

Article

Active Vibration Control of a Cantilever Beam Structure Using Pure Deep Learning and PID with Deep Learning-Based Tuning

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Abstract: Vibration is a major problem that can cause structures to wear out prematurely and even fail. Smart structures are a promising solution to this problem because they can be equipped with actuators, sensors, and controllers to reduce or eliminate vibration. The primary objective of this paper is to explore and compare two deep learning-based approaches for vibration control in cantilever beams. The first approach involves the direct application of deep learning techniques, specifically multi-layer neural networks and RNNs, to control the beam's dynamic behavior. The second approach integrates deep learning into the tuning process of a PID controller, optimizing its parameters for improved control performance. To activate the structure, two different input signals are used, an impulse signal at time zero and a random one. Through this comparative analysis, the paper aims to evaluate the effectiveness, strengths, and limitations of each method, offering insights into their potential applications in the field of smart structure control.

Keywords: smart structure; cantilever beam; piezoelectric transducers (PZTs); deep learning (DL); neural network (NN); recurrent neural networks (RNNs); long short-term memory (LSTM); proportional–integral–derivative (PID) controller; tuning PID controller; Genetic Algorithm (GA)



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1. Introduction

Cantilever beams are a fundamental element in structural engineering, widely used in various applications, including civil engineering structures, aircraft, and machinery. These beams, fixed at one end and free at the other, are prone to vibrations when subjected to external forces. Such vibrations can lead to structural fatigue and failure if not adequately controlled. To address this, smart materials like piezoelectric transducers (PZTs) are employed as sensors and actuators to monitor and mitigate vibrations. PZT materials have the ability to convert mechanical energy into electrical energy and vice versa, making them ideal for vibration control in smart structures.

A smart structure is a structural system that can sense and respond to its environment. It is typically made up of a conventional structure (such as a beam, plate, or shell) with embedded sensors and actuators. The sensors measure the state of the structure, such as its strain or displacement. The actuators then take action to control the structure's response, such as by changing its shape or stiffness.

Piezoelectric zirconate titanate (PZT) materials are a type of smart material that can be used to make sensors and actuators for smart structures. They generate an electric charge when they are deformed, while deformed when an electric field is applied to them [1]. This property makes them ideal for sensing and controlling the vibrations of structures. Engineering structures can be made vibration-free by using these smart materials. Engineering applications for piezoelectric smart structures are quite promising [2].

Vibration is a widespread problem in many engineering structures, such as buildings and bridges. It can cause damage to the structure, reduce its lifespan, and make it uncomfortable or even dangerous to use. Structural vibration control has always received a lot of research interest from the civil and control engineering community [2]. Several studies have been conducted to control and reduce the vibration of structures, and various control technologies have been tested and applied to solve this issue. Piezoelectric made of lead zirconate titanate (PZT) is a type of smart material that can be used to control vibrations in structures. PZTs produce an electric charge when they are deformed, or conversely, deform when an electric field is applied to them [3]. This property can be used to generate forces or moments that can be used to counteract the vibrations of a structure.

The application of deep learning to control systems has gained significant traction, offering new methods for enhancing the precision and adaptability of these systems. In the domain of vibration control for cantilever beams, deep learning techniques such as multi-layer neural networks and Recurrent Neural Networks (RNNs) present promising alternatives to traditional control strategies. These methods are highly effective at detecting complex patterns in data, which can lead to more accurate and efficient control of smart structures. The ability of deep learning models to refine control strategies beyond what is possible with conventional methods positions them as a cutting-edge solution in this domain.

Proportional–integral–derivative (PID) controllers have long been the industry standard for control systems due to their straightforward design and proven effectiveness. However, the challenge of tuning PID controllers to consistently achieve optimal performance across diverse operating conditions remains a significant limitation. Traditional tuning techniques, though widely used, may not fully exploit the capabilities of PID controllers, particularly in complex and variable environments. The integration of deep learning into the PID tuning process offers a novel solution to this challenge. By employing multi-layer neural networks, the PID parameters—proportional, integral, and derivative gains—can be optimized, resulting in a more responsive and effective control system. This hybrid approach, which combines the established robustness of PID control with the innovative adaptability of deep learning, represents a significant advancement in the field of vibration control for cantilever beams.

There have been many studies on the use of PZTs to control the vibration of structures. Studies have investigated the use of PZTs to control the vibration of cantilever beams subjected to a variety of excitations, including random excitation, impact excitation, and parametric excitation [4]. These studies have shown that PZTs can be effective in suppressing vibrations under a wide range of conditions. In addition to the location of the PZTs, the type of controller used also affects the effectiveness of vibration control.

Several different controllers have been used in studies of PZT-based vibration control, including linear controllers, nonlinear controllers, and intelligent controllers. In one of the recent studies, the analytical vibration models of a damped cantilevered beam under a PID controller have been discussed. The beam damping coefficient and integration of the voltage limit for the PZT actuator were considered by the model.

According to analytical results, the PID controller effectively suppresses vibration, and implementing the actuator voltage limit results in a rapid reduction in vibration [5].

A piezoelectric layered smart plate was used to test the developed control techniques under varied conditions. Based on the first-order shear deformation (FOSD) hypothesis, an electro-mechanically coupled finite element (FE) model of smart structures was built to design a suitable controller for the vibration suppression of thin-walled smart structures when considering the vibrations caused by various disturbances, which include both free and forced vibrations, and a PID control was utilized to dampen both the forced and free vibrations [6,7].

In another study, a fuzzy logic controller was used for a smart cantilever beam for active vibration control. The smart cantilever beam experiences an impact force at the free end of the beam, which causes it to vibrate. The piezoelectric sensor layer generates a sensor

voltage as a result of these disturbances, which the fuzzy logic controller uses as an input. Using 49 if–then rules, a fuzzy logic controller determined the actuator voltage. When this voltage is delivered to the piezoelectric actuator layer, the smart structure responds by producing a control force. Three diverse types of piezoelectric materials were utilized for active vibration control [8,9].

Also, an adaptive controller has been applied to the vibration control in many structures. For example, an adaptive robust sliding mode vibration control (SRVC) scheme for a flexible beam used a piezoceramic sensor and actuator. The controller is designed to be robust to uncertainties in the system parameters and external disturbances. The controller can adjust its parameters automatically in response to changes in the system. The implementation of the controller on a flexible beam with a piezoceramic sensor and actuator results in reducing the vibration. The experiments show that the SRVC controller can effectively suppress the vibration of the beam under the influence of uncertainties and disturbances [10].

The main contribution of this paper is to explore and compare two deep learning-based approaches for vibration control in cantilever beams.

- a. The first approach involves the direct application of deep learning techniques, specifically multi-layer neural networks and RNNs, to control the beam’s dynamic behavior.
- b. The second approach, which is not reported yet in the literature, integrates deep learning into the tuning process of a PID controller, optimizing its parameters for improved control performance.

To activate the structure, two different input signals are used, an impulse signal at time zero and a random one. Through this comparative analysis, the paper aims to evaluate the effectiveness, strengths, and limitations of each method, offering insights into their potential applications in the field of smart structure control.

The paper is organized as follows. Section 2 gives a brief description of smart materials, while Section 3 summarizes the mathematical modeling of the beam’s dynamic system. The system design of the cantilever beam is given in Section 4, while Section 5 summarizes the dataset generation via the Genetic Algorithm. The deep learning approach for vibration control leverages a Recurrent Neural Network (RNN) specifically with long short-term memory (LSTM) cells described in Section 6 with some simulation results using deep learning (DL) control alone. Section 7 presents the simulation results when applying the proportional–integral–derivative (PID) controller enhanced with deep learning (DL) technique. The comparative analysis is reported in Sections 8 and 9 concludes the work.

2. Basics of Smart Materials

Smart materials are materials that can change their properties, electrical and/or mechanical characteristics, or even their functionality in response to external stimuli, such as stress, electricity, or magnetic field. This makes them different from conventional materials, which have fixed properties. Smart materials are often implanted into systems whose fundamental properties can be advantageously adjusted to adapt to performance needs. According to Takagi’s definition of smart materials, they respond to numerous environmental changes in the best possible ways and perform as intended [11]. The “stimulus” and “response” that go along with the prevalent use of smart materials as actuators and sensors are shown in Table 1.

Civil engineers are becoming increasingly engaged in smart materials because of the expanding tendency toward building more environmentally friendly structures with higher structural performance. Smart materials can provide features like fast response, self-actuation, flexibility, self-monitoring, and self-healing, and these features are the major benefits of smart material actuators and required conditions. They can determine the nature and extent of any problem; act appropriately to solve the problem; and, finally, store the processes in memory and learn to use the information gathered by sensors [12].

Table 1. Sensor and Actuator Material Classes.

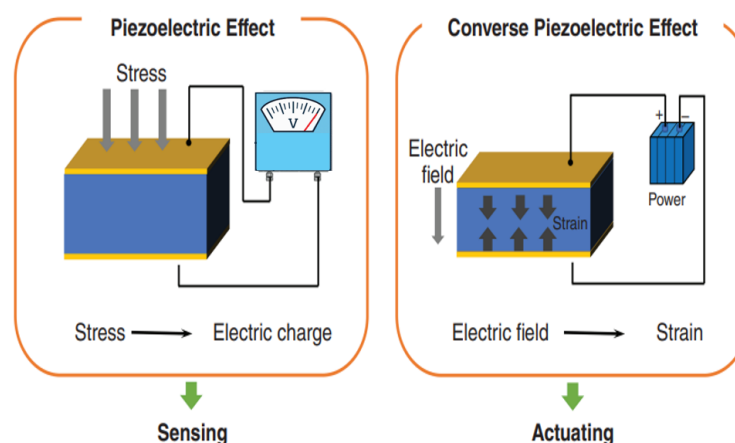
	Material Class	Stimulus	Response
Sensors	Pyroelectric	Temperature Change	Electric Polarization
	Piezoelectrics	Mechanical Strain	Electric Polarization
	Electrostrictors	Mechanical Strain	Electric Polarization
	Magnetostrictors	Mechanical Strain	Change in Magnetic Field
	Electroactive Polymers	Mechanical Strain	Electric Polarization
	Electroluminescent	Electric Field	Light Emission
	Photoluminescent	Incident Light	Light Emission
	Electrochromic	Electric Field	Color Change
Actuators	Piezoelectrics	Electric Current	Mechanical Strain
	Electrochromic	Electric Current	Mechanical Strain
	Magnetostrictors	Magnetic Field	Mechanical Strain
	Shape Memory Alloys	Temperature Change	Mechanical Strain
	Electroactive Polymers	Electric Field	Mechanical Strain
	Electrorheological Fluids	Electric Field	Viscosity Change
	Magnetorheological Fluids	Magnetic Field	Viscosity Change

Thus, smart structures can detect and react to external disturbances in real time with active control, serving as a foundation in the future [13].

The sensory structure has sensors but no actuators to keep track of the structure's condition. While the adaptive architecture does not have sensors, it contains actuators, which allow for controlled changes in the system states. To efficiently regulate the states of the system, the sensors and actuators are integrated into a closed loop system, which results in controlled architecture, which combines sensory and adaptive architecture. A controlled structure with integrated sensors and actuators that carry out structure and control functions is known as an active structure. Smart architecture is an active architecture with distributed actuators and sensors as well as highly integrated control logic and electronics.

Piezoelectric Materials

One of the most common smart materials is piezoelectric material. Only non-conductive materials exhibit the piezoelectric material effect [14]. The piezoelectric effect explains how mechanical stress and electrical voltage interact in solids. When some non-conducting materials are under mechanical stress, they can produce electric charges on their surfaces. Alternatively, when certain materials are subjected to an electric field, they can produce a mechanical strain, known as the piezoelectric effect or piezoelectricity [3]. Figure 1 illustrates this effect schematically.

**Figure 1.** The Piezoelectric Effect.

3. Modeling of the Beam

Modeling of the beam's dynamic system was carried out by Shawn Le [15]. A state model of a flexible aluminum cantilever beam with a pair of PZT actuators and a single PZT sensor was built based on the Euler–Bernoulli beam theory.

3.1. Euler–Bernoulli Beam Theory

The Euler–Bernoulli beam theory is the linear theory of beam elasticity, providing a method for estimating the load-carrying and deflection properties of beams [16]. The Bernoulli–Euler beam theory is based on two key assumptions, and in most situations, these assumptions yield answers that are “good enough” for design. As illustrated in Figure 2, the two fundamental assumptions are that “plane sections remain plane” and “deformed beam angles (slopes) are small” [13].

