NEURAL NETWORK BASED ACTIVE STRUCTURAL CONTROL

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by

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ABSTRACT

The current trend in structural engineering is to employ flexible structures, which frequently have motion problems. This result has promoted the use of active control in order to improve the vibration response characteristics. An active control system consists of three major elements: a) sensors, b) a controller, and c) actuators.

The primary objective of this research study is to explore the potential of using neural networks as controllers for active structural control. For the purposes of this evaluation, an idealized shear beam model of a 5-story building structure is subjected to gust wind and earthquake loading. Control of this structure involves maintaining the displacements and accelerations within prescribed limits. The controller monitors the excitation and the response of the structure, and decides on an appropriate action. This action can be either the application of independent self-equilibrating forces on each story, referred to as active control, or the adjustment of the stiffness and damping of each story, referred to as adaptive control.

The results obtained from simulations of controlled and uncontrolled structures are very promising. The control system succeeds in reducing substantially the response of the structure for all cases. Major concerns were the training of the neural network required to satisfy all the conflicting control objectives, and the effect of time delay on the stability of the control process. The results indicate that the response time of the neural network controller is minimal with respect to the time required for the actuators. In order to obtain a more complete understanding of the capabilities of neural networks for active control, more complex models should be examined. Difficulties with respect to the implementation and maintenance of active control systems, as well as issues related to the expense, response time of the actuators, and energy requirements for civil structures also need further consideration.

Thesis Supervisor: Jerome J. Connor Jr.
Title: Professor of Civil and Environmental Engineering

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To my family and Dominic

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1.1 Introduction to Structural Motion Control

Modern structures require more demanding design and construction procedures. Engineers are pushing the envelope by introducing taller structures, thinner cross sections, and longer spans from support to support. These trends result in more slender structures with serious motion and stability problems. An additional complication is the constraint imposed by motion sensitive equipment. Facilities such as hospitals, microchip manufacturers, labs, etc require essentially motion free environments. The satisfaction of these requirements has created the need for high performance structures, and generated interest in the use of active motion control systems. This type of control system monitors the state of the structure, decides on the appropriate action and applies this action to the structure. The decision mechanism, or *controller*, can be based on a prescribed algorithm, or a non-algorithmic methodology such as a fuzzy system, or a neural network. A neural network is a highly interconnected web of many simple processors, where one set of information is propagating and processed to conclude to the desired result. In the present research study, the applicability of an active motion control system employing a neural network as the decision system in investigated.

1.2 Why use active control

High performance facilities usually have very low tolerance for vibration. An active control system is capable of maintaining the structure in the desired state. It provides very accurate control and it is able to fine-tune the profile of the structure. These capabilities are the outcome of the intrinsic characteristics of the system. The first stage of the control procedure includes monitoring the state of the structure and the environment. This information is transmitted to the controller, which decides on the appropriate action to correct the state of the structure when needed. The final stage is the realization of this action. This whole procedure can be achieved in real time. The information accumulated in the first stage allows the controller to adapt its action specifically to the current conditions, i.e. state of the structure and environmental impact. The combination of these conditions can be unique and therefore it requires a specific action that the active control system is able to apply. On the other hand, passive control systems are not appropriate for unanticipated excitation events because they behave in a prescribed manner for a prescribed loading. They are unable to adapt their behavior specifically to the circumstances. Therefore, they are capable of controlling the structure only for a limited set of situations. The final response of the structure will never be as accurate as is with the assistance of an active control system.

1.3 Why use Neural Networks

Engineers are using various tools in order to manage successfully the problems arising in their tasks. These tools are based from basic mathematics, and material laws to advanced algorithms. Considering their powerful characteristics, it is obvious that neural networks can be one of these tools. Neural networks are able to develop problems and solutions in the same way that engineers think. They are able to recognize and formulate problems. For example, they are able to interpret potential problems by monitoring the state of a system. This problem is usually referred to as inverse mapping. Furthermore, neural networks, just like engineers, are able to synthesize solutions to the formulated problems. They explore the feasible solution space and select the "optimal" solution under some specific criteria. In addition, they are able to predict and classify complex behaviors of the observed systems and can analyze potential solutions to these problems. Finally, neural networks are not sensitive to the noise included in the input signal. They are able to distinguish the original signal and provide accurate results regardless of the noise.

These powerful characteristics evidence that neural networks can be very useful tools for engineers in order to solve complex problems in the fields of classification, prediction, modeling, optimization, diagnosis, and control.

1.4 Scope of the research

The scope of this research study is to explore the potential of artificial neural networks for active control of civil structures. The control problem considered here is focused on limiting excessive motion in structures. These structures either can have motion problems or they are required to be vibration free in order to be used for high performance operations. Therefore, for the purposes of this research study, a structural system is created with an embedded motion problem. Several severe excitations are applied to this structure. On the other hand, several strict objective limits are established. In order to meet these objectives an active control system is attached to the structure. The efficiency of this system is evaluated using several cases. The function of the controller, in the active control system, is provided by a neural network, and the primary objective of this study is to investigate the feasibility of using neural networks as controllers of an active control system. To achieve this objective, a general neural network for active control is created, trained and evaluated.

1.5 Organization

The material is presented at a level which assumes essentially no background in the fields of neural networks and control. Basic background material is provided in chapters 2 and 3. For more extensive analysis and information on these fields, references are provided to the reader.

Chapter 2 contains an introduction to the basic concepts of active control. Issues of feedback, controllability, observability, stability, and time delay are addressed. The difference between active and passive control is explained, and the categories of fully and semi active control are illustrated. Finally, several devices used in various applications of active control are described.

Chapter 3 provides an introduction to the field of neural networks. It provides some basic information regarding the neuron model and network architectures. It also investigates how the performance of the network is affected by the selection of the learning algorithm and the training set. In order for the reader to gain some feeling regarding the use of neural networks, a brief history of their evolution and a short list of their applications is provided.

Chapter 4 provides information on the structural system used as experiment for the purposes of this research study. The structural model, the active control system, and the neural network controller used are analyzed. The various loading conditions considered are also described.

Chapter 5 contains the data created from the active control experiment. The time history response of the structure from both the wind and the earthquake excitation cases is presented. The impact of time delay on the response of the active control system is addressed. Moreover, the effect of training on the efficiency of the neural network is illustrated.

In Chapter 6 the data created from the adaptive control experiment is presented. Once more the time history response of the structure under the wind and earthquake excitations is displayed. Exhibits for the behavior of the control system and the neural network controller are obtained. Finally, a comparison between the active control and the adaptive control attempts is presented.

Chapter 2

Introduction to Active Control

2.1 Introduction

Modern facilities enforce strict design constraints to ensure optimum performance. One way to satisfy these constraints is the introduction of an active control system. An active control system can be defined as the arrangement that uses energy to control the state, response, or outcome of another system to a prescribed manner. This system monitors the field of interest, decides and applies a specific set of actions in order to accomplish its task. Therefore, an active control scheme is constructed by three main elements: i) *sensors*, to record the state of the system under control and the impact of its environment, ii) a *controller*, to decide on the required correcting action, and iii) *actuators*, that will execute the orders of the controller. Figure 2.1 provides schematically the connectivity of an active control system. The impact of the environment can be any input or other parameter that is able to change the current state of the examined system.

In civil engineering applications, an active control system can be employed to satisfy the constraints and requirements of a high performance structure. These constraints frequently include motion restrictions. This field is explored in the present research study. The active control system that is considered here is implemented in order to control the motion of a structure, and to limit it within some prescribed limits. There are various applications of active control in the area of interest of civil engineers.

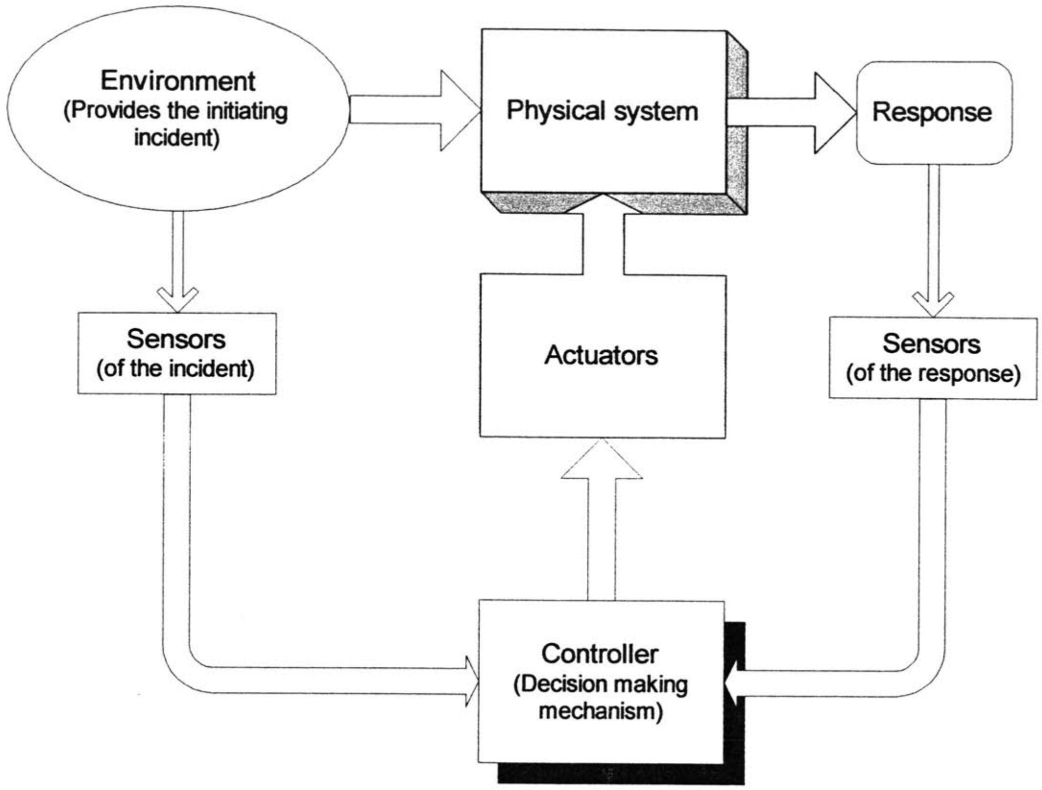


Figure 2.1: Connectivity of an active control system

2.2 Applications of Active Control

The technological improvement on various fields of science has forced the used of active control systems. One field of application is microchip manufacturing facilities. The explosion of information technology pushed the need for faster and smaller processors. In order to manufacture these processors, the microchip facilities need to be completely vibration and dust free. These constraints force the use of active control systems to check and correct any interference with the manufacturing process.

On the other hand, not only microchip manufacturing facilities require vibration free environments. Hospitals, where using laser and other high precision techniques for surgeries, require motion free environments. Moreover, the introduction of taller buildings, thinner cross sections, and longer spans between supports are creating structures that may have motion problems. The higher standards of living, embedded in modern communities, do not allow for motion sick structures. People are becoming more and more sensitive on vibrations, which consequently creates more strict requirements on the comfortable level of motion. Not only the comfortable level of motion is a consideration in modern structures, but also stability and strength issues. These requirements can be preserved with the implementation of active control systems. Thus, active control systems can be used to control the motion to skyscrapers, telecommunication towers and antennas, long span beams and bridges. It can also be used to control the tension of the cables in cable stay bridges, the strain in pre-stressed beams, the shape of concave telecommunication plates for accurate signal, etc.

2.3 Active vs. Passive Control

There exist two major categories of structural control, namely *active* and *passive*. The active by definition is the system that can adapt its properties according to the initiating event. On the other hand, passive control systems have fixed properties and they respond in a specified manner under any excitation. The major difference of an active and a passive control system is that the first one requires an external source of energy. This may constitute a significant disadvantage for the case that the external source of energy is limited, and there exist the possibility that it will be unavailable during the period of an incident. On the other hand, the passive control systems do not require external source of energy, but are unable to control accurately the structure. They respond in an appropriate way only for the excitation that they are designed for. They are unable to handle effectively a large variety of excitations and they can be completely useless in case of unexpected excitations. Active control schemes are capable of responding in a number of ways under any excitation, providing accurate control and reinstating the structure to the desired response profile. In order to minimize the significant disadvantage of the active control schemes to require external energy, semi-active devices are developed. The semi-active devices have reduced energy requirements. More information for semi-active devices is provided in a later section.

In order to control the motion of the structure, the active control system generates a secondary vibration profile which, by superposition, eliminates the original vibration profile. Therefore, the active system provides energy to the structure in such a way as to eliminate the energy provided by the external loading. This configuration provides almost unlimited capabilities to the active control systems. However, there exist cases in which this secondary deformation profile may increase the final response of the structure instead of reduce it. This can happen, due to an unexpected time delay between the time of the decision and the real time of the action, an issue that will be discussed in a later section. On the other hand, passive systems cannot destabilize the structure as soon as they can only store or dissipate energy.

Another major disadvantage of active control systems is their cost. These systems are usually expensive to buy, install and maintain. They also require additional effort during the design phase of a structure. In order to provide accurate control the location of the devices has to be carefully selected. Furthermore, in order to implement the controller all possible scenarios during their life span need to be predicted. The implementation of these systems requires experienced personnel to install the devices and additional care during the whole construction phase of the structure.

On the other hand, passive control systems are not inexpensive, but they are not as expensive as active systems. The devices used in passive control are usually simple and there exists a large variety of them in the market. In contrast, the active control devices are usually very expensive and rare. The technology involved in these devices is not mature enough to produce alternatives that will offer reliable solutions in active control needs. More information on devices is provided in a later section. Moreover, the incorporation of these systems into the structural system does not require extensive design or construction effort. They require experienced personnel to install them, but their maintenance and operation is more trivial than the one of the active systems.

It is a common strategy to use both control approaches in a structure. The passive system is used to control the general motion of the structure and the active system is used to fine tune various profiles, like deformation, stress, acceleration, reaction and so on, depending on the control objective. In that way, one is able to benefit from the advantages of both approaches and avoid as much as possible the disadvantages. The active control system with the objective to fine tune the response of the structure will not be able to destabilize it. Furthermore, it will require lower capacity devices, which results in lower cost of implementation and operation of the system.

2.4 Basic Background

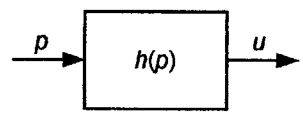
In active structural motion control the controller responds to a set of inputs with a set of actions that have to be made such that to preserve the structure in the desired state. In pure active control this set of actions are forces applied on the structure in order to create a secondary vibration mode that by superposition will eliminate the original vibration caused by the external loading. Therefore, this control activity can be considered as changing the excitation applied on the structure. However, in active control, the set of actions decided by the controller can be more than simply applying forces to the structure. The controller may decide to change the properties of the structure or the controller itself. Therefore, the set of actions can include also changes in the geometry, connectivity, properties of the elements of the structure, or the decision system in real time, meaning throughout the duration of the incident. This case, were the properties of the structural system or the controller are able to change in real time, is referred to as *adaptive control*. An application of a simple adaptive control scheme is presented in Chapter 6.

Consequently, an active control system monitors the behavior of the structure and decides on the appropriate action to reinstate the structure in the desired profile. The parameters monitored by the controller can vary from the excitation input to the response of the structure. In the case when the decision of the controller is based only on the excitation input of the structure, then the system is referred to as *open loop control* or *feedforward*. When the controller monitors both the excitation and the response of the structure, then the system is referred to as *closed loop control* or *feedback*. These two cases are illustrated by the left-hand side and right-hand side loops in Figure 6.1. Schematically this connectivity is presented in Figure 6.2 taken from Connor (to be published). In this figure, the behavior of the system is described by a function $h(p)$. This function provides the response of the structure under a specific excitation p. For the case of a passive system the response of the structure is simply:

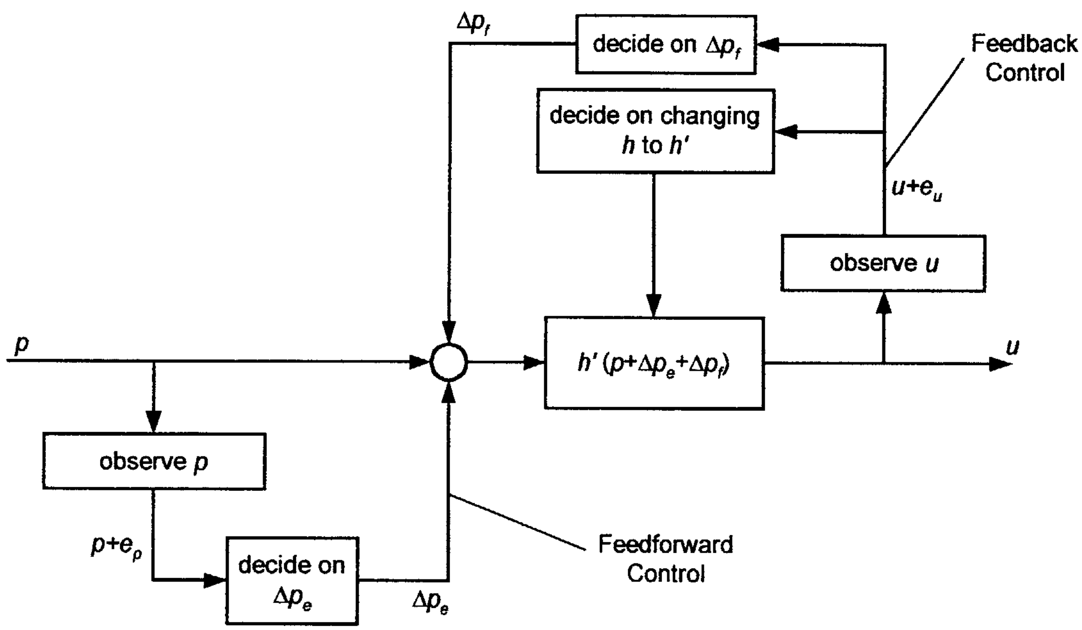
$$u = h(p) \tag{2.1}$$

An active control system has a variety of possible actions in order to respond at a specific input. It can select to adjust the loading condition on the structure, by applying forces, according to the excitation, Δp_e, and according to the response of the structure, Δp_f. These actions represent the feedforward and feedback control respectively. In addition to the above, the controller may decide to change the behavior of the structure, by changing the properties like stiffness and/or damping. This would result in the model presented here in changing the structural behavior function from h to h'. This action is considered to be in the field of adaptive control. Considering all the above the response of the structure under adaptive control would be:

$$u = h'(p + \Delta p_e + \Delta p_f) \tag{2.2}$$



(a) Passive



(b) Active

Figure 2.2: Passive and active feedback diagrams (Connor, to be published)

In Figure 6.2 the e_p and e_u are the noise of the sensors to the input of the controller from the excitation and the structural response respectively. This noise may affect the efficiency of the control system, since it can interfere substantially with the decision process of the controller.

The nature of the control system is defined by the nature of the problem that the controller is called to solve. Therefore, the control can be quasi-static or dynamic depending on the nature of the excitation that is applied to the structure. Considering the model used above, the application of quasi-static or dynamic excitation also affects the nature of function h, which describes the behavior of the structure. In quasi-static control, the only response variables are the displacements of the structure. Moreover, the only structural property considered is the stiffness. The controller observes the excitation magnitude and the response of the structure at a specific instance in time, without considering the previous state of the structure. On the other hand, in dynamic control the response variables are the displacements, and velocities. The properties of the structure considered in the analysis are the mass, stiffness and damping. Moreover, the geometrical characteristics of the structure affect significantly its response. The information on the state of the structure from the previous time points is now important for the controller.

In the feedback type of control the current state of the structure is useful in determining the next set of active control forces required to preserve the structure under the objective limits. The feedback loop provides to the controller information regarding the current displacement, velocity and acceleration profile of the structure. A common strategy for algorithmic type controllers is to calculate this force by using the displacements and velocities information, namely *negative displacement and velocity feedback*. Equation (2.3) describes the calculation of this set of forces.

$$F = -k_v\dot{u} - k_d u \tag{2.3}$$

The parameters k_v and k_d are the velocity and displacement feedback coefficients respectively. The word negative is used here to describe the nature of this feedback. The force calculated using this method is opposite to the direction of the current displacement and velocity profile of the structure. The application of this set of forces, calculated with this method, can be considered as changing indirectly the damping and stiffness of the structure, considering that the forces are proportional to the displacements and velocities profile.

These control actions are expected to change the state of the structure in order to meet one or more prespecified objectives. Parameters like displacements, velocities, accelerations, and reactions can represent the set of objectives that the active control system attempts to preserve within some prescribed limits. The error of the objective response of the structure, represented by u^* from the total response after the control attempt is:

$$e = u_o + u_c - u^* \tag{2.4}$$

where u_o and u_c is the response created by the excitation and the control forces respectively. The parameter u_c is a function of the control forces. Therefore, one is able to identify the optimal set of control forces, by finding the minimum value of the error. Ideally, one wants to obtain $e = 0$, which is not always feasible. A more realistic approach is to request the least square sum of the errors to be minimum. There exist many methods to obtain the optimal value of active forces based on minimizing the error of the response. However, it is not within the objectives of this research to explore this field. More information on this subject is contained in Connor (to be published).

One very important issue affecting the efficiency of active control systems is the selection of the monitored parameters and the applied forces. Factors like the number and the placement of the monitored parameters and forces are critical for the feasibility of the control. The monitored parameters have to provide adequate information for the state of the structure. On the other hand, the number and placement of forces has to be adequate to control the structure in the desired way. If the number or the location of the forces is not adequate, it is not feasible to minimize the error of the response of the structure. In the same way, if the number or placement of the monitored parameters is not sufficient to describe the state of the structure, the controller is unable to decide on the optimal active force distribution. These issues arise more and more as the number of degrees of freedom of the structure increases. In systems with large number of degrees of freedom the control procedure becomes more complicated as the higher modes are contributing more in the response of the structure. The issues related to the monitored parameters are usually referred to as *observability*, and the ones related to the control forces as *controllability*.

Related with controllability arise several issues regarding the effect of the application of a control force, in order to control a specific objective parameter, to the rest of the objectives. For these issues the connectivity and variation of the active forces are to be considered. For example, one is able to apply sets of forces in such a pattern that they control the portion of interest of the structure but they cancel each other outside this part. In that way, the application of a control force at the specific portion of the structure does not affect the displacement profile for the rest of it. These forces are commonly referred to as *self-equilibrating forces*. The connectivity and effectiveness of this pattern is illustrated in Chapters 4 and 5. Furthermore, the variability in time of the forces changes the acceleration profile of the structure. For example, one may control the displacement profile of the structure by applying active forces in an impulsive manner, but at the same time increase substantially the acceleration profile. Therefore, considering issues like the aforementioned ones is critical for the planning stage of the control system and they influence the substantially its effectiveness.

Due to the fact that an active control scheme provides energy to the structure the danger of creating extreme cases becomes obvious. The controller may wrongly apply forces that will bring the structure to a magnified or even an unstable state. Cases were the response of the controlled structure was magnified from the uncontrolled one, are illustrated in Chapters 5 and 6. Therefore, a stability criterion needs to be established in order to prevent the controller from destabilizing the structure. Such a criterion can be obtained by monitoring the response of the structure and limiting the action of the controller when it approaches extreme situations due to the control action. An alternative method can be applied for the case of negative velocity and displacement feedback proportional active force. In this case, one can limit the values of the forces coming from the velocity or displacement to be less than the corresponding values of the real damping and stiffness respectively.

The phenomenon of controllers magnifying the response of structures can be the result of several circumstances. Assuming that the controller is correctly created to control the structure under a range of possible excitations, a very likely cause of the observed instability can be the time delay between the control instants in time. There exists some time from the point that the sensors collect the information for the state of the structure to the point that the actuators apply the orders of the controller. This time is spent in the operation of the 3 major elements of a control system. The first part includes the time spent on collecting the data with the sensors and transmitting it to the controller. The second part includes the time that the controller needs to decide on the required action. The final part is the time required from the actuators to respond and apply the magnitude of force ordered by the controller. From the 3 described operations the most time consuming one is the last. Usually, the time required for the sensors and the controller is minor compared with the reaction time of the actuators. Therefore, the controller has to decide on what the controlling action should be at time t_2 with information collected at time t_1. The difference of these values is the time delay between the actions of the control system and the real response of the structure. This time delay is able to interfere with the operation of the controller and it is able to result in the destabilization of the structure. Therefore, the minimization of this time delay and the creation of a controller that is able to respond in a correct manner despite the presence of this time difference are major considerations for the engineer who designs the control system.

More extensive description of all the above issues is included in Connor (to be published).

2.5 Fully Active vs. Semi Active

There exist two major categories of devices for active control, namely *fully-active* and *semi-active*. One important distinction is the energy required for the operation of these devices. The other significant difference is on the way that the action of each one is applied on the system. The use of a device from the first or the second category marks the procedure of control and the nature of the active action.

The fully-active devices are actuators which supply mechanical power to the system. Examples of such devices are the electromagnetic shakers, piezoelectric ceramics and films, magnetostrictive and electrohydraulic actuators. Actuators such as these can be used to generate a secondary vibrational response, which by superposition with the original response, caused by the external excitation, could reduce the overall response of the system. These devices usually require large amounts of external energy in order to operate and apply the forces required from the controller.

Semi-active devices behave as essentially passive elements. They only have the ability to store or dissipate energy. However, their mechanical properties can be adjusted to offer variable properties to the system. For this reason these devices are also called adaptive. Semi-active devices can be constructed with the use of shape memory alloys, and electro or magneto rheological fluids. The energy required for the operation of these devices is substantially lower from the energy required for the operation of the fully-active systems. Some of these devices control the flow of a fluid and therefore they only spend energy in order to open and close small valves. Other semi-active devices are applying a magnetic or electric field through the mass of an adaptive material, which adjusts its properties according to that field. Both of these operations do not require large amounts of energy. On the other hand, the fully-active devices spend the energy in large servomotors, fluid accumulators, and magnetic actuators. More information on devices for active and semi active control is provided in the next section.

2.6 Devices for Active Control

In this section the discussion concerns materials employed in the devices used in active control. These devices implement the decisions of the controller. Usually, their task is to apply forces at specific places on the structure. For the case of adaptive control, these materials may also have to adjust their properties, like stiffness and damping. There exist a large range of available devices used in active control. The selection of one device for the purposes of a specific system is based on the requirements of the output magnitude, and the response time, as well as constraints enforced by the environment. Generally, civil structures require devices that are able to provide large forces with fast response time. For example, for the case of a force actuator the required magnitude is at the order of meganewtons. Moreover, the response time is dominated by the time variability of the external excitation. Therefore, in case the control system attempts to restrain the response of a structure under an earthquake excitation, the required response time of the actuators is in the order of milliseconds. This requirement loosens up for the case of wind excitation where the intensity is lower than that of an earthquake. Finally, the environmental constraints on the selection of the actuator concern issues like the energy consumption and the health risks involved with its operation, as well as its size and reliability. In addition to the above a major factor for the selection can be the cost of the device, plus the cost of operation and maintenance.

The most well known and widely used types of actuators are the devices that base their operation on hydraulic and electromechanical principles. The force production mechanism of hydraulic actuators is based on differential hydraulic pressure on two opposite surfaces of a plate connected to a piston. The electromechanical actuators generate force by moving the piston with a gear mechanism driven by a rotating electric motor. They are both capable of providing large forces in a linear manner. The force magnitude can easily rise up to the order of several meganewtons. On the other hand, their response time is not appropriate for very intense excitations as soon as it lies at the order of seconds. Their technology is well established and their operation is not hazardous for the environment. Therefore, cost of such a device is not unreasonable. However, because of their moving parts and high-pressure pipes they evolve an increased risk of breakdown. Another disadvantage is their large energy requirements in order to operate.

In the same pattern with the devices described above, the electromagnetic actuators provide the produced force with a piston. The difference is that the piston in this case is moving due to a strong magnetic field produced by two electromagnets. Their operation is simple and reliable. The force output can reach the orders of meganewtons while the response time is at the order of milliseconds. However, their major disadvantage is that in order to produce forces with high magnitude, they require large energy supplies. Moreover, the magnetic field produced from a large electromagnetic actuator may be harmful for the human life. Finally, their cost is not established yet as soon as large electromagnetic actuators are only customly made and they are usually very expensive.

All the above actuators are evolving the use of several components that are providing the force through a piston. However, there exist several physical materials that under specific circumstances can change their shape and therefore when connected to a fixed point provide strain and consequently force. Materials as such are the piezoelectric films and shape memory alloys and they usually referred to as adaptive materials.

In the category of piezoelectric films belong materials like piezoceramic or piezopolymer films. These materials have the property of expanding or contracting when exposed to an electric current. Their response time can be considered as instantaneous but the provided force magnitude is very small, in the order of hundreds of newtons. Moreover, they are not reliable as soon as they break down very easily and they have a short life span. These materials are very sensitive in voltage variations. Piezoceramic films are very brittle and piezopolymer films burn up due to arcs. On the other hand, the requirements of these materials in terms of the external provided energy are small. Finally, considering the force magnitude that piezoceramic films are able to supply their price is unreasonably high. However, the piezopolymer material is fairly inexpensive.

The next adaptive material considered here is the shape memory alloys. This is a material that after any applied deformation remembers its initial shape and it can return to it when heated up. The most commonly used shape memory alloy is NiTiNOL, which is a nickel-titanium alloy. This material is usually produced in wires and when voltage is passed through it, heats up and undergoes a martensitic transformation. The force produced by this transformation is usually small and can reach the order of some kilonewtons. One disadvantage of the use of this material as an actuator is its response time. It requires several seconds in order to restore its initial shape. Furthermore, the NiTiNOL is an extremely expensive material. However, the energy requirements of shape memory alloys are usually small.

Another category of adaptive materials, that can be used to create devices used in adaptive control, are the electro and magneto rheological fluids. These fluids have the property that when they are subjected to an electric or magnetic current respectively, they change their viscosity and stiffness. They harden and for the extreme cases they approach the pure solid nature. Therefore, they can be considered as the ideal materials to be used in adaptive control devices in order to adjust the properties of a structure. The output magnitude they provide is adequate for civil structures. The energy consumption is small but not minor, since they require several thousand volts to operate. However, their time response is very small and varies at the range of milliseconds. Moreover, they are usually inexpensive as materials. The whole connectivity of the materials to constitute the device is also trivial, while for example they can replace the viscous fluid in a pure viscous damper. The completed device will also include a system that will apply the electric or magnetic current through the mass of the fluid. These devices have been tested several times and have been proven very reliable and efficient.

One is able to create devices that can be used in adaptive control by adjusting in real time the properties of regular devices used in passive control. This can be implemented by changing the connectivity and employing adaptive configurations. Thus, one is able to create a variable damping viscous damper by employing a valve and modify the orifice at the internal side of the damper. By controlling the openings inside the viscous damper, one is able to adjust the properties of a regular viscous damper and therefore satisfy the requirements for damping according to the specific excitation. Another example of an adaptive device can be an adjustable stiffener, which can be implemented by employing several stiffness elements and change the connectivity of the structure with these elements in real time.

These are the most common from the large variety of materials used in active and adaptive control systems. There exist several other systems that have not been adequately tested yet. More information on materials that can adapt their properties can be provided by material science books and conference proceedings on smart materials.

Chapter 3

Introduction to Neuron Model and Network Architectures

3.1 Introduction

The creation and introduction of models in nowadays systems has become very complicated, since they are more complicated and demanding. The use of artificial *Neural Networks* in order to model structures, plants, adaptive filters, optimization etc. makes the procedure easier due to their powerful characteristics. The increase in interest in this area of artificial intelligence is illustrated by the number of real life applications as well as research papers. Neural networks, as the name implies, attempt to simulate the operation of the brain. A neural network is a highly interconnected network of many simple processors, called neurons. Each processor preserves only one piece of information at a time and it is capable of very simple calculations. Every single neuron makes the simple operation of the sum of the weighted incoming signals and a bias term. The result then, is fed into a transfer function. The ultimate product is finally transmitted to other neurons. One appealing characteristic of the neural networks is their capability of self-organization or learning. Neural networks are not algorithms, with prespecified outputs corresponding on certain inputs; one does not program an equation. On the contrary, they are trained after several examples of the concepts to be captured. The network internally organizes itself to be able to reproduce these examples. After that it is able to produce approximately correct results for a large range of inputs. Moreover, they are rather insensitive to noise in the input signal.

