



# Neural Network Approach to the Inverse Kinematic Control of Robotic Manipulator

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**IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR  
THE AWARD OF THE DEGREE BACHELOR OF  
ENGINEERING**

# CERTIFICATION

This is to certify that the project work titled “Neural Network Approach to the Inverse Kinematic Control of Robotic Manipulators” was carried out by:

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# DEDICATION

We dedicate this project to the Almighty God and all who have supported us throughout our academic journey.

# ACKNOWLEDGEMENTS

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# ABSTRACT

Robots are becoming more relevant across multiple industries; therefore, it is important for engineers to innovate in all aspects of this technology. This Project explores the concept of inverse kinematic control in robotics, its significance, difficulties and explores a solution using Neural networks. It presents an analysis of the forward kinematics of various robot arms-using the Denavit-Hartenberg method- as a way to generate the data set for training and testing the Neural network, until a suitable performance benchmark was reached.

The information on the robot arms that were analyzed was gotten from manufacturers publications, open to the public. Some of the robot arms considered includes; ABB IRB 1600; a 6dof robot arm, FANUC LR Mate 200iC; a 6dof robot arm, The Universal Robots UR10; a 6dof robot arm, among others. This project considers one of the simplest machine learning models for regression analysis, the Artificial Neural Network (ANN)

The trained model displayed high accuracy in predicting the suitable joint angles, with all trained models having a R squared value above 0.70

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# Chapter 1

## Introduction

### **1.1. Background to study**

A robot manipulator can be referred to as a mechanical component that is designed to manipulate various objects in its environment with the aim of carrying out various tasks. In present day Robotic manipulators are used in many various fields such as medicine, machine manufacturing, space exploration, military, etc. In these fields, robots are given tasks that are too complex, dangerous or impossible for humans to do. The introduction of robotics into an industry is usually marked by improved productivity and profitability of the industry.

Robot manipulators can perform various tasks depending on the industry and problem application. These tasks can include material handling, welding, painting, assembling of parts, packaging, handling hazardous materials, operations.

Robotic manipulators for a task are chosen based on parameters such as work envelope (which is the region or space were the robot can operate in) and the degree of freedom of the robotic manipulator, the degree of freedom determines the type of motion the end effector/tool of the robotic arm can under go and also the type of position the tool/end effector can assume in space, with a low degree of freedom robotic arm having limited types of motion and poses, and a high degree of freedom robotic arm has higher variability in the type of motion it can undergo and poses it can assume.



Figure 1-1 A robotic manipulator holding a camera

## 1.2. Statement of problem

Robots are becoming more relevant across multiple industries; therefore, it is important for engineers to innovate in all aspects of this technology.

The concept of inverse kinematic control in robotics is significant as it greatly aids the automation of processes using Robots, this is an important problem as most of the times in the industry robots are required to do tasks that can only be accomplished with inverse kinematics (only the end effector details as known), tasks which may include, surgery, painting, machining, 3d printing, etc. However, inverse kinematic equations are difficult to solve analytically therefore it becomes important that we have methods that give inverse kinematics solutions quickly with a high degree of accuracy.

Methods that can be used in solving inverse kinematics problems of robot manipulators include;

- Abridged analytical methods
- Numerical analysis methods
- Machine learning techniques

## **1.3. Aim**

The aim of this project is to build an Artificial Neural Network model capable of solving the inverse kinematics problem of 6 DOF Robotic Manipulators and implement in their control

## **1.4. Objectives**

- Identifying neural network models relevant to the solution of inverse kinematics of complex robotic manipulators
- Build a neural network capable of solving the inverse kinematics of complex robotic manipulators

## **1.5. Scope of Project**

This project covers

- Making a forward kinematic analysis of the robotic arm to generate joint angles and end effector data pairs.
- Building, Training and testing an Artificial Neural Network model for the inverse kinematics of the selected robotic arms with the data gotten from their forward kinematics analysis.
- Analyzing and studying the results from the ANN model

## **1.6. Methodology**

- Research and selection of popular robotic arms with useful applications
- Research on methods for forward kinematics and inverse kinematic analysis of robot arms
- Research on suitable Artificial Intelligence models for Inverse kinematics of selected robot arms
- Analyze and generate data sets on the selected robot arms
- Build and train Artificial Intelligence on the datasets generated
- Test and evaluate the performance of the models

- Draw conclusions based on the results

# Chapter 2

## Literature Review

### **2.1. Robotic manipulators: significance and uses**

Robotics is a rapidly growing and versatile field with widespread applications in manufacturing, healthcare, transportation, and various other industries. Robots effectively undertake dangerous, repetitive, or arduous tasks, enhancing productivity, efficiency, and safety. Additionally, they offer opportunities for companionship, education, and entertainment, enriching our lives in multiple dimensions.(Wagaa et al., 2023)

In manufacturing, robots aid in welding, assembly, and painting, augmenting productivity and product quality while minimizing workplace injuries. In healthcare, they contribute to surgery, rehabilitation, and companionship for elderly patients, improving care quality and reducing healthcare costs. Robots play vital roles in transportation through self-driving cars, delivery services, and airport maintenance, enhancing safety, efficiency, and convenience. In education, robots engage students in subjects like science, engineering, and mathematics, making learning more interactive and captivating. Moreover, robots perform entertaining tasks, from show performances to providing companionship and interactive gaming experiences.

Robotic technology continues to advance, making robots more sophisticated, versatile, and affordable. As they expand their capabilities, robots will find even more extensive applications in various aspects of our lives. However, challenges such as cost, safety, and public acceptance remain to be addressed. Despite these challenges, the benefits of robotics, including increased productivity, enhanced safety, reduced costs, and improved product and service quality, outweigh the drawbacks. As robots continue to evolve, they hold the potential to revolutionize multiple industries and positively impact our daily lives.

A Robotic manipulator is a machine that is used to manipulate objects in the environment. It is a type of robot that has a structure consisting of several rigid links connected by joints. The joints allow the links to move relative to each other, which gives the manipulator the ability to move its end-effector (the part of the manipulator that interacts with the environment) in a variety of ways. The number of links in a robotic manipulator can vary. The links are typically made of metal, such as aluminum or steel, but they can also be made of other materials, such as carbon fiber. The joints in a robotic manipulator can be either rotary or linear. Rotary joints allow the links to rotate around a fixed axis, while linear joints allow the links to move back and forth in a straight line. The type of joints that are used in a robotic manipulator determines the range of motion that the manipulator has. For example, a manipulator with rotary joints can only rotate the links, while a manipulator with linear joints can only move the links back and forth. The type of joints also affects the speed and accuracy with which the manipulator can move.

The end-effector of a robotic manipulator is the part of the manipulator that interacts with the environment. The end-effector can be a variety of different devices, such as a gripper, a welding torch, or a camera(fig 1-1).

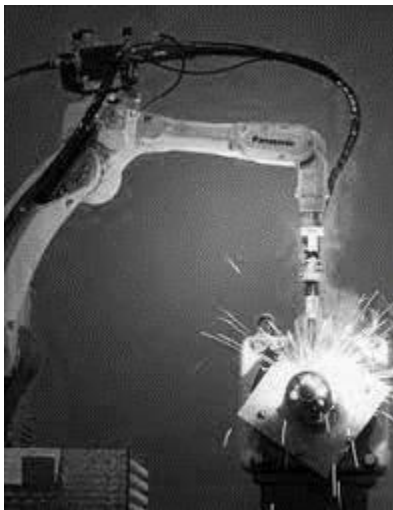


Figure 2-1 A robotic manipulator welding

The motion of a robotic manipulator is controlled by its control system. The control system receives input from the manipulator's sensors, such as cameras and proximity sensors, and uses this input to generate commands for the actuators. The control system must be able to track the position and orientation of the end-effector, as well as the forces and torques that are acting on it.

Some common applications for robotic manipulators include:

- Manufacturing: Robotic manipulators are used in manufacturing to automate tasks such as welding, painting, and assembly. (Filipescu et al., 2020)
- Medical: Robotic manipulators are used in medicine to perform surgery, deliver medication, and assist with rehabilitation.
- Search and rescue: Robotic manipulators are used in search and rescue to locate and extract victims from hazardous environments.
- Space exploration: Robotic manipulators are used in space exploration to assemble and maintain spacecraft, as well as to collect samples from other planets.

Robotic manipulators are versatile machines that can be used in a wide variety of applications. As the field of robotics continues to develop, we can expect to see even more innovative and sophisticated robotic manipulators being developed in the future.

- The number of degrees of freedom (DOF) of a robotic manipulator is the number of independent ways that the end-effector can move. The DOF of a robotic manipulator is determined by the number of links and joints in the manipulator.
- The reach of a robotic manipulator is the maximum distance that the end-effector can reach from the base of the manipulator. The reach of a robotic manipulator is determined by the length of the links in the manipulator.
- The payload of a robotic manipulator is the maximum weight that the end-effector can carry. The payload of a robotic manipulator is determined by the strength of the links and joints in the manipulator

### **2.1.1. Parallel manipulators**

Parallel manipulators are made up of a series of parallel links and joints. The end-effector is attached to the end of the parallelogram formed by the links. Parallel manipulators have a smaller range of motion than serial manipulators, but they are easier to control. (Hu, 2014)

### **2.1.2. Serial manipulators**

A serial manipulator is a type of robotic manipulator that is made up of a series of links and joints that are connected in a chain. The end-effector is attached to the last link in the chain. The links are typically made of metal, such as aluminum or steel, but they can also be made of other materials, such as carbon fiber. The joints in a serial manipulator can be either rotary or linear. Rotary joints allow the links to rotate around a fixed axis, while linear joints allow the links to move back and forth in a straight line. The motion of a serial manipulator is achieved by the rotation of the joints in the chain. The rotation of each joint causes the next link in the chain to rotate, and so on. This causes the end-effector to move in a specific direction. The range of motion of a serial manipulator is limited by the number of links and joints in the chain. Serial manipulators are the most common type of robotic manipulator. They are relatively simple to control and they are versatile.(Hu, 2014),

## **2.2. Forward Kinematics**

The process of determining the end-effector's position and orientation (pose) in relation to a robot's base, given the joint angles and lengths of its links, is described by forward kinematics. A series of geometric transformations, typically involving the Denavit-Hartenberg parameters or transformation matrices, is used to calculate the transformation from one joint to the next, eventually reaching the end-effector. This critical calculation forms the basis for robot control, allowing the accurate navigation and manipulation of robotic arms in various applications, from manufacturing and surgery to space exploration and more. A fundamental understanding of

forward kinematics is deemed essential for programming robots to perform specific tasks with precision and efficiency.(Mohammad Amin, 2023)

## 2.3. Degrees of Freedom

Degrees of Freedom represents the number of independent parameters that define the configuration of a mechanical system. In the context of serial manipulators (also known as serial robotic arms), the DOF refers to the number of independent movements or joints the manipulator possesses.(Shah et al., 2013)

For a serial manipulator, the formula to calculate the DOF is given by:

$$\text{DOF} = N - (J + 1)$$

where:

- DOF is the Degrees of Freedom of the serial manipulator,
- N is the total number of links in the manipulator (including the end-effector or tool),
- J is the total number of closed loops in the manipulator's kinematic chain.

The term  $(J + 1)$  accounts for the constraint introduced by the closed kinematic loops. In a serial manipulator, each joint introduces one degree of freedom (rotation or translation) except for the last joint (end-effector) which has one less DOF as it is restricted to follow the motion of the last link.

It's important to note that this formula assumes that the manipulator is in its fully constrained state, i.e., all joints are actuated and controllable. In some cases, manipulators may have passive or redundant degrees of freedom, which are not powered or controlled. In such instances, the DOF calculation may need to be adjusted accordingly.(Fang & Tsai, 2003)

Forward kinematics is achieved by considering the joint angles and link lengths to sequentially determine the pose of each joint, eventually yielding the overall pose of the end-effector. In essence, forward kinematics establishes a mathematical relationship that enables us to map joint

configurations to the position and orientation of the robot's working end, serving as a crucial component in robot control and path planning.

The Denavit-Hartenberg (DH) parameters convention is a systematic method used in robotics to describe the geometry and kinematics of robotic manipulators. Four parameters are assigned to each joint-link connection: the link length ( $a$ ), the link twist ( $\alpha$ ), the link offset ( $d$ ), and the joint angle ( $\theta$ ). These parameters establish a standard reference frame for each joint, allowing for consistent and efficient forward and inverse kinematics calculations. The DH convention simplifies the representation of complex robot structures and enables the construction of transformation matrices that describe the relative pose of successive joints in a manipulator, facilitating precise control and motion planning.

The rationale underlying the Denavit-Hartenberg (DH) parameters lies in the idea that these four parameters [the link length ( $a$ ), link twist ( $\alpha$ ), link offset ( $d$ ), and joint angle ( $\theta$ )] represent the essential types of motion needed to align one axis with the previous one in a robotic manipulator. By systematically defining these parameters the DH convention establishes a standard framework that allows for the precise description of relative motion between adjacent links.

## 2.4. Inverse kinematics

The necessity of inverse kinematics in robotic manipulators lies in its role of calculating the joint angles or configurations required to attain a desired end-effector position and orientation. It is crucial for robot control and precise motion planning.

Inverse kinematics involves using the desired end effector position and pose to calculate the joint angles that will lead to the positions. It is difficult to solve due to its inherent complexity arising from the non-linear and often highly coupled relationships between joint angles and the end-effector's position and orientation. Inverse kinematics becomes particularly challenging for robots with complex geometries and multiple degrees of freedom, as solving for the required joint angles involves solving non-linear equations with multiple variables, which can have multiple solutions or even be unsolvable in certain configurations.

## 2.5. Analytical Solutions

Analytical solutions of the inverse kinematics of robot arms involve the use of geometric principles to get an expression or a series of expressions that maps the end effector position to the Robot parameters (A. Raheem et al., 2016)(joint variables).

Advantages:

- **Speed and efficiency:** Analytical methods can be faster and more efficient than numerical methods, especially for simple robotic arms. This is because analytical methods do not require iterative calculations, which can be time-consuming.
- **Range of applicability:** Analytical methods can be used to solve a wider range of IK problems than numerical methods. This is because analytical methods are based on the underlying geometry of the robotic arm, which can be used to derive closed-form solutions for the inverse kinematics problem.
- **Robustness to errors:** Analytical methods can be more robust to errors in the input data than numerical methods. This is because analytical methods do not rely on iterative calculations, which can be sensitive to errors.

Disadvantages:

- **Limited applicability:** Analytical methods may not be able to solve all IK problems. This is because analytical methods are based on the underlying geometry of the robotic arm, and some robotic arms may have geometries that cannot be represented by analytical methods.
- **Complexity:** Analytical methods can be more complex to implement and use than numerical methods. This is because analytical methods require a deeper understanding of the underlying geometry of the robotic arm.
- **Accuracy:** Analytical methods may not be as accurate as numerical methods. This is because analytical methods are based on simplified models of the robotic arm, and these models may not be accurate enough for some applications.

Although computationally tasking Analytical solutions of arms may exist such as  
But they are outside the scope of this report

## 2.6. Neural Networks

Inverse kinematics (IK) is a challenging problem in robotics, involving determining the joint angles of a robotic arm to position the end-effector at a desired location. Traditional methods like analytical and numerical approaches can be computationally expensive and sensitive to errors in input data, making real-time solutions difficult. However, machine learning methods such as neural networks (NNs) present a promising alternative for IK problem-solving.(Tarkhov et al., 2023)

ML algorithms can be trained on known IK solutions, enabling them to efficiently predict joint angles for new target positions in real-time applications. Moreover, ML's robustness to input data errors allows for accurate results even with imperfect data. The flexibility of ML algorithms also permits them to be adapted to various robotic arms and applications, as they can learn from diverse datasets.(A. Raheem et al., 2016)

Advantages of ML and NNs in IK include improved efficiency, making them suitable for applications requiring rapid responses to environmental changes. Their robustness enhances reliability, overcoming limitations of traditional methods. ML's ability to adapt to various IK problems further broadens their potential applications.

The increasing popularity of ML and NNs for IK in robotics is evident in successful applications, such as controlling robotic arms in manufacturing, leading to heightened productivity and precision. In surgical settings, ML algorithms enable more accurate and less invasive procedures. Moreover, in search and rescue missions, ML-controlled robotic arms have played a crucial role in saving lives during disaster situations.

As ML and NN technologies continue to advance, their significance in IK problem-solving in robotics is expected to grow. This development will expand the capabilities of robotic arms, leading to their application in a wider range of fields and enhancing the efficiency and reliability of robotics as a whole

## 2.7. Similar work done in the past

(Šegota et al., 2021) utilized a Feed Forward Multilayer Perceptron to calculate the inverse kinematics of robotic manipulators, the model was trained using Homogenous transformation matrices gotten with the aid of the Denavit-Hartenberg Convention. Multiple models, with varying combinations of hyperparameters (), were built and trained to determine the optimum combination of parameters,

(Kamlesh Shah et al., 2020) employed the use of MATLAB to build and train a Deep Artificial Neural Network to solve the inverse kinematics of a 5 Axis (or 5dof) serial Robot, with rotary joints, (an articulated robot arm) The data set for training the model was generated using the forward kinematics transformation matrix of the robot arm, an experimental model of the robot arm was built to validate the solutions generated by the DANN model, end effector positions were measured in real time with a smart camera system and image processing software. The experiment recorded a deviation of  $\pm 0.1$  rads.