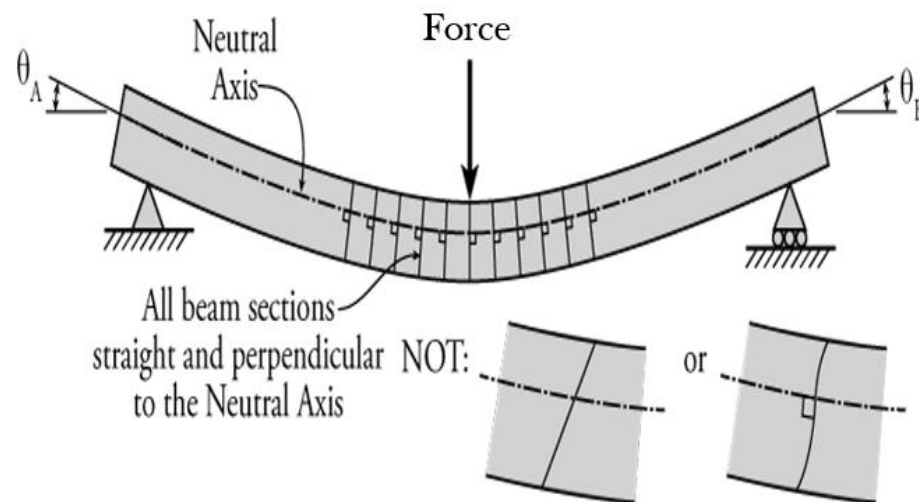


Figure 2. Assumption that the Plane Sections Remain Plane.

3.2. Dynamic Modeling of the Beam

Figure 3 shows a piezoelectric cantilever beam. At one end, the beam is fixed, whereas at the other, it is free. As indicated in Figure 3, two piezoelectric actuator patches and one piezoelectric sensor are utilized. The beam's dynamic modeling is the transfer function relating the input voltage of the actuator to the voltage induced by the piezoelectric sensor. The beam's dynamic model is shown in the following Equations [15].

A model of the structure is obtained through a modal analysis procedure. This approach finds a solution to the partial differential equation describing the dynamics of the flexible structure [17]:

$$\rho_b A_b \frac{\partial^2 w}{\partial t^2} + E_b I_b \frac{\partial^4 w}{\partial x^4} = M_a \frac{\partial^2 R(x)}{\partial x^2} \quad (1)$$

where

ρ_b is the mass density of the beam sensor material;

A_b is the cross-sectional beam sensor area;

E_b is the Young's Modulus of the beam sensor;

I_b is the first moment of inertia, $I_b = \frac{b_a h_b^3}{3}$;

h_b is the thickness of the beam sensor;

b_a is the width of the beam sensor;

W is the beam transverse displacement;

M_a is the bending moment acting on the beam;

$R(x)$ is $H(x - x_{a1}) - H(x - x_{a2})$;

R is the generalized location function;

H is the Heaviside function;

x_{a1} and x_{a2} are the locations of the actuators.

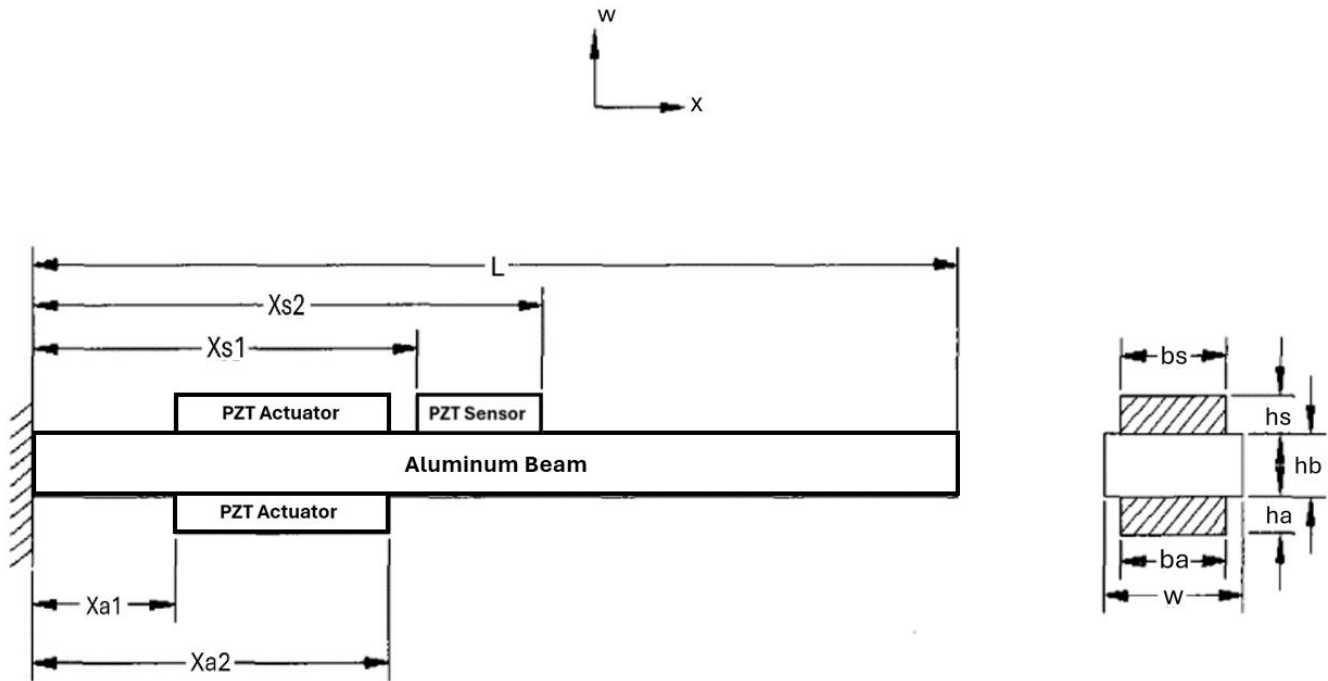


Figure 3. Cantilever Beam with Two PZT Actuators and Sensor.

The equation of the beam actuator dynamics system is:

$$\ddot{\eta}_i(t) + 2\xi_i\omega_{ni}\dot{\eta}_i(t) + \omega_{ni}^2\eta_i(t) = k_a[\phi'_i(x_{a2}) - \phi'_i(x_{a1})]V_a(t) \quad (2)$$

where

$\eta_i(t)$ represents the temporal functions;

ξ_i is damping;

ω_{ni} is the natural frequency.

$$k_a = \frac{\frac{1}{2}E_a d_{31} b_a (h_b + h_a)}{\rho_a A_a}$$

where

E_a is the Young's Modulus of the beam actuator;

d_{31} is the electric charge constant;

b_a is the width of the actuator;

h_a is the thickness of the actuator;

ρ_a is the mass density of the beam actuator material;

A_a is the cross-sectional beam actuator area;

ϕ_i is the mode shape;

$V_a(t)$ is the actuator voltage;

$(\cdot)$ denotes the time derivative and $(')$ denotes the space derivative.

Taking the Laplace transform of the beam sensor dynamics system gives:

$$V_s(s) = k_s \sum_{i=1}^N \frac{[\dot{\phi}_i(x_{s2}) - \dot{\phi}_i(x_{s1})]}{C_s b_s (x_{s2} - x_{s1})} \quad (3)$$

The expression for $V_s(s)$ in terms of the input voltage $V_a(s)$ gives:

$$\frac{V_s(s)}{V_a(s)} = \sum_{i=1}^N \frac{k_s k_a [\dot{\phi}_i(x_{s2}) - \dot{\phi}_i(x_{s1})] [\dot{\phi}_i(x_{a2}) - \dot{\phi}_i(x_{a1})]}{C_s b_s (x_{s2} - x_{s1}) (s^2 + 2\xi_i \omega_{ni} s + \omega_{ni}^2)} \quad (4)$$

3.3. Parameter Analysis of the PZT Cantilever Beam System

Tables 2 and 3 show the parameters of the aluminum cantilever beam and details regarding the properties and locations of the PZT (Lead Zirconate Titanate) actuators and sensors within the beam system, respectively, as sourced from [13]. These parameters and properties are essential for understanding the dynamic behavior and actuation/sensing capabilities of the beam system.

Table 2. Parameters of Aluminum 6064 Beam.

Properties	Units	Beam
E (Young Modulus)	lb/in ²	1.09×10^7
ρ (density)	lb/in ³	0.0975
w (width)	In	0.6
t (thickness)	In	0.05
l (Length)	In	11.8

Table 3. Parameters of PZT PSI-4A4E.

Properties	Units	Sensor	Actuator
d_{31}	m/V	-1.90×10^{-10}	-1.90×10^{-10}
g_{31}	Vm/N	-1.16×10^{-2}	-1.16×10^{-2}
k_{31}		0.35	0.35
b_a (Width)	in	0.4	0.4
t (Thickness)	in	0.0105	0.0105
L (Length)	in	0.5	1
x_1 (Location on Beam)	in	1.5	0
x_2 (Location on Beam)	in	2	1

In this work, we investigated the dynamic characteristics of a flexible beam, aiming to understand its behavior under different conditions. The resulting model was constructed based on three modes of shape, which illustrate various ways the beam can bend or vibrate. Moreover, we integrated experimental data from [15] regarding the beam's natural vibration frequencies, which were determined to be 95.3618 Hz for mode 1, 597.5569 Hz for mode 2, and 1714 Hz for mode 3. Additionally, the damping coefficient was found to be 0.01. These pivotal experimental findings played a significant role in shaping our model development and subsequent analysis.

This study aims to understand the vibrational behavior of a cantilever beam with three modes of shape and analyze the collective influence of these modes on the beam system. First, we will derive the transfer function for each of the first three modes of shape and subsequently combine them to represent the beam's overall dynamic behavior. We substitute the experimental values into Equation (4) to get the following:

Transfer function of first mode shape:

$$\frac{V_{s1}(s)}{V_{a1}(s)} = \frac{-2.944}{s^2 + 1.95s + 9506} \quad (5)$$

Transfer function of second mode shape:

$$\frac{V_{s2}(s)}{V_{a2}(s)} = \frac{-37.11}{s^2 + 11.79s + 3.475e5} \quad (6)$$

Transfer function of third mode shape:

$$\frac{V_{s3}(s)}{V_{a3}(s)} = \frac{80.56}{s^2 + 32.56s + 2.651e6} \quad (7)$$

Now, we combine the individual transfer functions obtained by summing them, providing insights into the integrated dynamic behavior of the beam.

$$\frac{V_s(s)}{V_a(s)} = \frac{40.51 s^4 - 304.5 s^3 - 7.88e7 s^2 - 2.65e8 s - 3.381e12}{s^6 + 46.3 s^5 + 3.008e6 s^4 + 4.884e7 s^3 + 9.498e11 s^2 + 2.201e12 s + 8.757e15} \quad (8)$$

4. Cantilever Beam System Design

The system uses a step function with a final value of zero as the reference input, indicating the desired steady-state position where no residual vibration remains. The system is subjected to two types of disturbances: an impulse disturbance and a random disturbance modeled by a Gaussian distribution.

The impulse disturbance is applied at $t = 0$, representing a sudden force that excites the beam, inducing immediate vibrations that propagate through the entire system, affecting its dynamics from the onset. The random disturbance, following a Gaussian distribution, simulates continuous and unpredictable environmental forces affecting the system over time. Both disturbances introduce significant forces, causing high levels of vibration in the cantilever beam. The system's response is observed through the voltage generated by the piezoelectric sensor, which captures the beam's oscillations and serves as the output signal for control and analysis.

A low-pass filter is integrated into the system to enhance stability by filtering out high-frequency noise and disturbances while preserving critical low-frequency signals. The block diagram of the open-loop system with a low-pass filter under disturbance is shown in Figure 4. The cutoff frequency, $f_c = 11$ Hz, was selected based on system output analysis to eliminate irrelevant signals while retaining essential information. This frequency results in a time constant T , which determines the rate at which the filter responds to changes in input. The time constant T is calculated using the formula:

$$T = \frac{1}{2\pi f_c}$$

where f_c is the chosen cutoff frequency. Substituting $f_c = 11$ Hz yields a time constant of approximately 0.0144 s.

The filter's behavior is described by the transfer function:

$$H(s) = \frac{1}{1 + sT}$$

where $H(s)$ represents the filter's output-to-input ratio as a function of the complex frequency variable s , and T is the time constant. This transfer function ensures that frequencies higher than the cutoff are attenuated while lower frequencies pass through with minimal distortion. Incorporating the low-pass filter improves system performance by ensuring smoother responses, reducing noise, and maintaining signal fidelity, which is essential for effective vibration control under both impulse and random disturbance conditions.

