



## Prediction of Kinematics Modelling of 2R Planner Robot using ANN

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**Abstract:** The study of robotics is now an emerging field in the research area. The robot has two types of as serial and parallel manipulator. In this work the serial manipulator of 2DOF planner robot has been considered and the prediction of kinematics modelling has been done. The kinematics modelling of a 2R planner robot has been done for the inverse and forward kinematics. The mathematical modelling of kinematics equations can help to derive the similar type of mathematical modelling for higher degree of freedom robot. The different set of output value of corresponding kinematics modelling have been tabulated in this work. The artificial neural network ANN has been implemented here for testing and validation of the extracted values from the derived equations. The Scaled Conjugate Gradient function has been used in ANN modelling for the prediction process. The regression result of testing is 0.99 which implies that regression analysis has been converged and this validation results are almost 87% accurate which is quite desirable as a prediction

**Key Words:** 2-R Planner Robot, Serial Robot, Inverse kinematics, Forward kinematics, Prediction, ANN.

### 1. INTRODUCTION :

Robots are replacing human work force to a huge extent and so the study of robot and their kinematics analysis have now emerging research field. There are different applications of robotic study in mechanical, electrical, electronics, computer science engineering [1-2]. The inverse kinematics modelling is required to find out the end effector position with help of each link length and movement [2-4]. The forward kinematics is essential to extract each link movement with help of the end effector position and each link length [1, 4-5]. But these mathematical modelling of higher degree of freedom robotic system [5-6] is complicated to derive by simple mathematical algebraic formulations. The DH matrix will be required for such systems. These type of kinematics equations can be helpful for the idea of the parallel manipulators [7-9]. The control of motion of the manipulator can be done with help of modern controllers [10-11].

The prediction of the kinematics for robot even without the application of their kinematic equation itself will be helpful in the preliminary understanding and preliminary process planning of designing a robot very efficiently. In past few years researchers viewed their interest in the field of estimation or prediction along with optimization with help of soft computing model. Daya et al. [12] applied the artificial neural network ANN for solving the inverse kinematics modelling of robotics design. ANN has been implemented to find out the solution of the kinematics of the manipulator [13], inverse kinematics of robotics problems [14]. The prediction capability of the ANN has been also used by Almusawi et al. [15] to solve inverse kinematics of robotic arm for Denso VP6242.

The mathematical modelling of forward and inverse kinematics for 2R serial manipulator have been formulated in the next section followed by the structure and the modelling of ANN in the section 3. In the results and discussion section the different set of values extracted from the inverse and forward kinematics have been used for the testing and validation process of ANN. Researchers or designers can use this model to get a proper prediction even without using the kinematic equations which will help them to get a very clear understanding about the design criteria of the robot.



## 2R planner robot and its Mathematical Modelling of Forward and Inverse Kinematics

The Fig. 1 depicts the 2R planner manipulator with link length  $l_1$ , and  $l_2$  of link 1 and 2 respectively and  $\theta_1$  and  $\theta_2$  are angle of  $l_1$  w.r.t X axis and  $l_2$  w.r.t  $l_1$  respectively. The end effector position have been taken here as X, Y and  $\varphi$

where  $\varphi = \theta_1 + \theta_2$  (2.1)

X and Y are coordinate in x and y respectively. The forward and inverse kinematic equations have been given in next.

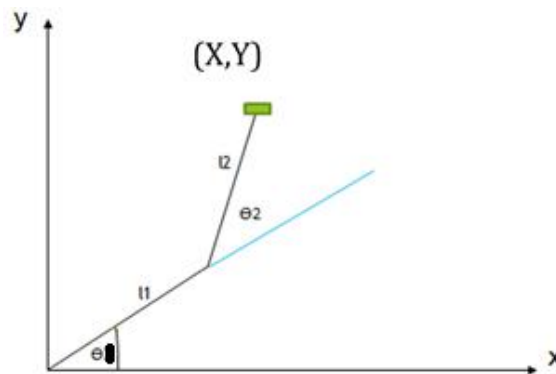


Fig.1 2R serial planner manipulator.