(Ibarra-Pérez et al., 2022) uses a dataset optimization technique based on the Taguchi optimization technique( a technique that...) on the dataset used to train an Artificial Neural Network on the inverse kinematics of a 6 DoF robotic manipulator. The model reached a high percentage of accuracy in prediction, maintaining a margin of error of less than 5%

(Lu et al., 2022) proposes a strategy called “joint space segmentation” in building and training a Multilayer Perceptron (MLP) for the inverse kinematics of 6Dof robot arms

They use an architecture where two models are trained simultaneously, one model is responsible for 5 outputs (representing 5 joint angles) and the other model is responsible for the remaining 1 output (representing the last joint angle), The method showed higher accuracy compared to other models

(Tagliani et al., 2022) uses scaled conjugate as a method of training an ANN for the Inverse kinematics of Robotic manipulators, the dataset used to train the model was generated using the Denavit-Hartenberg Parameters conventions, the experiment was validated with the simulation of

a 6dof robot (IRB140) with the ABB Robot studio software and experimentally with a 6 DOF robot (FANUCLRMate200iC) The project recorded a mean absolute error of 0.370-0.699mm

(Castellani et al, 2008) tests the effectiveness of the Bees Algorithm (a parameter optimization algorithm motivated by the foraging patterns of Honey Bees) in training Multilayer Perceptron Neural Networks to solve the inverse kinematics of an Articulated Robotic Arm. The experiment was compared with back propagation algorithm and an evolutionary algorithm. The results prove the remarkable robustness of the Bees Algorithm, which consistently trained the neural networks to model the kinematics data with very high accuracy

# Chapter 3

## Methodology

### 3.1. Kinematic Analysis of Robots using The Denavit-Hartenberg (DH) convention

The Denavit-Hartenberg (DH) convention is a useful method for calculating the forward kinematics of a robotic arm. It standardizes the representation of a robotic arm's geometry, simplifying forward kinematics calculations. Understanding forward kinematics is fundamental in robotic arm design, control, and programming, enabling engineers to grasp arm movement and optimize its performance effectively. Rather than attaching reference frames to each link in an arbitrary fashion, in the Denavit-Hartenberg convention a set of rules for assigning link frames is observed

The DH convention defines four parameters for each link in a robot:

1. The link twist  $\alpha_{i-1}$  is the angle from  $\hat{z}_{i-1}$  to  $\hat{z}_i$ , measured about  $x^{i-1}$ .
2. The link offset  $d_i$  is the distance from the intersection of  $x^{i-1}$  and  $\hat{z}_i$  to the origin of the link- $i$  frame (the positive direction is defined to be along the  $\hat{z}_i$ -axis).
3. The joint angle  $\phi_i$  is the angle from  $x^{i-1}$  to  $x^i$ , measured about the  $\hat{z}_i$ -axis.
4. The length of the mutually perpendicular line, denoted by the scalar  $a_{i-1}$ , is called the link length of link  $i-1$ .

The DH parameters are usually listed in a table, with one row for each link in the robot. The table is then used to construct a transformation matrix for each link, which can be used to calculate the position and orientation of the end-effector of the robot.

consider a DH table for a 6-DOF serial manipulator:

Table 3-1 example of DH parameter table

Link	Link Length (a)	Link Twist( $\alpha$ )	Link Offset (d)	Joint Angle ( $\theta$ )
1	a1	$\alpha1^\circ$	d1	$\theta1$
2	a2	$\alpha2^\circ$	d2	$\theta2$
3	a3	$\alpha3^\circ$	d3	$\theta3$
4	a4	$\alpha4^\circ$	d4	$\theta4$
5	a5	$\alpha5^\circ$	d5	$\theta5$
6	a6	$\alpha6^\circ$	d6	$\theta6$

The DH table specifies the location and orientation of the coordinate frames attached to the links of the robot. The first column lists the link number, the second column lists the distance between the  $z$ -axes of the two links, the third column lists the angle between the  $z$ -axes of the two links, the fourth column lists the distance between the  $x$ -axes of the two links, and the fifth column lists the angle between the  $x$ -axes of the two links.

## **3.2. Materials**

The Robot arms considered for this project and their Denavit-Hartenberg tables are presented in the following:

### **3.2.1. ABB IRB 1600**

The first arm considered is the ABB IRB 1600. It is an industrial robot arm designed and manufactured by ABB Robotics, one of the world's leading robotics companies.

The ABB IRB 1600 is a 6-degree-of-freedom (6-DOF) industrial robot arm, i.e. it has six rotational joints that allow it to move in multiple directions. It is designed for a wide range of manufacturing and automation applications, including welding, material handling, assembly, and more. It has compact design, high precision, and flexibility, making it suitable for various industries and production environments.

A picture of the arm can be shown below.

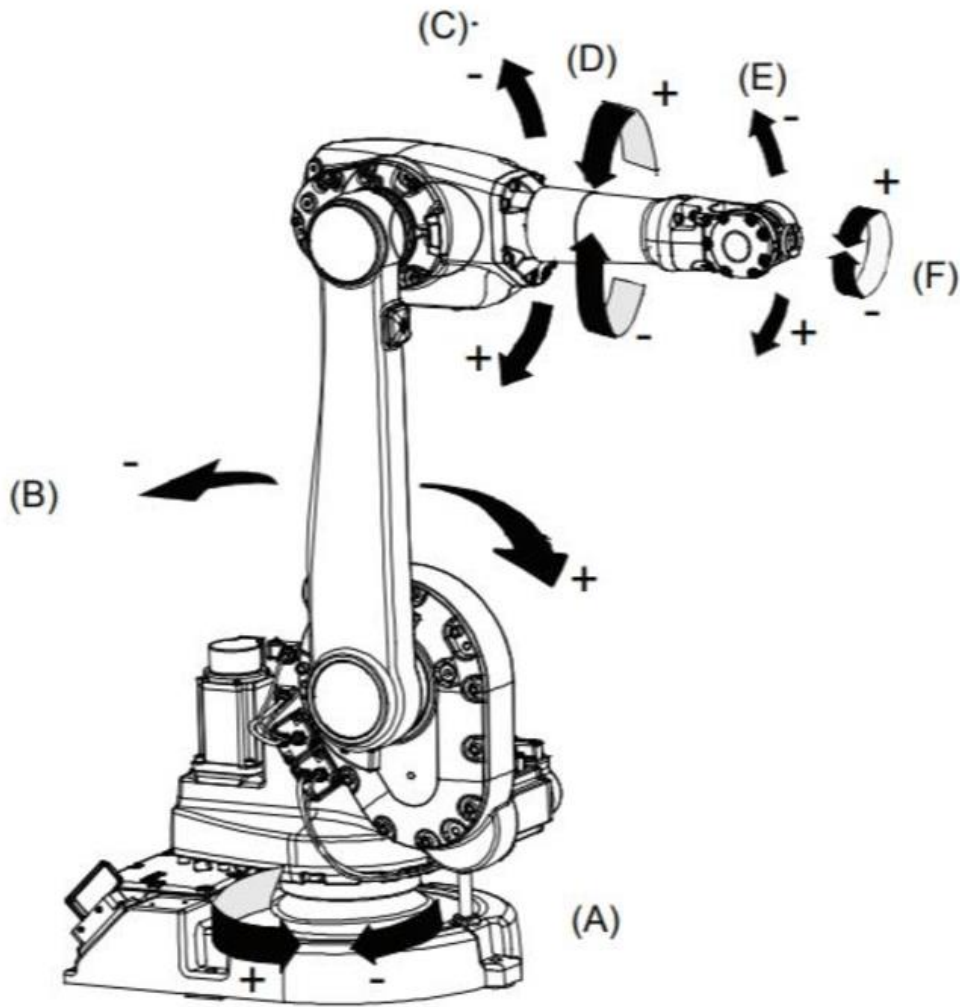


Figure 3-1 The ABB IRB 1600

Table 3-2 DH table for The ABB IRB 1600

s/n	$\theta$	$\alpha$	r	d
1	$\theta_1$	90	0.3	0.649
2	$\theta_2$	0	1.2	0
3	$\theta_3$	90	0.250	0
4	$\theta_4$	90	0	1.320
5	$\theta_5$	90	0	0

6	$\Theta_6$		0	0.290
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### 3.2.2. THE FANUC LR MATE 200IC

The FANUC LR Mate 200iC is an industrial robotic arm developed by FANUC Corporation, a Japanese robotics company. It is known for its compact size, high precision, and versatility in a wide range of industrial applications. The LR Mate 200iD is designed to perform various tasks, including material handling, assembly, and machine tending.

A picture of the arm can be shown below.

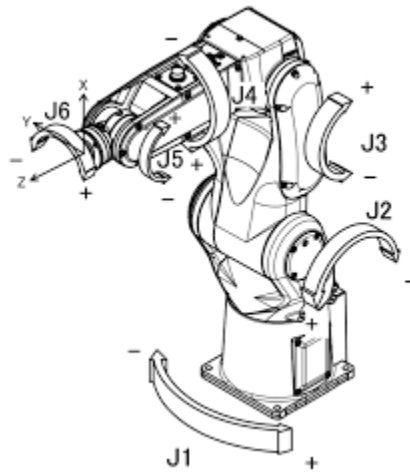


Figure 3-2 The FANUC LR Mate 200iC

Table 3-3 DH table for The FANUC LR Mate 200iC

s/n	$\Theta$	$\alpha$	r	d
1	$\Theta_1$	-90	75	330
2	$\Theta_2$	180	300	0
3	$\Theta_3$	90	-75	0
4	$\Theta_4$	-90	0	-320

5	$\theta_5$	90	0	0
6	$\theta_6$	180	0	-80

### 3.2.3. THE UNIVERSAL ROBOT UR10

The Universal Robots UR10 is a collaborative robotic arm designed and manufactured by Universal Robots, a Danish robotics company. The UR10 is part of Universal Robots' line of collaborative robots, also known as COBOTS. These robots are intended to work safely alongside humans in various industrial and commercial applications, enhancing productivity and flexibility in manufacturing environments.

A picture of the arm is shown below;



Figure 3-3 The Universal robot Ur10

Table 3-4 DH table for The Universal Robot Ur10

$s/n$	$\theta$	$\alpha$	$r$	$d$
-------	----------	----------	-----	-----

1	$\theta_1$	90	0	127
2	$\theta_2$	0	612	0
3	$\theta_3$	0	572	0
4	$\theta_4$	90	0	164
5	$\theta_5$	-90	0	115
6	$\theta_6$	0	0	92

### 3.2.4. The Kuka KR Agilus industrial robot.

The KUKA KR AGILUS is a series of compact industrial robot arms manufactured by KUKA Robotics, a German robotics company known for its innovative automation solutions. They were initially designed to be fast, precise, and versatile, making it well-suited for various applications in industries like automotive, electronics, plastics, and more. Despite its compact size, the KR AGILUS robot offers high payload capacities and exceptional performance, making it ideal for tasks that require agility and accuracy.

A picture of the arm can be shown below;

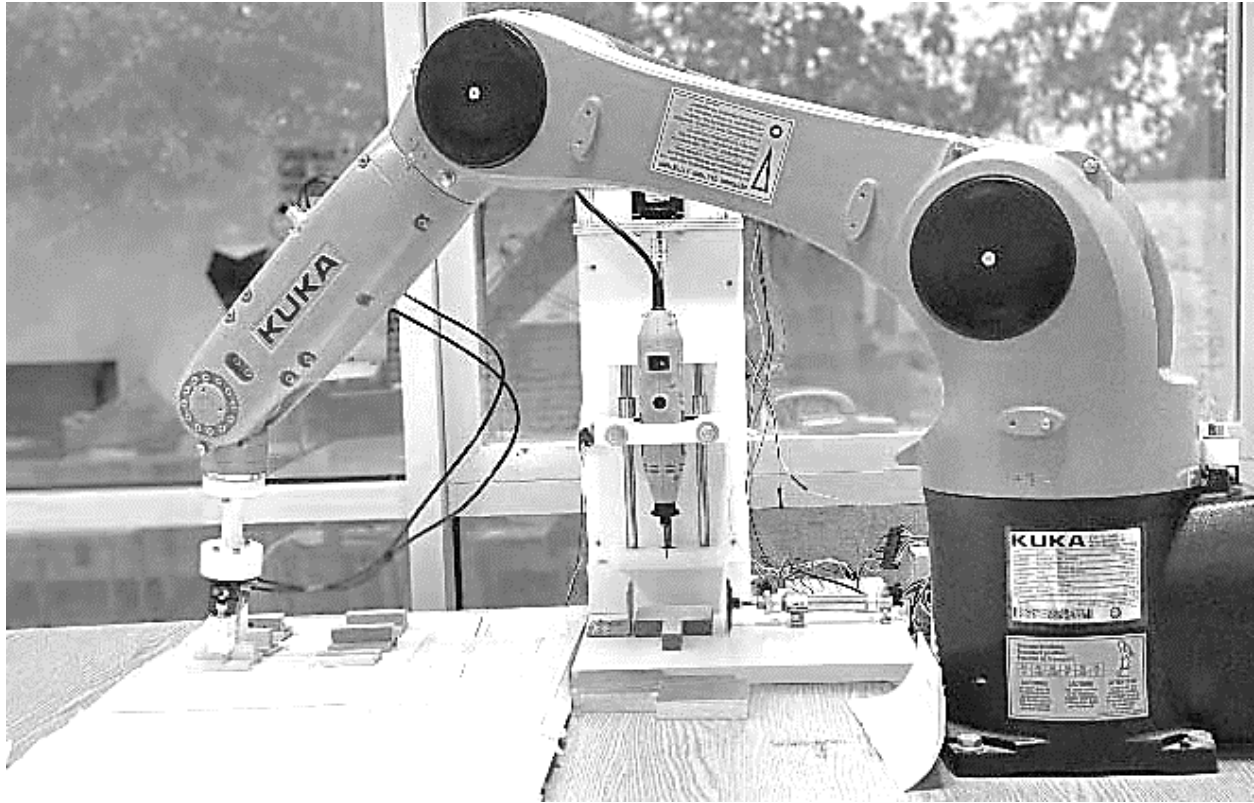


Figure 3-4 The KUKA KR AGILUS

Table 3-5 DH table for The KUKA KR AGILUS

s/n	$\theta$	$\alpha$	r	d
1	$\theta_1$	90	180	400
2	$\theta_2$	180	600	135
3	$\theta_3$	-90	120	135
4	$\theta_4$	90	0	620
5	$\theta_5$	-90	0	0
6	$\theta_6$	0	0	115

### 3.2.5. The Yaskawa Motoman GP series.

The Yaskawa Motoman GP series is a family of industrial robot arms that are designed and manufactured by Yaskawa Electric Corporation's Motoman Robotics division. They can be used for various automation applications in industries such as automotive, electronics, metalworking, and more. This is because they are mostly known for their versatility, high performance, and reliability, making it a popular choice for industrial automation tasks.

This analysis focuses on the Yaskawa Motoman GP7 model of the GP series. A picture of the arm can be shown below.



Figure 3-5 The Yaskawa Motoman GP

Table 3-6 DH table for The Yaskawa Motoman GP

s/n	$\theta$	$\alpha$	r	d
1	$\theta_1$	0	40	330
2	$\theta_2$	0	445	0
3	$\theta_3$	0	40	0

4	$\theta_4$	90	0	440
5	$\theta_5$	-90	0	0
6	$\theta_6$	-90	0	80

### 3.2.6. 4DOF ROBOT ARM

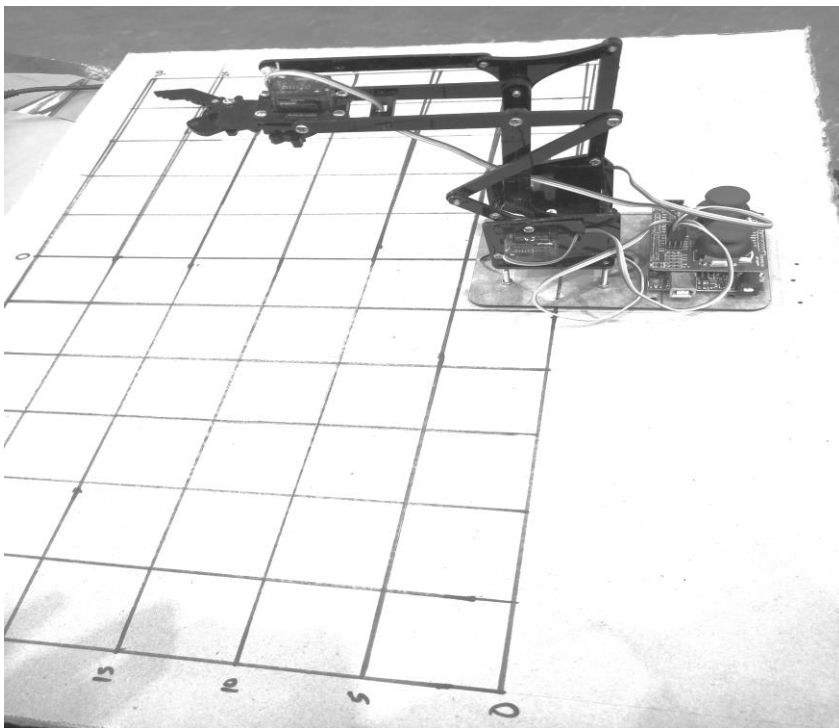


Figure 3-6 A 4 DOF Robot Arm

## 3.3. Neural Network Models

The model takes seven inputs which are a representation of the desired joint angles and outputs

- 6 values of the joint angles, in the case of the 6dof robots OR
- 4 values of joint angles in the case of the 4dof robot.