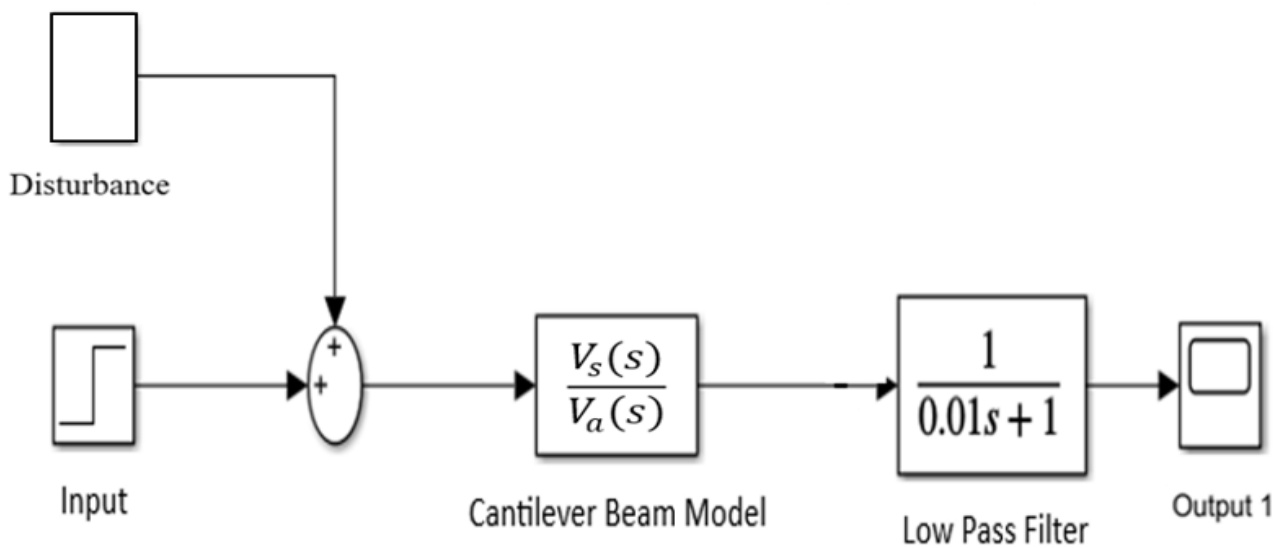


Figure 4. Block Diagram of Open Loop System with Low-Pass Filter under Disturbance.

5. Dataset Generation Using Genetic Algorithm

The Genetic Algorithm (GA) was employed to tune the PID parameters. The GA explores different combinations of proportional, integral, and derivative gains in PID tuning to find the set that minimizes the Integral Time Absolute Error (ITAE) after starting with random values for the PID parameters. The ITAE criterion is a performance measure that considers both the magnitude and duration of the error over time, defined as:

$$ITAE = \int_0^{\infty} t \cdot |e(t)| dt$$

where $e(t)$ is the error at time t .

The GA algorithm iteratively searches for the optimal PID parameters that minimize this criterion. For our study, we used 50 generations and a population size of 100, with the default selection, crossover, and mutation functions. Figure 5 illustrates the data generation process flowchart.

The process was repeated two thousand times with varying disturbances to generate the dataset. At each iteration, the previous input ($N - 1$), current input (N), previous disturbance ($N - 1$), current disturbance (N), previous output ($N - 1$), current output (N), error, and PID parameters (K_p , K_i , and K_d) were recorded. The dataset is divided into training (70%), validation (20%), and testing (10%) sets. The Levenberg–Marquardt backpropagation algorithm is chosen as the training function, and the mean squared error loss function used for the evaluation. This dataset will train the pure deep learning controller by analyzing the input and output signals to capture their relationship, enabling the prediction of the required control signal. For PID tuning with deep learning, the deep neural network will use the previous input ($N - 1$), current input (N), previous disturbance ($N - 1$), current disturbance (N), previous output ($N - 1$), and current output (N) as inputs, with the PID parameters (K_p , K_i , and K_d) as outputs.

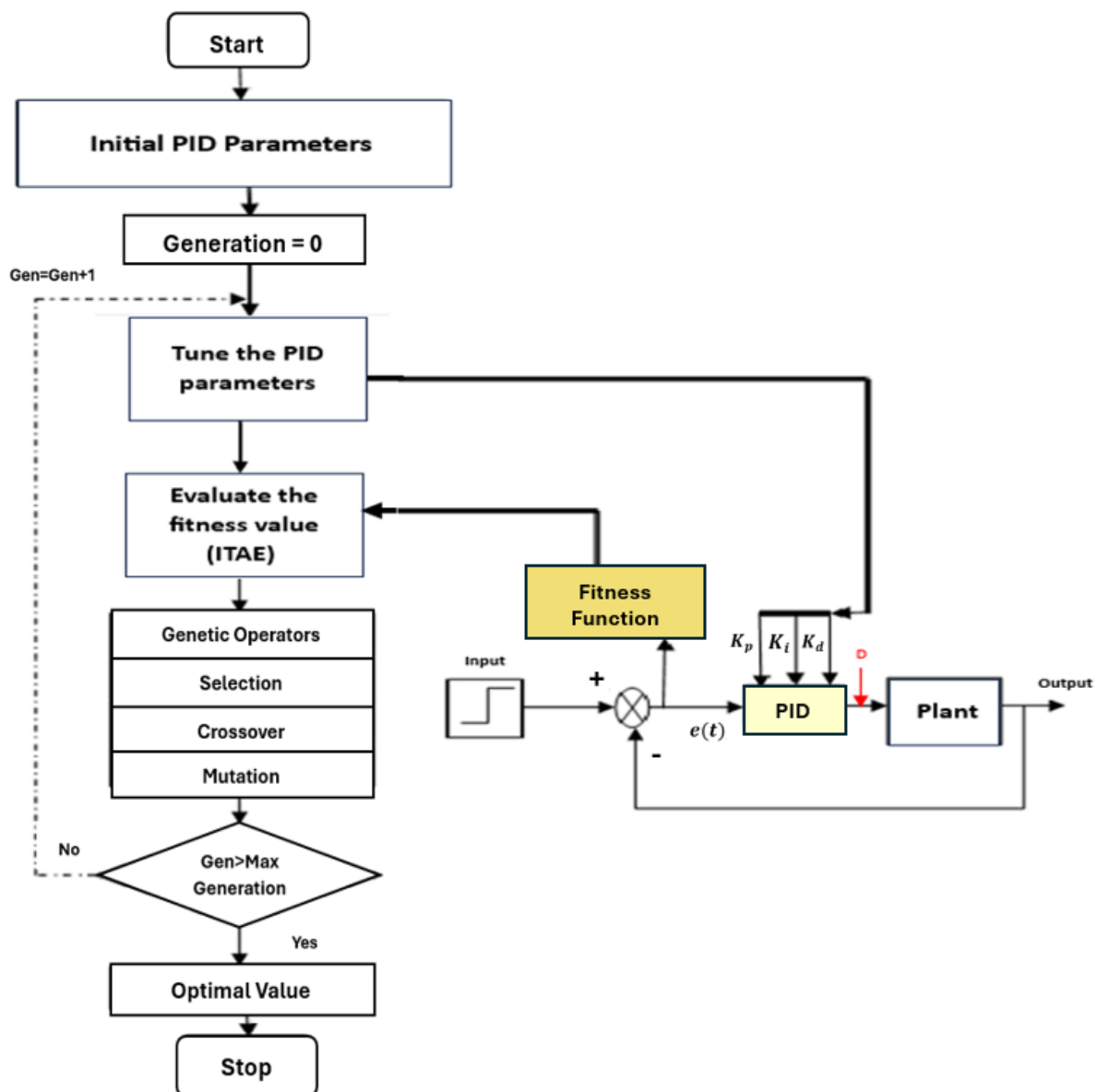


Figure 5. Genetic Algorithm-Based PID Tuning Process Flowchart.

6. RNN with LSTM for Vibration Control

Firstly, our deep learning approach for vibration control leverages a Recurrent Neural Network (RNN) specifically with long short-term memory (LSTM) cells. This selection is driven by the inherent sequential nature of the data we are dealing with. Each data point is influenced by the ones before it, creating a temporal dependency that traditional control methods struggle to capture. RNNs excel at handling such sequential data by processing them step-by-step and incorporating past knowledge into their current output [18].

Furthermore, effective control strategies often rely on considering past events that can have lingering effects. LSTM addresses this challenge. As a special type of RNN, LSTM is designed to capture long-term dependencies within the data [18,19]. It has internal mechanisms that allow it to learn and remember information over extended periods, making it well-suited to our control strategy. Figure 6 illustrates the process of creating an RNN with LSTM and demonstrates its capability to manage long sequence input.

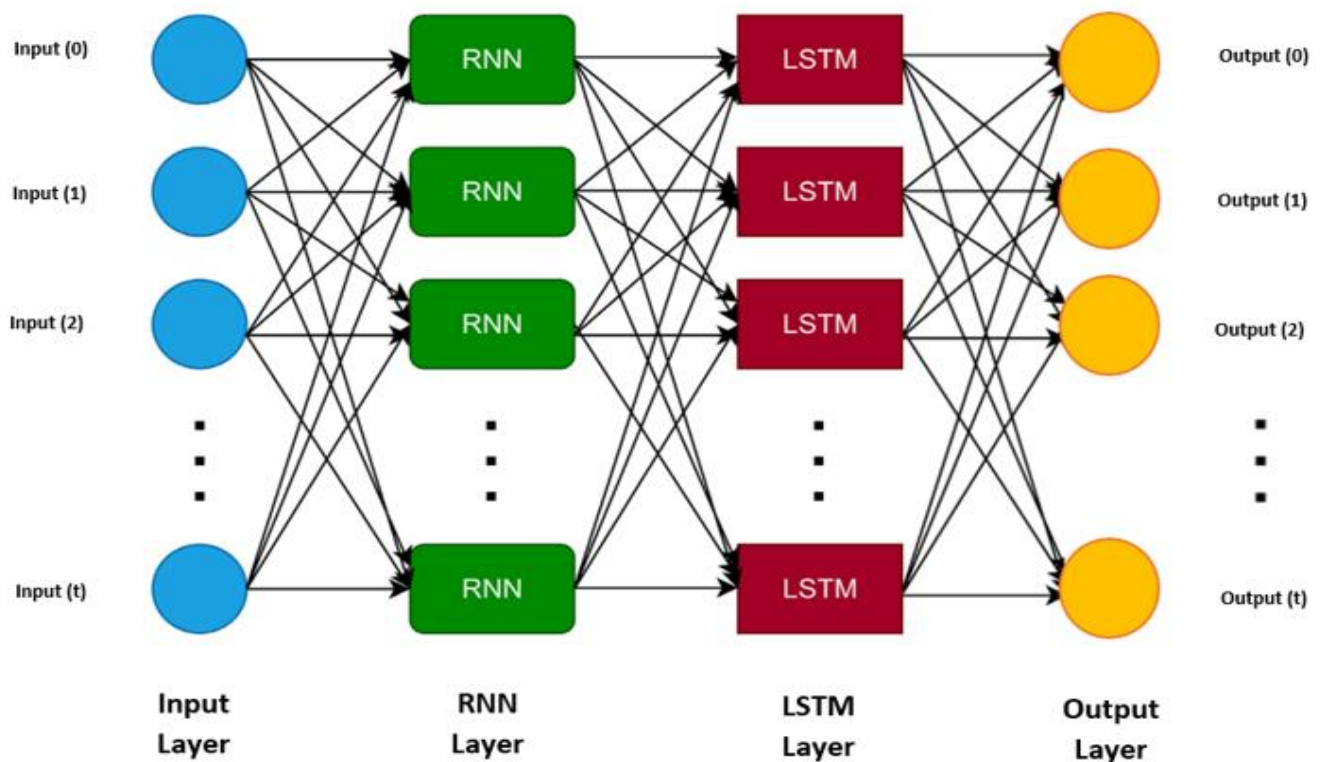


Figure 6. Recurrent Neural Network with Long Short-Term Memory.

6.1. Deep Learning Design

The deep learning (DL) RRN LSTM controller was designed to manage the vibration of the cantilever beam, relying on data generated from sensor measurements. Its architecture comprised RNN layers featuring long short-term memory (LSTM) cells. The controller's input entailed time-series data reflecting vibration measurements from the sensor attached to the beam, while its output consisted of control signals applied to the actuator for vibration suppression.

The vibration dataset with a size of 1000 samples was generated from the relation between the PZT sensor and actuator which is used for training and performance evaluation. Various vibration scenarios were simulated, incorporating both impulse and random disturbances.

