# Computational Intelligence-based Evaluation of a 3-DOF Robotic-arm Forward Kinematics

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***Abstract* — Robotic manipulator- forward Kinematics involves the assurance of end-effector arrangements from connecting joint boundaries. The traditional mathematical calculation of controller forward -Kinematics is monotonous and tedious. Accordingly, it is important to execute a strategy that precisely performs forward energy while wiping out the disadvantages of the mathematical calculation technique. Versatile Neuro-Fuzzy Inference System (ANFIS) is a computational knowledge strategy that has been effectively executed for expectation purposes in assorted logical orders. This present examination's essential goal was to evaluate the productivity of ANFIS in foreseeing 3-levels of opportunity automated controller Cartesian directions from connecting joint boundaries. A speculative 3-level of opportunity automated controller has been considered in this investigation. Model preparing information has been obtained by mathematical forward kinematics calculation of the controller's end effector arrangements. Nine datasets have been utilized for model preparing, while five datasets have been utilized for model testing or approval. The ANFIS model's precision has been surveyed by figuring the Mean outright Percentage Error (MAPE) between the real and anticipated end-effector Cartesian directions. Because of Mean Absolute Percentage Error (MAPE), the created ANFIS model has forecast correctness's of 63.35% and 80.07% in foreseeing x-directions and y-organizes, separately. Accordingly, ANFIS can be dependably executed as a commendable substitute for the customary arithmetical calculation method in anticipating controller Cartesian directions. It is suggested that the precision of other computational knowledge methods like Particle Swarm Optimization (PSO) and Support Vector Machines (SVM) be evaluated.***

**Index Terms- Robotic manipulator forward Kinematics, Adaptive Neuro-Fuzzy Inference System (ANFIS).**

## I. INTRODUCTION

In robotics technology, it is frequently important to have the option to "map" joint directions to end effector facilitates. This guide or the system used to acquire end effector organizes from joint directions is called direct/forward Kinematics [1]. Robot kinematics gives numerical devices to show and dissect the development and design of automated controllers, a fundamental part of robot control. Dissimilar to Inverse Kinematics which infers joint points and positions from a known end-effector position, forward Kinematics is moderately simple to register. This is because the calculation of the adjustment of positions that outcome from the movement of each joint includes fundamental geometry. If more than one connection is included, the last position is dictated by playing out the computations for one joint after another. For sequential chains and other open chains the immediate kinematics methodology is genuinely straight forward. Then again, a similar strategy turns out to be more confounded if the system contains at least one shut circle. Moreover, the immediate Kinematics may deliver more than one arrangement or no arrangement in such cases.

It is a highly monotonous and troublesome interaction to process the Cartesian directions for bigger informational indexes, thus creating or deciding the best computational insight model to play out this undertaking precisely. Innovative advances have prompted computational knowledge forecast procedures appropriate for on the web and ongoing control execution. As indicated by IEEE, computational knowledge (CI) is the hypothesis, plan, application and improvement of naturally and etymologically spurred computational standards. There are many orders in CI with Neural Networks, Fuzzy Systems, and Evolutionary Computation being the customary columns. These orders have prompted improved productivity in current innovation. Because they are a crucial piece of the current industry, mechanical controllers have supplanted physical work in many touchy creation tasks that request the most extreme accuracy and repeatability [2].

Preceding robotic manipulator organization, it is indispensable to set up its work encompasses precisely. This is accomplished by planning mechanical arm joint boundaries into end-effector Cartesian directions. The traditional mathematical Cartesian directions calculation strategy is tedious, and monotonous, particularly when the information is enormous [3]. It is thus important to discover reasonable substitutions to the regular calculation method to kill the featured disadvantages. Robot controllers are a set of connections associated by joints. They are multi-input and multi yield (MIMO), nonlinear, time variation, unique dubious frameworks and are grown either to supplant human work in numerous fields.

A. Computational Intelligence

Computational Intelligence (CI) is the hypothesis, plan, application and advancement of naturally and phonetically inspired computational standards [6]. The three fundamental mainstays of CI are Neural Networks, Fuzzy Systems and Evolutionary Computation. The expectation technique utilized in this examination is ANFIS. Versatile Neuro-Fuzzy Inference System (ANFIS) is a part of Computational Intelligence wherein computational models address the human mind. The two periods of computational insight improvement are reproduction of human experience kept by rule-based ends and utilizing ANFIS and ANN.

