Fuzzy-PI Conroller Tuned With GWO, WOA And TLBO For 2 DOF Robot Trajectory Control

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Abstract: In this study, a manipulator robot with two degrees of freedom was controlled by Fuzzy-PI adjust by three meta-heuristic algorithms (Grey wolf optimizer (GWO), Whale Optimization Algorithm (WOA) and Teaching–learning-based optimization (TLBO)). The scale factors of the fuzzy system of the Takagi-Sugano type (the width of the membership functions) and the parameters of PI were optimized by those three algorithms under the cost function of the absolute magnitude of the mean error (MAE). In order to investigate the robustness of the proposed controller we considered the friction forces. The results of the simulation prove the controller's effectiveness to following a given trajectory.

Keywords: Fuzzy-PI; GWO; WOA; TLBO; Robot trajectory control.

1. INTRODUCTION

For linear systems and some non-severe non-linear systems, the PID controller has been widely used in industrial control processes due to its simple structure and robust performance under a wide range of operating conditions. However, it is quite difficult to determine the optimal PID parameters because the system parameters are coupled, nonlinear and time dependent. In the process of tuning a PID controller, three constants must be selected so that the closed loop system gives the desired response. The desired response should have minimal settling time with little or no overshoot in the closed loop system step response. Several numerical approaches such as the fuzzy logic algorithm (FLC) [1] and evolutionary algorithms [1-5] have been used for the optimal design of the PID controller [6].

FLC is a popular technique that has aroused increasing interest in recent decades because it is based on linguistic structure, and its performance is robust enough for nonlinear systems. However, FLC including some parameters such as linguistic control rules and limits and type of membership functions must be set for a given system. A major disadvantage of FLC is that the tuning process becomes more difficult and time consuming as the number of inputs and outputs of the system increases [6].

In order to extract the optimal parameters from the Fuzzy-PI, the control objective can be formulated as an optimization problem, and there is some difficulty in finding the parameters of the controller. Optimization problems can be solved using meta-heuristic optimization methods or other methods such as neural networks. [7] Developed fuzzy neural networks (FNN) for the navigation of a mobile robot and the movement control of a redundant manipulator. They used PSO to train FNNs capable of accurately producing the crisp control signals for robot systems. [8] Introduced a new hybrid approach for the training of the Adaptive Network Based Fuzzy Inference System (ANFIS) and used PSO for the training of the procedural parameters in the antecedent part. The authors in [9] described a Takagi-Sugeno (TS) -type neuro-fuzzy system (NFS) formed by PSO for the dynamic modeling of model two- and three-link robot manipulators. [15] In their study, Craziness-Based Particle Swarm Optimization (CRPSO) and Binary Coded Genetic Algorithm (GA) were used to obtain the optimal PID gains. [6] They used PSO to adjust the parameters of FLC and PID to force the dynamics of the manipulator robot to follow a given trajectory. In [18,19] they opted for HBBO and GWO to find the near optimal parameter of Fuzzy-PI controller applied to 2 DOF robot.

In this study, three algorithms are presented (WGO, WOA and TLBO) to adjust the parameters of the Fuzzy-PI in order to force a manipulator robot with two degrees of freedom to follow a given trajectory under the presence of the frictional forces.

2. DYNAMIC MODEL OF PLANAR RPBOT

Robot dynamic analysis studies a relationship between joint torques/forces applied by actuators and the position, speed and acceleration of the robot arm with respect to time. The dynamic equations of the robot are generally represented by the following coupled nonlinear differential equations:

$$\tau=D(q)\ddot{q}+C(q,\dot{q})+G(q) \quad (1)$$

Where D(q) is the inertia matrix, $C(q,\dot{q})$ is the Coriolis / centripetal matrix, G(q) is the gravity vector and τ is the control input torque. The joint variable q is a vector n containing the joint angles for rotary joints. The dynamics of the planar robot with 2 degrees of freedom can be calculated by:

