Trajectory Planning &Inverse Kinematics analysis of Pioneer 2 Manipulator using Different Machine Learning Techniques

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***Abstract*— the primary objective of robot manipulators is to achieve desired orientation and point of end effector in order to accomplish the pre-established task. Inverse Kinematic Analysis will be used in the robot pioneer 2 to obtain a successful solution to design and operate the arm. This paper considers a 5-dof revolute Pioneer2 manipulator which is compact, low cost and lightweight. When the DOF of the robots increase the inverse kinematic problem becomes more and more complex and gives n number of joint configurations for the same position. This results in making the standard solution for this problem becomes trickier. To overcome the computational complexity of kinematic analysis of Pioneer 2 robot, the objective of this study is to perform intelligent computation of inverse kinematics with the use of machine learning technique that consists of linear regression, K-Nearest Neighbor algorithm and Artificial Neural Network. By comparing three algorithms R -square values and RMSE values, it is observed that KNN algorithm is giving better results. Therefore, KNN can be used better solution of inverse kinematics with fast results and high accuracy. Then the smooth trajectory is achieved using cubic spline interpolation.**

Keywords—Inverse Kinematics, KNN, ANN, Linear Regression, Pioneer2,

I. INTRODUCTION

Industrial robots or robot manipulators are automated machines used in industries for process which require high precision, flexibility and repeatability that manual labor cannot provide. This manipulator control is the one of the main research area in robotics. Forward kinematics talks about the position of end effector from particular values of the joint parameters using kinematic equations used for a robotic calculation. Inverse kinematics makes use of a given orientation and point with respect to the start and calculate the various joint parameters which is required to end the chain.

In this research paper [1], the author explained about the industrial robots which are used in the sector where the manpower is can't be worked. As many researchers have proposed to optimize the errors in different DOFs. So, the author used some technique to solve these errors that are ANFIS, PSO, DE. By optimizing the working function of robot then there will be accurate decision making by the robot. In [2], Due to its high accuracy and good precision of robots. These robots are used in major sector like medical, military and industrial application. This paper talks about the improvement of kinematics in robot and robot dynamics. The paper presented research and differentiate between joint space and the Cartesian space in robot kinematics. In [3] they presented about BQGA which is the optimization algorithm to represent population element. Hence, this paper proposes an improvement plan for these problems in BQGA. In [4] the author presented the planning approach which is an energy-based trajectory using machine learning for IRs. They showed in-terms of method architecture, robotics movement digitalization, hybrid algorithm and optimization process. In this research paper [5], they presented a brief reviews and discussion about common S-curve. Sigmoid jerk S-curve trajectory is described, simulation on manipulator with three and six DOFs are addressed. In this paper [6], the prediction of optimal joint angels of the robot manipulator with the help of neural network predictors are used. The experiment implemented using KUKA, KR and details about industrial implementation, robot manipulator, and predictor for the neural network. In this paper [7], the main aim is to reduce the mean square error of the neural network-based solution of inverse kinematic problem using GSA. The solutions of both the forward and inverse kinematic problems for 6R PUMA robot are solved. In [8] the author presented about optimization of algorithm and scenarios in the robot with the help of inverse kinematics equations is described. The manipulated result is compared with the graph and tables. The working function of 5-DOF pioneer is explained in [9] which includes inverse kinematics with the help of forward kinematics. In [10] the authors prove that correct kinematic analysis helps in optimizing the design of the robot and guiding the movement of joints for effective functioning. An analytical solution for the inverse kinematics of a robotic arm is derived with five degrees of freedom. In [11], the difficulties in solving the Inverse kinematic equations of 2, 3, 5 DOF redundant robot manipulators arises due to the presence of uncertain, time varying and non-linear equations having transcendental functions are explained. In [12], the modeling and control of Pioneer 2 robotic arms are discussed and explained about the ineffective solutions of robotic manipulators with high degrees of freedom the difficulties in solving the Inverse kinematic equations arises due to the presence of uncertain, non-linear equations having transcendental functions. In [13], authors discussed inverse kinematics which can be solved by methods such as iterative, DH notation and transformation equation. In [14], the different machine learning techniques such as Linear regression, K- Nearest Neighbor algorithm and Artificial Neural network are used for the prediction of properties in manufacturing for the type of supervised regression problems. In [15, 16] the kinematic analysis of 5- DOF robot manipulator designed for serving various applications are explained. A pioneer 2 robot which is a 5DOF robot have a list of advantages which include adjustable action, suitable operation, compact volume etc. So, in the process of making Pioneer 2 robot more precise, different algorithms like KNN, ANN and linear regression are proposed for the kinematic analysis of the same robot manipulator in this paper.