Throughout the training process, the Adam optimizer was employed to minimize the mean squared error (MSE) between the predicted and actual control signals. The controller was trained across multiple epochs, with a batch size of 500. Figure 7 shows the closed loop of the system with the deep learning controller.

After designing the deep learning controller, our next step involves evaluating its effectiveness in controlling cantilever beam vibrations under varying conditions. To achieve this, we will evaluate its performance in mitigating vibrations caused by both impulse disturbance and continuous random disturbance, each tested individually.

6.2. System Vibration Control Under Impulse and Random Disturbances

This section explores the application of deep learning techniques for controlling vibrations in systems subjected to impulse and random disturbances. The impulse disturbance is applied at 0 s to introduce a sudden, high-intensity force, such as a shock or impact, allowing the full effect of the disturbance on the system to be observed from the initial moment. This tests the controller's ability to stabilize the system immediately after the disturbance. In contrast, random disturbances act continuously over time, representing unpredictable forces such as environmental noise. The study examines how the deep learning model predicts the optimal control signal to enhance system response. By leveraging

these advanced algorithms, the research provides robust solutions for vibration mitigation, improving overall system stability and performance across various operational scenarios.

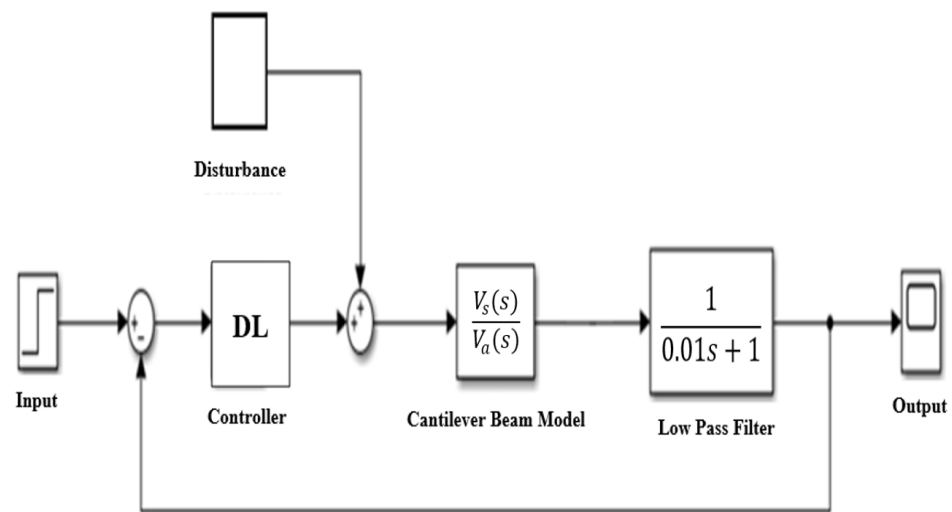


Figure 7. Closed Loop System with Deep Learning Controller under Disturbance.

6.2.1. Control System Affected by Impulse Disturbance

In the scenario where an impulse disturbance occurs at 0 s, the system's behavior is analyzed to assess its immediate response. The reference input is set to 0 V to represent an equilibrium level, indicating that the system is stable before the disturbance is introduced. Figure 8 shows the behavior of the system after the disturbance has occurred.

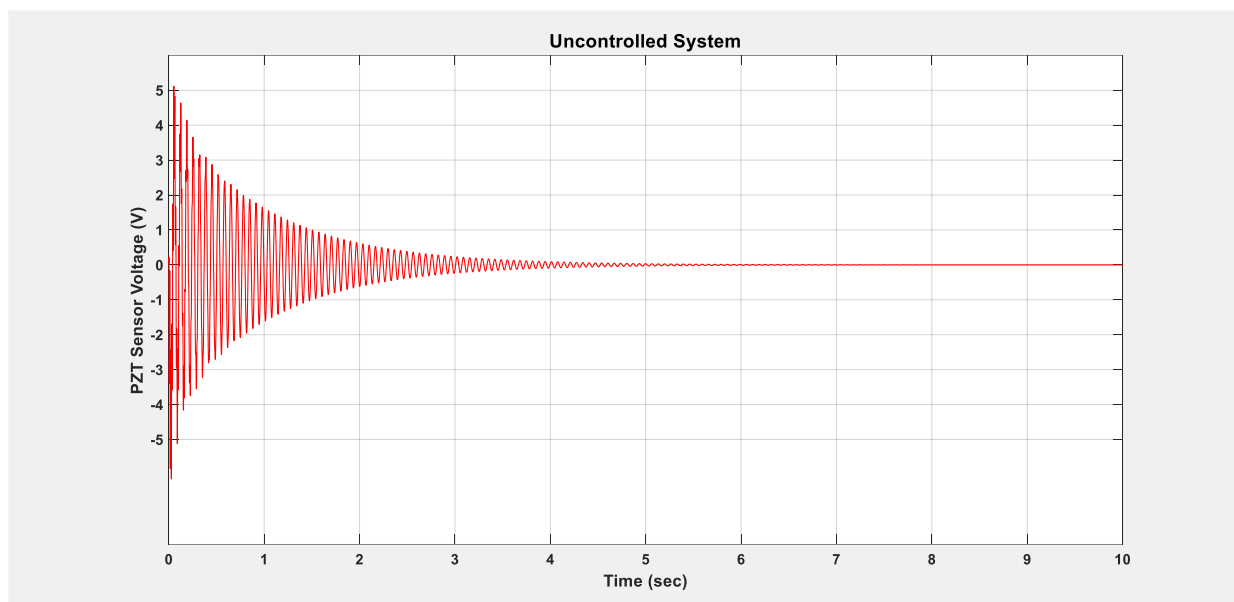


Figure 8. Voltage Response of PZT Sensor before Vibration Control (under Impulse Disturbance).

The trained recurrent neural network processes the uncontrolled system output under impulse disturbance conditions and predicts the appropriate control signal to reduce and mitigate the vibrations of the cantilever beam. By analyzing the relationship between the system output and input, the network generates an effective control response. As illustrated in Figure 8, the status of the beam is monitored, and based on this analysis, the network produces the control signal shown in Figure 9. This control signal is specifically designed

to counteract the detected disturbances and stabilize the beam's vibrations. Figure 10 illustrates the behavior of the system with the deep learning controller.

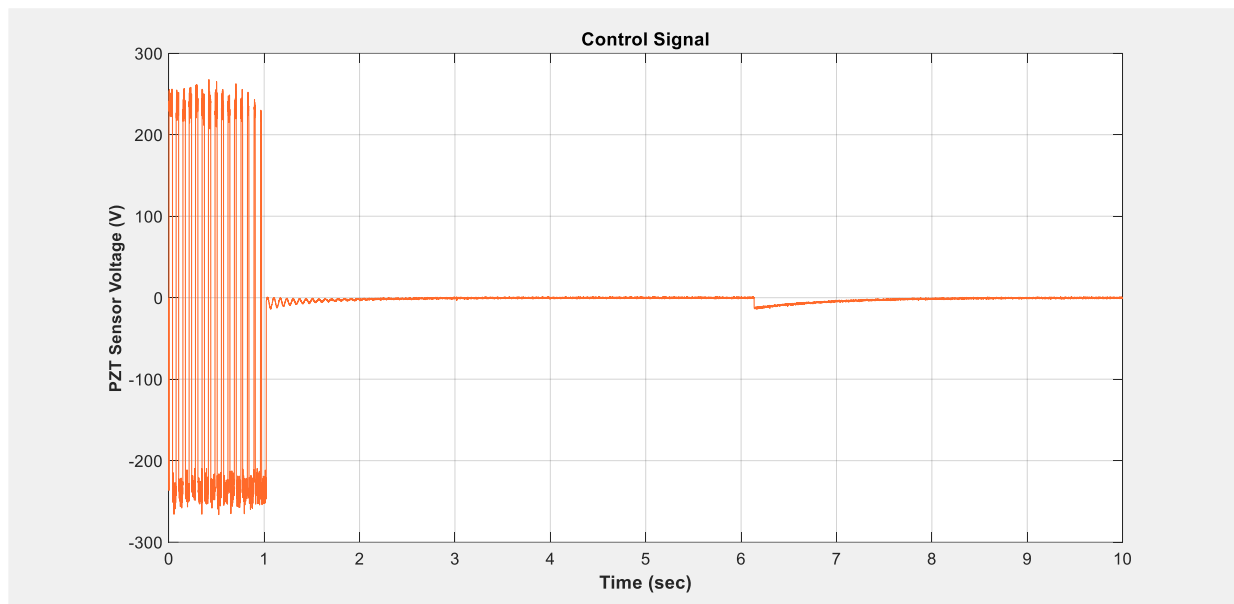


Figure 9. System Control Signal.

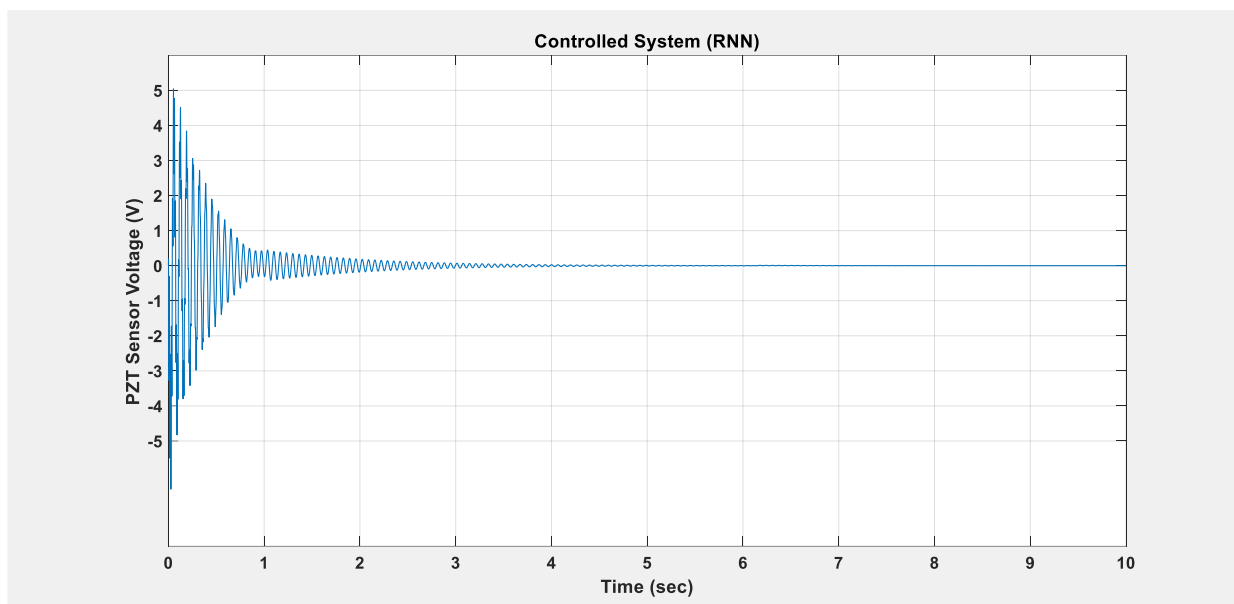


Figure 10. Voltage Response of PZT Sensor after Vibration Control with Deep Learning Controller (under Impulse Disturbance).

Figure 11 illustrates the difference in system performance before and after implementing the deep learning controller. The vibration of the beam is significantly reduced, especially in the first 3 s. The system achieves a settling time of 3.34 s. The Integral Time Absolute Error (ITAE) measures an exceptionally low value of 1.5818, indicating the system's efficiency in reducing both the magnitude and duration of error. Additionally, the mean squared error (MSE) is 5.9703×10^{-9} , underscoring the predictive precision of the controller.

