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Prediction of Inverse Kinematics Solution of APUMA Manipulator Using ANFIS

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ABSTRACT:

In this paper, a method for forward and inverse kinematics analysis of a 5-DOF and a 7-DOF Redundant manipulator is proposed. Obtaining the trajectory and computing the required joint angles for a higher DOF robot manipulator is one of the important concerns in robot kinematics and control. When a robotic system possesses more degree of freedom (DOF) than those required to execute a given task is called Redundant Manipulator. The difficulties in solving the inverse kinematics (IK) equations of these redundant robot manipulator arises due to the presence of uncertain, time varying and non-linear nature of equations having transcendental functions. In this thesis, the ability of ANFIS (Adaptive Neuro-Fuzzy Inference System) is used to the generated data for solving inverse kinematics problem.

The proposed hybrid neuro-fuzzy system combines the learning capabilities of neural networks with fuzzy inference system for nonlinear function approximation. A single-output Sugeno-type FIS (Fuzzy Inference System) using grid partitioning has been modeled in this work. ANFIS have been successfully used for prediction of IKs of 5-DOF and 7-DOF Redundant manipulator in this work. After comparing the output, it is concluded that the predicting ability of ANFIS is excellent as this approach provides a general frame work for combination of NN and fuzzy logic. The Efficiency of ANFIS can be concluded by observing the surface plot, residual plot and normal probability plot. This current study in using different nonlinear models for the prediction of the IKs of a 5-DOF and 7-DOF Redundant manipulator will give a valuable source of information for other modelers.

INTRODUCTION

Introduction to Robotics

Word robot was coined by a Czech novelist Karel Capek in 1920. The term robot derives from the Czech word robota, meaning forced work or compulsory service. A robot is reprogrammable, multifunctional manipulator designed to move material, parts, tools, or specialized devices through various programmed motions for the performance of a variety of tasks [1]. A simpler version it can be define as, an automatic device that performs functions normally ascribed to humans or a machine in the form of a human.

Components and Structure of Robots

The basic components of an industrial robot are:

- The manipulator
- The End-Effector (Which is a part of the manipulator)
- The Power supply
- The controller

Robot Manipulators are composed of links connected by joints into a kinematic chain. Joints are typically rotary (revolute) or linear (prismatic). A revolute joint rotates about a motion axis and a prismatic joint slide along a motion axis. It can also be define as a prismatic joint is a joint, where the pair of links makes a translational displacement along a fixed axis. In other words, one link slides on the other along a straight line. Therefore, it is also called a sliding joint. A revolute joint is a joint, where a pair of links rotates about a fixed axis. This type of joint is often referred to as a hinge, articulated, or rotational joint.

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Redundant Manipulator

A manipulator is required have a minimum of six degree of freedom if it needs to acquire any random position and orientation in its operational space or work space. Assuming one joint isrequired for each degree of freedom, such a manipulator needs to be composed of minimum of six joints. Usually in standard practice three degree of freedom is implemented in the robotic arm so it can acquire the desired position in its work space. The arm is then fitted with a wrist composed of three joints to acquire the desired orientation. Such a manipulator is called non-redundant.

A redundant manipulator offer several potential advantages over a non-redundant manipulator. The extra DOF that require for the free positioning of manipulator can be used to move around or between obstacles and thereby to manipulate in situations that otherwise would be inaccessible. Due to the redundancy the manipulators become flexible, compliant, extremely dextrous and capable of dynamic adaptive, in unstructured environment.

Degree of Freedom (DOF)

The number of joints determines the degrees-of-freedom (DOF) of the manipulator. Typically, a manipulator should possess at least six independent DOF: three for positioning and three for orientation. With fewer than six DOF the arm cannot reach every point in its work environment with arbitrary orientation. Certain applications such as reaching around or behind obstacles require more than six DOF. The difficulty of controlling a manipulatorincreases rapidly with the number of links. A manipulator having more than six links is referred to as a kinematically redundant manipulator.