$$\begin{pmatrix}\tau_1\\ \tau_2\end{pmatrix}= \begin{pmatrix}(m_1+m_2)l_1^2+m_2l_2^2+2m_2l_1l_2\cos\theta_2 & m_2l_2^2+m_2l_1l_2\cos\theta_2\\ m_2l_2^2+m_2l_1l_2\cos\theta_2 & m_2l_2^2\end{pmatrix} \begin{pmatrix}\ddot{\theta}_1\\ \ddot{\theta}_2\end{pmatrix}+\begin{pmatrix}-m_2l_1l_2\left(2\dot{\theta}_1\dot{\theta}_2+\dot{\theta}_2^2\right)\sin\theta_2\\ m_2l_1l_2\dot{\theta}_1^2\sin\theta_2\end{pmatrix} + \begin{pmatrix}(m_1+m_2)gl_1\cos\theta_1+m_2gl_2\cos(\theta_1+\theta_2)\\ m_2gl_2\cos(\theta_1+\theta_2)\end{pmatrix} \quad (2)$$

Where m_i is the mass of the link, l_i is the length of the link, g is the gravity $\theta,\dot{\theta}$ and $\ddot{\theta}$ respectively, are the positions, speeds and accelerations of the joints.

3. GREY WOLF OPTIMIZER (GWO)

The GWO algorithm mimics the hierarchy of leadership and the hunting mechanism of gray wolves in the wild. Four types of gray wolves such as alpha, beta, delta and omega are used to simulate the leadership hierarchy. [10] The mechanism of this algorithm is simple. The first groups of alpha wolves are the pack leaders and, therefore, influence more powerfully in the research space. At the end of the run, the best individual will join the alpha group. The basic steps in hunting a gray wolf are following, chasing, surrounding and attacking the prey [13].

Initially, the following equations are proposed for the modeling of the encirclement of the prey [14]:

$$\vec{D}=\left|\vec{C}.\vec{X}_p^t-\vec{A}.\vec{X}^t\right| \quad (3)$$

$$\vec{X}^{t+1}=\vec{X}_p^t-\vec{A}.\vec{D} \quad (4)$$

Where t is the current iteration, $\vec{X}_p^t$ is the prey position vector, and $\vec{X}^t$ indicates the position vector of a gray wolf. $\vec{A}$and$\vec{C}$. are vectors which have three different random numbers and which help the candidate solutions by moving them in the search space calculated as follows:

$$\vec{A}=2.\vec{a}.\vec{r}_1-\vec{a} \quad (5)$$

$$\vec{C}=2.\vec{r}_2 \quad (6)$$

The parameter $\vec{a}$ is the exploration factor which starts with a value of 2 and decreases over the course of iterations until it reaches 0 and $\vec{r}_1$, $\vec{r}_2$ are random vectors in [0, 1].

The position of the best search agents can be calculated by the following equations:

$$\begin{cases}\vec{D}_\alpha=\left|\vec{C}_1.\vec{X}_\alpha-\vec{X}\right|\\ \vec{D}_\kappa=\left|\vec{C}_2.\vec{X}_\kappa-\vec{X}\right|\\ \vec{D}_\delta=\left|\vec{C}_3.\vec{X}_\delta-\vec{X}\right|\end{cases} \quad (7)$$

$$\begin{cases}\vec{X}_1=\left|\vec{X}_\alpha-\vec{A}_1.\vec{D}_\alpha\right|\\ \vec{X}_2=\left|\vec{X}_\kappa-\vec{A}_2.\vec{D}_\kappa\right|\\ \vec{X}_3=\left|\vec{X}_\delta-\vec{A}_3.\vec{D}_\delta\right|\end{cases} \quad (8)$$

When $|A|<1$, the wolves attack towards the prey, which represents an exploitation process.

4. WHALE OPTIMIZER ALGORITHM (WOA)

The WOA mimics the social behavior of humpback whales. The algorithm is in-spired by the bubble-net hunting strategy. The mechanism of WOA is very similar to GWO and the main difference is the simulated hunting behavior with random or the best search agent to chase the prey and the use of a spiral to simulate bubble-net attacking mechanism of humpback whales.

Initially, the following equations are proposed for the modeling of the encirclement:

$$\vec{D}=\left|\vec{C}.\vec{X^*}(t)-\vec{A}.\vec{X}(t)\right| \quad (10)$$

$$\vec{X}(t+1)=\vec{X^*}(t)-\vec{A}.\vec{D} \quad (11)$$

Where *t* indicates the current iteration, $\vec{A}$and $\vec{D}$are coefficient vectors,$X^*$is the position vector of the best solution obtained so far, $\vec{X}$is the position vector. It is worth mentioning here thatX^*should be updated in each iteration if there is a better solution.