For the ANFIS structure with two sources of info and one yield, the standard base contains the Takagi-Sugeno fluffy assuming guideline as follows:

$$If\ x\ is\ A\ and\ y\ is\ B\ then\ z\ is\ f(x,y)$$

where A and B are the fuzzy sets in the antecedents and $z = f(x,y)$ is a crisp function in the consequent. Usually $f(x,y)$ is a polynomial for the input variables x and y. For a first-order two rule Sugeno fuzzy inference system, the two rules may be stated as:

Rule 1:

$$If\ x\ is\ A_1\ and\ y\ is\ B_1\ then\ f_1 = p_1x + q_1y + r_1 \quad (1)$$

Rule 2:

$$If\ x\ is\ A_2\ and\ y\ is\ B_2\ then\ f_2 = p_2x + q_2y + r_2 \quad (2)$$

Layer 1: Membership functions for input boundaries are contained in this layer. The instances of enrolment capacities utilized in Layer 1 are three-sided and ringer formed. The enrolment work for layer one is given by (3):

$$O_i^1 = \mu_{A_i}(x) \quad (3)$$

Where $x$ = node i input
$A_i$ = linguistic variable associated with node i

Layer 2: The weight of every enrollment work is checked in layer 2. Info factors from layer 1 are gotten and it addresses the fluffy arrangements of the input boundaries. Participation esteem calculation happens at this stage and the level of enrollment to a given set is resolved. The consequence of layer 2 is sent to layer 3. Approaching signs are intensified in this layer. The terminating strength of the capacity is addressed by (4):

$$O_i^2 = \mu_{A_i}(x)\mu_{B_i}(y) \quad (4)$$

Where i = 1:2

Layer 3: The alternative name of layer 3 is the rule layer. The nodes in this layer perform fuzzy rule pre-condition matching. At this level, the ratio of the ith rule's firing strength to the sum of all firing strengths is calculated as presented by (5):

$$O_i^3 = \overline{W_i} = \frac{W_i}{W_1+W_2} \quad (5)$$

Where i = 1:2

Layer 4: The alternative name for this layer is the defuzzification layer. This gives the output of the inference system. The node function at this stage is given by (6):

$$O_i^4 = f_i\overline{W}_i(P_ix + Q_iy + R_i) \quad (6)$$

Where i = 1:2

Layer 5: Transformation of fuzzy results and the summation of all incoming signals are computed at this stage. The output is given by (7):

$$O_i^5 = sytem\ output \quad (7)$$

Where i = 1:2

B. Optimal Forward Kinematic Modelling of a Stewart Manipulator using Genetic Algorithms

Omran et al, (2009) utilized Genetic Algorithms (GA) to display ideal forward Kinematics of a Steward controller. In the investigation, squared blunder cost work was anticipated. In contrast with the customary Taylor extension strategy, the created model figured out how to decrease the computational cost by 65%.

C. ANFIS Based solution to the Inverse Kinematics of a 3DOF planar manipulator

In a paper by Adrian Duka, ANFIS was utilized for registering the reverse kinematics answer for a 3DOF planar controller. This exploration paper resolved to discover a solution for the converse kinematics of a 3 DOF automated controller utilizing fuzzy neuro methodology. A Duka additionally considered presenting the direction of the end effector as a condition used to figure the precise situation of the joints through an ANFIS organization.

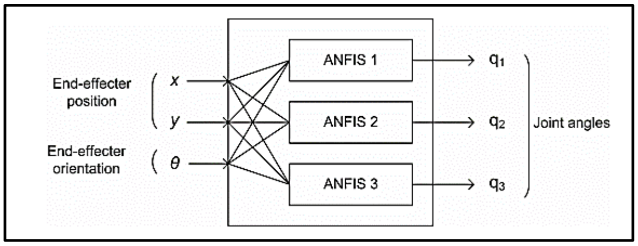


Fig. 1: ANFIS Architecture for computing inverse kinematics of a 3DOF manipulator

Random joint angle values (q1, q2, q3) covering specific ranges were generated and using forward kinematics equations the corresponding localization of the end effector was computed(x, y, ϴ). The inverse information contained in the data set was learned.

D. Adaptive Neuro-Fuzzy Inference System for Kinematics of 6DOF robotic arm

A 6 DOF Robotic Arm was considered for dissecting the Kinematics and the blunder related to the framework in the examination paper by Karna Patel. The ANFIS is prepared utilizing the information obtained from Forwarding Kinematics to participate work for each joint. This participation work maintains a strategic distance from the intricate computations identified with the backwards Kinematics.

E. Kinematic estimation with neural networks for robotic manipulators

In a research paper by Michail Theofanidis and group, multi-facet feed forward neural organizations were applied in assessing the forward Kinematics of a 7DOF Sawyer Robotic arm. After preparing various models with various boundaries, the proposed engineering was found, for example, the quantity of units per level and the quantity of levels, on the equivalent dataset with various goals.

