PROJECT TITLE – **MACHINE LEARNING MODEL DEVELOPMENT FOR A SOFT PNEUMATIC DRIVEN ROBOT**

By

R.M.T.N.K. RATHNAYAKA(E/17/286)

PIYUMI BHAGYA S. (E17/259)

K.G.K.R. BANDARA (E/17/024)

ME 325-MECHANICAL ENGINEERING GROUP PROJECT

presented in partial fulfillment of the requirements.
for the degree of B.Sc. Engineering degree

University of Peradeniya

29th January 2023

Supervised by:

Dr. D.H.S Maithreepala, Department of Mechanical Engineering
Faculty of Engineering

DECLARATION

We, R.M.T.N.K. Rathnayaka (E/17/286), S. Piyumi Bhagya (E/17/259), K.G.K.R. Bandara (E/17/024) declare that this project report, entitled ‘Machine Learning Model Development For A Soft Pneumatic Driven Robot’, is our own work and that all sources used in its preparation have been acknowledged and referenced according to the guidelines set out by Department of Mechanical Engineering Faculty of Engineering. We further declare that this project report has not been submitted for examination or assessment in any other course or program.

Signed:

R.M.T.N.K. Rathnayaka (E/17/286)

S. Piyumi Bhagya (E/17/259)

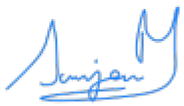
K.G.K.R. Bandara (E/17/024)

Date: 29.01.2023

APPROVAL

We, the undersigned, hereby approve the MACHINE LEARNING MODEL DEVELOPMENT FOR A SOFT PNEUMATIC DRIVEN ROBOT report submitted by R.M.T.N.K. Rathnayaka (E/17/286), S. Piyumi Bhagya (E/17/259), K.G.K.R. Bandara (E/17/024). The report accurately reflects the scope, objectives, and outcomes of the project and is deemed to be complete and of good quality.

Signed,



Dr D.H.S Maithreepala

29.01.2023

ACKNOWLEDGEMENT

We would like to express our sincerest gratitude to all those who have supported and assisted us in the successful completion of this project.

Firstly and specially, we would like to thank our project supervisor, Dr. D.H.S Maithreepala, for his invaluable guidance, support and encouragement throughout the course of this project. Their expertise and knowledge in the field of data Science and Machine Learning were essential in the successful development of our model.

We would also like to extend our appreciation to the Department of Mechanical Engineering Faculty of Engineering for providing us with the necessary resources and facilities to complete this project. We would also like to acknowledge the contributions of our colleagues and peers, who have provided us with valuable feedback and suggestions throughout the project.

Finally, we would like to thank our families and friends for their unwavering support and understanding during the course of this project.

… # ABSTRACT

In this project, we developed a machine-learning model for a soft pneumatic-driven robot hand with the capability of performing axial bending and twisting movements. The objective of this project was to design a model that can effectively control the movement of the robot hand through the use of soft pneumatic actuators for axial bending and twisting movements. The model was trained using a dataset obtained for the axial, bending and twisting unit cells, from a finite element model, and was validated using experimental data. The model achieved more than 90 percent accuracy on the validation set and was able to successfully control the axial bending and twisting movements of the robot hand with desired movement control. Our results show that the proposed model is able to achieve high precision and accuracy in controlling the robot hand and it opens up new possibilities for the use of soft pneumatic robots in various fields.

The methodology of this project involved the selection of appropriate machine learning algorithms and techniques, the creation and preprocessing of the dataset, the training and validation of the model, and the testing of the model on the robot hand. One of the biggest challenges faced during this project was the lack of a large dataset for training, however, we overcame this challenge by using various data augmentation techniques.

The significance of this project lies in the potential for the use of soft pneumatic robots in various fields such as manufacturing, healthcare, and rehabilitation. The model developed in this project can be used as a basis for future research in the field of soft pneumatic robots and machine learning. The scope of this project can be further extended by incorporating additional movements or by exploring alternative control methods. We believe that this project will pave the way for more advanced soft pneumatic robots that can perform a wide range of movements with high precision and accuracy.

TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Act. -Actuators

AI -Artificial Intelligence

ANN -Artificial Neural Networks

API -Application Programming Interface

Ch. -Chapter

CNN -Convolutional Neural Networks

CSV -Comma-Separated Values

K-means -K-means Clustering Algorithm

KNN -K-Nearest Neighbor

LR -Linear Regression

MDS -Multidimensional Scaling

ML -Machine Learning

PCA -Principal Component Analysis

PR -Polynomial Regression

R2 -R-squared

RNN -Recurrent Neural Networks

SQL -Structured Query Language

SVM -Support Vector Machine

UMAP -Uniform Manifold Approximation and Projection

Chapter 1

INTRODUCTION

Soft robots, also known as compliant or flexible robots, are a rapidly growing field in robotics. Unlike traditional rigid robots, which are made of hard materials like metal or plastic, soft robots are made of flexible materials like silicone or rubber. This allows them to bend, twist, and deform in ways that rigid robots cannot, making them ideal for a wide range of applications.

One of the key advantages of soft robots is their ability to interact with the environment in a more natural and safe way. Unlike rigid robots, which can be dangerous if they come into contact with humans or other objects, soft robots can deform and conform to their surroundings, reducing the risk of damage or injury. This makes them well-suited for applications such as grasping delicate objects, performing surgery, and interacting with humans. Another advantage of soft robots is their ability to adapt to changing environments. Because they are made of flexible materials, they can change shape to fit into tight spaces or navigate through complex environments. This makes them useful for a wide range of tasks, such as search and rescue operations, exploration of difficult-to-reach areas, and even space exploration.

There are several different types of soft robots that are being developed. Some, like the "octobot," are completely soft and are powered by internal gas or liquid pressure. Others, like the "soft hand," have a combination of soft and rigid elements and are powered by electric motors. Still others, like the "soft exosuit," are worn by the user and are designed to assist with movement.

The development of soft robots is still in its early stages, and there are many challenges that must be overcome before they can be widely used. One of the biggest challenges is finding ways to power and control the robots. Because they are made of soft materials, it can be difficult to embed traditional motors and sensors in them. Researchers are also working on developing new materials and manufacturing techniques that will make it easier to create soft robots. One of the biggest challenges in designing soft robots is finding ways to power and control them. Because they are made of soft materials, it can be difficult to embed traditional motors and sensors in them. Researchers are working on developing new materials and manufacturing techniques that will make it easier to create soft robots. This includes the use of 3D printing, which allows for the creation of complex and precise structures, and the use of new materials like shape memory alloys, which can be used to create muscles and actuators. In addition to design challenges, there are also economic challenges in the field of soft robotics. Soft robots are often more expensive to produce than traditional rigid robots, due to the cost of the materials used and the complexity of the manufacturing process. This can make it difficult for small companies and startups to enter the market. Additionally, the lack of standardization in the field can make it difficult for companies to scale their products and reach a wider market.

Artificial Intelligence (AI) is playing an increasingly important role in the field of soft robotics. By using AI algorithms, soft robots can be programmed to adapt and respond to their environment in real-time, making them more versatile and useful for a wide range of applications. However, despite the potential benefits, there are also a number of challenges that must be overcome in order to effectively use AI in soft robotics. One of the main benefits of using AI in soft robots is the ability to adapt to changing environments. Soft robots are able to change shape and adapt to different situations, and by using AI algorithms, they can be programmed to recognize and respond to different objects and environments. This makes them well-suited for a wide range of tasks, such as grasping delicate objects, performing surgery, and exploring difficult-to-reach areas. Another advantage of using AI in soft robots is the ability to improve their performance. AI algorithms can be used to optimize the control of soft robots, allowing them to move more efficiently and precisely. Additionally, AI can be used to improve the grasping capabilities of soft robotic hands, making them more effective at manipulating objects.

One of the main challenges of using AI in soft robotics is the lack of data. Soft robots are still a relatively new technology and there is a limited amount of data available for training AI algorithms. This makes it difficult to create accurate and reliable models that can be used to control soft robots. Additionally, the lack of standardization in the field can make it difficult to compare different models and algorithms Another challenge is the limited computational power of soft robots. Unlike traditional rigid robots, which are often powered by powerful computers and sensors, soft robots are typically powered by internal gas or liquid pressure. This makes it difficult to embed large amounts of computational power in the robot, which can limit the complexity of the AI algorithms that can be used.

A soft robotic hand is a type of robotic hand that is designed to be flexible and adaptable, much like a human hand. It is made up of several basic unit elements, including axial, bending, and twisting elements. These elements work together to provide the hand with a wide range of movement and dexterity. The axial element is responsible for linear movement, such as gripping and releasing objects. It is typically made up of a linear actuator, such as a pneumatic or hydraulic cylinder, that is connected to the hand's fingers or thumb. The actuator is controlled by a computer or other electronic device, which sends signals to the actuator to move the fingers or thumb in a specific direction. The bending element is responsible for the hand's ability to bend and flex its fingers or thumb. It is typically made up of a flexible material, such as a silicone or rubber, that is connected to the fingers or thumb. The material is controlled by a computer or other electronic device, which sends signals to the material to bend or flex the fingers or thumb in a specific direction. The twisting element is responsible for the hand's ability to rotate its fingers or thumb. It is typically made up of a motor, gear train, and a flexible shaft that connects to the fingers or thumb. The motor is controlled by a computer or other electronic device, which sends signals to the motor to rotate the fingers or thumb in a specific direction.

In this project, we aimed to address this challenge by developing a mathematical model for a soft pneumatic driven robot hand with the capability of performing three major movements: axial, bending, and twisting. The objective of this project was to design a model that can effectively control the movement of the robot hand through the use of soft pneumatic actuators for these three major movements. Instead of using complex neural network models, we used simple mathematical imputations to develop a simpler model, which still achieved high precision and accuracy in controlling the robot hand.

The methodology of this project involved the selection of appropriate mathematical techniques, the creation and preprocessing of the dataset, the training and validation of the model, and the testing of the model on the robot hand. One of the biggest challenges faced during this project was the lack of a large dataset for training, however, we overcame this challenge by using various data augmentation techniques.

The results of this project demonstrate the potential for using mathematical models in the control of soft pneumatic robots for specific movements. The model developed in this project can be used as a basis for future research in the field of soft pneumatic robots and mathematical control. The future scope of this project includes incorporating additional movements and exploring alternative control methods.

This report will provide a detailed description of the methodology, results, and conclusions of this project, as well as the future scope of this research.

Chapter 2

LITERATURE REVIEW

2.1 INTRODUCTION

Soft robots have emerged as a promising technology in the field of robotics due to their potential for safe interaction with humans and delicate objects. However, the control of soft robots is challenging due to the complex and nonlinear behavior of the soft materials used in their design. Machine learning (ML) algorithms have shown promising results in controlling soft robots. In this project, a ML model was developed to control a soft pneumatic-driven robot hand capable of axial bending and twisting movements. This literature review explores the state of the art in soft robotics and the use of ML algorithms in controlling soft robots. The review is based on the references provided in the project summary, along with other relevant sources.

2.2 STATE OF THE ART

Soft robotics is a rapidly developing field that combines soft materials, actuators, sensors, and control systems to create robots with compliant and adaptable structures. Soft robots have several advantages over traditional rigid robots, including safer human-robot interaction, better adaptability to unstructured environments, and improved ability to manipulate delicate objects. However, soft robots pose significant challenges for control due to the nonlinear behavior of soft materials and the complexity of their dynamics.

Calixto et al. (2015) provide a comprehensive review of the state of the art in soft robotics, including materials, sensors, actuators, and control systems. The authors describe several types of soft materials used in soft robots, including elastomers, hydrogels, and composites. They also discuss various types of actuators, including pneumatic, hydraulic, and shape-memory alloys. The authors emphasize the importance of sensor feedback for effective control of soft robots and discuss various types of sensors used in soft robots, including pressure sensors, strain sensors, and capacitive sensors. Finally, the authors describe several control strategies for soft robots, including model-based and model-free approaches, and discuss the challenges and opportunities for future research in soft robotics.

Rus et al. (2015) provide a comprehensive review of the materials, actuators, sensors, and control systems used in soft robotics. The authors describe several types of soft materials used in soft robots, including elastomers, hydrogels, and composites. They also discuss various types of actuators, including pneumatic, hydraulic, and shape-memory alloys. The authors emphasize the importance of sensor feedback for effective control of soft robots and discuss various types of sensors used in soft robots, including pressure sensors, strain sensors, and capacitive sensors. Finally, the authors describe several control strategies for soft robots, including model-based and model-free approaches, and discuss the challenges and opportunities for future research in soft robotics.

2.3 USE OF MACHINE LEARNING

ML algorithms have shown promising results in controlling soft robots. ML algorithms can learn the complex and nonlinear behavior of soft materials and provide effective control strategies. ML algorithms can be used for modeling, control, and optimization of soft robots. ML algorithms can be applied to a wide range of soft robots, including soft manipulators, soft grippers, and soft exoskeletons.

Saha et al. (2015) provides a review of soft robotics as a new frontier in robotics research. The authors discuss the potential of ML algorithms in controlling soft robots and provide several examples of soft robots controlled using ML algorithms. The authors emphasize the importance of data-driven approaches for effective control of soft robots and describe various types of ML algorithms used in soft robotics, including neural networks, support vector machines, and decision trees. The authors also discuss the challenges and opportunities for future research in soft robotics using ML algorithms.

Caluwaerts et al. (2016) provide a review of soft robotics past, present, and future. The authors describe several examples of soft robots controlled using ML algorithms and emphasize the importance of data-driven approaches for effective control of soft robots. The authors discuss various types of soft robots, including those that use pneumatic actuation, and highlight the benefits of using soft materials in robot design. The authors also note that the field of soft robotics is still in its infancy, and much work remains to be done in terms of developing new materials and actuators, as well as improving control methods.

In recent years, there has been a significant increase in research efforts to develop soft robots using ML algorithms. Ge et al. (2019) provide a comprehensive review of soft robotics from materials to systems, where they discuss various types of soft robots and their applications. The authors emphasize the importance of developing effective control strategies for soft robots and note that ML algorithms are a promising approach to achieving this goal.

One of the primary challenges in controlling soft robots is the complex and nonlinear behavior of the materials used in their construction. Soft materials such as silicone or elastomers exhibit nonlinear responses to external stimuli such as pressure, temperature, or deformation. Additionally, soft robots typically have multiple degrees of freedom, which make them difficult to model accurately. ML algorithms offer a promising solution to these challenges by allowing for data-driven modeling of soft robot behavior.

Rus et al. (2015) provide a review of soft robotics focusing on the materials, actuators, sensors, and control methods used in their construction. The authors discuss the various types of soft materials used in soft robot design, including elastomers, hydrogels, and shape-memory polymers. The authors also highlight the importance of developing novel actuators and sensors that can be integrated into soft robot designs to enable precise control and sensing.

ML algorithms have been used in a variety of ways to control soft robots. For example, Li et al. (2021) developed a ML-based controller for a soft robot arm that was able to learn the inverse kinematics of the robot using reinforcement learning. The authors showed that their controller was able to accurately control the movements of the soft robot arm in a variety of tasks, including grasping and lifting objects.

Another approach to controlling soft robots using ML algorithms is to use data-driven models to predict the behavior of the robot under different conditions. Calixto et al. (2015) developed a finite element model of a soft pneumatic-driven robot hand and trained a ML-based controller to predict the behavior of the hand under different loading conditions. The authors showed that their controller was able to accurately predict the behavior of the robot hand, and they suggest that their approach could be used to develop more advanced soft robots in the future.

ML algorithms have also been used to develop controllers for soft robots that can adapt to changing environments or unexpected disturbances. For example, Cheng et al. (2021) developed a ML-based controller for a soft robot that was able to adapt to unexpected disturbances in real-time. The authors used a deep reinforcement learning algorithm to train their controller, which was able to adapt to changing environmental conditions and disturbances without the need for explicit programming.

In conclusion, the field of soft robotics has seen significant growth in recent years, and ML algorithms offer a promising approach to developing effective control strategies for soft robots. The use of data-driven modeling and adaptive control methods has the potential to enable soft robots to perform a wide range of tasks with high precision and accuracy. While there are still many challenges to be overcome in the field of soft robotics, the advances made in ML-based control strategies offer exciting opportunities for the future development of soft robots.

Chapter 3

DATA VISUALIZATION AND UNDERSTANDING

3.1 INTODUCTION

The field of soft robotics has seen rapid growth in recent years, with many researchers focusing on developing novel, flexible robotic systems that can adapt to changing environments and perform a wide range of tasks. One area of particular interest is the development of soft robotic hands, which have the potential to provide a new level of dexterity and versatility for robots. However, the complexity and nonlinearity of soft robotic systems make their control and modeling a challenging task.

To address this challenge, this project aims to develop a reduced order machine learning model for a soft robot hand. The model will be based on data collected from a physical prototype of a soft robotic hand and will be used to predict the hand's behavior under different actuation and environmental conditions.

The first step in the development of such a model is to understand and visualize the data that will be used for training and validation. This chapter, "Data Visualization and Data Understanding," serves as an introduction to the data that will be used in the project. The data was collected from a physical prototype of a soft robotic hand, which was actuated using pneumatic pressure. The data includes measurements of the hand's position, shape, and kinematics under different actuation conditions, as well as environmental factors such as temperature and humidity.

The data was collected in a raw format and required pre-processing and cleaning before it could be used for analysis. The data was then organized and stored in a structured format, such as CSV or excel, for further processing.

In this chapter, different types of data visualizations such as histograms, scatter plots, and heat maps will be used to better understand the data and identify any patterns or relationships. These visualizations will help to uncover any underlying structure in the data and will aid in the selection of appropriate features for the machine learning model. Additionally, this chapter will also discuss about the significance of understanding and visualizing the data, which is the key to building an accurate and reliable machine learning model. With a good understanding of the data, the model can be trained on relevant features and be less prone to overfitting, thus providing better generalization capabilities. In summary, this chapter sets the foundation for the analysis and modeling that will be presented in the subsequent chapters. It provides an overview of the data that will be used in the project, including the sources of the data, the format in which it

was obtained, and any pre-processing or cleaning that was necessary. Additionally, it provides a brief overview of the types of data visualizations that will be used to better understand the data, and the importance of understanding and visualizing the data in building an accurate and reliable machine learning model.

We have three data sets for three basics unit cell movements. There are four inputs and five outputs for each data sets.

Table 3.1: Input Variables

Inputs	**Description**
Input1	Internal pressure
Input2	X components of external forces
Input3	Y components of external forces
Input4	Z components of external forces

Table 3.2: Output Variables

Outputs	**Descriptions**
Output1	Magnitude of displacement
Output2	X components of displacement
Output3	Y components of displacement
Output4	Z components of displacement
Output5	Resultant force

3.2 DATA VISUALIZATION

We had three data sets for three basic unit cell movements and we plotted the all input and output data for understanding data,

There are many tools available for data visualization, and the choice of tool depends on the specific needs of the project and the type of data being visualized. Plotly is a popular library for data visualization that allows you to create interactive and customizable plots and charts. It provides a wide range of chart types such as line plots, bar plots, scatter plots, heat maps, and more. Plotly also allows you to easily add interactivity to your plots, such as hover text, zoom, and pan, which can be useful for exploring and understanding the data.

3.2.1 Axial data set

Axial data set contains internal pressure, three basic components of external forces as inputs and three basic components of displacement, magnitude of displacement and resultant force as outputs. Histograms provide a graphical representation of the data distribution and can give us insights into the skewness, symmetry, shape, and central tendency of the data as well as outliers, clusters, and gaps in the data. Scatterplots allow us to see the distribution of data points, the spread and density of the data, and the presence of any unusual observations.