The vectors $\vec{A}$and $\vec{D}$are calculated as follows:

$$\vec{A}=2.\vec{a}.\vec{r}-\vec{a} \quad (12)$$

$$\vec{C}=2.\vec{r} \quad (13)$$

Where $\vec{a}$ is linearly decreased from 2 to 0 over the course of iterations (in both exploration and exploitation phases) and $\vec{r}$is a random vector in [0,1].

Secondly, the Bubble-net attacking phase are modeled by the following equations:

$$\begin{cases}\overrightarrow{X^*}(t)-\vec{A}.\vec{D} & \text{if } p<0.5 \\ \overrightarrow{D'}.e^{bl}.\cos(2\pi l)+\overrightarrow{X^*}(t) & \text{if } p\geq 0.5\end{cases} \quad (14)$$

Where $\overrightarrow{D'}=\left|\overrightarrow{X^*}(t)-\vec{X}(t)\right|$ indicates the distance of the ith whale to the prey (best solution obtained so far), bis a constant for defining the shape of the logarithmic spiral, lis a random number in [-1,1], and p is a random number in [0,1].

Note that humpback whales swim around the prey within a shrinking circle and along a spiral shaped path simultaneously. To model this simultaneous behavior, we assume that there is a probability of 50% to choose between either the shrinking encircling mechanism or the spiral model to update the position of whales.

In addition to the bubble-net method, the humpback whales search for prey randomly. The mathematical model of the search is as follows:

$$\vec{D}=\left|\vec{C}.\overrightarrow{X_{rand}}-\vec{X}\right| \quad (15)$$

$$\vec{X}(t+1)=\left|\overrightarrow{X_{rand}}-\vec{A}.\vec{X}\right| \quad (16)$$

Where $\overrightarrow{X_{rand}}$is a random position vector (a random whale) chosen from the current population [16].

5. TEACHEING LEARNING BASED OPTIMIZATION (TLBO)

TLBO is a population-based method and uses a population of solutions to proceed to the global solution. This algorithm describe the effect of influence of teachers on the output of learners in the class. Teachers and learners are the two vital component of this algorithm and it consists of two parts (teacher phase and learner phase).

In the teacher phase TLBO simulate the learning of the students through teacher, during this process teacher conveys knowledge among the learners and puts efforts to increase the mean results of the class. This mechanism is described by the following equation:

$$X_{new}=X-r(X_{best}-T_f.X_{mean}) \quad (17)$$

Where X_{new}, X, X_{mean}, X_{best} are respectively the new solution, current solution, the mean of solution, best soulution, $T_f$is a teaching factor that decides the value of mean to be changed, and r is a random number in the range [0, 1]. The value of T_f can be either 1 or 2, which is again a heuristic step and decided randomly with equal probability as T_f= round[1 + rand(0, 1){2 − 1}].

In the second phase (learners phase), TLBO mimics the learning of the student through the interactions among themselves. The students gains the knowledge by discussing and interacting with the other students consequently the learners will learn new information if other learner has more knowledge than him or her. This kind of process is modelled by the following equations:

$$X_{new}=X-r(X-X_p) \text{ if } f<f_p \quad (18)$$

$$X_{new}=X-r(X_p-X) \text{ if } f>f_p \quad (19)$$

Where X_{new}, X, X_p, are respectively the new solution of leaner, old solution of leaner, current solution of the partner. fandf$_p$ are the fiteness value of the lerner and the partner respectively. For more detail, consult [17].

6. OPTIMIZATION OF FUZZY-PI WITH GWO, WOA AND TLBO

Fig. 1. Represents the simulation diagram of Fuzzy-PI. The GWO, WOA and TLBO have been proposed to adjust scaling factors of membership functions (MFs) of Fuzzy system and the parameters of PI. 15 triangular-type MFs and 25 rules were used in each FLC (see Figs. 2-4).

