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A REVIEW ON ANALYSIS OF REDUNDANT MANIPULATOR USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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Abstract

This thesis proposes a method for the forward and inverse kinematics analysis of 5-DOF and 7-DOF nonspecific manipulations. Obtaining trajectories and calculating required joint angles for high DOF robotic manipulators is one of the important concerns in robotic kinematics and control. When the degree of freedom (DOF) required to perform a given task in a robotic system exceeds, it is said to be a redundant manipulator. Difficulties in solving the inverse kinematic (IK) equations of these redundant robotic manipulations arise due to the non-linear nature of the equations with uncertain, time varying and transcendental functions. In this thesis, the ability of ANFIS (Adaptive Neuro-Fuzzy Inference System) is used to generate data to solve the inverse kinematics problem. The proposed hybrid neuro-fuzzy system combines the learning capability of neural networks with fuzzy inference systems for nonlinear function approximations.

Keywords: *Robotics, DOF, Redundant Manipulator, Adaptive Neuro-Fuzzy.*

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1. INTRODUCTION

Czech novelist Karel Capek coined the term robot in 1920. The word robot is derived from the Czech word robota, which means forced work or compulsory service. A robot is a reprogrammable, multifunctional manipulator designed to move materials, parts, instruments or specialized equipment through various programmable motions to perform various tasks [1]. Like a simpler version, it can be defined as an automatic device that acts as a human in general or as a machine.

1.1 History of Robotics

The first industrial robot was named UNIMATE; It is the first programmable robot designed by George Devol in 1954, who coined the term Universal Automation. The first UNIMATE was installed at General Motors' plant to work with heated die-casting machines.

Figure 1: The first industrial robot: UNIMATE

In 1978, the PUMA (Programmable Universal Machine for Assembly) robot was developed by Victor Scheinmann at the leading robot company Unimation with General Motors' design support. These robots are widely used in different organizations like Nokia Corporation, NASA, Robotics and Welding Organization.

Robotic manipulators have chain links attached to joints to form a kinetic chain. Joints are usually rotational (curved) or linear (prismatic). Inverted joints rotate along the axis of motion, and prismatic joints slide along the axis of motion. It can also be defined as a prismatic joint, which is a joint in which a pair of links form a translational displacement along a fixed axis. In other words, one link slides over another in a straight line. That's why it is also called a slip joint. An inverted joint is a joint in which a pair of links is rotated about a fixed axis. This type of joint is often called a hinge, joint, or reverse joint.

1.2 Redundant Manipulator

A manipulator must have at least six degrees of freedom if it is required to achieve any random position and orientation in its operational location or workspace. Let's say there is an addition. Such manipulations must be composed of at least six joints for each degree of freedom required. Typically, in standard practice, three degrees of freedom are applied to the robotic arm to allow it to attain the desired position in its work space. The hand is then fitted with a wrist made of three joints to obtain the desired orientation. Such manipulations are called non-redundant. Although non-redundant manipulations are kinetically simple to design and solve, non-redundancy leads to two fundamental problems: singularity and the inability to avoid obstacles. The eccentricity of the robotic manipulator is present in both the hand and the wrist and can occur anywhere within the manipulator's scope. When passing through these singularities, the manipulator can lose some degree of freedom, resulting in uncontrollability in those directions [4]. Obstacle avoidance is another desirable feature for effectively planning motion trajectories, especially for manipulators designed to perform demanding tasks in compressed environments [5]. The two problems can be solved by adding degree of freedom to the manipulator [6]. These additional degrees of freedom can be added to the joints, effectively becoming singular in some positions such as the shoulder, elbow or wrist. And therefore help overcome eccentricities or avoidance of obstacles. So, a redundant manipulator must have at least one degree of freedom (DOF) higher than the number required for the normal free state. Redundant can also be defined as when a manipulator can reach a specified location with more than one linkage configuration; the manipulation is said to be redundant. From a general point of view, any robotic system in which the method of achieving a given task is not unique can be said to be redundant.

