ENHANCING REINFORCEMENT LEARNING BY A FINITE REWARD RESPONSE FILTER WITH A CASE STUDY IN INTELLIGENT STRUCTURAL CONTROL

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ABSTRACT

In many reinforcement learning (RL) problems, it takes some time until a taken action by the agent reaches its maximum effect on the environment and consequently the agent receives the reward corresponding to that action by a delay called action-effect delay. Such delays reduce the performance of the learning algorithm and increase the computational costs, as the reinforcement learning agent values the immediate rewards more than the future reward that is more related to the taken action. This paper addresses this issue by introducing an applicable enhanced Q-learning method in which at the beginning of the learning phase, the agent takes a single action and builds a function that reflects the environment's response to that action, called the reflexive $\gamma$-function. During the training phase, the agent utilizes the created reflexive $\gamma$-function to update the Q-values. We have applied the developed method to a structural control problem in which the goal of the agent is to reduce the vibrations of a building subjected to earthquake excitations with a specified delay. Seismic control problems are considered as a complex task in structural engineering because of the stochastic and unpredictable nature of earthquakes and the complex behavior of the structure. Three scenarios are presented to study the effects of zero, medium, and long action-effect delays and the performance of the Enhanced method is compared to the standard Q-learning method. Both RL methods use a neural network to learn to estimate the state-action value function that is used to control the structure. The results show that the enhanced method significantly outperforms the performance of the original method in all cases, and also improves the stability of the algorithm in dealing with action-effect delays.

Keywords Reinforcement learning · Neural networks · Structural control · Earthquake · Seismic control · Smart structures

1 Introduction

Reinforcement learning (RL) is an area of machine learning concerned with an agent that learns to perform a task so that it maximizes the (discounted) sum of future rewards. For this, the agent interacts with the environment by letting it select actions based on its observations. After each selected action, the environment changes and the agent receives a reward that indicates the goodness of the selected action. The difficulty is that the agent does not only want to obtain the highest immediately obtained reward, but wants to optimize the long-term reward intake (return). The
return or discounted sum of future rewards depends on all subsequent selected actions and visited states during the decision-making process.

In the literature, RL methods have been successfully applied to make computers solve different complex tasks, which are usually done by humans. Developing autonomous helicopters [39], playing Atari games [37], controlling traffic network signals [7], and mimicking human’s behavior in robotic tasks [28] are some examples for applications of RL methods in solving real-world problems.

As a development, we have applied RL to the seismic control problem in structural engineering as one of the most complex structural problems due to the stochastic nature of the earthquakes and their wide frequency content, which makes them unpredictable and also destructive to many different structures.

The main part of the control system in a smart structure is the control algorithm that determines the behavior of the controller device during the external excitations. This paper describes the use of reinforcement learning (RL) [46] combined with neural networks to learn to apply forces to a structure in order to minimize an objective function. This objective function consists of structural responses including the displacement, the velocity and the acceleration of some part of the structure over time.

The difficulty in intelligent structural control is that applied forces to stabilize the structure usually reach to their maximum effect on the building after a specific time period. Moreover, the magnitude and the direction of the structural responses changes rapidly in the time during the earthquake excitations. These issues makes determination of the Q-values difficult for the agent and results in poor learning performance. To deal with this problem, we introduce a novel RL method that is based on a finite reward response filter. In our proposed method, the agent does not receive a reward value only based on the change of the environment in a single time step, but uses the combined rewards during a specific time period in the future as feedback signal. We compare the proposed method to the conventional way of using rewards for single time steps using the Q-learning algorithm [49] combined with neural networks. For this, we developed a simulation that realistically mimics a specific building and earthquake excitations. The building is equipped with an active controller that can apply forces to the building to improve its responses. The results show that using the proposed finite reward response filter technique leads to significant improvement in the performance of the controller compared to when it is trained by the conventional RL method.