3.2 History of artificial Neural Networks

Research on neural networks is driven by the desire to understand and replicate the functionality of the human brain. The initial development of neural networks was based on the way that the biological neurons were idealized to be. In the history of development of the artificial neural networks several milestones emerged. In 1942 McCulloch and Pitts presented the first simple static nonlinear model for a neuron. In 1949 Hebb introduced the first learning rule. He also illustrated that one can memorize an object by adapting the weights. In 1958 Rosenblatt published a book on perceptrons, a machine that is capable of learning how to classify information by adapting the weights. Widrow and Hoff introduced adalines and least mean square (LMS) rule in the period of 1960 to 1962. In 1969 Minsky and Papert presented the theoretical limits of perceptrons, indicating that the perceptron could not solve the "exclusive or" type of problem. This finding resulted to a 23-year period of no important action to that field. Only a small group of researchers continued working on that field and only, after 23 years of torpidity, Hopfield was able to present in 1982 that neural networks are capable of solving a large number of problems of the traveling salesman type. The introduction of internal layers and backpropagation provided the answer to the problem that was stated by Minsky and Papert. In the same year, Kohonen described the self-organizing map. In 1986 Rumelhart proved the usefulness of the back-propagation algorithm in solving problems containing complex relationships. The very same year competitive learning was introduced by Von Der Malsburg, whilst in 1987 Grossberg introduced the adaptive resonance theory. Also in 1987 Minsky presented that knowledge systems evolve in blocks of specialized agents rather than as a homogeneous network. In 1988, Chua and Yang introduced cellular neural networks, which are networks with neurons connected only to their nearest neighbors. From that time until now, research is focused on optimizing the architecture and training scenarios for a range of practical applications.

3.3 Applications of Neural Networks

Artificial neural networks have an extensive list of applications in real life actions and can be used to solve various problems. Their powerful characteristics are making them useful tools for characterization, prediction, control, detection, and identification problems. Fields like aerospace, automotive banking, defense, electronics, entertainment, finance, insurance, manufacturing, medical, oil, gas, robotics, speech recognition and compression, securities, telecommunications, and transportation are some of the areas that artificial neural networks have been applied successfully. The 1988 DARPA Neural Network Study (DARPA, 1988) lists some of the applications of neural networks. Applications of neural networks in civil engineering are not very common even nowadays. On the other hand, several research studies present the potential for the use of neural networks in civil engineering applications, like damage detection (Peetathawatchai, 1996), classification, modeling, and control. The use of neural networks for control is within the scope of this research work.

3.4 Neuron model

A neural network is a highly interconnected network of many simple processors. Figure 3.1 illustrates the connectivity of these processors, called neurons, inside the network. Each connection is a channel where the neurons interchange information.

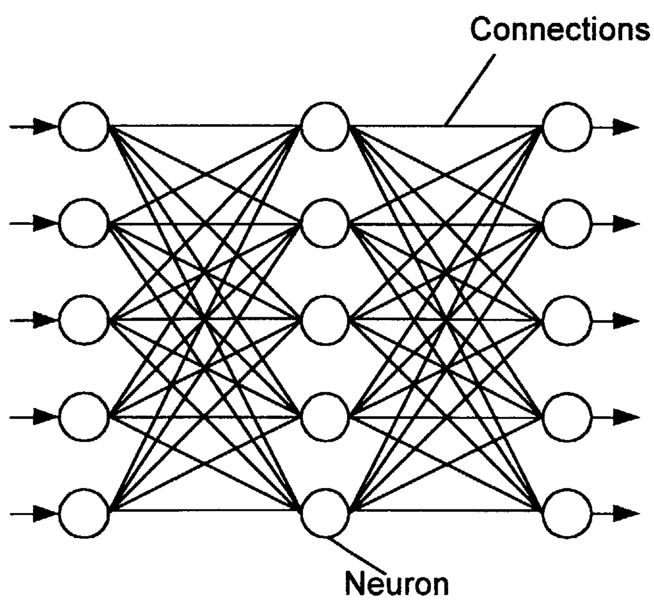


Figure 3.1: Neural Network

The operation of each neuron is illustrated in figure 3.2. Each neuron is activated by receiving signals from other neurons, that are connected, and processes them with very simple calculations. These calculations are restricted to summing of the weighted incoming signals plus a bias term, and feeding the result to a transfer function. The ultimate product is finally transmitted to the neurons which are connected with the output of the neuron under consideration.

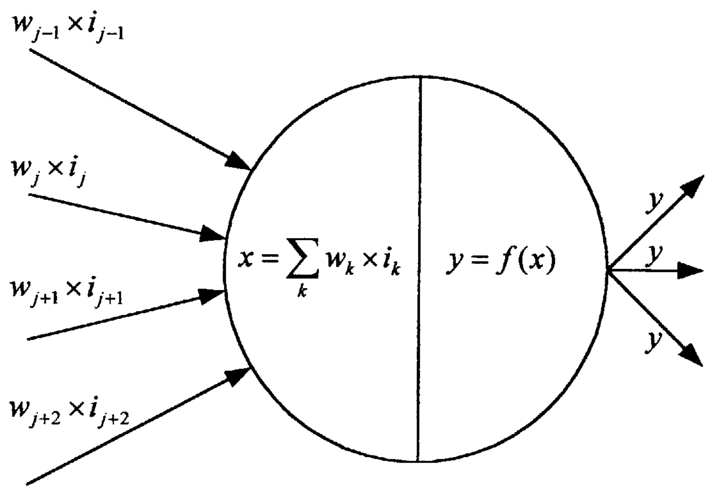


Figure 3.2: Simple Neuron

In Figure 3.2 the input from the j'th connection to the neuron is denoted as i_j. This input is multiplied by w_j, the weight that is assigned to this connection. Usually a bias term b_j is also added to this product to provide an independent judge to each connection. The result of the operation at the left hand side part of the neuron can be described with the following equation:

$$x = \sum_k (w_k \times i_k + b_k) \tag{3.1}$$

where k is the number of the connections that are feeding the neuron. The result is then fed in a transfer function $f(x)$. The output of the neuron can be described then by:

$$y = f(x) = f(\sum_k (w_k \times i_k + b_k)) \tag{3.2}$$

This transfer function can be a linear or nonlinear representation of x and is required to satisfy the specifications and the constraints of the problem that the neuron is trying to solve. Several common transfer functions are included in the Table 3.1.

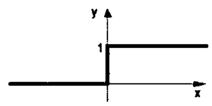
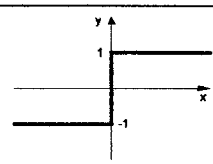
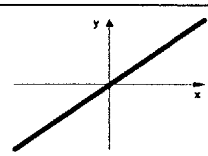
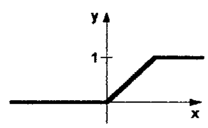
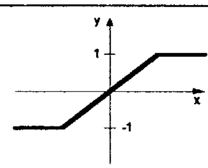
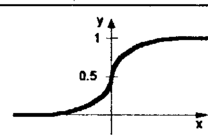
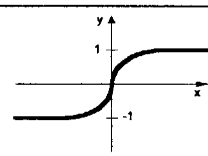
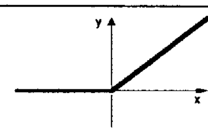
Description	**Graph**	**Input/Output Relation**
Step		$y=0 \quad x<0$ $y=1 \quad x\geq 0$
Symmetrical Step		$y=-1 \quad x<0$ $y=+1 \quad x\geq 0$
Linear		$y=x$
Saturating Linear		$y=0 \quad x<0$ $y=x \quad 0\leq x\leq 1$ $y=1 \quad x>1$
Symmetric Saturating Linear		$y=-1 \quad x<0$ $y=x \quad 0\leq x\leq 1$ $y=+1 \quad x>1$
Log-Sigmoid		$y=\frac{1}{1+e^{-x}}$
Hyperbolic Tangent Sigmoid		$y=\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$
Positive Linear		$y=0 \quad x<0$ $y=x \quad x\geq 0$
Competitive		$y=1 \quad \text{neuron with max } x$ $y=0 \quad \text{all other neurons}$

Table 3.1: Common transfer functions (Hagan et. al., 1996)

These functions are supported from the computer program MATLAB, which is used in this research, even though one may create and use new functions that satisfy his needs. The result of this function represents the output of the neuron and is consequently transmitted to the next set of neurons that are fed by this neuron, most often neurons that belong to the next layer.

3.5 Network Architectures

A neural network is composed by a number of interconnected neurons. These neurons can be positioned in such layout that they are able to operate in parallel, as it is illustrated in Figure 3.1. In fact this parallel operation is desirable because it is providing to neural networks some of their powerful characteristics. The parallel distributed neurons are considered to form layers. One or more such layers exist in a network. The inputs of the neurons of a particular layer are transmitted from the neurons in the previous layer. Consequently, the outputs of these neurons consist the inputs of the neurons of the next layer. The inputs of the first layer are the inputs that are fed to the network. Similarly, the outputs of the last layer are the output of the network. Accordingly, the first layer, that is transmitting the inputs to the neural network, is called input layer, the last layer is called output layer and the intermediate layers are called hidden layers, as shown in Figure 3.3. With this pattern the information is propagating and processed from layer to layer within the network. The number of neurons participating in each layer of a network may vary among the different layers. Moreover, the transfer function within the neurons of a specific layer may differ in order to satisfy the constraints and characteristics of the problem that the network is proposed to solve.

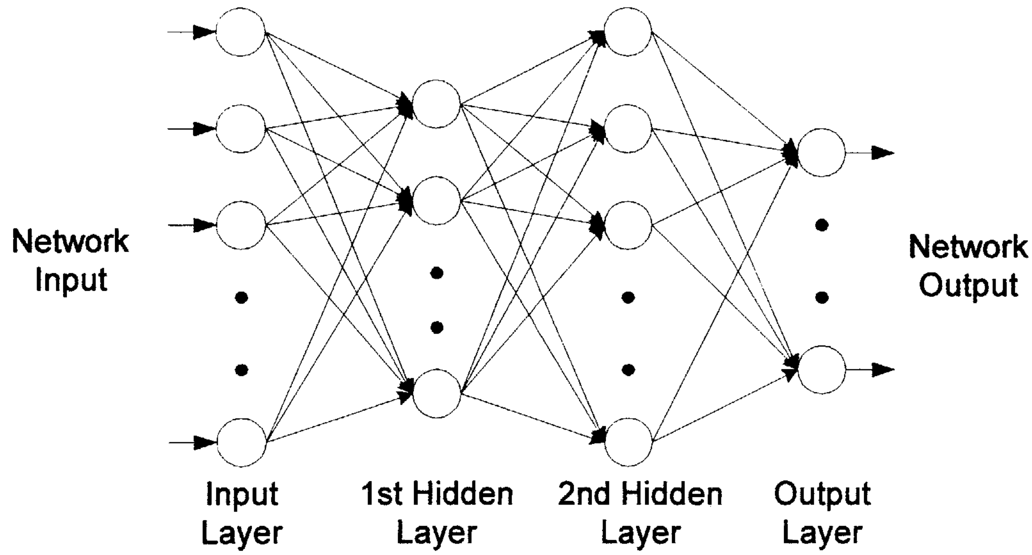


Figure 3.3: Multilayer feedforward neural network

Multilayer networks are more powerful than single-layer networks. It can be proven that a two-layer network having a sigmoid transfer function in its first layer and a linear transfer function in its second layer is able to approximate any function, with a finite number of discontinuities, (Rumelhart et. al., 1986). A well known architecture is the multilayer neural network, with neurons connected in a feedforward pattern. In such a network the information propagates within the neurons from one layer to the next layer, until it reaches the output layer. In feedforward networks, neurons are not connected with other neurons that belong to a previous or the same layer. The weighted inputs of the neurons of an intermediate layer are the outputs of neurons in the previous layer. If one considers that equation 3.2 describes the output of the previous layer, then the output of a neuron at the intermediate layer is written as:

$$z = f\left(\sum_m w_m \times y_m + b_m\right) = \sum_m \left\{ w_m \times f\left(\sum_k \left(w_k \times i_k + b_k\right)\right) + b_m \right\} \tag{3.3}$$

where m is the number of input connections to this neuron and w_m are the weights of the connections between the previous neurons and this neuron.

A very widely used network is the Perceptron (Rosenblatt, 1962). This network is a very simple type of feedforward network. Single layer Perceptrons using a threshold transfer function are able to classify continuous or binary string inputs into two categories. Of course multilayer perceptrons are more powerful and can be used in complex classification problems. Minsky and Papert analyzed the single layer perceptron and demonstrated that the network is able to solve linearly separable problems of the type "exclusive and", but cannot handle nonlinearly separable problems such as the "exclusive or" problem. This limitation of the single layer perceptron resulted in a dramatic decrease in research activity for 23 years. Two major findings reversed this decline in research. Firstly, Hopfield showed that the "exclusive or" problem can be solved by including internal layers of neurons in the network. Secondly, Rumelhart introduced the training scheme based on backpropagation that significantly reduced the training time.

Another well-known category of neural networks is the Recurrent networks. The difference from the feedforward networks is that in these networks the neurons are connected with other neurons regardless of their position in the network, i.e. previous or next layer, as appears in figure 3.4. They may even have a connection to themselves. These networks to produce an output usually iterate over themselves for many cycles until a certain convergence criterion is met. Elman and Hopfield networks belong in this category. Elman networks are two-layer backpropagation networks, with the addition of a feedback connection from the output of the hidden layer to its input. This feedback path allows Elman networks to learn to recognize and generate temporal patterns, as well as spatial patterns (Elman, 1990). This makes Elman networks useful in such areas as signal processing and prediction where time plays a dominant role. The Hopfield network is a one-layer unsupervised training recurrent network with fully connected symmetrically weighted elements. It is used to store one or more stable target vectors. It can also act as error correction or vector categorization networks. Input vectors are used as initial conditions to the network, which recurrently updates until reaches a stable output vector. However, Hopfield networks may have spurious stable points that lead to incorrect answers, and that's why are seldom used in practice. For more information on Hopfield networks refer to Li et al (1989).

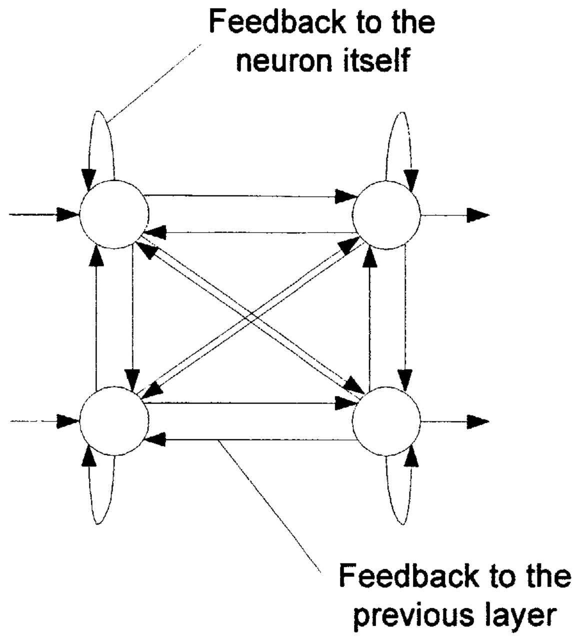


Figure 3.4: Recurrent Neural Network

The Radial Basis Function Network is a one-hidden layer feedforward network with mixed nonlinear transformations in the hidden layer, and linear transformation in the output layer. Radial basis networks may require more neurons than standard feedforward backpropagation networks, but often they can be designed in a fraction of the time it takes to train standard feedforward networks (Chen et al, 1991).

Several other architectures and training methods having unique advantages on particular applications have been proposed by researchers, like Grossberg, Kohonen, Albus etc.

3.6 Learning - Training

The issue of training a neural network is critical for its successful operation. The pattern of learning as well as the selection of the training set are providing to the network some of its good or bad characteristics. After the initial selection of the number of layers and neurons used, the architecture of the network and the transfer functions of the neurons, it is time to adjust the weights of the connections among the neurons as well as the bias terms. This adjustment procedure is called training or learning of the network. In general there exist 3 major categories of learning; supervised, unsupervised, and self-supervised.

In the supervised learning procedure the network is presented with several examples were the correct answer is known in advance. An external "teacher" is supervising the network and feeds it with an error signal when needed. The network using this error signal adjusts its weights and biases to meet the example requirements. After a number of iterations, the network response becomes within an acceptable limit of error. This procedure is also called in the literature "reinforcement learning" or "learning with a critic".

The unsupervised learning procedure uses the input data to adjust the network parameters, i.e. weights and biases, without knowing in advance the correct answer. There is no external "teacher" that provides the error. Instead, throughout the learning procedure, the input data is formulating internal groups. By the end of the training period the network is capable to separate and categorize the given data into certain groups. This characteristic is making these networks useful tools in classification problems and vector quantization. In the literature these networks are also called "self-organization networks".

Finally, in the self-supervised learning the network is evaluating its performance internally by using competitive layers and self-organizing maps. In that way, it is able to create an error signal, which is again fed into the network. Using this error signal the network is adjusting its weights and biases until a certain acceptable error limit is reached. A more extensive description of these networks is included in Kohonen (1987).

Each learning method uses a specific algorithm to find the "optimal" combination of the network parameters, for the problem that is attempting to solve. These algorithms are generally employing traditional parameter optimization procedures such as the least square minimization, gradient descent, simulated annealing, Newton algorithms and so on. There also exist more complicated algorithms that are employed to improve the performance of networks in terms of training time and detecting the global optimal solution.

A very popular learning rule for multilayer feedforward neural networks is "Backpropagation learning". Backpropagation is a supervised learning procedure, which was created by generalizing the least mean square approach, which is also referred to as Widrow-

Hoff learning rule. In this procedure the error is first calculated for the output layer. The connection weights and biases of the layer are updated. Then the error propagates backwards to the previous hidden layer, where its parameters are adjusted. The backpropagation of the error continues until the input layer is reached. The whole training procedure ends when the error at the output layer becomes less than an acceptable level. In the advantages of this method are included its simplicity and reliability. However, the method requires more computational effort than other methods. Furthermore, there exists the possibility that the solution procedure will lock on local optimal solutions instead of the global one. Researchers have improved the speed of convergence of the method by varying the step size throughout the training procedure as well as including a momentum term on it. There has been also been extensive research to improve the method of backpropagation such as the resilient backpropagation, the Newton's method, the Quasi-Newton algorithm, the Conjugate gradient algorithm, and the Stochastic Gradient Descent. For more information on backpropagation and on the improved method refer to Widrow et al (1985), Rumelhart et al (1986), and Hagan et al (1996).

A more advanced training algorithm is the Levenberg-Marquardt algorithm. This algorithm is mentioned here because it was used for the training of the neural networks used in this research study. The Levenberg-Marquardt algorithm is a variation of the Newton's method that was designed for minimizing the functions that are sums of squares of other nonlinear functions. For a description of the algorithm one can search in Hagan et al (1994) and Hagan et al (1996). The great advantage of this algorithm is that it achieves very fast and accurate convergence. It is able to converge much faster than the other algorithms for most of the cases. Moreover, the algorithm is capable of training the network very accurately keeping the level of errors very low. On the other hand, it is a very demanding algorithm from the computational point of view. It requires very fast processor and large amounts of memory to run efficiently. For this reason, the Neural Network Toolbox of the MATLAB program includes a reduced memory Levenberg-Marquardt training algorithm.

One of the most important decisions in the learning procedure is the selection of the training set. During the learning procedure the neural network will be presented several examples of what is going to meet in real life. These examples have to be representative of the whole feasible input and output space. The presented examples have to be selected and structured in such a way so as the network to be able to reproduce the feasible solutions space after the training cycle. There are many tradeoffs in the selection of the training set. The larger the training set, the better the representation of the solutions space, but the more the training time needed. Moreover, if the training set is too large, the network will start to respond correctly only to this data input and will loose its capability to generalize the problem. This means that if it will be presented with data that has different characteristics from what it was trained, the network will respond in a similar manner with the training set. Then the network is called "overtrained" and it has lost the beneficial property of neural networks to provide almost correct answers to problems, even if the input is totally new from what it was trained. This means that the programmer has to exercise extreme caution in the selection of the training set such that to represent the solutions space but not to overtrain the network.

There are two different techniques of supervised training that can be applied, incremental and batch training. In the incremental training approach, the weights and biases of the network are updated each time an example input is presented to the network. In batch training the weights and biases are updated only after the entire training set of inputs have been presented to the network. In that way, the change of the weights and biases is affected by the error of the complete training set. This is usually desirable because this difference on the weights and biases leads to the global optimal solution and not the local optimal solution that each example may have. Moreover, it is computationally more efficient because the training algorithm run only once in each training iteration.

The appropriate type of network architecture and training is difficult to be determined. There are many aspects affecting these decisions such as the nature of the problem to be solved and the type of constraints. In general, there are also many other criteria to be considered. There exist also many conflicting parameters such as the desired speed of training as well as the degree of accuracy are important considerations. The size and selection of the training set is also an important factor, as it was mentioned before. Consequently the number of layers, the number of neurons in each layer, and the transfer functions that will satisfy the constraints are major decisions. Finally, the computer resources may constrain the decision process because of the computational effort and the amount of memory needed from specific methods. Considering all of the above parameters that affect the performance of the network it is impossible to decide which is the optimal architecture for a specific problem. The usual approach is to select several candidates and evaluate each of them in order to identify the best choice.

Chapter 4

Virtual Simulation

4.1 Introduction

This research study examines the feasibility of using artificial neural networks as controllers for active motion control. To test the effectiveness of this type of controller, one has to use some kind of model of a real structure. For this research, the model used is a virtual model of a 5-story structure. The response of the structure due to the external loading and the controller's signals is generated with a computer program. The response of the members of this structure is considered to be linear at all times. The connectivity of the system is shown schematically in Figure 4.1.

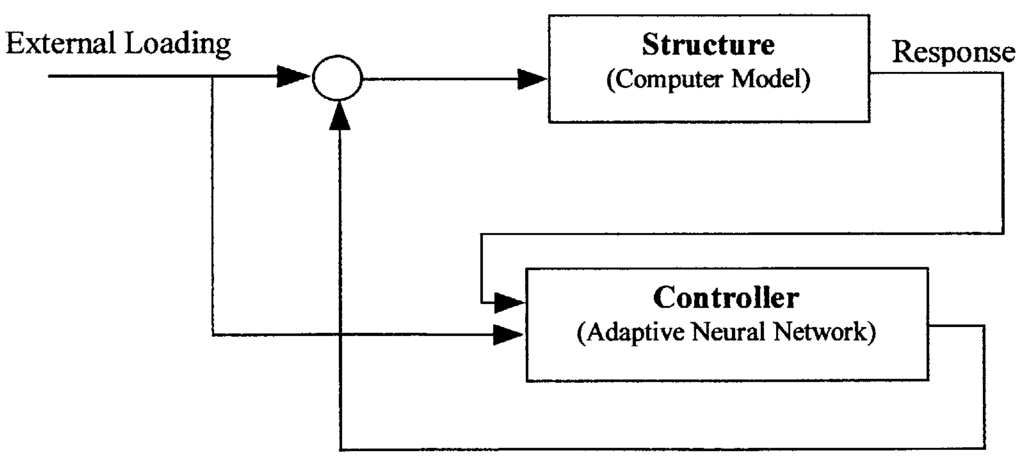


Figure 4.1: Control system

4.2 Structure Model

The test structure considered in this research is the 5-story building, shown in Figures 4.1 and 4.2. The building has a rectangular cross section with dimensions 5m and 15m length. The height of each floor is taken as 4m, resulting in a total height of 20m. The shape of the cross section results in a very slender structure on the one direction. This slenderness leads to a serious motion problem on this direction. Thus, one has to employ active control methods to constrain this motion problem. To further emphasize the motion problem the stiffness of the structure is reduced.

As it was mentioned before, a computer model is used to simulate the structural behavior. A basic assumption of the structural model is that each floor is infinitely stiff and thus there is no rotation of the beam-column connections. The columns are considered to deform as shear beams, which means that there is no rotation of any cross section of the column. All the members are considered to be linear elastic. Moreover, the motion is considered to be planar, which, in addition to the above assumptions and simplifications, results to a building with only 5 degrees of freedom. The simplicity of the model makes it feasible to increase the complexity of the excitation, generate the time history response and the simulation step by step, and monitor the behavior of the neural network controller. On the other hand, a major disadvantage of the computer model is that it does not include non-linear behavior due to inelastic deformation of the members of the structure. Plastic deformations modify the stiffness and damping of the structure and therefore may result to large differences to the response. In order to gain a complete understanding of the behavior of the controller, one should introduce a structural model, which would include the inelastic deformations of the structure. However, the neural network controller is able to generalize its response and update its knowledge regarding the behavior of the structure, based on new information provided during real time control. Therefore, one can claim that the controller, created with the elastic structural model, is able to adjust its response, in order to control successfully the nonlinear structure.

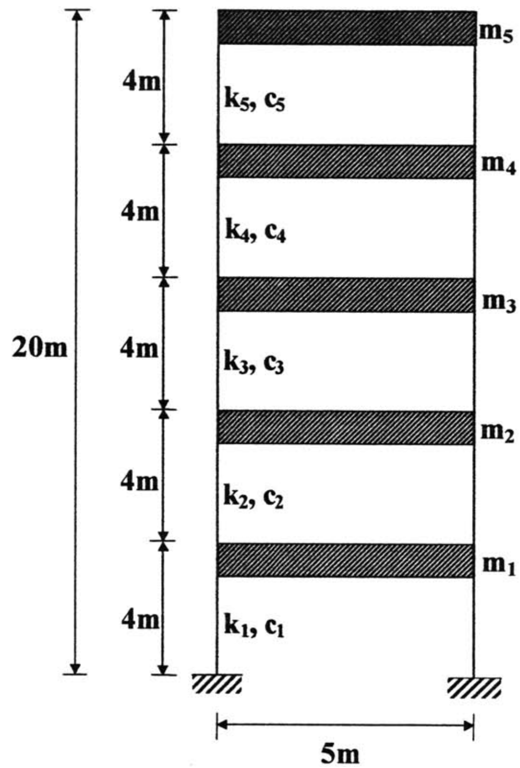


Figure 4.2: Side view of the structure

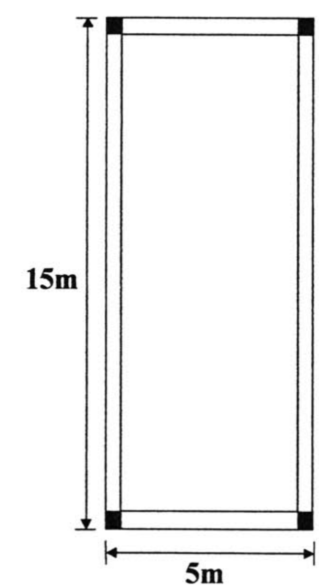


Figure 4.3: Section of the structure

The various parameters, like mass, stiffness, and damping, which describe the structural characteristics of the building, are defined such that the virtual model resembles a real structure. These numbers are used to simulate the response of the structure with the computer model. They do not affect the behavior of the controller as it can be trained to control any structure with any shape and values for the characteristic parameters.

To evaluate approximate values for the masses of each floor the total volume of the building was considered $V=5\times15\times20=1500m^3$. Considering concrete to be used as the building material, 20% of the total volume is estimated to be concrete. This results to a material volume of $V_c=1500\times0.2=300m^3$. Finally, the mass of this concrete volume, considering the density of concrete as $25kN/m^3$, is $M=25\times300=7500kN$. If this mass is evenly distributed throughout the floors, then the mass of each floor will be $m_1=m_2=m_3=m_4=m_5=1500kN$. In case a different mass distribution was employed, the effectiveness of the controller would not have been affected. As it was mentioned before, the neural network controller can be trained to control any structure.

To estimate values for the stiffnesses of the stories, Rayleigh quotient is used (Chopra, 1995). It is known that Rayleigh quotient provides an adequate approximation for a frequency of the structure, when it is provided with an approximation of the corresponding mode shape. Rayleigh quotient is defined as:

$$R=\frac{\Phi^T K\Phi}{\Phi^T M\Phi} \tag{4.1}$$

where Φ is the mode shape, K is the stiffness matrix, and M is the mass matrix. Finally, R is the approximation of the square of the frequency of the structure. A rule of thumb is that the dominant period of a building will be equal to the n/10, were n is the number of stories. Therefore, a typical value for the dominant period of the testing building is $T_1=5/10=0.5sec$, or in terms of frequency $\omega_1=2\pi/T_1=12.566rad/sec$. Assuming a linear first mode shape, $\Phi_1^T=[1\ 0.8\ 0.6\ 0.4\ 0.2]$, and equating the square of above frequency with the Rayleigh quotient, one can get the stiffness matrix. Making the assumption that the stiffnesses at all stories is the same, one obtains the following results:

$$M=\begin{bmatrix} m_5 & 0 & 0 & 0 & 0 \\ 0 & m_4 & 0 & 0 & 0 \\ 0 & 0 & m_3 & 0 & 0 \\ 0 & 0 & 0 & m_2 & 0 \\ 0 & 0 & 0 & 0 & m_1 \end{bmatrix} = 1500\times\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.2}$$

$$K=\begin{bmatrix} k_5 & -k_5 & 0 & 0 & 0 \\ -k_5 & k_5+k_4 & -k_4 & 0 & 0 \\ 0 & -k_4 & k_4+k_3 & -k_3 & 0 \\ 0 & 0 & -k_3 & k_3+k_2 & -k_2 \\ 0 & 0 & 0 & -k_2 & k_2+k_1 \end{bmatrix} = k\begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ -1 & 2 & -1 & 0 & 0 \\ 0 & -1 & 2 & -1 & 0 \\ 0 & 0 & -1 & 2 & -1 \\ 0 & 0 & 0 & -1 & 2 \end{bmatrix} \tag{4.3}$$

where $k=k_1=k_2=k_3=k_4=k_5$ due to the above assumption

$$R=\omega^2=(12.566 rad/\sec)^2 \tag{4.4}$$

$$\Phi_1^T K \Phi_1 = \frac{1}{5}k \tag{4.5}$$

$$\Phi_1^T M \Phi = 2.2m = 2.2\times 1500kN \tag{4.6}$$

which results to k=2,605,576kN/m. This value represents the stiffness of the building in the slender direction. The initial assumption that the slender direction of the structure will have a period of the order of 0.5 sec produced this value for the stiffness, which for the purpose of this research study is quite high. To emphasize the motion problem of the structure, this value is reduced to k=1,000,000kN/m. It will be shown later, that the controller will detect this lack of stiffness and will try to restore it, a fact which becomes apparent in Chapter 6 where adaptive control is considered.

Finally, to evaluate values for the material damping, the case of stiffness proportional damping is considered (Chopra, 1995). This assumption is realistic considering that the moving parts of the structure, the elements that will provide the damping, will be the columns that are the members providing stiffness as well. In real structures, damping is produced from yielding, or friction action of the members. However, the structural members in this model are considered to function like pure viscous dampers. Therefore, the damping value evaluated here represents the damping of an equivalent, to the produced yield or friction, viscous damper.

In the stiffness proportional damping case, the damping matrix is equal to the stiffness matrix multiplied by a coefficient a.