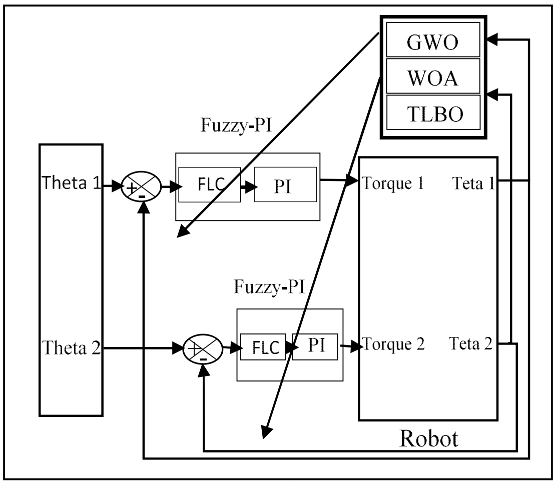

Fig. 1 Control diagram for robot planar.

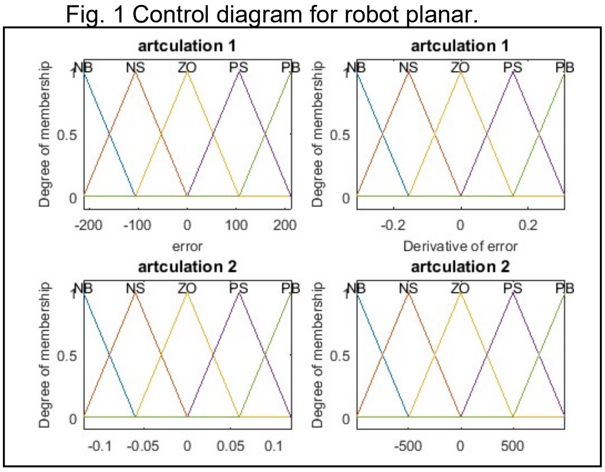

Fig. 2 Memberships functions of joint 1 and 2 after optimization by GWO.

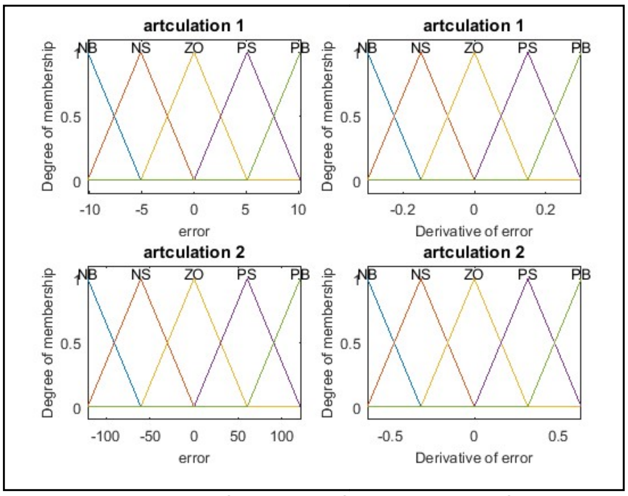

Fig. 3 Memberships functions of joint 1 and 2 after optimization by WOA.

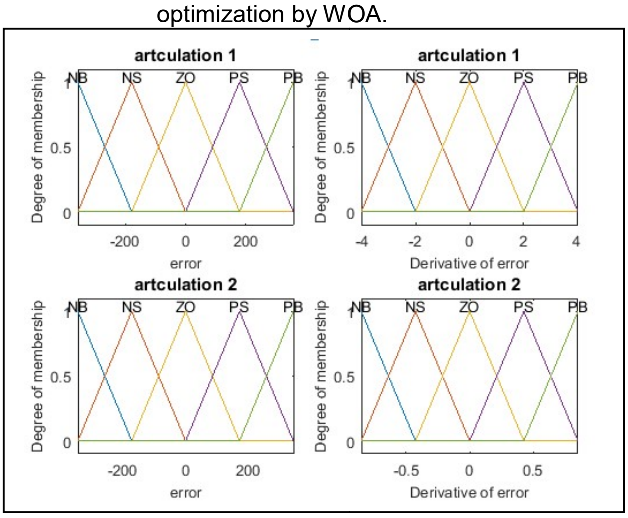

Fig. 4 Memberships functions of joint 1 and 2 after optimization by TLBO.

The optimization was performed under the following cost function of the absolute magnitude of the mean error (MAE):

$$MAE=\sum_{i=1}^{N}|e_1(i)|+|e_2(i)| \qquad (20)$$

Where $e_1(i)$ is the error of the trajectory of the ith sample for the first joint, $e_2(i)$is the error of the trajectory of the ith sample for the second joint, N is the number of samples.