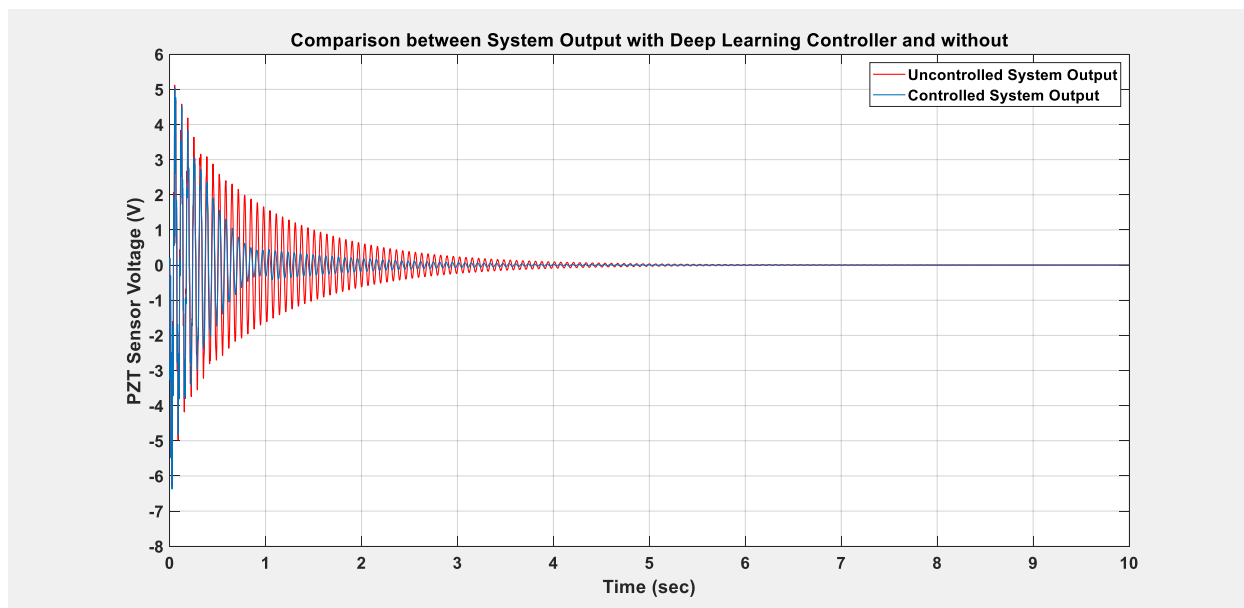


Figure 11. Voltage Response of PZT Sensor in the Cantilever with Deep Learning Controller and without Controller.

6.2.2. Control System Affected by Random Disturbance

The RNN will be employed to control the cantilever beam vibrations under the influence of continuous random disturbances. Figure 12 displays the random disturbance signal, representing the unpredictable external factors impacting the system's performance. Figure 13 shows the behavior of uncontrolled system output, showcasing its actual response in the absence of the controller amidst the presence of random disturbance.

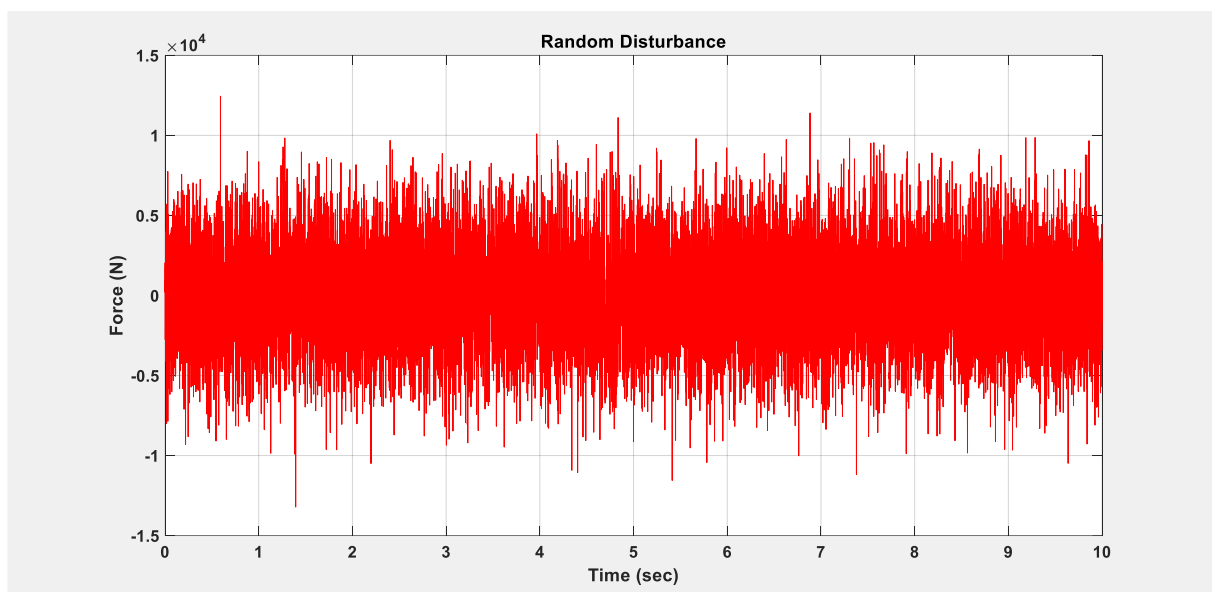


Figure 12. Random Disturbance.

The trained recurrent neural network processes the uncontrolled system output under random continuous disturbance conditions and produces the appropriate control signal to mitigate the vibrations of the cantilever beam. By continuously monitoring the behavior of the beam. The network analyzes the relationship between the system's output and the disturbances. Based on this analysis, it generates the control signal shown in Figure 14, designed to counteract the detected disturbances and reduce the beam's vibrations effectively.

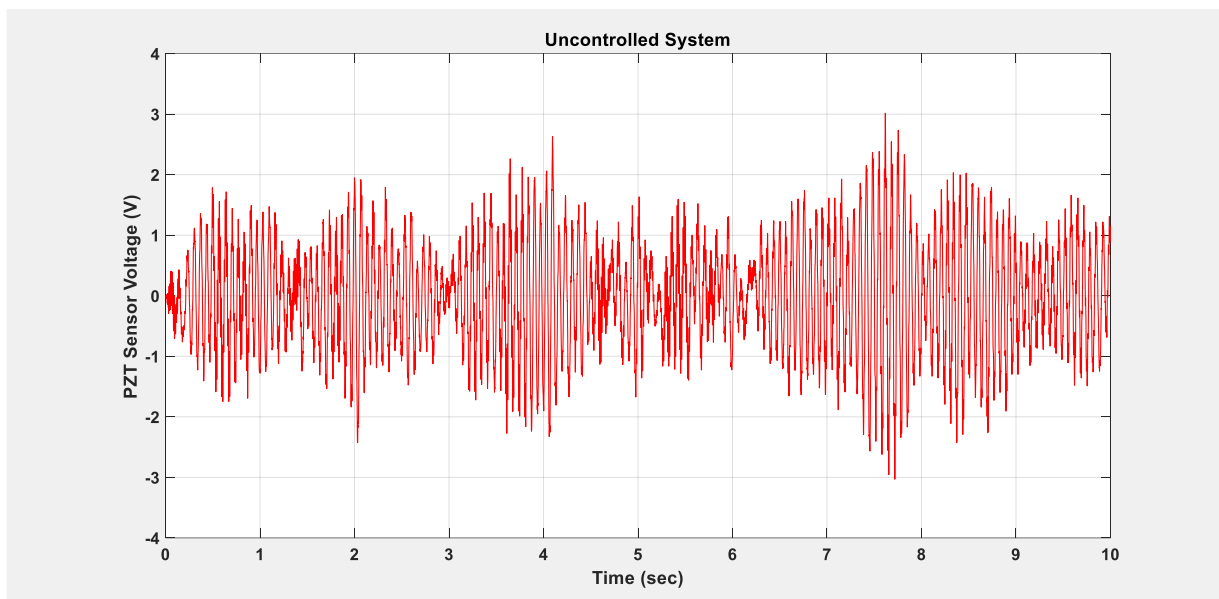


Figure 13. Voltage Response of PZT Sensor before Vibration Control (under Random Disturbance).

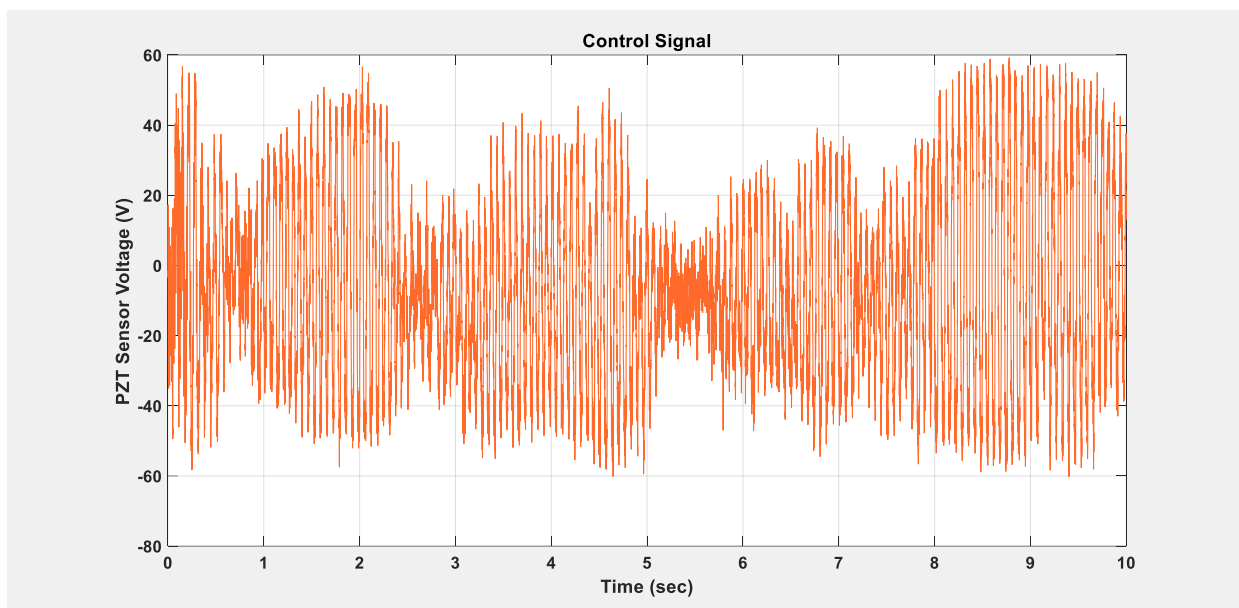


Figure 14. System Control Signal.

The generated control signal adapts to the varying conditions, ensuring that the vibrations are minimized. Figure 15 illustrates the improved behavior of the system with the deep learning controller applied, demonstrating its effectiveness in maintaining reduced vibration levels over time. This enhanced control performance highlights the network's capability to adjust and provide control signals in response to continuous disturbances.

Figure 16 illustrates the effectiveness of the deep learning (DL) controller in mitigating vibrations caused by continuous disturbances. The DL controller consistently adapts to the varying nature of the disturbances, effectively reducing vibrations with notable improvements in key areas. Despite the persistence of these disturbances, the controller ensures that the vibrations remain minimal, demonstrating its robustness and adaptability. The system achieves an Integral of Time-weighted Absolute Error (ITAE) of 6.4588 and a mean squared error (MSE) of 0.9690, highlighting the controller's precision and reliability in maintaining control under prolonged, dynamic conditions.

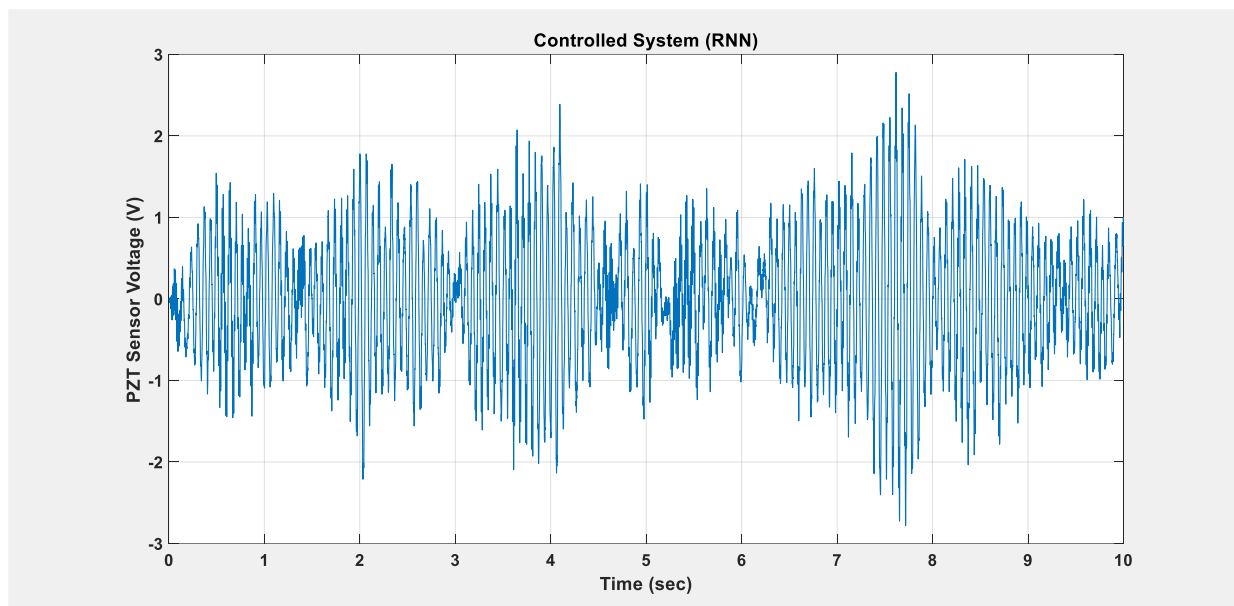


Figure 15. Voltage Response of PZT Sensor after Vibration Control with Deep Learning Controller (under Random Disturbance).