3.2.1.1 Input data Distribution

Histograms

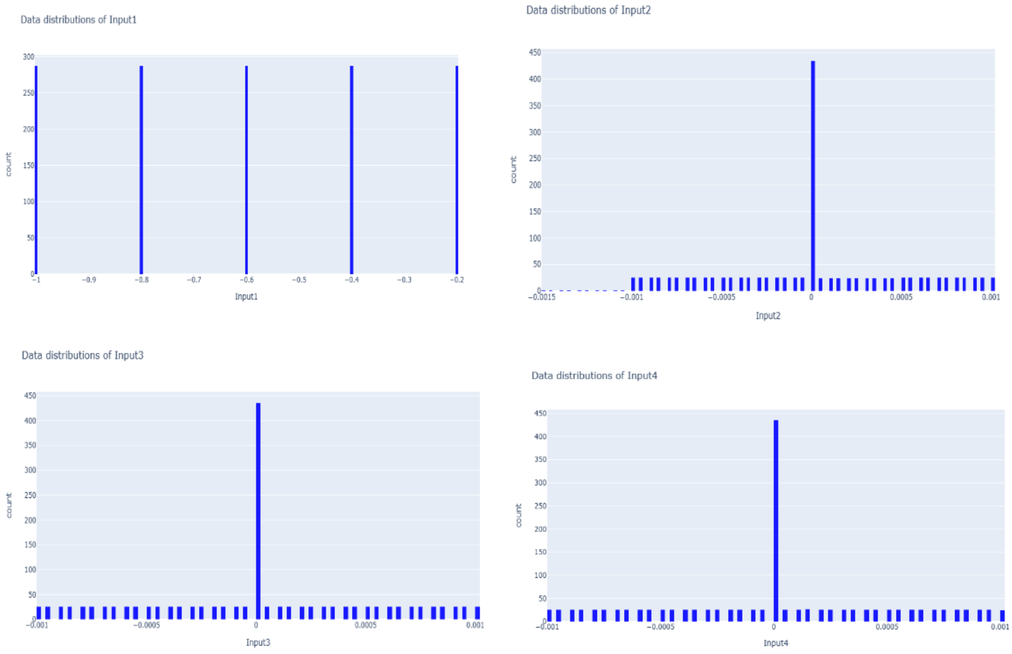


Figure 3.1: Histograms for Input Data (Axial)

From these histograms for inputs, it can be observed that the data are similarly distributed for most part. For input1 there are gaps between the data, but data are similarly distributed. From histograms input 2, 3 and 4, the columns for data except for 0 are similarly distributed, but there is a huge deviation in 0.

Scatter plots

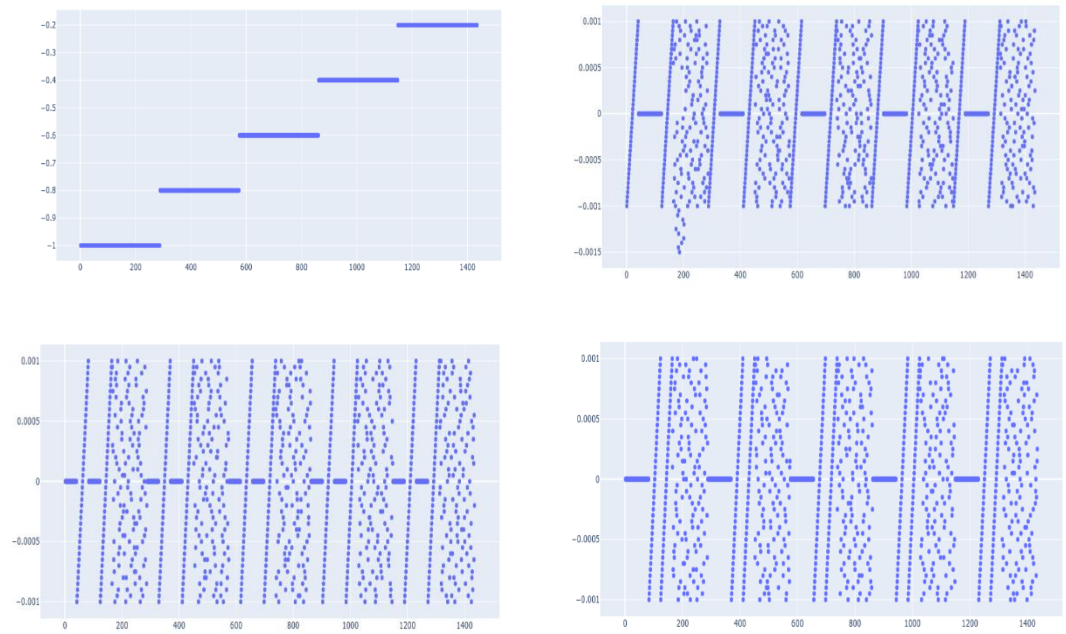


Figure 3.2: Scatter plots for Input Data (Axial)

In scatterplots there are some patterns that can be observed. In scatterplot for input 1, the pattern is like steps. Input 2, 3 and 4 plots display a uniformly distributed patten as well as a scattered pattern. This pattern repeats for every 4 data sets. These kind of patterns makes it easier to understand the connection between the data.

3.2.1.2 Output data Distribution

Histograms

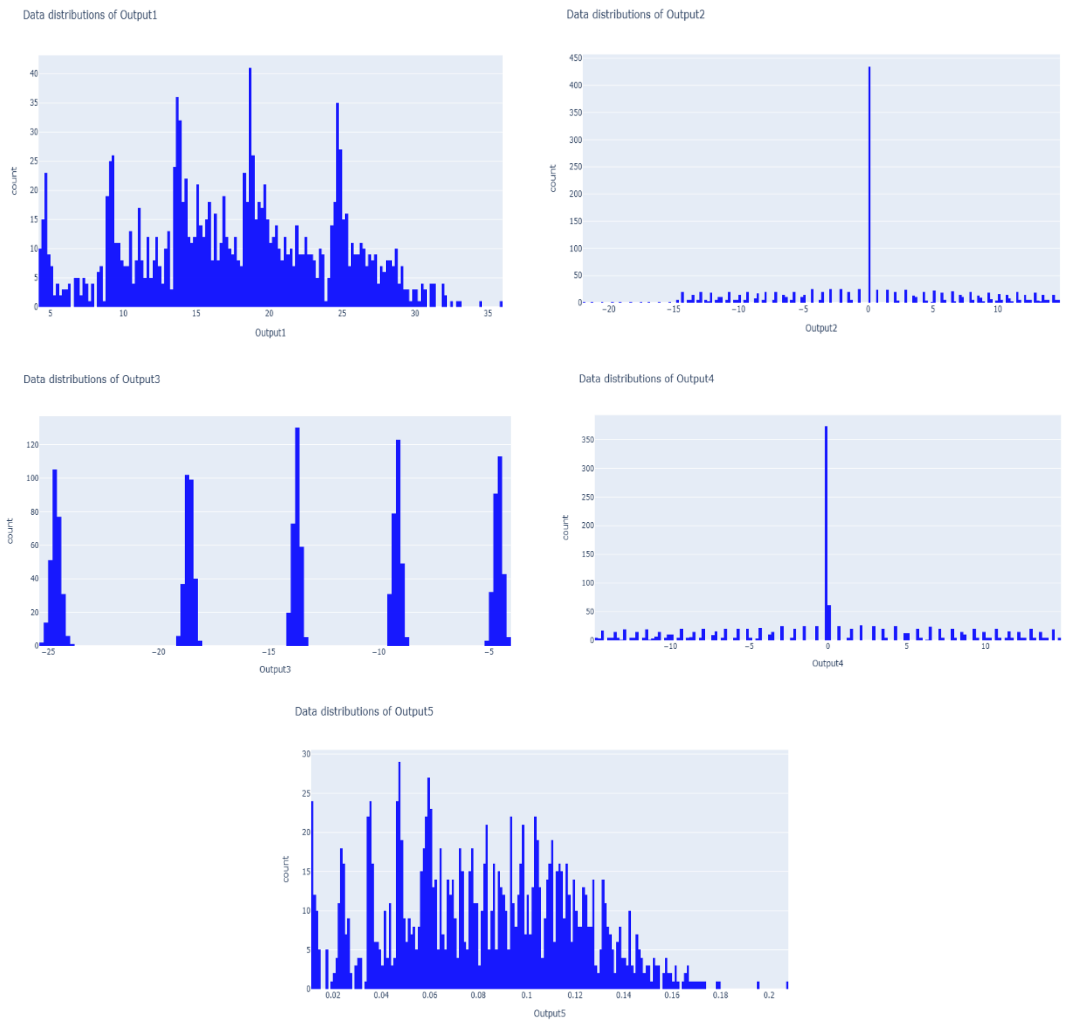


Figure 3.3: Histograms for Output Data (Axial)

From these histograms for outputs, it can be observed that the data are similarly distributed for some of the outputs. Also, for output 3, there is a repetitive pattern. In histograms for output 2 and output 4, there are some gaps between data. Output 1 and 5 histograms shows that there are almost no gaps between the columns but data is distributed with various deviations.

Scatter plots

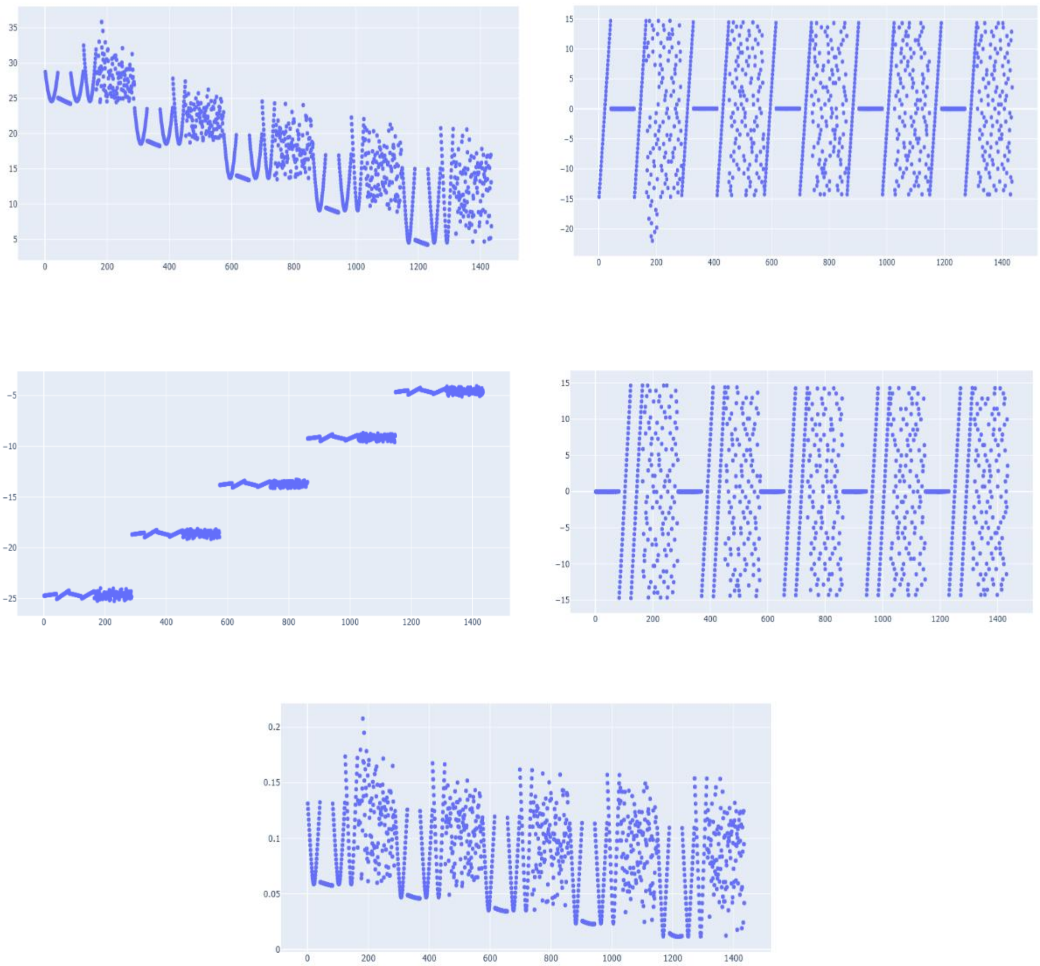


Figure 3.4: Scatter Plots for Input Data (Axial)

According to these scatter plots for outputs of the axial dataset, there are some repetitive patterns can be observed. In output 1, output 3 and output 5 pattern repeats for every 5 data sets. Output 1 and output 5 patterns are descending along the y axis, and output 3 pattern is ascending along the y axis. Scatter plots for output 2 and output 3 shows different patterns which are repeating for every 4 data sets.

3.2.1.3 Input-Output data Distribution

Input 1 with all the outputs

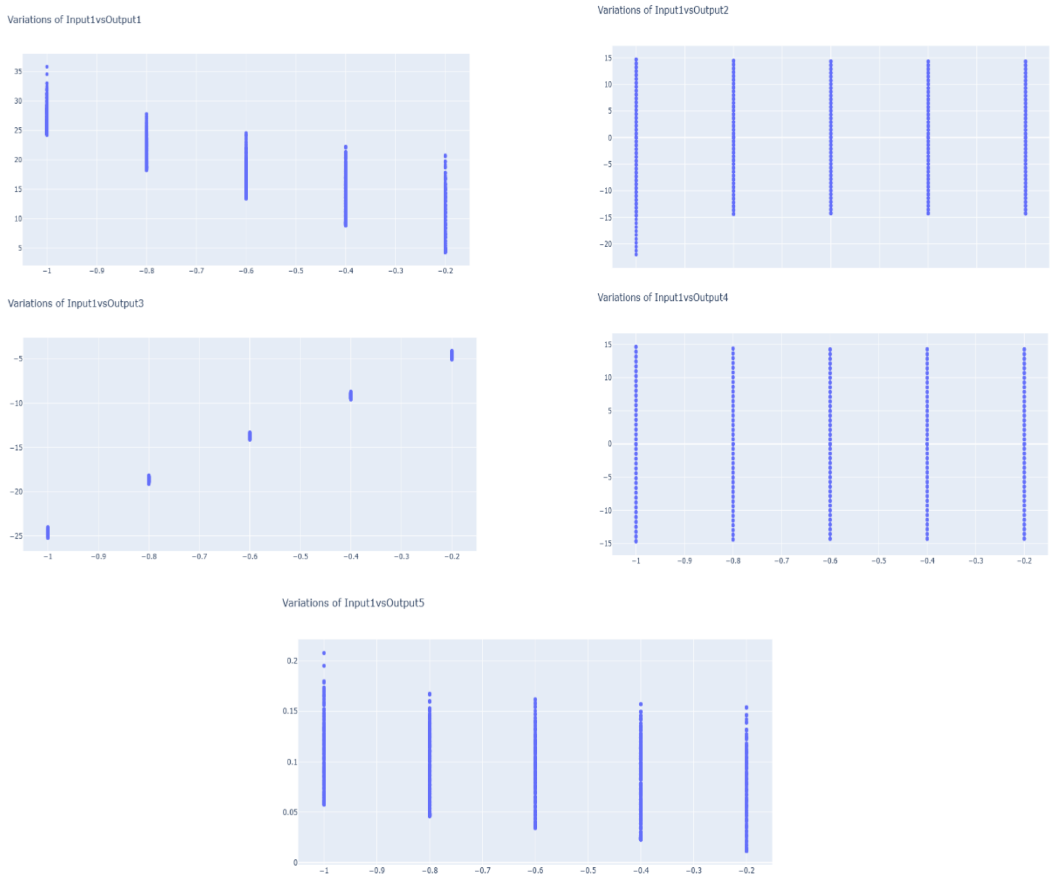


Figure 3.5: Input1-Outputs Data Distributions (Axial)

These scatterplots show the relationships between the input 1 and the outputs. According to above plots it can be observed that there are no deviations in the data. For one data the output varies in multiple places. All the above plots display this behavior. Also, the data very closely packed creating straight lines. This can happen because there are multiple dimensions to the plots where the output varies with the other variables aka inputs.

Input 2 with all Outputs

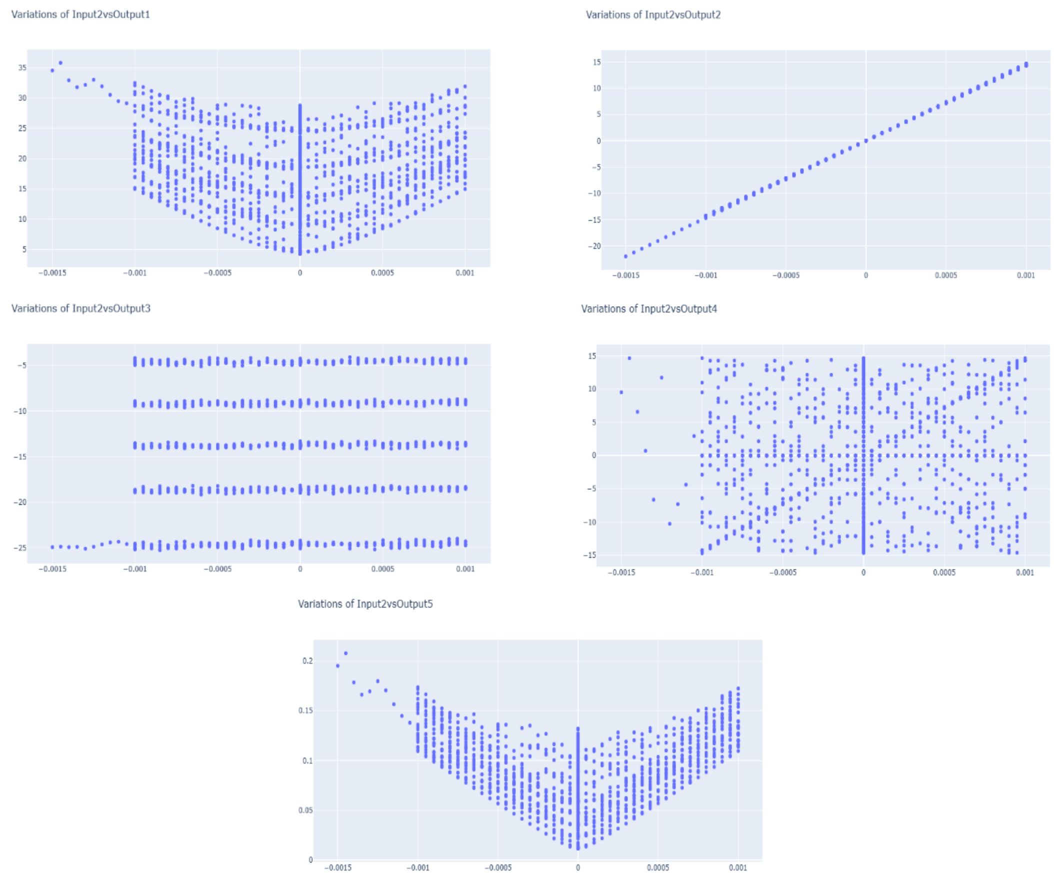


Figure 3.6: Input2-Outputs Data Distributions (Axial)

Relationship between input 2 and outputs is shown in above plots. The relationships are different from each other here. It can be observed that input 2 has a linear relationship with output 2. Also input 2 has a complex relationship with output 4. There is a linear relationship can be observed between them as well as data packed straight lines mentioned above where there is a dimensional effect on the relationship. Relationship between input2 and output 1 and output 5 seems to be similar where the dimensional effect also can be observed. It seems like output 3 does not change with input 2, but the lines occurs in intervals. This also can be happened due to the dimensional effect because the lines are in different dimensions which creates a step like pattern.