2. LITERATURE REVIEW

Obtaining the inverse kinematics solution has been one of the main concerns in robot kinematics research. The complexity of the solutions increases with higher DOF due to robot geometry, non-linear equations (i.e. trigonometric equations occurring when transforming between Cartesian and joint spaces) and singularity problems. Obtaining the inverse kinematics solution requires the solution of nonlinear equations having transcendental functions. Despite the difficulties and time-consuming of solving the inverse kinematics of a complex robot, researchers used traditional methods like algebraic [14], geometric [15], and iterative [16] procedures. But these methods have their drawbacks, as algebraic methods do not guarantee closed-form solutions. In the case of geometric methods, closed-form solutions for the first three joints of the manipulator must exist geometrically. The iterative methods converge to only a single solution depending on the starting point and will not work near singularities [17].

In other words, for complex manipulators, these methods are time-consuming and produce highly complex mathematical formulations, which cannot be modelled concisely for a robot to work in the real world. Calderon et al. [18] proposed a hybrid approach to inverse kinematics and control, and a resolve motion rate control method is experimented with to evaluate their performances in terms of accuracy and time response in trajectory tracking. Xu et al. [19] proposed an analytical solution for a 5-DOF manipulator to follow a given trajectory while keeping the orientation of one axis in the end-effector frame by considering the particular position problem. Gan et al. [20] derived complete analytical inverse kinematics (IK) model, which can control the P2Arm to any given position and orientation in its reachable space so that the P2Arm gripper mounted on a mobile robot can be controlled to move to any reachable position in an unknown environment. The utilization of artificial neural networks (ANN) and fuzzy logic for solving the inverse kinematics equation of various robotic arms are also considered by researchers. Hasan and Assadi [21] adopted an application of ANN to the solution of the IK problem for serial robot manipulators. In his study, two networks were trained and compared to examine the effect of the Jacobian matrix on the efficiency of the inverse kinematics solution.

A Kinematically redundant manipulator is a robotic arm posses an extra degree of freedom (DOF) than those required to establish an arbitrary position and orientation of the end- effector. A redundant manipulator offers several potential advantages over a non-redundant Manipulator. The extra DOF that require for the free positioning of the manipulator can be used to move around or between obstacles and thereby manipulate in situations that otherwise would be inaccessible [22],[23],[24]. Due to the redundancy, the manipulators become flexible, compliant, extremely dextrous and capable of dynamic adaptive in the unstructured environment [25].

The redundancy of the robot increases with increasing in DOF and there exist many IK solutions for a given end-effector configuration for this type of robot. So various researchers have proposed many methods to solve the

IK equation of redundant manipulators. L. Sciavicco et al. [26] used inverse jacobian, pseudo inverse jacobian or jacobian transpose and solved the IK problem of 7-DOF redundant manipulator iteratively. But the main drawback of this method is that it is slow and suffer from singularity issue. Shimizu et al. [27] proposed an IK solution for the PA 10-7C 7-DOF manipulator and considered arm angle a redundancy parameter. In his study, a detailed analysis of the joint angle variation with the arm angle parameter is considered, which is then utilised for redundancy resolution. However, link offsets were not considered in his work. An analytical solution for IK of a redundant 7-DOF manipulator with link offset was carried out by G.K Singh and J. Claassens [28].

They have considered a 7-DOF Barrett whole arm manipulator with link offset and concluded that the possibility of in-elbow and out-elbow poses of a given end-effector pose arises due to the presence of link offset. They also presented a geometric method for computing the joint variable for any geometric pose. Dahm and Jublin [29] used angle parameters as redundancy and derived a closed-form inverse solution of the 7-DOF manipulator. They also analysed the parameter limitation caused by a joint limit based on geometric construction. The analysis has its own drawback, as priority is being given to one of the wrist joint limits. Based on the closed-form inverse solution and using angle parameters by Dahm and Joublin in their work, Moradi and Lee [30] minimised elbow movement by developing a redundancy resolution method.

Due to the presence of non-linearity, complexity, and transcendal function as well as singularity issues in solving the IK, various researchers used different methods like iteration, geometrical, closed-form inverse solution, redundancy resolution as discussed in the above theory. But some researchers also adopted methods like algorithms, neural network, neuro-fuzzy in recent year for solving the non-linear equation arises in different areas such as civil engineering for constitutive modelling [31], structural analysis and design [32], structural dynamics and control [33], for non-destructive testing methods of material [34] and many disciplines including business, engineering, medicine, and science [35]. Liegeois [36]

First introduced a gradient projection algorithm to utilise the redundancy to avoid the mechanical joint limit. In his work, he obtained a homogeneous solution by considering the pseudo-inverse method and projecting it onto the null space of the jacobian matrix, but the selection of an appropriate scalar coefficient that determines the magnitude of self-motion and oscillation in the joint trajectory is the main drawback of this algorithm. One of the main drawbacks to utilize redundant manipulators in an industrial environment is joint drift. The well known Closed-loop inverse kinematics (CLIK) algorithm was proposed by Siciliano [37] to overcome the joint drift for open-chain robot manipulators by including the feedback for the end-effector's position and orientation. Wampler [38] proposed a least square method to generate the feasible output around singularities by utilising a generalised inverse matrix of jacobian, known as robust singularity pseudoinverse.

