda. Thus, no surprise if the invention of the airplane in the early 20th century by the Wright brothers was actually an attempt to gather a biological function (flying) by replicating biological structures in the birds (wings, tails, and so on).

1.3.2 The Rise of Artificial Intelligence

Thinking machines and artificial intelligence have been depicted in mythologies and popular culture, from the tales of Talos to HAL9000 of *2001: A Space Odyssey*. The desire to create an artificial intelligence has probably arisen from the necessity to ease human's tasks.

In recent news, Google DeepMind developed an artificial intelligence named AlphaGo that was able to defeat professional human players [15]. This is viewed as an important milestone for the field of artificial intelligence due to the complex nature of the game of Go. Artificial intelligence has been successfully defeated humans in chess (1994, IBM's Deep Blue v. Garry Kasparov) [16] and even *Jeopardy!* (2011, IBM's Watson v. Brad Rutter and Ken Jennings) [17]. However, Go is considered to be different.

The complexity of a game of Go, particularly to be mastered by a computer program, had been well recognized since 1960s when mathematician Irving Good pointed out the challenges in making a computer program that is able to master Go.

> "In order to programme a computer to play a reasonable game of Go, rather than merely a legal game--it is necessary to formalise the principles of good strategy, or to design a learning programme. The principles are more qualitative and mysterious than in chess, and depend more on judgment. So I think it will be even more difficult to programme a computer to play a reasonable game of Go than of chess." —I. J. Good, 1965 [18]

Good compared the complex nature of the Go game with chess, the more well known board game in the Western culture. In a Go game, there are about 250 possible moves in each step (compared to 35 in chess). Also, a typical Go game usually lasts longer (about 150 moves in Go, compared to 80 in chess). Lastly, the number of possible board configuration at the end of a Go game is higher than the number of atoms in the universe. Considering these, Go is viewed as the most challenging classic game for artificial intelligence [15].

Due to the abundant possibilities in a Go game, some experts claim that moves in a Go game are decided more intuitively rather than just a purely logical decision—this is why Go is hard to be programmed. Giving intuition to a computer is something that was beyond human's imagination in the decades before the rise of the artificial intelligence.

1.3.3 Neural Network: A Technique That Gives a Computer Intuition

The key to how Google DeepMind was able to develop a successful algorithm that can master Go is by giving AlphaGo an ability to learn from previous Go games played by humans. To give a learning ability to a computer, they combine deep neural networks and Monte Carlo tree search [15]. Two artificial neural networks are employed: "value network" to evaluate board positions and "policy network" to select moves. Then a search algorithm that combines these networks and the Monte Carlo tree search are introduced, and demonstrates strong performance in Go games.

The artificial neural networks embedded in the algorithm inside the AlphaGo are trained by numerous Go games, and they are taught to reinforce its understanding of the moves that can provide a higher winning chance. By these procedures, AlphaGo gains its "intuition," which is made possible by the technique of artificial neural network.

But, what is artificial neural network? The artificial neural network is a computational model that is philosophically inspired by a biological neural network. Artificial neural network is humans' attempt to replicate biological function of neural structure in animals' brains (like when Wright brothers replicated biological functions in birds to mimic their ability to fly). In the next discussions, the artificial neural network will often be shortened as simply "neural network," while the biological neural network will always be referred as "biological neural network."

1.3.4 Biological and Artificial Neural Networks

The human brain is believed to be the home of our mind. In the brain, information is transferred and processed by a network of nerve cells called a neural network. A biological neural network is created by a big number of neurons. A neuron consists of a cell body and two types of branches: axons (transmitters) and dendrites (receivers). An illustration of a biological neural network is shown in Figure 1.2.

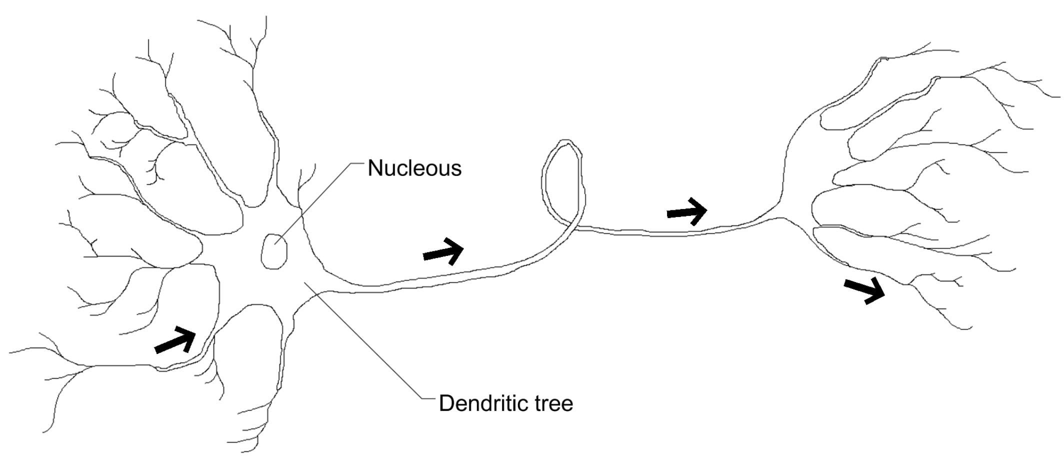


Figure 1.2. Biological neuron

Neurons are linked together in a neural network. Each neuron meets at a contact point called a synapse. Each synapse has a gap called a synaptic space which measures about 0.1 micrometers where chemical and electrical signals are passed from one neuron to another. A diagram of a synapse is illustrated in Figure 1.3. When the neuro-transmitter diffuses across the synaptic gap, it activates the receptor in the receiving cell. An electrically positive transmission fron the neuro-transmitter will stimulate the receptor to process an excitation while an electrically negative transmission will be processed as an inhibitation. These provide a basic understanding of how information is transferred in a brain.

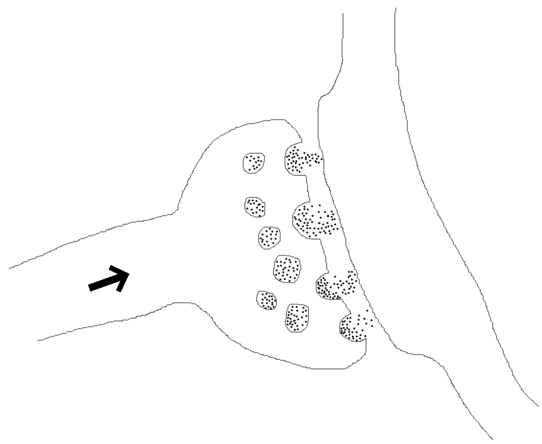


Figure 1.3. Synapse

This procedure has been adopted by computer scientists to develop the artificial neural network. The architecture of an artificial neural network can be categorized into three groups: input, target, and hidden layer(s). The last is optional to be present in an artificial neural network. Each neuron contains a number that will be computed by a simple numerical operation.

The fundamental neural network is the feedforward neural network. This network only allows the information to be transferred forward and hierarchically. Neurons are connected to each other through synapses. Every synapse contains a weighting parameter that will multiply the value transmitted from the previous neuron to the next one. The simplest neural network consists of one input neuron, one target neuron, and no hidden layer. The next simplest neural network contains two input neurons and one target neuron (again, no hidden layer). Another parameter that can enhance the performance of a neural network is a bias term that is included in every neuron in hidden and target layers. Through several “training” processes, a set of input and target data are mapped by adjusting the weighting parameter and the bias term that determines the performance of the network.

1.3.5 Neural Network Procedure

The artificial neural network is powerful mainly because of its ability to “learn” through “training.” By the training procedure, the neural network is able to map between a set of data that are consisted of “inputs” and “targets.” The network generates some iterations to find the best parameters that can provide the best representation of the input-output relationship. The parameters involved in this network include hidden layers, some weighting values and bias terms, and the number of neurons in each layer.

Even though the neural network offers a powerful tool to model a complex system, many people argue its validity since there is no general mathematical framework presented in this technique. In general, a neural network is designed for a particular problem, so then it might not be suitable as a general solution. However, there are advantages of the technique, including modeling non-linearity in a structure, compensating for time delay, dealing with external noise disturbances in the environment, and so on.

Along with arguments regarding employing neural network as a “black box,” some more detailed questions may need to be considered. In Machine Learning course (CS 156) at California Institute of Technology, Professor Yaser Abu-Mostafa explained a situation in which he was doing a consulting job for a bank and was asked to make a neural network model to help the decision-making process of credit approval [19]. After the network has been designed, the bank asked the professor to explain the function of the hidden layers. It turned out that the question had nothing to do with the performance of the model. In fact, the question was asked based on a legal issue. Professor Abu-Mostafa ended his story with half-joking, "If you deny credit for someone, you have to tell them why. You cannot send a letter to someone [that] says, 'Sorry, we deny your credit because lambda is less than 0.5.' "

From the story, it is important to understand that the neural network is a black box but also that it is crucial for us to be able to interpret its results and take any responsibilities that might come from the network results. As a black box, the mathematical parameters in a neural network do not all have a physical interpretation.

Another question that may arise is about the topology of the neural network: how are the nodes or neurons connected? The most basic form of neural network is the feedforward neural network. The key operation of this type of neural network is that the flow only moves forward (there is no feedback included) and it cannot jump so it has to flow hierarchically. This type of neural network is also commonly referred as a concurrent neural network or a static neural network [20]. The opposite of this type of neural network is a recurrent neural network or a dynamic neural network [20]. In general, a dynamic neural network can provide better performance, yet it is also more difficult to train this type of neural network. The dynamic neural network offers a more powerful tool that is less prevalent than the static neural network. The strongest advantage of the dynamic neural network compared to the static one is the time series "memory" presented in the network that allows the hidden nodes to consider inputs from a previous time.

1.4 Intuitive Wireless Sensor Network

If an adult human sees Leonardo da Vinci's Mona Lisa, perhaps the most famous painting in the world, they most probably can recognize in a second that it is a painting of a lady. Humans will do it almost effortlessly. However, to perform this simple operation on a computer is a very complicated task to do. First, the computer has to process the millions of pixels of the image and distinguish each of its characteristics: color, texture, shape, and so on. Then, these properties must be compared with the information of known objects in nature such as mountains, guitars, or a pair of denim. Even these may not be sufficient for the computer to be able to successfully recognize the Mona Lisa as a painting of a lady because unique characteristics of each woman's physical appearance can create complexity that might fail an image-recognition algorithm.

Google DeepMind's AlphaGo, an artificial intelligence system designed to play Go, an ancient Eastern Asia's board game, defeated the Go's world champion, Lee Sedol of South Korea [21]. This victory of AlphaGo against Lee Sedol demonstrated a machine that can beat human world champion for the first time. The reason it took so long to build a machine that can beat a human in a professional Go game is the nature of complexity found in the game. Go is usually played more intuitively rather than based solely on logical decisions. AlphaGo, the latest milestone achievement in the field of artificial intelligence, has once again proven that a computer with intuition is no longer beyond our imagination.

In the measurement of structural responses using a wireless sensor network, time delay and data loss commonly occurring can potentially degrade the performance of the control system if they are not carefully compensated. However, wireless time delay is typically found to be constant and data loss can be addressed by learning patterns in previous wireless measurements. If a neural network is deployed in the wireless sensor network, and it is trained by several past measurements, it can be expected that the neural network will be able to compensate for the presence of time delay and data loss in future measurements. If the training of the neural network is successful, then a wireless sensor network with intuition (based on previous measurement data) can be manifested.

1.5 Goal of the Study

It is discussed in the previous sections that wireless communication can potentially degrade the performance of a structural control system if it is not carefully compensated in sensors. Therefore, in this study, the use of artificial neural networks is proposed to deal with these challenges present in a wireless sensor network. Then, the neural network will be deployed in a wireless control system to improve the structural control performance.

To achieve this goal, the neural network is trained with several wireless measurement records. This training is intended to allow the network to learn about the time delay and data loss patterns in wireless measurements. An effective neural network is achieved when the network can compensate for these effects when applied to new situations and excitations.

1.6 Thesis Organization

This thesis is divided into six chapters. The first chapter provides an introduction to the goals of the study that involves three main keywords: structural control, wireless sensor networks, and artificial neural networks. Chapter 2 mainly explores the theoretical background of the study. Mathematical equations and corresponding theories from previous research are explained in this chapter. Methodology is discussed in Chapter 3. The specific case study used and the strategy proposed in the thesis is discussed here. Results and discussions of the study are given in Chapter 4 and Chapter 5. Chapter 4 explains the numerical simulation; Chapter 5 discusses the laboratory experiment. Finally, conclusions and future work are summarized in the final chapter, Chapter 6.

2. BACKGROUND

Wires are commonly used as the traditional approach for providing communication between components in a control system, i.e. sensor, control device, and computer control. For control systems applied to small-scale structures, this choice may be appropriate, but this may lead to challenges when larger structures are examined. To keep costs low and provide convenience in installation or maintenance, a wireless system is considered as an alternative to its wired counterpart. A major advantage of this system is it improves scalability of the system because the cost and the installation flexibility do not vary significantly in larger scale structures [4].

Wireless communication introduces significantly more time delay compared to the wired system and also has a potential to create data loss in the system [22, 23]. The presence of time delay and data loss may significantly reduce the performance of the control system that is not designed specifically to accommodate these parameters in its control strategy [24].

The objective of this research is to offer an artificial intelligence system that can incorporate the presence of time delay and data loss in the system, so that a robust performance can be achieved. In this chapter, extensive discussion on the performance reduction in the system due to wireless time delay and data loss is presented.

2.1 Wireless Sensor Network

Application of wireless sensor network for structural control purposes has attracted attention due to its flexible and rapid installation, and the low cost of the system for large scale structures compared to its wired counterpart [4]. Numerous advances have been achieved through the various research in the field of wireless sensor networks. This research has led to successful implementations of wireless sensing systems for sensor-centric computing [25], damage detection [26], mode shape estimation [27], and even “active” sensing applications, where the sensors have the ability to influence its environment to eliminate dependency on ambient vibrations for excitation [28]. These achievements have supported the realization of wireless sensors that can perform feedback control function [4].

Traditional approaches conducted in many research do not accommodate time delay and data loss occurred in the wireless sensor network deployed on large structures [14]. Previous studies show that the presence of time delay and data loss due to wireless communication could potentially reduce the performance of a wireless structural control system [29]. The difficulty to represent the cyber-physical environment of a wireless structural control is mainly caused by the lack of realistic tools to determine the wireless and structural part of the wireless structural control system. Research proposing a realistic cyber-physical case study of wireless structural control systems has been conducted [30]. To undertake the issue of time delay in a wireless system, many techniques have been proposed, such as using an integrated simulator [31] and intelligent sink placement [7].

Following a series of well-received benchmark problems for structural controls to offer a universal evaluation of the performance of structural systems, a new benchmark problem considering a wireless structural control using an active mass damper has been developed and available to be utilized for research purposes. This benchmark problem is considered to be useful to help researchers to investigate the presence of time delay and data loss in a wireless structural control system [14].

Since sensor failure also appears as one of the major issues in a wireless sensor network, detection of intermittent faults in sensor nodes play significant role. An efficient fault detection method with low detection latency, low energy overhead, and high detection accuracy has been demonstrated [12].

Another promising feature of a wireless structural control system is its possibility to be integrated with a structural health monitoring system. The possibility of a wireless sensing unit to be deployed in a wireless structural control system challenges the classical control design approaches with range, latencies, and data losses stand as major objectives in the system [32].

2.1.1 Wireless Control Strategy

Wireless control strategies are often categorized into four different groups: (1) centralized control; (2) decentralized control; (3) partially decentralized control; and (4) hierarchically decentralized control. In a centralized control system, measurements from each subsystem are sent to a central control unit to make a control decision for the whole system. Then, after the control decision has been made, control commands are sent back to each subsystem or control device. The drawback of this system is its high dependency on the central control unit; a single point failure in a centralized controller may mean the whole system must stop working.

In a decentralized control, each subsystem has its own local controller and there is no data sharing among different subsystems. The system's architecture allows the system to be more reliable than the centralized control system and also minimizes the wireless communication delay in the system. However, the performance of each local control unit may be different from one to another, and its impact on the stability and performance of the global system is not well understood.

In a partially decentralized control system, the architecture is similar to that of the decentralized control system, yet it allows data sharing between each subsystem controller. Therefore, it has the benefits of decentralized control system, but it also takes on some features of the centralized control unit due to the increased communication among the subsystem controllers.

The final type of the wireless control strategy is the hierarchically decentralized control system. In this system, it employs supervisory controllers to coordinate the behavior of local controllers to improve the global performance and stability of the system.

2.1.2 Applications and Devices

There are several alternatives of wireless protocols that can be chosen for structural controls. Table 2.1 compares the specifications among the most popular wireless devices that are available on the market, i.e. ZigBee, Wi-Fi, and Bluetooth. ZigBee and Wi-Fi are preferred due to their ability to cover a wider range (up to about 100 m) compared to Bluetooth (that only reaches about 10 m radius). Wi-Fi provides the fastest transmission rate among these three. However, for wireless sensor networks with small package size, ZigBee is preferable due to its low power requirements.

Network topologies that can be employed for wireless sensor network using ZigBee protocol are illustrated in Figure 2.1. Each topology has a single coordinator. The coordinator typically performs various tasks, including arranging the network and distributing address to the other nodes. Either a router or an end-device could be attached to the coordinator. An end-device could be connected to either a coordinator or router.

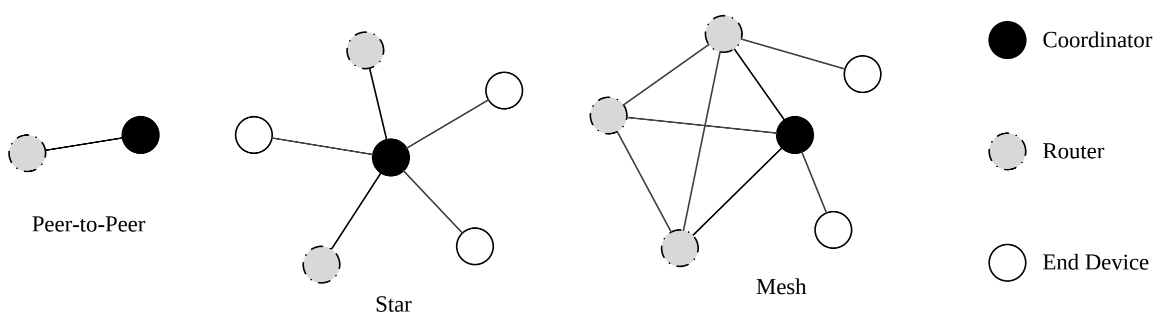


Figure 2.1. Topologies of wireless sensor networks

Multiple access method must be provided when multiple devices communicate through a coordinator. Multiple access method is a protocol that allows several terminals to be sent into the same transmission medium and share its capacity. Several common types of multiple access methods are multiple access with collision avoidance

Table 2.1 Specification of some wireless protocols

Standard	ZigBee	Wi-Fi	Bluetooth
IEEE specification	802.15.4	802.11 a/b/g/n	802.15.1
Frequency band	868/915 MHz; 2.4 GHz	2.4 GHz; 5 GHz	2.4 GHz
Max signal rate	250 kB/s	54 MB/s	0.72 MB/s
Bit time (μs)	4	0.0185	1.39
Max data payload (bytes)	102	2312	339
Max overhead (bytes)	31	58	158
Nominal TX/RX power	-25 – 0 dBm	15 – 20 dBm	0 – 10 dBm
Nominal range	100 m	100 m	10 m
Number of RF channels	16	14	79
Channel bandwidth	2 MHz	22 MHz	1 MHz
Network topology	Ad-hoc, peer-to-peer, star, or mesh	Point to hub	Ad-hoc, very small networks
Power consumption	Very low	High	Medium
Applications	Remote control, battery-operated product	Internet connection, file transfer	Wireless USB, headset

(CSMA/CA), time division multiple access (TDMA), and frequency division multiple access (FDMA).

The study in this thesis is based on the implementation of an Arduino based wireless sensing platform discovered in previous study [33]. The platform uses Arduino Due. This platform has 54 digital I/O pins which allow the system to be amenable for various types of applications. It has 12 analog inputs and the programming language is based on C/C++ language. For the sensing module, a tri-axial accelerometer ADXL 345 by Analog Device is utilized. An analog to digital conversion (ADC) board is used to provide force measurements from force transducer as demonstrated in previous studies [34].

2.2 Artificial Neural Networks

Classical control algorithms (optimal control, pole assignment, independent modal space, bounded state control method, etc.) provide a variety of tools for implementing robust control solutions to address vibration control in a linear or non-linear environment. However, structures do not behave precisely as represented by their mathematical models. Many sources of non-linearity, uncertainty, and noise in measurement may limit the performance of the control system due to a lack of understanding in the control system. The emergence of artificial neural network offers a promising alternative to address this problem. As method to develop an input-output relationship without requiring a precise mathematical representation, this technique offers a possibility to tackle uncertainties appearing in these control problems.