In order to test the performances of the proposed algorithms we have engaged 50 agent of research and 60 iterations to tune the parameters of Fuzzy-PI.

7. RESULTS AND DISCUSSION

The purpose of the controller is to force the angles of the robot θ_1 and θ_2 to follow the desired trajectory defined by: $y_{d1,2}=0.3.\sin t$under the presence of a frictional force defined by : $F(q)=\begin{pmatrix}10.\dot{\theta}_1+3.\mathrm{sign}(\dot{\theta}_1)\\10.\dot{\theta}_2+3.\mathrm{sign}(\dot{\theta}_2)\end{pmatrix}$

The robot parameters are : m_1=1kg, m_2=1.5kg, l_1=1m, l_2=0.8m.

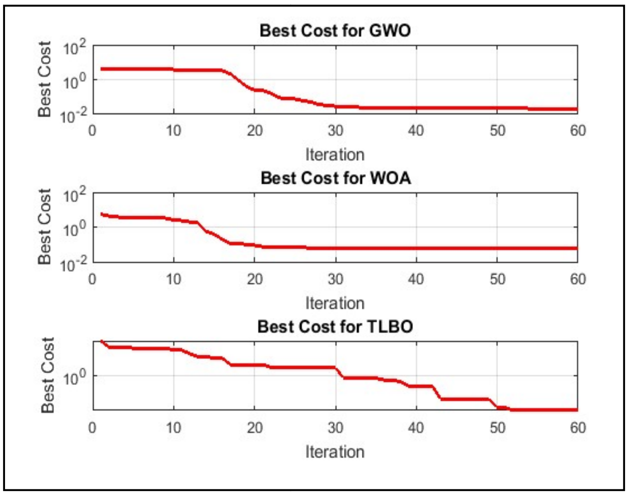

Fig. 5 Best fitness values obtained by GWO, WOA and TLBO.

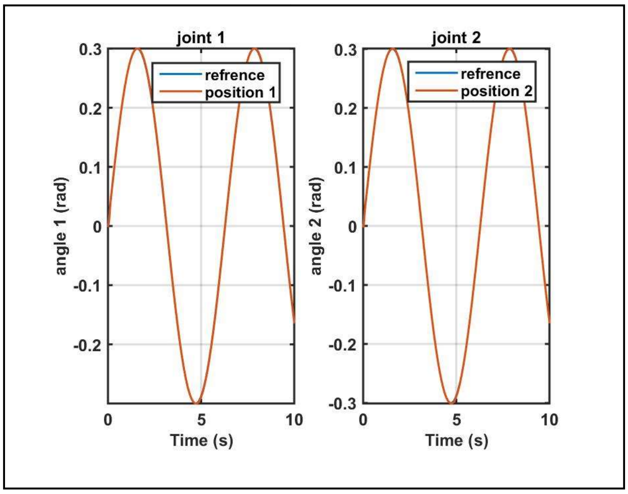

Fig. 6 Results obtained by GWO for angular positions.

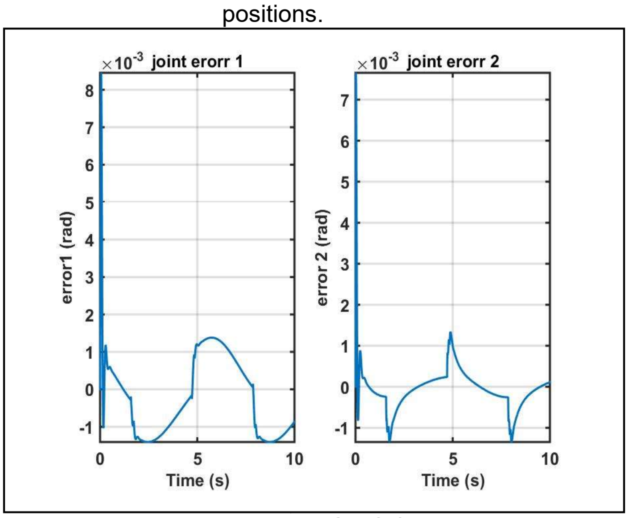

Fig. 7 Results obtained by GWO for Errors.

