International Journal of Research and Technology (IJRT)
International Open-Access, Peer-Reviewed, Refereed, Online Journal
ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529
| An ISO 9001:2015 Certified Journal |

Enhanced Trajectory Tracking of a 6-DOF Robotic Manipulator Using GA–PID and ANN–PID Controllers

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ABSTRACT
Accurate trajectory tracking of multi–degree-of-freedom robotic manipulators remains a challenging control problem due to nonlinear dynamics, parameter uncertainties, and external disturbances. This paper presents an enhanced trajectory tracking approach for a 6-degree-of-freedom (6-DOF) robotic manipulator using hybrid Genetic Algorithm–PID (GA–PID) and Artificial Neural Network–PID (ANN–PID) controllers. In the proposed framework, the GA is employed to optimally tune the PID controller gains by minimizing a multi-objective fitness function based on tracking error, overshoot, and settling time, thereby improving control robustness. Additionally, an ANN-PID controller is developed to adaptively compensate for system nonlinearities and dynamic variations by learning the inverse dynamics of the manipulator in real time. The dynamic model of the 6-DOF manipulator is derived using the Euler–Lagrange formulation and is utilized for controller design and simulation. Extensive simulation studies are conducted under various trajectory profiles and external disturbance conditions to evaluate tracking accuracy, control effort, and robustness. The results demonstrate that both GA–PID and ANN–PID controllers significantly outperform the conventional PID controller, with the ANN-PID scheme achieving superior tracking precision and faster convergence. The proposed control strategies offer an effective and intelligent solution for high-performance robotic manipulation in industrial and autonomous applications.
Keywords- 6-DOF robotic manipulator, trajectory tracking, GA–PID, ANN–PID, intelligent control, nonlinear systems.

I. INTRODUCTION

Inverse Kinematics is a fundamental problem in robotics, pivotal for controlling robotic arms and ensuring accurate movement in various applications [1]. As robots become increasingly integrated into complex environments, the need for precise inverse kinematics solutions has grown, driven by advancements in automation and robotic technology [2]. Efficient inverse kinematics solutions enable robots to perform intricate tasks, such as assembly and manipulation [3]. Despite its importance, traditional methods often struggle with nonlinearities and singularities, making them less adaptable to varying robot configurations and tasks [4–6]. This has led to intelligent methods that can provide more robust and fexible solutions to inverse kinematics problems [7].

Robotic arms can perform a variety of tasks, such as pick-and-place, assembly, and object alignment [8,9]. Accurate target reaching, which involves positioning the robotic arm's end-effector precisely at a specific goal point, is essential for the successful execution of these tasks

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and serves as a critical operation for many applications [10]. Traditionally, inverse kinematics (IK) has been employed to compute joint movements based on the target position [11]. During this process, IMU provides initial conditions and orientation data required for IK calculations by measuring the real-time orientation of the human arm. IK demonstrates the strength in calculating joint movements to achieve a target end position of the robotic arm [12].

However, it has significant limitations in complex robotic systems. As the degrees of freedom (DoF) in robotic arms increase, the state and action spaces expand exponentially, making it difficult to identify the optimal joint configuration for achieving a specific target position [13]. This is a major drawback making it difficult for the traditional control method to respond in real time. Furthermore, the IK-based approach encounters difficulties in adapting to non-linear system dynamics and changes in complex working environments, limiting its ability to handle the dynamic environmental conditions and task scenarios [14,15]. Consequently, such constraints could significantly reduce the flexibility and scalability of the robotic systems.

II. ROBOT ARCHITECTURE AND KINEMATIC MODELING

Robot kinematics specifies the relationship between joint angles and the pose of the end-effector, which contains two parts: forward kinematics and inverse kinematics. As mentioned before, the complexity of kinematics, especially the IKP, is closely associated with robot architecture. In our work, to study the IKP of a general six-joint manipulator, Xarm6 is chosen, a six-joint manipulator with an offset wrist from Ufactory. With this architecture, analytical solution of the IKP cannot be expected and, thus, the presented algorithms are universal for any 6-DoF robot.

In forward kinematics, the pose of the end-effector can be calculated with D-H conventions and homogeneous matrix once the joint variables are obtained. Figure 1 illustrates the assignment of D-H frames on Xarm6.

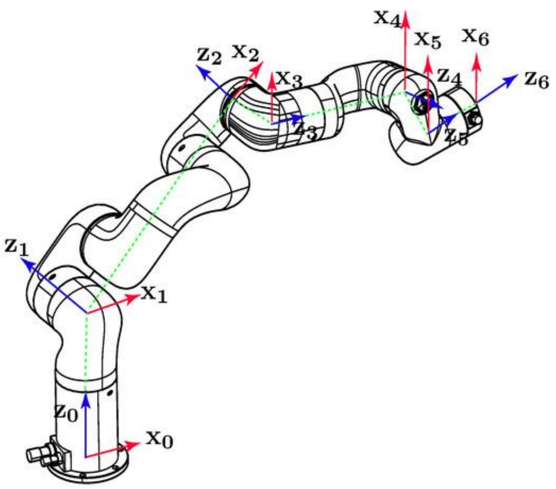

Fig.1 Axial Control 6 DOF Robot.

