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RESEARCH ARTICLE

Modeling and Control of a 3DOF Robot Manipulator Using Artificial Fuzzy-Immune FOPID Controller

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ABSTRACT A robotic manipulator is a highly nonlinear, coupled system with many inputs and outputs (MIMO). These days, with the development of technology, using robots has become very common in various fields. It is difficult for the control experts to create an effective controller for this system, so it is preferable to design a non-linear controller that gives an accurate, more efficient controller and good results in robustness and uncertainty. Two distinct controllers for a 3-DoF robotic manipulator are developed and evaluated in this research's context of Industry. During the investigation, two primary control strategies are introduced. One of the first is a fuzzy-immune PID controller that employs joint position error as inputs. A second type is a fuzzy-immune FOPID controller. The PID controller is a particular case of FOPID controller when $\lambda = \mu = 1$. The research underscores the significance of precise parameter calibration and data acquisition in optimizing the performance of a control system. The parameters of controllers are tuned using the clonal selection algorithm. The controllers' efficacy was verified through quantitative analysis that employed performance indices, including mean square error (MSE). The robot manipulator is constructed with MATLAB. The proposed technique, which combines intelligent control methods, offers a promising hybrid control design. Our software implementation has demonstrated that the fuzzy immune FOPID controller is more efficient in terms of reduced tracking error of the manipulator for its dynamic control in the joint space than other controllers typically used in practice. The positioning control system utilizes Fuzzy Immune PID and FOPID control techniques. All controllers were designed using MATLAB.

INDEX TERMS Clonal selection algorithm (CSA), fuzzy logic controller (FLC), immune system, fractional order proportional integral derivative controller.

I. INTRODUCTION

A robot manipulator, often called a robotic arm or just a manipulator, is a mechanical device that simulates a human arm's movements to execute various activities. These machines are essential to industrial automation, manufacturing processes, and research applications. The rigid segment in the robot manipulator is called links, which are connected by joints. The joints enable the robot to navigate various orientations and accomplish multiple movements. The terminal part of the robotic arm is usually equipped with a gripper or end effector, responsible for interacting with the surroundings and

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performing specific activities such as object manipulation, welding, painting, or component assembly.

Designing a controller for a robot manipulator entails developing algorithms and control techniques that empower the robotic arm to execute its tasks with precision and efficiency [1]. However, PID controllers are limited in their effectiveness in controlling nonlinear, unpredictable, and interconnected systems. The FOPID controller concept was proposed by authors in [2] to improve the robustness and efficiency of PID control systems. Specifically, robot manipulators utilize FOPID controllers for fractional-order path tracking. As robotics problems are nonlinear, many researchers have developed intelligent methods for robot control [3].

In [4], a fuzzy position control method for three-link manipulators was created. The control method is founded on a nonlinear dynamic model constructed using the Lagrange-Euler formulation. The computer simulation results demonstrated excellent accuracy in tracking positions.

In [5], the authors introduced the fuzzy PID optimized by GA to enable a 3DOF robot to accurately track a desired trajectory. Based on the data, the recommended controller demonstrated superior performance compared to the traditional controller.

An adaptive PID controller using fuzzy logic for automatic parameter adjustment is created for the robot [6]. The suggested controller outperforms a conventional fuzzy PID controller, according to the results.

A hardware-in-the-loop (HIL) simulation approach is constructed in [7]. The authors designed a FO fuzzy controlled and compared it with fuzzy, FOPID, and PID controllers. The simulation results stated that the FO fuzzy controller gave an effective result compared with other controllers. The kinematics of the manipulator are analyzed using a variety of methods, including the gravitational search method, particle swarm optimization method, and genetic approach [9]. An adaptive fuzzy controller is designed in [8] for trajectory problems. The simulation results show the efficacy of the control approach which gives good results.

Many papers focus on the dynamic and kinematics of multi-link robot manipulators, for example, in a previous study [10], a technique was introduced to analyze the kinematics equations of a 3DOF robot manipulator. The modeling process was carried out using the Solid Edge software. The problem of trajectory tracking of the planar parallel 3DOF manipulators is investigated in [11].

The study in [12] focused on analyzing a high-speed 3DOF parallel manipulator to enhance production efficiency. The work in [13] examined the motion characteristics of a three-link robot manipulator in the auto industry. The matrix Lagrange equations are commonly employed to analyze the dynamics of the 3DOF robot manipulators [14].

In [15] authors designed a PID controller for a single robot manipulator. The simulation result gives a good effective result for path-tracking problems.

In [16] FO self-tuned fuzzy PID and FOSTFOPID controllers are designed for controlling a 3DOF robot manipulator. The parameters of controllers are tuned using the cuckoo search algorithm. The results show that FOSTFOPID gives the best performance compared with other controllers. The multi-link space manipulator is modeled in [17] and then a neural network is designed to examine the model uncertainty of the robot. The stability of the controller is examined using the Lyapunov theory. In [18] the dynamic and kinematic model of the robot is given.

The authors in [19] introduced a study on the modeling and control of a 3DOF robot manipulator. They employed a self-tuning fuzzy sliding mode controller (STFSMC) for trajectory tracking. The system's stability was examined with the Lyapunov direct technique. The simulation results indicated that the designed controller exhibits improved tracking performance, robustness, and insensitivity to any variant in applied model parameters, in comparison to other traditional controllers.

A self-adjusting adaptive fuzzy controller is designed in [20]. The Lyapunov-based reasoning is used to examine the stability of the closed-loop system. This controller gave good results for the trajectory tracking problem.

A self-tuning fuzzy PID is designed in [21]. A particle swarm optimization is used to tune this controller. The results indicated an important enhancement in transient response and tracking accuracy.

In [22] a control method using an optimal fuzzy FOPID controller is designed. The performance of the proposed controller is examined with many controllers such as fuzzy and fuzzy-PID controllers. Parameters of controllers are optimized using CSA. The results demonstrated that fuzzy FOPID had superior performance compared to other approaches under model uncertainty and different load conditions.

This paper focuses on constructing an optimal fuzzy immune FOPID controller for robot tracking of a 3DOF robot manipulator. A fuzzy immune PID controller is intended to perform a comparison study. CSA is utilized to tune the parameters of controllers.

The main contribution of this study was incorporating the effect of using a cascade of the immune system, fuzzy logic variable, classical PID, and FOPID controllers for controlling the path tracking of the robot manipulator, which allowed for a noticeable improvement in system response. We worked with the position and path tracking, giving small errors near zero. This should incorporate, in addition to the joint acceleration variable, the error variable with adaptive reset to improve the transient and stationary behavior in the presence of load conditions, disturbances, and model uncertainty. So, the primary contributions of this work can be outlined below:

- A thorough and comparative evaluation is done on two intelligent control strategies: the fuzzy-immune Controller and the fuzzy-immune FOPID controller, specifically implemented on a 3-DoF robotic arm. The study demonstrates the accuracy and general effectiveness of

TABLE 1. Symbols used in this paper.