### 1.1 Forward Kinematics

From the Fig.1, it can be said that X & Y-coordinate of the end effector is basically the summation of the X & Y-coordinates of the individual links. The coordinates can be written with help of (2.1) and Fig.1 as

$$X = l_1 C_1 + l_2 C_{12} \quad (2.2a)$$

$$Y = l_1 S_1 + l_2 S_{12} \quad (2.2b)$$

where  $C_1 = \cos\theta_1$ ,  $S_1 = \sin\theta_1$ ,  $C_{12} = \cos(\theta_1 + \theta_2)$ ,  $S_{12} = \sin(\theta_1 + \theta_2)$  (2.2c)

The end effector position can be extracted by using (2.2a), (2.2b) and (2.2c) which are forward kinematics equations.

### 1.2 Inverse Kinematics

In inverse kinematics, the position of end effector (X, Y) are given and  $\theta_1$  and  $\theta_2$  have to be found out. From (2.2a) and (2.2b) it can be written that

$$X^2 + Y^2 = (l_1 C_1 + l_2 C_{12})^2 + (l_1 S_1 + l_2 S_{12})^2 \quad (2.3a)$$

$$[\because C_1^2 + S_1^2 = \cos^2\theta_1 + \sin^2\theta_1 = 1 \text{ and } C_{12}^2 + S_{12}^2 = \cos^2(\theta_1 + \theta_2) + \sin^2(\theta_1 + \theta_2) = 1] \quad (2.3b)$$

$$= l_1^2 + l_2^2 + 2l_1 l_2 [\cos\theta_1 \cos(\theta_1 + \theta_2) + \sin\theta_1 \sin(\theta_1 + \theta_2)] \quad (2.3c)$$

$$= l_1^2 + l_2^2 + 2l_1 l_2 \cos\theta_2 \quad (2.3d)$$

Hence using (2.3d)  $\theta_2 = \cos^{-1} \frac{X^2 + Y^2 - l_1^2 - l_2^2}{2l_1 l_2}$  (2.4a)

Hence using (2.1) and (2.4b), the value of  $\theta_1$  can be extracted as

$$\theta_1 = \varphi - \theta_2 \quad (2.4b)$$

The angular movement of each link length can be found out by using (2.4a) and (2.4b) which are inverse kinematics equations.



## 2. Artificial Neural Networks -ANN Architecture

The Artificial Neural Network-ANN first proposed by Warren McCulloch and Walter Pitts in 1943. First computational model of ANNs was based on algorithm known as threshold logic. Artificial neural networks are computing system inspired by the biological neural networks of animal brain. ANN consist of number of connected units known as neurons. Each connection of neurons passes the signal from input neuron to the neuron of next layer. It consist three layers called input layer, hidden layer and output layer. Input variable is connected to the input layer and similarly output variable is connected to the output layer of the model which has been depicted in the Fig. 2. To work with ANN a pretty big set of data used to train the model then another set of data is required to validate the accuracy of the model. The set of data and the corresponding training with validation have been done in the next section.

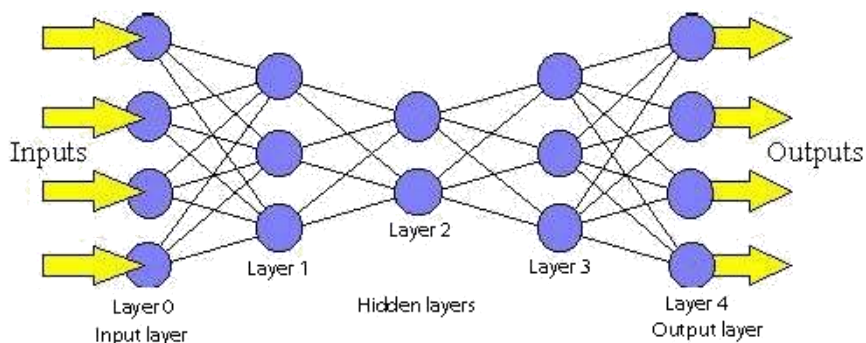


Fig.2 Multilayer feed forward neural network architecture

## 3. Results and Discussion :

### 3.1 Set of Data extracted from the forward and inverse kinematics mathematical modelling for training and validation of ANN

