

ACTIVE VIBRATION CONTROL OF A SMART STRUCTURE

BY

AHMED ABDULRAHMAN ABDULLAH MOHAMMED

A Thesis Presented to the
COLLEGE OF GRADUATE AND INTERDISCIPLINARY STUDIES
KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE
In
SYSTEM AND CONTROL ENGINEERING

December 2023

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN- 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by **Ahmed Abdulrahman Abdullah Mohammed** under the direction of his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN SYSTEMS & CONTROL ENGINEERING.**



Dr. Mujahed Al-Dhaifallah
Department Chairman

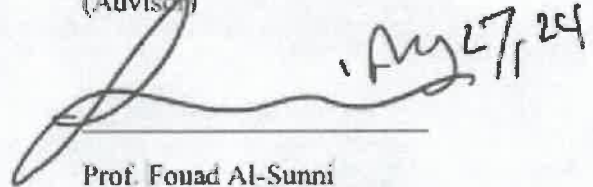


Prof. Suliman Al-Homidan
Dean of Graduate Studies

Date



Prof. Abdulkahid Al-Saif
(Advisor)



Prof. Fouad Al-Sunni
(Member)



Prof. Sami El-Ferk
(Member)



© Ahmed Abdulrahman Abdullah Mohammed

2023

To my beloved family, whose love and sacrifice have been my greatest source of strength

ACKNOWLEDGMENTS

First and foremost, I offer my sincerest gratitude to Allah for giving me the strength, patience, and guidance to complete this journey.

My deepest appreciation is extended to my advisor, Prof. Abdulwahid Al-Saif, whose expertise and understanding were my guiding light through this academic endeavor. Your patience and commitment to excellence have been a driving force behind my work.

I am deeply grateful to the members of my thesis committee, Prof. Fouad Al-Sunni, and Prof. Sami El-Ferik, for their time, critical insights, and constructive suggestions that have greatly improved this thesis. A special thanks to Prof. Fouad Al-Sunni for encouraging me to explore this research area; his guidance has truly made a difference.

My heartfelt thanks go to my family, whose unwavering support and love have been my sanctuary. To my parents, who have always believed in me and instilled in me the virtues of hard work and perseverance, I dedicate my achievements. To my beloved wife, for her unconditional love and prayers, and to my son Abdulrahman, who has been a source of joy and inspiration. To my siblings, for their endless positivity and support.

Lastly, my friends deserve a note of thanks for their unwavering support and for their contribution to this journey in various ways, your support has not gone unnoticed. I extend my appreciation to all those who have supported me in any form during this academic endeavor. Your role in this journey was invaluable.

TABLE OF CONTENTS

ACKNOWLEDGMENTS	V
TABLE OF CONTENTS.....	VI
LIST OF TABLES	IX
LIST OF FIGURES	X
LIST OF ABBREVIATIONS.....	XV
ABSTRACT.....	XVI
ملخص الرسالة	XIX
CHAPTER 1 INTRODUCTION	1
1.1 Introduction and Motivation	1
1.2 Thesis Objectives and Contribution.....	3
1.3 Methodologies	4
1.4 Thesis Organization	7
CHAPTER 2 LITERATURE REVIEW	10
2.1 Active Vibration Control of Smart Materials.....	10
2.2 Self-Tuning PID Parameters Methods	13
CHAPTER 3 THEORETICAL BACKGROUND.....	16
3.1 Structural Engineering: Active, Adaptive, Smart	16
3.2 Vibration Control.....	17
3.2.1 Active Vibration Control.....	18
3.3 Basics of Smart Materials	19

3.3.1	Piezoelectric Effect.....	22
CHAPTER 4 SMART STRUCTURE DYNAMIC MODEL.....		23
4.1	Euler-Bernoulli Beam Theory	23
4.2	Dynamic Modeling of the Cantilever Beam with PZT Materials	24
4.3	Parameter Analysis of the PZT-Cantilever Beam System	27
4.4	System Design	30
4.4.1	Low-Pass Filter	34
4.4.2	Open Loop System Affected by Impulse Disturbance	35
4.4.3	Open Loop System Affected by Random Disturbance.....	37
CHAPTER 5 CONTROLLER DESIGN.....		38
5.1	Introduction	38
5.2	Proportional – Integral – Derivative Control Design	40
5.3	Genetic Algorithm	41
5.3.1	Tuning PID Controller Using Genetic Algorithms	42
5.3.2	GA-PID Controller Results.....	44
5.4	Neural Network	57
5.4.1	Tuning PID Controller Using Neural Network	57
5.4.2	Neural Network Design	58
5.4.3	Training and Validation Loss Plots.....	60
5.4.4	Error Histogram	61
5.4.5	NN-PID Controller Results	62
5.5	Fuzzy Logic	72
5.5.1	Tuning PID Controller Using Fuzzy Logic.....	73
5.5.2	Design and structure of the self-tuning fuzzy PID Controller.....	74

5.5.3	Fuzzy PID Controller Results.....	80
5.6	Deep Learning.....	88
5.6.1	RNN with LSTM for Vibration Control.....	90
5.6.2	Deep Learning Design.....	91
CHAPTER 6 COMPARATIVE ANALYSIS		102
6.1	Analysis of System Control under Impulse Disturbance.....	103
6.2	Analysis of System Control under Continuous Random Disturbance.....	104
CHAPTER 7 CONCLUSION.....		106
REFERENCES.....		108
VITAE.....		113

LIST OF TABLES

Table 1: Sensor and Actuator Material Classes [42]	20
Table 2: Parameters of Aluminum 6064 Beam.	28
Table 3: Parameters of PZT PSI-4A4E	28
Table 4: PID Controller Parameters Tuned Using GA of the System Affected by Impulse Disturbance	48
Table 5: PID Controller Parameters Tuned Using GA of the System Affected by Random Disturbance	55
Table 6: PID Controller Parameters Tuned Using NN of the System Affected by Impulse Disturbance	65
Table 7: PID Controller Parameters Tuned Using NN of the System Affected by Random Disturbance	70
Table 8: Fuzzy Rules for <i>K_p</i>	79
Table 9: Fuzzy Rules for <i>K_i</i>	80
Table 10: Fuzzy Rules for <i>K_d</i>	80
Table 11: PID Controller Parameters Tuned Using Fuzzy Logic of the System Affected by Impulse Disturbance	83
Table 12: PID Controller Parameters Tuned Using Fuzzy Logic of the System Affected by Random Disturbance	87
Table 13: Key Performance Metrics for the Controllers under Impulse Disturbance	102
Table 14: Key Performance Metrics for the Controllers under Continuous Random Disturbance	103

LIST OF FIGURES

Figure 1: Literature Review Structure	15
Figure 2: General Framework of Smart Structures Categories. [43]	21
Figure 3: The Piezoelectric Effect [46]	22
Figure 4: Assumption of the Plane Sections Remain Plane [48].....	23
Figure 5: Cantilever Beam with Pair of PZT Actuators and Sensor [47].....	24
Figure 6: Block Diagram of Open Loop System with Impulse Disturbance	30
Figure 7: Block Diagram of Open Loop System with Random Disturbance	31
Figure 8: Reference Input	31
Figure 9: Impulse Disturbance	32
Figure 10: Voltage Response of PZT Sensor in the Cantilever Beam	32
Figure 11: Random Disturbance	33
Figure 12: Voltage Response of PZT Sensor in the Cantilever Beam	33
Figure 13: Block Diagram of Open Loop System with Low-Pass Filter under Impulse Disturbance.....	35
Figure 14: Voltage Response of PZT Sensor under Impulse Disturbance (with Low-Pass Filter)	36
Figure 15: Block Diagram of Open Loop System with Low-Pass Filter under Random Disturbance.....	37
Figure 16: Voltage Response of PZT Sensor under Random Disturbance (with Low-Pass Filter)	37
Figure 17: Block Diagram of Closed Loop System.....	41
Figure 18: Block Diagram of Closed Loop System under Impulse Disturbance	44
Figure 19: Reference Input	45

Figure 20: Impulse Disturbance	46
Figure 21: Voltage Response of PZT Sensor under Impulse Disturbance (with Low-Pass Filter).....	46
Figure 22: Fitness Value VS. Generation Plot.....	47
Figure 23: Voltage Response of PZT Sensor before Vibration Control (under Impulse Disturbance)	48
Figure 24: System Control Signal.....	49
Figure 25: Voltage Response of PZT Sensor After Vibration Control with GA-PID (under Impulse Disturbance).....	49
Figure 26: Voltage Response of PZT Sensor in the Cantilever Beam with GA-PID Controller and without.	50
Figure 27: Block Diagram of Closed Loop of under Random Disturbance	51
Figure 28: Reference Input	52
Figure 29: Random Disturbance.....	52
Figure 30: Voltage Response of PZT under Random Disturbance (with Low-Pass Filter) .	53
Figure 31: Fitness Value VS. Generation Plot.....	54
Figure 32: Voltage Response of PZT Sensor before Vibration Control (under Random Disturbance)	55
Figure 33: System Control Signal.....	56
Figure 34: Voltage Response of PZT Sensor After Vibration Control with GA-PID (under Random Disturbance)	56
Figure 35: Voltage Response of PZT Sensor in the Cantilever Beam with GA-PID Controller and without.	57
Figure 36: Designed Neural Network	59
Figure 37: Training and Validation Plot	60

Figure 38: Error Histogram	61
Figure 39: NN-PID Self Tuning Algorithm	62
Figure 40: Reference Input	63
Figure 41: Impulse Disturbance of the System.....	64
Figure 42: Voltage Response of PZT Sensor before Vibration Control (under Impulse Disturbance).....	64
Figure 43: System Control Signal	66
Figure 44: Voltage Response of PZT Sensor After Vibration Control with NN-PID (under Impulse Disturbance)	66
Figure 45: Voltage Response of PZT Sensor in the Cantilever Beam with NN-PID and without.	67
Figure 46: Reference Input	68
Figure 47: Random Disturbance	69
Figure 48: Voltage Response of PZT Sensor before Vibration Control (under Random Disturbance).....	69
Figure 49: Control Signal	71
Figure 50: Voltage Response of PZT Sensor after Vibration Control with NN-PID (under Random Disturbance).....	71
Figure 51: Voltage Response of PZT Sensor in the Cantilever Beam with NN-PID Controller and without.	72
Figure 52: Basic Structure of a Fuzzy PID Controller.....	75
Figure 53: Mamdani Fuzzy Logic System.....	76
Figure 54: Membership Function of Error "e"	76
Figure 55: Membership Function of Change in Error "ec"	77
Figure 56: Membership Function of K_p	77

Figure 57: Membership Function of K_i	78
Figure 58: Membership Function of K_d	78
Figure 59: Reference Input	81
Figure 60: Impulse Disturbance of the System	82
Figure 61: Voltage Response of PZT Sensor before Vibration Control (under Impulse Disturbance).	82
Figure 62: System Control Signal.....	83
Figure 63: Voltage Response of PZT Sensor after Vibration Control with FL-PID (under Impulse Disturbance).	84
Figure 64: Voltage Response of PZT Sensor in Cantilever Beam with FL-PID Controller and without.	84
Figure 65: Reference Input	85
Figure 66: Random Disturbance of the System	85
Figure 67: Voltage Response of PZT Sensor before Vibration Control (under Random Disturbance).	86
Figure 68: System Control Signal.....	87
Figure 69: Voltage Response of PZT Sensor after Vibration Control with FL-PID (under Random Disturbance)	87
Figure 70: Voltage Response of PZT Sensor in the Cantilever Beam with FL-PID Controller and without.	88
Figure 71: Creating Recurrent Neural Network with Long Short-Term Memory	91
Figure 72: Closed Loop System with Deep learning Controller under disturbance.	92
Figure 73: Reference Input	93
Figure 74: Impulse Disturbance of the System	94

Figure 75: Voltage Response of PZT Sensor before Vibration Control (under Impulse Disturbance).....	94
Figure 76: System Control Signal	95
Figure 77: Voltage Response of PZT Sensor after Vibration Control with Deep Learning Controller (under Impulse Disturbance).	96
Figure 78: Voltage Response of PZT Sensor in the Cantilever with Deep Learning Controller and without.....	97
Figure 79: Reference Input	98
Figure 80: Random Disturbance	98
Figure 81: Voltage Response of PZT Sensor before Vibration Control (under Random Disturbance).....	99
Figure 82: System Control Signal	100
Figure 83: Voltage Response of PZT Sensor after Vibration Control with Deep Learning Controller (under Random Disturbance).....	100
Figure 84: Voltage Response of PZT Sensor in the Cantilever Beam with Deep Learning Controller and without.....	101

LIST OF ABBREVIATIONS

PZT	:	Lead Zirconate Titanate (Piezoelectric)
PID	:	Proportional-Integral-Derivative
GA	:	Genetic Algorithm
NN	:	Neural Network
FL	:	Fuzzy Logic
DL	:	Deep Learning
RNN	:	Recurrent Neural Network
LSTM	:	Long Short-Term Memory
ITAE	:	Integral Time Absolute Error
MSE	:	Mean Squared Error
MEMS	:	Micro-Electromechanical System
LQR	:	Linear Quadratic Regulator
FOPDT	:	First Order Plus Dead-Time
SMC	:	Sliding Mode Controller

ABSTRACT

Full Name : Ahmed Abdulrahman Abdullah Mohammed
Thesis Title : Active Vibration Control of a Smart Structure
Major Field : System & Control Engineering
Date of Degree : December 2023

Vibration control in cantilever beam structures is crucial for maintaining structural integrity and functionality in various engineering applications. This thesis introduces an innovative approach to vibration mitigation using piezoelectric lead zirconate titanate (PZT), referred to as the shortened form of the chemical symbols Pb (ZrTi), integrated as smart materials within cantilever beam systems. The study involves the development and comparative analysis of a Proportional-Integral-Derivative (PID) control strategy under two distinct disturbance scenarios: random and impulsive.

The PID parameters are intelligently tuned using three advanced techniques: genetic algorithms (GAs), neural networks (NNs), and fuzzy logic. Also, the work involves designing a pure deep learning controller to control and reduce the structure vibration.

In the initial phase, the PID controller's parameters are meticulously optimized using genetic algorithms (GAs) to achieve optimal vibration damping under both types of disturbances. The parameters, refined through GAs, provide a high-quality dataset that serves for training a purpose-designed neural network (NN). The NN aims to further

enhance the PID tuning process by capturing the complex relationships between the system's response and the control parameters. Complementing this, a fuzzy logic (FL) controller is developed to fortify the control strategy, leveraging its inherent robustness against system uncertainties and adeptness in managing vibration control processes.

In subsequent stages, a deep learning controller incorporating long short-term memory (LSTM) architecture is designed. This controller adapts the vibration control system by analyzing data from the PZT sensor and predicting the requisite control signal for the PZT actuator. Inspired by observations during the implementation of the PID controller, this model extrapolates the relationship between cantilever beam vibration and the corresponding control signal necessary for its attenuation.

Through MATLAB software simulations, this thesis demonstrates the efficiency of each intelligent tuning method in refining the PID controller's performance. The findings underscore that integrating these intelligent techniques with conventional PID controllers yields substantial improvements in the cantilever beam system's responsiveness under unpredictable environmental conditions. Moreover, the thesis presents the aptitude of deep learning controllers in discerning complex system dynamics and predicting control signals for vibration damping.

By combining PID classical control with adaptable and learning capabilities through intelligent optimization techniques, this thesis contributes to the field of smart structures and vibration control. Furthermore, it underscores the effectiveness of pure deep learning methodology in controlling structural vibrations, leveraging the capabilities of PZT sensors and actuators.

ملخص الرسالة

الاسم الكامل: أحمد عبدالرحمن عبدالله محمد

عنوان الرسالة: التحكم النشط بالاهتزازات لهيكل ذكي

التخصص: هندسة نظم التحكم

تاريخ الدرجة العلمية: ديسمبر 2023

يعد التحكم في الاهتزازات في الهياكل الكابولية أمراً حاسماً للحفاظ على سلامة البنية التحتية ووظائفها في مختلف التطبيقات الهندسية. تقدم هذه الرسالة نهجاً مبتكراً للتخفيف من الاهتزازات باستخدام مواد ذكية بايزوكهربائية (PZT) مدمجة في نظام الهيكل الكابولي. يتضمن العمل تطوير وتحليل مقارن لاستراتيجية التحكم النسبي التكاملي التفاضلي (PID) تحت سيناريوهات اضطرابات مختلفة: عشوائية واندفاعية. يتم تعديل معاملات المتحكم النسبي التكاملي التفاضلي (PID) بذكاء باستخدام ثلاث تقنيات متقدمة: الخوارزميات الجينية (GA)، والشبكات العصبية (NN)، والمنطق الضبابي (FL).

في البداية، يتم تحسين معاملات المتحكم النسبي التكاملي التفاضلي (PID) باستخدام الخوارزميات الجينية (GA) لتحقيق تخميد فعال للاهتزاز تحت كلا نوعي الاضطرابات. المعاملات المُحسنة المُستخلصة عبر الخوارزميات الجينية (GA) توفر مجموعة بيانات عالية الجودة التي تُستخدم لتدريب شبكة عصبية (NN) مُصممة خصيصاً لهذا الغرض. تهدف الشبكة العصبية (NN) إلى صقل عملية ضبط المتحكم النسبي التكاملي التفاضلي (PID)، ملتقطة العلاقات المعقدة بين استجابة النظام ومعاملات التحكم. ولتعزيز استراتيجية التحكم أكثر، يتم تطوير متحكم بالمنطق الضبابي (FL)، مستغلاً متانته الفطرية ضد عدم اليقين في النظام وقدرته على إدارة عملية التحكم في الاهتزاز.

في المرحلة التالية، تم تصميم متحكم تعلم عميق (DL) يدمج هندسة الذاكرة القصيرة الطويلة (LSTM). كيف هذا المتحكم نظام التحكم بالاهتزاز عن طريق تحليل بيانات من جهاز استشعار PZT وتوقع الإشارة التحكمية اللازمة لمحرك PZT. مستوحى من الملاحظات أثناء تنفيذ متحكم PID، يتوسع هذا النموذج في العلاقة بين اهتزاز الهيكل الكابولي والإشارة التحكمية المقابلة الضرورية لتخفيف هذا الاهتزاز.

تُظهر الرسالة فعالية وكفاءة كل طريقة ضبط ذكية من خلال محاكاة برنامج MATLAB، تشير النتائج إلى أن دمج هذه التقنيات الذكية مع المتحكم النسبي التكاملي التفاضلي (PID) يمكن أن يحسن بشكل كبير من استجابة نظام الهيكل الكابولي تحت ظروف بيئية غير متوقعة. علاوة على ذلك، يقدم البحث قدرة متحكمات التعلم العميق على استيعاب ديناميات النظام المعقدة وتوقع إشارات التحكم اللازمة لتخفيف الاهتزاز.

من خلال الجمع بين المتحكم الكلاسيكي PID والقدرات القابلة للتكيف والتعلم من خلال تقنيات الضبط الذكية، يساهم هذا البحث في مجال الهياكل الذكية والتحكم في الاهتزازات. وبالإضافة إلى ذلك، يسلط الضوء على فعالية منهجية التعلم العميق النقية في التحكم في الاهتزازات الهيكلية، مستفيداً من قدرات أجهزة استشعار PZT ومحركاتها.

CHAPTER 1

INTRODUCTION

1.1 Introduction and Motivation

Vibration is an omnipresent phenomenon in the field of engineering structures and systems, often presenting significant challenges due to its potential to cause material fatigue, structural damage, and undesired noise [1]. These implications can have a considerable impact on the system's overall performance and durability. Among various structures, the cantilever beam is a commonly encountered structure and is susceptible to vibrations [2].

Cantilever beams, defined by one fixed end and one free end, are integral to a diverse range of engineering systems. They feature prominently in large-scale civil engineering applications such as a balcony, as well as in smaller scale applications such as those found in micro-electromechanical systems (MEMS) [3]. The vibrational behavior of these beams, in response to both external and internal disturbances, represents an essential area of research within the broader field of structural dynamics.

A promising avenue to address the issue of structural vibration lies in the field of smart materials, specifically, piezoelectric materials like Lead Zirconate Titanate (PZT) [4]. PZT is known for its direct piezoelectric effect, i.e., its ability to convert mechanical energy into electrical energy and vice versa [5]. This unique characteristic enables PZT materials to function as both sensors, detecting vibrations, and actuators, controlling vibrations [6].

The application of PZT patches to a cantilever beam results in a system that can effectively control the beam's vibration [7]. The PZT patch, in its role as a sensor, is capable of detecting the beam's vibration and generating an electrical signal proportional to the vibration [7]. This signal can be processed by a controller, which determines a control voltage based on the detected vibration. When this control voltage is applied to the PZT patch, it triggers a mechanical strain in the PZT material, which in turn generates a force that counteracts the vibration of the beam, reducing the vibrational energy [8].

The use of PZT materials with cantilever beams is a promising way for active vibration control, providing a potential solution to the widespread issue of structural vibration [8]. The capability to effectively control vibrations carries extensive implications, from enhancing the lifespan and performance of engineering structures to increasing user comfort and safety.

1.2 Thesis Objectives and Contribution

This thesis aims to study integrating PZT materials with cantilever beams for active vibration control. The study seeks to comprehend the modeling of a cantilever beam coupled with PZT sensor and actuators, focusing on controlling system vibrations through the design of efficient controllers, and subsequently comparing their efficacy.

The first objective is to design a Classical Proportional – Integral - Derivative (PID) controller to stabilize the system. A PID controller is a fundamental starting point due to its extensive prevalence in various control systems, demonstrating its robust and reliable performance [9].

However, PID controllers often require fine-tuning of their parameters for optimal performance, a task which can be challenging to achieve in practice [9]. Therefore, the second objective of this study is to design different intelligent techniques capable of enhancing the PID controller by tuning its parameters automatically. Different intelligent techniques such as Genetic Algorithms (GA), Neural Networks (NN), and Fuzzy Logic Controllers (FL) will be investigated and used to tune the PID parameters.

The third objective is to design a pure deep learning controller that is a predictive model can accurately predict the vibration response of a cantilever beam and generate the corresponding control signals required to suppress vibrations using PZT actuator.

Finally, this research aims to compare the performance of integrating each intelligent tuning method with the PID controller, as well as utilizing deep learning technique, for controlling system vibrations. The comparison will be based on the, settling time, mean squared error (MSE), and integral time absolute error (ITAE). The overall goal is to identify the most efficient control strategy for active vibration control of cantilever beams using PZT materials.

1.3 Methodologies

The methodologies employed in this thesis constitute a systematic approach to enhancing the active vibration control of a Cantilever beam with PZT smart materials. Firstly, a PID controller is designed, which is then fine-tuned for enhanced performance using three intelligent tuning techniques. These methods were selected for their capability to adaptively optimize the PID parameters, thereby enhancing the system's efficiency under varying conditions of disturbance. Secondly, a deep learning controller is designed to learn the system's behavior and utilize this knowledge to predict the PZT actuator's actions, thereby reducing the structure's vibrations.

- Genetic Algorithm for PID Tuning

Initially, a Genetic Algorithm (GA) was designed to tune the PID parameters of the system. The GA's robust search capabilities provide an efficient means of exploring the parameter space to identify optimal settings. This technique was first applied to scenarios

where the system was affected by random disturbances, allowing for the development of a tuning strategy that could accommodate unpredictable environmental variations.

Subsequently, the methodology was extended to address scenarios wherein the system experienced impulse disturbances. Here, the GA was tasked with identifying PID settings that could counteract sharp inputs while maintaining overall system stability.

- Neural Network-Based PID Tuning

Leveraging the dataset generated from the GA optimized PID controller, a Neural Network (NN) was developed. This NN was trained with the GA generated data, enabling it to learn the relationship between system behavior and the appropriate PID parameters. The goal of this phase was to create a predictive model capable of adjusting the PID parameters based on the learned data.

- Fuzzy Logic Controller for PID Tuning

The final approach involved the design of a Fuzzy Logic Controller (FL) for PID tuning. The construction of the FL was informed by insights obtained from both the dataset generated by the GA method and the performance characteristics observed from the NN method. The FL rules were carefully constructed to reflect the nuanced relationships between the system's behavior and the PID parameters. This FL was intended to provide

a more intuitive form of control, translating the observed system states into linguistic variables and leveraging human-like reasoning to adjust the PID parameters.

- Pure Deep Learning Controller

The process of developing a pure deep learning controller for managing cantilever beam vibrations involves several stages. It begins with the collection of a dataset containing information on beam states and the corresponding actions of the PZT actuator. Subsequently, a deep learning architecture is designed to effectively capture the complex relationships within the dataset. Following data preprocessing, the model undergoes training, validation, and fine-tuning to optimize its performance. Evaluation of the model's efficacy is conducted using a separate test dataset. This iterative process allows for the continual refinement and optimization of the Deep Learning Controller, ensuring its efficacy in effectively managing cantilever beam vibrations.

In summary, the methodologies employed in this thesis present a systematic and robust approach to enhancing the active vibration control of a Cantilever beam with PZT smart materials. Beginning with the design and fine-tuning of a PID controller using intelligent tuning techniques, including Genetic Algorithm, Neural Network, and Fuzzy Logic Controller, the study addresses varying disturbance conditions effectively. Subsequently, the development of a Pure Deep Learning Controller extends the scope by leveraging complex relationships within the dataset to optimize beam vibration management. This process of refinement and optimization underscores the efficacy of the proposed

methodologies in effectively mitigating cantilever beam vibrations across diverse scenarios, offering valuable insights for future research and application in structural engineering and control systems.

1.4 Thesis Organization

This thesis is organized to methodically address the research on active vibration control using smart materials, with a particular focus on self-tuning PID parameters methods. The structure of the thesis is as follows:

1- Introduction

The initial chapter sets the context and importance of the research in the domain of vibration control and smart materials. It begins with a general introduction to the subject, followed by the delineation of the thesis objectives and its contributions to the field. The methodologies employed throughout the research are then described, concluding with an outline of the thesis structure and a brief summary of each chapter.

2- Literature Review

In the second chapter, there is an extensive review of existing literature, which explores the current knowledge and developments in the field. It encompasses a thorough

examination of active vibration control of smart materials and delves into various self-tuning methods for PID parameters, highlighting their application in vibration control.

3- Theoretical Background

The third chapter provides the essential theoretical background for the study. It discusses the principles of active vibration control, introduces the basics of smart materials, and explains the piezoelectric effect. These topics are crucial for understanding the research's experimental and analytical work.

4- Smart Structure Dynamic Model

The fourth chapter is dedicated to the dynamic modeling of the smart structure. It includes a detailed mathematical model of a cantilever beam incorporated with piezoelectric (PZT) materials and describes the design of the physical system that has been developed and used in the experimental phase of the research.

5- Controller Design

The fifth and pivotal chapter presents the design and results of the controllers. It starts with the design process of the PID controller tailored for the smart structure vibration control system. It then reports on the results of tuning the PID controller using various methods which are genetic algorithms, neural networks, and fuzzy logic, and analyzes the

performance of each. Finally, it introduces the design of a deep learning controller and shows its efficacy in mitigating vibrations in the cantilever beam.

6- Comparative Analysis

The comparative analysis section evaluates the performance of PID controllers tuned via genetic algorithm, neural network, and fuzzy logic, alongside a deep learning controller (RNN LSTM) in managing cantilever beam vibrations with PZT smart materials. The controllers are assessed under impulse and continuous random disturbance scenarios using metrics such as settling time, peak, ITAE, and MSE. This analysis highlights each controller's strengths and weaknesses, providing insights into their effectiveness and efficiency in different disturbance conditions.

7- Conclusion

The conclusion section summarizes the comparative analysis of PID controllers tuned via genetic algorithms, neural networks, and fuzzy logic, alongside a deep learning RNN LSTM controller, for managing cantilever beam vibrations with PZT smart materials. It highlights their performance strengths under different disturbance scenarios and underscores the need for control strategies to manage the structure's vibration.

CHAPTER 2

LITERATURE REVIEW

2.1 Active Vibration Control of Smart Materials

The realm of smart materials and structures has been the focal point of extensive research over the years, fueled by their potential to revolutionize a multitude of applications, including structural health monitoring, aerospace, and mechanical engineering [10]. A key area of interest within this field is the integration of smart materials, such as Piezoelectric Materials, with conventional structures to enhance their performance and adaptability to environmental stimuli [11].

Piezoelectric materials like PZT, which possess the unique ability to convert mechanical energy into electrical energy and vice versa, have drawn significant attention [12] [13]. This feature, known as the piezoelectric effect, allows these materials to respond to mechanical stress by generating an electric charge, and conversely, to experience strain when subjected to an electric field [12] [13]. This bidirectional energy conversion is particularly useful in controlling vibrations, and hence, these materials find widespread use in various structures, especially cantilever beams, which are a common structural element in many applications [14].

Cantilever beams with integrated PZT patches have been the subject of numerous studies centered around vibration control [15]. Researchers such as Sharvari and Jayesh have demonstrated that the PZT patches could effectively reduce vibration amplitude in these beams [16]. Further studies have explored the optimal placement of PZT patches for maximum vibration control, thereby highlighting the potential of PZT as a smart material in structural engineering [16].

To fully exploit the capabilities of PZT in controlling vibrations, several control methods have been studied and implemented [17]. Notably, the PID control strategy has proven to be effective in reducing beam vibration. Studies by Saurabh and Rajeev have highlighted the successful implementation of a PID control algorithm on a cantilever beam with PZT patches, which significantly reduced the settling time [18].

However, various control methods were employed in this area. For instance, optimal control strategies, such as the Linear Quadratic Regulator (LQR), have also been employed [19]. Hadeer and Hatem proposed an LQR controller for a cantilever beam with PZT, leading to optimal vibration reduction [19].

In addition to the aforementioned methods, adaptive control strategies have also been explored. These strategies adjust the controller parameters based on the system's input-output data, thereby ensuring a tailored response to external stimuli [20]. The

implementation of adaptive robust sliding mode vibration control. The implementation of the controller on a flexible beam with a piezoceramic sensor and actuator results in reducing and suppressing the vibration. Furthermore, the experiments show the robustness of the controller since it is successfully demonstrated by adding mass to the flexible beam [21].

Furthermore, a fuzzy logic controller was employed for active vibration control in a smart cantilever beam. The beam, experiencing an impact force at its free end, initiates vibrations. These disturbances are detected by the piezoelectric sensor layer, producing a sensor voltage that serves as an input for the fuzzy logic controller. This controller, constructed with a set of 49 if-then rules, computes the necessary actuator voltage. Upon the delivery of this voltage to the piezoelectric actuator layer, the smart structure reacts by generating a corresponding control force. This research demonstrates the effectiveness of using a fuzzy logic controller in managing vibrations in a smart cantilever beam [22].

Also, one approach involves the design of a neural network-based controller to modulate the optimal voltage across piezoelectric patches affixed to the cantilever beam. This technique merges a neurocontroller with a Kalman Filter to deduce precise actuator commands, enhancing the dynamic response of the structure. the system's performance with and without control was compared, the neurocontroller has shown a remarkable capacity to reduce vibration responses [23].

In conclusion, the integration of PZT in structures such as cantilever beams presents a significant opportunity for effective vibration control. The various control strategies discussed above, shown in figure 1, have shown promising results, and as research in this field continues. It is anticipated that more effective and efficient methods will emerge, further enhancing the performance of these smart structures.

2.2 Self-Tuning PID Parameters Methods

The Proportional-Integral-Derivative (PID) controller remains a mainstay in industrial control systems due to its simplicity, robustness, and cost-effectiveness [24]. However, the effectiveness of PID controllers is profoundly tied to their parameter tuning, a subject that has seen substantial research.

Historically, pioneers like Ziegler-Nichols and Cohen-Coon developed the initial tuning methods [25]. However, these methods often fail to deliver optimal performance across different systems. Ziegler and Nichols' method is known for substantial overshoot, while Cohen and Coon's method is limited to systems that can be modeled by first-order plus dead-time (FOPDT) models [25].

In recent years, optimization-based tuning methods have emerged as a promising area of research. These include Genetic Algorithms (GAs), Particle Swarm Optimization (PSO),

and Ant Colony Optimization (ACO), which have demonstrated efficacy in finding optimal PID parameters [26], [27]. However, they require substantial computational resources and time, limiting their real-time applicability [28].

Recently, novel methodologies leveraging machine learning (ML) and artificial intelligence (AI) have started to show promise. For instance, reinforcement learning (RL), a machine learning technique, has been used to tune PID controllers effectively, providing a real-time solution with minimal overshoot [29][30]. These methods have demonstrated their ability to handle non-linearities and uncertainties in the system more effectively than traditional methods. However, these advanced methods often require computational infrastructure and are more complex to implement [31].

In conclusion, while traditional methods like Ziegler-Nichols and Cohen-Coon provide a basis for PID controller tuning, they often fall short in performance across various systems. Modern techniques, such as optimization-based methods and emerging AI/ML-based tuning methods, offer improved performance but require more computational resources and sophistication [32]. Therefore, ongoing research is needed to balance performance, computational demands, and ease of implementation in PID controller tuning methodologies. Figure 1 summarizes the methods employed for tuning PID parameters, alongside the control techniques applied in mitigating structural vibrations.

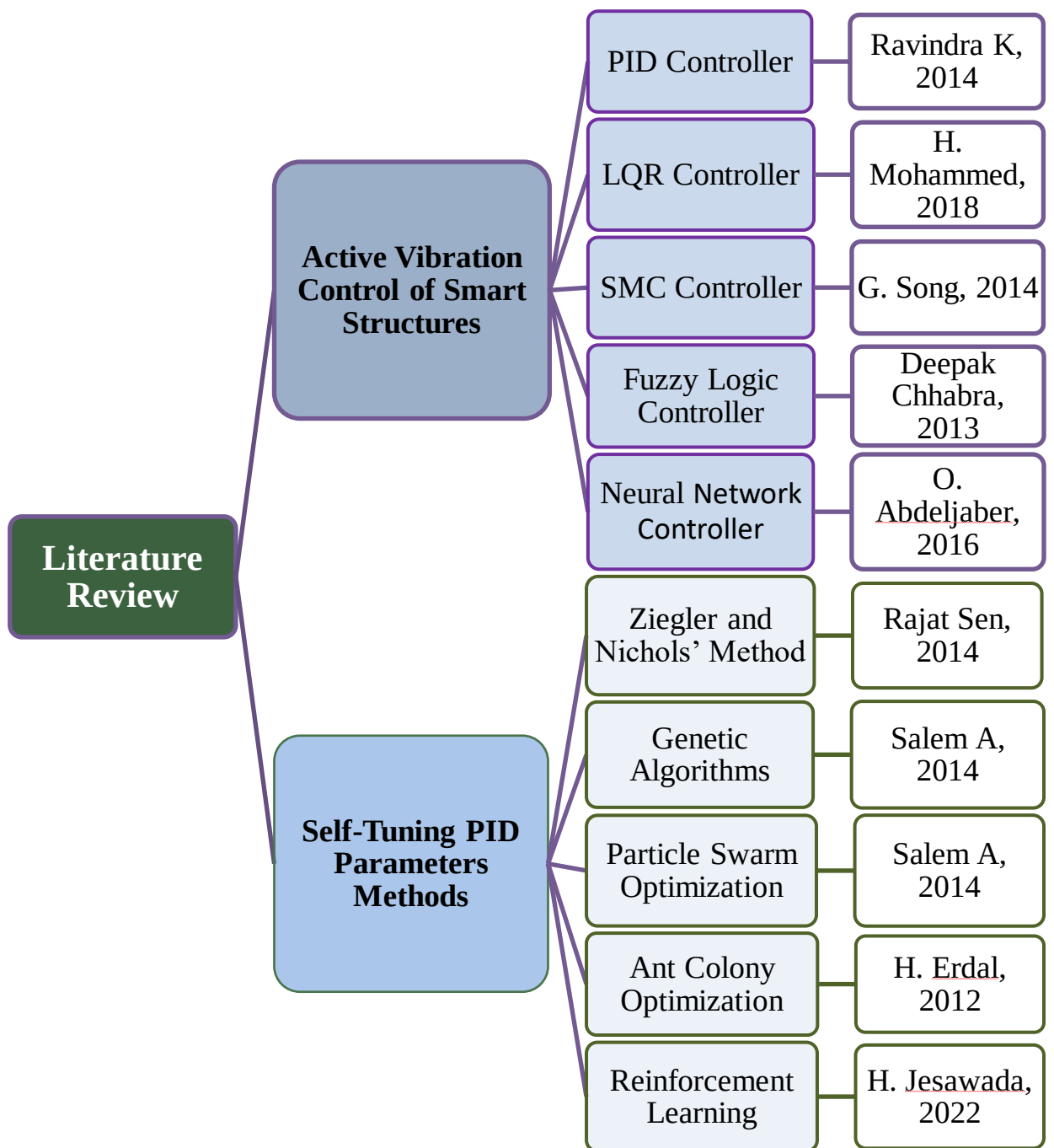


Figure 1: Literature Review Structure

CHAPTER 3

THEORETICAL BACKGROUND

3.1 Structural Engineering: Active, Adaptive, Smart

In the field of engineering, a new wave of structures is emerging with the ability to respond and adapt to their environment. These structures fall under the umbrella terms of active structures, adaptive structures, and smart structures, all with interconnected functionalities.

Active structures are structures with the built-in capacity to change their form, configuration, or inherent properties [33]. This is achieved through the use of sensors, actuators, and control systems that allow the structure to adjust its behavior based on external stimuli. For example, a building that can dampen vibrations during an earthquake is an example of an active structure [33].

Adaptive structures are specific types of active structures that focus on the ability to modify their geometry or inherent structural characteristics [33]. This adaptation can be triggered by external factors, either through remote commands or through automatic means based on sensor data. For instance, an adaptive wing on an airplane might change its shape to optimize lift based on airspeed [34].

The term smart structure is often used interchangeably with active structure. However, it can also imply a higher level of intelligence, as referenced in various research papers on the classification of smart structures [35]. Smart structures not only respond to the environment but also have the potential to make decisions and optimize their behavior based on complex data analysis. This is a developing field of research, envisioning structures that can not only react but also strategically adapt for improved performance and efficiency [35].

3.2 Vibration Control

Mechanical and structural systems often experience vibrations, a phenomenon that can lead to hazardous issues if not effectively controlled. To address this, two primary types of vibration control are employed: passive and active. Passive vibration control systems use devices like dampers and springs to absorb and dissipate the vibrational energy, thus mitigating its overall impact [36]. In contrast, active vibration control adopts a proactive approach, utilizing an array of sensors and actuators specifically designed to detect and negate vibrations [37]. These components function collaboratively to counteract the vibrations, thereby ensuring the system's stability [37].

