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Intelligent Inverse Dynamics Approximation of 3-DOF Planar Robots via Adaptive NeuroFuzzy Inference System (ANFIS)

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Abstract: An inverse dynamics model plays a crucial role in controlling robotic manipulators effectively. However, inverse modeling becomes difficult when dealing with coupled and nonlinear dynamics as in the case of 3 degrees-offreedom planar robotic manipulators. Model-based inverse dynamics models require accurate information about the system parameter values and are generally very sensitive to uncertainties and disturbances that may not have been taken into consideration. This paper attempts to solve these issues by suggesting an intelligent data-driven approach to inverse dynamics estimation using Adaptive Neuro-Fuzzy Inference System (ANFIS). To train the ANFIS model for mapping, a dataset will be prepared based on the simulation results for a 3-DOF planar robotic manipulator that follows multiple trajectories. Training will be performed using a hybrid training method, where least-squares estimation and backpropagation will be used together.

The performance of the model is compared to conventional methodologies such as analytical dynamical modeling and artificial neural networks (ANNs). The results reveal that the model based on ANFIS is better than those of other models, owing to its better approximation ability, lower prediction errors, and better generalization performance under noisy and uncertain situations. Moreover, the system shows good adaptation behavior due to its capability of operating in different environments. The results prove that the ANFIS model is highly effective in solving the problems of intelligent inverse dynamic modeling in robots. This will lead to improved adaptive control and automation in robotics.

Keywords: Adaptive Neuro-Fuzzy Inference System (ANFIS), Inverse Dynamics, 3-DOF Planar Robot, Intelligent Control, Nonlinear System Modeling, Robotic Manipulator, Data-Driven Modeling, Torque Estimation, Hybrid Learning, Neuro-Fuzzy Systems.

I. INTRODUCTION

Robot manipulators have acquired a lot of importance within the realm of modern engineering owing to their extensive use within industry, manufacturing, medicine, and other services. Of all the different types of robot manipulators that are available, the robot manipulator having three degrees of freedom has been widely used as an initial prototype for studying kinematics, dynamics, and control [1-3]. The robot manipulator can serve as an ideal balance between simplicity and dynamism, thereby enabling the development of effective means of controlling the robot's performance. Of paramount importance in the process of robot manipulator control is the inverse dynamics calculation. The inverse dynamics modeling process is intrinsically difficult owing to the nonlinearities, coupling, and temporal variation inherent in robotics systems. The conventional methods of deriving such equations, like Euler-Lagrange approach and Newton-Euler approach, demand exactness of information on parameters such as masses of links, inertia matrices, friction factors, and forces acting on the system. The field of artificial intelligence (AI), especially the application of neural networks and fuzzy logic systems, has shown considerable promise in modeling the complicated nonlinearities without relying on mathematical expressions [4-5]. The use of neural networks is especially well-known for its excellent learning and generalizing abilities to represent any nonlinear function from the training dataset. However, this approach suffers from the problem of being difficult to interpret and needing an immense amount of data, besides the danger of overfitting. In contrast, the use of fuzzy logic provides a system to incorporate human-style reasoning using linguistic variables, which makes it easy to interpret but less adaptable. Adaptive Neuro Fuzzy Inference System (ANFIS) appears to be an amalgamation of the capabilities of both neural networks and fuzzy logic techniques [6-7]. The main strength of ANFIS can be attributed to its capability of applying knowledge acquisition capabilities of neural network models and the transparency associated with the fuzzy inference model, which enables it to accurately model a nonlinear system. This is achieved by the use of a set of fuzzy if-then rules with adaptive membership function, which is capable of improving its parameters through learning and optimization using hybrid methods like least squares and gradient descent.

