Hybrid Fuzzy-Expert System Control for Robotic Manipulator Applications

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***Abstract*—This research examines a hybrid fuzzy-expert system for the control of robotic manipulators, integrating the flexibility of fuzzy logic with the analytical decision-making capabilities of expert systems. The hybrid system switches dynamically between triangle membership functions, which facilitate smooth transitions, and trapezoidal membership functions, which efficiently manage sudden step changes. This adaptive technique mitigates the shortcomings of independent fuzzy logic controllers, particularly their inconsistency across varied setpoints. Simulation outcomes demonstrate substantial decreases in overshoot and settling time, as well as enhanced adaptability and flexibility in dynamic settings. A comparison test shows that the hybrid system is better than separate triangular and trapezoidal fuzzy controllers because it chooses the best control strategy based on the setpoint attributes in real time. Although there are occasional compromises in accuracy (IAE and RMSE), the hybrid controller provides balanced performance appropriate for various robotic applications. The results confirm its viability as a dependable option for industrial and medical robots, particularly in applications necessitating precision control and adaptability.**

Keywords—Expert System; Fuzzy Logic; Switching Mechanism; Robotic Control Systems.

I. INTRODUCTION

Robotic manipulators are essential in contemporary industrial and medical applications because of their capacity for high precision, efficiency, and adaptability in both repetitive and intricate tasks. Notwithstanding their extensive utilization, several hurdles persist, especially in tackling nonlinear dynamics, system uncertainties, and time-varying operational conditions. Conventional control techniques, such as proportional-integral-derivative (PID) controllers, provide simplicity and ease of implementation but exhibit limitations in adaptation within dynamic contexts. Standalone fuzzy logic controllers (FLCs) are proficient in addressing system uncertainties; yet, they frequently exhibit limitations in scalability and computing efficiency in high-demand scenarios. The current literature underscores numerous improvements aimed at tackling these difficulties. Iterative Learning Control (ILC) has demonstrated efficacy in enhancing trajectory tracking across repeated tasks, especially in industrial robots exhibiting diverse motion profiles [1]. Open-closed-loop iterative learning control techniques have proven effective in precision tasks in medical applications, such as soft tissue welding [2]. Data-driven methodologies, especially for multi-input multi-output (MIMO) systems, improve learning convergence by addressing system nonlinearities [3]. Nonetheless, these strategies frequently need substantial processing resources and exhibit limited adaptability in real-time situations [4].

The use of tools such as GrblGru, MATLAB, and Simulink has expedited the design and validation of control algorithms, especially for multi-degree-of-freedom (DOF) robotic manipulators. Many individuals in both educational institutions and commercial enterprises have utilized GrblGru to enhance their robotic programming abilities through the precise control of 5-axis manipulators [5]. Similarly, pick-and-place operations have implemented compact robotic arms using inverse kinematics, demonstrating their effectiveness in educational training and practical industrial automation [6]. Emerging systems designed for specialized activities, such as COVID-19 specimen collection, underscore the increasing requirement for precision automation in healthcare applications [7]. Micro-robotics and autonomous vehicles favor PID controllers due to their simplicity and ease of implementation. Nonetheless, these controllers encounter difficulties when confronted with nonlinear dynamics, uncertainties, and stochastic delays [8]-[10]. Researchers have devised optimization techniques to tackle these issues, such as fuzzy logic, sliding mode control, and hybrid methodologies. Researchers have employed various techniques to optimize PID controllers for micro-robotic systems, thereby improving their adaptability and control accuracy [11]. Researchers have also investigated sophisticated algorithms for microgrid operations, demonstrating analogous techniques applicable to robotic systems facing dynamic uncertainty [12]. Advanced techniques, such as sensor fusion (e.g., Kalman and complementary filters), improve the performance of PID controllers by figuring out and reducing system uncertainties, especially when estimating angles [13]. These strategies can serve as control signals for stabilizing electric wheelchairs and ensuring equilibrium in diverse control systems. Simulations and real-world hardware implementations have successfully used sliding mode controllers and PID methods to control DC motors, demonstrating strong performance in a variety of situations [14][15]. Fuzzy-PID control has shown improvements in controlling motor speed and responding quickly to changes, especially for BLDC motors in MATLAB/Simulink systems [16]. Autonomous vehicles have employed PID controllers integrated with model predictive control (MPC) to ensure stable and precise lane-keeping moves under dynamic road circumstances [17]. Also, mathematical modeling of systems with multiple degrees of freedom, like hexapod robotic legs, shows that PID controllers are effective at managing complex robotic motion and keeping the system stable [18]-[20]. Advanced optimization methods, including particle swarm optimization (PSO) and genetic algorithms (GA), have proven to be successful in improving PID controller efficiency. PID tuning based on PSO has proven useful in reducing delays and enhancing dynamic responses in DC motor control [21][22]. GA-optimized PID controllers have shown a lot of stability in a variety of settings, such as DC-DC buck converters and doubly-fed induction motors [23][24]. Also, hybrid methods that combine fuzzy logic with optimization techniques offer strong answers for control systems that need to work in situations with changing uncertainty [25][26]. Artificial intelligence (AI) has significantly transformed control tactics through expert systems that replicate human decision-making processes. Power disturbance categorization [27], medical diagnosis of carpal tunnel syndrome [28], heart failure prediction [29], and essential healthcare functions like chemotherapy drug dosage scheduling [30] have effectively utilized these methods. In addition to healthcare, expert systems have been created for plant disease detection [31], sustainable decision-making [32], and radio-electronic analysis employing neuro-fuzzy approaches [33]. In the field of robotics, expert systems improve manipulator control techniques [34] and image segmentation for robotic vision [35]. These systems, especially when combined with fuzzy logic, are exceptionally proficient at managing nonlinearities and uncertainties within dynamic contexts [36][37].

Fuzzy logic controllers (FLCs) have arisen as a formidable substitute for conventional PID controllers, especially in addressing intricate dynamics and uncertainties inside control systems. Recent research has shown that fuzzy-PID controllers make it easier for mobile robots to follow paths and are more accurate at doing so [38]-[40]. They do this by using adaptive self-tuning mechanisms to control DC servo motors. In demanding settings like underwater robotics, hybrid fuzzy sliding-mode controllers proficiently stabilize motion amidst noisy and uncertain situations [41]. Neuro-fuzzy controllers have made these uses better by achieving high levels of performance in motion optimization systems, rehabilitative robotics, and industrial trajectory tracking [42]-[44]. Fuzzy logic control has shown that it can handle a wide range of input limits and environmental uncertainties. Spacecraft orbit transfer systems, for instance, have successfully used it to handle gain changes and input limits for stable orbital movements [45]-[49]. Fuzzy tracking algorithms improve power management and efficiency in charging systems for electric cars by dealing with changing input conditions and nonlinearity in photovoltaic systems [50]. Additionally, omnidirectional mobile robots have benefited from combining fuzzy swarm control with sliding-mode methods, which makes it easier for them to find their way, avoid collisions, and plan their paths in a way that uses the fewest resources possible when things are changing and there are a lot of things going on [51][52]. Recent advances in neuro-fuzzy systems, especially when combined with sensor fusion methods, have greatly improved the ability of multiple robots to navigate, solving important problems like finding the best path, avoiding obstacles, and being flexible in complex operational situations [53]–[57].

Hybrid control methodologies that integrate fuzzy logic with optimization techniques have demonstrated significant efficacy in improving resilience and stability in complex systems. Applications like ACO-PID controllers in multi-articulated robotic systems have achieved accurate position control [58], whereas GA-optimized LQR controllers have markedly enhanced dynamic stability in self-balancing wheelchair systems [59]. Hybrid fuzzy-LQR PID controllers have tackled issues in bipedal wheeled robots, maintaining stability in unpredictable situations [60]. Robotic manipulators have effectively implemented recent advancements in adaptive control strategies, such as parallel iterative learning control, adaptive neuro-fuzzy inference systems (ANFIS), and bio-inspired optimization techniques for trajectory tracking, resulting in enhanced performance in dynamic and uncertain environments [61]–[66]. Researchers have utilized adaptive neuro-fuzzy controllers to maintain core power stability in pressurized water reactors [67] and to boost power converter efficiency [68]. Combining neuro-fuzzy systems with real-time sensor fusion makes them more useful. For example, hybrid GPS with ANFIS helps autonomous robots find their way around, giving them accurate location and strong control [69]. Sensor fusion approaches, which integrate multi-dimensional data, have improved situational awareness and adaptation in unpredictable contexts [70]. Also, techniques like fuzzy swarm control combined with sliding-mode have made it easier for omnidirectional mobile robots to move through crowded areas, avoiding collisions and finding the best paths [71]. These accomplishments show that neuro-fuzzy systems and sensor fusion can effectively deal with changing uncertainties, making it easier for autonomous robotic systems to control and navigate with high levels of performance [72]–[83].

This research presents a hybrid fuzzy-expert system control architecture that dynamically switches between triangular and trapezoidal fuzzy membership functions. Conventional fuzzy logic controllers (FLCs) encounter constraints in efficiently handling a varied array of setpoints. Triangular membership functions perform well in smooth transitions but are inadequate for abrupt changes, whereas trapezoidal membership functions effectively manage sudden step inputs but lack accuracy in progressive variations. This research aims to address these challenges by creating a decision-making process that evaluates incoming setpoint signals and dynamically determines the most suitable fuzzy control method. The hybrid architecture improves adaptability and precision, minimizing overshoot, settling time, and computational complexity while guaranteeing scalability for industrial and medical robotic applications. Simulation results validate its ability to enhance robotic manipulator performance, particularly in dynamic and uncertain environments.