Efforts have been made to document the applications of neural network in civil engineering [35]. Studies of implementation of neural networks in structural control problems start with active control systems [36, 37]. Satisfying results are achieved in those studies. An attempt to take the advantage of these results for a wireless structural control system is made in this study. It is expected that by utilizing neural network features, issues appearing in a wireless structural control system, such as time delay and data loss, can be counteracted. Previous studies have shown that neural network can be beneficial in dealing with time delay [38] and sensor failures [39], although it is not performed using a wireless sensor network.

Artificial neural networks, often shortened as neural networks, are initially an attempt from some researchers to replicate a living organisms' brain functionality.

The initial development was based on the idealization of how the biological neurons work [40]. The objective of neural networks is to develop an input-output relationship mapping of a system that is not mathematically well-defined. It offers an easy procedure to model a system without requiring to determine the precise mathematical relationships involved. However, the absence of the mathematical representation is also often viewed as a flaw that may lead to false interpretation of results if one fails to define a good neural network model.

A neural network is generated by a set of "neurons." These neurons are actually a set of processors that has an ability to perform a simple calculation. Each neuron is connected to the other neurons, so together all neurons create a highly interconnected network. One bias parameter is also set for every single neuron. Then an incoming signal is transmitted to the first neuron, and a simple operation of the sums of the weighted incoming signals and the bias term is generated, and fed into a transfer function. Then, the result is transmitted from neuron to neuron until it reaches the last neuron and produces the ultimate output.

One of the most promising features of the neural network is its ability to learn. Neural networks should not be viewed as an algorithm since users of the system do not program the equation with the prescribed outputs corresponded to certain inputs. On the other hand, a neural network creates its architecture by being trained with several input-output data set. The network then organizes itself to map the input-output relationship that can capture the correlation between those two states.

2.2.1 Neuron Model

A neural network is created to map a mathematically-unknown, input-output relationship. These networks consist of a number of neurons, here a term for processors. In a neural network, the neurons are connected to each other based on "training" to develop the most optimum solutions the particular problem.

Each neuron has the ability to perform a simple calculation (limited to simple summation operations). In each connection, neurons exchange information. A signal is received from the former neuron to the next one that is connected to each other. When the information is transmitted, simple calculation is performed, i.e. summation of the weighted incoming signal value and a bias parameter. The result of this calculation then will be fed into a function. Finally, the ultimate product is transmitted to the next connected neuron until it reaches the last neuron to produce the final result.

2.2.2 Network Architecture

A neural network consists of a number of interconnected neurons. Each neuron is one part of a particular layer. A signal is transmitted from the input to the output of the neural network through these hidden layers. The number of neurons and layers included in a neural network is determined by the architect or the designer of the neural network. More neurons and layers often yield a better capability in modeling a complex relationship, yet too many result in overfitting issues for a simple model.

Perhaps the simplest type of neural network is the feedforward neural network shown in Figure 2.2. In this type of neural network, the procedure is only allowed to move forward hierarchically.

In each neuron of neural networks, a transfer function is embedded to allow the network to achieve certain level of performance. This transfer function is shown as θ in Figure 2.2. Various types of transfer function can be used in the neuron, such as logarithmic-sigmoid, hyperbolic tangent sigmoid, and linear function. In this study, generally logarithmic-sigmoid transfer function is employed in the neurons to allow the network to be able to deal with non-linearity.

2.2.3 Learning and Training

Training plays a critical role in the success of a neural network system. The network is created based on the pattern that is learned during the training process.

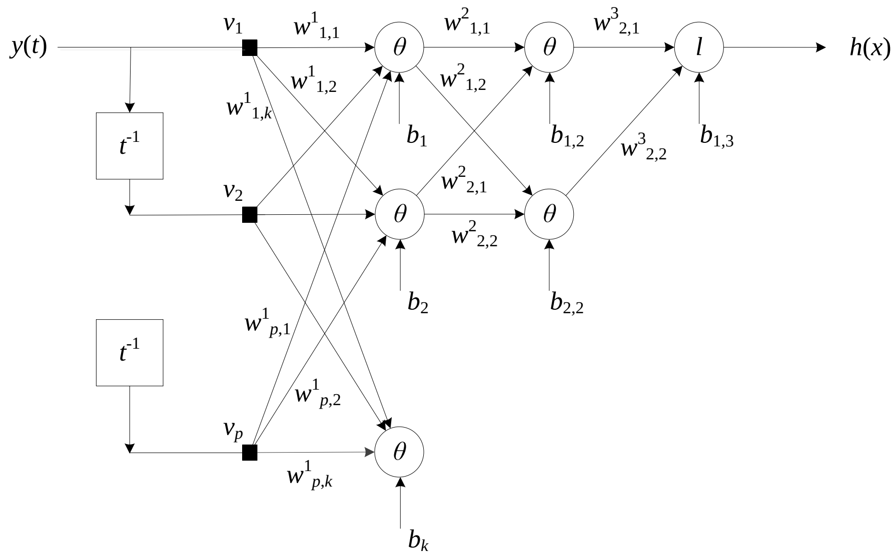


Figure 2.2. Architecture of a feedforward neural network

After selecting the number of layers and neurons, setting the architecture of the neural network, the weighting and bias parameter of each neuron connection need to be adjusted in the process called training.

In general, neural network training can be categorized into three kinds: supervised, unsupervised, and self-supervised. The objective of the neural network training is to find the optimal arrangement of the network parameters for the particular problem. In this study, the training algorithm that is used is called the Levenberg-Marquardt algorithm. This algorithm is generally a modified version of Newton's method that is designed for minimizing a function of sum of squares of non-linear functions. The advantage of this algorithm is its fast running time and its great degree of convergence. Nevertheless, this algorithm requires relatively demanding computational cost. Furthermore, fast processor and big capacity of memory are needed to run this algorithm efficiently.

Another important step in designing the neural network is choosing the training set. The training set includes corresponding inputs and outputs. The training set needs to be selected properly, so that a reasonable solution can be achieved as a result of the trained neural network system.

Generally, larger training sets mean better representation of the solution space, but it also means more training time is required. Moreover, too much training set might also result in overtraining issue. Overtraining appears when the neural network losses its ability to provide reasonable solutions due to training sets that lead the neural network to a model that does not represent the investigated problem.

2.2.4 Design Workflow

The workflow of the design of the neural network is presented as follows:

1. *Collecting data.* After the data have been collected, it is important to understand the nature of the data to ensure that a high quality data are used for the neural network training. Richness of the range of data is also required to cover the required network because, basically, neural networks do not have the ability to accurately extrapolate beyond this range. Pre-processing the data before feeding them into the network training can produce a more efficient training.

2. *Creating the network.* The key of neural network object are inputs, outputs, hidden layers, biases, input weights, and layer weights.

3. *Configuring the network.* In the configuration, we choose the settings for processing inputs and outputs that will yield best network performance.

4. *Initializing the weights and biases.* Although the weights and biases will be updated during the training, different choices of initial values of weighting and bias parameters may yield a different performance. Therefore, an appropriate value of the initial weighting and bias parameter may want to be considered in designing a neural network.

5. *Training the network.* There are two basic types of neural network training: incremental training and batch training. In incremental training, the network

updates the weights and biases each time an input is presented. In batch training, the network updates the weights and biases only after all the inputs are presented. In general, the incremental training yields better performance, but the batch training operates more efficient computational procedures.

6. *Validating the network.* One of the major problems that wants to be avoided in a neural network training is overfitting. Overfitting appears when more training yields worse performance. To avoid this issue, validation procedure is set to provide an early-stopping procedure when an overfitting issue is discovered. One solution to prevent overfitting is by using a small size of neural network [20].

7. *Using the network.*

2.2.5 Pre-Training

One of the most basic questions in designing a good neural network is to decide the number of hidden layers to be used. There is a great debate on deciding how many layers to be used for neural network; some say more than two hidden layers are not necessary for a neural network [41], although other might say that using three or more hidden layers can give better performance on the network [42].

One strong statement was expressed explicitly in the title of a conference paper "Why Two Hidden Layers Are Better Than One." [43] Other advise on how do we choose number of layers is articulated in a paper by Hayashi, Sakata, and Gallant [44]. It is said in the paper, "Never try a multilayer model for fitting data until you have first tried a single-layer model."

Clearly, it is challenging to determine which topology is better. Since there is no "absolute truth" in the field of neural networks, any approach may be effective depending on the problem that is being investigated. However, it should be remembered that the simplest rule-of-thumb that can be used in implementing neural network is by choosing single-layer first, and then adding layers if good performance has not been achieved yet.

2.2.6 Implementation

As mentioned before, the training algorithm used for this study is the Levenberg-Marquardt algorithm, which sometimes also often referred as the damped least-squares method. This algorithm's basic principle is to find the optimum solution that minimizes the sum of the squares of the errors made in the results of every single equation. It is a regression approach used for non-linear systems.

The type of neural network utilized in this study is the feedforward neural network. It was the first and is the simplest type of artificial neural network. In a feedforward network information always moves one direction (forward, from the input nodes through the hidden layers to the output nodes); it never goes backwards. Because of its behavior in moving only in one direction, this type of neural network is usually referred to as static. Since in this model node is not allowed to make a cyclic loop, the learning process in this model is usually slow to achieve convergence. Therefore, dynamic neural networks are also considered in this study. In dynamic neural network, feedback from both the hidden layer and the output layer to the input layer is allowed to occur.

Dynamic neural networks are typically more powerful than static neural networks. However, dynamic networks are also more difficult to train. Another useful feature in dynamic neural networks is memory, so that it allows the network to learn patterns in time series. Due to its features, this type of neural network has been utilized in diverse areas, such as forecasting inflation [45] and modeling rainfall-runoff phenomena [46].

In this study, the performance of both static and dynamic neural network are compared in terms of their ability to compensate the wireless structural control problems. The main focus of this study is to tackle the presence of time delay and data loss which exists as one of the characteristics of the wireless sensor network. Parameters set in the neural network training (bias and weighting parameter, number of layers, neurons, etc.) are investigated using a trial and error process. The reliability of the training result is verified by looking at the regression of the results, auto-correlation of the inputs and outputs, and the histogram of the mean squared error values of the training results.

2.3 Control Algorithm

As discussed previously, the type of the wireless control strategy chosen for the system will play role in the performance and efficiency of the control system. Each alternative of the wireless control strategies (decentralized control, partially decentralized control, and centralized control) is considered in this study.

2.3.1 State-Space System Model

Formulation and solution of a modern control problem lies in the state-space representation of the system [47]. The equation of motion to model a lumped mass shear structure with n-degree-of-freedom (DOF) in elastic manner is given by the following equation:

$$\mathbf{M}\ddot{\mathbf{x}}\,(t) + \mathbf{C_d}\dot{\mathbf{x}}\,(t) + \mathbf{K}\mathbf{x}\,(t) = -\mathbf{M}\ell\ddot{x}_g\,(t) + \mathbf{L}\mathbf{u}\,(t)\,, \tag{2.1}$$

where $\mathbf{M}$, $\mathbf{C_d}$, and $\mathbf{K}$ correspond to the mass, damping, and stiffness matrices, respectively. The structural responses (absolute acceleration, relative velocity, and relative displacement) are represented by $\ddot{\mathbf{x}}$, $\dot{\mathbf{x}}$, and $\mathbf{x}$ (also in respective manner) which are relative to the base of the structure and $\ddot{\mathbf{x}}, \dot{\mathbf{x}}, \mathbf{x} \in \mathbf{R}^{n\times 1}$. The absolute ground acceleration input is $\ddot{x}_g$, and $\ell \in \mathbf{R}^{n\times 1}$ is a vector in which each term is unitary. Control forces $\mathbf{u} \in \mathbf{R}^{m\times 1}$ are applied to the structure in the location described by the matrix $\mathbf{L} \in \mathbf{R}^{n\times m}$. The variable t represents the continuous time variable.

To put the equation of motion into an input-output model, Equation 2.1 is reformulated in its state-space representation as

$$\dot{\mathbf{z}}\,(t) = \mathbf{A}\mathbf{z}\,(t) + \mathbf{B}\mathbf{u}\,(t) + \mathbf{E}\ddot{x}_g\,(t)\,, \tag{2.2}$$

where the state is $\mathbf{z}^T = \{\mathbf{x}^T \dot{\mathbf{x}}^T\} \in \mathbf{R}^{2n\times 1}$ and

$$\mathbf{A} = \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\mathbf{C_d} \end{bmatrix} \in \mathbf{R}^{2n\times 2n},$$

$$\mathbf{B} = \begin{bmatrix} \mathbf{0} \\ \mathbf{M}^{-1}\mathbf{L} \end{bmatrix}, \quad \mathbf{E} = \begin{bmatrix} \mathbf{0} \\ -\ell \end{bmatrix}.$$

The system output, $\mathbf{y} \in \mathbf{R}^{p\times 1}$, can be measured from sensors installed on the structure and is represented by a linear sum of the state of the system and the applied control forces,

$$\mathbf{y}\left(t\right) = \mathbf{Cz}\left(t\right) + \mathbf{Du}\left(t\right) + \mathbf{F}\ddot{x}_g\left(t\right), \tag{2.3}$$

with $\mathbf{C} \in \mathbf{R}^{p\times 2n}$, $\mathbf{D} \in \mathbf{R}^{p\times m}$, and $\mathbf{F} \in \mathbf{R}^{p\times 1}$. The details of the state-space system model of a shear structure can be found in various textbooks [47, 48].

2.3.2 Digitization Procedure

Most control systems today use digital computers for the controllers, therefore digitization procedure is required [49]. In digital control system environment, the continuous-time state-space model needs to be converted into the discrete-time domain with time step T_s using the discretization described as follows

$$\mathbf{z}\left(k+1\right) = \mathbf{\Phi z}\left(k\right) + \mathbf{\Gamma u}\left(k\right) + \mathbf{\Lambda}\ddot{x}_g\left(k\right), \tag{2.4}$$

where

$$\mathbf{\Phi} = e^{\mathbf{A}T_s} \in \mathbf{R}^{2n\times 2n},$$

$$\mathbf{\Gamma} = \left(\int_0^{T_s} e^{\mathbf{A}T_s} d\tau\right)\mathbf{B} \in \mathbf{R}^{2n\times m}, \quad \mathbf{\Lambda} = \left(\int_0^{T_s} e^{\mathbf{A}T_s} d\tau\right)\mathbf{E} \in \mathbf{R}^{2n\times 1},$$

where $e^{\mathbf{A}T_s} \approx \left(\mathbf{I} + \frac{1}{2}\mathbf{A}T_s\right)\left(\mathbf{I} - \frac{1}{2}\mathbf{A}T_s\right)^{-1}$ is used in Tustin's method or bilinear approximation. More discussions on digitization procedures can be found in Franklin, et al. (1990) [49].

2.3.3 Optimal Linear Quadratic Regulator (LQR) Control

The linear quadratic regulator (LQR) is one of the most discussed control algorithm in control textbooks [50]. LQR is very attractive because of it allows the control designer to minimize the response of the structure, $\mathbf{y}$, and the control effort, $\mathbf{u}$, together [51]. The trajectory of the control force, $\mathbf{u}$, is determined in the LQR control algorithm by minimizing the scalar function, $\mathscr{J}$, provided as follows

$$\mathscr{J}(\mathbf{u}) = \sum_{k=1}^{\infty} \left(\mathbf{z}^T(k)\,\mathbf{Q}_1\mathbf{z}(k) + \mathbf{u}^T(k)\,\mathbf{Q}_2\mathbf{u}(k)\right), \tag{2.5}$$

The matrices $\mathbf{Q}_1$ and $\mathbf{Q}_2$ are often referred as the state cost matrix and input state matrix, respectively. They are defined as $\mathbf{Q}_1 = \mathbf{C_{LQR}}^T\mathbf{C_{LQR}}$ and $\mathbf{Q}_2 \in \mathbf{R}^{p\times p}$ with $\mathbf{C_{LQR}}$ representing a linear mapping between the state vector and the response vector to be regulated. In the mathematical form, this can be written as $\widetilde{\mathbf{y}} = \mathbf{C_{LQR}}\mathbf{z}$.

The equation of the optimal control trajectory is given as follows:

$$\mathbf{u}(k) = \left[\left[\mathbf{Q}_2 + \mathbf{\Gamma}^T\mathbf{P}\mathbf{\Gamma}\right]^{-1}\mathbf{\Gamma}^T\mathbf{P}\mathbf{\Phi}\right]\mathbf{z}(k) = \mathbf{G}\mathbf{z}(k), \tag{2.6}$$

with the linear gain matrix, $\mathbf{G} \in \mathbf{R}^{m\times 2n}$, and the Riccati matrix, $\mathbf{P} \in \mathbf{R}^{2n\times 2n}$, obtained by solving the algebraic Riccati equation as follows

$$\mathbf{P} = \mathbf{\Phi}^T\left[\mathbf{P} - \mathbf{P}\mathbf{\Gamma}\left[\mathbf{Q}_2 + \mathbf{\Gamma}^T\mathbf{P}\mathbf{\Gamma}\right]^{-1}\mathbf{\Gamma}^T\mathbf{P}\right]\mathbf{\Phi} + \mathbf{Q}_1, \tag{2.7}$$

Franklin, et al. (1994) [52] provides a detailed discussion on the optimal LQR technique.

2.3.4 Kalman State Estimation

In most structural control systems, only absolute acceleration is measured in each time step due to practicality and economical issue [4]. To enable the use of output feedback, the Kalman filtering technique is utilized to provide an estimation of the state, $\hat{\mathbf{z}}$, by using the measured output vector of the structure, $\mathbf{y}\left(k\right)$.

The Kalman estimator presumes the structure is disturbed at its base by the scalar excitation $w\left(k\right)$ with a covariance R_w. Based on the state equation

$$\dot{\mathbf{z}}\left(k+1\right)=\mathbf{\Phi}\mathbf{z}\left(k\right)+\mathbf{\Gamma}\mathbf{u}\left(k\right)+\mathbf{\Lambda}w\left(k\right) \tag{2.8}$$

and the output measurement of the system corrupted by white noise, $\mathbf{v}\left(k\right)\in\mathbf{R}^{p\times 1}$ with covariance $\mathbf{R_v}\in\mathbf{R}^{p\times p}$ is given by

$$\mathbf{y}\left(k\right)=\mathbf{C}\mathbf{z}\left(k\right)+\mathbf{D}\mathbf{u}\left(k\right)+\mathbf{H}w\left(k\right)+\mathbf{v}\left(k\right). \tag{2.9}$$

The goal of the estimation function is to minimize the steady state error covariance of $E\left[\|\mathbf{z}(k)-\hat{\mathbf{z}}(k)\|^2\right]$ with the observer gain matrix, $\mathbf{L}\left(k\right)\in\mathbf{R}^{2n\times p}$, that is given by the following equation

$$\mathbf{L}\left(k\right)=\mathbf{P_e}\mathbf{C}^T\mathbf{R_v}^{-1}. \tag{2.10}$$

Finally, the estimation gives

$$\dot{\hat{\mathbf{z}}}\left(k\right)=\left(\mathbf{\Phi}-\mathbf{L}\left(k\right)\mathbf{C}\right)\hat{\mathbf{z}}\left(k\right)+\mathbf{L}\left(k\right)\mathbf{y}\left(k\right)+\left(\mathbf{\Gamma}-\mathbf{L}\left(k\right)\mathbf{D}\right)\mathbf{u}\left(k\right) \tag{2.11}$$

where the desired control force $\mathbf{u}\left(k\right)$ is given by

$$\mathbf{u}\left(k\right)=-\mathbf{K}\mathbf{z}\left(k\right) \tag{2.12}$$

and $\mathbf{P_e}$ can be obtained by solving the algebraic Riccati equation

$$\mathbf{\Phi}\mathbf{P_e}+\mathbf{P_e}\mathbf{\Phi}^T-\mathbf{P_e}\mathbf{C}^T\mathbf{R_v}^{-1}\mathbf{C}\mathbf{P_e}+\mathbf{\Lambda}R_w\mathbf{\Lambda}^T. \tag{2.13}$$

In the previous equation, the estimator gain matrix, $\mathbf{L}(k) \in \mathbf{R}^{2n\times p}$, is intended to minimize the estimation error by considering the error in the measurement.

Discussion on Kalman filter can be found in Franklin, et al. (1994) [52].

2.4 Wireless Control System Limitations

Wireless sensor networks offer some major advantages to be exploited in structural control applications. However, some limitations may prevent the system from performing in the same level of performance as in its wired counterparts.

One challenge that is encountered in the wireless communications is time delay. Adding latency to the system also reduces the overall effectiveness of the controller.

Data loss is the second challenge that appears in wireless communications. Some studies show that data loss may degrade the performance of wireless control systems. Self-acknowledging protocols for data transmission (TCP/IP) ensure data transmission, yet introduce time delay. Typical data packet loss occurred in wireless communication is commonly attributed to radio interference—either human-made or natural [53]. This radio interference might cause data errors. For small time rate problems, such as seismic applications, these errors might cause significant issue on the system.

Lastly, wireless communication does require a large amount of power relative to the power available on the wireless platform. Especially for battery powered wireless sensors, wireless radios demand greater power needs than any other hardware component. Thus, communication should be minimized to extent sensor lifetime.