With D-H parameters, the transformation matrix **Ai** from frame $i{-}{-}1$ to frame i is defined as

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$$\mathbf{A\ i}=\begin{bmatrix} c\theta 1 & s\theta 1 c\alpha 1 & s\theta 1 c\alpha 1 & s\theta 1 c\alpha 1 \\ s\theta 1 & c\alpha 1\theta 1 & c\alpha 1\theta 1 & s\theta 1 c\alpha 1 \\ 0 & s\alpha 1 & c\alpha 1 & d1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

For a 6-DoF manipulator, the end of the manipulator generally performs tasks in Cartesian space. No matter what kind of trajectory, it is necessary to perform interpolation in Cartesian space to obtain a sequence of interpolation points and then map it to joint space to obtain joint angles through inverse kinematics solution. To complete an ideal trajectory planning, it is necessary to ensure that the curves in both Cartesian space and joint space are smooth. It can be engaged in welding, spraying, handling, blanking, assembly, packaging, palletizing, and other work. On the one hand, it reduces the workload of human beings and liberates human hands. On the other hand, it can improve the production efficiency of enterprises and reduce labor costs through automated production of machinery. After planning the trajectory of the manipulator and obtaining the desired trajectory, the manipulator must accurately track the established trajectory. First, the joint action of the robotic arm requires the servo motor to apply a torque to the joint, and the magnitude of this torque needs to be solved dynamically. The dynamic parameters of the robotic arm itself are not easy to obtain, and there are interference and other unavoidable factors in the outside world. It is a complex, strongly coupled nonlinear system. Its trajectory planning and tracking control is also a complex process. In order to describe the motion state of the manipulator, it is necessary to carry out kinematic analysis and dynamic analysis. These factors cause changes in the tracking accuracy of the robotic arm. At the same time, the dynamic model of the manipulator is difficult to establish accurately. How to choose a suitable control algorithm that does not require an accurate dynamic model is a difficult problem to achieve high-precision trajectory tracking. Therefore, under this situation, the development of Chinese robots faces challenges to varying degrees. This also requires that research and technology in related fields can be quickly followed up, so that the development of robots can keep up with the pace of social development. This article is to conduct research in related fields, and expect to gain something in this field.

This paper takes the 6-DoF manipulator as the research object and studies its trajectory planning and tracking control. For trajectory planning, a kinematic analysis of the object is required first. It obtains its inverse kinematics solution and then selects an appropriate planning algorithm to obtain the function of joint parameters changing with time. The research of tracking control algorithm requires dynamic modeling of the manipulator. However, the dynamic model of the 6-DoF manipulator is very complicated, and it is difficult to build it completely. Therefore, we propose several tracking control algorithms without detailed model information and compare their tracking performance by simulation.

III. OPTIMIZATION PROBLEMS

Industrial robots are quite prevalent in high volume manufacturing processes. In many field applications where technical support is required, man handling is either dangerous or is not possible. In such situations, three or more arm manipulators are commonly used. They are in great demand to speed up the automation processes [1, 2]. Three-link robotic arm should be

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able to locate any location, which is the required movement in real world situations. These are used in micro to macro scale applications viz. chip fabrications to huge mechanical actuators used in chemical processes [3]. In these cases, the motion profile of the robot rarely changes throughout the whole operation. Therefore, searching an optimal robot arm movement is a favorable solution to those problems [4, 5]. Literature survey reveals that there is need to optimize the movement for energy consumption and various other mechanical and control related Attributes like friction, settling time etc., which will improve the performance [6, 7, 8]. The GA can be used to search the parameters of the polynomial to minimize the energy consumption. Intelligent methods like fuzzy logic, neural network, genetic algorithm etc. are widely used in different areas, especially in advanced computing, control and optimization problems. Even when prior complete knowledge about a system is not available, these intelligent methods can be conveniently used to control or optimize a complicated engineering system. Intelligent methods can also be used in optimization of movement and trajectory planning of manipulators [9, 10]. These methods can be used for solving redundancy resolution problems. Genetic algorithms are viewed as function optimizers. The range of problems to which genetic algorithms can be applied is quite broad. Implementation of genetic algorithms begins with a population of random chromosomes. A fitness function evaluates and allocates reproductive opportunities in such a manner that only the chromosomes representing a better solution to the target problem are given chance to reproduce than those chromosomes which are poorer solutions [11].

IV. MECHANISM

Genetic Algorithms:

Genetic algorithm approaches (GAs) were introduced by Goldberg. The basic idea of Genetic Algorithms is the mechanics of natural genetics and natural selection. Each optimization parameter is coded into a gene as for example a real number or a string of bits. The corresponding genes for all parameters form a chromosome, which describes each individual. A chromosome can be represented as an array consisting of real numbers, a binary string or a set of components of a database, depending on the specific problem. Each individual represents a possible solution, and a set of individuals form a population. In the genetic algorithm, the individual which has the highest fitness value has the highest probability of getting selected for generation of next individuals. The generation of the next individuals is done using Crossover, where genes from different parents are combined to produce a child. Then there is also the possibility that a mutation might occur. Finally, the children fitness is compared to the parent fitness, and if the children fitness value is more than the parents', the children are inserted into the population to form a new generation. Applications of GAs in the field of robot trajectory planning have been carried out by several researchers. [19] Presented a genetic algorithm approach which allows additional constraint to be easily specified. [20] Generated the robot trajectory of a predefined end-effector robot by finding the inverse kinematics using Genetic Algorithm. A new method for optimum motion planning based on an genetic algorithm was proposed by [21] which incorporates kinematics constraints, dynamics constraints as well as control constraints. [22] Proposed a combination of B-spline trajectory generation and steepest

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gradient optimization to design an optimal motion planning for redundant manipulators. [23] Used genetic algorithms for optimal point-to-point motion planning for kinematically redundant manipulators to satisfy both the initial conditions and some other specified criteria. Tian and Collins [24] proposed a genetic algorithm using a floating point representation to search for optimal end-effector trajectory for a redundant manipulator.