The rest of this paper is organized as follows. Section 2 explains the background of different control systems that have been used for the structural control problem. Section 3 describes the used RL algorithms and theories. Section 4 explains the novel method. Section 5 presents the case study by describing the structural model, dynamics of the environment, and the details of the simulation. Section 6 explains the experimental set-up. Section 7 presents the results, and finally Section 8 concludes this paper.

2 Background in Structural Control Systems

In the literature, several types of control algorithms have been studied for the structural control problem, which can be categorized in four main categories: Classical, Optimal, Robust, and Intelligent. These different approaches will be shortly explained below.

Classical Control Systems. Classical approaches are developed based on the proportional-integral-derivative (PID) control concept. Here, the controller continuously calculates an error value as the difference between the desired
set-point (SP) and the measured process value (PV). The errors over time are used to compute a correction control force based on the proportional (P), integral (I), and derivative terms (D). Two types of structural controllers that use the classical approach are feedback controllers and feedforward controllers [19, 26, 29, 14, 25, 21]. Although such control systems may work well in particular cases, they do not take the future effects into account when computing control outputs, which can lead to sub-optimal decisions with negative consequences.

**Optimal Control.** Optimal control algorithms aim to optimize an objective function while considering the problem constraints. When the system dynamics are described by a set of linear differential equations and the cost function is defined by a quadratic function, the control problem is called a linear-quadratic control (LQC) problem [30]. Several studies have been carried out on optimal control of smart structures. One of the main solutions for such control problems is provided by the linear quadratic regulator (LQR) [3]. The LQR solves the control problem using a mathematical algorithm that minimizes the quadratic cost function given the problem characteristics [45]. Such algorithms are widely used for solving structural control problems. Ikeda et al. [23] utilized an LQR control algorithm to control the lateral displacement and torsional motions of a 10-story building in Tokyo using two adaptive TMDs (ATMDs). This building had afterwards experienced one earthquake and several heavy storms and showed a very good performance in terms of reducing the motions. In another study, Deshmukh and Chandiramani [17] used an LQR algorithm to control the wind-induced motions of a benchmark building equipped with a semi-active controller with a variable stiffness TMD.

Controllers often also have to deal with stochastic effects due to the mentioned uncertainties [16]. Model predictive control (MPC) algorithms use a model to estimate the future evolution of a dynamic process in order to find the control signals that optimize the objective function. Mei et al. [35] used MPC together with acceleration feedback for structural control under earthquake excitations. In their study, they utilized the Kalman-Bucy filter to estimate the states of systems and performed two case studies including a single-story and a three-story building, in which active tendon control devices were used. Koerber and King [29] utilized MPC to control the vibrations in wind turbines.

Although these optimal control algorithms can perform very well, they rely on having a model of the structure that is affected by the earthquake. This makes such methods less flexible and difficult to use for all kinds of different structural control problems.

**Robust Control.** Robust control mainly deals with uncertainties and has the goal to achieve robust performance and stability in the presence of bounded modeling errors [31]. In contrast to adaptive control, in robust control the action-selection policy is static [2]. $H_2$ and $H_\infty$ control are some typical examples of robust controllers that synthesize the controllers to achieve stabilization regarding the required performance. Initial studies on $H_2$ and $H_\infty$ control were conducted by Doyle et al. [20]. Sliding mode control (SMC) is another common control method for nonlinear systems in which the dynamics of the system can be altered by a control signal that forces the system to “slide” along a cross-section of the system’s normal behavior. Moon et al. [38] utilized SMC and the LQC formulation for vibration control of a cable-stayed bridge under seismic excitations. They evaluated the robustness of the SMC-based semi-active control system using magnetorheological (MR) dampers which are controlled using magnetic fields. In another research, Wang and Adeli [48] proposed a time-varying gain function in the SMC. They developed two algorithms for reducing the sliding gain function for nonlinear structures. Although robust control methods can be used to guarantee a robust performance, they also require models of the structural problem and often do not deliver optimal control signals for a specific situation.

