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Selection and Evaluation of Robotic Arm based Conveyor Belts (RACBs) Motions: NARMA(L2)-FO(ANFIS)PD-I based Jaya Optimization Algorithm

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ABSTRACT

Scholars worldwide have shown considerable interest in the industrial sector, mainly due to its abundant resources, which have facilitated the adoption of conveyor belt technologies like Robotic Arm-Based Conveyor Belts (RACBs). RACBs rely on four primary movements: (i.e., joint, motor, gear, and sensor), which can have a significant impact on the overall motions and motion estimation. To optimize these operations, an assistive algorithm has been developed to enhance the effectiveness of motion by achieving favorable gains. However, each motion requires specific criteria for Fractional Order Proportional Integral Derivative (FOPID) controller gains, leading to various challenges. These challenges include the existence of multiple evaluation and selection criteria, the significance of these criteria for each motion, the trade-off between criterion performance for each motion, and determining critical values for the criteria. As a result, the evaluation and selection of the Proposed Jaya optimization algorithm for RACB motion control becomes a complex problem. To address these challenges, this study proposes a novel integrated approach for selecting the Jaya optimization algorithm in different RACB motions. The approach incorporates two evaluation methods: the Nonlinear Autoregressive Moving Average with exogenous inputs (NARMA-L2) controller for Neural Network (NN) weighting of the criteria, and the Adaptive Neuro-Fuzzy Inference System (ANFIS) for selecting the Jaya optimization algorithm. The approach consists of three main phases: RACB-based NARMA-L2 Controller Identification and Pre-processing, Development of NARMA-L2 controller-based NARMA(L2)-FO(ANFIS)PD-I, and Evaluation of FOPID criteria based on JOA. The proposed approach is evaluated based on NARMA(L2)-FO(ANFIS)PD-I that given 0.4074, 0.3156, 0.3724, 0.1898 and 0.2135 for K_p_joint, K_i_motor, K_d_sensor, λ_gear, and μ_N respectively, which verifies the soundness of the proposed methodology.

1. Introduction

Recently, robotic arm has been taking a lot of interest in most countries and others worldwide. Thus, exploring surround current world and understanding what insights sort can be reached by their interest have become important [1]. The importance is not surprises that given the facts that most of Robotics Arms with Conveyor Belts (RACBs) are composed of joints, sensors, gears, and motors, were importance for move objects from a point to another, manufacturing facility, and production line purposes. From a viewpoint, the robotic arm performs a precise movement toward the behavior of end-effectors, in turn can benefit most areas in research and Scientifics community, via producing insights and valuable knowledges in areas of sciences [2]. However, manages several types of objects within the suction cups, grippers, and specialized tools. Parts of object detections were the races between countries for develop objects manipulator technology that can detect and locate various tasks on the conveyor belts, pick, and place operations. RACBs were first invented in 1954 at an robots and industrialization by George Devol in the Italy [3]. RACBs are widely found in various industries, such as packaging, warehousing, logistics, and manufacturing [4]. These arms have become popular for productivity, efficiency, and accuracy by automatic repetitive tasks are fundamentals for reducing, manual labor and production process to the improvement [5]. The RACBs integration had impact on various industries, leading to increased productivity, flexibility, and efficiency in industrials processes. The key aspects towards the industries, and technologies such, efficiency within automation, flexibility, safety, advancement in kinematics, innovations issues, industry adoption 4.0, and connectivity. In addition, the technologies development in the industries which vary depends on the application, and specific sector, the RACBs integration has been significant process improvement and a significant automation driver in various industries.

RACBs operate by relying on four major points, known as equipment, including joints, sensors, gears, and motors [6]. In addition to the fundamental equipment involved, RACBs movements depend on the control coordination called "Dimensions on Equipment Control" [7]. However, in RACBs equipment, significant attention should be paid to the available gains that could adverse effect the RACBs movements and the motion estimation. Some scientists prioritize joints and sensors while others depend on gears and motors and four main motions on the essential of their needs, i.e., whether for going down to handle the cube or climbing for moving the cube to the other sides [8]. Given the important of RACBs motions, many scholars have attempted to enhance methods and modellings contributed to RACBs motions [9]. Moreover, recent realization from the literatures exposed that most problems should be considered, given the obtainable of most methods in RACBs optimization. Those methods mainly purposes are for reaching appropriate gains via the FOPID controller, ANFIS controller, and NARMA-L2 controller. The challenges are available in a reality scenario, RACBs motions vary hence, the appropriate models, and methods employed also differ due to the distinct measurements associated with each motion, referred to as FOPID gains [10]. The FOPID gains play a vital role in the analysis of RACBs motion, and as a result, significant research efforts have been dedicated to obtaining the most optimal gains. However, there are notable challenges in dealing with the variations and differences in gains. These variations can have a significant impact, particularly considering the different priorities and levels of importance associated with RACBs motions. A prime illustration of this is evident when considering a motion where an RACBs is oriented downwards to handle a cube. In such scenarios, the necessary gains and their respective importance levels vary depending on the motion's joint directionality and in relation to the motors, gears, and sensors used to measure the deviation of the rotation axis [11].

However, RACBs motion encounters certain issues, such as the significance of gains and the potential conflicts that arise when utilizing these gains in RACBs motions. For instance, there exists an inverse relationship between the first gain and the latter, where an increase in one corresponds to a decrease in the other. Another significant issue pertains to the movement motions within the RACBs during rotation. To address these challenges, optimization, ANFIS, and

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NARMA-L2, are currently being used as algorithms, methods, and controls for tuning the FOPID controller to obtain optimal values.

The utilization of optimization algorithms allows for the application of cost function analysis in various scientific domains. In the context of RACBs, these algorithms facilitate the tuning of FOPID controller values, enabling the search for improved parameter configurations. Optimization techniques are applied to control the four primary motions of RACBs [12]. Numerous studies have addressed and presented works focusing on the utilization of various optimization algorithms with RACBs. Each of these techniques relies on its unique mathematical equations and estimated parameters, considering different values to be taken into account [13]. The optimization algorithm is primarily employed to control the movement motions of RACBs. These algorithms measure and adjust the selected areas between the handled cube on the right and the handled cube on the left. The right arm or left arm of the RACBs is determined based on the motion's directionality.

ANFIS is utilized within the internal components of FOPID gains in RACBs to optimize and fine-tune their values. By employing ANFIS, the fuzzy inference system dynamically adapts and adjusts the FOPID gains in response to the inputs and system dynamics of RACBs. ANFIS harnesses the strengths of both fuzzy logic and neural networks to create a hybrid model that effectively learns and optimizes the FOPID gains. This integration allows ANFIS to intelligently modify the parameters of the FOPID controller, thereby enhancing its performance and improving the control of RACBs motions. Using ANFIS in the FOPID controller for RACBs offers numerous benefits. Firstly, ANFIS enables the controller to adapt and adjust its parameters based on inputs and system dynamics, ensuring effective responses to system changes and uncertainties. Additionally, ANFIS optimizes parameter tuning through its hybrid model, combining fuzzy logic and neural networks, resulting in more accurate and suitable parameter values that enhance control and efficiency in RACBs motions. Moreover, ANFIS enhances robust control by fine-tuning FOPID gains for improved tracking and stabilization, even in the presence of disturbances. The integration of ANFIS also enables adaptive control, allowing the controller to dynamically adjust parameters in real-time to varying conditions, ensuring optimal performance across different operating scenarios [14].

NARMA-L2, an artificial neural network-based approach, is integrated with the RACBs model to capture the system's nonlinear dynamics. The FOPID controller, alongside ANFIS, can be simulated within the NARMA-L2 framework to enhance control effectiveness for RACBs. The combined outcome of integrating the FOPID controller and ANFIS within NARMA-L2 offers several advantages. Firstly, it enables accurate modeling and control of the complex nonlinear behavior exhibited by RACBs. NARMA-L2 captures these nonlinearities, while the FOPID controller and ANFIS optimize control actions based on system inputs and dynamics. Moreover, the integration of the FOPID controller and ANFIS enhances control accuracy, resulting in improved tracking, stability, and precision in RACBs motions. Additionally, this combination facilitates adaptive control, allowing the system to dynamically adjust to changes and uncertainties in real-time. By combining the FOPID controller with ANFIS within the NARMA-L2 framework for RACBs, the resulting system benefits from accurate modeling, enhanced control accuracy, and adaptive control capabilities, leading to improved overall performance in controlling RACBs motions and the purpose of planning regarding whether to moving the RACBs towards the left or right direction. In this context, the selection of mechanisms and values for tuning can be determined by the enhancement using these techniques [15]. The main challenge arises when utilizing an optimization algorithm that relies on a single cost function, while each technique, such as NARMA-L2 and ANFIS, is evaluated based on a specific mathematical model for RACBs. This poses a difficulty in determining the optimal requirements for each technique to work in a high velocity and stability in motion results [16], How has the optimization process contributed to FOPID gains, and what does the current literature say about this topic. Many scientific studies have employed various optimization techniques for RACBs motions to explore their impact on controller gains [17].

Numerous research studies have utilized optimization techniques to enhance the four major motions of RACB systems, (i.e., joint, motor, gear, and sensor). To provide an overview of the previous research in this area, Table 1 presents a summary of the collected information and the criteria employed for motion types across various optimization techniques.