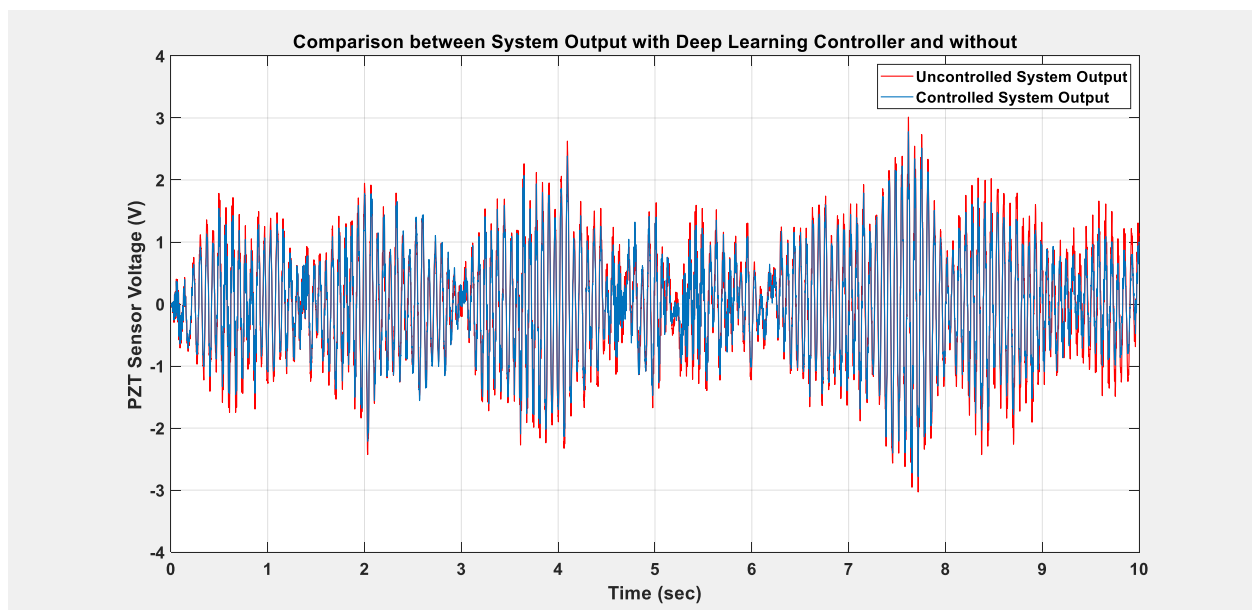


Figure 16. Voltage Response of PZT Sensor in the Cantilever Beam with Deep Learning Controller and without Controller.

7. Proportional—Integral—Derivative (PID) Controller Enhanced with Deep Learning (DL)

7.1. Overview of PID Control

The proportional—integral—derivative (PID) controller is one of the most widely used control strategies in engineering due to its simplicity and effectiveness in a broad range of applications [20]. It works by adjusting the control input based on three terms: the proportional term, which responds to the current error; the integral term, which accounts for the accumulation of past errors; and the derivative term, which anticipates future errors based on the rate of change [21]. This combination allows the PID controller to maintain stability and performance in systems, making it particularly useful in applications like vibration control, process control, and robotics.

However, the effectiveness of a PID controller heavily relies on tuning its parameters to suit the specific dynamics of the system being controlled. Tuning these parameters manually or through traditional methods can be time-consuming and may not result in optimal performance, especially in complex or dynamic environments. This is where deep learning techniques come into play, offering the potential to enhance PID control by automating the tuning process and improving overall system response.

7.2. Enhancing PID Control with Deep Learning

Deep learning provides a robust solution for enhancing the performance of PID controllers by automating the tuning of the controller's parameters. Through multi-layer neural networks, deep learning models learn to optimize the proportional, integral, and derivative gains in response to system data, ensuring that the PID controller achieves optimal performance without manual intervention (see [22] and the references therein). These models process input data, such as error signals or sensor readings, and adjust the PID parameters to improve control accuracy, minimize steady-state errors, and respond effectively to changing conditions.

By integrating deep learning into the PID tuning process, the controller gains adaptability, leading to enhanced performance in tasks like vibration management or other complex control scenarios. This adaptability allows the controller to automatically maintain optimal settings, ensuring efficiency and responsiveness even under varying operating conditions [22]. This hybrid approach yields a more precise and efficient control system, significantly reducing the effort involved in parameter tuning while enhancing overall system performance.

7.3. Design of Multi-Layer Deep Learning for PID Tuning

The design of the deep learning multi-layer network for tuning the PID controller is structured to consider several key inputs: the reference input, disturbance, output vibration, and error signal (see Figure 17). This architecture allows the network to analyze the overall system behavior and provide optimized PID parameters that reduce the cantilever beam vibration.



Figure 17. Closed Loop System with DL-PID Controller under Disturbance.

The reference input represents the desired state or target for the cantilever beam. The disturbance accounts for external forces or conditions that may disrupt the system's performance, such as impulse and random disturbances. The output vibration is monitored to track the actual behavior of the system under these disturbances, and the error signal is calculated as the difference between the reference input and the output vibration.

These inputs are fed into the deep learning model, which consists of multiple layers, including input, hidden, and output layers. The hidden layers in the network process the input data, learning the complex relationships between the reference, disturbances, vibrations, and error signals. By doing so, the model can predict the optimal proportional, integral, and derivative (PID) gains required to minimize the error and mitigate the effects of disturbances.

The network's output is the tuned PID parameters, which are adjusted to ensure that the system responds efficiently to changes in disturbances and maintains stability. This design allows the deep learning model to adapt the PID controller's performance, improving control accuracy and reducing the time and effort required for manual tuning. Through this multi-layer architecture, the deep learning network effectively enhances the traditional PID control system, enabling it to handle complex and varying conditions with greater precision.

Deep Learning Network Architecture for PID Controller Parameter Tuning

Figure 18 illustrates a deep learning network architecture designed to process input features and generate corresponding outputs through hidden layers. The network begins with an input layer that takes in seven features, which represents a combination of system states, sensor readings, disturbances, and error signals. These inputs provide the network with a comprehensive view of the system's operational conditions, ensuring that it has all the necessary information to make the prediction. These initial data are then passed into the network's hidden layers for further processing.

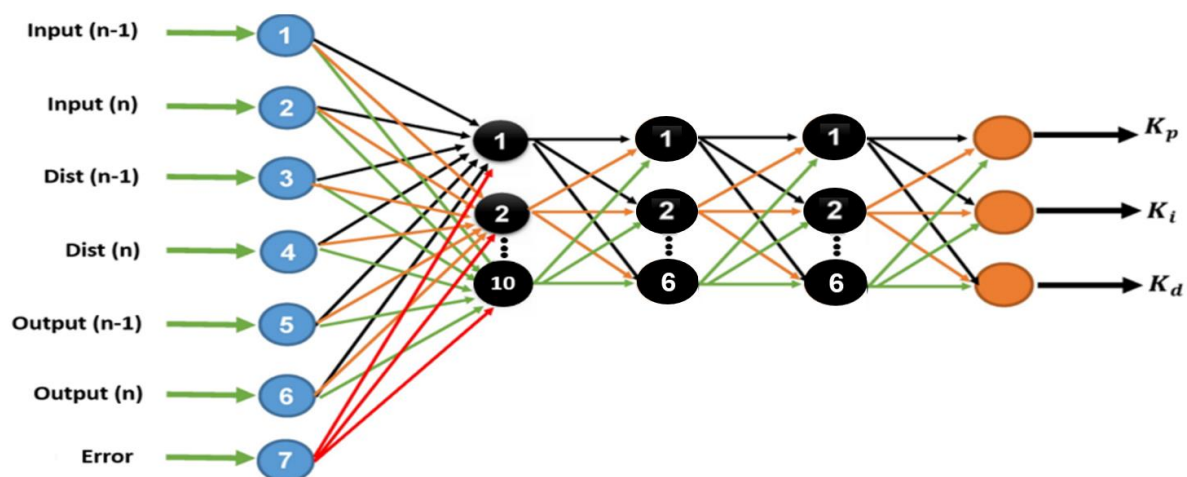


Figure 18. Deep Learning Network.

The first hidden layer, consisting of 10 neurons, applies learned weights and biases to the input data. This layer is followed by an activation function, which introduces complexity into the model's behavior, enabling it to capture and understand intricate patterns and relationships within the data. This layer transforms the raw inputs into higher-level representations that are more suitable for making accurate predictions.

The second and third hidden layers each contain six neurons and further refine the data as they pass through the network. Like the first hidden layer, these layers also apply weights, biases, and activation functions to the transformed data. By progressively processing the input data through these hidden layers, the network learns a hierarchical representation of the system, allowing it to make more accurate and informed decisions. This design is particularly effective in scenarios where the relationships between inputs and outputs are complex.

Finally, the network outputs three values, corresponding to the proportional gain (K_p), integral gain (K_i), and derivative gain (K_d) of a PID controller. These gains are adjusted based on the network's analysis of the input data, which includes the previous and current

states of the system, disturbances, and the error signal. By providing these outputs, the network effectively tunes the PID controller parameters, allowing for precise control of the system. The combination of traditional PID control and deep learning enables the system to handle complex control tasks more effectively, improving both accuracy and efficiency.

7.4. System Vibration Control Under Impulse and Random Disturbances

This section investigates the dynamics of vibration control systems when subjected to impulse and random disturbances. It examines the system's response to each type of disturbance and demonstrates how deep learning techniques can be utilized to tune PID controllers effectively. By integrating these advanced approaches, the study aims to improve vibration mitigation strategies and enhance system stability and performance across diverse operating conditions.

7.4.1. Control System Affected by Impulse Disturbance

In the scenario where an impulse disturbance occurs at time 0 s, the system's behavior is analyzed. The reference input is a unit step with amplitude zero, and Figure 19 presents the resulting output signal to observe how the system reacts to this disturbance.

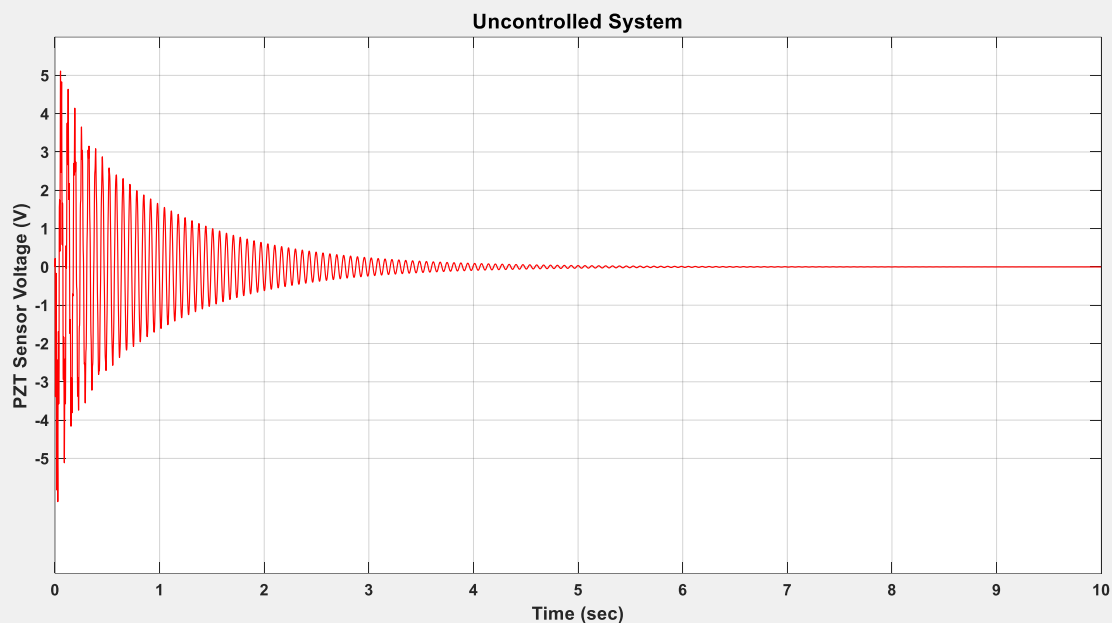


Figure 19. Voltage Response of PZT Sensor before Vibration Control (under Impulse Disturbance).