Symbol	Meaning
FOPID	The fractional controller contains five parameters ($k_p, k_i, k_d, \lambda, and\ \mu$)
PID	The classical controller contains three parameters ($k_p, k_i, and\ k_d$). PID controller is special case of FOPID controller
CSA	An optimization algorithm called clonal selection algorithm.
FLC	Nonlinear controller named fuzzy logic controller
GA	Genetic Algorithm
DOF	Degree of freedom
FO	Fractional order
FOSTFOPID	Fractional order self-tuning fractional order proportional integral derivative
q	Joint displacement
k_p	Proportional constant
k_i	Integral constant
k_d	Differential constant
λ	Integration order
μ	Differentiation order
U	Control signal
M(q)	Inertia matrix
$C(q, \dot{q})$.	Coriolis and centrifugal
L	Length of link
m	mass of link
l	Distance between the joint and the center of mass of the link
J	Moment of inertia of the link around its center of mass
B	Immunological feedback
T_s	Mouse trophoblast stem cell
T_h	Conventional trophoblast helper cell
$\varepsilon(k)$	Antigen's stability
k	the reaction speed
k_1	Inspiration factor
k_2	Suppression factor
d	Immune response delay time.
$f(\Delta B(k-d))$	Interaction between antigen and antibody
µimmune	The equilibrium effect
e	The error is the difference between the desired and actual value
$\dot{e}$(t)	The change of error
q_d	Desired position
n(t)	External disturbance

both controllers, as evidenced by thorough evaluations, notably in terms of trajectory tracking.

- The PID and FOPID controller settings are efficiently tuned using a clonal selection technique, as it is challenging to tune multiple parameters simultaneously using analytical approaches. In addition, the performance of the fuzzy immune FOPID control scheme is evaluated by comparing it to its traditional equivalents (fuzzy immune PID) under various load situations, model uncertainty, and external disturbances.
- If we implement this project practically, this work enhances the subject of industrial robots providing a quantitative analysis supported by performance measures. This approach facilitates a direct and quantifiable assessment of the controllers, allowing for a clear and measurable comprehension of their efficacy in real-life situations. This strategy greatly enhances the establishment of evaluating criteria, thereby strengthening the significance and practicality of the controllers in sophisticated industrial settings.

The abbreviations of notations and the meanings that are used in this paper are given in Table 1.

The organization of this paper is as follows: section I introduces the dynamic model of the robot manipulator after providing a literature review in Section I. Section II describes the artificial immune system. Sections III and IV respectively cover the fundamental concepts of fuzzy, PID, and FOPID controllers. The simulation results are presented in section V. The conclusion is given in section VI.

Comparison With Another Work: A thorough examination was undertaken to compare our suggested methodology with existing research endeavors, with particular emphasis on important criteria including accuracy, recall, and precision. Our study surpasses previous research in the field of reducing error and tracking, showcasing improved performance in these crucial measurements. Through evaluation, our methodology demonstrates exceptional performance across all measures, hence highlighting its efficacy in reliably and precisely identifying and reducing errors near zero. For example in references [5], [6], [9], and [22] and From simulation results in these references, the error of joints is larger than the error in our study. Table 2 provides a comparison between the control methods, optimization methods, and the degree of freedom for robot manipulators that were used in previous studies and our study.

II. THE DYNAMIC MODEL OF 3DOF ROBOT

Equation 1 presents the dynamic motion equation for a n-link robotic manipulator [23] as follows:

$$M\,(q)\,\ddot{q} + C\,(q,\dot{q})\,\dot{q} = U \tag{1}$$

$$M(q) = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix}; U = \begin{bmatrix} U_1 \\ U_2 \\ U_3 \end{bmatrix}; q = \begin{bmatrix} q_1 \\ q_2 \\ q_3 \end{bmatrix};$$

$$\dot{q} = \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix}; \ddot{q} = \begin{bmatrix} \ddot{q}_1 \\ \ddot{q}_2 \\ \ddot{q}_3 \end{bmatrix}$$

$$C\,(q,\dot{q}) = \begin{bmatrix} C_{11}\,(q,\dot{q}) & C_{12}\,(q,\dot{q}) & C_{13}\,(q,\dot{q}) \\ C_{21}\,(q,\dot{q}) & C_{22}\,(q,\dot{q}) & C_{23}\,(q,\dot{q}) \\ C_{31}\,(q,\dot{q}) & C_{32}\,(q,\dot{q}) & C_{33}\,(q,\dot{q}) \end{bmatrix} \tag{2}$$

where:

$$C_{11} = -a_5\,(\dot{q}_2+\dot{q}_3)\,sin\,(q_2+q_3) - a_3\dot{q}_2 sin\,(q_2) - a_6\dot{q}_3 sin\,(q_3)\,;$$

TABLE 2. A comparison study between the previous study and our study.

Ref.	Methods of control/design robot only	Method of tuning Tuning	Performance test	Degree of freedom
4	Fuzzy controller			3
5	PD, PID, and Fuzzy PID controllers	Genetic algorithm		3
6	A fuzzy logic-based precompensation followed by a fuzzy self-tuning fuzzy PID controller	Supervisory hierarchical fuzzy controller (SHFC)		3
7	The controllers mentioned are Fuzzy-PID, PID, FOPID, and FO fuzzy PID controllers.		Robustness test (model uncertainties and disturbance rejection)	3
8	A serial robot manipulator is designed.	The mentioned algorithms are genetic algorithm, particle swarm optimization, quantum particle swarm optimization, and gravitational search algorithm.		4
9	Adaptive neuro-fuzzy inference system and Sliding mode control	Particle swarm optimization		3
10	The experimental system is developed with a working mode conversion.			3
11	The 3D mechanical components of the robotic manipulator are created using Solid Edge ST4 in a virtual environment. These components are then imported into the ADAMS virtual prototype environment.			3
12	a 1T2R quick-action parallel manipulator was designed.			3
13	The 2PRU-1PRS PM is examined and the results are presented for the specific scenario of using the 2PRU-1PRS for testing vehicle components.			3
14	3-DOF cylindrical manipulator is implemented	Genetic algorithm		3
15	A Real-time PID controller and experimental device are implemented.			1

TABLE 2. *(Continued.)* **A comparison study between the previous study and our study.**

16	The controllers mentioned are the fractional-order self-tuned fuzzy PID, fractional-order fuzzy PID, and integer-order self-tuning fuzzy PID controllers.	Cuckoo search algorithm	Rejection of disturbances, suppression of noise, and handling of uncertainties in the model.	3
17	Adaptive terminal sliding mode controller utilizing a neural network (NN)		The stability was tested using the Lyapunov theory	2
18	3DOF robot is implemented.			3
19	Controllers such as self-tuning fuzzy sliding mode, PID, sliding mode, and fuzzy sliding mode are used.		The stability was tested using the Lyapunov direct method	3
20	A fuzzy logic network and a self-adjusting adaptive fuzzy logic system are created.		The stability is tested via Lyapunov	3
21	a self-tuning particle fuzzy PID and fuzzy PID controllers.	Particle swarm optimization		4
Our study	Artificial immune feedback system-fuzzy PID and Artificial immune feedback system- fuzzy FOPID	Clonal selection algorithm	Load conditions, model uncertainty, and disturbance conditions	3