**Intelligent Control.** Intelligent control algorithms are capable of dealing with complex problems consisting of a high degree of uncertainty using artificial intelligence techniques. The goal is to develop autonomous systems that can sense the environment and operate autonomously in unstructured and uncertain environments [40]. Intelligent control uses various approaches such as fuzzy logic, machine learning, evolutionary computation, or combinations of these methods such as neuro-fuzzy [25] or genetic-fuzzy [24] controllers. In the last decade, algorithms such as neural networks [13, 18], evolutionary computing [49, 15], and other machine learning methods [51, 56] have been used to develop intelligent controllers for smart structures.

An issue with fuzzy controllers is the difficulty to determine the best fuzzy parameters to optimize the performance of the controller. In this regard, various methods have been developed to optimize the parameters for fuzzy-logic control [4, 5, 6, 27]. This optimization process can be based on online and offline methods and has also been used for the vibration control problem of smart structures [8, 41, 43, 44].

Neural controllers have been investigated in a few studies [11, 10, 22] in which neural networks are utilized to generate the control commands. In these studies, the neural network has been trained to generate the control commands based on a training set dictated by another control policy. The disadvantage is that these methods have little chance to outperform the original control algorithm, and therefore can only make decisions faster. Madan [33] developed a method to train a neural controller to improve the responses of the structure to earthquake excitations using a modified...
counter-propagation neural network. This algorithm learns to compute the required control forces without a training set or model of the environment.

Rahmani et. al. [42] were the first to use reinforcement learning (RL) to develop a new generation of structural intelligent controllers that can learn from experiencing earthquakes to optimize a control policy. Their results show that the controller has a very good performance under different environmental and structural uncertainties. In the next section, we will explain how we extended this previous research by using finite reward response filters in the RL algorithm.

3 Reinforcement Learning for Structural Control

In RL, the environment is typically formulated as a Markov decision process (MDP) [46]. An MDP consists of a state space \( S \), a set of actions \( A \), a reward function \( R(s, a) \) that maps state-action pairs to a scalar reward value, and a transition function \( T(s, a, s') \) that specifies the probability of moving to each next possible state \( s' \) given the selected action \( a \) in the current state \( s \). In order to make the intake of immediate rewards more important compared to rewards received far in the future, a discount factor \( 0 \leq \gamma \leq 1 \) is used.

3.1 Value functions and policies

When the transition and reward functions are completely known, MDPs can be solved by using dynamic programming (DP) techniques [12]. DP techniques rely on computing value functions that indicate the expected return an agent will obtain given its current state and selection action. The most commonly used value function is the state-action value function, or Q-function. The optimal Q-function \( Q^*(s, a) \) is defined as:

\[
Q^*(s, a) = \max_{\pi} E(r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots + \gamma^N r_{t+N})
\]

Where \( E \) is the expectancy operator which takes into account all stochastic outcomes, \( r_t \) is the emitted reward at time step \( t \), and \( N \) is the horizon (possibly infinite) of the sequential decision-making problem. The maximization is taken with respect to all possible policies \( \pi \) that select an action given a state.

If the optimal Q-function is known, an agent can simply select the action that maximizes \( Q^*(s, a) \) in each state in order to behave optimally and obtain the optimal policy \( \pi^*(s) = \arg \max_a Q^*(s, a) \).

Bellman’s optimality equation [12] defines the optimal Q-function using a recursive equation that relates the current Q-value to the immediate reward and the optimal Q-function in all possible next states:

\[
Q^*(s, a) = R(s, a) + \gamma \sum_{s'} T(s, a, s') \max_b Q^*(s', b)
\]

Value iteration is a dynamic programming method that randomly initializes the Q-function and then uses Bellman’s optimality equation to compute the optimal policy through an iterative process:

\[
Q_{t+1}(s, a) \leftarrow R(s, a) + \gamma \sum_{s'} T(s, a, s') \max_b Q_t(s', b)
\]

When this update is done enough times for all state-action values, it has been shown that \( Q_t \) will converge to \( Q^* \).