See appendix for code snippets

### 3.3.1. The NN Model for the 6DOF Manipulators

The NN Model for the 6DOF Manipulators was split in to two with each part responsible for 3 outputs only

Table 3-7 model architecture for the 6dof robotic arms (a)

layers	Input layer	Hidden layer1	Hidden layer2	Hidden layer3	Hidden layer4	Hidden layer5	Hidden layer6	Hidden layer7	Hidden layer8	Hidden layer 9	Output layer
Number of nodes	7	512	256	256	128	128	64	64	32	32	3
Type of activation function		ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	

Table 3-8 model architecture for the 6dof robotic arms (b)

layers	Input layer	Hidden layer1	Hidden layer2	Hidden layer3	Hidden layer4	Hidden layer5	Hidden layer6	Hidden layer7	Hidden layer8	Hidden layer 9	Output layer
Number of nodes	7	512	256	256	128	128	64	64	32	32	3
Type of activation function		ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	

### 3.3.2. The model architecture for the 4dof model

Table 3-9 model architecture for the 4dof robot arm

layers	Input layer	Hidden layer1	Hidden layer2	Hidden layer3	Hidden layer4	Hidden layer5	Hidden layer6	Hidden layer7	Hidden layer8	Hidden layer9	Output layer
Number of nodes	7	512	256	256	128	128	64	64	32	32	4
Type of activation function		ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU	

# Chapter 4

## Result

The Result of all the models built are presented below;

**Dataset generated for arms** :- The dataset generated for all the arms(the 6 dof arm models and the 4dof live testing model) was gotten by generating random angles while strictly following the specified range limit of each joint according to the manufacturer’s manual. A total of 100,000 different data entries were generated using a function to generate the dataset. For the 6dof models, a total of 6 different joint angle combinations were generated for each entry while for the 4dof model, a total of four different joint angle combinations were generated for each entry. Forward kinematics was done using this different joint angle combinations to obtain the quaternion representation and x,y,z position of the end effector for each joint angle. For the 6dof manipulators, the combination of the 6 joint angles, the quaternion representation, and the end effector position formed the total dataset (13 columns). While for the 4dof manipulator, the four joint angles, the end effector position, and the quaternion representation formed the total dataset (11 columns). This data was then split into training and test data for the neural networks model. Each of these angles are generated in radians for the models to be trained and evaluated on. The total generated dataset was split into 80,000 for training and 20,000 for test. Twenty out of the complete 100,000 data sets generated (training and test) for all the arm models can be shown below.

### 4.1. Arm 1

Table 4-1 Result comparison for each predicted vs actual (first 20 values of table)

<b>x_predicted</b>	<b>y_predicted</b>	<b>z_predicted</b>	<b>x_actual</b>	<b>y_actual</b>	<b>z_actual</b>
<b>2409.8541</b>	<b>190.7337</b>	<b>1157.5796</b>	<b>2387.0929</b>	<b>269.3849</b>	<b>1379.6588</b>

-1184.5587	2285.9261	140.2789	-1277.1028	2272.6844	46.3644
1828.2322	1396.2749	1636.1265	1719.9136	1294.9423	1867.5192
-1904.5516	1019.6171	-68.2975	-1980.5305	1055.0535	13.9894
-280.8689	2000.4092	1557.7839	-353.7540	1995.8426	1606.6902
-1171.8058	2253.8726	192.6211	-1070.1199	2203.8941	130.0086
1480.2687	1102.3807	1656.6080	1501.4472	987.8685	1773.2111
915.5779	1823.1846	2088.8874	875.1902	1843.0737	2147.1465
-709.5761	1082.3103	2998.1515	-648.5154	874.6369	2939.2040
2141.3110	276.6836	2106.7832	2055.7201	310.2088	2296.2594
-2295.3000	401.3176	72.8277	-2377.1927	356.4353	170.3101
439.3049	2072.6757	1817.9119	352.9935	2026.0235	1919.8006
-744.8202	632.5968	2872.0891	-439.4544	441.0260	2941.2973
1856.3986	1238.7889	-244.7906	1856.6838	1467.6098	-18.7268
1115.3468	2377.6561	439.3190	930.2274	2222.1807	345.4716
-875.0212	2384.3806	1581.4169	-975.5007	2140.3540	1954.8657
1618.0011	913.1367	-235.7239	1604.1660	953.7861	-217.1425
1592.6160	1255.5635	-0.3503	1457.4524	1346.4441	60.8205
1755.5468	99.9585	2095.2109	1647.6111	182.8979	2317.9147

-10.6199	2213.7995	278.1757	-11.6187	2237.8111	374.2108
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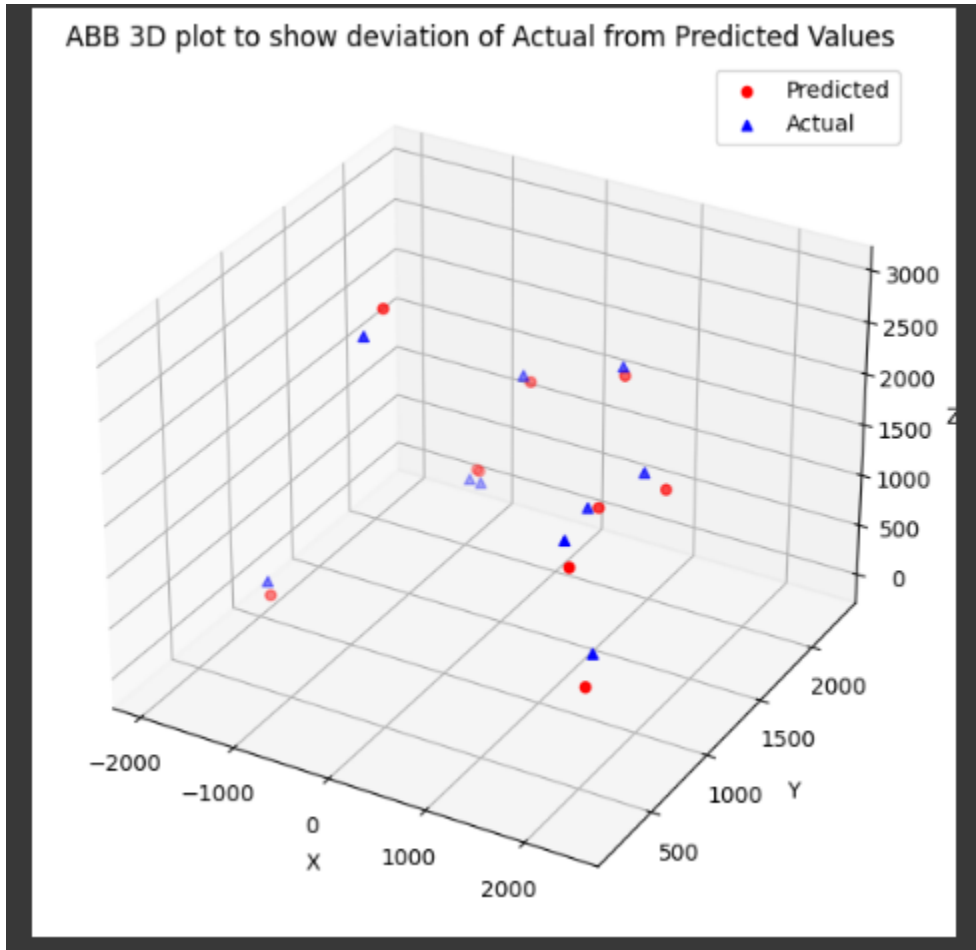


Figure 4-1 Result comparison for each predicted vs actual(graph)

### 4.1.1. Discussion

Form the tables and the graphs of the result above it was observed that the Neural Network model could predict the desired joint angles to a significant degree of accuracy, the worst performing models having errors within 1 to 2 decimal places

## 4.2. Arm 2

Table 4-2 Result comparison for the fanuc arm first 20 predicted vs actual values.

x_predicted	y_predicted	z_predicted	x_actual	y_actual	z_actual
302.8865	111.2329	456.7143	318.7981	111.6372	462.5276
-62.5091	63.7427	543.5907	-63.1501	59.1925	548.3676
128.3358	205.2312	449.7896	122.9626	196.4552	456.3627
-146.5845	88.4684	653.8550	-143.6651	70.1168	648.1994
-141.6141	400.3419	427.4375	-137.2669	400.5091	424.8362
-108.7351	189.7162	607.0702	-116.8793	191.1013	615.7218
334.0468	273.8032	312.0277	332.5049	292.3125	321.2323
10.9525	96.8377	467.9763	25.9097	104.3026	475.3968
-176.2844	79.8613	386.1423	-188.0324	85.7720	377.4940
-12.6643	78.7978	280.4204	-45.7883	59.6553	284.4882
-155.5138	-38.1914	578.1656	-140.7503	-48.4510	570.0675
5.9535	229.7219	490.3152	3.0095	216.8364	495.7398
-128.8176	31.5402	415.3602	-122.7231	12.7120	410.8432
17.9192	101.2634	533.7480	17.6708	100.0176	539.7666
94.6406	243.9582	599.1063	99.2731	254.0748	619.1675

-102.9502	35.1999	388.4167	-102.1033	29.0420	388.9069
225.3638	209.2584	659.9805	216.3452	193.4980	677.6174
259.7779	284.3523	642.9933	244.7312	295.5448	644.6179
308.3297	27.1843	445.0004	300.0858	46.4011	443.0746
-99.5246	321.2684	562.8790	-90.3326	353.0322	569.9731

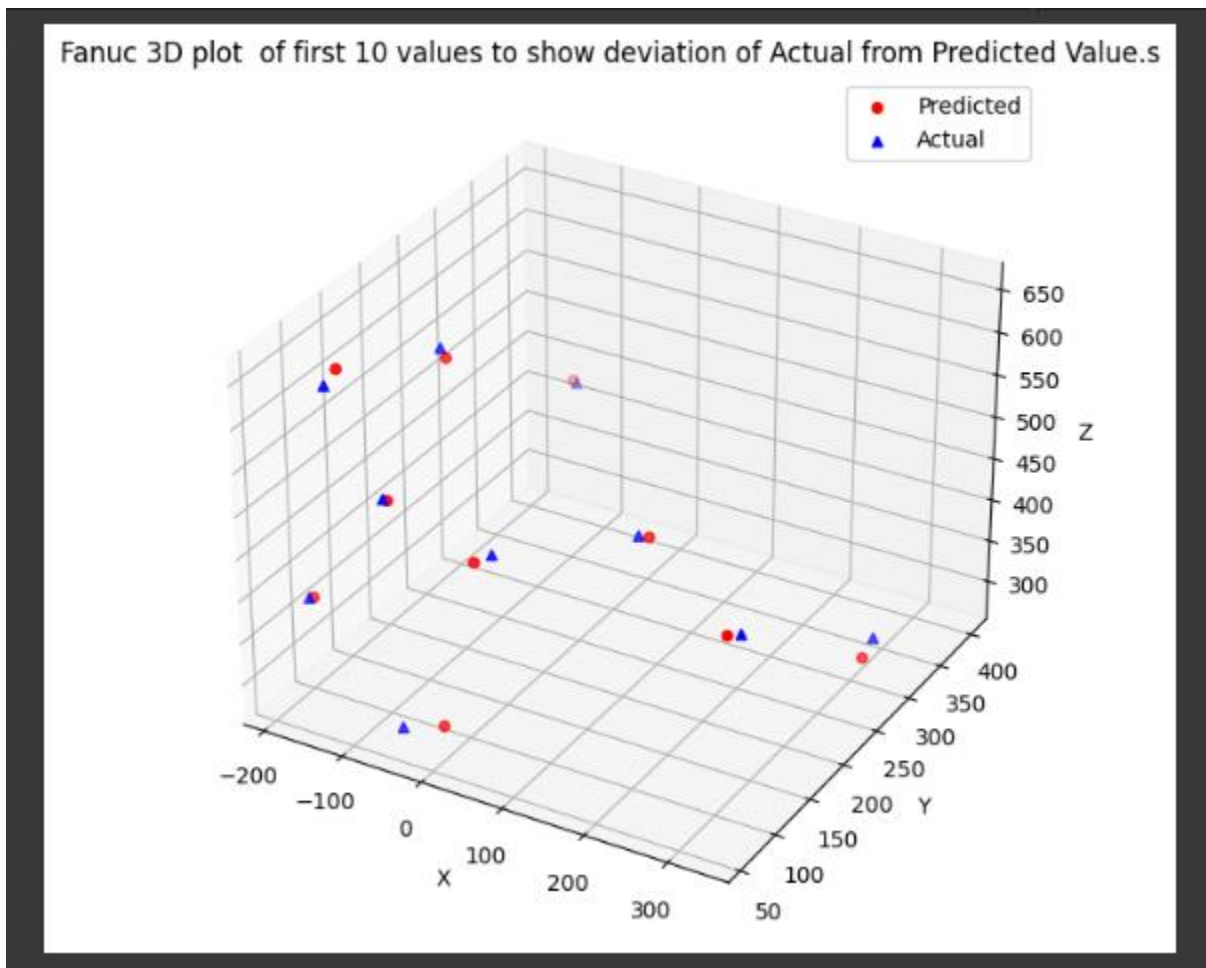


Figure 4-2 Result comparison for each predicted vs actual(graph).

### 4.2.1. Discussion

Form the tables and the graphs of the result above it was observed that the Neural Network model could predict the desired joint angles to a significant degree of accuracy, the worst performing models having errors within 1 to 2 decimal places

### 4.3. Arm 3

Table 4-3 Result comparison for each predicted vs actual (table).

x_predicted	y_predicted	z_predicted	x_actual	y_actual	z_actual
-188.9601	-207.6755	1257.8822	-143.7640	-219.1075	1296.8362
-431.4633	1002.9546	459.6879	-420.1675	1021.9228	463.4497
-434.1977	-622.1768	1071.6883	-407.3294	-644.0693	1101.0744
-900.2541	787.3260	578.6576	-921.0602	768.4131	571.3808
410.1213	-570.9638	1145.9366	390.1220	-544.7256	1202.6824
-287.8428	991.1510	613.7645	-289.6986	985.1771	668.3930
-808.7300	-795.4385	712.7552	-780.6692	-803.7963	814.7537
23.6890	-577.5500	1069.4068	23.0089	-586.6013	1105.0071
1015.8080	-576.5372	-66.5664	1004.5107	-566.0583	-77.9419
-561.5195	-330.9341	893.3660	-487.2781	-323.5224	935.8870
-946.3534	321.7446	872.5754	-1000.4454	270.2718	824.1568

<b>130.3898</b>	<b>-718.7301</b>	<b>1065.1433</b>	<b>159.0338</b>	<b>-701.3426</b>	<b>1125.4518</b>
<b>775.0253</b>	<b>-273.0519</b>	<b>-603.7808</b>	<b>883.8818</b>	<b>-339.4422</b>	<b>-468.6864</b>
<b>996.4304</b>	<b>518.4072</b>	<b>676.0017</b>	<b>971.8302</b>	<b>554.7162</b>	<b>682.9887</b>
<b>559.2887</b>	<b>746.1535</b>	<b>817.1806</b>	<b>545.7414</b>	<b>736.4701</b>	<b>841.4485</b>
<b>430.8566</b>	<b>-473.5041</b>	<b>1061.2394</b>	<b>409.3032</b>	<b>-395.4083</b>	<b>1115.4109</b>
<b>1140.5578</b>	<b>470.3159</b>	<b>500.5583</b>	<b>1172.8548</b>	<b>477.9504</b>	<b>460.9613</b>
<b>944.8362</b>	<b>588.8271</b>	<b>728.2520</b>	<b>928.6147</b>	<b>616.0387</b>	<b>746.6273</b>
<b>-1050.7377</b>	<b>-355.9790</b>	<b>625.1597</b>	<b>-1023.8335</b>	<b>-393.6229</b>	<b>698.0759</b>
<b>105.3389</b>	<b>709.3994</b>	<b>1111.0325</b>	<b>120.8587</b>	<b>768.2789</b>	<b>1090.7692</b>

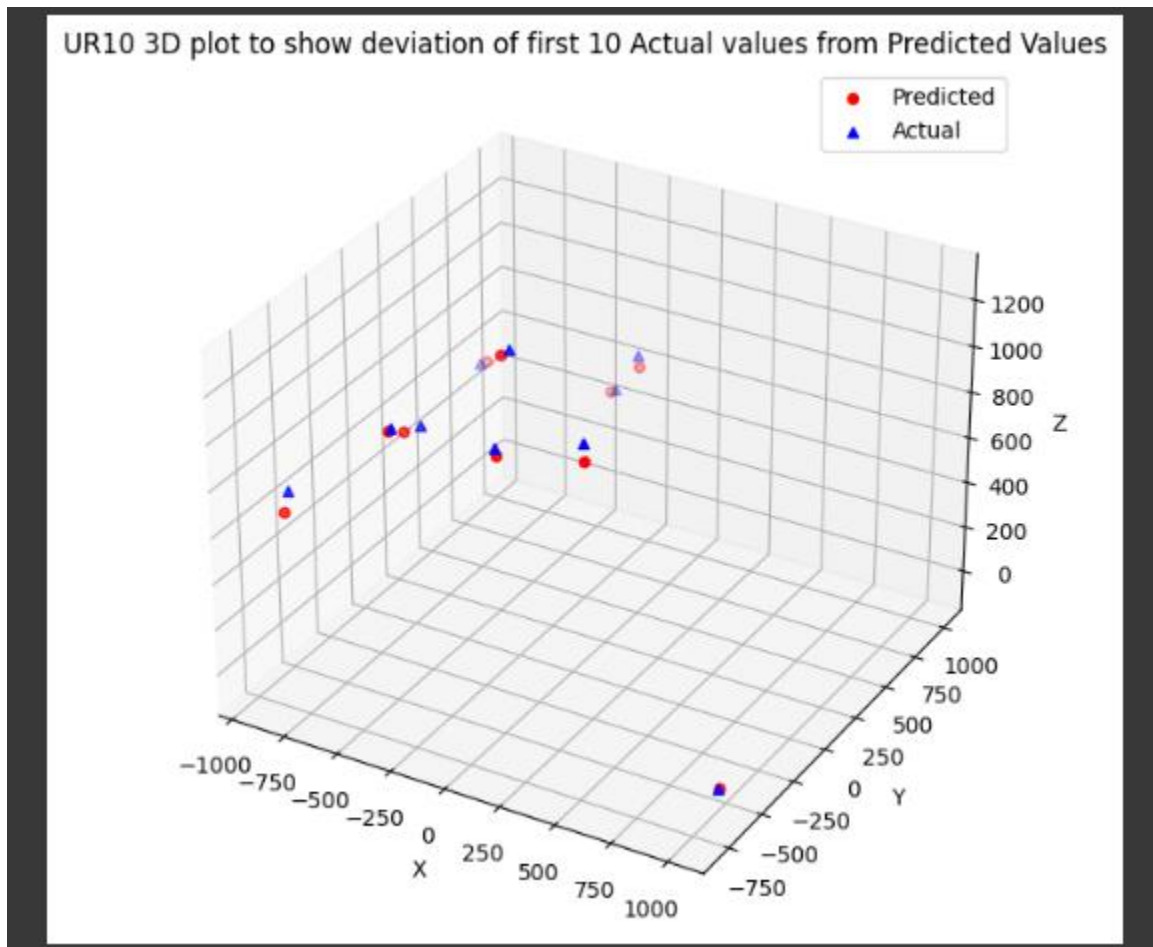


Figure 4-3 Result comparison for each predicted vs actual(graph).