$C = a \times K$

$$\begin{bmatrix} c_5 & -c_5 & 0 & 0 & 0 \\ -c_5 & c_5+c_4 & -c_4 & 0 & 0 \\ 0 & -c_4 & c_4+c_3 & -c_3 & 0 \\ 0 & 0 & -c_3 & c_3+c_2 & -c_2 \\ 0 & 0 & 0 & -c_2 & c_2+c_1 \end{bmatrix} = a \times \begin{bmatrix} k_5 & -k_5 & 0 & 0 & 0 \\ -k_5 & k_5+k_4 & -k_4 & 0 & 0 \\ 0 & -k_4 & k_4+k_3 & -k_3 & 0 \\ 0 & 0 & -k_3 & k_3+k_2 & -k_2 \\ 0 & 0 & 0 & -k_2 & k_2+k_1 \end{bmatrix} \tag{4.7}$$

Assuming a damping ratio for the first mode of ξ=0.02 the coefficient a takes the value:

$$a = \frac{2\xi_1}{\omega_1} = \frac{2 \times 0.02}{12.566} = 3.18 \times 10^{-3} \tag{4.8}$$

which results to the values for the material damping of each floor:

$$c_1 = c_2 = c_3 = c_4 = c_5 = c = 3183.19 \text{kN} \times \text{sec/m} \tag{4.9}$$

The structural model is now fully defined. The time history response of the structure, where dynamic behavior is considered, is generated with the Newmark's integration method (Bathe, 1996).

4.3 Neural Network Architecture

The control function of this scheme is carried out by a neural network. The particular neural network used is a feed forward neural network with feedback learning. Several networks are developed and trained for each particular case considered. Each network has one input layer, two hidden layers, and one output layer. In MATLAB, the input layer's function is to provide the input for the first internal layer of the network. The number of the neurons in each layer is different for each one of the excitation cases considered. Increasing the complexity of the excitation cases introduces more constraints to the neural network controller and therefore requires larger number of variables. In order to respond to this increased demand of variables, one needs to increase the number of neurons in the hidden layers.

The number of neurons is adjusted to accommodate for the increased complexity of the problem, but the transfer functions of the neurons in each layer are the same in all the cases considered. For the first hidden layer, the hyperbolic tangent sigmoid transfer function (tansig) of MATLAB is used. This function is described by the following equation:

$$y = \frac{2}{(1+e^{-2*x})} - 1 \tag{4.10}$$

Tansig is named after the hyperbolic tangent function (tanh) $y = \frac{e^x - e^{-x}}{e^x + e^{-x}}$, which has the same shape. However, tanh may be more accurate and is recommended for applications that require the hyperbolic tangent. Tansig is mathematically equivalent to tanh. The difference is that it runs faster than the MATLAB implementation of tanh, but the results can have very small numerical differences. This function is a good trade off for neural networks, where speed is important and the exact shape of the transfer function is not.

For the second hidden layer and the output layer, the linear transfer function (purelin) is used. This function just transmits the bias and the weighted sum of the input signals that are coming to the neuron. A layer of neurons with linear transfer function can be used in a number of ways. With the selection of the weights and the bias of the layer the input signal is magnified by the appropriate amount needed. Moreover, neurons with linear transfer functions can be used for categorization, but if only the areas to be separated are linearly separable. For example, a single neuron is able to capable to separate two regions, if they can be divided with a straight line.

This combination of transfer functions allows a network to describe any function with adequate precision. In the control case, which is the subject of this research study, this selection of transfer functions is useful in a number of ways. The tansig function categorizes the input and propagates a homogeneous information signal to the next layer. In that way, this layer is filtering any noise in the input signal as well as transmits the information categorized ready to be processed from the next layers. The layers, with the linear transfer function, magnify the incoming signal in order to create a response of the network that will be adequate for the purpose that it is created.

4.4 Selection of the training set

One of the most important steps on the creation of a ready-to-use neural network is training. Training provides to the network the knowledge on how to respond at each input signal. All the networks used in this research study are trained with the Levenberg-Marquardt algorithm, (see section 3.6). During the training procedure, the network is presented with examples, which are representative of the feasible input and desired solution space. The network has to be presented with examples that represent both the extreme and regular cases for the input and output. Therefore, time histories of the response of the structure for various loading conditions were created in advance of the training. Then, the needed action, to restore the structure in its desired condition, was found. The choice of the training set is made by selecting some sequences of the response, that are representative of the behavior of the structure. Under the supervision of the selected response sequences and using the training algorithm, the network is trained until the prespecified error acceptance is met. This error is commonly set equal to e=0.01. This represents the sum of squares of the error of the response from the desired solution, of all the training examples. In order to examine the effectiveness of the controller, after the end of the training attempt, the complete time history of the excitation is applied to the structure and the response of the controller is monitored. In case the network does not respond in the desired way, which means that the structural response does not meet the objectives, there is a need to train it more. However, one has to be careful not to overtrain the network for a specific excitation. An overtrained network responds in the desired way only in the example used for the training. It is not able to respond successfully for another excitation. That is why, in most cases in this research, the training set is selected from examples of many different cases. The objective of the training is to make the network understand the dynamic behavior of the structure, and therefore to be able to respond successfully under any excitation. In real life structures, where the mass, damping and the stiffness may differ from time to time due to change of use and nonlinear phenomena, real time training is useful during operation time, to capture the new information and update the knowledge that the controller has for the structure.

4.5 Cases considered

To test the active motion control system, the structure is subjected to a set of excitations. The two basic loading conditions considered in this research are wind and earthquake. The objective of the control is to keep the response of the structure within some prescribed limits. Response measures are either the relative displacements or the accelerations of the stories. The prescribed limits are 0.01 meter of displacement and 2% of the gravity acceleration $g=9.87 m/sec^2$. These limits are based on strength as well as serviceability issues, such as building, equipment or human comfort. The characteristics of the excitations and the output of the controller are discussed in the following sections.

In order to explore the capabilities of the controller many tests are implemented. Simple models and excitations are employed first. As the level of understanding of the behavior of the controller increased, the research involved more complex models and excitations. The tests can be separated into two major categories. The first category represents the classic active control case, where the input signals may be the relative displacements or accelerations of each floor level of the structure, the wind velocity, or the ground motion depending on the excitation. The output of the controller is a force applied on the bracing of each floor. Initially, the response of the structure is considered to be quasi-static. This implies that no inertia terms are considered in the calculation of the response. The applied excitation is a wind force at each floor level, which changes magnitude in according to a periodic function. The objective is to reduce the relative displacements of each floor.

The next step takes into account the dynamic response of the structure. Initially the same, with the quasi-static case, wind loading and objectives are considered. This experiment presents the difficulties of controlling a structure under dynamic loading. After that more complex excitation conditions are considered including real earthquakes and studying the behavior for different earthquake characteristics. Finally, the objective shifted in controlling the maximum acceleration of the structure.

The second category of tests concerns adaptive control, where one has the ability to change the characteristics of the structure, like stiffness and damping, over time. In this series of tests, the input of the controller is the relative displacements and the velocities of each floor level of the structure regardless of the form of the excitation. The output of the controller is the change of the stiffness and damping at each floor level. The excitations here are various winds, with and without random distribution, and real earthquakes. The response of the structure is always considered as dynamic, and the objective is to control both the displacements and the accelerations.

4.6 Loading conditions

As mentioned above the two basic loading conditions considered in this research are wind and earthquake. For the case of wind loading, and because there are no time histories of winds, like the ones that exist for earthquakes, several assumptions have to be made. The wind considered is the category of gust wind with period of 5 sec and speed of 100 miles per hour. These values are typical for several major cities in the world. Another assumption is that the wind blows with this speed at the top of the height of the building (20m) and calms down linearly as it approaches the ground. At the ground level the speed of wind is zero. Considering the above data and assuming a linear distribution of the loading over the height, the values of the forces at each floor level are calculated. The wind acts at the wide side of the building, as is shown in Figure 4.4, and creates a motion problem at its slender direction. The wind is assumed to vary in a sinusoidal way with respect to time. In several cases, when there is a need for random vibration, not pure harmonic, this periodical loading is adjusted by introducing a random variable in the magnitude and the period with a variation up to a level of 50%.

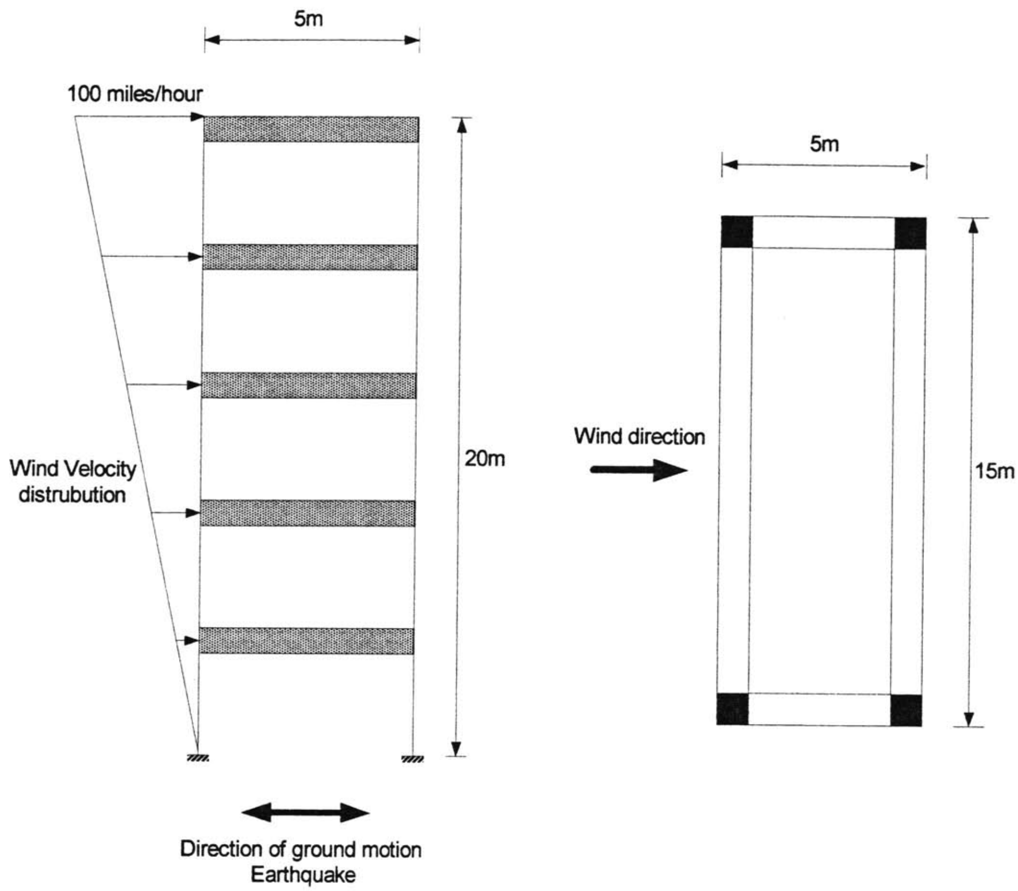


Figure 4.4: Loading conditions

For the case of earthquake excitation, the El Centro (S00E), Taft (S69E), and Kobe (NS) earthquakes are used. As shown in Figure 4.4, the ground acceleration is applied at the slender direction of the building. The El Centro and Taft earthquakes are commonly used because of their substantially different characteristics. The El Centro earthquake has a peak acceleration of 3.41m/sec^2, the Taft earthquake has a peak acceleration of 1.76m/sec^2, and the Kobe earthquake has a peak acceleration of 8.18m/sec^2. Furthermore, the El Centro and the Kobe earthquakes are very impulsive while the Taft earthquake has a larger dominant period and therefore excites more the higher modes of the structure. It becomes obvious that the behavior of a structure will differ significantly under these excitations. The behavior of the controller is tested under these substantially different excitations. The ability of the neural network to generalize is demonstrated, with the condition that the network is adequately trained to control the structure and not overtrained for the specific excitation.

4.7 Output of the controller

When the neural network controller is fed with the response of the structure, it provides useful information on what to do to preserve the structure in the desired condition. Depending on the case considered, the response of the controller is either a set of forces applied on the structural frame, or a set of additional stiffness and damping at each story level. As illustrated in Figure 4.5, the forces are applied on the structure such that to provide a set of self-equilibrating forces in each story. This means that the forces are acting only on the story that are applied and they cancel out over the rest of the height of the structure. Thus, there is no coupling between the deformations produced from the control forces. In other words, the application of one control force does not affect the deformation profile of other floors. It is not unusual phenomenon, the application of a control force at one point to worsen the displacement profile at another point of the structure. The self-equilibrating force configuration is not capable of creating such undesirable conditions. The controller adjusts the control force magnitudes at discrete time points according to the input signals. These forces are applied smoothly, varying in a linear manner between the desired magnitudes at each control point, in order to avoid imposing additional accelerations on the structure due to their application.

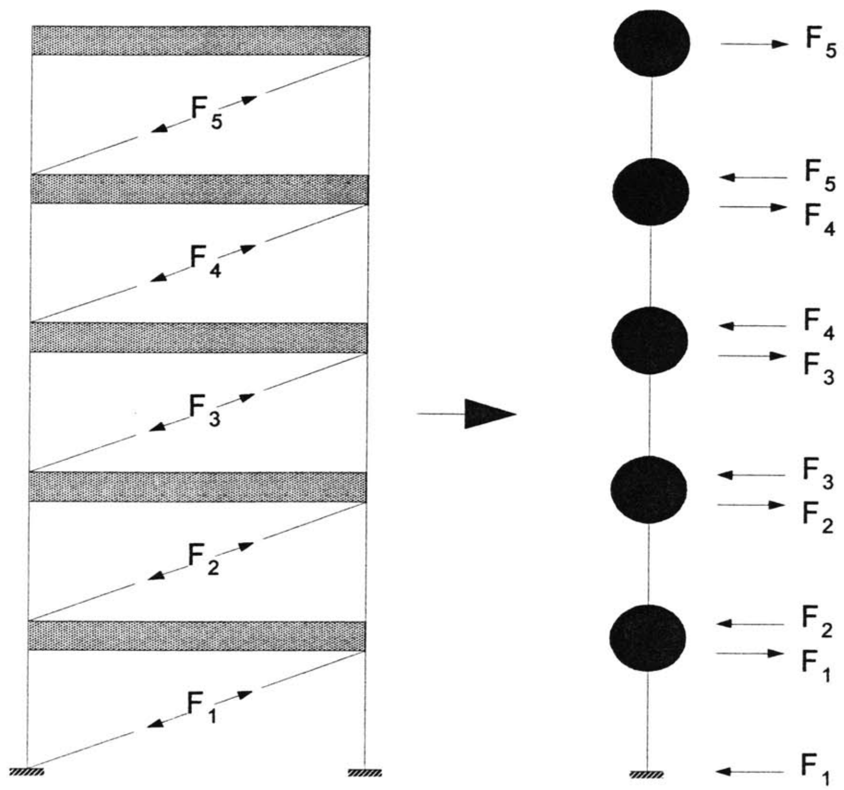


Figure 4.5: Self-equilibrating forces

For the case of adaptive control, where the controller is adjusting the stiffness and damping of each story, the implementation is different. The controller sends signal to specific devices, like the ones described in Chapter 2, and increases the stiffness and damping at a particular floor when needed. The case of added stiffness is easily visualizable as long as one can imagine it like increasing stiffness to the columns. In real life, in order to achieve the required stiffness increase, stiffness generating devices can be added in the structural frame, in a diagonal element or a chevron bracing. The mathematical representation is written as follows:

$$K_{final} = K_{structural} + K_{control} =$$

$$= \begin{bmatrix} k_5 & -k_5 & 0 & 0 & 0 \\ -k_5 & k_5+k_4 & -k_4 & 0 & 0 \\ 0 & -k_4 & k_4+k_3 & -k_3 & 0 \\ 0 & 0 & -k_3 & k_3+k_2 & -k_2 \\ 0 & 0 & 0 & -k_2 & k_2+k_1 \end{bmatrix} + \begin{bmatrix} k_5^C & -k_5^C & 0 & 0 & 0 \\ -k_5^C & k_5^C+k_4^C & -k_4^C & 0 & 0 \\ 0 & -k_4^C & k_4^C+k_3^C & -k_3^C & 0 \\ 0 & 0 & -k_3^C & k_3^C+k_2^C & -k_2^C \\ 0 & 0 & 0 & -k_2^C & k_2^C+k_1^C \end{bmatrix} \quad (4.11)$$

where k_1, k_2, k_3, k_4, and k_5 are the structural stiffnesses of the stories and k_1^C, k_2^C, k_3^C, k_4^C, and k_5^C are the control added stiffnesses.

For the case where damping is needed, there is one more thing to be defined. Damping can be added such that to be connected with -or like- the stiffness elements of the structure. In this case consequently the damping matrix has the form of the stiffness matrix. Otherwise, damping can be connected with the mass elements of the structure, i.e. floor, and then the damping matrix takes the form of the mass matrix. It is a common approach in dynamic modal analysis to assume that damping is either stiffness or mass proportional, or both (Chopra, 1995). In the control case, the values of the control damping are arbitrary and selected by the controller. Therefore, one cannot assume that the control damping matrix is stiffness or mass proportional. The form of the matrix is a consequence of the placement of the devices that are intended to apply control damping, see Figure 4.6. Therefore, the mathematical representation for the two configurations is written as:

- for the damping matrix with the stiffness formulation

$$C_{final} = C_{structural} + C_{control} =$$

$$= \begin{bmatrix} c_5 & -c_5 & 0 & 0 & 0 \\ -c_5 & c_5+c_4 & -c_4 & 0 & 0 \\ 0 & -c_4 & c_4+c_3 & -c_3 & 0 \\ 0 & 0 & -c_3 & c_3+c_2 & -c_2 \\ 0 & 0 & 0 & -c_2 & c_2+c_1 \end{bmatrix} + \begin{bmatrix} c_5^C & -c_5^C & 0 & 0 & 0 \\ -c_5^C & c_5^C+c_4^C & -c_4^C & 0 & 0 \\ 0 & -c_4^C & c_4^C+c_3^C & -c_3^C & 0 \\ 0 & 0 & -c_3^C & c_3^C+c_2^C & -c_2^C \\ 0 & 0 & 0 & -c_2^C & c_2^C+c_1^C \end{bmatrix} \quad (4.12)$$

- for the damping matrix with the mass formulation

$$C_{final} = C_{structural} + C_{control} =$$

$$= \begin{bmatrix} c_5 & -c_5 & 0 & 0 & 0 \\ -c_5 & c_5+c_4 & -c_4 & 0 & 0 \\ 0 & -c_4 & c_4+c_3 & -c_3 & 0 \\ 0 & 0 & -c_3 & c_3+c_2 & -c_2 \\ 0 & 0 & 0 & -c_2 & c_2+c_1 \end{bmatrix} + \begin{bmatrix} c_5^C & 0 & 0 & 0 & 0 \\ 0 & c_4^C & 0 & 0 & 0 \\ 0 & 0 & c_3^C & 0 & 0 \\ 0 & 0 & 0 & c_2^C & 0 \\ 0 & 0 & 0 & 0 & c_1^C \end{bmatrix} \quad (4.13)$$

where c_1, c_2, c_3, c_4, and c_5 are the structural damping of the stories and c_1^C, c_2^C, c_3^C, c_4^C, and c_5^C are the control added damping.

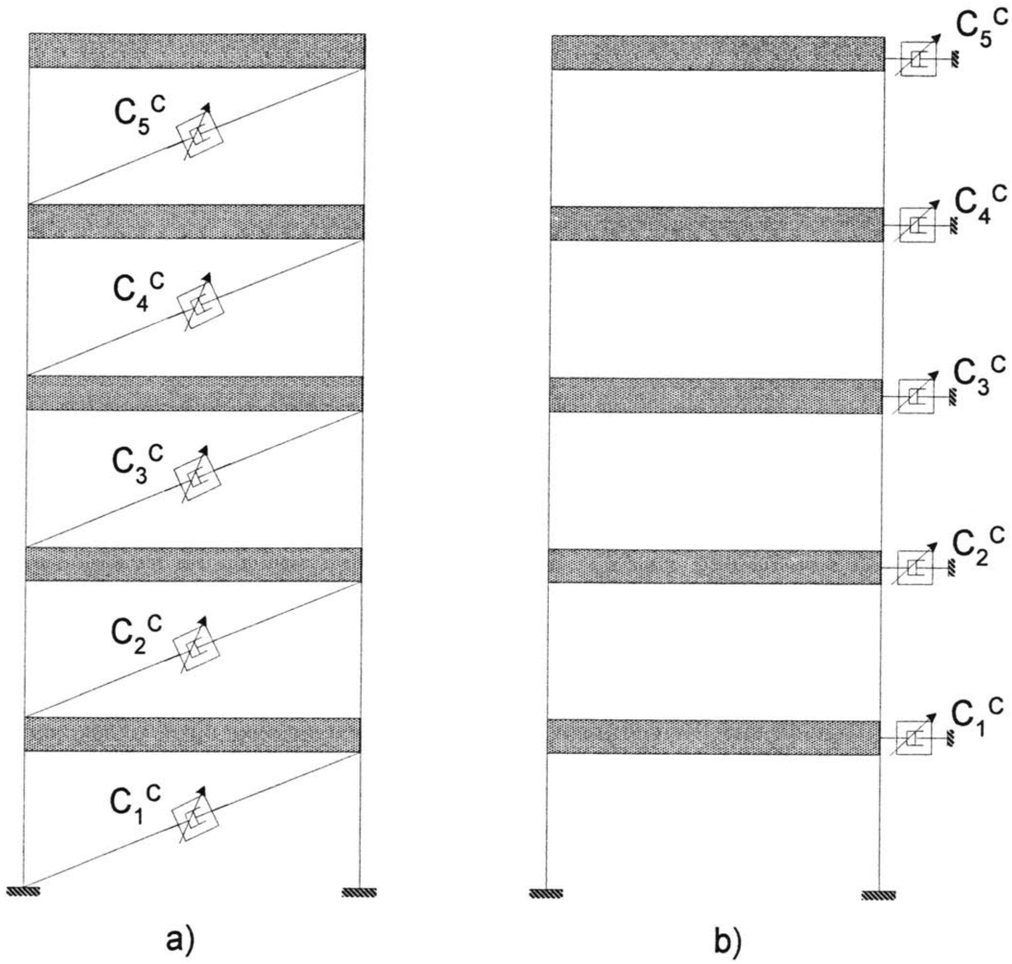


Figure 4.6: a) Stiffness formulated damping, b) Mass formulated damping (with variable damping device)

4.8 Computational System Used

The computations were carried out using a portable computer with a Pentium II processor at 300 MHz speed. The memory available on the system is 128 MB of ram with access speed of 66MHz. The operating system of the computer is Windows 98. It should be noted that the performance data obtained with the portable computer is conservative. The components of portable computers are not as fast as the corresponding components of regular desktop or tower based computers are. For example, the memory access speed for the case of a desktop or tower based computer, of the same age with the portable, is 100 MHz vs. the 66MHz of the portable computer.

The neural network is created with the assistance of the program MATLAB, version 5.2.0. Using the neural network toolbox, version 3.0 which is included in the MATLAB software, makes very easy to create and test neural network architectures such that to explore all the possible candidates for solving a particular problem and find the best one. Moreover, it includes many subroutines with ready-made functions and algorithms that help to create and train the neural network. The fact that the program MATLAB is used instead of some computer language, like Fortran or C++, may do the procedure of creating and training neural networks faster, but it doesn't provide the fastest response that one can obtain. It is true that, if the networks were created in a computer language like the ones mentioned above, its response would have been faster.

The performance of the network in terms of training and response time is distorted due to the use of a portable computer and the program MATLAB. The response time of the network is critical for active control. The time delay from the various components of a control system is able to destabilize the structure, as it is already mentioned in Chapter 2 and as it is illustrated in the result chapters. For real applications, one should expect to use a powerful computer system, designated only for the purpose of the controller, and use a powerful computer language like the ones mentioned above. This implementation would result in a much faster controller than the one presented here. However, even with this system the results are useful because they provide an estimate of the time needed by such a controller. On the other hand, the iterations required to train the network, using the same training set and learning algorithm are independent of the capabilities of the system.

4.7 Limitations and future work

There are several limitations within the context of this research study, which can constitute the material for future work on this field. One can examine the effect of retracting one by one the assumptions made at the beginning of this study. The framework of this study is the implementation of a controller for reducing the motion in one direction of a slender structure. To realize this, actuators are placed at each story to apply forces or change the stiffness and damping of the structure. Various excitations are considered in order to explore the capabilities of the controller, such as gust winds and earthquakes. The model of the structure is very simple assuming only one degree of freedom for motion at each floor level. This model is built such that to identify the difficulties of training the controller successfully. The controller is required to understand the dynamic behavior of the structure under intense loading. However, this simple model of the structure does not allow to introduce any abnormal behavior of the structure due to nonlinear plastic deformations of the material. It is very likely that under such intense loading conditions parts of the structure will deform inelastically, which would change dramatically the response of the structure and consequently the desired response of the controller.

Furthermore, in a future study the structure can be controlled for displacements in two directions as well as for rotation and twisting. This fact would require more sensors and actuators per floor such that to have sufficient information for the state of the structure at any instant of time. The placement of the actuators matters in this case because they must have the correct direction such that to control all the desired motions. The use of more actuators will help to avoid concentration of forces at specific points of the structure as soon as the total required control force will be applied in small parts and will be dispersed over the cross section.

For intense excitations, like the ones considered, the deformation state of the structure should be monitored with a time interval on the order of milliseconds. Therefore, in order to achieve satisfying results a fast control scheme is required. The implementation of a fast neural network controller is feasible, as it will be illustrated in the following chapters. The presented network can get faster if it will be implemented in a faster computer system with the use of a robust computer language.

Finally, a major issue is the lack of actuator devices that can satisfy the requirements of this study. The actuators in this study are assumed to respond in milliseconds and provide any magnitude of force, stiffness, or damping needed by the controller. There are few devices that are able to provide such a high output, but they all lack in response time. On the other hand, devices with fast response time lack on the output magnitude. Moreover, in real life applications the reliability of these devices is another major issue. Considering the rapid evolution of the technology, it is not unreasonable to expect in the future a reliable actuator scheme with high output provided in minor response time.

Chapter 5

Active Control experiment

5.1 Introduction

In this section the results from the active control of the 5-story building are presented. In the figures that follow both the controlled and uncontrolled responses are reported. The controller in this chapter attempts to restore the structure in the desired state by applying forces in each story. In order to explore the capabilities of the controller, the selected excitations have substantially different characteristics. The excitations considered here are: periodic wind; random wind; and the El Centro (S00E), Taft (S69E) and Kobe (NS) earthquakes. The input of the controller is the relative displacements of the structure and either the wind velocity or ground acceleration depending on the excitation.

5.2 Quasi-static response - Wind excitation

In this case, the response of the structure is assumed to be quasi-static. The structure is subjected to a wind excitation. The wind is assumed to follow a periodic function, with a period of 5 sec and a magnitude that is randomly adjusted within an order of magnitude. This adjustment serves in creating an irregular excitation that the controller cannot memorize. The objective of the control is to suppress the relative displacements of the stories under 0.01m. Finally, in order to explore the effectiveness of the controller under different input parameters, two cases are considered. Firstly, only the relative displacements of the structure are fed on the controller. For the second case, the wind velocity is included as an input parameter. Considering these two cases the effectiveness of open and closed loop control is examined. The first example represents the case of closed loop control or feedback. The second example represents the case where both feedforward and feedback information is obtained. Figures 5.1 and 5.2 contain the time history of the displacements of the first floor for the two cases described above. The first floor is chosen here, because it is carries the entire lateral load and therefore has the highest transverse shear.

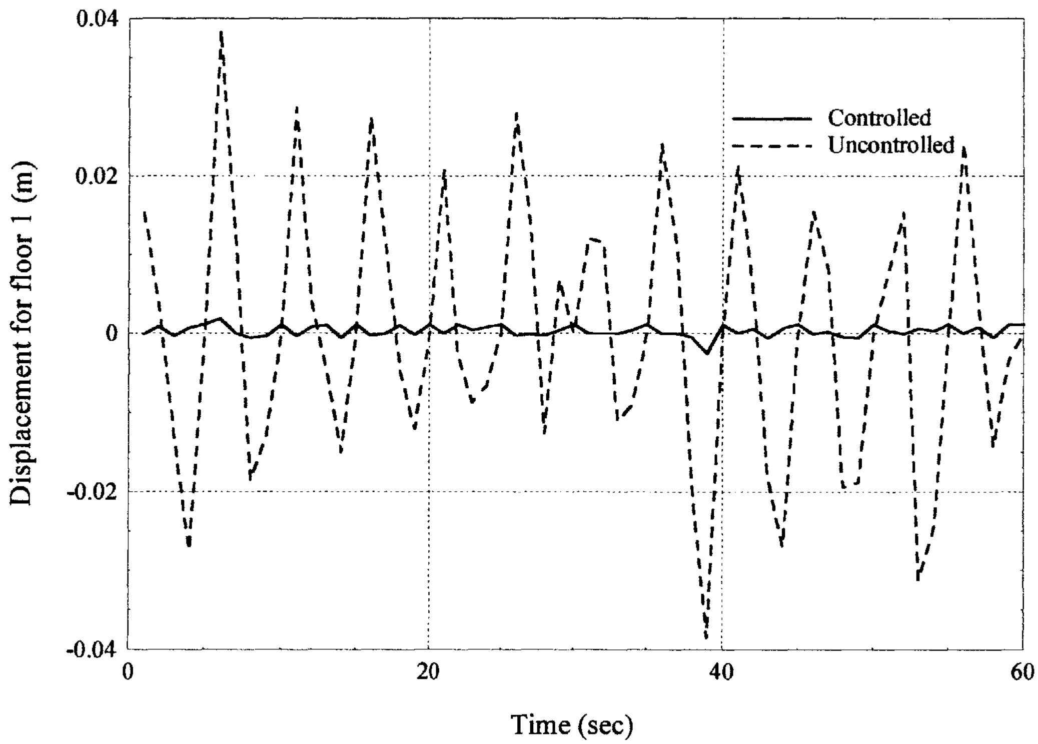


Figure 5.1: Displacements for the 1st floor (without velocity input) - Quasi-static response, Wind

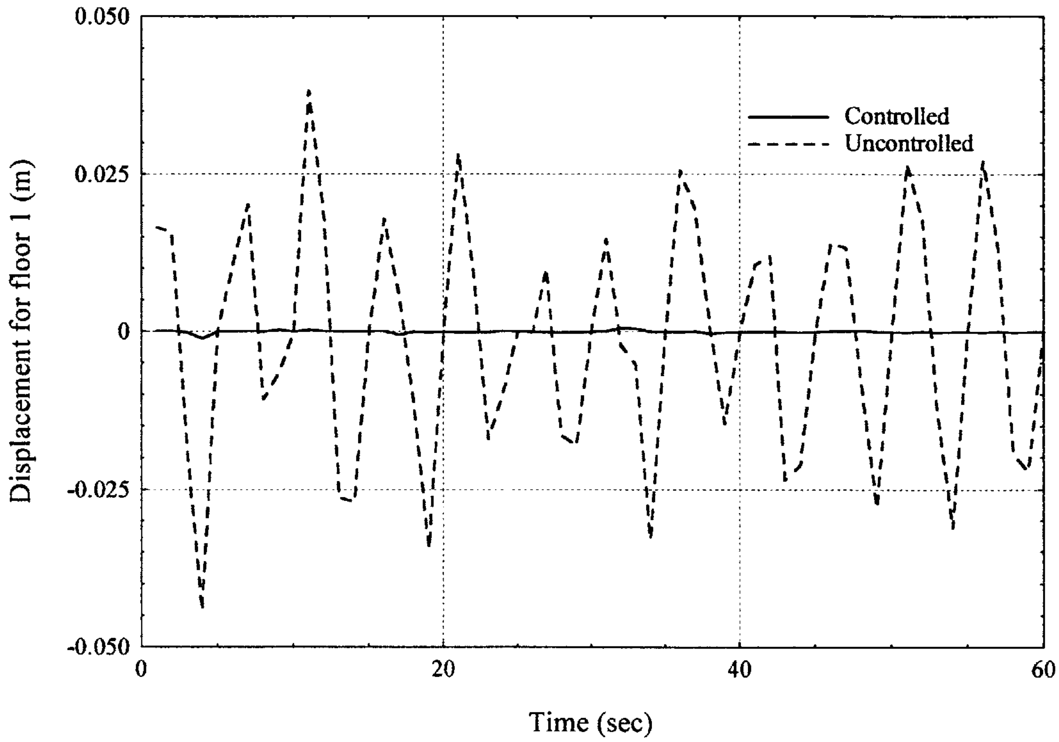


Figure 5.2: Displacements for the 1st floor (with velocity input) - Quasi-static response, Wind

Figures 5.1 and 5.2 present that the neural network successfully controlled the structure in both closed loop control and the combination open-closed loop control. In other words, in both cases the objective to limit the maximum displacement of the structure under 0.01m is achieved. However, the controlled structure vibrates more in the first rather than the second case. The controller in the second case has almost eliminated completely the vibration. This observation indicates that the information of the excitation magnitude is useful to the controller. The controller, with the wind velocity input, is able to distinguish whether the reduction of the response of the structure, at a particular time, is due to the application of the control forces or the decrease of the excitation magnitude.