FORWARD KINEMATICS AND INVERSE KINEMATICS

In this section of the thesis the forward kinematics and the inverse kinematics of the 5-DOF and 7-DOF redundant manipulator is discussed. The Denavit-Hartenberg (D-H) notation for these two manipulators is discussed with steps used for deriving the forward kinematics is presented. Then this chapter is concluded with the solution of inverse kinematics for the 5-DOF redundant manipulator is given. The forward kinematics is concerned with the relationship between the individual joints of the robot manipulator and the position (x,y, and z) and orientation (□) of the end-effector. Stated more formally, the forward kinematics is to determine the position and orientationof the end-effector, given the values for the joint variables ($\square_i$, a_i, d_i, $\square_i$) of the robot. The joint variables are the angles between the links in the case of revolute or rotational joints, and the link extension in the case of prismatic or sliding joints. The forward kinematics is to be contrasted with the inverse kinematics, which will be studied in the next section of this chapter, and which is concerned with determining values for the joint variables that achieve a desired position and orientation for the end-effector of the robot.

ANFIS Architecture

ANFIS stands for adaptive neuro-fuzzy inference system developed by Roger Jang [57]. It is a feed forward adaptive neural network which implies a fuzzy inference system through its structure and neurons. He reported that the ANFIS architecture can be employed to model nonlinear functions, identify nonlinear components on-line in a control system, and predict a chaotic time series. It is a hybrid neuro-fuzzy technique that brings learning capabilities of neural networks to fuzzy inference systems. It is a part of the fuzzy logic toolbox in MATLAB R2008a software of Math Work Inc [58]. The fuzzy inference system (FIS) is a popular computing frame work based on the concepts of fuzzy set theory, fuzzy if-then rule, and fuzzy reasoning. It has found successful application in a wide variety of fields, such as automatic control, data classification, decision analysis, expert system, time series prediction, robotics, and pattern recognition. The basic structure of a FIS consists of 3 conceptual components: a rule base, which contains a selection of fuzzy rules: a database, which define the membership function used in fuzzy rules; a reasoning mechanism, which

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performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion. The basic FIS can take either fuzzy input or crisp inputs, but outputs it produces are almost always fuzzy sets. Sometime it is necessary to have a crisp output, especially in a situation where a FIS is used as a controller. Therefore, method of defuzzification is needed to extract a crisp value that best represent a fuzzy set.

The system identification includes the following steps

- Specify and parameterize a class of mathematical model representing the system to be identified.
- Perform parameter identification to choose the parameters that best fit the training data.
- Conduct validation tests to see if the model identified responds correctly to an unseen data set.
- Terminate the procedure once the results of the validation tests are satisfactory. Otherwise, another class of model is selected and steps 2 through step 4 are repeated.

From the above discussions, it is concluded that ANFIS is a fuzzy rule-based model using neural network like structure (i.e. involving nodes and links). It consists of five layers implementing fuzzy inference systems as schematically shown in Figure 12. The square nodes are adaptive nodes and the circle nodes are fixed ones. Figure 12 shows a simple ANFIS model that has been used in this work with three inputs (x, y, and z), seven membership functions for each input, and 343 rules for three inputs. The first layer of ANFIS determines the degree to a fuzzy condition involving the given input by using membership functions (A_i and B_i). The second layer evaluates the truth value (matching degree) of the premise of each rule in the rule base. The third layer normalizes these truth values. The fourth layer computes the consequent of each rule. Finally, the fifth layer computes the aggregate output of all the rules.

ANFIS Architecture used for 5-DOF Redundant manipulator:

The coordinates and the angles obtained from forward kinematics solutions are used as training data to train ANFIS network with the triangular membership function with a hybrid learning algorithm. For solving the inverse kinematics equation of 5-DOF Redundant manipulator, in this work, considers the ANFIS structure with first order Sugeno model containing 343 rules. For the neuro-fuzzy model used in this work, 1024 data points analytically obtained using forward kinematics, of which 776 are used for training and the remaining 248 are used for testing (or validating). Color coding of branches characterize the rules and indicate whether *and*, *or*, *not* are used in the rules. The input is represented by the left-most node and the output by the right-most node. The node represents a normalization factor for the rules. Clicking on the nodes indicates information about the structure. To start the training, GENFIS1 function is used. GENFIS1 uses the grid partitioning and it generates rules by enumerating all possible combinations of membership functions of all inputs; this leads to an exponential explosion even when the number of inputs is moderately large. For instance, for a fuzzy inference system with 3 inputs, each with seven membership functions, the grid partitioning leads to 343 (=7^3) rules. GENFIS1 use a given training data set to generate an initial fuzzy inference system (represented by a FIS matrix) that can be fine-tuned via the ANFIS command. GENFIS1 produces a grid partitioning of the input space and a fuzzy inference system where each rule has zero coefficients in its output equation.