Table 1 illustrates the optimization techniques employed and the criteria utilized to enhance movement motions in RACBs (Robotic Arm Conveyor Belts). The table includes a total of seven optimization techniques, namely Conveyor Belt Based Pick and Place Application, Control algorithm [18], Non-Smooth Mechanics [19], Gauss-Newton Algorithm [20], Algorithmic Thinking [5], Conveyor Belt Based Pick and Place Application [21], and Artificial Bee Colony Algorithm [22]. The table demonstrates that diverse movement motions and controller gains have been applied to the criteria (G1, G2, G3, G4). Specifically, in the study by [23], self-tuning techniques (G1, G2, G3, G4) were utilized to enhance the joint and motor motion of RACBs. Similarly, employed G1, G2, G3, and G4 to develop the sensor, gear, and joint of the RACB [19], employed G1, G2, G3, and G4 to improve the motor, joint, and gear in RACBs [20], used G1, G2, and G3 to enhance the motion of the joint in RACBs. In the work by [5], self-tuned value sets were employed to develop sensor motion in RACBs, while [21] utilized all criteria (self-tuned value sets) to enhance motion, sensor, and gear in an RACB. Finally, [22] utilized criteria G1 and G2 to improve the motor motion of a robotics arm, based on many variations of estimated values on the RACB. The existing literature highlights the variation in criteria and the optimization techniques employed for RACB motion control. Consequently, there is a need for a more valuable solution that can effectively select the appropriate optimization algorithm for each criterion. This study aims to address this crucial gap by providing further analysis and an in-depth discussion of this major problem. It is importance notice that all four controller criteria significantly impact the RACBs system. The selection of control system parameters with a high proportional value (G1) results in a quick response time. However, an excessively high proportional value can lead to instability or oscillation. The integral term (G2) allows for faster error correction but may result in larger overshoots. Increasing the parameter size can reduce overshoot, but it would also decrease the overall response time. While the controller is linear, RACBs are inherently nonlinear due to other elements present. Table 1 demonstrates that various optimization methods have been proposed in the literature to address a wide range of RACB motion and route control scenarios, considering the key criteria discussed earlier. However, several prominent problems have emerged.

Table 1. Optimization techniques-based RACB studies

Authors	Type of Controller	Techniques	Controller Gains (G)			
			$G1/K_p$	$G2/K_i$	$G3/K_d$	$G4/N$
[5]	Arduino Yun	Algorithmic Thinking	N/A	N/A	N/A	N/A
[18]	Kinematic Controller	Control algorithm	0.85	0.75	0.95	0.80
[19]	Ballistic Motion and Sliding	Non-Smooth Mechanics	0.60	0.45	0.25	0.35
[20]	Cascaded-PID Controller	Gauss-Newton Algorithm	0.52	0.037	0.74	N/A
[21]	Atmega328 Arduino	Conveyor Belt Based Pick and Place Application	N/A	N/A	N/A	N/A
[22]	Embedded Controller	Artificial Bee Colony Algorithm	0.01	0.99	N/A	N/A
[23]	Low-Cost Embedded Controller	Conveyor Belt Based Pick and Place Application	N/A	N/A	N/A	N/A

Firstly, selecting and implementing the optimal values for optimization techniques in RACB motion routes is challenging due to the presence of multiple criteria. Secondly, determining the relative weights of each criterion is essential when deciding on an optimization algorithm. While not all criteria hold the same importance, they influence the choice of optimization technique. Thirdly, the trade-off between the efficiency of different values in optimization methods concerning various criteria poses a challenge. For instance, an increase in sensors may not always lead to a corresponding increase in motors. Negative correlations between factors must be considered during the selection process, as not all criteria can be optimized simultaneously. Lastly,

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the critical value problem arises when a criterion's performance does not improve linearly with an increase or decrease in its value. Instead, there exists a threshold beyond which the performance is no longer considered optimal. This threshold significantly affects the motion path of RACBs, as the optimal motion control optimization method typically encompasses a range of values. Due to these four challenges, determining the best values for optimization methods in RACB motion control is a complex task. The current study aims to address this issue through the application of the Jaya Optimization Algorithm (JOA) based NARMA-L2-ANFIS for FOPID.

The implementation of Robotic Arm-based Conveyor Belts (RACBs) presents numerous substantial contributions to the progress of the industrial sector:

- Enhanced Efficiency and Productivity: RACBs streamline various functions within industrial operations, resulting in heightened efficiency and productivity. These robotic arms excel at handling repetitive and labour-intensive tasks, executing them with remarkable precision and speed, consequently accelerating production cycles.
- Economic Benefits: By diminishing the reliance on manual labor and minimizing errors, RACBs yield substantial long-term cost savings in operational expenditures. They can operate continuously without experiencing fatigue, ensuring consistent output and long-term cost-efficiency.
- Elevated Quality Control: Equipped with sensors and cameras, RACBs perform real-time quality assessments of products. They are adept at identifying defects and anomalies, thereby guaranteeing that only top-tier items reach the market. This, in turn, reduces wastage and rework expenses.
- Augmented Safety: Robotic arms possess the capability to handle hazardous materials and execute perilous tasks within industrial settings, thus shielding human workers from potential risks. This significantly enhances workplace safety and mitigates the occurrence of accidents.
- Flexibility and Adaptability: RACBs are often programmable and can swiftly adapt to varying tasks and product specifications. This adaptability empowers manufacturers to respond promptly to shifts in market demands and customize products more efficiently.
- Optimal Space Utilization: Robotic arms are designed to operate within confined spaces and are engineered to maximize space utilization. This attribute proves especially invaluable in industries where available space is a premium resource.
- Unwavering Consistency and Precision: RACBs exhibit unparalleled precision and consistency across a spectrum of tasks, including material handling, welding, painting, and assembly. This unwavering precision significantly elevates product quality and reliability.
- Data Gathering and Analysis: Many RACBs are furnished with sensors that collect data during their operations. This data can subsequently be subjected to analysis, pinpointing areas for process optimization, predictive maintenance strategies, and overarching operational enhancements.
- Competitive Edge: Enterprises that invest in RACB technology gain a distinct competitive advantage within their respective markets. They can produce high-Caliber products more efficiently, respond promptly to market fluctuations, and effectively meet the demands of discerning customers.
- Sustainability: RACBs can be programmed to optimize resource consumption, including energy and materials, thus contributing to sustainable manufacturing practices and mitigating their environmental footprint.

The incorporation of RACB represents a pivotal step forward for the industrial sector. It leads to heightened operational efficiency, substantial cost savings, elevated quality standards, enhanced workplace safety, adaptability to market changes, efficient space utilization, and ultimately, sustainable manufacturing practices, all of which contribute to industry advancement and competitiveness.

In this paper, the evaluation and selection problem of optimal values for RACBs motion control is addressed through the utilization of the Jaya Optimization Algorithm (JOA) as a novel approach. JOA is an extension of optimization theory that aims to recover every problem with a decision leading to the desired goal. It is a systematic approach that considers the inherent tensions between evaluation criteria and the range of possible decisions faced by individuals. The JOA algorithm incorporates control-tuning procedures to assist in the planning, structure, and problem-solving stages of selection. It relies on metaheuristics and other forms of automated decision-making. By utilizing a Simulink file, JOA can process a case where the significance of evaluation criteria is determined. While certain optimization techniques such as Eagle Strategy-Particle Swarm Optimization (ES-PSO) [24] and Control Algorithm (CA) [25], are commonly found in the research literature, there remains a theoretical void despite their usage. This study employs the JOA to calculate the importance weights of criteria for controller gain selection and evaluation in the movement of robotic arm-based conveyor belts (RACBs), aiming to prevent instability issues. The JOA considers a subjective-based robust selection method in the Simulink environment, considering group controller gains or criterion selection approaches when making a final decision. It addresses trade-offs, important value determination, and evaluation criterion trade-offs through the application of cost-benefit analysis. The main contribution and novelty of this study can be summarized as follows:

a) Optimized RACB motions using FOPID & JOA for efficiency.

b) Modelled robotic arm conveyor with JOA & NARMA-L2-FO-ANFIS-PD-I control.

c) Validated JOA with NARMA-L2-FO-ANFIS-PD-I gains for diverse RACB motions.

The paper is divided into the following sections: Section 2 discusses the kinematics mechanism of RACB and RACB blocks on MATLAB-Simulink. Section 3 presents the three phases of methodology where RACB based NARMA-L2 controller identification and pre-processing, development of NARMA-L2 controller-based NARMA(L2)-FO(ANFIS)PD-I, and evaluation of FOPID criteria based JOA are all discussed. Section 4 presents the results and discussion, Section 5 presents the study implications of this article, Section 6 presents the conclusion of the following article.

2. Kinematics Mechanism of RACB

A robotic arm integrated with conveyor belts combines rotational and translational motions to manipulate objects. The arm consists of interconnected joints and links, allowing for precise control of its end effector's position. The conveyor belts introduce an additional element of motion by transporting objects along a predetermined path, facilitating interaction with the objects. To mathematically describe the system's kinematics, the forward kinematics equation is employed. This equation establishes a relationship between the joint angles or positions of the robotic arm and the position and orientation of the end effector within the workspace. The specific form of the forward kinematics equation depends on the type and configuration of the robotic arm [26]. Different arm types, such as Cartesian, cylindrical, or spherical arms, have their own distinct forward kinematics equations, which utilize trigonometric functions, matrix transformations, or other mathematical representations to determine the end effector's pose based on the joint values. The incorporation of conveyor belts introduces a time-dependent aspect to the system. To comprehensively describe the motion of objects on the conveyor belts and their interaction with the robotic arm, the kinematic mechanism of the system integrates both joint motion and conveyor belt motion. Mathematical equations, such as the forward kinematics equation, provide a framework for representing the relationship between joint values and the position and orientation of the end effector. Fig. 1 illustrates the concept of motion in a three-link planar arm [27].

