

# Design and Evaluation of a GWO-Assisted Digital Controller for Robotic Manipulators

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**Abstract—** This paper presents a Self-Adaptive Grey Wolf Optimization-Based Fuzzy Sliding Mode Controller (SAGWO-FSMC) for the nonlinear PUMA 560 manipulator. Initially, fuzzy rules are derived from system characteristics. Then, SAGWO optimizes adaptive membership functions.

Comparative analysis with SMC, FSMC, and GWO-SMC shows that SAGWO-FSMC achieves enhanced accuracy and performance over existing control approaches.

**Index Terms—** PUMA 560, robotic manipulator, joint angles, fuzzy model, SAGWO, SMC, SAGWO-FSMC, Nonlinear Control.

## I. INTRODUCTION

Over the past few years, robots have become integral to industrial automation, carrying out precise tasks such as welding and painting. However, controlling robotic manipulators remains challenging due to unmodeled dynamics, friction, flexibility, and external disturbances.

Accurate trajectory tracking under varying payloads and uncertain parameters demands robust, adaptive control strategies.

Various control methods have been explored, including feedback linearization, decentralized control, model predictive control, adaptive control, and sliding mode control (SMC). Among these, SMC stands out for its robustness and simplicity in handling nonlinear, multi-input multi-output (MIMO) systems. It uses discontinuous control to guide system states along a predefined path, ensuring stability under uncertainties [01][02][3].

Despite its advantages, traditional SMC suffers from chattering—high-frequency oscillations that can harm actuators—and sensitivity to disturbances. To address this, researchers have integrated SMC with artificial intelligence techniques such as neural networks and fuzzy logic. Fuzzy logic, in particular, effectively reduces chattering and improves robustness.

This paper introduces a Self-Adaptive Grey Wolf Optimization-based Fuzzy Sliding Mode Controller (SAGWO-FSMC) for regulating joint angles in robotic manipulators, with a focus on the PUMA 560 arm. The method involves: (a) extracting system dynamics using a fuzzy inference system, and (b) optimizing controller parameters via the SAGWO algorithm. The effectiveness of the proposed controller is evaluated against conventional SMC, FSMC, and GWO-SMC approaches by analyzing joint angles, displacement, and mean displacement error, demonstrating superior tracking precision and robustness in the presence of uncertainties [4][5].

## II. RELATED WORKS

In 2008, Liu rongcheng, Dai wenzhan and Xu sen [1] introduced an adaptive grey fuzzy prediction controller utilizing an improved residual error model. Their approach effectively enhanced system prediction accuracy by integrating grey theory with fuzzy control. This study provides a strong foundation for hybrid intelligent control strategies in nonlinear dynamic systems.

In 2011 T. C. Kuo, Y. J. Huang, and B. W. Hong [2] proposed an adaptive sliding mode controller for robotic manipulators to improve tracking performance. The method addressed system uncertainties and nonlinearities, ensuring stable trajectory tracking. Their results demonstrated enhanced robustness and control accuracy compared to conventional approaches.

Earlier, in 2012, Lian [3] proposed the Enhanced Self-Organizing Fuzzy Sliding-Mode Controller (EASFSC), which used optimized fuzzy membership functions and rules to improve control stability. It was tested on a 2-link robot and showed fewer learning cycles, less tracking error, and increased actuator life.

In 2016, Vijay and Jena [4] combined SMC with an Adaptive Neuro-Fuzzy Inference System (ANFIS). Their method used PID-based sliding surfaces and Particle Swarm Optimization (PSO) for parameter tuning. The adaptive model handled disturbances well and improved real-time performance.

## III. DIGITAL CONTROLLER FOR 560 DOF ROBOTIC ARM

### A. Manipulator Model

The motion dynamics of a serial n link robotic manipulator can be formulated as in Eq. (1) Here  $u$  indicates the the joint displacement vector,  $\dot{u}$  represents joint velocity vector,  $\tau$  indicates actuator torque vector. The inertia properties are described by the symmetric positive definite matrix  $M(u)$ ,  $c(u, \dot{u})$  accounts for centripetal and Coriolis torques. The gravitational torque vector  $g(u)$  is derived as the gradient of the potential energy function  $U(u)$ .