$$
\begin{aligned}
C_{12} &= -a_5\left(\dot{q}_1+\dot{q}_2+\dot{q}_3\right)sin\left(q_2+q_3\right)-a_3\left(\dot{q}_1+\dot{q}_2\right)\\
&\quad sin\left(q_2\right)-a_6\dot{q}_3 sin\left(q_3\right);\\
C_{13} &= -a_5\left(\dot{q}_1+\dot{q}_2+\dot{q}_3\right)sin\left(q_2+q_3\right)\\
&\quad -a_6\left(\dot{q}_1+\dot{q}_2+\dot{q}_3\right)sin\left(q_3\right);\\
C_{21} &= a_5\dot{q}_1 sin\left(q_2+q_3\right)+a_3\dot{q}_1 sin\left(q_2\right)-a_6\dot{q}_3 sin\left(q_3\right);\\
C_{22} &= -a_6\dot{q}_3 sin\left(q_3\right);\\
C_{23} &= -a_6\left(\dot{q}_1+\dot{q}_2+\dot{q}_3\right)sin\left(q_3\right);\\
C_{31} &= a_5\dot{q}_1 sin\left(q_2+q_3\right)+a_6\left(\dot{q}_1+\dot{q}_2\right)sin\left(q_3\right);\\
C_{32} &= a_6\left(\dot{q}_1+\dot{q}_2\right)sin\left(q_3\right);\\
C_{33} &= 0.\\
M_{11} &= a_1+a_2+a_4+2a_3cos\left(q_2\right)+2a_5cos\left(q_2+q_3\right)\\
&\quad +2a_6cos\left(q_3\right);\\
M_{12} &= M_{21}=a_2+a_4+a_3cos\left(q_2\right)+a_5cos\left(q_2+q_3\right)\\
&\quad +2a_6cos\left(q_3\right);\\
M_{13} &= M_{31}=a_4+a_5cos\left(q_2+q_3\right)+a_6cos\left(q_3\right);\\
M_{22} &= a_2+a_4+2a_6cos\left(q_3\right);\\
M_{23} &= M_{32}=a_4+a_6cos\left(q_3\right);\\
M_{33} &= a_4.\\
a_1 &= j_1+m_1l_1^2+\left(m_2+m_3\right)L_1^2;\\
a_2 &= j_2+m_2l_2^2+m_3L_2^2;\\
a_3 &= \left(m_3L_2+m_2l_2\right)L_1;\\
a_4 &= j_3+m_3l_3;\\
a_5 &= m_3l_3L_1;\\
a_6 &= m_3l_3L_2.
\end{aligned}
$$

Figure 1 explains the 3DOF robot manipulator.

The robot's parameters are given in Table 3:

III. CONCEPT OF IMMUNE SYSTEM

A. IMMUNE FEEDBACK CONTROLLER

The immune system of the body maintains a complex network of interconnected B cells to identify antigens. Both excitatory and inhibitory connections are demonstrated by B cells. This connection increases network stability. If the affinities they

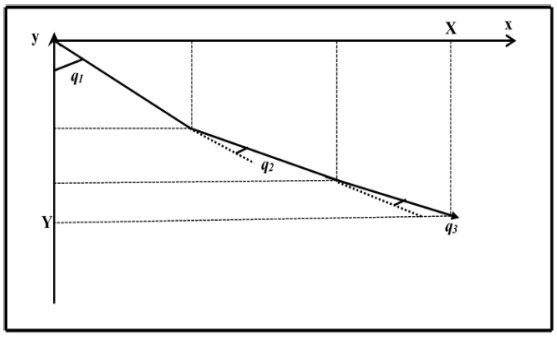


FIGURE 1. 3 link robot manipulator.

TABLE 3. Parameters of the robot.

Parameters	Values	units
l_1	1	m
l_2	1	m
l_3	1	m
L_1	0.5	m
L_2	0.5	m
L_3	0.5	m
m_1	1	kg
m_2	1	kg
m_3	1	kg
j_1	0.0833	Kg.m^2
j_2	0.8333	Kg.m^2
j_3	0.8333	Kg.m^2

share exceed a predetermined threshold, Two B cells will be related. Moreover, the power of the relationship is closely correlated with the degree of affinity they possess [24]. The immunological mechanism functions as a feedback control system. Figure 2 describes the immunological processes that are in operation.

An immune fuzzy FOPID controller is a nonlinear controller with strong robustness and precis tuning created by an immune instrument. The feedback instrument's standard is described in Figure 2 [24].

$$B(k) = T_h(k) - T_s(k) \tag{3}$$
$$T_h(k) = k_1 \varepsilon(k) \tag{4}$$
$$T_s(k) = k_2 \{f[\Delta B(k-d)]\} \varepsilon(k) \tag{5}$$

From eq. 3 and 4. It appears as follows:

$$\begin{aligned} B(k) &= k_1 \varepsilon(k) - k_2 \{f[\Delta B(k-d)]\} \varepsilon(k) \\ &= k\{1 - \mu f[\Delta B(k-d)]\} \varepsilon(k) \end{aligned} \tag{6}$$

where $k = k_1$, $\mu = k_2 / k_1$. Choosing μ, k correctly is crucial to the immunological feedback controller's function [25]. Equation 6 is similar to the PID controller law as below:

$$U(k) = k_p e(k) \tag{7}$$
$$U(k) = k_p \{1 - \mu f[U(k), \Delta U(k-d)]\} \varepsilon(k) \tag{8}$$

The combination of an immune proportional controller with a PID controller results in a highly effective control

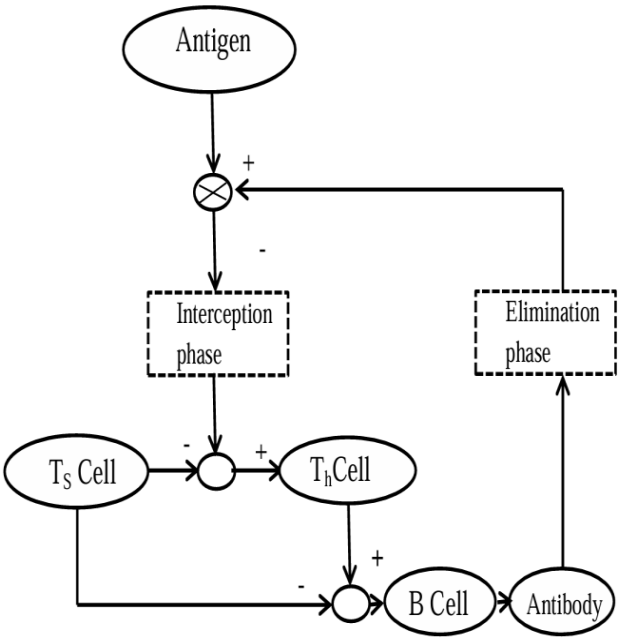


FIGURE 2. The operation of the immune system.

known as the IMF PID. This controller law can be expressed as: [26]:

$$\begin{aligned} U(k) = k_p\{1 - \mu f[U(k), \Delta U(k-d)]\}(1 + T_i/(z-1) \\ + T_d(z-1)/z)\varepsilon(k) \end{aligned}$$

B. CLONAL SELECTION ALGORITHM

These algorithms are essentially Darwinian, using selection based on antigen affinity and antibody interaction, modification based on somatic hypermutation, and reproduction based on copying cell division. Three processes are included in the basic concept of clonal selection: affinity maturation, clonal expansion, and clonal selection itself. Often referred to as the clever algorithm, this particular method uses real parameter values instead of binary-coded parameters. All members of the set are cloned. This algorithm works very well for multi-objective problem optimization. This algorithm's steps are shown in Figure 3 [24].