The forward and inverse kinematic prediction of 2R planner robot has been done in this work by ANN. For the forward kinematics of Fig.1 the given data are  $L_1$ ,  $L_2$ ,  $\theta_1$ ,  $\theta_2$  and the extracted values by (2.2a) and (2.2b) are X and Y which have to be predicted. Similarly in case of inverse kinematics of Fig.1 the given data are  $L_1$ ,  $L_2$ , X, Y and the extracted values by (2.4a) and (2.4b) are  $\theta_1$  and  $\theta_2$  which have to be predicted. There are 68 set of values mentioned in Table 1 which are extracted from forward and inverse kinematics equations. The set of values in Table 1 is required for the training and validation purpose for the corresponding kinematics modelling.

Table:1 Set of data extracted from forward and inverse kinematics mathematical modelling

Set No.	L1 (cm)	L2 (cm)	$\theta_1$ (degree)	$\theta_2$ (degree)	$\varphi$ (degree)	X (cm)	Y (cm)
1	8	5	20	22	42	11.23	6.08
2	8	5	25	10	35	11.35	6.23
3	8	5	28	32	60	9.56	8.08
4	8	5	30	20	50	10.14	7.83
5	8	5	35	38	73	8.01	9.37
6	8	5	45	30	75	6.95	10.49
7	8	5	47	50	97	4.84	10.81
8	8	5	52	43	95	4.49	11.28
9	8	5	60	65	125	1.13	11.02
10	8	5	63	72	135	0.096	10.66
11	8	5	74	50	124	-0.59	11.83
12	8	5	80	60	140	-2.44	11.09
13	8	5	83	37	120	-1.52	12.27
14	8	5	85	90	175	-4.3	8.4
15	8	5	95	100	195	-5.53	3.29



16	10	8	20	22	42	15.34	8.77
17	10	8	25	10	35	15.61	8.81
18	10	8	28	32	60	12.82	11.62
19	10	8	30	20	50	13.80	11.12
20	10	8	35	38	73	10.53	13.38
21	10	8	45	30	75	9.14	14.79
22	10	8	47	50	97	5.84	15.25
23	10	8	52	43	95	5.45	15.84
24	10	8	60	65	125	0.41	15.21
25	10	8	63	72	135	-1.11	14.56
26	10	8	74	50	124	-1.71	16.24
27	12	7	20	22	42	16.47	8.78
28	12	7	25	10	35	16.60	9.08
29	12	7	28	32	60	14.09	11.69
30	12	7	30	20	50	14.89	11.36
31	12	7	35	38	73	11.87	13.57
32	12	7	45	30	75	10.29	15.24
33	12	7	47	50	97	7.33	15.72
34	12	7	52	43	95	6.77	16.42
35	12	7	60	65	125	1.98	16.12
36	12	7	63	72	135	0.49	15.64
37	12	7	74	50	124	-0.60	17.33
38	15	10	20	22	42	21.52	11.82
39	15	10	25	10	35	21.78	12.07
40	15	10	28	32	60	18.24	15.70
41	15	10	30	20	50	19.41	15.16
42	15	10	35	38	73	15.21	18.16
43	15	10	45	30	75	13.19	20.26
44	15	10	47	50	97	9.01	20.89
45	15	10	52	43	95	8.36	21.78
46	15	10	60	65	125	1.76	21.18
47	15	10	63	72	135	-0.26	20.43
48	15	10	74	50	124	-1.45	22.70
49	6	4	80	32	112	-0.45	9.61
50	6	4	83	20	103	-0.16	9.85
51	6	4	85	38	123	-1.65	9.33
52	6	4	95	30	125	-2.81	9.25
53	6	4	74	50	124	-0.58	9.08
54	6	4	20	43	63	7.45	5.61
55	6	4	25	65	90	5.43	6.53
56	6	4	28	72	100	4.60	6.75
57	6	4	30	50	80	5.89	6.93
58	6	4	35	22	57	7.09	6.79
59	18	13	45	10	55	20.18	23.37
60	18	13	47	32	79	14.75	25.92
61	18	13	52	20	72	15.09	26.5
62	18	13	60	38	98	7.19	28.40
63	18	13	63	30	93	7.49	29.02
64	18	13	74	50	124	-2.30	28.08
65	18	13	63	43	106	4.58	28.53
66	18	13	74	65	139	-4.84	25.83
67	18	13	20	72	92	16.46	19.14
68	18	13	25	50	75	19.67	20.16