The organization was prepared to utilize the backpropagation calculation with the mean squared mistake of the yield units as a measurement. During the backpropagation interaction, an adam analyzer was utilized. To create the preparation dataset of the organization, 4 million irregular kinematic setups of joint points with their comparable Cartesian positions were used. Due to the size of the dataset, the organization was prepared with a group size of 100 units and 30 ages. Additionally, 10% of the dataset was utilized for cross approval and 10% for testing purposes. The following results were obtained:

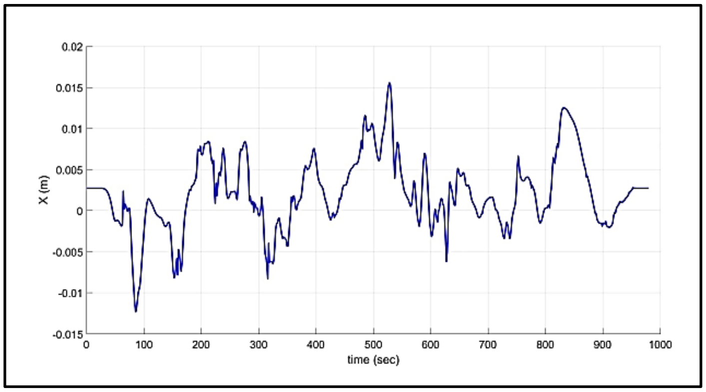


*Fig. 2. The error between the forward kinematic equation and the network in the x dimension*

The networks achieved 99.997% validation accuracy after the training was complete.

## II. METHODOLOGY

In this part, the stages associated with accomplishing the exploration targets are featured. These stages range from robot choice through deciding the forward Kinematics of the chosen robot to foreseeing the Cartesian directions. In conclusion, the Adaptive Neuro-fuzzy framework Inference System (ANFIS) expectation results are dissected.

A. Determining forward kinematics using basic trigonometry

The ANN and ANFIS modelling have been carried out on a planar three degree of freedom robotic manipulator presented in Figure 3.1. The models have been used to predict end-effector Cartesian coordinates for a given combination of joint angles ($\Theta_1$, $\Theta_2$ and $\Theta_3$). The manipulator links are of lengths $L_i$. The basic trigonometric conversion has been employed to obtain the manipulator forward kinematic equations as:

$$x = L_1 \times \cos(\Theta_1) + L_2 \times \cos(\Theta_1 + \Theta_2) + L_3 \times \cos(\Theta_1 + \Theta_2 + \Theta_3) \quad (8)$$

$$y = L_1 \times \sin(\Theta_1) + L_2 \times sin(\Theta_1 + \Theta_2) + L_3 \times \sin(\Theta_1 + \Theta_2 + \Theta_3) \quad (9)$$

The joint combinations and corresponding end-effector Cartesian coordinates will be obtained using (8) and (9). For this study, the link lengths ($L_i$) are equal at 2 units each. The set of 14 data samples is split into 9 training sets and 5 validation sets.

**TABLE 1 DATASET FOR THE DIFFERENT CONFIGURATIONS OF THE ROBOT ARM**

| Configuration | Ɵ1 [radians] | Ɵ2 [radians] | Ɵ3 [radians] |
|---|---|---|---|
| 1 | 0.998 | -0.525 | 1.26 |
| 2 | 2.713 | -2.66 | 2.625 |
| 3 | 2.503 | -2.275 | 1.68 |
| 4 | 2.31 | -0.49 | 0.525 |
| 5 | 2.8 | -2.573 | 1.19 |
| 6 | 1.803 | -1.26 | 0.263 |
| 7 | 1.61 | -0.263 | 0.105 |
| 8 | 0.35 | -1.225 | 0.21 |
| 9 | 1.208 | -0.875 | 0.158 |
| 10 | 2.975 | -2.695 | 1.523 |
| 11 | 0.7875 | -1.3125 | 0.315 |
| 12 | 0.595 | 0.525 | 0.9975 |
| 13 | 2.275 | -1.575 | 0.1925 |
| 14 | 2.0125 | -1.575 | 0.0525 |

### *B. Evaluation of Model Accuracy*

The accuracy of the models is evaluated using the Mean Absolute Percentage Error (MAPE) method. MAPE indicates how much error in predicting compared with the real value. It is calculated as follows:

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{At - Ft}{At}\right|$$

M = mean absolute percentage error

n = number of times the summation iteration happens

At = actual value

Ft = forecast value

### C. Adaptive Neuro-Fuzzy Inference System Modeling

The ANFIS model process flow followed in this research is shown in Figure 3.2. Use is made of the ANFIS toolbox in the MATLAB environment.