5.3 Dynamic response - Wind excitation

The complexity of the control operation increases with the introduction of the dynamic response of the structure. Initially, the same wind excitation is used, but to simplify the case, the random adjustment of the wind magnitude is removed. The objective of the training is again to limit the relative displacements of the stories to be under 0.01m. However, when the dynamic response of the structure is considered, the magnitude of the velocities and accelerations is emerging as another concern. The plots of the time history of the accelerations and velocities for the 5th floor, after the first training cycle, are presented in Figures 5.4 and 5.5. The selection of the floor, which the response history is presented, is not of a great importance, as soon as the controller is trained to create a uniform deformation shape throughout the height of the building. However, the 5th floor is selected here because the acceleration and velocity response history of the top floor is the greatest for the uncontrolled structure.

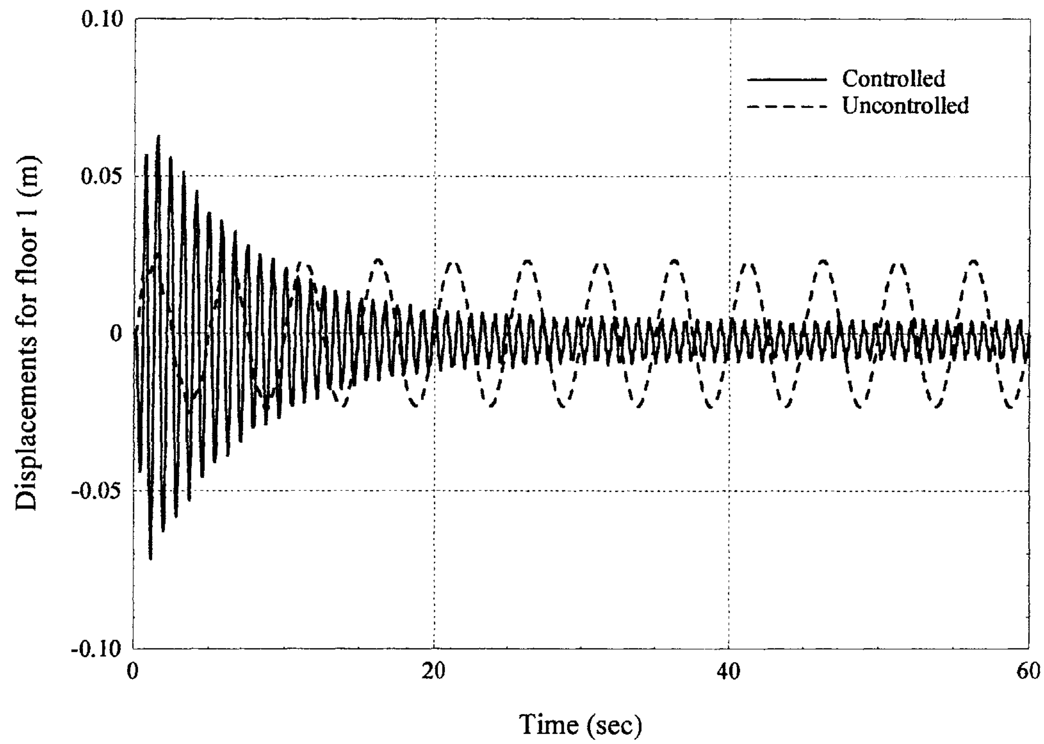


Figure 5.3: Displacements for the 1st floor (1st training attempt) - Dynamic response, Wind

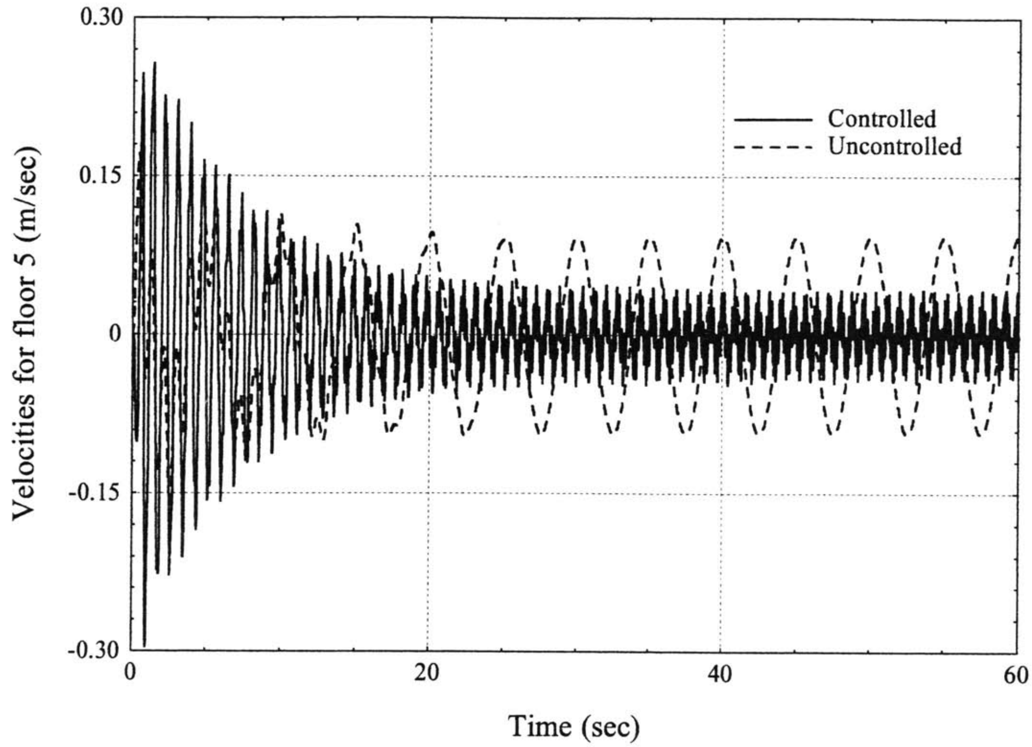


Figure 5.4: Velocities for the 5th floor (1st training attempt) - Dynamic response, Wind

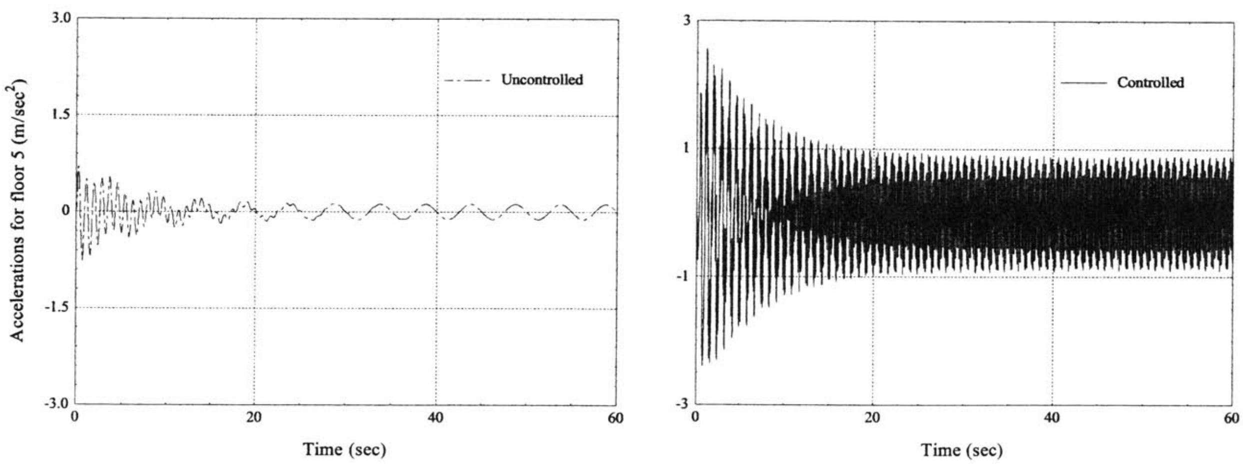


Figure 5.5: Accelerations for the 5th floor (1st training attempt) - Dynamic response, Wind

The results presented above, show that the controller magnifies, instead of reduces, the response of the structure. These results are generated after the first training cycle of the network. It is evident that the network is poorly trained to face the dynamic response of the structure. For the case of the displacements of the first floor, the control attempt magnifies the response of the structure for the first 10 seconds. After this initial time period, the controller understands the behavior of the structure and manages to reduce the displacement profile to meet the objective response. In a period of 20 seconds the response is slightly less than 0.01m, the case for which it was trained. The same pattern appears in the plot for the velocities of the fifth floor. However, the response of the structure in terms of acceleration is never reduced under the uncontrolled case. The general shape of the time history for the acceleration is the same with the time history of the displacement or the velocity, but the magnitude is almost 3 times larger from the uncontrolled case. This behavior is attributed to the time delay that exists between the point that the controller accepts the input signal and the time that the controller's decision is applied to the structure. As presented in Chapter 2, this time gap can be analyzed into three pieces: i) the time that the sensors need to send the signal to the controller; ii) the time that the controller needs to decide on the controlling action; and iii) the time that the actuators, which will apply the forces, need to respond, from the point that they will receive the output signal of the controller. The time spent on the first action is usually minor. The time spent on the response of the actuators depends on the nature of the device. In this research study, the focus is on the controller. The time spent on the controller decision procedure, using the neural network scheme and the computer system described in the previous chapter, is of the order of 0.02 seconds. Consequently, the controller has to decide on the action that will be applied at time $t+\Delta t$ with information received at time t. The variable Δt stands for the above described time gap. This case represents a classical example of instability due to the application of active control. Additional examples are presented in the section were earthquakes are considered as the excitation of the structure.

Figures 5.3 to 5.5 illustrate the controller's inability, with this level of training, to control accelerations. On the contrary, the control actions magnify the response of the structure for the first seconds, a fact that may be critical. Further training of the network is needed such that obtain the necessary information for the dynamic behavior of the structure and to include the effect of time delay. After this training procedure the controller should be able to face successfully any excitation condition like the one presented above. To illustrate this, the structure is subjected again to wind excitation, but the magnitude and period are now adjusted randomly from their initial values. The introduction of these random variables does not produce a realistic wind excitation history, but illustrates that the network has learned the actual dynamic characteristics of the structure and it does not simply predict the response of the structure due to the previous steady-state harmonic excitation. The results for this case are presented in Figures 5.6, 5.7 and 5.8.

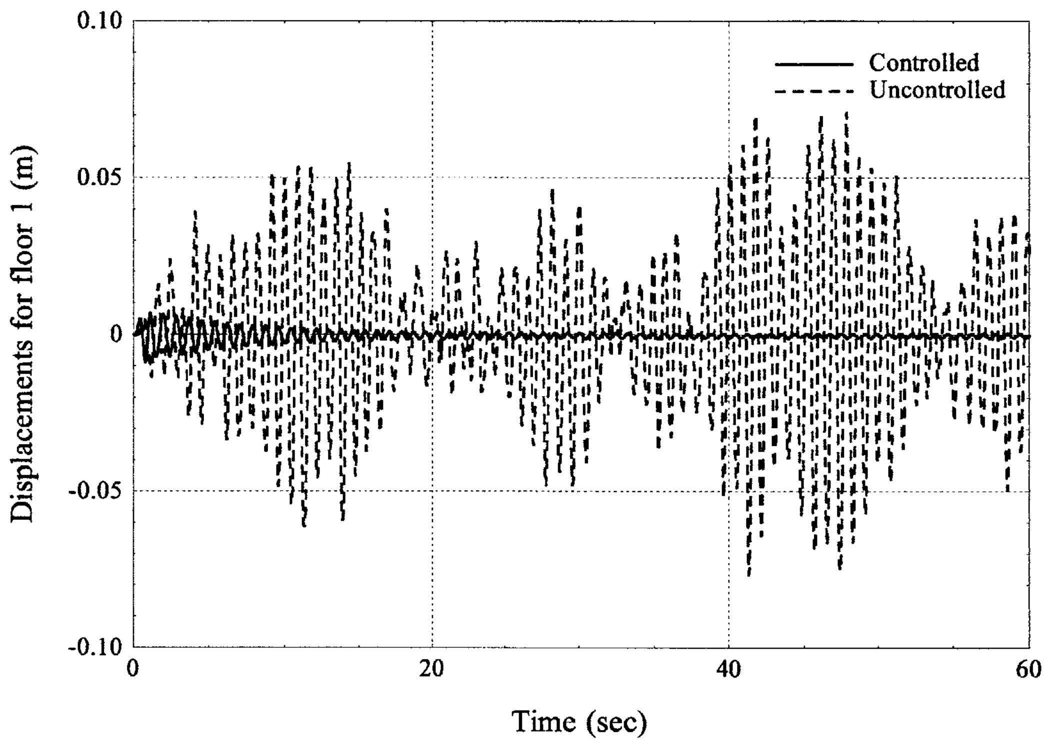


Figure 5.6: Displacements for the 1st floor (Completely trained controller) - Random Wind

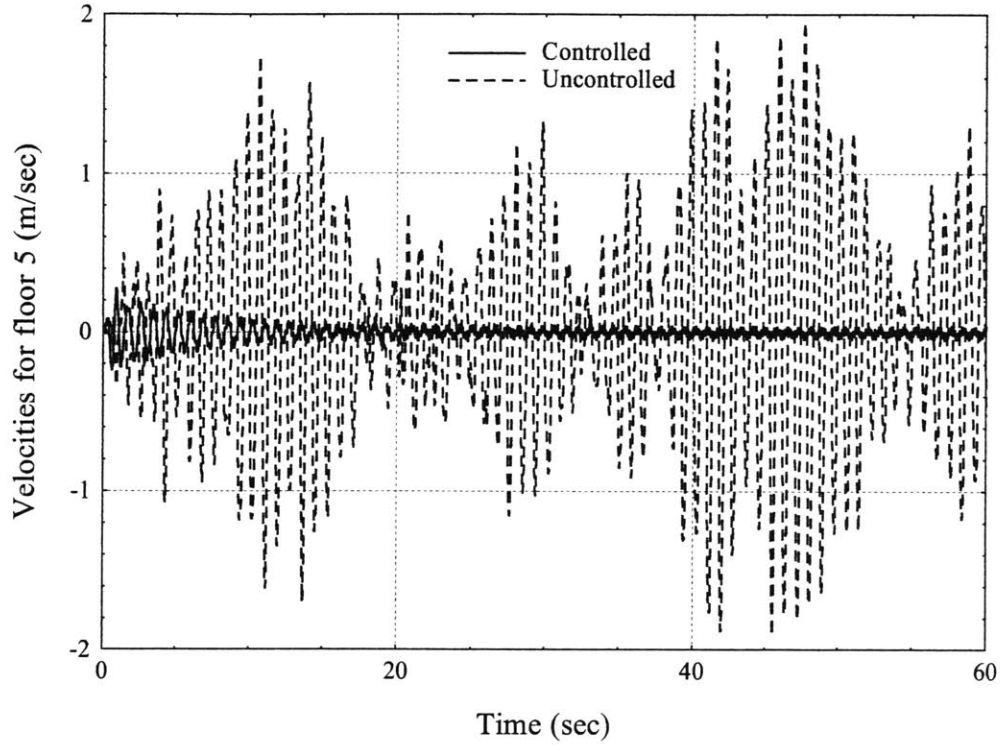


Figure 5.7: Velocities for the 5th floor (Completely trained controller) - Random Wind

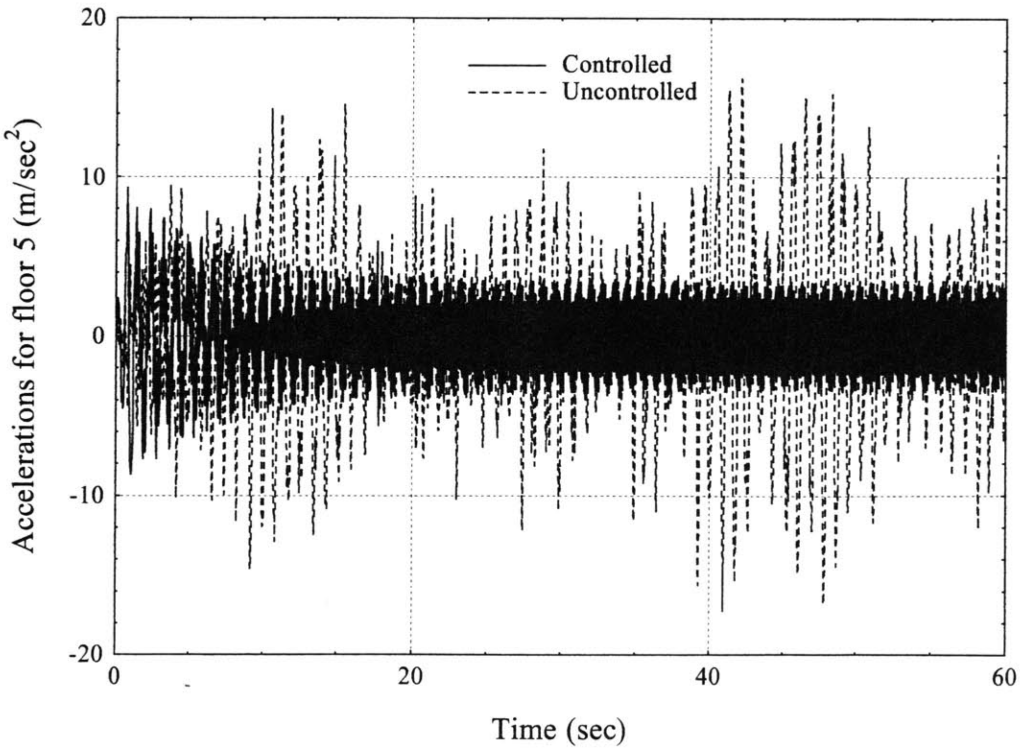


Figure 5.8: Accelerations for the 5th floor (Completely trained controller) - Random Wind

Comparing the results of the control before and after the final training of the network, one is able to notice that the behavior of the controller is significantly improved. Its operation is very successful, as the target maximum displacement of 0.01m is met at all times. The response of the structure not only does not exceed the objective, but also diminishes almost completely after the first 15 seconds. Furthermore, even the response of the structure in terms of velocities and accelerations is decreased after the application of the control forces. The network seems to understand the dynamic behavior of the structure and therefore it is well trained.

It is important at this point to provide an indication of the cost, in terms of time, to train the network. The termination criterion of the training is to meet an error goal, which is the sum of squares of the error of the response from the desired solution, for all the training examples. This error goal is set by default to 0.01. The initial training of the network is achieved in 241 epochs, with total computational time of 3537.16 seconds. An epoch is defined as one learning iteration of the network over all the examples provided in the training set. After this iteration the error is calculated and the variables of the network, weights and biases, are adjusted to correct the network's response.

In order to correct the response of a poorly trained network, a new training set has to be selected and the previously selected weights and biases has to be re-adjusted. In Chapter 4, it was presented that the training set consists of time histories sequences provided by the uncontrolled response of the building. These sequences are selected from critical points of the complete time history that describe how the structure behaves under dynamic loading. Moreover, the training set includes the correct control action, for the specific time history, such that the network to be able to understand the relationship between the response of the structure and the applied control forces. Both the selection of the training set as well as the learning procedure are time consuming tasks. They require experienced engineers with deep understanding of the behavior of the neural networks and of the problem that they attempt to solve.

The final training attempt in this case was completed in 335 epochs, with a total computational time of 5326.54 seconds. The amount of time needed to complete a training cycle is not representative of the case. These numbers are machine dependent, which means that a more powerful system would require less time to solve the problem. The independent parameter is the number of epochs required to meet the error goal. Any computer system that will try to train the same network, using the same training set, the same learning algorithm, and the same starting point for the weights and biases, will need the same number of epochs to meet the error requirement. The time needed is presented here to provide a relative feeling with the computational capabilities of the system used. It should be clear that a more complex application, such as a structure with more degrees of freedom or nonlinear behavior, would require a larger network, and more training examples to achieve the desired behavior of the controller. Consequently, it will need more training epochs and time to meet the error requirement. In Figures 5.9 and 5.10 the error vs. the learning cycles, for the two training attempts, is presented. These figures present the path that the learning algorithm followed on the feasible solution space curve. If the network had only two variables, one would have been able to represent this solution error space in a contour plot, and examine the path that the algorithm selected.

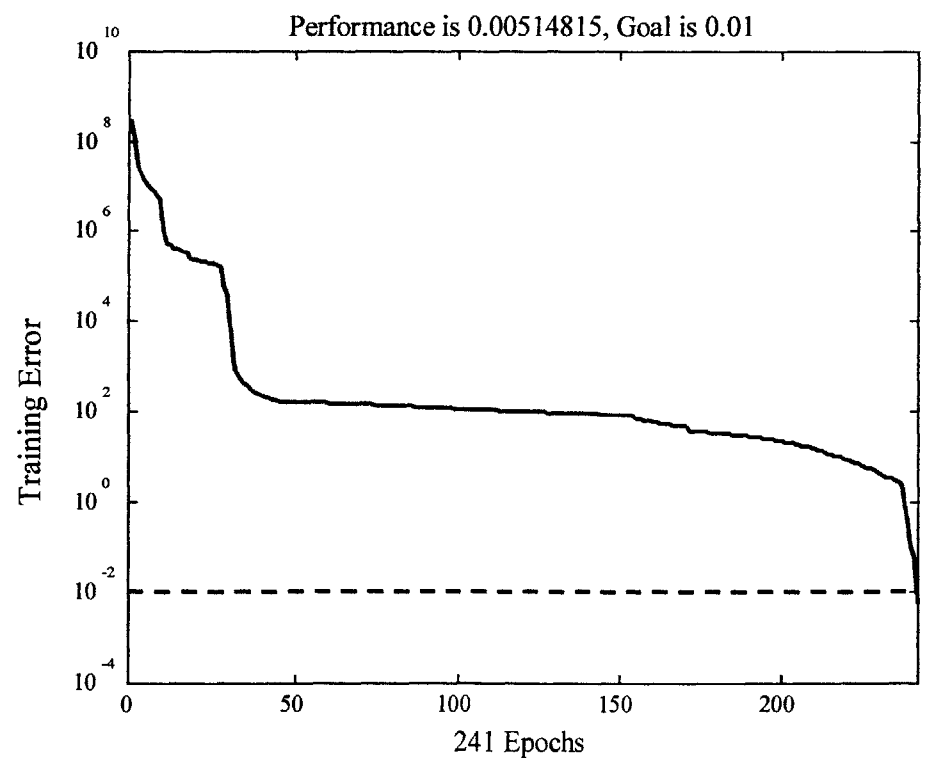


Figure 5.9: Plot of the error throughout the initial training procedure

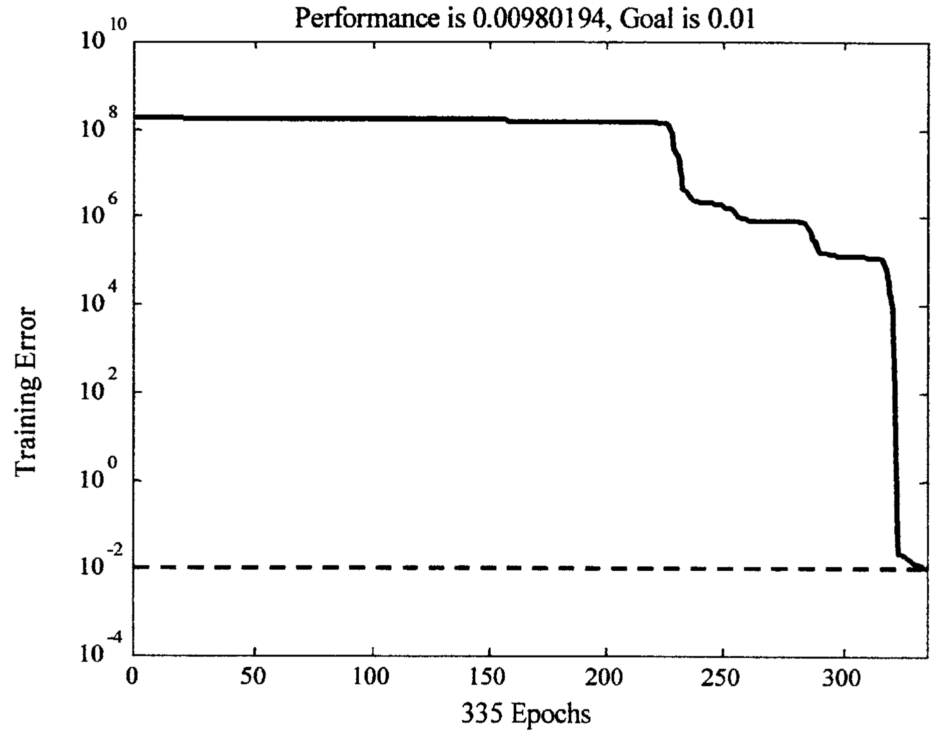


Figure 5.10: Plot of the error throughout the final training procedure

5.4 Earthquake excitation

In order to explore in greater depth the capabilities of the controller, the next test involved earthquake excitations. The earthquakes selected for this phase are the El Centro (S00E), the Taft (S69E), and Kobe (NS). The earthquakes are discretized in a 0.02-second time interval, which is consistent with the mean time that the controller needs to respond. The first two earthquakes are a classical pair of test earthquakes because of their substantially different characteristics. The Kobe earthquake also constitutes an important test because of its very impulsive shape and large magnitude. Information regarding these excitations was given in Chapter 4. In the case where the structure is subjected to earthquake excitation, both the displacements and accelerations are significantly higher than the target values. Therefore, the objective of the control for this phase is to limit both displacements and accelerations. These two objectives create a complex control situation, because the actions to control displacements and accelerations are sometimes conflicting. The limits for the two objectives are 0.01m for the displacements and 2% of the gravity acceleration or 0.2m/sec^2 for the accelerations. The first earthquake used to train and test the network is the El Centro earthquake, Figure 5.11. The time histories for the displacements, velocities, and accelerations are presented in Figures 5.12, 5.13, and 5.14

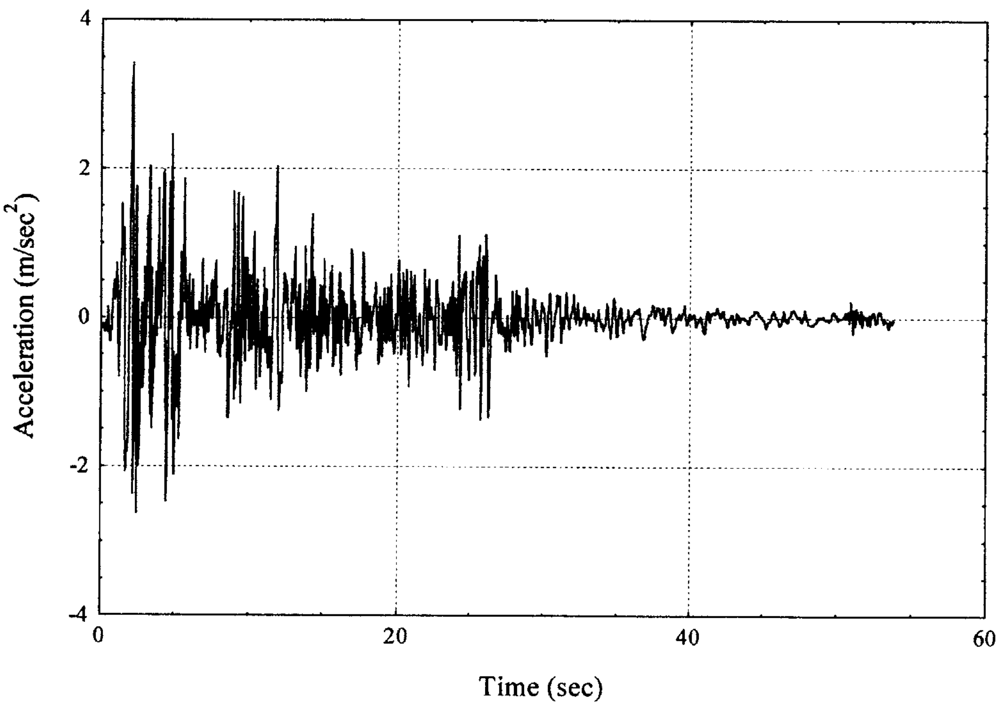
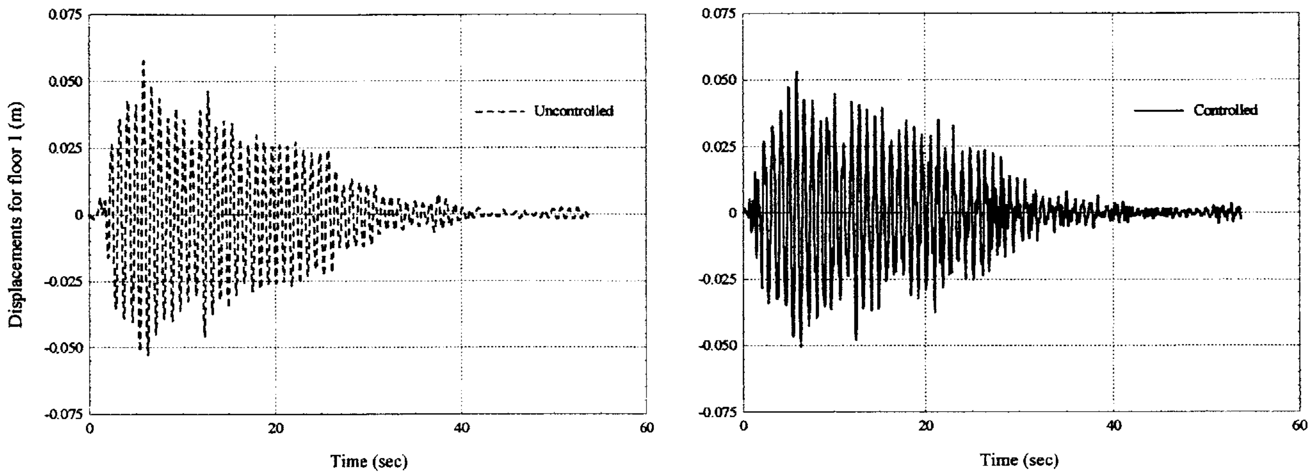
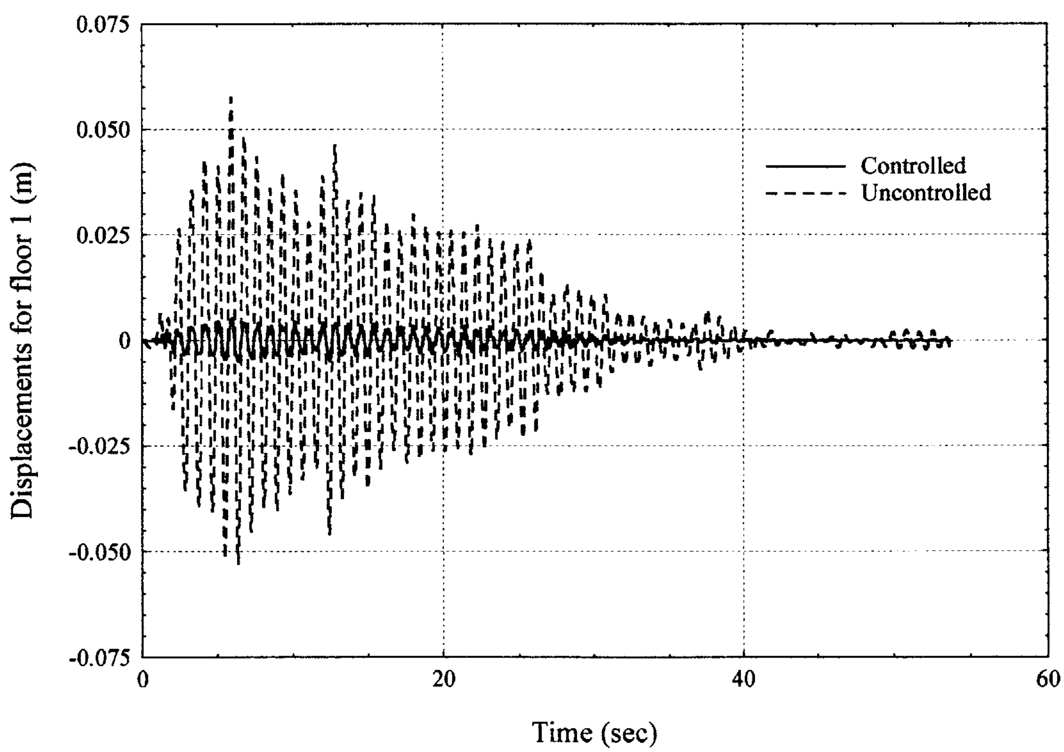