3.2.1 Active Vibration Control

Active vibration control represents the pinnacle of modern engineering efforts to mitigate the potentially destructive effects of dynamic forces on structures and machinery. This type of control system is distinguished by its ability to adapt to changing vibration patterns in real time, providing a tailored response to the specific disturbances experienced by the system [38].

This method employs sensors to monitor and detect vibrations or undesirable movements within buildings or structures. Upon identifying such motion, the system activates a powered actuator which then exerts a precisely calculated force to counteract and suppress the vibrations, thereby stabilizing the structure [39].

The effectiveness of active control strategies is influenced by various critical parameters, such as the strategic placement of the piezoelectric transducers (PZTs), the selection of the control algorithm, and the nature of the external disturbances [37]. While active control techniques are generally adept at damping vibrations, their complexity is higher compared to passive control approaches due to the need for real-time data processing and response execution.

3.3 Basics of Smart Materials

Smart materials stand out in the world of material science due to their dynamic nature [40]. Unlike conventional materials with static properties, smart materials are engineered to change their physical state, be it electrical, mechanical, or functional, upon exposure to external stimuli such as light, electrical currents, or magnetic fields [40].

These adaptive materials are increasingly integrated into systems where their dynamic properties can be leveraged to meet varying performance demands. As defined by Takagi, smart materials are designed to intelligently respond to a multitude of environmental stimuli in the most effective manner, ensuring their behavior aligns with intended functions [41].

The interplay between "stimulus" and "response" is central to the role of smart materials, particularly in their application as actuators and sensors, as indicated in Table 1. This table illustrates the various stimuli these materials can detect or act upon and the corresponding responses they exhibit.

Table 1: Sensor and Actuator Material Classes [42]

	Material Class	Stimulus	Response
Sensors	Pyroelectrics	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
	Electrostrictors	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

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 are the major benefits of smart material actuators and sensors [42].

Thus, smart structures can detect and react to external disturbances in real time with active control to fulfill the required conditions. It 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 actions taken as a foundation in the

future [43]. Smart structures can be classified, Figure 2 shows the relationship between these different structure types.

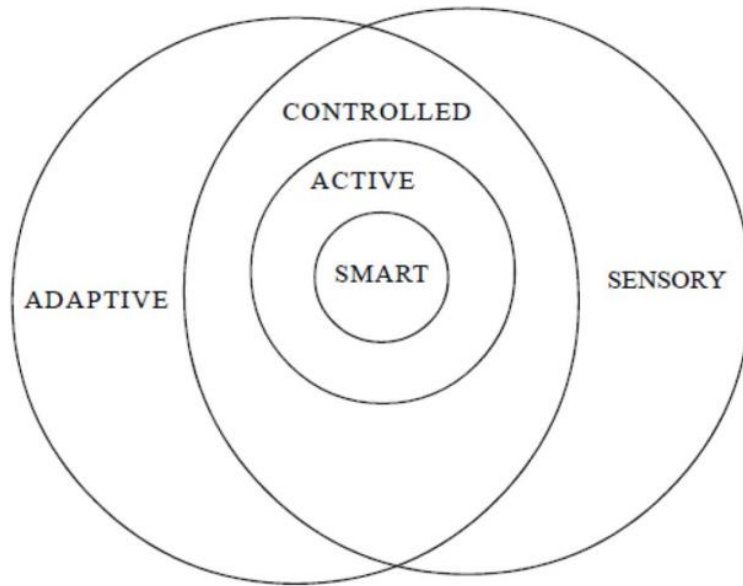


Figure 2: General Framework of Smart Structures Categories. [43]

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, sensors and actuators are integrated in 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 c.

3.3.1 Piezoelectric Effect

One of the most common smart materials is piezoelectric material [44]. Only non-conductive materials exhibit the piezoelectric material effect [45]. 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 [46]. Figure 3 illustrates this effect schematically.

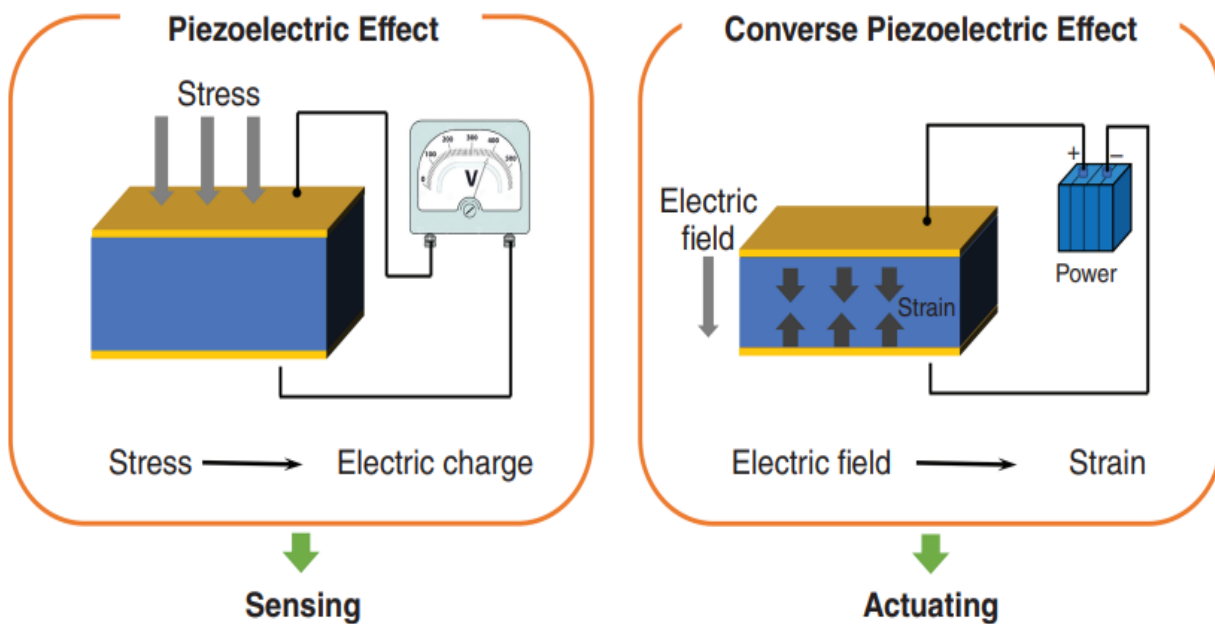


Figure 3: The Piezoelectric Effect [46]

CHAPTER 4

SMART STRUCTURE DYNAMIC MODEL

Modeling of the Beam's dynamic system was made by Shawn Le [47]. A state model of a flexible aluminum cantilever beam with a pair of PZT actuators and a single PZT sensor was built based upon the Euler-Bernoulli Beam theory.

4.1 Euler-Bernoulli Beam Theory

Euler-Bernoulli Beam Theory is the theory of beam elasticity providing a method for estimating the load-carrying and deflection properties of beams [48]. 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. The two fundamental assumptions are that "plane sections remain plane" and "deformed beam angles (slopes) are small" [49].

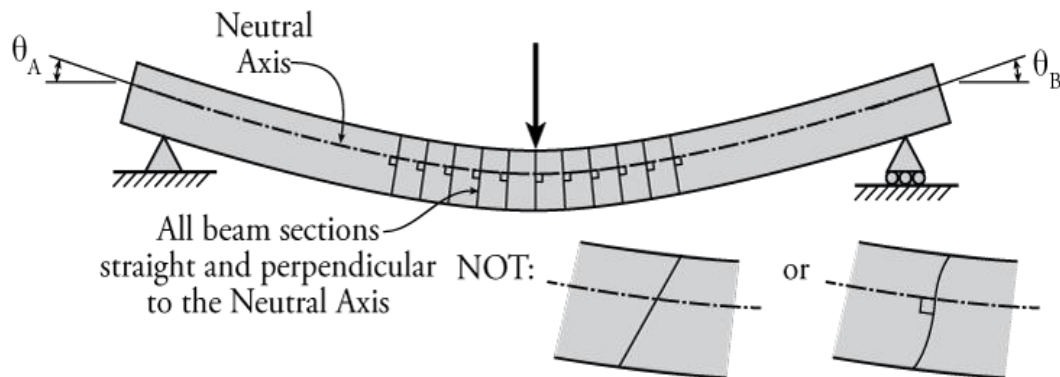


Figure 4: Assumption of the Plane Sections Remain Plane [48]

4.2 Dynamic Modeling of the Cantilever Beam with PZT Materials

Figure 4 shows a piezoelectric cantilever beam. At one end, the beam is fixed, whereas, at the other, it is free. As indicated in Figure 5, 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 [47].

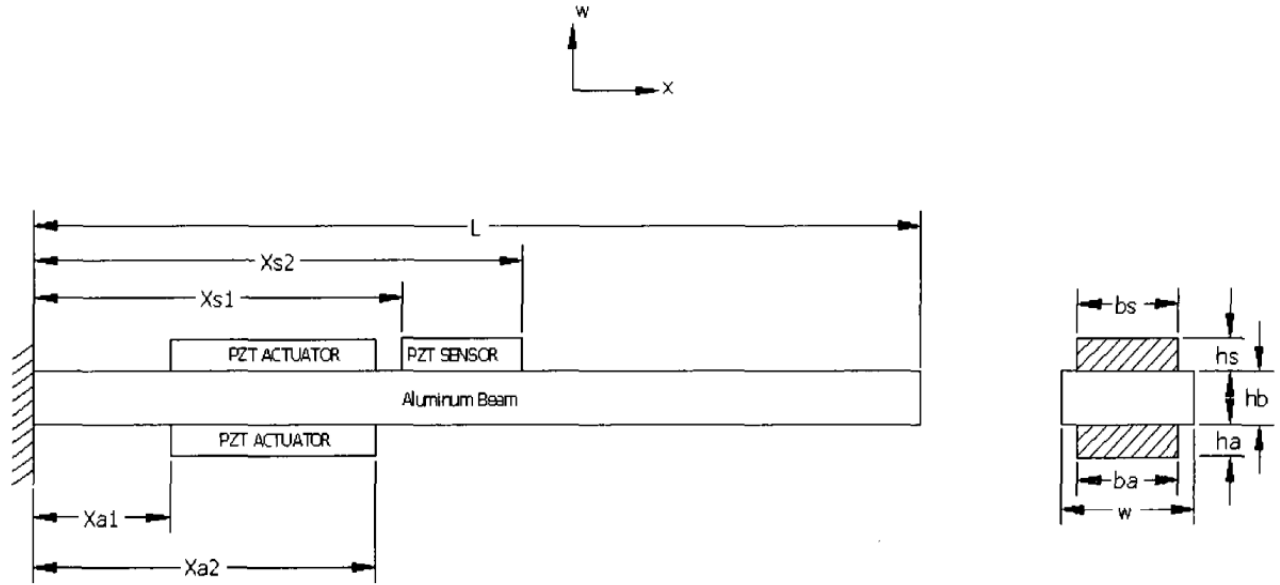


Figure 5: Cantilever Beam with Pair of PZT Actuators and Sensor [47]

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 [50]:

$$\rho_b A_b \frac{\partial^2 w}{\partial t^2} + E_b I_b \frac{\partial^4 w}{\partial x^4} = M_a \frac{\partial^2 R(x)}{\partial x^2} \quad (4.1)$$

where

ρ_b is the mass density of beam sensor material

A_b is the cross sectional beam sensor area

E_b is the Young's Modulus of beam sensor

$$I_b \text{ is the first moment of inertia, } I_b = \frac{b_a h_b^3}{3} \quad (4.2)$$

h_b is the thickness of beam sensor b_a is the width of beam sensor

W is the beam transverse displacement

M_a is the bending moment acting on beam.

$$R(x) \text{ is } H(x-x_{a1}) - H(x-x_{a2}) \quad (4.3)$$

where R is the generalized location function and H is the Heaviside function, x_{a1}

and x_{a2} are locations of the actuators.

The equation of the beam actuator dynamics system is:

$$\ddot{\eta}_i(t) + 2\xi_i \omega_{ni} \dot{\eta}_i(t) + \omega_{ni}^2 \eta_i(t) = k_a [\phi'_i(x_{a2}) - \phi'_i(x_{a1})] V_a(t) \quad (4.4)$$

where (.) denotes time derivatives and (') represents space derivatives.

where

$\eta_i(t)$ is temporal functions.

ξ_i is damping.

ω_{ni} is the natural frequency.

$$k_a = \frac{\frac{1}{2} E_a d_{31} b_a (h_b + h_a)}{\rho_a A_a} \quad (4.5)$$

E_a is the Young's Modulus of 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 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

Taking the Laplace transform of the beam actuator dynamics system is:

$$V_a(s) = \sum_{i=1}^N \frac{s^2 + 2\xi_i \omega_{ni} s + \omega_{ni}^2}{k_a [\phi'_i(x_{a2}) - \phi'_i(x_{a1})]} \quad (4.6)$$

The elastic deflection of the flexible beam caused by the voltage applied to the actuating piezoelectric is described by the equation above.

The equation of the beam sensor dynamics system is:

$$V_s(t) = k_s \sum_{i=1}^N \frac{\eta_i(t) [\phi'_i(x_{s2}) - \phi'_i(x_{s1})]}{c_s b_s (x_{s2} - x_{s1})} \quad (4.7)$$

where

$V_s(t)$ is the sensor voltage

x_{s1} and x_{s2} are locations of the sensor.

$$k_s = -b_s \left(\frac{t_b}{2} + t_a \right) \left(\frac{k_{31}^2}{g_{31}} \right) \quad (4.8)$$

k_{31} is the coupling coefficient.

g_{31} stands for the voltage coefficient of piezoelectric.

C_s is the capacitance per unit area of the piezoelectric sensor.

$b_s(x_{s2} - x_{s1})$ is the surface area of the piezoelectric element.

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

$$V_s(s) = k_s \sum_{i=1}^N \frac{[\phi'_i(x_{s2}) - \phi'_i(x_{s1})]}{C_s b_s(x_{s2} - x_{s1})} \quad (4.9)$$

The equation (4.10) is the transfer function describing the relation between the voltage applied to the actuator $V_a(s)$ and the voltage induced in the piezoelectric sensor $V_s(s)$.

$$\frac{V_s(s)}{V_a(s)} = \sum_{i=1}^N \frac{k_s k_a [\phi'_i(x_{s2}) - \phi'_i(x_{s1})] [\phi'_i(x_{a2}) - \phi'_i(x_{a1})]}{C_s b_s(x_{s2} - x_{s1}) (s^2 + 2\xi_i \omega_{ni} s + \omega_{ni}^2)} \quad (4.10)$$

4.3 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 sensor within the beam system, respectively, as sourced from [47]. 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	1.09E+07
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	-1.90E-10	-1.90E-10
g_{31}	Vm/N	-1.16E-02	-1.16E-02
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 thesis, 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 illustrates various ways the beam can bend or vibrate. Moreover, we integrated experimental data from Shawn [44] 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 their collective influence 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 (4.10):

Transfer function of first mode shape:

$$\frac{V_{s1}(s)}{V_{a1}(s)} = \frac{-2.944}{s^2 + 1.95s + 9506} \quad (4.11)$$

Transfer function of second mode shape:

$$\frac{V_{s2}(s)}{V_{a2}(s)} = \frac{-37.11}{s^2 + 11.79s + 3.475e5} \quad (4.12)$$

Transfer function of third mode shape:

$$\frac{V_{s3}(s)}{V_{a3}(s)} = \frac{80.56}{s^2 + 32.56s + 2.651e6} \quad (4.13)$$

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

$$\frac{V_s(s)}{V_a(s)} = \frac{40.51 s^4 - 304.5 s^3 - 7.88e7 s^2 - 2.65e8 s - 3.381e12}{s^6 + 46.3 s^5 + 3.008e6 s^4 + 4.884e7 s^3 + 9.498e11 s^2 + 2.201e12 s + 8.757e15} \quad (3.14)$$

The transfer function indicates a type 0 system as there are no terms in the denominator containing 's', which signifies the absence of integrators.

4.4 System Design

The system comprises two inputs: the step function with a final value of zero, representing the reference input, and the disturbance. It encounters two different types of disturbances individually: an impulse disturbance and a random disturbance modeled by a Gaussian distribution. These disturbances, characterized by significant force, induce high vibration in the cantilever beam system. The resulting system output is observed through the voltage induced in the piezoelectric sensor.

This study enables a comprehensive examination of the system's response to various disturbance scenarios, providing valuable insights into the system's behavior under different conditions. Figures 6 and 7 below illustrate the block diagram of the system when affected by an impulse disturbance and a random disturbance, respectively.

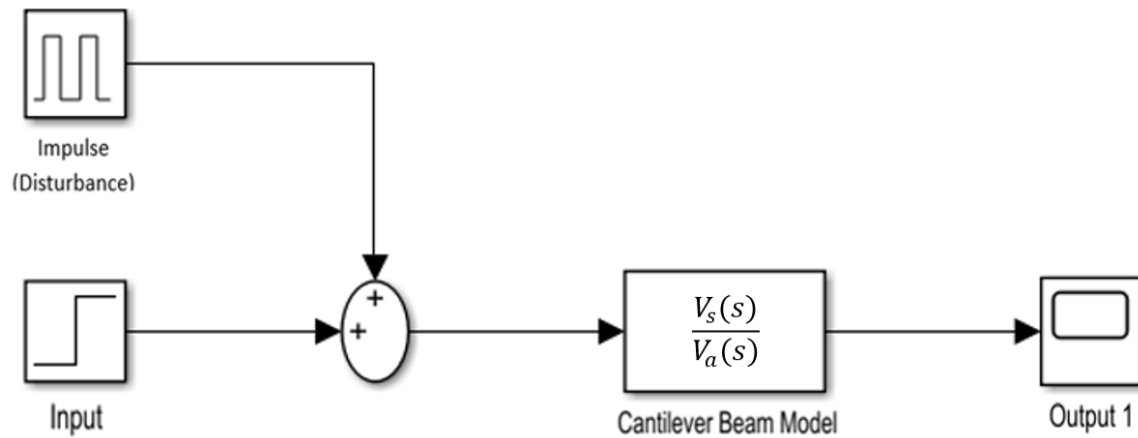


Figure 6: Block Diagram of Open Loop System with Impulse Disturbance

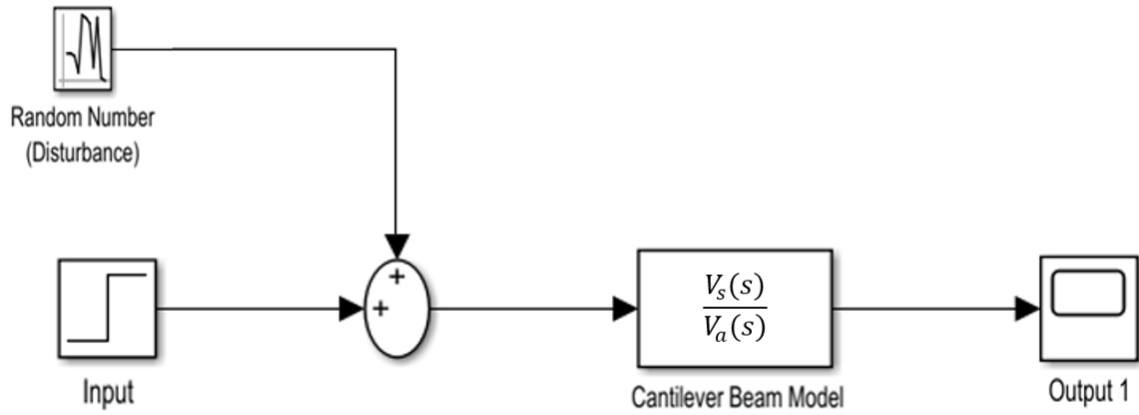


Figure 7: Block Diagram of Open Loop System with Random Disturbance

The subsequent figures 8-12 show signal plots of the reference input, impulse disturbance, system output under impulse disturbance, random disturbance, and system output under random disturbance.

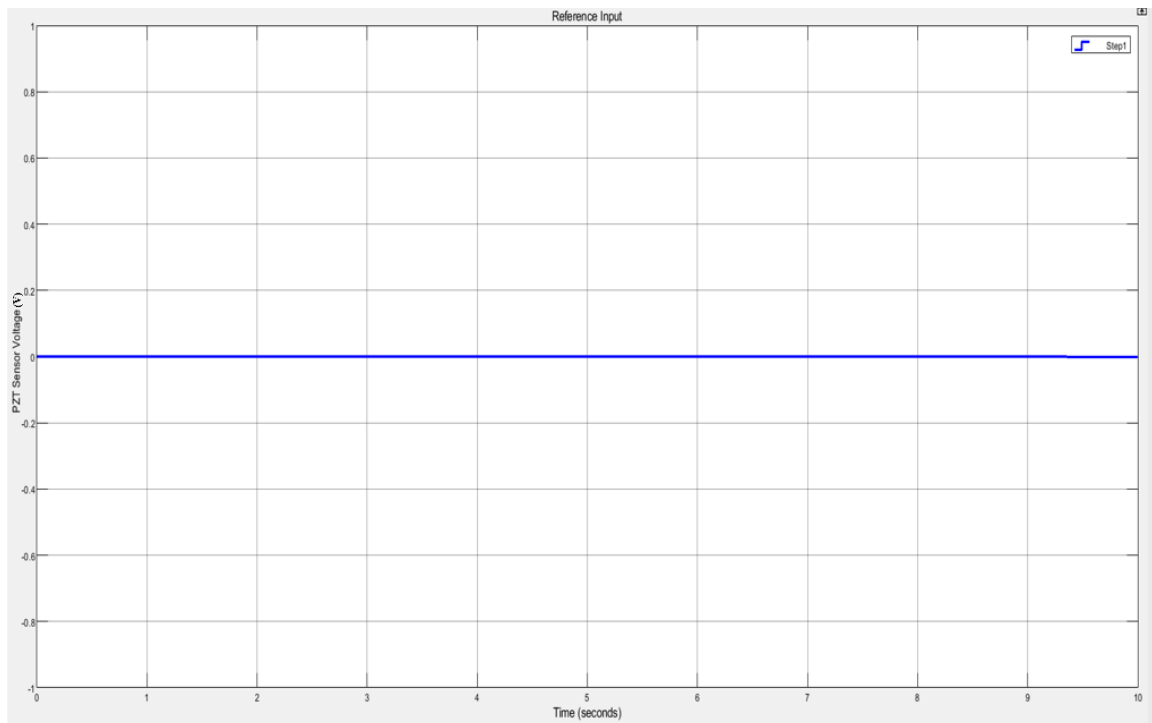


Figure 8: Reference Input

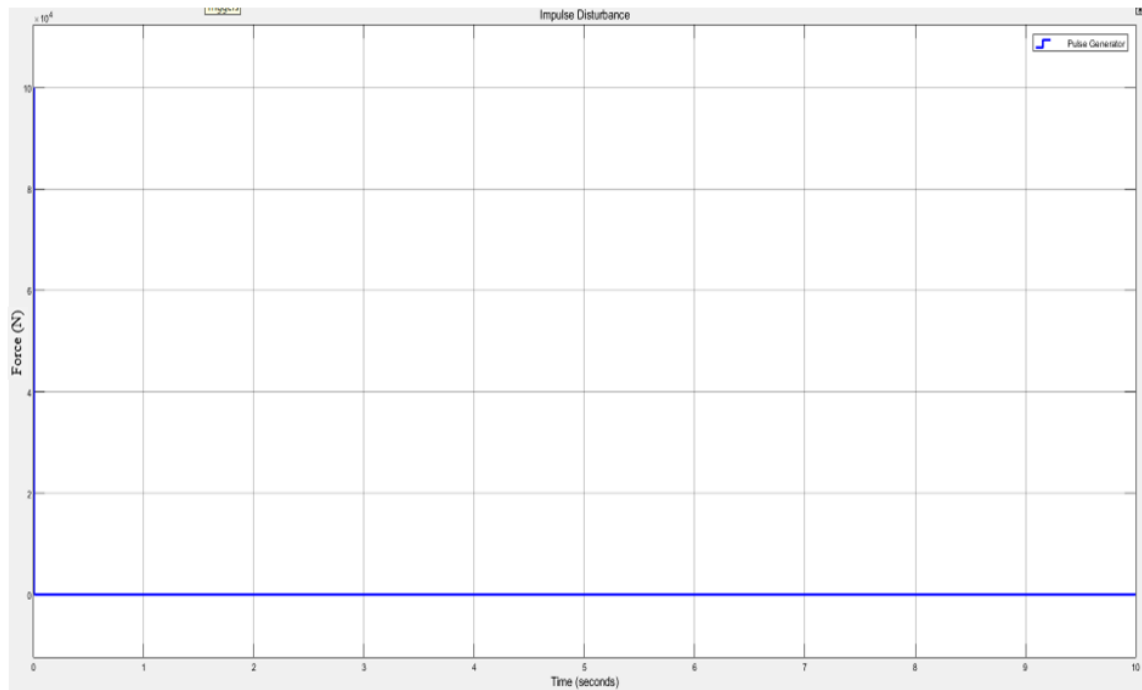


Figure 9: Impulse Disturbance

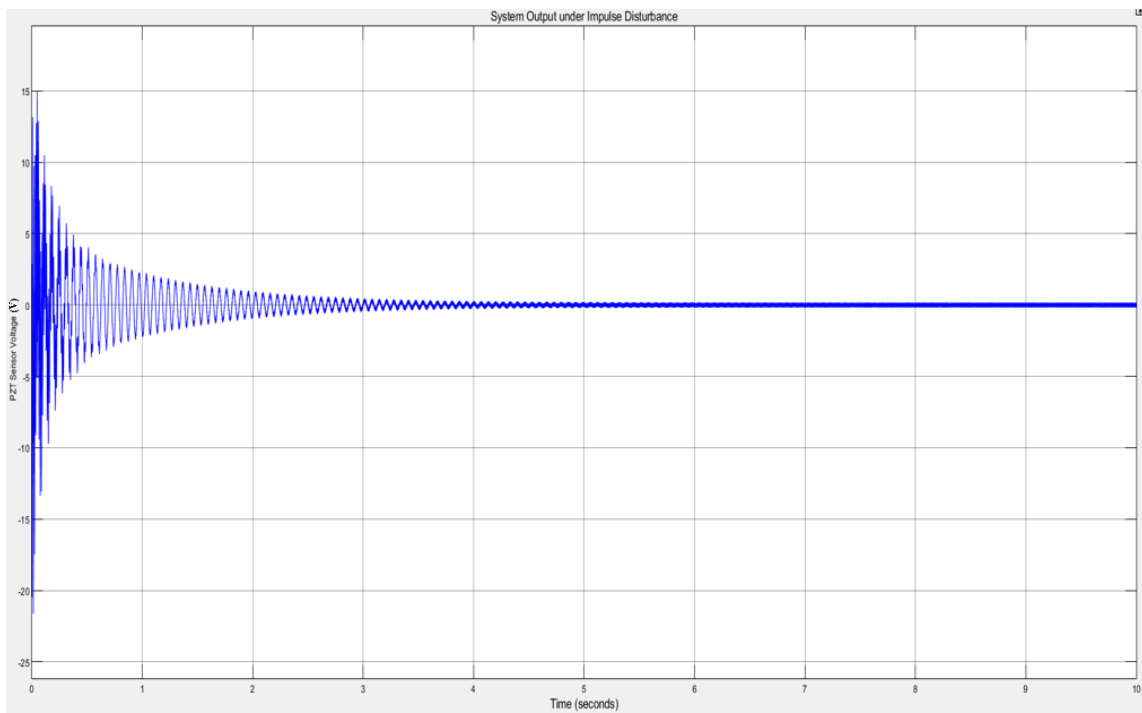


Figure 10: Voltage Response of PZT Sensor in the Cantilever Beam

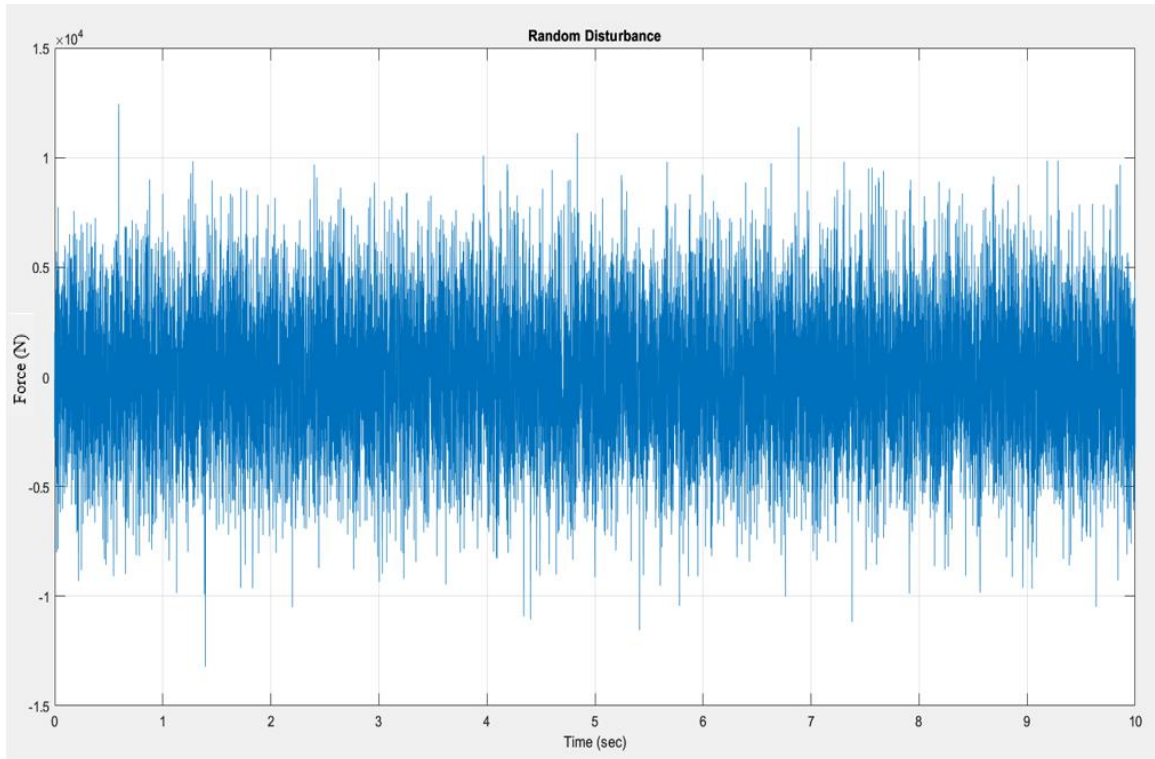


Figure 11: Random Disturbance

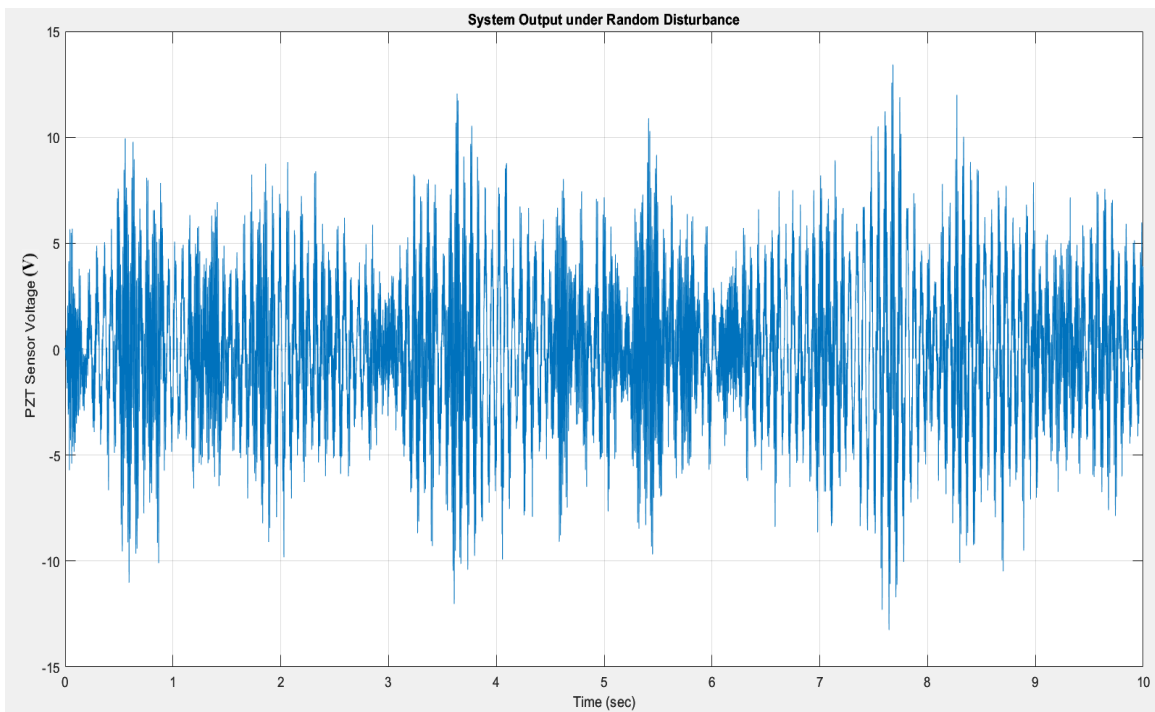


Figure 12: Voltage Response of PZT Sensor in the Cantilever Beam

4.4.1 Low-Pass Filter

The integration of a low-pass filter is worthy, as it serves to enhance stability by effectively addressing high-frequency noise and disturbances while preserving essential low-frequency signals [51]. This proactive decision underscores precision and reliability, ensuring smoother responses and mitigating the impact of unwanted fluctuations within the system.

The selection of the cutoff frequency for the low-pass filter was based on the observation of previous system output plots, aiming to eliminate unwanted signals while retaining pertinent information. After evaluating these plots, a cutoff frequency of 11 Hz was chosen to strike an optimal balance. With this frequency determined, the next step involved defining the transfer function of the low-pass filter. The transfer function, denoted as

$$H(s) = \frac{1}{1+sT} \quad (4.15)$$

where T represents the time constant, characterizes the filter's frequency-dependent behavior. Calculating the time constant T was crucial for ensuring effective signal filtration. Utilizing the formula

$$T = \frac{1}{2\pi f_c} \quad (4.16)$$

where f_c is the chosen cutoff frequency of 11 Hz, yielded a time constant of approximately 0.0144 seconds.

Integrating the filter into the system's architecture allows us to examine its influence on output behavior. This integration facilitates the evaluation of the filter's effects on noise attenuation and signal fidelity, key aspects of system performance. Figures 13-16 illustrate the block diagram incorporating the low-pass filter and showing the system's output under both impulse and random disturbance conditions.

4.4.2 Open Loop System Affected by Impulse Disturbance

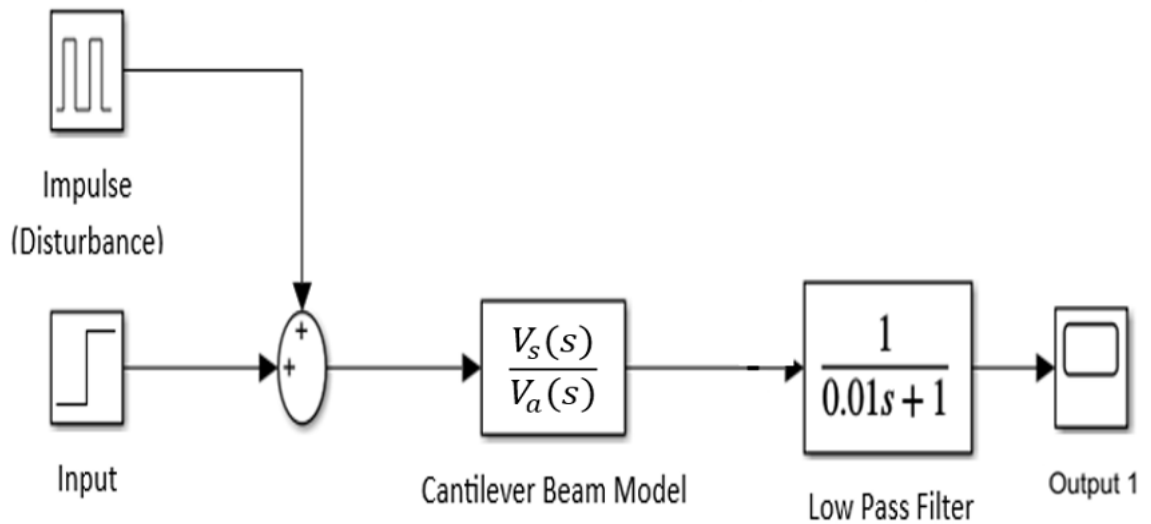


Figure 13: Block Diagram of Open Loop System with Low-Pass Filter under Impulse Disturbance

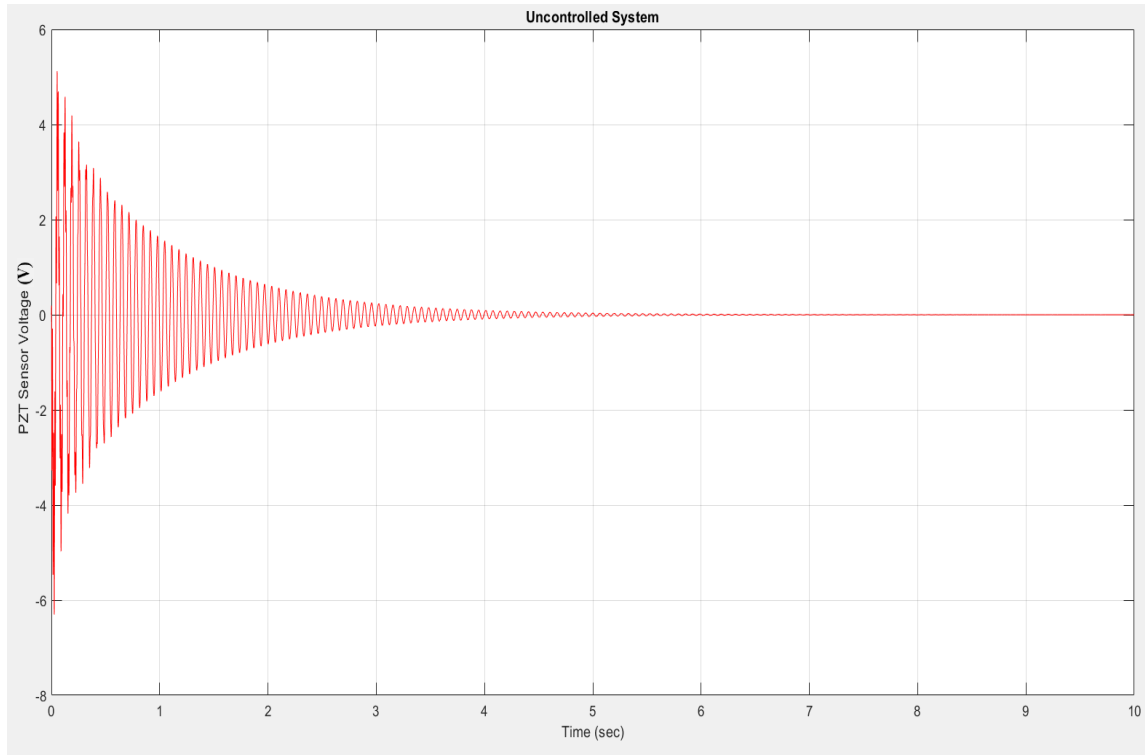


Figure 14: Voltage Response of PZT Sensor under Impulse Disturbance (with Low-Pass Filter)

Following the integration of the low-pass filter, distinct improvements are evident in the system's output. Previously, the signal exhibited a wide-ranging amplitude oscillating from -21.7 to 15 Hz, accompanied by considerable noise. However, with the filter, the signal's amplitude became more constrained, now ranging from -6.1 to 5 Hz, while the previously prevalent noise diminished noticeably.