The training and validation for each kinematics have been executed with help of the data mentioned in Table 1. The training data have been taken as first 48 set of data from the Table 1 and the remaining 20 set of data have considered for validation for both of forward and inverse kinematics modelling.

### 3.2 Training of ANN model for Forward Kinematics

The input variables of ANN for forward kinematics are 4 as  $L_1, L_2, \theta_1, \theta_2$  and number of neuron in the hidden layers specified is as 40, output layers are 2 as X and Y mentioned in Fig.3. Transfer function specified has been taken as Scaled Conjugate Gradient, number of epoch specified as 100 specified in the Fig 4.(a). The iteration status and the regression plot have been depicted in Fig. 4 (b). It can also be revealed from Fig. 4(b) that the value of R as 0.99 which implies that regression analysis has been converged and this model can be applied for validation.

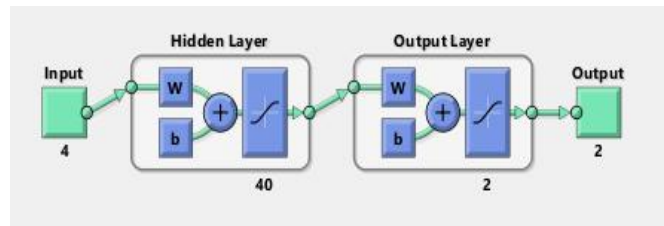


Fig. 3 ANN structure for the forward kinematics prediction

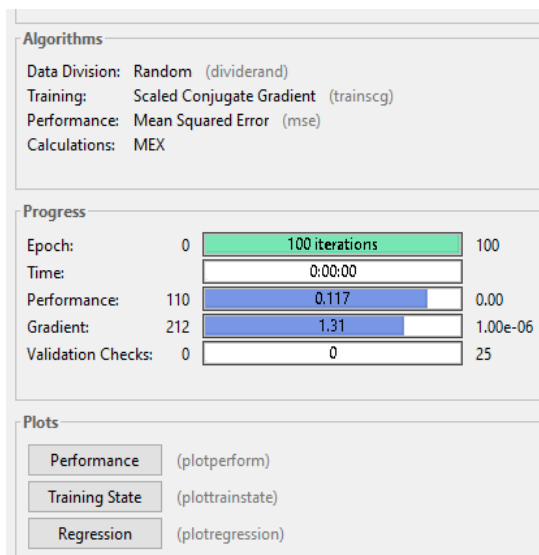
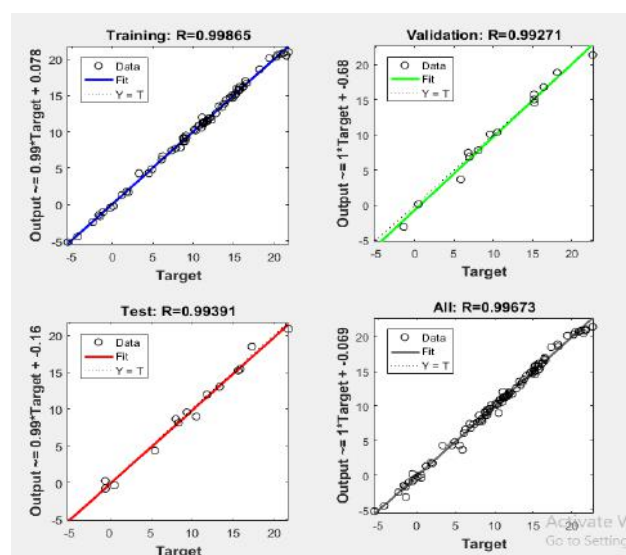