Due to the adapting and learning nature, ANN is an efficient method to solve non-linear problems. So it has a wide range of applications in the manufacturing industry, precisely for the Electro discharge machining (EDM) process. Various authors have adopted ANN with different training algorithms, namely the Levenberg-Marquardt algorithm, scaled conjugate gradient algorithm, Orient descent algorithm, Gaussi Netwon algorithm and with different activation functions like logistic sigmoid, tangent sigmoid, pure lin, to model the EDM process. Mandel et al. [39] used ANN with back propagation as a learning algorithm to model the EDM process. They concluded that considering different input parameters such as roughness, material removal rate (MRR), and Tool wear rate (TWR) are found to be efficient for predicting the response parameters. Panda and Bhoi [40] predicted MRR of D2 grads steel by developing an artificial feed-forward NN model based on Levenberg-Marquardt's back propagation technique and logistic sigmoid activation function. The model performs faster and provides a more accurate result for predicting MRR. Goa et al. [41] considered different algorithms like the L-M algorithm, resilient algorithm, and Gausi-Newton algorithm to an established different model for the machining process. After several training of models and comparing the generalisation performance, they conclude that the L-M algorithm provides faster and more accurate results. Despite the NN approach by different authors as discussed above, some authors have also adopted the neuro-fuzzy (NF) method for solving non-linear and complex equations. Although ANN is very efficient in adapting and learning, they have the negative attribute of a 'black box'. To overcome this drawback, various authors adopted neuro-fuzzy methods like ANFIS. This can be justified as ANFIS combines the advantage of ANN and fuzzy logic techniques without having any of their disadvantage [42]. The neuro-fuzzy system

Are must widely study hybrid systems nowadays, due to the advantages of two very important modelling techniques i.e. NN [43] and Fuzzy logic [44]. Malki et al. [45] adopted adaptive neuro fuzzy relationships to model the UH-60A Black Hawk pilot floor vertical vibration. They have considered 200 data of UH-60A helicopter flight envelop for training and testing purpose. They conducted the study in two parts i.e. the first part involves level flight conditions and the second part involves the entire (200 points) database including maneuver condition. They concluded from their study that neuro fuzzy model can successfully predict the pilot vibration. LI ke et.al. [46] applied ANFIS to solve the forecast problem of microwave effect by adopting microwave parameters and its threshold as variable. Then they develop an ANFIS model to study its forecasting ability. By comparing the output of ANFIS with training and testing data, they concluded with good forecasting ability, small error and low data requirement are found with ANFIS. Srinivasan et.al. [47] applied ANFIS based on PD plus I controller to the dynamic model of 6-DOF robot manipulator (PUMA Robot). Numerical simulation using the dynamic model of 6-DOF robot arm shows the effectiveness of the approach in trajectory tracking problems. Comparative evaluation with respect to PID, fuzzy PD+I controls are presented to validate the controller design. They concluded that a satisfactory tracking precision could be achieved using ANFIS based PD+I controller combination than fuzzy PD+I only or conventional PID only. Roohollah Noori et.al [48], predicted daily carbon monoxide (CO) concentration in the atmosphere of Tehran by means of ANN and ANFIS models. In this study they used Forward selection (FS) and Gamma test (GT) methods, for selecting input variables for developing hybrid models with ANN and ANFIS. They concluded that Input selection improves prediction capability of both ANN and ANFIS models and it not only reduces the output error but reduces the time of calculation due to less input variable. U. Yüzgeç et.al., [49], investigates different modelling approaches and compares for drying of baker's yeast in a fluidized bed dryer based on ANN and ANFIS. In this work they investigates four modelling concepts: modelling based on the mass and energy balance, modelling based on diffusion mechanism in the granule, modelling based on recurrent ANN and modelling based on ANFIS, to predict the dry matter of product, product temperature and product quality.