2.5 Summary

This chapter discusses the background of this study. The study focuses to overcome the presence of time delay and data loss existed in wireless sensor networks. Artificial neural networks are utilized to deal with these problems. Discussions on the control algorithm used in this study are also presented, including the state-space system model, the LQR control, and the Kalman state estimation. At last, limitations presented in wireless sensor network system are reviewed.

3. METHODOLOGY

As discussed in the earlier chapters, the presence of time delay and data loss in wireless communication could potentially reduce the performance of the control system. This chapter is conducted to verify and assess that statement. After demonstrating this in parts of these influences, the implementation of neural networks to improve the wireless structural control system is discussed. This chapter provides a description of on the approaches that are used in the study.

In general, this study can be categorized into two parts: (1) the study of time delay, data loss, and sensor failure significance in the wireless control system; (2) the study of artificial neural network application to improve the performance of the wireless control system.

3.1 Experimental Structure

A three-story steel frame structure is utilized in this study (Figure 3.1). There are four columns at each floor; each column has dimension of 1.25 in by 1/8 in and is made of steel with a Young's modulus of 3×10^7 psi. The height of each floor is 12 in.

For sensing system of the experimental structure, three wired sensors are located at each floor. The reading from these sensors are acquired in real-time by a dSPACE control unit (dSPACE GmbH, Paderborn, Germany) that can perform a data acquisition and control decision making using dSPACE real-time system that is connected to MATLAB/Simulink.

For control device, an MR damper is attached to the first story of the structure. The MR device is connected to a "wonder box" that will send a control signal to the

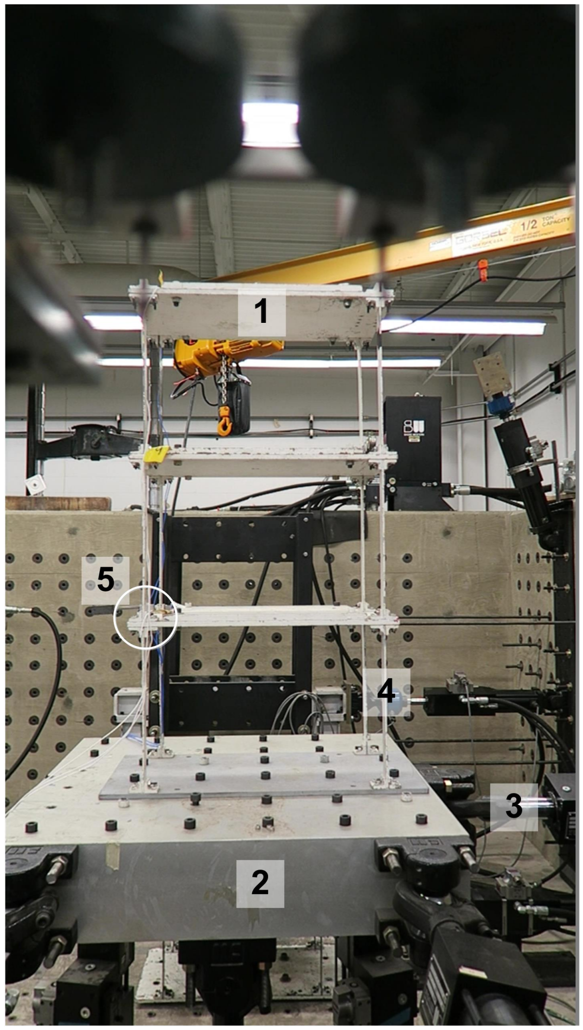


Figure 3.1. Experimental structure: (1) lumped mass steel plates; (2) shaking table; (3) actuator; (4) structural column; (5) accelerometers

control device during the experiment. The wonder box obtains the command from the control computer that is connected to the dSPACE unit.

Other data acquisition system, a VibPilot system, is also utilized in the experiment. The purpose of the use of VibPilot is to provide a better data acquisition procedure than the dSPACE (VibPilot has greater range of sampling frequency in the data acquisition, compared to the dSPACE). Moreover, the results acquired from the VibPilot can also be compared to the ones from the dSPACE, thus a crosscheck can be performed in order to avoid a false data interpretation or wrong measurement (due to errors in calibration or other reasons).

The experimental structure is placed on top of a six degree-of-freedom shaking table. The shaking table is attached to four actuators that could provide the excitation of the shaking table. The test specimens are the property of the Intelligent Infrastructure Systems Laboratory at Bowen Laboratory, Purdue University.

3.2 Numerical Model

A numerical model of the experimental structure is developed to perform the numerical simulations of the system (Figure 3.2). The structure is modeled as a lumped mass system with 50 lb of mass on each floor. Based on the physical behavior of the structure, the damping ratio of the structure is modeled to be 0.5%. The structure is excited by a one-dimensional ground acceleration in the numerical simulations. One wireless sensor is deployed on each story; all the sensors collect the absolute acceleration data from each floor.

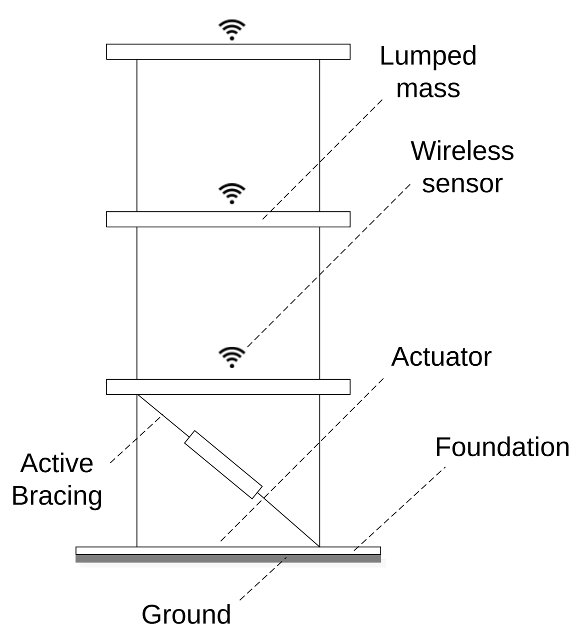


Figure 3.2. Numerical model of 3-story shear building

Time delay in a wireless system is mostly determined by the sensor network setup. To build a realistic wireless model, time division multiple access (TDMA) wireless network model is adopted. TDMA gives 10 ms time slot to each sensor in the model [31,54]. Therefore, here the values of time delay presented in this numerical simulation is varied from 0 ms to 40 ms (with an increment of 10 ms). Data loss in the system is generated using a Bernoulli distribution for the simulations conducted. The probability of data loss is varied from 0% to 100%. The case in which sensor failure occurs is thus represented by the 100% loss case. Each combination of time delay and data loss in each sensor is studied. Therefore the most important sensor in the structure, in terms of the one that is most influential to the control performance, can be determined.

3.3 Ground Acceleration Input

Two signals are used as the base disturbance of the structure: a band-limited white noise and simulated Kanai-Tajimi earthquake. The band-limited white noise signal is intended to train the neural network for a range of amplitudes, while the Kanai-Tajimi earthquake is utilized to enable the network to learn about the change of amplitude and dynamic characteristics of a an excitation similar to an earthquake.

The synthetic earthquake records are produced a band-limited white noise that is processed by the Kanai-Tajimi filter. The Kanai-Tajimi filter is defined by the equations below,

$$S_{\ddot{x}_g,\omega_g}\left(w\right) = \frac{S_0\left(4{\zeta_g}^2{\omega_g}^2 w + {\omega_g}^4\right)}{\left(w^2 - {\omega_g}^2\right)^2 + 4{\zeta_g}^2{\omega_g}^2 w^2}, \tag{3.1}$$

$$S_0 = \frac{0.03\zeta_g g^2}{\pi\omega_g\left(4{\zeta_g}^2+1\right)}\left(1\text{s}\right), \tag{3.2}$$

where ω_g is chosen to be 37.3 rad/s and ζ_g is 0.3 [33].

A band-limited white noise is generated using sampling frequency of 1000 Hz and noise power of 3×10^{-3} for 60-second duration.

3.4 Nominal Active Controller Design and Performance

3.4.1 Evaluation Criteria

To evaluate the controller performance, four evaluation criteria are chosen based on the peak and RMS response quantities of the structure. These evaluation criteria are obtained from the benchmark problem for an active bracing system [55]. In general, smaller values indicate a more superior controller.

The first two criteria examine the ratio of the peak of the response history between the controlled structure and the uncontrolled structure. J_1 investigates the interstory drift, while J_2 evaluates the absolute acceleration of the structure. The equations are

$$J_1 = \max\left\{\max_t \left\{\frac{\|d_1(t)\|}{d_{1_0}}, \frac{\|d_2(t)\|}{d_{1_0}}, \frac{\|d_3(t)\|}{d_{1_0}}\right\}\right\}, \tag{3.3}$$

$$J_2 = \max\left\{\max_t \left\{\frac{\|\ddot{x}_1(t)\|}{\ddot{x}_{1_0}}, \frac{\|\ddot{x}_2(t)\|}{\ddot{x}_{1_0}}, \frac{\|\ddot{x}_3(t)\|}{\ddot{x}_{1_0}}\right\}\right\}. \tag{3.4}$$

The next criterion (J_3) is based on the maximum RMS value of the interstory drift due to all admissible ground motions. The formula of the third criterion is given by

$$J_3 = \max_{\omega_g, \zeta_g} \left\{\frac{\sigma_{d_1}}{\sigma_{x_{3_o}}}, \frac{\sigma_{d_2}}{\sigma_{x_{3_o}}}, \frac{\sigma_{d_3}}{\sigma_{x_{3_o}}}\right\} \tag{3.5}$$

where σ_{d_i} is the RMS interstory drift for the i-th floor, and $\sigma_{x_{3_o}}$ is the RMS relative displacement of the third floor of the uncontrolled structure over all types of ground motions considered. The interstory drifts are given by $d_1(t) = x_1(t)$, $d_2(t) = x_2(t) - x_1(t)$, and $d_3(t) = x_3(t) - x_2(t)$.

The fourth criterion (J_4) is based on the maximum RMS value of the absolute acceleration in all the earthquakes considered. The equation is

$$J_4 = \max_{\omega_g, \zeta_g} \left\{\frac{\sigma_{\ddot{x}_{a_1}}}{\sigma_{\ddot{x}_{a_{3_o}}}}, \frac{\sigma_{\ddot{x}_{a_2}}}{\sigma_{\ddot{x}_{a_{3_o}}}}, \frac{\sigma_{\ddot{x}_{a_3}}}{\sigma_{\ddot{x}_{a_{3_o}}}}\right\} \tag{3.6}$$

where $\sigma_{\ddot{x}_{a_i}}$ is the RMS absolute acceleration for the i-th floor, and $\sigma_{\ddot{x}_{a_{3_o}}}$ is the RMS absolute acceleration of the third floor of the uncontrolled structure.

3.5 Neural Network Design Methodologies

Artificial neural networks are implemented to compensate time delay, data loss, and sensor failure in the wireless control system. Two schemes for artificial neural network implementation are demonstrated. In both implementations, measured absolute acceleration are employed as the input for the neural network training. As the target (or output) of the training, control force is used for the first scheme while the other scheme uses the computed "ideal" responses as the target. Therefore, in the first scheme, the neural network is utilized as a controller of the system while the second scheme it is used as the estimator of the system (by still using the nominal control algorithm for the controller).

To generate training data for the neural network, a simulation of the system is performed using the scheme that is illustrated in Figure 3.3. Two ground disturbances are used to produce training input sets. These two base disturbances are generated using a Kanai-Tajimi spectrum [56,57] with ω_g of 37.3 and ζ_g of 0.3 and a band-limited white noise with noise power of 0.03 and a sampling frequency of 1000 Hz.

As depicted in Figure 3.3, the excitation due to the base disturbance on the structure produces simulated structural responses. Absolute acceleration of the structure is recorded at each time step using the simulated wireless accelerometer placed at each floor of the structure. Due to the wireless characteristics, time delay and data loss are simulated in this acceleration measurement.

For design, a neural network setup is prepared to map the relationship between the measured absolute acceleration and the "ideal" absolute acceleration (i.e. the value of absolute acceleration with no time delay and data loss). Note that in the experiment or real application, the "ideal" value represents the measurement from

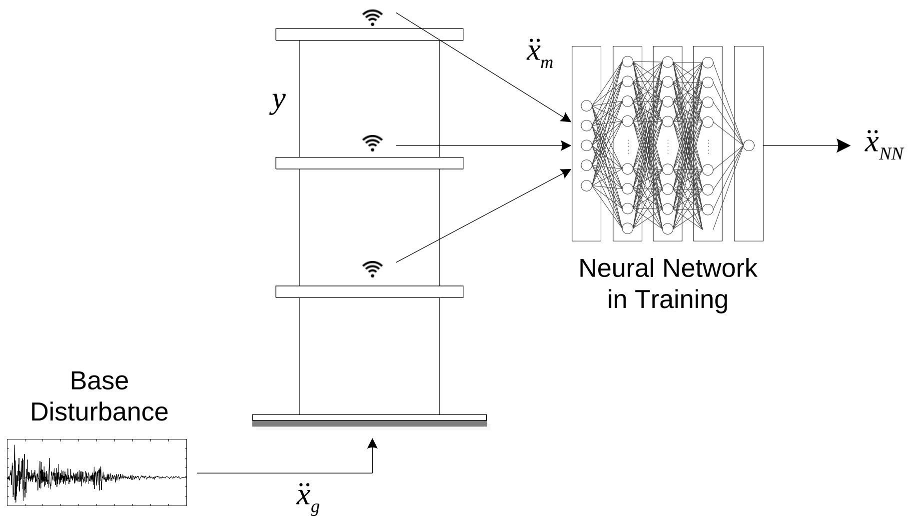


Figure 3.3. Schematics of training of neural network

the wired sensors, although realistically speaking, wired sensors will have noise and may have some time delay as well.

After the neural network architecture is produced from the training, the resulting network is tested (evaluated) with historical earthquake record. Specifically, the 1940 El Centro earthquake is used here to demonstrate the control strategy's ability to perform under any type of ground excitation.

The schematic of the wireless control system scheme in operation is presented in Figure 3.4. Different ground disturbance is generated to excite the three story building model. The structural responses are collected by the wireless accelerometer, and labeled here as measured absolute acceleration, $\ddot{x}_m$. Then, $\ddot{x}_m$ is corrected using the neural network that has been previously trained using the approach shown in Figure 3.3 to produce the corrected absolute acceleration, $\ddot{x}_c$. The corrected absolute acceleration $\ddot{x}_c$ is then fed into the Linear-quadratic-Gaussian (LQG) control strategy, which is the combination of a Kalman filter (or often referred as the linear-quadratic estimator, LQE) and a linear-quadratic regulator (LQR). Using the control algorithm, a control force is computed and applied to the structure to control the building's motion. The duration of the numerical simulation is 60 sec for each excitation case in both training and operation.

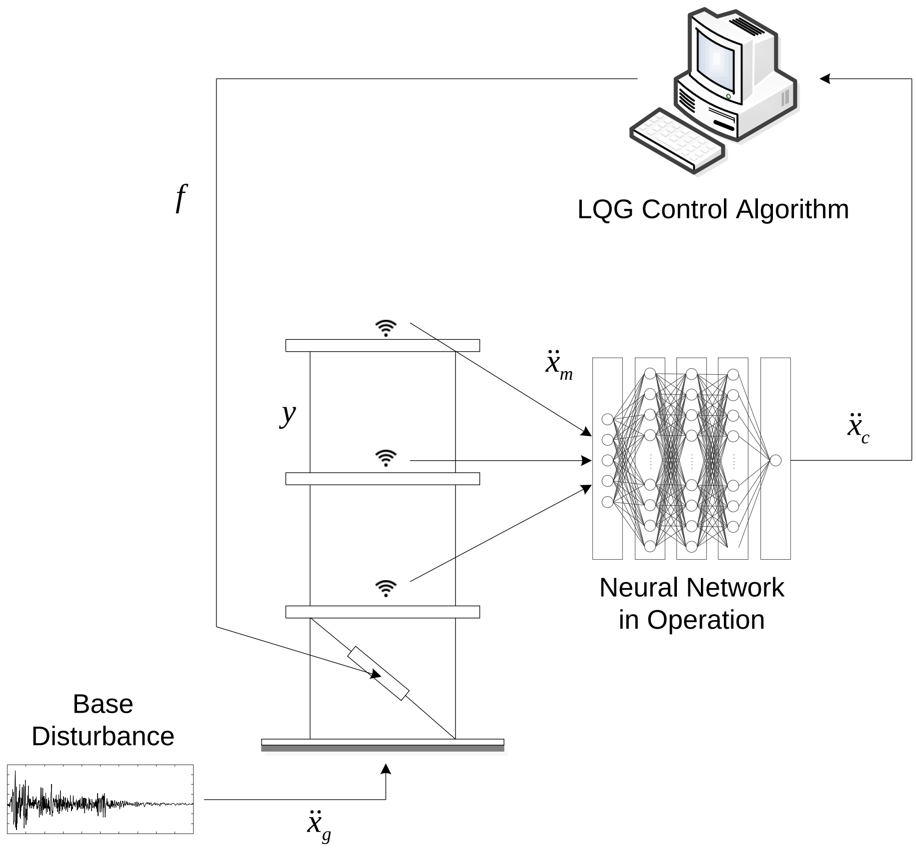


Figure 3.4. Schematics of trained neural network in operation

As mentioned before, a strong motive for using the neural network technique for control purposes is to take advantage of its feature to represent an input-output relationship without requiring a precise mathematical model. This technique offers several benefits for structural control, such as in randomness environment of structural loads (like winds or earthquakes), non-linearity in structural materials, time delay, and unknown data loss pattern in the wireless system unit.

Various studies have been conducted to successfully perform neurocontroller systems [36–38,58]. In this study, a neural network is deployed to mimic the performance of LQG by compensating for the presence of time delay in the wireless sensor network.

Also, other neural network approach that is conducted in this study is by taking advantage of neural network to minimize the effects of the not-so-well-known behavior of the data loss in data transmission.

For this particular neural network strategy, a nonlinear autoregressive (NAR) neural network is used and the Levenberg-Marquardt algorithm is chosen as the training method. The architecture of NAR neural network is illustrated in Figure 3.5.

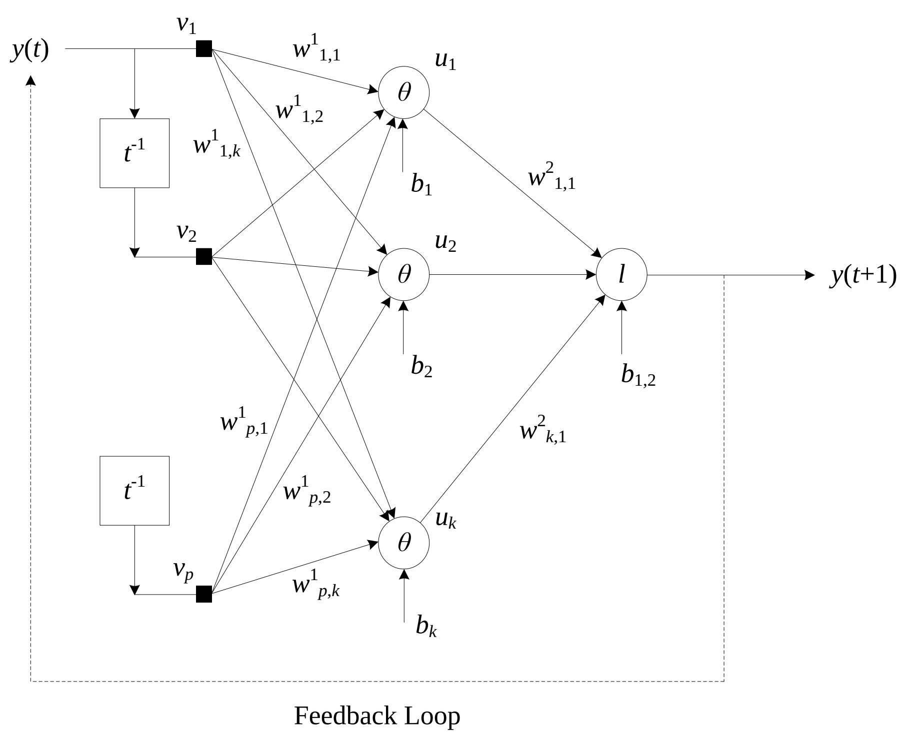


Figure 3.5. Architecture of nonlinear autoregressive neural network

In the NAR neural network, the network is intended to predict the future value using its past values as the inputs. In the illustration in Figure 3.5, the target $y\,(t+1)$ is forecasted using $y\,(t)$ as the input. As can be found as well in the other types of neural networks, the NAR can also have multilayers and multineurons in its architecture. Each input may have some delay parameters to provide a time delay in assisting the new input value into the system (this delay could later be removed during the implementation of the network in operation). Each input is connected through a network that has its own weighting parameter. The weighting parameter is adjusted during the training to give the best model for the system. Then, this network is connected to a neuron that contain a nonlinear function with each own bias parameter. After the last layer is computed, the network is merged into one linear function (that has its own bias parameter as well) to provide the final influence to the result before it computes the output.