4.4.3 Open Loop System Affected by Random Disturbance

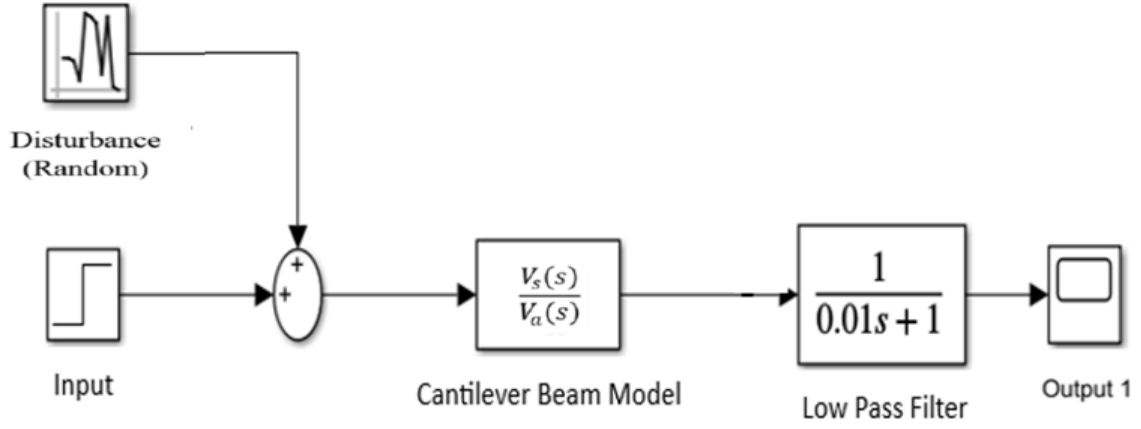


Figure 15: Block Diagram of Open Loop System with Low-Pass Filter under Random Disturbance

Furthermore, when the system is under random disturbance, the signal displayed a wide-ranging amplitude oscillating from -13.5 to 13.5 Hz, accompanied by high noise. However, with the implementation of the filter, the signal's amplitude became more confined, now ranging from -3 to 3 Hz, while the previously prevalent noise significantly decreased.

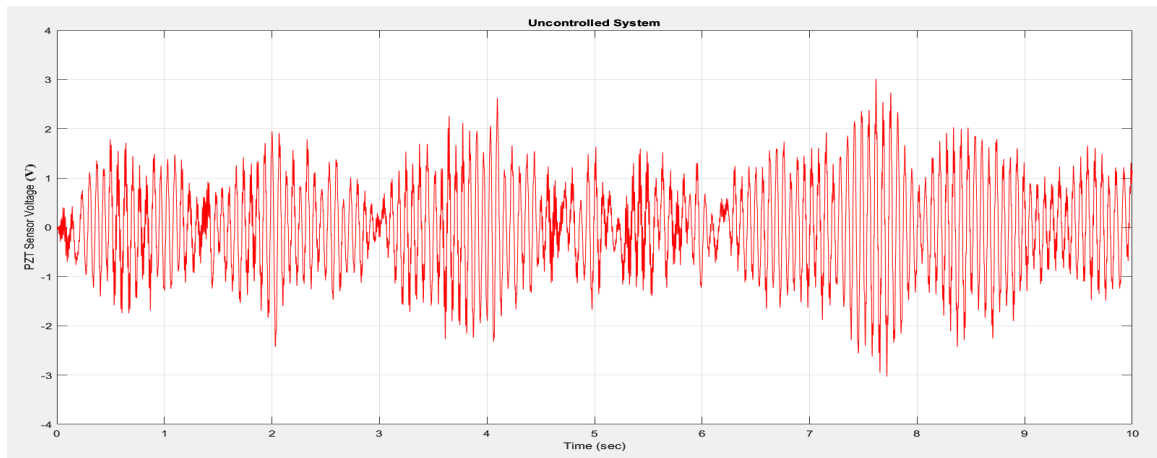


Figure 16: Voltage Response of PZT Sensor under Random Disturbance (with Low-Pass Filter)

CHAPTER 5

CONTROLLER DESIGN

5.1 Introduction

Controller design is an essential component of engineering systems, influencing their performance, stability, and responsiveness. This section explores the principles and methodologies underlying the design of various controllers to address the design of controllers tailored for the cantilever beam system to control its vibrations. Each controller provides a unique perspective on optimizing system performance in vibration control.

Proportional-integral-derivative (PID) controllers have long been the cornerstone in the realm of control engineering due to their simplicity and effectiveness in a wide range of applications. The design of a PID controller for a cantilever beam with PZT material presents a unique challenge. The unique properties of PZT materials to convert electrical signals into mechanical displacement make them ideal actuators for vibration control in cantilever beams. The main objective is to mitigate unwanted vibrations that can lead to mechanical fatigue or failure [52].

The traditional PID controller needs to be meticulously designed to ensure the system's stability and achieve the desired vibration attenuation. It requires an accurate tuning of its parameters, proportional (P), integral (I), and derivative (D) gains, which are usually determined based on the dynamic model of the beam and the PZT material. However, the performance of a PID controller can be significantly influenced by the variability in the system dynamics due to changes in the operating conditions or the characteristics of the PZT material.

In this thesis, we address the challenge of enhancing the performance of the PID controller for vibration suppression in a cantilever beam with PZT materials through self-tuning methodologies. Recognizing the limitations of conventional tuning methods, we explore the potential of intelligent techniques that can adaptively adjust the PID parameters in real time, ensuring optimal control across varying conditions and system dynamics. Specifically, we investigate three self-tuning strategies: Genetic Algorithms (GA), Neural Networks (NN), and Fuzzy Logic (FL). Each of these techniques offers a unique approach to the self-tuning problem. GAs through evolutionary optimization, NNs by learning from data and approximating the control function, and Fuzzy Logic by applying expert knowledge in a rule-based manner. Furthermore, we address the challenge of designing a pure deep learning controller by understanding the relationships between system components to control and mitigate cantilever beam vibration. The thesis aims to demonstrate the effectiveness and practicality in enhancing the vibration control performance of the cantilever beam system. Through detailed analysis and comparison,

we illustrate how these methods can improve control accuracy, adaptability, and overall system stability under varying conditions and dynamic environments.

5.2 Proportional – Integral – Derivative Control Design

Designing a Proportional – Integral – Derivative (PID) controller involves representing the controller's function within a block diagram. In the block diagram, as shown in figure 15, the PID controller is typically depicted as a single block with three parameters: proportional gain (K_p), integral gain (K_i), and derivative gain (K_d). The input signal, reference or setpoint, is compared with the feedback signal for the system output. The error signal is obtained by subtracting the feedback signal from the reference signal. This error signal is then fed into the PID controller block.

The proportional branch multiplies the error by the proportional gain (K_p), providing an immediate response to the current error. The integral branch integrates the error over time, amplified by the integral gain (K_i), addressing accumulated errors over time. The derivative branch considers the rate of change of the error signal, multiplied by the derivative gain (K_d), contributing to the controller's responsiveness to changes.

The output of each branch is summed to generate the control signal which is applied to the system. The system's output is then fed back, closing the loop. The block diagram

succinctly illustrates how the PID controller modulates the input signal to minimize the error between the desired setpoint and the actual system output. Adjusting the PID gains allows us to fine-tune the controller's response to achieve desired system performance.

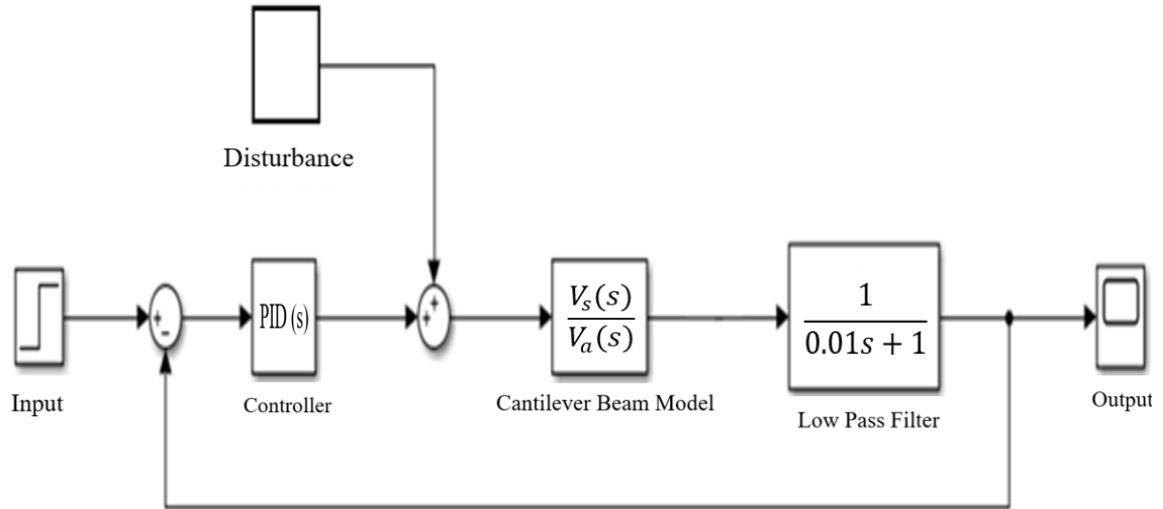


Figure 17: Block Diagram of Closed Loop System

5.3 Genetic Algorithm

Genetic Algorithm (GA) is a class of optimization algorithms inspired by the process of natural selection, which is a mechanism of evolution in biological systems. These algorithms mimic the principles of biological evolution, such as reproduction, mutation, recombination, and selection to solve complex optimization and search problems [53].

The core concept behind GA is the survival of the fittest. A population of candidate solutions, known as individuals or chromosomes, evolved toward better solutions over

successive generations. Each individual is evaluated based on a fitness function that quantifies the quality of the solution it represents. The fittest individuals are more likely to be selected for reproduction, passing their genes to the next generation [54].

During the evolutionary process, various operators such as selection, crossover (also known as recombination), and mutation are applied to create a new generation of individuals that potentially have better fitness scores. Over time, the population converges towards an optimal or near-optimal solution [54].

GA is particularly useful for solving complex problems where traditional optimization methods struggle, such as those involving a large search space, multiple conflicting objectives, or discrete variables. Their adaptability and robustness make them a popular choice for a wide array of applications in science, engineering, economics, and other fields.

5.3.1 Tuning PID Controller Using Genetic Algorithms

Tuning PID parameters is a critical aspect of controller design, and various methods, including Genetic Algorithms (GA) and the Integral Time Absolute Error (ITAE) criterion, have proven effective in achieving optimal performance. Genetic Algorithms, inspired by the principles of natural selection, involve a population of potential solutions over multiple generations. In the context of PID tuning, GA explores different

combinations of proportional, integral, and derivative gains to find the set that minimizes a defined performance metric, such as ITAE.

The ITAE criterion is a performance measure that considers both the magnitude and duration of the error over time. It is expressed as the integral of the absolute error multiplied by time. Tuning PID parameters using GA and ITAE involves defining an objective function that quantifies the system's performance, and the GA algorithm iteratively searches for the optimal PID parameters that minimize this criterion.

This approach offers several advantages. GA's ability to explore a broad solution space complements ITAE's focus on minimizing integral error. The iterative nature of GA allows for a systematic search for optimal PID parameters, contributing to the generation of a comprehensive dataset characterizing the system.

In summary, tuning PID parameters using GA and ITAE provides a robust methodology for achieving optimal controller performance. The combination of GA's evolutionary search capabilities and ITAE's comprehensive performance assessment contributes to the efficient and effective tuning of PID controllers, enhancing stability, responsiveness, and overall system control.

5.3.2 GA-PID Controller Results

The PID controller is applied to the system, and the genetic algorithm is utilized to optimize the PID parameters for improved system performance. The genetic algorithm is initialized with a specified number of variables, lower and upper bounds, and optimization options.

The GA is then executed to find the optimal PID parameters that minimize the objective function. The resulting parameters are stored, and the system is simulated again using the optimized PID controller. The performance of the system is evaluated, and the Integral Time Absolute Error (ITAE) is calculated. The ITAE values provide insights into the system's behavior and the effectiveness of the PID controller in mitigating disturbances.

$$ITAE = \int_0^{\infty} t \cdot |e(t)| dt \quad (5.1)$$

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

A. Control System Affected by Impulse Disturbance

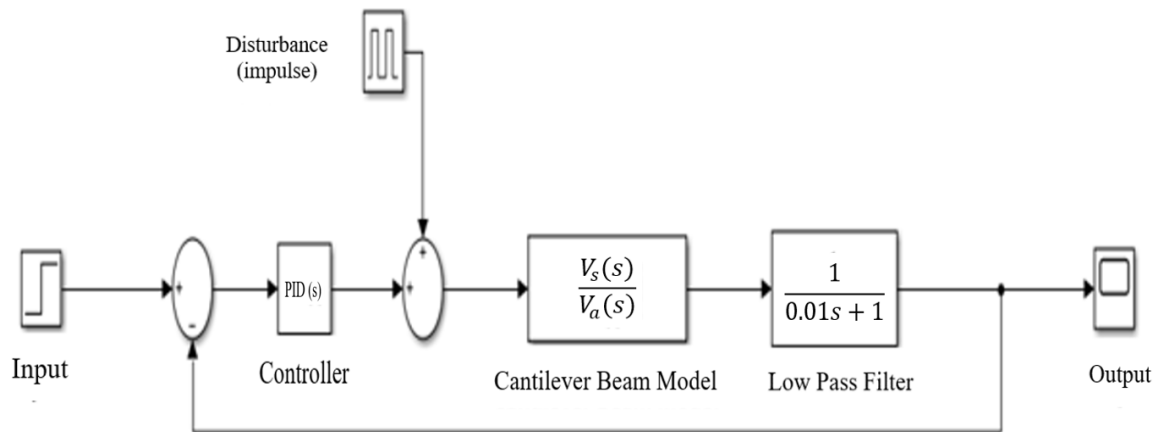


Figure 18: Block Diagram of Closed Loop System under Impulse Disturbance

The system experiences an impulse disturbance, as illustrated in Figure 18, and is initiated precisely at 0 seconds, as detailed in Figure 20. Subsequently, Figures 19 and 21 present the intended reference input and the uncontrolled system's output signal. Notably, the output signal exhibits significant oscillatory behavior, with amplitudes varying between -6.1 V and 5 V. This deviation is considerable when compared to the reference input.

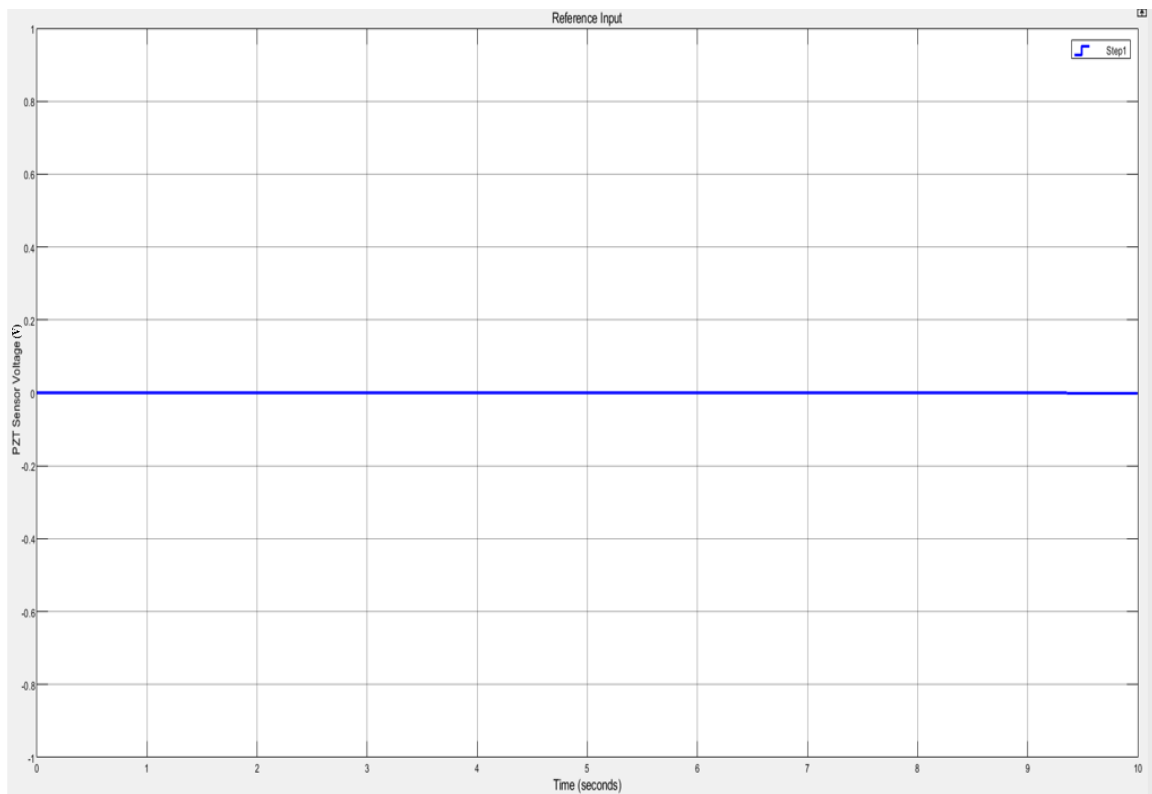


Figure 19: Reference Input

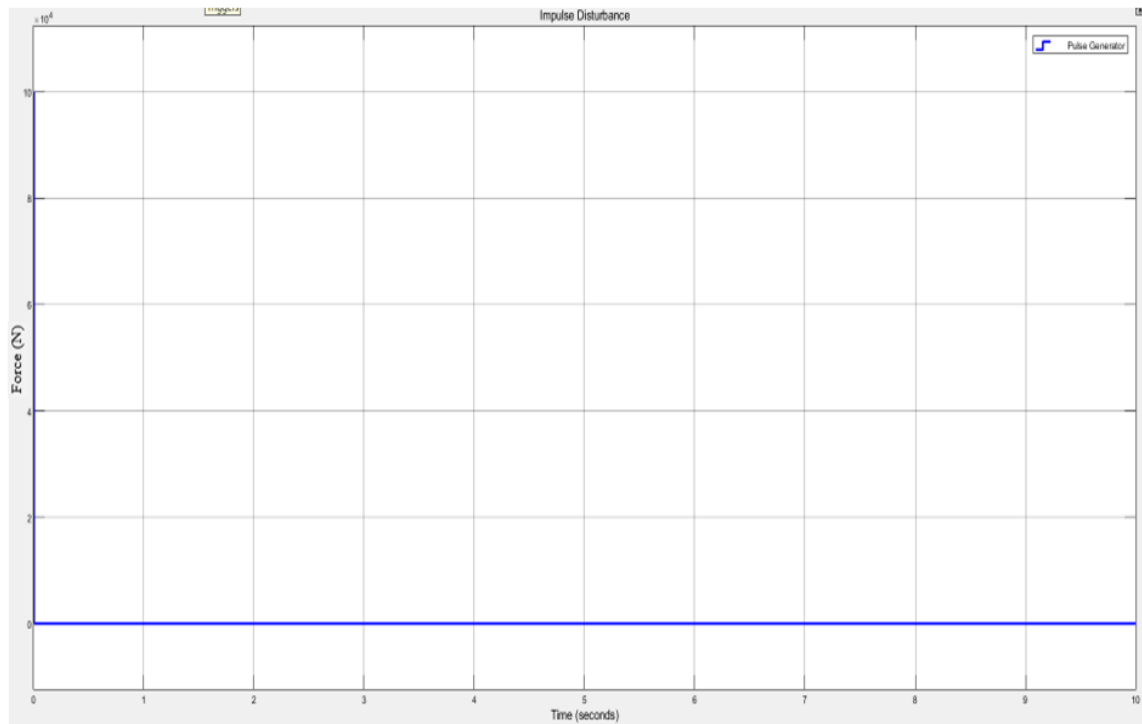


Figure 20: Impulse Disturbance

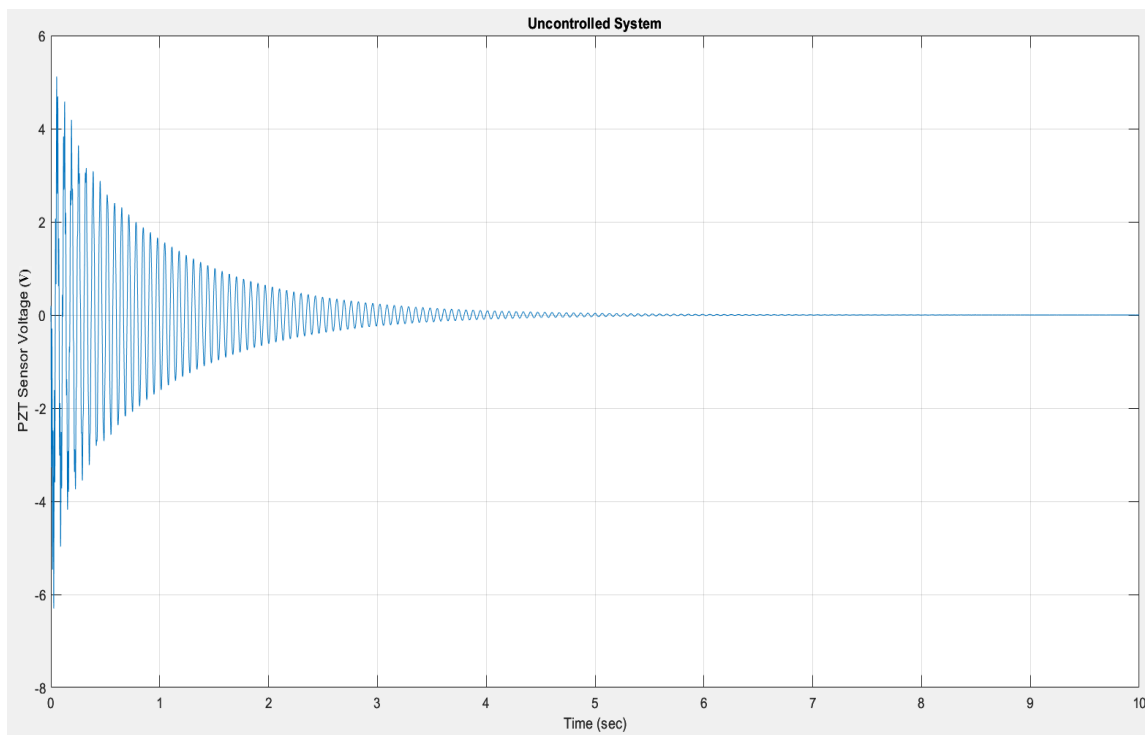


Figure 21: Voltage Response of PZT Sensor under Impulse Disturbance (with Low-Pass Filter)

To mitigate this disturbance and enhance system stability, we implemented a PID controller and tuned its parameters through the application of a Genetic Algorithm.

The "fitness value vs. generation" plot, figure 22, in the Genetic Algorithm (GA) exhibits a distinctive pattern, highlighting a significant decrease in fitness values up to the 7th generation, followed by a stable level from the 8th to the 50th generation. The initial decline suggests effective optimization and convergence during the early generations, while the subsequent stability implies that the GA has reached a point where further improvements are limited. The Integral Time Absolute Error (ITAE) measures a low value of 1.0255 and the Mean Squared Error (MSE) is 1.1251e-13, underscoring the predictive precision of the controller.

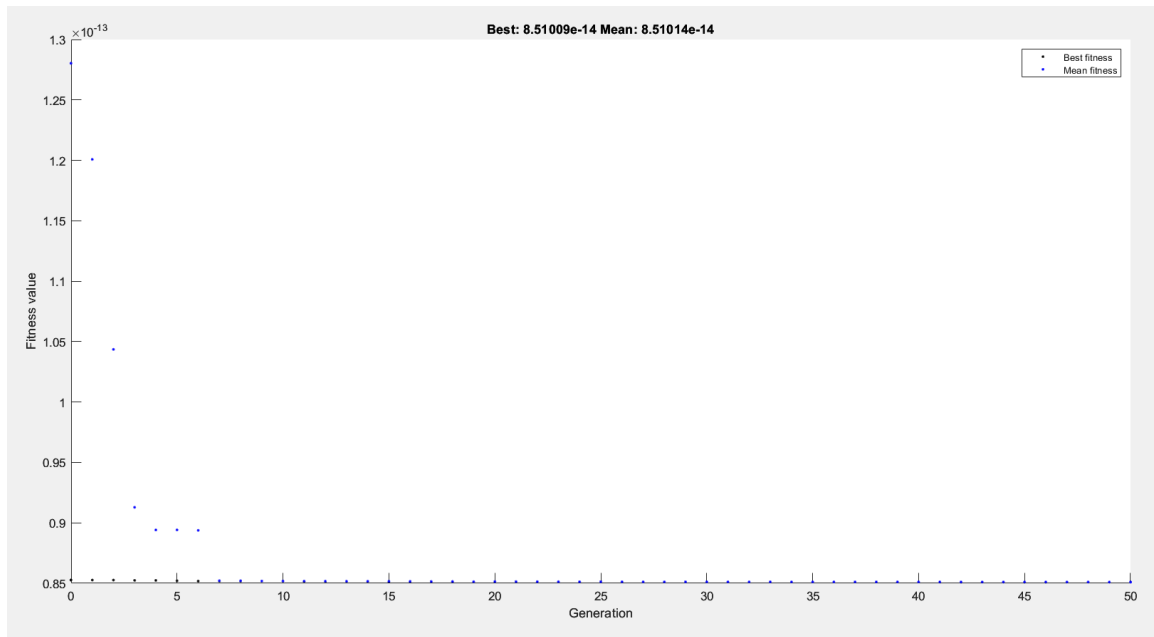


Figure 22: Fitness Value VS. Generation Plot

The outcome of tuning the PID parameters is shown in Table 5:

Table 4: PID Controller Parameters Tuned Using GA of the System Affected by Impulse Disturbance

K_p	K_i	K_d
230	-2960	120

After the implementation of the optimized PID controller using GA, the system's peak reduces to 4.107 V at 0.061 s, compared to 5.120 V at 0.053 s before the controller was applied. The settling time after applying the tuned PID controller is 1.88 s. This precise tuning is evident in the Integral Time Absolute Error (ITAE) value of 8.83427e-14, showcasing a proficient reduction in both error magnitude and persistence over time. Furthermore, the Mean Squared Error (MSE) is 1.1251e-13, emphasizing the controller's predictive accuracy. Effective noise mitigation results in a stable system output. Figures 23-25 depict the uncontrolled system output and control signal, as well as the controlled system output, respectively.

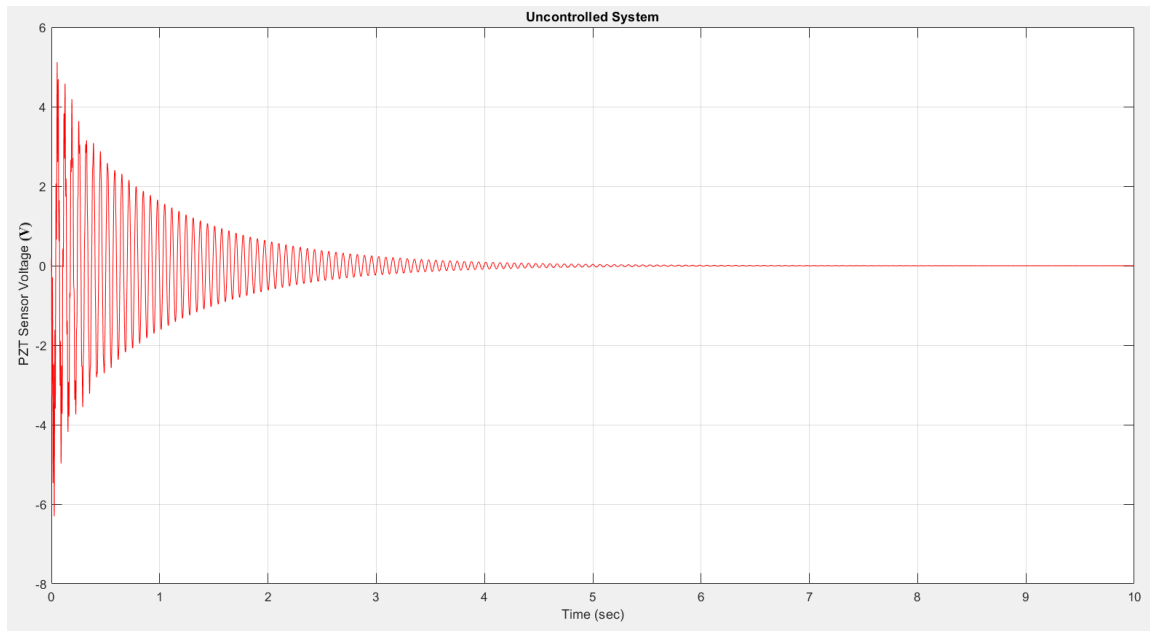


Figure 23: Voltage Response of PZT Sensor before Vibration Control (under Impulse Disturbance)

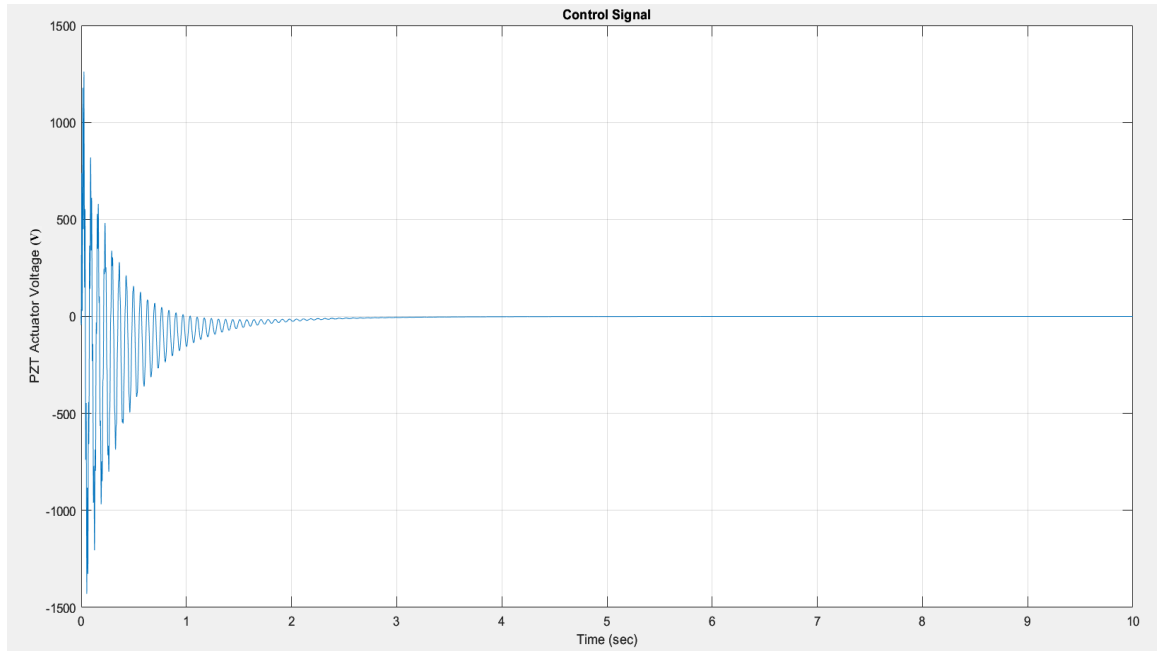


Figure 24: System Control Signal

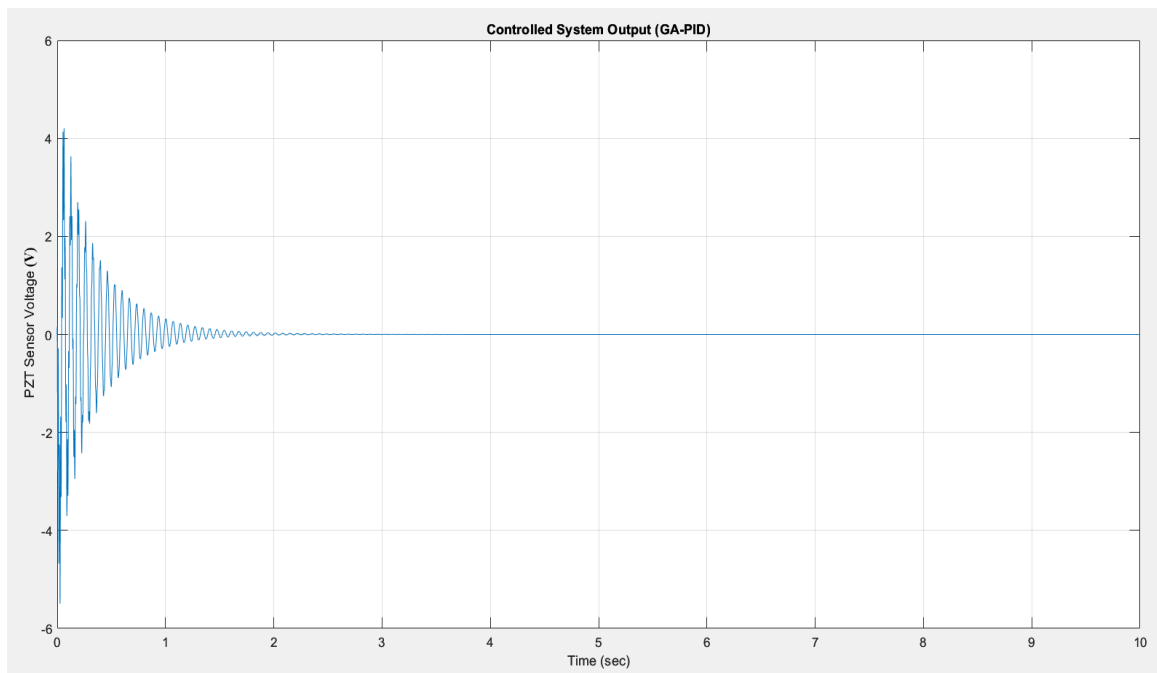


Figure 25: Voltage Response of PZT Sensor After Vibration Control with GA-PID (under Impulse Disturbance)

Figure 26 illustrates the difference in system performance before and after implementing the GA-PID controller. The vibration of the beam is significantly reduced, and the settling time is achieved at 1.88 seconds.

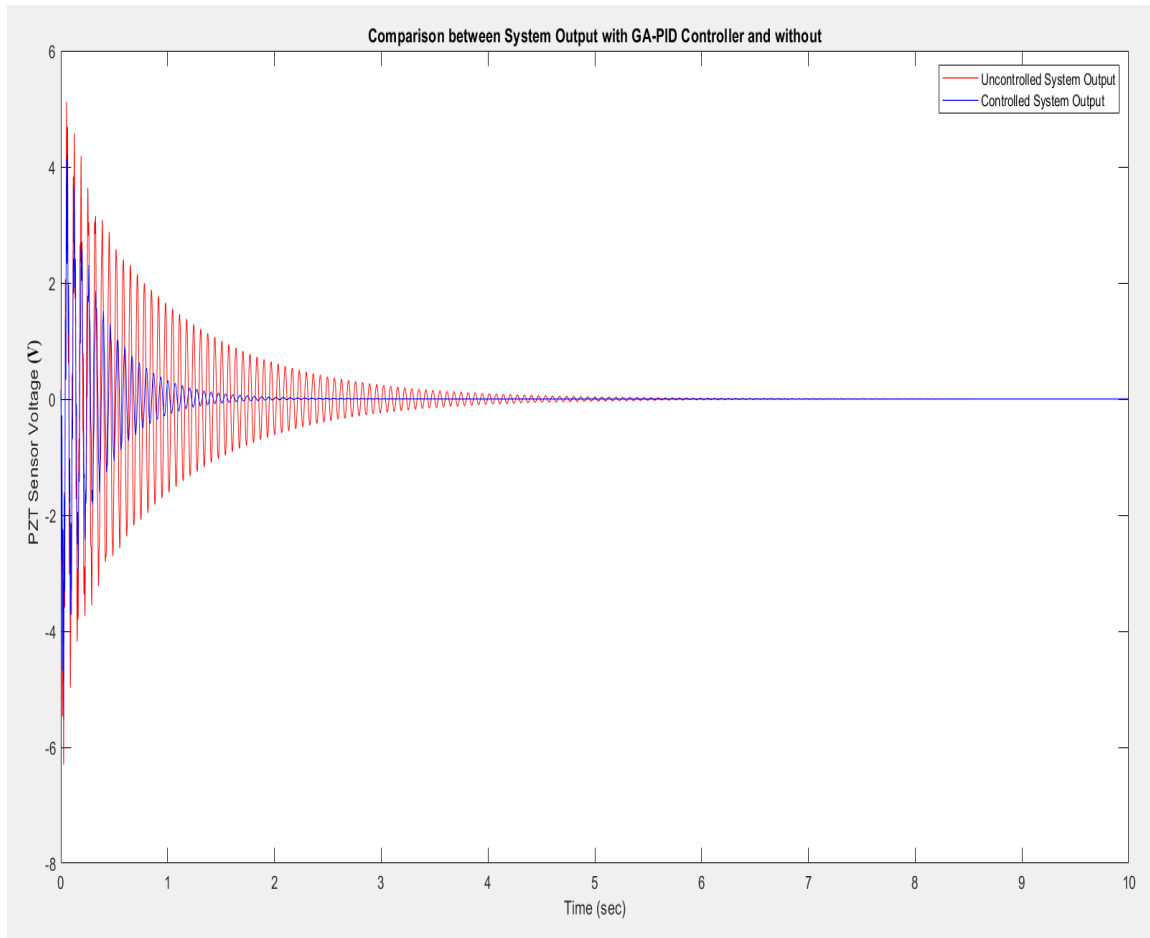


Figure 26: Voltage Response of PZT Sensor in the Cantilever Beam with GA-PID Controller and without.