IV. FUZZY LOGIC CONTROLLER

The steps of designing FLC are given below [27]:

a. Define the input and output variables for the Fuzzy Logic Controller (FLC). The research includes two FLC inputs, namely e (t) and $\dot{e}$(t), as well as one output, as depicted in Fig.4.
b. Define membership functions and the fuzzy sets to fuzzy I/P and O/P variables. This is illustrated in Fig.5 for the two inputs and one output. Each input variable in the fuzzy control system is represented by seven fuzzy sets, ranging from negative big (NB) to positive big (PB).
c. The inference mechanism rule used to establish the input-output link will be described. The control rules

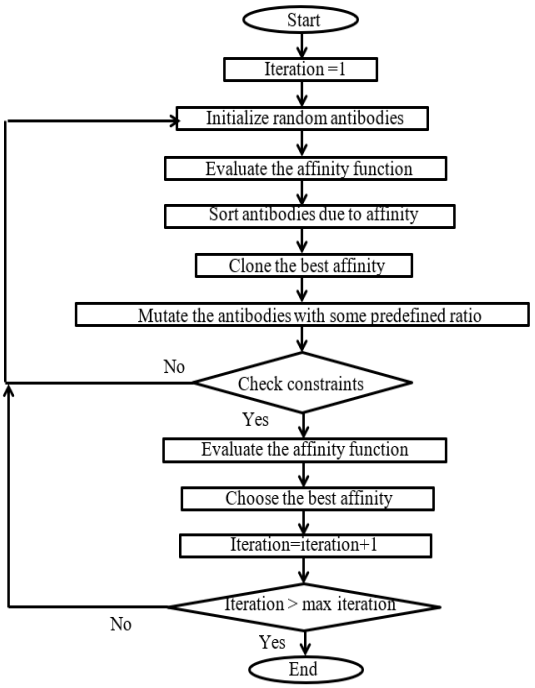


FIGURE 3. Flowchart of the clonal selection algorithm.

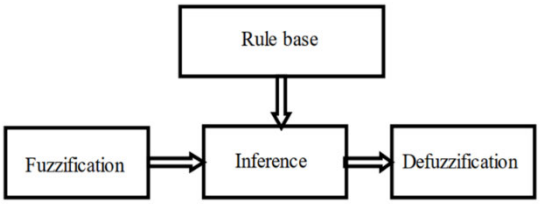


FIGURE 4. The primary structure of FLC.

utilized in this study for fuzzy immune FOPID and fuzzy immune PID controllers employing the Mamdani (max-min) inference mechanism are presented in Table 4 [16].

d. Defuzzify the output variable. The most often used approach, the center of gravity (COG) method, is used here. The control activity is the inference mechanism [16]:

$$COG = \frac{\sum_{i=1}^{m} \mu(f_i)\, f_i}{\sum_{i=1}^{m} \mu\,(f_i)}$$

- T-S fuzzy system:

The inference system developed by Takagi and Sugeno is similar to the Mamdani inference system. The surgeon made a single major regulation adjustment. Instead of employing a fuzzy set, he opted to utilize a mathematical function based on the input variable.

Examine the T-S fuzzy system [28]: Rule $\boldsymbol{i}$: IF $\boldsymbol{w_1(t)}$ is $\boldsymbol{\mathcal{G}_1^i, \ldots}$ and $\boldsymbol{w_\varphi(t)}$ is $\boldsymbol{G_\varphi^i}$, THEN

$$\begin{cases} \dot{x}(t) = A_i x(t) + B_i u(t) + D_i f(t) \\ z(t) = L x(t) \end{cases}$$

TABLE 4. Fuzzy logic controller rules.

U		Fractional Rate of Change of Error						
		NB	NM	NS	Z	PS	PM	PB
e	NB	NM	NS	NS	NS	Z	PS	PM
	NM	NM	NM	NM	NS	PS	PM	PM
	NS	NB	NM	NM	NS	PM	PB	PB
	Z	NB	NB	NM	Z	PM	PB	PB
	PS	NB	NB	NM	PS	PM	PM	PB
	PM	NM	NM	NS	PS	PM	PM	PM
	PB	NM	NS	Z	PS	PS	PS	PM

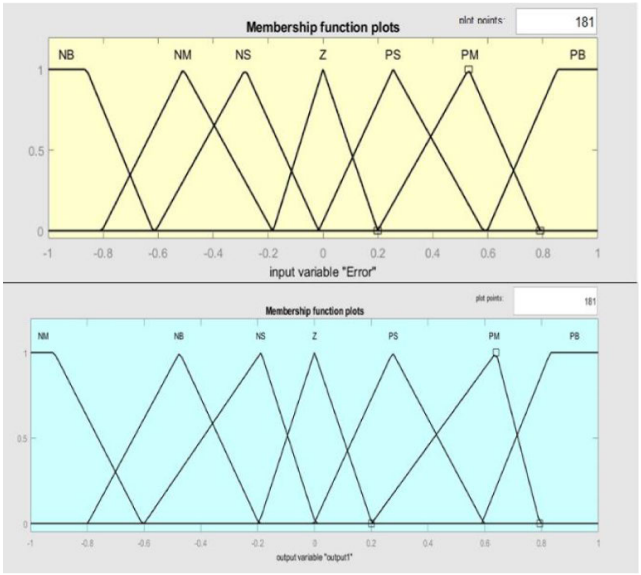


FIGURE 5. Membership functions's input and output.

The variables $\boldsymbol{w_1(t), \ldots, w_\varphi(t)}$ indicate the premise variables, while $\boldsymbol{\mathcal{G}_\varphi^i (i = 1, \ldots, l)}$ denotes fuzzy set, the state $\boldsymbol{x(t)\mathbb{R}^n}$ refers to a state in n-dimensional space. The notation $\boldsymbol{u(t) \in \mathbb{R}^g}$ represents control input, $\boldsymbol{f(t) \in \mathbb{R}^{n_f}}$ represents an external disturbance that is a member of the $\boldsymbol{L_2[0, \infty) space, z(t) \in \mathbb{R}^{n_z}}$ represents the performance output matrix, $\boldsymbol{L}$ is the control performance output matrix, and the matrices $\boldsymbol{A_i, B_i, D_i}$, and $\boldsymbol{L}$ have constant parameters.

The following overall fuzzy model can be deduced:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{l} \kappa_i(w(t)) \left[A_i x(t) \right. \\ \left. + B_i u(t) + D_i f(t)\right] \\ z(t) = L x(t) \end{cases}$$

The term $\boldsymbol{\kappa_i(w(t))}$ denotes the normalized membership function (MF).

$$\kappa_i(w(t)) = \frac{v_i(w(t))}{\sum_{i=1}^{\varphi} v_i(w(t))}, v_i(w(t)) = \prod_{a=1}^{\varphi} \mathcal{G}_a^i\,(w_a(t))$$

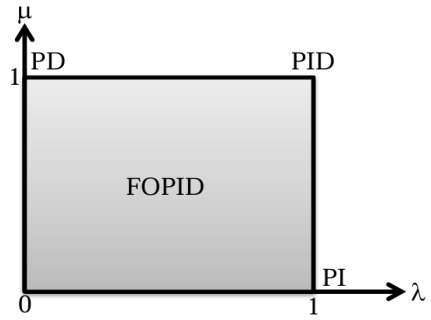


FIGURE 6. Fractional order PID controller plane.

TABLE 5. CSA's parameters.

Parameters	values
Number of antibodies	40
Clone's number	20
Inferior limit	0
Superior limit	500
Max. gen.	50
Mutation factor	80
Eliminate threshold	1
Selection of Clones	0.5

TABLE 6. Parameters of CSA-PID in Fuzzy-Immune PID controller.

Gains	PID_1	PID_2	PID_3
k_p	159.0386	478.5306	56.0292
k_i	451.1407	119.8349	418.8583
k_d	111.5225	88.5119	414.8683

$$\kappa_i(w(t)) \geq 0, \sum_{i=1}^{l} \kappa_i(w(t)) = 1$$

The expression $\mathcal{G}_a^i(w_a(t))$ represents the degree of membership of $w_a(t)$ in $\mathcal{G}_a^i$.