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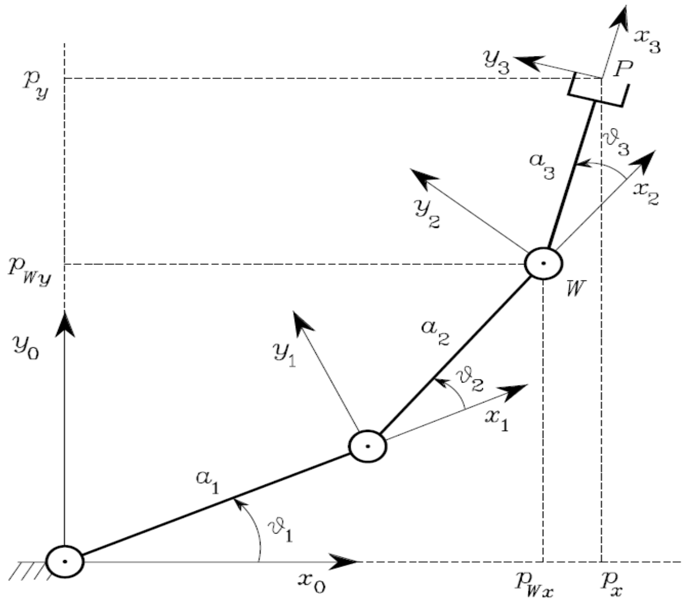


Fig. 1. Planar arm based three links [27]

In Fig. 1, we have a three-link planar arm where the frames of the links are depicted. To simplify the design, we have chosen the revolute axes to be parallel. As a result, we aligned all the axes xi along the direction of the relative links, with x0 being arbitrarily chosen. Additionally, all the axes lie in the plane defined by (x0, y0). By adopting this configuration, the parameter di becomes zero, and the angles between the axes xi directly represent the joint variables. Given that all the joints in this system are revolute, the homogeneous transformation matrix defined in equation (1) possesses identical structure for every joint as present in Fig. 2 [28], namely,

$$A_i^{i-1}(\vartheta_i) = \begin{bmatrix} c_i & -s_i & 0 & a_i c_i \\ s_i & c_i & 0 & a_i s_i \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad i = 1, 2, 3. \tag{1}$$

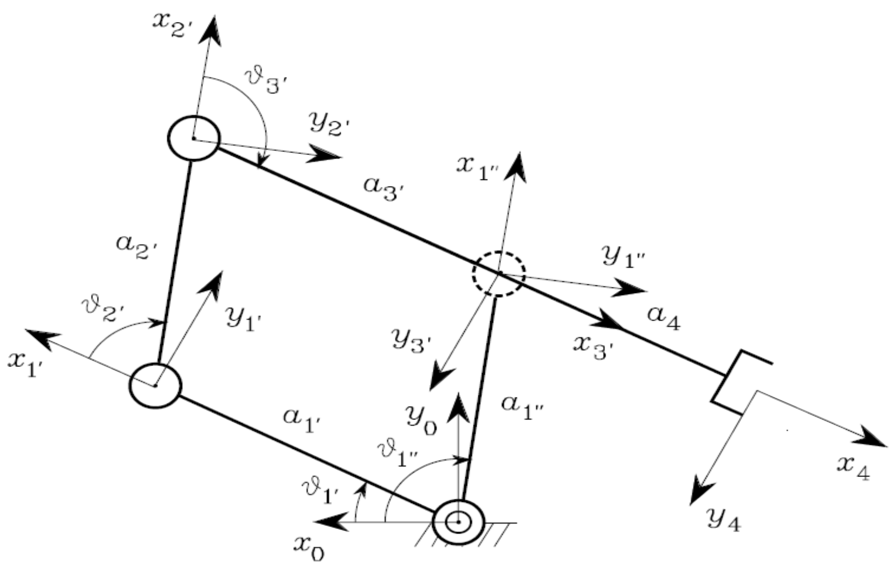


Fig. 2. Arm based parallelogram [28]

The direct computation in kinematics function as depicts in equation (2):

$$T_3^0(q) = A_1^0 A_2^1 A_3^2 \begin{bmatrix} c_{123} & -s_{123} & 0 & a_1c_1+a_2c_{12}+a_3c_{123} \\ s_{123} & c_{123} & 0 & a_1s_1+a_2s_{12}+a_3s_{123} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

Given that q is a vector represented as q = [ϑ1 ϑ2 ϑ3] T, it is important to note that the unit vector z_3^0 in Frame 3 aligns with $z_0 = [0\ 0\ 1]^T$, this alignment is due to the revolute joints being parallel to the z_0 axis. Consequently, p_z equals zero, and all three joints contribute to determining the end-effector position within the structure's plane. It is essential to highlight that Frame 3 and the end-effector frame (Fig. 2) do not coincide because the resultant approach unit vector aligns with x_3^0 rather than z_3^0. Assuming both frames share the same origin, a constant transformation can be established.

$$\boldsymbol{T_e^3} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

A constant transformation is required, with n aligned within z_0. In Fig. 3 [29], we observe an anthropomorphic arm that shares similarities with a two-link planar arm but includes an additional rotation around a plane's axis. This implies that the parallelogram arm could be utilized as a substitute for the two-link planar arm, a configuration often seen in industrial robots with an anthropomorphic design. The figure depicts the frames of the arm's links. Frame 0's origin is chosen at the intersection of z_0 and z_1, where d_1 equals zero. Additionally, z_1 and z_2 are parallel, and the selection of axes x_1 and x_2 follows the same pattern as the two-link planar arm. The DH parameters for this configuration are provided in Table 2 [29].

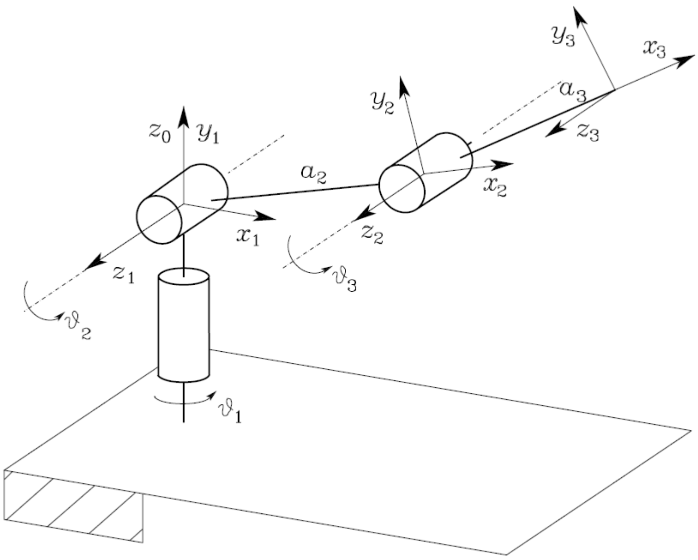


Fig. 3. Arm based anthropomorphic [29]

Table 2. DH parameters based anthropomorphic arm [29]

Link	a_i	α_i	d_i	ϑi
1	0	π/2	0	ϑ1
2	$a2$	0	0	ϑ2
3	$a3$	0	0	ϑ3

The matrices (2) represent the homogeneous transformation for individual joints.

$$A_1^0(\vartheta_1)=\begin{bmatrix} c_1 & 0 & s_1 & 0 \\ s_1 & 0 & -c_1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$A_i^{i-1}(\vartheta_i)=\begin{bmatrix} c_i & -s_i & 0 & a_i c_i \\ s_i & c_i & 0 & a_i s_i \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} i=2,3. \tag{5}$$

When calculating the direct kinematics function, as shown in equation (2), the following result is obtained:

$$T_3^0(q)=A_1^0A_2^1A_3^2\begin{bmatrix} c_1c_{23} & -c_1s_{23} & s_1 & c_1(a_2c_{2+}a_3c_{23}) \\ s_1c_{23} & -s_1s_{23} & -c_1 & s_1(a_2c_{2+}a_3c_{23}) \\ s_{23} & c_{23} & 0 & a_2s_{2+}a_3s_{23} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

Given the vector $q=[\vartheta 1\ \vartheta 2\ \vartheta 3]T$, it is important to note that z_3 is aligned with z_2. Consequently, Frame 3 does not align with the end-effector frame depicted in Fig. 4. To establish the appropriate alignment, a constant transformation would be required [30].