### 4.3.1. Discussion

Form the tables and the graphs of the result above it was observed that the Neural Network model could predict the desired joint angles to a significant degree of accuracy, the worst performing models having errors within 1 to 2 decimal places

## 4.4. Arm 4

Table 4-4 Result comparison for each predicted vs actual (table)

x_predicted	y_predicted	z_predicted	x_actual	y_actual	z_actual
925.4178	322.3457	354.6286	908.1530	259.6541	327.1963
-329.2310	413.8270	-181.7480	-289.7602	396.3276	-147.2705
480.1234	532.3448	235.0839	493.7699	565.8419	248.2363
-597.8412	288.5849	-239.9229	-559.0185	284.4924	-270.9445
-343.1659	932.2661	477.2992	-306.3788	996.3567	450.3053
-460.8177	748.5527	-177.5895	-386.6402	684.3652	-128.3826
771.3447	666.7681	655.8230	797.9556	636.2261	671.7149
219.4756	513.3239	100.9062	184.2060	505.2507	122.6684
-568.9542	366.8871	508.4564	-550.9643	347.4680	519.8716
142.1805	140.7974	316.3166	157.4335	141.1511	300.7163
-636.5676	-120.1371	-68.8848	-597.3166	-47.5429	-139.0785
50.6859	694.1969	189.5256	59.5847	728.0925	160.1787
-453.8705	205.9908	377.1029	-455.7606	211.1686	374.2455
247.2144	339.9363	-157.9272	268.9929	354.5296	-154.3256
264.7360	813.3901	-115.2256	322.0790	807.0565	-90.2988

-288.6690	350.6774	205.7233	-305.6720	342.6642	196.9839
611.4609	524.6727	-233.1362	702.6635	533.3352	-237.9968
635.9691	735.8211	-87.6838	695.5513	785.1782	-88.9020
807.3777	161.4211	370.0009	839.7944	120.9949	360.4083
-202.3010	990.4088	55.5553	-187.6301	996.8218	72.2784

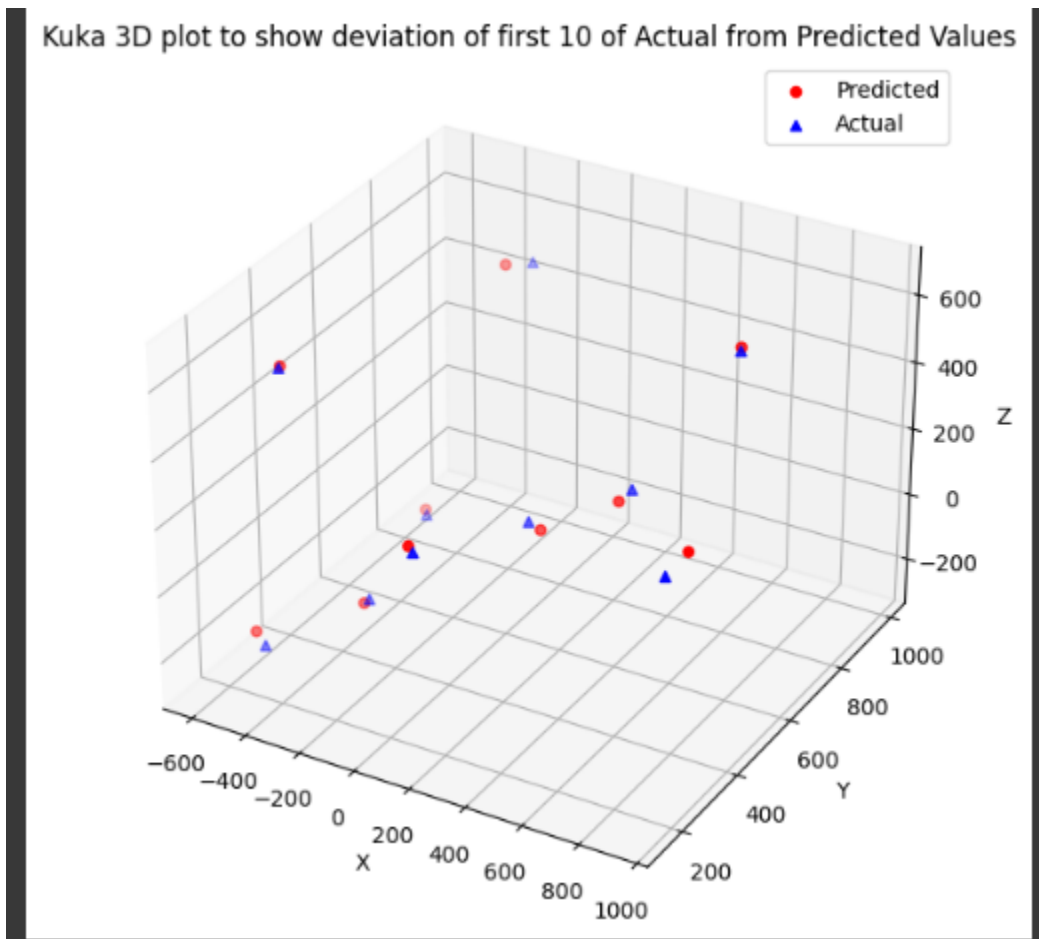


Figure 4-4 Result comparison for each predicted vs actual(graph)

### 4.4.1. Discussion

Form the tables and the graphs of the result above it was observed that the Neural Network model could predict the desired joint angles to a significant degree of accuracy, the worst performing models having errors within 1 to 2 decimal places

## 4.5. Arm 5

Table 4-5 Result comparison for each predicted vs actual (table)

<b>x_predicted</b>	<b>y_predicted</b>	<b>z_predicted</b>	<b>x_actual</b>	<b>y_actual</b>	<b>z_actual</b>
298.1205	396.3232	697.5022	312.1497	377.0167	696.8390
229.6466	424.5335	714.1481	217.7731	432.5360	709.9100
197.9537	486.6595	723.0829	193.5747	488.1848	727.6765
57.1475	507.4120	848.5765	71.6975	512.7340	849.2028
-54.4360	470.8718	786.0307	-86.9176	470.9041	801.8525
181.9480	431.2457	725.7670	160.4170	433.4368	727.0453
149.6694	515.1637	768.2568	119.3350	510.4969	770.7723
180.1302	461.3538	813.2920	129.2242	471.3350	815.4503
-419.1582	226.2533	698.6273	-419.6445	222.5643	698.0190
319.1106	414.7111	705.8304	352.5034	387.6142	710.1508
1.7865	525.0684	727.8872	-34.0545	519.1155	737.1595

<b>51.9032</b>	<b>521.2339</b>	<b>823.9893</b>	<b>25.0531</b>	<b>517.1021</b>	<b>829.5405</b>
<b>-488.7267</b>	<b>193.3726</b>	<b>763.8372</b>	<b>-485.4926</b>	<b>200.1909</b>	<b>755.6182</b>
<b>507.8893</b>	<b>218.6235</b>	<b>739.6401</b>	<b>517.1032</b>	<b>195.0192</b>	<b>741.8377</b>
<b>310.5755</b>	<b>344.1245</b>	<b>771.8792</b>	<b>286.4044</b>	<b>341.5282</b>	<b>768.9430</b>
<b>-107.0624</b>	<b>496.0582</b>	<b>693.8727</b>	<b>-111.3466</b>	<b>495.0346</b>	<b>693.3472</b>
<b>515.8535</b>	<b>142.6576</b>	<b>791.3405</b>	<b>501.6887</b>	<b>140.9579</b>	<b>798.5898</b>
<b>423.8982</b>	<b>246.2733</b>	<b>825.2599</b>	<b>406.9852</b>	<b>266.9146</b>	<b>819.2256</b>
<b>183.7126</b>	<b>453.4012</b>	<b>846.7043</b>	<b>182.5207</b>	<b>452.8649</b>	<b>847.4857</b>
<b>186.6761</b>	<b>445.9553</b>	<b>722.0487</b>	<b>178.6495</b>	<b>445.8303</b>	<b>730.1937</b>

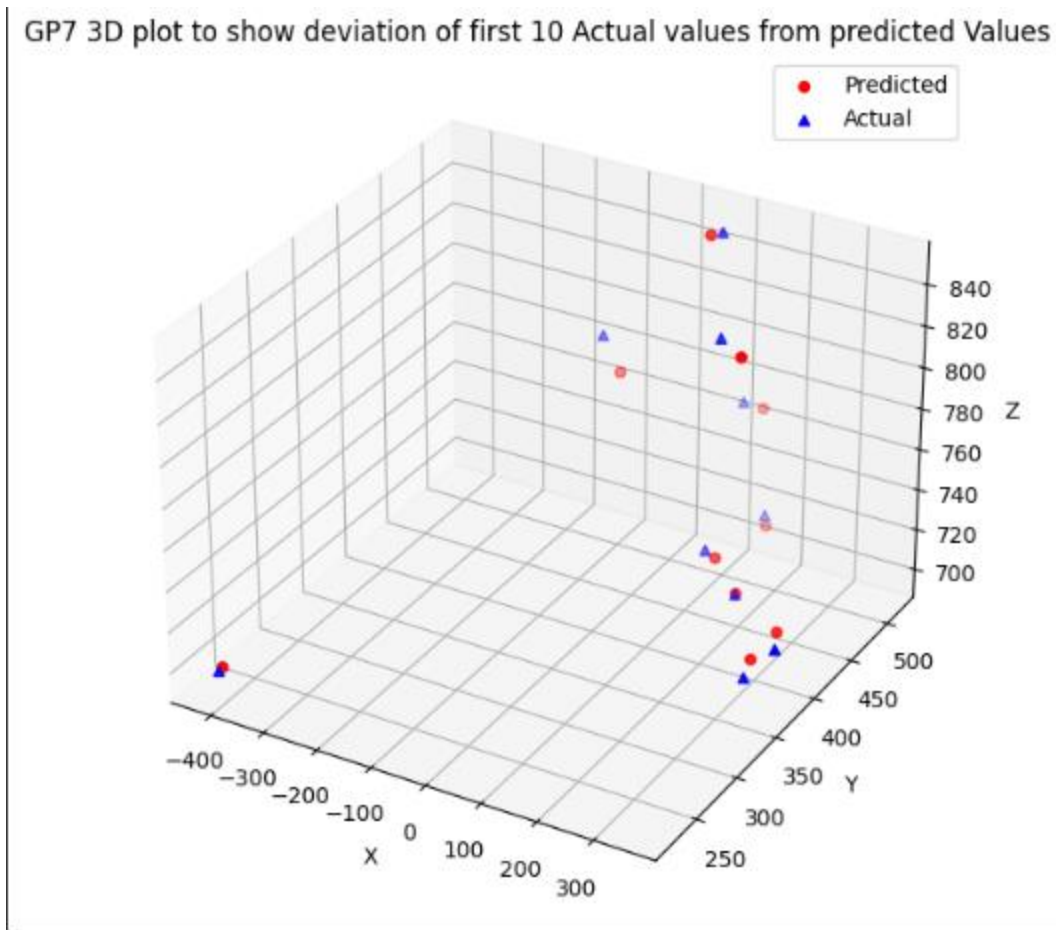


Figure 4-5 Result comparison for each predicted vs actual(graph)

### 4.5.1. Discussion

Form the tables and the graphs of the result above it was observed that the Neural Network model could predict the desired joint angles to a significant degree of accuracy, the worst performing models having errors within 1 to 2 decimal places

## 4.6. Arm 6

Table 4-6 Result comparison for each predicted vs actual (table)

x_predicted	y_predicted	z_predicted	x_actual	y_actual	z_actual

8.7748	-13.6719	-0.2667	8.5066	-13.8398	-0.2145
10.2711	-13.0384	2.2972	10.0157	-13.2776	2.2848
16.2447	0.2331	0.3478	16.2441	-0.3481	0.4555
1.2836	16.6613	2.2205	1.2308	16.6824	2.2006
16.4008	-4.4554	1.6149	16.4267	-4.3539	1.6191
16.9819	-1.4384	-1.4406	16.9642	-1.5916	-1.4566
10.1415	13.2748	2.2262	10.2314	13.2047	2.2270
9.5867	-13.1288	0.8233	9.2112	-13.3984	0.9091
17.0607	2.2216	-0.1755	17.1292	1.6169	-0.1491
9.9133	-12.9556	1.6701	9.5485	-13.2365	1.7302
8.1314	14.7857	1.9485	8.2655	14.7276	1.9156
9.5289	13.1736	-0.8914	9.5316	13.1681	-0.8040
14.4492	8.5611	2.1033	14.6416	8.2567	2.0787
6.7601	-15.1874	2.2884	6.5605	-15.2825	2.2850
9.5086	-14.1228	1.5076	9.3480	-14.2271	1.5151
6.0344	15.1265	1.3912	6.2319	15.0467	1.3979
15.2581	6.7127	2.2598	15.5092	6.1035	2.2617
15.2544	5.5872	-0.2543	15.2678	5.5494	-0.2002

13.8570	8.8781	2.2197	14.0172	8.6393	2.2323
16.2796	4.2510	-2.0489	16.5650	2.7900	-2.0976

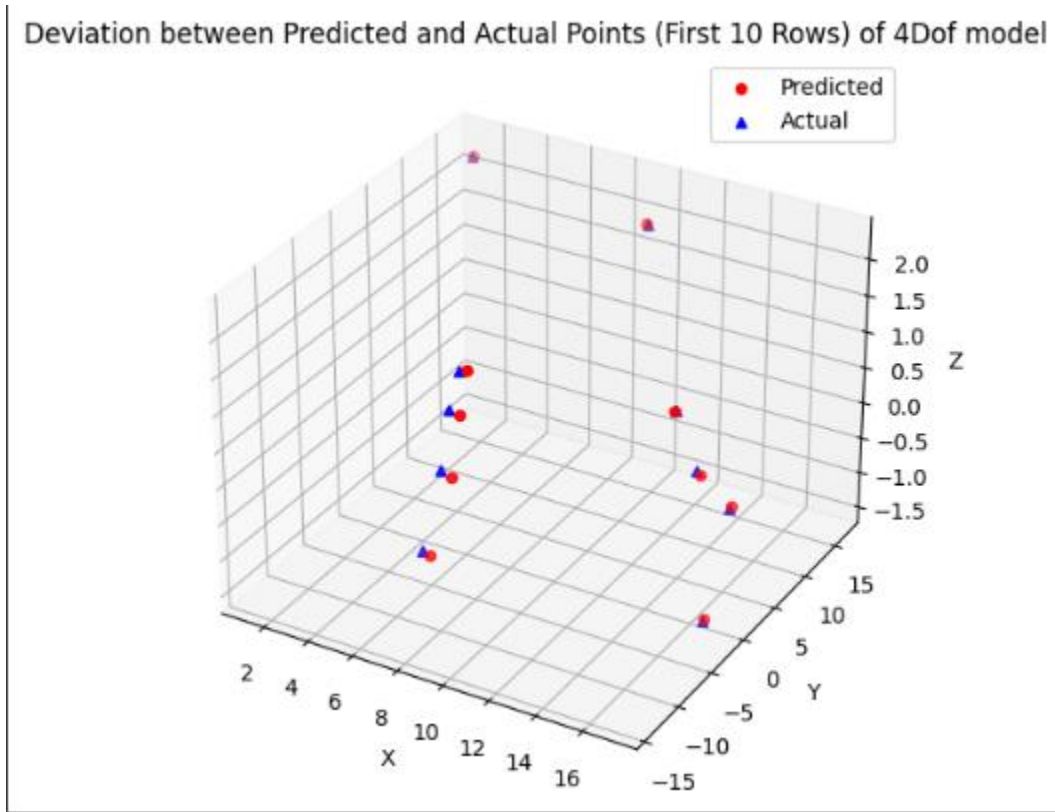


Figure 4-6 Result comparison for arm 6 predicted vs actual(graph)

### 4.6.1. Discussion

Form the tables and the graphs of the result above it was observed that the Neural Network model could predict the desired joint angles to a significant degree of accuracy, the worst performing models having errors within 1 to 2 decimal places

### 4.7. Model Performance

Table 4-7 Model Performance

Arms	Model name	Mean squared error	R squared value
------	------------	--------------------	-----------------

1	ABB IRB 1600	0.0819	0.8402
2	Fanuc LR Mate 200iD	0.0209	0.9490
3	Universal Robots UR10	0.0240	0.9412
4	KUKA KR AGILUS	0.0896	0.7813
5	Yasakawa Motorman GP series	0.0860	0.7908
6	Model no.5(4Dof model)	0.2045	0.7288

With performance like these, models can be applied in fields requiring moderate precision.