Input 3 with all the Outputs

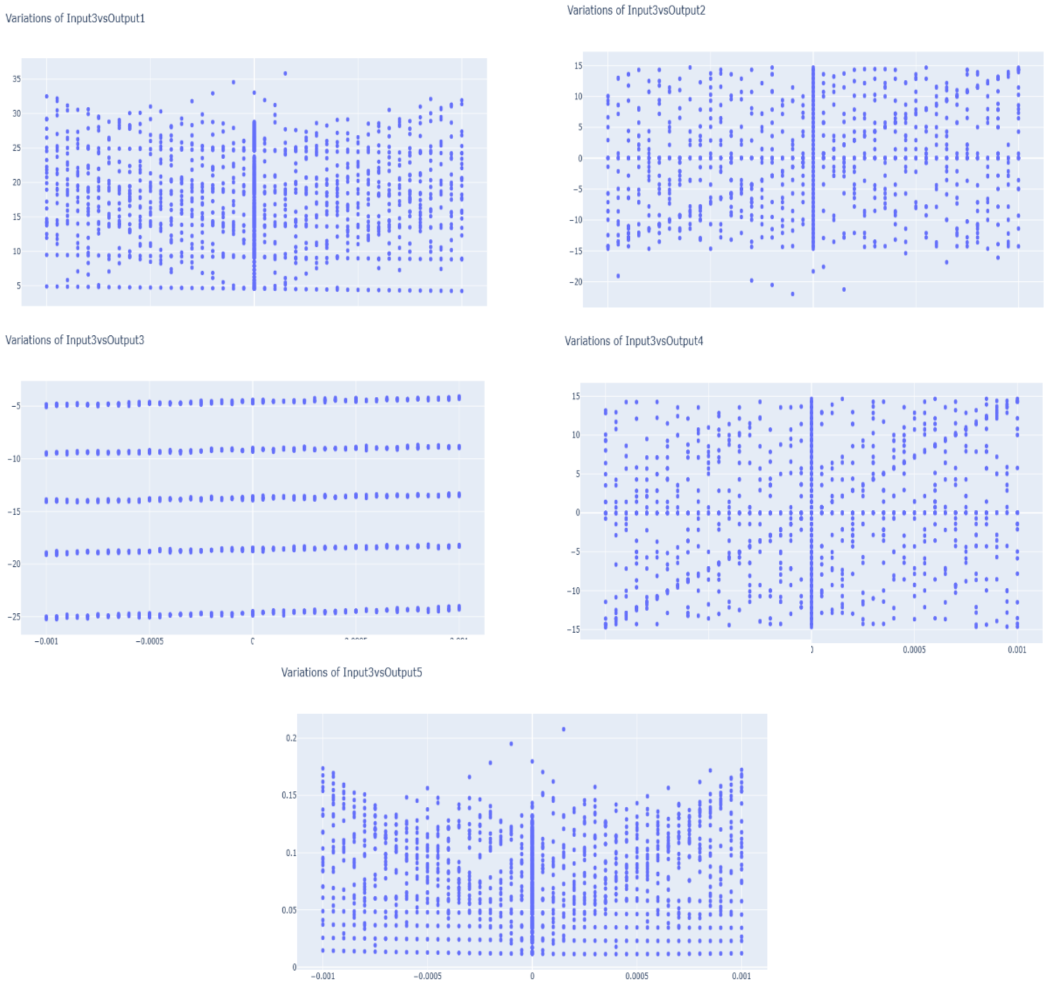


Figure 3.7: Input3-Outputs Data Distributions (Axial)

There are no visible relationships between input 3 and the outputs that can be observed in 2d plane. But the dimensional effect can be clearly seen in the plots. Thus the patterns would be able to see with 3d space.

Input 4 with all the Outputs

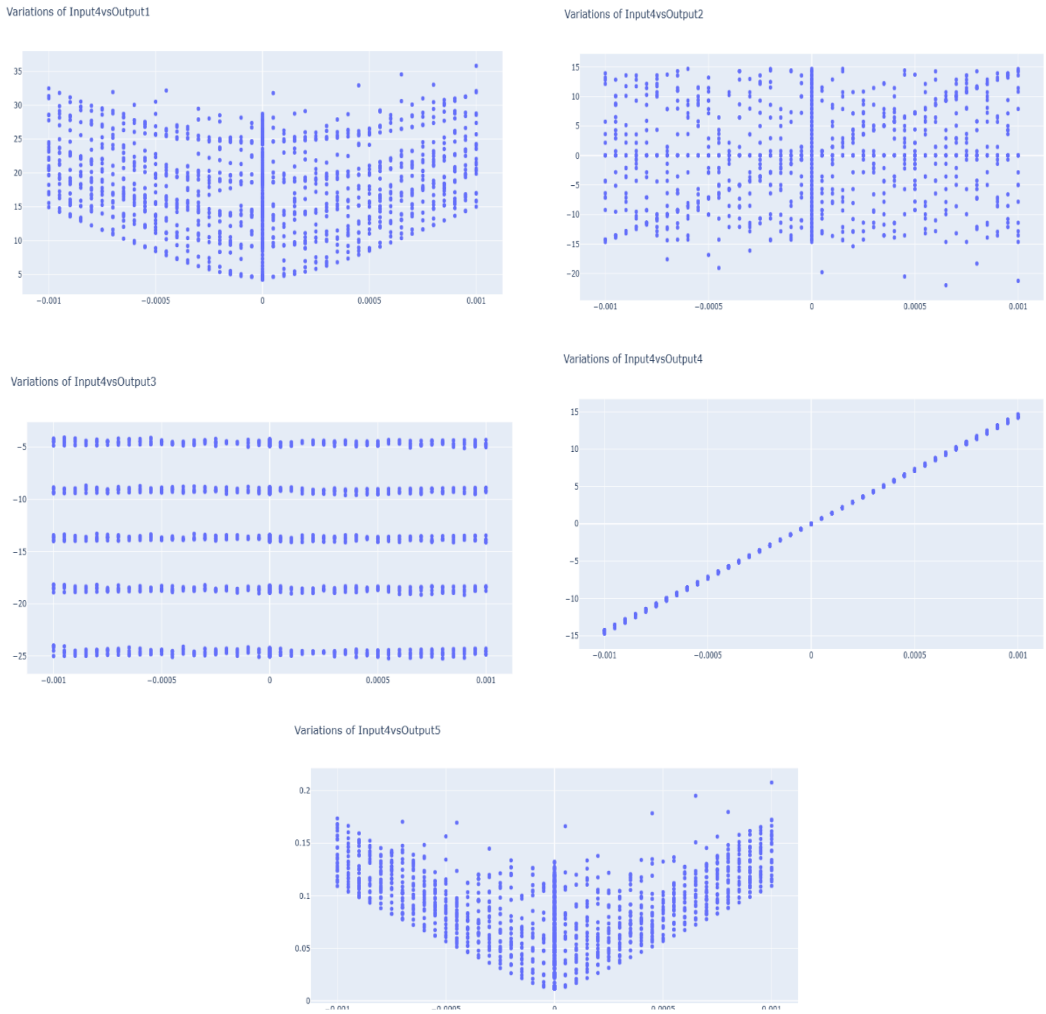


Figure 3.8: Input4-Outputs Data Distributions (Axial)

It can be seen that the relationship between input 4 and output 4 is linear. Input 4 and output 2 also have a complicated relationship. Between them, as well as the data-packed straight lines indicated above when there is a dimensional effect on the relationship, a linear relationship may be seen. Where the dimensional impact may also be seen, there appears to be a comparable relationship between input 4 and output 1 and output 5. Although it appears that input 4 has no effect on output 3, the lines do appear at regular intervals. The fact that the lines are of various dimensions and hence provide a step-like pattern further explains how this could have occurred.

3.2.2 Bending data set

1.2.2.1 Input data Distribution

Histograms for Inputs

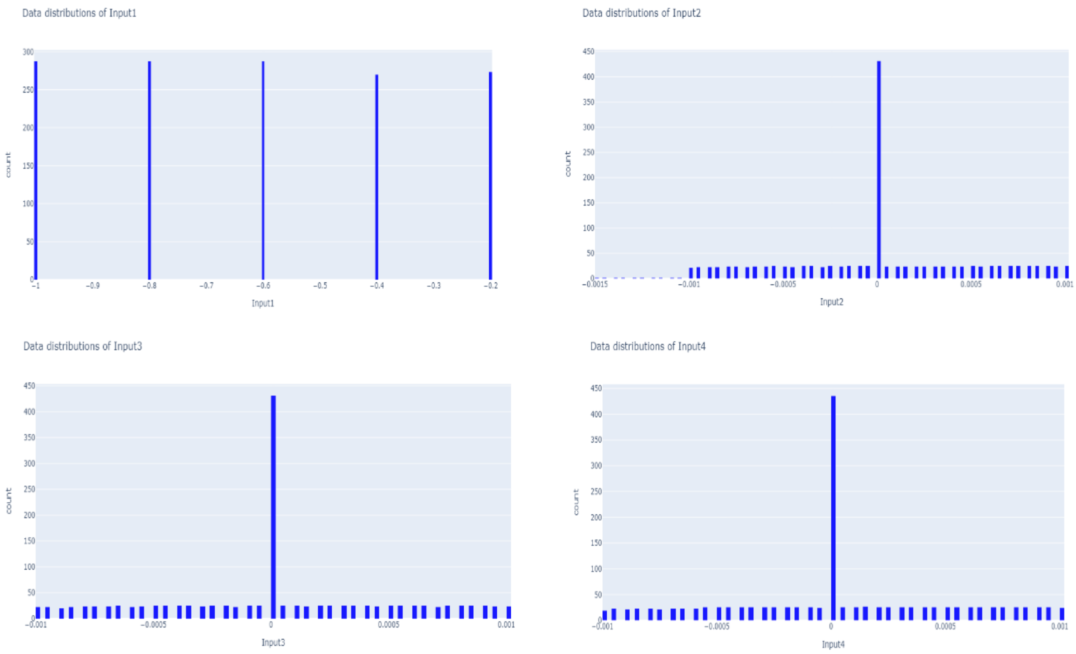


Figure 3.9: Histograms for Input Data (Bending)

As shown in above figures it can be observed that the distribution of data is similar to the distribution of axial data inputs.

Scatter plots for Inputs

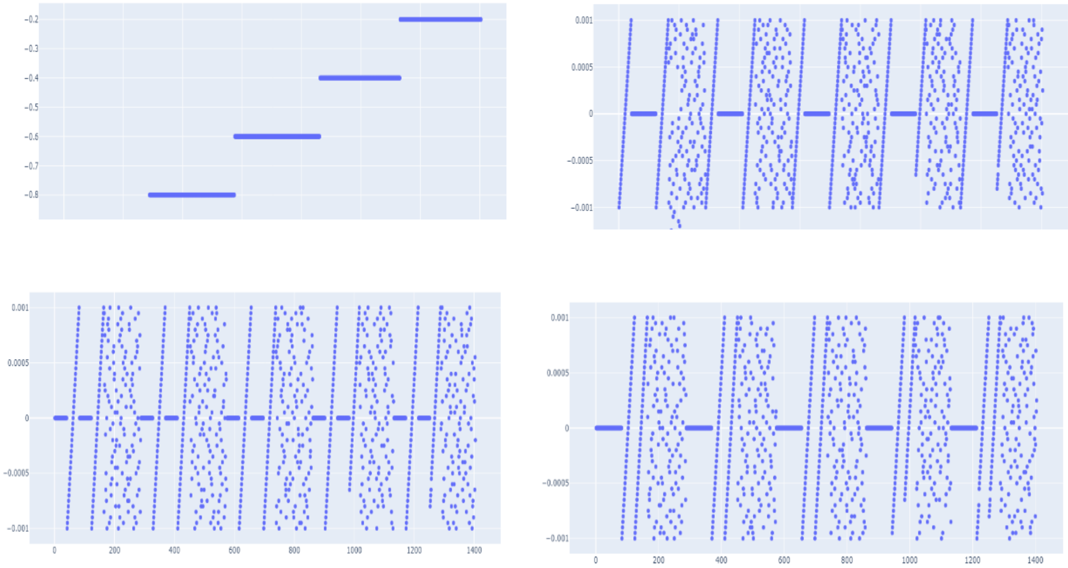


Figure 3.10: Scatter Plots for Input Data (Bending)

As shown in above figures it can be observed that the patterns of data is similar to the patterns obtained from axial data inputs.

3.2.2.2 Output data Distribution

Histograms for Outputs

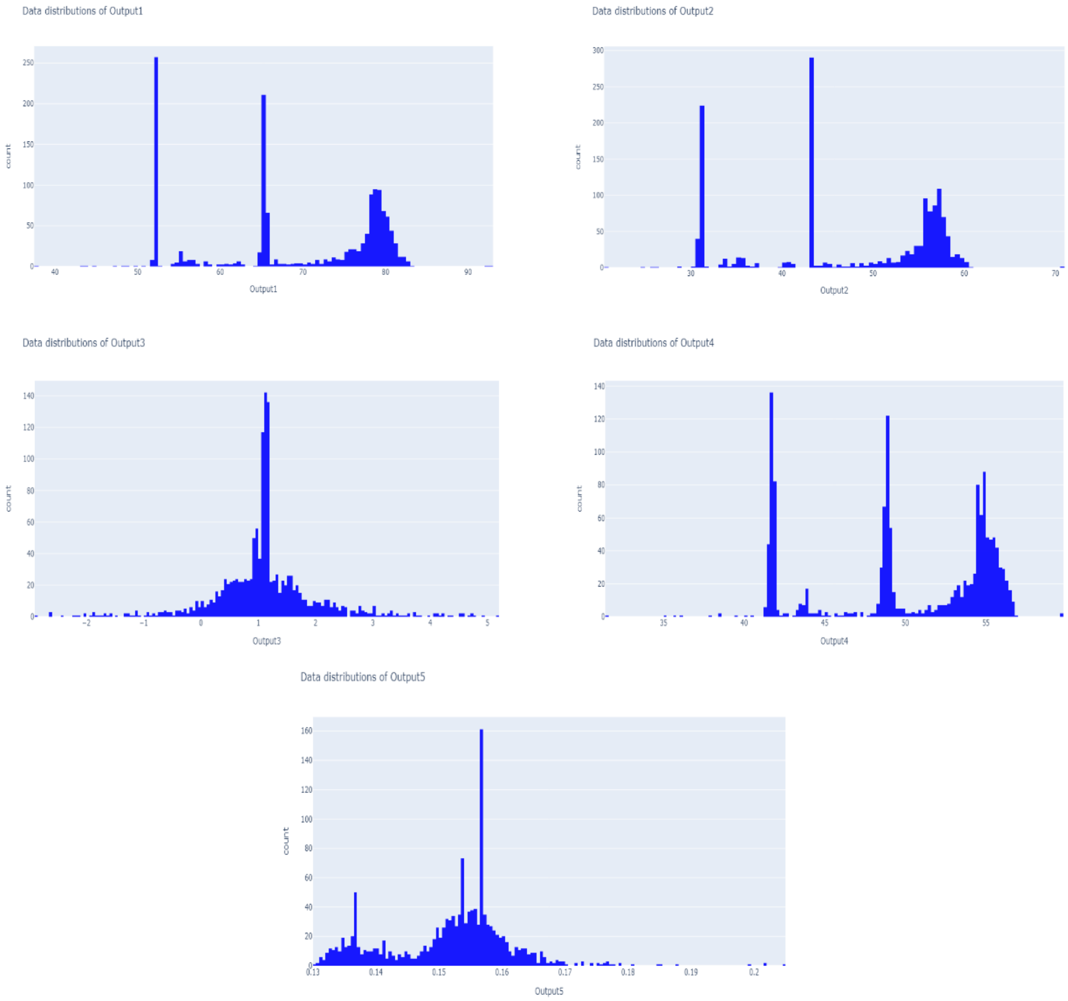


Figure 3.11: Histograms for Output Data (Bending)

According to these histograms, the data are not uniformly distributed. The data are distributed for a long range, but there are few data points that occurs more than the others and those occurrences are very higher than. The gaps between the data points are minimum in almost all the outputs.

Scatter plots for Outputs

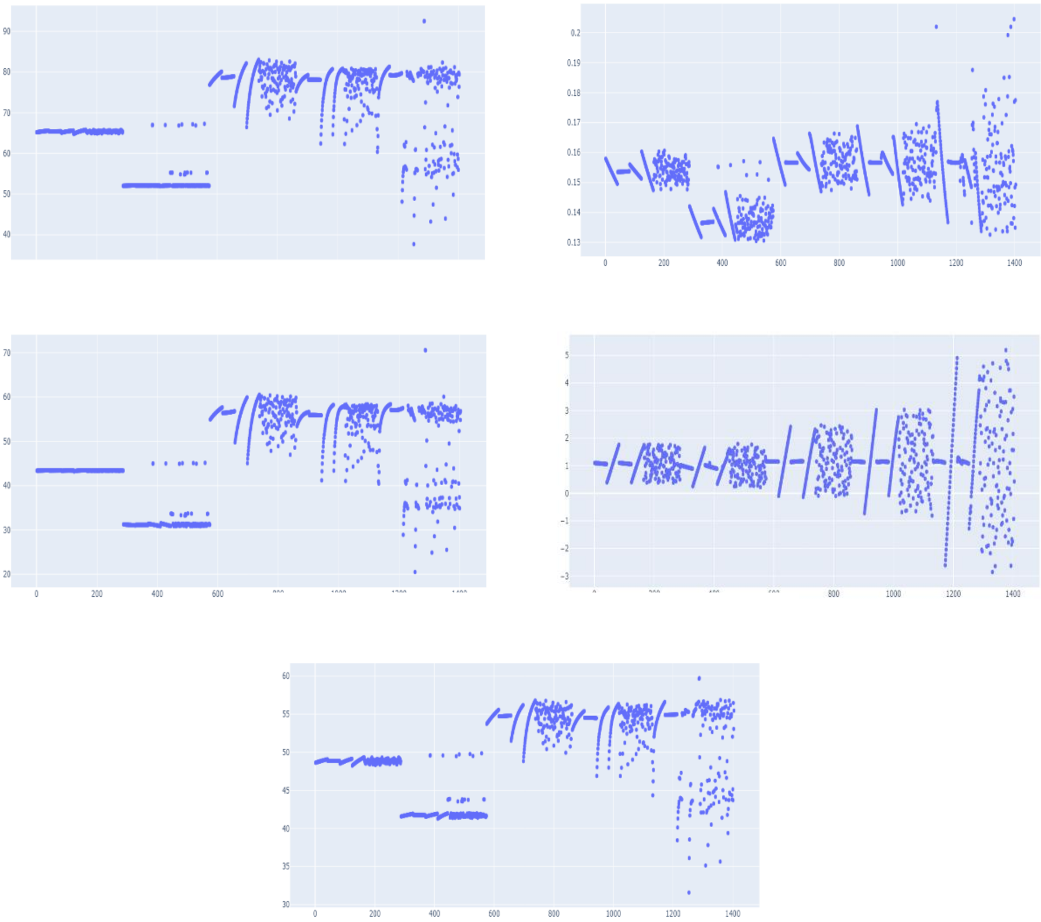


Figure 3.12: Scatter Plots for Output Data (Bending)

There are some visible patterns in all the outputs. These patterns are not repetitive like in the axial data, but the patterns can be divided and can be used because the data set margins can be observed in all the plots. Output 1, output 3 and output 4 patterns shows similar behavior and output 2 and 4 shows similar patterns.