A problem with such dynamic programming methods is that usually the transition function is not known beforehand. Furthermore, for very large state spaces the algorithm would take an infeasible amount of time. Therefore, reinforcement learning algorithms are more efficient as they allow an agent to interact with an environment and learn to optimize the policy while focusing on the most promising regions of the state-action space.

3.2 Q-learning

Q-learning [49] is one of the best-known RL algorithms. The algorithm is based on keeping track of state-action values (Q-values) that estimate the discounted future reward intake given a state and selected action. In the beginning the Q-function is randomly initialized and the agent selects actions based on its Q-function and the current state. After each
selected action, the agent obtains an experience tuple \((s, a, s', r)\) where \(s'\) is the next state and \(r\) the obtained reward. Q-learning then adjusts the Q-function based on the experience in the following way:

\[
Q(s, a) = Q(s, a) + \alpha (r + \gamma \max_b Q(s', b) - Q(s, a))
\] (4)

Where \(\alpha\) is the learning rate.

During the learning phase, the agent improves its estimations and after an infinite amount of experiences of all state-action pairs the Q-values will converge to the optimal Q-values \(Q^*(s, a)\) [49]. In order to learn the optimal policy, the agent has to make a trade-off between exploitation and exploration. When the agent exploits its currently learned Q-function, the agent selects the action with the highest value. Although exploiting the Q-function is expected to lead to the highest sum of future rewards, the agent also has to perform exploration actions by selecting actions which do not have the highest Q-value. Otherwise, it will not experience all possible state-action values and most probably not learn the optimal policy. In many applications, the \(\epsilon\)-greedy exploration policy is used that selects a random action with probability \(\epsilon\) and the action with the highest Q-value otherwise.

### 3.3 Q-learning with neural networks

Before we explained the use of lookup tables to store the Q-values. For very large or continuous state spaces this is not possible. In such problems, RL is often combined with neural networks that estimate the Q-value of each possible action given the state representation as input. Combining an RL algorithm with a neural network has been used many times in the past, such as for learning to play backgammon at human expert level [47] in 1994.

Q-learning can be combined with a multi-layer perceptron (MLP) by constructing an MLP with the same number of outputs as there are actions. Each output represents the Q-value \(Q(s, a)\) for a particular action given the current state as input. These inputs can then be continuous and high-dimensional and the MLP will learn a Q-function that generalizes over the entire input space. For training the MLP on an experience \((s, a, s', r)\), the target-value for the output of the selected action \(a\) is defined as:

\[
TQ(s, a) = r + \gamma \max_b Q(s', b, \theta)
\] (5)

Where \(\theta\) denotes all adjustable weights of the MLP. The MLP is trained using backpropagation to minimize the error \((TQ(s, a) - Q(s, a, \theta))^2\). Note that the MLP is randomly initialized and is trained on its own output (bootstrapping). This often causes long training times and can also lead to instabilities.

Mnih et al. made the combination of deep neural networks and RL very popular by showing that such systems are very effective for learning to play Atari games using high-dimensional input spaces (the pixels) [37]. To deal with unstable learning, they used experience replay [32], in which a memory buffer is used to store previous experiences and each time the agent learns on a small random subset of experiences. Furthermore, they introduced a target network, which is a periodically copied version of the Q-network. It was shown that training the Q-network not on its own output, but on the values provided by the target network, made the system more stable and efficient.

### 4 Enhancing Q-Learning with Reward Response Filters

There are many decision-making problems in which an action does not have an immediate effect on the environment, but the effect and therefore also the goodness of the action is only shown after some delay. Take for example an archer that aims a bow and shoots an arrow. If the arrow has to travel a long distance, there would be no immediately observable reward related to the actions of the archer. In structural control, a similar problem occurs. When a device is controlled to produce counter forces against vibrations in a structure caused by an earthquake, then the effects of the control signals or actions incur a delay. This makes it difficult to learn the correct Q-function and optimize the policy.