$$M(u)\ddot{u} + c(u, \dot{u}) + g(u) = \tau \quad (1)$$

Assume that all joints of the robotic arm are connected through revolute joints. Let  $u_d$  represent the desired joint positions, while  $u_d$  is considered a twice-differentiable vector function. The actuator torques are then determined using a suitable control law, ensuring that Eq. (2) is satisfied to meet the control objective.

$$\lim_{t \rightarrow \infty} u(t) = u_d(t) \quad (2)$$

In this study “DOF PUMA-560 robot”, is considered, which consists of six revolute joints [14][16]. The kinematic and dynamic characteristics of the PUMA-560 manipulator are incorporated into the model. The arm utilizes commercially available DC servo motors. Consequently, the power and dimensional specifications of the PUMA-560 actuators are used to derive the electrical parameters of the motors for comparison [17].

### B. Proposed System Model

The Self-Adaptive Grey Wolf Optimization-based Fuzzy Sliding Mode Controller (SAGWO-FSMC) is designed to manage the uncertainties present in nonlinear systems. Unlike traditional control strategies, it avoids high-frequency switching actions. The Adaptive Fuzzy Sliding Mode Controller (AFSMC) enhances the precision of tracking the desired response and is widely adopted because it automatically tunes the key parameters of the Sliding Mode Controller (SMC) to minimize chattering. This increases system robustness and safeguards performance against parameter variations[6][7]. The overall configuration of the proposed control scheme is depicted in Figure 1.

### C. Design of Digital Controller

Design of sliding surface

The error dynamics can be expressed as,

$$c_i = a_i - b_i \quad (3)$$

Where  $i=1, 2, 3 \dots$

$$P(c_1, t) = P_a(a_1, t) - P(c_1 + a_1, t) \quad (4)$$

$$Y() = Y_a(t, a) - Y_b(t, b) \quad (5)$$

The equations of error dynamic are:

$$\dot{c}_1 = c_2 \quad (6)$$

$$\dot{c}_2 = c_3 \quad (7)$$

$$\dot{c}_3 = -xc_3 - c_2 + P(c_1, t) + Y(\cdot) - v \quad (8)$$

The standardized state-space representation of the error dynamics can be written as follows,

$$\dot{c}_1 = c_2 \quad (9)$$

$$\dot{c}_2 = c_3 \quad (10)$$

$$\dot{c}_3 = -xc_3 - c_2 + P(c_1, t) + Y(\cdot) - v = c_4 \quad (11)$$

$$\dot{c}_4 = -xc_4 - c_3 + P(c_1, t) + Y(\cdot) - \dot{v} \quad (12)$$

The sliding surface can be expressed as,

$$u = c_4 - c_4(0) + \int_0^t \sum_{k=1}^4 e_k c_k dt = 0 \quad (13)$$

Where  $c_4(0)$  denotes the initial state of  $c_4$ . Taking the derivative of the equation (13) can be written as,

$$\dot{c}_4 = -\sum_{k=1}^4 e_k c_k \quad (14)$$

The matrix below specifies the error states used in equation (14).

$$\dot{\underline{c}} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -e_1 & -e_2 & -e_3 & -e_4 \end{bmatrix} \underline{c} = \underline{M}\underline{e} \quad (15)$$

Where  $\dot{\underline{c}} = [\dot{c}_1 \quad \dot{c}_2 \quad \dot{c}_3 \quad \dot{c}_4]^T$ .  $c_j$  can be obtained by selecting the eigenvalues of  $\underline{M}$  corresponding to the characteristic polynomial

$$H(c) = \dot{c}_4 + \sum_{k=1}^4 e_k c_k \quad (16)$$

$H(c)$  is Hurwitz. The system's response speed is directly related to the chosen eigenvalues[8] [9][10].