Figure: 5.11: El Centro S00E Accelerogram

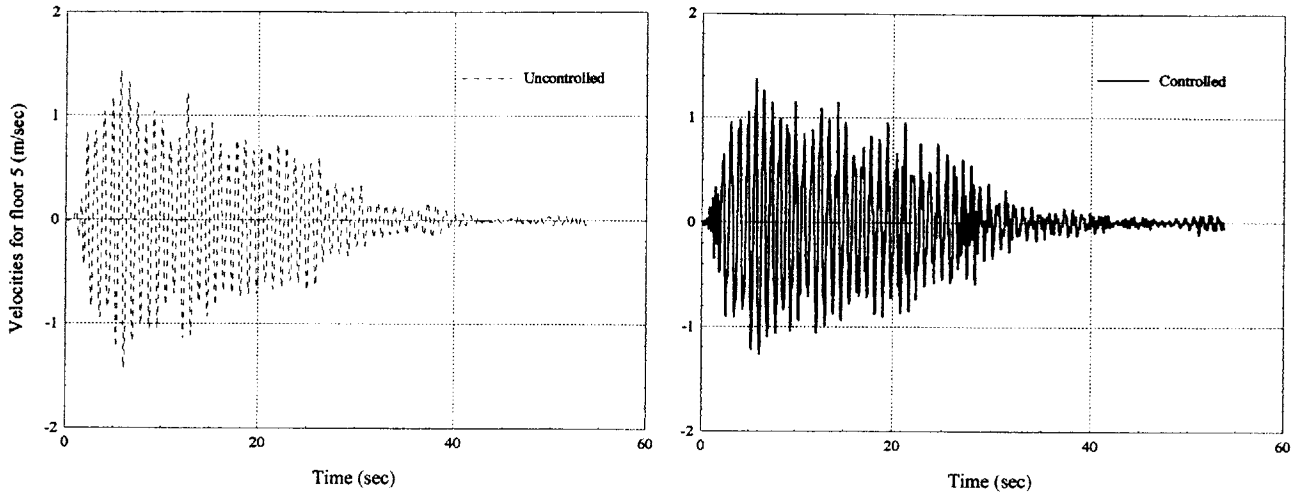


a) Initial training

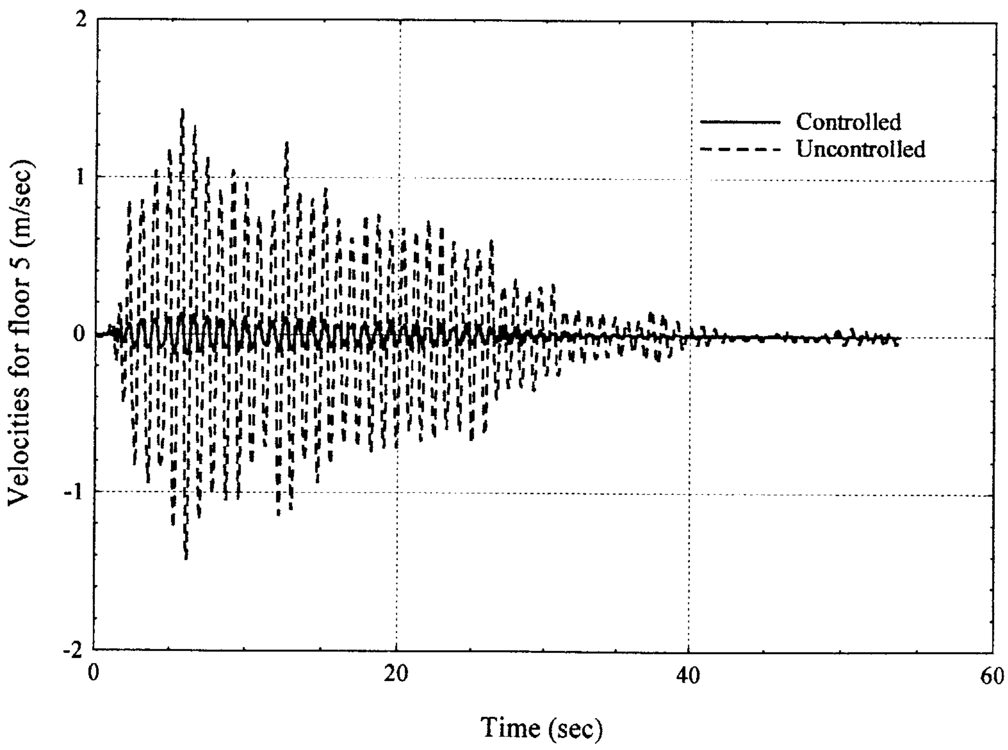


b) Final training

Figure 5.12: Displacements for the 1st floor - El Centro

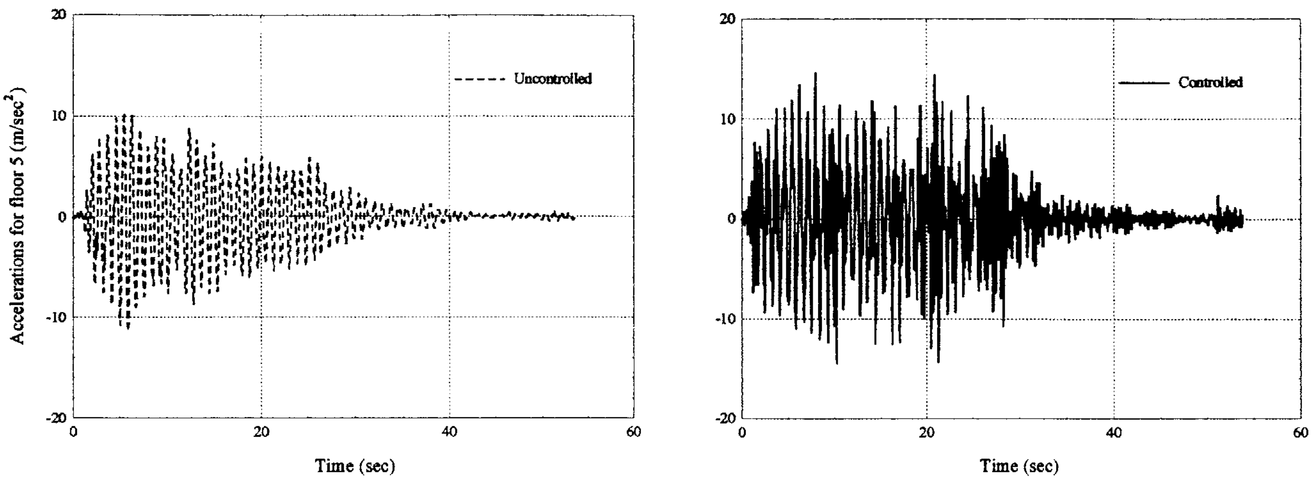


a) Initial training

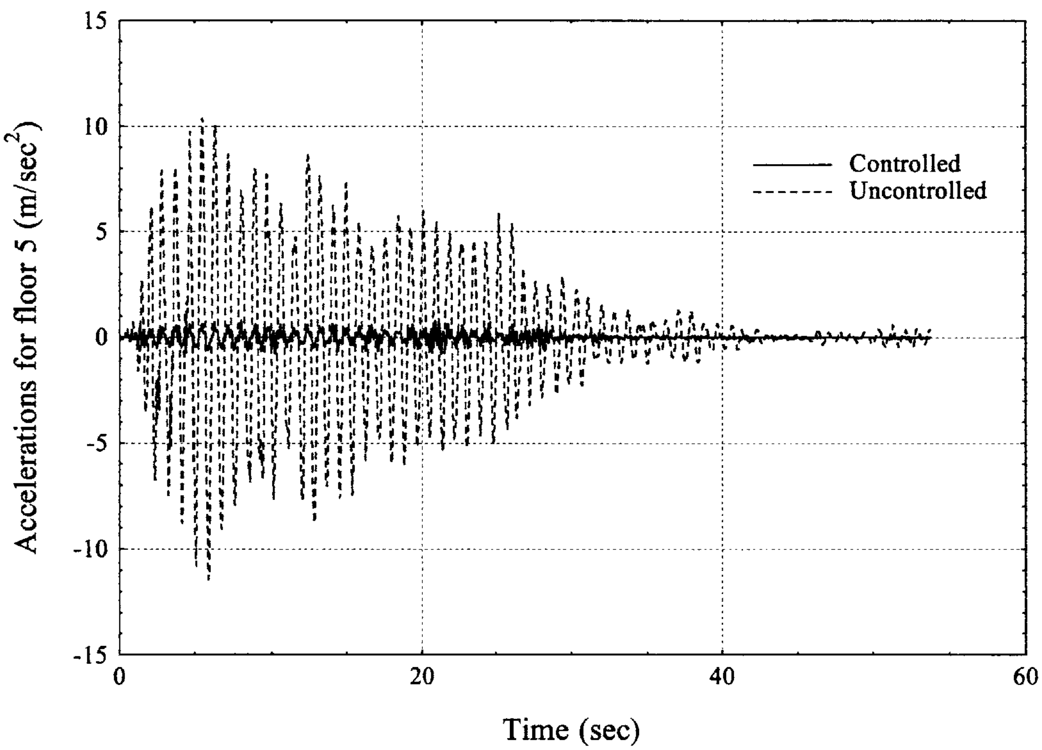


b) Final training

Figure 5.13: Velocities for the 5th floor - El Centro



a) Initial training



b) Final training

Figure 5.14: Accelerations for the 5th floor - El Centro

The results after the initial training are not satisfactory, since the controller does not succeed in reducing the response of the structure. The controller just shifts the response in a later time. The magnitudes of the uncontrolled and controlled response are of the same order, for the displacements and velocities. For the case of the accelerations, the response of the controlled structure is magnified from the uncontrolled case. The network needs additional training. The same conclusion was derived when the dynamic response of the structure was first introduced in the wind excitation case. The major difference is that here the excitation is completely arbitrary, and therefore the network is unable to find a pattern to control the structure throughout the duration of the excitation. This happened with the wind case, where even the poorly trained network was able to reduce the response after several seconds of the start point of the excitation incident. The training of the network for the case of the earthquake with the two control objectives is a very complex procedure. The network has to be presented with an extensive number of examples in order to understand the behavior of the structure and to be able to control both displacements and accelerations. All the possible combinations of response and excitation load have to be included in the training set. One should be very careful though, not to overtrain the network for the case of the particular excitation. Moreover, the training set should be very large, because this will result in a very large training time or even in the inability of the network to get trained. Attempting to satisfy all of the above statements, a new training set is created. After several training iterations, the network presented an acceptable behavior, as shown in part b of Figures 5.10, 5.11 and 5.12. The response is significantly reduced in every case and the objectives are generally satisfied. There exist only few points in the acceleration time history above the desired limit.

Based on the results produced after the final training, the network seems to be able to control the structure, under the El Centro earthquake excitation. In order to explore the capabilities and behavior of the controller under different earthquake excitations, the structure is subjected to the Taft and Kobe earthquakes. The El Centro and Kobe earthquakes are very impulsive in nature, whereas the Taft earthquake, Figure 5.15, has a significantly higher dominant period. Therefore, Taft will excite stronger more slender structures, or higher modes rather than the first mode of the structure. The structure selected as the testing model here is slender and has reduced stiffness, (see Chapter 4). Consequently, it is very likely that the structure will behave in a different manner under the Taft and the El Centro excitation. The results for the displacements, velocities and accelerations of the structure under the Taft earthquake for the controlled and uncontrolled case are presented in Figures 5.16, 5.17 and 5.18.

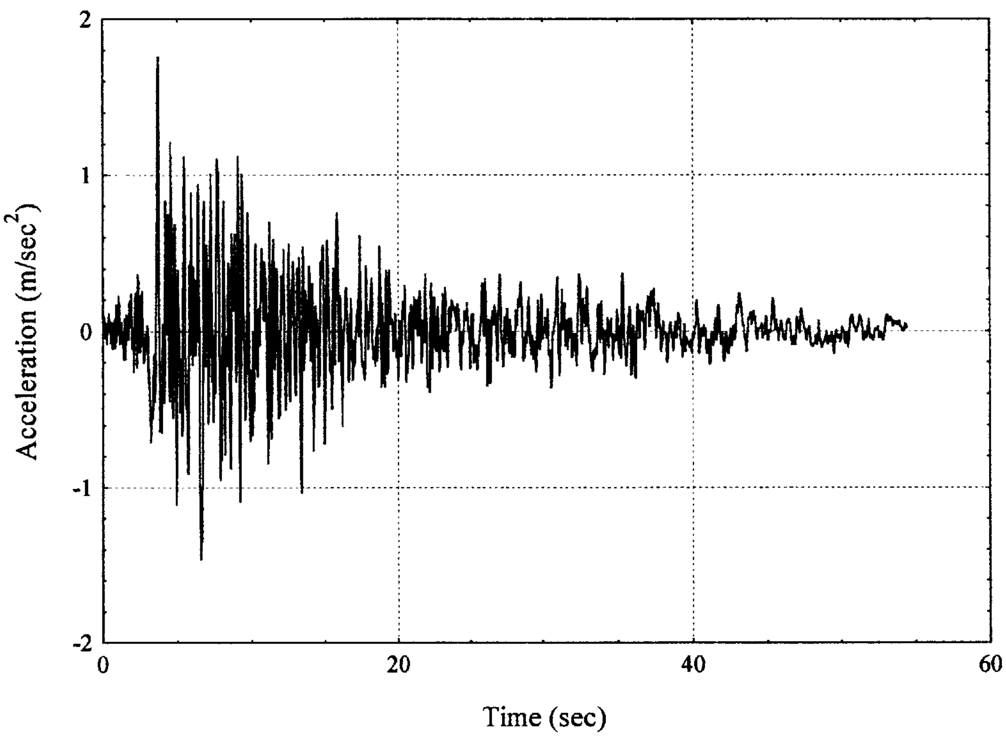


Figure 5.15: Taft S69E Accelerogram

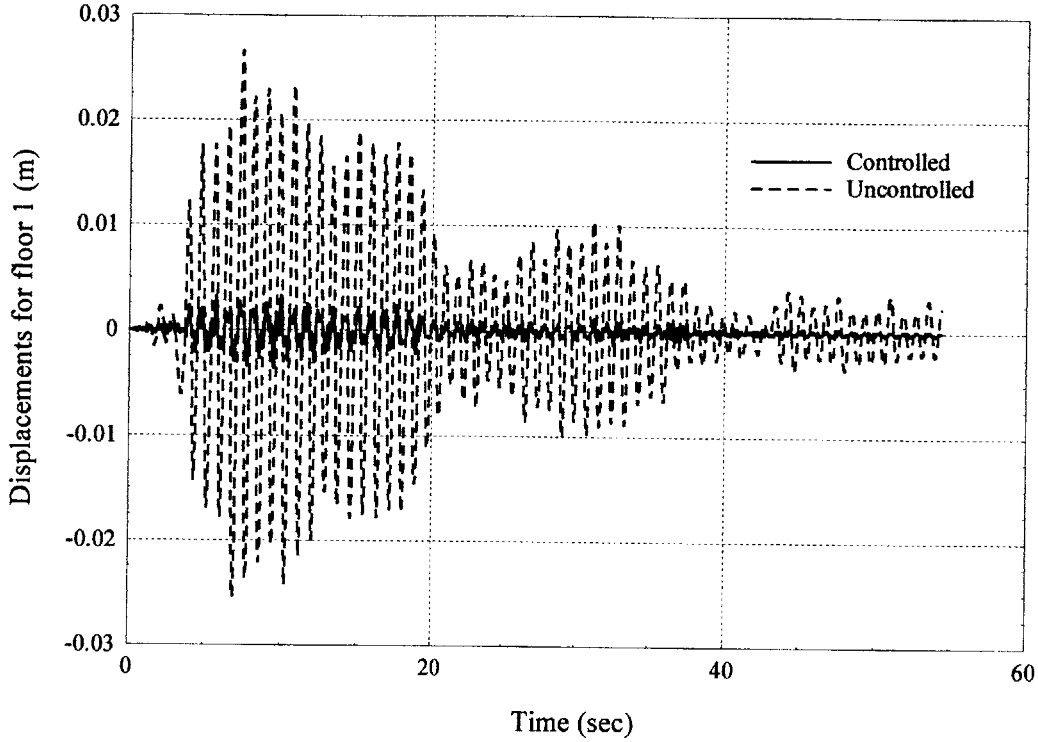


Figure 5.16: Displacements for the 1st floor - Taft

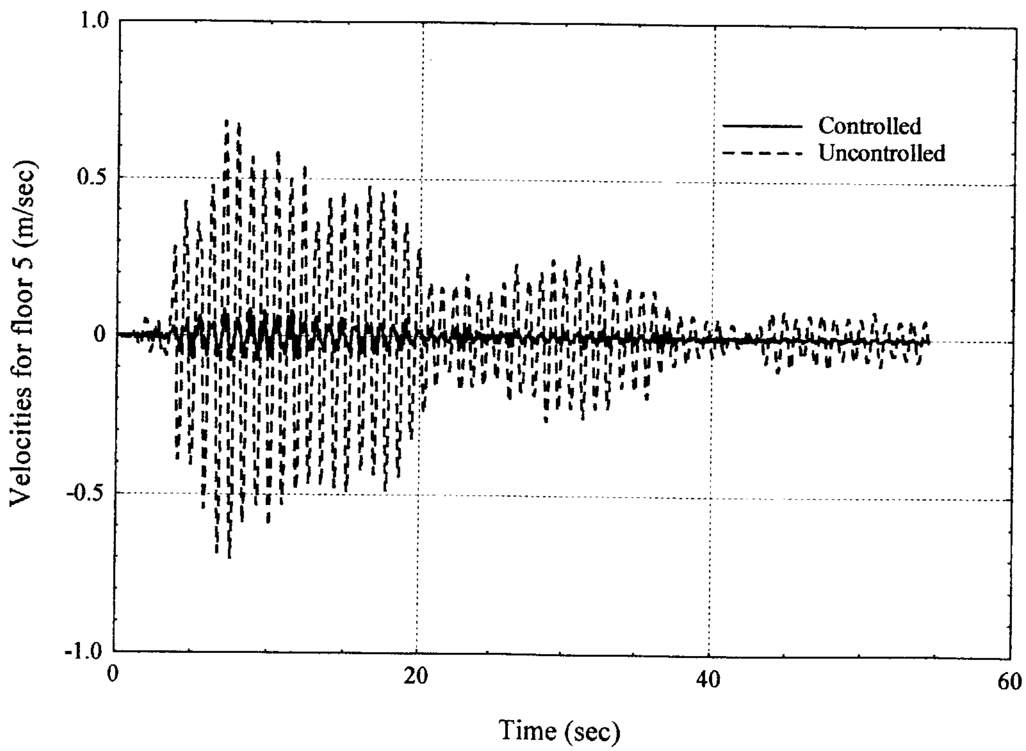


Figure 5.17: Velocities for the 5th floor - Taft

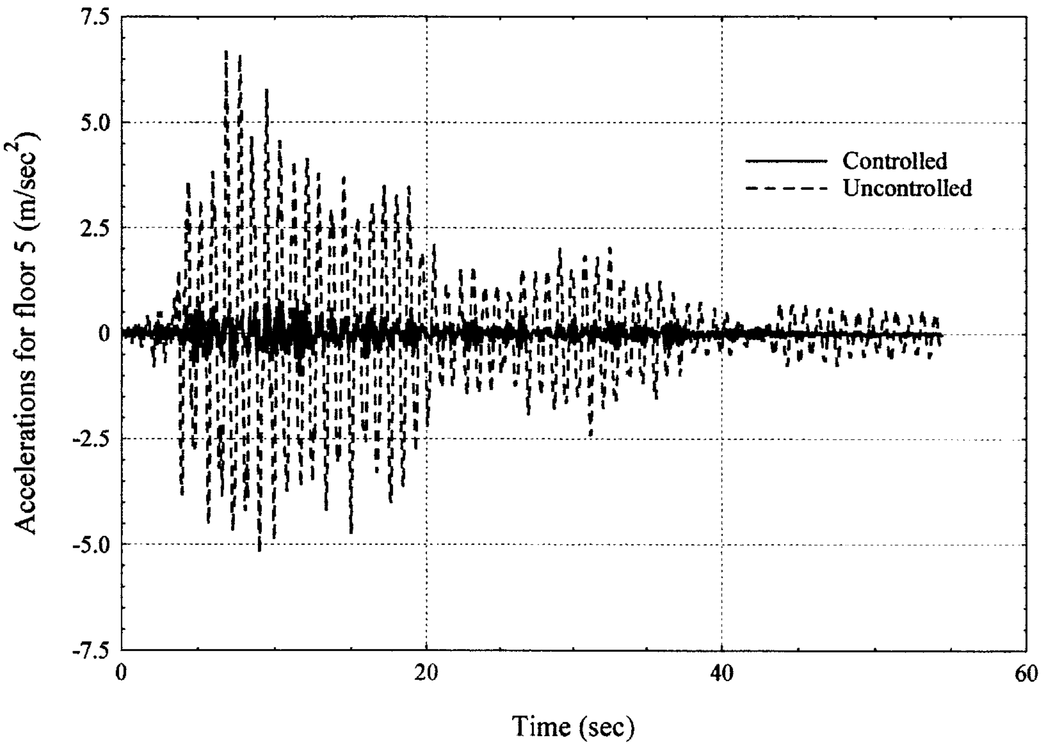


Figure 5.18: Accelerations for the 5th floor - Taft

Observing the results of the response of the structure under the Taft excitation, it clear that the network is able to control the structure efficiently. The controller reduced the response under the prescribed limits of the objectives for the most of the time. There are only few violations of the upper limit throughout the acceleration time history. An important observation here is that the controlled acceleration time history response has higher frequency from the uncontrolled one, (see Figure 5.18). This means that the acceleration changes sign more times in the controlled case from the uncontrolled one, for a specified time interval. The controller is applying excessive forces on the structure, in its attempt to control both displacements and accelerations. In order to correct the response of the structure due to the excessive amount of force that it applied in the previous step, it activates another set of forces. This constant sequence creates very high frequency vibrations that are observed here with the nature of accelerations. From the energy needed to implement the active control scheme perspective, this pattern of control is obviously not efficient. It spends unnecessary energy for applying forces of excessive magnitude and then to generate correcting forces to control the response. In a real application the energy supply is limited, especially at the duration of an incident like an earthquake. This means that the control mechanism will need to store the required energy somehow, in case of a power shutdown. Therefore, it is not desirable to have a controller that spends the most of the supplied energy to correct its own actions. However, the energy consumption of the control system is not the main issue of this research study. In a real life application, the network should be trained such that to control the structure with the minimum required energy.

In order to establish the effectiveness of the controller, the structure is subjected to the Kobe earthquake. This earthquake has very high peak ground acceleration ($8.18 m/sec^2$), as shown in Figure 5.19. The major part of the energy of this earthquake is released within the period of 5 to 10 seconds of its duration. The shape of the acceleration time history creates strong impulsive excitation in this period. The results for the time histories of displacements, velocities, and accelerations are presented in Figures 5.20, 5.21, and 5.22 respectively.

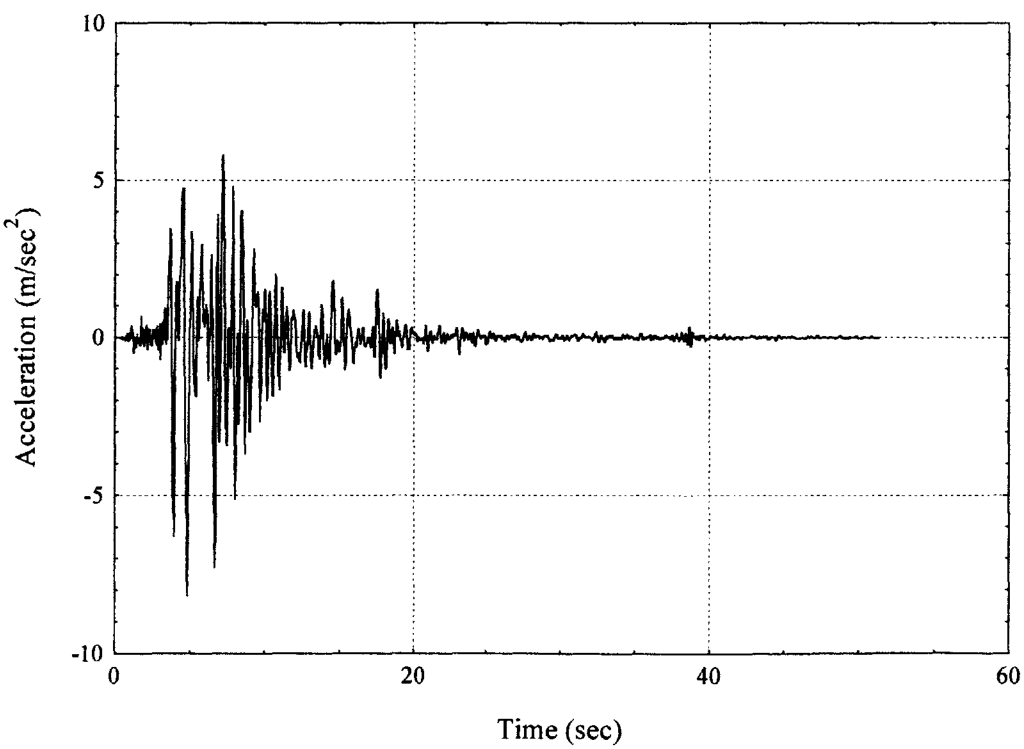


Figure 5.19: Kobe NS Accelerogram

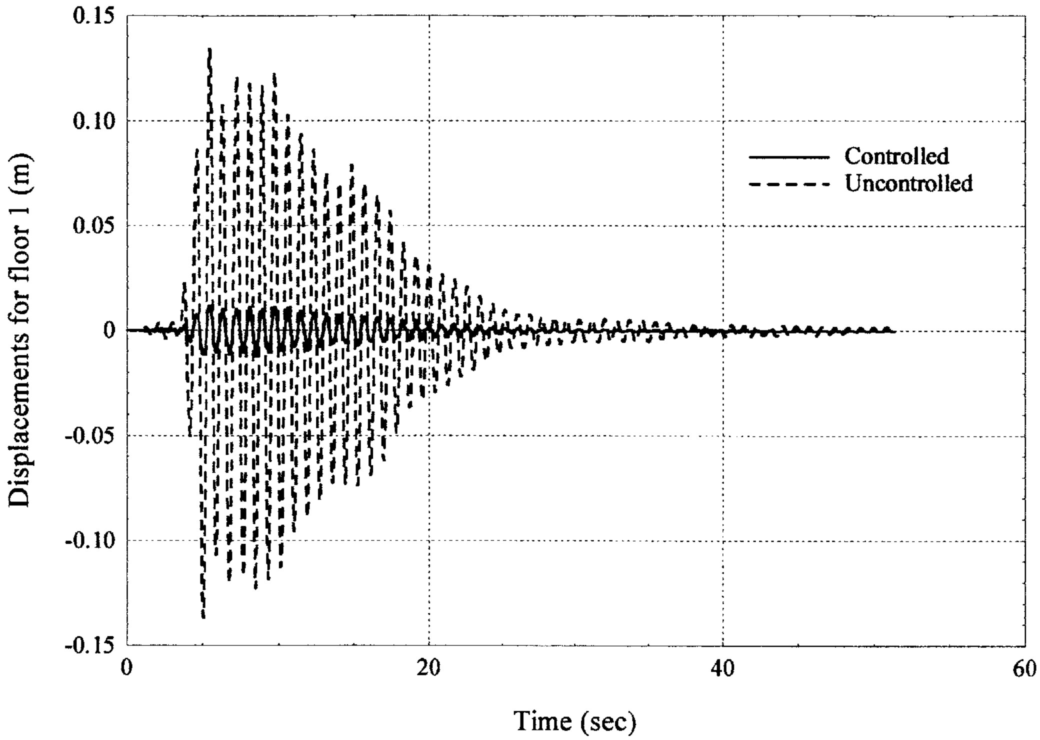


Figure 5.20: Displacements for the 1st floor - Kobe

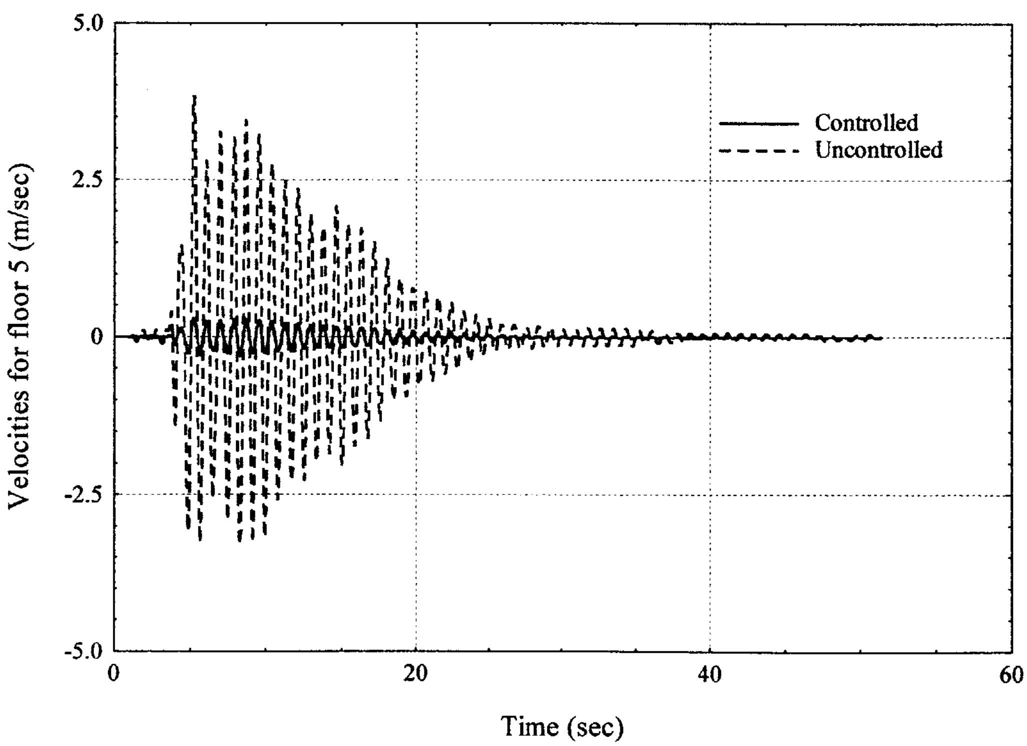


Figure 5.21: Velocities for the 5th floor - Kobe

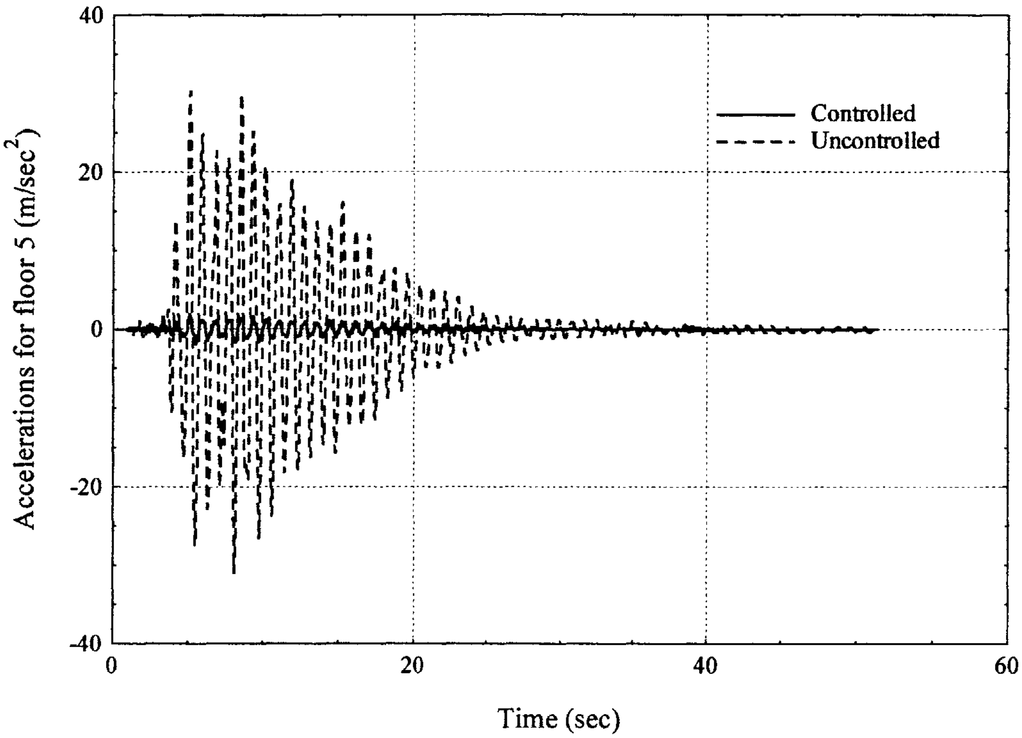


Figure 5.22: Accelerations for the 5th floor - Kobe

Considering the values of the response presented on the time history plot, the control of a structure subjected to the Kobe earthquake is not a trivial task. The impulsive nature of the Kobe earthquake results in high values for the acceleration of the uncontrolled structure. The controller succeeds in limiting the displacements at all times to less than 0.01m. On the other hand, the acceleration limit is violated several times throughout the duration of the earthquake. However, the response of the structure in terms of accelerations is significantly reduced from the uncontrolled case, where the structure developed accelerations of the order of 3 times the gravity acceleration. The controller manages to limit the maximum acceleration of the structure below 3m/sec^2, a 10 times reduction. Additionally, the plots present a normal time history, with a smooth transition from the positive to the negative values of the response. After the 10th second of the duration of the earthquake the response of the structure decays. This is due to the significantly reduced energy provided by the earthquake after that point in time. The response of the structure looks like the response of a damped structure under free vibration. Considering all the above observations, one can suppose that the behavior of the network is satisfactory, even if the acceleration objective limit is not met.