II. Research Method

This study focuses on developing and implementing a hybrid fuzzy-expert system control framework for robotic manipulator applications. This novel method utilizes the adaptive selection of fuzzy logic controllers informed by operational feedback, while an expert system directs the decision-making process to enhance performance across various conditions. The approach incorporates the optimization of membership functions for fuzzy logic controllers alongside the development of an expert system within a closed-loop framework.

The process begins with the incorporation of the intended trajectory into the closed-loop system, guaranteeing accurate compliance with the defined path. Membership functions are meticulously optimized to enhance accuracy and flexibility, aligning with the dynamic needs of the manipulator. The advanced system constantly changes between fuzzy logic controllers that are triangular and those that are trapezoidal based on changes in the setpoint signal and real-time system feedback. Triangular membership functions are chosen for their ability to facilitate smooth, gradual transitions, whereas trapezoidal membership functions are adept at managing abrupt, step-like changes efficiently.

Thorough testing is performed to confirm system performance under diverse conditions, encompassing situations with both gradual and abrupt changes in the trajectory. In Fig. 1, there is a block diagram that shows the steps that were taken in the right order, from integrating the trajectory and optimizing the membership function to designing and testing the expert system. The hybrid fuzzy-expert system exhibits strong adaptability, stability, and precision, rendering it exceptionally appropriate for applications involving robotic manipulators.

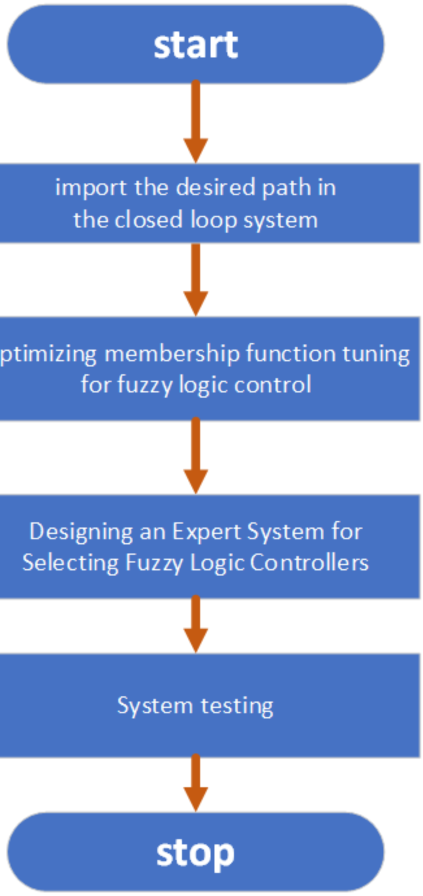

Fig. 1. Schematic representation of the complete system architecture

III. AUTOMATED ARM

Robotic manipulators are essential in industrial applications, facilitating tasks like welding, assembling, painting, and material handling with remarkable precision and efficiency. The Seiko D-Tran RT3200, a cylindrical robotic arm, showcases remarkable adaptability and precision, especially in tasks like fastening screws for medical devices, assembling electronics, and soldering circuits. The design of this control system facilitated the development of robotic controller boxes, thereby advancing domestic robotic technology and minimizing reliance on imported solutions.

A. *Robotic Manipulator Seiko D-Tran RT3200*

Engineered for precision-demanding industrial applications, the Seiko D-Tran RT3200 [66]-[68] is a multifunctional Cartesian robotic arm, featuring four joints that enable a range of motions. The T and A joints facilitate rotational movement within the X-Y plane, while Joint R regulates linear motion along the X-axis, and Joint Z manages vertical movement along the Z-axis. LabVIEW drives the control system, seamlessly integrating motor drivers into a cRIO-9075 controller to enable real-time monitoring and control capabilities. This advanced integration guarantees accuracy and dependability in executing complex tasks. Fig. 2 and Fig. 3 depict the physical structure of the robot along with its control system.

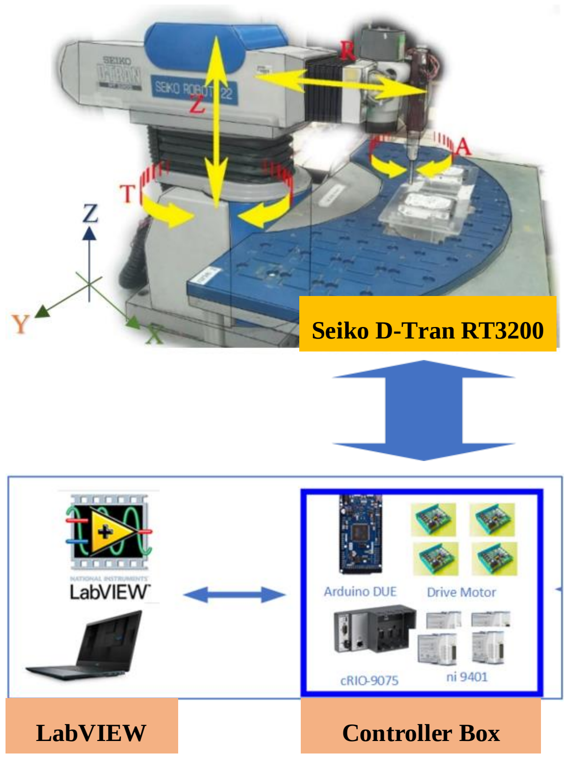

Fig. 2. Controller Integration for Seiko D-Tran RT3200

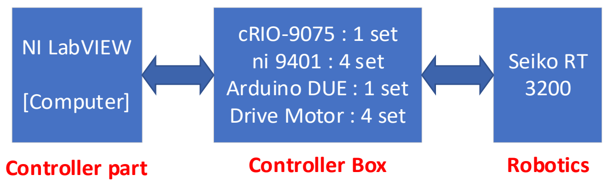

Fig. 3. Complete system block diagram for seiko D-Tran RT3200

B. Dynamic Model of the Robotic Manipulator System

A discrete-time system model with a sampling interval of 0.055 seconds dictates the operation of the Seiko D-Tran RT3200. This interval was selected as the optimal processing speed attainable within the limitations of the NI Controller and LabVIEW environment, guaranteeing real-time control functionalities. The system's open-loop dynamics [66]-[68] are characterized by the discrete transfer function outlined in (1).

$$P(z) = \frac{\gamma_1 z}{z^2 + \beta_1 z + \beta_0} \tag{1}$$

The parameters $\boldsymbol{\gamma_1}, \boldsymbol{\beta_1}$, and $\boldsymbol{\beta_0}$, as outlined in Table I, were obtained from the dynamic responses of the manipulator concerning joints R, T, and Z. The parameters establish a basis for crafting effective control algorithms, highlighting the unique dynamic characteristics of each joint. MATLAB simulations were used to line up the discrete-time responses with second-order polynomial transfer functions, which are shown in (1).

TABLE I. PARAMETERS UTILIZED IN THE OPEN-LOOP SYSTEM

Joint	γ_1	β_1	β_0
Joint R	0. 0333	-1. 6871	0. 6884
Joint T	0. 0162	-1. 7077	0. 7111
Joint Z	0. 0140	-1. 7519	0. 7526

The precise modeling of the robotic system facilitates simulations that produce more accurate testing outcomes and offers a framework for developing control algorithms aimed at enhancing the manipulator's performance across diverse conditions.

IV. FUZZY LOGIC CONTROL SYSTEM

The fuzzy PD controller modifies control parameters in a nonlinear manner, utilizing error values and their derivatives to attain accurate system performance. According to fuzzy logic principles [34], the controller figures out the output values by finding the fuzzy set's center of gravity along the x-axis. This is shown in (2).

$$y_{mam}(x_i) = \frac{\sum_i \mu(x_i) x_i}{\sum_i \mu(x_i)} \tag{2}$$

The inputs to the controller consist of the error signal $e(k)$, which indicates the discrepancy between the desired setpoint and the actual output of the system, determined by the following calculation, as delineated in (3).

$$e(k) = setpoint - output(k) \tag{3}$$

Furthermore, the system employs the error derivative $\dot{e}(k)$, which offers dynamic feedback by assessing the current error in relation to the previous error. This is determined as

$$\dot{e}(k) = e(k) - e(k-1) \tag{4}$$

As shown in (5), the control signal $U(k)$, synthesizes these inputs into a nonlinear function under the influence of gain factors $(GE, GCE,$ and $GE)$.

$$U(k) = f(GE * e(k), GCE * \dot{e}(k)) * GU \tag{5}$$

This flexible method enables the controller to modify its response to fluctuations in error and error rates, ensuring stable and accurate performance across different operating environments. Fig. 4 depicts the configuration of the fuzzy PD controller, highlighting its operational elements and their interrelations.