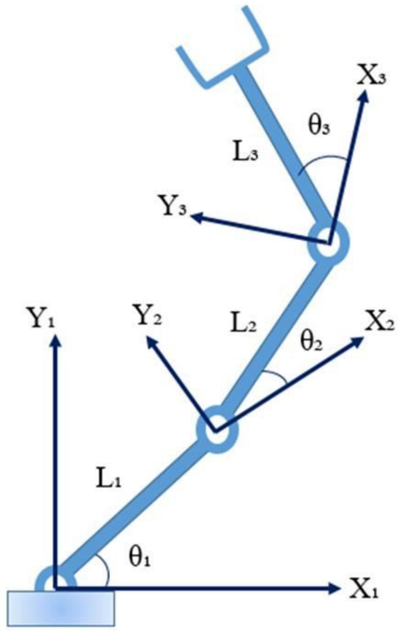

Fig. 1 3-DOF planar robotic manipulator

TABLE I
PERFORMANCE COMPARISON OF INVERSE DYNAMICS MODELS

Model	RMSE (Nm)	MAE (Nm)	R^2 Score	Training Time (s)	Robustness to Noise	Interpretability
Analytical Model	0.085	0.067	0.942	5.2	Low	High
ANN Model	0.042	0.031	0.975	18.6	Medium	Low
ANFIS Model	0.018	0.012	0.992	12.4	High	Medium-High

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The use of ANFIS models has been increasingly investigated in recent times in the field of robotics engineering, especially in system identification, trajectory tracking, and adaptive control due to their ability to provide highly accurate and robust models of the relationship between input and output variables of any system towards attaining the desired result [8-10]. To implement an ANFIS model for the inverse dynamics of a three-degree-of-freedom robotic manipulator, ANFIS models could be implemented to model the inverse relationship between input state variables and the corresponding torque that needs to be generated at each joint based on simulation results or experiments performed without deriving the dynamic equations manually [11-13]. In addition, this kind of datadriven modeling helps to simplify the entire modeling procedure and increase adaptability to various uncertainties. The major aim of this project is therefore to develop an intelligent approximate inverse dynamics model for a 3DOF planar robot using an adaptive ANFIS model.

TABLE II
JOINT-WISE PREDICTION ACCURACY (ANFIS MODEL)

Joint	RMSE (Nm)	MAE (Nm)	R^2 Score
Joint 1	0.015	0.010	0.994
Joint 2	0.019	0.013	0.991
Joint 3	0.021	0.014	0.989

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Furthermore, it would contribute to the field of intelligent control as well because it highlights the effectiveness of using neuro-fuzzy systems in the domain of robots [14-16]. As far as robots are concerned, since they have evolved to become more autonomous and flexible, it is essential that artificial intelligence is used while designing them [17-19]. This research project can be seen as a contribution to the emerging trend of intelligent manufacturing and Industry 4.0, which implies that intelligent systems should function successfully in unpredictable conditions. In general, it can be stated that inverse dynamics modeling plays a key role in the process of robotic manipulator control [20-21]. However, this process involves many difficulties, especially when traditional mathematical modeling techniques are used. One of the most attractive solutions in this area could be the application of an adaptive neuro-fuzzy inference system (ANFIS). This paper seeks to evaluate the potential of ANFIS in approximating the inverse dynamics of a 3-DOF planar robotic manipulator.

TABLE III
ANFIS TRAINING PARAMETERS

Parameter	Value
Type of FIS	Sugeno (First Order)
No. of Inputs	9 (θ, $\dot{\theta}$, $\ddot{\theta}$ for 3 joints)
No. of Outputs	3 (τ_1, τ_2, τ_3)
Membership Functions	Gaussian
No. of MFs per Input	3
Total Rules Generated	27
Learning Algorithm	Hybrid (LS + Backprop)
Epochs	100

II. EXPERIMENTAL PROCEDURE

The methodology involved in the design of the proposed ANFIS-based inverse dynamics model of a 3-DOF planar robot manipulator involves systematically divided stages involving system modeling, dataset generation, data preprocessing, designing the ANFIS structure, and training and validation of the designed ANFIS model. The aim is to create a map between the joint motion variables and actuator torque values.