Most of the researchers have studied only a limited numbers of nonlinear model using ANFIS and ANN, as discussed above in the above theory. Despite the widespread application of these nonlinear mathematical models in various field such as in civil engineering, manufacturing industry, marketing field, business field, some authors have carried out a comparison study using different nonlinear models of NN and NF, which gives a valuable information for modellers. Mahmut Bilgehan [50], carried out the buckling analysis of slender prismatic columns with a single non-propagating open edge crack subjected to axial loads, using ANFIS and ANN model. The main feature of his work is to study the feasibility of using ANFIS and NN for predicting the critical buckling load of fixed-free, pinned-pinned, fixed-pinned and fixed-fixed supported, axially loaded compression rods. After the comparative study made using NN and NF technique, he concluded that the proposed ANFIS architecture with Gaussian membership function is found to perform better than the multilayer feed forward ANN learning by back propagation algorithm. Mahmut Bilgehan [51], again considered the same model of NN and NF as used for analysis of slender prismatic columns, and had successfully applied it for the evaluation of relationships between concrete compressive strength and ultrasonic pulse velocity (UPV) values using experiment data obtained from many cores taken from different reinforced concrete structure having different ages and unknown ratio of concrete mixture. He carried out a comparative study of NN and NF technique on the basis of statistical measure to evaluate the performance of the model used. Then by comparing the result, he found that the proposed ANFIS architecture performed better than the multilayer feed-forward ANN model.

In the present study, ANFIS is implemented to analyze the kinematics equation of PArm 5-DOF robot manipulator having 6-DOF end-effector and 7-DOF redundant manipulator. Jang [52] reported that the ANFIS 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. The learning algorithm tunes the membership functions of a Mamdani or Sugeno-type Fuzzy Inference System using the training input-output data. According to Jang [53], ANFIS is divided into two steps. For the first step of consequent parameters training, the least square (LS) method is used and the output of ANFIS is a linear combination of the consequent parameters. After the consequent parameters have been adjusted, the premise parameters are updated by gradient descent principle in the second step. It is concluded that ANFIS use the hybrid learning algorithm that combines least square method with gradient descent method to adjust the parameter of membership function. The detail coverage of ANFIS can be found in (Jang, [52]; Jang, [53]; Sadjadian et al., [54]). Due to its high interpretability and computational efficiency and built-in optimal and adaptive techniques, ANFIS is widely used in pattern recognition, robotics, nonlinear regression, nonlinear system identification and adaptive system processing and also it can be used to predict the inverse kinematics solution. It is to be noted that ANFIS is suitable for solving complex, nonlinear mathematical equation for control of higher DOF robot manipulators.

3. CONCLUSION

This thesis aims to obtain the inverse kinematic solutions of redundant manipulators such as 5-DOF Redundant manipulators and 7-DOF Redundant manipulators. The inverse kinematic equation of these manipulator manipulators contains non-linear equations, time-varying equations and transcendental functions. Due to the complexity of solving this type of equation by the geometric, iterative or algebraic methods is very difficult and time-consuming. It is very important to solve the inverse kinematics solution for this type of redundant manipulator to know the exact operational space and avoid obstacles. So various researchers have applied various methods for solving the kinematic equation. L. Sciavicco et al. [7] used inverse jacobian, pseudo inverse jacobian or jacobian transpose and solved the IK problem of 7-DOF redundant manipulator iteratively. But the main drawback of this method is that it is slow and suffer from singularity issue. Shimizu et al. [8] proposed an IK solution for the PA 10-7C 7-DOF manipulator and considered arm angle a redundancy parameter. In his study, a detailed analysis of the joint angle variation with the arm angle parameter is considered, which is then utilised for redundancy resolution. However, link offsets were not considered in his work. Some authors also applied ANN due to its adapting and learning nature. Although ANN is very efficient in adapting and learning, they have the negative attribute of a ‘black box’. Various authors adopted neuro-fuzzy methods like ANFIS (Adaptive Neuro-fuzzy Inference system) to overcome this drawback. This can be justified as ANFIS combines the advantage of ANN and fuzzy logic techniques without having any of their disadvantage [9]. The neuro-fuzzy system is must widely studied hybrid system nowadays due to the advantages of two very important modelling techniques, i.e. NN [10] and Fuzzy logic [11]. So, the goal of this thesis is to predict the inverse kinematics solution for the redundant manipulator using ANFIS. As a result, suitable posture and trajectories for the manipulator can be planned to execute different work in various fields.