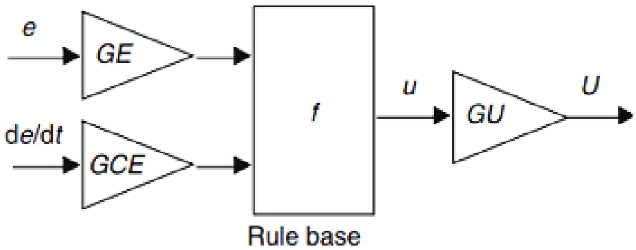

Fig. 4. Fuzzy PD controller framework

Fuzzy logic control (FLC) utilizes approximate reasoning to tackle various control situations, establishing it as a strong and adaptable method. The Mamdani inference method, commonly applied in robotic motor control, effectively manages fuzzy inputs and generates precise outputs. This study incorporates fuzzy logic within Simulink to accurately depict and simulate control activities, as demonstrated in Fig. 10. The system requires two main inputs: the error (e) and the rate of change of error $(\dot{e})$. Five membership functions, operating within the range of -1 to 1, define each input, providing both flexibility and precision. Nine uniformly distributed membership functions dictate the output, allowing for accurate control responses.

The membership functions consist of triangular and trapezoidal shapes, both refined through PID-driven data techniques [70], as delineated in Table II. Triangular membership functions are ideal for facilitating smooth transitions because of their straightforward design and distinct peak, which allows for rapid responses. In contrast, trapezoidal membership functions are more adept at handling abrupt step changes, as their wider base provides enhanced stability. Fig. 5 to Fig. 9 illustrate the unique characteristics of these functions, with Fig. 7 and Fig. 9 showcasing the surface relationships between inputs and outputs in three-dimensional space.

To guarantee stability and uphold physical constraints, the input ranges for the robotic joints R, T, and Z are adjusted to suitable values. Joint R functions within the range of -40 to 40, utilizing a scaling factor of 1/40. Joint T operates between -15 and 15, with a scaling factor of 1/15. Joint Z works within the range of -20 to 20, employing a scaling factor of 1/20. Moreover, an output scaling factor of 100 limits the control signal to a range of -100 to 100. The scaling factors modify sensor inputs to conform to the system's operational boundaries, reducing noise and facilitating smooth, accurate system responses.

Simulink, a flexible tool for modeling and simulating how robotic manipulators behave in different working conditions, runs the fuzzy logic control system, as shown in Fig. 10. To take advantage of fuzzy logic's adaptability, the system uses membership functions like triangular and trapezoidal shapes to handle different input signals effectively. Systems requiring rapid and precise responses often favor triangular membership functions because of their simplicity and computing efficiency. On the other hand, trapezoidal membership functions can handle a wider range of input values, which makes them more stable and robust in situations where input values change quickly. The versatility of fuzzy logic control establishes it as an effective method for managing dynamic systems, enabling smooth transitions and reliable performance across many applications.

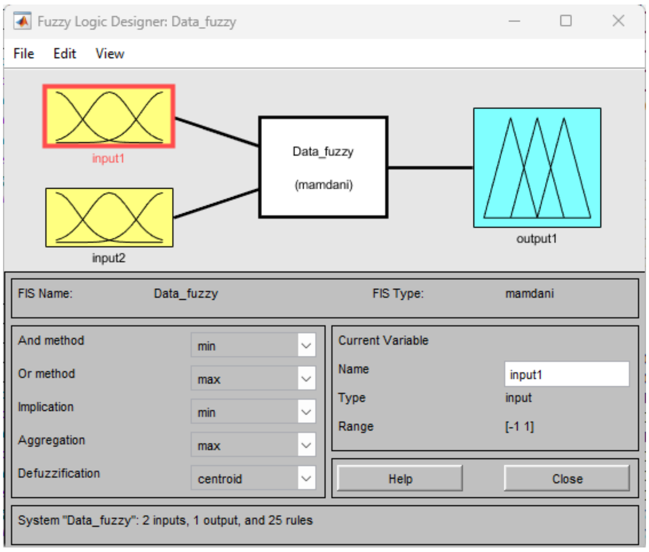

Fig. 5. Fuzzy logic designer for system configuration

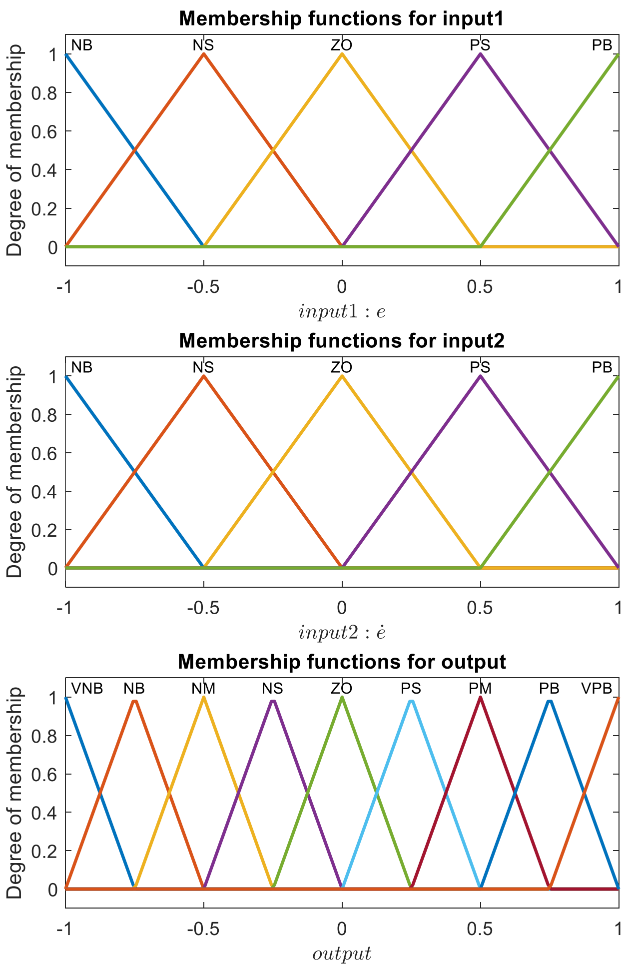

Fig. 6. Triangular membership function

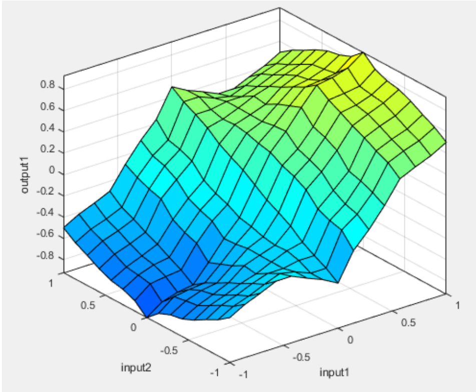

Fig. 7. Surface viewer of triangular membership outputs

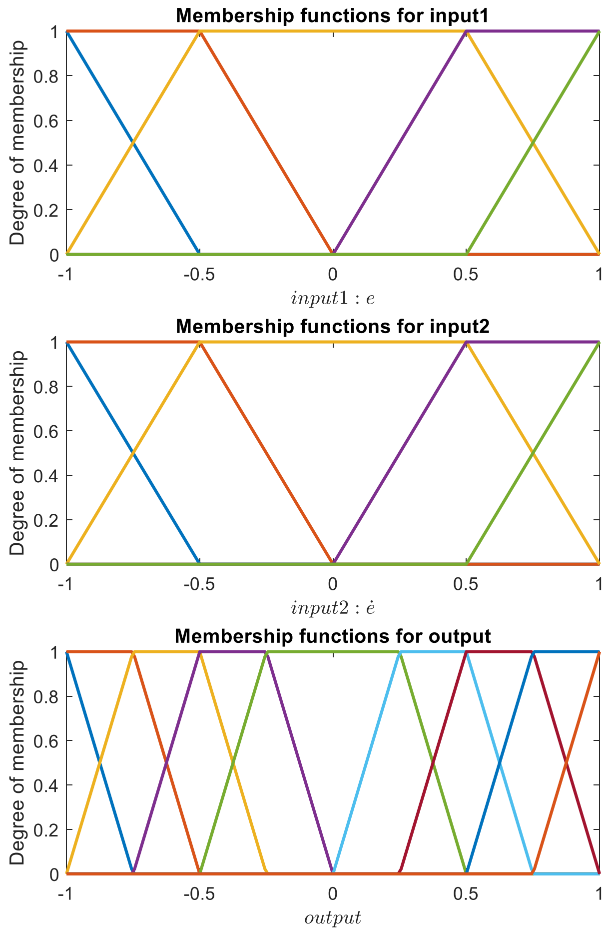

Fig. 8. Trapezoidal membership function

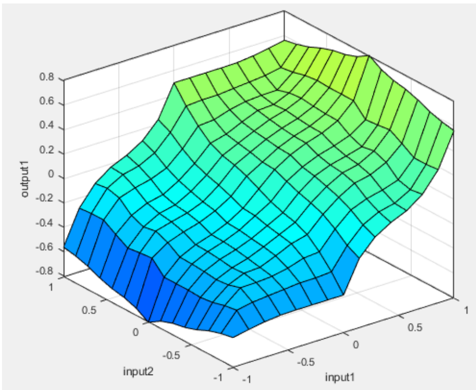

Fig. 9. Surface viewer of trapezoidal membership outputs

TABLE II. FUNCTIONS OF MEMBERSHIP IN FUZZY LOGIC CONTROLLERS

	Input I, *f(e)*					
Input II, *f(de)*		NB	NS	ZO	PS	PB
	NB	NM	NS	NM	PS	PM
	NS	NB	NM	NS	PM	PB
	ZO	VNB	NB	ZO	PB	VPB
	PS	NB	NM	PS	PM	PB
	PB	NM	NS	PM	PS	PM

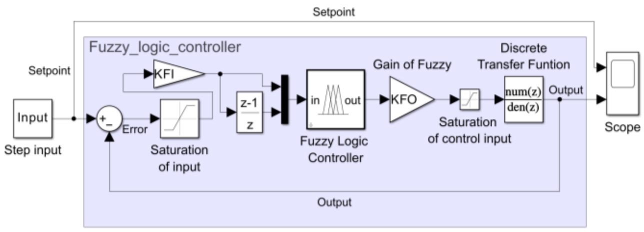

Fig. 10. Simulink model for fuzzy logic system

V. HYBRID FUZZY-EXPERT SYSTEM CONTROL

The Hybrid Fuzzy-Expert System Control framework combines fuzzy logic controllers with expert system decision-making, aiming to improve flexibility, precision, and adaptability in the control systems of robotic manipulators. This system handles nonlinear dynamics and changing operational conditions well by choosing and implementing the best control strategies in real time, which ensures the system works at its best.