TABLE IV
PERFORMANCE COMPARISON OF INVERSE DYNAMICS MODELS

Model	RMSE (Nm)	MAE (Nm)	R^2 Score	Training Time (s)	Robustness to Noise	Interpretability
Analytical Model	0.085	0.067	0.942	5.2	Low	High
ANN Model	0.042	0.031	0.975	18.6	Medium	Low
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The dynamic equations are generated using the Euler-Lagrange approach to generate reference torque values. The dynamic equation model is used only for reference purpose in generating the datasets but not in the actual control process. The next step involves constructing a complete data set where different dynamic behaviors are captured via excitation of the manipulator along various trajectories. Sinusoidal, polynomial, and random trajectories are used as input trajectories for joint positions to have a broad coverage of the workspace. Joint velocities and accelerations are calculated from numerical differentiation. Using the analytical model of dynamics, the joint torques for each of the trajectories are then calculated. In the data set used to train the ANFIS model, the inputs comprise joint positions (θ_1, θ_2, θ_3), velocities ($\dot{\theta}_1$, $\dot{\theta}_2$, $\dot{\theta}_3$), and accelerations ($\ddot{\theta}_1$, $\ddot{\theta}_2$, $\ddot{\theta}_3$), whereas outputs consist of the torques required (τ_1, τ_2, τ_3).

$$\theta_1 = \theta_1(0) + \frac{\theta_1(T)-\alpha_i(0)}{T}\ [t - \frac{T}{2\pi}\sin(\frac{2\pi}{T}t) \quad (1)$$

$$\dot{\theta}_1 A = \pi r^2 \frac{\theta_1(T)-\theta_1(0)}{T}\ [1 - \cos(\frac{2\pi}{T}t)] \quad (2)$$

$$\ddot{\theta}_1 = \frac{\theta_1(T)-\theta_1(0)}{T}\ [\frac{2\pi}{T} sin(\frac{2\pi}{T}t)] \quad (3)$$

Kinematic solutions for the manipulator:

$$X = X_0 + L_2 sin\theta_2 + L_3 sin(\theta_2 + \theta_3) \quad (4)$$

$$Y = Y_0 + [L_2 cos\theta_2 + L_3 cos(\theta_2 + \theta_3)] sin\theta_2 \quad (5)$$

$$Z = Z_0 + L_2 sin\theta_2 + L_3 sin(\theta_2 + \theta_3) \quad (6)$$

$$\theta_1 = \tan^{-1}\frac{Y}{X} \quad (7)$$

TABLE V
ANOVA FOR INVERSE DYNAMICS PREDICTION ERROR (ANFIS MODEL)

Source of Variation	Degrees of Freedom (DF)	Sum of Squares (SS)	Mean Square (MS)	F-Value	p-Value	Contribution (%)
Joint Position (θ)	2	0.0125	0.00625	18.42	0.0003	21.3
Joint Velocity ($\dot{\theta}$)	2	0.0189	0.00945	27.85	0.0001	32.2
Joint Acceleration ($\ddot{\theta}$)	2	0.0217	0.01085	31.96	0.0000	36.9
Error	93	0.0316	0.00034	—	—	9.6
Total	99	0.0847	—	—	—	100

The process continues with preprocessing of the data before training the model. In order to improve the performance of the algorithm, all input and output data variables are normalized to fall within the same range of values, usually either between zero and one or minus one and one. After normalization, the data set is split into training, validation, and testing data sets using the proportions of 70:15:15, respectively.

The design of the ANFIS is done by implementing a first-order Sugeno-type fuzzy inference system. Membership functions for each input variable are defined and set up, usually Gaussian bell-shaped membership functions, that are initialized uniformly or by applying any clustering technique like subtractive clustering or fuzzy c-means. The amount of membership functions depends on an accuracy/complexity tradeoff. This leads to an automatically created rule base which is the set of fuzzy if–then rules defining the dependency between inputs and outputs.

To train the ANFIS, a hybrid learning algorithm that employs least-squares estimation for updating the consequent parameter and gradient descent for updating the premise parameter is applied. The training process cycle entails an analysis of the input signal in determining its output and error before applying back propagation to minimize the root mean square error (RMSE) of the predicted torque.