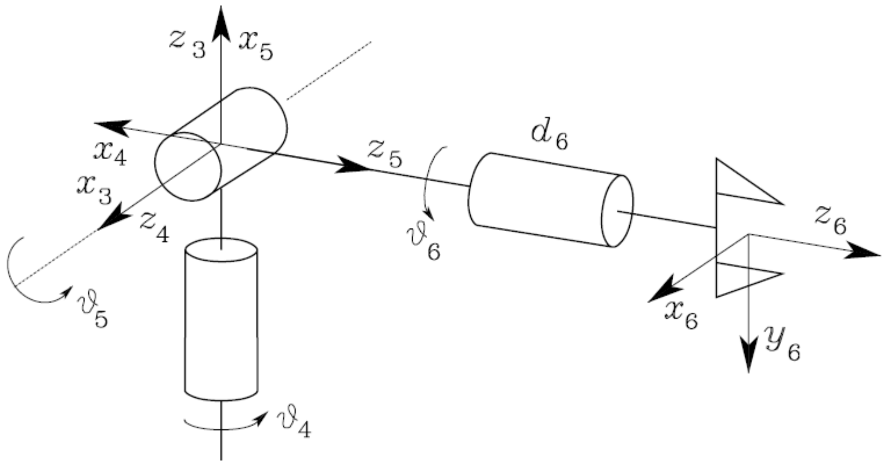


Fig. 4. Wrist based spherical [30]

In Fig. 5, after computing the direct kinematics function, the position and orientation of the end-effector frame can be expressed as follows, while keeping the other transformation matrices unchanged [31]:

$$p_6^0=\begin{bmatrix} a_2c_1c_2+d_4c_1s_{23}+d_6(c_1(c_{23}c_4s_5+s_{23}c_5)+\ s_2s_4s_5 \\ a_2s_1c_2+d_4s_1s_{23}+d_6(s_1(c_{23}c_4s_5+s_{23}c_5)-\ c_1s_4s_5 \\ a_2s_2-d_4c_{23}+d_6(s_{23}c_4s_5-c_{23}c_5) \end{bmatrix} \tag{7}$$

Then,

$$n_6^0=\begin{bmatrix} c_1(c_{23}(c_4c_5c_6-s_4s_6)-s_{23}s_5c_6+s_1(s_4c_5c_6+c_4s_6) \\ s_1(c_{23}(c_4c_5c_6-s_4s_6)-s_{23}s_5c_6-c_1(s_4c_5c_6+c_4s_6) \\ s_{23}(c_4c_5c_6-s_4s_6)+c_{23}s_5c_6 \end{bmatrix} \tag{8}$$

$$s_6^0 = \begin{bmatrix} c_1(-c_{23}(c_4c_5s_6 + s_4c_6) + s_{23}s_5s_6 + s_1(-s_4c_5s_6 + c_4c_6) \\ s_1(-c_{23}(c_4c_5s_6 + s_4c_6) + s_{23}s_5s_6 - c_1(-s_4c_5s_6 + c_4c_6) \\ -s_{23}(c_4c_5s_6 + s_4c_6) - c_{23}s_5s_6 \end{bmatrix} \quad (9)$$

$$a_6^0 = \begin{bmatrix} c_1(c_{23}c_4s_5 + s_{23}c_5) + s_1s_4s_5 \\ s_1(c_{23}c_4s_5 + s_{23}c_5) - c_1s_4s_5 \\ s_{23}c_4s_5 - c_{23}c_5 \end{bmatrix} \quad (10)$$

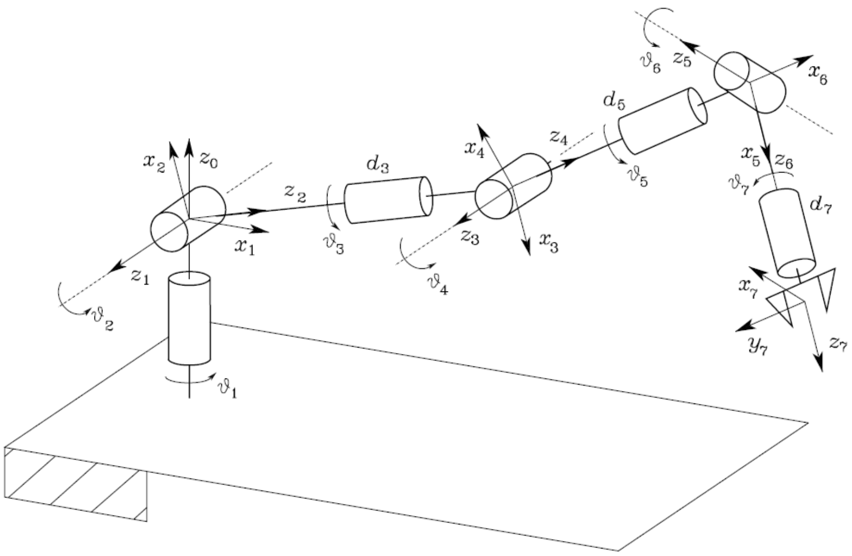


Fig. 5. Manipulator based DLR [31]

When setting d_6 to zero, the position of the intersection of the wrist axes can be determined. In this scenario, the vector p^0 mentioned in equation (7) corresponds to the vector p_3^0 in the case of the anthropomorphic arm described in equation (6). d_4 represents the length of the forearm (a_3), and in Fig. 5, axis x_3 is rotated by $\pi/2$ compared to axis x_3 in Fig. 4.

In Fig. 6, we are considering the parallelogram arm. Due to the presence of a closed chain, we initially consider an equivalent open-chain arm with a tree structure. Along one branch of the tree, let's denote the distances of the centers of mass of the three links as $\mathcal{J}_1$, $\mathcal{J}_2$, and $\mathcal{J}_3$, and along the other branch, the distance of the center of mass of the single link as $\mathcal{J}_4$". Similarly, the masses of the respective links are denoted as $m_{\mathcal{J}_1}$, $m_{\mathcal{J}_2}$, $m_{\mathcal{J}_3}$, and $m_{\mathcal{J}_1}$", and their moments of inertia relative to their centers of mass are denoted as $I_{\mathcal{J}_1}$, $I_{\mathcal{J}_2}$, $I_{\mathcal{J}_3}$,, and $I_{\mathcal{J}_{1''}}$. For simplicity, we neglect the contributions of motors. By using the chosen coordinate frames, we can compute the Jacobians in equations (7) to (8), (9), and (10) [32].

$$J_p^{(\mathcal{J}_1')} = \begin{bmatrix} -\mathcal{J}_{1'}s_{1'} & 0 & 0 \\ \mathcal{J}_{1'}c_{1'} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} J_p^{(\mathcal{J}_2')} = \begin{bmatrix} -a_{1'}s_{1'} - \mathcal{J}_2s_{1'2'} & -\mathcal{J}_{2'}s_{1'2'} & 0 \\ a_{1'}c_{1'} + \mathcal{J}_{2'}c_{1'2'} & \mathcal{J}_2c_{1'2'} & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (11)$$

$$J_p^{(\mathcal{J}_3')} = \begin{bmatrix} -a_{1'}s_{1'} - a_{2'}s_{1'2'} - \mathcal{J}_{3'}s_{1'2'3'} & -a_{2'}s_{1'2'} - \mathcal{J}_{3'}s_{1'2'3'} & -\mathcal{J}_{3'}s_{1'2'3'} \\ a_{1'}c_{1'} + a_{2'}c_{1'2'} + \mathcal{J}_{3'}c_{1'2'3} & a_{2'}c_{1'2'} + \mathcal{J}_{3'}c_{1'2'3'} & -\mathcal{J}_{3'}c_{1'2'3'} \\ 0 & 0 & 0 \end{bmatrix} \quad (12)$$

$$J_p^0 = \begin{bmatrix} -\mathcal{J}_{1''}s_{1''} \\ \mathcal{J}_{1''}c_{1''} \\ 0 \end{bmatrix} \quad (13)$$

$$J_0^{(\mathcal{J}_1')} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \; J_0^{(\mathcal{J}_2')} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 1 & 0 \end{bmatrix} \; J_0^{(\mathcal{J}_3')} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \quad (14)$$

Then,

$$J_0^{(\mathcal{J}_1'')} = \begin{bmatrix}0\\0\\1\end{bmatrix} \tag{15}$$

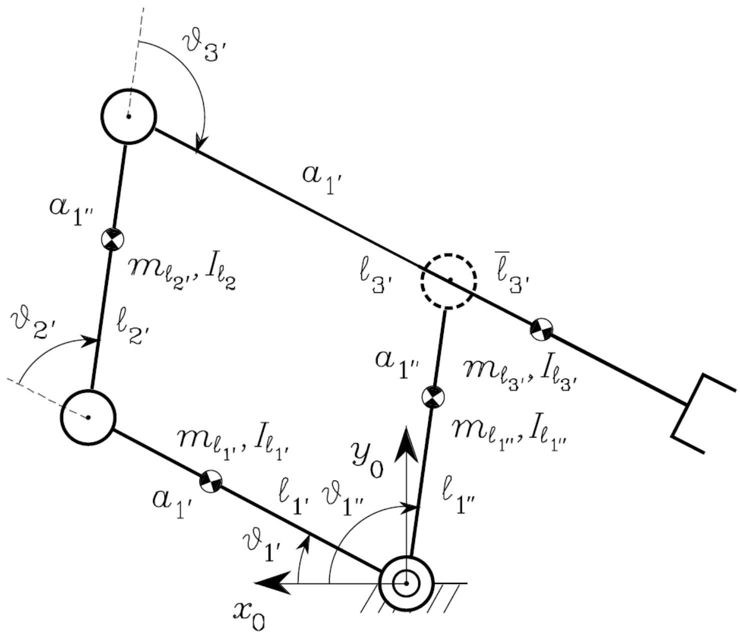


Fig. 6. Degree-Of-Freedom (DOF) based parallelogram [32]