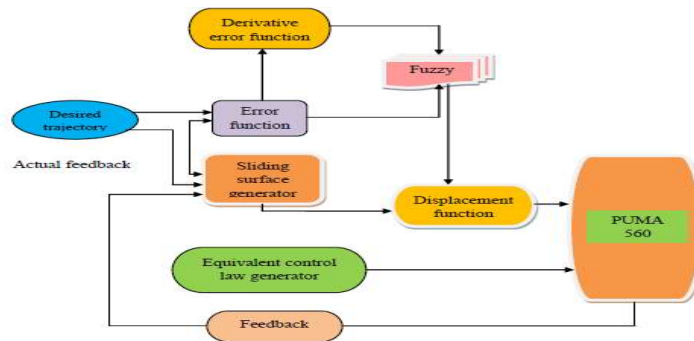


Fig 1. Architecture of adaptive fuzzy based SMC control scheme

#### D. Proposed Controlling Scheme

Figure 1 presents the architecture of the control scheme based on an adaptive fuzzy system. The simulation model is developed to control the joint angles of the PUMA 560 robotic arm [11] [12]. In this system, feedback from the actual PUMA 560 robot is provided to the control law generator. This feedback is compared with the desired trajectory to calculate the error (E) and its rate of change (DE). Based on these values, the sliding surface generator produces the activation signal. At the same time, the sliding mode controller constants are adaptively tuned through the fuzzy logic system enhanced by the meta-heuristic SAGWO algorithm [13][14]. This approach enables generation of the joint angles in a fixed format with reduced error.

The fuzzy system takes two inputs:  $E$  and  $DE$ . Based on their values, these inputs are divided into seven categories: Zero (Z), Positive Small (PS), Positive Medium (PM), Positive Big (PB), Negative Small (NS), Negative Medium (NM), and Negative Big (NB). The categories Z, PS, PM, NS, and NM are represented using triangular membership functions, while PB and NB are represented using trapezoidal membership functions [15].

Using these input classifications, the fuzzy system produces a set of rules that correspond to the sliding mode controller (SMC) constants. Thus, the resulting SMC constants are fully determined by the values of  $E$  and  $DE$ . Table I lists the rules or SMC constants derived by the fuzzy system [16][17].

Figure 2 shows the fuzzy membership functions. The triangular membership function is defined in Eq. (24), where  $r$  represents the lower limit, the upper limit is given by  $t$ ,  $x$  is the input value, and  $s$  is the desired value. In the same way, the trapezoidal membership function is described in Eq. (25), where  $r$  and  $u$  are the lower and upper support limits, and they satisfy certain range conditions. The range values of these membership functions used for the SMC are listed in Table II [18] [19].

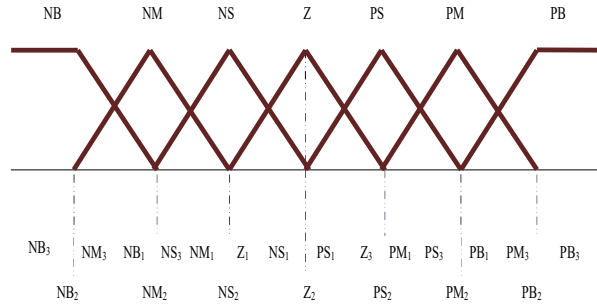


Fig.2 Demonstration of fuzzy membership function

$$\mu_1(x) = \begin{cases} 0, & x \leq r \\ \frac{x-r}{t-r}, & r < x \leq t \\ \frac{s-x}{s-t}, & t < x < s \\ 0, & x \geq s \end{cases} \quad (24)$$

$$\mu_2(x) = \begin{cases} 0, & (x < r) \text{ or } (x > s) \\ \frac{x-r}{u-r}, & r \leq x \leq u \\ 1, & u \leq x \leq v \\ \frac{s-x}{s-v}, & v \leq x \leq s \end{cases} \quad (25)$$

TABLE I. FUZZY SYSTEM-DERIVED RULES OR SMC PARAMETERS

| E/DE | NB | NM | NS | Z  | PS | PM | PB |
|------|----|----|----|----|----|----|----|
| NB   | NB | NB | NB | NB | NM | NS | Z  |
| NM   | NB | NB | NB | NM | NS | Z  | PS |
| NS   | NB | NB | NM | NS | Z  | PS | PM |
| Z    | NB | NM | NS | Z  | PS | PM | PB |
| PS   | NM | NS | Z  | PS | PM | PB | PB |
| PM   | NS | Z  | PS | PM | PB | PB | PB |
| PB   | Z  | PS | PM | PB | PB | PB | PB |