The model validation process will entail evaluating the performance of the model in generalizing by using test data, which was not part of the training process. Also, comparisons are made with other conventional analytical models and neural network models alone to prove the supremacy of the ANFIS system.

Finally, the ANFIS model will be incorporated in the simulation system for inverse dynamics calculations to verify its effectiveness in real-time inverse dynamics computations. Torque predictions by the ANFIS model will be fed into the manipulator, and motion tracking results are observed to ensure conformity to the desired trajectories. Below is the S/N ratio analysis based on the ANOVA output for inverse dynamics prediction error. As the objective is to minimize the prediction error in torque, hence “Smaller-the-Better” type S/N ratio criteria will be utilized:

$$S/_N = -10\log\left(\frac{1}{n}\sum\frac{1}{y^2}\right) \quad (8)$$

TABLE VI
S/N RATIO RESPONSE TABLE (SMALLER-THE-BETTER)

Factor	Level 1 (dB)	Level 2 (dB)	Level 3 (dB)	Delta	Rank
Joint Position (θ)	28.45	30.12	31.05	2.60	3
Joint Velocity ($\dot{\theta}$)	29.10	32.25	33.40	4.30	2
Joint Acceleration ($\ddot{\theta}$)	30.85	34.10	35.95	5.10	1

III. RESULTS AND DISCUSSION

The performance of the ANFIS as an inverse dynamics estimator of the three-degree-of-freedom (3-DOF) planar robot manipulator was simulated to verify its capability. The results show that the ANFIS can be used reliably for estimating the joint torques given the input motion parameters, namely joint positions, velocities, and accelerations. The training phase involved fast convergence because of the use of hybrid learning that incorporated least squares estimation and gradient descent. The RMSE dropped dramatically during the first few epochs before converging at a certain point after a finite number of epochs. This indicates that the system efficiently learned the non-linear relationship between the input and output parameters. In this case, the outcome of the root mean square error was quite low at the end of the process.

In the testing phase, validation of the model was done through the use of test data so as to check the generality of the model.The ANFIS model performed exceptionally well and demonstrated low mean absolute error (MAE) and high correlation between the predicted and reference values with coefficient of determination (R^2) closer to unity for all the three joints.

The comparative study involved a comparison between ANFIS model, conventional analytical model, and a conventional ANN model. It must be noted that while an analytical model always gives accurate solutions in ideal situations, it is not always the case when there is some level of uncertainty associated with parameters. The ANN model performs slightly worse in terms of accuracy and stability as compared to ANFIS due to lack of rule-based decision making in the process of ANN model construction. The figure 2 above shows the training surfaces of three ANFIS (Adaptive Neuro-Fuzzy Inference System) models created for three different joint angles. In each plot (subplot a, b, and c), the nonlinear relation between inputs and output, which has been learned by ANFIS models, is presented in the form of a 3D surface, where Input1 and Input2 (probably related to two control variables) are plotted in the horizontal direction and the predicted joint angle in the vertical direction. As the images show, each ANFIS model has been able to learn a particular kind of dynamic of the joint. That means there was different behavior for each joint. This visualization technique is widely used in robot manipulation control problems or inverse kinematic problems to evaluate the accuracy of trained ANFIS models.