According to equation (8), (9), and (10), the inertia matrix based virtual arm consisting of joints $\vartheta 1$, $\vartheta 2$, and $\vartheta 3$ can be expressed as follows [33]:

$$B'(q') = \begin{bmatrix} b_{1'1'}(\vartheta_{2'}, \vartheta_{3'}) & b_{1'2'}(\vartheta_{2'}, \vartheta_{3'}) & b_{1'3'}(\vartheta_{2'}, \vartheta_{3'}) \\ b_{2'1'}(\vartheta_{2'}, \vartheta_{3'}) & b_{2'2'}(\vartheta_{3'}) & b_{2'3'}(\vartheta_{3'}) \\ b_{3'1'}(\vartheta_{2'}, \vartheta_{3'}) & b_{3'2'}(\vartheta_{3'}) & b_{3'3'} \end{bmatrix} \tag{16}$$

$$\begin{gathered} b_{1'1'} = I\mathcal{J}_{1'} + m_{\mathcal{J}_1'}\mathcal{J}_{1'}^2 + I\mathcal{J}_{2'} + m_{\mathcal{J}_2'}\left(a_{1'}^2 + \mathcal{J}_{2'}^2 + 2a_{1'}\mathcal{J}_{2'}c_{2'}\right) \\ +I\mathcal{J}_{3'} + m_{\mathcal{J}_3'}\left(a_{1'}^2 + a_{2'}^2 + \mathcal{J}_{3'}^2 + 2a_{1'}a_{2'}c_{2'} + 2a_{1'}\mathcal{J}_{3'}c_{2'3'} + +2a_{2'}\mathcal{J}_{3'}c_{3'}\right) \end{gathered} \tag{17}$$

$$\begin{gathered} b_{1'2'} = b_{2'1'} = I\mathcal{J}_{2'} + m_{\mathcal{J}_2'}\left(\mathcal{J}_{2'}^2 + a_{1'}\mathcal{J}_{2'}c_{2'}\right) \\ +I_{\mathcal{J}_3'} + m_{\mathcal{J}_3'}\left(a_{2'}^2 + \mathcal{J}_{3'}^2 + a_{1'}a_{2'}c_{2'} + a_{1'}\mathcal{J}_{3'}c_{2'3'} + 2a_{2'}\mathcal{J}_{3'}c_{3'}\right) \end{gathered} \tag{18}$$

$$b_{1'3'} = b_{31} = I\mathcal{J}_{3'} + m_{\mathcal{J}_3'}\left(\mathcal{J}_{3'}^2 + a_{1'}\mathcal{J}_{3'}c_{2'3'} + a_{2'}\mathcal{J}_{3'}c_{3'}\right) \tag{19}$$

$$b_{2'2'} = I\mathcal{J}_{2'} + m_{\mathcal{J}_2'}\mathcal{J}_{2'}^2 + I\mathcal{J}_{3'} + m_{\mathcal{J}_3'}\left(a_{2'}^2 + \mathcal{J}_{3'}^2 + 2a_{2'}\mathcal{J}_{3'}c_{3'}\right) \tag{20}$$

$$b_{2'3'} = I\mathcal{J}_{3'} + m_{\mathcal{J}_3'}\left(\mathcal{J}_{3'}^2 + a_{2'}\mathcal{J}_{3'}c_{3'}\right) \tag{21}$$

$$b_{3'3'} = I\mathcal{J}_{3'} + m_{\mathcal{J}_3'}\mathcal{J}_{3'}^2 \tag{22}$$

2.1. RACB Blocks on MATLAB-Simulink

The RACB model contains two major components: input control and arm, their responsibilities for convert gripper, Logical Link Control (LLC) to I/O Belt, and I/O Belt to the normalized bus within joint commands for the arm trajectory and finger position [33]. This model is designed using six transforms of arm; $Base, Pivot, Bicep, Forearm, Wirst, and\ Gripper$ and revolution (estimation of degrees) for each motion. In addition, the main conveyors environment was applied for handling to move load box (cube) [34]. In final, the $Gripper\ Force\ Damper$ in terms of apply 6-DOF and damping force between double frames with a certainly range ($Px, Py, and\ Pz$) used for transform sensor are depicts in Fig. 7.

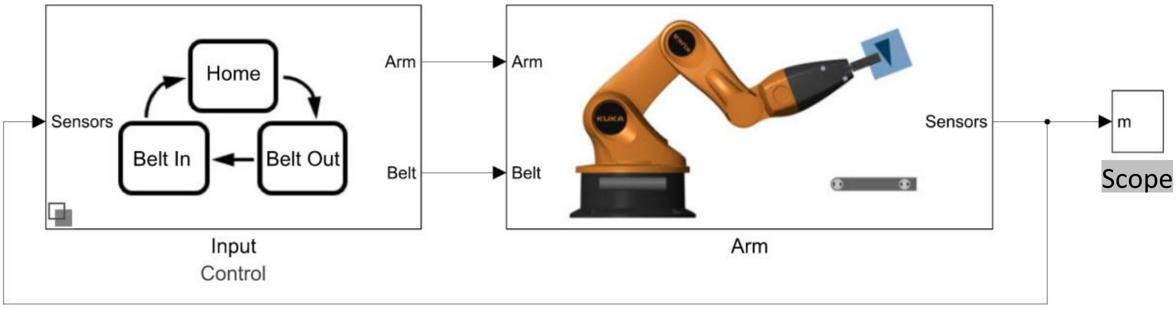
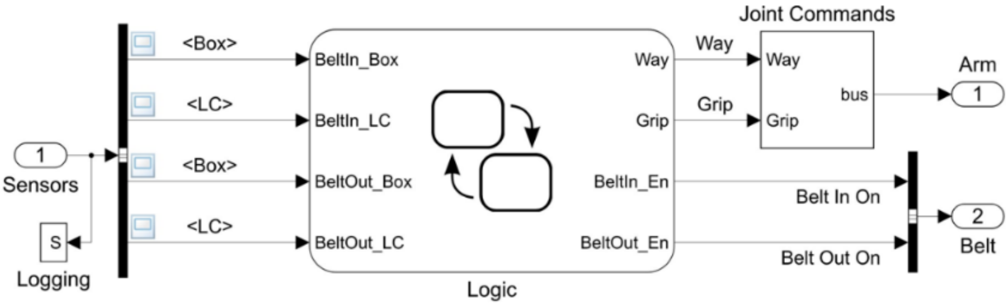
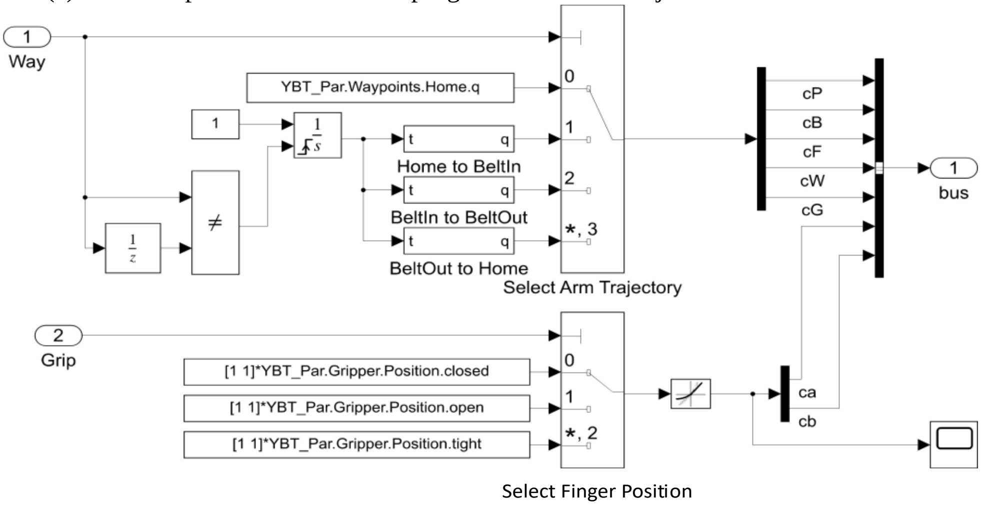