3.5.1 Time Delay Compensation

Time delay in control feedback strategies could be very consequential if it is not deliberately considered during control designs [59]. Figure 3.6 shows how time delay is exhibited in active control systems.

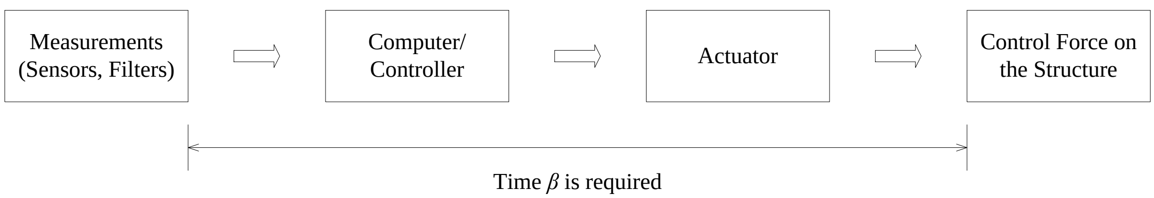


Figure 3.6. Time delay in active control systems

As illustrated in Figure 3.6, pure time delays occur because [59]:

1. time taken in real-time data acquisition from digital sensors attached at various locations on the structure;
2. time taken in data processing (filtering) for feeding the inputs to the control algorithm that produces the corresponding control signal to the actuator;
3. time taken by the digital controller to compute the appropriate control force to be assigned into the structure.

Note that these are also tire lags due to the dynamics of the active control device [47]. The time delay presented in the control application may introduce an unsynchronized application of the control force in the structure, which could potentially degrade the performance of the control system or may even induce instabilities. Because of that, it is essential to design a control system that can compensate for the presence of time delay. In this particular problem, the time delay that is specifically observed here is the pure time delay which occurs due to the features of wireless communications. Therefore, the time delay here can be defined as the difference of the time that the wireless sensors could provide compared to the measurements that could be obtained from the systems using wired sensors.

Hiratsuka et al. [60] proposed an one strategy to deal with the time delay issue with a captivating analogy of the pipeline model illustrated in Figure 3.7.

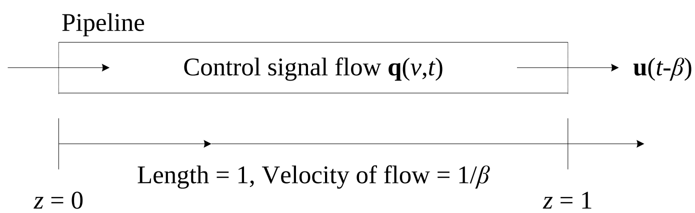


Figure 3.7. Pipeline analogy

Figure 3.7 shows that a pipeline analogy may be used to model a control strategy to compensate the occurrence of time delay in control systems. In the pipeline with the unit length z, the control signal $\mathbf{u}$ flows with a rate of $\mathbf{q}\,(v, t)$. At the start of the pipeline, where the delay is 0, the control signal corresponds to $\mathbf{u}\,(t)$. As the control signal goes through the pipeline and reaches the end of the pipe (at $z = 1$ or β time delay), the control signal becomes $\mathbf{u}\,(t - \beta)$.

Without considering the neural network application, the best scenario for the LQR control scheme presented in Figure 3.4 is when no time delay and data loss are presented in the system. If time delay is 0 ms and data loss in the system is 0%, then the optimal performance of the LQG scheme can be achieved because the actual responses are very close to the "ideal" responses (there will be some differences due to sensor noise).

To realize a scheme close to this scheme, a neural network strategy is developed. Since measured accelerations are obtained from the wireless sensor, a neural network can be used to map the relationship between the measured acceleration (input) and the "ideal" acceleration (output). This "ideal" acceleration in the actual system refers to the case in which no time delay or data loss occur. Thus, this procedure can reasonably be implemented in the real world. For instance, to obtain the "ideal" accelerations in a laboratory experiment, a set of wired sensors can be used to obtain training data. After successfully applying the neural network training, then the neural network can be embedded into the system thus an LQG control scheme can be implemented more effectively.

Figure 3.8 illustrates how any delay present in wireless communications might affect the reading error. In Figure 3.8, if a measurement is intended at a particular time step, say at the time corresponding to the vertical dashed line, the value "A" is obtained from the wireless sensor at the structure. However that value does not correspond to the true value at this time, which is illustrated by "B," the value at the intersection of the vertical dashed line on the dotted ideal curve.

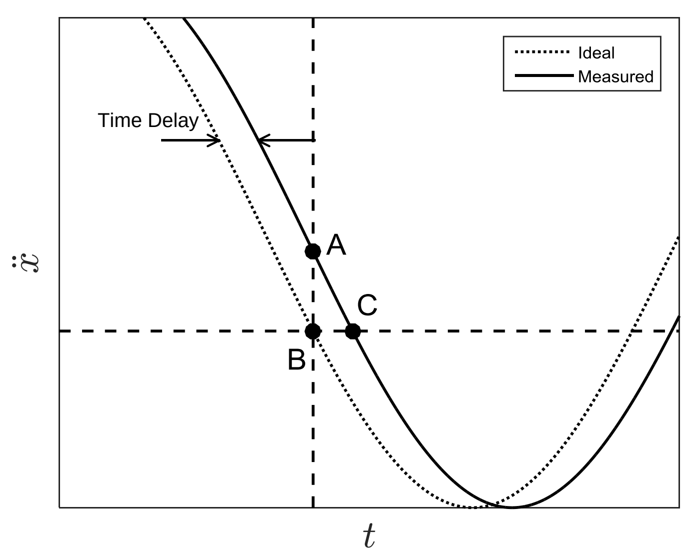


Figure 3.8. Time delay illustration in a wireless sensor measurement

To compensate for the time delay, an imaginary horizontal dashed line “C” is projected to intersect with the solid measured curve to give “C,” which represents the future value of “A” that is approximately close to “B.” The “C” value is, essentially, predicted using the neural network that has been trained to achieve this action, compensating the wireless sensor delays.

3.5.2 Data Loss Estimation

Data loss occurs in wireless sensor measurement as depicted in Figure 3.9. As shown in the figure, 19 data points are collected and create a perfect sinusoidal function in the ideal data. However, the measurement fails to transmit at two particular time step in this example, thus those two data are lost from the total of 19 data samples (around 10% data loss). Here, the data loss occurs at points 5 and 9.

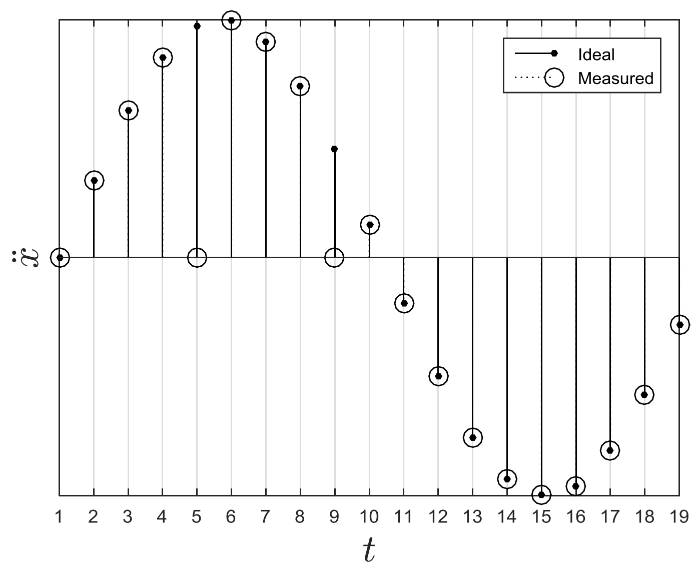


Figure 3.9. Data loss illustration in a wireless sensor measurement

During real-time structural control implementation, missing or false measurements may degrade the performance of the structural control system. From Figure 3.9, it is understood that the data loss gives the measurement with the value of 0, resulting the measurement to provide false output.

To compensate for the lost data, a neural network scheme is proposed as depicted in Figure 3.10. In the figure, the measured acceleration $\ddot{x}_m$ is corrected to the extent possible, if its value is equal to 0, using the neural network that would predict the future value using the previous values (several time steps behind) as the input. If the measured value is not equal to 0, then the value is taken as it is (no neural network is used).

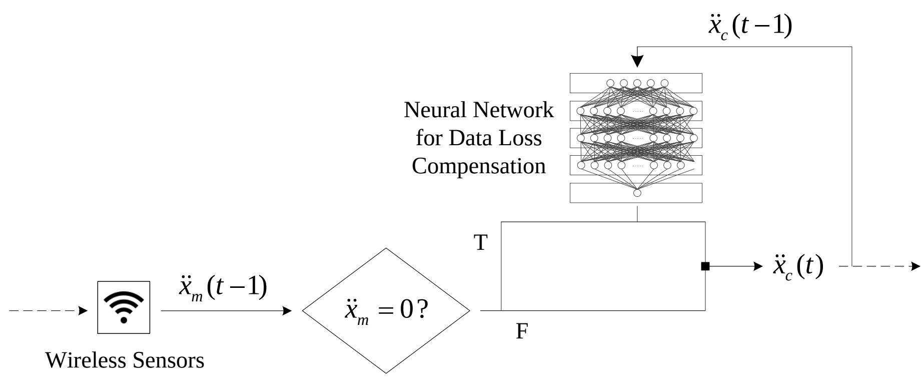


Figure 3.10. Schematics of neural network for data loss compensation

Although, this strategy offers a logical way to deal with data loss, it should be acknowledged that measurement of 0 does not always portray a false measurement. As shown in Figure 3.9, in data point 1, both ideal and measured values indicate the value of 0. Therefore, using the scheme, this situation would also be considered as a false measurement. Thus, the neural network would also be implemented for this case, although it was unnecessary. However, in a real measurement, it is quite unlikely to have any measurement that gives an exact value of 0. In addition, even though the measurement yields an exact 0 value, a good performance has already been demonstrated by the neural network. Therefore, unnecessary neural network implementation will still also produce an acceptable result that corresponds to the real value.

3.6 Summary

A three degree-of-freedom shear structure is utilized in the experimental test and numerical study. An MR damper is employed as the control device for the experimental structure, while an active bracing system is used in the numerical model. Four criteria are used to evaluate the performance of the control systems. The schematics of neural networks are also discussed in this chapter for both training and operation to compensate for the presence of time delay and data loss in wireless sensor networks.

4. NUMERICAL SIMULATION

Numerical simulation is performed using the shear model that has been previously discussed in Chapter 3. To perform this simulation, MATLAB and Simulink are utilized. This study focuses on investigating the techniques discussed in Chapter 3 to compensate for the presence of time delay and data loss in wireless structural control systems. First, they are investigated separately. Then, both systems are combined to produce the neural network-embedded control system that can compensate for both time delay and data loss. An active control strategy is demonstrated in this numerical simulation. An active bracing system is used as the control device of the system.

4.1 Neural Network Design

In this study, neural networks are designed to compensate for the time delay and data loss present in wireless structural control systems. Different neural network strategies need to be applied in the two cases. Therefore, separate neural network implementations are demonstrated first. In the end, these two neural network implementations are integrated to work together in the same system. The schematic of the neural network training is shown in Figure 3.3.

The most important part in the training of a neural network is to understand the nature of the training data sets for both input and target data sets. Because the training scheme is to employ an NAR neural network, only the input data set is required for this neural network training.

Figure 4.1 provides a scatter plot of the measurement results with time delay in the sensor reading. Here a linear curve fit is determined for the data using regression analysis with the ideal and measured values. All points should be located on the linear regression line if no time delay is present. Because the response of the structure can be approached as a periodic function, it explains why some scatter distribution is placed at the top of the regression line while the others are located at the bottom of the regression line and the compositions of both groups have an approximately equal number.

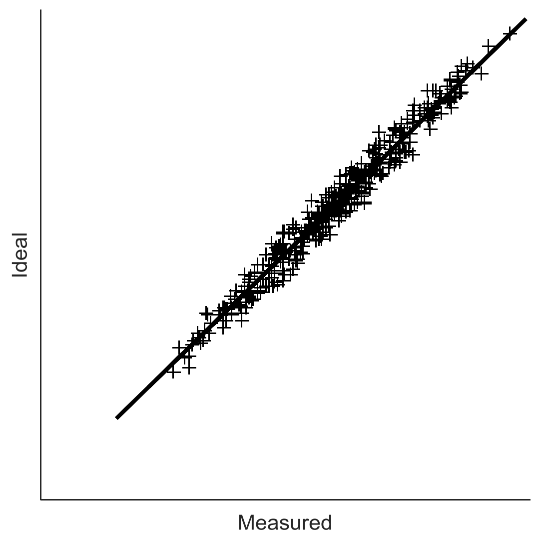


Figure 4.1. Scatter plot of the data with time delay in measurement from numerical simulations

When data loss occurs in the measurement, the measured value will have some discrepancies with the ideal value. Figure 4.2 depicts the scatter plot of the case where data loss occurs in the measurement. Two cases are presented in the figure, i.e. the 5% and 25% data loss cases. Although not shown, it is obvious that no data loss case should give a $y = x$ relationship here. As data loss is introduced into the system, the data will become more disperse and a linear regression coefficient can be found. It is discovered in the figure that the 25% data loss case has a more steep inclination in the regression line compared to the 5% data loss case, which is supposed to have closer distribution with the 0% data loss case. It is also worth noticing that the gradient of the regression line is greater than 1 for the case where data loss is introduced, which explains that for the ideal value (the y axes) has a greater amplitude than the measured value (the x axes). This observation confirms that the presence of data loss in the measurement reduces the maximum amplitude of the response, which can lead to an undesirable outcome in the system.

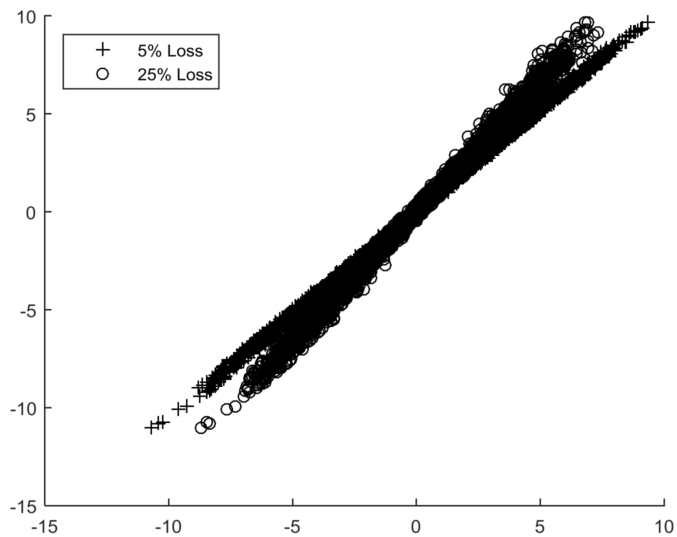


Figure 4.2. Scatter plot of the data with data loss in measurement from numerical simulations

Another useful approach to help understand the data is by creating a histogram plot of the data. A histogram of sample measurements which could potentially induce some data loss is shown in Figure 4.3. Both cases, the one without data loss and the one with 25% data loss, demonstrate a normal distribution with the same mean. Nevertheless, the histogram with data loss has more density at the mean. This is caused by the failure of the sensor to capture the high amplitude measurements and production of more measurements with values of 0 whenever data loss occurs (recall, the mean is about 0).

The first neural network training conducted is to deal with data loss problem. Separate neural networks are designed to process each acceleration of each story. For this case, six sets of time series of inputs are prepared with the same output. These six inputs are obtained from the same data loss value of 10% generated to follow a

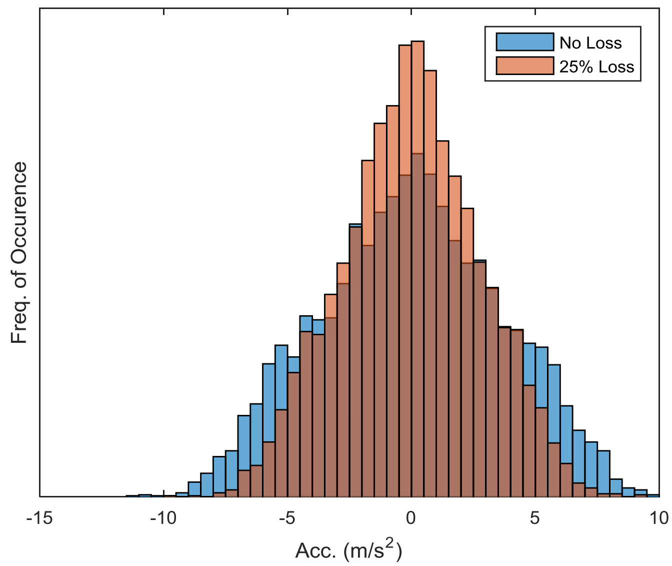


Figure 4.3. Histogram plot of the data with data loss in measurement

Bernoulli distribution with different initial seeds. The target of the neural network is the ideal corresponding floor acceleration record, which also can be represented by the case where data loss is equal to 0%. An illustration of how erroneous reading may be given by the wireless sensor due to data loss is shown in Figure 4.4.

For each neural network, the network is independently trained ten times. The normalized mean square error value of each training is recorded to help determining the best neural network.

For the neural network training, the data set on hand is randomly divided into three groups randomly using a proportion of 70% for training, 15% for validation, and 15% for testing. The training data set is used to generalize the network architecture. The validation data set is needed to avoid overfitting. The network validates each time the degree of accuracy is reduced in each validation step, and the network stops its training if six validation failures are reached consecutively. The testing data set is required to confirm the performance of the neural network. After the training,

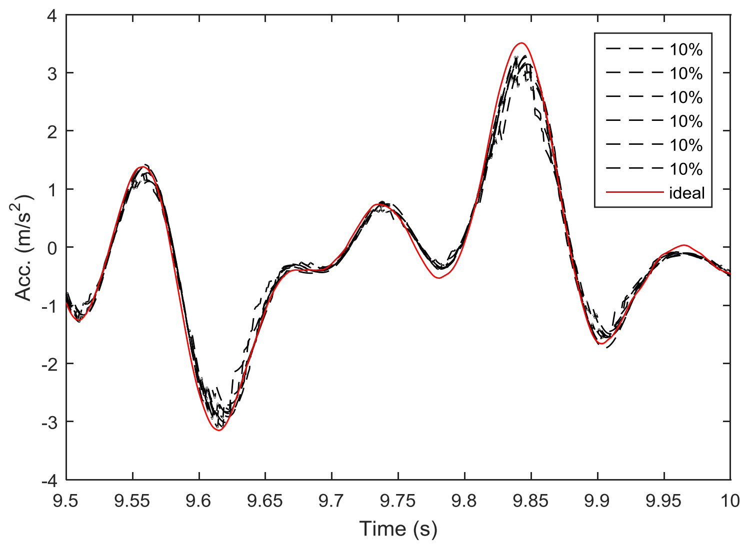


Figure 4.4. Erroneous measurement due to data loss

the performance of the trained neural network is tested using responses from several historical earthquakes.

4.2 Neural Network Performance

In this study, neural networks are proposed to compensate for the occurrence of time delay and data loss in the system. Thus, the performance must be evaluated in terms of these goals.

The performance of the wireless sensing are evaluated while measuring structural responses of an excitation of the three-story shear building due to earthquakes. Time delay and data loss is added to the system to simulate the wireless characteristics. The "ideal" measurement values, the one that is not interfered with time delay and data loss, are still kept to be later utilized as a reference. A NNWCF is utilized to correct the measurement from the wireless sensing system. The performance of the NNWCF is evaluated by comparing its NRMS (normalized root mean square) error to the NRMS error of the measurements from wireless sensors. The equation of

NRMS used to compute error between two arbitrary signals, an evaluated signal and a reference signal, is given as follows

$$E_{\mathrm{NRMS}} = \sqrt{\frac{\sum_{i=1}^{n}(x_{ri} - x_i)^2}{\sum_{i=1}^{n}(x_{ri} - \bar{x_r})^2}} \tag{4.1}$$

where x_{ri} is the reference signal, $\bar{x_{ri}}$ is the mean of the reference signal, and x_i is the evaluated signal.

Table 4.1 and Table 4.2 show the calculated NRMS errors between the ideal signals, as the reference signals, and both the measured signals and the corrected signals (using the NNWCF). Results from four earthquakes are shown. The NNWCF is demonstrated to show a superior performance in improving the measurements of a wireless sensor network for both pure time delay problem and pure data loss problem.

In the pure time delay problem (Table 4.1), the results shown use a NNWCF that is designed to compensate for wireless delay of 10 ms. However, it is still shown that the NNWCF still can improve the measurement of a wireless sensing system when wireless delay of 20 ms is incorporated. Therefore, it is reasonable when the results show a more superior performance of the NNWCF in dealing with the time delay of 10 ms (it improves the performance from an error of 16–23% to 2–7%), compared to the one with time delay of 20 ms (from an error of 32–46% to 16–27%).

In the pure data loss problem (Table 4.2), five data loss cases are examined, i.e. 5%, 10%, 15%, 20%, and 25%. The NNWCF is designed to deal with any amount of data loss. Here, a superior NNWCF performance is shown up to data loss of 25% with error values after the NNWCF corrects the measurement range from 0.1% to 0.4% (meanwhile, the error values of the wireless sensors range from 22% to 51%).