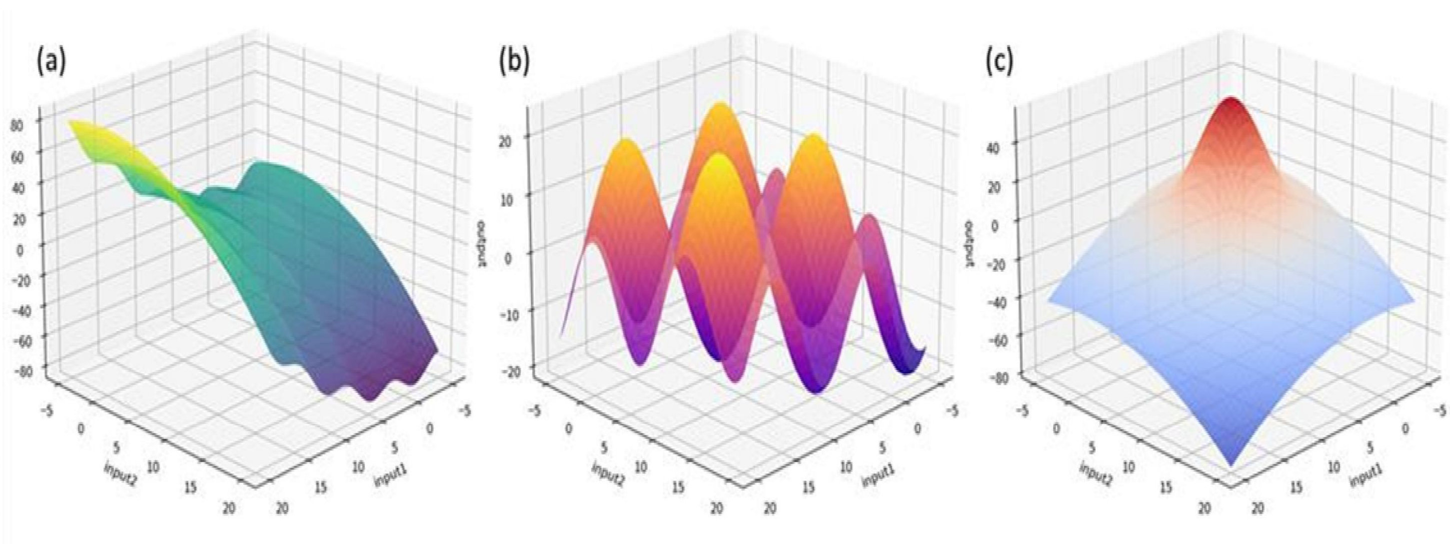


Fig. 2 The three ANFIS networks' training sets for the three joint angles.

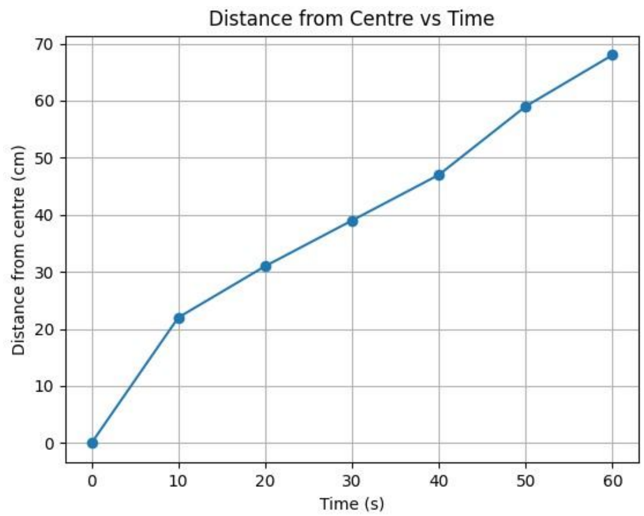


Fig. 3 Movement of End-effector.

It is presumed that in this experiment, the manipulator of 3 DOF robotic arms will move in the X-Y directions; the force of gravity acts in –ve direction of Y-axis. The joint angle required for calculating the joint torques (equations 1, 2, and 3). For this experiment, it is assumed that T = 10 seconds. The initial and final joint angle values are $\theta_1(0) = 0$ and $\theta_1(T) = \pi$. The end-effector trajectory will also depend on the time factor. Figure 3 illustrates the end-effector trajectory of 3-DOF robotic arms. The end-effector trajectory is seen to increase gradually with time. The joint trajectory, joint torque, and end-effector trajectory analyses were carried out using Robo-analyzer software. Figure 4 represents the joint angle and its time derivative. The joint angle increases gradually with time, whereas the joint velocity gradually increases but reduces after 60 seconds.