3.2.2.3 Input-Output data Distribution

Input 1 with all the Outputs

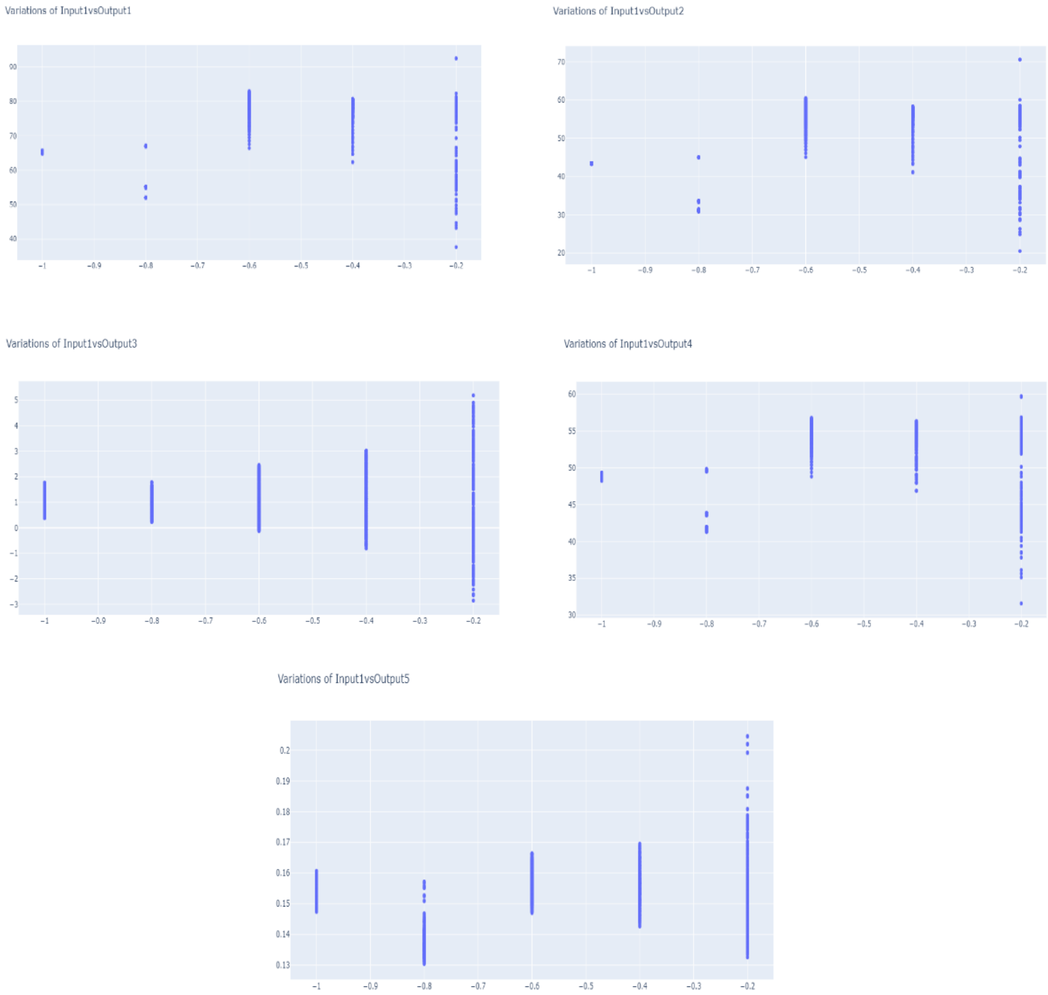


Figure 3.13: Input1-Outputs Data Distributions (Bending)

There are no deviations in the data, as can be seen from the preceding charts. The output varies in many places for a single data. The charts mentioned above all exhibit this trend. The data is also very tightly packed, resulting in straight lines. This is possible because to the plots' various dimensions, where the result varies depending on the other variables, or inputs.

Input 2 with all the Outputs

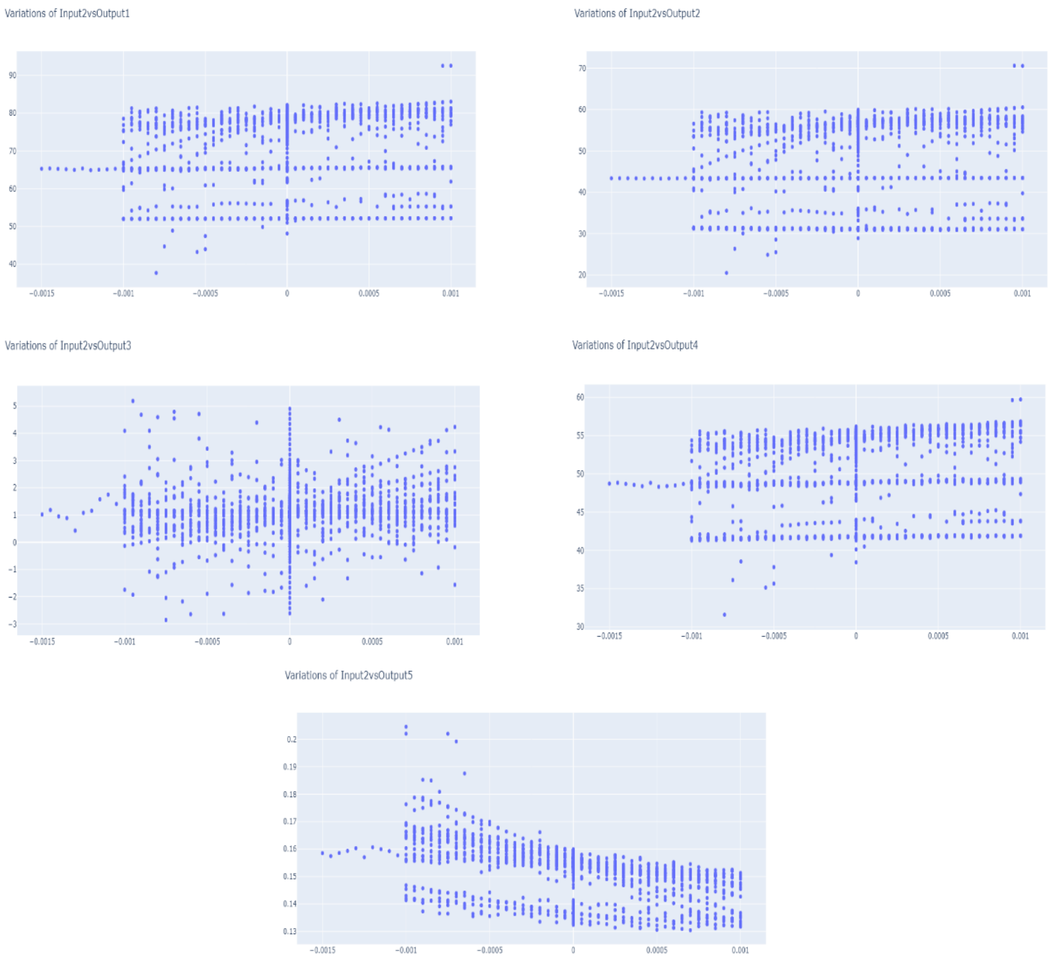


Figure 3.14: Input2-Outputs Data Distributions (Bending)

In the 2d plane, there are no discernible connections between input 2 and the outputs. But the charts make the dimensions effect quite evident. As a result, the patterns would be seen in three dimensions.

Input 3 with all the Outputs

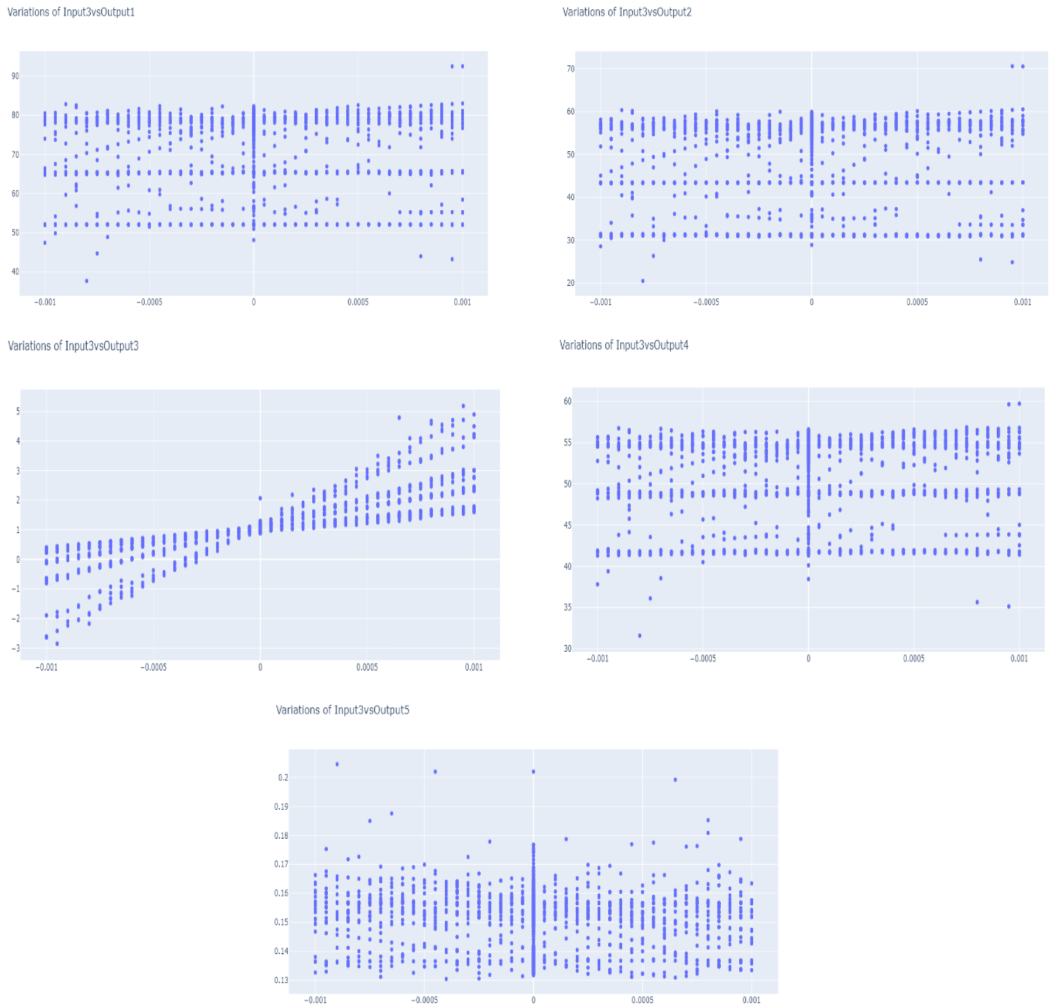


Figure 3.15: Input3-Outputs Data Distributions (Bending)

Input 3 with output 1, output 2, output 4 and output 5 is affected by the dimensional effect thus the relationships are not visible in the 2d plane. A linear pattern can be observed in the plot between input 3 and output 3 but it is also affected by the dimensional effect.

Input 4 with all the Outputs

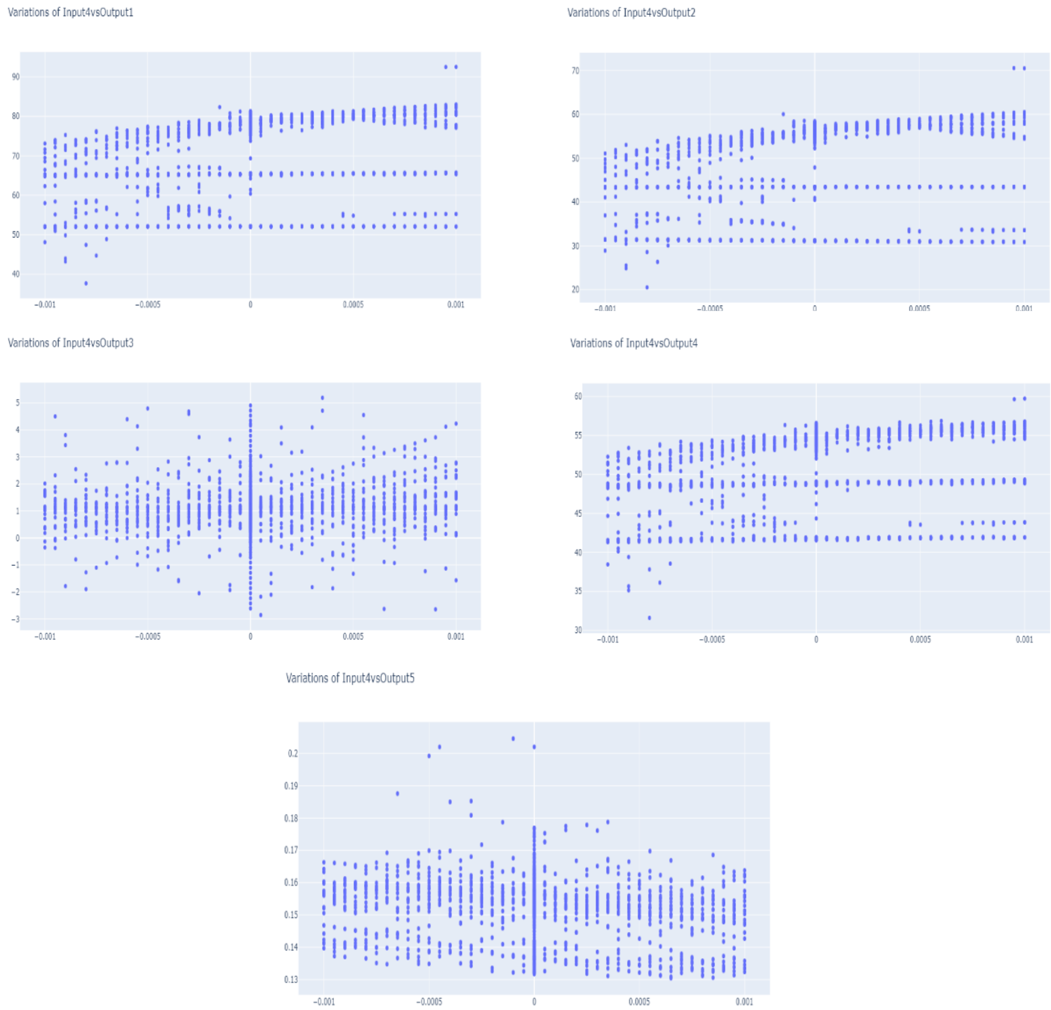


Figure 3.16: Input4-Outputs Data Distributions (Bending)

There are no discernible connections between input 3 and the outputs that can be seen in the two-dimensional plane. The plots, however, show the dimensional effect very clearly. As a result, in three dimensions, the patterns would be visible.

3.2.3 Twisting Data set

3.2.2.1 Input data Distribution

Histograms for Inputs

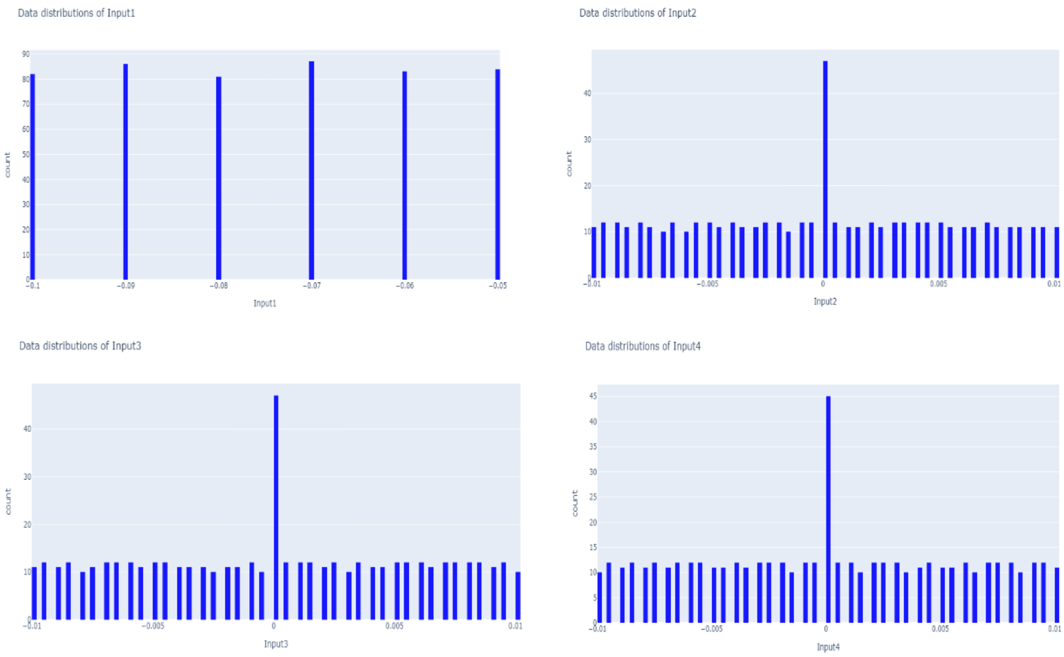


Figure 3.17: Histograms for Input Data (Twisting)

These histograms shows the distribution and range of the twisting data. According the plots it can be observed that distribution is similar to the axial and bending data, but occurrence of data has increased on the both sides of the plot for input 2, input 3 and input 4.

Scatter plots for Inputs

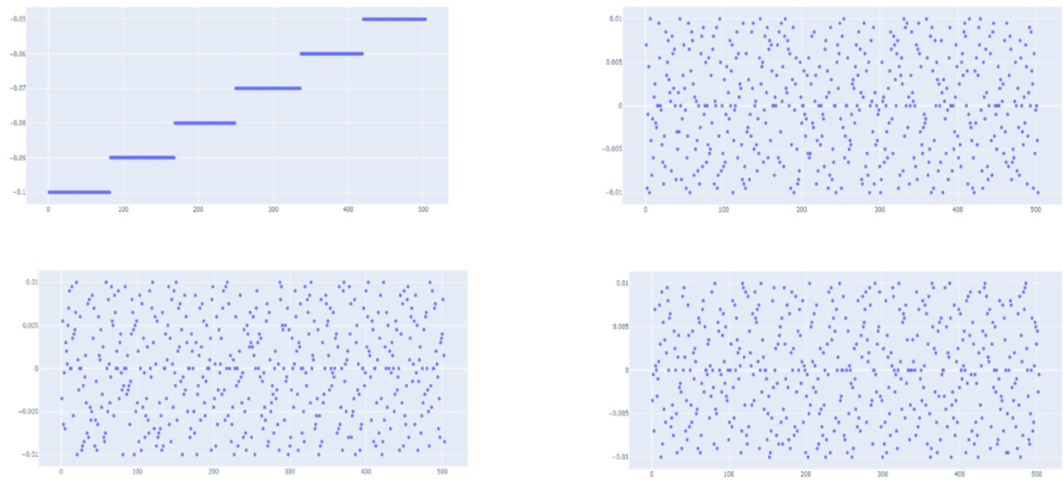


Figure 3.18: Scatter Plots for Input Data (Twisting)

Considering above scatter plots, it can be observed that except for the input 1 there is no visible patterns in plots for other inputs. The data scattered on the 2d plane. To make sure about the patterns the data for input 2, 3 and 4 should be plotted on the 3d plane.