This paper introduces an enhanced Q-learning method for solving sequential decision-making problems in which the maximal effects of actions occur after a specific time-period or delay. In this method, the agent initially builds a finite reward response filter based on the response of the environment to a single action. Afterwards, that function is used for determining the reward for a selected action. The proposed method initially allows the agent to make some observations about the behavior of the environment, so that it can later better determine the feedback of the executed actions. As a result, the agent should be able to learn a better Q-function and increase its performance. For example, if the agent knows that an action \(a_t\), taken at time step \(t\), will affect the environment at time step \(t + 5\), there is no reason to use the obtained rewards in the range of \([t, t + 4]\) for determining the action value for the selected action, \(a_t\).
In the developed method, the agent takes a single action at the beginning of the training and observes the response of the environment. Based on the observed effects, the agent builds a finite reward response filter, also called reflexive $\gamma$-function, that reflects the influence of the actions on the environment as shown in Figure 1. The computed function is a normalized response of the environment to the single taken action. As an example, in the structural control problem, the agent (controller system) applies a unit force to the roof of the building and observes the displacement responses as a function of time. Then, it considers the absolute values of the peak responses to build the reward response filter. After the function reaches its maximum value, it will be gradually decreased to zero. As the most important point is the time at which the action effect reaches its maximum, the gamma function is cut after the time step in which the response of the environment is reduced by $p$ percent of its peak value. In the experiments we set $p = 15\%$. Note that the main idea can be used for other problems by constructing different ways of creating the reward response filter.

During the learning phase, the agent computes the target Q-values $TQ(s,a)$ by multiplying the reflexive $\gamma$-function with the immediate rewards during the time interval $[t_0, t_0 + \Delta t_\gamma]$ and adding the maximum Q-value of the successor state $s' = s_{tm}$ as follows:

$$TQ(s,a) = \sum_{j=0}^{n} (\gamma_j r_j) + \gamma_{n+1} \max_a Q(s',a')$$  \hspace{1cm} (6)$$

where $\gamma_j$ values are obtained from the reflexive $\gamma$-function, and:

- $r_j$: immediate reward value at time $t_0$
- $n$: number of the time steps in reflexive $\gamma$-function.
- $t_0$: time when agent takes action $a$
- $tm$: time step after $t_0 + \Delta t_\gamma$
- $\Delta t_\gamma$: time duration of reflexive $\gamma$-function
- $s'$: successor state at time $t_0 + \Delta t_\gamma$
Note that our method is related to multi-step Q-learning [46] in which the Q-function is updated based on the rewards obtained in multiple steps. The differences are: 1) In the proposed method, the time duration of the finite reward response filter is determined automatically at the start of the experiment. 2) The proposed method does not use exponential discounting of future rewards, but determines the discount factors based on the observed effects of actions on the environment. 3) It is possible that the immediate rewards after taking an action have zero gamma values and therefore are excluded by the algorithm in updating the Q-value.

5 Case Study

As a case study, we train an agent as a structural controller to reduce the vibrations of a single-story building, subjected to earthquake excitations. The structural system of the building comprises a moment frame which is modeled as a single degree of freedom (SDOF) system. The mathematical model of the structure (the environment) is developed in Simulink software in which an analysis module determines the structural responses. The mass, stiffness, and damping of the structure are the constant values of the model during the simulations. The inputs to the analysis module include the earthquake acceleration record as an external excitation and the control forces which are the transformed values of the control signals, generated by the neural network. The outputs of the analysis module are the displacement, velocity and the acceleration responses of the frame.

Action-effect delays are considered in the model using a delay-function which applies input excitation to the frame after a constant delay. Based on the value of the delay between the occurrence of an external excitation and when it affects the structure, three simulation scenarios including no delay, medium delay (5 seconds) and a long delay (10 seconds) are considered and the performance of the enhanced method is compared to the original method.