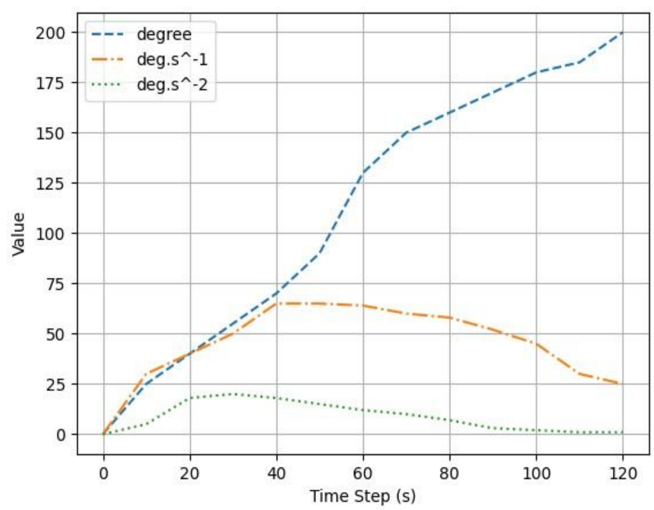


Fig. 4 The trajectory 3 DOF robotic arm's joint angles.

Further evidence is found from graphical representation. The torque tracking plot showed that the results produced by the ANFIS model matched very well with the torque curves without any deviation. Moreover, the error plot showed that the deviations remained low and were evenly spread out, thereby implying no presence of any bias. Furthermore, the ANFIS model was capable of performing well under disturbance conditions, which proves its robustness.

Another notable point to make is about the model complexity. It is seen that while more complex models with a higher number of membership functions provide better accuracy, they consume more computational resources. The current ANFIS model is the most efficient one, offering good accuracy along with computational simplicity. In terms of control, the simulation-based implementation of the developed ANFIS inverse dynamics model indicated the better capability of tracking trajectory.

This is evidenced by the successful tracking process carried out with negligible errors between the target and actual positions, which suggests that the estimated torques from the ANFIS model are accurate enough to be used in actual control. This proves the applicability of the method in practice where exact dynamic models may not be available. On the whole, it can be stated that the results indicate that ANFIS is indeed an efficient technique to approximate the inverse dynamics of robotic manipulators. Unlike the traditional techniques for modeling, ANFIS is capable of overcoming their deficiencies and provide a robust solution. It is shown that it is due to the hybridization of ANFIS that makes it superior to separate systems.

IV. CONCLUSION

This research work has proposed an intelligent solution for the inverse dynamics problem approximation for a 3-DOF planar robotic manipulator through ANFIS architecture. The suggested technique was able to overcome several problems that exist in traditional models including the need for precise system parameters and sensitivity to uncertainties. The advantage of the data-driven method made it possible for ANFIS to capture the nonlinear nature of joint kinematics and actuator torques. It has been found out that the ANFIS model is highly capable in terms of providing a good estimate of torques with very low errors compared to reference values. When compared to other traditional techniques and neural network, the model showed better efficiency because of its ability to learn from the data and provide intelligent reasoning. Also, it showed good robustness when applied to noisy and variable input signals. Finally, by implementing the trained ANFIS model in a control loop, it was shown that the model can produce desirable results in terms of trajectory tracking with reduced error values.

Data Availability: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of interest: The authors have no conflicts to disclose.

REFERENCES

[1] A. Ming, Z. Xie and T. Yoshida, “Yamashiro, M., Tang, C. and Shimojo, M., Home Service by a Mobile Manipulator System, Information and Automation,” ICIA International Conference, China, 464–469, 2008.

[2] A. Salehi, F. Piltan, M. Mousavi, A. Khajeh and M. R. Rashidian, “Intelligent robust feed-forward Fuzzy feedback linearization estimation of PID control with application to continuum Robot,” Information Engineering and Electronic Business, vol. 1, pp. 1-16, 2013.

[3] R. Barua, S. S. Kumar, A. Mallik. and A. Singh., A. “Experimental analysis the dynamic model of 3DOF robotic arm,” Journal of Mechanical Robotics, vol.6(1), pp. 20-26, Mat Journal, 2021.

[4] W. Jing, R. J. Yan, K. Shin, C. Han and I-Ming Chen, “A 3-DOF quick-action parallel manipulator based on four linkage mechanisms with high-speed cam,” Mechanism and Machine Theory, vol. 115, pp. 168-196, 2017.