Based on the previous approach, the fuzzy weighted memory controller is

$$u(t) = \sum_{j=1}^{l} \kappa_j(w(t)) \left(K_j x(t)\right)$$

The challenge is to determine the controller gain K_j, and **theinputfunctionr**(s) i which satisfies the integral of r(s) from -χ to 0 equal to 1. To simplify the presentation, we will use the abbreviations κ_i and κ_j for $\kappa_i(w(t))$ and $\kappa_j(w(t))$, respectively.

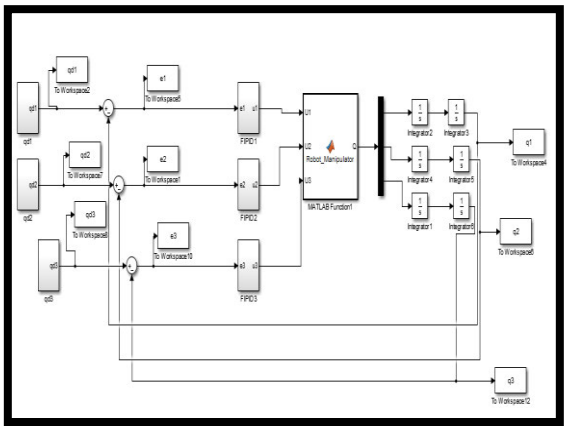


FIGURE 7. Simulink diagram of Fuzzy-Immune PID control schemes.

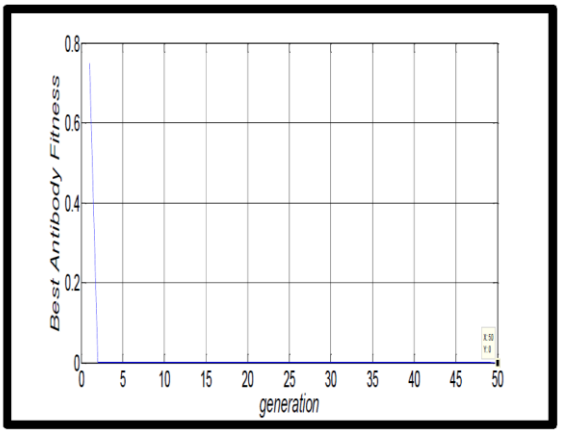


FIGURE 8. Fitness values versus generation for the proposed control scheme.

The combination of the controller and system yields the subsequent closed-loop fuzzy system.

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{l} \sum_{j=1}^{l} \kappa_i \kappa_j \left[\left(A_i + B_i K_j\right) x(t) + D_i f(t) \right. \\ \left. + B_i F_j \int_{-\chi}^{0} r(s) x(t+s) ds \right] \\ z(t) = L x(t) \end{cases}$$

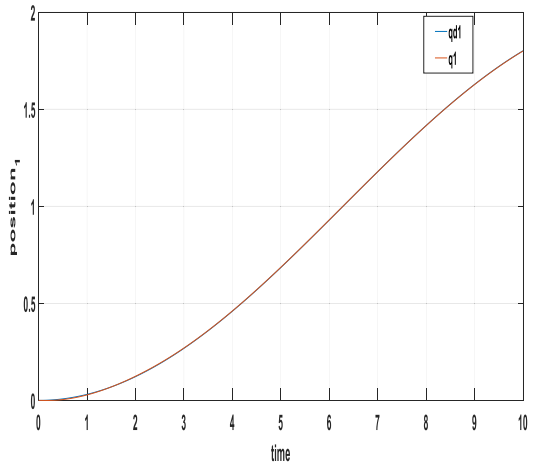
By defining

$$\mathbf{r}(s) = \left[r(s)\ r_1(s)\ \cdots\ r_q(s) \right]^\top$$
$$\mathbf{R}(s) = \mathbf{r}(s) \otimes I_n, I = \left[I_n\ 0_{n \times qn} \right]$$
$$\mathcal{R}(t) = \int_{-\chi}^{0} \mathbf{R}(s) x(t+s) ds$$

The function r(s) satisfies the property $\dot{\mathbf{r}}(s) = \mathcal{R}\mathbf{r}(s)$ and $\mathcal{R} \in \mathbb{R}^{n(q+1) \times n(q+1)}$.

From above we can conclude that in Sugeno each rule generates two values:

1. Rule output level which is either a constant value or linear function of the input values.
2. Rule firing strength derived from the rule antecedent.



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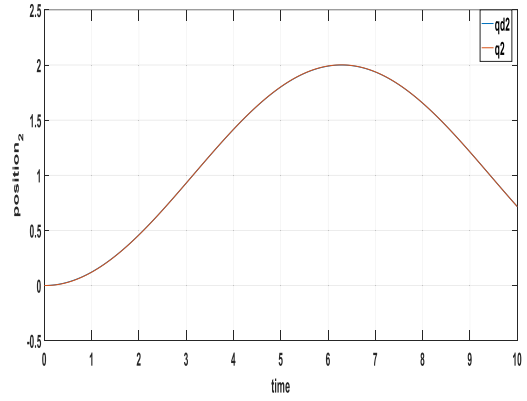

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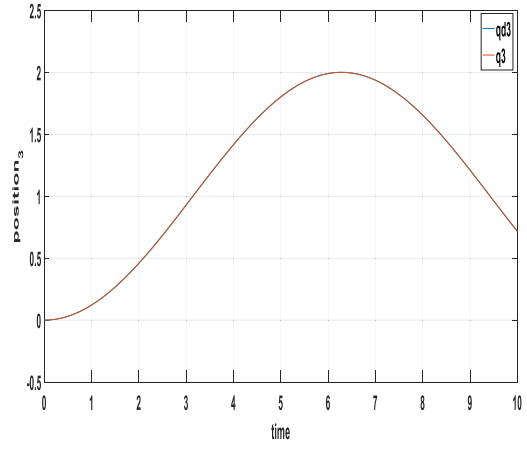


(c)

FIGURE 9. Links' desired and actual paths using fuzzy immune PID controller.

The final output of the system is the weighted average over all rules outputs:

$$output = \frac{\sum_{i=1}^{N} w_i Z_i}{\sum_{i=1}^{N} w_i}$$

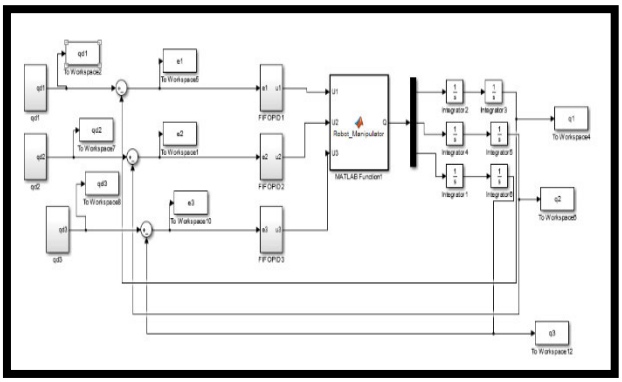


FIGURE 10. Simulink diagram of Fuzzy-Immune FOPID control schemes.