5.1 Agent

The intelligent controller consists of a neural network called Q-net which receives as inputs the current state, including the structural responses and the external excitation from the analytical model, and generates the Q-values. The action corresponding to the maximum Q-value will then be sent to the actuator module which transforms the control signals to the force values and passes that to the analysis module. In addition to Q-net, a secondary stabilizer (target) net is also developed to improve the performance of the learning module, as was proposed by Volodymyr Mnih et al. [37] in the experience replay learning method. During the learning phase the Q-net is trained to improve its performance by learning the Q-values. The training algorithm and the hyper-parameters are presented in Table 1.

| hidden layers number | training algorithm | learning rate |
|----------------------|--------------------|---------------|
| 2                    | back propagation   | 0.99          |

Table 1: Neural network’s training parameters

5.2 Environment

The concept of the intelligent control of the frame is schematically shown in Figure 2. As it is shown, a moment frame is subjected to the earthquake excitation and the control system transforms the control signals from the neural network to the horizontal forces on the frame using an actuator. The mass of the frame is 2000 kg, which is considered as a condense mass at the roof level, the stiffness is $7.9 \times 10^6$ [N/s], and the damping is $250 \times 10^3$ N.S/m. The natural frequency $\omega$, and the period $T$ of the system are as follows:

$$\omega = \sqrt{\frac{k}{m}} = \sqrt{\frac{7.9e6}{2000}} = 62.84 \frac{1}{s}$$  \hspace{1cm} (7)

$$T = \frac{2\pi}{\omega} = 0.1 \text{ s}$$  \hspace{1cm} (8)
5.3 Environment dynamics

The Equation of the motion for the moment frame under the earthquake excitation and the control forces is as follow:

\[ m \ddot{u} + c \dot{u} + ku = -m \ddot{x}_g + f \]  

(9)

in which \( m, c, k \) are the mass, damping and the stiffness matrices, \( \ddot{x}_g \) is the ground acceleration, and \( f \) is the control force. \( u, \dot{u}, \) and \( \ddot{u} \) are displacement, velocity, and acceleration vectors respectively.

By defining the state vector \( x \) as:

\[ x = \{ u, \dot{u} \}^T \]  

(10)

The state-space representation of the system would be:

\[ \dot{x} = Ax + Ff + G\ddot{x}_g \]  

(11)

\[ y_m = C_m x \]  

(12)

Considering \( v = \{ \ddot{x}_g, f \} \), Equation (11) can be written as:

\[ \dot{x} = Ax + Bv \]  

(13)

in which:

\[
A = \begin{bmatrix}
0 & 1 \\
-\frac{k}{m} & -\frac{c}{m}
\end{bmatrix} = \begin{bmatrix}
0 & 1 \\
-3947.8 & -125.66
\end{bmatrix}
\]

\[
B = \begin{bmatrix}
0 & 0 \\
-1 & 1
\end{bmatrix} = \begin{bmatrix}
0 & 0 \\
-1 & 5 \times 10^{-4}
\end{bmatrix}
\]

\[
C_m = \begin{bmatrix}
1 & 0 \\
0 & 1
\end{bmatrix}
\]
5.4 Earthquake excitation

In order to train the intelligent controller, the acceleration record of Landers earthquake is considered which is obtained from the NGA strong motion database [1] (See Figure 3).