[5] F. Romdhani, F. Hennebelle, M. Ge, P. Juillion, R. Coquet and J. François Fontaine, "Methodology for the assessment of measuring uncertainties of articulated arm coordinate measuring machines", Measurement Science& Technology, vol. 25, 2014.

[6] R. Barua and D. K. Das, “Trajectory path analysis of omnidirectional three wheeled robot (OTWR),” Journal of Mechanical Robotics, vol.6 (2), pp. 20-25, Mat Journal, 2021.

[7] B. Arian, H. Danaei, H. Abdi and S. Nahavandi “Kinematic and dynamic analysis of the Gantry-Tau, a 3-DoF translational parallel manipulator.” Applied Mathematical Modelling, vol. 51,, pp. 217-231, 2017

[8] R. Barua, S. Mandal and S. Mandal, “ Motion analysis of a mobile robot with three omni-directional wheels”, International Journal of Innovative Science, Engineering & Technology,vol.2(11), pp. 644-648, 2015.

[9] R. Fernando and R. Kelly , “Experimental evaluation of model-based controllers on a direct-drive robot arm,” Mechatronics, vol. 11, pp. 267-282, 2001.

[10] M.T. Das and L.C. Dulger, “Mathematical modelling, simulation and experimental verification of a scara robot”, Simulation Modelling Practice and Theory 13, pp.257–271, 2005.

[11] V. Filip, “Dynamic modeling of manipulators with symbolic computational method,” The Publishing House of the Romanian Academy, Proceedings of the Romanian Academy, Series A. vol. 9(3), pp. 1, 2008.

[12] F. Lin and R.D. Brandt, “An optimal control approach to robust control of robot manipulators,” National Science Foundation, pp. 1-19, 1997.

[13] R. Subasri, R. Meenakumari, R. Velnath, S. Pongiannan and M. S. Kumar, “Model identification of 3R palnar Robot using Neural Network and Adaptive Neuro-Fuzzy Inference System,” In 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA) IEEE, pp. 1666-1672, 2021.