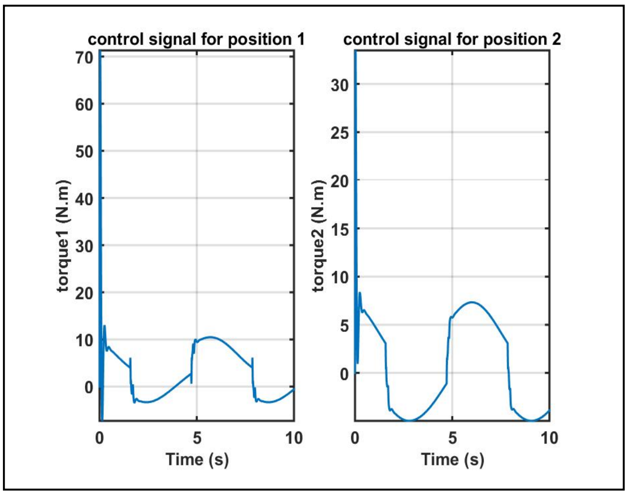

Fig. 8 Results obtained by GWO Control signals.

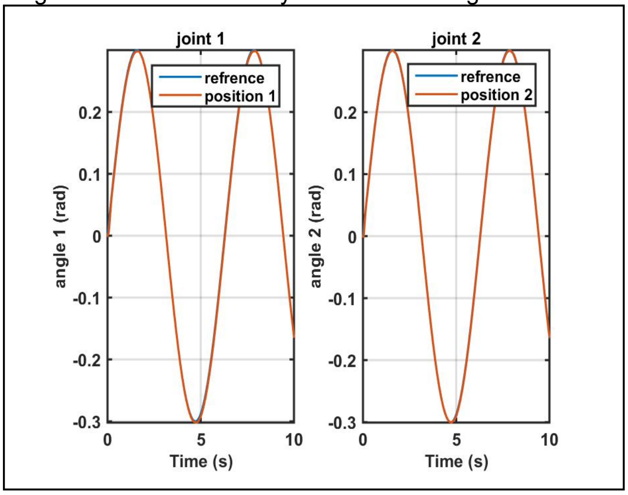

Fig. 9 Results obtained by WOA for angular positions.

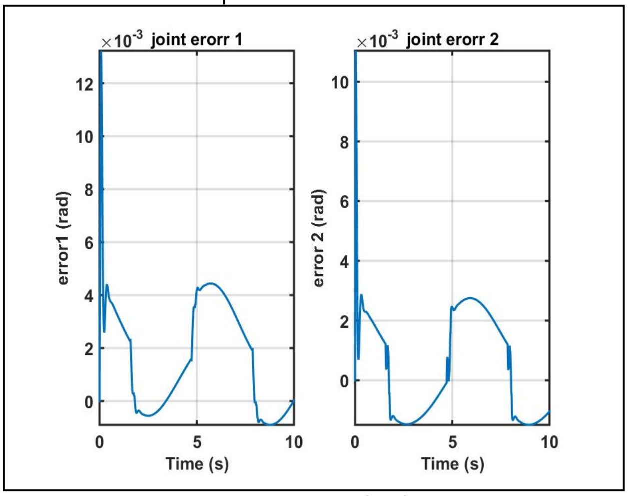

Fig. 10 Results obtained by WOA for Errors.

Fig. 5. Depicts the fitness value of GWO, WOA and TLBO, and the best value obtained by those algorithms are 0.018, 0.056 and 0.211, respectively.

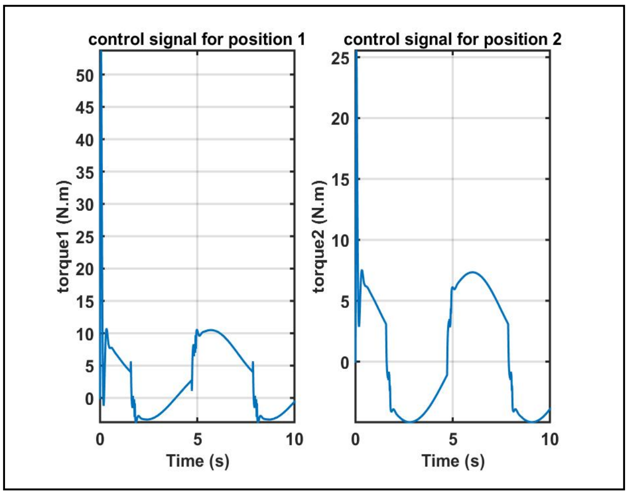

Fig. 11 Results obtained by WOA Control signals.