Fuzzy System Initialization: At this stage, both preparing and checking datasets are stacked from record to the work space and consequently to the ANFIS GUI. The client information has 3 info boundaries to be specific Ɵ1, Ɵ2 and Ɵ3. The cartesian directions X and Y are the yield of the framework.

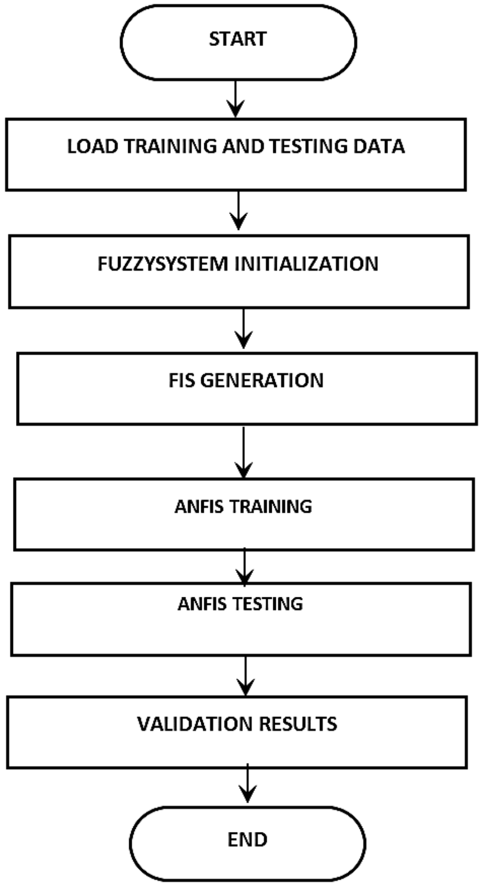


Fig. 3. ANFIS Model Process Flow

Age of Fuzzy Inference framework: This stage trails stacking the information into the framework. The Inference framework is produced by FIS order in the ANFIS proofreader GUI. Start learning Process: The default resilience of 0 is utilized in this examination. The default number of ages in MATLAB is 3. The worth isn't adequate for preparing. Subsequently, 50 ages are utilized in this exploration. The ages are the quantity of cycles that should be done until information starts to overfit. Approval of Results: Once the preparation cycle has been finished the outcomes are tried by correlation with testing information. In this examination, nine informational collections are utilized as preparing information, while the leftover five datasets are utilized as testing information.

## III. RESULTS

### A. End Effector Cartesian Coordinate Prediction Results by Basic Trigonometry .

*The determined Cartesian coordinates values of the x and y by the basic forward kinematic equations are tabulated in Table 2.*

*TABLE 2: PREDICTION OF END EFFECTOR COORDINATES BY BASIC TRIGONOMETRY*

| ϴ1 [radians] | ϴ2 [radians] | ϴ3 [radians] | X-coordinate (Xe) | Y-coordinate (Ye) |
|---|---|---|---|---|
| 0.998 | -0.525 | 1.26 | 2.54 | 4.56 |
| 2.713 | -2.66 | 2.625 | -1.61 | 1.83 |
| 2.503 | -2.275 | 1.68 | -0.32 | 3.53 |
| 2.31 | -0.49 | 0.525 | -3.24 | 4.85 |
| 2.8 | -2.573 | 1.19 | 0.37 | 3.1 |
| 1.803 | -1.26 | 0.263 | 2.64 | 4.42 |
| 1.61 | -0.263 | 0.105 | 0.6 | 5.93 |
| 0.35 | -1.225 | 0.21 | 4.73 | -2.08 |
| 1.208 | -0.875 | 0.158 | 4.37 | 3.46 |
| 2.975 | -2.695 | 1.523 | -0.51 | 2.83 |
| 0.7875 | -1.3125 | 0.315 | 5.09 | 0.39 |
| 0.595 | 0.525 | 0.9975 | 1.49 | 4.63 |
| 2.275 | -1.575 | 0.1925 | 1.49 | 4.37 |
| 2.0125 | -1.575 | 0.0525 | 2.72 | 3.59 |

B. End Effector Cartesian coordinate Prediction Results using ANFIS

The information boundaries to the ANFIS model are the three joint point positions addressed in Table 2. The 14 informational collections were separated into 9 preparing informational collections and 5 testing informational collections in this examination. It is vital to guarantee that the chosen testing informational collection is illustrative of the current absolute information, just as all future information.

1) ANFIS Prediction of X Cartesian coordinates
The dataset was imported into the MATLAB workspace. It was loaded to the ANFIS graphical user interface. Figure 4 shows the screenshot of the data loading stage from the MATLAB workspace to the ANFIS graphical user interface

During the FIS generating stage, the sub-clustering option was selected as it yielded reasonable results and is fast compared to the grid partition option. The default parameters of Sub clustering were used, as seen in Figure 5.