Figure 4.5 and Figure 4.6 are shown to illustrate of the comparison between cases evaluated in Table 4.1 and Table 4.2. It is observed in both figures the ability of the NNWCF to correct the measurement of a wireless sensor network that is very similar to the ideal value, the case that is not able to obtained in the real practice.

Table 4.1 NRMS errors before and after the implementation of the NNWCF for pure time delay problems

Earthquake	Floor	10 ms Time Delay		20 ms Time Delay	
		Measured	NN-Corrected	Measured	NN-Corrected
El Centro	1	23%	7%	46%	27%
	2	17%	3%	33%	18%
	3	17%	3%	34%	18%
Northridge	1	18%	4%	36%	20%
	2	16%	3%	32%	17%
	3	16%	3%	33%	17%
Loma Prieta	1	16%	3%	33%	17%
	2	16%	2%	32%	16%
	3	16%	2%	32%	16%
Kocaeli	1	16%	3%	32%	17%
	2	16%	2%	32%	16%
	3	16%	2%	32%	16%

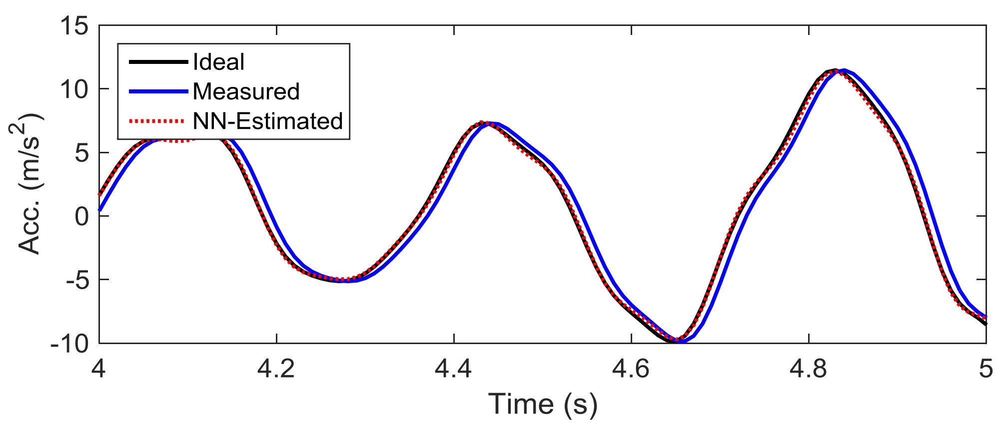


Figure 4.5. Neural network performance for 10 ms time delay compensation

Table 4.2 NRMS errors before and after the implementation of the NNWCF for pure data loss problems

Data Loss	Earthquake	El Centro			Northridge			Loma Prieta			Kocaeli		
	Floor	1	2	3	1	2	3	1	2	3	1	2	3
5%	Measured	23%	23%	23%	23%	22%	22%	22%	22%	22%	22%	22%	22%
	NN-Corrected	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.4%	0.3%	0.2%	0.3%	0.1%	0.1%
10%	Measured	32%	32%	32%	32%	32%	32%	32%	32%	32%	31%	31%	31%
	NN-Corrected	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.4%	0.3%	0.2%	0.3%	0.1%	0.1%
15%	Measured	39%	39%	39%	39%	39%	39%	39%	39%	39%	38%	38%	39%
	NN-Corrected	0.3%	0.2%	0.1%	0.2%	0.1%	0.1%	0.4%	0.3%	0.2%	0.3%	0.1%	0.1%
20%	Measured	45%	45%	45%	45%	45%	45%	45%	45%	45%	44%	45%	45%
	NN-Corrected	0.3%	0.2%	0.1%	0.2%	0.1%	0.1%	0.4%	0.3%	0.2%	0.3%	0.1%	0.1%
25%	Measured	50%	50%	50%	50%	50%	50%	51%	51%	51%	50%	50%	50%
	NN-Corrected	0.3%	0.2%	0.1%	0.2%	0.1%	0.1%	0.4%	0.3%	0.2%	0.3%	0.1%	0.1%

The strategy to employ neural network to deal with data loss seems to accomplish the desired performance as well (as shown in Figure 4.6). The sudden jumps (to 0 value) due to data loss create erroneous measurements that could have serious impacts on the control system. The neural network proposed here corrects these measurements each time the measurement delivers a value of 0. (In this study, the undefined values occurred due to data loss is defined as 0, although other approaches may also be pursued, such as using the previous value, etc.)

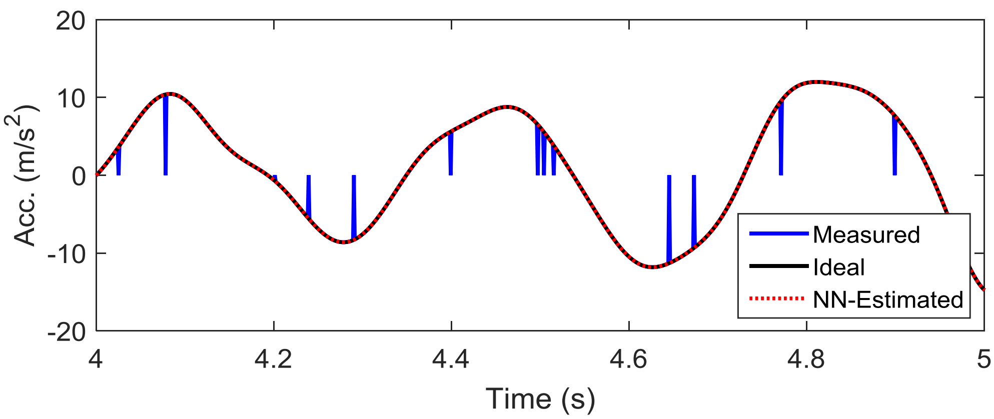


Figure 4.6. Neural network performance for 1% data loss compensation

In Figure 4.6, the case of data loss of 1% is shown (although the case is not investigated in Table 4.2) for an illustrative purpose. The time history responses of a higher data loss case will be more difficult to look at due to high numbers of sudden jumps in the measured signals.

4.3 Active Control Design

The LQG controller is employed for this particular control strategy. An active bracing system placed at the first floor of the structure is utilized as the control device. As discussed previously in Chapter 2, the LQG control strategy uses a weighting parameter, q, to determine the "aggressiveness" of control to the system. Usually, better control performance in terms of response reductions requires more "cost," which in this case, is represented by the control force provided by the active mass driver, although this tendency is not always found in all control problems.

As stated previously, four evaluation criteria are used in this study. However, for the controller design stage, only RMS evaluation criteria are used. The reason for this is to simplify the decision-making process and to avoid the evaluation that is only based on single value. The RMS considers the entire responses, thus it represents the general system performance better. Therefore, only J_3 and J_4 are used in this design process.

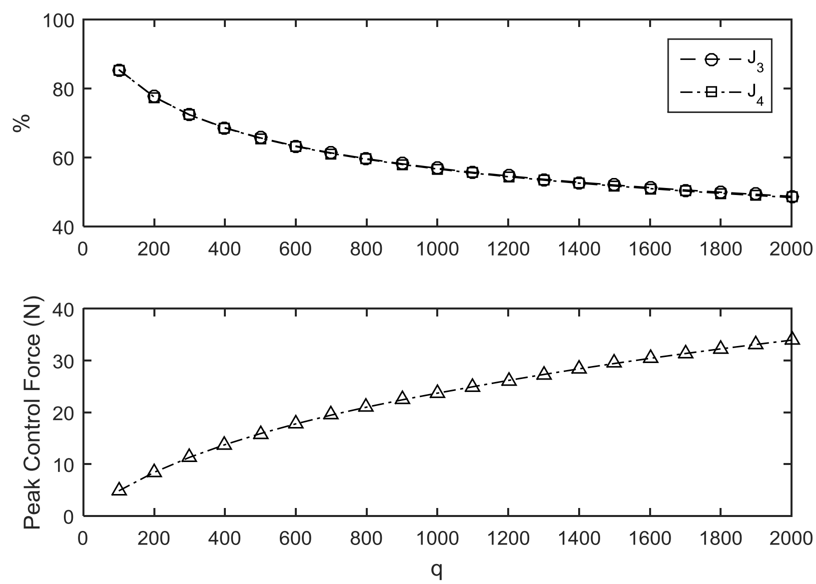


Figure 4.7. Control design options with various values of the weighting parameter q evaluated using the El Centro earthquake

Several simulations with various values of the weighting parameter q are conducted and the results are shown in Figure 4.7. The range of q values used in this simulation ranges from 1×10^2 to 2×10^3. As shown in Figure 4.7, lower J_3 and J_4 are achieved with higher values of q. However, the peak control force also increases, requiring more force from the actuator, which might be limited in real world problems and add expense to the system. To design a reasonable controller, the best control performance needs to be achieve while also considering a reasonable peak control force value. For this case, a q of 1×10^3 is used since it provides a reasonable peak control force value, 24 N. Also, the control performance of that particular q value shows a superior response reduction, about 57% reduction in both RMS value of the interstory drift and absolute acceleration. The details of the designed control performance and requirement is presented in Table 4.3.

Table 4.3 Detail of the designed active control performance and requirement evaluated using the El Centro earthquake

Criteria	Value
Peak control force	23.65 N
J_1	81.51%
J_2	77.59%
J_3	56.76%
J_4	56.57%

4.4 Influence of Time Delay and Data Loss on Nominal Controller

This study is motivated by presence of time delay, data loss, and sensor failure in a wireless structural control system. Simulations are conducted here to demonstrate how the performance of the control system is reduced due to time delay, data loss, and sensor failures. The study is focused on the implementation of an active control system with an active bracing system as the control device. The LQG control algorithm is adopted.

4.4.1 Simulation Procedure

Numerical simulations are performed with various wireless time delay and data loss values to determine how those features affect the performance of the control system in both applications. Sensor failure is also considered in this study which is represented by the case where data loss probability is equal to 100%. An active control strategy is examined (Figure 3.2).

In a wireless sensor network, time delay is mostly determined by the sensor network setup. The modeling of the time delay is determined based on data transmission time per step, and is determined in this study to be 10 ms. Since three sensors are used in this case study, the largest transmission delay is four steps, therefore the value of time delay is varied from 0 ms to 40 ms.

Data loss in transmission in the wireless sensor network is modeled as a Bernoulli distribution. The data loss is modeled in each sensor independently, representing the actual situation where loss is independent in each sensor. The range of loss probability modeled in the study is from 0% (no loss, 100% data transmission) to 100% (sensor failure).

Time delay is model to occur in all sensors. Alternatively, data loss is modeled in three separate cases: (1) all three sensors have the same loss probability; (2) two of three sensors have the same loss probability; and (3) one of three sensors has the same loss probability.

4.4.2 Simulation Results

The active control system and the three-story building response is simulated with the 1940 El Centro earthquake excitation. Various time delay and data loss values described in Subsection 4.4.1 considered to assess the impact of data loss and time delay on this control system performance. The performance of the control system is evaluated based on four criteria: peak of story drift (J_1), peak of absolute acceleration (J_2), RMS of story drift (J_3), and RMS of absolute acceleration (J_4)—all represent the ratio of the controlled system with the uncontrolled system. The various control performance values, measured using all evaluation criteria when data loss occur in all three sensors deployed on the structure, evaluated using band-limited white noise as base disturbance with noise power of 0.01 and sampling frequency of 1000 Hz is illustrated in Figure 4.8.

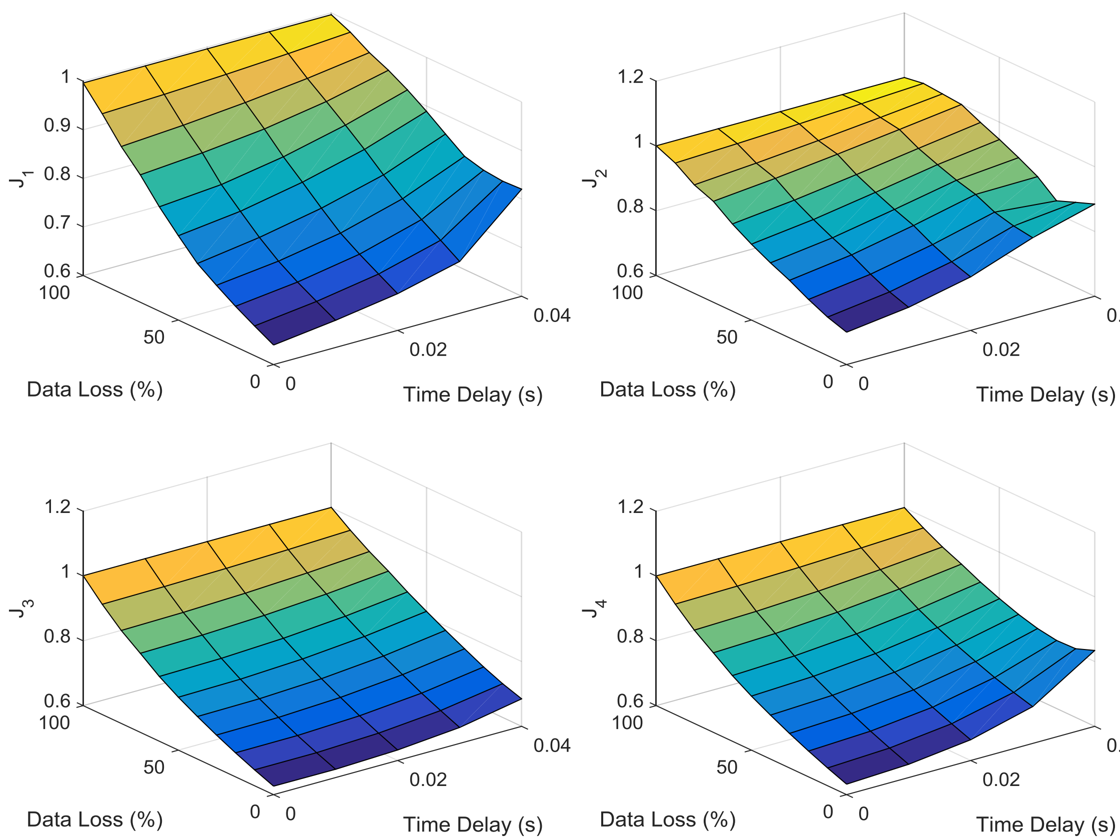


Figure 4.8. Control performance when time delay or data loss occurs in all sensors evaluated using band-limited white noise as base disturbance

An important conclusion is reached from Figure 4.8: time delay or data loss does, indeed, degrade the performance of the control system, for this particular system. These tendencies are clearly observed from all evaluation criteria. From the simulation, the best performance is found when zero time delay and zero data loss are considered in the system.

Another noteworthy finding is noticed when data loss is only assumed in the third floor sensor (see Figure 4.9). This specific case yields instabilities in the system that were not discovered in the previous case, in which data loss occurs in all sensors. These instabilities exist with extreme delay values (30 and 40 ms) with extreme data loss (more than 40% data loss). Although such extreme time delay and data loss would be preferably avoided before employing the system on a real structural implementation, the results demonstrate that the third floor sensor—or the sensor on the top floor, in general—is often the sensor with the highest degree of importance in the wireless sensor network for a shear building type of structure. In this regards, this study confirms a previous conclusion [31].

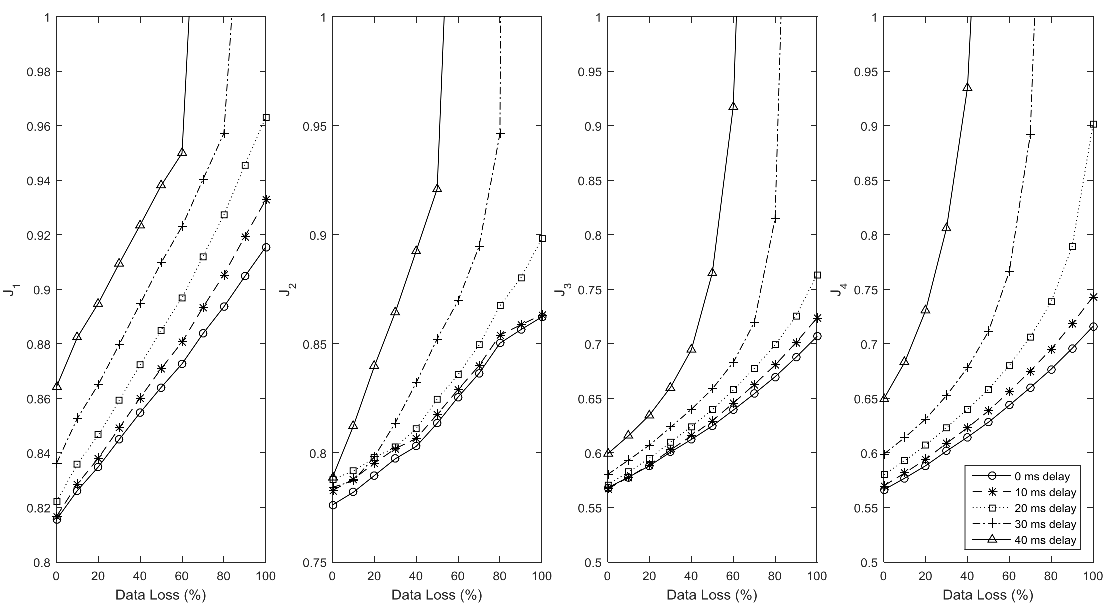


Figure 4.9. Control performance using band-limited white noise as base disturbance when time delay or data loss occurs in wireless sensor on the third floor

4.5 Wireless Control Performance with Neural Network

The aim of this work is to avoid the undesired performance degradation in the structural control system by compensating for the presence of time delay and data loss in the system. Neural networks are employed to achieve this goal. As discussed in Section 3.3, the network is trained using several base disturbances on the structure, i.e. band-limited white noise (to train the network about certain amplitudes) and synthetic earthquake (to train the network about the time-varying characteristic of an earthquake response). After a satisfactory training has been attained, the performance of the neural network is tested using several historical earthquakes, such as the 1940 El Centro earthquake, the 1989 Loma Prieta earthquake, the 1994 Northridge earthquake, and the 1999 Kocaeli earthquake.

The objective of the control system in structural application is obviously to reduce the structural motion during the excitation of the dynamic loading. Therefore, the goal to have the building experiences as little motion as possible. To reach this goal, the structural responses with the neural network need to be compared with those of the uncontrolled structure using the evaluation criteria that have been proposed (shown in Subsection 3.4.1). In general, lower results indicate a more superior controller performance.

In this numerical simulations, two cases are examined. In the first case, 10 ms time delay parameter is incorporated to the sensor measurement, while two data loss cases—the 10% and 25% data loss—are generated in the second case. In both cases, comparison with the ideal case is also given to demonstrate the idea of how the system should perform in wired-control systems. It is expected for the neural network to improve the performance of the control system after some degradation is shown due to the wireless features of time delay and data loss.

4.5.1 Time Delay Compensation

In this part, only time delay is included in the study (no data loss given in the system). As mentioned previously, four criteria are used to evaluate the performance of the control system. Four recorded earthquakes are subjected as the base disturbance of the system, thus fair evaluation can be made based on various and significant true historical events. The four earthquakes that are chosen in this study are the 1940 El Centro earthquake, the 1994 Northridge earthquake, the 1989 Loma Prieta earthquake, and the 1999 Kocaeli earthquake. All studied earthquakes were located in the United States, except for the Kocaeli earthquake which hit Turkey. The evaluations are summarized in Table 4.4.

Since four evaluation criteria (J_1, J_2, J_3, and J_4), four earthquakes (El Centro, Northridge, Loma Prieta, and Kocaeli), and two delay cases (10 ms and 20 ms time delay) are used in this study, therefore this produces 24 performance comparisons to decided the neural network's legitimacy to be adopted for improving the control performance. Although two time delay cases are presented here, only one neural network function is designed, i.e. to compensate for 10 ms time delay. Therefore when the network shows a superior control performance in the 20 ms time delay case, that demonstrates that the network's ability to improve the performance even though the time delay value is found to be in a higher number.

The results shown in Table 4.4 are illustrated in bar charts in Figure 4.10.

The deeper look on how the neural network could improve the control performance can be figured by looking on its control forces produced due to the base disturbances (see Figure 4.11).

Basically, both the systems without and with neural network administers a more or less same performance. However, if the comparison is looked more closely, there is a certain gap of time delay between the control force produced by the system without neural network compensator and the system with neural network. This gap is most likely corresponds to the time delay induced in the system measurement.