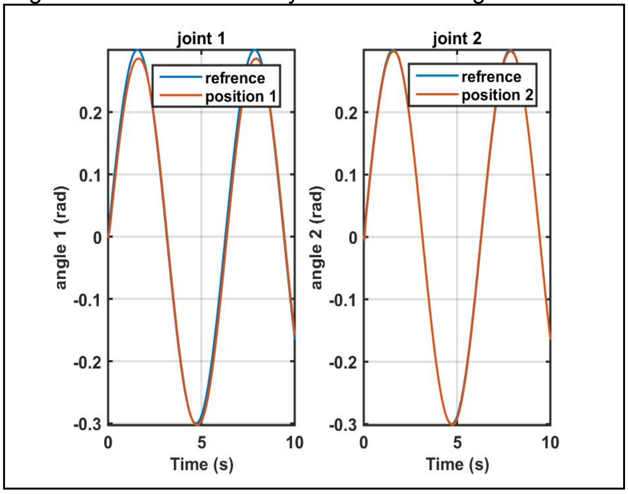

Fig. 12 Results obtained by TLBO for angular positions.

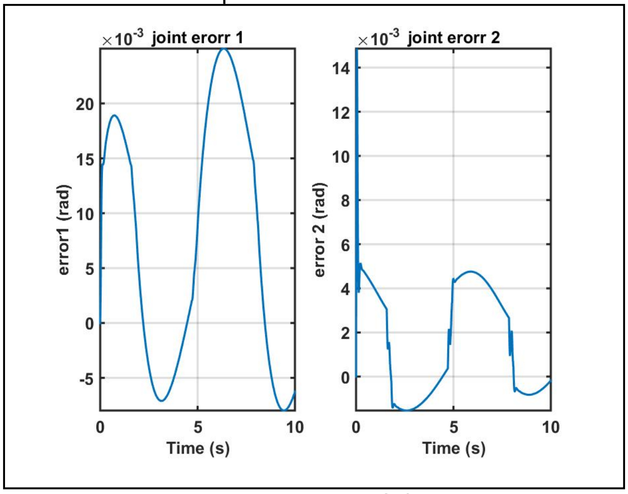

Fig. 13 Results obtained by TLBO for Errors.

Figs. 6-14. Highlights the positions of joint 1 and 2, errors and the control signals obtained by GWO, WOA and TLBO for initials conditions x_0=[0,0].

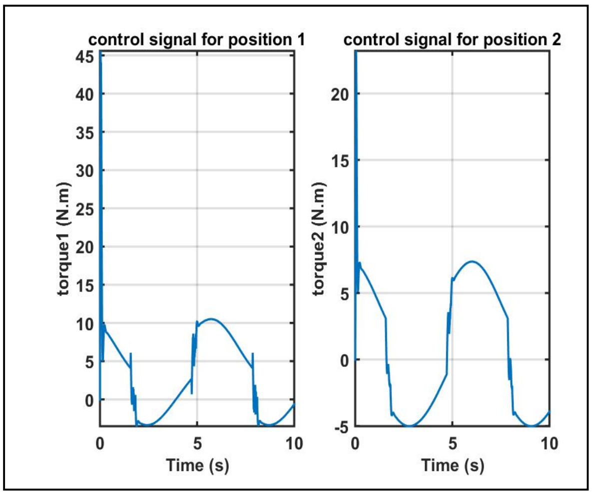

Fig. 14 Results obtained by TLBO for Control signals

It is clear from those results that the outputs of the system track perfectly and rapidly the desired inputs and represent an error of the order of 10^{-3} for GWO and WOA and 10^{-2} for TLBO. One can see that GWO perform better than other algorithms.

8. CONCLUSION

In this paper, we used Fuzzy-PI to Control a two-degree manipulator robot to follow a given trajectory. The fuzzy system that was used is of the Takagi-Sugano type. Three algorithms (GWO, WOA and TLBO) were chosen to adjust the fuzzy system's scaling factor and PI parameters. In order to examine the robustness of the controller we considered the frictional forces. The results of the simulation show the performance of the proposed controller to reproduce a desired trajectory. For further studies, we will test the performance of those algorithms with different cost functions.

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