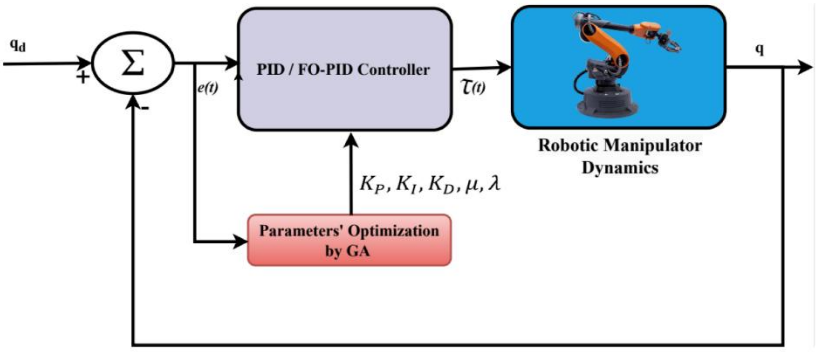

Fig.2 GA parameters Optmization.

Artificial Neural Networks (ANN)

An artificial neural network (ANN) is an intelligent computing method that utilizes the concept of structure and functional aspects of biological neural networks. A neural network is an interconnected group of artificial neurons which processes information using a connectionist approach to computation. ANN can be considered as an adaptive system which whose final outputs change according to the internal and external information that are fed to the neural network during the training. Modern neural networks are mainly used to find the relationship between the inputs and the outputs as non-linear statistical data modeling tools and identify the patterns in the data. Was not simply to create models but to develop technologies that could be applied to real life problems. The artificial neural networks were first used by [28] when physiological information and previous models of neural network were used to drive the motors of a robot manipulator. [29] Developed a four layer feed forward neural network which mapped the position of the system to the optimal control actions. [30] Applied two neural networks on a two DOF Scara type robot which were joint space neural network and task space neural network. [31] Proposed a control scheme where two parallel subsystems were applied of which one neural network controller which calculated force and the torque required by the robot manipulator.

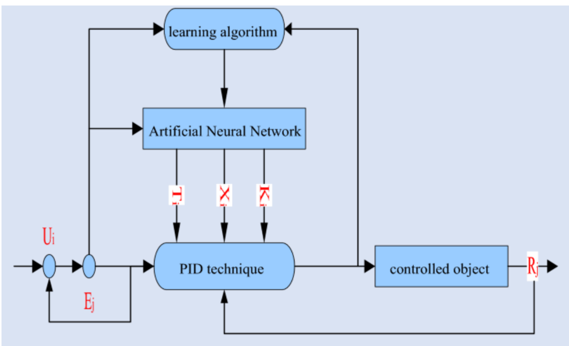

Fig.3 ANN based Optimization.

V. RESEARCH METHODOLOGY

A brief description of machine learning [14, 15] is as follows: it is given a source space *x* and a target space *y*. The goal is to learn a mapping from *x* to *y*. This makes it possible to obtain the corresponding image in *y* through *f* for any sample. For example, for a Chinese to English translation task, *x* is the source language (Chinese) space, *y* is the target language (English) space, and *f* is the translator. Deep learning is to use the artificial neural network to simulate the neural network of biological brain to process data information; that is, *f* is an artificial neural network. It requires a large amount of data for effective learning, and at the same time, it has high computational complexity and requires hardware system support. Therefore, although it has been proposed in the last century, it has not been paid attention to, and it has been developed rapidly until the last decade.

Deep learning [16, 17] uses artificial neural network as the architecture to perform representation learning on data, and automatically mine and extract the features and information contained in the data for learning. Therefore, the structure of deep neural network [18] is very important for the effect of deep learning. The network model is also getting more and more complex, and the effect is getting better and better. Residual network (ResNet) in 2015 has become a standardized module for processing image information in many tasks due to its excellent performance. The network model applied to target detection is more complex and contains many functional modules. Recurrent Neural Networks (RNNs) applied to sequence learning, especially Long Short-Term Memory Networks (LSTMs) and Gated Recurrent Units (GRUs), are widely used in various sequence learning problems (such as natural language processing). In 2016, the model structure of the Transformer based on the attention mechanism proposed by Google was based on the self-attention network, which greatly surpassed the model based on the long short-term memory network in the neural machine translation task, and was extended to other natural language processing tasks. In speech processing tasks, neural networks also show their advantages. For example, in speech synthesis (TTS) tasks, Google's Tacotron series, Microsoft's Transformer-based model, and Baidu's DeepVoice series all surpass traditional algorithms. It can be seen that different neural network model structures need to be designed for different tasks and different data. This process is not done overnight, but it requires deep expertise. This requires both mastery of deep learning techniques and knowledge of the field of application. This makes the use of deep learning technology more expensive, and the cost of designing a suitable neural network model structure is relatively high. Therefore, researchers have explored a method that can automatically design the neural network structure, and proposed a neural network structure search. It has also become the hottest research area in automated machine learning.