Fig. 4 (a) Iteration status



(b) regression plots for the forward kinematic analysis

### 3.3 Validation of ANN Model for Forward Kinematics

The extracted or actual data X and Y from set no 49 to 68 have been taken from the Table 1 and these data have been validated in the Fig. 5(a) and 5(b). The graphical representation of Fig.5 represents that the simulated or predicted data merge the actual data obtained from the equations. The regression coefficient obtained by comparing the two set of data of X and Y is 0.87 which reflects that the results are almost 87% accurate which is quite desirable as a prediction.

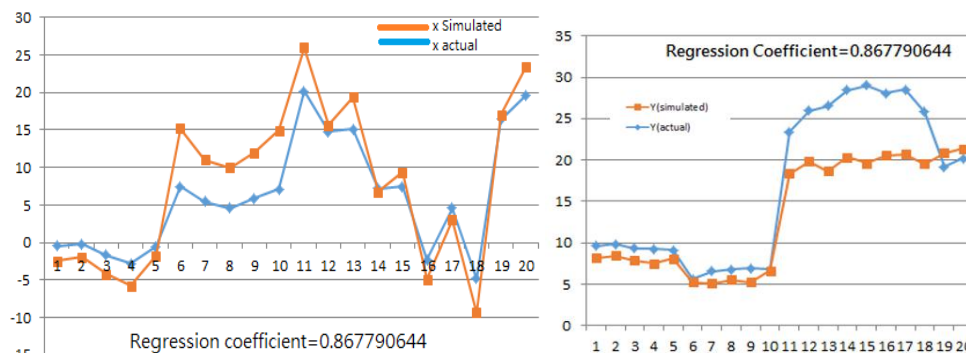


Fig. 5(a) Variation of X

(b) variation of Y obtained from equation and ANN

### 3.4 Training of ANN model for Inverse Kinematics

The input variables of ANN for inverse kinematics are 5 as  $L_1$ ,  $L_2$ ,  $X$ ,  $Y$ ,  $\varphi$  and number of neuron in the hidden layers specified is as 25, output layers are 2 as  $\theta_1$  and  $\theta_2$  mentioned in Fig.6. Transfer function specified has been taken as Scaled Conjugate Gradient, number of epoch specified as 1000 specified in the Fig 7(a). The iteration status and the regression plot have been depicted in Fig. 7(b). It can also be revealed from Fig. 7(b) that the value of R as 0.99 which implies that regression analysis has been converged and this model can be applied for validation.