B. Control System Affected by Random Disturbance

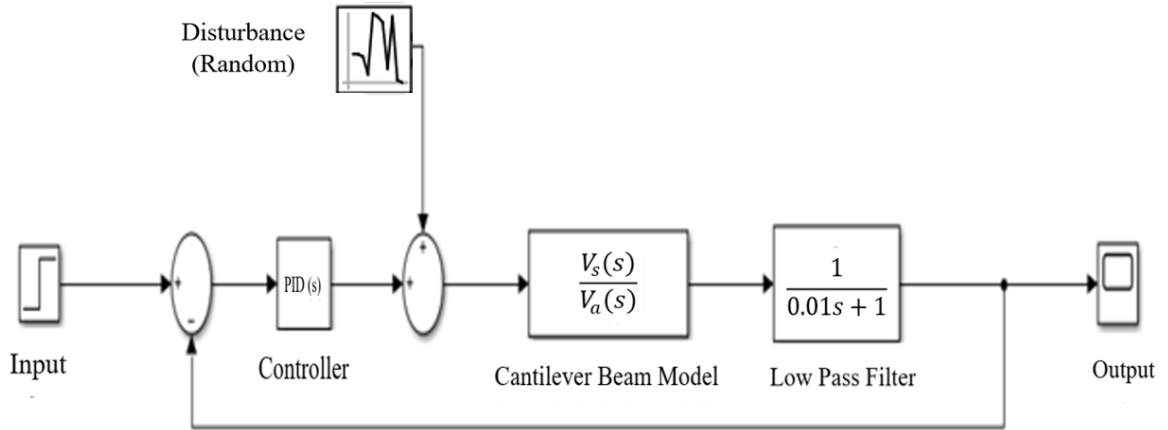


Figure 27: Block Diagram of Closed Loop of under Random Disturbance

In this section, the system will be subjected to a continuous random disturbance, visually represented in Figure 27, and thoroughly plotted in Figure 29. Following this, Figures 28 and 30 represent the reference input and the uncontrolled system's output signal, respectively. It's noteworthy that the output signal exhibits significant oscillations, characterized by amplitudes ranging between -3 V and 3 V. This signifies a notable deviation from the reference input.

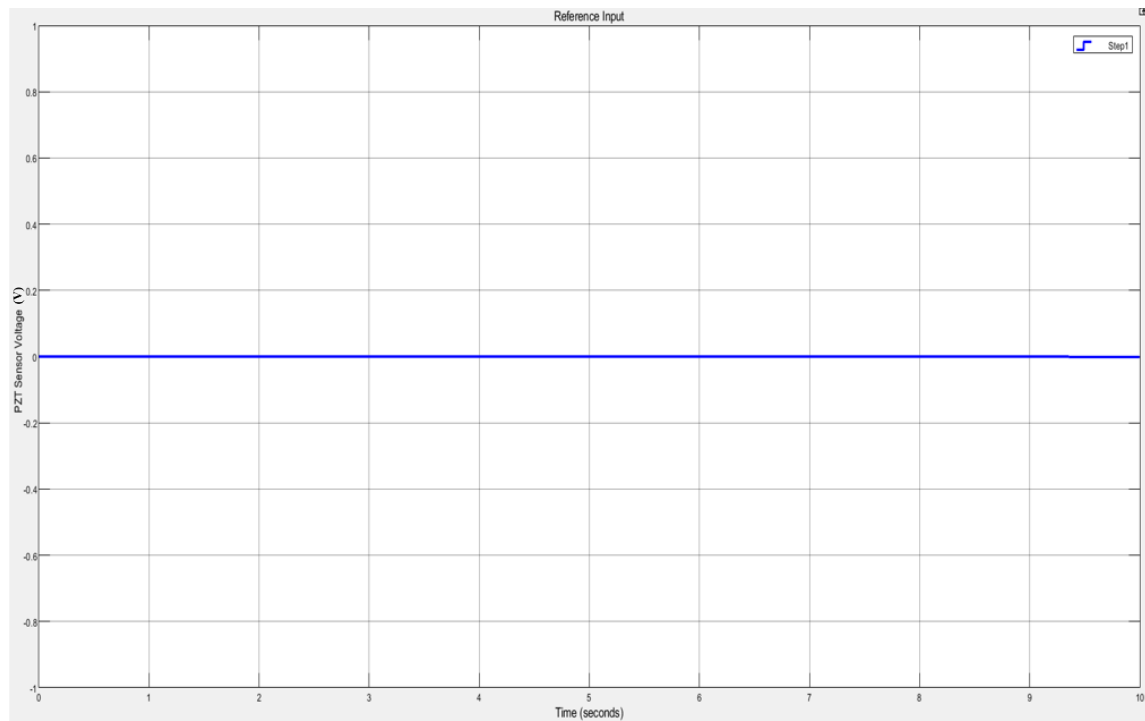


Figure 28: Reference Input

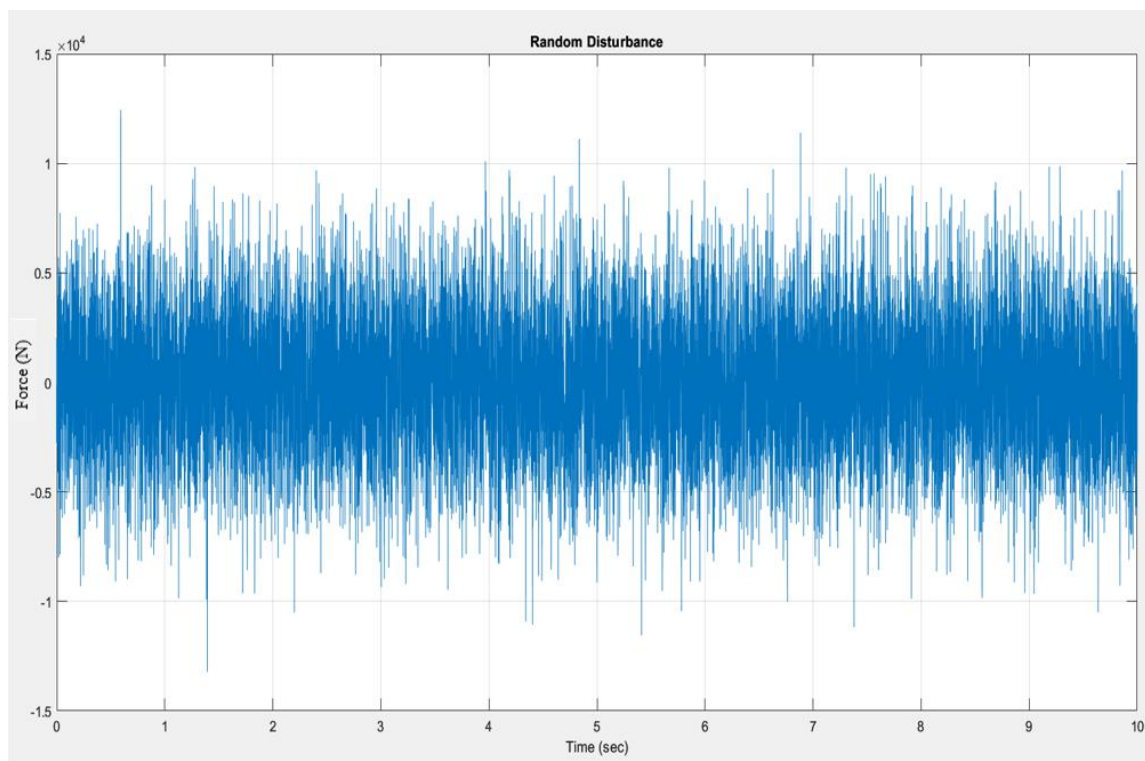


Figure 29: Random Disturbance

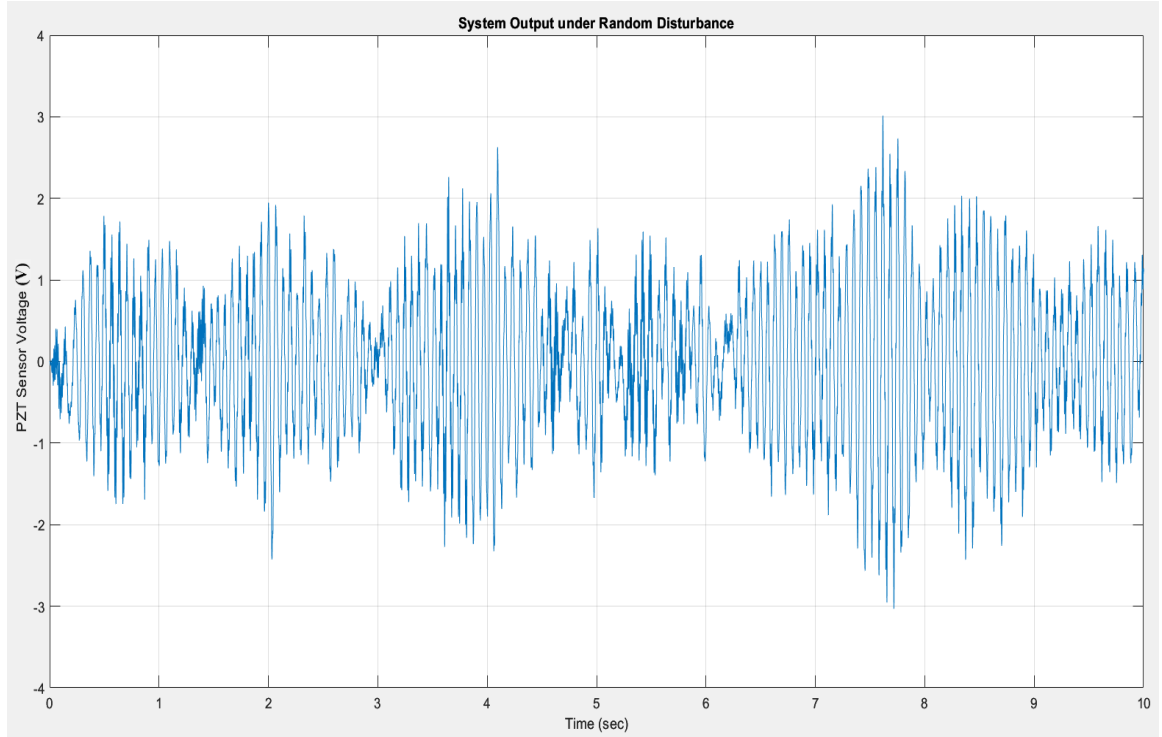


Figure 30: Voltage Response of PZT under Random Disturbance (with Low-Pass Filter)

To mitigate this disturbance and enhance system stability, we implemented a PID controller and tuned its parameters through Genetic Algorithm.

The "fitness value vs. generation" plot, figure 31, in a Genetic Algorithm (GA) provides a visual representation of how the fitness of the individuals in the population evolves over successive generations. In this plot, the x-axis typically represents the generations, indicating the progression of the algorithm over time, while the y-axis represents the fitness values.

At the beginning of the optimization process, fitness values vary widely among individuals in the initial population. As the GA progresses through generations, the algorithm selects, recombines, and mutates individuals, aiming to improve their fitness with respect to the defined objective function. The plot shows how the average or best fitness in the population changes over time.

Figure 30 shows the "fitness value vs. generation" plot in the Genetic Algorithm (GA) exhibits a distinctive pattern, highlighting a significant decrease in fitness values up to the 7th generation, followed by a stable level from the 8th to the 50th generation. The initial decline suggests effective optimization and convergence during the early generations, while the subsequent stability implies that the GA has reached a point where further improvements are limited. The Integral Time Absolute Error (ITAE) measures a low value of 3.2245 and the Mean Squared Error (MSE) is 0.6869.

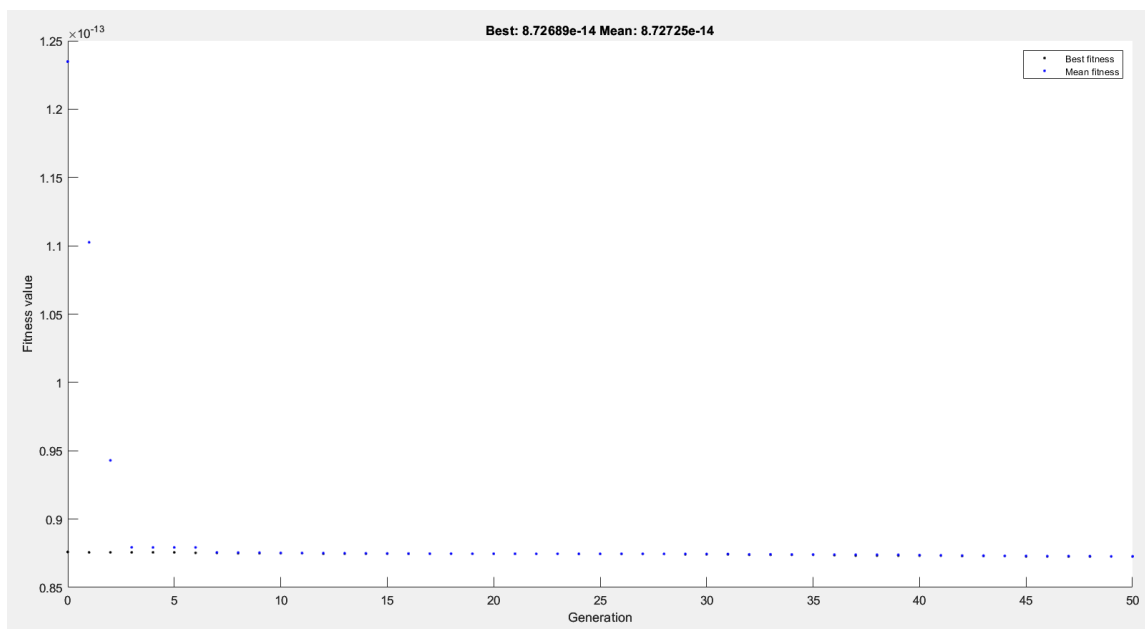


Figure 31: Fitness Value VS. Generation Plot

The outcome of tuning the PID parameters is in Table 5:

Table 5: PID Controller Parameters Tuned Using GA of the System Affected by Random Disturbance

K_p	K_i	K_d
690	-2930	170

After the implementation of the optimized PID controller using GA, the system's peak oscillation was reduced to 1.264 V at 1.404 s, compared to 3.014 V at 3.014 s before the controller was applied. The range of the oscillations decreases notably. This precise tuning is evident in the Integral Time Absolute Error (ITAE) value of 0.865, showcasing a proficient reduction in both error magnitude and persistence over time. Furthermore, the Mean Squared Error (MSE) is 0.6869, emphasizing the controller's predictive accuracy. Figures 32-34 depict the uncontrolled system output and control signal, as well as the controlled system output, respectively.

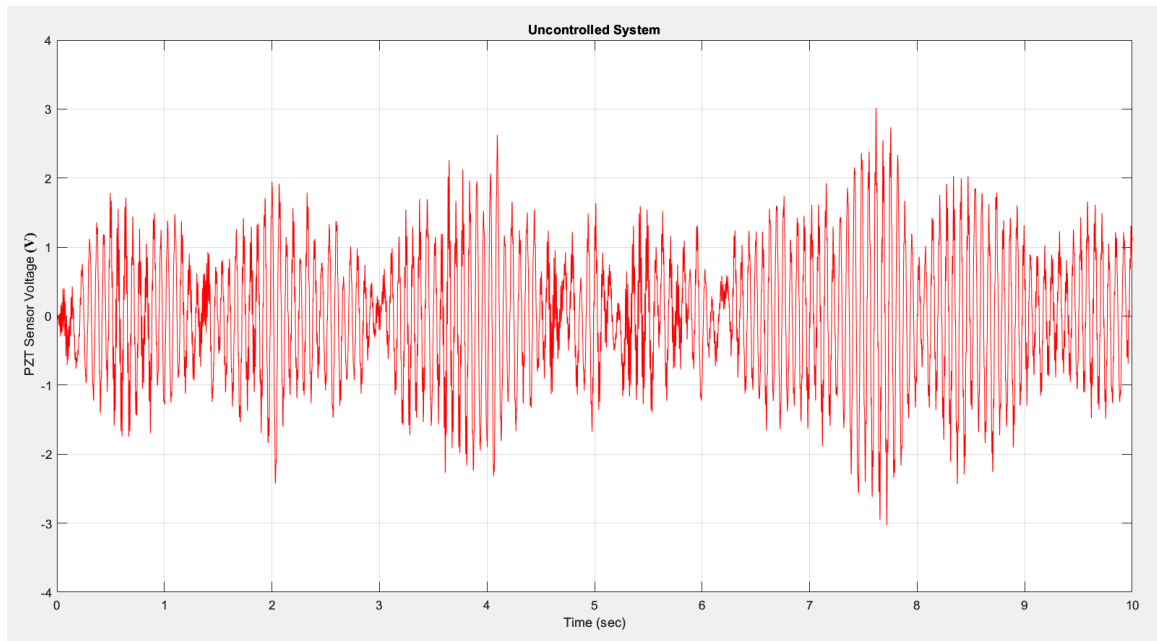


Figure 32: Voltage Response of PZT Sensor before Vibration Control (under Random Disturbance)

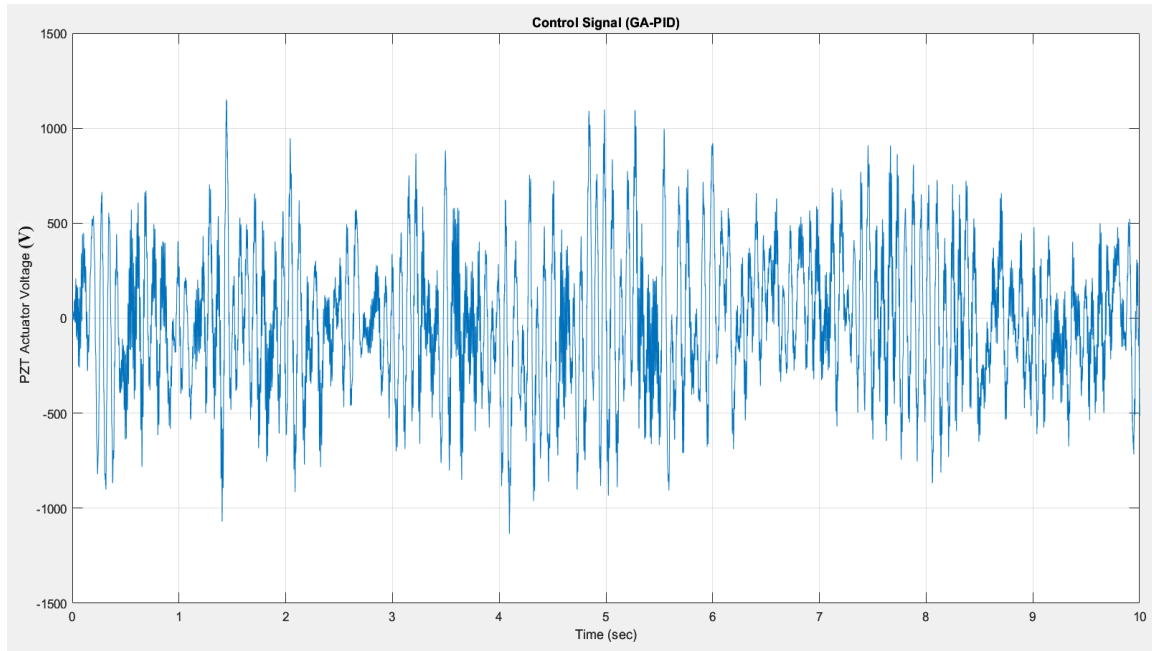


Figure 33: System Control Signal

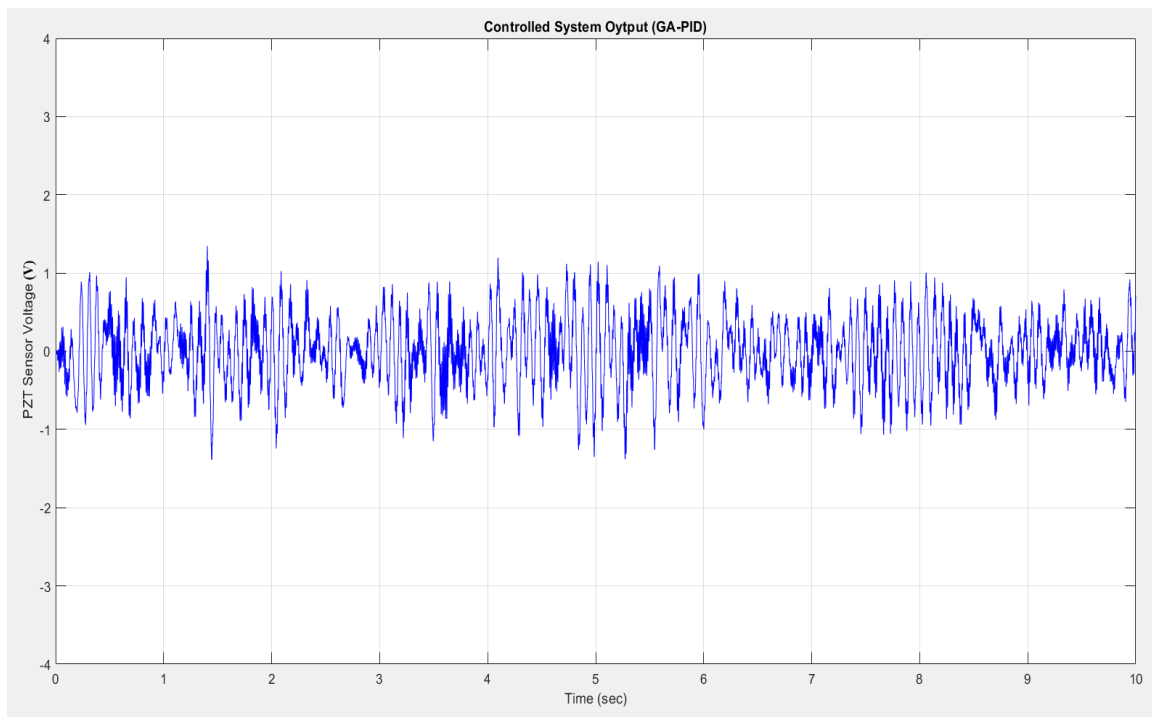


Figure 34: Voltage Response of PZT Sensor After Vibration Control with GA-PID (under Random Disturbance)

Figure 35 demonstrates the effectiveness of the GA-PID controller in minimizing vibration caused by continuous disturbance. The system with the tuned PID controller reduces the vibration to a range of -1 to 1 V.

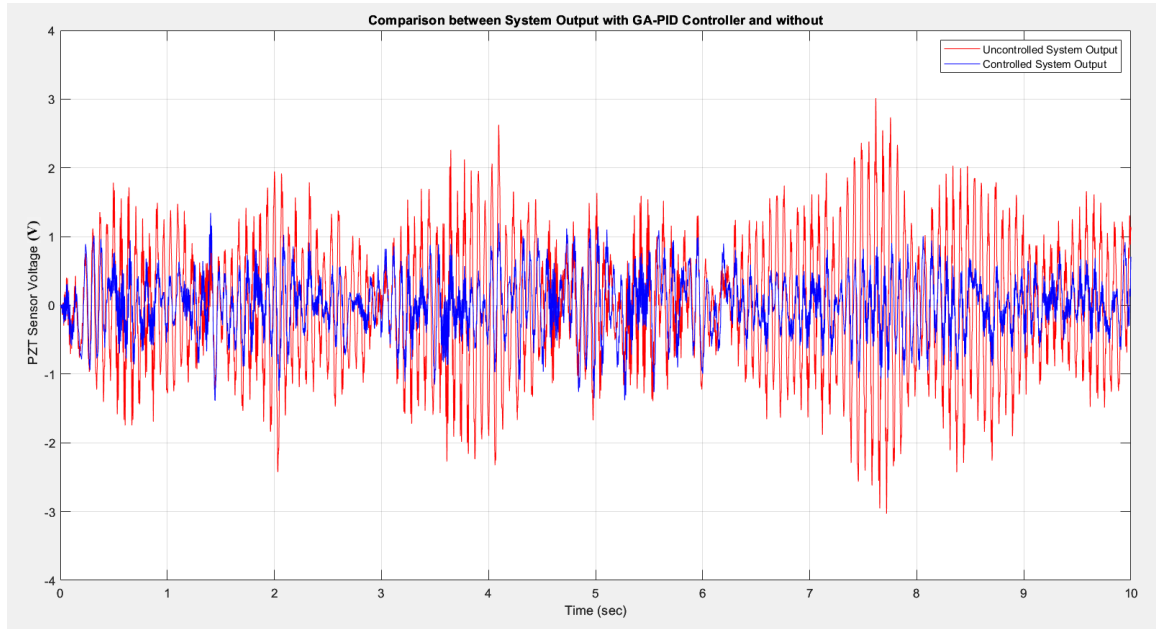


Figure 35: Voltage Response of PZT Sensor in the Cantilever Beam with GA-PID Controller and without.

5.4 Neural Network

5.4.1 Tuning PID Controller Using Neural Network

After the initial tuning of PID controllers using a genetic algorithm (GA) to efficiently explore the parameter space and identify optimal solutions, a subsequent layer of refinement can be introduced through the application of neural networks (NN). In this approach, the dataset utilized by the neural network for learning is generated by the GA, establishing a seamless connection between the optimization method and the adaptive learning process.

The genetic algorithm serves as an effective tool for evolving PID parameters and enhancing overall control performance. Once the GA identifies a promising set of parameters, it generates a dataset that includes the system's response to different situations. This dataset becomes the training for the neural network, allowing it to learn from the historical data produced by the GA's exploration of the parameter space.

The neural network then plays a pivotal role in the ongoing adaptation of the PID parameters. By learning from the dataset generated by the GA, the neural network refines the PID parameters to minimize error and disturbance. This tuning process ensures that the controller remains effective in diverse and changing conditions, contributing significantly to increase stability.

5.4.2 Neural Network Design

The designed neural network contains seven inputs: previous input (N-1), last input (N), previous disturbance (N-1), last disturbance (N), previous output (N-1), last output (N), and the error. Additionally, the network features three outputs, corresponding to the " K_p " value, " K_i " value, and " K_d " value. This neural network, designed with a single hidden layer, incorporates ten neurons, as illustrated in figure 36:

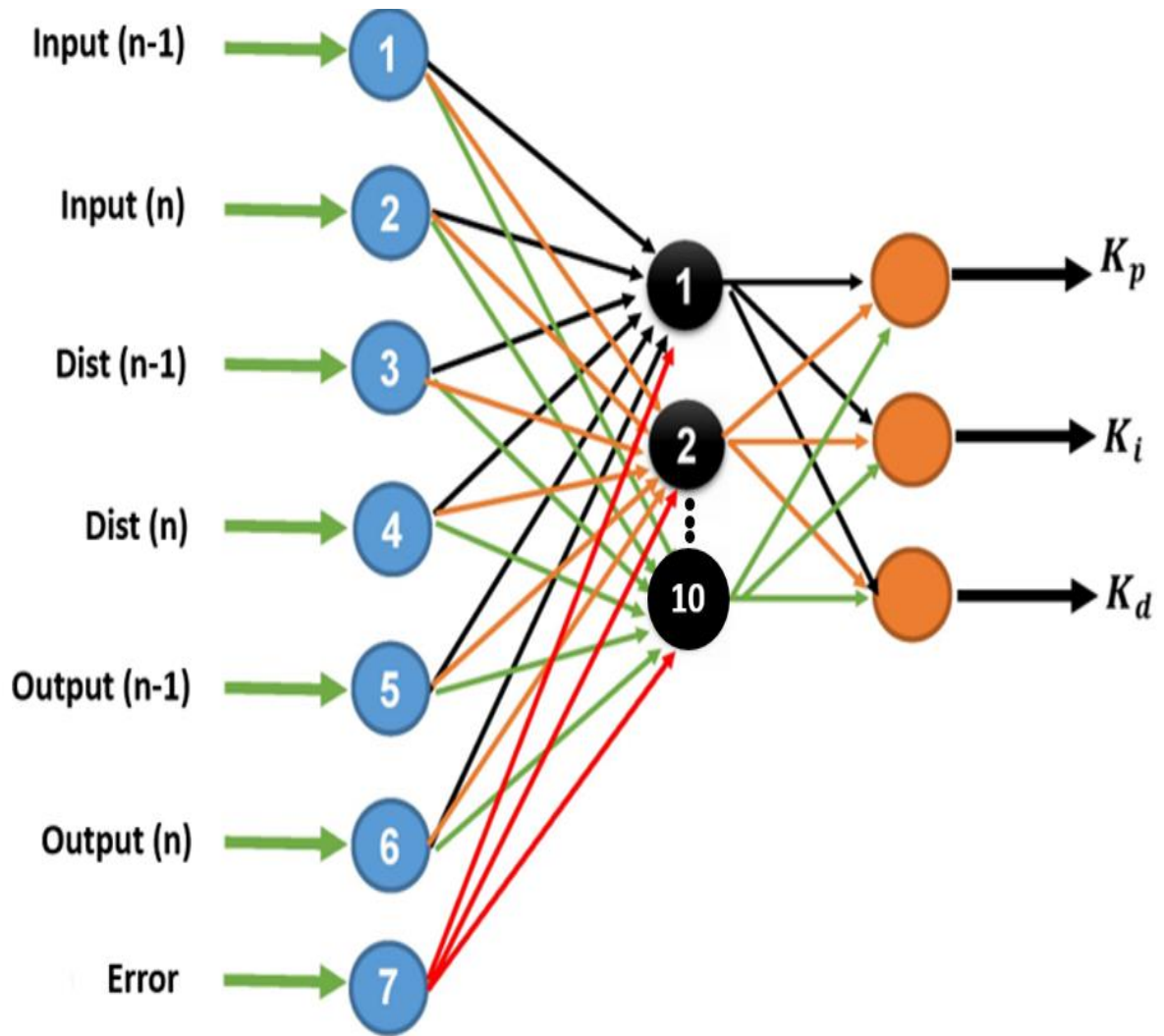


Figure 36: Designed Neural Network

The neural network is trained and tested using the dataset that is generated using Genetic Algorithms. The dataset contains two thousand data samples. 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.

5.4.3 Training and Validation Loss Plots

The training and validation loss plot is a crucial tool in understanding how well a neural network is learning from the training data and generalizing to unseen data. Figure 37 shows the scaled training and validation loss plots for the designed neural network:

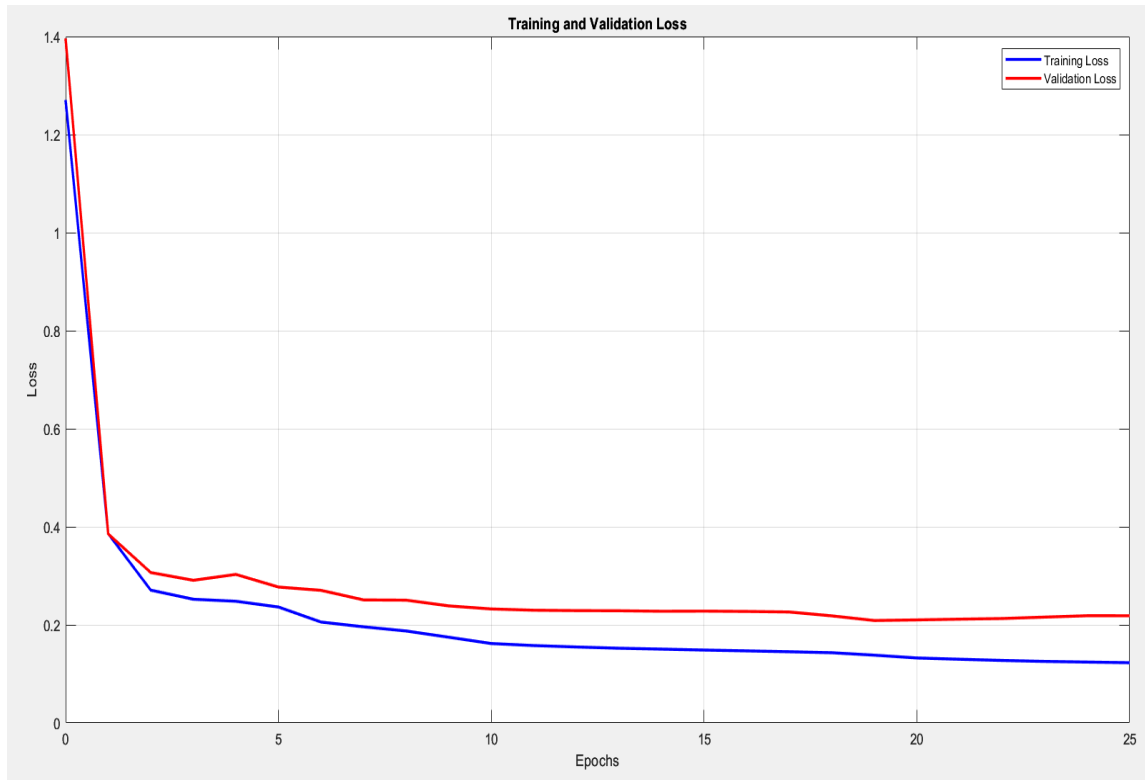


Figure 37: Training and Validation Plot

The training loss decreases steadily over epochs. This indicates that the network is learning and improving its predictions on the training data. The validation loss follows a similar decreasing trend to the training loss. Both lines are decreasing together, which indicates that the network is generalizing well to unseen data.

5.4.4 Error Histogram

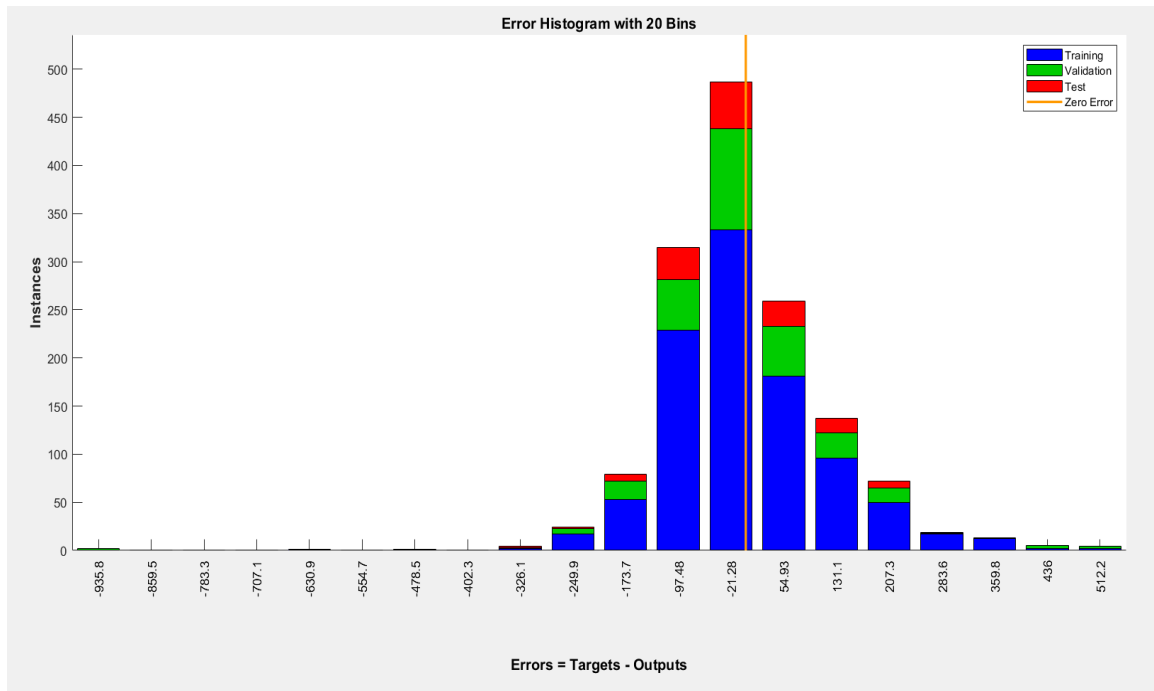


Figure 38: Error Histogram

The error histogram of the neural network provides a comprehensive visual representation of its performance across training, validation, and testing sets, see figure 38. It shows the difference between the actual dataset values, targets, and the predicted values, outputs, generated by the network. The fact that the histogram incorporates data from these sets allows for a precise examination of the model's ability to generalize to new, unseen data.

One notable feature of the histogram is the occurrence of zero error crossing the highest column. This occurrence suggests that a significant proportion of predictions made by the designed neural network align precisely with the true values, indicating a high level of

accuracy. The crossing of the zero-error bar over the height error column underscores the reliability of the model in making predictions that closely match the proper outcomes.

The histogram's highest peak, centered at an error value of -21.28, suggests a notable aggregation of predictive errors around this value. This clustering indicates that a considerable portion of the predictions align closely within a narrow margin of error. Despite the presence of these errors, their magnitude is relatively small, particularly when considered in the context of the expected output scales: K_p and K_d each have a scale up to 1000, and K_i up to 3000.

5.4.5 NN-PID Controller Results

The designed NN-PID, illustrated in Figure 39, has been well-trained using a generated dataset of size 2000. In this section, it will be tested to tune the PID controller parameters to enhance the control of structural vibration under two different conditions.

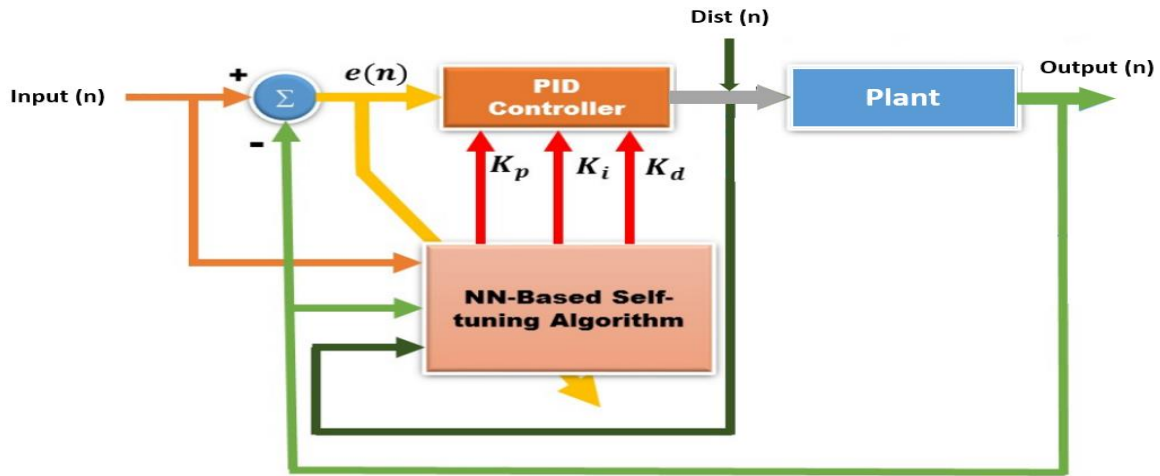


Figure 39: NN-PID Self Tuning Algorithm

A. Control System Affected by Impulse Disturbance

In the scenario where an impulse disturbance occurs at time 0 seconds, the system's behavior is analyzed. Figure 40 presents the reference input, while Figure 41 shows the impulse disturbance. To understand the system's response to this disturbance, refer to Figure 42, which illustrates the resulting output signal.