## 4.8. Problems faced

- Deployment of the neural networks code from python environment to Arduino environment is proving to be very difficult and the angles generated by the neural networks has to be passed in manually on the Arduino side.
- Normal neural networks approach proved to be less effective so more advanced techniques needed to be used especially for the 6 degree of freedom robot arms.

# Chapter 5

## Conclusion and Recommendations

### 5.1. Conclusions

The effectiveness of neural networks approach in solving the inverse kinematics problem of a neural manipulator largely depends on the complexity and problem type it is being applied in. Neural networks work better for 6dof manipulators and below.

Neural networks are effective enough in solving the inverse kinematics problem of robot manipulators although more research and improvements have to be made to make them deployable and used more commonly and effectively in the industry.

### 5.2. Recommendations

Due to limited time, data from live experiment could not be presented in this report, this could be addressed in future research

This project focused on the use of a relatively simple Neural Network model, other more complex models exist and their use in inverse kinematic problems should be explored

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# APPENDIX

## Code Snippet For 6dof Model

```
# Import the necessary libraries
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from tensorflow.keras.callbacks import EarlyStopping

# Load the CSV data
data = pd.read_csv('/content/drive/MyDrive/joint_positions_abb (3).csv')

# Split features (input) and labels (output)
features = data.iloc[:, :-7].values # Last 7 columns are features
labels = data.iloc[:, :-7].values # First 6 columns are labels

# Split data into training, validation, and test sets
x_train, x_test, y_train, y_test = train_test_split(
    features, labels, test_size=0.2, random_state=42)

# Define the first TensorFlow model for the first four outputs
abb_model1 = tf.keras.Sequential([
    tf.keras.layers.Dense(512, activation='relu', input_shape=(7,)),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(32, activation='relu'),
    tf.keras.layers.Dense(32, activation='relu'),
    tf.keras.layers.Dense(3) # Output the first four values
])
```

```
# Define the second TensorFlow model for the last three outputs
abb_model2 = tf.keras.Sequential([
    tf.keras.layers.Dense(512, activation='relu', input_shape=(7,)),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(32, activation='relu'),
    tf.keras.layers.Dense(32, activation='relu'),
    tf.keras.layers.Dense(3) # Output the last three values
])

# Compile both models
optimizer_1 = tf.keras.optimizers.Adam(learning_rate=0.001)
optimizer_2 = tf.keras.optimizers.Adam(learning_rate=0.001)
abb_model1.compile(optimizer=optimizer_1, loss='mean_squared_error')
abb_model2.compile(optimizer=optimizer_2, loss='mean_squared_error')

# Define early stopping callback
early_stopping = EarlyStopping(monitor='val_loss', patience=4, restore_best_weights=True)

# Train model1
print("Training abb model1...")
abb_model1.fit(x_train, y_train[:, :3], epochs=20, batch_size=32, validation_data=(x_test, y_test[:, :3]), callbacks=[early_stopping])
print("Training of abb model1 completed.")

# Train model2
print("Training abb model2...")
abb_model2.fit(x_train, y_train[:, 3:], epochs=20, batch_size=32, validation_data=(x_test, y_test[:, 3:]), callbacks=[early_stopping])
print("Training of abb model2 completed.")
```

```

# Make predictions using both models
y_preds1 = abb_model1.predict(x_test)
y_preds2 = abb_model2.predict(x_test)

# Combine the predictions to form the final prediction variable
abb_final_predictions = np.hstack((y_preds1, y_preds2))

# Evaluate the combined model's performance
mse = np.mean(np.square(abb_final_predictions - y_test))
print('Mean Squared Error (Combined Model):', mse)

# Calculate the mean of the actual target values from the test set (mean_y_test)
mean_y_test = np.mean(y_test, axis=0)

# Calculate the total sum of squares (TSS)
TSS = np.sum(np.square(y_test - mean_y_test))

# Calculate the RSS (residual sum of squares)
RSS = np.sum(np.square(y_test - abb_final_predictions))

# Calculate R-squared (R²)
R_squared = 1 - (RSS / TSS)

print("R-squared value:", R_squared)

```

## Code Snippet for Generation of Dataset

```

# Import the necessary libraries
import numpy as np
import math # For mathematical operations.
import csv # To save generated training and test data into a CSV file.

# Function to generate random angles within specified ranges.
def generate_joint_angles():
    """
    This function generates random angles within specified ranges.
    The angle ranges should be specified in radians form.
    """
    joint1 = np.random.uniform(0, np.pi) # 0-180 degrees
    joint2 = np.random.uniform(0, np.pi * 0.5) # 0-90 degrees
    joint3 = np.random.uniform(0, np.pi * 0.5) # 0-90 degrees
    joint4 = np.random.uniform(0, np.pi) # 0-180 degrees
    joint5 = np.random.uniform(0, np.pi * 0.5) # 0-90 degrees
    joint6 = np.random.uniform(0, np.pi) # 0-180 degrees
    return [joint1, joint2, joint3, joint4, joint5, joint6]

# Create a function that performs the forward kinematics of the robot manipulator.
def forward_kinematics(theta):
    """
    This function takes in the theta values for the specific problem and calculates the corresponding end effector position.
    The theta values should be passed into the function in radians form too.
    """
    # DH parameters for the ABB IRB 1600
    a = [300, 1200, 250, 0, 0, 0] # link lengths (mm)
    alpha = [np.pi/2, 0, np.pi/2, np.pi/2, np.pi/2, 0] # link twists
    d = [649, 0, 0, 1320, 0, 290] # link offsets (mm)

    # Homogeneous transformation matrices
    T = np.eye(4) # initial transformation matrix (identity matrix)

    for i in range(len(theta)):
        # Call parameters for the transformation matrix.
        cos_theta = np.cos(theta[i])

```

```

# Call parameters for the transformation matrix.
cos_theta = np.cos(theta[i])
sin_theta = np.sin(theta[i])
cos_alpha = np.cos(alpha[i])
sin_alpha = np.sin(alpha[i])

# Denavit-Hartenberg transformation matrix
A = np.array([[cos_theta, -sin_theta * cos_alpha, sin_theta * sin_alpha, a[i] * cos_theta],
              [sin_theta, cos_theta * cos_alpha, -cos_theta * sin_alpha, a[i] * sin_theta],
              [0, sin_alpha, cos_alpha, d[i]],
              [0, 0, 0, 1]])

# Update the transformation matrix
T = np.dot(T, A)

# Extract the end effector position from the transformation matrix
end_effector_pos = T[:3, 3]

# Create the quaternion representation of the XYZW-rotation
m_00 = T[0, 0]
m_01 = T[0, 1]
m_02 = T[0, 2]
m_10 = T[1, 0]
m_11 = T[1, 1]
m_12 = T[1, 2]
m_20 = T[2, 0]
m_21 = T[2, 1]
m_22 = T[2, 2]

w = math.sqrt((1 + m_00 + m_11 + m_22) / 2)
x = (m_21 - m_12) / (4 * w)
y = (m_02 - m_20) / (4 * w)
z = (m_10 - m_01) / (4 * w)

quart = np.array([w, x, y, z])

```

```

w = math.sqrt((1 + m_00 + m_11 + m_22) / 2)
x = (m_21 - m_12) / (4 * w)
y = (m_02 - m_20) / (4 * w)
z = (m_10 - m_01) / (4 * w)

quart = np.array([w, x, y, z])

final_pos = np.concatenate((end_effector_pos, quart))
return final_pos

# Generate 100,000 random sets of joint angles.
np.random.seed(123) # For reproducibility.
joint_angles = np.array([generate_joint_angles() for _ in range(100000)]) # Generate angles separately for each joint.

# Calculate forward kinematics for each set of joint angles.
final_positions = []
for angles in joint_angles:
    position = forward_kinematics(angles)
    final_positions.append(position)

final_positions = np.array(final_positions)

# Combine joint angles and end effector positions.
data = np.hstack((joint_angles, final_positions)) # Horizontally stack up the joint parameters with the corresponding end effector position

# Save joint angles and end effector positions to a CSV file
with open('joint_positions_abb.csv', 'w', newline='') as file: #The `newline` argument is used to ensure that the CSV file is written with consistent newline characters.
    writer = csv.writer(file)
    writer.writerow(['Joint1', 'Joint2', 'Joint3', 'Joint4', 'Joint5', 'Joint6', 'X', 'Y', 'Z', 'q1', 'q2', 'q3', 'q4']) # Write header with xyz being the end effector p
    writer.writerows(data) # Writes rows of entries to the csv file from the data we stacked using `np.hstack()`

print("CSV file generated successfully.")

CSV file generated successfully.

```

# Arm 1 (ABB IRB 1600):

For the ABB IRB 1600 robot arm, the data was generated

Testing data set for arm (First 20 values)

Table A-1 Testing data set for arm 1 (First 20 values)

<u>0.4504</u>	<u>1.5686</u>	<u>0.4212</u>	<u>0.2400</u>	<u>1.3908</u>	<u>1.3005</u>	<u>1151.7</u> <u>841</u>	<u>481.58</u> <u>75</u>	<u>2846.4</u> <u>774</u>	<u>0.8440</u>	<u>-0.0089</u>	<u>-0.2233</u>	<u>0.5215</u>
<u>1.4024</u>	<u>0.5211</u>	<u>0.3419</u>	<u>0.7640</u>	<u>1.0954</u>	<u>2.8027</u>	<u>599.30</u> <u>81</u>	<u>2460.7</u> <u>707</u>	<u>806.01</u> <u>37</u>	<u>0.4075</u>	<u>-0.2163</u>	<u>0.0828</u>	<u>-0.6363</u>
<u>0.9177</u>	<u>0.6286</u>	<u>0.4214</u>	<u>1.9236</u>	<u>1.3900</u>	<u>2.7618</u>	<u>1698.6</u> <u>959</u>	<u>1779.8</u> <u>229</u>	<u>855.20</u> <u>38</u>	<u>0.1724</u>	<u>0.3836</u>	<u>-0.3927</u>	<u>0.4373</u>
<u>0.5474</u>	<u>0.2539</u>	<u>1.1320</u>	<u>2.7063</u>	<u>0.6006</u>	<u>2.2408</u>	<u>2206.9</u> <u>311</u>	<u>1264.3</u> <u>018</u>	<u>851.43</u> <u>81</u>	<u>0.7918</u>	<u>0.3394</u>	<u>-0.4720</u>	<u>0.0726</u>
<u>1.5085</u>	<u>0.7038</u>	<u>0.8909</u>	<u>0.1103</u>	<u>0.6740</u>	<u>1.9869</u>	<u>162.97</u> <u>25</u>	<u>2291.9</u> <u>524</u>	<u>1881.5</u> <u>308</u>	<u>0.1902</u>	<u>0.0400</u>	<u>0.3131</u>	<u>-0.6256</u>
<u>0.2618</u>	<u>0.2962</u>	<u>1.1643</u>	<u>1.2764</u>	<u>0.2965</u>	<u>0.6337</u>	<u>2449.5</u> <u>759</u>	<u>572.45</u> <u>47</u>	<u>1157.4</u> <u>722</u>	<u>1.0881</u>	<u>0.2610</u>	<u>-0.3668</u>	<u>-0.0370</u>
<u>1.5952</u>	<u>0.1700</u>	<u>0.3185</u>	<u>1.3379</u>	<u>0.2451</u>	<u>1.5884</u>	<u>14.726</u> <u>1</u>	<u>2206.2</u> <u>506</u>	<u>59.794</u> <u>9</u>	<u>0.7954</u>	<u>0.1575</u>	<u>-0.0668</u>	<u>0.5591</u>
<u>1.2902</u>	<u>0.1264</u>	<u>0.5964</u>	<u>2.2128</u>	<u>1.5034</u>	<u>3.0704</u>	<u>889.59</u> <u>25</u>	<u>2249.8</u> <u>633</u>	<u>-</u> <u>124.30</u> <u>34</u>	<u>0.1228</u>	<u>0.4506</u>	<u>-0.3649</u>	<u>0.4001</u>
<u>2.9228</u>	<u>0.3100</u>	<u>0.1505</u>	<u>0.0342</u>	<u>0.5325</u>	<u>0.9220</u>	<u>-</u> <u>2218.8</u> <u>130</u>	<u>498.61</u> <u>59</u>	<u>232.89</u> <u>81</u>	<u>0.4667</u>	<u>0.0183</u>	<u>-0.0186</u>	<u>-0.6670</u>
<u>1.5352</u>	<u>0.2933</u>	<u>0.7106</u>	<u>1.4589</u>	<u>1.3611</u>	<u>3.0711</u>	<u>376.40</u> <u>51</u>	<u>2650.8</u> <u>748</u>	<u>557.00</u> <u>78</u>	<u>0.4284</u>	<u>-0.3788</u>	<u>0.2356</u>	<u>-0.5051</u>
<u>0.7537</u>	<u>0.4455</u>	<u>1.0376</u>	<u>2.9413</u>	<u>0.6215</u>	<u>1.2615</u>	<u>1824.3</u> <u>513</u>	<u>1666.0</u> <u>079</u>	<u>1155.1</u> <u>821</u>	<u>0.6583</u>	<u>0.5841</u>	<u>-0.1821</u>	<u>-0.1318</u>

<u>2.7018</u>	<u>0.7627</u>	<u>0.3434</u>	<u>1.2878</u>	<u>1.1984</u>	<u>1.8280</u>	- <u>2060.3</u> <u>413</u>	<u>1256.1</u> <u>968</u>	<u>1224.8</u> <u>289</u>	<u>0.4576</u>	<u>-0.3404</u>	<u>-0.1877</u>	<u>-0.5446</u>
<u>2.3200</u>	<u>0.4907</u>	<u>0.6846</u>	<u>0.4765</u>	<u>1.0956</u>	<u>0.5622</u>	- <u>1710.4</u> <u>983</u>	<u>2012.6</u> <u>517</u>	<u>1199.1</u> <u>708</u>	<u>0.3171</u>	<u>0.1176</u>	<u>0.0990</u>	<u>0.6717</u>
<u>1.7585</u>	<u>0.7673</u>	<u>0.8003</u>	<u>1.3710</u>	<u>0.6726</u>	<u>2.2953</u>	- <u>247.29</u> <u>41</u>	<u>2251.2</u> <u>054</u>	<u>1764.4</u> <u>056</u>	<u>0.0846</u>	<u>-0.3257</u>	<u>0.3352</u>	<u>-0.5289</u>
<u>1.9179</u>	<u>1.1730</u>	<u>0.4394</u>	<u>3.1087</u>	<u>1.4911</u>	<u>1.0241</u>	- <u>692.63</u> <u>26</u>	<u>1942.5</u> <u>464</u>	<u>1770.2</u> <u>826</u>	<u>0.0291</u>	<u>0.6378</u>	<u>0.3049</u>	<u>0.0102</u>
<u>1.4895</u>	<u>0.6493</u>	<u>0.3783</u>	<u>1.1687</u>	<u>1.4949</u>	<u>0.5596</u>	<u>472.65</u> <u>60</u>	<u>2524.6</u> <u>359</u>	<u>1014.5</u> <u>862</u>	<u>0.7992</u>	<u>0.2709</u>	<u>0.2886</u>	<u>0.4285</u>
<u>3.0948</u>	<u>0.5555</u>	<u>0.5733</u>	<u>2.1807</u>	<u>1.3440</u>	<u>0.9842</u>	- <u>2477.9</u> <u>378</u>	<u>347.82</u> <u>83</u>	<u>824.70</u> <u>05</u>	<u>0.0737</u>	<u>0.2614</u>	<u>0.5327</u>	<u>0.3828</u>
<u>2.9533</u>	<u>0.6630</u>	<u>0.5800</u>	<u>0.7905</u>	<u>0.4120</u>	<u>0.4484</u>	- <u>2293.7</u> <u>105</u>	<u>521.12</u> <u>43</u>	<u>1362.1</u> <u>352</u>	<u>0.2106</u>	<u>0.3129</u>	<u>0.1079</u>	<u>0.6159</u>
<u>2.1831</u>	<u>0.5740</u>	<u>0.6437</u>	<u>1.8889</u>	<u>0.3126</u>	<u>1.4590</u>	- <u>1289.5</u> <u>491</u>	<u>1983.2</u> <u>666</u>	<u>1147.9</u> <u>411</u>	<u>0.6160</u>	<u>0.4353</u>	<u>-0.0289</u>	<u>0.4635</u>
<u>2.2097</u>	<u>0.9512</u>	<u>0.1624</u>	<u>2.0398</u>	<u>0.0106</u>	<u>2.7996</u>	- <u>1208.8</u> <u>335</u>	<u>1631.9</u> <u>045</u>	<u>1394.2</u> <u>645</u>	<u>0.0995</u>	<u>0.2509</u>	<u>-0.2789</u>	<u>0.5973</u>
<u>2.8495</u>	<u>1.2631</u>	<u>1.0325</u>	<u>0.2848</u>	<u>0.0434</u>	<u>1.0998</u>	- <u>1206.5</u> <u>478</u>	<u>366.44</u> <u>08</u>	<u>2671.8</u> <u>961</u>	<u>0.1646</u>	<u>-0.5442</u>	<u>0.3342</u>	<u>-0.2923</u>