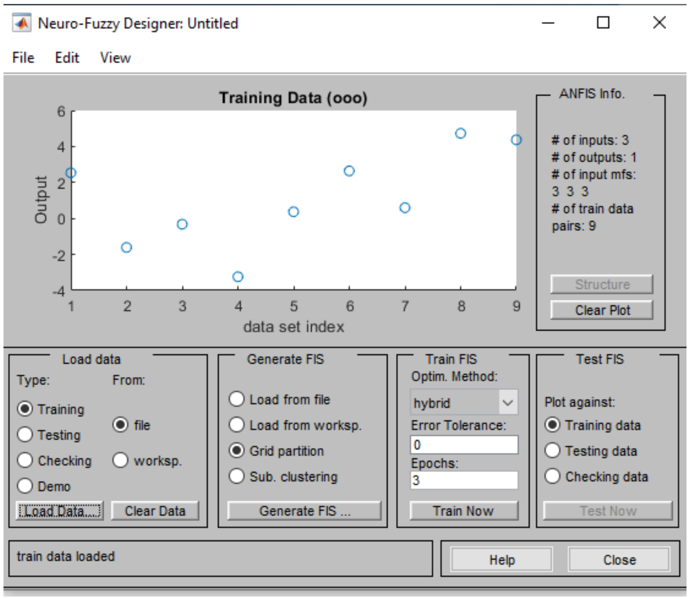


Fig. 4. Data loading for x-coordinates

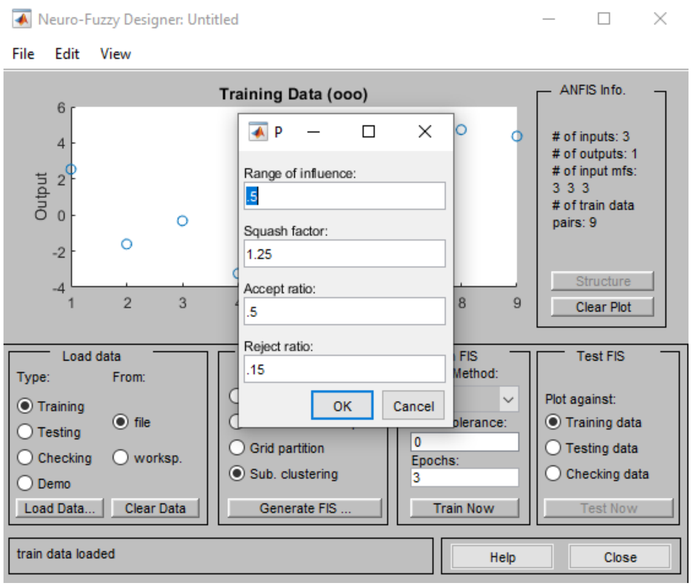


Fig. 5. Sub clustering parameters

The FIS preparing stage was caught in Figure 5. It is seen that age 50 blunders are 7.7704e-07. The bend shows the blunder decrease at every age for the 50 ages utilized in this examination. It is seen that the base blunder target was reached at age 50 after which there could have been no further mistake decrease.

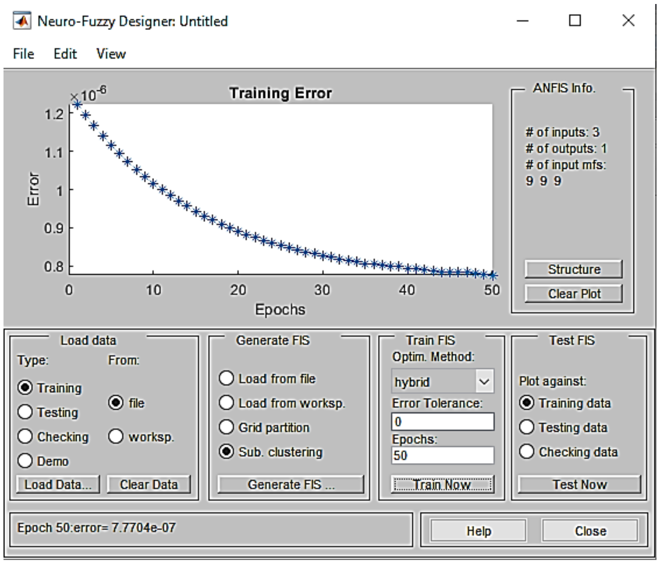

Fig.6 Fuzzy Inference System Training Stage

The FIS test plot against preparing information appears in Figure 6. The geometry determined upsides of x are appeared by the blue spots while anticipated qualities are appeared by red dabs. The covering of plots portrays high expectation exactness. It is seen from this figure that all anticipated yields for preparing information are near the determined yields of preparing information