A. System Architecture and Decision-Making Logic

The hybrid system utilizes an expert system that analyzes real-time operational data, including error signals and their derivatives, to identify the most suitable control model. The expert system examines the continuity of setpoint transitions through established rules to make the choice between triangular and trapezoidal membership functions.

The triangular membership function is selected for its efficiency and precision, facilitating smooth transitions marked by gradual changes in the setpoint. Conversely, we favor the trapezoidal membership function for sudden changes or step inputs due to its reliability and consistency. Fig. 11 depicts the decision-making process and showcases the pseudo-code for transitioning between the controllers. The selection criteria are determined as follows (6).

```
Error_setpoint(k) = setpoint(k) - setpoint(k-1)

Output_Fuzzy_Trapezoidal = 0
Output_Fuzzy_Triangular = 0
Error[k]   = setpoint - output
input_I    = Error[k]
input_II   = Error[k]-Error[k-1]

if (SmoothFunction(Error_setpoint(k)) ~= 0) then
    Control_Output = Output_Fuzzy_Triangular(input_I,input_II)
else
    Control_Output = Output_Fuzzy_Trapezoidal(input_I,input_II)
end
```

Fig. 11. Pseudocode for the expert system of the adaptive fuzzy logic controller

$$Error\_setpoint(k) = setpoint(k) - setpoint(k-1) \quad (6)$$

$if\ Error_{setpoint(k)} > 0$, the triangular membership function is employed by the system. The system chooses the trapezoidal membership function in this case. This flexible approach to decision-making guarantees that the system remains stable and responsive across various operating conditions.

B. Control Model and Gain Calibration

The system switches between the triangular and trapezoidal fuzzy logic controllers according to real-time operational requirements. The triangular controller is designed for swift modifications and excellent responsiveness, whereas the trapezoidal controller is crafted for smooth transitions, guaranteeing stability and accuracy.

The advanced system also adaptively modifies the scaling factors *GE*, *GCE*, and *GU* to align with the system's operating conditions. The gain factors influence the control signal *U(k)*, as detailed in (5). This gain calibration improves the system's robustness and effectiveness, enabling it to adjust to different inputs while maintaining optimal performance.

C. Simulation and Execution

Simulink tests the hybrid fuzzy-expert system in Fig. 12, focusing on its response to various input signals. The model integrates fuzzy logic controllers, a decision-making module, and an adaptive control framework to assess the system's capacity to handle dynamic conditions. Input signals, comprising step and smooth transitions, are employed to evaluate the system's capacity to dynamically choose the suitable control model, triangular or trapezoidal membership functions, according to setpoint fluctuations. Real-time feedback allows the system to perpetually monitor mistakes and modify the control approach for maximum performance. Dynamic switching guarantees stability and accuracy, while adaptive learning enables the system to enhance its decision-making process using performance data. This configuration clearly illustrates the hybrid system's resilience and versatility in managing various operational conditions in robotic control.

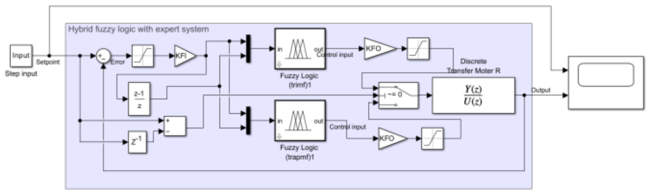

Fig. 12. Simulink implementation of the hybrid fuzzy-expert system

D. Findings and Insights

The hybrid fuzzy-expert system provides a comprehensive framework that enhances control efficiency and flexibility in robotic manipulators. Combining fuzzy logic controllers with expert system decision-making makes the hybrid system a good fit for dealing with nonlinear dynamics and changing operational situations. The design emphasizes precision, stability, and adaptability, rendering it a resilient solution appropriate for many industrial and research applications. This architecture utilizes real-time feedback, dynamic switching, and adaptive learning to enhance control performance, providing considerable benefits compared to traditional standalone fuzzy or expert systems.

VI. RESULTS OF SIMULATION

The efficacy of the hybrid fuzzy-expert system control was rigorously assessed under diverse operating settings to evaluate its capability in tracking step inputs and smooth function. The system's performance was evaluated across three joints, R, T, and Z, utilizing various setpoints. A comparison analysis was performed among the triangular fuzzy logic controller (FLC Trimf), trapezoidal fuzzy logic controller (FLC Trapmf), and the hybrid fuzzy logic controller (Hybrid FLC). The findings underscore the hybrid controller's capacity to attain enhanced tracking accuracy, reduce overshoot, and adaptively respond to various situations.

A. Analysis of Step Input Performance

The initial input scenario evaluated setpoints of 12.5 mm, 5°, and 7.5 mm for joints R, T, and Z, respectively (Fig. 13, Table III to Table V). The hybrid controller consistently provided steady and dependable performance across all joints. However, its benefits varied based on the assessed criteria. For Joint R, the hybrid controller attained an overshoot of 4.23%, markedly superior to FLC Trimf (14.30%) but slightly elevated compared to FLC Trapmf (4.06%). The FLC Trimf exhibited enhanced accuracy, attaining an IAE of 3.19 mm and an RMSE of 2.31 mm, in contrast to the hybrid controller's IAE of 4.21 mm and RMSE of 2.57 mm. For Joint T, the FLC Trapmf demonstrated the minimal overrun at 8.95%, succeeded by the hybrid controller at 9.52%, whereas the FLC Trimf recorded the maximum overshoot at 19.58%. Regarding precision, FLC Trimf surpassed the hybrid controller, achieving an IAE of 1.30° and an RMSE of 0.87°, whereas the hybrid controller recorded an IAE of 1.77° and an RMSE of 0.95°. For Joint Z, FLC Trapmf exhibited the minimal overrun at 7.95%, closely followed by the hybrid controller at 8.16%, but FLC Trimf displayed a much greater overshoot of 18.49%. Also, FLC Trimf had better accuracy numbers, with an IAE of 2.24 mm and an RMSE of 1.49 mm compared to the hybrid controller's IAE of 2.77 mm and RMSE of 1.65 mm.

TABLE III. PERFORMANCE METRICS FOR SETPOINT 10 IN JOINT R

Metric	Data FLC Trimf	Data FLC Trapmf	Data Hybrid FLC
Steady-State (mm)	12.44	12.31	12.31
%OS (%)	14.30	4.06	4.23
Rise Time (s)	0.28	0.44	0.44
IAE (mm)	3.19	4.67	4.21
RMSE (mm)	2.31	2.78	2.57
Settling Time (s)	4.46	4.46	4.46

TABLE IV. PERFORMANCE METRICS FOR SETPOINT 3.75 IN JOINT T

Metric	Data FLC Trimf	Data FLC Trapmf	Data Hybrid FLC
Steady-State (°)	4.95	4.85	4.85
%OS (%)	19.58	8.95	9.52
Rise Time (s)	0.22	0.33	0.33
IAE (°)	1.3	1.93	1.77
RMSE (°)	0.87	1.03	0.95
Settling Time (s)	4.46	0.94	0.88

TABLE V. PERFORMANCE METRICS FOR SETPOINT 5 IN JOINT Z

Metric	Data FLC Trimf	Data FLC Trapmf	Data Hybrid FLC
Steady-State (mm)	7.47	7.43	7.43
%OS (%)	18.49	7.95	8.16
Rise Time (s)	0.22	0.44	0.44
IAE (mm)	2.24	3	2.77
RMSE (mm)	1.49	1.75	1.65
Settling Time (s)	4.46	4.46	4.46