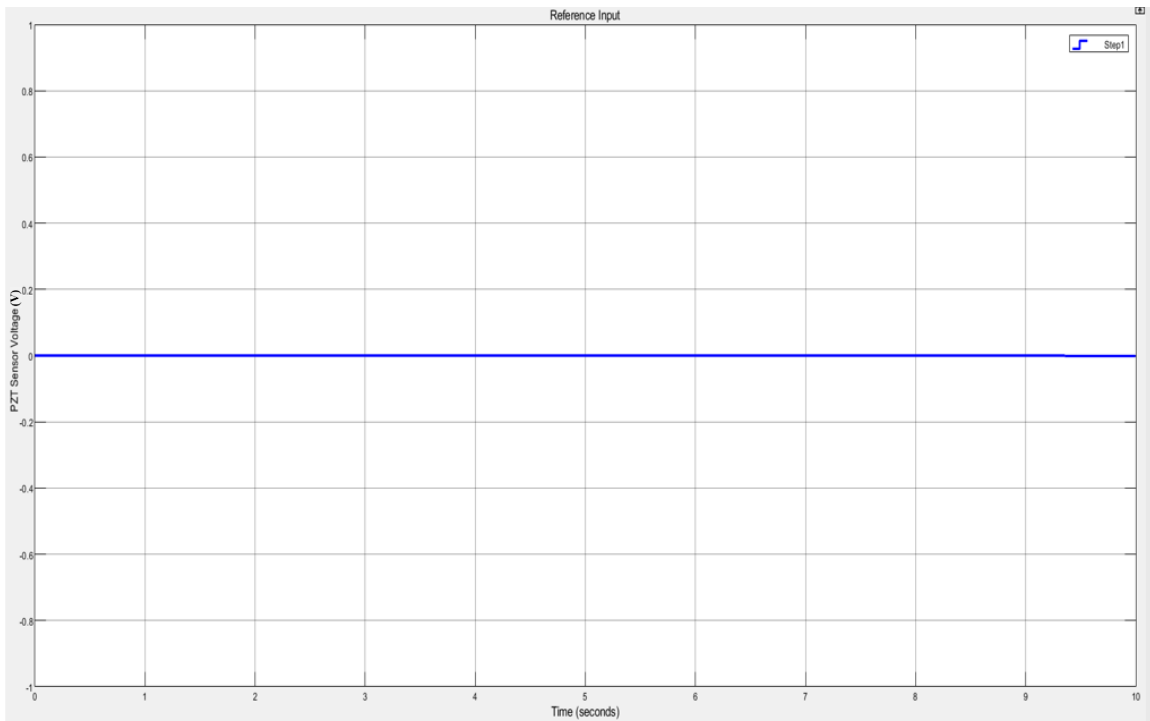


Figure 40: Reference Input

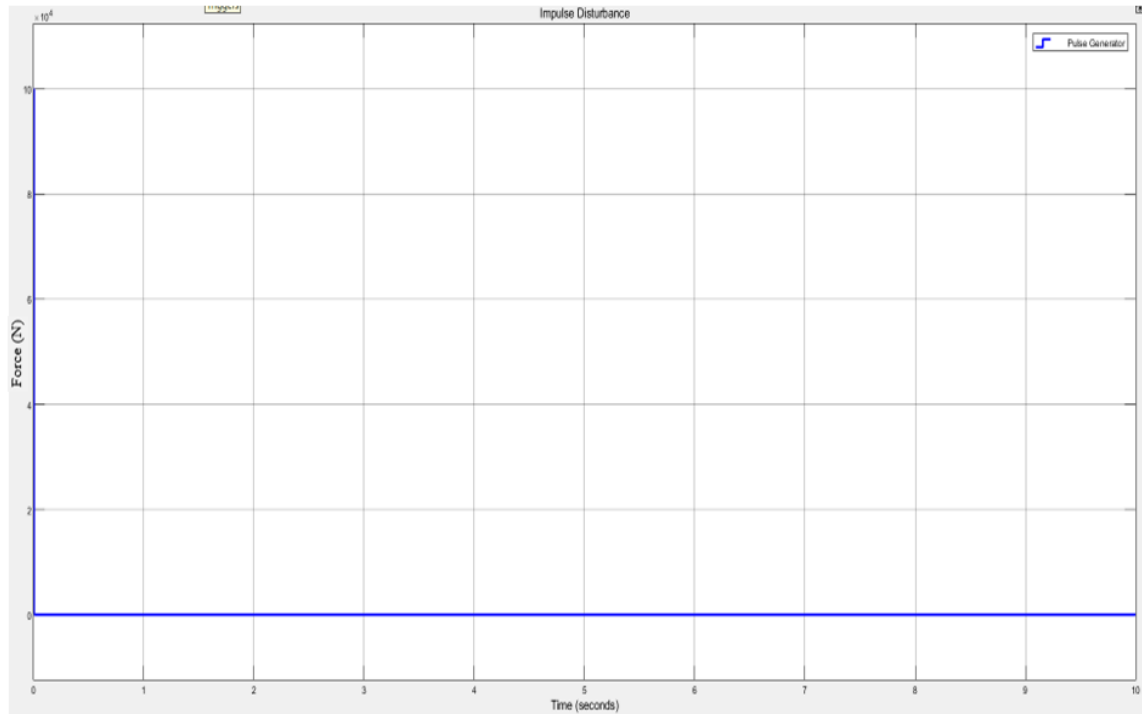


Figure 41: Impulse Disturbance of the System

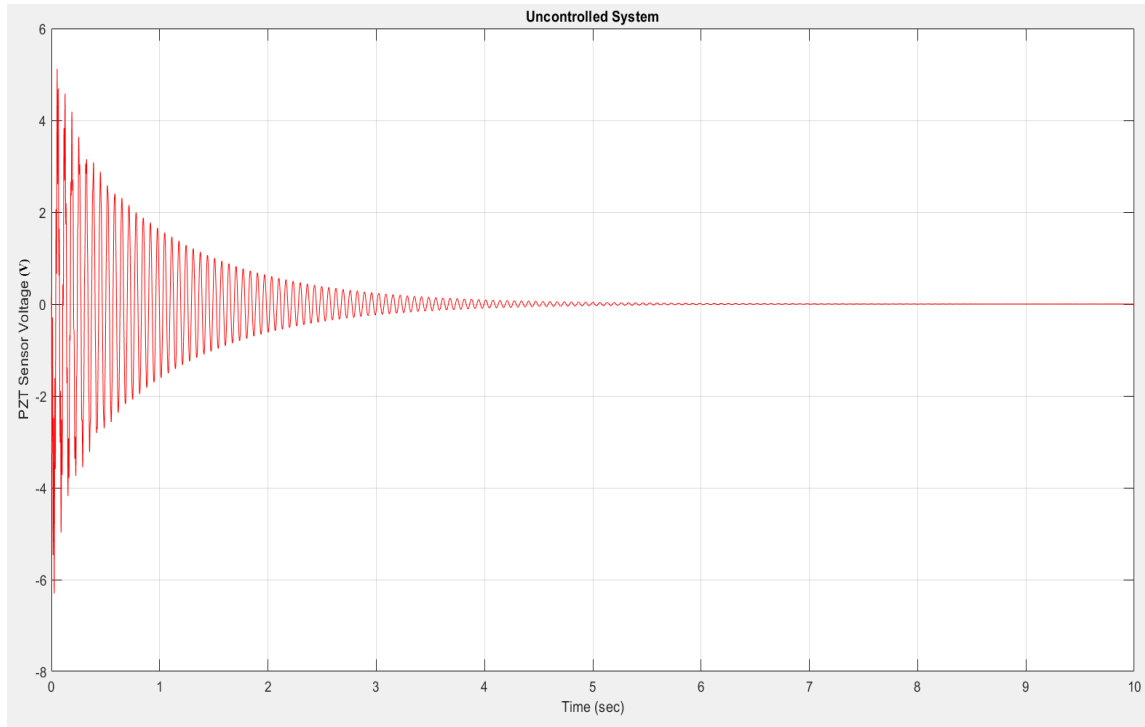


Figure 42: Voltage Response of PZT Sensor before Vibration Control (under Impulse Disturbance).

The PID parameters recommended by the resulting trained network are presented in Table 7. These results demonstrate the network's proficiency in inferring suitable PID parameters for diverse test conditions. It shows the adaptability of the trained network in tailoring the PID controller to meet the specific requirements of the system.

Table 6: PID Controller Parameters Tuned Using NN of the System Affected by Impulse Disturbance

K_p	K_i	K_d
233.5	-2877.9	113.5

Following the implementation of the optimized PID controller, the system achieves a settling time of 1.84 seconds. Remarkably, the Integral Time Absolute Error (ITAE) measures an exceptionally low value of 0.9178, indicating the system's efficiency in reducing both the magnitude and duration of error. Additionally, the Mean Squared Error (MSE) is 7.8594e-14, underscoring the predictive precision of the controller. Moreover, the controller effectively suppresses disturbance, leading to a significant reduction in vibration. Figures 43 and 44 illustrate the control signal and the system behavior after implementing the NN-PID controller.

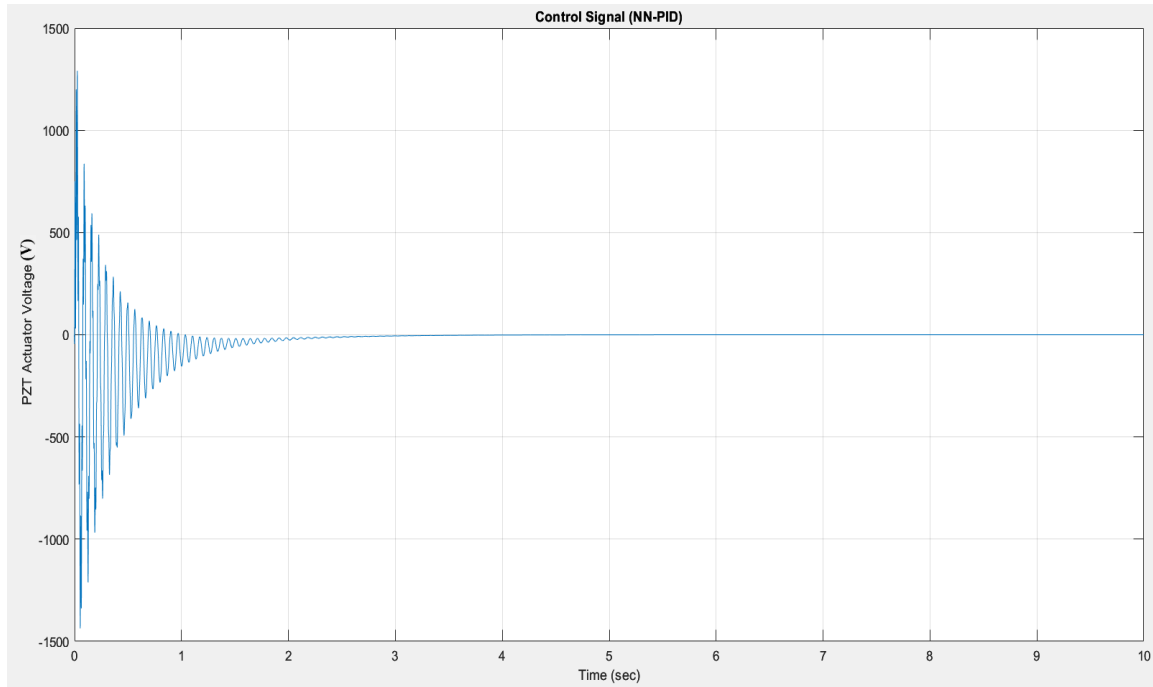


Figure 43: System Control Signal

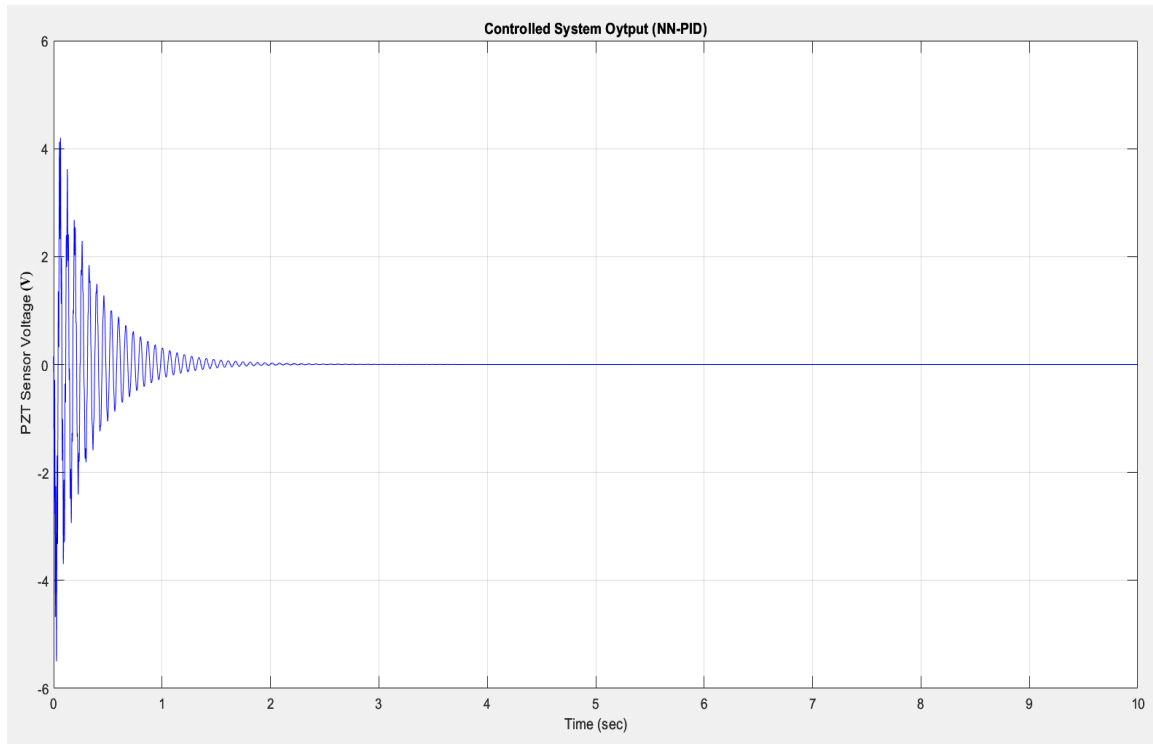


Figure 44: Voltage Response of PZT Sensor After Vibration Control with NN-PID (under Impulse Disturbance)

Figure 45 illustrates the difference in system performance before and after implementing the NN-PID controller. The vibration of the beam is significantly reduced, and the settling time is achieved at 1.84 seconds.

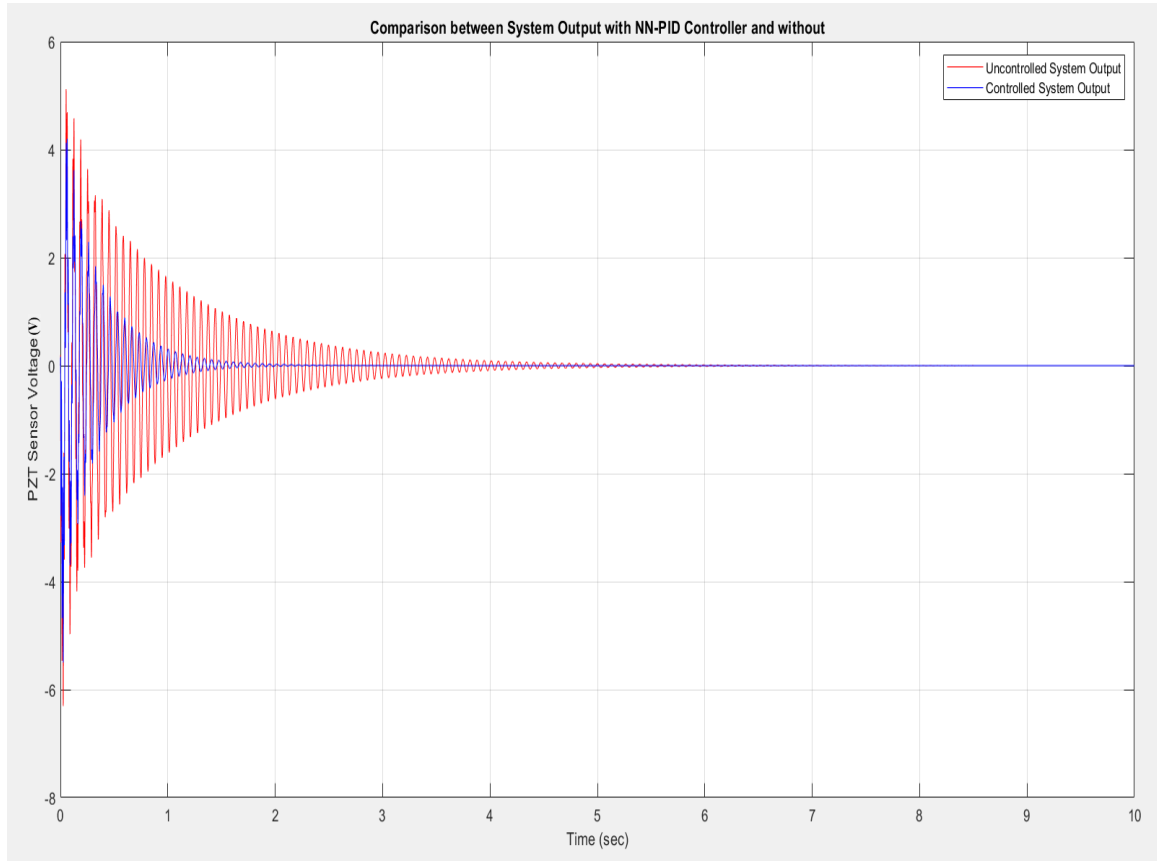


Figure 45: Voltage Response of PZT Sensor in the Cantilever Beam with NN-PID and without.

B. Control System Affected by Random Disturbance

The network will be employed to fine tune the PID parameters of the system under the influence of continuous random disturbances. Figure 46 illustrates the reference input signal, while Figure 47 displays the random disturbance signal, representing the unpredictable external factors impacting the system's performance. Figure 48 depicts the

uncontrolled output signal of the system, showcasing its actual response in the absence of the controller amidst the presence of the random disturbance.

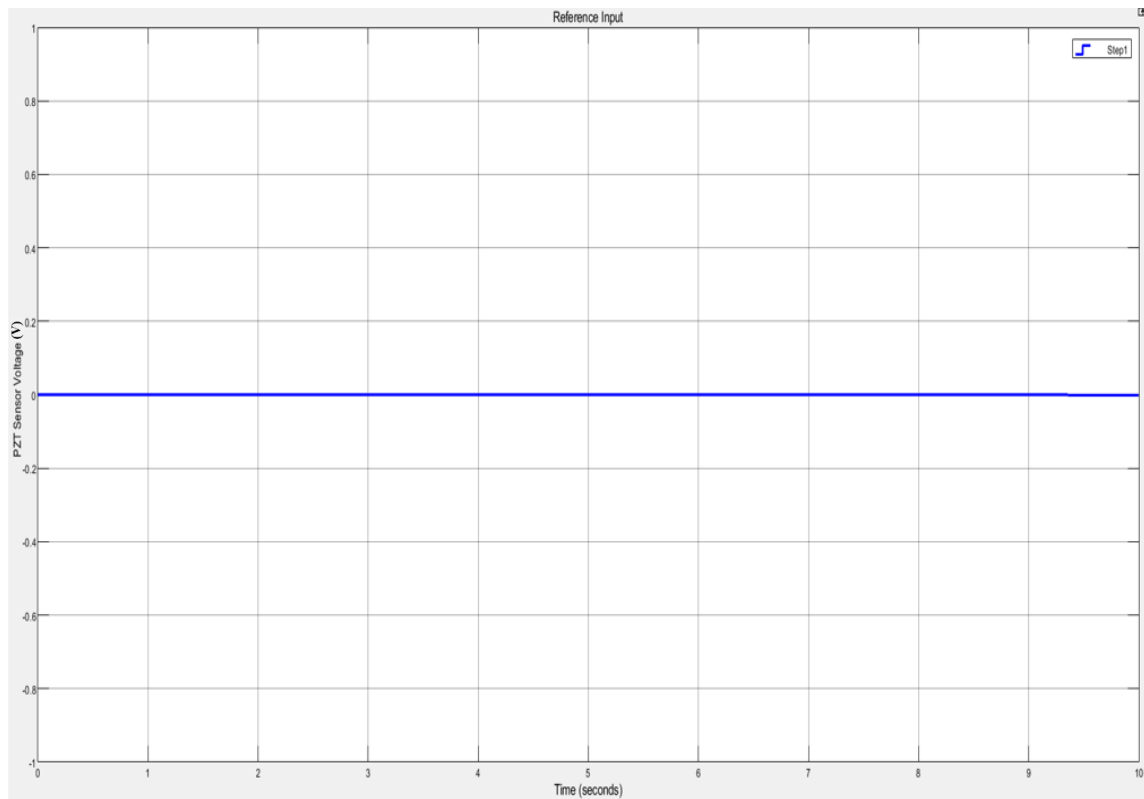


Figure 46: Reference Input

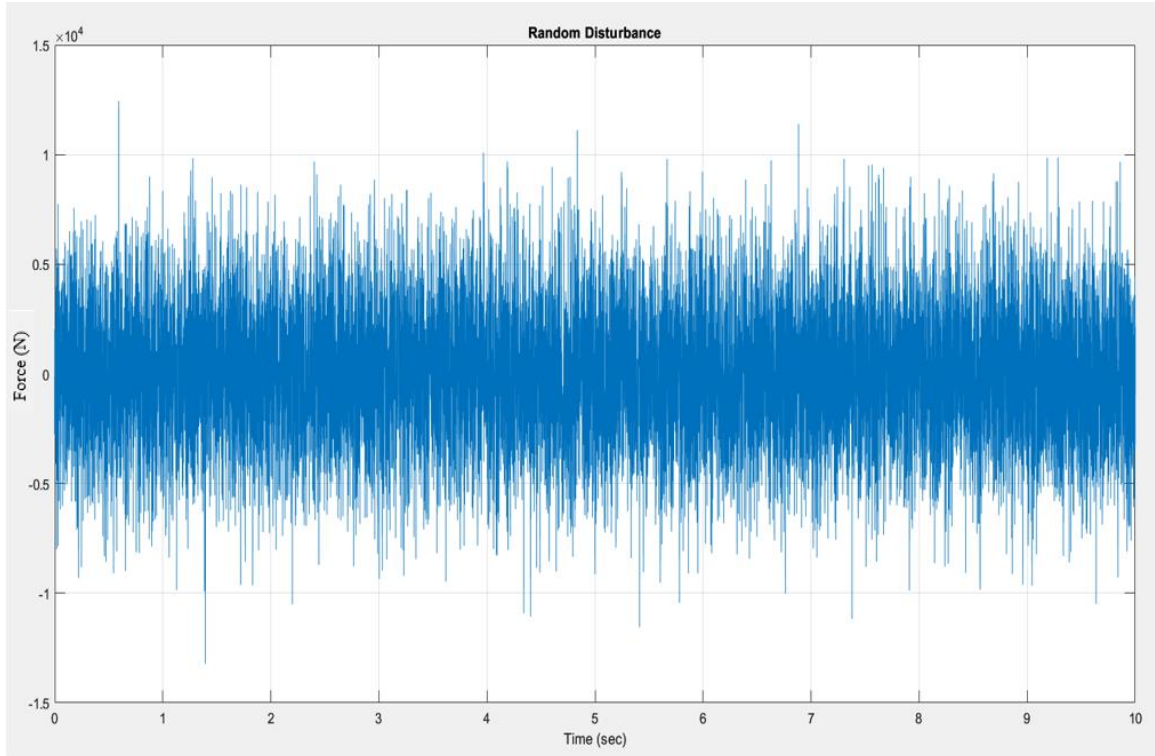


Figure 47: Random Disturbance

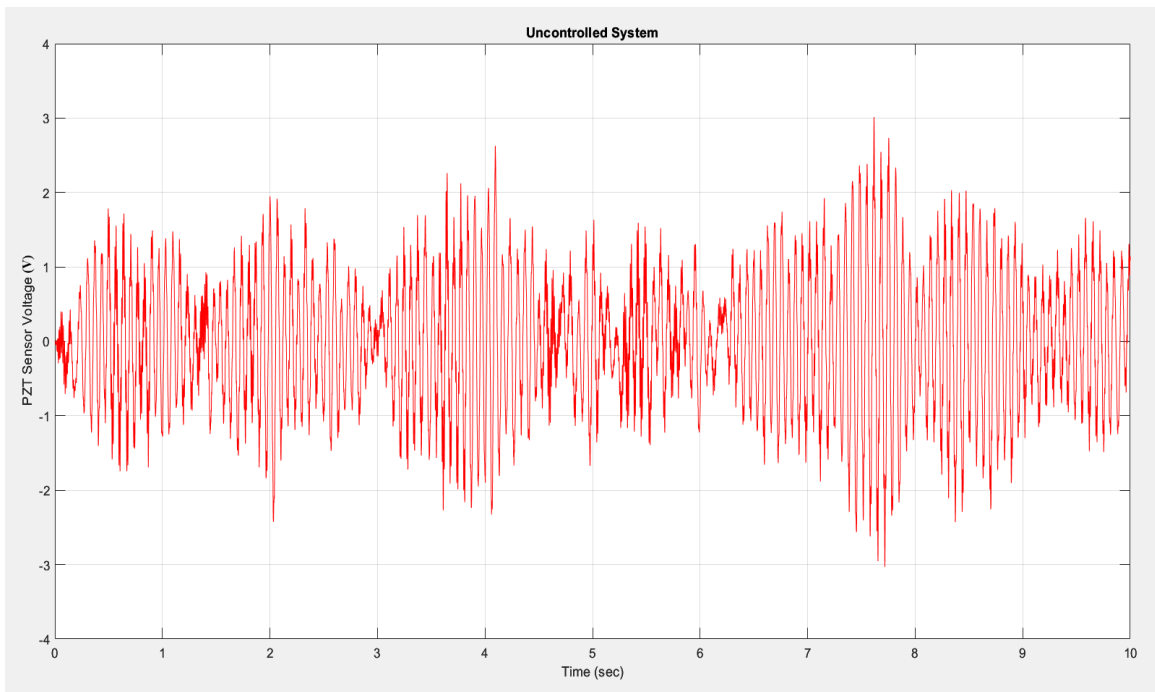


Figure 48: Voltage Response of PZT Sensor before Vibration Control (under Random Disturbance).

The PID parameters recommended by the network are presented in Table 6. These results highlight the network's ability to infer and suggest suitable PID parameters for a range of test conditions, illustrating the trained network's proficiency in adapting the PID controller to system requirements.

Table 7: PID Controller Parameters Tuned Using NN of the System Affected by Random Disturbance

K_p	K_i	K_d
802.6	-2263.8	241.1

Following the implementation of the optimized PID controller using the designed neural network, the system's peak oscillation was significantly reduced to 1.237 V at 1.404 seconds, compared to 3.014 V at 3.014 seconds before the controller was applied. The range of oscillations decreased notably. Remarkably, the Integral Time Absolute Error (ITAE) measures an impressive 0.9178, indicating the system's efficiency in reducing both the magnitude and duration of the error. Additionally, the Mean Squared Error (MSE) is notably low at 0.5973, further highlighting the predictive accuracy of the controller. Figures 49-50 depict the system control signal and the controlled system output, respectively.

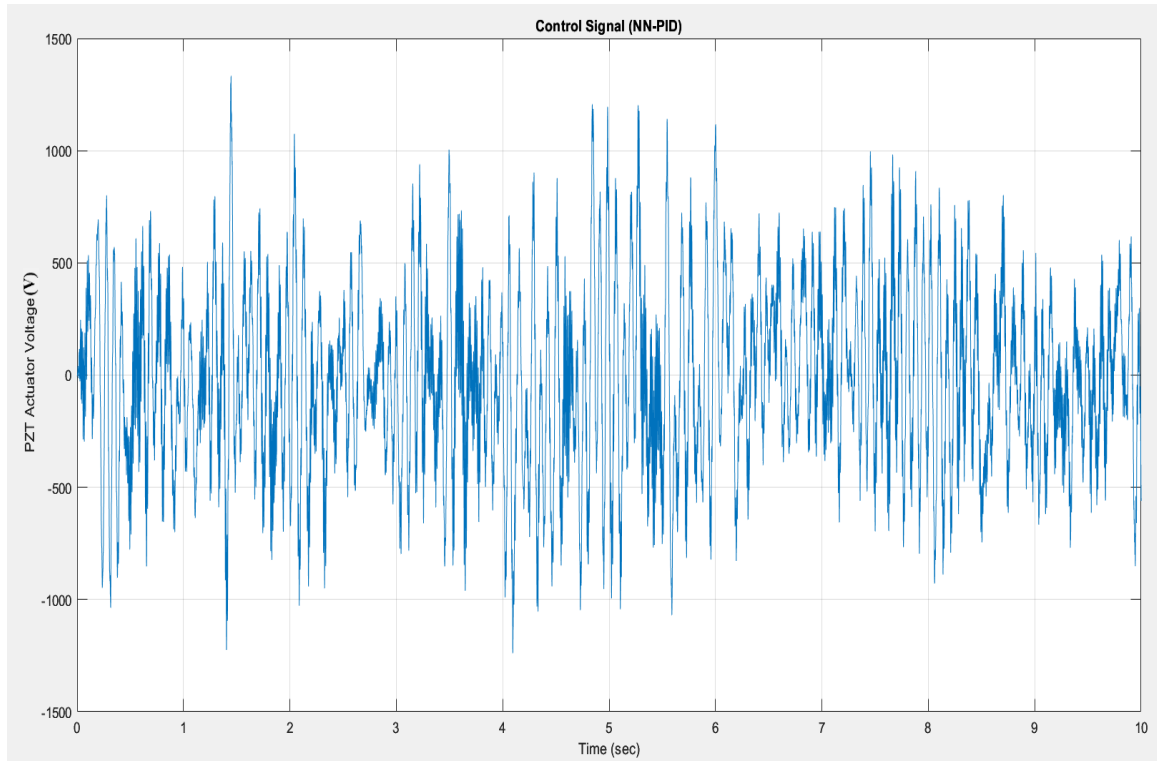


Figure 49: Control Signal

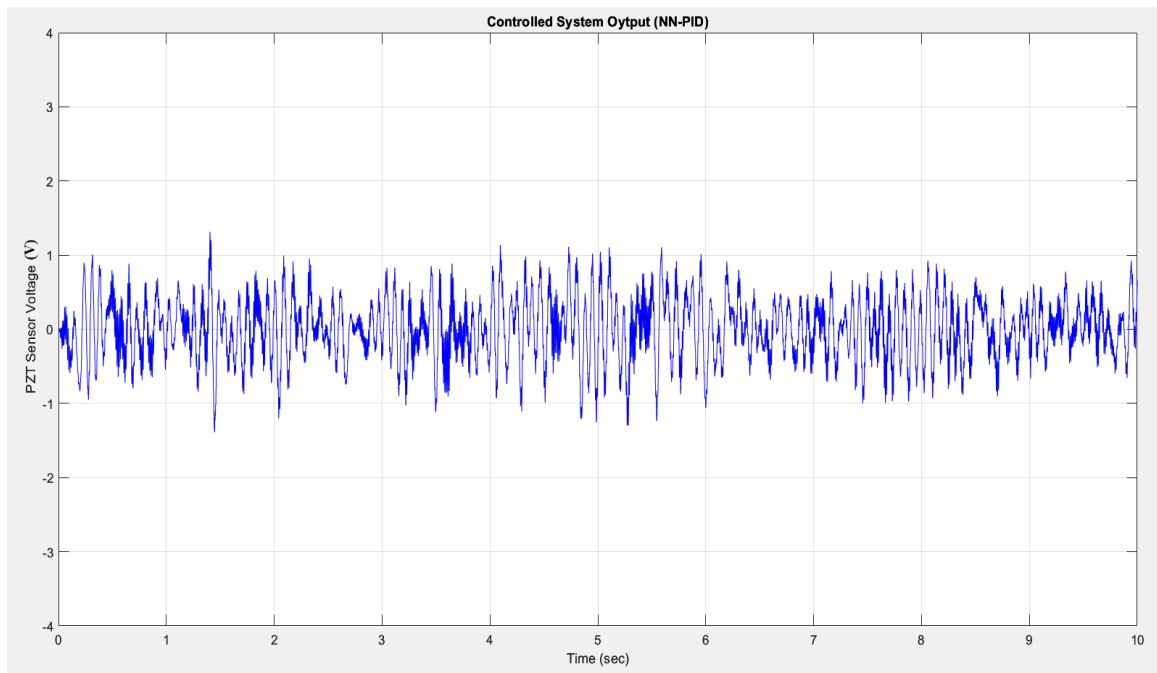


Figure 50: Voltage Response of PZT Sensor after Vibration Control with NN-PID (under Random Disturbance)

Figure 51 demonstrates the effectiveness of the NN-PID controller in minimizing vibration caused by continuous disturbance. The system with the tuned PID controller reduces the vibration to a range of -1 to 1 V.

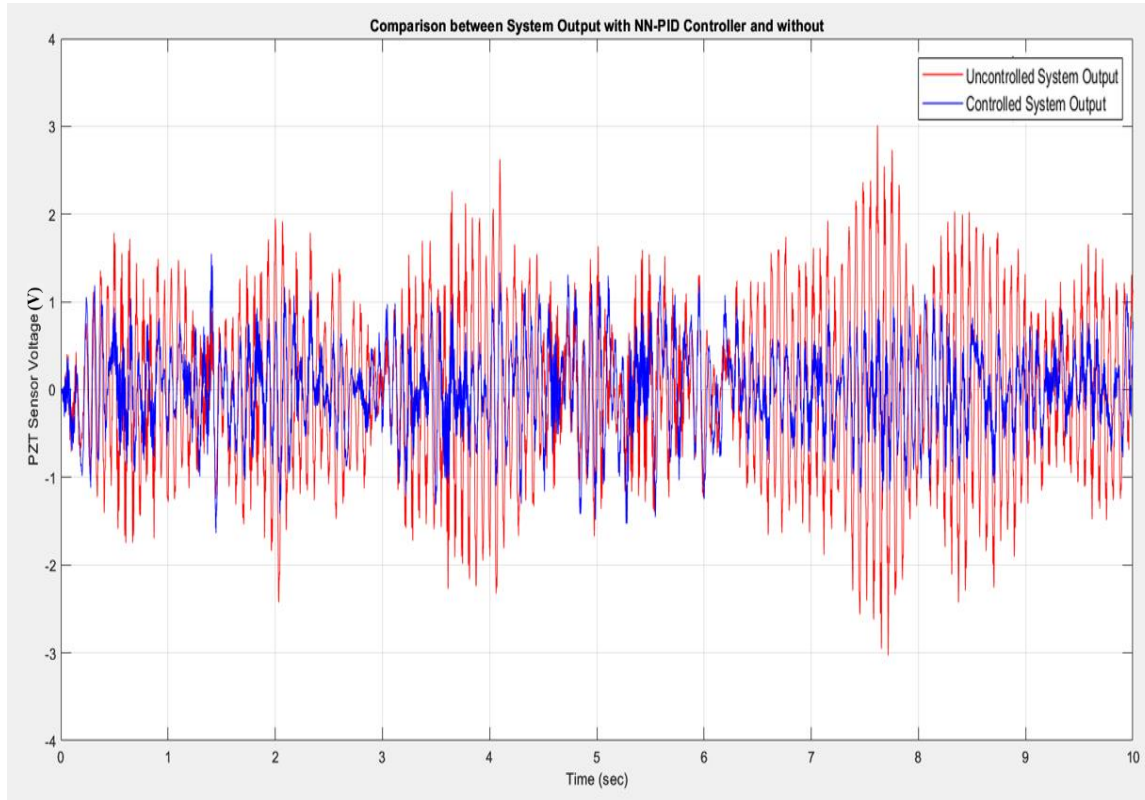


Figure 51: Voltage Response of PZT Sensor in the Cantilever Beam with NN-PID Controller and without.

5.5 Fuzzy Logic

Fuzzy Logic Controllers (FL) are a class of knowledge-based control systems that utilize fuzzy set theory to map inputs to outputs. Unlike conventional control systems that require a precise model of the system and work on binary logic (true or false, 0 or 1), fuzzy logic deals with reasoning that is approximate rather than fixed and exact. This

approach mimics how humans make decisions, by considering all possible values between 0 and 1 [55].

Fuzzy controllers are designed with a series of rules based on expert knowledge, which are written in the form of IF-THEN statements. These rules are processed by the fuzzy inference system, which operates on fuzzy sets, to determine the control action. The main components of FL include a fuzzification interface, which converts input data into suitable linguistic values; an inference system, which simulates human reasoning by applying a set of rules to the fuzzy inputs; and a defuzzification interface, which converts the fuzzy conclusions back into crisp output for the control system.

FL controllers are particularly useful in systems where a precise mathematical model is difficult to obtain, or the system behavior is too complex to be described in conventional terms. They excel in handling uncertainty and imprecision, making them suitable for a wide range of applications.

5.5.1 Tuning PID Controller Using Fuzzy Logic

Incorporating fuzzy logic into PID parameter tuning is an effective way to deal with the complexities of control systems that experience non-linear behavior or that operate under varying conditions. Fuzzy Logic Controllers (FLCs) automate the PID tuning process by employing fuzzy set theory to manage the imprecision typical in dynamic systems.

The process starts with fuzzification, where numerical values of error and change in error are converted into fuzzy linguistic terms. Based on this information, an inference is made using a predetermined set of rules which dictate how the PID parameters should be adjusted. This is analogous to how a human expert might decide on tuning the parameters based on their experience and knowledge of the system's behavior.

After inference, the fuzzy output is transformed into concrete adjustments for the PID gains through defuzzification. This results in a set of PID parameters that are continuously adapted to the system's needs, ensuring optimal performance despite changing conditions or system nonlinearities.

By integrating fuzzy logic with PID control, the resulting system gains the ability to self-tune in real-time, providing a significant advantage over traditional PID controllers that require manual tuning and may not respond adequately to dynamic changes in the system.