![Figure 3: Landers earthquake record, obtained from Pacific Earthquake Engineering Research (PEER) Center](image)

5.5 State

The state shall include all the required data for determining the actions to be an Markov state. In this regard, for the structural control problem, the ground accelerations as well as the structural responses including acceleration, velocity, and displacement responses are included in the each state $S_t$. Based on the author’s experience, including the displacements in the last three time steps helps the agent to understand the direction of the motion which is important specially when reaching the maximums in the oscillations.

$$\{u_t, u_{t-1}, u_{t-2}, v_t, a_t, \ddot{u}_{g,t}\} \in S_t \quad (14)$$

where:

- $u_t$: displacement in time $t$
- $v_t$: velocity in time $t$
- $a_t$: acceleration in time $t$
- $\ddot{u}_{g,t}$: ground acceleration in time $t$

5.6 Reward Function

In reinforcement learning, the reward function determines the goodness of the taken action. In this regard, a multi-objective reward function is defined including four partial rewards:

**Displacement response**

The first partial reward function reflects the performance of the controller in terms of reducing the displacement responses:

$$R_{1,t} = 1 - \frac{|u_t|}{u_{max}}$$

in which, $u_t$ is the displacement value of the frame at time $t$ and $u_{max}$ is the maximum uncontrolled displacement response.

**Velocity response**

This partial reward evaluates the velocity response of the frame:
\[ R_{2,t} = 1 - \frac{|v_t|}{v_{max}} \]

in which \( v_t \) is the velocity response of the frame at time \( t \) and \( v_{max} \) is the maximum uncontrolled velocity response.

**Acceleration response**

The performance of the controller in terms of reducing the acceleration responses of the frame is evaluated by \( R_{3,t} \):

\[ R_{3,t} = 1 - \frac{|a_t|}{a_{max}} \]

in which \( a_t \) is the acceleration response of the frame at time \( t \) and \( a_{max} \) is the maximum uncontrolled acceleration response.

**Actuator force**

The goal of the fourth partial reward is to evaluate the required energy by applying a penalty value equal to 0.005 to the actuator force in each time-step:

\[ R_{4,t} = f_t \times P_a \]

in which:

- \( f_t \) = Actuation force at time \( t \) (N)
- \( P_a \) = Penalty value for unit actuator force (= 0.005)

By combining the four partial rewards, the reward value \( R_t \) at time \( t \) will be calculated:

\[ R_t = R_{1,t} + R_{2,t} + R_{3,t} + R_{4,t} \]

### 6 Training

Following the experience-replay method, in each training episode, many experiences were recorded in the experience-replay memory buffer. The algorithm then randomly selected 100 of the records from the experience replay buffer and experiences were selected by the key state selector function as proposed in [42] to train the Q-net. The target network was updated every 50 training episodes. The learning parameters have been tuned during preliminary experiments and are shown in Table 2.

For balancing the exploration and exploitation during the learning phase, the agent followed the \( \epsilon \)-greedy policy which means that in each state, it took the action with the maximum expected return, but occasionally it took random actions with a probability of \( \epsilon \). In this research, a decreasing \( \epsilon \)-value technique is utilized so that its value gradually reduces from 1 in the beginning to a minimum value of 0.1.

### 7 Results

During the learning phase, the controller was trained for three scenarios including zero delay (\( \Delta t_d = 0 \) s), medium delay (\( \Delta t_d = 5 \) s), and long delay (\( \Delta t_d = 10 \) s). In each scenario, the original and the enhanced methods were utilized and the maximum-achieved performance of the controller was recorded as presented in Tables 3 to 5. The corresponding uncontrolled and controlled displacement responses of the frame are demonstrated in Figure 3. The results show that the enhanced method has significantly improved the performance in all scenarios. Even without action-effect delays, the performance of the enhanced method in terms of reducing the displacement responses is 46.1% which is much better than the original method that minimizes the displacement with 7.1%.
Table 3: Seismic responses of the fame in case of zero delay. (Dis. = Displacement (cm), Vel. = Velocity (m/s), Acc. = Acceleration (m/s²)).

| Learning method | Uncontrol. | Controlled | Improvement |
|-----------------|------------|------------|-------------|
| Original method | Peak Dis. 4.39 | 4.06 | 7.1% |
|                 | Peak Vel. 0.91 | 0.83 | 8.7% |
|                 | Peak Acc. 22.97 | 16.84 | 26.7% |
| Enhanced method | Peak Dis. 4.39 | 2.36 | 46.1% |
|                 | Peak Vel. 0.91 | 0.54 | 41.0% |
|                 | Peak Acc. 22.97 | 14.28 | 37.8% |