5.5 Conclusion

The objective of this research is to explore the effectiveness of neural networks used as controllers in structural motion control problems. This research attempts to illustrate the feasibility of neural networks for active control applications. Considering the behavior of the controller for wind and earthquake excitation, it is evident that neural networks have potential. It is feasible to create and train a neural network to reduce the response of a structure. Moreover, neural networks appear to be robust enough to face real life applications, with adequate accuracy and effectiveness depending on the training. The controller, after a carefully prepared learning procedure, is able to handle a large variety of loading conditions. Furthermore, with a response time of 0.02 seconds, the neural network is able to control structures under high intensity loading conditions, like earthquakes. Recall from Chapter 4, that this response time can be reduced substantially with the use of a more powerful computational system, and the implementation of the neural network in a stable computer environment and language.

In parallel with the effort to explore the capabilities of the neural network controller, the benefits of active control are also presented. It appears that by using a control system, one is able to reduce the response of the structure substantially, even when the excitation is very intense. Such a system can be used to correct the behavior of a structure with motion problems, or it can be used as a part of an integrated motion protection system in a high performance structure. With the assistance of active control systems, engineers are able to create structures that push the design envelope to new limits. On the other hand, one should be very careful with the use of active systems, since they provide energy to the structure, which may magnify the response instead of reduce it. These situations are caused by time delay issues, as it is illustrated above, and they are able to create unstable conditions to the structure. Of course, the implementation of such systems is very expensive and their introduction in regular civil structures is not a trivial task. Moreover, the fact that they assume the existence of a power supply under any condition is usually a major problem. Active control systems require substantial amounts of energy. For this reason the emergence of semi-active control systems is essential, that require small amounts of energy for their operation. These devices are usually used in adaptive control, which is the subject of Chapter 6.

Chapter 6

Adaptive Control experiment

6.1 Introduction

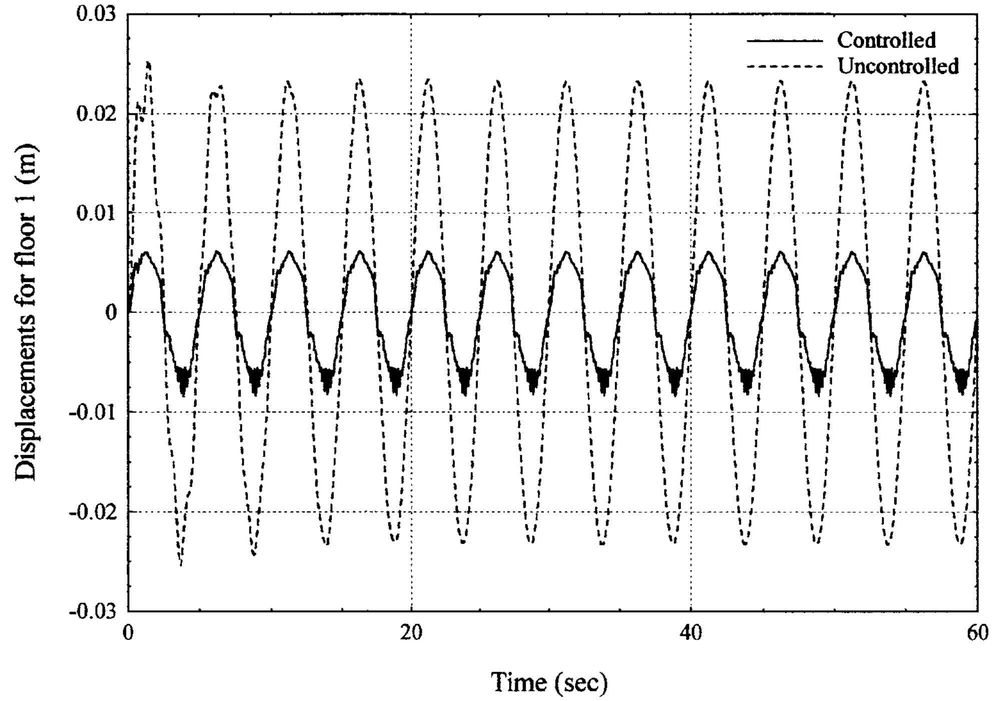
The need for a control scheme that does not require a large amount of energy was identified in the previous chapter. Moreover, the notion of a structure that can adaptively change its characteristics when needed is appealing for structural engineers. Therefore, the control strategy followed in this Chapter is to adjust the stiffness and damping at each story, instead of applying forces. The actions ordered by the controller can be implemented by devices that can change their stiffness or damping, such as the electro or magneto rheological fluid devices and variable orifice viscous dampers discussed in Chapter 2. The inputs of the controller are the relative displacements and velocities at each floor level. The output signals are the additional stiffness and damping needed to limit the structural motion. This desired state, which is the objective of the control, is maximum relative displacement per story less than 0.01m and maximum acceleration less than 2% of the gravity acceleration. Regarding damping, two cases are considered. Firstly, the variable-damping device is connected at each story with the stiffness elements, for example in a diagonal bracing, and hereinafter referred to as stiffness formulated damping. Secondly, the variable-damping device to be connected at each floor level, and hereinafter referred to as mass formulated damping. More information on this issue is provided in Chapter 4. The excitation conditions considered here are the identical to the excitations considered in the active control case, namely: two winds i) steady state periodic wind, and ii) periodic wind with random adjustment of the period and magnitude; and three earthquakes i) El

Centro (S00E), ii) Taft (S69E), and iii) Kobe (NS). In order to create a controller that is able to face excitations of any nature, only one neural network is created and trained to control the structure in an adaptive manner. Following the same presentation pattern with Chapter 5, the figures presented in this chapter include the displacements for the first floor, and the velocity and acceleration for the fifth floor. In addition to the above, the adaptive stiffness for the first floor and the adaptive damping for the fifth floor are presented. This selection is a consequence of the output of the controller, which is the greatest for these floors. This result is expected because the first and fifth floor experience the maximum relative displacement and velocity respectively. The term adaptive stiffness and damping is referred to the added part of these parameters to the initial values of stiffness and damping that the structure has before the control.

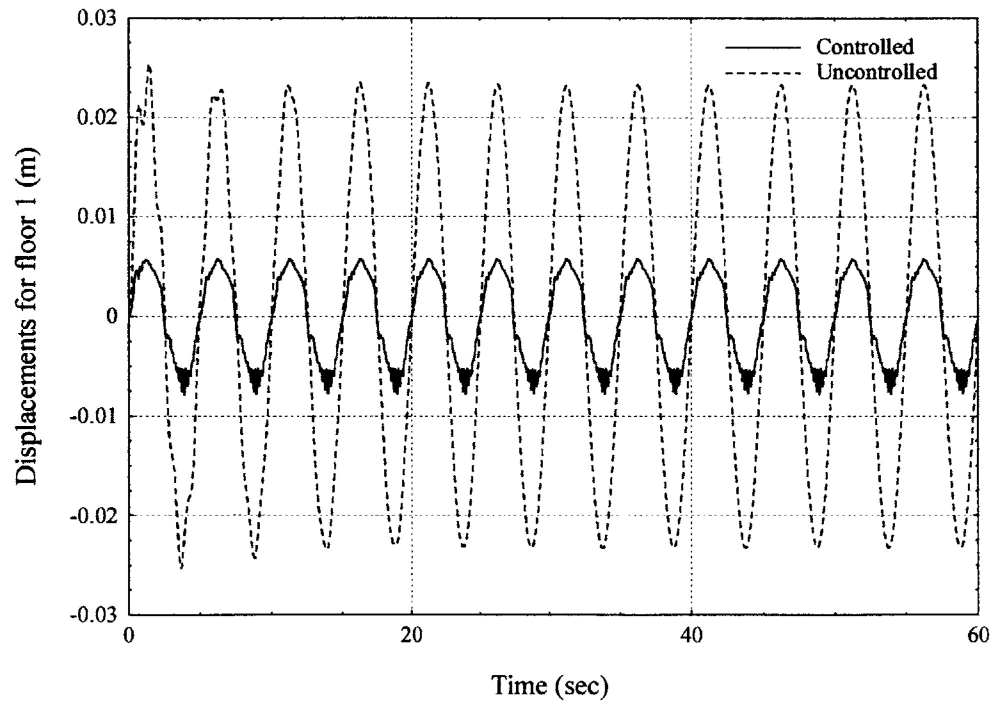
A more advanced controller would include inputs of the wind velocity and the ground acceleration such that to take advantage of the excitation information. In that way, it would be able to distinguish the nature of the loading and therefore respond differently for each case. It would also eliminate excessive tremors at the time history response of the controlled structure. This attempt would evolve more extensive training of the neural network, for both cases of loading conditions, as well as the selection of the training set would be more difficult. This statement is true because in the same training set one has to include both cases of excitation. Using this training set the neural network has to learn the behavior of the structure according to the nature of each loading condition.

6.2 Wind excitation

Initially, the wind excitation is a steady state periodic loading with period 5 seconds and magnitude 100 miles per hour. The objectives of the control are to limit the relative displacements and accelerations of the stories under the aforementioned thresholds. Figures 6.1 to 6.5 present the results of the first training cycle, for both configurations of adaptive damping.

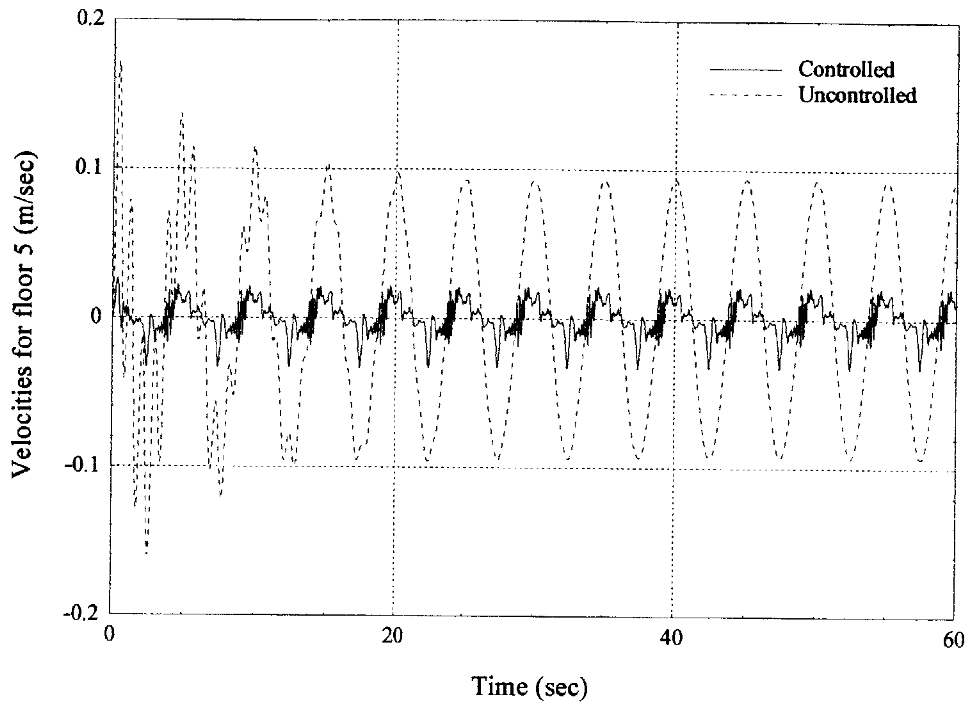


(a)

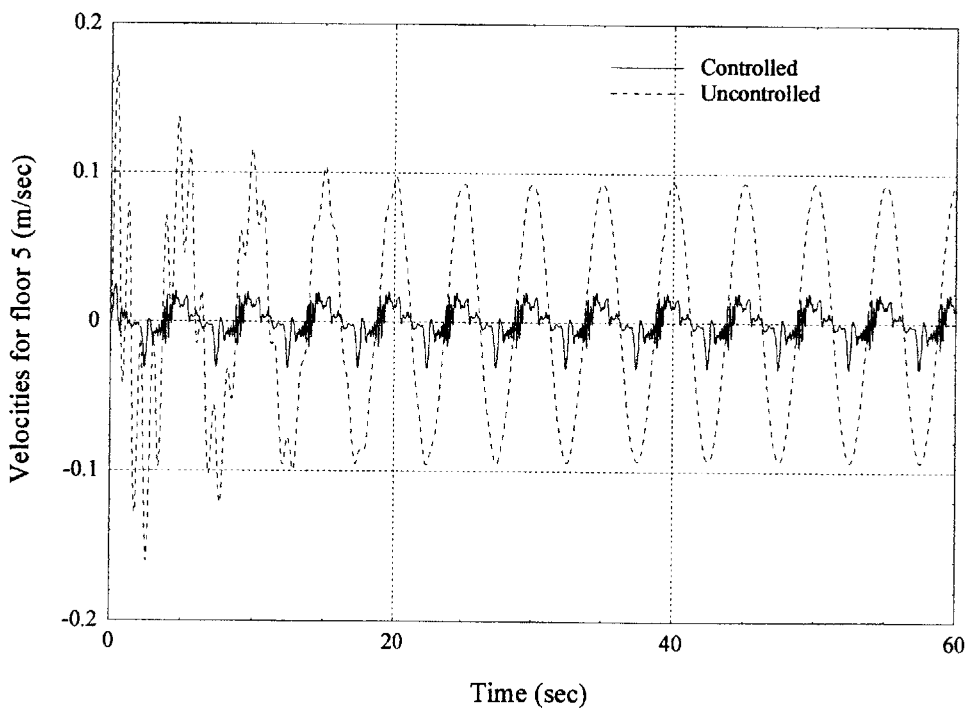


(b)

Figure 6.1: Displacements for the 1st floor - Steady state Wind
a) Stiffness formulated damping, b) Mass formulated damping

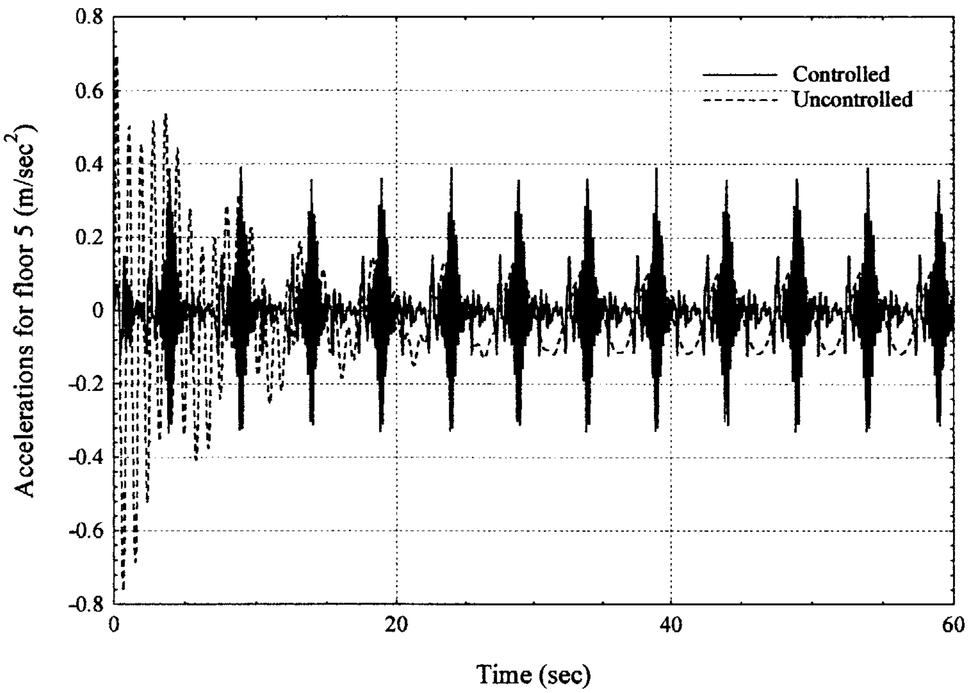


(a)

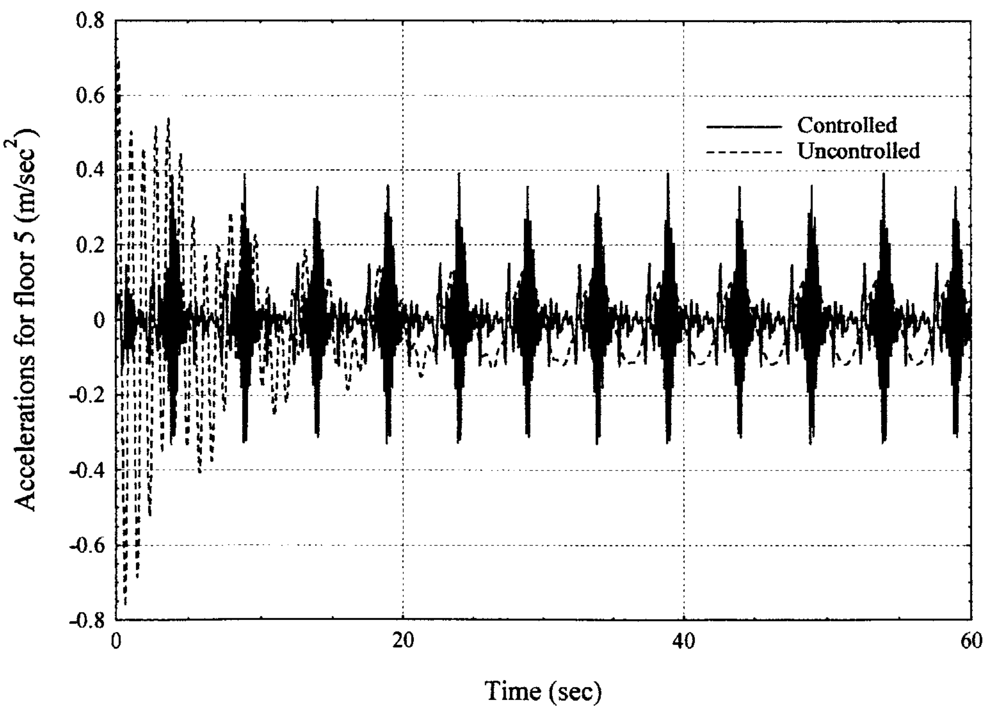


(b)

Figure 6.2: Velocities for the 5th floor - Steady state Wind
a) Stiffness formulated damping, b) Mass formulated damping

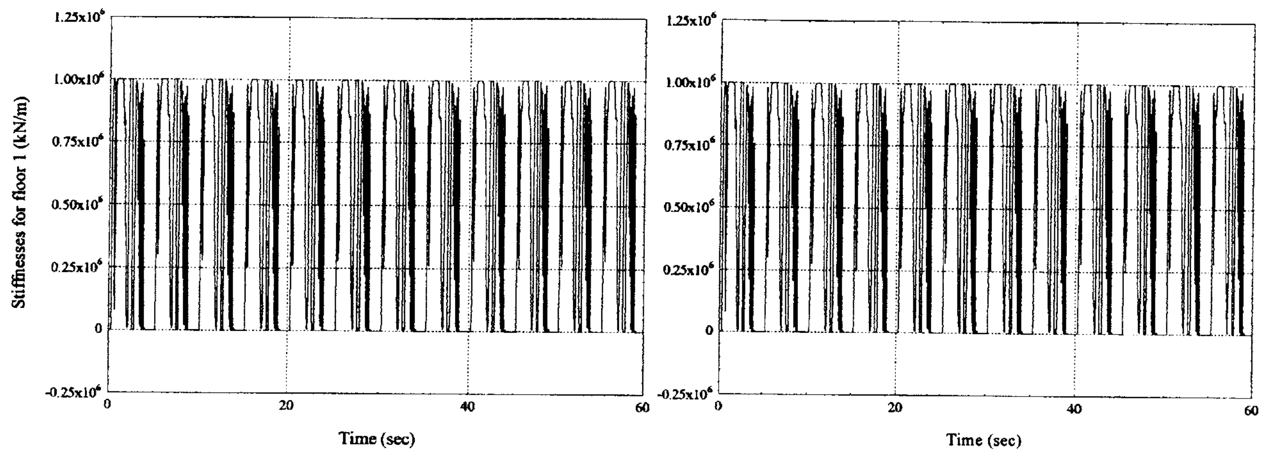


(a)



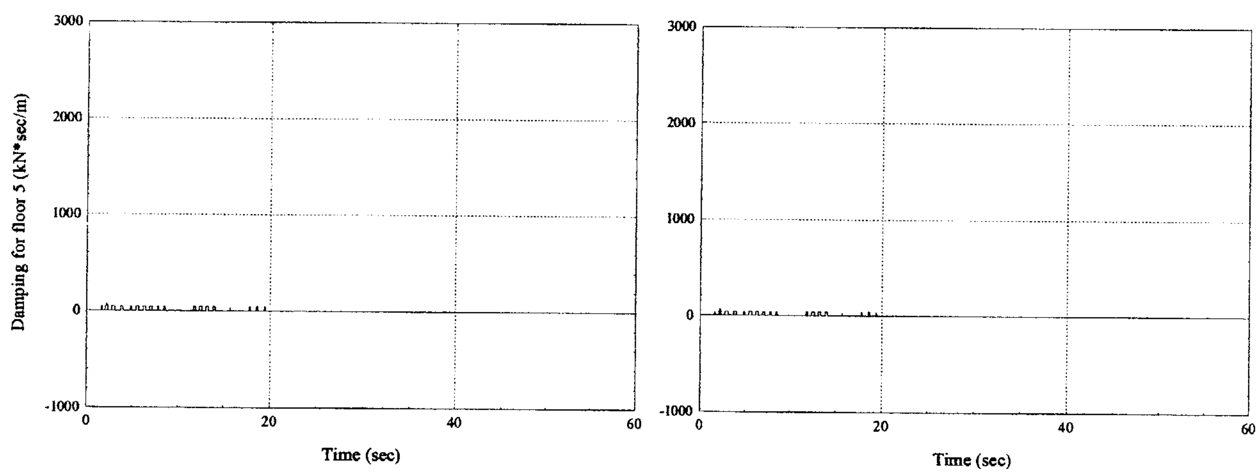
(b)

Figure 6.3: Accelerations for the 5th floor - Steady state Wind
a) Stiffness formulated damping, b) Mass formulated damping



(a) (b)

Figure 6.4: Adaptive Stiffness for the 1st floor - Steady state Wind
a) Stiffness formulated damping, b) Mass formulated damping



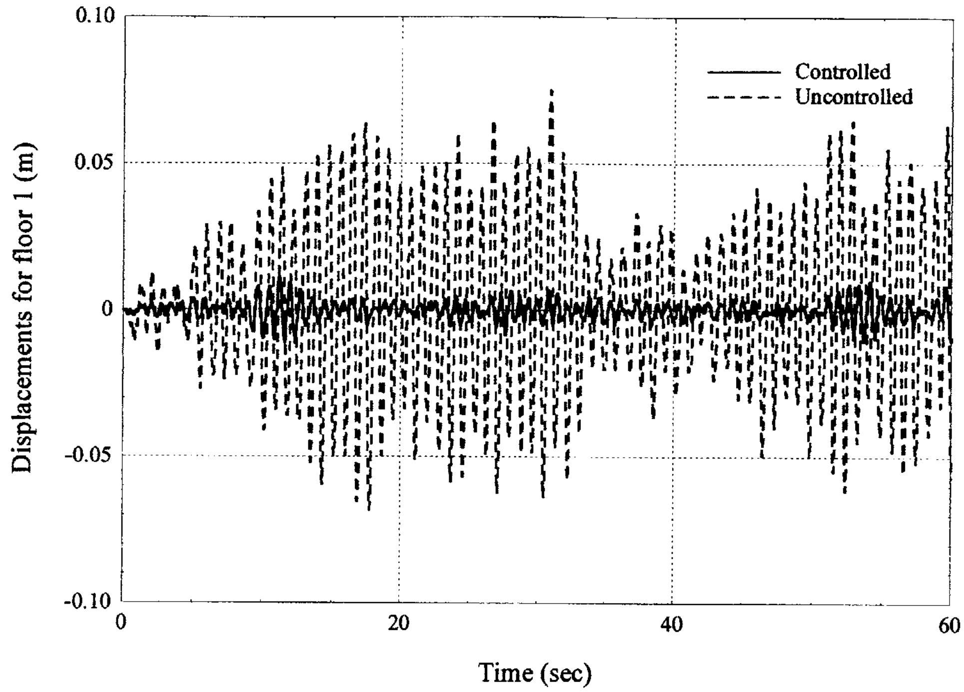
(a) (b)

Figure 6.5: Adaptive Damping for the 5th floor - Steady state Wind
a) Stiffness formulated damping, b) Mass formulated damping

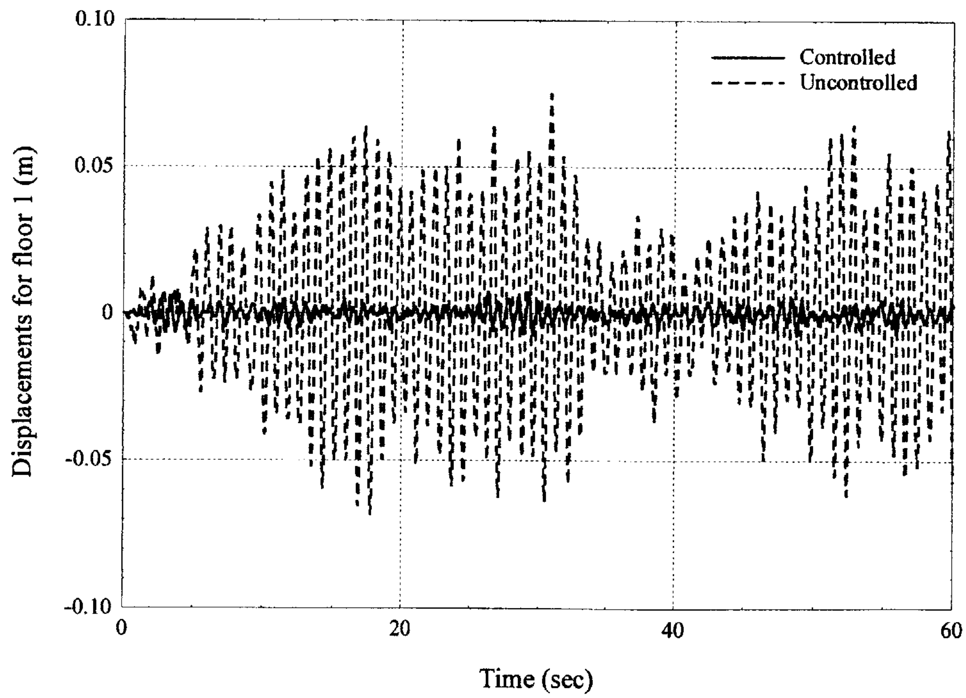
The response of the structure of this control cycle indicates that the controller is poorly trained. Despite the fact that the displacement objective is always met, there exist several micro vibrations of the time history response of the structure. These vibrations are becoming more intense in the velocity time history plot, and transform to major vibrations in the acceleration plot. This latter plot shows that the structure vibrates vigorously from time to time, not only exceeding the objective acceleration limit, but also exceeding the response of the uncontrolled structure. The time points of these strong vibrations in the acceleration plot correspond to the time points of the displacement micro vibration of the structure, i.e. the lower end of the controlled displacement plot. This kind of behavior for such a simple excitation case is unreasonable. This is the only case where adaptive control magnifies the response of the structure in terms of acceleration. In the case that the system only adds stiffness and damping on a specific structure, adaptive control is not able to destabilize it, i.e. the control action will never increase the displacement response. The above system is also not able to increase the velocity response of the structure. The acceleration magnification of the controlled structure can be explained by the intense increase of the stiffness of the structure by the controller. In order to control the displacement profile, the controller adds stiffness to the system. This conflict between the control objectives results in the observed vibrations. One solution to this problem is to train the controller to add stiffness more gradually, starting earlier in time from the point that it is required. Damping has no effect on this irregular response. The controller decided that for this steady state excitation the structure needs no additional damping. The plots of the adaptive damping indicate that only minor quantities of additional damping are used and only for the first 20 seconds where the response of the structure is not yet stabilized to the steady state response. This is the reason why the plots of the response for the two configurations of the adaptive damping are practically the same.

It is important to observe that the controller recognized the lack of stiffness of the structural system. Recall from Chapter 4 that stiffness was deliberately removed from the structure to create, in conjunction with its slenderness, a system with motion problems. The amount of the added stiffness by the controller is very close to the amount of stiffness removed from the initially calculated one.