Table 4.4 Performance of pure time delay cases without and with the NNWCF

Earthquake	Time Delay (ms)	Strategy	J_1	J_2	J_3	J_4
El Centro	10	w/o NN	0.84	0.79	0.58	0.60
		w/ NN	0.82	0.79	0.57	0.58
	20	w/o NN	0.86	0.80	0.60	0.63
		w/ NN	0.83	0.78	0.58	0.59
Northridge	10	w/o NN	0.83	0.80	0.55	0.57
		w/ NN	0.83	0.79	0.55	0.56
	20	w/o NN	0.83	0.81	0.56	0.58
		w/ NN	0.83	0.80	0.55	0.56
Loma Prieta	10	w/o NN	0.85	0.90	0.58	0.58
		w/ NN	0.86	0.90	0.57	0.56
	20	w/o NN	0.83	0.90	0.59	0.59
		w/ NN	0.84	0.90	0.57	0.57
Kocaeli	10	w/o NN	0.88	0.89	0.54	0.55
		w/ NN	0.87	0.88	0.54	0.54
	20	w/o NN	0.88	0.90	0.55	0.57
		w/ NN	0.87	0.88	0.54	0.55

Therefore, by looking at this figure, it could be concluded that the neural network has been successfully compensated the issue of time delay presented in the wireless sensor network. Moreover, this compensator scenario has also been proven to work by these numerical simulations.

4.5.2 Data Loss Estimation

The results for data loss cases with the El Centro earthquake are summarized in Table 4.5. As shown in these two tables, the system with a neural network embedded

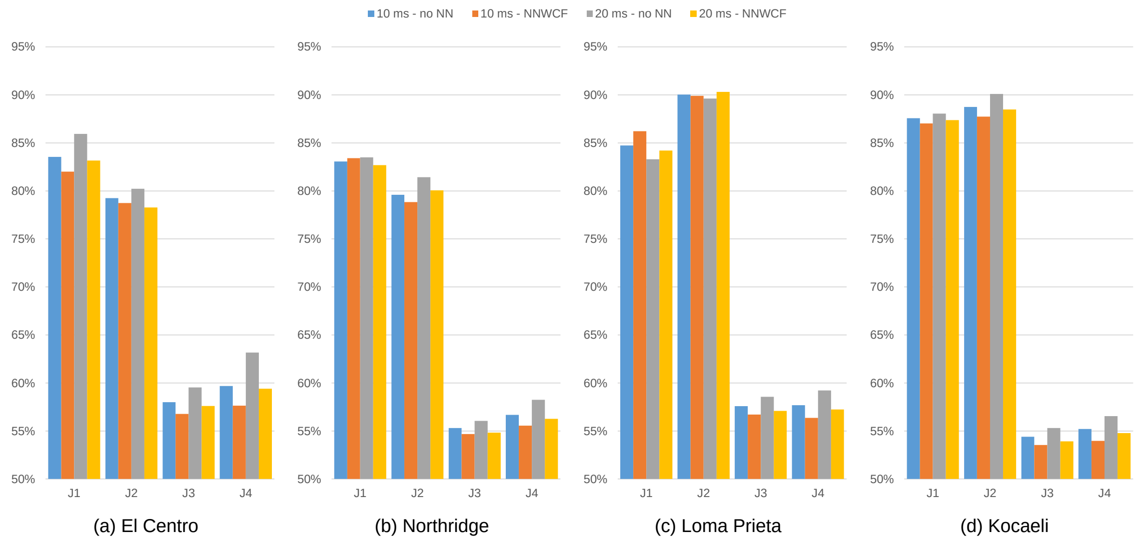


Figure 4.10. Performance of pure time delay cases without and with the NNWCF

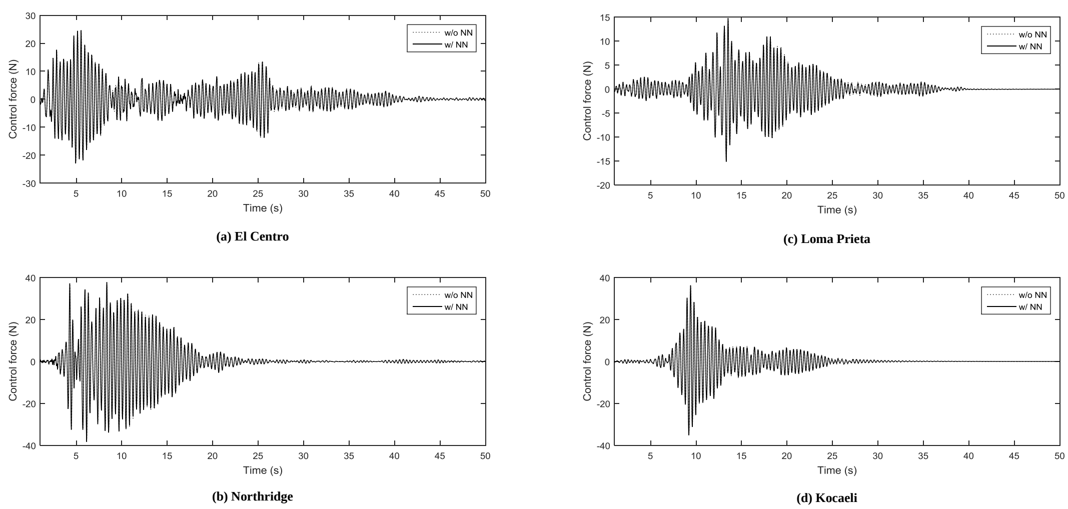


Figure 4.11. Control forces produced from control schemes without and with neural network for time delay compensation due to four evaluated earthquakes: (a) El Centro; (b) Northridge; (c) Loma Prieta; (d) Kocaeli

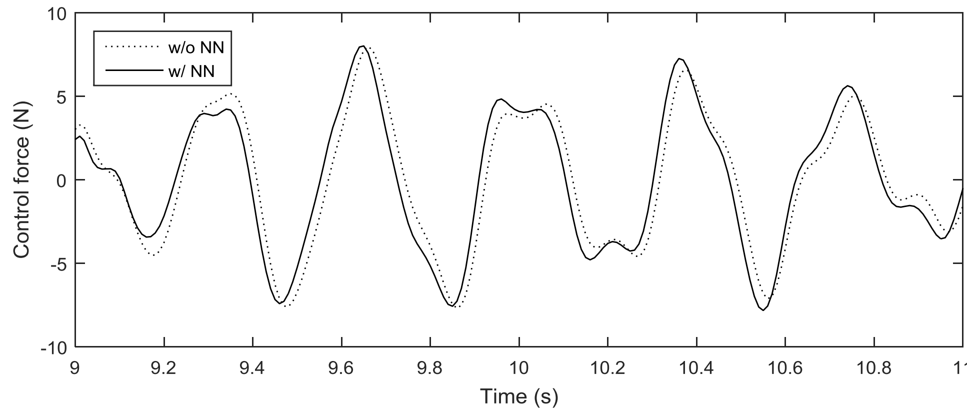


Figure 4.12. Deeper look of control forces produced from control schemes without and with neural network for time delay compensation due to the El Centro earthquake

always performs better than the corresponding case without the neural network in all evaluation criteria.

It is obvious that when no data loss is introduced into the system, the system produces the same performance. This verifies the implementation because in the neural network system, the strategy ignores unnecessary compensation which might happen when the actual measurement value is equal to 0. This approach accounts for the very small possibility that an exact value of 0 will appear in the real measurement. Also, even if an exact zero value appears, the performance of the neural network has shown to produce good results. Therefore, any unnecessary compensation will still produce a good result and performance degradation is not significant.

It is also observed that the control performance improvement provided by the neural network is larger as the value of data loss increases. This demonstrates that the neural network could deal with a significant amount of data loss as high as 25% is considered here.

Table 4.5 shows the performance of the systems without and with the NNWCF when subjected to the El Centro earthquake. Six data loss cases are given: 0%, 5%, 10%, 15%, 20%, and 25% data loss. In all case presented here, the system with the NNWCF always outperforms the performance of the system without the NNWCF, except for the case where no data loss are presented. For the case where no data loss occurs, the system with the NNWCF still shows a similar level of performance with the system without the NNWCF. This means that the NNWCF does not degrade the performance of the controller, even when the parameters desired to be compensated for are not presented.

Table 4.5 Performance of pure data loss cases without and with the NNWCF

Data Loss	Scenario	Evaluation Criteria			
		J_1	J_2	J_3	J_4
0%	w/o NN	0.82	0.78	0.57	0.57
	w/ NN	0.82	0.78	0.57	0.57
5%	w/o NN	0.83	0.82	0.61	0.60
	w/ NN	0.82	0.82	0.60	0.59
10%	w/o NN	0.91	0.83	0.65	0.65
	w/ NN	0.89	0.82	0.63	0.63
15%	w/o NN	1.0	0.91	0.70	0.70
	w/ NN	0.97	0.89	0.67	0.67
20%	w/o NN	1.0	0.95	0.76	0.76
	w/ NN	0.99	0.92	0.71	0.71
25%	w/o NN	1.1	1.0	0.82	0.82
	w/ NN	1.1	1.0	0.76	0.75

Results of El Centro earthquake shown in Table 4.5 are illustrated in bar charts in Figure 4.13.

Other interesting finding in Table 4.5 is shown when 25% data loss occurs in the system. In both evaluations of peak responses, interstory drift (J_1) and absolute

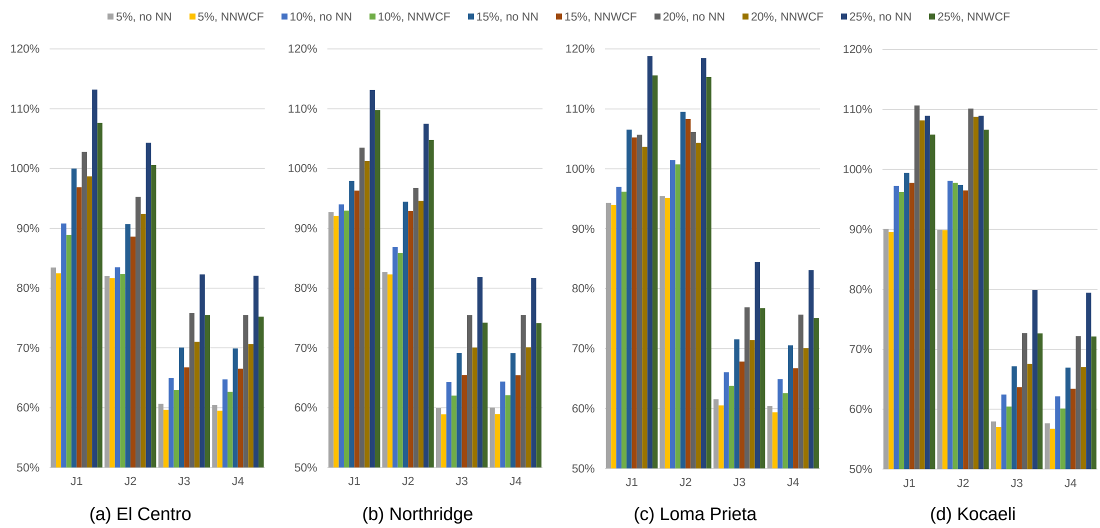


Figure 4.13. Performance of pure data loss cases without and with the NNWCF

acceleration (J_2), the responses of the controlled structure, in both with and without the NNWCF, exceed the responses of the uncontrolled structure. This demonstrates how the data loss occurred may degrade the controller performance to the level where it performs worse than the system without the controller. However, it is important to be noticed that the peak value often occurs in only one place (exactly what happens in this case). Usually this occurs in the start of the peak of the ground excitation. At this stage, the control algorithm probably has not gained a sufficient information to control that high increment occurs in the earthquake. Therefore, it fails to reduce the responses of the structure. However, this only occurs in a very short period of time before the control procedure has finally been able to figure out the appropriate control force required for the structure when the ground disturbance has been gradually become more stable. Therefore, extra attention needs to be paid when looking at the evaluation criterion of the peak value of responses since it may only represent one particular point during the whole responses.

Similar tendencies are found with the Northridge earthquake (Table 4.6). The system with the NNWCF shows a more superior performance than the system without

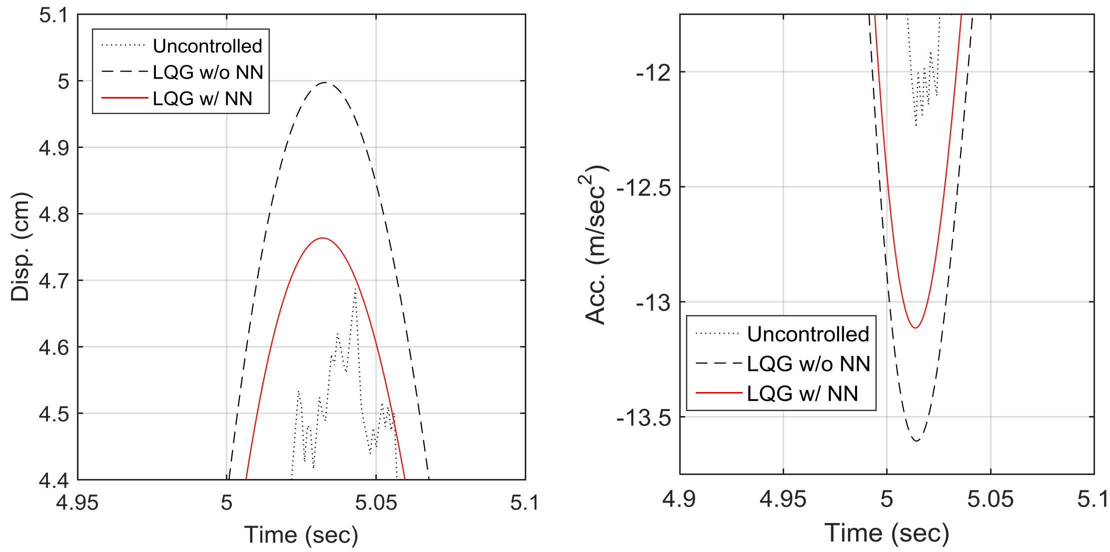


Figure 4.14. Peak responses of the controlled structure exceeds the responses of the uncontrolled structure during the El Centro earthquake when 25% data loss occurs

the NNWCF. The same observation of the peak interstory drift and absolute acceleration in the controlled systems that exceed the peak of the responses in the uncontrolled structure is also found in the Northridge earthquake. This finding strengthens the theory that suggests how the data loss may cause a serious problem in the structural control system when it is not handled carefully.

Results from the Loma Prieta earthquake and the Kocaeli earthquake are also shown (Table 4.7 and Table 4.8).

The evaluation criteria may give a quantitative portrayal of the performance of control system. However, the criteria make some generalization as well. For instance, the peak value of the interstory drift may only occur at a single floor at a single time. The evaluation criteria alone does not provide a complete picture. Several evaluation criteria might need to be evaluated together. To get a deeper look into the system's performance, both the peak and the RMS values of the interstory drifts and absolute

Table 4.6 Evaluation criteria values between cases without and with neural network for the Northridge earthquake

Data Loss	Scenario	Evaluation Criteria			
		J1	J2	J3	J4
0%	w/o NN	0.87	0.79	0.56	0.56
	w/ NN	0.87	0.79	0.56	0.56
5%	w/o NN	0.93	0.83	0.60	0.60
	w/ NN	0.92	0.82	0.59	0.59
10%	w/o NN	0.94	0.87	0.64	0.64
	w/ NN	0.93	0.86	0.62	0.62
15%	w/o NN	0.98	0.94	0.69	0.69
	w/ NN	0.96	0.93	0.65	0.65
20%	w/o NN	1.0	0.97	0.76	0.76
	w/ NN	1.0	0.95	0.70	0.70
25%	w/o NN	1.1	1.1	0.82	0.82
	w/ NN	1.1	1.0	0.74	0.74

Table 4.7 Evaluation criteria values between cases without and with neural network for the Loma Prieta earthquake

Data Loss	Scenario	Evaluation Criteria			
		J_1	J_2	J_3	J_4
0%	w/o NN	0.90	0.90	0.58	0.56
	w/ NN	0.90	0.90	0.58	0.56
5%	w/o NN	0.94	0.95	0.62	0.60
	w/ NN	0.94	0.95	0.61	0.59
10%	w/o NN	0.97	1.0	0.66	0.65
	w/ NN	0.96	1.0	0.64	0.63
15%	w/o NN	1.1	1.1	0.72	0.71
	w/ NN	1.1	1.1	0.68	0.67
20%	w/o NN	1.1	1.1	0.77	0.76
	w/ NN	1.0	1.0	0.71	0.70
25%	w/o NN	1.2	1.2	0.84	0.83
	w/ NN	1.2	1.2	0.77	0.75

Table 4.8 Evaluation criteria values between cases without and with neural network for the Kocaeli earthquake

Data Loss	Scenario	Evaluation Criteria			
		J1	J2	J3	J4
0%	w/o NN	0.88	0.87	0.54	0.54
	w/ NN	0.88	0.87	0.54	0.54
5%	w/o NN	0.90	0.90	0.58	0.58
	w/ NN	0.90	0.90	0.57	0.57
10%	w/o NN	0.97	0.98	0.62	0.62
	w/ NN	0.96	0.98	0.60	0.60
15%	w/o NN	0.99	0.97	0.67	0.67
	w/ NN	0.98	0.97	0.64	0.63
20%	w/o NN	1.1	1.1	0.73	0.72
	w/ NN	1.1	1.1	0.68	0.67
25%	w/o NN	1.1	1.1	0.80	0.79
	w/ NN	1.1	1.1	0.73	0.72

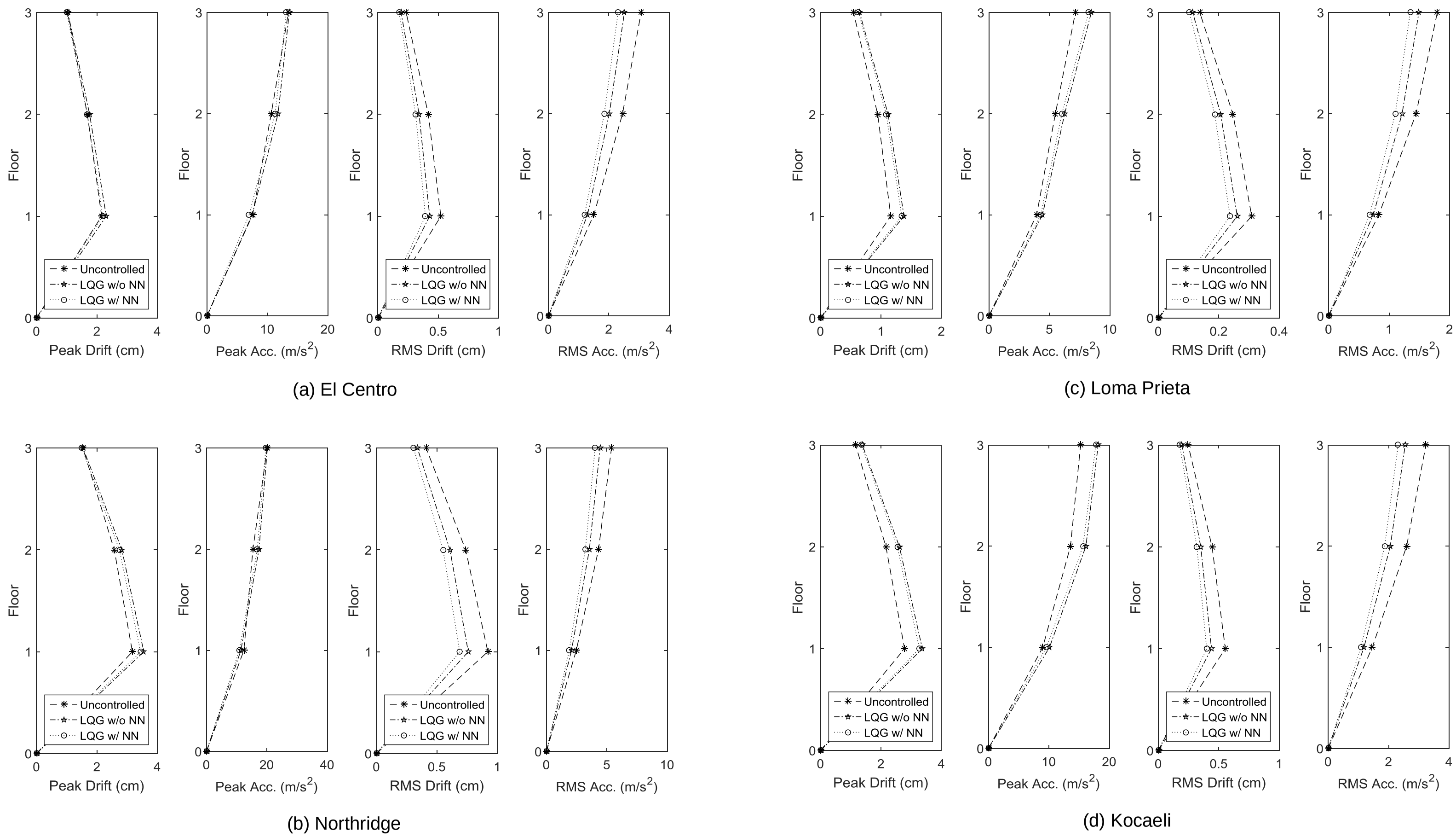


Figure 4.15. Peak and RMS response profiles with data loss of 25%

accelerations of each floor are computed (see Figure 4.15). The results shown here are obtained from the simulation using the distributed 25% data loss.