ANFIS Architecture used for 7-DOF Redundant manipulator:

For solving the inverse kinematics equation of 7-DOF Redundant manipulator, in this work, the grid partitioning option in the ANFIS toolbox is used. For each input, 7 membership function (Gaussian membership) are used along with 343(=7^3) fuzzy rules are applied for all three inputs. For the neuro-fuzzy model used, 2187 data points are analytically obtained from MATLAB, of which 1640 are used for

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training and the remaining 547 are used for testing (validating). The model structure for the 7-DOF Redundant manipulator used in ANFIS can be viewed as similar to the structure obtained for 5-DOF Redundant manipulator as discussed in the previous section. The model structure obtained for 7-DOF manipulator. The Anfis information used for solving the 7-DOF Redundant manipulator for this work is tabulated in Table. 4.

Table 4. ANFIS information used for solving 7-DOF Redundant manipulator

3 inputs	: Cartesian coordinates: x, y, and z
1 output	: joint coordinate (θ)
7 member functions each input node	: Sugeno types
Number of nodes	: 734
Number of linear parameters	: 1372
Number of nonlinear parameters	: 42
Total number of parameters	: 1414
Number of training data pairs	: 1638
Number of checking data pairs	: 2187
Number of fuzzy rules	: 343

RESULT AND DISCUSSION:

In this section of the thesis the surface plots, the residual plots and the normal probability plots for the 5-DOF and 7-DOF redundant manipulator is carried out. The surface plots obtained for this type of manipulators explains the efficiency of the ANFIS methodology.

The residual plots obtained by comparing the predicted data from the ANFIS and the analytical data show that, the data predicted using ANFIS methodology deviate very less from the analytical data. The last section of this chapter is concluded with obtaining the normal probability plots. The details of the plots are explains in the following section.

Normal probability plot analysis of Training data for all joint angle of 5-DOF Redundant manipulator

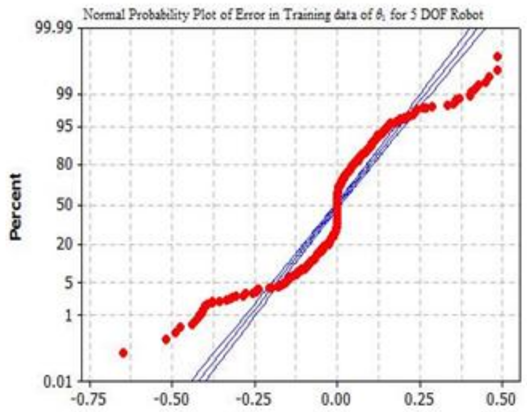

Figure 1: Normal probability plot for residuals (Training data of θ_1)

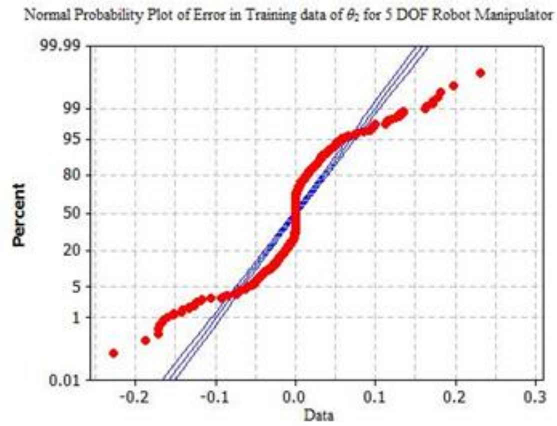

Figure 2: Normal probability plot for residuals (Training data of θ_2)

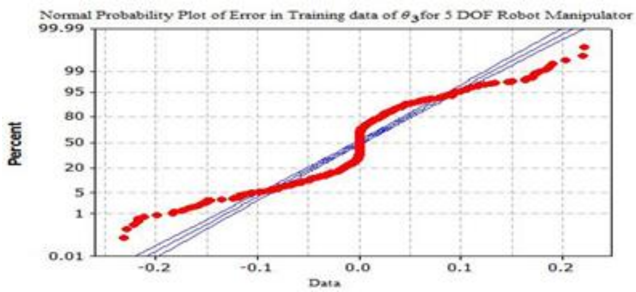

Figure 3: Normal probability plot for residuals (Training data of θ_3)