Fig. 7. Overall input control and arm model on MATLAB-Simulink

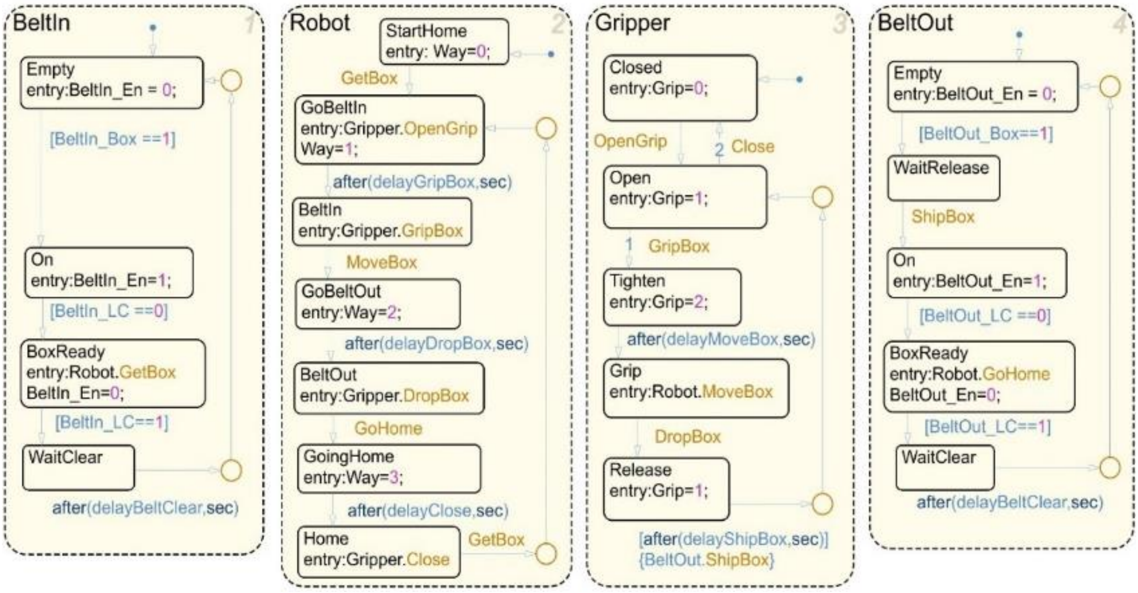
The input control for the RACB to be understandable by arm environment was contained by $belt\ in - Home - belt\ out$, such as LLC and joint commands. LLC components convert the belts I/O programmed consideration to belts I/O motions [35]. Moreover, way and grip components were converting the way and grip programmed consideration to a bus for both trajectory and position selection. The aim is for combining the considerations of motions, and trajectory, position selection on belts I/O; these components were used for motion, position, and trajectory to achieve the formatting for the RACB environment within 6-DOF gripper force [36] as depict in Fig. 8 part (a) LLC component to convert all programmed belts and joint commands on RACB, Fig. 8 part (b) Joint commands to convert both way, and grip in a bus on RACB, and Fig. 8 part (c) Internal block of a programmed relation in LLC component, Fig. 9 part (a) Environment and directivity motions on RACB, Fig. 9 part (b) Conveyors, Load Box (Cube), and gripper damper on RACB, Fig. 9 part (c) Belt I/O, and angles of transform on RACB, and Fig. 9 part (d) 6-DOF measured for gripper force damper on RACB.



(a) LLC component to convert all programmed belts and joint commands on RACB

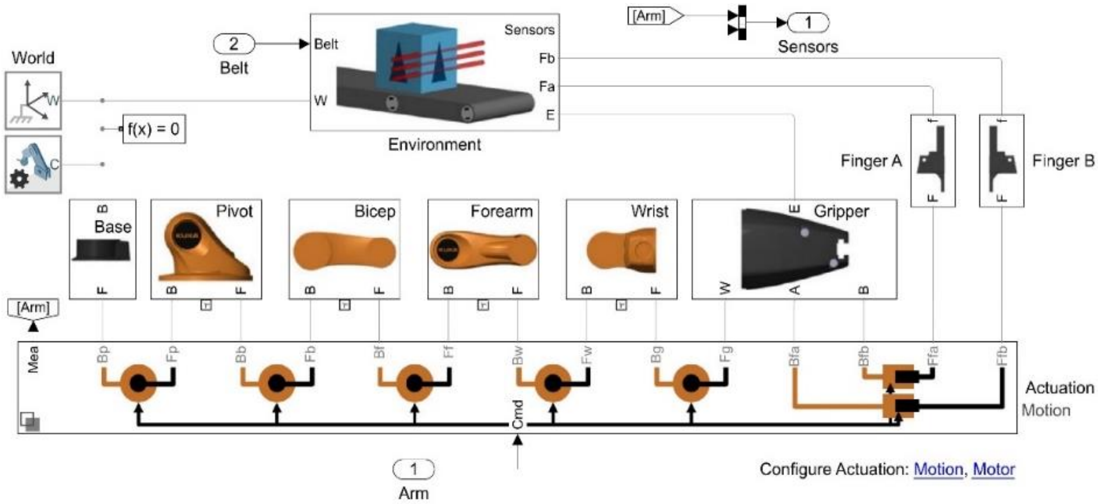


(b) Joint commands to convert both way, and grip in a bus on RACB

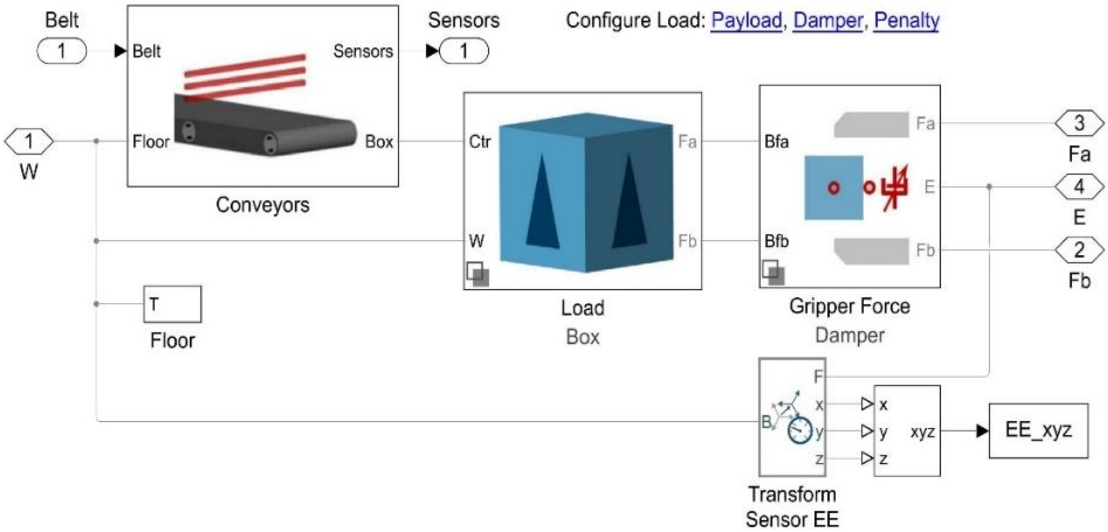


(c) Internal block of a programmed relation in LLC component

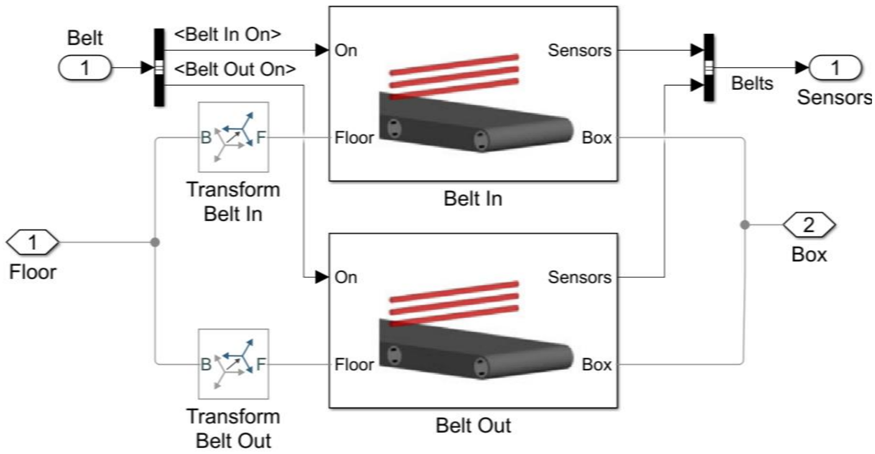
Fig. 8. LLC components and joint commands on MATLAB



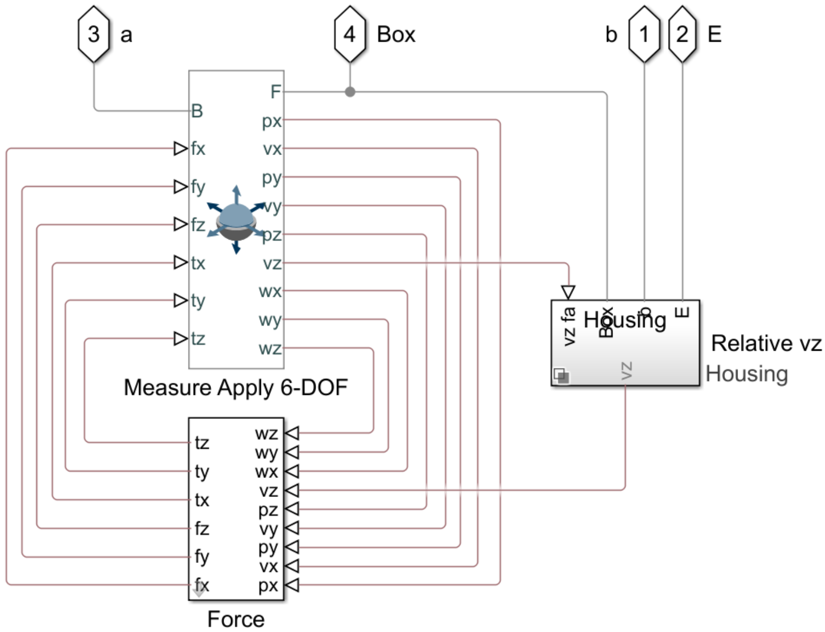
(a) Environment and directivity motions on RACB



(b) Conveyors, load box (cube), and gripper damper on RACB



(c) Belt I/O, and angles of transform on RACB



(d) 6-DOF measured for gripper force damper on RACB

Fig. 9. Arm components internal block model on MATLAB

3. Methodology

This section is split into three phases, as described in Fig. 10. The first phase is Robotic Arm based Conveyor Belts (RACB) and NARMA-L2 controller concerning identification and pre-processing. The development of NARMA-L2 controller-based NARMA(L2)-FO(ANFIS)PD-I including, FOPID Criteria based ANFIS, and ANFIS (MF) Data are formulated in the second phase. The third phase uses an optimization process to evaluate the Jaya optimization algorithm based on FOPID criteria, were extracted from the evaluation of FOPID criteria based JOA.