5.5.2 Design and structure of the self-tuning fuzzy PID Controller

The self-tuning fuzzy PID controller is an advanced control mechanism that takes two primary inputs: the error (e) and the rate of change of error (ec) as shown in figure 31. It employs a set of fuzzy control rules to dynamically adjust the PID parameters. The essence of self-tuning lies in defining a fuzzy relationship among these PID parameters and the inputs (e and ec). By applying fuzzy logic principles, the controller modifies K_p ,

K_i , and K_d to suit varying control requirements that emerge as e and ec change, thereby ensuring optimal and static performance from the control system.

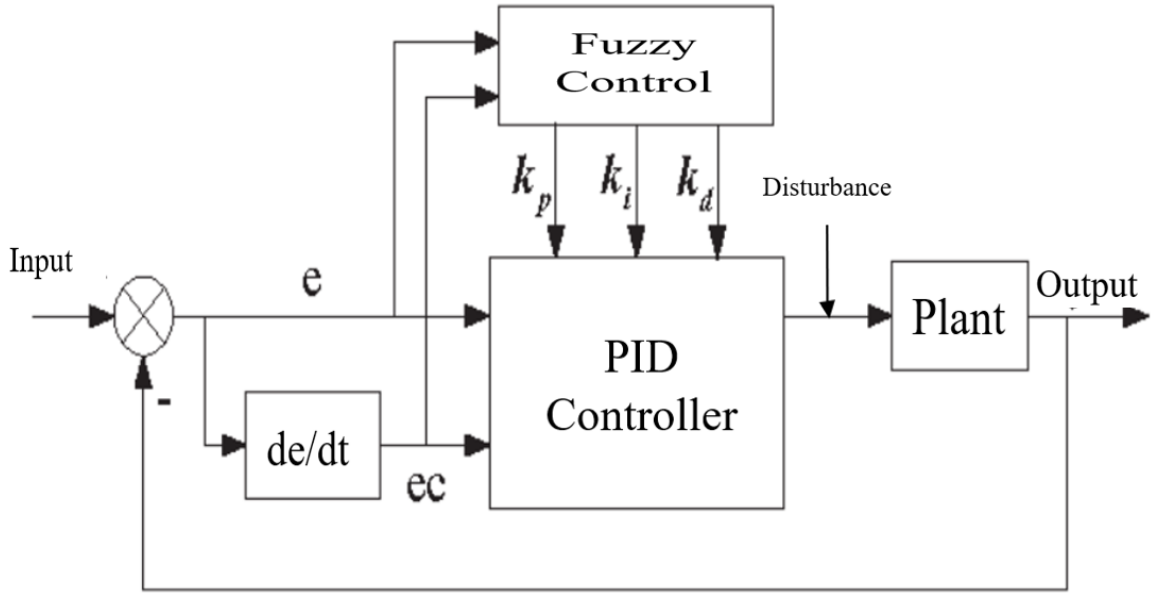


Figure 52: Basic Structure of a Fuzzy PID Controller

The performance of the fuzzy self-tuning PID controller is obtained using MATLAB. A fuzzy controller with two inputs and three outputs was designed as shown in figure 53, with the corresponding membership functions and fuzzy rules meticulously established to facilitate effective tuning.

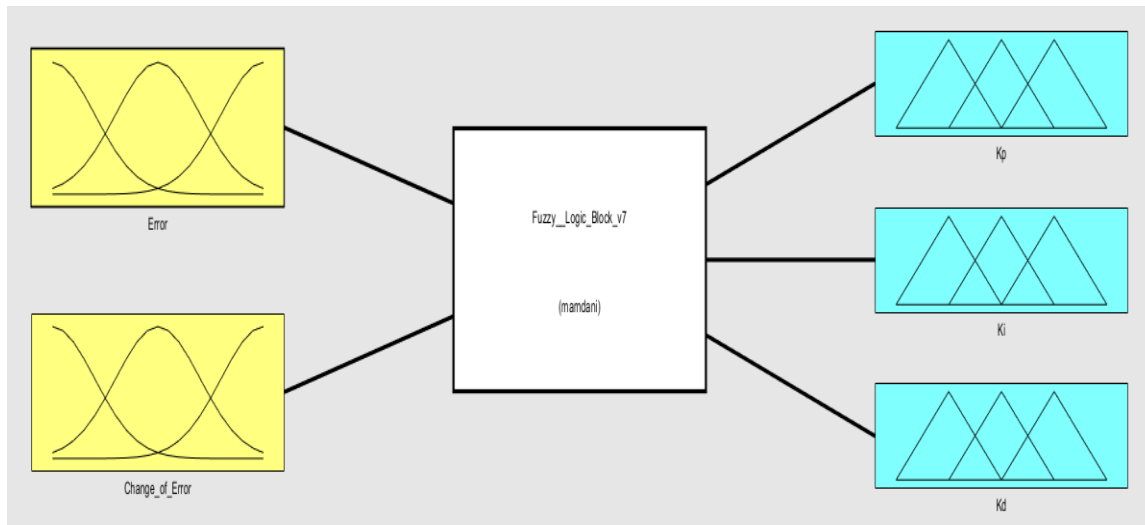


Figure 53: Mamdani Fuzzy Logic System

The membership functions for the linguistic variables "error (e)," "change in error (ec)," proportional gain (K_p), integral gain (K_i), and derivative gain (K_d) are depicted in Figures 54 to 58, respectively.

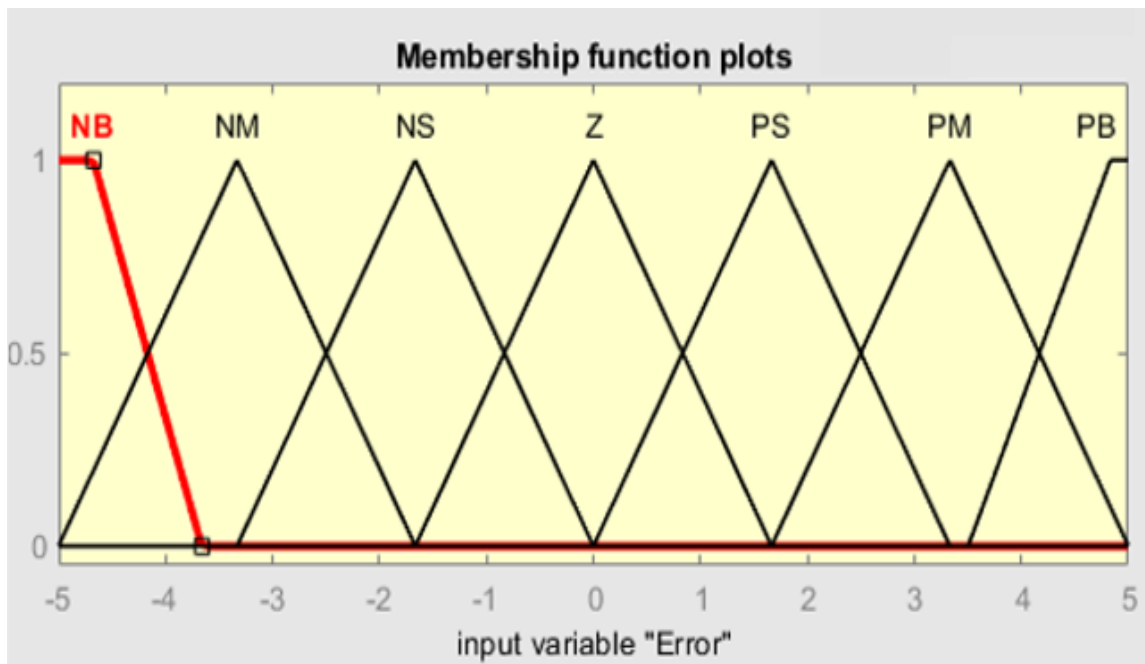


Figure 54: Membership Function of Error "e"

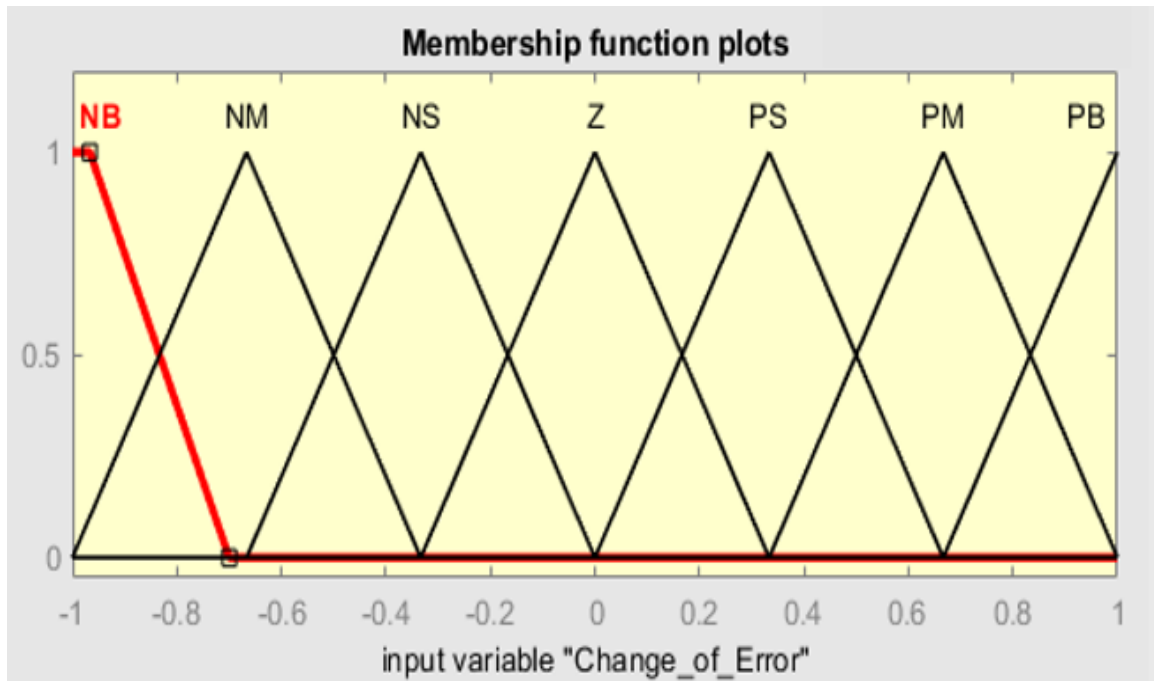


Figure 55: Membership Function of Change in Error "ec"

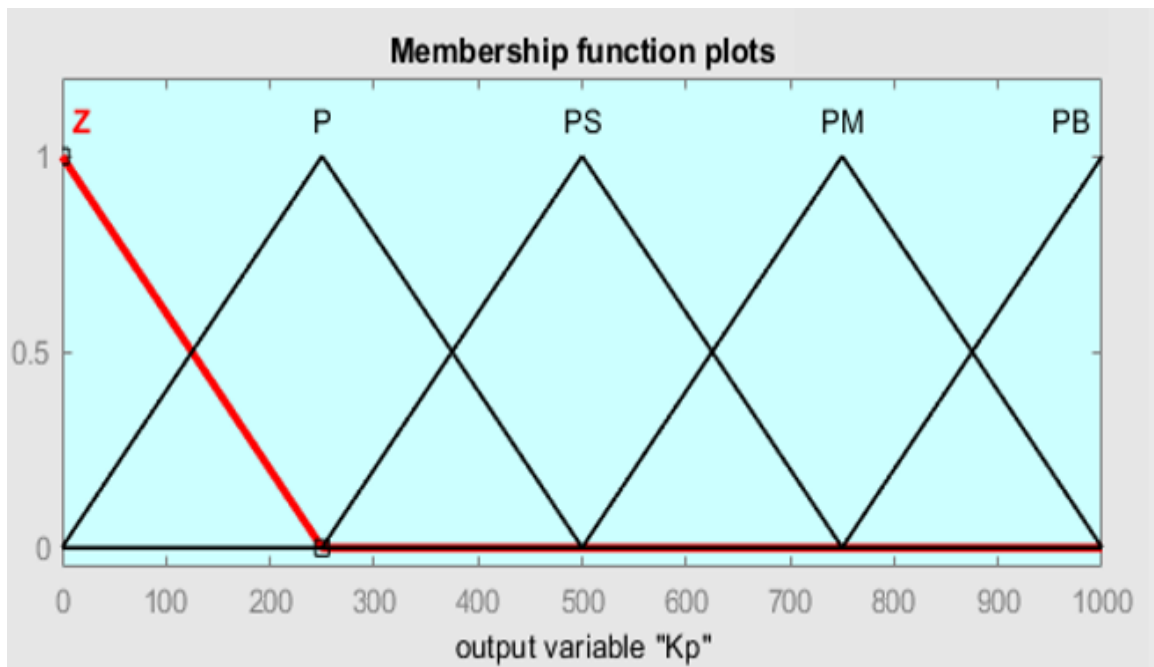


Figure 56: Membership Function of K_p

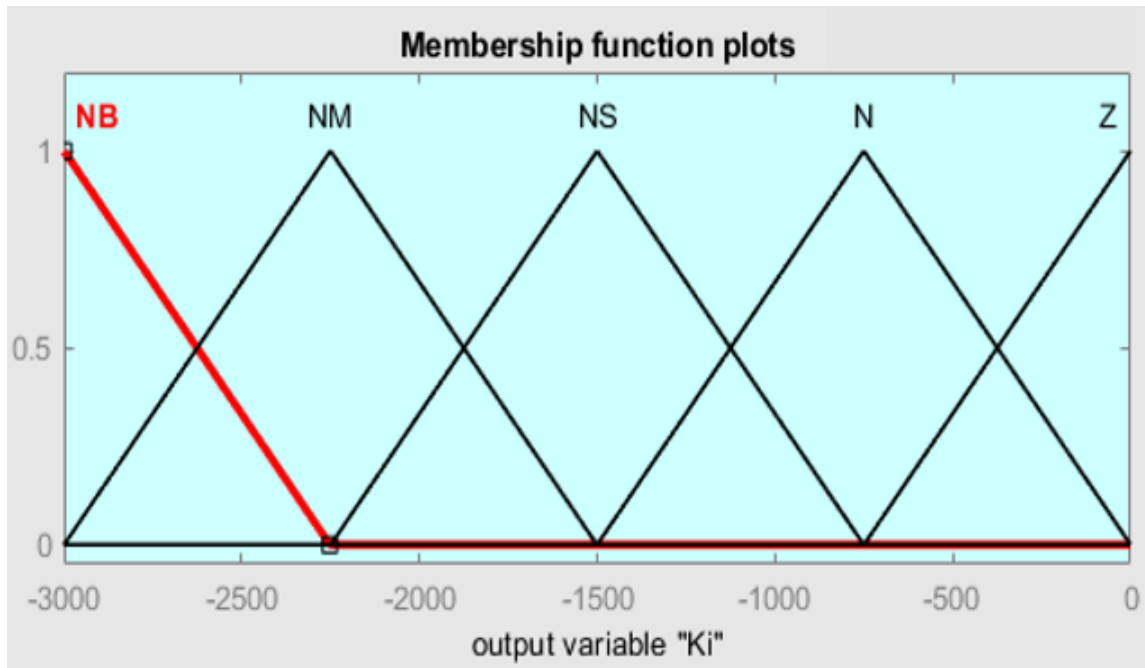


Figure 57: Membership Function of K_i

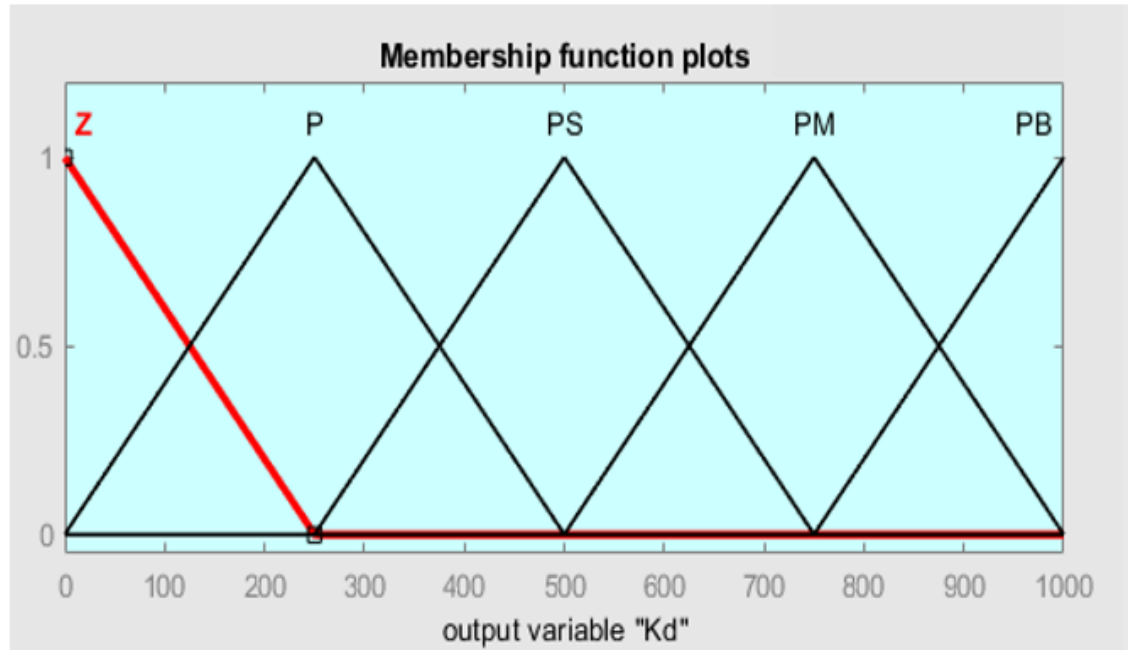


Figure 58: Membership Function of K_d

The selection of linguistic variables for "e" and "ec" involves assigning seven fuzzy values: NB (negative big), NM (negative medium), NS (negative small), Z (zero), PS (positive small), PM (positive medium), and PB (positive big). This distribution allows the controller to interpret the extent of error or change in the error with a graded level of severity, from large negative deviations to large positive ones. By categorizing the inputs and PID parameters into the shown linguistic values in Figures 56 to 58, the fuzzy PID controller can apply human-like reasoning to the process of control system adjustment, resulting in a more nuanced and responsive control strategy.

The linguistic rule set is the cornerstone of a fuzzy controller, effectively translating an expert's understanding into a structured framework that the controller can utilize. Tables 8-10 show the IF-THEN rules:

Table 8: Fuzzy Rules for K_p

e \ ec	NB	NM	NS	Z	PS	PM	PB
NB	PS	PS	PS	PS	PS	P	P
NM	PB	PB	PM	PM	PM	PB	PB
NS	PS	PS	P	P	P	PS	PS
Z	P	P	P	P	P	P	P
PS	PS	P	P	P	PS	P	PS
PM	PM	PB	PM	PB	PB	PB	PB
PB	PB	PB	PM	PM	PM	PB	PB

Table 9: Fuzzy Rules for K_i

$\begin{matrix} ec \\ e \end{matrix}$	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NM	NB	NB	NB
NM	NB	NM	NM	NM	NM	NB	NB
NS	NM	NM	NB	NM	NB	NM	NB
Z	NM	NM	NB	NM	NB	NB	NB
PS	NB	NB	NB	NB	NB	NM	NB
PM	NM	NB	NM	NM	NM	NB	NB
PB	NB	NB	NM	NM	NM	NB	NB

Table 10: Fuzzy Rules for K_d

$\begin{matrix} ec \\ e \end{matrix}$	NB	NM	NS	Z	PS	PM	PB
NB	PM	PM	PS	PM	PM	PS	PM
NM	P	PS	PS	PS	PS	PS	P
NS	PM	PM	PS	PS	P	P	PM
Z	PS	PS	PM	PM	PM	P	PM
PS	PB	PS	PS	PM	P	PS	PM
PM	P	PM	PS	PS	PS	PS	PM
PB	PM	PS	PS	PS	PB	PS	P

5.5.3 Fuzzy PID Controller Results

The performance of the fuzzy self-tuning PID controller is obtained using MATLAB. A fuzzy controller with two inputs and three outputs was designed, with the corresponding membership functions and fuzzy rules meticulously established to facilitate effective tuning. This technique will be applied to tune the PID controller for the smart cantilever beam system, which will be tested under two distinct conditions: firstly, when subjected to a random disturbance, and secondly, when affected by an impulse disturbance.

A. Control System Affected by Impulse Disturbance

To validate our approach, the fuzzy logic technique was applied to adjust the PID controller parameters on a system subjected to an impulse disturbance at time of 0 sec. Figures 59-61 show the reference input, impulse disturbance, and uncontrolled system output, respectively.

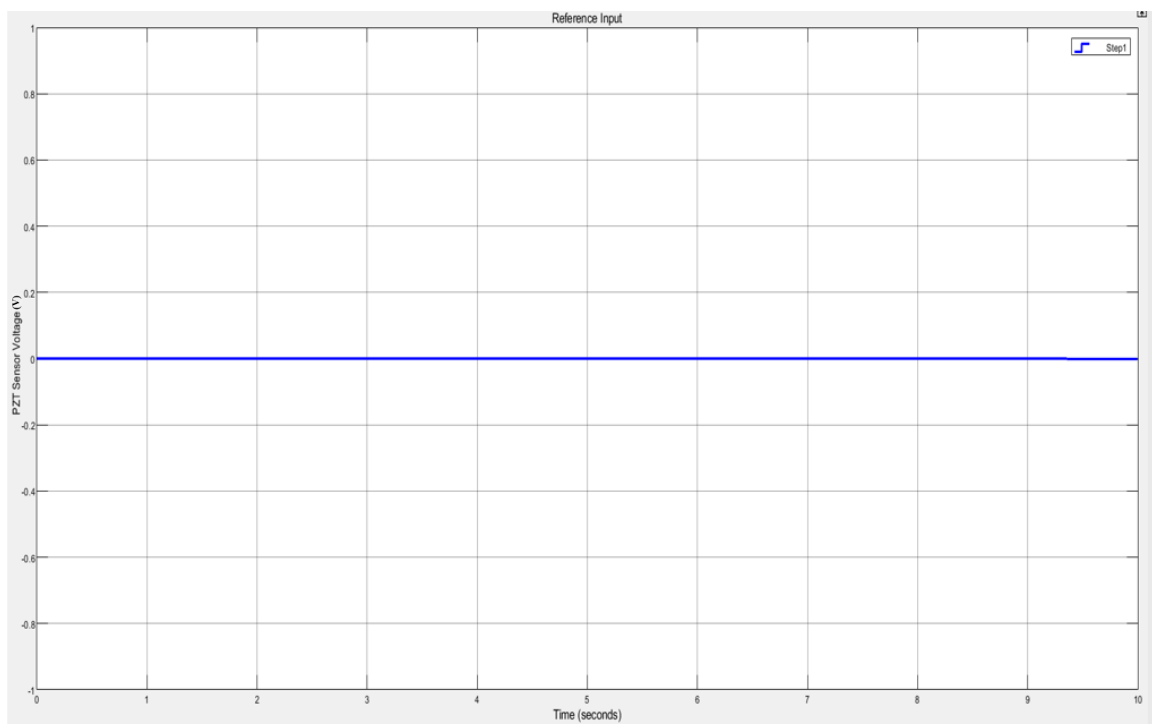


Figure 59: Reference Input

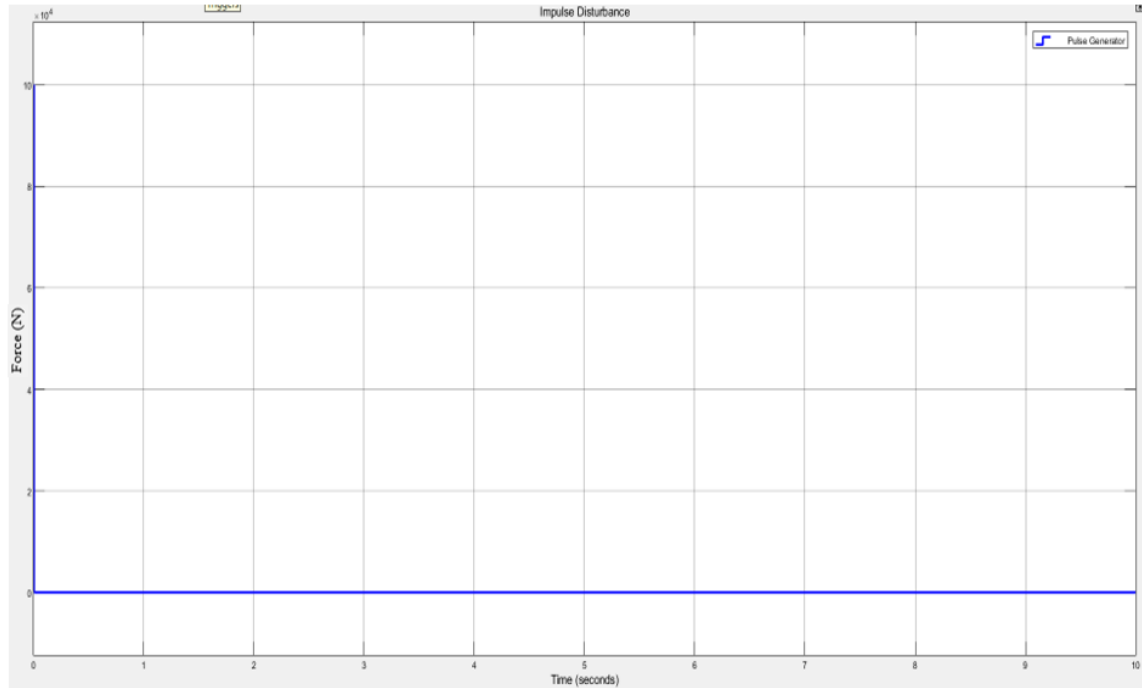


Figure 60: Impulse Disturbance of the System

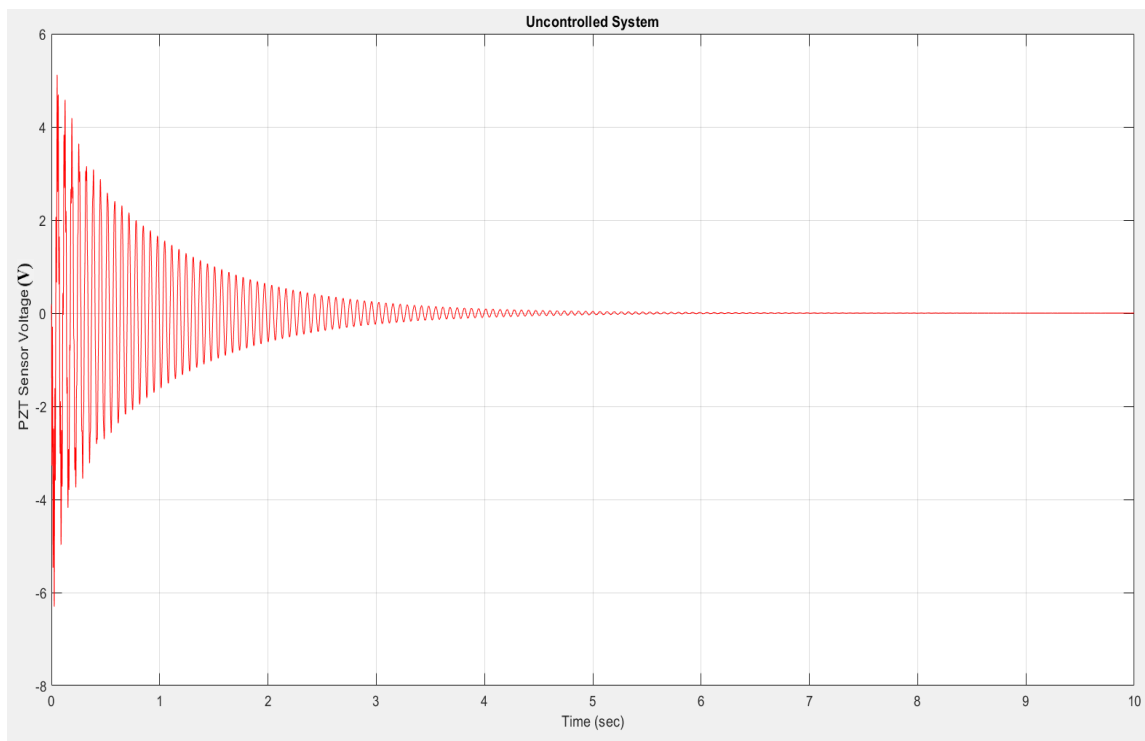


Figure 61: Voltage Response of PZT Sensor before Vibration Control (under Impulse Disturbance).

The fine-tuned parameters are detailed in Table 12. After the utilization of the optimized PID controller using fuzzy logic, the system achieves a settling time of 1.85 seconds. The Integral Time Absolute Error (ITAE) measures an exceptionally low value of 0.9509, indicating the system's efficiency in reducing both the magnitude and duration of error. Additionally, the Mean Squared Error (MSE) is 2.5391e-13, underscoring the predictive precision of the controller. Moreover, the controller effectively suppresses disturbance, leading to a significant reduction in vibration. Figures 62 and 63 illustrate the control signal and the system behavior after implementing the FL-PID controller.

Table 11: PID Controller Parameters Tuned Using Fuzzy Logic of the System Affected by Impulse Disturbance

K_p	K_i	K_d
220	-2752.31	82.8

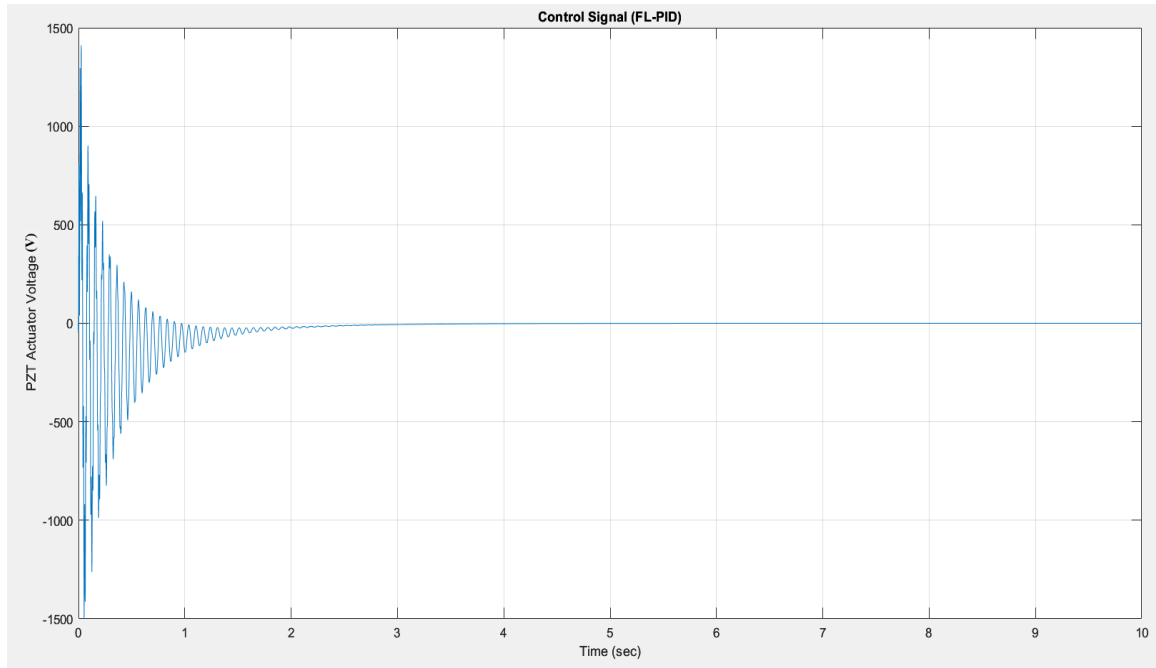


Figure 62: System Control Signal

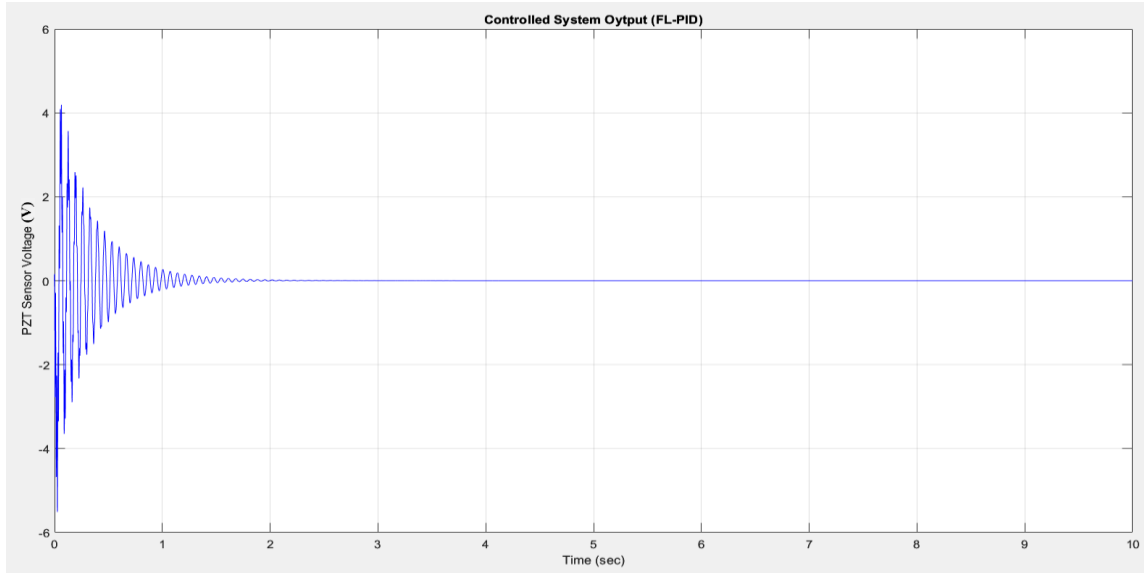


Figure 63: Voltage Response of PZT Sensor after Vibration Control with FL-PID (under Impulse Disturbance).

Figure 64 illustrates the difference in system performance before and after implementing the FL-PID controller. The vibration of the beam is significantly reduced, and the settling time is achieved at 1.85 seconds.

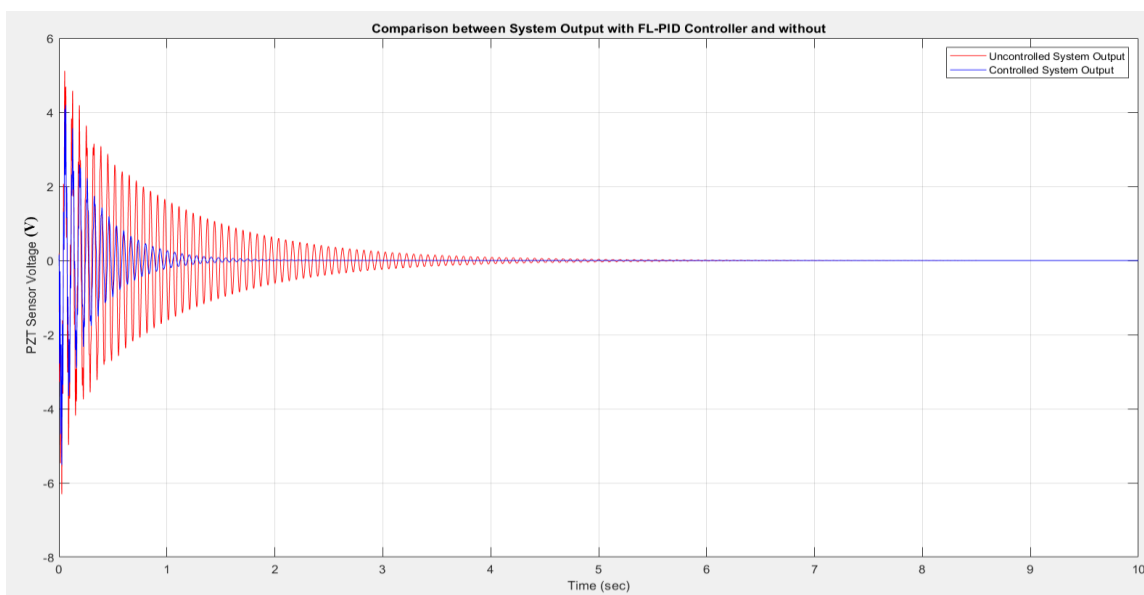


Figure 64: Voltage Response of PZT Sensor in Cantilever Beam with FL-PID Controller and without.

B. Control System Affected by Random Disturbance

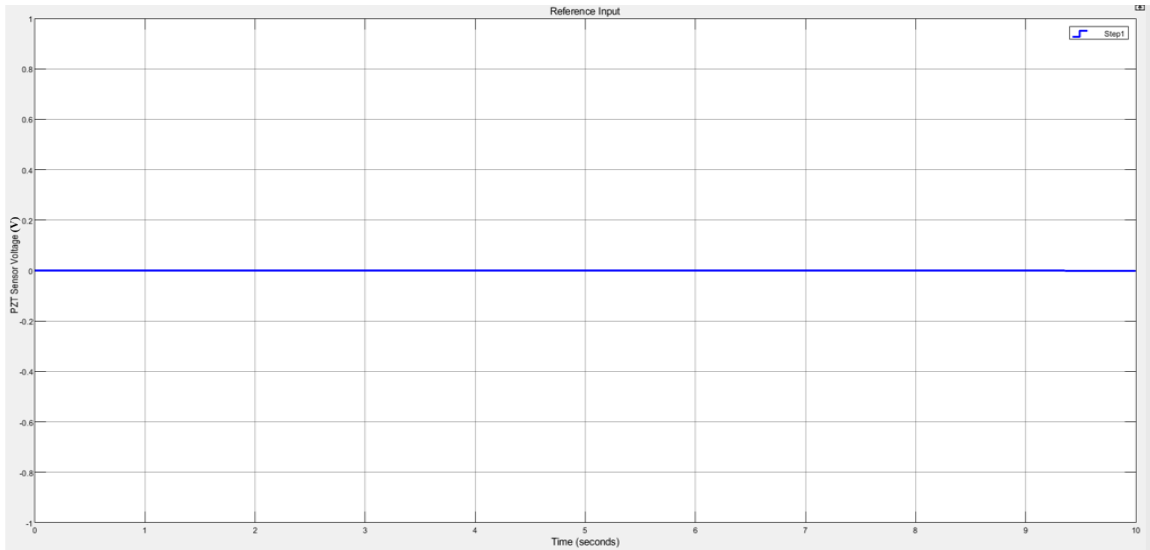


Figure 65: Reference Input

The reference input for the system is illustrated in Figure 66. A continuous random disturbance, affecting the system, is captured in Figure 67. The system's uncontrolled output, revealing the effects of the disturbance, is shown in Figure 68.