REFERENCES

[1] Deb S.R. Robotics technology and flexible automation, Tata McGrow-Hill Publishing Company Limited. New-Delhi, 2008.

[2] Clarke, R. Asimov’s Laws of Robotics: Implications for Information Technology- part II, Computer, 27(1), September (1994): pp.57–66.

[3] Martin, F.G. Robotic Explorations: A Hands-On Introduction to Engineering, Prentice Hall, New Jersey, 2001.

[4] Featherstone R. Position and velocity transformations between robot end-effector coordinates and joint angles. International journal of Robotic Research, SAGE Publications, 2(2), (1983), pp. 35-45.

[5] Nieminen and Peetu, et al. Water hydraulic manipulator for fail safe and fault tolerant remote handling operations at ITER, Fusion Engineering and Design, Elsevier, Vol. 84, (2009), pp. 1420-1424.

[6] Hollerbach J.M. Optimum kinematic design for seven degree of freedom manipulator, Second International Symposium on Robotics Research. Cambridge: MIT Press, (1985): pp. 215-222.

[7] Sciavicco L. and Siciliano B. Modelling and Control of Robot Manipulators , Springer Second edition, (2000), Chapter 3, pp. 96.

[8] Shimizu M., Kakuya H. Yoon W, Kitagaki K., and Kosuge K., Analytical Inverse Kinematic Computation for 7-DOF Redundant Manipulators with Joint Limits and its application to Redundancy. Resolution, IEEE Transaction on Robotics, October (2008), 24(5).

[9] Vassilopoulos A.P and Bedi R. Adaptive neuro-fuzzy inference system in modelling fatigue life of multi-directional composite laminates, Computation and Material Science.43 (2008): pp. 1086-1093.

[10] Haykin S., Neural Networks- A Comprehensive Foundation, McMillan College Publishing, New York, 1998.

[11] Mendel J.M. Fuzzy logic system for engineering: A tutorial, Proceeding, IEEE. 83(3) (1995): pp. 345-377.

[12] Ke L., Hong-ge M., Hai-jing Z. Application of Adaptive Neuro-Fuzzy Inference System to Forecast of Microwave Effect, IEEE Conference Publications, (2009) , pp. 1- 3.

[13] Alavandar S. and Nigam M. J. Adaptive Neuro-Fuzzy Inference System based control of six DOF robot manipulator, Journal of Engineering Science and Technology Review,1 (2008): pp.106- 111.

[14] Craig J.J. Introduction to Robotics: Mechanisms and Controls, Addison-Wesley, Reading, MA, 1989.

[15] Lee G.C.S. Dynamics and Control, Robot Arm Kinematics, Computer, 15(1982), Issue.12: pp. 62-79.

[16] Korein J.U and Balder N.I. Techniques for generating the goal-directed motion of articulated structures', Institute of Electrical and Electronics Engineers Computer Graphics Applications, 2(1982), Issue. 9: pp. 71-81.

[17] Srinivasan A and Nigam M.J. 'Neuro-Fuzzy based Approach for Inverse Kinematics Solution of Industrial Robot Manipulators', International Journal of Computers, Communications and Control, III(2008), No. 3: pp. 224-234.

[18] Calderon C.A.A., Alfaro E.M.R.P, Gan J.Q. and Hu H. Trajectory generation and tracking of a 5-DOF Robotic Arm. CONTROL, University of Bath, (2004).

[19] De X., Calderon C.A.A., Gan J.Q., H Hu. An Analysis of the Inverse Kinematics for a 5- DOF Manipulator, International Journal of Automation and Computing, (2) (2005): pp. 114-124.

[20] Gan J.Q., Oyama E., Rosales E.M. and Hu, H. A complete analytical solution to the inverse kinematics of the Pioneer 2 robotic arm, Robotica, Cambridge University Press. 23(2005): pp. 123–129.

[21] Hasan A.T. and Al-Assadi H.M.A.A. Performance Prediction Network for Serial Manipulators Inverse Kinematics solution Passing Through Singular Configurations, International Journal of Advanced Robotic Systems, 7(2010), No. 4: pp. 10-23.

[22] Conkur E. S. and Buckingham R. Clarifying the definition of redundancy as used in robotics. Robotica, 15 No 5 (1997): pp. 583-586.