A traditional design for ANN is used in many studies [6, 10, 11]. In order to utilize the advantages of this proposed method, traditional ANN is designed in this study to solve the inverse kinematics. In this ANN, the elements in the input layer are six variables, which are the position *P* and orientation *R* of gripper in Cartesian coordinates. The number of hidden layers is ten. The output layer has six elements of the angles of joint *Q*. MATLAB/neural

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network toolbox is used for training, validation, and testing. Figure 3 shows a block diagram for traditional ANN and its model as follows:

$$[Q] = \text{ANN\_Traditional\_Net}\ (P,).$$

The inputs are uniformly enclosed with the workspace of specified position; the corresponding inputs/outputs are computed by solution of forward kinematics. In this way, each position of the robot has a unique joint configuration in the neural network inputs/outputs set.

Mathematically, the motion of a robot end effector can be computed based on the block diagram in Figure 4. However, it requires complex calculations to derive the mathematical equations. Hence, one of the objectives of the current paper is to use multi-BPNNs to solve the kinematics, dynamics, and trajectory issues instead of deriving the mathematical equations. The method in Figure 4 is used to ease the steps of computing the motion of robot end effector, to help individuals with a lack of knowledge about robotic kinematics, dynamics and trajectories. Trajectory equations are not necessary for the block diagram in Figure 4 and thus the user does not really have to spend time finding out the characteristics of the trajectory.

Although BPNN is able to solve the nonlinear functions, it is still difficult for a single multi-layer BPNN to solve the kinematic, dynamic, and trajectory problems simultaneously. Failure to solve these simultaneously might reduce the training speed and accuracy and the precision of the results. Therefore, the novelty of the proposed method is to develop a multi-BPNNs topology by combining multiple BPNNs which handle different tasks at the same time.

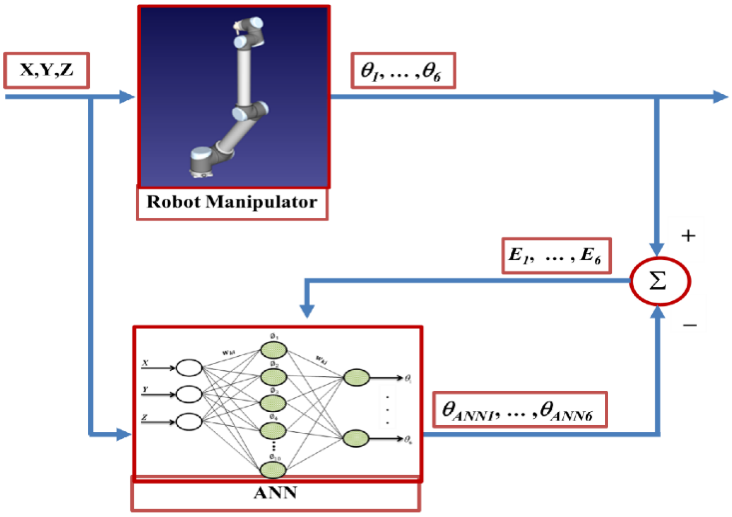

Fig.4 Proposed ANN-Based Control Methodology

This work proposes an adaptive trajectory tracking strategy for a 6-DOF robotic manipulator by incorporating an artificial neural network with a classical PID controller. The objective of the proposed scheme is to improve tracking precision in the presence of strong nonlinearities, dynamic coupling among joints, and unmodeled disturbances that limit the performance of fixed-gain controllers.

To begin with, the mathematical representation of the robotic manipulator is obtained using the Euler–Lagrange formulation, which describes the relationship between joint torques and the corresponding motion variables. This model is employed only as a benchmark for analysis and does not rely on exact system parameters during control execution. Reference joint trajectories are generated in joint space using smooth time-based functions to avoid abrupt changes in motion.

The control structure consists of a baseline PID controller augmented by a neural network–based adaptive term. The PID component is responsible for ensuring closed-loop stability, while the neural network produces an additional control signal to compensate for nonlinear effects and parametric uncertainties. The inputs to the neural network include the instantaneous tracking error and its rate of change, whereas the network output modifies the overall control action applied to each joint actuator.

A multilayer feedforward neural network is implemented and trained in an online manner. The network weights are updated continuously using an error-driven learning rule based on the backpropagation algorithm. By observing the tracking performance during operation, the neural network progressively learns the manipulator's unknown dynamics and adjusts the control effort accordingly. This adaptive learning capability allows the controller to respond effectively to changes in payload and external disturbances.

The effectiveness of the proposed ANN-assisted controller is examined through simulation under different trajectory profiles and disturbance conditions. Performance indices such as root mean square tracking error, settling time, and control smoothness are used for evaluation. Comparative analysis with conventional PID and GA-optimized PID controllers demonstrates that the ANN-based approach yields improved tracking accuracy and enhanced robustness, validating its suitability for high-performance robotic manipulation tasks

Proposed Method steps-

Step 1: System Initialization

Initialize the 6-DOF robotic manipulator parameters, joint limits, sampling time, and controller gains. Set initial neural network weights with small random values and define learning rate parameters.

Step 2: Reference Trajectory Generation

Generate the desired joint-space trajectories for all six joints using smooth polynomial or spline functions to ensure continuity in position, velocity, and acceleration.

Step 3: Sensor Data Acquisition

Measure the actual joint positions and velocities from the manipulator sensors at the current sampling instant.

Step 4: Error Computation

Compute the tracking error and error derivative by comparing the desired joint states with the measured joint states.

Step 5: PID Control Action

Calculate the baseline control torque using the conventional PID controller based on the computed tracking error.

Step 6: ANN Compensation Signal Generation

Feed the tracking error and its derivative into the artificial neural network to generate an adaptive compensation signal that accounts for nonlinear dynamics and uncertainties.