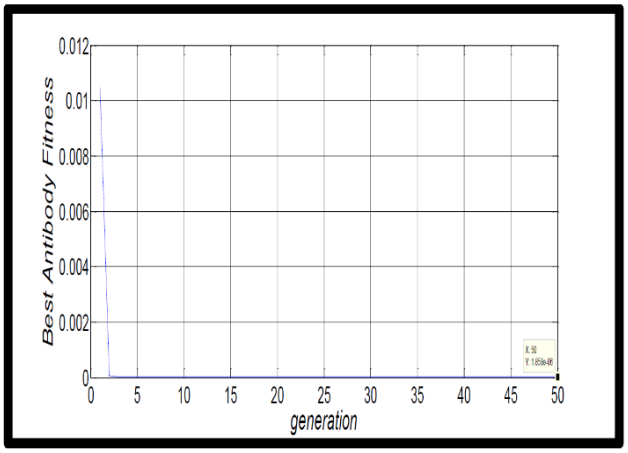


FIGURE 11. Affinity values versus generation.

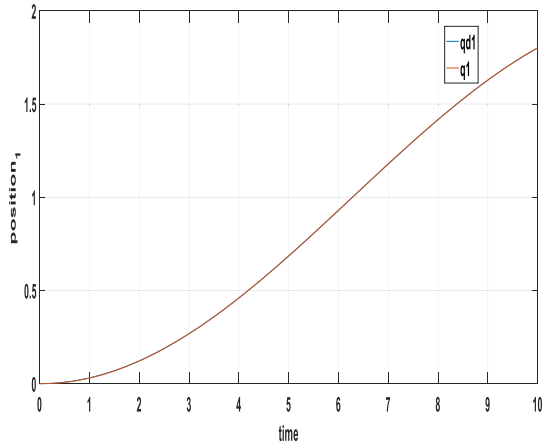
TABLE 7. Parameters of CSA-FOPID in Fuzzy-Immune FOPID controller.

Parameters	$FOPID_1$	$FOPID_2$	$FOPID_3$
k_p	481.2575	497.8153	228.417
k_i	369.2676	253.9697	51.8521
k_d	447.3124	165.5428	245.015
λ	0.275979	0.97848	0.97947
μ	0.979645	0.674736	0.704792

V. PRINCIPLES OF PID AND PI^{λ} D^{μ}

Many scientists are now adopting fractional order controllers to improve the robustness of their systems. Several studies imply that PID controllers are less efficient than FOPID. The integration and differentiation orders of the fractional order controller are two additional control parameters that may increase flexibility and stability. FOMCON is one of MATLAB's toolboxes for fractional-order modeling and control. PID controller can be expressed as below [28]:

$$u(s) = \left(k_p + k_i \frac{1}{s} + k_d s\right) e(s) \tag{9}$$



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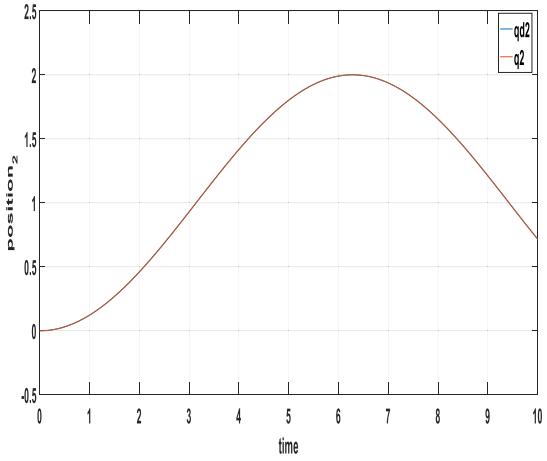

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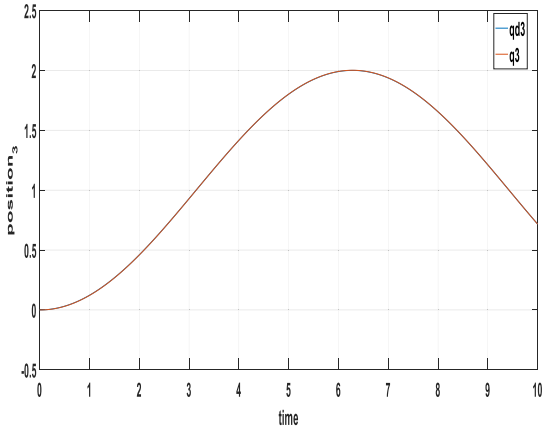


(c)

FIGURE 12. Links' desired and actual paths using fuzzy immune FOPID controller.

The FOPID controller equation is as follows:

$$\lambda\mu u\,(s) = \left(k_p + k_i\frac{1}{s} + k_d s\right) e(s),\ (\lambda, \mu > 0) \qquad (10)$$

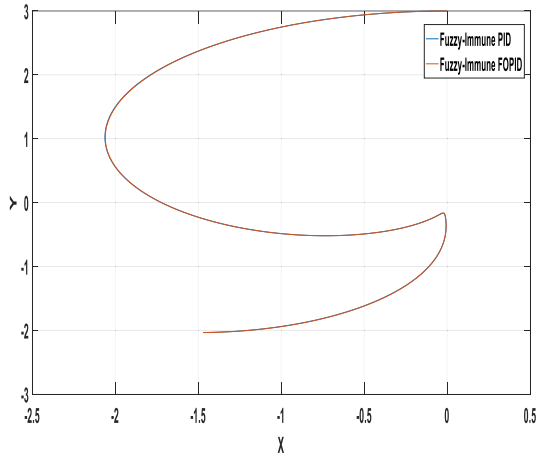


FIGURE 13. End effector of suggested controllers.

From (10) we notice that $PI^{\lambda}D^{\mu}$ is a PID controller extension [2]. The utilization of integration and differentiation orders provides more flexibility for adjusting the controller, resulting in enhanced precision and robustness of the control action. The diagram below illustrates the classification of FOPID controllers based on their corresponding value λ and μ.

VI. SIMULATION RESULTS

The results for path tracking and uncertainty in the model for proposed controllers are discussed in this section. The selected trajectory is stated as follows:

- **First Proposed Trajectories**

$$q_{d1} = 1 - \cos(0.25t)\,;\ q_{d2} = q_{d3} = 1 - \cos(0.5t)\,;$$

PID and FOPID controller parameters were obtained and given in Table 4. The parameters of the optimization algorithm are given in Table 5.

Mean square error (MSE) is the difference between set values and actual values [29], [30]. MSE can be written as:

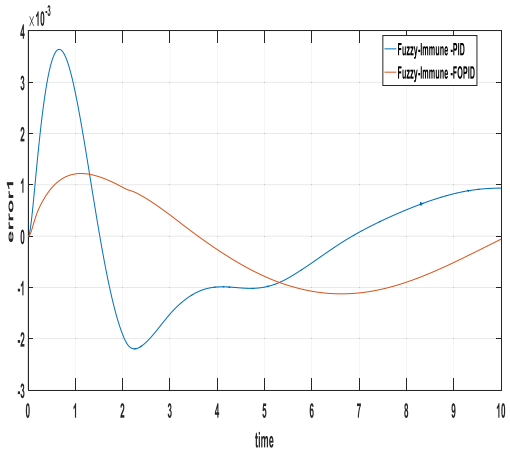
$$Antibody\ Fitness = \sum e_1^2/length(e_1) + \sum e_2^2/length(e_2) + \sum e_3^2/length(e_3)$$

- **Results for first proposed trajectories**

A. SIMULATION RESULTS OF FUZZY-IMMUNE PID CONTROLLER

Figure 6 displays the Simulink schematic of the IMF Fuzzy PID controller. The graph in Figure 7 displays the fitness values plotted against the number of generations. The optimal parameters of PID control schemes are given in Table 6.

Figures 9 and 12 show the expected and real positions of the robot manipulator under robust testing, which were controlled using the proposed controllers. Path tracking by end effector utilizing controllers is compared in Figure 13. All controllers are compared for both link errors in Figure 14.