Predicted data set for arm :- The predicted dataset is gotten from the neural networks model after it is trained on the training dataset. After the training on the training dataset, the model is tested on

the x,y,z position of the end effector, and the quaternion representation of the end effector frame (7 columns in total) from the test dataset, and it makes predictions of the 6 joint angles of the test dataset. The deviation of the predicted values from the actual values tells about the model performance and accuracy. The first 20 predicted values can be shown below;

Table A-2 Predicted data set for arm 1

joint1	joint2	joint3	joint4	joint5	joint6
0.1777	0.6774	0.4429	1.4027	0.9855	0.7552
2.1103	0.0606	0.6624	0.7517	0.9240	2.7758
0.6943	0.7943	0.8676	2.7349	1.0053	2.4963
2.6941	0.1025	0.3547	1.8231	0.3451	1.2765
1.7601	0.9982	0.3063	2.1477	0.4262	0.3526
2.0995	0.1370	0.5326	0.5897	0.8884	0.6413
0.6573	1.2122	0.2261	2.9961	0.8549	1.1190
1.1506	0.8456	0.9783	1.1725	0.3519	1.4819
2.3501	1.2815	1.0904	1.0862	1.4910	1.0163
0.2182	0.8429	1.1536	2.2997	1.1067	1.2317
3.0355	0.1175	0.5510	1.8246	0.5897	0.2946
1.4090	0.8713	0.7778	2.2582	0.4605	2.5704
2.6140	1.4033	1.2232	2.2542	0.8678	1.6267

0.6647	0.0749	0.5335	2.4713	1.2319	2.9766
1.1557	0.1726	0.6638	0.2889	0.8437	2.4944
1.9747	0.6392	1.1050	2.6647	1.4727	0.8738
0.5396	0.1143	0.1430	2.8454	0.6015	0.4539
0.7749	0.2975	0.0243	1.6932	0.8550	2.8482
0.1193	1.2107	0.4273	1.5425	0.3880	2.5178

### Training data set for arm 1(First 20 values)

Table A-3 Training data set for arm 1(First 20 values)

Joint1	Joint2	Joint3	Joint4	Joint5	Joint6	X	Y	Z	q1	q2	q3	q4
2.1880 22477	0.4494 66616	0.3563 3743	1.7320 06428	1.1301 39215	1.3292 28147	- 1170.8 68173	2097.0 54687	491.87 83786	0.4311 9878	0.3726 20247	0.2519 71711	0.5011 79919
3.0811 61601	1.0757 28038	0.7554 46064	1.2318 73515	0.5390 62767	2.2903 77205	- 1816.2 10854	250.54 38329	2270.0 78582	0.6922 86211	- 0.4831 38625	0.1748 78641	- 0.3408 51112
1.3778 15342	0.0937 41821	0.6252 46454	2.3184 80945	0.2866 5734	0.5511 97948	505.30 79003	2272.3 44212	105.30 99843	1.2481 47547	0.3103 73421	0.0698 71037	- 0.0965 31354
1.6699 17891	0.8353 9282	0.9965 14695	2.6685 68684	1.1379 71763	1.9195 86972	- 104.17 98316	2259.5 48536	1863.3 53779	0.0457 42606	0.6725 45071	- 0.1411 78219	0.1650 11337
2.2696 22823	0.5073 02676	0.5682 96291	0.7171 10089	0.4613 64945	1.9822 69955	- 1509.1 55658	1927.8 92821	1033.6 99149	0.3621 05559	- 0.1993 51799	0.1734 15312	- 0.6304 01365

0.2893 56203	0.6812 56209	0.6767 97646	1.5509 57476	0.6688 92656	0.9809 97564	2307.0 01029	499.22 38358	1421.9 03801	1.0758 14887	0.3374 18414	- 0.3028 73213	0.0712 19472
1.3394 22134	1.4033 32416	1.4830 83089	1.5765 66414	0.9801 03005	0.3632 25901	360.99 32747	481.94 22109	3015.9 40986	0.1130 60149	0.6047 11129	- 0.1391 13323	0.3343 29604
0.9967 81739	0.6516 0749	1.3607 95243	0.7868 28736	0.7587 48448	3.0962 27382	1253.6 23701	1678.4 59486	2204.3 54473	0.3957 11921	0.1996 14321	0.4217 74897	- 0.4930 64983
1.6320 10634	0.9627 3247	0.1894 83065	2.5960 26188	0.9472 84635	1.7123 81645	- 3.8823 86522	2060.3 0066	1210.7 36682	0.6361 00609	0.5893 37356	- 0.0431 9722	0.2228 44082
1.0768 24342	0.4777 11818	0.6550 56957	2.1403 69481	1.3751 64391	1.6035 39066	1420.3 99672	2132.4 26773	752.19 97303	0.5303 18044	0.5798 19461	- 0.1138 33484	0.2837 99267
2.1027 11264	0.9203 86984	0.9815 96126	2.1195 98166	1.3231 48407	0.2613 64764	- 895.92 4302	1995.3 41336	2107.8 24038	0.2035 81298	0.4515 60573	0.4307 97078	0.3164 5788
2.3991 80404	0.3827 50246	0.3050 84713	1.7984 26572	0.1503 4487	2.7813 36253	- 1632.7 74329	1555.5 35863	451.33 26349	0.1929 2876	- 0.1989 69038	0.1574 78071	- 0.6529 2159
1.9705 60763	1.1363 39758	0.0253 35699	1.8674 62826	0.8745 96135	0.4993 8645	- 550.90 47198	1850.6 0946	1456.0 89947	0.8378 08422	0.3990 71061	0.2800 21083	0.2947 02805
0.4808 85206	1.0925 35229	0.5007 17132	2.1738 88797	0.8708 23172	1.2219 24266	1842.0 61141	755.02 2904	1863.9 60772	0.7184 5382	0.5082 07359	- 0.3221 33082	0.0944 01188
2.9063 89433	1.3220 9214	0.5613 98785	0.1369 46622	0.4787 2857	1.2509 37213	- 1443.5 9332	364.69 44116	2502.7 57772	0.4916 16076	- 0.3658 87248	0.2753 80482	- 0.4794 48141
2.2146 93483	1.5635 05447	0.5590 69764	2.3956 1461	0.9317 60122	2.1730 45289	- 620.52 00619	1089.8 41975	2517.5 62491	0.2023 24569	- 0.6607 27655	0.1307 83598	- 0.1900 0213

0.4747 80894	0.6265 53415	0.3783 35559	1.0789 98891	0.8060 1982	2.0942 62789	2222.2 56859	934.84 3708	1046.9 56683	0.7711 64015	0.1534 80275	- 0.2484 6283	0.5157 87304
0.3327 21319	0.2056 09308	0.5057 65954	2.0783 6566	1.3296 88869	1.7381 0921	2327.0 18625	543.75 50597	20.448 44444	0.8966 55117	0.4669 50548	- 0.2525 45482	0.1310 73894
2.6843 41658	0.6045 0182	0.4976 09265	1.1129 55302	0.2687 34709	2.6047 34162	- 2072.5 80558	1096.7 47065	1114.4 60648	0.6894 62721	- 0.2459 04012	0.2334 0974	- 0.5159 5678

## Arm 2 (Fanuc LR mate 200iC):-

First 20 testing data set for the Fanuc arm.

Table A-4 First 20 testing data set for arm 2

0.4504	1.5686	0.4212	0.1200	1.3908	1.3005	281.76 42	146.70 30	306.99 20	1.2661	0.0399	-0.0860	-0.3004
1.4024	0.5211	0.3419	0.3820	1.0954	2.8027	17.439 3	260.77 00	556.67 49	0.8133	0.3051	0.0868	-0.4837
0.9177	0.6286	0.4214	0.9618	1.3900	2.7618	112.17 30	252.85 40	505.51 79	0.2652	0.3992	-0.1330	-0.5526
0.5474	0.2539	1.1320	1.3532	0.6006	2.2408	- 10.830 7	45.094 5	435.93 80	0.1172	- 0.3765	0.0050	0.5957
1.5085	0.7038	0.8909	0.0552	0.6740	1.9869	4.0956	109.84 81	488.46 55	1.2391	0.2912	0.0473	-0.1706
0.2618	0.2962	1.1643	0.6382	0.2965	0.6337	-4.8040	13.128 0	427.13 26	1.0235	0.2162	-0.3057	-0.3128
1.5952	0.1700	0.3185	0.6690	0.2451	1.5884	- 17.457 8	222.26 86	659.13 05	1.3116	0.1308	-0.0085	-0.2296

1.2902	0.1264	0.5964	1.1064	1.5034	3.0704	- 33.544 5	141.30 65	532.12 21	0.0845	- 0.5166	-0.1368	0.4611
2.9228	0.3100	0.1505	0.0171	0.5325	0.9220	- 301.14 24	66.261 5	640.82 59	0.7600	0.1238	0.0432	0.5817
1.5352	0.2933	0.7106	0.7295	1.3611	3.0711	- 48.422 6	105.63 53	496.99 53	0.2866	0.4581	0.2578	-0.4507
0.7537	0.4455	1.0376	1.4706	0.6215	1.2615	15.483 0	78.091 7	475.77 23	0.5956	0.2491	-0.1656	-0.5673
2.7018	0.7627	0.3434	0.6439	1.1984	1.8280	- 300.51 08	91.972 8	496.39 07	1.2552	0.2994	0.0385	0.1226
2.3200	0.4907	0.6846	0.2382	1.0956	0.5622	- 100.46 36	83.362 5	510.77 82	0.8325	0.4137	-0.0909	0.3839
1.7585	0.7673	0.8003	0.6855	0.6726	2.2953	- 61.748 3	156.01 72	500.36 16	1.0855	0.2395	0.0343	-0.3832
1.9179	1.1730	0.4394	1.5543	1.4911	1.0241	- 195.08 58	304.87 33	346.94 11	1.0344	0.1412	-0.4610	0.0045
1.4895	0.6493	0.3783	0.5844	1.4949	0.5596	- 22.353 7	267.57 81	500.65 97	1.1068	0.2506	-0.3365	0.1329
3.0948	0.5555	0.5733	1.0904	1.3440	0.9842	- 215.85 23	- 59.102 3	507.75 12	0.9660	0.4415	-0.0294	0.2663
2.9533	0.6630	0.5800	0.3952	0.4120	0.4484	- 237.90 54	32.782 6	545.98 06	0.6838	0.1170	-0.0190	0.6075

2.1831	0.5740	0.6437	0.9444	0.3126	1.4590	- 137.09 56	160.49 68	556.03 63	1.3825	0.1256	-0.0081	-0.0796
2.2097	0.9512	0.1624	1.0199	0.0106	2.7996	- 286.71 36	384.76 31	421.18 95	0.9079	- 0.0313	-0.2681	-0.4702
2.8495	1.2631	1.0325	0.1424	0.0434	1.0998	- 173.40 62	51.620 7	451.35 24	0.9769	- 0.0579	-0.0322	0.5070
0.8605	1.5499	0.6088	1.0385	1.2188	2.6724	143.67 77	266.28 06	326.16 99	0.4898	0.1435	-0.2870	-0.5806

First 20 predicted data set for the fanuc arm.

Table A-5 First 20 predicted data set for arm 2

joint1	joint2	joint3	joint4	joint5	joint6
0.2309	0.8476	0.2950	0.5094	1.5229	0.6811
2.1359	0.1101	0.5669	0.2509	1.2215	2.8967
0.7225	0.9540	0.7178	1.2059	1.1793	2.1609
2.5765	0.1001	0.4235	0.7127	0.0724	1.6260
1.8526	1.0231	0.2452	0.6035	0.5754	0.2237
2.0492	0.2353	0.2303	0.1218	1.2363	1.0756
0.5342	1.2646	0.2661	1.4380	0.9735	0.8211
1.2836	0.8310	0.9983	0.3683	0.6282	1.2386

<b>2.4601</b>	<b>1.4687</b>	<b>0.8602</b>	<b>0.6794</b>	<b>1.3490</b>	<b>1.1104</b>
<b>0.3053</b>	<b>0.5210</b>	<b>1.5382</b>	<b>1.4412</b>	<b>1.4745</b>	<b>0.5967</b>
<b>2.9965</b>	<b>0.1762</b>	<b>0.5048</b>	<b>1.0076</b>	<b>1.0996</b>	<b>0.3184</b>
<b>1.4175</b>	<b>0.9375</b>	<b>0.7854</b>	<b>1.2334</b>	<b>0.3972</b>	<b>2.5369</b>
<b>2.4352</b>	<b>1.4211</b>	<b>1.1965</b>	<b>1.3828</b>	<b>0.8612</b>	<b>1.7682</b>
<b>0.7460</b>	<b>0.1261</b>	<b>0.7448</b>	<b>1.2339</b>	<b>0.9683</b>	<b>2.9499</b>
<b>1.1435</b>	<b>0.3795</b>	<b>0.2553</b>	<b>0.2302</b>	<b>0.9603</b>	<b>2.7257</b>
<b>2.0350</b>	<b>0.9048</b>	<b>1.1823</b>	<b>1.3124</b>	<b>1.4060</b>	<b>0.9049</b>
<b>0.5848</b>	<b>0.1833</b>	<b>0.0988</b>	<b>1.1277</b>	<b>0.7655</b>	<b>0.2269</b>
<b>0.7553</b>	<b>0.3032</b>	<b>0.0114</b>	<b>0.9890</b>	<b>0.4483</b>	<b>2.7164</b>
<b>0.0453</b>	<b>1.1634</b>	<b>0.6685</b>	<b>0.9769</b>	<b>0.2002</b>	<b>1.9354</b>
<b>1.7362</b>	<b>0.4914</b>	<b>0.1424</b>	<b>0.6553</b>	<b>1.1901</b>	<b>0.1700</b>

**First 20 training data set for arm 2.**

Table A-6 First 20 training data set for arm 2

<b>Joint1</b>	<b>Joint2</b>	<b>Joint3</b>	<b>Joint4</b>	<b>Joint5</b>	<b>Joint6</b>	<b>X</b>	<b>Y</b>	<b>Z</b>	<b>q1</b>	<b>q2</b>	<b>q3</b>	<b>q4</b>
<b>2.1880</b>	<b>0.4495</b>	<b>0.3563</b>	<b>0.8660</b>	<b>1.1301</b>	<b>1.3292</b>	<b>- 193.56 87</b>	<b>177.50 34</b>	<b>563.57 67</b>	<b>1.2160</b>	<b>0.3443</b>	<b>- 0.1080</b>	<b>0.0112</b>

3.0812	1.0757	0.7554	0.6159	0.5391	2.2904	- 237.88 87	-9.3751	469.07 57	1.3864	0.1126	0.0267	0.0782
1.3778	0.0937	0.6252	1.1592	0.2867	0.5512	-1.1387	102.26 79	601.32 42	1.3030	0.2203	- 0.0952	-0.1340
1.6699	0.8354	0.9965	1.3343	1.1380	1.9196	- 82.992 7	121.10 35	441.74 58	0.7817	0.3732	- 0.1256	-0.4384
2.2696	0.5073	0.5683	0.3586	0.4614	1.9823	- 141.57 58	149.05 89	568.55 65	1.3659	0.1659	0.0734	-0.0261
0.2894	0.6813	0.6768	0.7755	0.6689	0.9810	181.12 13	90.157 8	524.31 84	0.9933	0.0556	- 0.2243	-0.4472
1.3394	1.4033	1.4831	0.7883	0.9801	0.3632	- 51.710 2	- 14.013 8	387.88 59	1.2244	0.1704	- 0.3063	0.0482
0.9968	0.6516	1.3608	0.3934	0.7587	3.0962	- 33.008 9	- 12.189 1	353.01 68	0.2730	0.4145	0.2097	-0.5154
1.6320	0.9627	0.1895	1.2980	0.9473	1.7124	- 89.120 6	431.67 97	410.81 45	1.0991	0.0815	- 0.3173	-0.3011
1.0768	0.4777	0.6551	1.0702	1.3752	1.6035	20.613 1	183.48 12	502.48 75	0.6831	0.3684	- 0.2953	-0.4005
2.1027	0.9204	0.9816	1.0598	1.3231	0.2614	- 120.77 00	71.832 6	423.31 51	1.0281	0.2804	- 0.3427	0.1992
2.3992	0.3828	0.3051	0.8992	0.1503	2.7813	- 228.90 42	197.29 45	622.25 01	1.1337	0.0419	0.0014	-0.4206
1.9706	1.1363	0.0253	0.9337	0.8746	0.4994	- 234.03 25	427.12 45	322.57 28	1.1632	- 0.1581	- 0.2271	0.2918

0.4809	1.0925	0.5007	1.0869	0.8708	1.2219	271.48 31	202.73 64	429.72 87	0.9203	- 0.0976	- 0.2391	-0.4707
2.9064	1.3221	0.5614	0.0685	0.4787	1.2509	- 328.75 17	76.188 8	399.51 31	0.9758	- 0.0799	- 0.0606	0.5019
2.2147	1.5635	0.5591	1.1978	0.9318	2.1730	- 248.74 36	231.77 30	310.34 55	1.1765	0.1744	- 0.2791	-0.2138
0.4748	0.6266	0.3783	0.5395	0.8060	2.0943	243.95 28	158.73 09	548.57 09	0.6679	0.1532	- 0.1439	-0.5868
0.3327	0.2056	0.5058	1.0392	1.3297	1.7381	128.55 17	115.27 35	558.87 30	0.2475	0.2960	- 0.3765	-0.5053
2.6843	0.6045	0.4976	0.5565	0.2687	2.6047	- 248.74 11	109.88 40	564.28 22	1.3695	0.0581	0.0310	-0.1637
1.0640	0.8677	0.9088	0.8192	0.0042	3.1050	85.881 7	155.19 32	497.72 25	0.1982	0.0103	0.0118	-0.7000

## Arm 3 (ur10 arm)

First 20 testing data set for the arm.