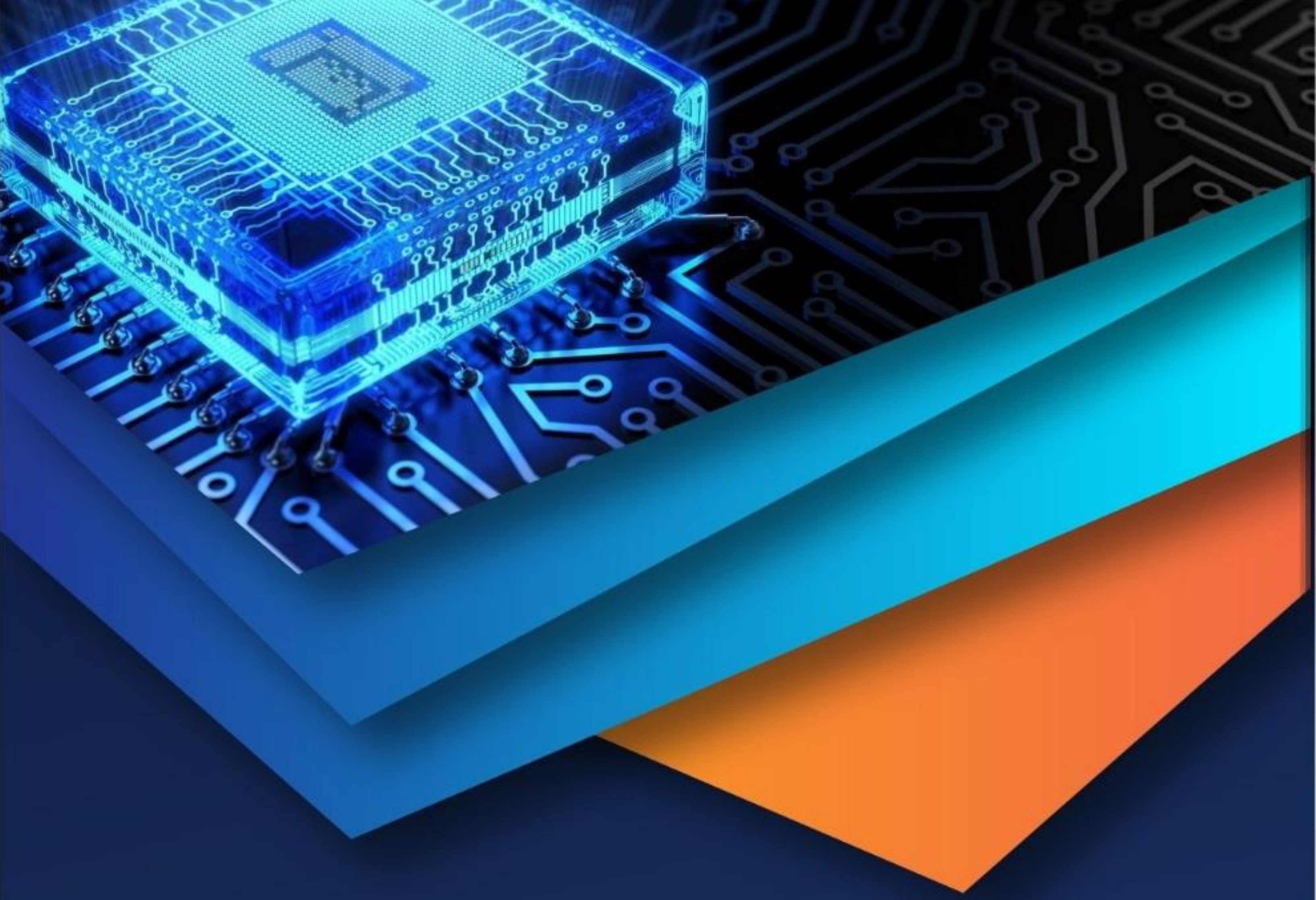
[14] I. Iliev and V. Iliev, “Modeling of inverse kinematics of a 3R robotic arm with adaptive Neuro Fuzzy-Inference system,” In 2025 International Conference Automatics and Informatics (ICAI), IEEE, pp. 84-88, 2025

[15] M. Chatavi, R. FesharakiFard and M. A. Khosravi, “Adaptive Neuro-Fuzzy based Forward Kinematics Analysis of a three DoF Delta Robot,” In 2022 10th RSI International Conference on Robotics and Mechatronics (ICRoM). IEEE, pp. 557-563, 2022,.

[16] K. Zeng, G. E., Luo, M. Wu and X., Lai, “Trajectory tracking for a 3-DOF robot manipulator based on PSO and adaptive neuro-fuzzy inference system,” In 2016 35th Chinese Control Conference (CCC), IEEE, pp. 973-977, 2016.

[17] S. Wasista, H. Tjandrasa and S. Djanali, “Design an Intelligent Balanced Control of Quadruped Legs Based on Adaptive Neuro-Fuzzy Inference System (ANFIS),” International Journal on Advanced Science, Engineering & Information Technology, vol. 13(3), 2023.

[18] M. Boukattaya, T. Damak and M. Jallouli, "Robust Adaptive Control for Mobile Manipulators, International Journal of Automation and Computing, vol. 8(1), pp. 8-13, 2011.
[19] M. Mirzadeh, M., Haghighi, S. Khezri, J. Mahmoodi and H., Karbasi, "Design Adaptive Fuzzy Inference Controller for Robot Arm," Information Technology and Computer Science,vol. 9, pp. 66-73, 2014.
[20] R. V. Mayorga and S. Chandana, "A neuro-fuzzy approach for the motion planning of redundant manipulators," In The 2006 IEEE International Joint Conference on Neural Network Proceedings, IEEE, pp. pp. 2873-2878, 2006.
[21] H. P. H. Anh and N. T. Nam, "Novel adaptive forward neural MIMO NARX model for the identification of industrial 3-DOF robot arm kinematics," International Journal of Advanced Robotic Systems, vol. 9(4), pp. 104, 2006.



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