II. Problem Description

This paper considers a 5-dof revolute Pioneer2 manipulator which is compact, low cost and lightweight. If the manipulator is redundant or having high DOF, then conventional solution for inverse kinematic problem becomes more complicated.

A. Working Environment

The structure of 5-dof revolute Pioneer2 manipulator is shown in Figure 1.

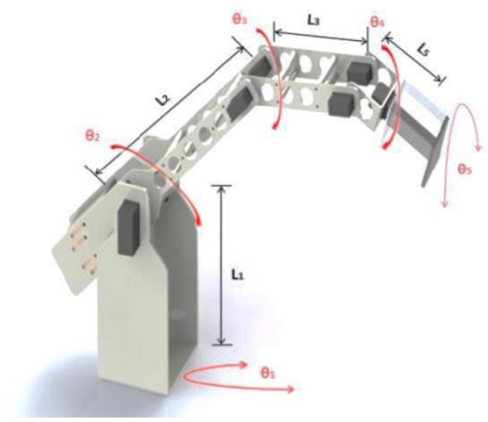

Fig. 1. Structure of 5-dof revolute Pioneer2 manipulator

The major application of this robot is for grasping and manipulation of objects like soda cans up to the weight limit of 150grams within the workspace. Joint of the Pioneer 2 are;

i. Joints rotations:
ii. Base rotation
iii. Shoulder rotation
iv. Elbow rotation
v. Wrist rotation
vi. Gripper mount
vii. Gripper fingers

All joints are driven by servo motors except gripper fingers. The joint limits and parameters taken for the research has presented in Table 1.

B. Objective

To overcome the computational complexity of kinematic analysis of Pioneer 2 robot, the objective of this study is to perform intelligent computation of inverse kinematics using different machine learning techniques such as linear regression, K-Nearest Neighbor algorithm and Artificial Neural Network.

III. Methodology

In this study, the data is generated using forward kinematics equations of a Pioneer 2 robot. Modelling of different machine learning algorithms is done using the generated data. Then the joint variables can be predicted using the machine learning models. Finally, the accuracy of algorithm is compared and best algorithm will be selected for the future predictions.

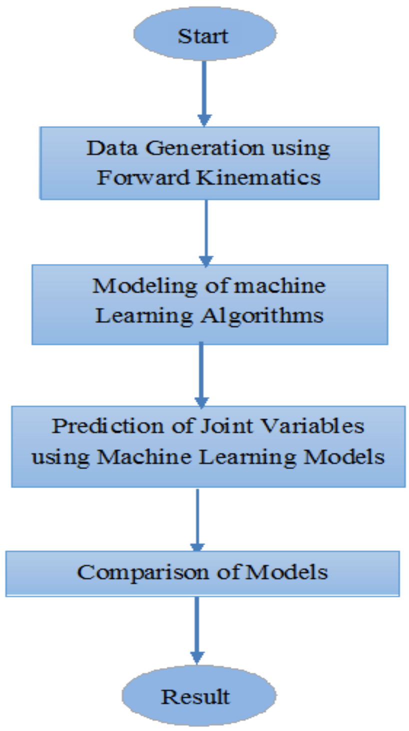

Fig. 2. Flow chart for methodology

TABLE I.

Data Set Generated Using Forward Kinematics

Sl.No	$\theta_1(^0)$	$\theta_2(^0)$	$\theta_3(^0)$	$\theta_4(^0)$	$\theta_5(^0)$	X(m)	Y(m)	Z(m)
1	-180	-180	-180	-180	-180	-190	9.18861E-15	150

2	-179.64	-179.64	-179.64	-179.64	-179.64	-190.0011518	0.476383123	150.9110546
3	-179.28	-179.28	-179.28	-179.28	-179.28	-190.0044746	0.963099826	151.8220659
..	..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..	..
998	179.28	179.28	179.28	179.28	179.28	-190.005	-0.92205416	148.1779
999	179.64	179.64	179.64	179.64	179.64	-190.001	-0.46611948	149.0889
1000	180	180	180	180	180	-190	1.83428E-11	150

A. Mathematical Modeling Of Pioneer 2 Robot

Different joint variable value ranges and constants are defined to find forward and inverse kinematics solutions of Pioneer 2 robot manipulator is presented in Table 1.