Considering the above results, the network has to be trained again to fine-tune its actions. The following plots show the response of the controlled structure under a random wind excitation. This wind excitation has the same initial period and magnitude with the excitation used before, but adjusted randomly within an order of 50% to create a more complicated loading condition.

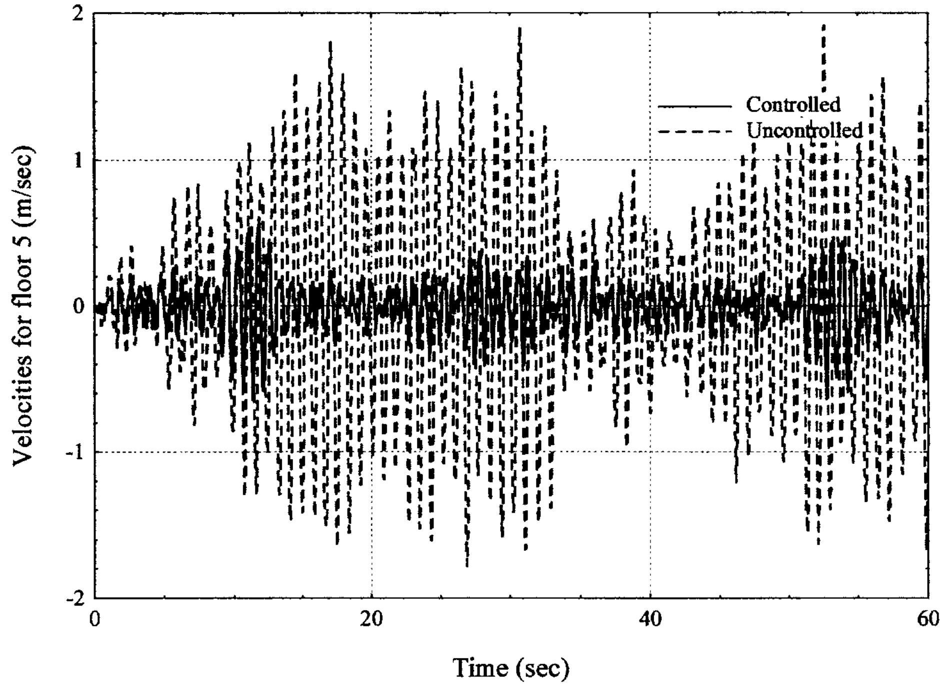


(a)

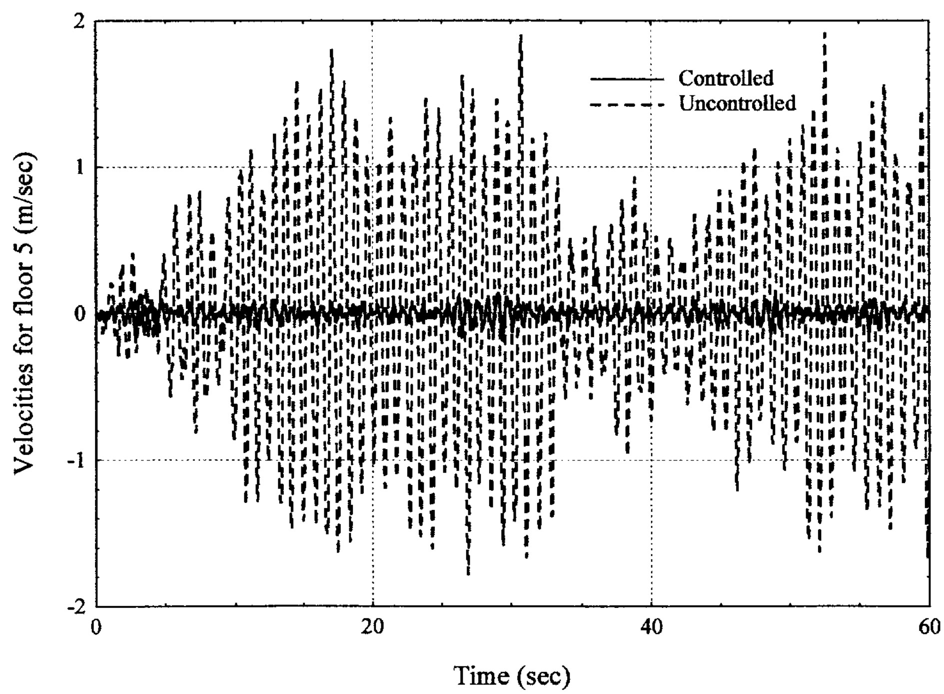


(b)

Figure 6.6: Displacements for the 1st floor - Random Wind
a) Stiffness formulated damping, b) Mass formulated damping

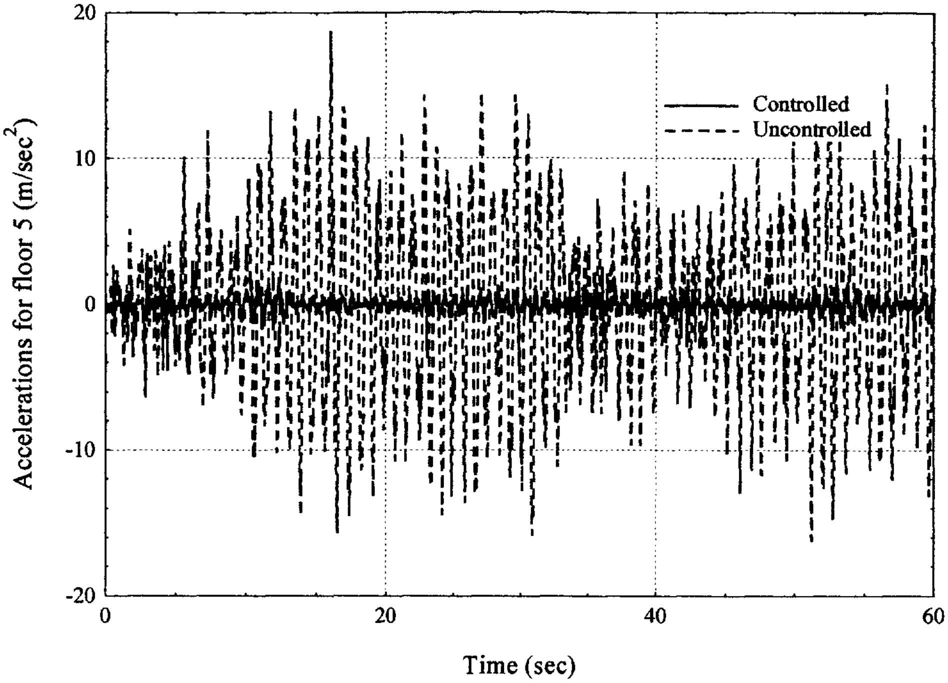


(a)

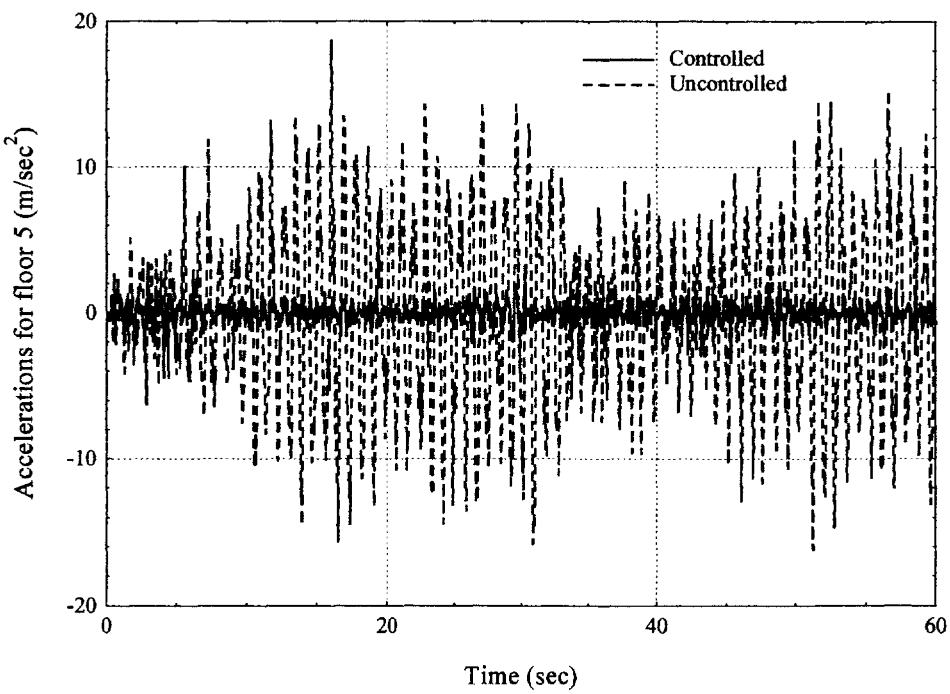


(b)

Figure 6.7: Velocities for the 5th floor - Random Wind
a) Stiffness formulated damping, b) Mass formulated damping



(a)



(b)

Figure 6.8: Accelerations for the 5th floor - Random Wind
a) Stiffness formulated damping, b) Mass formulated damping

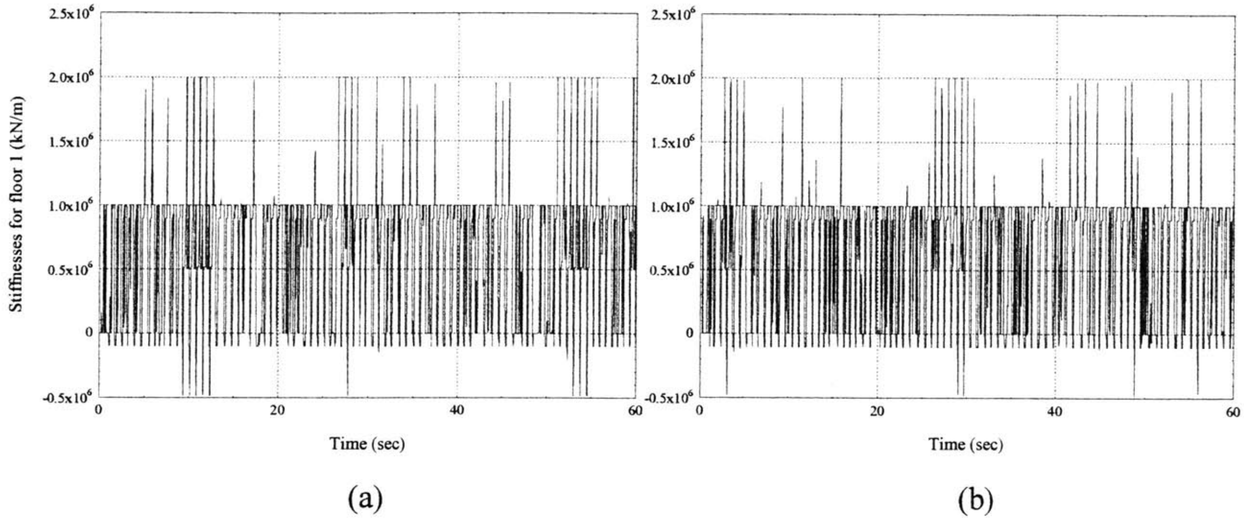


Figure 6.9: Adaptive Stiffness for the 1st floor - Random Wind
a) Stiffness formulated damping, b) Mass formulated damping

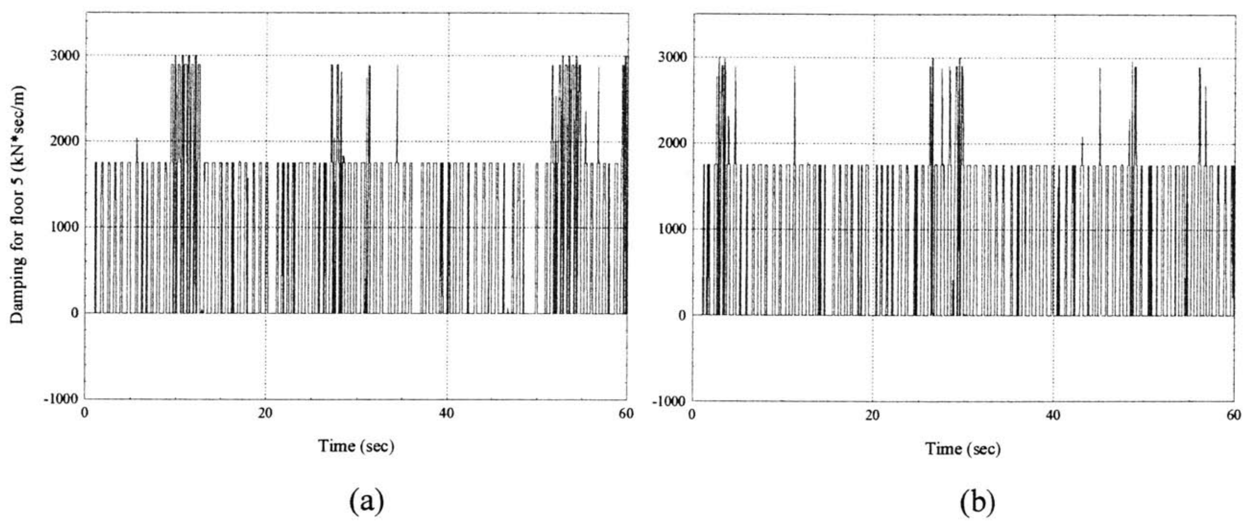


Figure 6.10: Adaptive Damping for the 5th floor - Random Wind
a) Stiffness formulated damping, b) Mass formulated damping

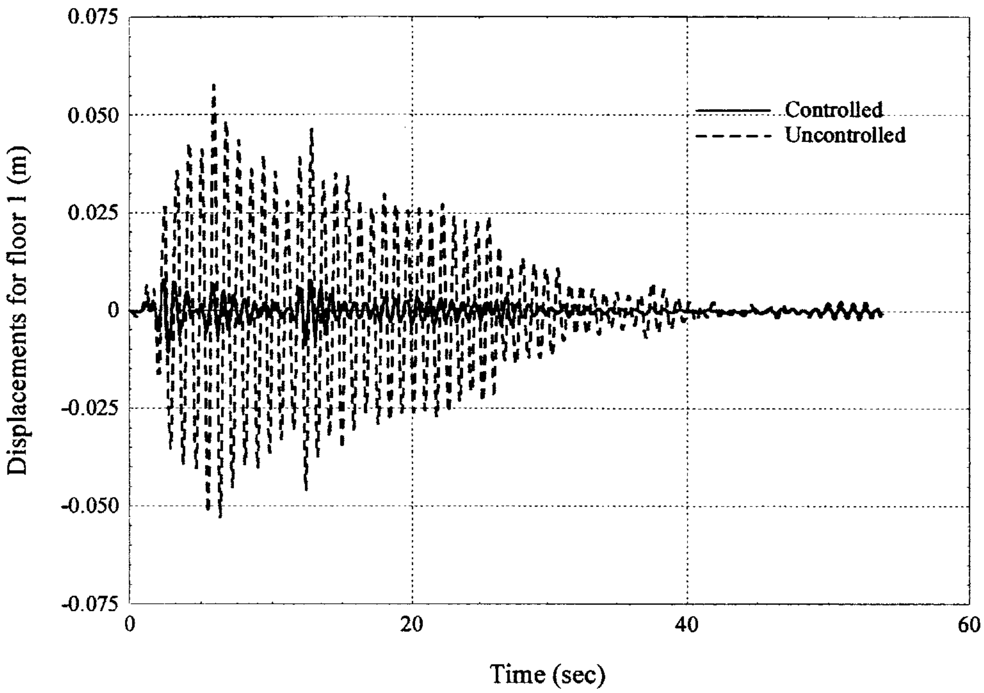
Figures 6.6 to 6.10 show the response of the structure, using the fully trained neural network controller. The structure is subjected to a randomly adjusted wind excitation to create conditions unexpected from the controller. The time history plots show that the controller is successful in reducing the response of the structure. The displacement goal is always met and there exist very few violations of the acceleration limit. The response of the controlled structure is always smooth without sudden vibrations.

In addition, it is clear that for this case, the mass formulated adaptive damping performs better than the stiffness formulated one. The response of the mass formulated adaptive damping is smooth and uniform throughout the excitation event, whereas the stiffness formulated damping has several areas of more intense vibration. Moreover, the data presented in Figures 6.9 and 6.10, shows that the mass formulated damping control requires less amounts of added stiffness and damping, which translates to less required energy.

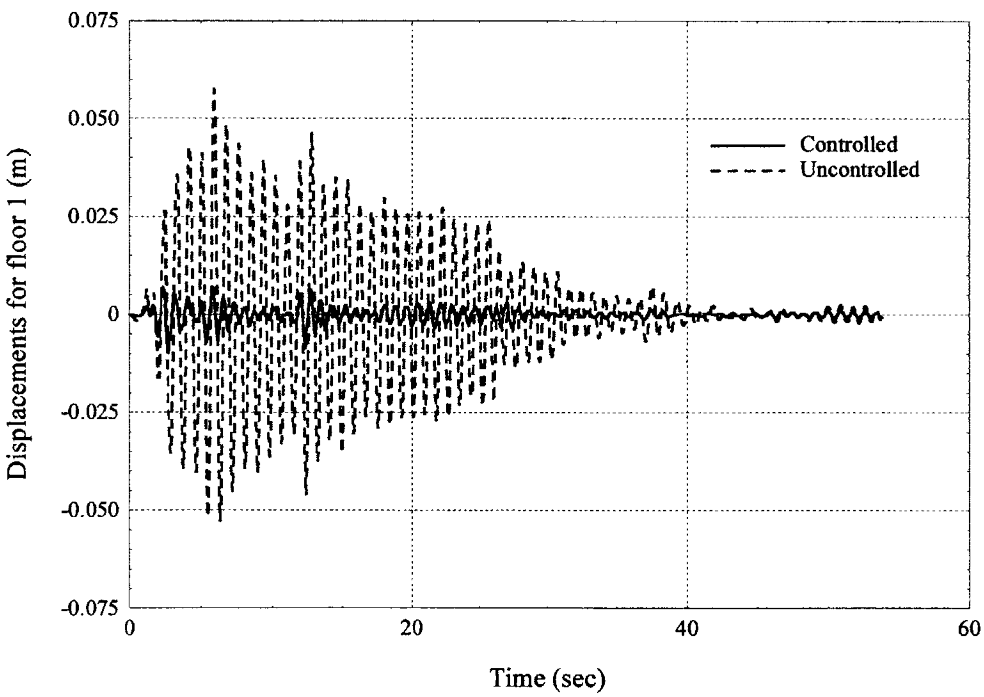
As shown in Figure 6.9, the controller applies several times negative stiffness to the structure. This means that in order to preserve the acceleration values low it needs to have a less stiff structure. This can be achieved if a small part of the initial stiffness of the structure is constantly provided by the adaptive stiffness devices. Reducing this constantly provided adaptive stiffness when needed would provide the same result with what is shown in Figure 6.9. This does not mean that the adaptive devices have to operate constantly. The lateral loads applied on a building in case of no wind or earthquake event are minimal and thus there is no need for high lateral stiffness. These devices will have to operate only in cases of intense environmental events. It should also be noted that the maximum accelerations objective is very strict. If this limit becomes higher to preserve just survival of the structure then there will be no need for reduction of the initial stiffness.

6.3 Earthquake excitation

In order to test the effectiveness of the controller in handling intense and unpredictable excitations, three earthquakes are applied. The earthquakes used are the same as the ones used in Chapter 5, namely El Centro (S00E), Taft (S69E), and Kobe (NS). The objectives of the control are the same as for the wind excitation case, i.e. to limit the relative displacement and acceleration. The neural network used to control the structure under these excitations is the final version used to control the wind excitation, with some additional training for the earthquake cases. This represents an attempt to create a general purpose control system capable of dealing with arbitrary loading. Figures 6.11 to 6.15 present the response of the controlled structure under the El Centro earthquake.



(a)



(b)

Figure 6.11: Displacements for the 1st floor - El Centro
a) Stiffness formulated damping, b) Mass formulated damping

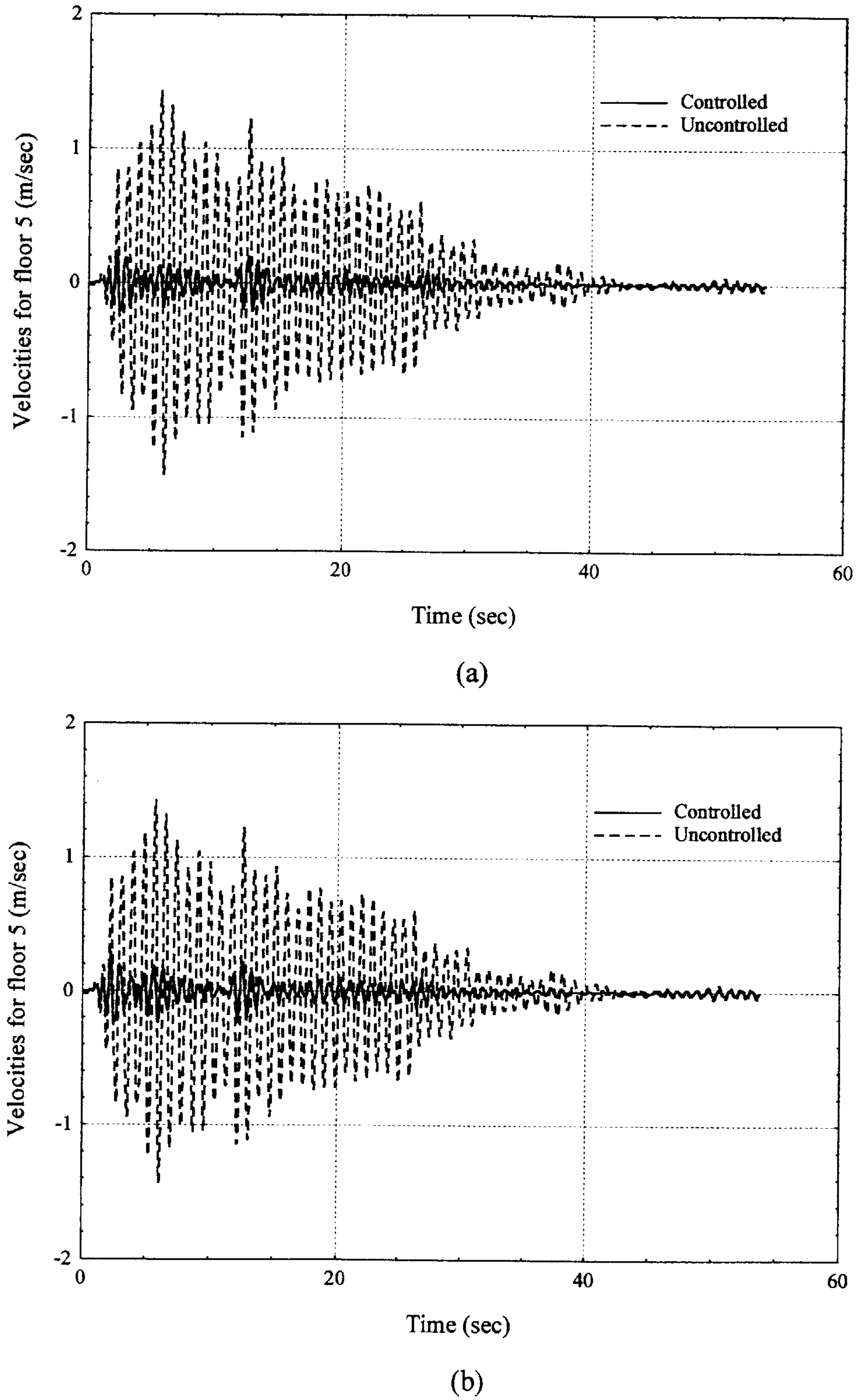
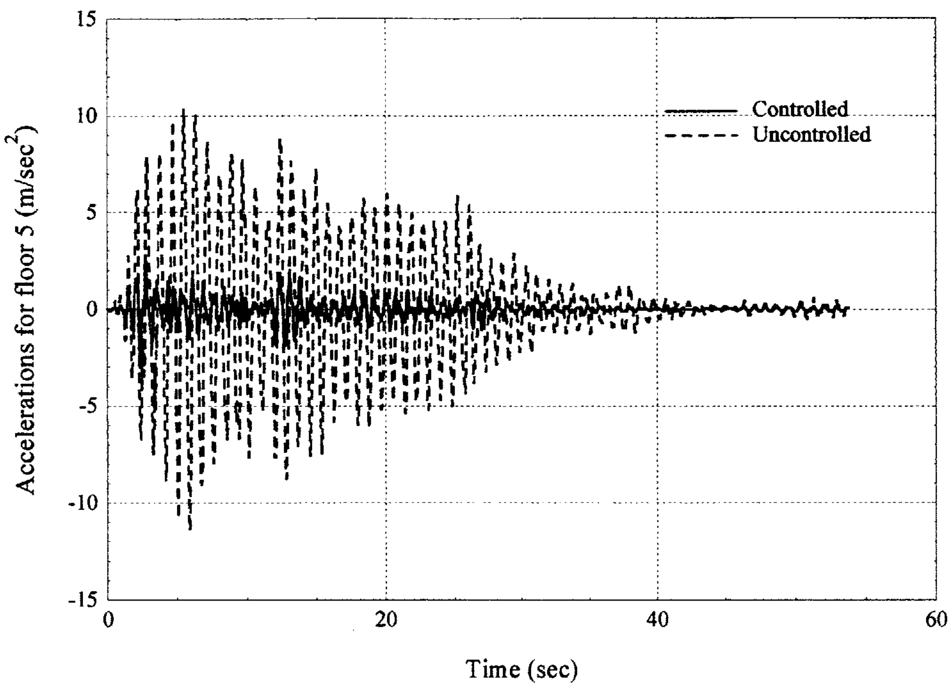
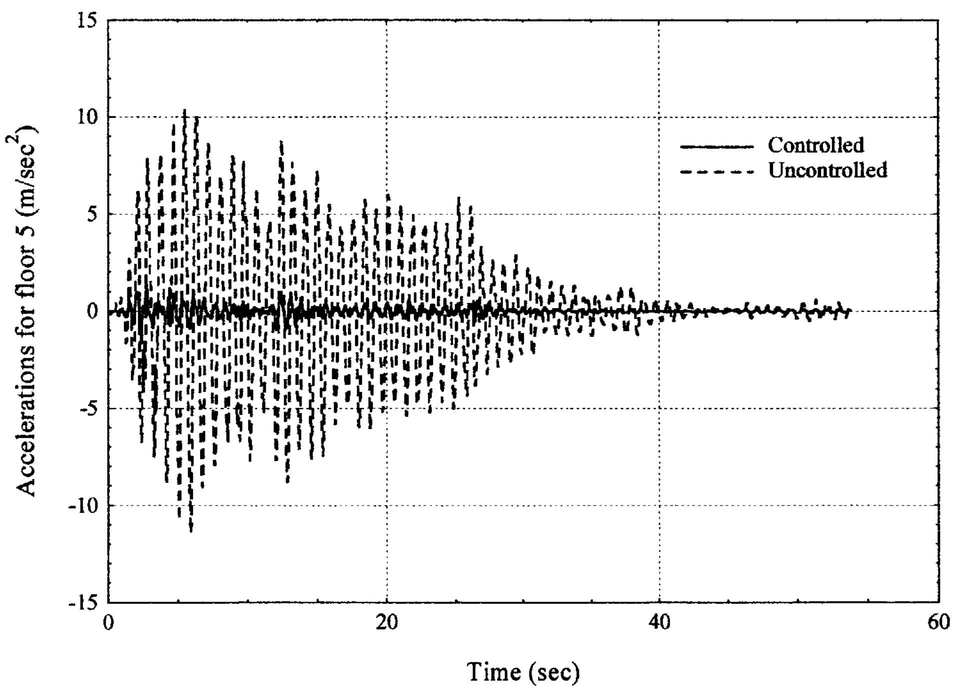


Figure 6.12: Velocities for the 5th floor - El Centro
a) Stiffness formulated damping, b) Mass formulated damping

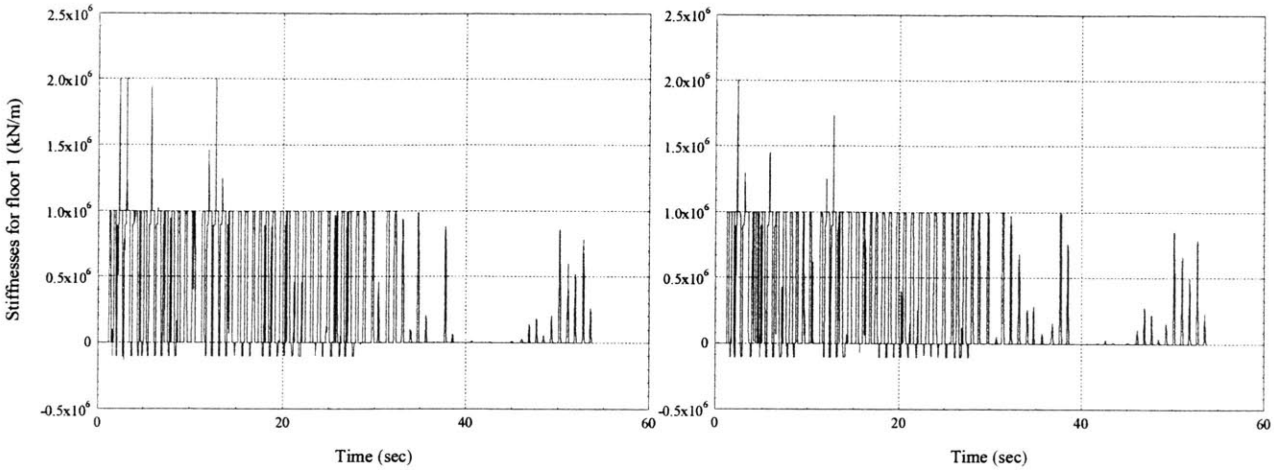


(a)



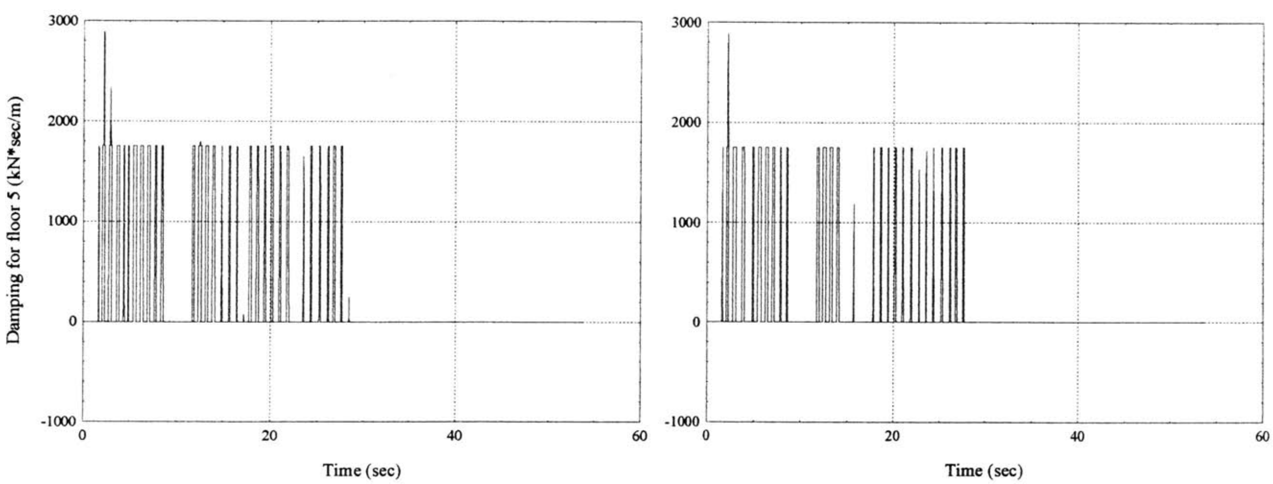
(b)

Figure 6.13: Accelerations for the 5th floor - El Centro
a) Stiffness formulated damping, b) Mass formulated damping



(a) (b)

Figure 6.14: Adaptive Stiffness for the 1st floor - El Centro
a) Stiffness formulated damping, b) Mass formulated damping



(a) (b)

Figure 6.15: Adaptive Damping for the 5th floor - El Centro
a) Stiffness formulated damping, b) Mass formulated damping

The results for the El Centro excitation show that the controller is able to reduce substantially the response of the structure under the earthquake excitation. It is important to note that the neural network used had only minor training for earthquake excitation. In addition, the adjustment of the network for the earthquake case does not affect the performance of the controller under wind excitation. The response of the structure under the wind excitation using the new neural network is essentially the same or better. It appears that the network increased its knowledge regarding the dynamic behavior of the structure. For the case of the El Centro excitation, the response is always within the prescribed limits for the displacement and it has only few violations for the acceleration. The time history responses for the displacement, velocity, and acceleration are smooth and the results corresponding to the two formulations for the adaptive damping are similar. The only significant difference is in the case of the acceleration; the time history provided by the mass formulated damping is very smooth and uniform with considerably reduced magnitude.