[23] Chiaverini S. Singularity-robust task-priority redundancy resolution for real time kinematic control of robot manipulators. IEEE Transaction on Robotics Automation, 13 No 3 (1997): pp. 398-410.

[24] Yoshikawa T. Foundation of Robotics: Analysis and Control. MIT Press (1988).

[25] Braganza D., Dawson D.M., Walker I.D., and Nath N. Neural Network Grasping Controller for Continuum Robots. IEEE Conference on Decision Control, (2006): pp.6445-6449.

[26] Sciavicco L. and Siciliano B. Modelling and Control of Robot Manipulators , Springer Second edition, Chapter 3, (2000), pp. 96.

[27] Shimizu M., Kakuya H., Yoon W., Kitagaki K., and Kosuge K. Analytical Inverse Kinematic Computation for 7-DOF Redundant Manipulators with Joint Limits and its application to Redundancy. Resolution, IEEE Transaction on Robotics, 24 No. 5: October. (2008).

[28] Singh G.K. and Claassens J., An Analytical Solution for the Inverse Kinematics of a Redundant 7DoF Manipulator with Link Offsets, The 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems. October (2010) :18-22. Taipei, Taiwan.

[29] Dahm P. and Joublin F. Closed form solution for the inverse kinematics of a redundant robot arm," Institute of Neuroinformatics, Ruhr-Univ. Bochum, 44780, Bochum, Germany, Internal Rep. 97-08, (1997).

[30] Moradi H. and Lee S. Joint limit analysis and elbow movement minimization for redundant manipulators using closed form method, In Advances in Intelligent Computing, Berlin/Heidelberg: Springer, Part 2, 3645(2005): pp. 423–432.

[31] Ghaboussi J., Garrett J.H. and Wu X. Knowledge-based modeling of material behaviour with neural networks, Journal of Engineering Mechanics. 117 (1991): pp.132–153.

[32] Consolazio G.R. Iterative equation solver for bridge analysis using neural networks, Computer-Aided Civil and Infrastructure Engineering. 15 (2000): pp.107–119.

[33] Chen H.M., Tsai K.H., Qi G.Z., Yang J.C.S., Amini F. Neural networks for structural control, Journal of Computing in Civil Engineering, 9(1995):pp.168–176.

[34] Bilgehan M., Turgut P. Artificial neural network approach to predict compressive strength of concrete through ultrasonic pulse velocity, Research in Nondestructive Evaluation. 21 (1) (2010): pp.1–17.

[35] Inel M. Modeling ultimate deformation capacity of RC columns using artificial neural networks, Enggineering Structure. 29 (2007): pp.329–335.

[36] Liegeois A. Automatic supervisory control of the configuration and behavior of multibody mechanisms, IEEE Transaction Systems on Man, and Cybernetics, 7 No. 12: (1977), pp. 868–871, ISSN 0018-9472.

[37] Sciavicco, L. & Siciliano, B. A solution algorithm to the inverse kinematic problem for redundant manipulators, IEEE Journal of Robotics and Automation, 4(4) (1988): pp. 303–310, ISSN 0882-4967.

[38] Wampler, C.W. Manipulator inverse kinematic solutions based on vector formulations and damped least-squares methods, IEEE Transaction on Systems, Man, and Cybernetics,16 No. 1 (1986):pp. 93–101, ISSN 0018-9472.

[39] Mandal D., Pal S.K., Saha P. Modeling of electrical discharge machining process using back propagation neural network and multi-objective optimization using non-dominating sorting genetic algorithm-II. J Mater Process Technol 186(2007): pp.154–162.

[40] Panda D.K., and Bhoi R.K. Artificial neural network prediction of material removal rate in electro-discharge machining. Material Manufaturing Process. 20 (2005): pp.645–672.

[41] Gao Q., Zhang Q., Su S., Zhang J., Ge R. Prediction models and generalization performance study in electrical discharge machining. Applied Mechanics and Materials .10 No.12(2008): pp.677–681. Cited by (since 1996).

[42] Vassilopoulos A.P and Bedi R. Adaptive neuro-fuzzy inference system in modelling fatigue life of multidirectional composite laminates, Computational Materials Science. (2008), pp. 1086-1093.

[43] Haykin S. Neural Networks-A Comprehensive Foundation, McMillan College Publishing, New York, (1998).