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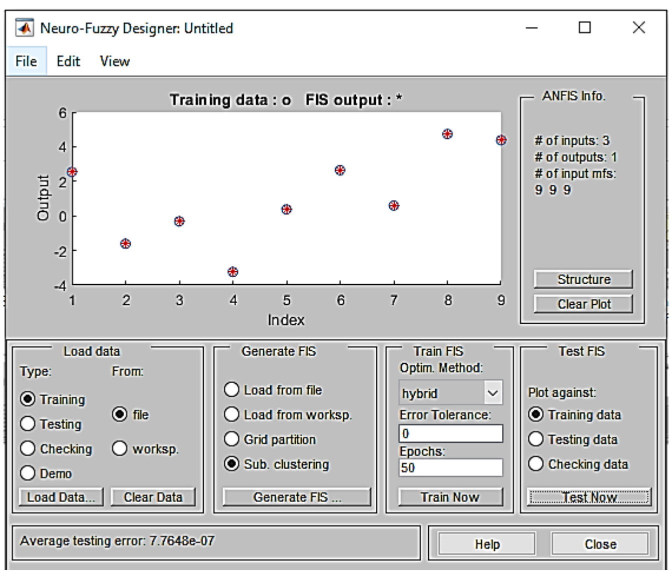

Fig. 7. Training set stage results (X-Cartesian Coordinates)

The FIS test plot against testing information appears in Figure 7. This is done to approve the ANFIS model. The exploratory upsides of x directions are appeared by the blue specks while anticipated qualities are appeared by red spots. The slight dissimilarity of the blue specks from the red dabs shows some peripheral blunder in the ANFIS Prediction model.

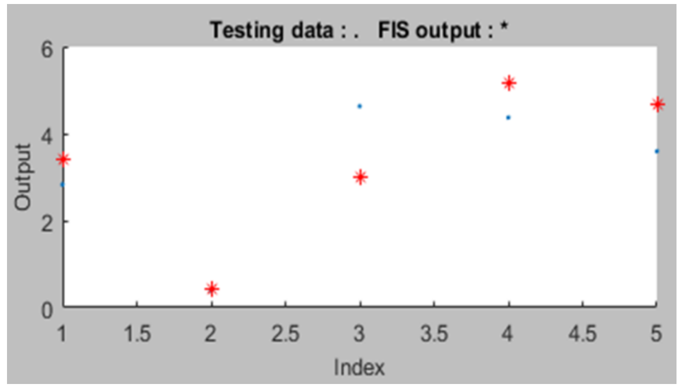


Fig.8. Predicted versus actual x-coordinate values for validation data

*2) ANFIS Prediction of Y Cartesian coordinates*

The dataset for y- coordinates were imported into the MATLAB workspace. It was also loaded to the ANFIS graphical user interface. Figure 8 shows the screenshot of the data loading stage from the MATLAB workspace to the ANFIS graphical user interface.

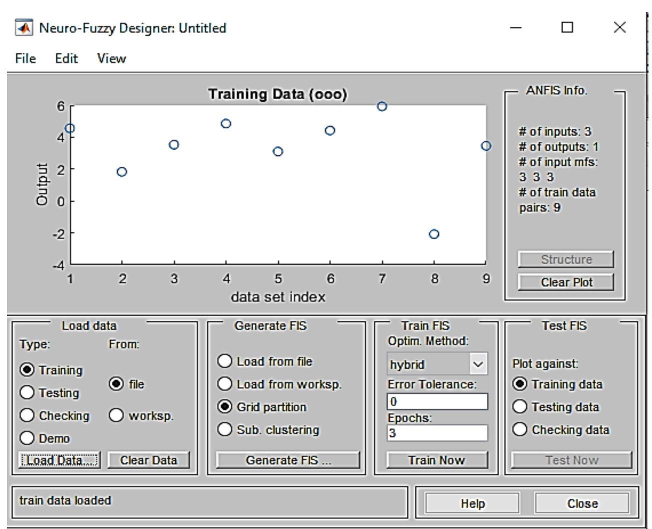

Fig. 9. ANFIS Model Data Loading Stage

The FIS generation stage utilizes the sub-clustering choice with the default boundaries appearing in Figure 9. The sub bunching technique has been utilized to create Fuzzy Inference System rules as it would be advised to prepare exactness rather than lattice dividing.