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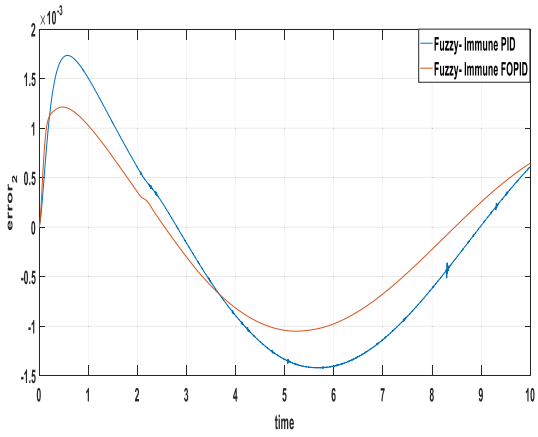

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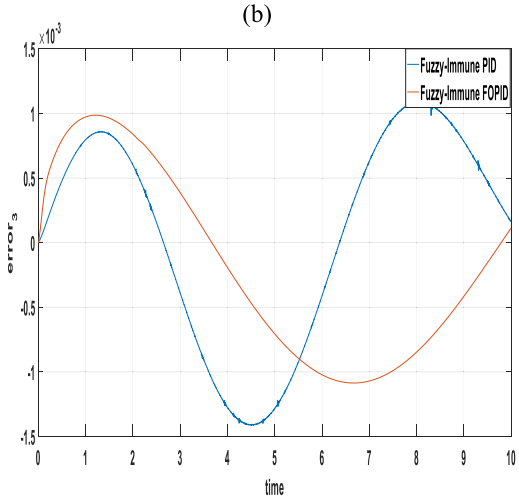


(c)

FIGURE 14. Errors using suggested controllers.

B. SIMULATION RESULTS OF FUZZY-IMMUNE FOPID CONTROL SCHEMES

The Simulink diagram showing the IMF Fuzzy FOPID control systems can be seen in Figure 10. The graph in Figure 11 displays the fitness values plotted against the number of generations. The optimal parameters of FOPID control schemes are given in Table 7.

- **Second Proposed Trajectories [16]**

$$q_{d1} = sin\,(0.2\pi t)\,;\, q_{d2} = sin\left(0.2\pi t - \frac{\pi}{4}\right),$$
$$q_{d3} = sin\left(0.2\pi t - \frac{\pi}{2}\right);$$

- **Results for the Second proposed trajectories**

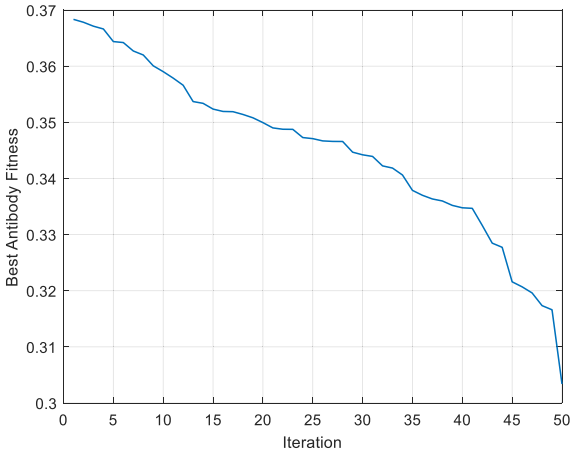


FIGURE 15. Fitness values versus generation for the proposed control scheme.

TABLE 8. Parameters of CSA-PID in Fuzzy-Immune PID controller.

Gains	PID_1	PID_2	PID_3
k_p	84.8950	215.3582	215.3582
k_i	83.0651	355.9493	355.9493
k_d	462.9763	180.0234	180.0234

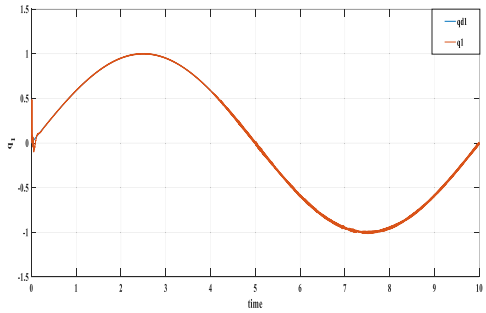
C. SIMULATION RESULTS OF FUZZY-IMMUNE PID CONTROLLER

The graph in Figure 15 displays the fitness values plotted against the number of generations. The optimal parameters of PID control schemes are given in Table 8.

Figures 16 and 18 show the expected and real positions of the robot manipulator under robust testing, which were controlled using the proposed controllers. Path tracking by end effector utilizing controllers is compared in Figure 19. All controllers are compared for both link errors in Figure 20.

D. SIMULATION RESULTS OF FUZZY-IMMUNE FOPID CONTROL SCHEMES

The graph in Figure 17 displays the fitness values plotted against the number of generations. The optimal



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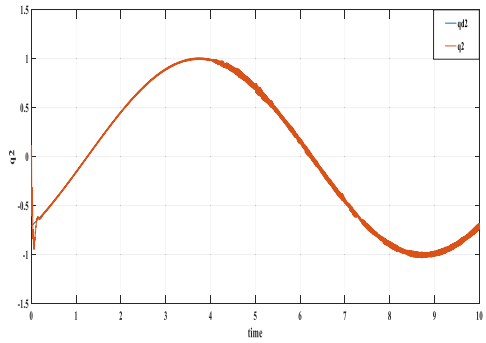

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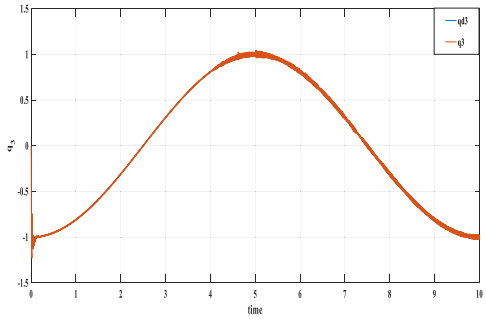


(c)

FIGURE 16. Links' desired and actual paths using fuzzy immune PID controller.

TABLE 9. Parameters of CSA-FOPID in Fuzzy-Immune FOPID controller.

Parameters	$FOPID_1$	$FOPID_2$	$FOPID_3$
k_p	120.28714	58.9271	339.1725
k_i	329.6197	271.6148	486.7698
k_d	211.8351	275.3491	493.2706
λ	0.4672	0.7388	0.4672
μ	0.5249	0.5249	0.5249

parameters of FOPID control schemes are given in Table 9.

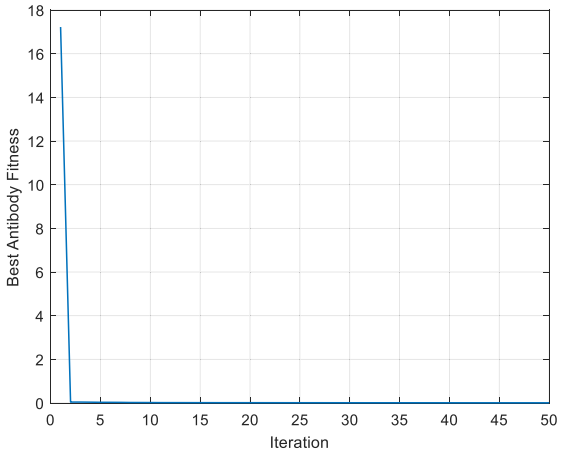


FIGURE 17. Affinity values versus generation.

TABLE 10. MSEs of $link_1$, $link_2$, and $link_3$.