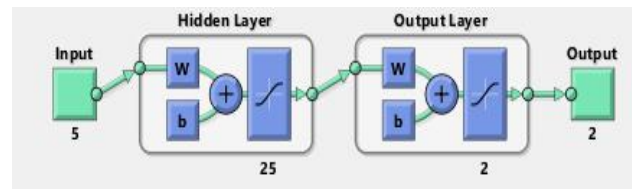


Fig. 6 ANN structure for the inverse kinematics prediction

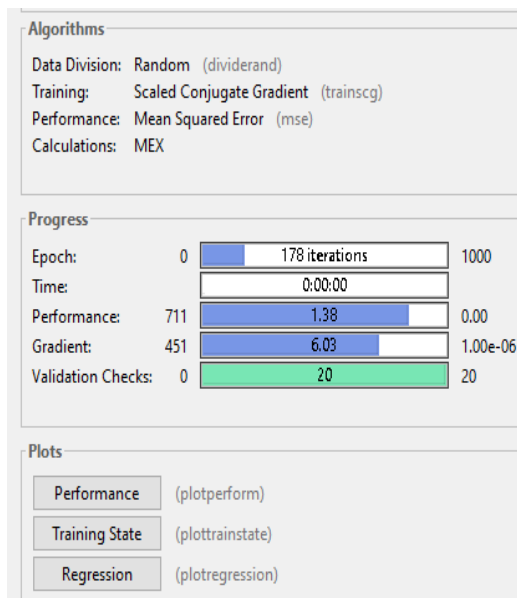
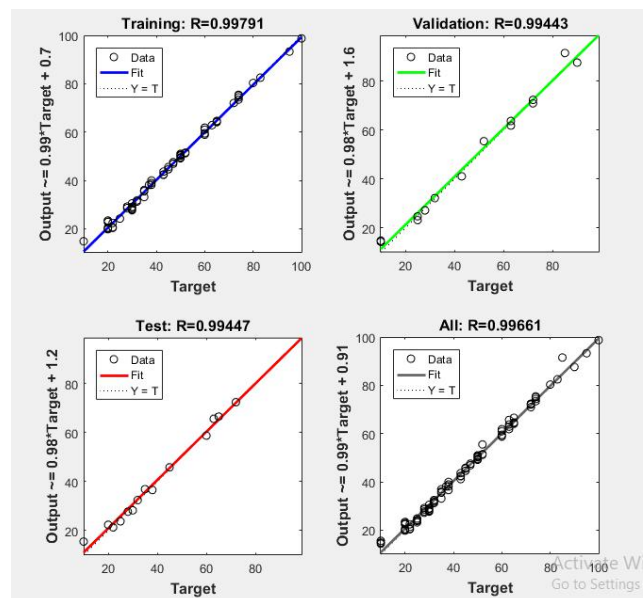


Fig. 7 (a) Iteration status



(b) regression plots for the inverse kinematic analysis

### 3.5 Validation of ANN Model for Inverse Kinematics

The extracted or actual data  $\theta_1$  and  $\theta_2$  from set no 49 to 68 have been taken from the Table 1 and these data have been validated in the Fig. 8(a) and 8(b). The graphical representation of Fig. 8 represents that the simulated or predicted data merge the actual data obtained from the equations. The regression coefficient obtained by comparing the two set of data of  $\theta_1$  and  $\theta_2$  is 0.90 which reflects that the results are almost 90% accurate which is quite desirable as a prediction.

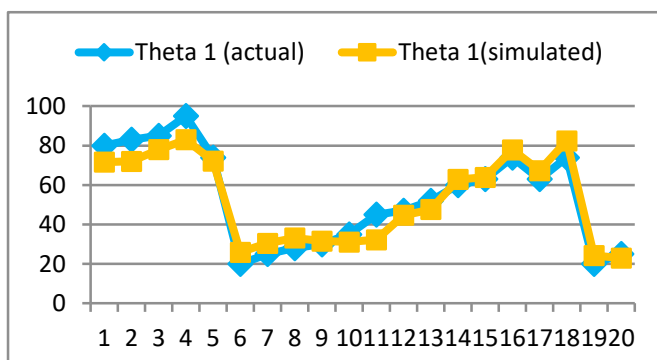
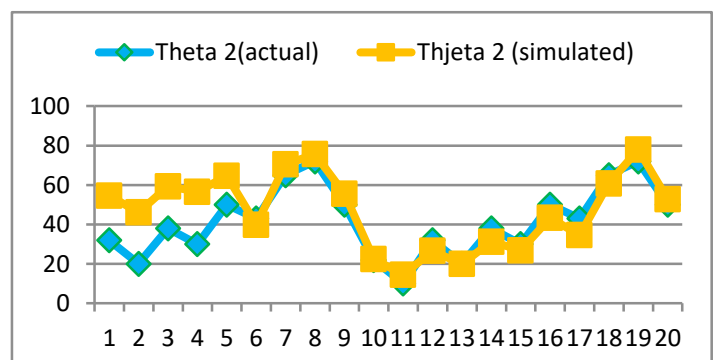