It is found that the systems with neural network consistently show better performance demonstration in the RMS values of the interstory drift and absolute acceleration. However, in some cases, the performance of a system without a neural network overcomes those of the case with the neural network embedded into the system in terms of the peak values (for both interstory drift and absolute acceleration). This may happen randomly because a single point has more extreme value, although it may not represent the system's general response. In this case, RMS surely becomes a better view of the system's entire response. In addition, the evaluation criteria results also show a consistent better demonstration of the systems with neural network in all evaluated criteria.

Lastly, it is always necessary to discuss the "cost" function of the control system. In this case, the cost of the control system can be represented as the required control force to achieve the results. Figure 4.16 shows a comparison of the external force required to control the system due to the El Centro, Northridge, Loma Prieta, and Kocaeli earthquake.

The first 20 seconds of the control force is shown in the figure. The control force required by the system with a neural network has a higher amplitude and is more smooth. Lower amplitude shown in the system without a neural network is most likely occurred due to the occurrence of zero response points in the measurement when data loss occurs. In response to those zero values, there is no need to control the structure, and a smaller control force is produced. Also, when data loss occurs, sudden jumps do appear in the measurement time history. This makes the response becomes less continuous and introduces high frequency dynamics. Although Kalman estimator can provide a smoother response, it does not guarantee an insensitivity of the control system to this effect. This issue may cause chattering in the control force that is undesirable, especially with an active control system. This chattering external force acts like an impulsive force and yields high frequency responses at times. Fortunately, chattering is not observed in the required control forces with the neural network. Therefore, the neural network can prevent this complication.

4.6 Performance of the NNWCF

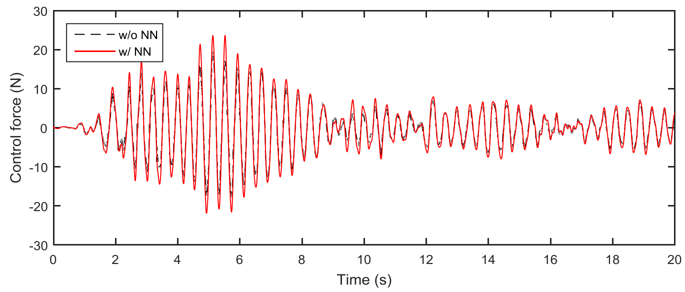
The NNWCF (Neural Network Wireless Correction Function) is created by combining both neural network functions that are specifically designed to compensate for time delay and data loss. The result shown in this section (Figure 4.17) demonstrates the performance of the NNWCF with the time delay of 10 ms and data loss of 25% presented in the wireless sensors.

Figure 4.17 shows the time history of the structural responses due to the El Centro earthquake in two time frames, the first ten seconds and from 20 to 30 seconds of the earthquake. It can be seen that the performance of the controller with the NNWCF in it shows a more superior performance. A reduction of the overall response, the main objective of the use of the control system, is also achieved.

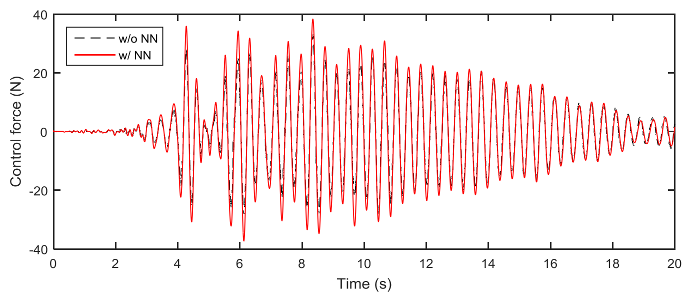
Moreover, since the NNWCF is used to achieve the ideal case of the control system without time delay and data loss, another evaluation of the system with the ideal case (where no time delay and data loss presents) is also demonstrated (see Figure 4.18). Again, the result shown in this figure utilized time delay of 10 ms and data loss of 25%. The ideal case has no time delay and data loss in the system. It can be obviously observed that the NNWCF improves the performance of the control system in a superior performance. The NNWCF assists the control performance to approach the performance of the ideal system, which is unachievable in the world of wireless sensor network. Therefore, it can be concluded that the performance of a wireless structural control system can be improved to approach the performance of the traditional wired structural control system, and the degradation of the control performance that could potentially occur can be avoided by utilizing the NNWCF.

4.7 Summary

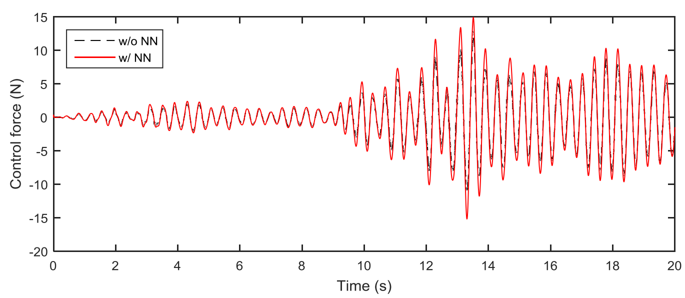
Numerical simulations are demonstrated in this chapter. To compensate for the presence of time delay and data loss, a neural network is designed. Before it is implemented to the system, the network is tested to ensure that it produces a fine result. An active controller is designed to be implemented in the three-story shear structure. Using the wireless structural control, the performance of the system with the neural network is compared with those of the case without the neural network. It is shown that the NNWCF is able to compensate for the presence of time delay and data loss in wireless structural control problems.



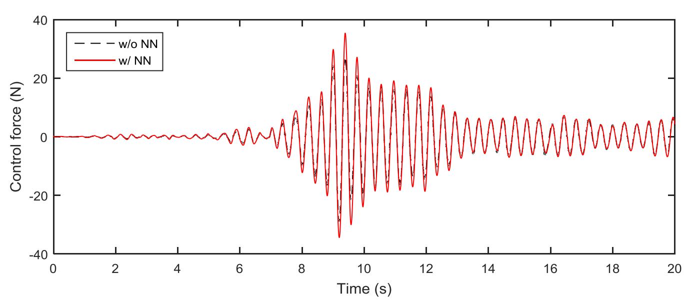
(a) El Centro



(b) Northridge



(c) Loma Prieta



(d) Kocaeli

Figure 4.16. Control force due to: (a) El Centro earthquake; (b) Northridge earthquake; (c) Loma Prieta earthquake; (d) Kocaeli earthquake

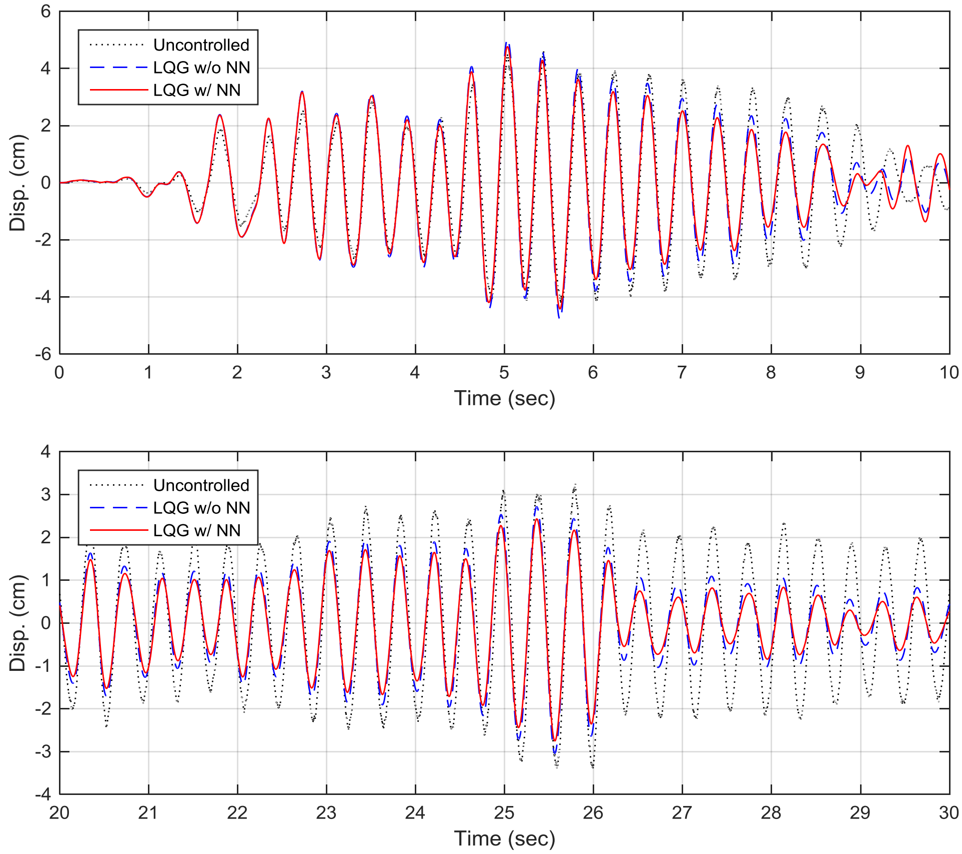
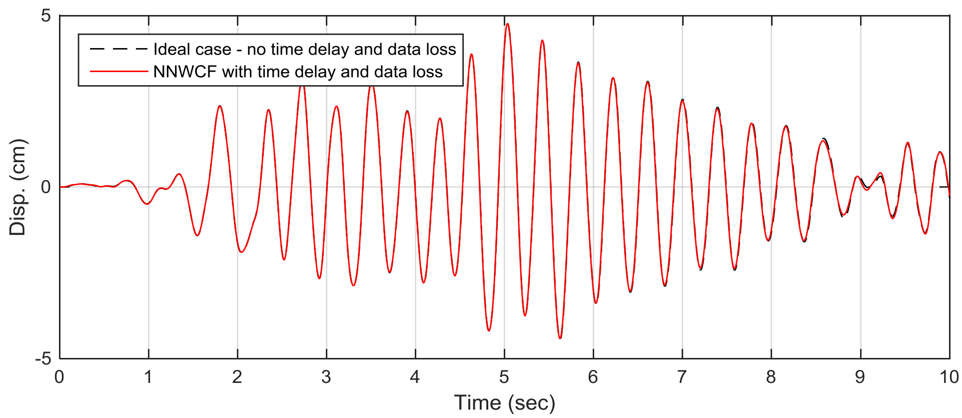


Figure 4.17. Responses from various cases due to El Centro earthquake



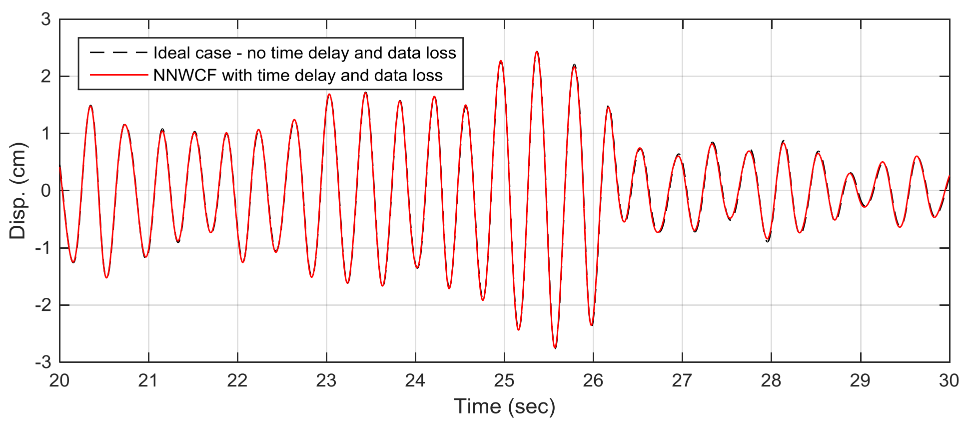


Figure 4.18. Comparison between the ideal case and the result of NNWCF-LGQ control system with time delay and data loss

5. LABORATORY EXPERIMENT

A laboratory experiment is performed to verify the performance of the NNWCF shown in the numerical simulation. Two experiments are considered to demonstrate the performance of the NNWCF: an excitation of a bare structure (without any control strategy) and an excitation of a controlled structure. Both experiments use the three-story shear building structure (discussed in Chapter 3). The building is placed on a six degree-of-freedom shake table that will generate a ground excitation to the building. For the controlled case, an MR damper is utilized on the first floor as the control device. The MR damper is attached to the first floor of the structure to administer the control forces required for the desirable performance.

Although the study focuses on the application of wireless sensor network in structures, no wireless sensors are employed in this experiment. Data from the wired sensors used in the experiment is used and realistic wireless characteristics are digitally simulated, i.e. time delay and data loss to enable control of the various parameters to examine their effects. Thus, the values of time delay and data loss in the system are adjusted to the actual time delay and data loss values usually observed in wireless sensor network application in structures.

Final control experiment has not been performed.

5.1 System Identification

Before the control system is employed to the structure, system identification is performed to determine the dynamic characteristics of the experimental structure and build a model for the control design purpose. System identification is performed by giving the structure a band-limited white noise as base acceleration. Wired sensors (PCB piezotronics accelerometers) are attached on each floor and at the base of the structure (attached to the shake table). All data are acquired using the VibPilot DAQ system. A sampling frequency of 1024 Hz is used for this system identification and anti-aliasing filters are built into the VibPilot DAQ system.

The following procedures need to be performed for system identification. First, sensors need to be placed in the accordance direction to the one-dimensional ground excitation. Then, the sensors are connected to the VibPilot DAQ. To operate the VibPilot, the M+P software is used so the parameters must be set in the software. Then, a band-limited white noise signals is generated as the base disturbance to the structure. While the base disturbance runs, data are acquired using the VibPilot system. After the data are collected, data processing is performed to obtain the transfer functions. The sets of transfer functions represent the input-output behavior of the system.

After the experimental transfer functions are obtained, the values of the experimental mass, stiffness, and damping matrices can be determined using the method developed by Ozdagli, et al. (2012) [61]. The mass matrix is initially set to the niminal values from the geometry and materials. Then, we update the model of the structure based on the newly determined parameters. The updated mass, damping, and stiffness in this study are determined to be

$$M_e = \begin{bmatrix} 22.73 & -1.22 & -3.99 \\ -1.22 & 22.05 & -0.90 \\ -3.99 & -0.90 & 21.56 \end{bmatrix} \text{kg},$$

$$C_e = \begin{bmatrix} 10.06 & 4.64 & -3.33 \\ 4.64 & 8.18 & 0.04 \\ -3.33 & 0.04 & 9.62 \end{bmatrix} \text{Ns/m},$$

$$K_e = \begin{bmatrix} 5.75 & 3.96 & -2.07 \\ 3.96 & 4.26 & -0.18 \\ -2.07 & -0.18 & 4.41 \end{bmatrix} \times 10^4 \text{N/m}.$$

Using the updated structural properties, a numerical transfer function is obtained for verification. The comparison of the magnitude of the transfer function of the experimental and the numerical model is provided in Figure 5.1, while the comparison of the phase of the transfer functions is illustrated in Figure 5.2.

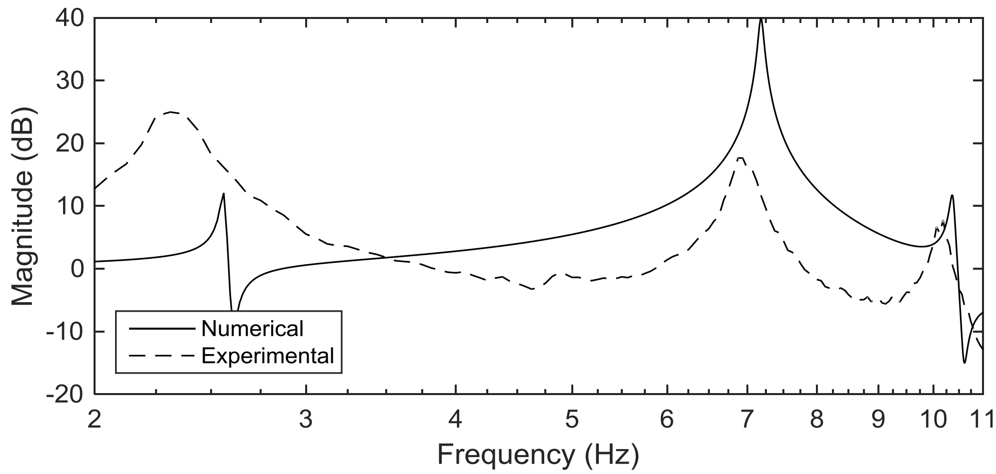


Figure 5.1. Magnitude of transfer function from ground acceleration to third floor acceleration

Natural frequencies from both numerical and experimental models are given in Table 5.1. From the natural frequency comparisons between the experimental and numerical models, it is found that there is about 0.25 to 0.35 Hz frequency difference between the natural frequencies obtained from the experimental and the numerical model.

5.2 Performance of NNWCF in Wireless Sensor Measurements

The Neural Network Wireless Correction Function (NNWCF) is designed to compensate for the presence of time delay and data loss in a wireless sensor network. The function's goal is to provide a better sensor measurement for the purpose of data acquisition or feeding-back the inputs for a control strategy.

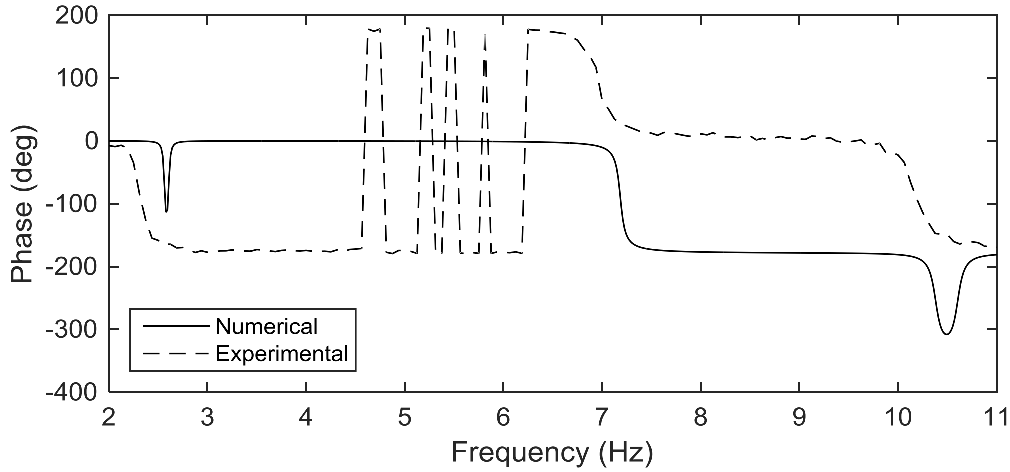


Figure 5.2. Phase of transfer function from ground acceleration to third floor acceleration

Table 5.1 Natural frequencies of the numerical and experimental model

Mode	Numerical (Hz)	Experimental (Hz)
1	2.56	2.31
2	7.19	6.88
3	10.38	10.19

In this section, an experiment with a three-story shear structure is conducted to demonstrat the NNWCF's performance shown in Chapter 4 using real data. For this experiment, data is acquired with wired sensors, but wireless characteristics, in terms of time delay and data loss, are induced to the measurement so that it resembles the nature of wireless sensor network.

Four historical earthquake records are used for this experiment: the 1940 El Centro earthquake, the 1994 Northridge earthquake, the 1995 Kobe earthquake, and the 1999 Chichi earthquake. Some scaling factors are used to adjust the magnitude of the earthquake to ensure an appropriate excitation is subjected to the structure to avoid yielding in the material or equipment damage. Scaling of 20% is used for Northridge; 35% for Chichi; 25% and 40% for El Centro; no scaling factor (factor of one) is used for Kobe. Results from various earthquakes are shown in Table 5.2. Table 5.3 shows the result of the experiments from El Centro earthquake using two different scalings: 40% and 25%. Both Table 5.2 and Table 5.3 are performed with 10 ms time delay for every case presented.

Values shown in Table 5.2 and Table 5.3 are the normalized root mean square error values computed with the Equation 4.1.

Figure 5.3 shows the responses of the structure in the experiment using 40%-magnitude El Centro earthquake with data loss of 5% that have been filtered using Kalman estimator. From Table 5.2, it can be seen that the systems with NNWCF outperform the results from systems without NNWCF. The effectiveness of the NNWCF is observed to be declining as more data loss is found in the system.

During this evaluation of the performance of NNWCF, some interesting observations were found and resulted in some improvements in the system that enhances the applicability for real world applications. These findings include the findings on noise and the strategy to consider the applied sampling rate.