Load (kg)	$Controller_1$	$Controller_2$
0	$1.849*10^{-6}$	$6.695*10^{-7}$
	$9.559*10^{-7}$	$5.226*10^{-7}$
	$6.725*10^{-7}$	$5.382*10^{-7}$
0.1	$2.112*10^{-6}$	$7.626*10^{-7}$
	$1.054*10^{-6}$	$5.809*10^{-7}$
	$7.214*10^{-7}$	$5.768*10^{-7}$
0.2	$2.412*10^{-6}$	$8.613*10^{-7}$
	$1.173*10^{-6}$	$6.423*10^{-7}$
	$7.764*10^{-7}$	$6.168*10^{-7}$
0.3	$2.724*10^{-6}$	$9.652*10^{-7}$
	$1.287*10^{-6}$	$7.071*10^{-7}$
	$8.288*10^{-7}$	$8.582*10^{-7}$

- **Robustness Test**

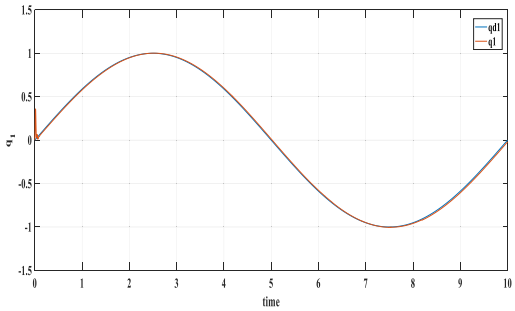
Load conditions and model uncertainty are used to examine robustness. The robustness test will be examined for the first proposed trajectory only.

E. LOAD CONDITIONS RESULTS

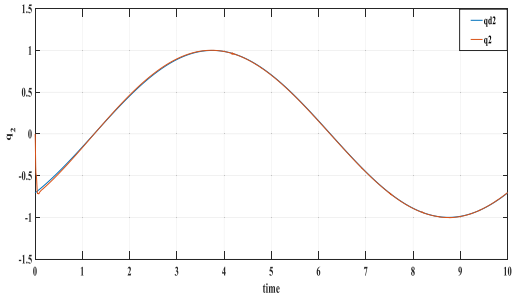
Table 10 explains the MSE for suggested controllers under load conditions.

F. MODEL UNCERTAINTY RESULTS

Table 11 explains the MSE for suggested controllers under model uncertainty.



(a)



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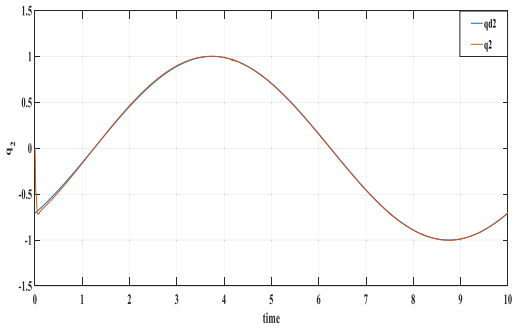


(c)

FIGURE 18. Links' desired and actual paths using fuzzy immune PID controller.

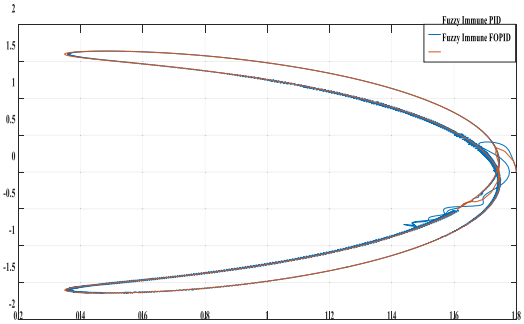
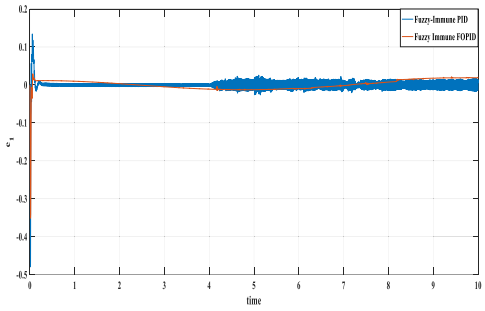


FIGURE 19. End effector of suggested controllers.

G. DISTURBANCE RESULTS

The robot manipulator model with external disturbance is given in the equation below:

$$M(q)\ddot{q} + B(q,\dot{q})\dot{q} + G(q) + n(t) = U$$



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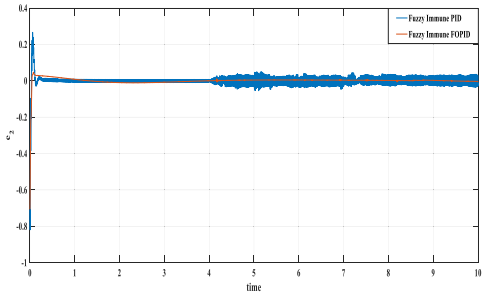

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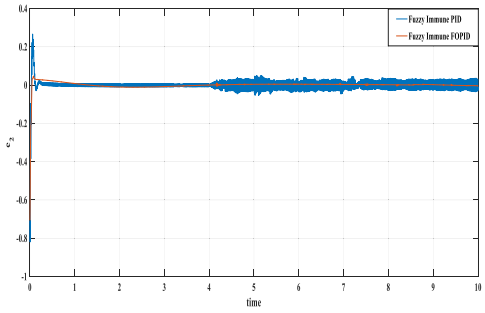

(c)

FIGURE 20. Errors using suggested controllers.

TABLE 11. MSEs of $link_1$, $link_2$, and $link_3$ under model uncertainty.

J_3 ($kg.m^2$)	$Controller_1$	$Controller_2$
0.8333	$1.849*10^{-6}$	$6.695*10^{-7}$
	$9.559*10^{-7}$	$5.226*10^{-7}$
	$6.725*10^{-7}$	$5.382*10^{-7}$
0.8433	$1.864*10^{-6}$	$6.729*10^{-7}$
	$9.692*10^{-7}$	$5.265*10^{-7}$
	$6.828*10^{-7}$	$5.467*10^{-7}$

In this paper $n(t) = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} N.m$

Table 12 explains the MSE for suggested controllers under external disturbance:

TABLE 12. MSEs of link1, link2, and link3 under disturbance.

n(t) (N.m)	Controller$_1$	Controller$_2$
1	$3.1356*10^{-6}$	$8.8626*10^{-7}$
	$1.5042*10^{-6}$	$8.7154*10^{-7}$
	$2.1482*10^{-6}$	$1.7839*10^{-6}$

VII. CONCLUSION

The proposed controllers are built in this study for a 3DOF robot manipulator to examine trajectory tracking. The fuzzy immune FOPID controller's performance is more efficient than that of other controllers. A clonal selection algorithm optimizes the PID and FOPID controller settings. According to the simulation results, based on figures and tables the fuzzy immune FOPID controller outperforms conventional controllers in terms of effectiveness and robustness when it comes to trajectory tracking. While this study explains the design of proposed controllers for trajectory tracking problems, one of the future works is to design another controller such as a sliding mode controller, or adaptive neuro-fuzzy controller, and then compare the performance of these controllers. Additionally, it can be used in other optimization algorithms (genetic algorithm, particle swarm algorithm, anti-colony algorithm, …etc.) to find the optimal parameters of PID and FOPID controllers. Finally, this can be implemented this idea practically in future work and using the robot in many applications such as tracking, welding and cutting, and packaging, material handling.

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