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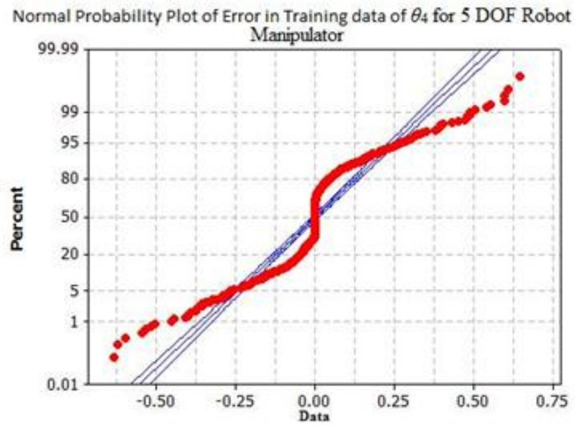

Figure 4: Normal probability plot for residuals (Training data of θ_4)

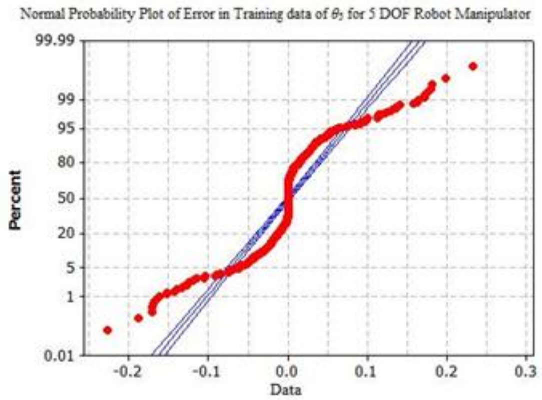

Figure 5: Normal probability plot for residuals (Training data of θ_5)

Normal probability plot analysis of Testing data for all joint angle of 5-DOF Redundant manipulator

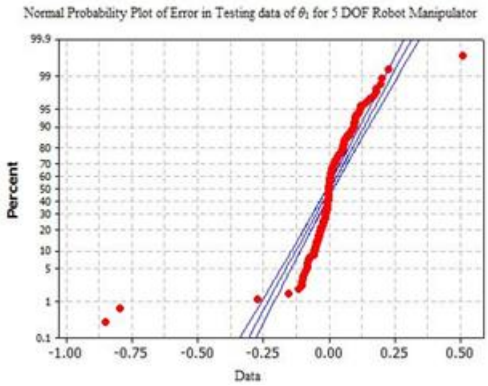

Figure 6: Normal probability plot for residuals (Testing data of θ_1)

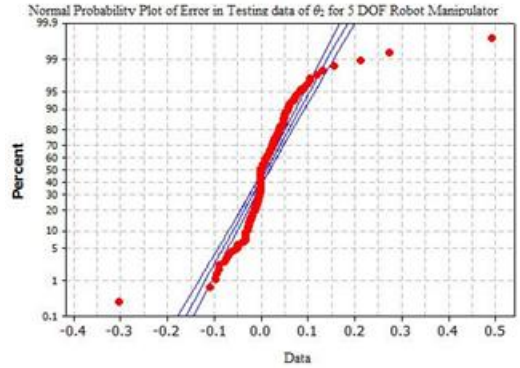

Figure 7: Normal probability plot for residuals (Testing data of θ_2)

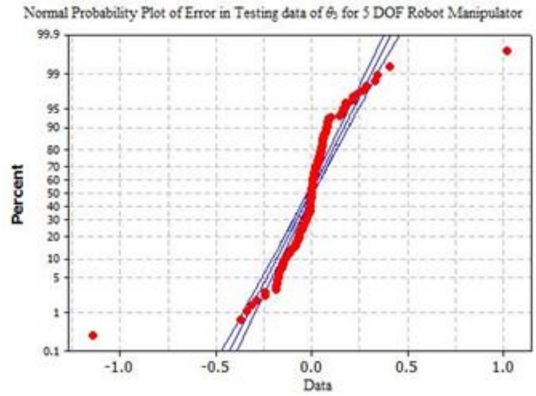

Figure 8: Normal probability plot for residuals (Testing data of θ_3)