3.1. Phase 1: RACB based NARMA-L2 Controller Identification and Pre-Processing

This phase identifies RACB based NARMA-L2 controller concerning one major section: the NARMA-L2 controller tuning involve; structural design of NARMA-L2 controller.

3.1.1. NARMA-L2 Controller Tuning

The NARMA-L2 controller entails the determination of suitable parameter values, including the coefficients for the Auto-Regressive (AR) and Moving Average (MA) components, to achieve optimal control performance. The major instructions for tuning the NARMA-L2 controller:

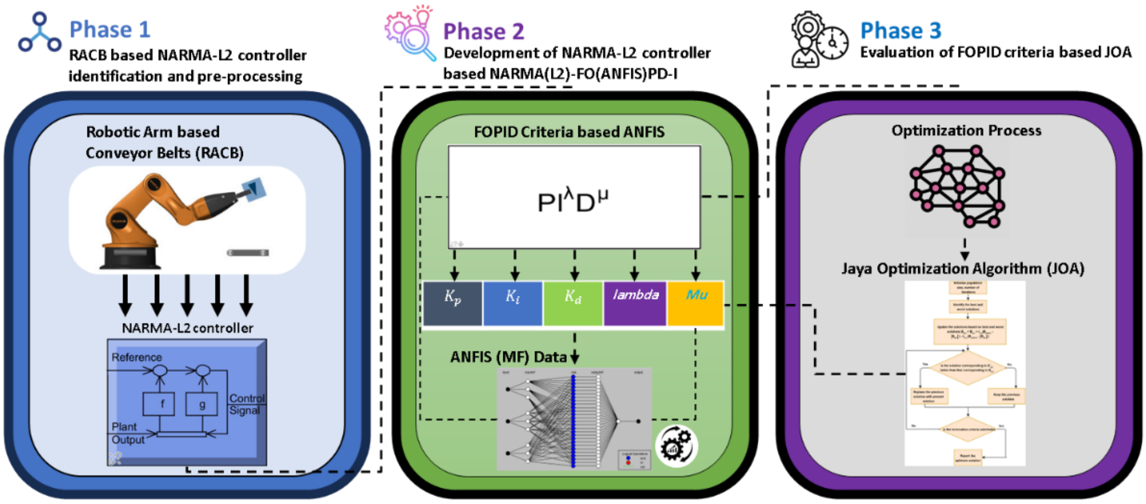


Fig. 10. Evaluation and selection of methodology phases

Collect input-output data from the target system to be controlled [37]. This data will be utilized for training and evaluation purposes during the tuning process known as data acquisition. Determine the appropriate structure for the NARMA-L2 model, including the consideration of past input and output terms within the AR and MA components. The selection should be based on the system's dynamics and complexity-based structure selection. Divide the collected data into separate training and validation sets. The training set is employed to estimate the model parameters, while the validation set is used to assess the performance of the tuned controller depending on Training and validation. Utilize suitable methods such as least squares, gradient descent, or optimization algorithms to estimate the model parameters [38]. The primary objective is to minimize the prediction error between the actual output and the predicted output of the NARMA-L2 model that estimates each parameter. According to the evaluation issue, the performance of the tuned NARMA-L2 controller using the validation data-based evaluation. In Iterative refinement, iteratively refine the model parameters based on the results of the performance evaluation. This may involve adjusting the number of past input and output terms, modifying the nonlinear functions within the AR and MA components, and applying regularization techniques to prevent overfitting. In analysis of robustness, Assess the robustness of the tuned NARMA-L2 controller against disturbances, noise, or uncertainties within the system. The equations (23), and (24) for each component can be represented as follows:

$$y(t1) = f\big(y(t-1), y(t-2), \dots, y(t-n), u(t-1), u(t-2), \dots, u(t-m)\big) \tag{23}$$

$$y(t2) = g\big(u(t-1), u(t-2), \dots, u(t-m)\big) \tag{24}$$

Where: $y(t1)$ represents the current output of the system. $f()$ is a nonlinear function that models the relationship between the past output values $(y(t-1), y(t-2), \dots, y(t-n))$ and the past input values $(u(t-1), u(t-2), \dots, u(t-m))$. n is the number of past output terms considered in the autoregressive model. m is the number of past input terms considered in the autoregressive model [39].

While: $y(t2)$ represents the current output of the system. $g()$ is a function that models the relationship between the past input values $(u(t-1), u(t-2), \dots, u(t-m))$ and the current output. m is the number of past input terms considered in the moving average model [40]. In addition, NARMA-L2 controller for RACB is classified into multiple blocks, as depicted in Fig. 11.

3.2. Phase 2: Development of NARMA-L2 Controller-based NARMA(L2)-FO(ANFIS)PD-I

The NARMA-L2 controller is a type of nonlinear controller that uses a neural network to model the dynamic behavior of the system and generate the control signal. When combined with

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FOPID criteria and ANFIS, it creates a hybrid intelligent control system that incorporates fractional order control [41]. The NARMA-L2 controller can be formulated by equation (25):

$$u(t) = F\big(y(t), y(t-1), \ldots, y(t-n+1), u(t-1), \ldots, u(t-m+1)\big) \tag{25}$$

When: $u(t)$ is the control signal at time t, $y(t)$ represents the system output at time t, n is the number of past output samples used for modeling the system dynamics, m is the number of past control samples used for modeling the system dynamics, F is a nonlinear function or a neural network that captures the system dynamics. To incorporate the FOPID criteria and ANFIS into the NARMA-L2 controller, we can modify the function F to include the FOPID controller structure and use ANFIS to optimize the parameters. The FOPID structure can be formulated by equation (25):

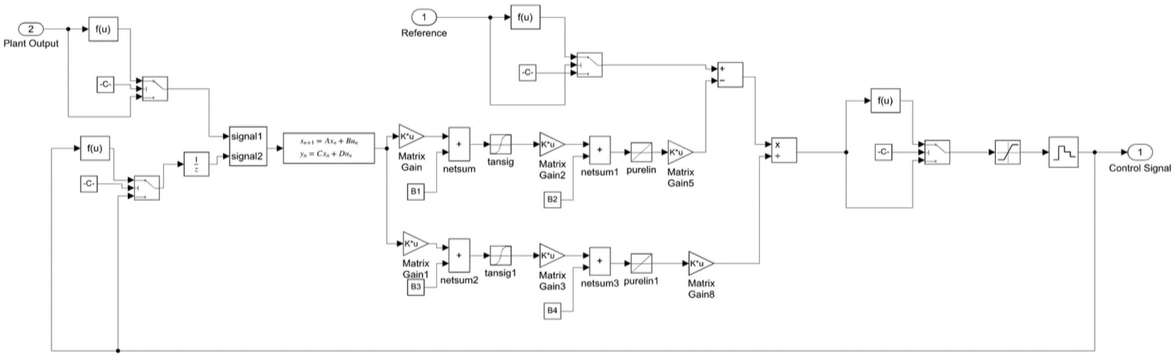


Fig. 11. Structural design of NARMA-L2 controller

$$u(t) = K_p * e(t) + K_i * \frac{D^{\{\lambda_i\}e(t)}}{D_p^{\lambda}} + K_d * \frac{D_d^{\lambda} e(t)}{D_d^{\lambda}} \tag{26}$$

Where e(t) is the error, and D^λ represents the fractional derivative, and integral operator. The ANFIS framework is used to train the parameters of the FOPID controller based on the FOPID criteria. It involves defining fuzzy if-then rules that map the input error (e(t)) to the output control signal (u(t)). The parameters of these fuzzy rules are learned through a combination of forward and backward passes in the training process. The training data for ANFIS consists of input-output pairs, where the inputs are the error and possibly other relevant system variables, and the outputs are the control signals [42].

By combining the NARMA-L2 structure, the FOPID criteria, and ANFIS training, the resulting controller can capture the nonlinear dynamics of the system and incorporate fractional order control based on the specified criteria. This hybrid approach allows for improved control performance in systems with nonlinearities and variable order dynamics [43], according to the ANFIS, 20 I/O MFs, and 50 epochs were used to identify and train the adaptive neuro-fuzzy controller as depicts in Fig. 12 part (a) FOPD-1 based ANFIS ((FO(ANFIS)PD-I)) Model on MATLAB, Fig. 12 part (b) ANFIS based 20 input MFs, Fig. 12 part (c) ANFIS based 20 output MFs, Fig. 12 part (d) FO(ANFIS)PD-I model based NARMA(L2) controller on MATLAB, and Fig. 12 part (e) NARMA(L2) controller associated with RACB model on MATLAB.