The trained recurrent neural network (RNN) is employed to tune the PID controller by processing the system's output under impulse disturbance. The network predicts the optimal PID parameters required to reduce and mitigate the cantilever beam's vibrations. By analyzing the relationship between system inputs and outputs, it adjusts the PID gains, ensuring an effective control response.

The PID parameters tuned by the network are summarized in Table 4, demonstrating the model's ability to infer suitable PID parameters across varying test conditions. This adaptability showcases the network's capacity to fine-tune the PID controller to match the system's specific requirements.

As shown in Figure 19, the status of the beam is monitored based on this data, the network tunes the PID controller to generate the control signal seen in Figure 20. This control signal is tailored to counteract the disturbance by adjusting the PID parameters, allowing the controller to effectively stabilize the beam's vibrations effectively.

Table 4. PID Controller Parameters Tuned Using Deep Learning of the System Affected by Impulse Disturbance.

K_p	K_i	K_d
324.3	−2887.8	269.1

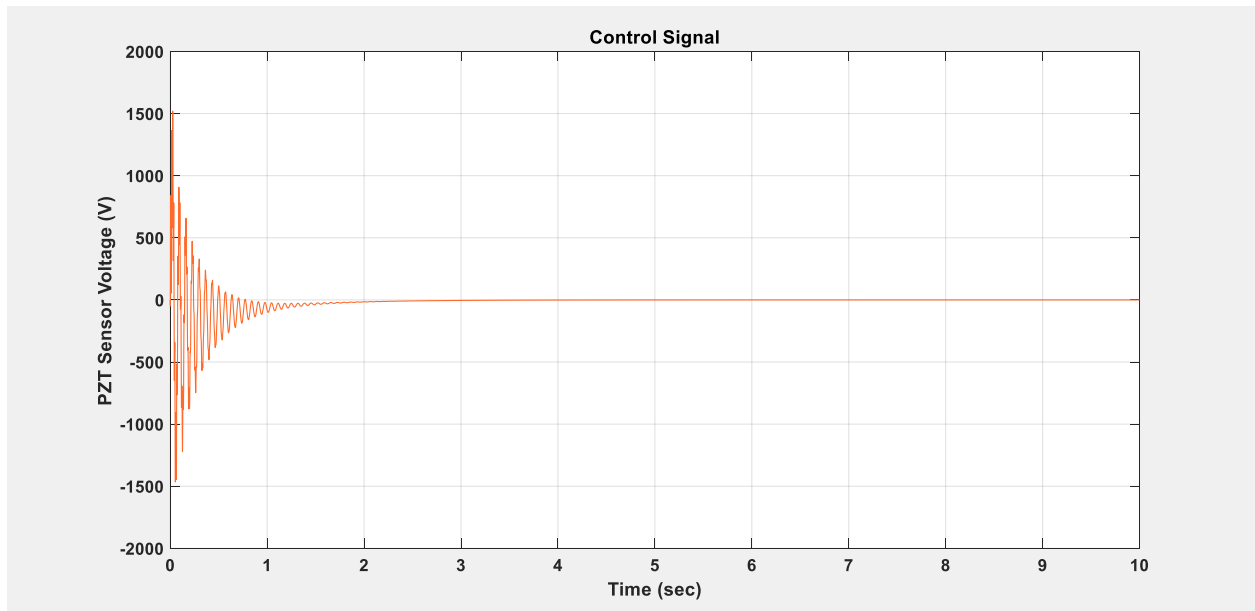
**Figure 20.** System Control Signal.

Figure 21 highlights the system's response after the deep learning-tuned PID controller is applied. The figures illustrate that the optimized PID gains provide improved vibration control, as the tuning adapts to disturbances. This approach emphasizes the advantage of integrating deep learning with traditional PID control, leading to more precise and adaptive vibration mitigation.

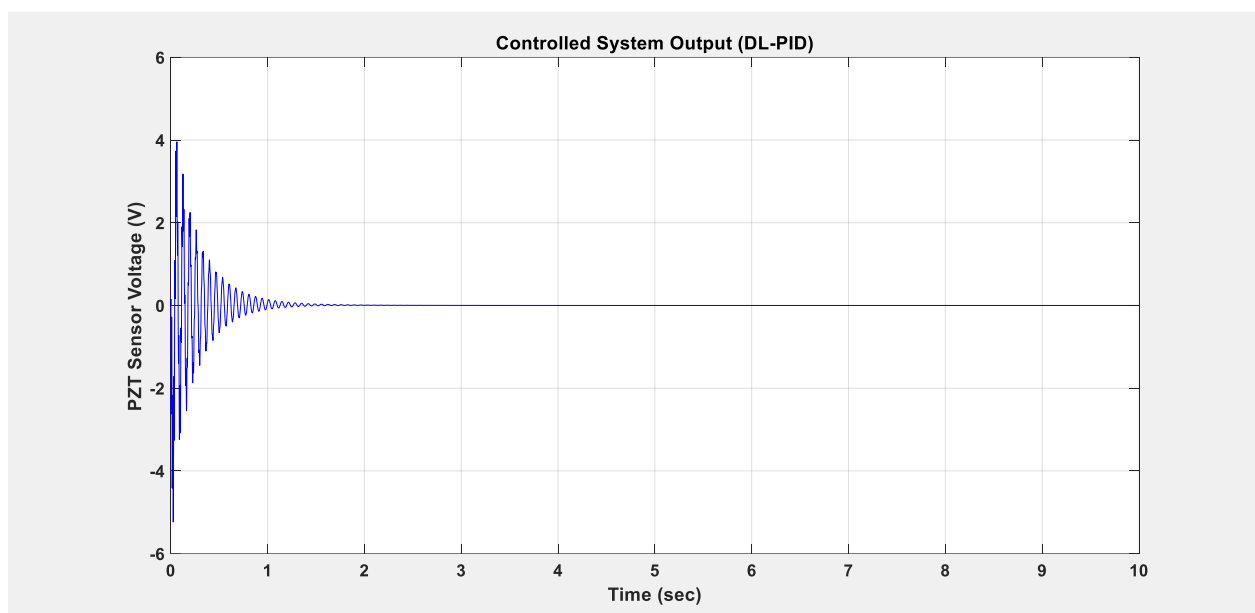
**Figure 21.** Voltage Response of PZT Sensor after Vibration Control with DL-PID Controller (under Impulse Disturbance).

Figure 22 compares the system's performance before and after the PID controller was tuned using deep learning. The beam's vibrations are significantly reduced, especially in the first second. With the deep learning-tuned PID controller, the system reaches a settling time of 1.15 s, showing improved stability. The Integral Time Absolute Error (ITAE) is reduced to an impressively low 0.7326, indicating the system's efficiency in minimizing both the magnitude and duration of the error. Additionally, the mean squared error (MSE) of 3.4370×10^{-14} further highlights the high predictive accuracy of the deep learning approach in optimizing the PID controller, resulting in more effective vibration control.

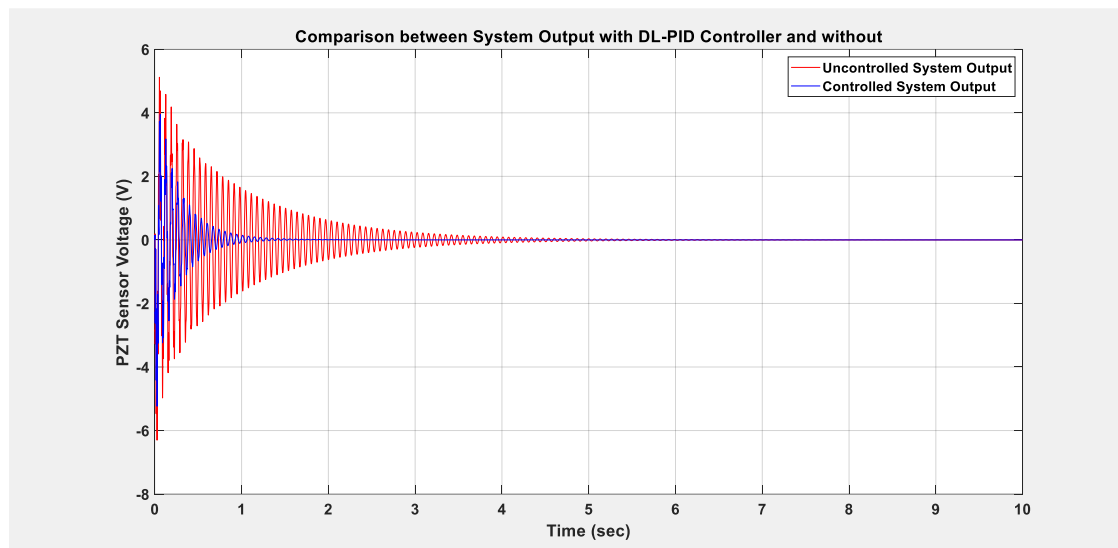


Figure 22. Voltage Response of PZT Sensor in the Cantilever with DL-PID Controller and without.

7.4.2. Control System Affected by Random Disturbance

In the scenario where a continuous random disturbance affects the cantilever beam, the system's response is carefully analyzed. The reference input is a unit step with an amplitude zero, and Figure 23 illustrates the random disturbance applied to the system. To observe the system's reaction to this disturbance, Figure 24 shows the resulting output signal before any control is applied.

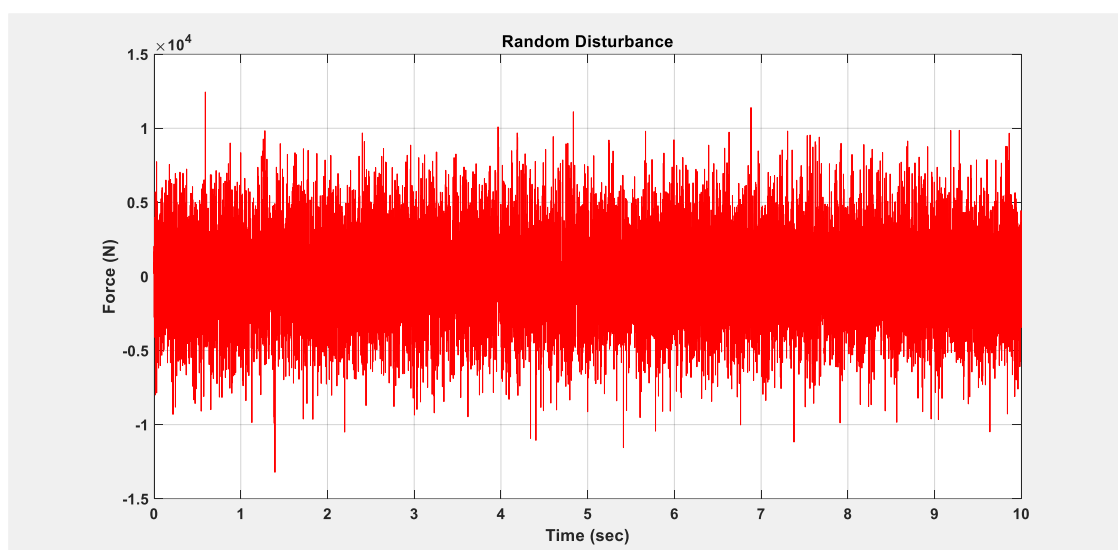


Figure 23. Random Disturbance of the System.