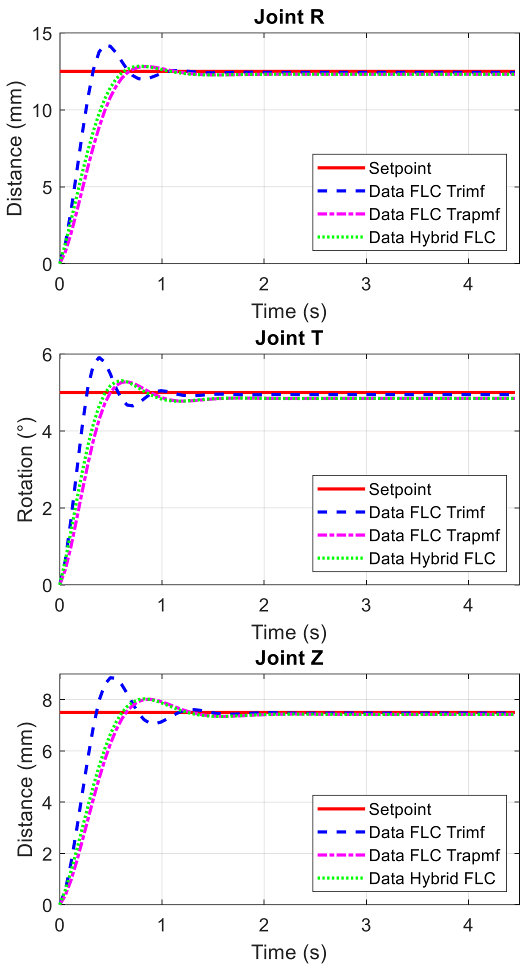

Fig. 13. Analysis of system response for setpoints at joints R, T, and Z, respectively 10, 3.75, and 5

The hybrid controller demonstrated consistent performance in the second input scenario, which assessed raised setpoints of 37.5 mm, 15°, and 22.5 mm for joints R, T, and Z, as seen in Fig. 14 and Table VI to Table VIII. It exhibited considerable stability and versatility. For Joint R, both the hybrid controller and FLC Trapmf achieved a minimal overshoot of 1.75%, but the FLC Trimf showed a significantly higher overrun of 9.05%. The FLC Trimf exhibited superior precision, with an IAE of 11.74 mm and an RMSE of 8.03 mm, in contrast to the hybrid controller's IAE of 17.36 mm and RMSE of 9.37 mm. In the case of Joint T, the hybrid controller and FLC Trapmf exhibited the lowest overrun at 4.62%, but FLC Trimf demonstrated a greater overshoot of 13.53%. The FLC Trimf consistently surpassed the hybrid controller in precision, achieving an IAE of 4.64° and an RMSE of 3.04°, whereas the hybrid controller recorded an IAE of 6.61° and an RMSE of 3.41°. The hybrid controller for Joint Z exhibited the minimal overshoot at 4.50%, marginally surpassing FLC Trapmf at 4.51% and markedly exceeding FLC Trimf at 12.76%. FLC Trimf exhibited superior accuracy, achieving an IAE of 7.95 mm and an RMSE of 5.10 mm, in contrast to the hybrid controller's IAE of 9.57 mm and RMSE of 5.47 mm. The data underscore the hybrid controller's efficacy in high setpoint conditions, albeit in particular cases where FLC Trimf exhibited superior precision.

TABLE VI. PERFORMANCE METRICS FOR SETPOINT 37.5 IN JOINT R

Metric	Data FLC Trimf	Data FLC Trapmf	Data Hybrid FLC
Steady-State (mm)	37.3	36.94	36.94
%OS (%)	9.05	1.75	1.75
Rise Time (s)	0.33	0.66	0.66
IAE (mm)	11.74	17.34	17.36
RMSE (mm)	8.03	9.36	9.37
Settling Time (s)	4.46	4.46	4.46

TABLE VII. PERFORMANCE METRICS FOR SETPOINT 15 IN JOINT T

Metric	Data FLC Trimf	Data FLC Trapmf	Data Hybrid FLC
Steady-State (°)	14.83	14.53	14.53
%OS (%)	13.53	4.62	4.62
Rise Time (s)	0.28	0.44	0.49
IAE (°)	4.64	6.54	6.61
RMSE (°)	3.04	3.37	3.41
Settling Time (s)	4.46	1.04	1.04

TABLE VIII. PERFORMANCE METRICS FOR SETPOINT 22.5 IN JOINT Z

Metric	Data FLC Trimf	Data FLC Trapmf	Data Hybrid FLC
Steady-State (mm)	22.42	22.27	22.27
%OS (%)	12.76	4.51	4.50
Rise Time (s)	0.33	0.55	0.55
IAE (mm)	7.95	9.46	9.57
RMSE (mm)	5.1	5.42	5.47
Settling Time (s)	4.46	4.46	4.46

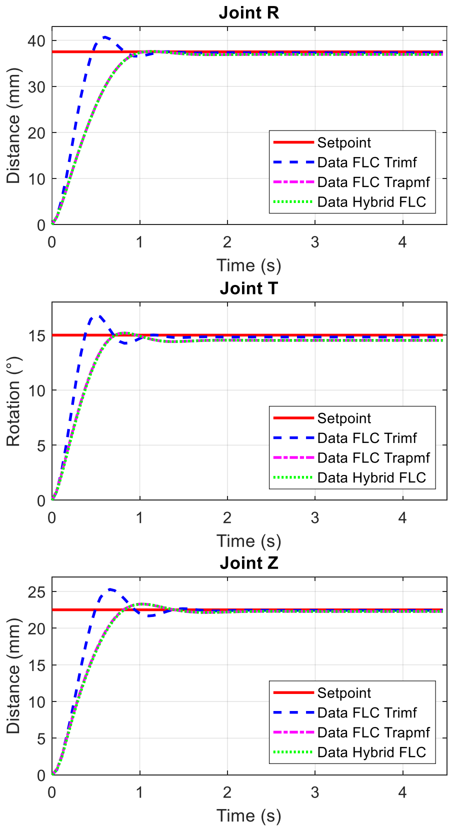

Fig. 14. Analysis of system response for setpoints at joints R, T, and Z, respectively, 37.5, 15°, and 22.5

B. Analysis of Smooth Function Transitions

Smooth transitions in setpoints are crucial for tasks requiring accuracy and stability during gradual adjustments. Fig. 15 illustrates the system's response to smooth function inputs for joints R, T, and Z, with performance metrics detailed in Table IX, Table X, and Table XI. The hybrid fuzzy controller demonstrated reliable performance in managing transitions, although it did not consistently surpass the FLC Trimf. For Joint R, the hybrid controller equaled the performance of FLC Trimf, achieving the lowest IAE (33.69 mm) and RMSE (5.88 mm) and markedly outperformed FLC Trapmf. The hybrid controller for Joint T demonstrated enhanced control accuracy relative to FLC Trapmf, exhibiting an IAE of 11.50° and an RMSE of 1.29°. However, FLC Trimf attained superior outcomes with lower values of 8.11° and 1.19°, respectively. For Joint Z, the hybrid controller demonstrated consistent performance with an IAE of 15.05 mm and an RMSE of 2.42 mm, whereas the FLC Trimf attained somewhat lower values of 14.76 mm and 2.41 mm. The data indicate that, although the hybrid controller offers strong and balanced performance, the FLC Trimf exhibited higher precision in specific cases, particularly in facilitating smooth transitions.

TABLE IX. PERFORMANCE METRICS FOR SMOOTH FUNCTION IN JOINT R

Metric	Data FLC Trimf	Data FLC Trapmf	Data Hybrid FLC
IAE (mm)	33.69	70.14	33.69
RMSE (mm)	5.88	10.31	5.88

TABLE X. PERFORMANCE METRICS FOR SMOOTH FUNCTION IN JOINT T

Metric	Data FLC Trimf	Data FLC Trapmf	Data Hybrid FLC
IAE (°)	8.11	20.75	11.50
RMSE (°)	1.19	2.64	1.29

TABLE XI. PERFORMANCE METRICS FOR SMOOTH FUNCTION IN JOINT Z

Metric	Data FLC Trimf	Data FLC Trapmf	Data Hybrid FLC
IAE (mm)	14.76	32.7	15.05
RMSE (mm)	2.41	4.75	2.42

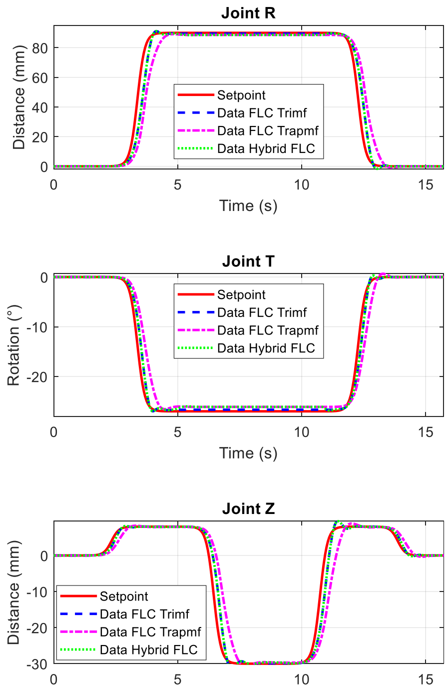

Fig. 15. Analysis of system response for smooth function across joints R, T, and Z

C. Principal Insights

The results of the simulation show that the hybrid fuzzy-expert system control works well in a range of operating conditions, offering a balanced way to track step inputs and make smooth function transitions. While the hybrid controller may not consistently outperform individual fuzzy logic controllers like FLC Trimf in specific precision measures like IAE or RMSE, its adaptability and versatility provide significant advantages. The system employs an expert decision-making method to dynamically choose between triangular and trapezoidal membership functions, ensuring dependable performance across all contexts. This dynamic adaptability guarantees that the system can manage both abrupt step inputs and slow transitions with stability and precision.