TABLE II.

JOINT VARIABLES OF PIONEER 2 ROBOT

Joints	θ_i (degree)	d_i(mm)	a_i(mm)	α_i(degree)
0	$\theta_1=\pm180$	$d_1=150$	$a_1=60$	-90
1	$\theta_2=\pm180$	0	$a_2=145$	0
2	$\theta_3=\pm180$	0	0	-90
3	$\theta_4=\pm180$	$d_2=125$	0	90
4	$\theta_5=\pm180$	0	0	-90
5	0	$d_3=130$	0	0

The data sets for training the algorithms were generated by using forward kinematic equations as follows

$$X = -d_3c_1s_{23}c_4s_5 - d_3s_1s_4s_5 + d_3c_1c_{23}c_5 + d_2c_2c_{23} + a_2c_1c_2 + a_1c_1$$

$$Y = -d_3s_1s_{23}c_4s_5 + d_3c_1s_4s_5 + d_3s_1c_{23}c_5 + d_2s_1c_{23} + a_2s_1c_2 + a_1s_1$$

$$Z = -d_3c_{23}c_4s_5 - d_3s_{23}c_5 - d_2s_{23}c_5 - d_2s_{23} - a_2s_2 + d_1$$

Where,

a_i= Link Length
d_i = Joint Distance
$c_i = \cos\Theta_i$, (i=1,2,3...n)
$s_i = \sin\Theta_i$,, (i=1,2,3...n)

The training data was first generated using the above formula for the input parameter X, Y and Z coordinates by using the different values of θ1,θ2,θ3,θ4 and θ5 which is shown in table 2. These data sets are used for the training, evaluation and testing the Linear Regression, KNN and MLP neural network. The proposed work is performed using python.

All the data science algorithms are having 3 main steps:

- Step1: Data Processing
- Step2: Modeling
- Step3: Validation

A. Data Processing

Application of data processing in material science is the important step of machine learning, because the performance of machine learning model mainly depends on data processing.

Data processing consists of two parts:

- Data selection
- Feature engineering.

1) Data Selection: In this study, A 1000 datasets were generated from forward kinematic equation, which includes joint variables and X,Y,Z Coordinates are shown in table 1.

2) Feature Engineering: Feature engineering means selecting the suitable input parameters for prediction of target. In this study X, Y and Z are considered as features for the prediction of Joint variables.

B. Modeling

The model building is necessary to analyses the data, after data processing. The steps involved in the modeling of algorithm are selection of algorithms, training and making predictions. Three machine learning techniques which is a part of data science such as LR, KNN and ANN are selected for modeling the above data. The modeling and predictions are made using python software.

1) Linear regression

Linear regression creates model which explains the relationship between input variable and output variable by fitting a linear equation for the given data.

2) *K-Nearest Neighbors (KNN)*

It is a type of supervised learning which can be used to solve both classification and regression problems. In this algorithm, the data points similar to the testing data point are identified as neighbors and output is derived. The predictions are made by observing the k neighbors. The steps to be followed in this algorithm is

Step 1: Feeding the data and initialize the K value based on size of data.

Step 2: Distance between test data and the current data for each example will be calculated.

Step 3: Sorting the ordered collection of distances and indices in ascending order.

Step 4: Picking the first K entry and get the corresponding response variables.

Step 5: If regression, return the mean of the K labels or mode of the K labels.