3.2.2.2 Output data Distribution

Histograms for Outputs

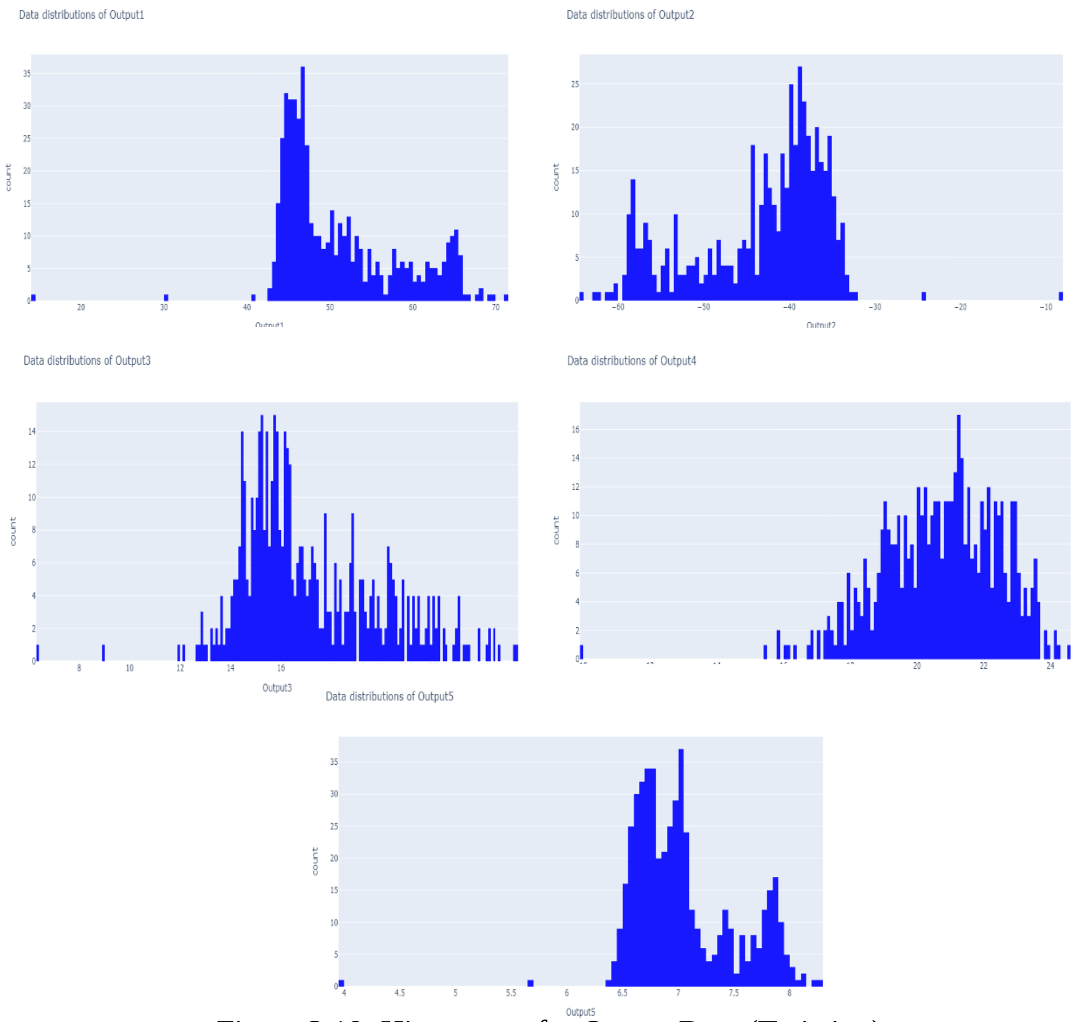


Figure 3.19: Histograms for Output Data (Twisting)

According to above histograms, it can be observed that the data is distributed on large range, but there are huge gaps between the smaller data of output 1, output 3, output 4 and output 4 and also there are huge gaps between the larger data of output 2. The Manhattan of the plot shows that the there are fewer gaps in between of the data for the rest of the data set.

Scatter plots for Outputs

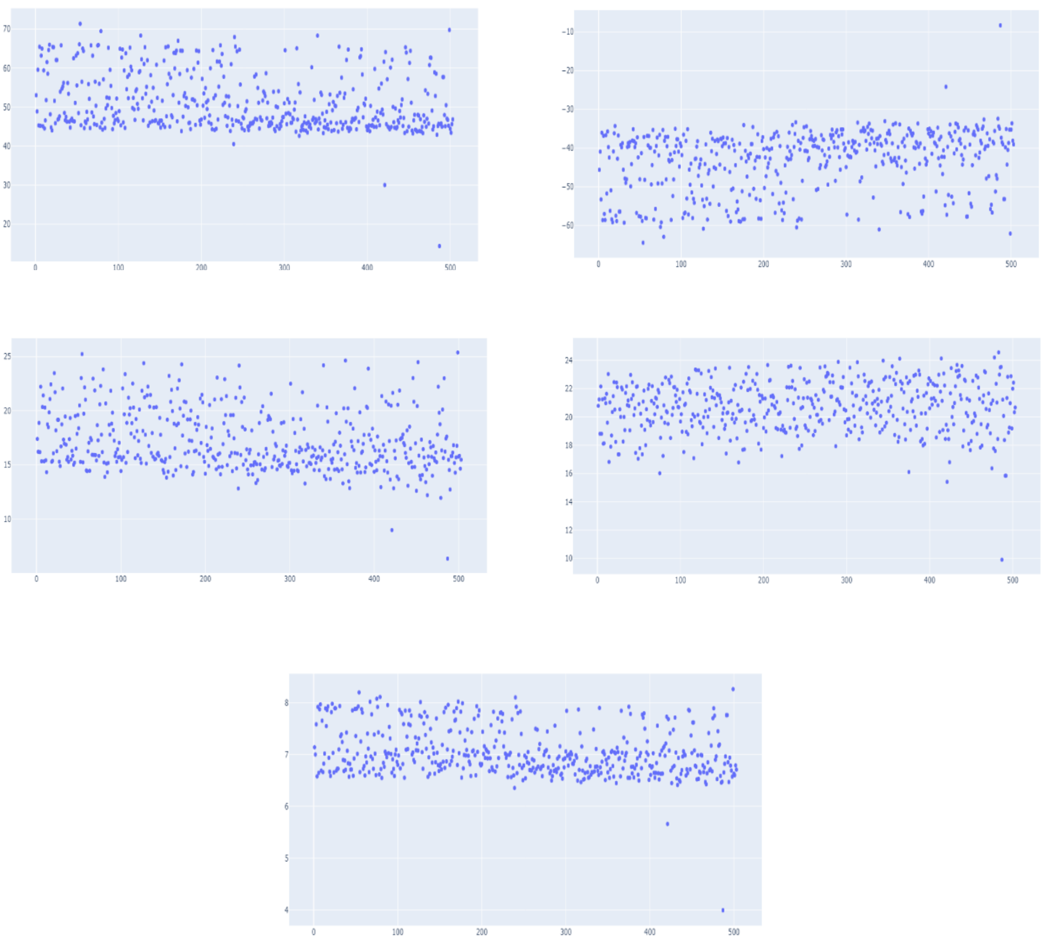


Figure 3.20: Scatter Plots for Output Data (Twisting)

As shown in the graph the data is scattered on a large range with no visible patterns in the data set. For output 1, output 3, output 4 and output 5 the data is scattered mostly around the higher range and for output 2 the data is around the lower range. Still there is a chance that a pattern can be visible in the 3d plane.

3.2.2.3 Input-Output data Distribution

Input 1 with all the Outputs

Figure 3.21: Input1-Outputs Data Distributions (Twisting)

These scatterplots that shows the relationship between input 1 with all the outputs, do not display any visible patterns on 2d plane. But since there are datapoints closely packed creating straight lines, it can be observed that the dimensional effect is there. Thus, the patterns may be visible in the 3d plane.

Input 2 with all the Outputs

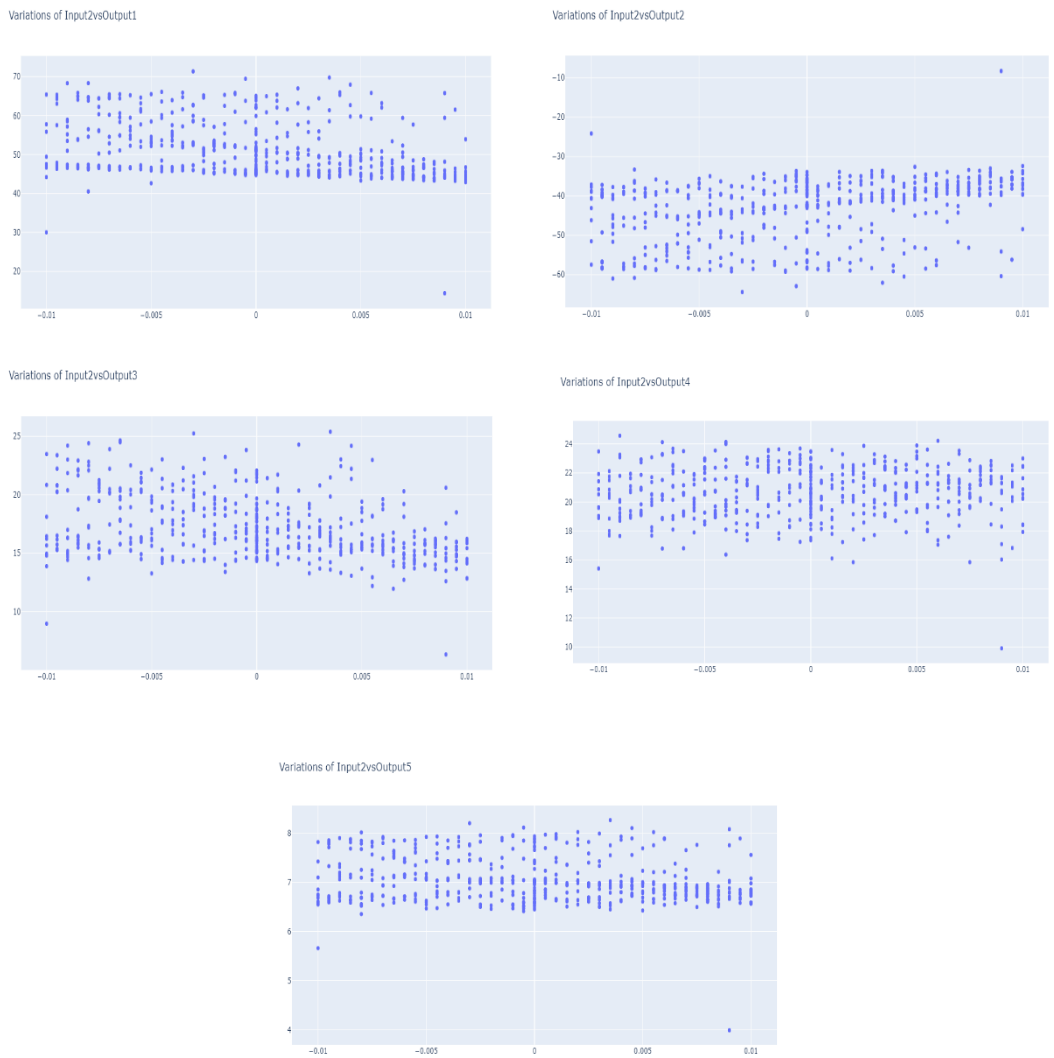


Figure 3.22: Input2-Outputs Data Distributions (Twisting)

There are no discernible patterns on the two-dimensional plane in these scatterplots, which depict the relationship between input 2 and all of the outputs. However, the plots are affected by dimensions. This may make the patterns visible in the three-dimensional plane.

Input 3 with all the Output

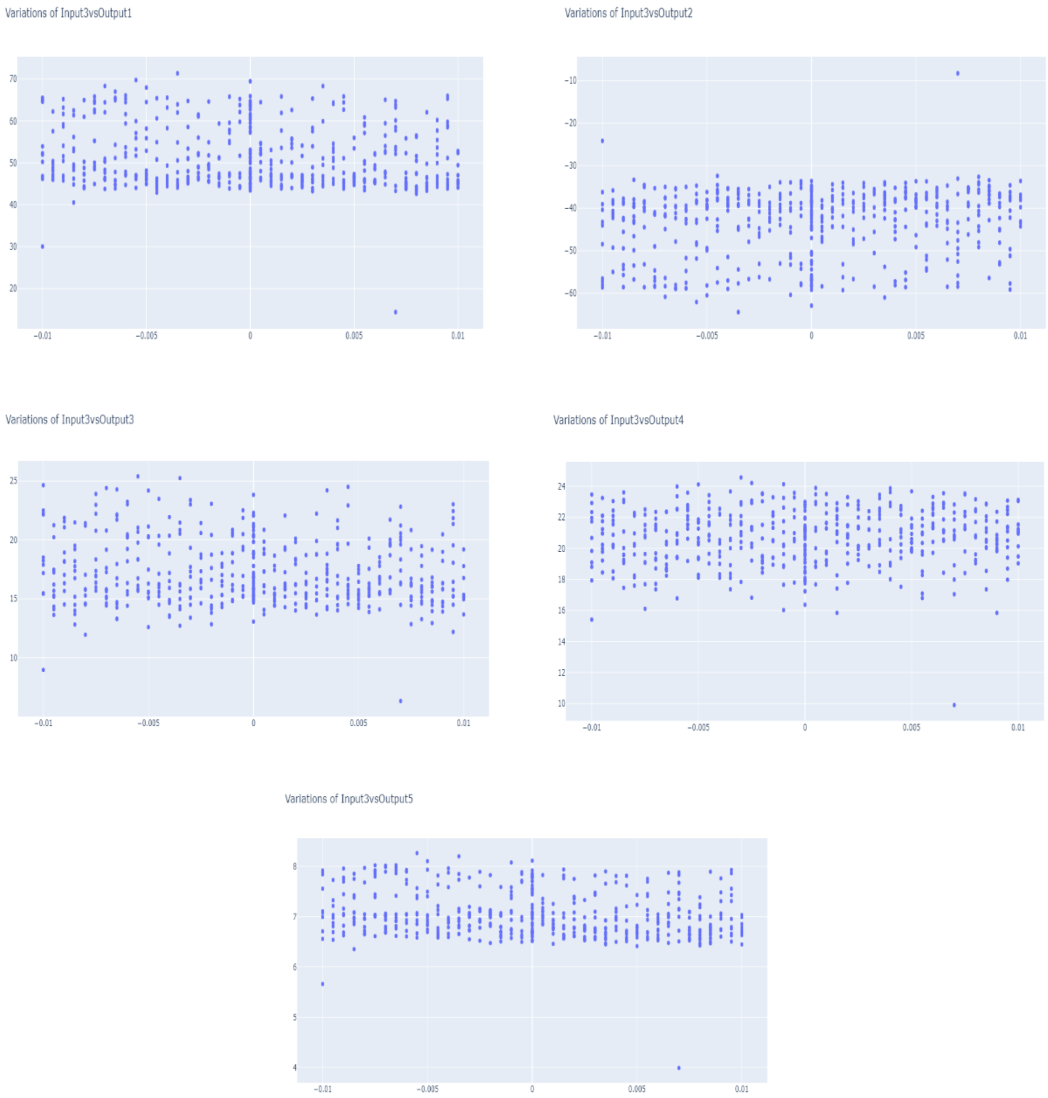


Figure 3.23: Input3-Outputs Data Distributions (Twisting)

On a two-dimensional plane, there are no discernible patterns in these scatterplots, which depict the relationship between input 2 and all of the outputs. The plots do, however, exhibit a dimensional effect. As a result, the patterns might be discernible in the three-dimensional plane.

Input 4 with all the Outputs

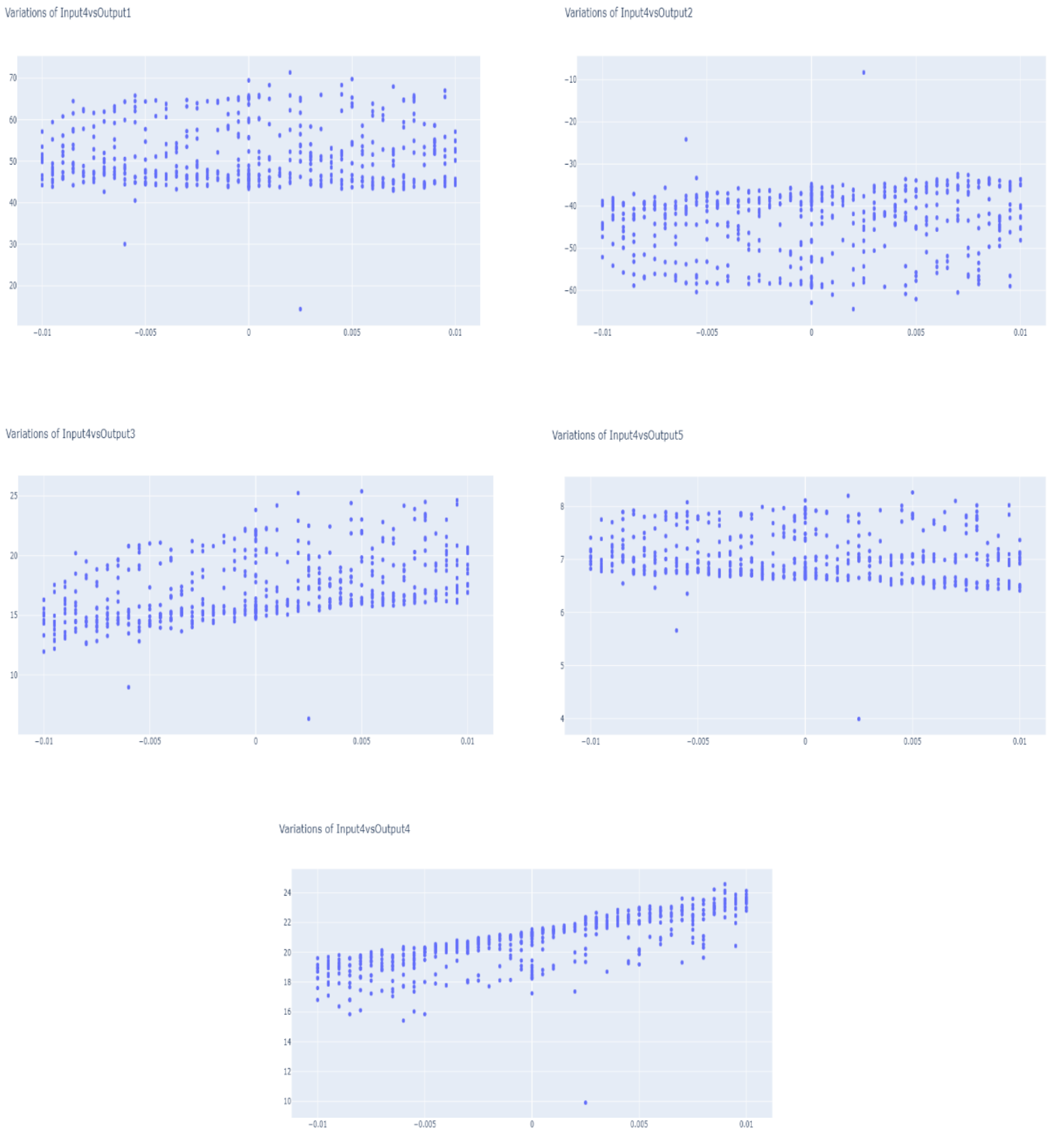


Figure 3.24: Input4-Outputs Data Distributions (Twisting)

These scatterplots, which depict the relationship between input 4 and all of the outputs, don't reveal any discernible patterns on a two-dimensional plane. The plots, however, are affected by dimensions. In the third-dimensional plane, the patterns may therefore be discernible.

3.3 CORRELATION ANALYSIS

Correlation analysis is a statistical technique used to examine the relationship between two or more variables. It measures the degree to which two variables are related, and whether this relationship is positive, negative, or neutral. The correlation coefficient (r) is a value that ranges from -1 to 1, where -1 indicates a strong negative correlation, 0 indicates no correlation, and 1 indicates a strong positive correlation.

In data analysis, correlation analysis is often used to identify relationships between variables that may not be immediately obvious. It can be useful for identifying patterns or trends in the data, and for understanding the underlying structure of the data. Correlation analysis can also be used to identify potential confounding variables that may affect the relationship between the variables of interest.

In soft robot hand project, correlation analysis can be used to understand the relationship between the pneumatic pressure applied to the hand and the resulting position and shape of the hand. This can help to identify which variables are most important for controlling the hand's behavior and can inform the design of the reduced order machine learning model.

Correlation analysis can be performed using various techniques, such as Pearson's correlation coefficient, Spearman's rank correlation coefficient, or Kendall's tau. The choice of technique depends on the type of data being analyzed and the specific research question. In our project we used python Sklearn package to do correlation analysis.