TABLE II. BOUNDS OF MEMBERSHIP FUNCTION FOR SMC

| X  | r               | T                                     | s               | u               | V               |
|----|-----------------|---------------------------------------|-----------------|-----------------|-----------------|
| NM | NB <sub>1</sub> | (NB <sub>2</sub> -NB <sub>1</sub> )/2 | NB <sub>2</sub> | -               | -               |
| NS | NM <sub>1</sub> | (NM <sub>2</sub> -NM <sub>1</sub> )/2 | NM <sub>2</sub> | -               | -               |
| PS | PM <sub>1</sub> | (PM <sub>2</sub> -PM <sub>1</sub> )/2 | PM <sub>2</sub> | -               | -               |
| PM | PB <sub>1</sub> | (PB <sub>2</sub> -PB <sub>1</sub> )/2 | PB <sub>2</sub> | -               | -               |
| NB | -               | -                                     | -               | NB <sub>1</sub> | NM <sub>2</sub> |
| PB | -               | -                                     | -               | PM <sub>2</sub> | PB <sub>1</sub> |

#### IV. RESULTS AND DISCUSSION

The proposed SAGWO-FSMC scheme, which integrates a fuzzy model with the SMC for controlling the robotic manipulator, was implemented in MATLAB. The corresponding simulink representation of the SAGWO-FSMC is presented in Fig. 3.

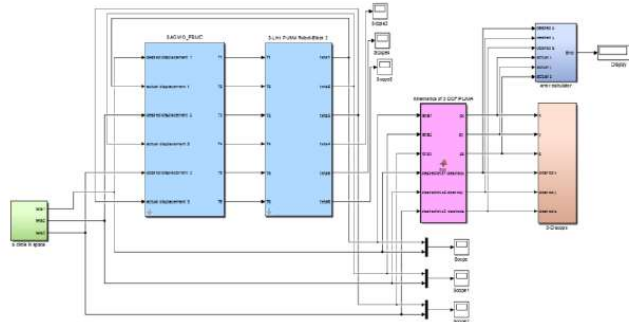


Fig.3 Simulink model of SAGWO-FSMC

This section explains the experimental results of the presented robotic controller. Figure 4 shows the convergence performance. As discussed earlier, the main goal of the experiment is to minimize the error between the actual response and the desired response (objective or cost function). The convergence characteristics of the traditional GWO-FSMC are compared with those of the proposed SAGWO-FSMC approach. The conventional GWO-FSMC starts at  $5 \times 10^{-3}$  and settles at  $3 \times 10^{-3}$ . In comparison, the presented SAGWO-FSMC also begins at  $5 \times 10^{-3}$  but converges to a smaller final value of  $3 \times 10^{-3}$ , showing better performance. The performance is also analyzed for three joint angles ( , and ) as shown in Fig. 5.

The analysis was carried out for 10 ms while observing the movement of the robot's joint angles. Figure 5(a) compares the actual joint angle with the desired one. The SAGWO-FSMC shows only a 0.5% deviation from the desired angle, whereas SMC shows 3%, and FSMC and GWO-FSMC show about 1.9% deviation. This shows that SAGWO-FSMC follows the desired joint angle more closely than the other controllers. Similarly, for the second joint angle in Fig. 5(b), SAGWO-FSMC deviates by 4.38%, which is better than the other methods. For the third joint angle shown in Fig. 5(c), SAGWO-FSMC again shows a deviation of 4.38% from the desired angle. Therefore, the proposed SAGWO-FSMC provides better control over the joint angles and closely matches the desired movement, proving to be superior to traditional SMC-based methods.