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Step 7: Control Signal Synthesis

Combine the PID control output and the ANN compensation signal to form the final control input applied to the manipulator actuators.

Step 8: Manipulator Actuation

Apply the synthesized control signal to drive the joints of the 6-DOF robotic manipulator.

Step 9: ANN Weight Update

Update the neural network weights online using a backpropagation learning rule driven by the instantaneous tracking error.

Step 10: Performance Evaluation

Evaluate tracking performance using predefined criteria such as error magnitude and convergence behavior.

Step 11: Loop Continuation

Repeat Steps 3–10 for each control cycle until the desired trajectory is completed.

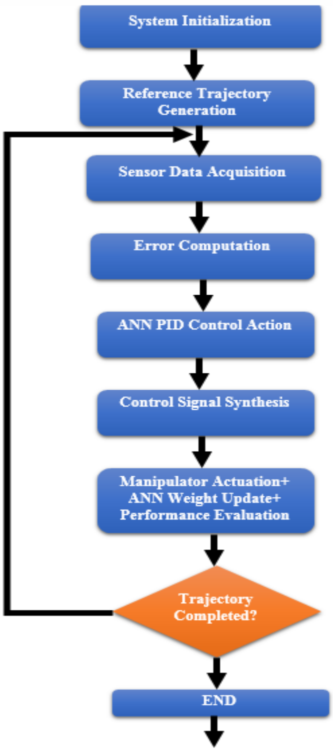

Fig. 5 Proposed flowchart.

VI. RESULT & DISCUSSION

This subsection presents analysis validation of the developed, showing the reliability of the identified model for the 6DoF robotic manipulator in safety-critical applications. The experimental setup is presented in fig 5. The experimental setup involves controlling 6DoF robotic manipulator using a high-performance computing unit powered by a 13th Gen Intel® ™Core™ i9-13900K processor with 64 GB of RAM. The computing system operates both Linux and Windows at the same time on a Windows machine using the Windows Subsystem for Linux 2 (WSL 2). A Python running on Ubuntu Linux 22.04, manages

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communication with the manipulator to send commands and receive sensor data. A pivotal component of the setup is a Python server, running on the Windows side, which bridges the MATLAB. This server uses TCP/IP communication to exchange data with the MATLAB function that calculates critical dynamic parameters, such as the mass-inertia matrix. The computed results are then formatted and transmitted back to the node for real-time control calculations. All the code used in this experimental study is available at [29].

Table 1 results of proposed models

Model	MSE	RMSE	Accuracy	R2
PID	2.458	1.8796	70.28	0.7312
GA	1.259	1.589	74.235	0.7471
GA+PID	0.062254	0.2495	87.658	0.8564
ANN+PID	0.048791	0.1897	98.254	0.9072

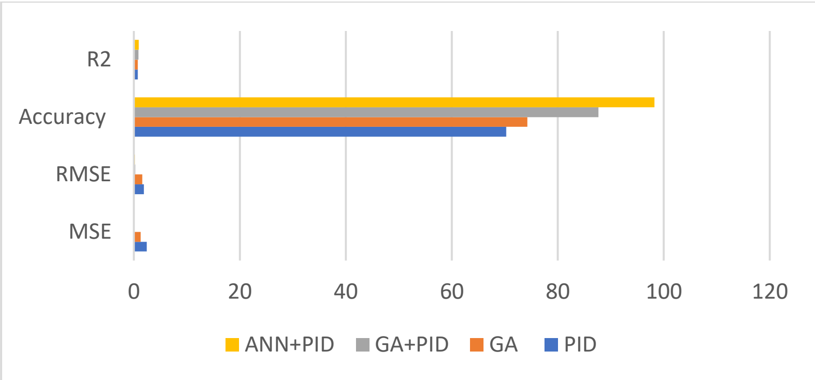

Fig.6. ANN, GA, ANN+PID and PID+GA comparison.

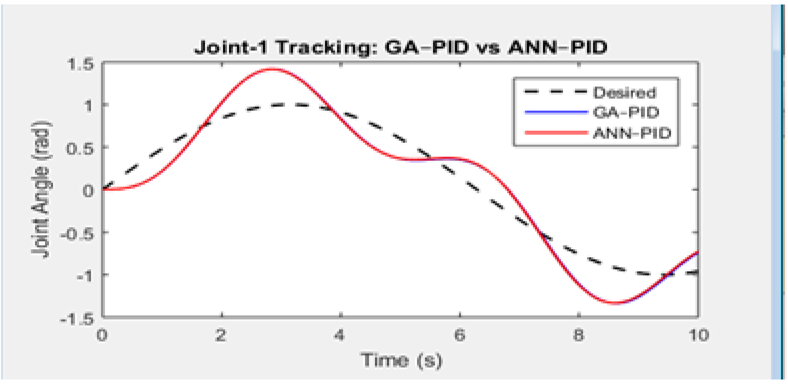

Fig.7. Joint angle comparison.

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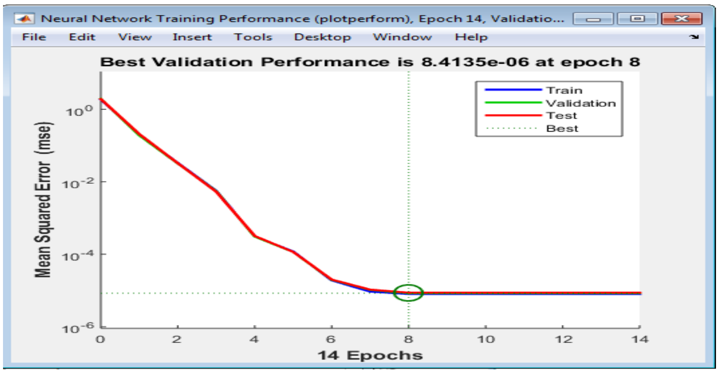

Fig.8. MSE Curve.