Table A-7 First 20 testing data set for the arm.3

0.4504	3.1372	0.4212	0.1200	1.3908	0.6502	- 926.20 12	- 648.29 27	43.255 9	1.1761	-0.1776	0.3044	-0.1731
1.4024	1.0423	0.3419	0.3820	1.0954	1.4014	294.26 85	501.16 85	1159.6 570	0.3010	-0.4724	0.4949	-0.0964
0.9177	1.2572	0.4214	0.9618	1.3900	1.3809	302.48 02	98.239 8	1335.2 139	0.7100	-0.2910	0.5324	0.0764

0.5474	0.5079	1.1320	1.3532	0.6006	1.1204	606.22 83	88.568 7	1101.2 958	0.8398	-0.0378	0.5191	-0.2297
1.5085	1.4077	0.8909	0.0552	0.6740	0.9934	225.51 65	- 173.46 60	1198.3 754	0.6889	-0.4499	0.3977	-0.1440
0.2618	0.5925	1.1643	0.6382	0.2965	0.3169	547.96 59	- 114.04 20	1097.0 307	0.0335	-0.2356	0.4941	-0.4473
1.5952	0.3400	0.3185	0.6690	0.2451	0.7942	225.51 27	1141.4 246	631.76 66	0.2197	-0.5326	0.1588	-0.4232
1.2902	0.2527	0.5964	1.1064	1.5034	1.5352	471.34 44	1020.8 674	667.53 71	0.2462	-0.4233	0.5496	0.0604
2.9228	0.6200	0.1505	0.0171	0.5325	0.4610	- 881.42 58	445.22 91	766.77 43	0.2217	-0.4544	- 0.3653	-0.3844
1.5352	0.5865	0.7106	0.7295	1.3611	1.5356	211.75 10	800.15 26	986.26 04	0.3308	-0.4725	0.4963	0.0555
0.7537	0.8909	1.0376	1.4706	0.6215	0.6308	314.37 69	- 32.450 6	1263.5 655	0.9553	-0.1181	0.4461	-0.2428
2.7018	1.5255	0.3434	0.6439	1.1984	0.9140	87.091 9	177.25 82	1327.7 411	0.5278	-0.6220	- 0.0080	0.2083
2.3200	0.9814	0.6846	0.2382	1.0956	0.2811	- 136.01 69	448.84 11	1165.4 757	0.3602	-0.6656	- 0.1303	-0.0866
1.7585	1.5346	0.8003	0.6855	0.6726	1.1476	288.31 94	- 253.47 95	1258.8 094	0.9478	-0.3290	0.4007	0.0810
1.9179	2.3459	0.4394	1.5543	1.4911	0.5121	514.24 88	- 917.88 33	890.95 21	1.2668	-0.1282	0.0384	0.2844
1.4895	1.2987	0.3783	0.5844	1.4949	0.2798	190.79	236.26	1287.7	0.4809	-0.6525	0.1283	-0.0014

						00	71	849				
3.0948	1.1109	0.5733	1.0904	1.3440	0.4921	- 322.82 85	199.99 42	1318.9 171	0.5360	-0.5261	- 0.2463	0.3013
2.9533	1.3259	0.5800	0.3952	0.4120	0.2242	- 22.729 5	257.10 36	1310.2 028	0.8140	-0.5382	- 0.1868	-0.0990
2.1831	1.1480	0.6437	0.9444	0.3126	0.7295	92.517 1	305.91 03	1337.7 279	0.9248	-0.4632	0.2565	-0.0765
2.2097	1.9023	0.1624	1.0199	0.0106	1.3998	481.50 31	- 218.89 92	1324.0 693	0.9776	-0.2125	0.4528	0.1046
2.8495	2.5262	1.0325	0.1424	0.0434	0.5499	1108.2 913	- 65.980 3	348.11 90	0.9207	-0.3836	0.3116	0.2094
0.8605	3.0999	0.6088	1.0385	1.2188	1.3362	- 641.83 69	- 1046.4 028	- 72.476 0	1.3232	0.1120	0.0541	0.2164

**Predicted data set for arm.**

Table A-8 Predicted data set for arm 3

joint1	joint2	joint3	joint4	joint5	joint6
0.1688	1.6252	0.5523	0.4118	1.4729	0.4766
2.1461	0.3066	0.2330	0.1381	1.3554	1.1631
0.6952	1.9303	0.7992	0.9955	1.1730	1.3498

2.6385	0.2621	0.3511	0.7005	0.0771	0.8081
1.8480	2.0865	0.3299	0.5978	0.6319	0.2543
2.0467	0.4103	0.3241	0.0949	1.1899	0.4377
0.5749	2.4985	0.4683	1.1516	0.8040	0.5860
1.1874	1.6932	1.0348	0.2580	0.6358	0.8916
2.4635	3.0664	0.7385	0.6776	1.3042	0.5562
0.2268	1.5817	1.5296	0.9786	1.2136	0.4560
3.0191	0.4906	0.5278	0.9662	1.1249	0.2599
1.4033	1.7772	0.9626	1.0041	0.4091	1.4551
2.5230	3.2776	1.2983	1.3201	0.8172	0.9334
0.6741	0.1879	0.6940	1.2178	0.9572	1.4434
1.1779	0.5376	0.4740	0.0922	0.7550	1.1549
2.0203	1.6159	1.1989	1.3004	1.3706	0.5357
0.5833	0.2600	0.2347	1.0961	0.6770	0.1541
0.7820	0.3663	0.4380	0.8310	0.4196	1.2942
0.0952	2.3694	0.8102	0.7509	0.1831	1.0540
1.7219	0.9411	0.2834	0.5933	1.0353	0.1007

### First 20 Training data set for the arm 3.

Table A-9 First 20 Training data set for the arm 3

Joint1	Joint2	Joint3	Joint4	Joint5	Joint6	X	Y	Z	q1	q2	q3	q4
2.1880	0.8989	0.3563	0.8660	1.1301	0.6646	- 239.38 86	688.45 26	1138.9 891	0.4785	-0.6629	0.0577	- 0.0071
3.0812	2.1515	0.7554	0.6159	0.5391	1.1452	904.04 74	188.69 87	896.02 29	0.6246	-0.3914	0.2215	0.4475
1.3778	0.1875	0.6252	1.1592	0.2867	0.2756	460.55 33	1041.5 709	677.39 64	0.2597	-0.5202	0.2109	- 0.4099
1.6699	1.6708	0.9965	1.3343	1.1380	0.9598	261.22 80	- 579.60 78	1135.5 034	1.1710	-0.1590	0.2296	0.2814
2.2696	1.0146	0.5683	0.3586	0.4614	0.9911	- 93.280 4	493.99 43	1222.1 949	0.6946	-0.5745	0.1539	- 0.1601
0.2894	1.3625	0.6768	0.7755	0.6689	0.4905	28.290 6	- 237.99 65	1326.7 336	0.4914	-0.1881	0.5142	- 0.3740
1.3394	2.8067	1.4831	0.7883	0.9801	0.1816	-7.7346	- 971.44 29	- 163.26 23	1.3319	0.1619	0.1729	0.0209
0.9968	1.3032	1.3608	0.3934	0.7587	1.5481	45.296 7	- 354.92 57	1089.4 028	0.9695	-0.0684	0.5097	0.0240
1.6320	1.9255	0.1895	1.2980	0.9473	0.8562	245.91 14	- 453.33 08	1321.1 062	1.0772	-0.3086	0.3168	0.1196
1.0768	0.9554	0.6551	1.0702	1.3752	0.8018	379.45 65	321.03 53	1261.1 429	0.7508	-0.4550	0.3900	- 0.0012

2.1027	1.8408	0.9816	1.0598	1.3231	0.1307	524.98 08	- 524.26 01	1041.4 004	1.2373	-0.2932	0.0219	0.1756
2.3992	0.7655	0.3051	0.8992	0.1503	1.3907	- 436.94 43	746.92 75	1084.9 530	0.9039	-0.4795	0.2336	- 0.1060
1.9706	2.2727	0.0253	0.9337	0.8746	0.2497	483.87 32	- 572.25 11	1142.5 274	1.0340	-0.4604	0.1440	0.0024
0.4809	2.1851	0.5007	1.0869	0.8708	0.6110	- 674.60 19	- 603.79 13	1013.2 746	1.0987	-0.0359	0.3686	- 0.2471
2.9064	2.6442	0.5614	0.0685	0.4787	0.6255	1109.3 102	- 13.220 9	502.02 79	0.9080	-0.4693	0.1206	0.2431
2.2147	3.1270	0.5591	1.1978	0.9318	1.0865	911.71 44	- 850.02 44	- 107.22 44	0.8385	0.1047	0.2033	0.5215
0.4748	1.2531	0.3783	0.5395	0.8060	1.0471	361.03 44	- 70.445 8	1289.4 900	0.3754	-0.2316	0.5876	- 0.2567
0.3327	0.4112	0.5058	1.0392	1.3297	0.8691	1052.2 368	166.86 13	786.11 21	0.2337	-0.3265	0.6069	- 0.1067
2.6843	1.2090	0.4976	0.5565	0.2687	1.3024	- 106.73 20	334.14 52	1320.7 155	0.8892	-0.5131	0.1946	0.0353
1.0640	1.7353	0.9088	0.8192	0.0042	1.5525	- 86.309 6	- 682.84 44	1112.9 253	0.9957	0.1960	0.4596	- 0.0498

## Arm 4 (The Kuka KR Agilus robot arm)

Dataset generated for arm: - The dataset was also generated using the same procedure as the other robot arms.

First 20 testing data set for the arm

Table A-10 First 20 testing data set for the arm 4

0.4504	1.5686	0.4212	0.1200	1.3908	1.3005	685.96 05	346.71 80	743.76 90	0.0798	0.6331	-0.3004	-0.0860
1.4024	0.5211	0.3419	0.3820	1.0954	2.8027	104.05 08	839.41 31	41.346 5	0.6103	0.4067	-0.4837	0.0868
0.9177	0.6286	0.4214	0.9618	1.3900	2.7618	443.50 65	732.42 23	137.20 16	0.7984	0.1326	-0.5526	-0.1330
0.5474	0.2539	1.1320	1.3532	0.6006	2.2408	204.64 82	199.05 62	12.621 3	0.7529	- 0.0586	-0.5957	-0.0050
1.5085	0.7038	0.8909	0.0552	0.6740	1.9869	30.480 2	552.05 53	81.830 8	0.5825	0.6196	-0.1706	0.0473
0.2618	0.2962	1.1643	0.6382	0.2965	0.6337	243.00 52	85.838 3	32.384 1	0.4325	0.5118	-0.3128	-0.3057
1.5952	0.1700	0.3185	0.6690	0.2451	1.5884	- 35.817 4	759.52 54	- 236.50 97	0.2616	0.6558	-0.2296	-0.0085
1.2902	0.1264	0.5964	1.1064	1.5034	3.0704	54.308 6	558.87 29	- 115.11 50	1.0332	- 0.0423	-0.4611	0.1368
2.9228	0.3100	0.1505	0.0171	0.5325	0.9220	- 904.59 96	200.15 71	- 117.10 34	0.2476	0.3800	0.5817	0.0432
1.5352	0.2933	0.7106	0.7295	1.3611	3.0711	- 56.192 1	528.75 36	- 29.878 9	0.9162	0.1433	-0.4507	0.2578

0.7537	0.4455	1.0376	1.4706	0.6215	1.2615	258.65 94	334.11 24	3.2522	0.4983	0.2978	-0.5673	-0.1656
2.7018	0.7627	0.3434	0.6439	1.1984	1.8280	- 854.90 15	331.22 29	224.00 68	0.5987	0.6276	0.1226	0.0385
2.3200	0.4907	0.6846	0.2382	1.0956	0.5622	- 426.19 77	422.78 34	18.751 2	0.8274	0.4163	0.3839	-0.0909
1.7585	0.7673	0.8003	0.6855	0.6726	2.2953	- 166.39 42	633.03 25	104.82 82	0.4790	0.5428	-0.3832	0.0343
1.9179	1.1730	0.4394	1.5543	1.4911	1.0241	- 421.24 19	827.47 27	564.90 27	0.2824	0.5172	0.0045	-0.4610
1.4895	0.6493	0.3783	0.5844	1.4949	0.5596	5.9418	852.02 33	163.54 61	0.5013	0.5534	0.1329	-0.3365
3.0948	0.5555	0.5733	1.0904	1.3440	0.9842	- 750.29 27	- 64.369 7	69.427 1	0.8830	0.4830	0.2663	-0.0294
2.9533	0.6630	0.5800	0.3952	0.4120	0.4484	- 779.59 09	130.51 94	52.813 2	0.2340	0.3419	0.6075	-0.0190
2.1831	0.5740	0.6437	0.9444	0.3126	1.4590	- 444.24 16	582.59 48	-8.7685	0.2511	0.6913	-0.0796	-0.0081
2.2097	0.9512	0.1624	1.0199	0.0106	2.7996	- 677.06 35	909.72 00	455.16 04	0.0625	- 0.4539	0.4702	0.2681
2.8495	1.2631	1.0325	0.1424	0.0434	1.0998	- 614.76 04	184.08 97	282.70 19	0.1159	- 0.4884	-0.5070	0.0322
0.8605	1.5499	0.6088	1.0385	1.2188	2.6724	427.70 53	639.92 61	664.11 85	0.2870	0.2449	-0.5806	-0.2870

Predicted data set for arm

Table A-11 Predicted data set for arm 4

joint1	joint2	joint3	joint4	joint5	joint6
0.2276	0.8695	0.2876	0.7867	1.2683	0.5257
2.1485	0.1113	0.5850	0.3914	1.1112	2.8494
0.7169	0.9340	0.7148	1.0844	1.2052	2.1803
2.6688	0.1095	0.4648	0.8075	0.0662	1.6171
1.7962	0.9883	0.2141	0.7613	0.3833	0.1812
2.0428	0.2289	0.2396	0.3253	1.0906	1.0894
0.6040	1.1506	0.2122	1.4455	0.8454	0.6838
1.1744	0.8476	0.9976	0.3873	0.5935	1.2555
2.4638	1.4881	0.8486	0.8653	1.3261	1.1641
0.2155	0.6753	1.5561	1.2541	1.2083	0.7771
3.0900	0.1668	0.5693	1.0100	0.9154	0.6317
1.4056	0.9123	0.7848	1.3350	0.3898	2.4718
2.5342	1.4825	1.2280	1.4049	0.8061	1.7883
0.7236	0.1068	0.7329	1.2950	1.0325	2.8988

1.1557	0.3571	0.2313	0.2195	0.8998	2.5319
2.0551	0.7569	1.1679	1.4925	1.4909	0.8778
0.5899	0.1417	0.0960	1.3296	0.6808	0.1402
0.7930	0.3272	0.0179	0.8782	0.6021	2.8469
0.1236	1.1702	0.6622	0.7549	0.0932	2.1660
1.6977	0.5088	0.1460	0.7858	1.1289	0.1237

### First 20 training data set for the arm 4

Table A-12 First 20 training data set for the arm 4

Joint1	Joint2	Joint3	Joint4	Joint5	Joint6	X	Y	Z	q1	q2	q3	q4
2.1880	0.4495	0.3563	0.8660	1.1301	1.3292	- 547.89 57	635.08 14	-0.5684	0.6886	0.6080	0.0112	- 0.1080
3.0812	1.0757	0.7554	0.6159	0.5391	2.2904	- 760.16 04	11.826 1	268.42 76	0.2251	0.6932	0.0782	0.0267
1.3778	0.0937	0.6252	1.1592	0.2867	0.5512	66.540 6	495.89 96	- 227.62 25	0.4407	0.6515	-0.1340	- 0.0952
1.6699	0.8354	0.9965	1.3343	1.1380	1.9196	- 157.36 12	556.79 19	170.02 90	0.7464	0.3908	-0.4384	- 0.1256
2.2696	0.5073	0.5683	0.3586	0.4614	1.9823	- 484.85 23	549.08 39	- 34.531 6	0.3318	0.6829	-0.0261	0.0734