[44] Mendel J.M. Fuzzy logic system for engineering: A tutorial, Proceeding of IEEE. 83(3) (1995): pp. 345-377.

[45] Heidar A., Kottapalli S. And Langari R. Adaptive Neuro-fuzzy Modeling of UH-60A Pilot Vibration, American Institute of Aeronautics and Astronautics. (2003).

[46] Ke L., Hong-ge M. and Hai-jing Z. Application of Adaptive Neuro-Fuzzy Inference System to Forecast of Microwave Effect, IEEE Conference Publications, (2009). pp. 1 – 3.

[47] AlavandarS. and Nigam M. J. Adaptive Neuro-Fuzzy Inference System based control of six DOF robot manipulator, Journal of Engineering Science and Technology Review 1 (2008) 106- 111.

[48] Roohollah Noori et.al. Uncertainty analysis of developed ANN and ANFIS models in prediction of carbon monoxide daily concentration, ELSEVIER, International journal for scientists and researchers in different disciplines interested in air pollution and its societal impacts, Atmospheric Environment, , 44(2010): pp. 476-482.

[49] Yüzgeç U. Et al. Comparison of Different Modeling Concepts for Drying Process of Baker's Yeast. 7th IFAC International Symposium on Advanced Control of Chemical Processes, Koç University Campus, Turkey. Vol. 7 Part.1,2009.

[50] Bilgehan M. Comparison of ANFIS and NN models—With a study in critical buckling load estimation, Applied Soft Computing, Journal of the World Federation on Soft Computing (WFSC), ELSEVIER, (2011),pp. 3779–3791.

[51] Bilgehan M. A comparative study for the concrete compressive strength estimation using neural network and neuro-fuzzy modeling approaches, Non-destructive Testing and Evaluation, Taylor and Francis, Vol. 26, No.1, March (2011): pp 35-55.

[52] Jang J. S. R., Sun C. T. and Mizutani E. Neuro-Fuzzy and Soft Computing, Prentice Hall, New York.1997.

[53] Jang J. S. R. 'ANFIS: Adaptive-Network-based Fuzzy Inference Systems', Transactions on Systems, Man, and Cybernetics, 23 No. 3(1993): pp. 665-685.

[54] Sadjadian H., Taghirad H. D. and Fatehi A. Neural Networks Approaches for Computing the Forward Kinematics of a Redundant Parallel Manipulator, International Journal of Computational Intelligence, 2, No. 1(2005): pp. 40-47.

[55] Spong M.W., Hutchinson S., and Vidyasagar M. Robot Dynamics and Control Second Edition, pp-62. January 28, 2004.

[56] Mittal R.K., Nagrath I.J. Robotics and Control. Tata McGraw-Hill publishing company, Delhi, 2007, pp. 76-79.

[57] Jang J. S. R., Sun C. T. and Mizutani E. Neuro-Fuzzy and Soft Computing, Prentice-Hall, New York,1997.

[58] Zadeh L.A. Fuzzy Logic Toolbox User Guide, The Math Works, Berkeley, CA, Version 2, January 10, 1995-1998.

[59] Sugeno M.and Kang G.T., Structure Identification of Fuzzy model, Fuzzy Sets and System, 28(1988): pp.15-33.

[60] Takagi T., Sugeno M. Fuzzy Identification of Systems and its Application to Modeling Control, IEEE Transaction on System, Man and Cybernetics, 15(1985): pp.116-132.

[61] Mamdani E.H., Assilian S. An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller, International Journal of Man-Machine Studies, 7 (1) (1975): pp.1-13.

[62] Tsukamoto Y. An Approach to Fuzzy Reasoning Method. In Madan M. Gupta, Rammohan K. Ragade, and Ronald R. Yager, editors, Advances in Fuzzy Set Theory and Applications, North-Holland, Amsterdam, 1979, pp.137-149.

[63] Jang J. S. R., Sun C. T., and Mizutani E. Neuro-Fuzzy and Soft Computing, Prentice Hall, NewYork, pp.96-97.

[64] Koivo H . ANFIS : Adaptive Neuro-Fuzzy Inference System. European, Symposium on Intelligent Technologies, Aachen, Germany, 2000.

[65] Chambers, John, William Cleveland, Beat Kleiner, and Paul Tukey, Graphical Methods for Data Analysis, Wadsworth,1983.