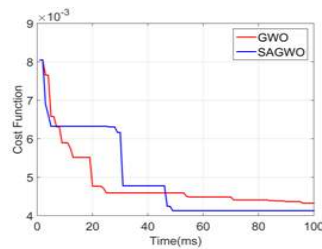


Fig. 4 Convergence analysis

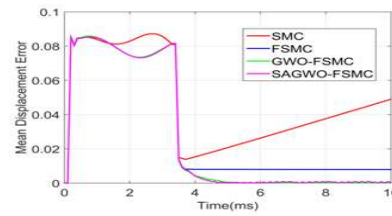


Fig. 7 Representation of average displacement error with time

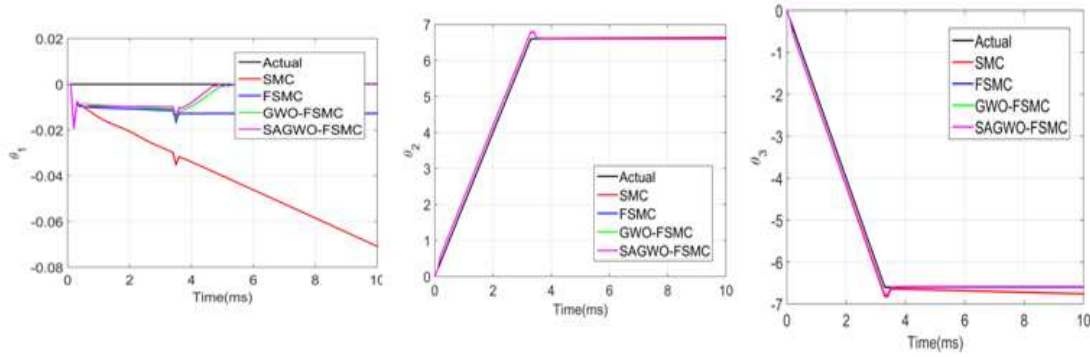


Fig. 5. Analysis of three joint angles with respect to time: (a) (b) and (c)

Figure 6 illustrates the time-varying behaviour of the three Cartesian displacements ( $x$ ,  $y$ , and  $z$ ). The effectiveness of the proposed SAGWO-FSMC is compared with the target reference model and also evaluated against traditional controllers such as SMC, FSMC, and GWO-FSMC. Ideally, the actual displacement trajectories should accurately follow the desired paths.

For the  $x$ -direction (Fig. 6(a)), SMC deviates by 9.52%, while FSMC and SAGWO-FSMC deviate only by 2.36% from the desired value. This indicates that SMC performs poorly, whereas the other two methods — especially SAGWO-FSMC — are much closer to the desired movement.

For the  $y$ -direction (Fig. 6(b)), SMC deviates by 1%, and FSMC, GWO-FSMC, and SAGWO-FSMC all show a very small deviation of 0.03%, indicating that all adaptive controllers perform well here.

In the case of  $z$ -direction (Fig. 6(c)), SAGWO-FSMC shows a deviation of 14.09% from the desired value, which is larger than other methods in this case.

Figure 7 depicts the variation of the average displacement error over time, representing the difference between the actual and desired trajectories. As observed, the mean displacement error for the SMC controller is relatively high at approximately 0.05, whereas it decreases to around 0.01 for the GWO-FSMC. With the proposed SAGWO-FSMC scheme, this error is further reduced to nearly zero, significantly outperforming the traditional methods. These results confirm the high effectiveness of the SAGWO-FSMC controller in minimizing tracking error.

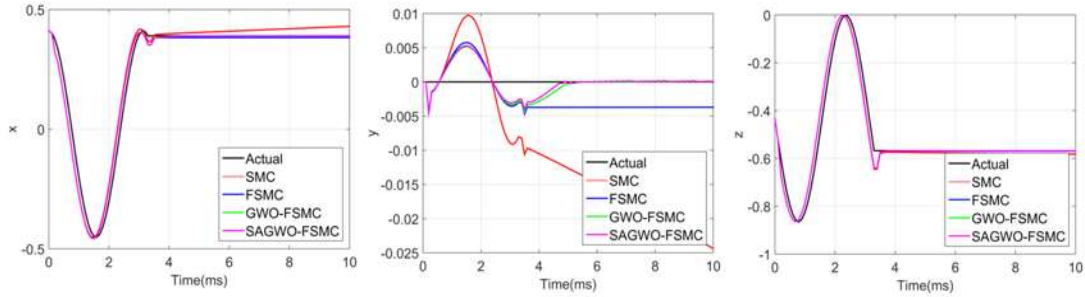


Fig. 6. Displacement analysis over time for (a) X, (b) Y, and (c) Z.

## V. CONCLUSIONS

This research seeks to optimize the performance of the PUMA 560 robotic arm. A Sliding Mode Controller (SMC) was used, but since it cannot always be directly applied to complex robotic systems, a fuzzy logic system was introduced. The experiment was done in two stages. In the first stage, data from the robot was collected and used to create fuzzy rules. In the second phase, the fuzzy rules were further improved using adaptive membership functions optimized by the Self-Adaptive Grey Wolf Optimization (SAGWO) algorithm. The resulting SAGWO-FSMC controller was evaluated against the reference model and compared with conventional controllers such as SMC, FSMC, and GWO-SMC. The findings indicate that the SAGWO-FSMC provides more precise control of the robot's joint angles and delivers superior performance compared to the other methods.

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