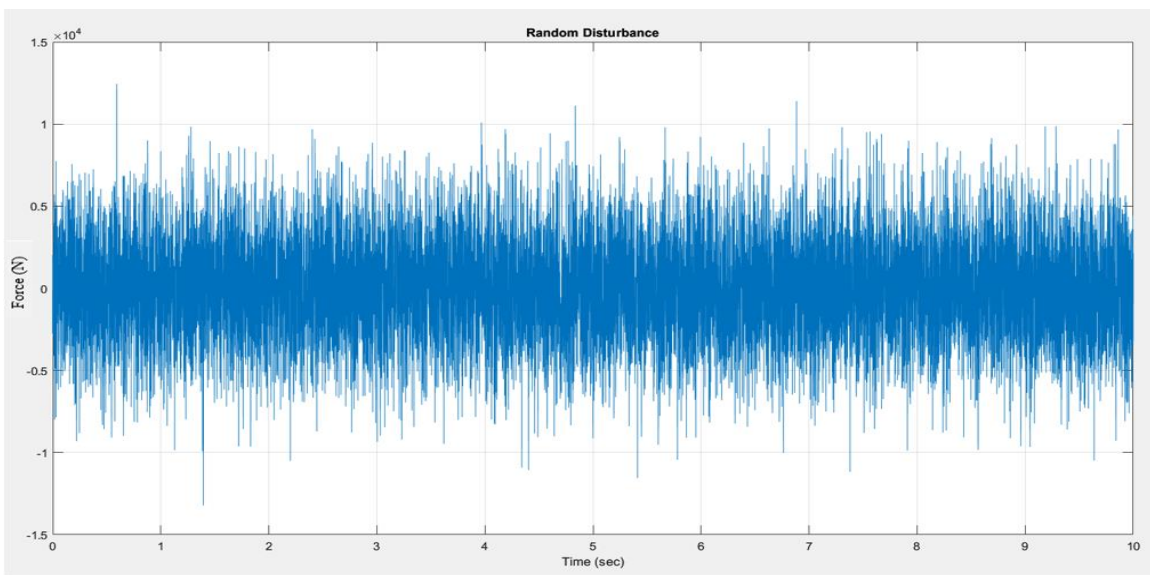


Figure 66: Random Disturbance of the System

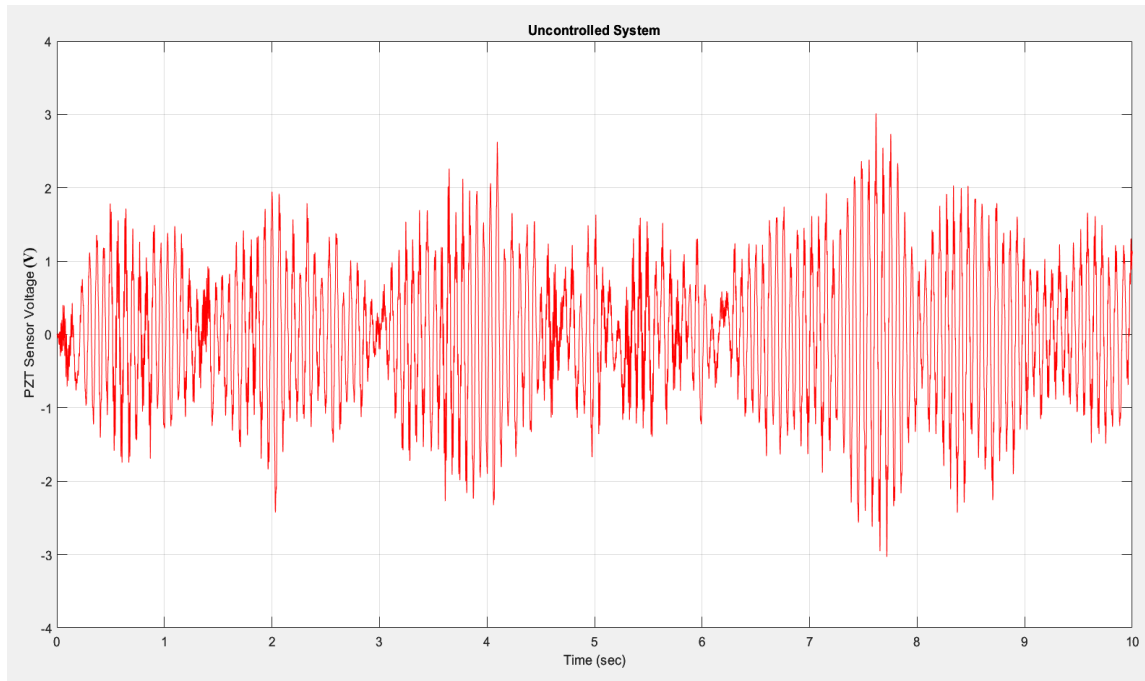


Figure 67: Voltage Response of PZT Sensor before Vibration Control (under Random Disturbance).

After constructing the fuzzy logic technique for the PID controller adjustment, the resulting parameters are presented in Table 11. Subsequently, Figure 69 illustrates the effect of the tuned PID controller on reducing the system vibration. The system's peak oscillation was significantly reduced to 1.272 V at 1.404 seconds, compared to 3.014 V at 3.014 seconds before the controller was applied. The range of oscillations decreased notably. Remarkably, the Integral Time Absolute Error (ITAE) measures an impressive 3.4631, indicating the system's efficiency in reducing both the magnitude and duration of the error. Additionally, the Mean Squared Error (MSE) is notably low at 0.9632, further highlighting the predictive accuracy of the controller. Figures 68 and 69 illustrate the control signal and the system behavior after implementing the FL-PID controller.

Table 12: PID Controller Parameters Tuned Using Fuzzy Logic of the System Affected by Random Disturbance

K_p	K_i	K_d
500	-2250	500.5

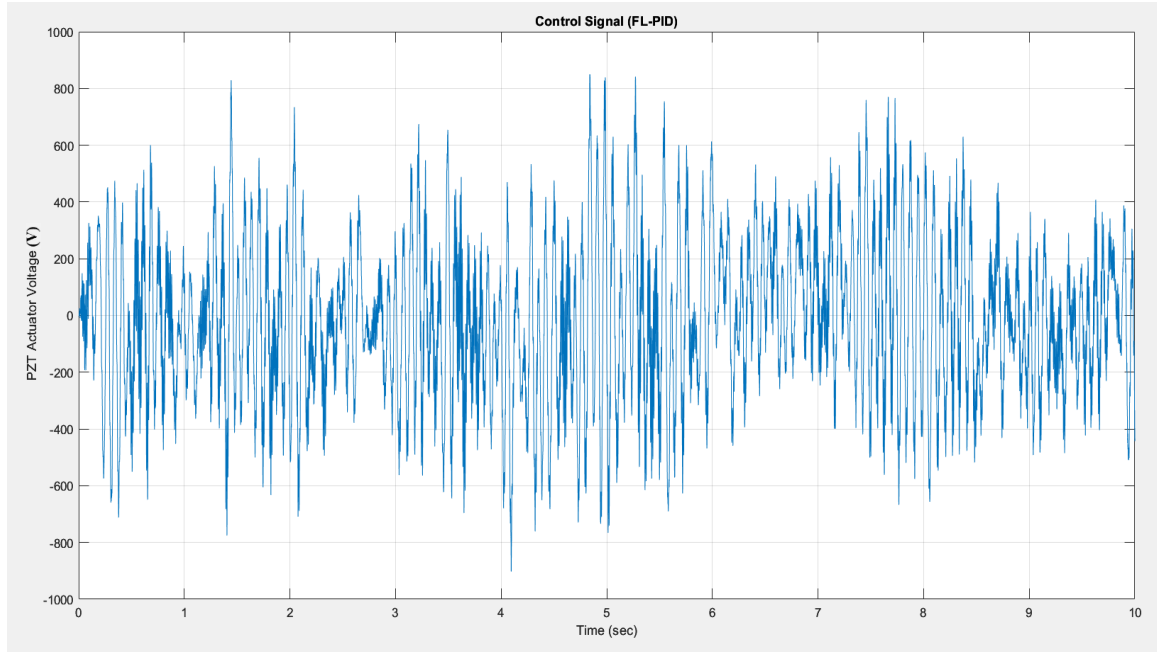


Figure 68: System Control Signal

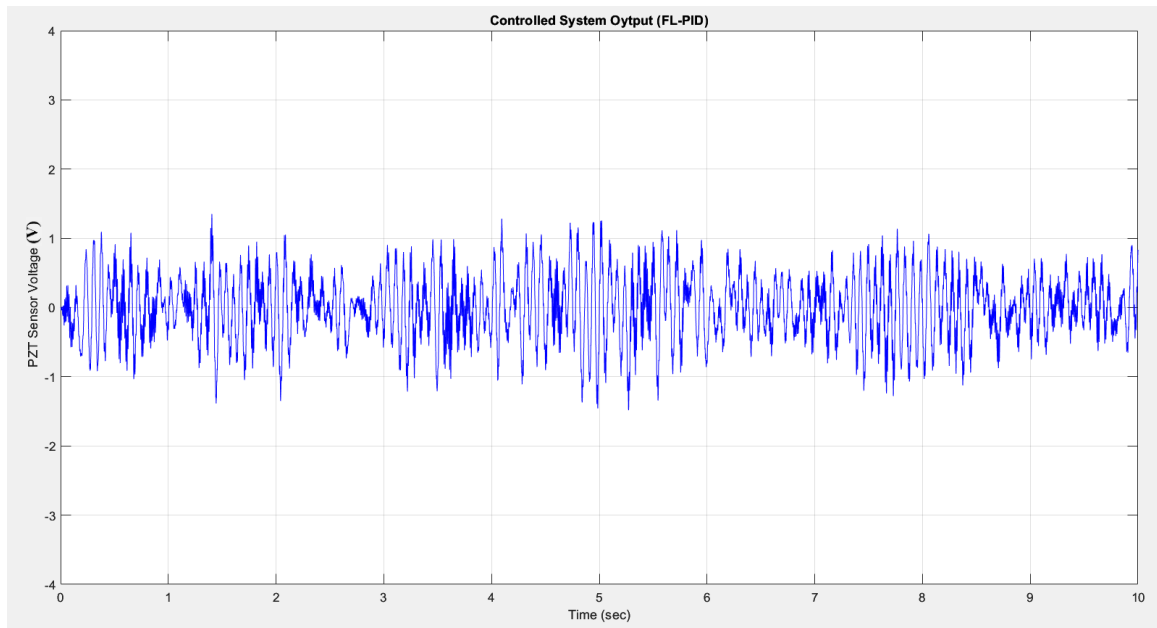


Figure 69: Voltage Response of PZT Sensor after Vibration Control with FL-PID (under Random Disturbance)

Figure 70 demonstrates the effectiveness of the FL-PID controller in minimizing vibration caused by continuous disturbance. The system with the tuned PID controller reduces the vibration to a range of -1 to 1 V.

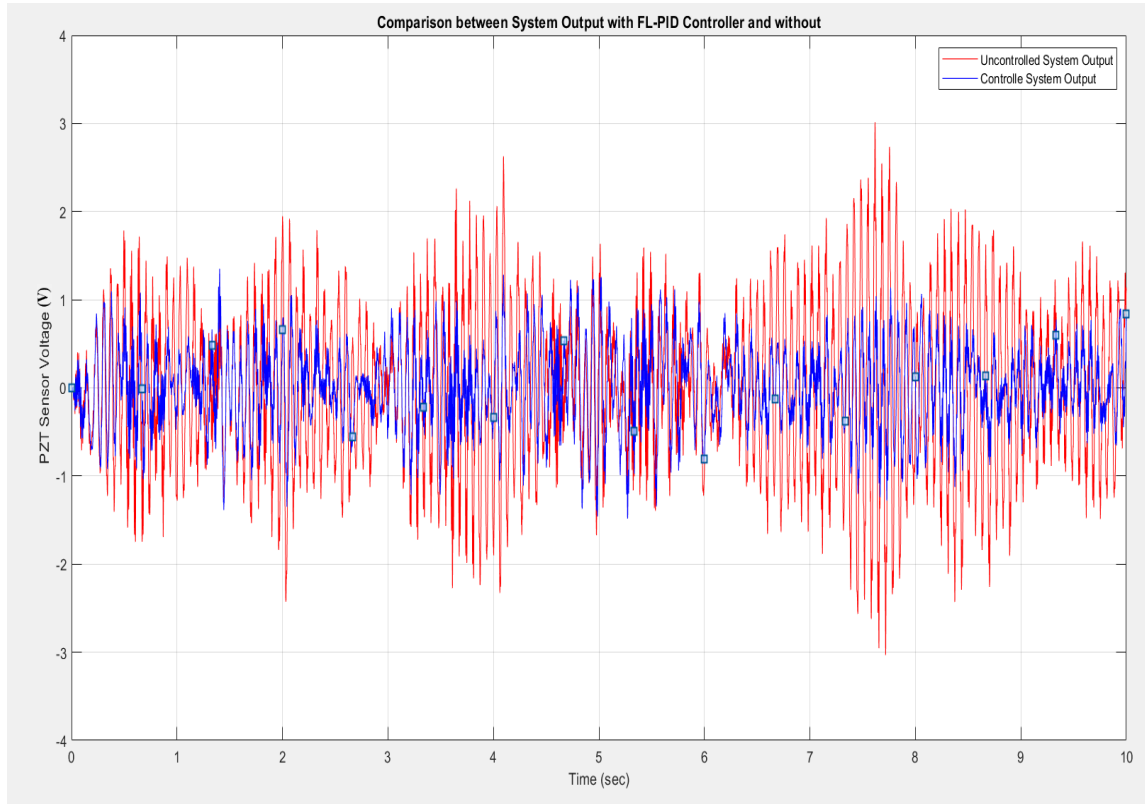


Figure 70: Voltage Response of PZT Sensor in the Cantilever Beam with FL-PID Controller and without.

5.6 Deep Learning

Deep learning has emerged as a powerful tool in various fields, offering remarkable capabilities in data analysis, pattern recognition, and predictive modeling. With its ability to learn complex patterns and relationships from large datasets, deep learning has found applications in diverse domains, including computer vision, natural language processing,

and robotics [56]. One promising application area is in the field of structural dynamics and vibration control, where deep learning techniques can be used to predict and mitigate vibrations in mechanical systems [57].

In previous sections we have designed the PID controller that has been employed for vibration suppression in cantilever beam. To enhance the efficiency and effectiveness of vibration control strategies, optimization methods such as genetic algorithm, neural network, and fuzzy logic have been integrated with PID controller. These hybrid approaches dynamically adjusted the PID parameters effectively, leading to improved control performance.

In this section, we aim to explore a novel approach to vibration control by designing a pure deep learning controller for cantilever beams. We seek to develop a predictive model that can accurately predict the vibration response of a cantilever beam and generate the corresponding control signals required to suppress vibrations using PZT actuator.

We propose to leverage the power of deep learning, specifically Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) cells, for vibration control. By harnessing the temporal dependencies and dynamics inherent in vibration data, we

aim to develop a deep learning controller that can adaptively learn and optimize control strategies.

We aim to evaluate the performance of the proposed pure deep learning controller in accurately predicting and controlling the vibration of cantilever beam under various conditions and disturbances.

5.6.1 RNN with LSTM for Vibration Control

Our deep learning approach for vibration control leverages 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 it step-by-step and incorporating past knowledge into their current output [58].

Furthermore, effective control strategies often rely on considering past events that can have lingering effects. LSTM address this challenge. As a special type of RNN, LSTM are designed to capture long-term dependencies within the data [58], [59]. They have internal mechanisms that allow them to learn and remember information over extended periods, making them well-suited for our control strategy. Figure 71 illustrates the

process of creating an RNN with LSTM and demonstrates its capability to manage long sequence input.

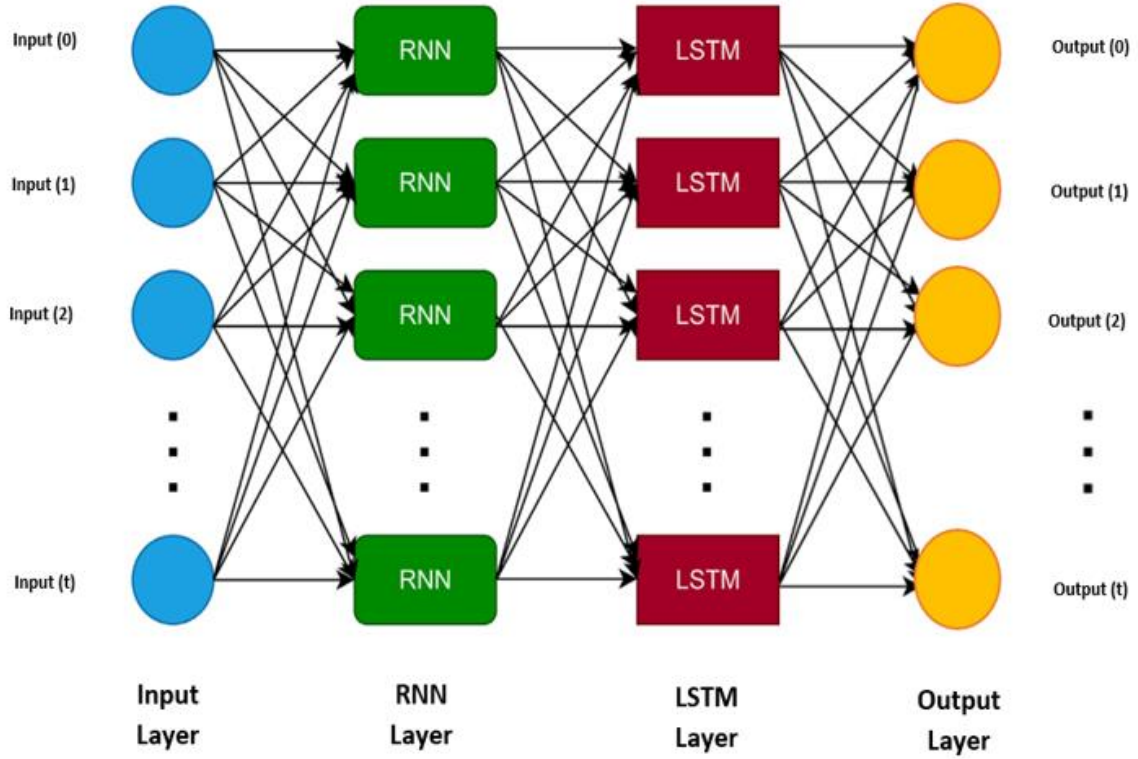


Figure 71: Creating Recurrent Neural Network with Long Short-Term Memory

5.6.2 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 recurrent neural network (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 size of 1000 samples was generated from the relation between the PZT sensor and actuator while employing the PID controller 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 72 shows the closed loop of the system with the deep learning controller.

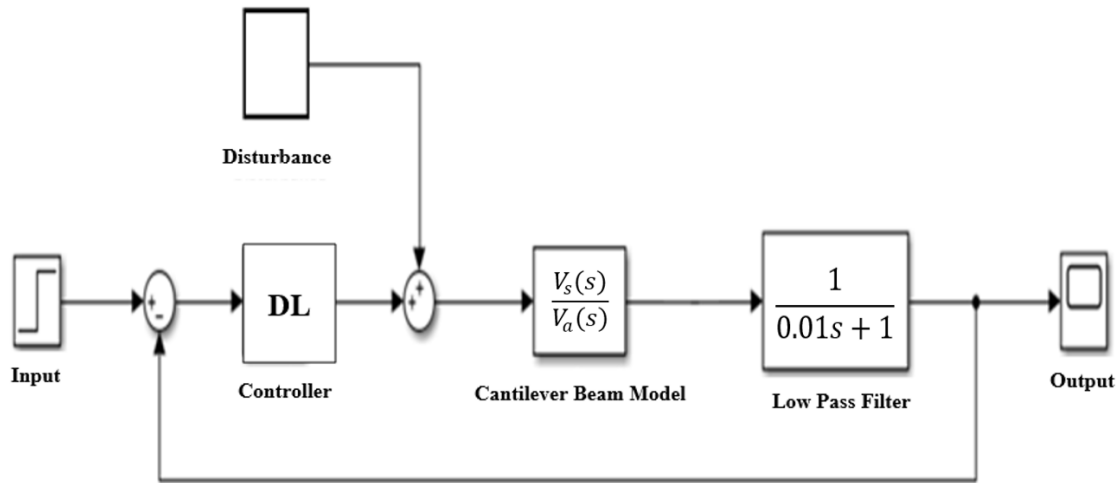


Figure 72: Closed Loop System with Deep learning Controller under disturbance.

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.

A. Control System Affected by Impulse Disturbance

In the scenario where an impulse disturbance occurs at time 0 seconds, the system's behavior is analyzed. Figure 73 presents the reference input, while Figure 74 shows the impulse disturbance. To understand the system's response to this disturbance, refer to Figure 75, which illustrates the resulting output signal.

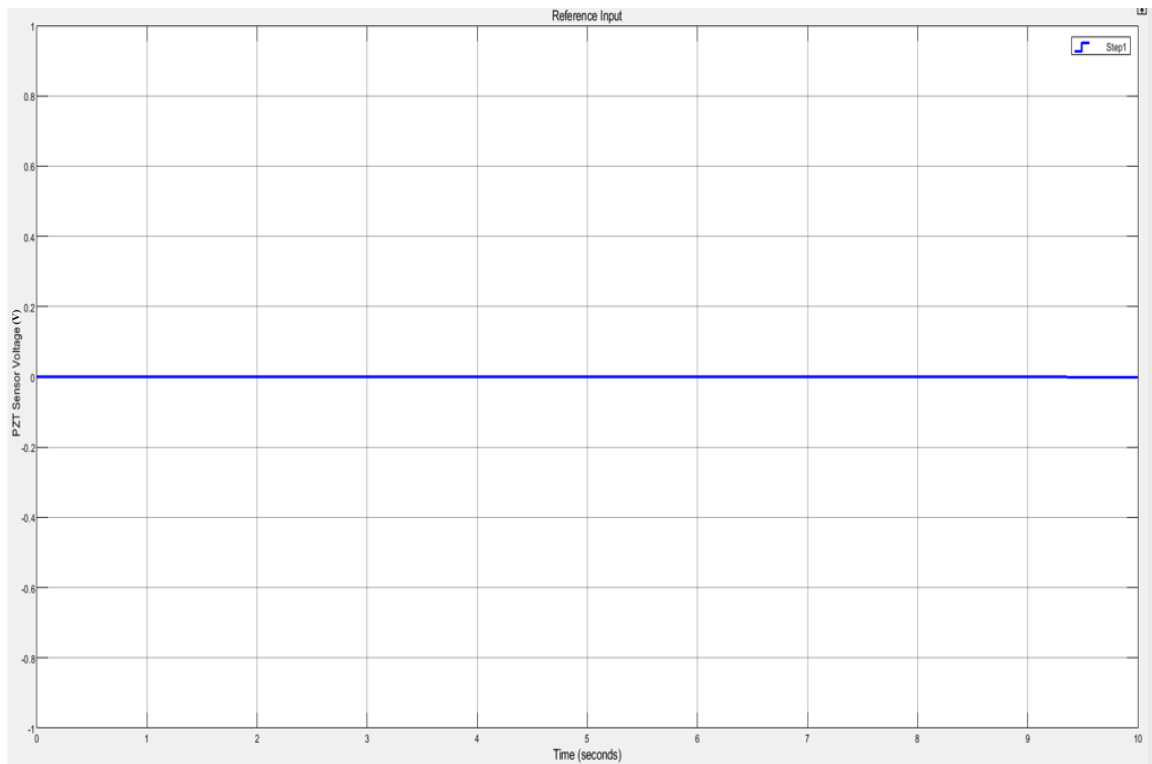


Figure 73: Reference Input

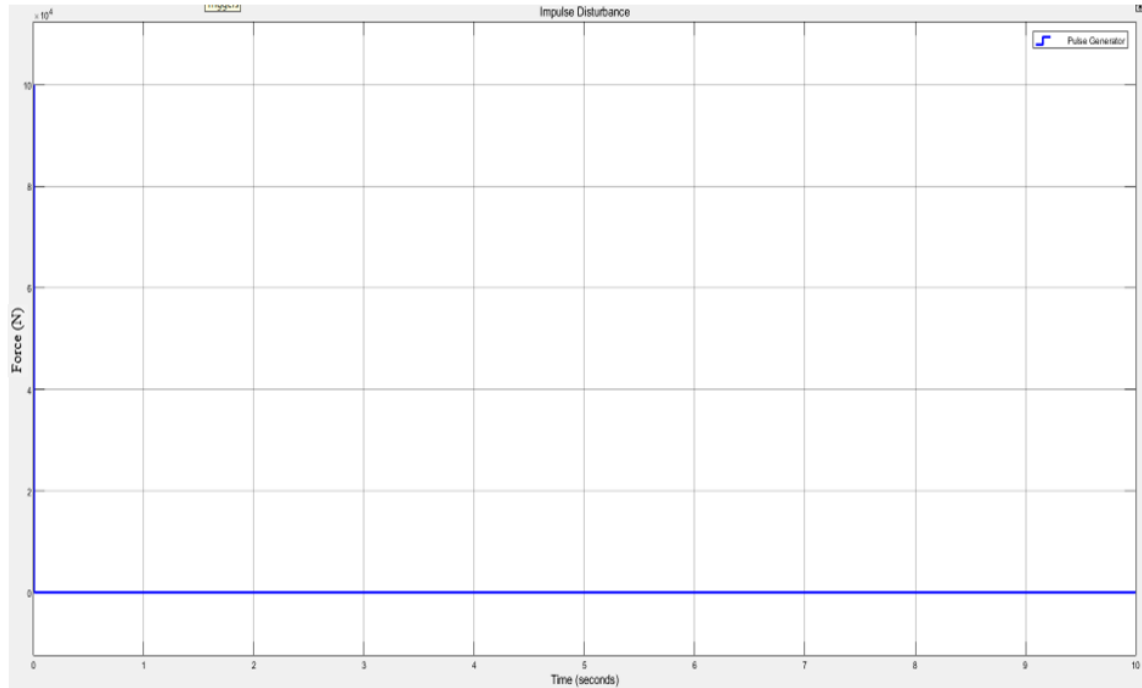


Figure 74: Impulse Disturbance of the System

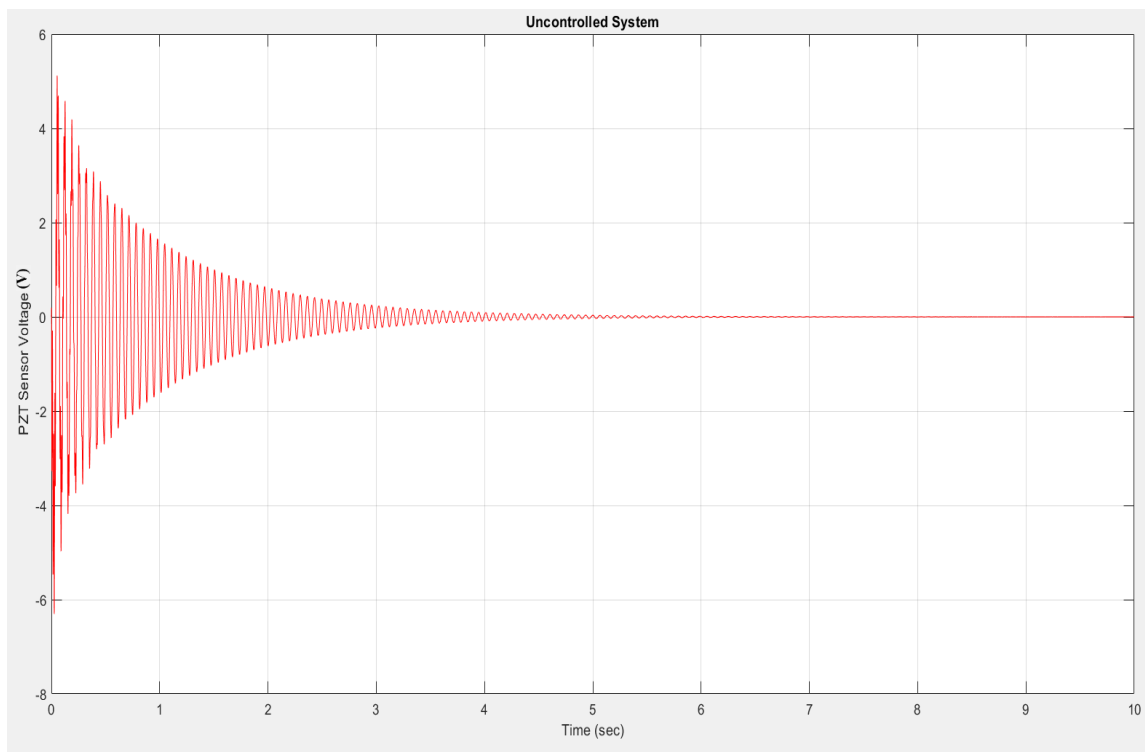


Figure 75: Voltage Response of PZT Sensor before Vibration Control (under Impulse Disturbance).

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 75, the status of the beam is monitored, and based on this analysis, the network produces the control signal shown in Figure 76. This control signal is specifically designed to counteract the detected disturbances and stabilize the beam's vibrations. Figure 77 illustrates the behavior of the system with the deep learning controller.

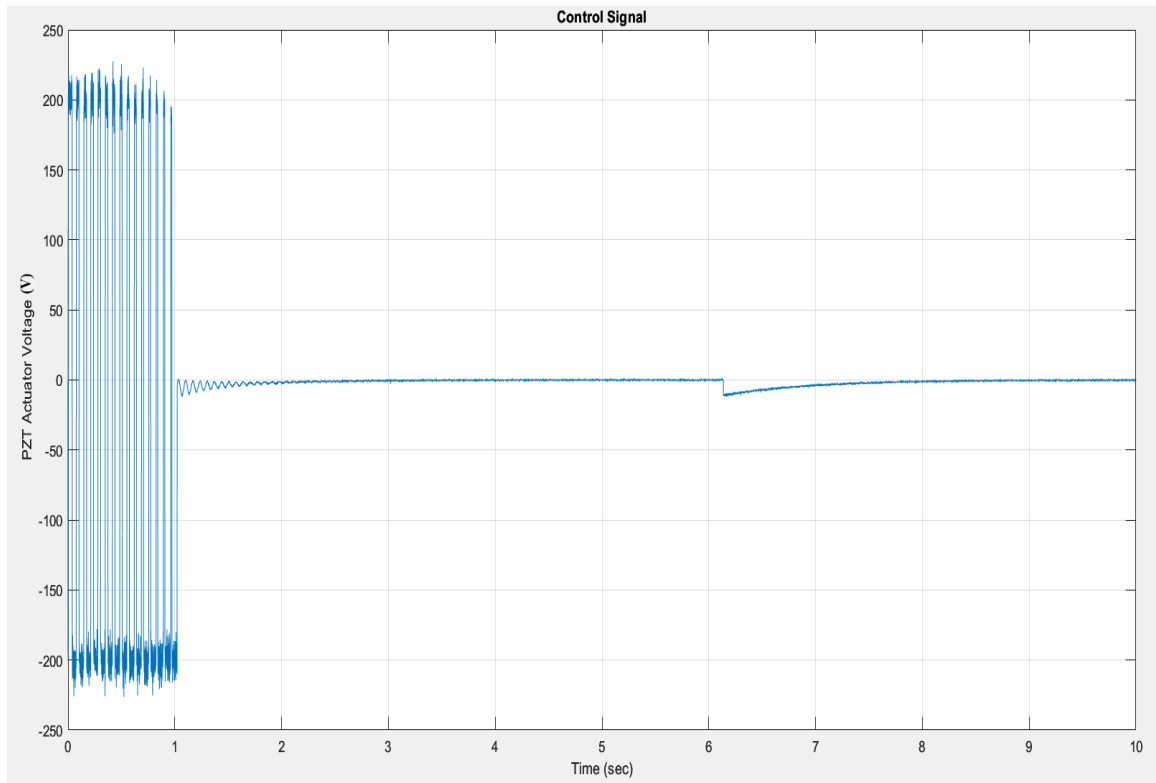


Figure 76: System Control Signal

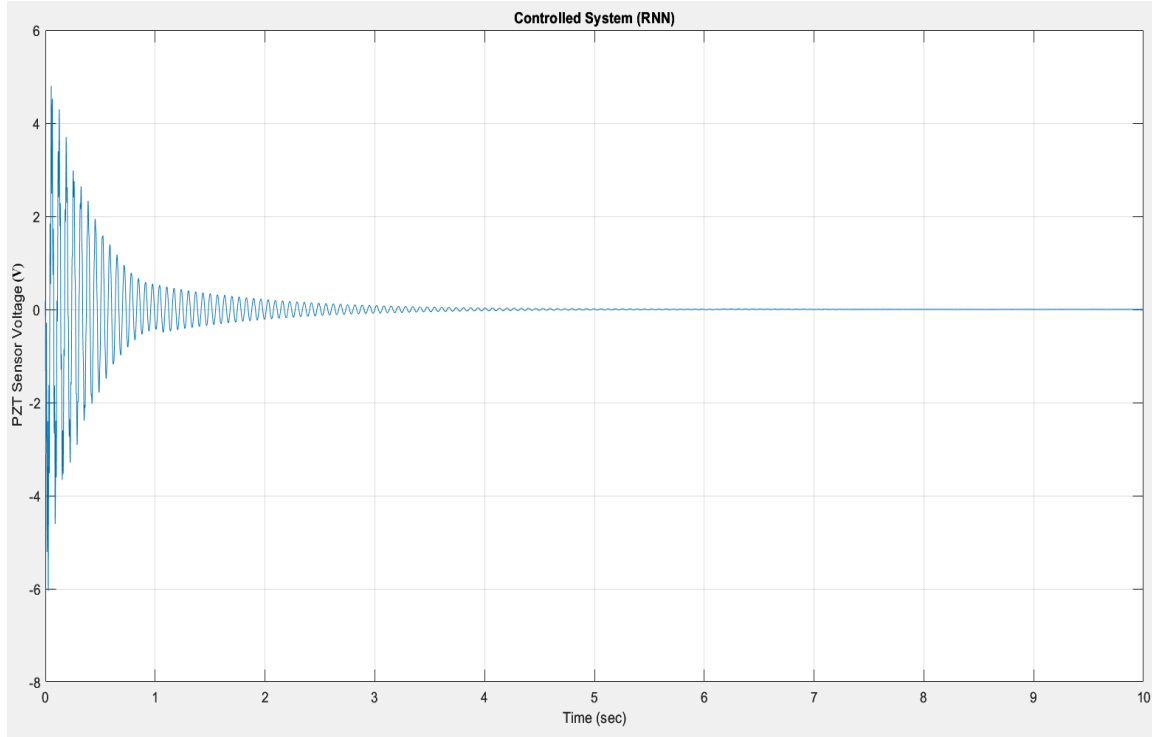


Figure 77: Voltage Response of PZT Sensor after Vibration Control with Deep Learning Controller (under Impulse Disturbance).

Figure 78 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 4 seconds. The system achieves a settling time of 3.34 seconds. 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 $5.9703e-09$, underscoring the predictive precision of the controller.

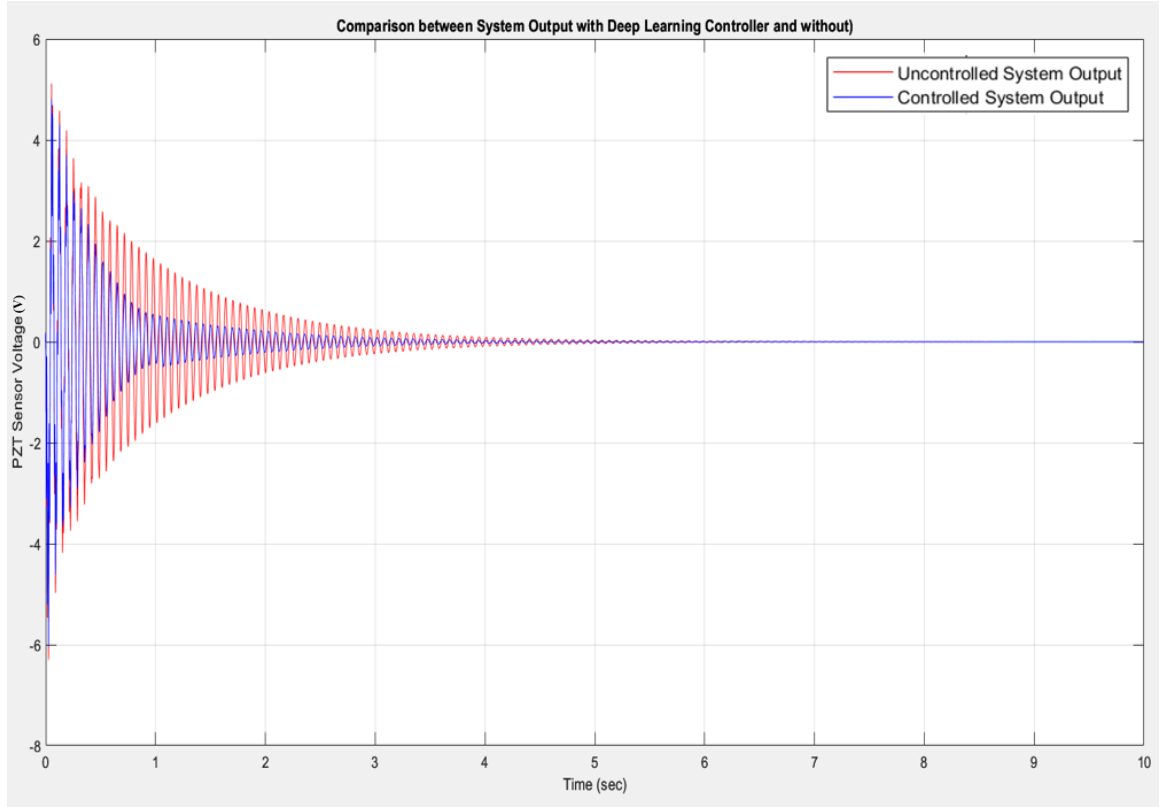


Figure 78: Voltage Response of PZT Sensor in the Cantilever with Deep Learning Controller and without

B. Control System Affected by Random Disturbance

The recurrent neural network will be employed to control the cantilever beam vibrations under the influence of continuous random disturbances. Figure 79 illustrates the reference input signal, while Figure 80 displays the random disturbance signal, representing the unpredictable external factors impacting the system's performance. Figure 81 shows the behavior of uncontrolled system output, showcasing its actual response in the absence of the controller amidst the presence of the random disturbance.