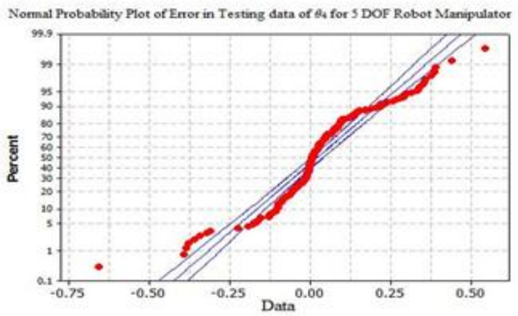

Figure 9: Normal probability plot for residuals (Testing data of θ_4)

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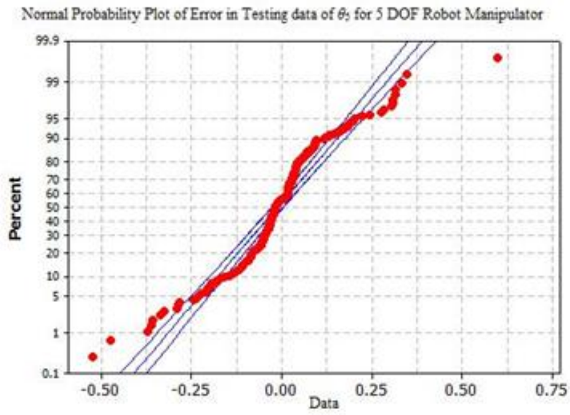

Figure 10: Normal probability plot for residuals (Testing data of θ_5)

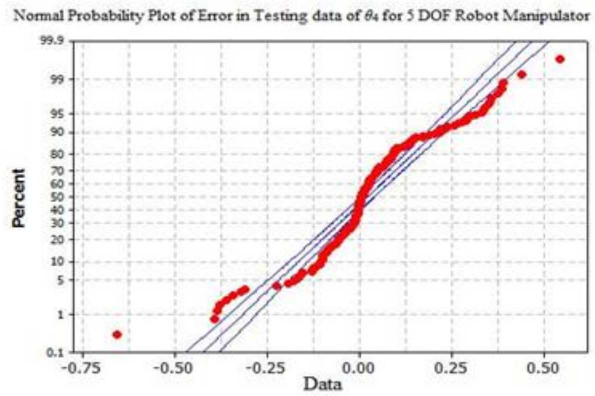

Figure 12: Normal probability plot for residuals (Training data of θ_5)

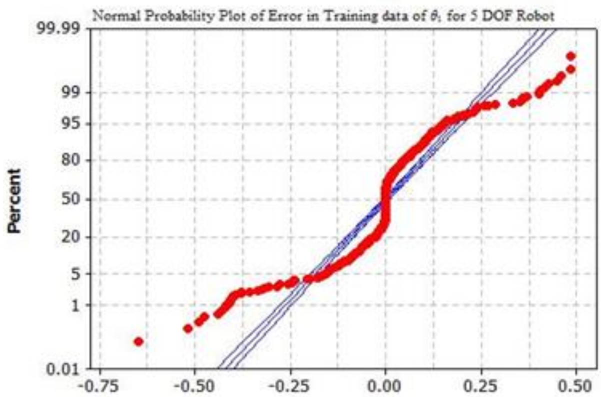

Figure 13: Normal probability plot for residuals (Training data of θ_7)

Normal probability plot analysis of Training data for all joint angle of 7-DOF Redundant manipulator

The normal probability analysis of training and testing data for θ_3 ,θ_5 ,and θ_7 of 7-DOF redundant manipulator is carried out in the following section similar to the 5-DOF Redundant manipulator. The data are plotted against a theoretical normal distribution in such a way that the points should form an approximate straight line. Departures from this straight line indicate departures from normality. It provides a good assessment of the adequacy of the normal model for a set of data. The Anderson-Darling test (AD Test) is also carried out similar to the 5-DOF Redundant manipulator, to compare the fit of an observed cumulative distribution function to an expected cumulative distribution function.