3.3.1Axial Data

3.3.1.1 Input - Output Correlation

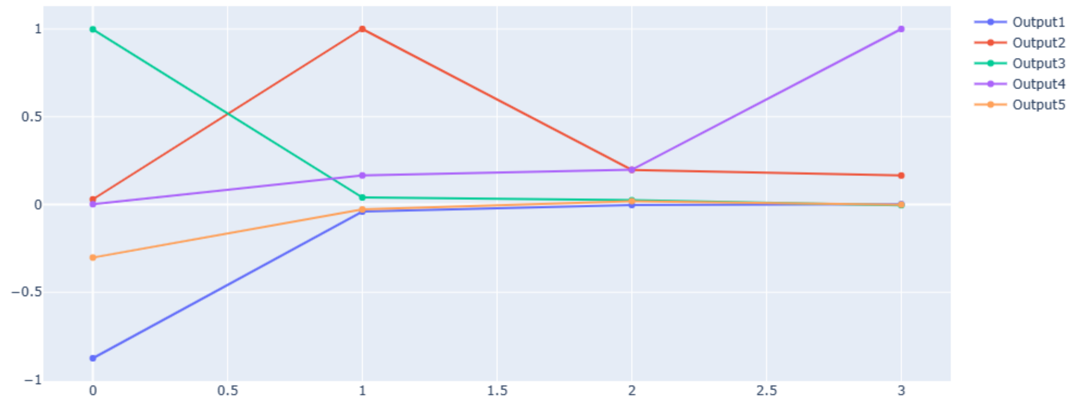


Figure 3.25: Inputs -Outputs Correlations-Axial Data

In the axial data set, Output1 represents the magnitude of Output1, Output2, and Output3, and therefore has a direct relationship with these outputs. Output2 was directly determined from the other outputs. Additionally, correlation analyses of Inputs and outputs were conducted between the other outputs and the inputs. The results of the analysis indicate that Output2 is highly correlated with Input1, Output3 is correlated with Input1, Output4 is correlated with Input3 and Input4, and Output5 is correlated with Input1, Input2, and Output4.

3.3.1.2 Output-Output Correlation

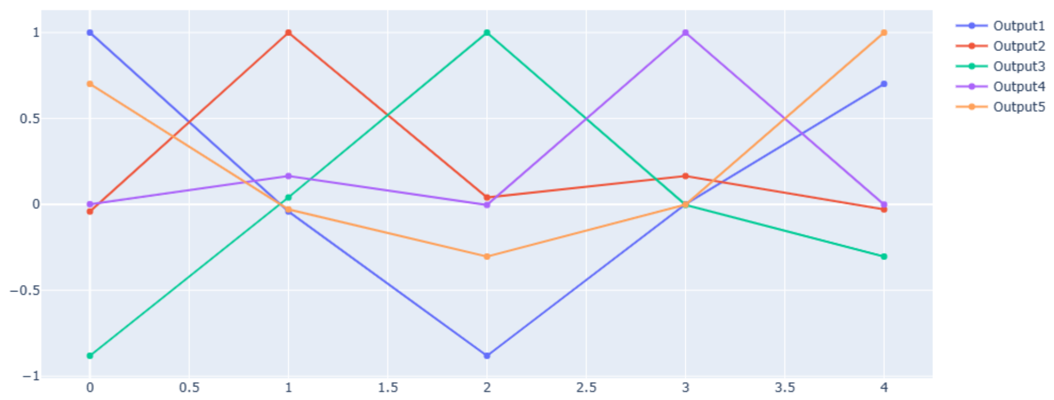


Figure 3.26: Output -Outputs Correlations-Axial Data

The correlation analysis of the output-output relationships indicates that Output2 is not highly correlated with the other outputs. On the other hand, Output3 exhibits a high correlation with Input1. Output4 also shows relatively low correlation with the other outputs. Finally, Output5 demonstrates a significant correlation with both Input1 and Input2.

3.3.2 Bending Data

1.3.2.1 Input - Output Correlation

In the Bending data set also, Output1 represents the magnitude of Output1, Output2, and Output3, and therefore has a direct relationship with these outputs. Output2 was directly determined from the other outputs. Additionally, correlation analyses of Inputs and outputs were conducted between the other outputs and the inputs. The results of the analysis indicate that Output2 is correlated with Input1and Input4, Output3 is correlated with Input2, Output4 is correlated with Input1 and Input4, and Output5 is correlated with Input2 and Input2.

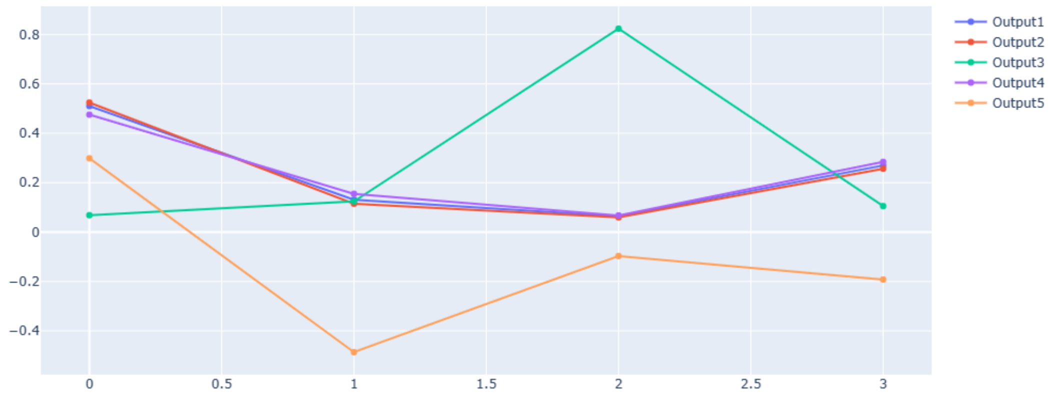


Figure 3.27: Inputs -Outputs Correlations-Bending Data

3.3.2.2Output-Output Correlation

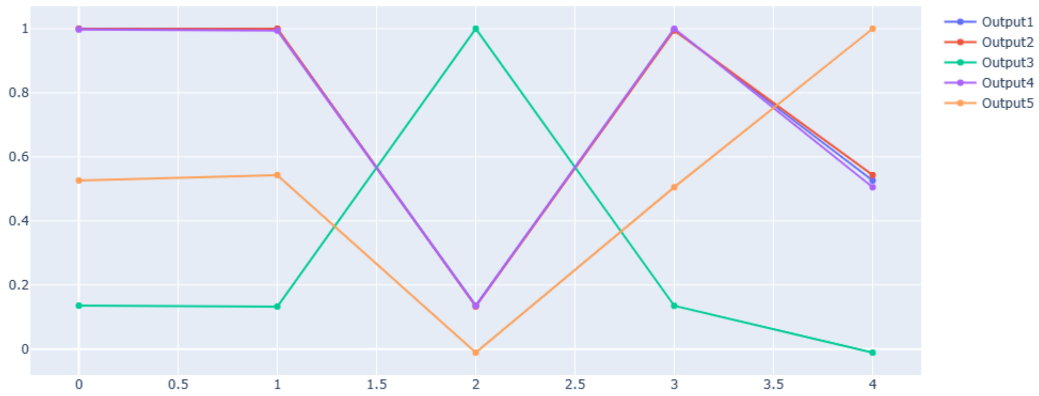


Figure 3.28: Output -Outputs Correlations-Bending Data

The correlation analysis of the output-output relationships indicates that is correlated with Output1 and Output3. On the other hand, Output3 not exhibits correlations with outputs. Output4 also shows relatively high correlation with the output1 and Output3. Finally, Output5 demonstrates relatively high correlation with the output3 and relatively less correlation with the output1

3.3.3 Twisting Data

3.3.3.1 Input - Output Correlation

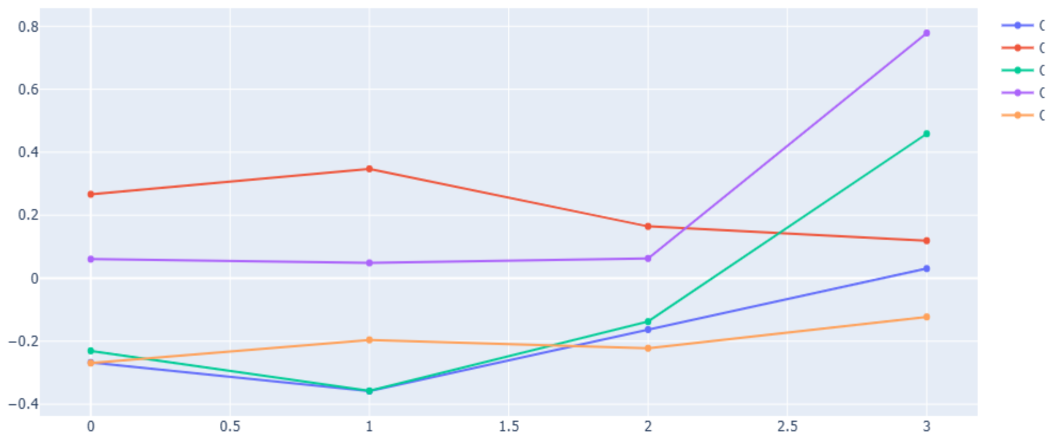


Figure 3.29: Inputs -Outputs Correlations- Twisting Data

In the Twisting data set also, Output1 represents the magnitude of Output1, Output2, and Output3, and therefore has a direct relationship with these outputs. Output2 was directly determined from the other outputs. Additionally, correlation analyses of Inputs and outputs were conducted between the other outputs and the inputs. The results of the analysis indicate that Output2 is correlated with Input1and Input4, Output3 is correlated with Input2, Output4 is correlated with Input1 and Input4, and Output5 is correlated with Input2 and Input2.

3.3.3.2 Output-Output Correlation

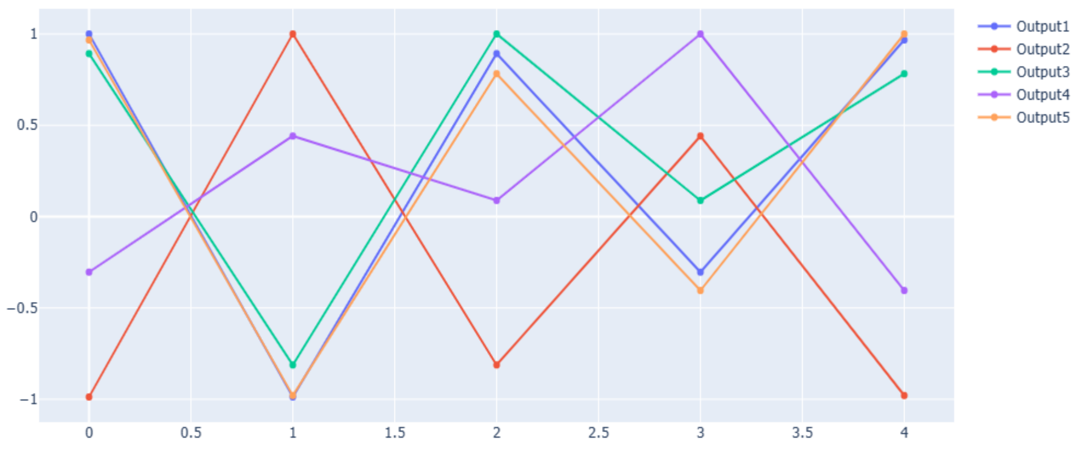


Figure 3.30: Outputs -Outputs Correlations-Twisting Data

The correlation analysis of the output-output relationships indicates that there is more correlation within the output data set, rather than between the axial and bending data sets. Specifically, Output2 is highly correlated with Output1, Output3, and Output4. Output3 exhibits significant correlations with Output2, Output3, and Output4. Output4 also shows a relatively high correlation with Output1 and Output3. Finally, Output5 demonstrates a relatively high correlation with Output1 and Output4, and relatively low correlation with Output3.

Chapter 4

MODEL DEVELOPING

4.1 INTRODUCTION

In this chapter, we will explore the process of model development in depth, which is a critical stage in the implementation of a successful machine learning solution. The primary objective of this phase is to construct a predictive model that accurately reflects the relationship between the input variables and the target variable, which is essential for producing reliable predictions. To achieve this, a thorough exploration of different algorithms and techniques will be conducted, including feature selection and hyperparameter tuning, in order to identify the most suitable model for the problem at hand.

In this chapter, a comprehensive overview of the steps taken to develop and assess the performance of the final model selected will be presented, including the methodologies that were used, the results obtained, and the interpretations of these results. This information is crucial for understanding the strengths and limitations of the model and for guiding further improvements and optimizations. In Chapter 1, data visualization and understanding were performed to gain insights into the data. Based on these insights, machine learning models were developed for three separate data sets, providing a comprehensive analysis of each set

4.2 MODEL DEVELOPMENT

In our data space, there are four inputs and five outputs. Through a correlation analysis, it was determined that some inputs have a linear relationship with the outputs, while others have a non-linear relationship. In accordance with our objectives, simple machine learning algorithms were utilized to develop the models. Linear regression was employed for the linear relationships, while polynomial regression was used for the non-linear relationships. The analysis and model development were performed in the PC space to achieve more accurate results.

Table 4.1: Input Data

Inputs	Description
Input1	Internal pressure
Input2	X components of external forces
Input3	Y components of external forces
Input4	Z components of external forces

Table 4.2: Output Data

Outputs	Descriptions
Output1	Magnitude of displacement
Output2	X components of displacement
Output3	Y components of displacement
Output4	Z components of displacement
Output5	Resultant force

Since output 1 is the magnitude of the x y z components of the displacement. Output1 was determined by the output2 output3 output4 by following equation.

$$\boldsymbol{output\ 1} = \sqrt{\boldsymbol{output2^2} + \boldsymbol{output3^2} + \boldsymbol{output4^2}}$$

To predict other output machine learning models were developed for three data sets. Python Scikit-learn library was used for developing model. Scikit-learn is an open-source machine learning library for Python that provides simple and efficient tools for data mining and data analysis. It is built on top of the NumPy, SciPy, and matplotlib libraries and integrates well with the rest of the scientific Python ecosystem (such as Pandas).**Scikit-learn** provides a wide range of machine learning algorithms for classification, regression, clustering, dimensionality reduction, model selection, and preprocessing.

4.2.1 Axial data set

For the axial data sets, linear regression was utilized for linear relationships and polynomial regression for non-linear relationships. Initially, the analysis and model development were conducted in the original input data space. Consideration was first given to all inputs and liner regression models for the outputs, resulting in an accuracy of approximately 40%. Subsequently, linear regression was employed for the outputs that showed linear relationships and polynomial regression for the outputs that showed non-linear relationships, leading to an increased accuracy of approximately 70%. To further improve accuracy, the results of the correlation analysis were considered, and models were developed using the most relevant and selected inputs.

Table 4.3: Inputs Correlations Results -Axial Data

Output	**Most correlated Inputs/Outputs**	**Relation ship**
Output2	Input1,Input2,input4	Linear
Output3	Input1,Input2,input4	Linear
Output4	Input1,Input2,input4	Linear
Output5	Input1,Output1	Non Linear

Output 2, Output 3, and **Output 4** were found to have a linear relationship with **Input 1, Input 2, and Input 4** through the correlation analysis. As a result, linear regression was employed as the model for **Output 2, Output 3, and Output 4. Output 5** was determined to have a non-linear relationship with Input 1 and Output 1, thus polynomial regression was utilized to predict **Output 5.** The determination of **Output 1** was based on the predictions made by **Output 2, Output 3, and Output 4.**

The **scikit-learn's LinearRegression** model was employed for both linear and polynomial regression model development. The function **'axial_unit_cell_model'** was utilized to train the axial data set. It receives the axial training data sets and returns two linear regression models. The function **'axial_unit_cell_predict'** was used to predict the results for a new data set by receiving the inputs and returning the predicted outputs. The **'axial_unit_cell_model_validation'** function was employed to validate the model. It receives the axial data sets and splits them into training and validation/test data sets. The model was trained using the training data sets and then validated using the validation/test data sets. The R2 score value was used as the accuracy metric, and graphs were plotted to visually validate the model.

4.2.2 Twisting data Set

For the Twisting sets, linear regression was utilized for linear relationships and polynomial regression for non-linear relationships. Initially, the analysis and model development were conducted in the original input data space. Consideration was first given to all inputs and liner regression models for the outputs, resulting in an accuracy of approximately 40%. Subsequently, linear regression was employed for the outputs that showed linear relationships and polynomial regression for the outputs that showed non-linear relationships, leading to an increased accuracy of approximately 70%. To further improve accuracy, the results of the correlation analysis were taken into account, and models were developed using the most relevant and selected inputs.

Table 4.4: Inputs Correlations Results -Twisting Data

Output	**Most correlated Inputs/Outputs**	**Relation ship**
Output2	Input1,Input2, Input2,Input4,Output4	Non Linear
Output3	Input1,Input2, Input2,Input4,Output2	Non Linear
Output4	Input1,Input2, Input2,Input4	Non Linear
Output5	Input1,Input2, Input2,Input4,Output1	Non Linear

Output 2 was found to have a non-linear relationship with **Input 1, Input 2, Input 3, and Input 4 a**s well **as Output 4**, thus 2nd-order polynomial regression was employed for the modeling. Similarly, Output 3 was determined to have a non-linear relationship **with Input 1, Input 2, Input 3, Input 2, and Output 4,** and therefore a 3rd-order polynomial regression was utilized for the modeling. **Output 4 and Output 5** were identified to have a non-linear relationship with **Input 1, Input 2, Input 3, Input 2, Output 4, and Output 1,** and therefore a 3rd-order polynomial regression was employed for their modeling

Its get total 78% accuracy for the modeling in original data space. For improve the accuracy PCA is done and analysis and modeling is done in the PC Space

The **scikit-learn's LinearRegression** model was employed for both linear and polynomial regression model development. The function **'twisting_unit_cell_model'** was utilized to train the axial data set. It receives the axial training data sets and returns two linear regression models. The function **'twisting_unit_cell_predict'** was used to predict the results for a new data set by receiving the inputs and returning the predicted outputs. The **'twisting_unit_cell_model_validation'** function was employed to validate the model. It receives the axial data sets and splits them into training and validation/test data sets. The model was trained using the training data sets and then validated using the validation/test data sets. The R2 score value was used as the accuracy metric, and graphs were plotted to visually validate the model.

4.2.3 Bending Data set.

For the Bending sets, linear regression was utilized for linear relationships and polynomial regression for non-linear relationships. Initially, the analysis and model development were conducted in the original input data space. Consideration was first given to all inputs and liner regression models for the outputs, resulting in an accuracy of approximately 20%. Subsequently, linear regression was employed for the outputs that showed linear relationships and polynomial regression for the outputs that showed non-linear relationships, leading to an increased accuracy of approximately 60%. To further improve accuracy, the results of the correlation analysis were taken into account, and models were developed using the most relevant and selected inputs.

Table 4.5: Inputs Correlations Results -Bending Data

Output	**Most correlated Inputs/Outputs**	**Relation ship**
Output2	Input1,Input2, Input4	Non Linear
Output3	Input1,Input3	Non Linear
Output4	Input1,Input2, Input4	Non Linear
Output5	Input1,Input2, Input4	Non Linear

Output 2 Output4 and Output5 was found to have a non-linear relationship with **Input 1, Input 2, Input 4**, and thus 2nd-order polynomial regression was employed for the modeling. Similarly, Output 3 was determined to have a non-linear relationship with **Input 1, Input3** therefore a 3rd-order polynomial regression was utilized for the modeling.