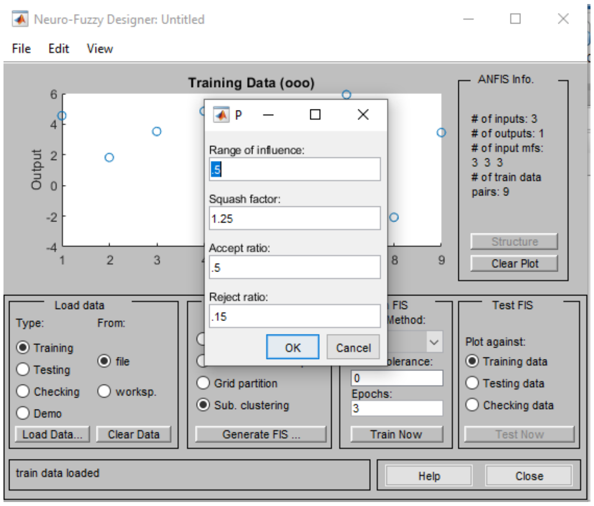


Fig. 10. FIS Generation stage

The ANFIS is prepared utilizing a resistance of 0 and 50 ages. The FIS preparing stage screen capture appears in Figure 10. It is seen that the age 50 mistake is 8.1065e-07. From the screen capture, it is also noticed that the base blunder target was reached at age 40, after which there could have been no further mistake decrease.

The FIS test plot against preparing information appears in Figure 10. The geometry determined upsides of y are appeared by the blue specks while anticipated qualities are appeared by red spots. The covering of plots portrays high expectation exactness. It is seen from this figure that all anticipated yields for preparing information are near the determined yields of preparing information.

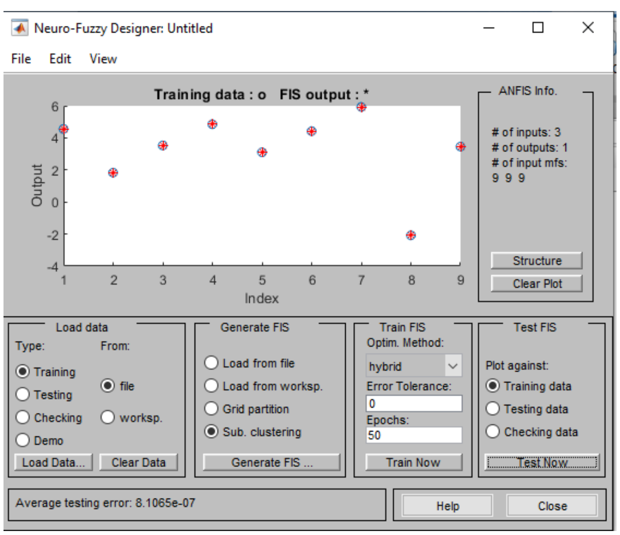


Figure 11: Training Set Stage Results (y- coordinates)

The FIS test plot against testing information appears in Figure 11. This is done to approve the ANFIS model. The test upsides of y arrange are appeared by the blue spots while anticipated qualities are appeared by red dabs. The slight uniqueness of the blue spots from the red dabs shows some minimal blunder in the ANFIS Prediction model.

3) MAPE Calculations for training output

The anticipated x-coordinate and y-coordinate values by ANFIS for preparing information are introduced in Table 8. The Mean Absolute Percentage Error (MAPE) values for x-directions and y-arranges preparing informational indexes in the expectation of end effector Cartesian directions utilizing the ANFIS model are discovered to be both at 0.00 %. These qualities show a 100.00 % forecast precision for the created ANFIS model for preparing information.

TABLE 3: ANFIS MODEL PREDICTION ACCURACY FOR TRAINING DATA

| **X-Coordinates** | | | **Y-Coordinates** | | |
|---|---|---|---|---|---|
| **Actual $X_e$** | **Predicted $X_e$** | **Absolute % Error** | **Actual $Y_e$** | **Predicted $Y_e$** | **Absolute % Error** |
| 2.54 | 2.54 | 0.00 | 4.56 | 4.56 | 0.00 |
| -1.61 | -1.61 | 0.00 | 1.83 | 1.83 | 0.00 |
| -0.32 | -0.32 | 0.00 | 3.53 | 3.53 | 0.00 |
| -3.24 | -3.24 | 0.00 | 4.85 | 4.85 | 0.00 |
| 0.37 | 0.37 | 0.00 | 3.10 | 3.10 | 0.00 |
| 2.64 | 2.64 | 0.00 | 4.42 | 4.42 | 0.00 |
| 0.60 | 0.60 | 0.00 | 5.93 | 5.93 | 0.00 |
| 4.73 | 4.73 | 0.00 | -2.08 | -2.08 | 0.00 |
| 4.37 | 4.37 | 0.00 | 3.46 | 3.46 | 0.00 |
| **MAPE** | | **0.00** | **MAPE** | | **0.00** |
| **Prediction Accuracy %** | | **100** | **Prediction Accuracy %** | | **100** |

4) MAPE Calculations for Validation data

The ANFIS model's predicted results for validation data are presented in Table 9. The Mean Absolute Percentage Error (MAPE) values for x-coordinates and y-coordinates validation data sets in predicting end-effector Cartesian coordinates using the ANFIS model are found to be 36.63 % and 19.93 %, respectively. These values indicate prediction accuracies of 63.35 % and 80.07 % for $X_e$ and $Y_e$, respectively.