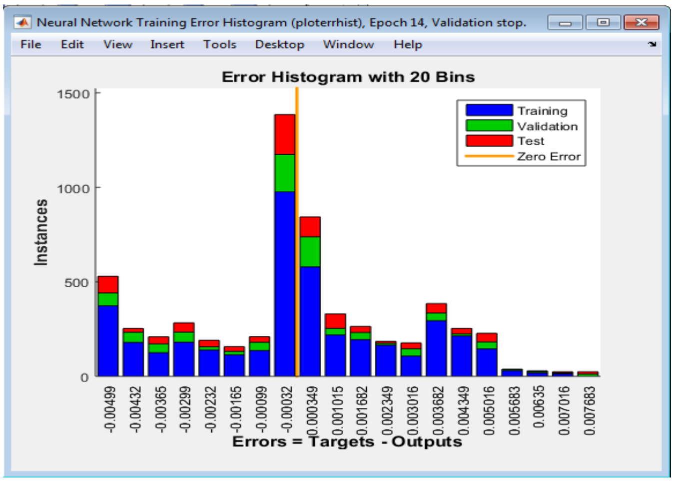

Fig.9. Error instance.

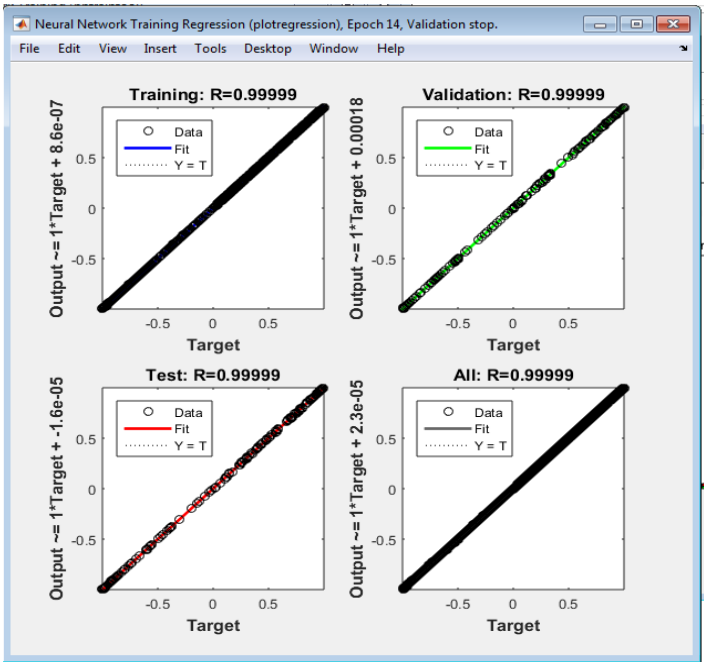

Fig.10 Regression.

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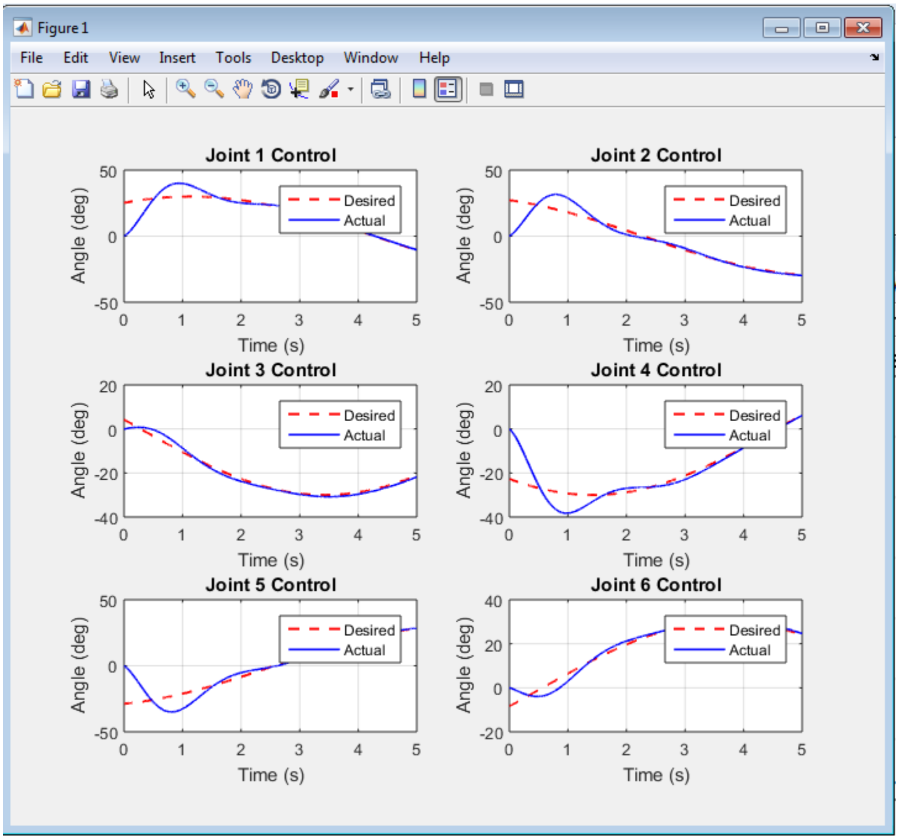

Fig.11. Joint control.