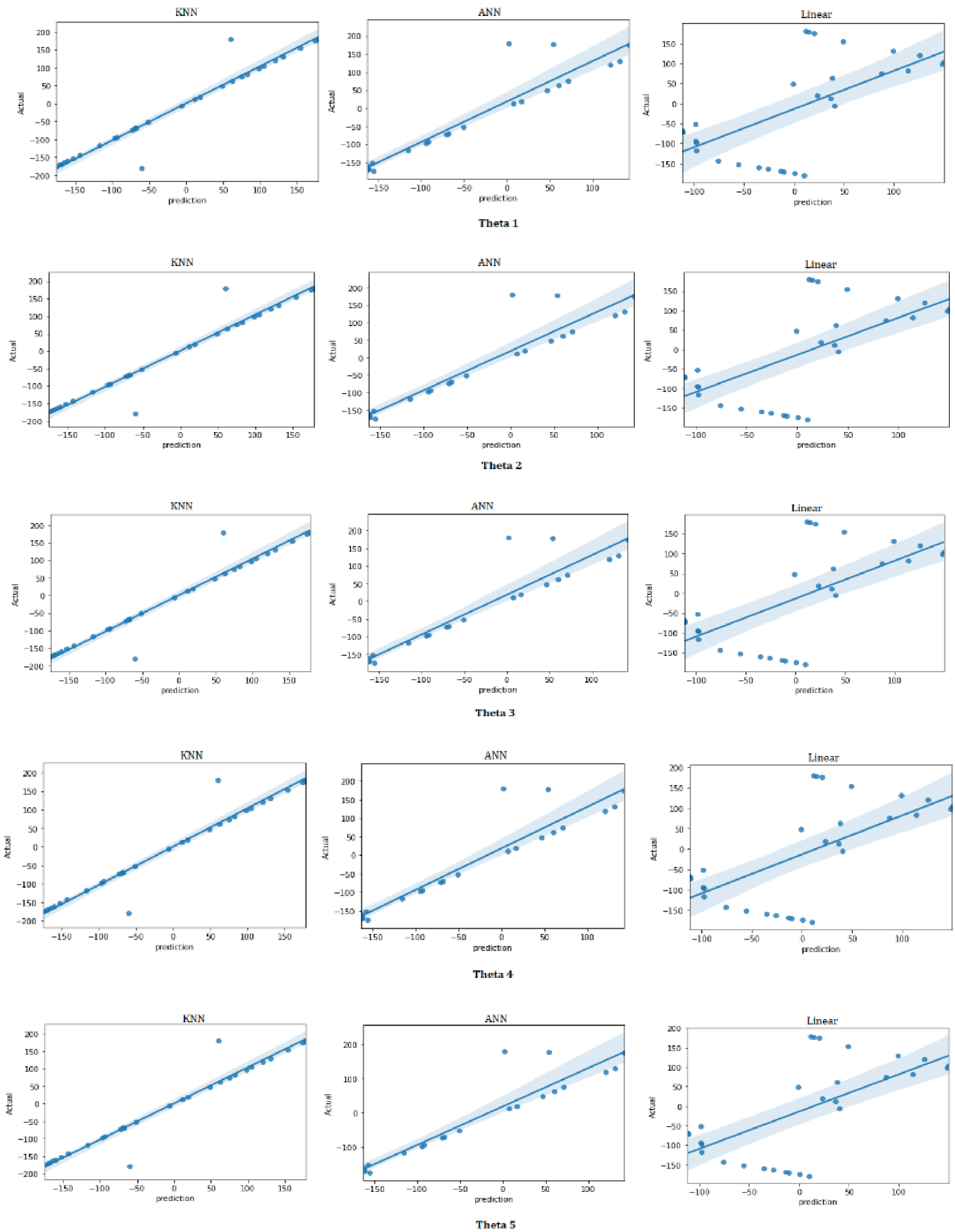

Fig. 3. Theta values predicted using KNN, ANN and Linear Regression versus actual values

3) Artificial Neural Network

In neural network [11], neurons are combined according to different architectures. Basically neurons are arranged in a layers consist of input layer, hidden layer and output layer. Each neuron receives input signals and connected with weightage which sum to an activation function. A suitable activation function transforms it into the output. The accuracy of network depends only on connected weightage values.

C. *Validation of model*

Validation of a model is conducted to test the performance and the accuracy of developed model. In every machine learning technique, the original data is divided in to a training set and test set. The training set of data is used for training of model and the validation is conducted by test set of data.