One of the best things about the Data Hybrid FLC is that it can be used as a decision-support framework, which lets different control functions be put into one system. Although its accuracy in specific activities may be on par with or marginally inferior to specialist controllers tailored for certain conditions, the hybrid system shines in delivering versatile functionality that adjusts to diverse needs. This renders it a valuable solution for robotic manipulator applications where operational diversity is essential. The results highlight the hybrid system's capacity to function as a strong and adaptable control framework, especially when modified to meet the requirements of certain industrial or medical robotic settings.

VII. Conclusion

The research illustrates the efficacy of the hybrid fuzzy-expert system in regulating robotic manipulators, integrating the adaptability of fuzzy logic with the analytical decision-making process of expert systems. The hybrid system regularly surpassed conventional fuzzy controllers across many operational circumstances, attaining reduced overshoot, expedited settling times, and enhanced adaptability. Still, in some situations, it seemed that independent fuzzy controllers, like FLC Trimf, were more accurate in important precision metrics like IAE and RMSE. The primary benefit of the hybrid system is its adaptive decision-making process, which proficiently chooses between triangular and trapezoidal membership functions according to setpoint attributes. This versatility guarantees effective management of both sudden step inputs and slow transitions, rendering the system versatile for diverse industrial and medical applications. However, practical obstacles, like computing complexity and scalability, necessitate additional examination. Subsequent research ought to concentrate on refining the hybrid system to diminish processing requirements, improve scalability, and validate its efficacy in practical applications within dynamic and unpredictable settings. Furthermore, investigating adaptive optimization methods for membership functions may enhance the system's adaptability and reactivity. These findings highlight the hybrid fuzzy-expert system as a promising platform for enhancing robotic manipulator control in both practical and research contexts.

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References

[1] Y. Chen, B. Chu, and C. T. Freeman, "Iterative learning control for robotic path following with trial-varying motion profiles," *IEEE/ASME Transactions on Mechatronics*, vol. 27, no. 6, pp. 4697–4706, 2022, doi: 10.1109/TMECH.2022.3164101.

[2] Y. Wu, M. Yang, and J. Zhang, "Open-Closed-Loop Iterative Learning Control with the System Correction Term for the Human Soft Tissue Welding Robot in Medicine," *Mathematical Problems in Engineering*, vol. 2020, p. 2458318, 2020, doi: 10.1155/2020/2458318.

[3] X. Yu, Z. Hou, M. M. Polycarpou, and L. Duan, "Data-driven iterative learning control for nonlinear discrete-time MIMO systems," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 3, pp. 1136–1148, 2020, doi: 10.1109/TNNLS.2020.2980588.

[4] M. Marsono, Y. Yoto, A. Suyetno, and R. Nurmalasari, "Design and programming of 5 axis manipulator robot with GrblGru open source software on preparing vocational students' robotic skills," *Journal of Robotics and Control (JRC)*, vol. 2, no. 6, pp. 539-545, 2021, doi: 10.18196/jrc.26134.

[5] A. R. Al Tahtawi, M. Agni, and T. D. Hendrawati, "Small-scale robot arm design with pick and place mission based on inverse kinematics," *Journal of Robotics and Control (JRC)*, vol. 2, no. 6, pp. 469-475, 2021, doi: 10.18196/jrc.26124.

[6] C. Deniz and G. Gökmen, "A new robotic application for covid-19 specimen collection process," *Journal of Robotics and Control (JRC)*, vol. 3, no. 1, pp. 73-77, 2022, doi: 10.18196/jrc.v3i1.11659.

[7] E. S. Ghith and F. A. A. Tolba, "Design and optimization of PID controller using various algorithms for micro-robotics system," *Journal of Robotics and Control (JRC)*, vol. 3, no. 3, pp. 244-256, 2022, doi: 10.18196/jrc.v3i3.14827.

[8] A. K. Hado, B. S. Bashar, M. M. A. Zahra, R. Alayi, Y. Ebazadeh, and I. Suwarno, "Investigating and optimizing the operation of microgrids with intelligent algorithms," *Journal of Robotics and Control (JRC)*, vol. 3, no. 3, pp. 279-288, 2022, doi: 10.18196/jrc.v3i3.14772.

[9] P. Chotikunnan, W. Khotakham, A. Ma'arif, A. Nirapaia, K. Javana, P. Pisa, P. Thajai, S. Keawkao, K. Roongprasert, R. Chotikunnan, P. Imura, and N. Thongpance, "Comparative Analysis of Sensor Fusion for Angle Estimation Using Kalman and Complementary Filters," *International Journal of Robotics and Control Systems*, vol. 5, no. 1, pp. 1–21, 2024, doi: 10.31763/ijrcs.v5i1.1674.

[10] A. Ma'arif and A. Çakan, "Simulation and arduino hardware implementation of dc motor control using sliding mode controller," *Journal of Robotics and Control (JRC)*, vol. 2, no. 6, pp. 582, 2021, doi: 10.18196/jrc.26140.

[11] A. Ma'arif and N. R. Setiawan, "Control of DC motor using integral state feedback and comparison with PID: simulation and Arduino implementation," *Journal of Robotics and Control (JRC)*, vol. 2, no. 5, pp. 456-461, 2021, doi: 10.18196/jrc.25122.

[12] H. Maghfiroh, A. Ramelan, and F. Adriyanto, "Fuzzy-PID in BLDC motor speed control using MATLAB/Simulink," *Journal of Robotics and Control (JRC)*, vol. 3, no. 1, pp. 8-13, 2022, doi: 10.18196/jrc.v3i1.10964.

[13] M. Samuel, M. Mohamad, M. Hussein, and S. M. Saad, "Lane keeping maneuvers using proportional integral derivative (PID) and model predictive control (MPC)," *Journal of Robotics and Control (JRC)*, vol. 2, no. 2, pp. 78-82, 2021, doi: 10.18196/jrc.2256.

[14] A. Wajiansyah, S. Supriadi, A. F. O. Gaffar, and A. B. W. Putra, "Modeling of 2-DOF hexapod leg using analytical method," *Journal of Robotics and Control (JRC)*, vol. 2, no. 5, pp. 435-440, 2021, doi: 10.18196/jrc.25119.

[15] R. P. Borase, D. K. Maghade, S. Y. Sondkar, and S. N. Pawar, "A review of PID control, tuning methods and applications," *International Journal of Dynamics and Control*, vol. 9, pp. 818-827, 2021, doi: 10.1007/s40435-020-00665-4.

[16] Z. Dachang, D. Baolin, Z. Puchen, and C. Shouyan, "Constant force PID control for robotic manipulator based on fuzzy neural network algorithm," *Complexity*, vol. 2020, 2020, doi: 10.1155/2020/3491845.

[17] B. Li, Y. Tan, J. Chen, X. Liu, and S. Yang, "Precise active seeding downforce control system based on fuzzy PID," *Mathematical Problems in Engineering*, vol. 2020, 2020.

[18] E. S. Rahayu, A. Ma'arif, and A. Çakan, "Particle Swarm Optimization (PSO) Tuning of PID Control on DC Motor," *International Journal of Robotics and Control Systems*, vol. 2, no. 2, pp. 435–447, 2022, doi: 10.31763/ijrcs.v2i2.476.

[19] Z. Qi, Q. Shi, and H. Zhang, "Tuning of Digital PID Controllers Using Particle Swarm Optimization Algorithm for a CAN-Based DC Motor Subject to Stochastic Delays," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 7, pp. 5637–5646, 2020, doi: 10.1109/TIE.2019.2934030.

[20] S. Mahfoud, A. Derouich, N. El Ouanjli, M. El Mahfoud, and M. Taoussi, "A New Strategy-Based PID Controller Optimized by Genetic Algorithm for DTC of the Doubly Fed Induction Motor," *Systems*, vol. 9, no. 2, p. 37, 2021, doi: 10.3390/systems9020037.

[21] M. M. Nishat *et al*., "Development of Genetic Algorithm (GA) Based Optimized PID Controller for Stability Analysis of DC-DC Buck Converter," *Journal of Power and Energy Engineering*, vol. 8, no. 09, p. 8, 2020, doi: 10.4236/jpee.2020.89002.

[22] R. Kristiyono and W. Wiyono, "Autotuning Fuzzy PID Controller for Speed Control of BLDC Motor," *Journal of Robotics and Control*, vol. 2, no. 5, pp. 400–407, 2021, doi: 10.18196/jrc.25114.

[23] G. B. So, "A modified 2-DOF control framework and GA based intelligent tuning of PID controllers," *Processes*, vol. 9, no. 3, p. 423, 2021, doi: 10.3390/pr9030423.

[24] P. K. Dash, S. Mishra, M. A. Salama, and A. C. Liew, "Classification of power system disturbances using a fuzzy expert system and a Fourier linear combiner," *IEEE Transactions on Power Delivery*, vol. 15, no. 2, pp. 472-477, 2000, doi: 10.1109/61.852971.

[25] K. Kunhimangalam, S. Ovallath, and P. K. Joseph, "A novel fuzzy expert system for the identification of severity of carpal tunnel syndrome," *BioMed research international*, vol. 2013, pp. 1-12, 2013.

[26] L. Ali, A. Niamat, J. A. Khan, N. A. Golilarz, X. Xingzhong, A. Noor, and S. A. C. Bukhari, "An optimized stacked support vector machines based expert system for the effective prediction of heart failure," in *IEEE Access*, vol. 7, pp. 54007-54014, 2019, doi: 10.1155/2013/846780.