Table 4: Seismic responses of the fame when the delay is 5 seconds (Dis. = Displacement (cm), Vel. = Velocity (m/s), Acc. = Acceleration (m/s²)).

| Learning method | Uncontrol. | Controlled | Improvement |
|-----------------|------------|------------|-------------|
| Original method | Peak Dis. 4.39 | 4.24 | 3.4% |
|                 | Peak Vel. 0.91 | 0.85 | 6.5% |
|                 | Peak Acc. 22.93 | 20.0 | 12.8% |
| Enhanced method | Peak Dis. 4.39 | 3.06 | 30.2% |
|                 | Peak Vel. 0.91 | 0.62 | 32.2% |
|                 | Peak Acc. 22.93 | 16.38 | 28.5% |

As it was expected, by increasing the action-effect delay from zero to 5 seconds, the performance of both methods is reduced, but still the enhanced method, that was utilizing the γ - function for estimating the Q-values, shows a better performance. For example, in case of having 5 seconds action-effect delays, the performance of the enhanced method in terms of reducing the displacement responses is 30.2% which is by far better than the value for the original method with 3.4%.

By studying the performance of both methods under a long action-effect delay (10 seconds), it is understood that the enhanced method not only significantly improves the performance of the training algorithm but also shows a higher stability in training an agent for different action-delays. For example, by increasing the delays from 5 seconds to 10 seconds, the performance of the original method in terms of improving the displacement response is dropped from 3.4% to 0.41%, which implies 87% performance reduction, while the performance of the enhanced method is reduced from 30.2% to 28.2% which indicates only 7% reduction in performance.

In order to better study the performance of both algorithms in case of experiencing long action-effects delays, the average reward values over the training episodes are presented in Figure 4. As it is shown, the agent achieves a much better performance within less training episodes when it uses the enhanced method for learning the Q-values.

Table 5: Seismic responses of the fame when the delay is 10 seconds (Dis. = Displacement (cm), Vel. = Velocity (m/s), Acc. = Acceleration (m/s²)).

| Learning method | Uncontrol. | Controlled | Improvement |
|-----------------|------------|------------|-------------|
| Original method | Peak Dis. 4.39 | 4.37 | 0.41% |
|                 | Peak Vel. 0.91 | 0.89 | 1.81% |
|                 | Peak Acc. 22.93 | 22.31 | 2.70% |
| Enhanced method | Peak Dis. 4.39 | 3.15 | 28.2% |
|                 | Peak Vel. 0.91 | 0.66 | 26.9% |
|                 | Peak Acc. 22.93 | 17.65 | 23.0% |
8 Conclusions

An enhanced Q-learning method is proposed in which the agent creates a $\gamma$ - function based on the environment’s response to a single action at the beginning of the learning phase, and uses that to update the Q-values in each state. The experimental results showed that the enhanced algorithm significantly improved the performance and stability of the learning algorithm in dealing with action-effect delays.

Considering the obtained results, the following conclusions are drawn:

1. The enhanced method has significantly improved the performance of the original method in all scenarios with different action-effect delays. Even without having any action-effect delays.
2. Increasing such delays results in a drop in the performance of the original method while the enhanced method has shown a stable performance with a small decrease in its performance.
3. It should be mentioned that in the developed method, the $\gamma$ - function remains constant during the training phase, which implies that the enhanced method is appropriate for environments with a static behavioral response to the agent’s actions.

In future work, it would be interesting to study the performance of the enhanced RL algorithm in more complex simulations using larger structures. We would also like to use the finite response reward filter for other problems in which there are delays in the effects of actions.
Figure 5: Uncontrolled/controlled roof displacement response of the frame when the controller was trained using the original method and enhanced method.

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