IV. RESULTS AND DISCUSSIONS

The above work is performed in Python3.7.Linear regression, KNN and ANN algorithms are used for training the network. In this work, the forward kinematics equations are used to generate the training data sets. A set of thousand data sets were first generated using forward kinematics for the input parameter X,Y and Z coordinates in mm. These data sets are used for the training, evaluation and testing the different machine learning algorithms.

Actual versus Prediction plots for each joint variable for three algorithms are shown in Figure 3.From the above graph, it is observed that KNN algorithm gives better fit compared to other two algorithms (ANN & LR). For θ1-θ5 it clearly shows the better fit of points with zero line. In KNN, points are uniformly speeded with Zero line and very less number of outliers. By comparing three algorithms R -square values, it is observed that KNN algorithm is giving better results.

TABLE III.

R^2 VALUE FOR JOINT VARIABLES

Technique	R Squared value
LR	91.3%
KNN	99.4%
ANN	60.5%

The highest R-squared value was obtained using the k-NN algorithm (99.4%). The R-squared values obtained using A-NN and Linear Regression are (91.3%) and (60.5%), respectively which is shown in Table.3.

RMSE values for the different percentage of training dataset (50% to 90%) are plotted in Figure 4, which shows the KNN algorithm gave the lowest RMSE value for all the different percentage of training datasets.

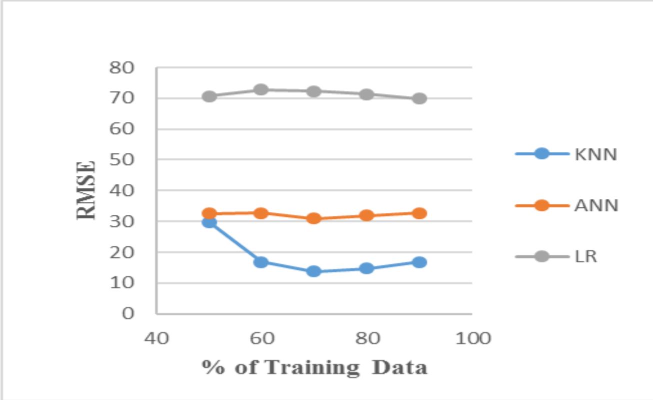

Fig. 4. Comparison of RMSE for LR, KNN and ANN

So KNN algorithm is chosen for prediction of joint variables. The initial point, final point and four intermediate control points in Cartesian space (X, Y) is shown in Table 4.

TABLE IV

CONTROL POINTS

Sl.No	X(mm)	Y(mm)	Z(mm)
1	-200	150	-400
2	-80	180	150
3	40	210	500
4	160	240	700
5	280	270	650
6	400	300	500

After validation, the three joint angles are predicted using the model by giving six points in Cartesian space. Control points defined in Cartesian space is given as an input and the path is obtained using cubic B –spline polynomials which is shown in figure.

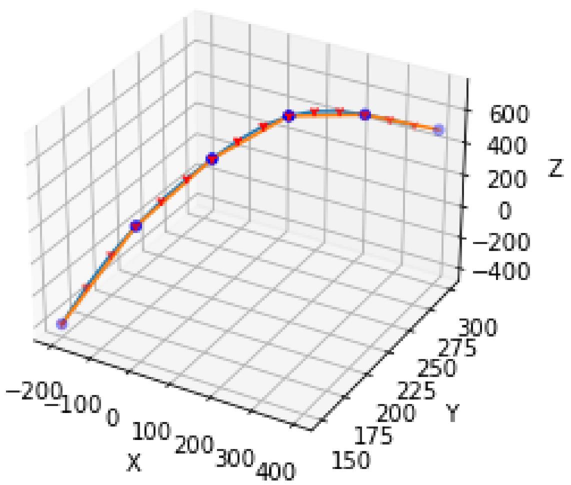

Fig. 5. Cubic Spline Interpolation

The predicted joint variables using KNN algorithm is given in table 5.

TABLE V

JOINT ANGLES OBTAINED

Sl.No	Θ_1 (deg)	Θ_2 (deg)	Θ_4 (deg)	Θ_4 (deg)	Θ_5 (deg)
1					
2					
3					
4					
5					
6					

Control points defined in joint space is given as an input and the path is obtained using cubic B –spline polynomials. From the path the position, velocity, acceleration and jerk values are obtained by varying the parameter u from 0 to 3.

u = (k/4).

u values can be obtained by varying the k value from 0 to 12.