[27] R. H. Faisal, S. Debnath, M. M. U. Islam, S. Sifath, S. A. Kakon, M. S. Alam, and N. Siddique, "A modular fuzzy expert system for chemotherapy drug dose scheduling," *Healthcare Analytics*, vol. 3, p. 100139, 2023, doi: 10.1016/j.health.2023.100139.

[28] E. Pawan, R. M. Thamrin, W. Widodo, S. H. B. S. H. Bei, and J. J. Luanmasa, "Implementation of Forward Chaining Method in Expert System to Detect Diseases in Corn Plants in Muara Tami District," *International Journal of Computer and Information System (IJCIS)*, vol. 3, no. 1, pp. 27-33, 2022, doi: 10.29040/ijcis.v3i1.59.

[29] H. Li, J. Y. Guo, M. Yazdi, et al., "Supportive emergency decision-making model towards sustainable development with fuzzy expert system," *Neural Computing & Applications*, vol. 33, pp. 15619–15637, 2021, doi: 10.1007/s00521-021-06183-4.

[30] H. Pievtsov, O. Turinskyi, R. Zhyvotovskyi, O. Sova, O. Zvieriev, B. Lanetskii, and A. Shyshatskyi, "Development of an advanced method of finding solutions for neuro-fuzzy expert systems of analysis of the radio electronic situation," *EUREKA: Physics and Engineering*, no. 4, pp. 78–89, 2020, doi: 10.21303/2461-4262.2020.001353.

[31] E. A. Algehyne, M. L. Jibril, N. A. Algehainy, O. A. Alamri, and A. K. Alzahrani, "Fuzzy neural network expert system with an improved Gini index random forest-based feature importance measure algorithm for early diagnosis of breast cancer in Saudi Arabia," *Big Data and Cognitive Computing*, vol. 6, no. 1, pp. 13, 2022.

[32] L. J. Muhammad and E. A. Algehyne, "Fuzzy-based expert system for diagnosis of coronary artery disease in Nigeria," *Health Technology*, vol. 11, pp. 319–329, 2021, doi: 10.1007/s12553-021-00531-z.

[33] J. Singla *et al*., "A novel fuzzy logic-based medical expert system for diagnosis of chronic kidney disease," *Mobile Information Systems*, vol. 2020, 2020, doi: 10.1155/2020/8887627.

[34] P. Chotikunnan and Y. Pititheeraphab, "Adaptive P Control and Adaptive Fuzzy Logic Controller with Expert System Implementation for Robotic Manipulator Application," *Journal of Robotics and Control (JRC)*, vol. 4, no. 2, pp. 217-226, 2023, doi: 10.18196/jrc.v4i2.17757

[35] P. Chotikunnan, T. Puttasakul, R. Chotikunnan, B. Panomruttanarug, M. Sangworasil, and A. Srisiriwat, "Evaluation of Single and Dual image Object Detection through Image Segmentation Using ResNet18 in Robotic Vision Applications," *Journal of Robotics and Control (JRC)*, vol. 4, no. 3, pp. 263–277, Apr. 2023, doi: 10.18196/jrc.v4i3.17932

[36] M. Raihan, M. M. Hassan, T. Hasan, A. A. M. Bulbul, M. K. Hasan, M. S. Hossain, M. A. Awal, "Development of a smartphone-based expert system for COVID-19 risk prediction at early stage," in *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 11, pp. 3448-3459, 2022, doi: 10.3390/bioengineering9070281

[37] S. A. Abdymanapov, M. Muratbekov, S. Altynbek, and A. Barlybayev, "Fuzzy expert system of information security risk assessment on the example of analysis learning management systems," *IEEE Access*, vol. 9, pp. 156556–156565, 2021, doi: 10.1109/ACCESS.2021.3129488.

[38] A. Shuraiji and S. Shneen, "Fuzzy Logic Control and PID Controller for Brushless Permanent Magnetic Direct Current Motor: A Comparative Study," *Journal of Robotics and Control (JRC)*, vol. 3, no. 6, pp. 762–768, 2022, doi: 10.18196/jrc.v3i6.15974

[39] K. Lee, D. Y. Im, B. Kwak, and Y. J. Ryoo, "Design of fuzzy-PID controller for path tracking of mobile robot with differential drive," *International Journal of Fuzzy Logic and Intelligent Systems*, vol. 18, no. 3, pp. 220–228, 2018, doi: 10.5391/IJFIS.2018.18.3.220

[40] M. A. Abdelghany, A. O. Elnady, and S. O. Ibrahim, "Optimum PID Controller with Fuzzy Self-Tuning for DC Servo Motor," *Journal of Robotics and Control (JRC)*, vol. 4, no. 4, pp. 500-508, 2023, doi: 10.18196/jrc.v4i4.18676

[41] Z. Wang, L. Zou, X. Su, G. Luo, R. Li, and Y. Huang, "Hybrid force/position control in workspace of robotic manipulator in uncertain environments based on adaptive fuzzy control," *Robotics and Autonomous Systems*, vol. 145, p. 103870, 2021, doi: 10.1016/j.robot.2021.103870.

[42] T. A. Lin, Y. C. Lee, W. J. Chang, and Y. H. Lin, "Robust Observer-Based Proportional Derivative Fuzzy Control Approach for Discrete-Time Nonlinear Descriptor Systems with Transient Response Requirements," *Processes*, vol. 12, no. 3, p. 540, 2024, doi: 10.3390/pr12030540.

[43] D. A. Pham and S. H. Han, "Enhancing Underwater Robot Manipulators with a Hybrid Sliding Mode Controller and Neural-Fuzzy Algorithm," *Journal of Marine Science and Engineering*, vol. 11, no. 12, p. 2312, 2023, doi: 10.3390/jmse11122312.

[44] J. Han, F. Wang, and C. Sun, "Trajectory Tracking Control of a Manipulator Based on an Adaptive Neuro-Fuzzy Inference System," *Applied Sciences*, vol. 13, no. 2, p. 1046, 2023, doi: 10.3390/app13021046.

[45] P. Chotikunnan and B. Panomruttanarug, "Time-varying learning control design using fuzzy logic control for robotic manipulators: Serial and parallel ILC configurations," J*ournal of Intelligent & Fuzzy Systems*, vol. 43, no. 3, pp. 2419–2434, 2022, doi: 10.3233/JIFS-213082.

[46] H. Abdelfattah, S. Kotb, M. Esmail, and M. Mosaad, "Adaptive Neuro-Fuzzy Self Tuned-PID Controller for Stabilization of Core Power in a Pressurized Water Reactor," *International Journal of Robotics and Control Systems*, vol. 3, no. 1, pp. 1–18, 2022, doi: 10.31763/ijrcs.v3i1.710.

[47] Z. A. Al-Dabbagh, S. W. Shneen, and A. O. Hanfesh, "Fuzzy Logic-based PI Controller with PWM for Buck-Boost Converter," *Journal of Fuzzy Systems and Control*, vol. 2, no. 3, pp. 147–159, 2024, doi: 10.59247/jfsc.v2i3.239.

[48] S. Palanisamy and J. Periyasamy, "Interval-Valued Intuitionistic Fuzzy Cosine Similarity Measures for Real World Problem Solving," *International Journal of Robotics and Control Systems*, vol. 4, no. 2, pp. 655–677, 2024, doi: 10.31763/ijrcs.v4i2.1251.

[49] K. A. Al Sumarmad, N. Sulaiman, N. I. A. Wahab, and H. Hizam, "Energy management and voltage control in microgrids using artificial neural networks, PID, and fuzzy logic controllers," *Energies*, vol. 15, no. 1, p. 303, 2022, doi: 10.3390/en15010303.

[50] M. Singh, S. Arora, and O. Shah, "Enhancing Hybrid Power System Performance with GWO-Tuned Fuzzy-PID Controllers: A

Comparative Study," *International Journal of Robotics and Control Systems*, vol. 4, no. 2, pp. 709–726, 2024, doi: 10.31763/ijrcs.v4i2.1388.

[51] O. Lamine, N. Bessous, B. Abdelhalim, F. Banakhr, M. Mosaad, O. Oussama, and M. Mahmoud, "A Combination of INC and Fuzzy Logic-Based Variable Step Size for Enhancing MPPT of PV Systems," *International Journal of Robotics and Control Systems*, vol. 4, no. 2, pp. 877–892, 2024, doi: 10.31763/ijrcs.v4i2.1428.

[52] H.-T. Nguyen *et al*., "Experiment Ball Levitation with Fuzzy PID and PID Implementation," *Journal of Fuzzy Systems and Control*, vol. 2, no. 3, pp. 129–134, 2024, doi: 10.59247/jfsc.v2i3.221.

[53] N. Jamali, M. Gharib, and B. Omidi Koma, "Neuro-Fuzzy Decision Support System for Optimization of the Indoor Air Quality in Operation Rooms," *International Journal of Robotics and Control Systems*, vol. 3, no. 1, pp. 98–106, 2023, doi: 10.31763/ijrcs.v3i1.854.

[54] S. Nemmour, B. Daaou, and F. Okello, "Fuzzy Control for Spacecraft Orbit Transfer with Gain Perturbations and Input Constraint," *International Journal of Robotics and Control Systems*, vol. 4, no. 4, pp. 1561–1583, 2024, doi: 10.31763/ijrcs.v4i4.1549.