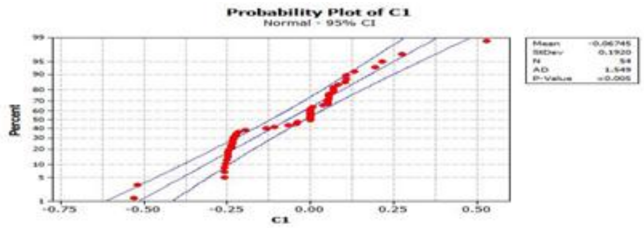

Figure 11: Normal probability plot for residuals (Training data of θ_3)

Normal probability plot analysis of Testing data for all joint angle of 7-DOF Redundant manipulator

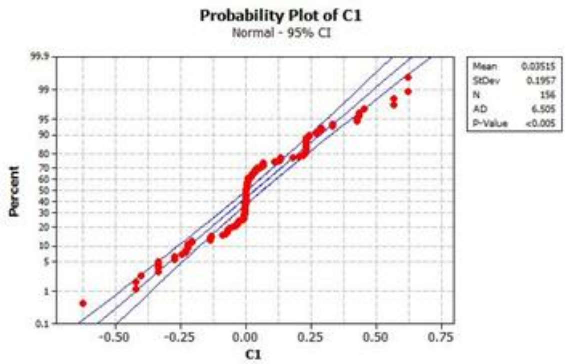

Figure 14: Normal probability plot for residuals (Testing data of θ_3)

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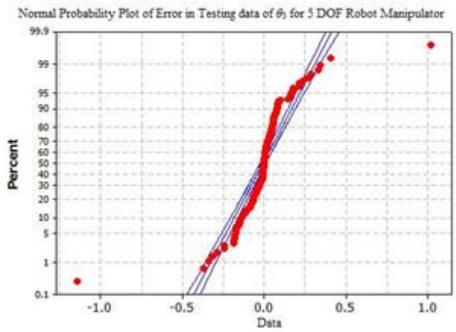

Figure 15: Normal probability plot for residuals (Testing data of θ_5)

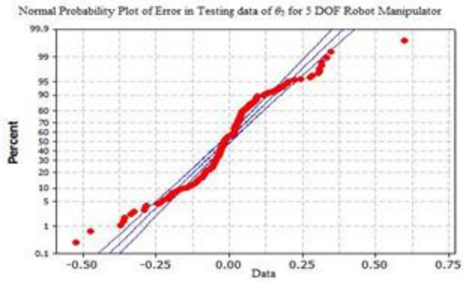

Figure 16: Normal probability plot for residuals (Testing data of θ_7)

Application of Artificial Neural Network (ANN):

In this work, an artificial neural network (ANN) model has also been adopted for estimating the IK solution of a 7-DOF redundant manipulator. A comparative study of both the techniques i.e ANFIS and ANN has been carried out. In this work, for the construction of model, 3-30-7 feed forward ANN, input layer consisting of 3 nodes, single hidden layer containing 20 nodes with tangent sigmoid activation function, and the output layer containing 7 nodes with linear activation function is used. The architecture of the neural network used in the analysis is shown in the Figure 17.

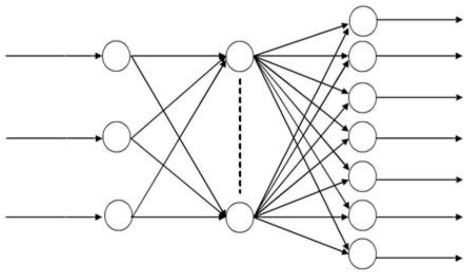

Figure 17: Schematic representation of Neural network used

According to these tables, for ANN and ANFIS model, the MSE values range between 1.06 and 2.25 and between 0.046 to 0.623 respectively and R^2 values range between 0.9150 to 0.9823 and 0.9448 to 0.9998 respectively. These are in narrow ranges. In all the analyses, the ANFIS model result in the better prediction of the inverse kinematics solution of the 7-DOF redundant manipulators. The ANFIS model outperformed the ANN model and provides the best performance i.e., lowest MSE, lowest MBE and highest R^2. The results of the study also indicate that the predictive capability of ANN models used is poor as compared to the ANFIS model used for solving inverse kinematics equation of 7-DOF redundant manipulator.The MSE of the training data for joint angles θ_1,θ_2,θ_3,θ_6, andθ_7 obtained fromANFIS model are acceptable and very low (0.124, 0.042, 0.373, 0.128, 0.231 respectively) as compare to ANN model which are very high (1.06, 0.142, 1.59, 1.62, 1.91 respectively). So the ANFIS model is more flexible than the model of ANN considered in this study for the prediction of inverse kinematics solution. This can be justified as the ANFIS approach provides a general frame work for the combination of neural networks and fuzzy logic. So the θ_7