Its get total 78% accuracy for the modeling in original data space. For improve the accuracy PCA is done and analysis and modeling is done in the PC Space

The **scikit-learn's LinearRegression** model was employed for both linear and polynomial regression model development. The function **'Bending_unit_cell_model'** was utilized to train the axial data set. It receives the axial training data sets and returns two linear regression models. The function **'Bending_unit_cell_predict'** was used to predict the results for a new data set by receiving the inputs and returning the predicted outputs. The **'Bending_unit_cell_model_validation'** function was employed to validate the model. It receives the axial data sets and splits them into training and validation/test data sets. The model was trained using the training data sets and then validated using the validation/test data sets. The R2 score value was used as the accuracy metric, and graphs were plotted to visually validate the model.

Chapter 5

EXPERIMENTS AND RESULTS

5.1 INTRODUCTION

In this chapter, the results of the analysis and modeling conducted in Chapter 2 are presented. The primary objective of this chapter is to present a comprehensive evaluation of the machine learning models developed and to demonstrate the accuracy of the models in accurately predicting the outcome of interest. In this section, the performance metrics used to evaluate the two models (Reduced order model and Neural network model) and the results obtained from each model are discussed in detail. R2 score is used for the evaluate the accuracy of each model.

The findings from this analysis provide valuable insights into the strengths and weaknesses of the models and provide a basis for selecting the best model for the problem at hand. The results are visualized using appropriate charts and tables to facilitate interpretation and facilitate understanding of the key findings.

5.2 AXIAL DATA SET

Based on the results of Axial data, the reduced order model achieved an accuracy of over 97%, which is greater than that of the neural network model. The table below presents the accuracy of each output, as well as the overall accuracy achieved.

Table 5.1: Results -Axial Data

Output	Accuracy (R2 score)
Output1	99.7
Output2	99.5
Output3	98.7
Output4	99.6
Output5	98.6
Overall Accuracy	99.1

Following figures show that variations between predicted value and Actual values of Output1(Resultant displacement of the Axial unit cell) for Reduced order model and and Neural network model.

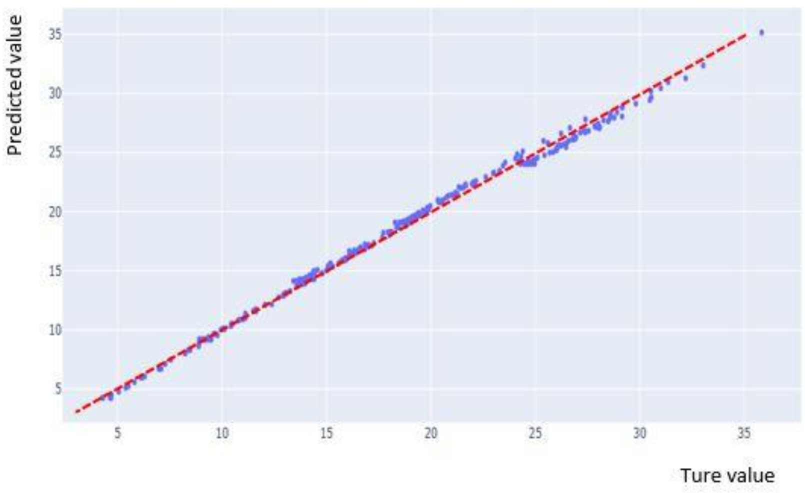


Figure 5.1: Predicted Vs Actual Value (Resultant Displacement) for Reduced order model -Axial Data

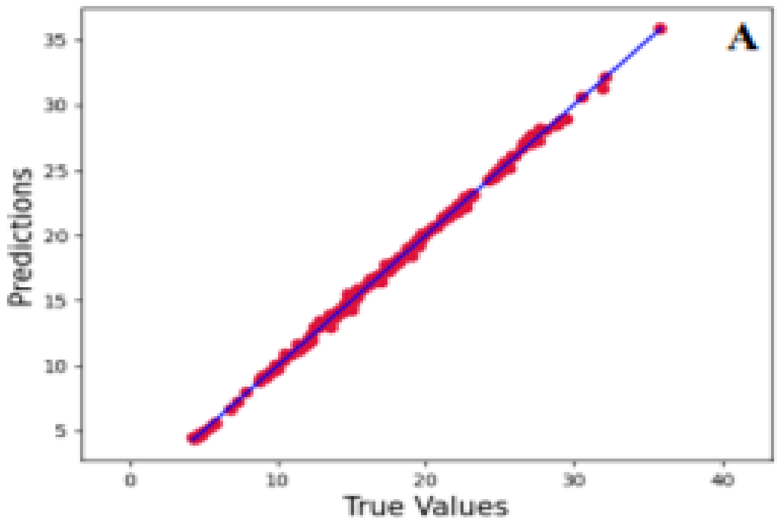


Figure 5.2: Predicted Vs Actual Value (Resultant Displacement) for Neural network model -Axial Data

Following figures show that variations between predicted value and Actual values of all Output of axial data set for Reduced order model

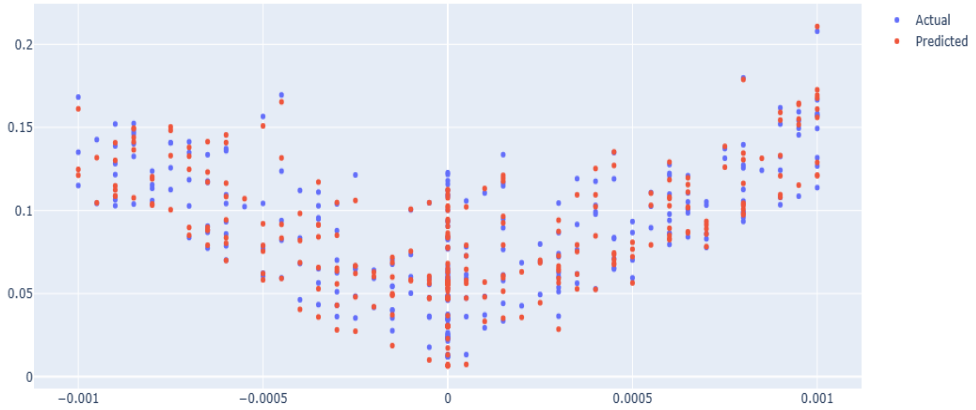


Figure 5.3: Predicted Vs Actual Value for Output1-Axial Data

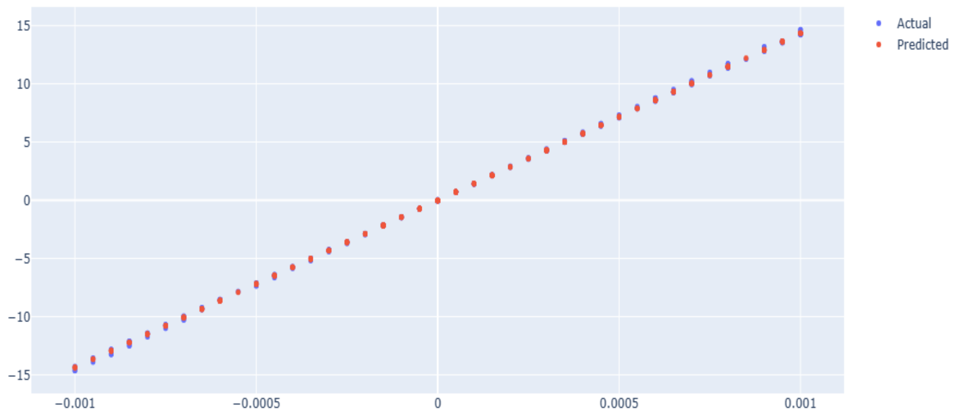


Figure 5.4: Predicted Vs Actual Value for Output2-Axial Data

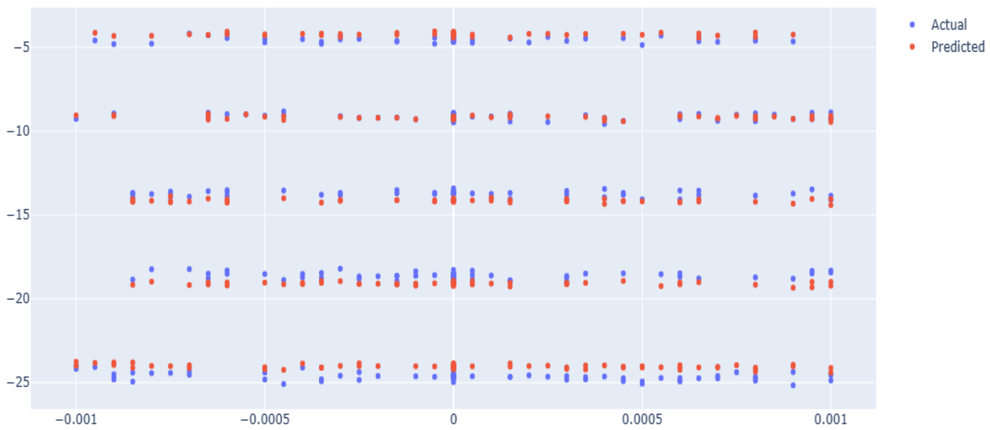


Figure 5.5: Predicted Vs Actual Value for Output3-Axial Data

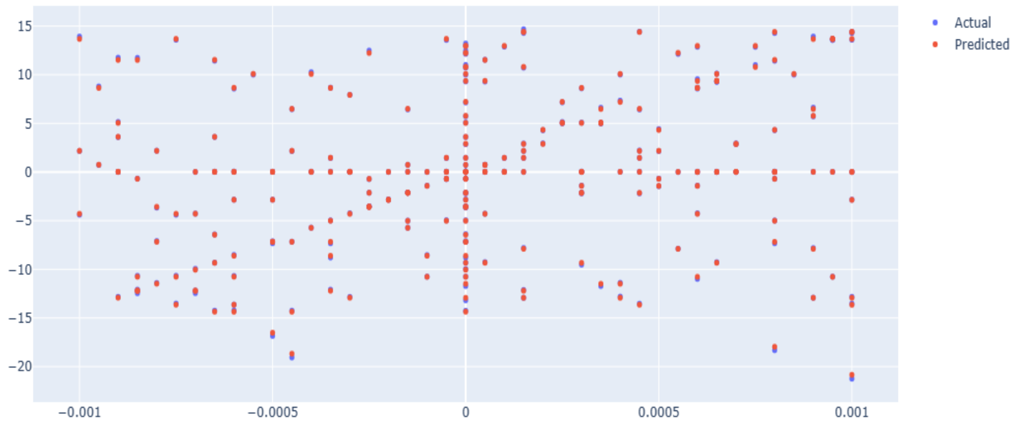


Figure 5.6: Predicted Vs Actual Value for Output4-Axial Data

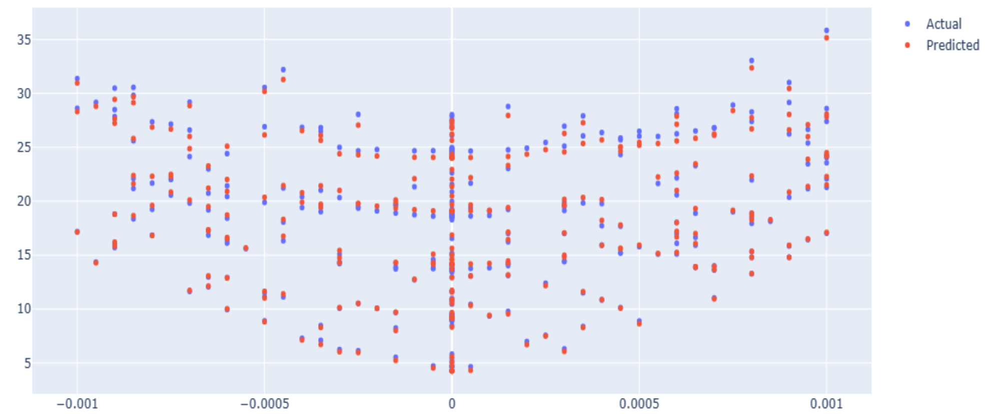


Figure 5.7: Predicted Vs Actual Value for Output5-Axial Data

5.3 BENDING DATA SET

Based on the results of Bending data, the reduced order model achieved an accuracy of over 97%, which is greater than that of the neural network model. The table below presents the accuracy of each output, as well as the overall accuracy achieved.

Table 5.2: Results -Bending Data

Output	Accuracy (R2 score)
Output1	99.7
Output2	98.5
Output3	98.7
Output4	99.6
Output5	97.6
Overall Accuracy	97.1

Following figures show that variations between predicted value and Actual values of Output1(Resultant displacement of the Axial unit cell) for Reduced order model and and Neural network model

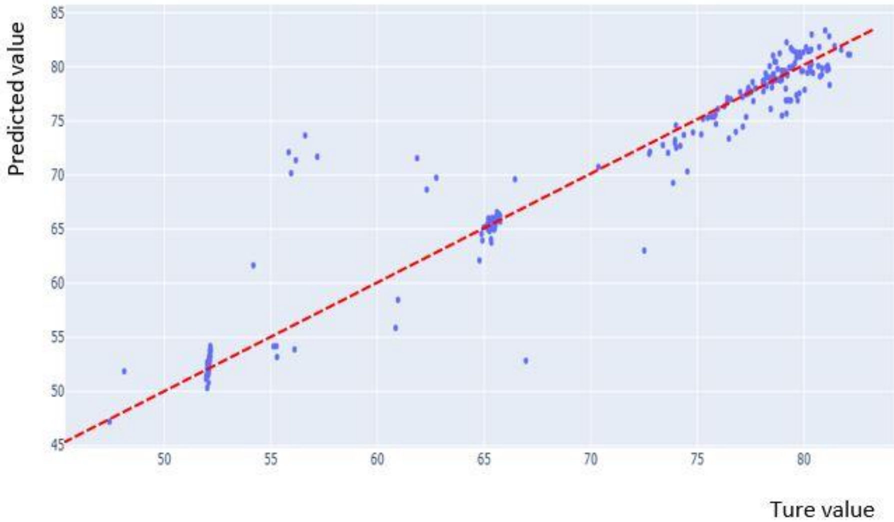


Figure 5.8: Predicted Vs Actual Value (Resultant Displacement) for Reduced order model -Bending Data

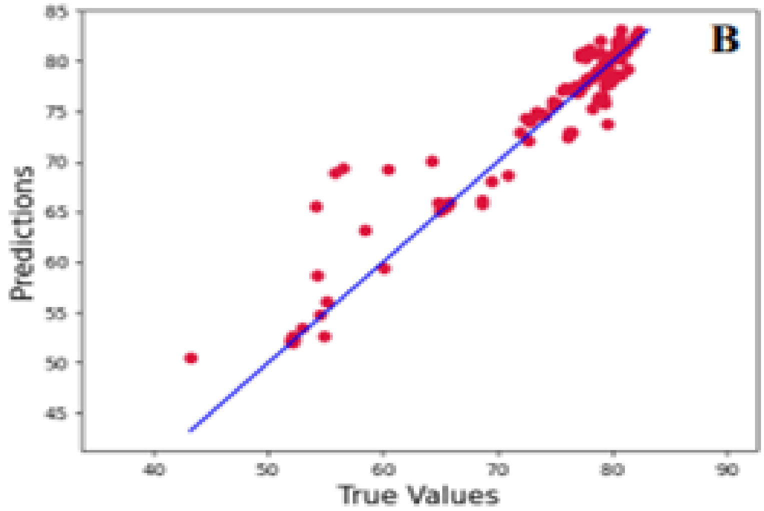


Figure 5.9: Predicted Vs Actual Value (Resultant Displacement)

for Reduced order model -Bending Data

Following figures show that variations between predicted value and Actual values of all Output of axial data set for Reduced order model