In conclusion, while both formulations for the adaptive damping meet the requirements, the mass formulated damping provides more efficient control of the structure. It requires less added stiffness and damping than the stiffness formulated damping in order to succeed the same and sometimes better results. The above statements are also true for the case of the wind excitation. Thus, there is no need to present results for both formulations of the adaptive damping. Due to the better performance provided by the mass formulated adaptive damping, the results of this formulation are presented for the following excitation cases.

In Figures 6.16 to 6.20 the time history response of the controlled structure subjected to the Taft earthquake is presented. The Taft earthquake has substantially different characteristics from the El Centro earthquake and provides another test of the efficiency of the controller under any excitation.

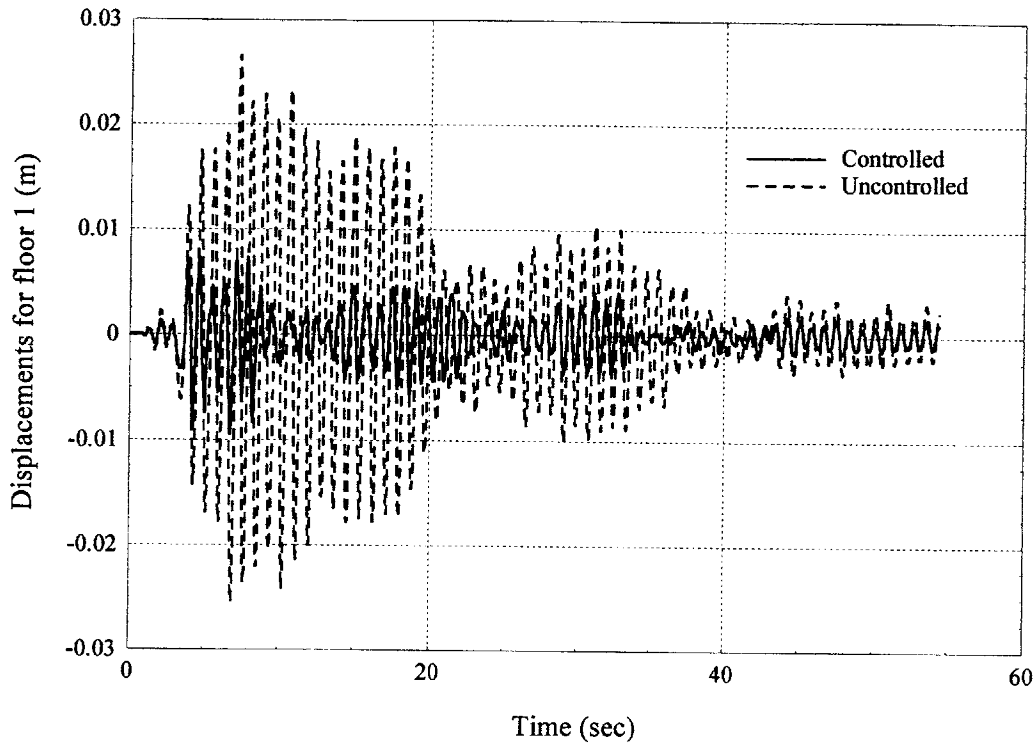


Figure 6.16: Displacements for the 1st floor - Taft (Mass formulated damping)

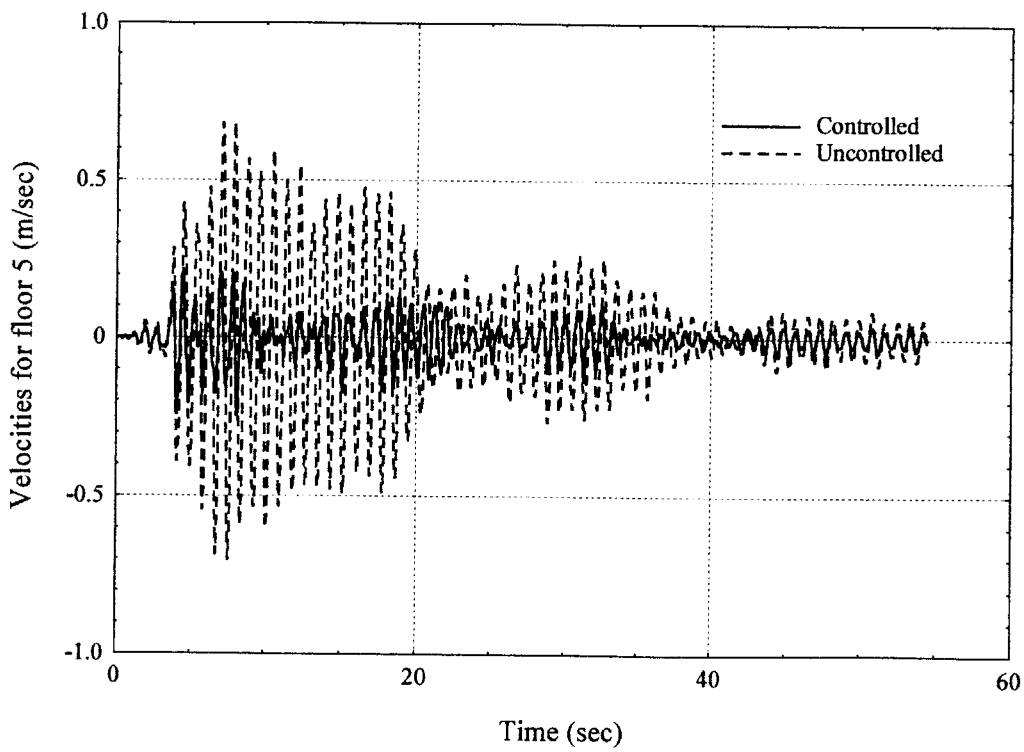


Figure 6.17: Velocities for the 5th floor - Taft (Mass formulated damping)

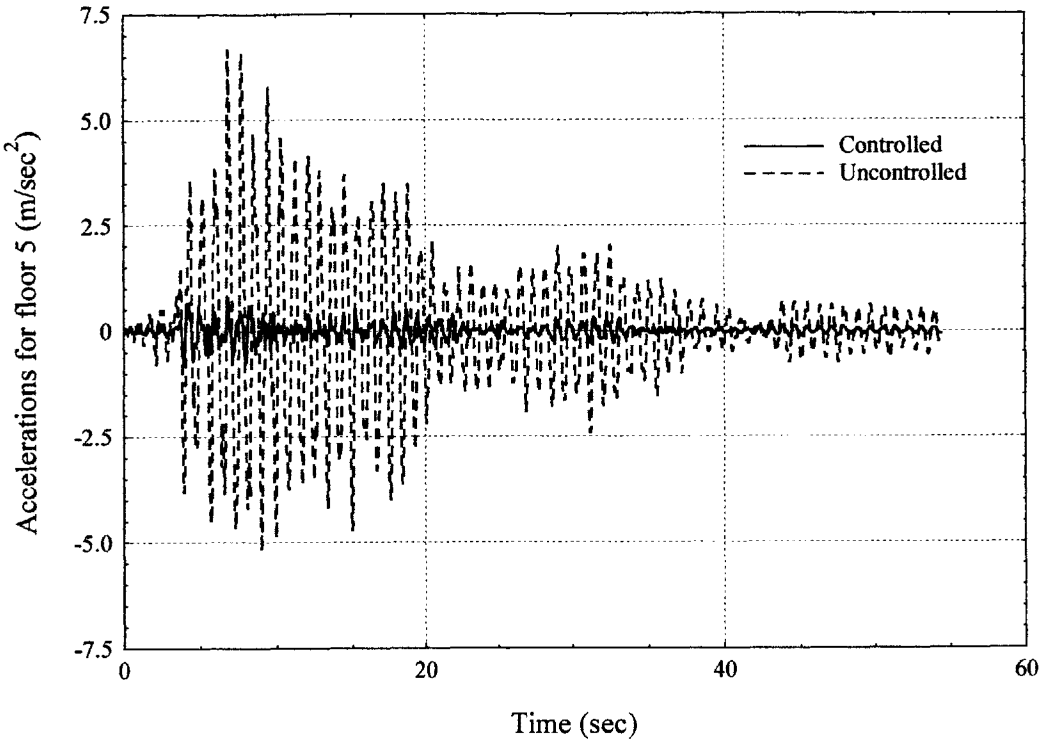


Figure 6.18: Accelerations for the 5th floor - Taft (Mass formulated damping)

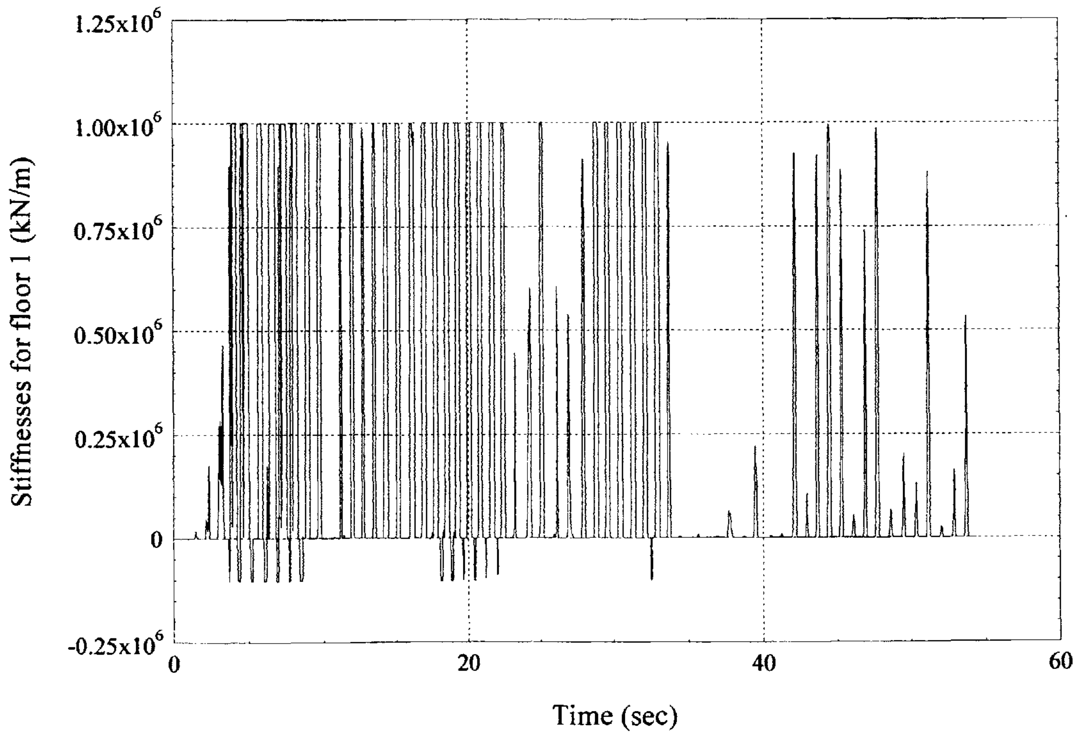


Figure 6.19: Adaptive Stiffness for the 1st floor - Taft (Mass formulated damping)

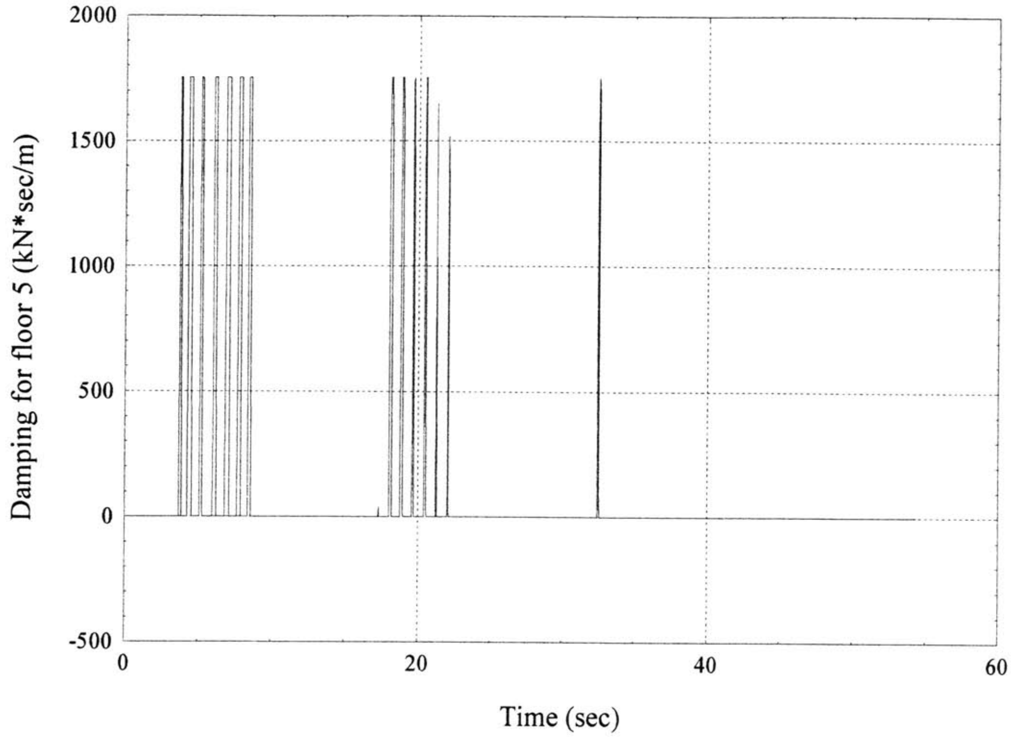


Figure 6.20: Adaptive Damping for the 5th floor - Taft (Mass formulated damping)

The results of the time history response of the controlled structure produced under the Taft earthquake are satisfying. The displacement objective is always met and there exist very few violations on the acceleration objective. The response of the structure in terms of displacements and velocities seems harsher than the one for the El Centro excitation. This result is misleading due to the different scale of the two plots. The Taft earthquake excites the structure less severely than the El Centro one. However, the control of the structure under the Taft excitation is not an easy task, due to the characteristics of the particular earthquake. For example, the reduction of the response of the structure between the controlled and the uncontrolled cases is not as large as it is for the case of the El Centro earthquake or the wind excitation. On the other hand, the adaptive stiffness and damping resources required for the control of the structure in the present case are less than those of the previous case.

The final test for the controller is the Kobe earthquake excitation. The results of the time history response for the structure subjected to the Kobe earthquake are presented in Figures 6.21 to 6.25.

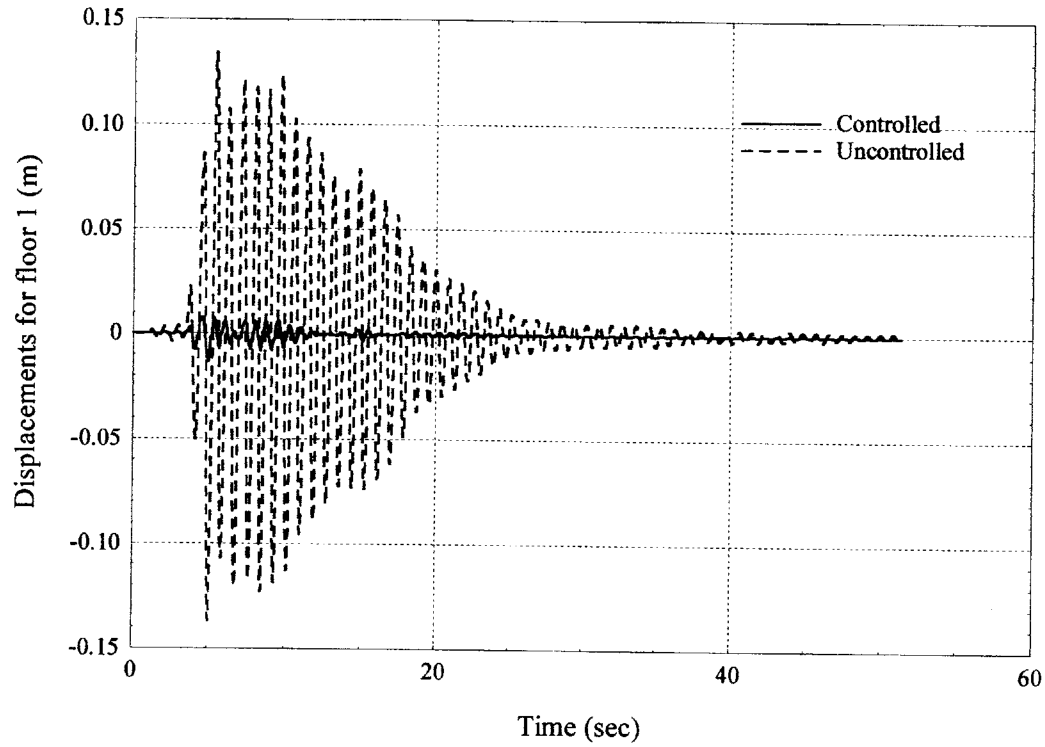


Figure 6.21: Displacements for the 1st floor - Kobe (Mass formulated damping)

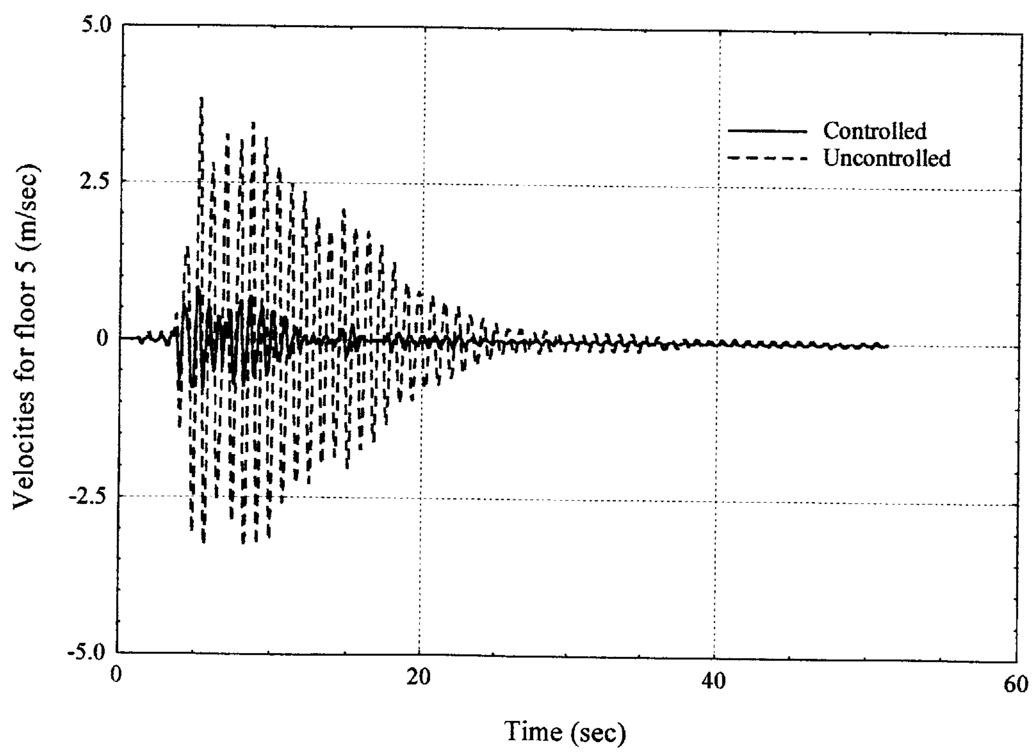


Figure 6.22: Velocities for the 5th floor - Kobe (Mass formulated damping)

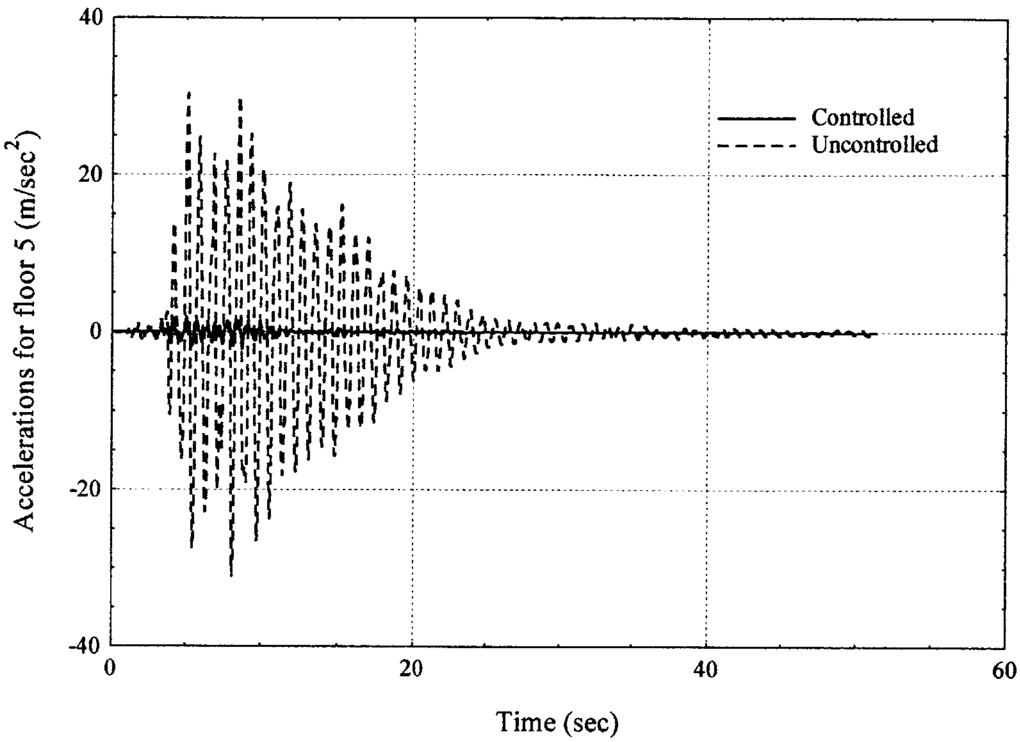


Figure 6.23: Accelerations for the 5th floor - Kobe (Mass formulated damping)

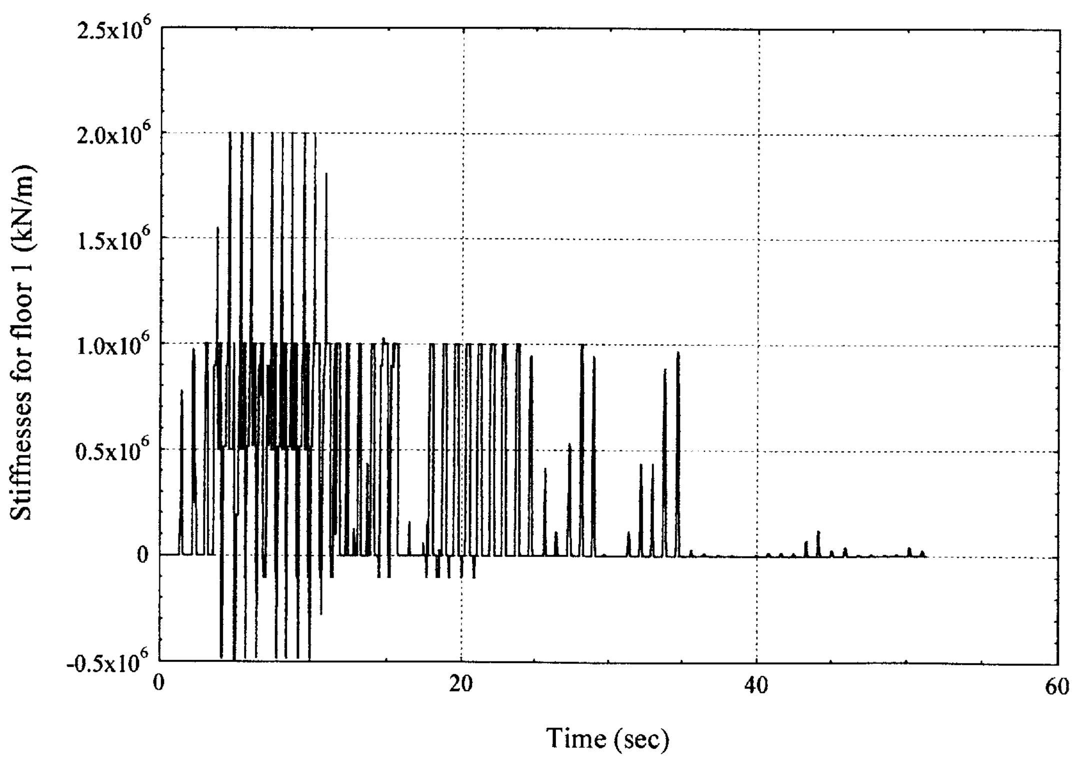


Figure 6.24: Adaptive Stiffness for the 1st floor - Kobe (Mass formulated damping)

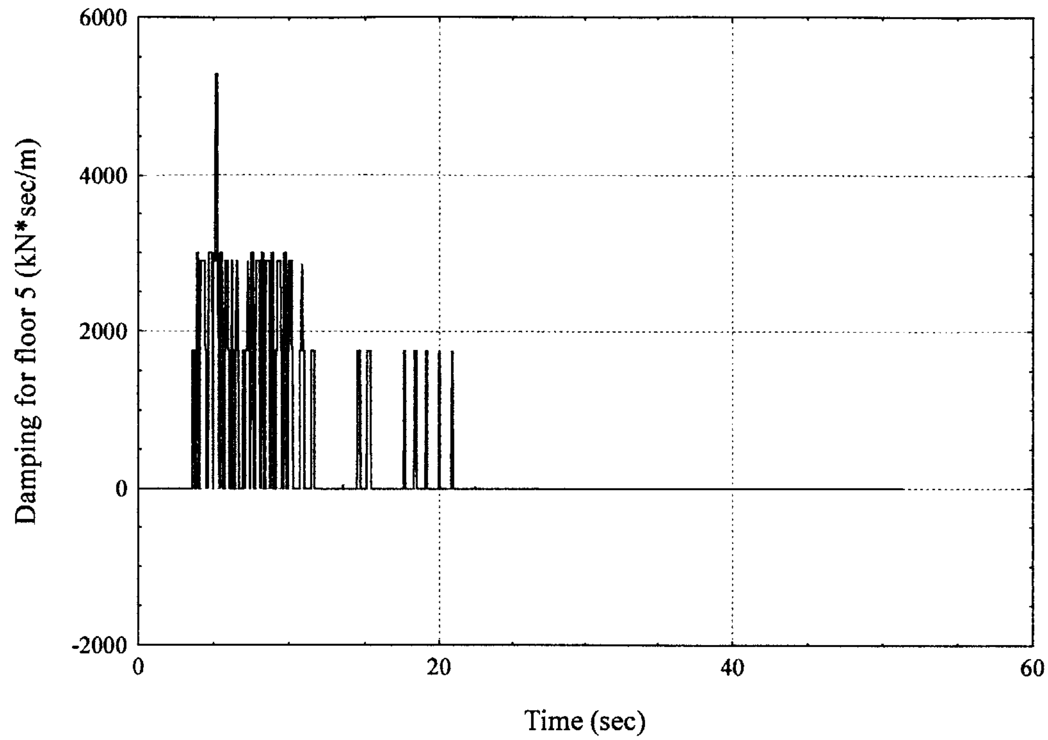


Figure 6.25: Adaptive Damping for the 5th floor - Kobe (Mass formulated damping)

The Kobe earthquake is an excitation with high peak ground acceleration and very impulsive nature. Moreover, the major part of the energy of the incident is released during the period of the 5th to the 10th second of the total duration. These characteristics create very interesting conditions from a control perspective. The uncontrolled structure vibrates vigorously for the first 10 seconds and then the vibration dies out as if the system had no external load. However, the controller succeeds to reduce substantially the response of the structure and to restrain it under the objective limits for most of the time. There exist only few violations of the acceleration objective. The controller spends considerable amounts of the adaptive stiffness and damping resources to preserve the structure in the desired state. The impulsive nature of the excitation forces the controller to reduce the stiffness of the structure several times, in order to limit the acceleration. The reduction of the stiffness is presented in the form of negative stiffness in the adaptive stiffness plot. Moreover, the amounts of adaptive damping used towards the same purpose are substantially larger than for the other excitation cases. The effort of the controller to control the displacements and accelerations by dissipating more energy becomes clear from the adaptive damping plot. All the activity on the adaptive damping plot is concentrated in the period of the 5^{th} to 10^{th} second. For the rest of the earthquake incident, only minor amounts of damping are used.

6.4 Conclusions

It is expected that a controller cannot behave perfectly under any excitation. However, the neural network controller using adaptive control methods succeeded to perform satisfactory under most of the circumstances. Generally, a set of representative of the location excitations is chosen in order to design a structure. In the present study, the excitations are selected in order to explore the capabilities of the controller under substantially different loading conditions. In real life, it is reasonable to expect a reduced diversity of the applied excitations. Considering the presented results becomes obvious that the task of controlling accelerations is not trivial. There is no case where the controller succeeded to preserve the accelerations under the objective for the total duration of the incident. Nevertheless, the response in terms of accelerations is always significantly reduced from the response of the uncontrolled structure. On the other hand, the response of the structure in terms of displacements is preserved under the objective at all instances in time and for all the excitations considered. Comparing the two formulations for the adaptive damping, the mass formulation is proven more effective in terms of response and more efficient in terms of the required resources.

6.5 Adaptive vs. Active Control

Concluding, the two control schemes, the active and adaptive control, are compared. Active control results in a very smooth and uniform response of the structure, provided the controller is well trained. Comparing the time histories of the active and adaptive control becomes obvious that the active control handles the structure better under the high intensity loading conditions considered here. Active control therefore offers more precise control, providing more capabilities in terms of the objectives and excitations. This "optimal" behavior of the active control scheme is inverted when the neural network is not sufficiently trained. In active control, the use of poorly trained networks is disastrous. The response of the structure is magnified rather than reduced, which may result to destabilization. On the other hand, the adaptive control scheme may be less effective in reducing the response, but it is unable to destabilize the structure. A poorly trained network in adaptive control can only increase the acceleration of the structure, but it will always reduce the response in terms of displacements and velocities. A sufficiently trained network provides satisfactory performance, which is directly comparable to the response provided by the active control scheme. Moreover, the training of an adaptive control scheme is less demanding than the training of an active control scheme. Additional care is required in active control in order to improve its skills in applying precisely the control forces throughout the structure. This task requires more extensive training sets, which consequently require more preparation and computational time.

Last but not least, the active control is less efficient in terms of the required than the adaptive control. In order an actuator to apply the large required amounts of forces consumes substantial amounts of energy. On the other hand, the devices used in adaptive control are energy efficient as soon as they employ values or electro-magnetic currents. This can be a major consideration for the selection of either system, because a powerful energy supply may not be available at the time of an excitation incident.

In this research study the efficiency of the active and adaptive control schemes is demonstrated. The potential of using a neural network in the place of a controller is explored and proven to be a useful tool, due to its adaptivity to the current circumstances, the ability to learn by its mistakes and the insensitivity to the noise of the signal. The selection of either control scheme of the two presented here is depends to the objectives and limitations of the design. The neural network technology is mature enough to support any structural control attempt.

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