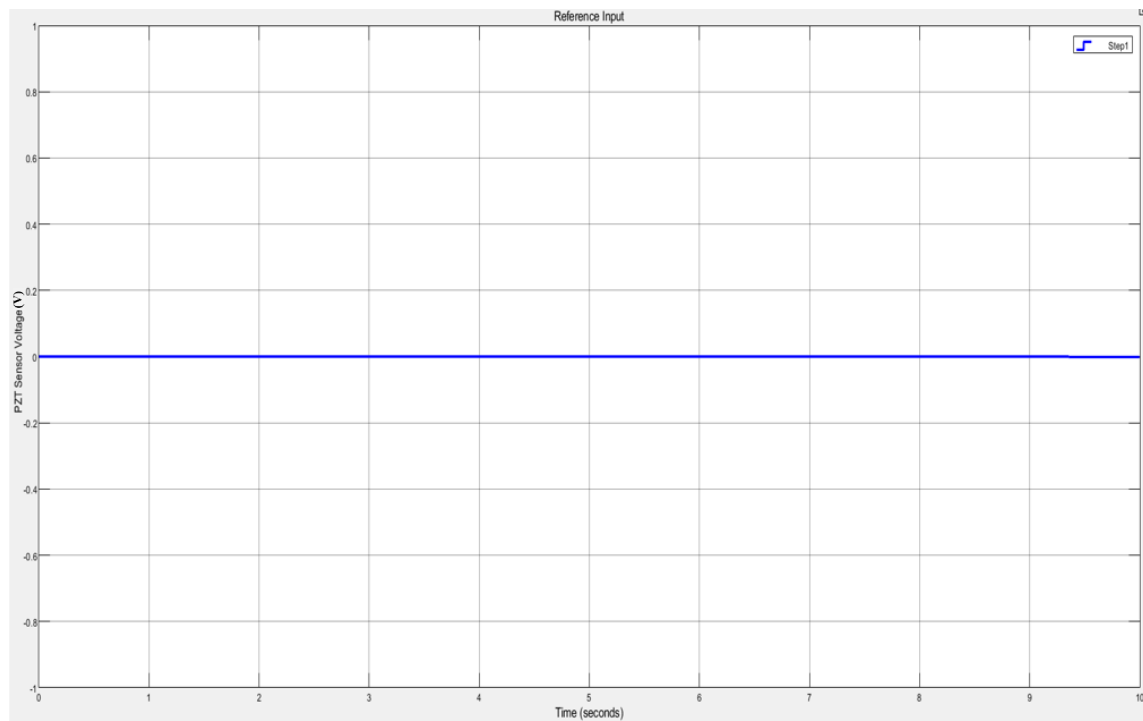


Figure 79: Reference Input

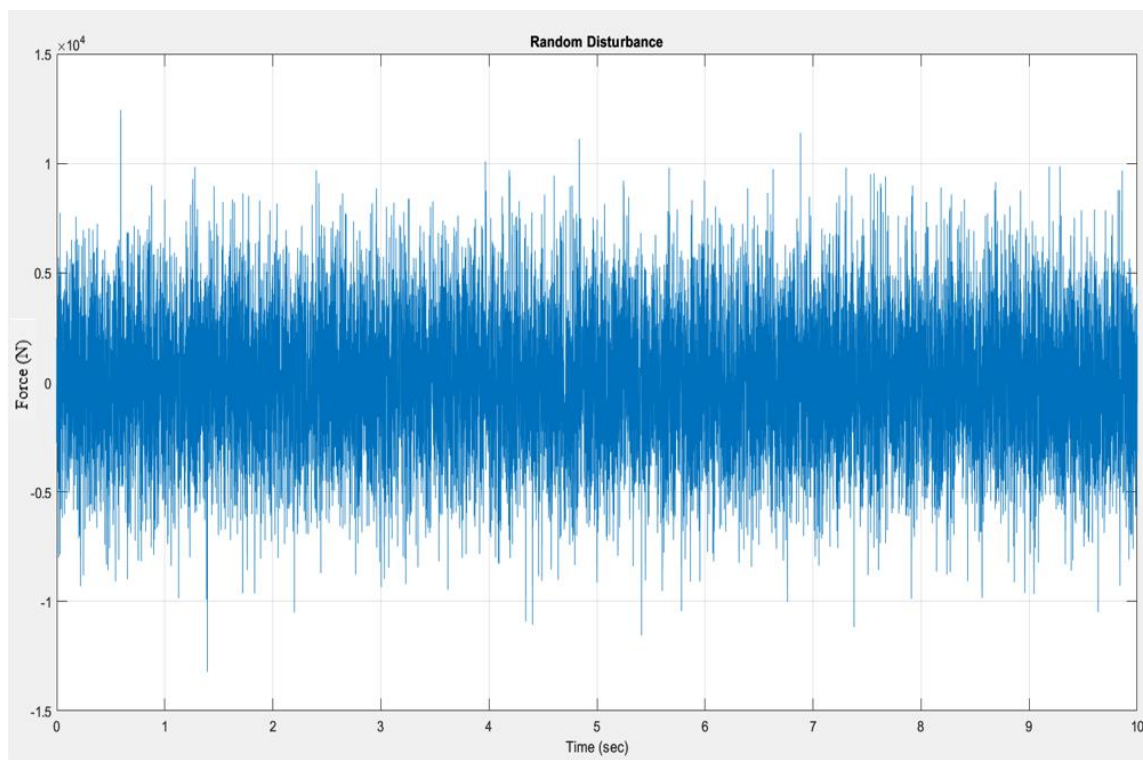


Figure 80: Random Disturbance

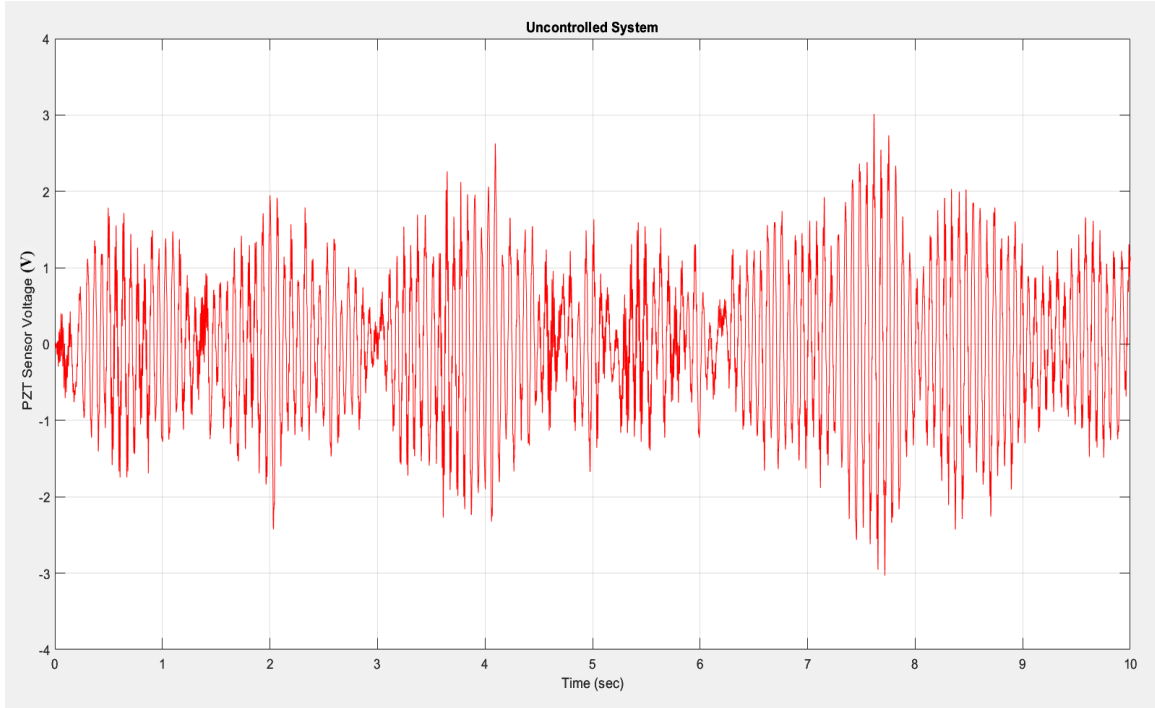


Figure 81: Voltage Response of PZT Sensor before Vibration Control (under Random Disturbance).

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 82, designed to counteract the detected disturbances and reduce the beam's vibrations effectively.

The generated control signal adapts to the varying conditions, ensuring that the vibrations are minimized. Figure 83 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.

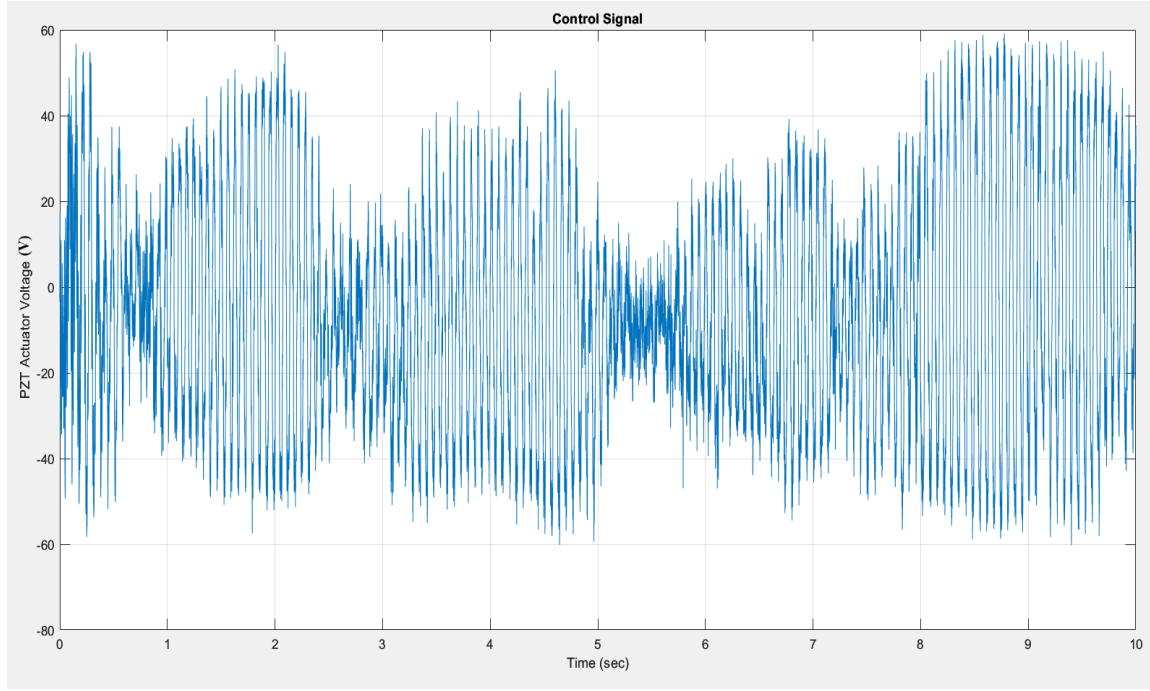


Figure 82: System Control Signal

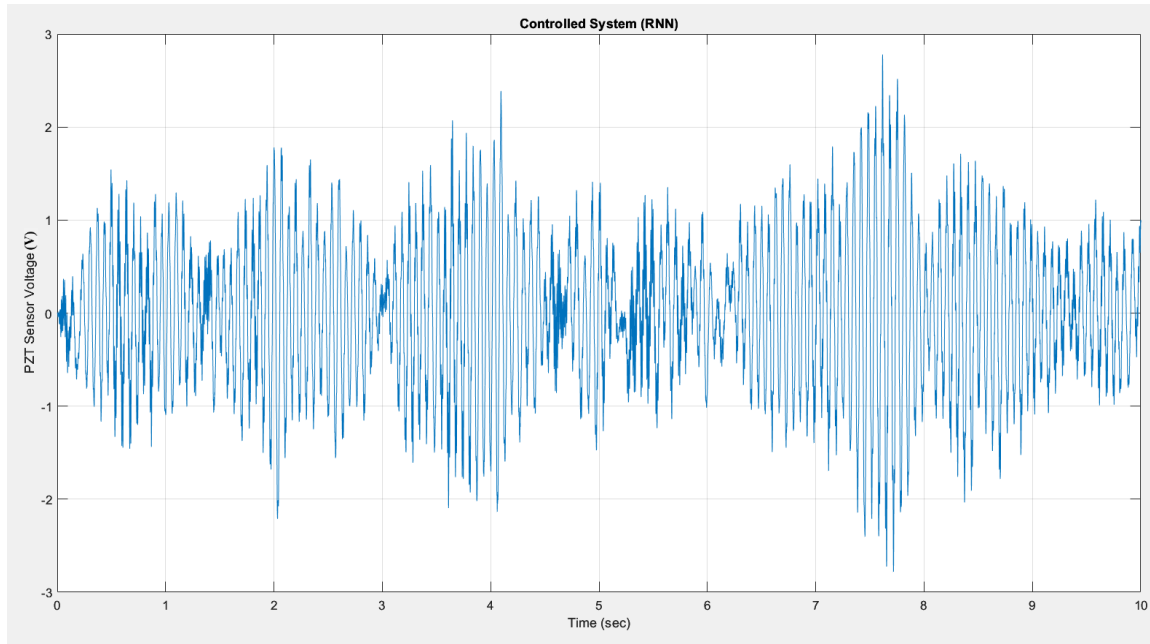


Figure 83: Voltage Response of PZT Sensor after Vibration Control with Deep Learning Controller (under Random Disturbance).

Figure 84 demonstrates the effectiveness of the deep learning controller in minimizing vibrations caused by continuous disturbances. The system with the DL controller reduces vibrations, with minimization being small and notable in some areas. In certain regions, the controller achieves vibration mitigation down to a range of 0.65 V. Despite the continuous nature of the disturbances, the deep learning controller consistently adapts and responds, ensuring that the vibrations are kept within a minimal range. This highlights the controller's ability to provide reliable performance and maintain control in the face of long and varying disturbances.

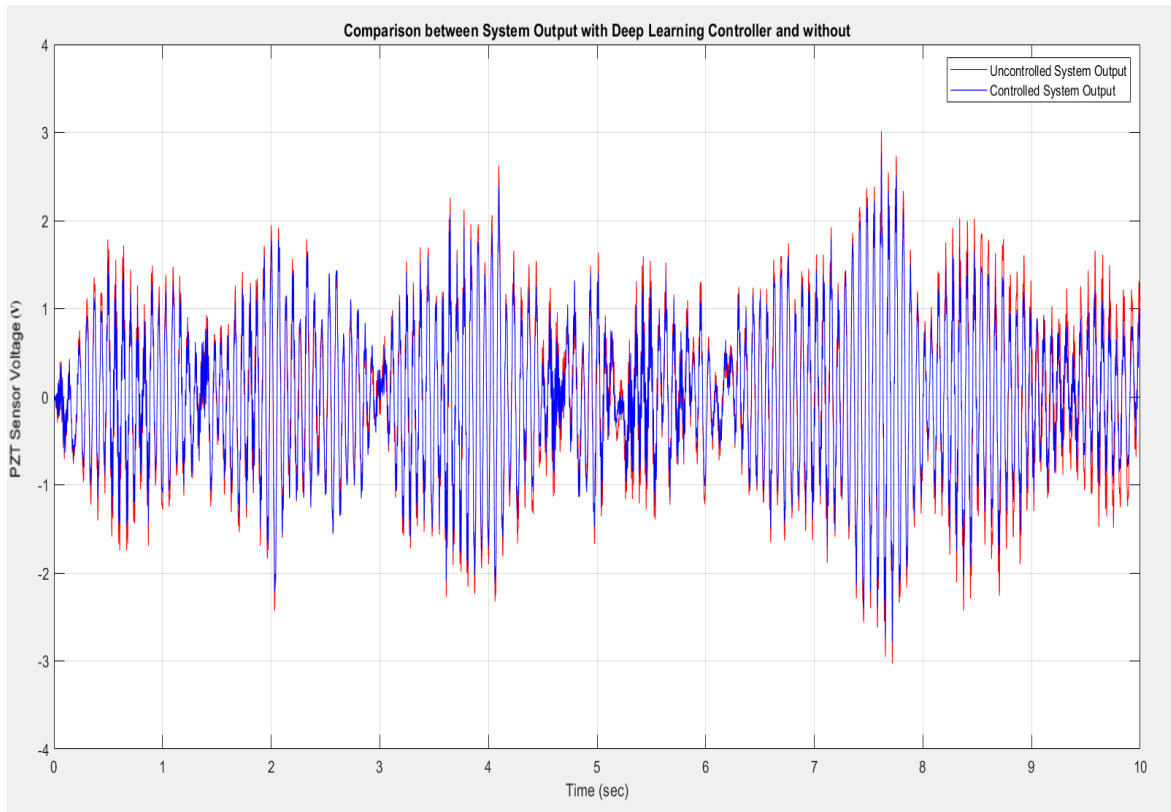


Figure 84: Voltage Response of PZT Sensor in the Cantilever Beam with Deep Learning Controller and without

CHAPTER 6

COMPARATIVE ANALYSIS

In In this chapter, we will compare the performance of the optimization techniques used for the PID controller and the performance of the designed pure deep learning controller. This comparative analysis will focus on evaluating their efficacy in controlling the vibrations of a cantilever beam system under two distinct types of disturbances: impulse and random disturbances. By examining key performance metrics such as vibration reduction, settling time, Integral Time Absolute Error (ITAE), and Mean Squared Error (MSE), we aim to highlight the strengths and weaknesses of each control strategy. This analysis will provide a comprehensive understanding of how these approaches perform in mitigating vibrations of cantilever beam structures.

Table 13 shows the tuned parameters of PID controller under the impulse disturbance and the key performance metrics for each method:

Table 13: Key Performance Metrics for the Controllers under Impulse Disturbance

Controller Type	K_p	K_i	K_d	Settling Time (s)	ITAE	MSE
GA-PID Controller	230	-2960	120	1.88	1.0255	1.1251e-13
NN-PID Controller	233.5	-2877.9	113.5	1.84	0.9178	7.8594e-14
FL-PID Controller	220	-2752.31	82.8	1.85	0.9509	2.5391e-13
Deep learning Controller	/	/	/	3.34	1.5818	5.9703e-09

Table 14 presents the tuned parameters of PID controller under the continuous random disturbance and the key performance metrics for each method:

Table 14: Key Performance Metrics for the Controllers under Continuous Random Disturbance

Controller Type	K_p	K_i	K_d	Peak Amplitude	ITAE	MSE
GA-PID Controller	690	-2430	170	1.264	3.2245	0.6869
NN-PID Controller	802.6	-2263.8	241.1	1.237	3.1332	0.5973
FL-PID Controller	500	-2250	500.5	1.272	3.4631	0.9632
Deep learning Controller	/	/	/	2.818	6.4588	0.9690

6.1 Analysis of System Control under Impulse Disturbance

In Table 13, we observe the performance of various PID controllers under impulse disturbance conditions. The GA-PID Controller achieves a settling time of 1.88 seconds, indicating its ability to quickly stabilize after a sudden disturbance. Its Integral of Time-weighted Absolute Error (ITAE) is 1.0325, reflecting its ability to minimize both the integral and the time-weighted components of error over the settling period. The Mean Squared Error (MSE) for this controller is remarkably low at 1.1251×10^{-13} , indicating highly accurate control performance.

Comparatively, the NN-PID Controller achieves a slightly faster settling time of 1.84 seconds, suggesting an optimized response to impulse disturbances. It demonstrates an improved ITAE of 0.9178, demonstrating its effective suppression of disturbances and

minimized deviation from the setpoint over time. The MSE is exceptionally low at $7.8594\text{e-}14$, underscoring its precise control output.

The FL-PID Controller exhibits a settling time of 1.85 seconds, closely paralleling the GA-PID Controller's performance. Its ITAE of 0.9509 and MSE of $2.5391\text{e-}13$ indicate effective control, but slightly higher error metrics compared to the NN-PID.

The approach of the Deep Learning Controller ensures adaptability to complex vibration of a cantilever beam, although it may initially show a longer settling time of 3.34 seconds. Its strength lies in minimizing cumulative error and maintaining stable performance over extended periods, making it ideal for vibration control scenarios. Its ITAE of 1.5818 and MSE of $5.9703\text{e-}09$ suggest effective control performance in handling impulse disturbances.

6.2 Analysis of System Control under Continuous Random Disturbance

Moving to Table 14, we analyze the performance metrics of PID controllers under continuous random disturbance scenarios. The GA-PID Controller exhibits a peak amplitude of 1.264, indicating the maximum deviation from the setpoint due to disturbance. Its ITAE of 3.2245 and MSE of 0.6869 reflect moderate performance in minimizing integral error and mean squared error over the disturbance period.

The NN-PID Controller achieves a lower peak amplitude of 1.237, suggesting better disturbance rejection capability. Its ITAE of 3.1332 and MSE of 0.5973 reflect its improved ability to suppress disturbances compared to other controllers in this scenario.

The FL-PID Controller, operating with shows a peak amplitude of 1.272, similar to the GA-PID Controller. Its ITAE of 3.4631 and MSE of 0.9632 indicate effective but slightly less optimized control performance compared to the NN-PID.

The Deep Learning Controller, despite showing a higher peak amplitude of 2.818 compared to other controllers, demonstrates promising performance in reducing vibrations based on the dataset we generated. With our limited equipment, it effectively monitors and mitigates vibrations, highlighting its potential. To further enhance its capability in handling vibrations caused by continuous disturbances, the Deep Learning Controller would benefit from a larger dataset for training. This would enable it to better adapt and improve its performance in complex and variable vibration scenarios.

CHAPTER 7

CONCLUSION

In this thesis, the study and analysis of a cantilever beam equipped with PZT smart materials have been presented, focusing on the design and implementation of advanced control strategies to mitigate vibration under distinct disturbance scenarios—impulse and random. The primary objective was to enhance the performance of a PID controller through various optimization techniques and to explore the feasibility of a deep learning approach for vibration monitoring and mitigation.

Initially, genetic algorithms were employed to systematically refine and optimize PID parameters, demonstrating notable improvements in control efficacy under both impulse and random disturbances. Subsequently, a neural network-based approach was investigated, leveraging its capability to learn complex relationships within the system and fine-tune PID parameters adaptively.

Further enhancing the PID controller's robustness, fuzzy logic was integrated, providing a rule-based tuning mechanism that effectively adjusted controller parameters based on system dynamics and disturbance characteristics. Each method, genetic algorithms, neural networks, and fuzzy logic, contributed distinct advantages in optimizing PID control, thereby enhancing the beam's vibration suppression capabilities significantly.

Furthermore, the designing of a deep learning-based controller, specifically utilizing Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) architectures, marked a good advancement. The deep learning model learned how the cantilever beam behaves and achieved effective results in monitoring and reducing vibrations.

In conclusion, the combination of traditional PID with optimization methods and the design of a pure deep learning controller provide robust strategies for mitigating structural vibrations.

REFERENCES

- [1] O. S. Manakova, M. A. Mayorov, and A. V. Sidorov, "Vibrations in engineering systems," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 666, no. 1, 2019, doi: 10.1088/1757-899X/666/1/012044.
- [2] M. Djidrov, V. Gavriloski, and J. Jovanova, "Vibration analysis of cantilever beam for damage detection," *FME Trans.*, vol. 42, no. 4, pp. 311–316, 2014, doi: 10.5937/fmet1404311D.
- [3] D. M. G. Preethichandra, T. G. Suntharavadivel, P. Kalutara, L. Piyathilaka, and U. Izhar, "Influence of Smart Sensors on Structural Health Monitoring Systems and Future Asset Management Practices," *Sensors*, vol. 23, no. 19, 2023, doi: 10.3390/s23198279.
- [4] J. L. Cao, S. John, and T. Molyneaux, "Piezoelectric-based Vibration Control in Composite Structures," no. January 2006, 2015.
- [5] A. K. Batra, A. Alomari, A. K. Chilvery, A. Bandyopadhyay, and K. Grover, "Piezoelectric Power Harvesting Devices: An Overview," *Adv. Sci. Eng. Med.*, vol. 8, no. 1, pp. 1–12, 2016, doi: 10.1166/ase.2016.1819.
- [6] A. Hashemi, J. Jang, and S. Hosseini-Hashemi, "Smart Active Vibration Control System of a Rotary Structure Using Piezoelectric Materials," *Sensors*, vol. 22, no. 15, pp. 1–21, 2022, doi: 10.3390/s22155691.
- [7] K. B. Waghulde, B. Sinha, M. M. Patil, and S. Mishra, "Vibration control of cantilever smart beam by using piezoelectric actuators and sensors," *Int. J. Eng. Technol.*, vol. 2, no. 4, pp. 259–262, 2010.
- [8] A. Aabid *et al.*, "A systematic review of piezoelectric materials and energy harvesters for industrial applications," *Sensors*, vol. 21, no. 12, pp. 1–27, 2021, doi: 10.3390/s21124145.
- [9] P. V. G. K. Rao, M. V. Subramanyam, and K. Satyaprasad, "Study on PID controller design and performance based on tuning techniques," *2014 Int. Conf. Control. Instrumentation, Commun. Comput. Technol. ICCICCT 2014*, pp. 1411–1417, 2014, doi: 10.1109/ICCICCT.2014.6993183.
- [10] B. A. Mir, "Keywords Smart Materials and Their Applications in Civil Engineering: An Overview Citation," *Int. J. Civ. Eng. Constr. Sci.*, vol. 4, no. 2, pp. 11–20, 2017, [Online]. Available: <http://www.aascit.org/journal/ijcecs>.
- [11] E. Varadha and S. Rajakumar, "Performance improvement of piezoelectric materials in energy harvesting in recent days – A review," *J. Vibroengineering*, vol. 20, no. 7, pp. 2632–2650, 2018, doi: 10.21595/jve.2018.19434.

- [12] M. B. V Patel and V. Patel, "Piezo Electricity Generation," vol. 2, no. 1, pp. 136–139, 2015.
- [13] A. Singh, "Preparation and characterization of piezoelectric materials," *2014 Int. Conf. Conver. Technol. I2CT 2014*, pp. 1–5, 2014, doi: 10.1109/I2CT.2014.7092213.
- [14] S. Paliwal and S. Yenuganti, "Experimental Analysis and Optimal Control of PZT Based Cantilever Beam Using Fuzzy-PID Controllers," *ICAN 2022 - 3rd Int. Conf. Comput. Anal. Networks - Proc.*, pp. 1–4, 2022, doi: 10.1109/ICAN56228.2022.10007350.
- [15] B. Ju, Z. Guo, Y. Liu, G. Qian, L. Xu, and G. Li, "Self-Sensing Vibration Suppression of Piezoelectric Cantilever Beam Based on Improved Mirror Circuit," *IEEE Access*, vol. 7, pp. 148381–148392, 2019, doi: 10.1109/ACCESS.2019.2946722.
- [16] S. S. Heganna and J. J. Joglekar, "Active Vibration Control of Smart Structure Using PZT Patches," *Procedia Comput. Sci.*, vol. 89, pp. 710–715, 2016, doi: 10.1016/j.procs.2016.06.040.
- [17] S. Mohammed and J. Haider, "Experimental and Simulation Study on Active Vibration Control of Thin Rectangular Plate by Smart Material under Harmonic Excitation," vol. 6, no. 1, pp. 49–63, 2015.
- [18] . S. K., "Active Vibration Control of Smart Piezo Cantilever Beam Using Pid Controller," *Int. J. Res. Eng. Technol.*, vol. 03, no. 01, pp. 392–399, 2014, doi: 10.15623/ijret.2014.0301068.
- [19] H. A. U.-Q. Mohammed and H. R. Wasmi, "Active Vibration Control of Cantilever Beam by Using Optimal LQR Controller," *J. Eng.*, vol. 24, no. 11, pp. 1–17, 2018, doi: 10.31026/j.eng.2018.11.01.
- [20] H. Tjahyadi, F. He, and K. Sammut, "Vibration control of a cantilever beam using multiple model adaptive resonant control," *IFAC Proc. Vol.*, vol. 37, no. 12, pp. 409–413, 2004, doi: 10.1016/S1474-6670(17)31503-3.
- [21] H. Gu and G. Song, "Adaptive robust sliding-mode control of a flexible beam using PZT sensor and actuator," *IEEE Int. Symp. Intell. Control - Proc.*, pp. 78–83, 2004, doi: 10.1109/isic.2004.1387662.
- [22] Amit Kumar and Deepak Chhabra, "Design of Fuzzy Logic Controller for Active Vibration Control of Cantilever Plate with Piezo -Patches As Sensor / Actuator," *Int. J. Mod. Eng. Res.*, vol. 9359, no. 8, pp. 34–44, 2013.
- [23] O. Abdeljaber, O. Avci, and D. J. Inman, "Active vibration control of flexible cantilever plates using piezoelectric materials and artificial neural networks," *J. Sound Vib.*, vol. 363, no. November, pp. 33–53, 2016, doi: 10.1016/j.jsv.2015.10.029.

- [24] S. B. Joseph, E. G. Dada, A. Abidemi, D. O. Oyewola, and B. M. Khammas, "Metaheuristic algorithms for PID controller parameters tuning: review, approaches and open problems," *Heliyon*, vol. 8, no. 5, p. e09399, 2022, doi: 10.1016/j.heliyon.2022.e09399.
- [25] R. Sen, C. Pati, S. Dutta, and R. Sen, "Comparison Between Three Tuning Methods of PID Control for High Precision Positioning Stage," *Mapan - J. Metrol. Soc. India*, vol. 30, no. 1, pp. 65–70, 2015, doi: 10.1007/s12647-014-0123-z.
- [26] M. Ünal, H. Erdal, and V. Topuz, "Trajectory tracking performance comparison between genetic algorithm and ant colony optimization for PID controller tuning on pressure process," *Comput. Appl. Eng. Educ.*, vol. 20, no. 3, pp. 518–528, 2012, doi: 10.1002/cae.20420.
- [27] M. I. Solihin, L. F. Tack, and M. L. Kean, "Tuning of PID Controller Using Particle Swarm Optimization (PSO)," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 1, no. 4, p. 458, 2011, doi: 10.18517/ijaseit.1.4.93.
- [28] A. Salem, M. Moustafa, and M. Ammar, "Tuning PID Controllers Using Artificial Intelligence Techniques.," *Int. Conf. Electr. Eng.*, vol. 9, no. 9th, pp. 1–13, 2014, doi: 10.21608/iceeng.2014.30369.
- [29] H. Jesawada, A. Yerudkar, C. Del Vecchio, N. Singh, S. Y. Jun, and A. P. Pid, "A Model-Based Reinforcement Learning Approach for PID Design."
- [30] Y. S. Lee and D. W. Jang, "Optimization of neural network-based self-tuning pid controllers for second order mechanical systems," *Appl. Sci.*, vol. 11, no. 17, 2021, doi: 10.3390/app11178002.
- [31] W. V Jahnavi, J. N. C. Sekhar, and A. S. Reddy, "A Review on PID Controller Tuning Using Modern Computational Algorithms," vol. 10, no. 8, pp. 160–168, 2023.
- [32] A. Salem, M. A. M. Hassan, and M. E. Ammar, "Tuning PID Controllers Using Artificial Intelligence Techniques Applied To DC-Motor and AVR System," *Asian J. Eng. Technol.*, vol. 02, no. 02, pp. 2321–2462, 2014, [Online]. Available: www.ajouronline.com.
- [33] Q. Wang and P. Teuffel, "Adaptive structures and design concept of transformable joints," *Int. J. Des. Nat. Ecodynamics*, vol. 12, no. 2, pp. 235–245, 2017, doi: 10.2495/DNE-V12-N2-235-245.
- [34] A. V. Ivchenko, N. Sharonov, and R. Ziatdinov, "New conceptual design of the adaptive compliant aircraft wing frame," *Eng. Sci. Technol. an Int. J.*, vol. 22, no. 5, pp. 1149–1154, 2019, doi: 10.1016/j.jestch.2019.10.004.
- [35] F. Anvar, N., Aung, T. H., Najam, "Smart systems for smart structures," *Technology*, no. January, pp. 33–39, 2016.
- [36] W. N. Patten and R. L. Sack, "Semiactive control of civil engineering structures,"

Proc. Am. Control Conf., vol. 1, pp. 1078–1081, 1994, doi: 10.1109/acc.1994.751913.

- [37] J. O. F. Theoretical and A. Mechanics, “ACTIVE VIBRATION CONTROL OF SMART COMPOSITE BEAMS USING PSO-OPTIMIZED SELF-TUNING FUZZY LOGIC CONTROLLER Nemanja Zorić, Aleksandar Simonović, Zoran Mitrović, Slobodan Stupar,” no. 1965, pp. 275–286, 2013.
- [38] B. Kavyashree, S. Patil, and V. S. Rao, “Review on vibration control in tall buildings: from the perspective of devices and applications,” *Int. J. Dyn. Control*, vol. 9, no. 3, pp. 1316–1331, 2021, doi: 10.1007/s40435-020-00728-6.
- [39] M. El Ajjaj, M. B. Kaczmarek, M. A. C. . van den Hurk, and S. H. HosseinNia, “Vibration suppression of a state-of-the-art wafer gripper,” *Euspen Sig Pmsc*, 2022, [Online]. Available: <https://repository.tudelft.nl/islandora/object/uuid%3A671bba53-1a84-4c64-9d3b-ef4319f0e1c1>.
- [40] I. N. Qader, M. Kök, F. Dagdelen, and Y. Aydogdu, “A Review of Smart Materials: Researches and Applications,” *El-Cezeri J. Sci. Eng.*, vol. 6, no. 3, pp. 755–788, 2019, doi: 10.31202/ecjse.562177.
- [41] S. Kamila, “Introduction, classification and applications of smart materials: An overview,” *Am. J. Appl. Sci.*, vol. 10, no. 8, pp. 876–880, 2013, doi: 10.3844/ajassp.2013.876.880.
- [42] A. Tabrizikahou, M. Kuczma, P. Nowotarski, M. Kwiatek, and A. Javanmardi, “Sustainability of civil structures through the application of smart materials: A review,” *Materials (Basel)*, vol. 14, no. 17, pp. 1–29, 2021, doi: 10.3390/ma14174824.
- [43] F. M. Nanotechnology, “State of the Art and Applications,” *Nano Tech Appl*, vol. 1, no. 2, pp. 1–5, 2018.
- [44] A. Aabid *et al.*, “A systematic review of piezoelectric materials and energy harvesters for industrial applications,” *Sensors*, vol. 21, no. 12, 2021, doi: 10.3390/s21124145.
- [45] Farahat and Baher Ismail, “Piezoelectric materials "Potentials and Constrains" Upgrading Designs and Techniques,” 2014, [Online]. Available: <http://www.bau.edu.lb/Library/Files/Architecture/Publications/Piezoelectric materials.pdf>.
- [46] K. Uchino, “Fundamentals of Piezoelectrics,” *Encycl. Smart Mater.*, no. i, pp. 1–21, 2021, doi: 10.1016/B978-0-12-803581-8.12129-0.
- [47] S. Le, “Active vibration control of a flexible beam,” no. June, 2009, [Online]. Available: http://scholarworks.sjsu.edu/etd_theses/3983/.
- [48] T. S. Chandok, “Simple Beam Bending : Evaluating the Euler-Bernoulli Beam

Theory.”

- [49] J. H. Klein, K. H. Kim, and F. W. Roush, “Team Theory,” *J. Oper. Res. Soc.*, vol. 39, no. 7, p. 695, 1988, doi: 10.2307/2582195.
- [50] G. L. C. M. De Abreu, “Spatial H_∞ Control of a Flexible Beam Containing Piezoelectric Sensors and Actuators,” *Mechatronics*, vol. 1, pp. 243–253, 2004.
- [51] G. Casiez, N. Roussel, and D. Vogel, “1€ filter: A simple speed-based low-pass filter for noisy input in interactive systems,” *Conf. Hum. Factors Comput. Syst. - Proc.*, pp. 2527–2530, 2012, doi: 10.1145/2207676.2208639.
- [52] E. Gülbahçe and M. Çelik, “Active vibration control of a smart beam by a tuner-based PID controller,” *J. Low Freq. Noise Vib. Act. Control*, vol. 37, no. 4, pp. 1125–1133, 2018, doi: 10.1177/1461348418782169.
- [53] A. Awada, R. Younes, and A. Ilinca, “Optimized Active Control of a Smart Cantilever Beam Using Genetic Algorithm,” *Designs*, vol. 6, no. 2, 2022, doi: 10.3390/designs6020036.
- [54] M. Tabassum, “a Genetic Algorithm Analysis Towards Optimization Solutions,” *Int. J. Digit. Inf. Wirel. Commun.*, vol. 4, no. 1, pp. 124–142, 2014, doi: 10.17781/p001091.
- [55] J. R. García-Martínez, E. E. Cruz-Miguel, R. V. Carrillo-Serrano, F. Mendoza-Mondragón, M. Toledano-Ayala, and J. Rodríguez-Reséndiz, “A PID-type fuzzy logic controller-based approach for motion control applications,” *Sensors (Switzerland)*, vol. 20, no. 18, pp. 1–19, 2020, doi: 10.3390/s20185323.
- [56] J. Chai, H. Zeng, A. Li, and E. W. T. Ngai, “Deep learning in computer vision: A critical review of emerging techniques and application scenarios,” *Mach. Learn. with Appl.*, vol. 6, no. March, p. 100134, 2021, doi: 10.1016/j.mlwa.2021.100134.
- [57] I. Z. Ghenni, H. M. Alwan, and H. M. Al-khafaji, “A Review of Smart Structures Vibration Control Strategies,” *Iraqi J. Comput. Commun. Control Syst. Eng.*, vol. 23, no. 3, pp. 171–185, 2023, doi: 10.33103/uot.ijccce.23.3.14.
- [58] R. M. Schmidt, “Recurrent Neural Networks (RNNs): A gentle Introduction and Overview,” no. 1, pp. 1–16, 2019, [Online]. Available: <http://arxiv.org/abs/1912.05911>.
- [59] J. Oruh, S. Viriri, and A. Adegun, “Long Short-Term Memory Recurrent Neural Network for Automatic Speech Recognition,” *IEEE Access*, vol. 10, pp. 30069–30079, 2022, doi: 10.1109/ACCESS.2022.3159339.

VITAE

Name :Ahmed Abdulrahman Abdullah Mohammed

Nationality :Yemen

Date of Birth :3/15/1996

Email :ahmedalemad805@gmail.com

Address :Saudi Arabia, Al-Khobar, Madinat Al Umal, 34441

Academic Background :I received my master's degree in control system engineering from King Fahd University of Petroleum & Minerals (KFUPM) in 2023, and bachelor's degree in control and instrumentation systems engineering from KFUPM in 2020. My areas of research interest are in the field of control systems, intelligent control, and renewable and sustainable energy.