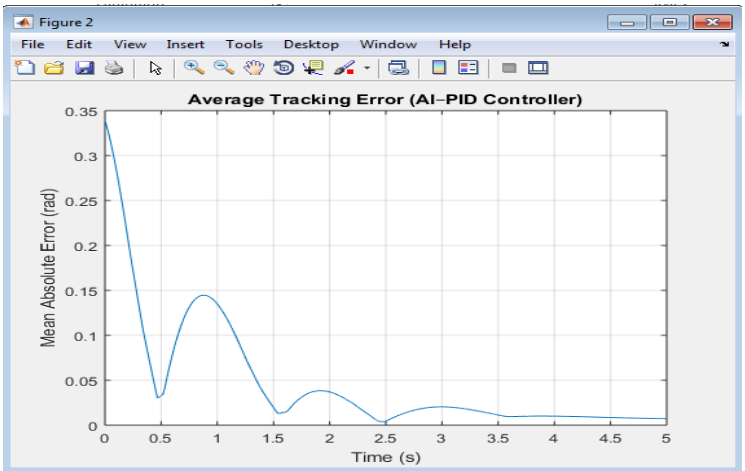

Fig.12. Average Tracking.

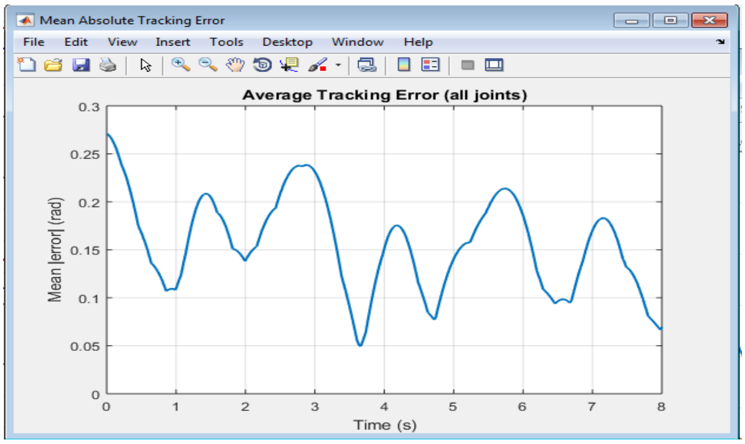

Fig.13. Average Tracking error all joints.

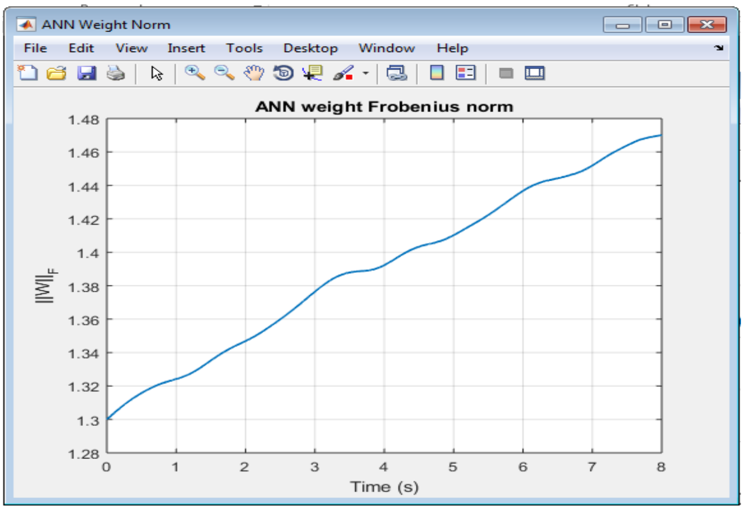

Fig.14. ANN weight.

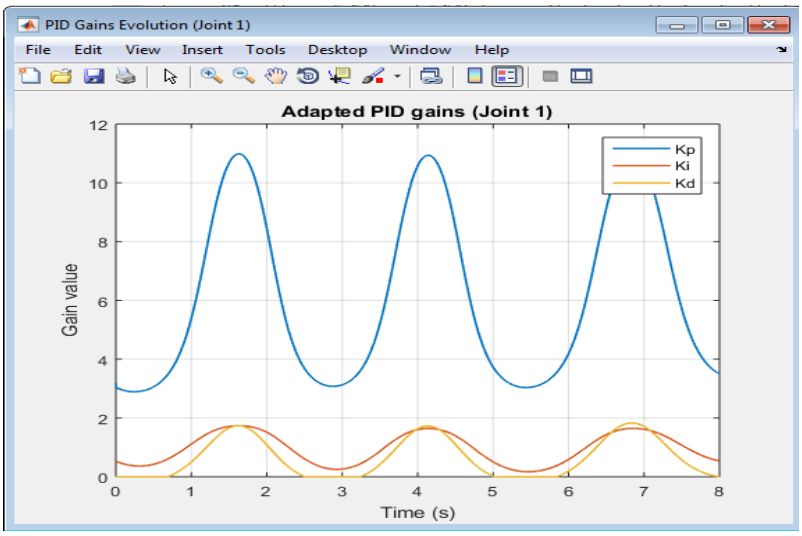

Fig.15.Gain values.