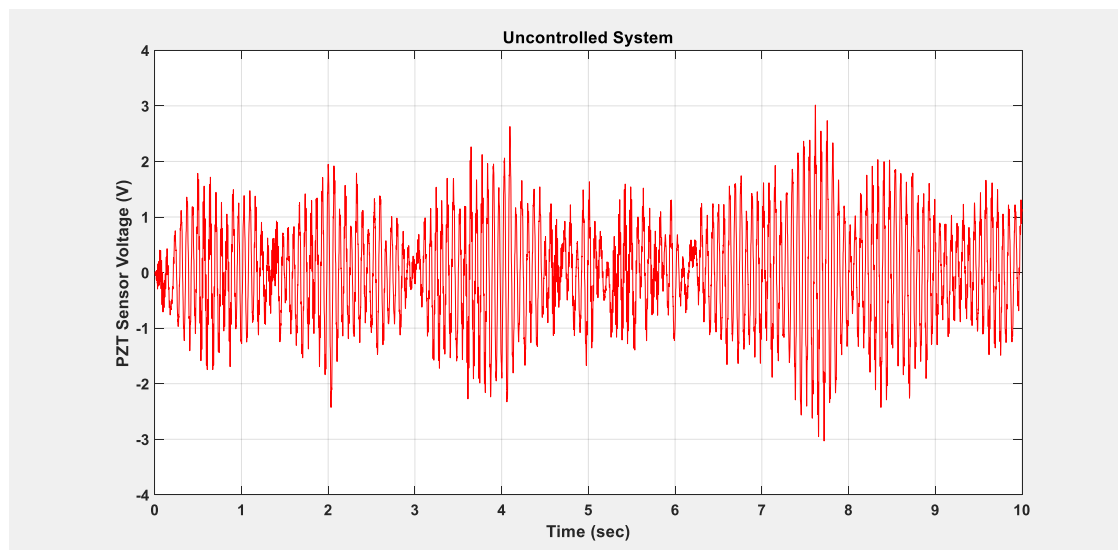


Figure 24. Voltage Response of PZT Sensor before Vibration Control (under Random Disturbance).

The trained deep neural network is employed to tune the PID controller by processing the uncontrolled system output under random disturbance conditions. The network predicts the optimal PID parameters necessary to reduce and mitigate the beam's vibrations. By dynamically adjusting the PID gains, the network ensures that the control response is both precise and effective.

The PID parameters tuned by the network are shown in Table 5, further demonstrating its capability to infer appropriate PID parameters across various test conditions. It shows the adaptability of the trained network in tailoring the PID controller to meet the specific requirements of the system.

Table 5. PID Controller Parameters Tuned Using Deep Learning of the System Affected by Random Disturbance.

K_p	K_i	K_d
661.4	−2049.3	182.6

As seen in Figure 24, the uncontrolled voltage response of the beam is monitored. Based on these data, the deep learning network tunes the PID controller, resulting in the control signal shown in Figure 25. This signal is specifically designed to counteract the detected random disturbances by adjusting the PID parameters, enabling the controller to stabilize the beam's vibrations efficiently.

Figure 26 demonstrates the system's behavior after applying the deep learning-tuned PID controller. The figures highlight how the optimized PID gains result in superior vibration control. This approach underlines the advantage of integrating deep learning with traditional PID control, offering more adaptive and precise vibration mitigation.

Figure 27 illustrates the difference in system performance before and after applying the tuned PID controller using deep learning. The beam's vibrations are noticeably reduced. With the DL-PID controller, the Integral Time Absolute Error (ITAE) is reduced to 3.2347, indicating the system's effectiveness in minimizing both the amplitude and duration of the error. Moreover, the mean squared error (MSE) of 0.7631 further highlights the predictive precision of the deep learning approach in optimizing the PID controller, resulting in more accurate and efficient vibration control.

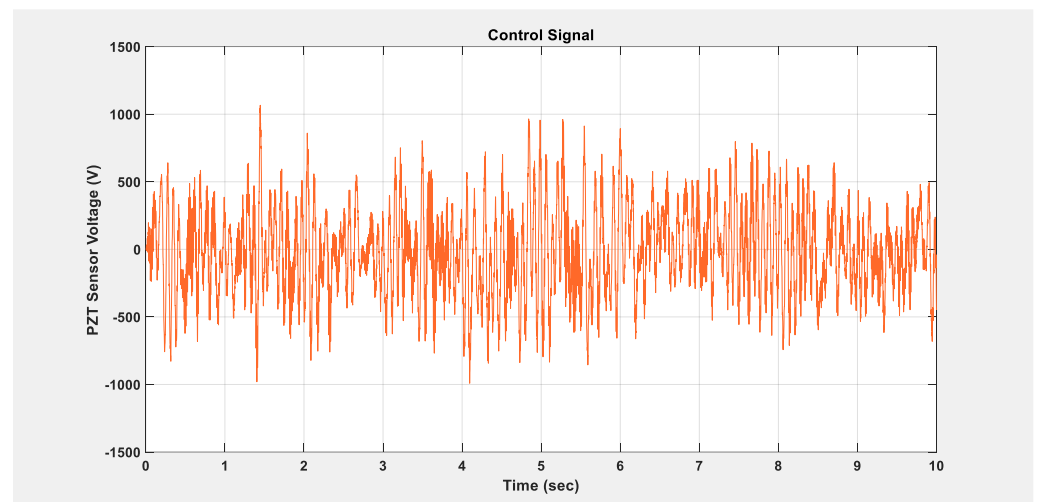


Figure 25. System Control Signal.

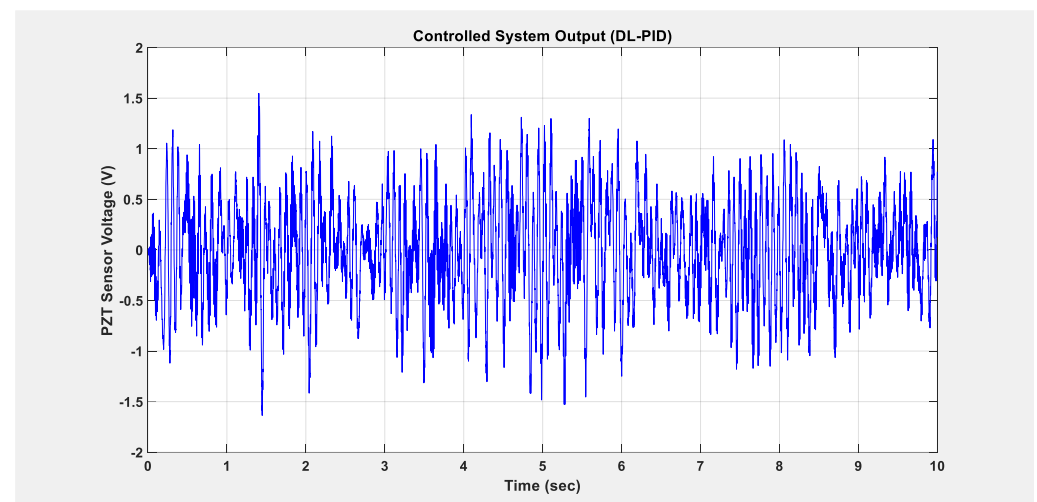


Figure 26. Voltage Response of PZT Sensor after Vibration Control with DL-PID Controller (under Impulse Disturbance).

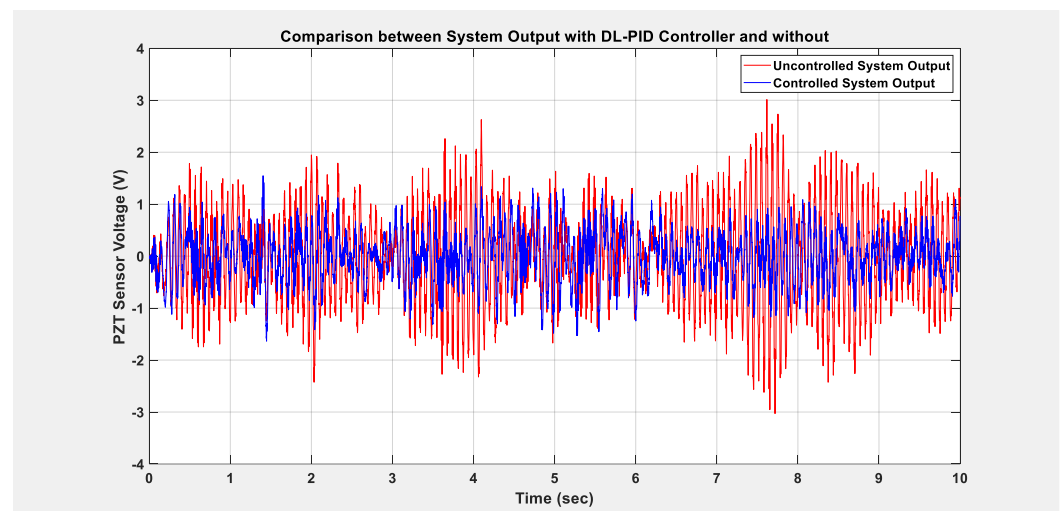


Figure 27. Voltage Response of PZT Sensor in the Cantilever with DL-PID Controller and without.

8. Comparative Analysis

The comparative analysis between the deep learning (DL) controller and the DL-PID controller reveals key differences in their performance when subjected to impulse and continuous random disturbances, as shown in Tables 6 and 7. Each controller's ability to manage system vibrations is evaluated using metrics such as settling time, ITAE (Integral Time Absolute Error), and MSE (mean squared error). The DL-PID controller, which combines traditional PID control with deep learning, potentially enhances control accuracy and stability compared to the standalone DL controller. By analyzing the data presented in Tables 6 and 7, we can better understand how each controller performs in stabilizing the system under different disturbance scenarios. The following subsections provide a detailed comparison based on the results from both impulse and continuous random disturbances.

Table 6. Key Performance Metrics for the Controllers under Impulse Disturbance.

Controller Type	K_p	K_i	K_d	Settling Time (s)	ITAE	MSE
DL Controller	-	-	-	3.34	1.5818	5.9703×10^{-9}
DL-PID Controller	324.3	-2887.8	182.6	1.15	0.7326	3.4370×10^{-14}

Table 7. Key Performance Metrics for the Controllers under Continuous Random Disturbance.

Controller Type	K_p	K_i	K_d	ITAE	MSE
DL Controller	-	-	-	6.4588	0.9690
DL-PID Controller	233.5	-2877.9	113.5	3.2347	0.7631

8.1. Comparative Analysis Under Impulse Disturbance

The performance of the deep learning (DL) controller and the DL-PID controller under impulse disturbance is summarized in Table 6. The key performance metrics evaluated include settling time, Integral Time Absolute Error (ITAE), and mean squared error (MSE).

Settling Time: The DL-PID controller outperforms the DL controller with a significantly faster settling time of 1.15 s compared to 3.34 s for the DL controller. This improvement demonstrates the effectiveness of the DL-PID structure in achieving quicker system stabilization.

ITAE: The ITAE of the DL-PID controller is 0.7326, which is considerably lower than the DL controller's 1.5818. A lower ITAE value indicates that the DL-PID controller manages disturbances more efficiently, minimizing the overall deviation from the setpoint over time.

MSE: The DL-PID controller also excels in terms of MSE, achieving a very low error of 3.4370×10^{-14} , while the DL controller shows a much larger error of 5.9703×10^{-9} . This further highlights the superior accuracy of the DL-PID controller in mitigating vibration under impulse disturbances.

In summary, the DL-PID controller outperforms the standalone DL controller under impulse disturbance across all metrics, delivering faster response times, reduced error, and better overall control of the cantilever beam's vibration.

8.2. Comparative Analysis Under Continuous Random Disturbance

In Table 7, the performance of both controllers is evaluated under continuous random disturbance, where the system is subjected to prolonged and unpredictable forces. The key metrics assessed include ITAE and MSE.

ITAE: The DL-PID controller achieves an ITAE value of 3.2347, which is an improvement over the DL controller's ITAE of 6.4588. This indicates that, even under continuous random disturbances, the DL-PID controller maintains better control by reducing the system's deviations from the setpoint more effectively.

MSE: The MSE value of 0.7631 for the DL-PID controller is lower than the DL controller's 0.9690, signifying more accurate vibration suppression. The DL-PID controller

demonstrates better precision in managing the random fluctuations caused by continuous disturbances.

Overall, the DL-PID controller exhibits superior performance compared to the DL controller under continuous random disturbance as well. While both controllers perform adequately, the added tuning of the PID parameters in the DL-PID controller ensures more effective disturbance rejection and vibration control.

This analysis reveals that incorporating PID parameters into the deep learning architecture significantly improves the control performance of the system, particularly in terms of response speed, error minimization, and handling of both impulse and continuous random disturbances.

9. Conclusions

In summary, this paper highlights the effectiveness of integrating traditional PID control with deep learning techniques to enhance vibration management in cantilever beams equipped with PZT smart materials. The comparative analysis of the deep learning (DL) controller and the DL-PID controller demonstrates that the latter offers superior performance in terms of response time, error minimization, and overall stability when subjected to both impulse and continuous random disturbances. This advancement underscores the potential of hybrid control strategies in achieving more precise and efficient system performance.

Additionally, the findings emphasize the importance of utilizing adaptive control methods that combine the strengths of conventional techniques with modern machine learning approaches. The DL-PID controller not only improves the accuracy of vibration suppression but also enhances the system's ability to respond to varying disturbance scenarios. Overall, the integration of deep learning with PID control represents a promising direction for future research and application in vibration control systems, paving the way for more resilient and effective engineering solutions.

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