Fig. 8(a) Variation of  $\theta_1$



(b) variation of  $\theta_2$  obtained from equation and ANN



The validation of forward kinematics and inverse kinematics have been depicted in the Figs. 5 and 8. The corresponding data of actual and simulated data have been also tabulated in the Table 2. The actual or extracted data have been taken from the data set 49 to 68 of Table 1 and the simulated data have been found out by the prediction of ANN.

**Table 2: Validated data of Forward and Inverse kinematics modelling**

Set No.	Validation of Forward Kinematics				Validation of Inverse Kinematics			
	X (Extracted From Equations)	Y (Extracted From Equations)	X (Simulated by ANN)	Y (Simulated by ANN)	$\theta_1$ (Extracted From Equations)	$\theta_2$ (Extracted From Equations)	$\theta_1$ (Simulated by ANN)	$\theta_2$ (Simulated by ANN)
	(cm)	(cm)	(cm)	(cm)	(degree)	(degree)	(degree)	(degree)
1	-0.45	9.61	-2.00	8.14	80	32	71.66217009	54.62123986
2	-0.16	9.85	-1.79	8.45	83	20	72.05606378	46.12999143
3	-1.65	9.33	-2.52	7.83	85	38	77.93367383	59.34364284
4	-2.81	9.25	-2.97	7.46	95	30	83.00598059	56.58108782
5	-0.58	9.08	-1.14	8.11	74	50	72.22091035	64.61383764
6	7.45	5.61	7.78	5.26	20	43	25.93175238	39.8650956
7	5.43	6.53	5.60	5.07	25	65	30.50642136	70.50557954
8	4.60	6.75	5.37	5.55	28	72	33.17902807	75.70430585
9	5.89	6.93	6.10	5.22	30	50	31.61472526	55.61090205
10	7.09	6.79	7.89	6.64	35	22	31.08854923	22.49804231
11	20.18	23.37	5.81	18.37	45	10	32.2286356	14.44416754
12	14.75	25.92	0.86	19.79	47	32	44.70381854	26.58002889
13	15.09	26.5	4.25	18.67	52	20	47.6100332	19.92855444
14	7.19	28.40	-0.39	20.33	60	38	62.84223829	31.20891611
15	7.49	29.02	1.85	19.62	63	30	63.87568192	26.85572122
16	-2.30	28.08	-2.56	20.59	74	50	77.91199259	43.30833133
17	4.58	28.53	-1.54	20.70	63	43	67.30904254	34.52178893
18	-4.84	25.83	-4.51	19.52	74	65	82.38460047	60.77794254
19	16.46	19.14	0.55	20.87	20	72	24.29833722	77.91851961
20	19.67	20.16	3.82	21.39	25	50	22.93902039	52.8405476

## 5. CONCLUSION :

The prediction of inverse and forward kinematics modelling of 2R serial manipulator has been done in this present work. The mathematical modelling of both kinematics have been formulated and the corresponding output values have been extracted. The extracted values from the derived mathematical modelling of the kinematics have been tabulated for the testing and validation of ANN modelling. The regression value of the testing of inverse and forward kinematics has been converged and the model has been applied for validation. The validation results also show 90% accurate result between the extracted values from the equations and the simulated values by ANN. The results prove that ANN can be implemented to predict the kinematics of such systems with higher degree of freedom system even without deriving the complicated mathematical modelling. The accuracy of prediction can also be verified with other type of prediction and optimization tool like GA, AHP, ABC.

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