TABLE 4: ANFIS MODEL PREDICTION ACCURACY FOR VALIDATING DATA

| **X-Coordinates** | | | **Y-Coordinates** | | |
|---|---|---|---|---|---|
| **Actual $X_e$** | **Predicted $X_e$** | **Absolute % Error** | **Actual $Y_e$** | **Predicted $Y_e$** | **Absolute % Error** |
| -0.51 | -0.04 | 92.15 | 2.83 | 3.40 | 20.14 |
| 5.09 | 5.06 | 0.58 | 0.39 | 0.44 | 12.82 |
| 1.49 | 2.02 | 35.57 | 4.63 | 3.51 | 24.19 |
| 1.49 | 2.03 | 36.24 | 4.37 | 5.17 | 18.31 |
| 2.72 | 2.21 | 18.75 | 3.59 | 4.46 | 24.23 |
| **MAPE** | | **36.65** | **MAPE** | | **19.93** |
| **Prediction Accuracy %** | | **63.35** | **Prediction Accuracy %** | | **80.07** |

To evaluate whether there is any proof that the real and anticipated Xe and Ye esteems have various methods, an unpaired t-test has been performed. The aftereffects of the unpaired t-test are introduced in Table 10. For both organized values (Xe and Ye), the invalid theory has been that the real and anticipated information methods are equivalent. Since the p-values for Xe and Ye are more prominent than 0.05, the invalid speculation can't be dismissed. It is subsequently inferred that the contrasts between anticipated and real information are viewed as not measurably huge. Table 4, SD, SEM, and N represent standard deviation, a standard mistake of the mean and populace size, separately.

*TABLE 5: UNPAIRED T TEST RESULTS*

| **Parameter** | **$X_e$** | | **$Y_e$** | |
|---|---|---|---|---|
| | **Actual $X_e$** | **Predicted $X_e$** | **Actual $Y_e$** | **Actual $Y_e$** |
| Mean | 2.06 | 2.26 | 3.16 | 3.40 |
| SD | 2.06 | 1.82 | 1.70 | 1.80 |
| SEM | 0.92 | 0.81 | 0.76 | 0.81 |
| N | 5 | 5 | 5 | 5 |
| P-Value | 0.87 | | 0.84 | |

The ANFIS model structure was also generated on MATLAB showing the different nodes and layers of the structure. Fig 12 illustrates this.

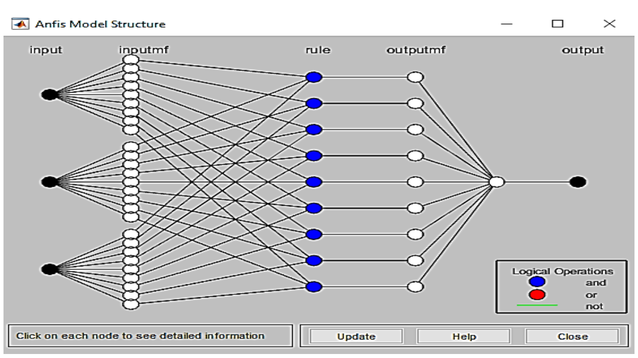


Fig. 12: ANFIS Model Structure

## IV. CONCLUSIONS

The exactness of the Adaptive Neuro-Fuzzy Inference System (ANFIS) in foreseeing the Cartesian directions of automated controller end effector has been evaluated. The joint point boundaries have been utilized as contributions to the ANFIS model in anticipating end-effector Cartesian directions. It has been seen that the ANFIS model has a Mean Absolute Percentage Error (MAPE) worth of 0.00% or 100% expectation exactness for Xe and Ye preparing information when the subgrouping technique has been utilized. The ANFIS model has Mean Absolute Percentage Error (MAPE) upsides of 36.65% and 19.93% or expectation exactnesses of 63.35% and 80.07% for Xe and Ye approval information, separately. Moreover, an unpaired t-test uncovered that the contrasts among anticipated and genuine information are viewed as not measurably huge. These perceptions show the reasonableness of the ANFIS model to anticipate automated controller end Cartesian effector directions.

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