0.2894	0.6813	0.6768	0.7755	0.6689	0.9810	674.20 44	252.80 77	67.958 1	0.1112	0.4966	-0.4472	- 0.2243
1.3394	1.4033	1.4831	0.7883	0.9801	0.3632	-2.1777	286.12 73	305.53 79	0.3407	0.6122	0.0482	- 0.3063
0.9968	0.6516	1.3608	0.3934	0.7587	3.0962	101.90 52	213.44 72	199.47 63	0.8290	0.1365	-0.5154	0.2097
1.6320	0.9627	0.1895	1.2980	0.9473	1.7124	- 155.23 50	1063.0 871	466.94 75	0.1630	0.5496	-0.3011	- 0.3173
1.0768	0.4777	0.6551	1.0702	1.3752	1.6035	227.84 41	631.83 65	31.951 2	0.7368	0.3415	-0.4005	- 0.2953
2.1027	0.9204	0.9816	1.0598	1.3231	0.2614	- 372.40 61	441.07 05	226.52 10	0.5608	0.5140	0.1992	- 0.3427
2.3992	0.3828	0.3051	0.8992	0.1503	2.7813	- 674.08 74	600.19 06	- 98.928 2	0.0838	0.5668	-0.4206	0.0014
1.9706	1.1363	0.0253	0.9337	0.8746	0.4994	- 487.31 32	971.11 78	696.90 06	0.3163	- 0.5816	-0.2918	0.2271
0.4809	1.0925	0.5007	1.0869	0.8708	1.2219	769.87 49	489.49 42	400.75 71	0.1952	- 0.4601	0.4707	0.2391
2.9064	1.3221	0.5614	0.0685	0.4787	1.2509	- 850.91 95	200.18 60	504.79 50	0.1599	- 0.4879	-0.5019	0.0606
2.2147	1.5635	0.5591	1.1978	0.9318	2.1730	- 556.07 65	597.63 22	703.39 03	0.3488	0.5882	-0.2138	- 0.2791
0.4748	0.6266	0.3783	0.5395	0.8060	2.0943	767.82 77	442.58 64	85.624 0	0.3064	0.3340	-0.5868	- 0.1439
0.3327	0.2056	0.5058	1.0392	1.3297	1.7381	570.13 63	298.86 81	- 114.75	0.5919	0.1238	-0.5053	- 0.3765

								60				
2.6843	0.6045	0.4976	0.5565	0.2687	2.6047	- 765.47 76	358.66 32	24.347 1	0.1162	0.6847	-0.1637	0.0310
1.0640	0.8677	0.9088	0.8192	0.0042	3.1050	318.75 67	574.85 54	118.39 36	0.0205	0.0991	-0.7000	0.0118

## Arm 5 (The Yasakawa Motoman GP arm)

Dataset generated for arm

Testing data set for arm

Table A-13 Testing data set for arm 5

0.2252	1.5686	0.4212	0.1200	2.7817	1.3005	- 63.938 2	454.55 65	695.12 63	0.4428	0.2651	- 0.5144	-0.3408
0.7012	0.5211	0.3419	0.3820	2.1909	2.8027	206.64 21	423.48 90	723.51 22	0.6987	0.0199	0.5632	0.2456
0.4589	0.6286	0.4214	0.9618	2.7799	2.7618	267.30 74	434.07 22	695.17 55	0.2982	-0.0065	0.5317	0.4415
0.2737	0.2539	1.1320	1.3532	1.2011	2.2408	493.42 06	265.12 56	798.90 44	0.5054	-0.4654	0.4649	0.0587
0.7542	0.7038	0.8909	0.0552	1.3480	1.9869	108.88 07	445.58 97	787.67 28	0.3277	-0.2931	0.6222	-0.0116
0.1309	0.2962	1.1643	0.6382	0.5929	0.6337	471.22 10	194.21 14	836.34 37	0.3418	0.0383	- 0.5756	0.3716
0.7976	0.1700	0.3185	0.6690	0.4902	1.5884	305.73 14	398.56 84	840.58 03	0.1494	-0.1189	0.5946	-0.3560
0.6451	0.1264	0.5964	1.1064	3.0068	3.0704	367.48	366.82	690.72	0.3558	0.1151	0.4890	0.4647

						06	69	52				
1.4614	0.3100	0.1505	0.0171	1.0651	0.9220	- 72.870 2	448.10 05	808.75 38	0.3677	0.0634	- 0.6483	0.2048
0.7676	0.2933	0.7106	0.7295	2.7221	3.0711	264.14 05	435.88 67	696.93 57	0.4703	0.0400	0.5055	0.4331
0.3768	0.4455	1.0376	1.4706	1.2430	1.2615	403.03 06	393.33 33	795.75 38	0.0387	-0.5199	0.4530	-0.1554
1.3509	0.7627	0.3434	0.6439	2.3969	1.8280	- 197.95 34	443.15 92	711.17 65	0.2701	0.4186	- 0.4885	-0.2606
1.1600	0.4907	0.6846	0.2382	2.1911	0.5622	7.6431	474.10 10	723.49 44	0.7523	0.3748	- 0.4669	-0.0093
0.8792	0.7673	0.8003	0.6855	1.3453	2.2953	39.073 4	499.41 89	787.88 99	0.4585	-0.4825	0.4469	0.1224
0.9590	1.1730	0.4394	1.5543	2.9822	1.0241	- 240.47 16	441.67 02	691.01 36	0.9295	0.5319	- 0.0313	0.0114
0.7448	0.6493	0.3783	0.5844	2.9898	0.5596	108.18 79	495.82 24	690.91 99	0.7887	0.3858	- 0.3481	-0.2728
1.5474	0.5555	0.5733	1.0904	2.6880	0.9842	- 232.14 19	461.93 03	698.08 87	0.7967	0.5604	- 0.1650	-0.0091
1.4766	0.6630	0.5800	0.3952	0.8239	0.4484	- 213.73 86	429.56 73	824.34 88	0.1974	0.2905	- 0.4951	0.4009
1.0916	0.5740	0.6437	0.9444	0.6253	1.4590	- 4.0645	513.31 50	834.86 52	0.4325	-0.4567	0.4323	-0.2405
1.1048	0.9512	0.1624	1.0199	0.0211	2.7996	- 212.02 23	461.43 74	849.98 21	0.9901	-0.4974	0.0663	-0.0560

1.4248	1.2631	1.0325	0.1424	0.0868	1.0998	- 422.43 82	217.31 30	849.69 90	0.7464	-0.4158	0.3105	-0.3023
0.4302	1.5499	0.6088	1.0385	2.4375	2.6724	- 129.03 19	470.09 39	709.02 39	0.0866	0.3881	- 0.4154	-0.4183

Predicted data set for arm

Table A-14 Predicted data set for arm 5

joint1	joint2	joint3	joint4	joint5	joint6
0.4681	0.5068	0.6745	0.4077	2.7051	0.7992
0.6075	0.5658	0.5625	0.4097	2.3436	2.8837
0.7430	0.5345	0.9653	0.9342	2.1975	2.4393
0.9986	0.4830	0.5643	0.7551	0.1889	1.6552
1.0873	0.7577	0.4967	0.5206	1.3690	0.0390
0.7432	0.5281	0.4756	0.2609	2.1567	1.1514
0.6509	0.7508	1.0929	1.0069	1.5926	0.7830
0.6878	0.6367	0.7453	0.5975	0.9990	1.2928
1.3339	1.4011	0.9934	0.6016	2.6729	1.2544
0.4035	0.5428	1.3042	1.0358	2.5016	0.6294
0.9419	0.7420	0.8719	1.0173	2.1252	0.3175

0.8823	0.6731	1.0354	0.9781	0.8300	2.7989
1.4424	1.4455	1.0736	1.2163	1.6479	1.9026
0.2208	0.2490	0.9754	1.2598	1.9601	3.1017
0.3854	0.5812	0.6148	0.2569	1.5473	2.7261
1.0557	0.7585	0.9970	1.0601	2.8292	0.6532
0.1780	0.1925	0.7867	1.0464	1.3008	0.1445
0.2894	0.3155	0.7222	0.4150	0.8083	2.9193
0.3520	0.8702	1.0926	0.4644	0.2880	2.3756
0.6651	0.6248	0.6793	0.4332	2.2135	0.1491

## Training data set for arm 5

Table A-15 Training data set for arm 5

Joint1	Joint2	Joint3	Joint4	Joint5	Joint6	X	Y	Z	q1	q2	q3	q4
1.0940	0.4495	0.3563	0.8660	2.2603	1.3292	75.0067	495.5743	719.1090	0.3995	0.3955	-0.5300	-0.1510
1.5406	1.0757	0.7554	0.6159	1.0781	2.2904	-376.0169	306.7781	807.8385	0.4730	-0.6217	0.1708	0.1686
0.6889	0.0937	0.6252	1.1592	0.5733	0.5512	389.3195	355.1155	837.2086	0.2503	0.1140	-0.5550	0.4041

0.8350	0.8354	0.9965	1.3343	2.2759	1.9196	- 13.189 7	536.88 23	718.14 83	0.3707	0.5979	- 0.2673	- 0.1917
1.1348	0.5073	0.5683	0.3586	0.9227	1.9823	14.913 2	477.66 12	818.29 17	0.4514	-0.3544	0.5541	- 0.1280
0.1447	0.6813	0.6768	0.7755	1.3378	0.9810	394.53 96	313.66 97	788.47 27	0.3285	0.2104	- 0.6387	0.1445
0.6697	1.4033	1.4831	0.7883	1.9602	0.3632	- 192.84 96	467.81 98	739.62 86	0.3656	0.5757	- 0.0281	0.3666
0.4984	0.6516	1.3608	0.3934	1.5175	3.0962	262.25 55	430.10 56	774.26 19	0.7844	-0.3263	0.3935	0.2913
0.8160	0.9627	0.1895	1.2980	1.8946	1.7124	- 4.6899	510.86 16	744.54 83	0.1052	0.5166	- 0.4667	- 0.1122
0.5384	0.4777	0.6551	1.0702	2.7503	1.6035	292.79 57	426.70 51	696.04 58	0.4184	0.3192	- 0.4933	- 0.3331
1.0514	0.9204	0.9816	1.0598	2.6463	0.2614	- 168.64 29	481.01 78	699.61 37	0.7932	0.5281	0.0422	0.2490
1.1996	0.3828	0.3051	0.8992	0.3007	2.7813	19.135 3	512.02 27	846.41 06	0.9258	-0.4633	0.2479	- 0.0982
0.9853	1.1363	0.0253	0.9337	1.7492	0.4994	- 154.01 10	441.26 91	755.80 39	0.5979	0.4384	- 0.4191	0.2069
0.2404	1.0925	0.5007	1.0869	1.7416	1.2219	210.20 72	463.34 85	756.39 84	0.2652	0.4417	- 0.5352	0.0300
1.4532	1.3221	0.5614	0.0685	0.9575	1.2509	- 386.86 59	208.39 77	816.04 81	0.2041	-0.5077	0.4317	- 0.2134
1.1073	1.5635	0.5591	1.1978	1.8635	2.1730	- 397.05 04	307.59 46	746.91 51	0.1361	0.6570	- 0.1250	- 0.2194

0.2374	0.6266	0.3783	0.5395	1.6120	2.0943	357.52 56	307.49 04	766.70 15	0.3609	-0.0682	0.6795	0.0333
0.1664	0.2056	0.5058	1.0392	2.6594	1.7381	492.15 75	164.23 22	699.12 24	0.0261	0.0737	- 0.5991	- 0.3681
1.3422	0.6045	0.4976	0.5565	0.5375	2.6047	- 144.39 98	472.82 93	838.72 06	0.8571	-0.4808	0.2904	- 0.0301
0.5320	0.8677	0.9088	0.8192	0.0084	3.1050	84.037 6	488.38 09	849.99 71	0.9996	-0.4999	0.0147	- 0.0105

## Arm 6 (4dof model)

Dataset generated for arm: Though, this arm is four degrees of freedom, the dataset was also generated using the previous methods but, in this case, four joint angles were generated for the four revolute joints unlike the previous cases where six joint angles were generated.

Testing data set for arm : -

Table A-16 Testing data set for arm

10.2340	13.0633	2.2979	1.3126	-0.0143	-0.0045	0.2627
10.7149	-12.5458	2.2693	0.9345	0.0565	-0.0120	-0.5276
4.1820	-15.7439	1.4422	1.0431	0.2121	-0.2197	-0.3670
5.1425	15.7440	2.2994	1.3019	0.0065	0.0049	0.2761
7.3090	15.5363	0.7075	1.0857	-0.3702	-0.1899	0.1795
15.7798	-3.9672	1.1642	1.1619	0.2760	-0.2175	0.1976

16.9526	1.4674	-1.5426	0.3680	-0.5144	-0.3912	-0.2202
14.4589	7.4416	-0.9675	0.5910	0.5705	-0.1725	0.2399
1.2973	16.8353	1.9232	1.3128	-0.1165	-0.1655	0.1679
4.3563	-15.7634	1.9249	0.9790	0.1576	-0.1262	-0.4687
11.3336	-11.8600	2.1091	0.6951	0.1436	0.0113	-0.5987
1.7097	16.4238	2.2800	1.2375	0.0334	0.0325	0.3391
5.1493	-15.5768	2.1125	1.3586	0.0498	-0.1338	-0.1349
14.0437	9.9244	-0.3770	0.7979	-0.3822	-0.3807	-0.2233
16.9928	1.4110	1.4060	1.0221	-0.2871	-0.1215	-0.3764
16.0252	-2.9644	-1.5229	0.5805	0.6069	-0.2172	0.0150
16.8161	-0.1873	2.0644	1.0812	-0.1483	-0.0602	-0.4268
15.8458	3.8664	-1.6496	0.4504	0.5934	-0.2778	0.1414
10.5760	12.6613	2.2681	1.3190	0.0558	0.0188	0.2482
14.5802	-7.3911	1.8866	1.1134	0.2120	-0.0007	-0.3810
4.1364	-15.7285	-1.0104	0.2835	0.5855	-0.1306	-0.3465
15.7881	5.0140	2.2996	1.2346	0.0052	0.0036	-0.3449

Predicted data set for arm :-

Table A-17 Predicted data set for arm 6

Predicted_Joint1	Predicted_Joint2	Predicted_Joint3	Predicted_Joint4
0.4957	2.3767	2.4519	0.1043
0.4478	1.5192	1.5730	2.1317
1.5096	2.2568	2.3037	2.0387
2.8169	1.4145	1.4635	0.3622
0.9984	1.1571	1.1921	0.4041
1.1705	0.4327	0.4612	0.3127
2.2426	1.4216	1.4660	0.4715
0.5474	2.1383	2.2081	2.5587
1.3568	0.7288	0.7656	1.9581
0.5353	1.9175	1.9822	2.4859
2.3552	1.2750	1.3065	1.1515
2.4304	2.5108	2.5996	0.0232
1.8387	1.3462	1.3788	2.0312
0.1925	1.4924	1.5489	0.3735
0.2799	1.1224	1.1632	1.7738
2.6594	2.0035	2.0592	0.7138

1.7474	1.4595	1.4948	2.3075
1.8471	2.3809	2.4423	0.7909
1.9636	1.6894	1.7172	1.9011
1.5527	0.2178	0.2538	2.0816

### Training data set for arm 6

Table A-18 Training data set for arm 6

Joint1	Joint2	Joint3	Joint4	X	Y	Z	q1	q2	q3	q4
2.1880	2.4275	1.3985	2.5023	12.0268	11.0446	1.7820	0.9523	0.2344	-0.0371	0.4658
0.8989	1.4675	1.5873	2.4461	14.9819	-7.1882	2.2913	1.4056	-0.0220	0.0214	0.0717
0.7127	0.0627	1.5592	0.0058	14.9786	-8.4667	0.1175	0.3604	-0.4569	-0.1686	-0.4799
1.7320	2.9011	1.5531	0.5658	15.7851	3.8600	0.5873	1.0222	0.3602	0.2376	-0.2294
2.2603	0.5628	2.1007	0.3863	9.5999	13.8224	2.0421	1.3321	-0.0992	-0.1349	-0.1683
1.3292	0.6894	1.2333	1.6457	17.0834	1.6193	0.7928	1.1556	-0.3997	0.0638	-0.0483
3.0812	1.1675	0.1144	0.6192	-4.7159	16.5150	-0.6552	0.8129	-0.1889	-0.5344	0.1166
2.1515	0.5729	0.3330	2.1782	10.6319	13.3267	-1.4191	0.5129	-0.6357	0.0085	0.1732
1.5109	1.8975	0.2418	1.3176	16.4965	4.4586	1.2382	1.2251	-0.3381	-0.0328	-0.0967
1.2319	1.5883	0.7610	1.7565	16.9865	-0.5408	1.6151	1.3009	-0.2635	0.0708	-0.0499

1.0781	0.3059	2.7621	2.2568	16.0088	-4.4295	2.2938	1.4067	-0.0216	0.0145	0.0682
2.2904	1.7557	2.2300	2.0239	11.0099	12.0164	1.5281	1.0746	0.2871	0.0385	0.3569
1.3778	2.2533	1.6632	1.7506	16.2619	-1.2513	1.6432	1.3093	0.2626	-0.0495	-0.0043
0.1875	0.3318	1.7018	1.7694	8.4801	- 14.8802	1.0269	0.9978	-0.2616	0.2645	-0.3357
1.2505	2.6705	1.5046	1.9329	15.8559	-3.6541	1.1771	1.2293	0.3292	-0.1169	0.0128
2.3185	0.2628	1.0485	0.9869	7.9876	15.2115	-0.5902	0.8593	-0.4408	-0.3462	0.0353
0.5733	2.0437	2.6568	0.8441	9.7955	- 12.9588	0.0273	0.6547	0.4925	-0.0671	-0.3818
0.5512	0.3437	0.1155	1.8875	12.3342	- 11.4338	-2.0617	0.3022	-0.5405	0.4266	-0.0554
1.6699	0.6308	2.5108	1.1605	15.7741	5.0860	2.3000	1.3971	0.0000	0.0000	-0.1096
1.6708	1.6119	2.6028	0.2166	15.9714	3.0888	1.0980	0.9842	0.2701	0.2403	-0.3566