If (0≤u≤1)

Angular Displacement Equation

$$Pi(k) = \theta i0(1-u)^3 + \frac{\theta i1}{4}(7u^3 - 18u^2 + 12u) + \frac{\theta i2}{12}(-11u^3 + 18u^2) + \frac{\theta i3}{6}(u^3)$$

Angular Velocity Equation

$$Vi(k) = \theta i0(-3(1-u)^2) + \frac{\theta i1}{4}(21u^2 - 36u + 12) + \frac{\theta i2}{12}(-33u^2 + 36u) + \frac{\theta i3}{2}(u^2)$$

Acceleration Equation

$$Ai(k) = \theta i0(6(1-u)) + \frac{\theta i1}{4}(42u - 36) + \frac{\theta i2}{12}(-66u + 36) + \theta i3 * u$$

Jerk Equation

$$Ji(k) = \theta i0(-6) + \theta i1(10.5) + \theta i2(-5.5) + \theta i3(1)$$

If (1≤u≤2)

Angular Displacement Equation

$$\theta i1\,\frac{(2-u)^3}{4} + \frac{\theta i2(7u^3 - 18u^2 + 5u - 18)}{12} + \frac{\theta i3(-7u^3 + 27u^2 - 27u + 9)}{12} + \theta i4\frac{(u-1)^3}{4}$$

Angular Velocity Equation

$$\theta i1\,\frac{-3(2-u)^2}{4} + \frac{\theta i2(21u^2 - 36u + 5)}{12} + \frac{\theta i3(-21u^2 + 54u - 27)}{12} - \theta i4\,\frac{3(u-1)^2}{4}$$

Acceleration Equation

$$\theta i1\,\frac{6(2-u)^1}{4} + \frac{\theta i2(42u - 36)}{12} + \frac{\theta i3(-42u + 54)}{12} + \theta i4\,\frac{6(u-1)}{4}$$

Jerk Equation

$$\theta i1(-1.5) + \theta i2\,(3.5) + \theta i3\,(-3.5) + \theta i4\,(1.5)$$

If (2≤u≤3)

Angular Displacement Equation

$$P_i(k) = \frac{\theta_{i2}(3-u)^3}{6} + \frac{\theta_{i3}(11u^3 - 81u^2 + 189u - 135)}{12} + \frac{\theta_{i4}(-7u^3 + 45u^2 - 93u + 63)}{4} + \theta_{i5}(u-2)^3$$

Angular Velocity Equation

$$Vi(k) = -\frac{\theta i2}{2}(3-u)^2 + \frac{\theta i3}{12}(33u^2 - 162u + 189) + \frac{\theta i4}{4}(-21u^2 + 90u - 93) - \theta i5(3(u-2)^2)$$

Acceleration Equation

$$Ai(k) = \theta i2(3-u) + \frac{\theta i3}{12}(66u - 162) + \frac{\theta i4}{4}(-42u + 90) + \theta i5(6(u-2))$$

Jerk Equation

$$Ji(k) = \theta i2(-1) + \theta i3(5.5) + \theta i4(-10.5) + \theta i5(6)$$

Total execution time and jerk are calculated using cubic spline equations. The generated cubic spline profile has minimum execution time and jerk as shown in Table 7.

TABLE VII
TIME AND JERK VALUES FOR CUBIC SPLINE TRAJECTORY

Cubic Spline Trajectory	
Time (sec)	
Jerk(rad/s^3)	

V. CONCLUSION

In this paper, three methods which are LR, KNN and ANN used to obtain the solution of inverse kinematics of Pioneer 2 robot. Forward kinematic equations of Pioneer 2 robot is used to generate the training data set for the machine learning algorithms. The difference in actual and predictions of Linear Regression, gives best results as compared to KNN and ANN. Therefore, KNN can be used better solution of inverse kinematics with fast results and high accuracy. Computational complexity of Inverse kinematics can be solved using forward kinematics with machine learning algorithms. Then the smooth trajectory is achieved using cubic spline interpolation. Future research will be, the same methodology can be used for other industrial robots by using different machine learning techniques.

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