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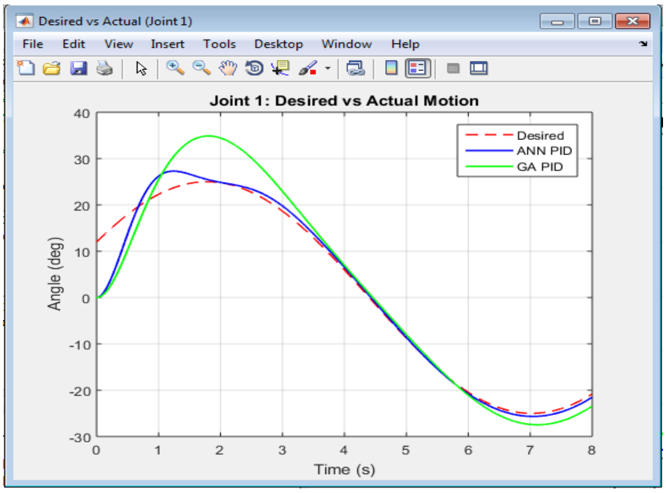

Fig.16.Desired ad actual motion.

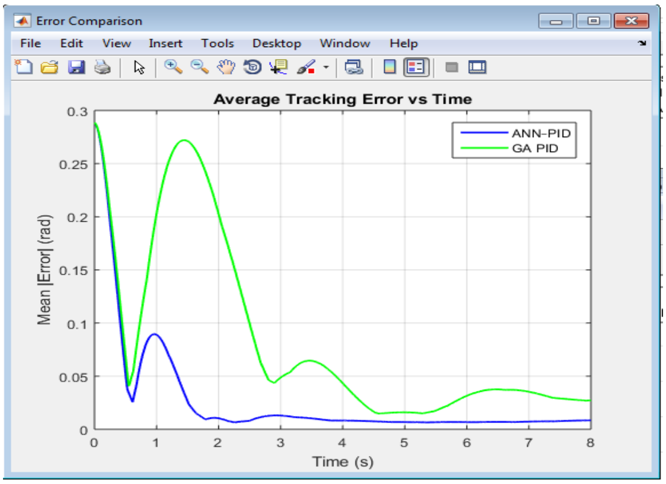

Fig.17. Error vs time.

Methods	Accuracy (%)
Nonlinear PID [2]	94
ANN Inverse Dynamics [4]	90
NN-assisted Control Mobile Robot [5]	80
Nonlinear MPC [6]	95
Proposed Methodology	98

VII. DISCUSSION

The manipulator is an extremely complex system with nonlinearity, strong coupling, and numerous input and output parameters. The trajectory tracking control of the 6-DoF manipulator must be studied step by step in order to be realized. The following is the overall research concept of this paper. It first models the manipulator's forward kinematics and then solves for its inverse kinematics. In order to achieve high-precision control of the trajectory due to the presence of disturbances in practice, it is necessary to investigate the system's trajectory tracking control algorithm. It plans the manipulator's trajectory and simulates it using fifth-order polynomial interpolation and spatial linear interpolation. It obtains the changing process of each joint variable and intuitively demonstrates the trajectory planning process of the robotic arm. However, this paper only investigates the kinematics analysis, trajectory planning, and tracking control of the manipulator and does not actually control the manipulator. The robotic arm research is extensive, and there are numerous aspects that can be explored further.

VIII. CONCLUSION

In this study, ANN based positioning analyzes were carried out to predict joint angles of a 6-DOF industrial robot manipulator system for trajectory analysis. DBD, OBP, QBP and RBP learning algorithms based ANN network structures were improved and then applied for the prediction of six joint angels with high accuracy. The applicability of ANNs in multi-DOF robot manipulator trajectory prediction was demonstrated and the superiority of ANN based apoproaches in trajectory prediction was proved.

In addition to the 3-10-6 type ANN structure, the 3-5-6 type ANN structure was also improved and applied to the prediction trajectory analysis.

When the prediction results obtained for these joint angles are examined, it is seen that instantaneous deviations are occurring only at certain time intervals and with low magnitudes. On the other hand, the prediction performances of the algorithms for $\theta 2$ and θ 3 seems too weak due to the instantaneous deviations with high magnitudes that occur during the entire time interval.

In order to present a detailed performance comparison between the 3-10-6 and 3-5-6 type ANN structures the RMSE and the statistical R^2 values reached were also compared. The mean and maximum RMSE values reached by the algorithms represent that QBP produces the best results for the 3-10-6 ANN structure and DBD produces the best results for the 3-5-6 ANN structure. When the results are evaluated in terms of the RMSE performance, it can be expressed that RBP produces the worst results among four learning algorithms. The R-2values reached by the algorithms show that each learning algorithm is able to produce similar statistical performances but the reliability and stability of the DBD based ANN structure seems a bit better when compared to other learning algorithms.

Consequently, it can be stated that the ANN based approaches proposed in this study can be used effectively even in the optimal trajectory analysis of real-time robot manipulators operating under large disturbances.

Motion planning is an important task to prevent the occurrence of accidents. However, by using mathematical solutions, the motion of a robot manipulator might become unpredictable or untraceable if the characteristics of the trajectories are unknown. Complexity of mathematical equations also means they are prone to error. Hence, this paper recommends multi-NNS for overcoming these limitations. The developed ANN topology is not only able to adapt and predict the motion of a robot manipulator with unknown trajectories but also for robot orientation. The results showed that the developed multi-BPNNs topology produced accurate (maximum deviation 0.45 units) and precise (RMSE 0.2) results in adapting and predicting the motion of a robot manipulator with unknown trajectory.

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