ANFIS models perform better than the ANN models in the prediction of inverse kinematic solution for 7-DOF redundant manipulator. By comparing the output from ANFIS and ANN model on the basis of global statistic i.e. MSE, MBE, and R^2, it can be concludes that the ANFIS model is more flexible than the ANN model considered in this research, for prediction of IKs. As the ANFIS approach provides a general frame work for combination of NN and fuzzy logic. The efficiency of ANFIS over ANN can also be concluded by observing the graphs and tables which shows the comparison MSE, MBE, R^2 for the two models. Based on comparison of the results of these two techniques, it is found that the proposed ANFIS model with Gaussian membership function is more efficient than the multilayer feed forward ANN using Levenberg-Marquardt (LM) algorithm for predicting the IK of the 7-DOF redundant manipulator.

CONCLUSION AND FUTURE WORK

CONCLUSION:

In this study, the inverse kinematics solution using ANFIS for a 5-DOF and 7-DOF Redundant manipulator is presented. The difference in joint angle deduced and predicted with ANFIS model for a 5-DOF and 7-DOF Redundant manipulator clearly depicts that the proposed method results with an acceptable error. The modelling efficiency of this technique was obtained by taking three end-effector coordinates as input parameters and five and seven joint positions for a 5-DOF and 7-DOF Redundant manipulator respectivly as output parameters in training and testing data of NF models. Also, the ANFIS model used with a smaller number of iteration steps with the hybrid learning algorithm. Hence, the trained ANFIS model can be utilized to solve complex, nonlinear and discontinuous kinematics equation complex robot manipulator; thereby, making ANFIS an alternative approach to deal with inverse kinematics. The analytical inverse kinematics model derived always provide correct joint angles for moving the arm end-effector to any given reachable positions and orientations.

As the ANFIS approach provides a general frame work for combination of NN and fuzzy logic. The efficiency of ANFIS for predicting the IK of Redundant manipulator can be concluded by observing the 3-D surface viewer, residual and normal probability graphs. The normal probability plots of the model are also plotted. The normal probability plot of residuals of training and testing data obtained from ANFIS shows that the data set of ANFIS are approximately normally distributed. The methods used for deriving the inverse kinematics model for the these manipulators could be applied to other types of robotic arms, such as the EduBots developed by the Robotica Ltd, Pioneer 2 robotic arm (P2Arm), 5-DOF Lynx 6 Educational Robot arm. It can be concluded that the solution developed in this paper will make the PArm more useful in application with unpredicted trajectory movement in unknown environment.

FUTURE WORK:

In this work a hybrid neuro-fuuzy technology is used for the study of inverse kinematics of redundant robot manipulator. ANFIS is adopted for solving the IK of higher DOF robot manipulator. Due to its compactness and adaptive nature this technology is highly efficiencyin predicting the IK of higher DOF robot manipulator. So this technology can used in different robot in different field to know the joint angles, orientations, and the robot working space to avoid osstacles.

The robotics industry has reached one plateau with the successful introduction of robots into automotive manufacturing for spot welding and painting, are two areas where robotic usage is almost universal. There are several other areas where the usage of robotics is in its infancy and this chapter is dedicated to brief descriptions of some of these fields along with a quick assessment of their current status.

A 20 meters long and 6-DOF remote robot manipulator is commonly used in space for repairing satellites and other coordinated activities on self-propelled platform. So ANFIS can be used to this robot for its free positioning and to determine its path. Apart from this, the neuro fuzzy technique can be used in various field to determine the positions and orientations. It can be used for:

- Under water manipulator
- Nuclear, toxic waste disposal and mining robot
- Firefighting, construction and agricultural robot
- Medical application

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