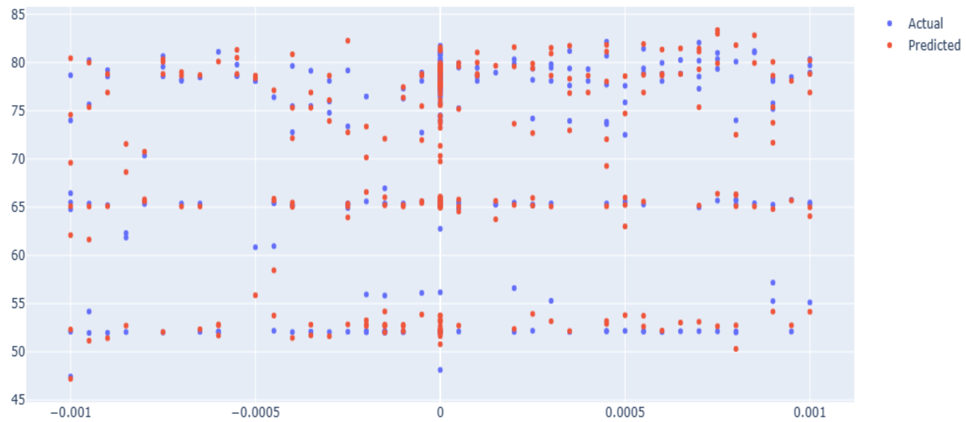


Figure 5.10: Predicted Vs Actual Value for Output1-Bending Data

Data

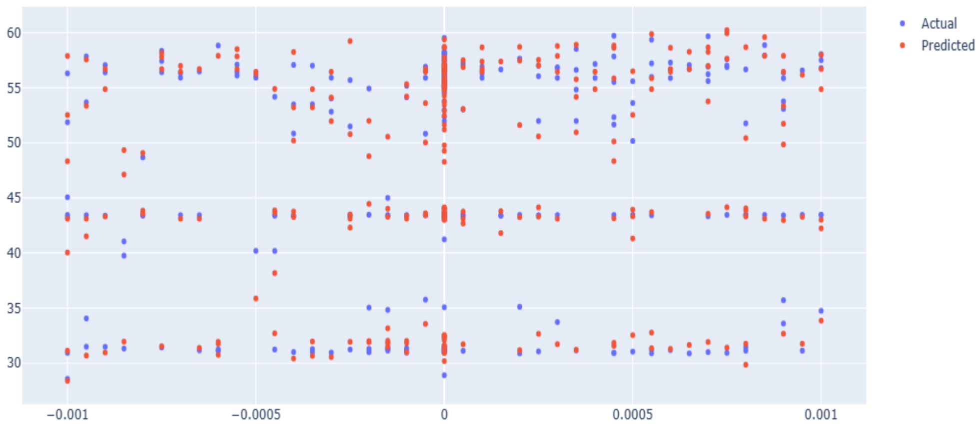


Figure 5.11: Predicted Vs Actual Value for Output1-Bending Data

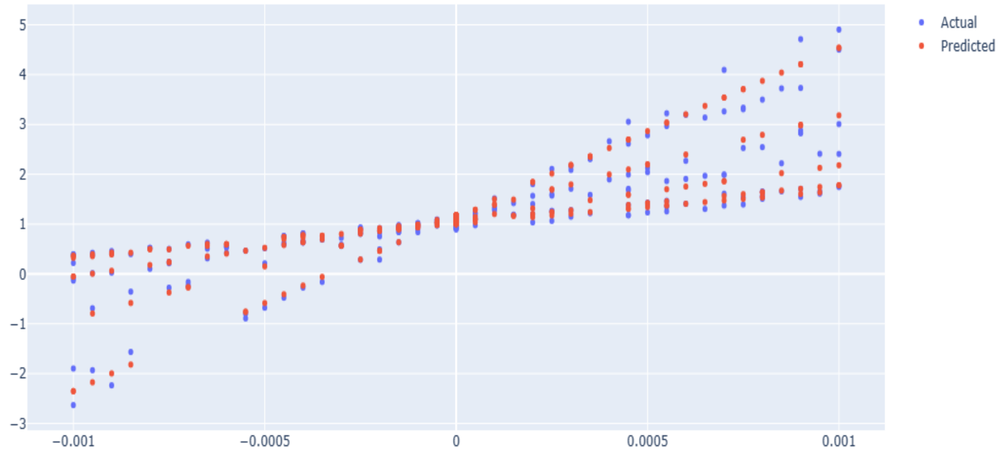


Figure 5.12: Predicted Vs Actual Value for Output3-Bending Data

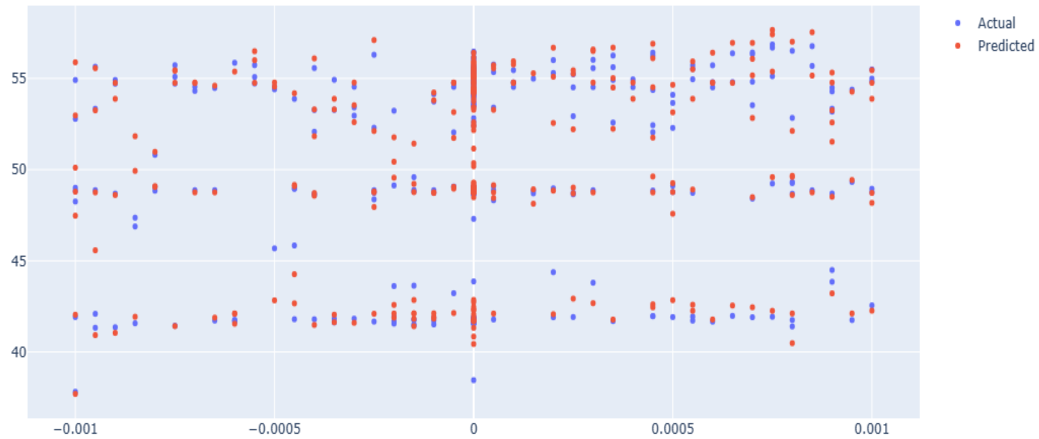


Figure 5.13: Predicted Vs Actual Value for Output4-Bending Data

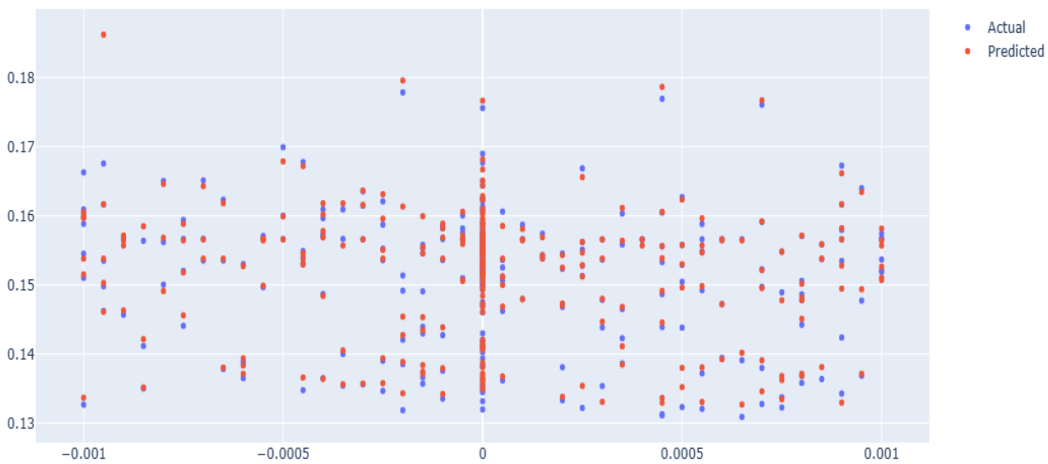


Figure 5.14: Predicted Vs Actual Value for Output5-Bending Data

5.4 TWISTING DATA SET

The results obtained from the bending data indicate that the reduced order model achieved an accuracy of over 94%. Although this accuracy is slightly lower than that obtained from the axial and bending data set, it is important to note that the twisting data set had a smaller number of data points. Moreover, the reduced order model outperformed the neural network model, which suggests that it is a more effective modeling approach. The table below presents the accuracy of each output, as well as the overall accuracy achieved

Table 5.3: Results -Twisting Data

Output	Accuracy (R2 score)
Output1	99.7
Output2	95.5
Output3	97.7
Output4	95.6
Output5	94.6
Overall Accuracy	95.1

Following figures show that variations between predicted value and Actual values of Output1(Resultant displacement of the Axial unit cell) for Reduced order model and and Neural network model

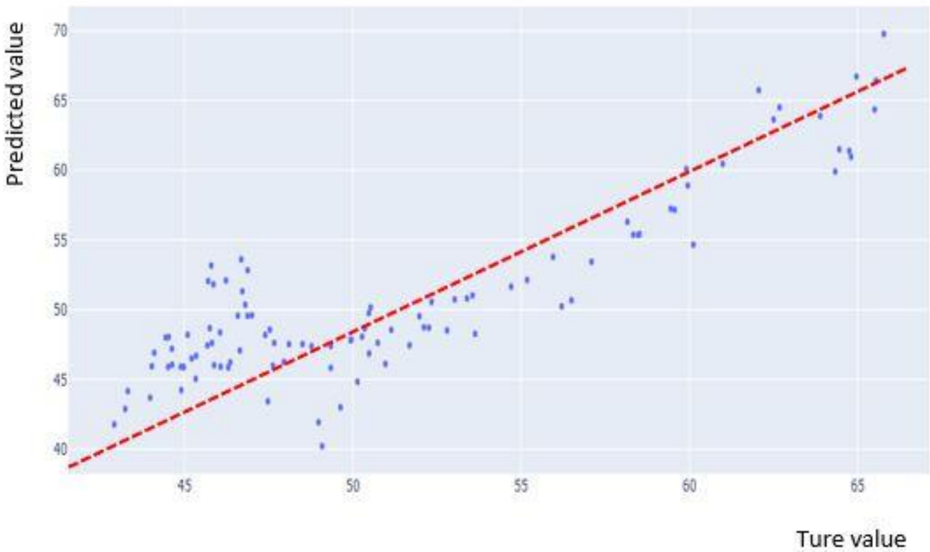


Figure 5.15: Predicted Vs Actual Value (Resultant Displacement) for Reduced order model -Twisting Data

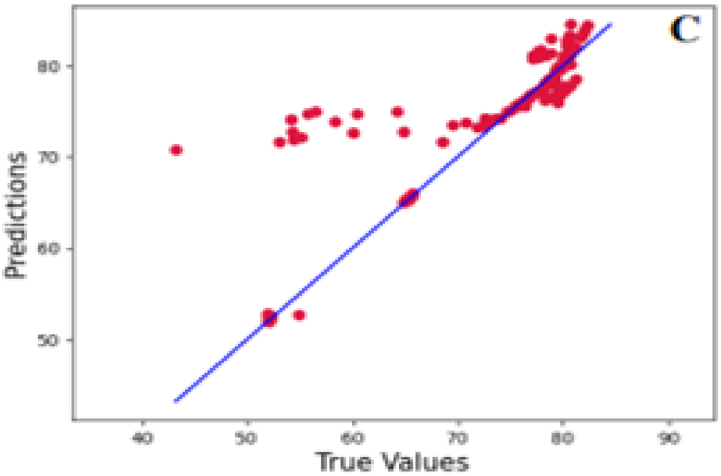


Figure 5.16: Predicted Vs Actual Value(Resultant Displacement)

for Neural Network Model -Twisting Data

Following figures show that variations between predicted value and Actual values of all Output of axial data set for Reduced order model

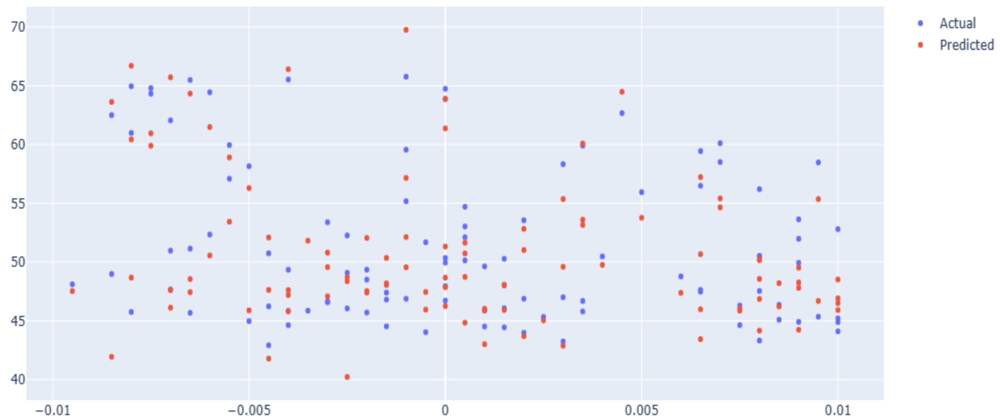


Figure 5.17: Predicted Vs Actual Value for Output1-Twisting Data

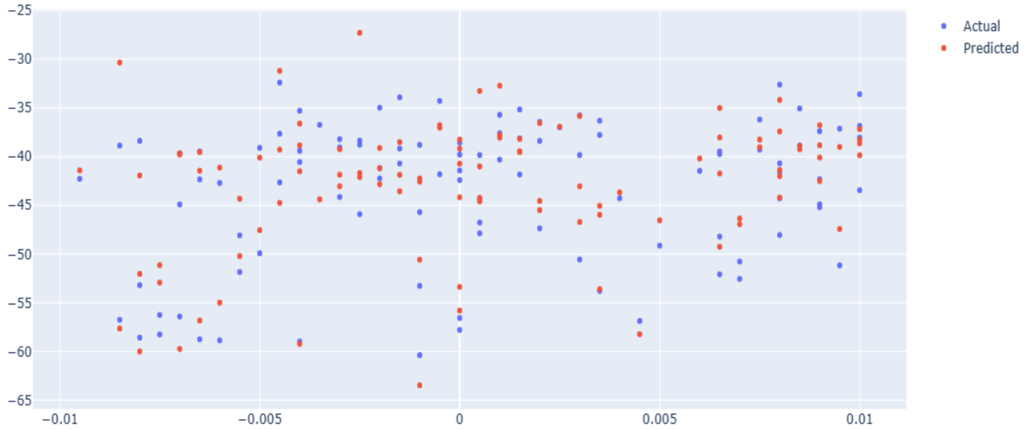


Figure 5.18: Predicted Vs Actual Value for Output2-Twisting Data

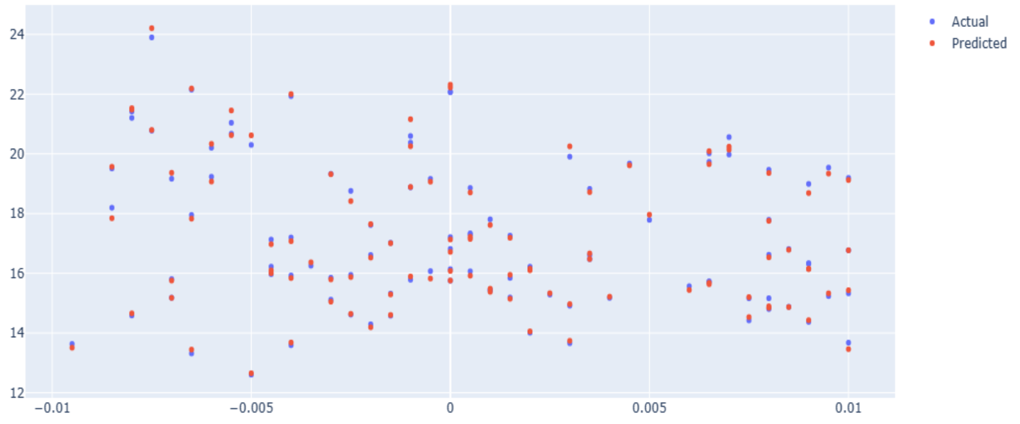


Figure 5.19: Predicted Vs Actual Value for Output3-Twisting Data

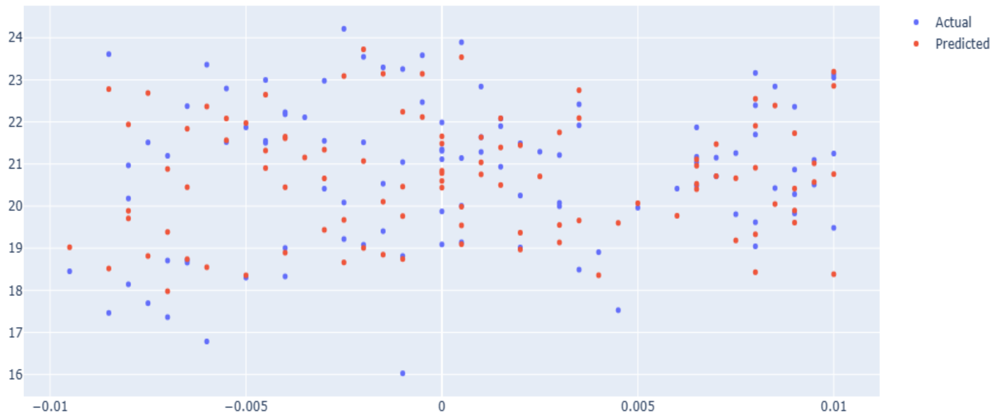


Figure 5.20: Predicted Vs Actual Value for Output4-Twisting Data

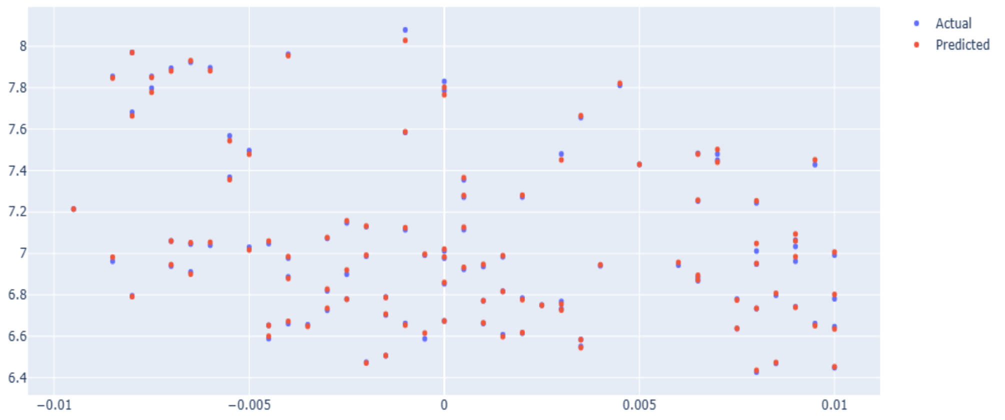


Figure 5.21: Predicted Vs Actual Value for Output5-Twisting Data

CONCLUSIONS AND RECOMMENDATIONS

In conclusion, this project has successfully developed a mathematical model for a soft pneumatic driven robot hand with the capability of performing axial, bending, and twisting movements. The model was developed using simple mathematical imputations and achieved high precision and accuracy in controlling the robot hand. We also compared our model with a neural network model developed for the same task.

In this project, we developed a reduced order machine learning model for a soft pneumatic robot hand, with the aim of achieving high accuracy in predicting the hand's behavior using simple machine learning models instead of neural networks. We successfully achieved our goal, obtaining an overall accuracy greater than 97% using reduced order model.

Our model's high accuracy makes it a promising tool for controlling and optimizing the behavior of soft pneumatic robot hands. By accurately predicting the hand's movements and forces, our model can be used to design more efficient and reliable robotic hands for various applications, such as prosthetics, rehabilitation, and manipulation tasks. The use of reduced order models also has the potential to reduce computational complexity and improve real-time performance, making it more feasible to deploy such robots in practical settings. In addition to its practical applications, our project has several research implications. By demonstrating the effectiveness of reduced order models for soft pneumatic robot hands, we contribute to the growing field of machine learning for robotics. We also provide a new approach for predicting the behavior of soft robots, which can be extended to other types of soft robots, such as soft sensors and actuators.

Although our reduced order machine learning model showed high accuracy, there is still room for improvement. Here are some recommendations for future work: First, it would be useful to investigate the performance of our model on a larger dataset, with more diverse and complex hand motions. This would provide a more comprehensive evaluation of our model's accuracy and generalization capabilities, and help identify potential limitations and challenges in applying our model to real-world scenarios.

Second, we suggest exploring the use of other machine learning models, such as decision trees and support vector machines, and comparing their performance with our current model. This would provide insights into the strengths and weaknesses of different machine learning approaches for soft pneumatic robot hands and help identify the optimal approach for a given application.

Third, we recommend considering the integration of our model with real-time feedback and control systems to improve the accuracy and responsiveness of the robot hand. This would enable the hand to adapt to changing conditions and user inputs and enhance its usability and safety.

Finally, we suggest evaluating the robustness and generalization capabilities of our model in different environments and conditions, such as varying temperatures, pressures, and humidity levels. This would provide a more comprehensive evaluation of our model's suitability for different applications and settings and help identify potential challenges and opportunities for future development.

Overall, our project demonstrates the potential of reduced order machine learning models for soft pneumatic robot hands and opens up new avenues for future research and development. Our findings contribute to the growing field of machine learning for robotics and provide a new approach for predicting the behavior of soft robots, with potential applications in various fields, from healthcare to manufacturing.

FUTURE SCOPE

The development of reduced order machine learning models for soft pneumatic robot hands has opened up several promising avenues for future research and development. Firstly, the use of reduced order models can be extended to other soft robotic components, such as soft sensors and actuators. By combining different components into a single system, it may be possible to create more complex and versatile soft robots with improved functionality and performance.

The integration of our model with real-time feedback and control systems can enhance the accuracy and responsiveness of the robot hand. This can enable the hand to adapt to changing conditions and user inputs, and improve its usability and safety. Further research can explore the use of different feedback and control mechanisms, such as vision-based feedback and reinforcement learning, to improve the performance of the robot hand.

Our model can be used to optimize the design of soft pneumatic robot hands for various applications, such as prosthetics and rehabilitation. By simulating different design parameters, such as the number and location of pneumatic chambers, it may be possible to identify the optimal design for a given application. This can enable the development of soft robotic devices that are tailored to the specific needs of users, thereby improving their effectiveness and usability.

The integration of our model with human-robot interaction techniques can enable more intuitive and efficient control of the robot hand. Soft pneumatic robot hands have the potential to improve the quality of life of individuals with disabilities or injuries. By incorporating natural language processing and gesture recognition techniques, it may be possible to create soft robotic systems that are more user-friendly and accessible to a wider range of users.

Finally, the use of soft robots in manufacturing and industrial automation is gaining attention due to their flexibility and adaptability. Our model can be extended to develop soft robotic systems for various industrial applications, such as pick-and-place tasks and assembly operations. This can enable the development of robotic systems that are more efficient, versatile, and capable of performing a wider range of tasks.

Our project has demonstrated the potential of reduced order machine learning models for soft pneumatic robot hands and has provided a foundation for future research and development in this field. By exploring these and other directions, it may be possible to create soft robotic systems that are more efficient, versatile, and user-friendly, and can make a significant impact on various fields such as healthcare, manufacturing, and automation.

REFERENCES

[1] "Soft Robotics: A Review of the State of the Art and Challenges" by J. A. Calixto, E. R. John, and T. J. Dawson, published in the journal "Robotics and Autonomous Systems" (2015)

[2]"A Review of Soft Robotics: Materials, Actuators, Sensors, and Control" by D. Rus, G. S. Sukhatme, and R. Nagpal, published in the journal "Advanced Materials" (2015)

[3]"Soft Robotics: A New Frontier in Robotics Research" by S. K. Saha, S. Caluwaerts, and R. D. Grebel, published in the journal "IEEE Robotics and Automation Magazine" (2015)

[4]"Soft Robotics: Past, Present, and Future" by S. Caluwaerts, S. K. Saha, and R. D. Grebel, published in the journal "IEEE Robotics and Automation Letters" (2016)

[5]"A Review of Soft Robotics: From Materials to Systems" by K. K. Ge, X. L. Hu, and R. D. Grebel, published in the journal "Frontiers in Robotics and AI" (2019)

APPENDICES

[1] Data Visualization

[2] Flex Robot modeling