5.2.1 Richness of Amplitude in Training Data

The training of the neural network used in this experiment uses the same training strategy discussed in Chapter 4. Therefore, in that chapter, it is discussed that one earthquake record that is used for evaluation is the El Centro earthquake with 100% magnitude. However, for this experiment, the earthquake must be scaled down so that the response of the structure reduced to avoid damage. However, the neural network is trained more to high amplitude responses. This conclusion is confirmed by looking at Table 5.3. From two El Centro earthquakes used here, the neural network performs better with the one with higher amplitude (40%, the closest one to

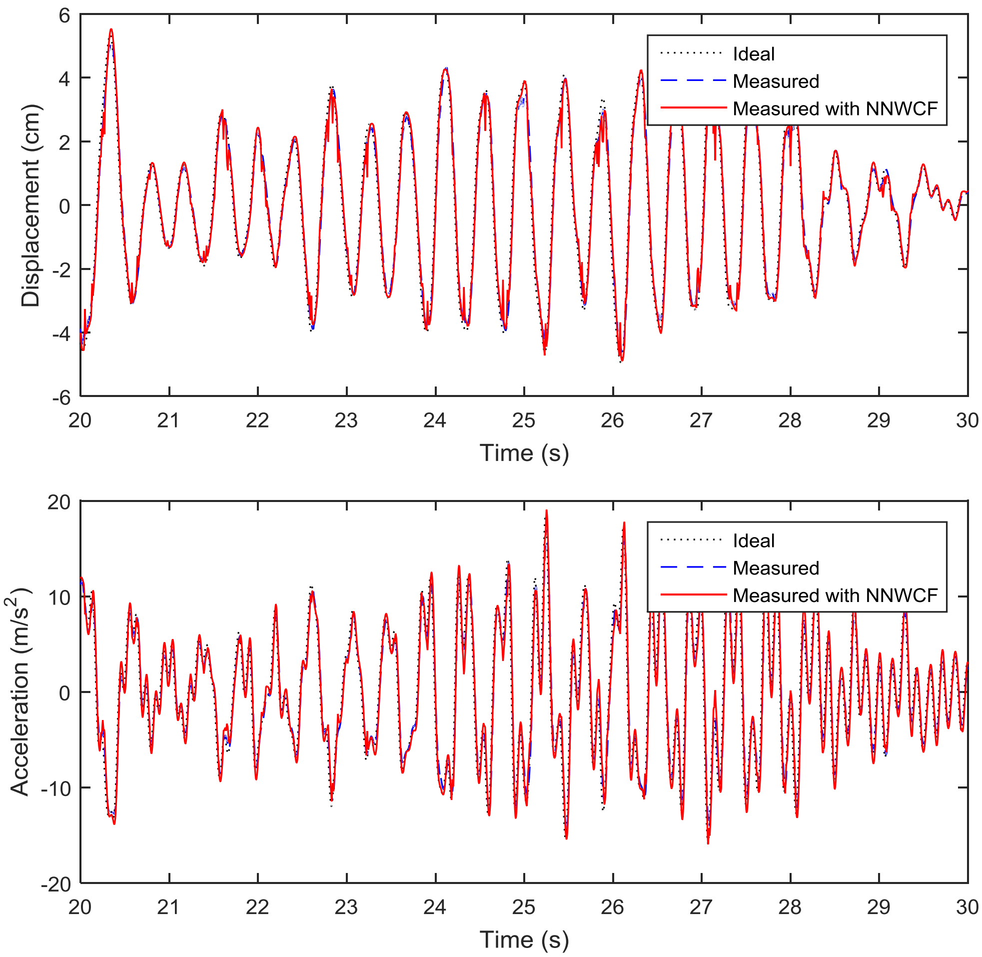


Figure 5.3. Structural responses in the experiment using El Centro earthquake with data loss of 5%

Table 5.2 NRMS error (with 10 ms time delay) of NNWCF in laboratory experiment from various earthquake excitations

Earthquake	Floor	Data Loss									
		1%		2%		3%		4%		5%	
		No NN	NN	No NN	NN	No NN	NN	No NN	NN	No NN	NN
El Centro (40%)	1	0.39	0.27	0.40	0.32	0.41	0.34	0.42	0.36	0.43	0.40
	2	0.27	0.21	0.28	0.27	0.30	0.30	0.32	0.33	0.33	0.37
	3	0.27	0.19	0.28	0.24	0.29	0.30	0.31	0.33	0.33	0.37
Kobe (100%)	1	0.40	0.30	0.42	0.35	0.44	0.39	0.46	0.44	0.47	0.48
	2	0.27	0.24	0.30	0.30	0.33	0.35	0.35	0.40	0.37	0.43
	3	0.31	0.24	0.34	0.31	0.36	0.34	0.38	0.39	0.40	0.44
Northridge (20%)	1	0.44	0.26	0.45	0.31	0.45	0.32	0.47	0.33	0.48	0.35
	2	0.28	0.17	0.30	0.24	0.31	0.26	0.34	0.28	0.35	0.31
	3	0.31	0.18	0.32	0.23	0.33	0.26	0.34	0.28	0.34	0.31
Chichi (35%)	1	0.40	0.27	0.40	0.33	0.42	0.36	0.43	0.39	0.44	0.43
	2	0.25	0.21	0.27	0.31	0.30	0.34	0.32	0.37	0.34	0.41
	3	0.28	0.22	0.32	0.29	0.35	0.32	0.37	0.36	0.39	0.38

Table 5.3 NRMS error (with 10 ms time delay) of NNWCF in laboratory experiment from El Centro with different scalings

Earthquake	Floor	Data Loss									
		1%		2%		3%		4%		5%	
		No NN	NN	No NN	NN	No NN	NN	No NN	NN	No NN	NN
El Centro (40%)	1	0.39	0.27	0.40	0.32	0.41	0.34	0.42	0.36	0.43	0.40
	2	0.27	0.21	0.28	0.27	0.30	0.30	0.32	0.33	0.33	0.37
	3	0.27	0.19	0.28	0.24	0.29	0.30	0.31	0.33	0.33	0.37
El Centro (25%)	1	0.41	0.28	0.42	0.34	0.43	0.37	0.44	0.40	0.45	0.42
	2	0.30	0.24	0.32	0.30	0.33	0.33	0.35	0.36	0.36	0.39
	3	0.29	0.23	0.31	0.28	0.33	0.32	0.34	0.35	0.35	0.38

the full magnitude El Centro record). This explains, in part, why the neural network performs in a superior manner in the numerical simulation but the performance is degraded in the experiment. Therefore, in designing a proper neural network, it is important to consider the appropriate richness of the amplitude of the training data so that the neural network will be able to compensate for any type of structural responses due to future unknown earthquakes.

5.2.2 Presence of Noise

Noise in the sensors can originate from many sources: motions from living things, machine vibrations, or electronic noise. This noise makes it impossible to obtain a noise-free measurements in a real world experiment. Therefore, a strategy to handle the presence of noise is needed to ensure that the NNWCF is performing well into the presence of noise.

An illustration of typical noisy data is depicted in Figure 5.4. These data are taken from a real measurement of structural response due to El Centro earthquake. It can be seen that the noise might be substantial. Also, realistic issues such as offsets need to be considered in the neural network implementation.

To deal with noise, the neural network training strategy is modified. In the neural network strategy to compensate for the presence of data loss, the network is trained with noisy data. Therefore, it will have a better ability to cope with the presence of noise in the system.

5.2.3 Strategy in Determining Sampling Rate

Sampling is the discretization of a continuous signal. Because we are working with digital control and equipment, sampling becomes an important parameter to be considered in the system's strategy. To avoid aliasing, first and foremost, the Nyquist frequncy must be considered. However, the capability of the performance of

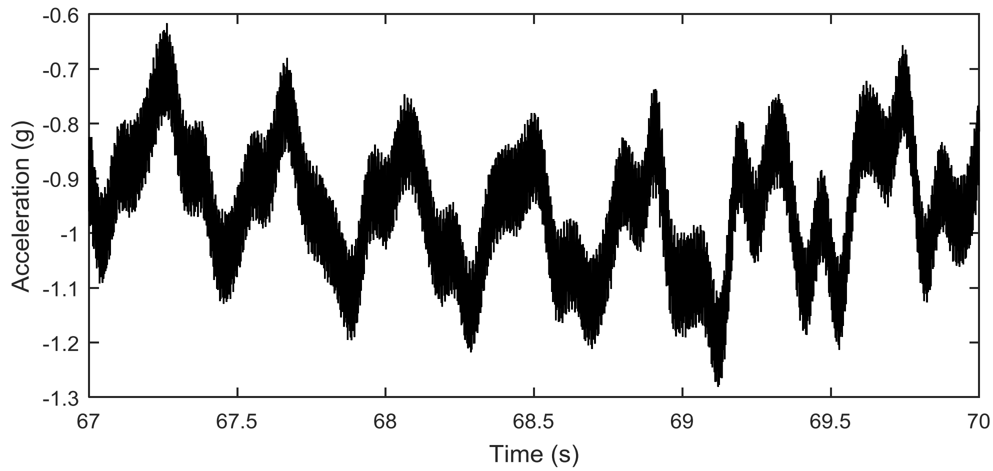


Figure 5.4. Illustration of noisy data

the equipment used in this experiment is far beyond the Nyquist frequency, therefore a limitation in data acquisition or data processing should not be an issue.

Nevertheless, it is important to remember that equipment operated of different sampling frequencies. For examples, in this experiment, the dSPACE system works at a frequency of 1000 Hz while the VibPilot DAQ works at a sampling frequency of 1024 Hz. Sampling rate conversion may not be applicable because most data-processing methods require that the sampling rate conversion be done using an integer number (which, in this case, does not work to convert 1024 Hz to 1000 Hz since 1024/1000, vice versa, does not give us an integer) to ensure deterministic data transfer (for instance, the default setting in MATLAB). Allowing non-deterministic data transfer may solve the issue, although the performance of the results may experience degradation.

An understanding of the sampling rate issue is needed when designing the neural network because the network is generated to work at a specific sampling rate. For this experiment, the neural network is chosen to have a sampling frequency of 1000 Hz, the lowest sampling frequency of the equipment used in the experiment, and the network is generated using this sampling rate.

5.2.4 Instability Issue

Neural network is a black box, therefore there is no way to ensure the stability of a control system that employs a neural network. To avoid the stability issue, a semi-active system can be proposed as a substitute of the active system because stability is guaranteed in semi-active systems.

One of the semi-active methods that can be proposed is by employing an MR damper as the semi-active control device. MR fluids contained in the device give a semi-active behavior due to a controllable nature of the material due to some magnetic or electric signals [62]. This feature characterizes a unique nonlinear behavior of the device that can be employed for a seismic protection purpose [63]. Setup of the semi-active control device is shown in Figure 5.5.

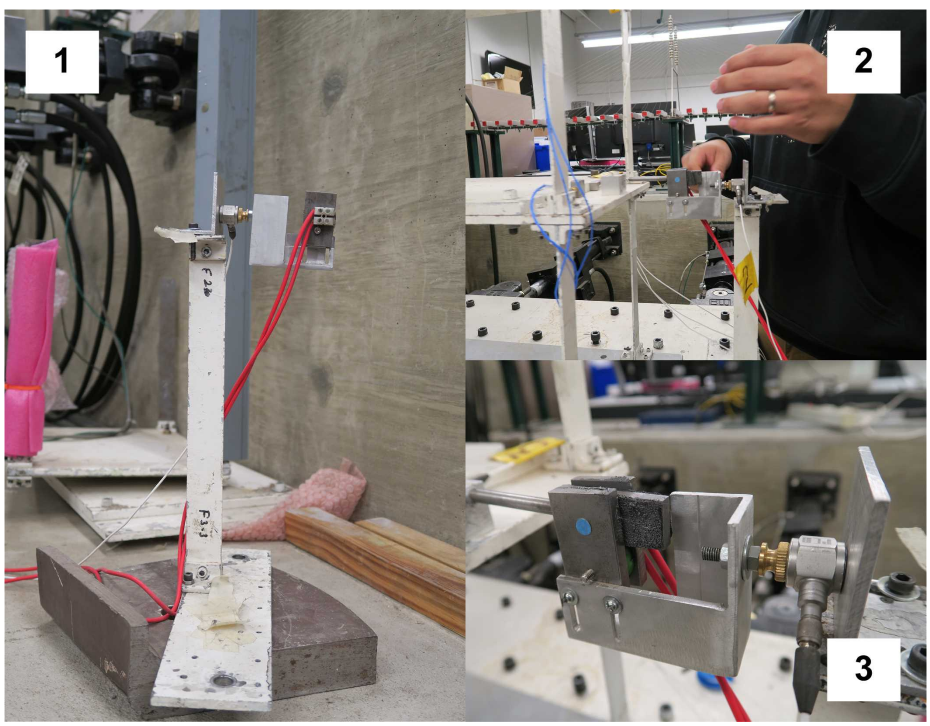


Figure 5.5. MR damper used in the laboratory experiment: (1) MR damper as the semiactive control device; (2) MR damper attached to the first floor of the structure; (3) the closed-up view of the MR damper

5.3 Summary

Laboratory experiment is discussed in this chapter. The experimental structure is modeled based on the same structure used in the numerical simulation. System identification is performed to determine the dynamic characteristics of the structure and build a model for the control design purpose. Then, the base of the structure is excited by various earthquake and the performance of the system without and with the NNWCF are evaluated. Four findings are concluded from the study on the effect of richness of amplitude in training data, noise, determined sampling rate, and stability of the system.

6. CONCLUSIONS

Wireless sensors offer an alternative to traditional wired options in structural control. However, the presence of time delay and data loss in a wireless sensor network will potentially degrade the performance of the control system.

The goal of this study is to develop a technique to improve the performance of a wireless structural control that compensates for time delay and data loss in a wireless sensor network. Artificial neural networks are used to achieve this goal.

The structural model studied in this thesis is a 3-story steel-frame shear building model. Wireless sensor networks are employed on each floor of the structure to collect the acceleration measurements of the building. Simple numerical simulations are performed to verify that this is a loss in performance if the wireless sensors are not accounted for in the design. After the verification is conducted, it is concluded that compensating for the presence of time delay and data loss is crucial for wireless structural control performance.

Artificial neural networks are already popular in many engineering applications for dealing with time delay and data loss issues. However, almost none of the current research proposes the use of the method to deal with both challenges in the same integrated system. By combining the compensators for both subjects together in the same system, this could provide an advantage as these parameters almost always come along together in any wireless sensor network problem. However, the approach to utilize the neural network to correct both the time delay and data loss is needed, and it is expected that this technique may be further improved to a more advanced stage.

The neural network is trained by using “ideal” structural response data obtained from the measurement without any time delay and data loss occurred in the wireless data transmission procedure. The unsupervised training procedure is conducted, and the neural network is generated. The neural network is employed to predict its future value. When data loss occurs, the neural network strategy can determine where there is a loss by either evaluating when the measurement gives a value of 0 or the same measurement with the previous one. In the proposed neural network, an “if” function is utilized to distinct between a “lost” data and an acquired measurement. When the recorded data is lost, the neural network is used to provide the associated predicted value using past values of the corrected data.

In the following sections, the conclusions of the study are divided into two groups: numerical simulation and laboratory experiment conclusions.

6.1 Numerical Simulation Conclusions

Some key findings from the numerical simulation are summarized as:

- *Time delay and data loss may degrade the performance of wireless structural control systems.* The presence of time delay and data loss has been viewed as one of the key challenges in employing wireless sensor network for structural control applications. It is demonstrated herein that the higher time delay and data loss present in the system, the more likely it is to get less efficient controller performance.

- *Training plays an important role to produce a good neural network function.* This one is an obvious statement since a neural network is generated from a set of training. Therefore, in designing a good neural network training, providing appropriate input data is crucial. For instance, it is learned from the laboratory experiment that noise may affect the neural network performance thus that the training should include data with noise present. Moreover, especially for seismic applications, the richness of frequency and amplitude contained in the training data is also important since there is no information about the characteristics of the future earthquakes that may strike our buildings.

- *Strategy of treating data loss may vary with the neural network application.* When data loss occurs, digital measurement usually yields no actual transmission but a numeric value is needed for calculations. The common approaches are to employ a value of 0 or use the previous measurement value for the "lost" data. The "if" function used in the proposed neural network depends on this strategy. However, this "if" function may induce some unnecessary neural network concerns in certain applications since measurements of 0 or repetitive measurements do not always infer a false measurement.

- *Data manipulation techniques may be implemented to enable more efficient neural network training.* Although computer capacities in the modern days are generally sufficient to perform simple neural network training, a more demanding training may be found in a more complex systems. In this case, some data manipulation techniques could be considered before training the neural network, such as decimation of the data or standardizing the data to some mean of 0 and standard deviation of 1.

- *Neural networks have demonstrated the ability to compensate for the presence of time delay and data loss in wireless sensor networks in the numerical simulation.*

- *A neural network is designed for a particular system, thus the network has to be adjusted for different problems.* The process of adjustment of the strategy includes determining the network architecture (number of hidden layers, neurons, etc.), re-training of the network, initializing the network parameters (weighting and bias parameter), and so on.

6.2 Laboratory Experiment Conclusions

Some key findings from the laboratory experiment are summarized as:

- *Training of the neural network should cover a sufficient amplitude to deal with future earthquakes.* The neural network is trained to a specific range of amplitude. If the trained amplitude of the neural network training does not provide a sufficient coverage of amplitude, significant performance degradation may be found.

- *Presence of noise may affect the performance of neural network.* Noise is unavoidable in the real world data acquisition and may be substantial to be considered in our system. Therefore, the neural network needs to be trained accordingly so that it has an ability to cope with the presence of noise.

- *Sampling rate should be considered since active and semi-active control systems operate with digital signals.* Neural network works with a specific sampling rate. In a strategy in which the neural network compensates for the presence of time delay, the convenience to operate a neural network to work with any correspondence sampling rate is taken into advantage to predict the future value by adjusting the sampling rate of the neural network in accordance to the constant delay value found in the wireless sensor network. However, some equipment uses a different sampling rate so that this situation may be taken into consideration when deciding the sampling rate of the neural network.

- *It is more appropriate to apply neural network for semi-active control systems rather than active control systems due to stability.* Instability must be avoided in structural control systems. Due to the nature of neural networks as black box, stability of the resulting controller with the neural network cannot be guaranteed. Therefore, the application of this technique in a semi-active control strategy may be preferred since the stability is guaranteed in semi-active control systems.

- *Neural networks have demonstrated the ability to compensate for the presence of time delay and data loss in wireless sensor networks in the laboratory experiment.*

6.3 Future Work

The ideas proposed in this thesis provide a nice concept that may be considered for future research opportunities. These are discussed below:

- *Explore a different type of neural network.* In this study, NAR is used. However, this is not the only strategy that can be employed to compensate for the presence of time delay and data loss in a wireless sensor network. Other possible neural network types that can be used for this particular problem are a feedforward neural network or a nonlinear autoregressive output (NARX) neural network. An illustration of the architecture of the feedforward neural network is shown in Figure 2.2. Unlike Figure 3.5, the input and target in Figure 2.2 come from a different function. Also, no feedback layer occurs in the feedforward neural network. This makes the feedforward neural network the simplest and purest form of neural network: only allowing hierarchical operations that move forward. Here, the feedforward neural network is not preferred in this study due to the absence of dynamic properties that the network can allow in the model. Since the problem here needs to accommodate challenges that occur in dynamic time series, this type of neural network may not be the best for this particular problem. In the NARX neural network, feedback loop is allowed and the network has memory that allows for the execution at a particular time step to be influenced by the value occurring in the previous or the next time step. The difference between the NARX and NAR neural network is only in the nature of the input and target. While in the NARX, the input and target comes from different natures, the NAR uses the input from the past value of the target (thus, the target is technically prediction of the future values of the input). However, mapping the input to target relationship is impractical when time delay presents in the original input sets of data. In employing this type of neural network to this kind of problem, the neural network is not *specifically designed to predict the future.* Therefore, whenever an input (which is delayed form of the target) is fed into the network, which has previously been trained with the data specified earlier, the best approximation that the network may provide is the same as the input, which would make the network pointless. The network in this case acts similar to regression function, although it could accommodate some nonlinearities with multi-layer features with a lot of *random* weighting parameters included. It could describe the relationship between both NAR and NARX functions. However, it will not be able to capture the predictions in responses, which is needed in this particular problem. Thus, all these reasoning lead to the utilization of the NAR neural network in the system.

- *Employ neural networks to substitute the system's controller.* The application of neuro-controller (usage of neural network as control system) has been used in several research and it would be interesting to see the implementation for this particular problem. Nevertheless, this approach is not adopted due to the same reasoning in the use of the system using NAR. It is an arduous task to model the system to model an input-target relationship without telling the system that it is actually expected to *predict the future.*

- *Conduct an experiment of the proposed neural network in a semi-active control system.* The experiment is required to verify the results shown in Chapter 4. A semi-active strategy is proposed to avoid the instability issue that may occur in an active control strategy.

- *Use an updating neural network.* In this study, Neural Network Wireless Correction Function (NNWCF) is proposed to improve wireless sensing measurements. However, the function is intended to be used for a specific system. When applying the system to different structures, redesign of the neural network is required, although it is not practical. To improve the practicality of the system, an updating neural network technique can be used. In this approach, the neural network will be trained during the operation of the system. Since the system is employed to provide measurements from a wireless sensor network, the data obtained from the measurements will be used as the training data to update the network. In other words, the network will experience a continuous training that will improve (and adjust) the network to a particular structural system. One issue that may appear from this approach is an overfitting. To avoid overfitting, a validation technique should be employed to ensure that the performance of the network does not degrade due to the continuous training. Other benefit of the system, it may be suitable to accommodate parameters in the structure that have so many uncertainties, such as mass in the building (an office can be at its full capacity during the day but has no people in it during the night).

- *Integrate the control system with a structural health monitoring.* Although a structural health monitoring and a structural control system do not come together, they both employ similar equipment and require a similar procedure in acquiring data of the structural responses. Therefore, integrating a wireless sensor network for both systems might be an efficient innovation for civil structures.

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