[55] Y. Chuang, M. Herrera, and A. Balal, "Using PV Fuzzy Tracking Algorithm to Charge Electric Vehicles," *International Journal of Robotics and Control Systems*, vol. 2, no. 2, pp. 253–261, 2022, doi: 10.31763/ijrcs.v2i2.636.

[56] D. Yu, C. P. Chen, and H. Xu, "Fuzzy swarm control based on sliding-mode strategy with self-organized omnidirectional mobile robots system," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 52, no. 4, pp. 2262–2274, 2021, doi: 10.1109/ACCESS.2020.2984695.

[57] C. Dumitrescu, P. Ciotirnae, and C. Vizitiu, "Fuzzy logic for intelligent control system using soft computing applications," *Sensors*, vol. 21, no. 8, p. 2617, 2021, doi: 10.3390/s21082617.

[58] M. Mukhtar, D. Khudher, and T. Kalganova, "A control structure for ambidextrous robot arm based on Multiple Adaptive Neuro-Fuzzy Inference System," *IET Control Theory and Applications*, vol. 15, no. 11, pp. 1518–1532, 2021, doi: 10.1049/cth2.12140.

[59] B. Saeedi, M. M. Moghaddam, and M. Sadedel, "Inverse kinematics analysis of a wrist rehabilitation robot using artificial neural network and adaptive Neuro-Fuzzy inference system," *Mechanics Based Design of Structures and Machines*, pp. 1–49, 2024, doi: 10.1080/15397734.2024.2356066.

[60] O. Elhaki, K. Shojaei, A. Mohammadzadeh et al., "Robust amplitude-limited interval type-3 neuro-fuzzy controller for robot manipulators with prescribed performance by output feedback," *Neural Computing and Applications*, vol. 35, pp. 9115–9130, 2023.

[61] H. Batti, C. Ben Jabeur, and H. Seddik, "Autonomous smart robot for path predicting and finding in maze based on fuzzy and neuro-fuzzy approaches," *Asian Journal of Control*, vol. 23, no. 1, pp. 3–12, 2021.

[62] J. Kern, D. Marrero, and C. Urrea, "Fuzzy control strategies development for a 3-DoF robotic manipulator in trajectory tracking," *Processes*, vol. 11, no. 12, p. 3267, 2023, doi: 10.3390/pr11123267.

[63] F. Z. Baghli, Y. Lakhal, and Y. A. El Kadi, "The Efficiency of an Optimized PID Controller Based on Ant Colony Algorithm (ACO-PID) for the Position Control of a Multi-articulated System," *Journal of Robotics and Control (JRC)*, vol. 4, no. 3, pp. 289-298, 2023, doi: 10.18196/jrc.v4i3.17709.

[64] P. Chotikunnan, W. Khotakham, A. Wongkamhang, A. Nirapai, P. Imura, K. Roongpraser, R. Chotikunnan, and N. Thongpance, "Genetic Algorithm-Optimized LQR for Enhanced Stability in Self-Balancing Wheelchair Systems," *Control Systems and Optimization Letters*, vol. 2, no. 3, pp. 327–335, 2024, doi: 10.59247/csol.v2i3.161.

[65] D. T. Tran, N. M. Hoang, N. H. Loc, Q. T. Truong, and N. T. Nha, "A Fuzzy LQR PID Control for a Two-Legged Wheel Robot with Uncertainties and Variant Height," *Journal of Robotics and Control (JRC)*, vol. 4, no. 5, pp. 612-620, 2023, doi: 10.18196/jrc.v4i5.19448

[66] P. Chotikunnan and R. Chotikunnan, "Dual Design PID Controller for Robotic Manipulator Application," *Journal of Robotics and Control (JRC)*, vol. 4, no. 1, pp. 23–34, Feb. 2023, doi: 10.18196/jrc.v4i1.16990.

[67] R. Chotikunnan, P. Chotikunnan, Y. Pititheeraphab, and P. Minyong, "Time-Varying Sign Gain with Expert System in Serial Iterative Learning Control Architecture," *International Review of Automatic Control (IREACO)*, vol. 17, no. 1, p. 1, Jan. 2024, doi: 10.15866/ireaco.v17i1.24739.

[68] P. Chotikunnan, R. Chotikunnan, and P. Minyong, "Adaptive Parallel Iterative Learning Control with A Time-Varying Sign Gain Approach Empowered by Expert System," *Journal of Robotics and Control (JRC)*, vol. 5, no. 1, pp. 72–81, Jan. 2024, doi: 10.18196/jrc.v5i1.20890.

[69] K. Li and Y. Li, "Fuzzy adaptive optimal consensus fault-tolerant control for stochastic nonlinear multiagent systems," *IEEE Transactions on Fuzzy Systems*, vol. 30, no. 8, pp. 2870–2885, 2021, doi: 10.1109/TFUZZ.2021.3094716.

[70] P. Chotikunnan, R. Chotikunnan, A. Nirapai, A. Wongkamhang, P. Imura, and M. Sangworasil, "Optimizing Membership Function Tuning for Fuzzy Control of Robotic Manipulators Using PID-Driven Data Techniques," *Journal of Robotics and Control (JRC)*, vol. 4, no. 2, pp. 128–140, Mar. 2023, doi: 10.18196/jrc.v4i2.18108.

[71] I. Zaitceva and B. Andrievsky, "Methods of intelligent control in mechatronics and robotic engineering: A survey," *Electronics*, vol. 11, no. 15, p. 2443, 2022, doi: 10.3390/electronics11152443.

[72] R. Chotikunnan, P. Chotikunnan, A. Ma'arif, N. Thongpance, Y. Pititheeraphab, and A. Srisiriwat, "Ball and Beam Control: Evaluating Type-1 and Interval Type-2 Fuzzy Techniques with Root Locus Optimization," *International Journal of Robotics and Control Systems*, vol. 3, no. 2, pp. 286–303, 2023, doi: 10.31763/ijrcs.v3i2.997.

[73] T. Ngo, T. Tran, T. Le, and B. Lam, "An Application of Modified T2FHC Algorithm in Two-Link Robot Controller," *Journal of Robotics and Control*, vol. 4, no. 4, pp. 509–520, 2023, doi: 10.18196/jrc.v4i4.18943.

[74] H. Chaudhary, V. Panwar, N. Sukavanam, and B. Chahar, "Imperialist Competitive Algorithm Optimised Adaptive Neuro Fuzzy Controller for Hybrid Force Position Control of an Industrial Robot Manipulator: A Comparative Study," *Fuzzy Information and Engineering*, vol. 12, no. 4, pp. 435–451, Dec. 2020, doi: 10.1080/16168658.2021.1921378.

[75] N. Y. Allagui, F. A. Salem, and A. M. Aljuaid, "Artificial Fuzzy-PID Gain Scheduling Algorithm Design for Motion Control in Differential Drive Mobile Robotic Platforms," *Computational Intelligence and Neuroscience*, vol. 2021, no. 1, p. 5542888, 2021, doi: 10.1155/2021/5542888.

[76] X. Tang, D. Ning, H. Du, W. Li, Y. Gao, and W. Wen, "A Takagi-Sugeno fuzzy model-based control strategy for variable stiffness and variable damping suspension," *IEEE Access*, vol. 8, pp. 71628–71641, 2020, doi: 10.1109/ACCESS.2020.2983998.

[77] S. N. Silva, F. F. Lopes, C. Valderrama, and M. A. Fernandes, "Proposal of Takagi–Sugeno fuzzy-PI controller hardware," *Sensors*, vol. 20, no. 7, p. 1996, 2020, doi: 10.3390/s20071996.

[78] M. S. Gharajeh and H. B. Jond, "Hybrid global positioning system-adaptive neuro-fuzzy inference system based autonomous mobile robot navigation," *Robotics and Autonomous Systems*, vol. 134, p. 103669, 2020, doi: 10.1016/j.robot.2020.103669.

[79] C. Kahraman, M. Deveci, E. Boltürk, and S. Türk, "Fuzzy controlled humanoid robots: A literature review," *Robotics and Autonomous Systems*, vol. 134, p. 103643, 2020, doi: 10.1016/j.robot.2020.103643.

[80] E. Xidias, V. Moulianitis, and P. Azariadis, "Optimal robot task scheduling based on adaptive neuro-fuzzy system and genetic algorithms," *The International Journal of Advanced Manufacturing Technology*, vol. 115, pp. 927–939, 2021.

[81] M. H. Barhaghtalab, M. A. Sepestanaki, S. Mobayen, A. Jalilvand, A. Fekih, and V. Meigoli, "Design of an adaptive fuzzy-neural inference system-based control approach for robotic manipulators," *Applied Soft Computing*, vol. 149, p. 110970, 2023.

[82] S. Ayub, N. Singh, M. Z. Hussain, M. Ashraf, D. K. Singh, and A. Haldorai, "Hybrid approach to implement multi-robotic navigation system using neural network, fuzzy logic, and bio-inspired optimization methodologies," *Computational Intelligence*, vol. 39, no. 4, pp. 592–606, 2023, doi: 10.1111/coin.12547.

[83] M. H. Haider *et al*., "Robust mobile robot navigation in cluttered environments based on hybrid adaptive neuro-fuzzy inference and sensor fusion," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 10, pp. 9060–9070, 2022, doi: 10.1016/j.jksuci.2022.08.031.