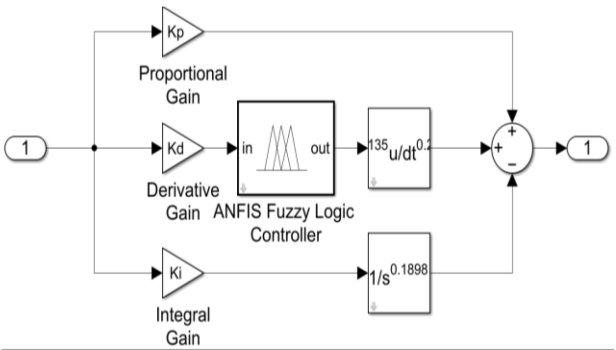
3.3. Phase 3: Evaluation of FOPID Criteria based JOA

This section depicts the optimization process based proposed Jaya Optimization Algorithm (JOA) with their processes and mathematical equations. In addition, the mechanism of calculation for a given algorithm was explained as follows:

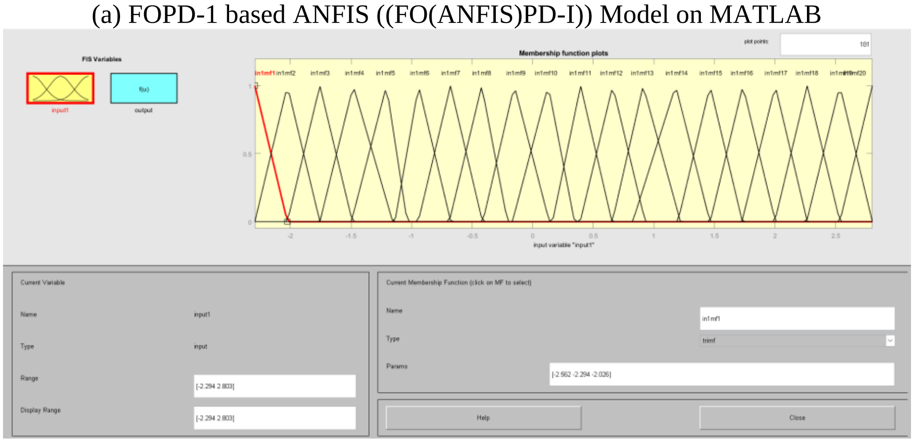
3.3.1. Optimization Process

Optimization is the process of seeking the most favorable solution or maximizing/minimizing an objective function while working within a set of given constraints. It entails formulating a mathematical model that accurately represents the problem and utilizing various methods to determine the optimal values for the decision variables. Let's consider a general optimization problem where we have a set of decision variables denoted as $x = (x_1, x_2, ..., xn)$. The objective is to find the values of these variables that optimize the objective function $f(x)$. Additionally, there might be constraints that restrict the values of the decision variables, expressed as $g_i(x) \leq 0$ for $i = 1, 2, ..., m$. Mathematically, the optimization problem can be stated as follows [44]: Minimize (or maximize) $f(x)$ subject to: $g_i(x) \leq 0$, for $i = 1, 2, ..., m$ $x \in X$

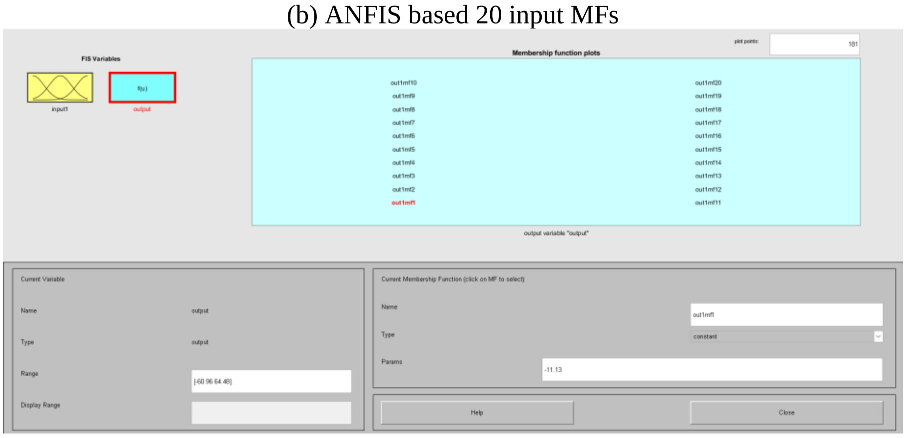
Thus, X represents the feasible region, which denotes the set of values satisfying the constraints. To solve such problems, a range of optimization algorithms and techniques are available. One commonly used approach is employing gradient-based methods like gradient descent or Newton's method for unconstrained optimization problems. These methods utilize the gradient (partial derivatives) of the objective function to iteratively update the decision variables and converge towards the optimal solution. For instance, in the case of minimizing the objective function $f(x)$ [45]. For constrained optimization problems, additional techniques such as Lagrange multipliers or penalty methods can be employed to handle the constraints while optimizing the objective function [46].



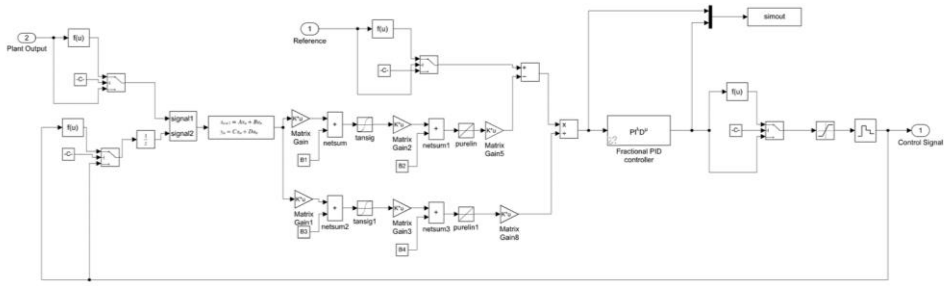
(a) FOPD-1 based ANFIS ((FO(ANFIS)PD-I)) Model on MATLAB



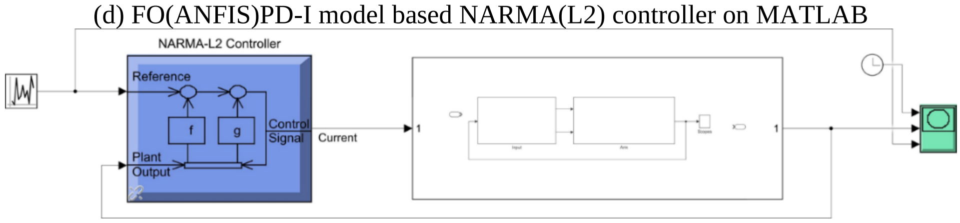
(b) ANFIS based 20 input MFs



(c) ANFIS based 20 output MFs



(d) FO(ANFIS)PD-I model based NARMA(L2) controller on MATLAB



(e) NARMA(L2) controller associated with RACB model on MATLAB

Fig. 12. Overall, NARMA(L2)-FO(ANFIS)PD-I model design on MATLAB

3.3.2. Jaya Optimization Algorithm

The Jaya optimization algorithm is a population-based metaheuristic approach inspired by the social behavior of individuals in a society. Introduced by R. V. Rao in 2016, it serves as an alternative to traditional optimization algorithms such as genetic algorithms and particle swarm optimization. The term "Jaya" represents the idea of joy or happiness, reflecting the algorithm's focus on exploration and exploitation in the search space. In the evaluation of RACB motion, the application of meta-heuristics, such as Jaya optimization, plays a pivotal role. These optimization techniques offer a systematic approach to fine-tuning the control parameters of RACBs, including those associated with Fractional Order Proportional Integral Derivative (FOPID) controllers. By harnessing the power of meta-heuristics, engineers and researchers can efficiently navigate the complex parameter space of RACB systems. Jaya optimization, in particular, focuses on exploiting the advantages of the best solutions while simultaneously improving upon the weaker ones. This approach enhances the overall adaptability and robustness of RACBs in dynamic environments. Meta-heuristics serve as valuable tools for achieving optimal performance, responsiveness to changing conditions, and the continuous improvement of RACB operations [47].

The Jaya algorithm follows a straightforward process: it maintains a population of potential solutions and iteratively updates them based on their performance. By doing so, it seeks to optimize a given objective function. Let's break down the key steps of the algorithm [48].

- Initialization: Determine the population size (N) and maximum number of iterations (MaxIter). Start with a population of N random solutions within the search space. Evaluate the objective function for each solution.
- Update the population: For each iteration ($\mathrm{t} = 1$ to $\mathrm{MaxIter}$): Identify the best and worst solutions in the population based on their objective function values. Update each solution in the population using equation (27):

$$\begin{aligned}\mathrm{Xi} = \mathrm{Xi} + \mathrm{rand(value)} * \left(\mathrm{Xbest(t)} - \mathrm{abs(Xi)}\right) - \mathrm{rand(value)} \\ * \left(\mathrm{Xworst(t)} - \mathrm{abs(Xi)}\right)\end{aligned} \tag{27}$$

Where: Xi represents the $\mathrm{i-th}$ solution in the population at iteration t, $\mathrm{Xbest(t)}$ refers to the best solution in the population at iteration t, $\mathrm{Xworst(t)}$ indicates the worst solution in the population at iteration t, $\mathrm{rand(value)}$ generates a random number between 0 and 1.

- Handle constraints: If any solution violates problem constraints, adjust or modify it to ensure compliance.

- Evaluate the objective function: Calculate the objective function value for each updated solution.
- Update the best solution: Determine the best new solution in the updated population.
- Termination condition: If the maximum number of iterations is reached or a termination criterion is met, stop the algorithm. Otherwise, proceed to step 2. The Jaya algorithm emphasizes both exploration and exploitation. Exploration is achieved through the random term, which introduces diversity and enables the algorithm to explore new regions of the search space. Exploitation is facilitated by the best and worst solutions, which guide the population towards promising areas of the search space [49]. The Jaya algorithm does not require specific parameter tuning, making its implementation relatively straightforward. However, it may be necessary to handle constraints or make additional adjustments to adapt it to specific problem domains. The Jaya optimization algorithm offers a simple yet effective approach to optimization problems. By striking a balance between exploration and exploitation, it efficiently searches for optimal solutions within the search space [50].

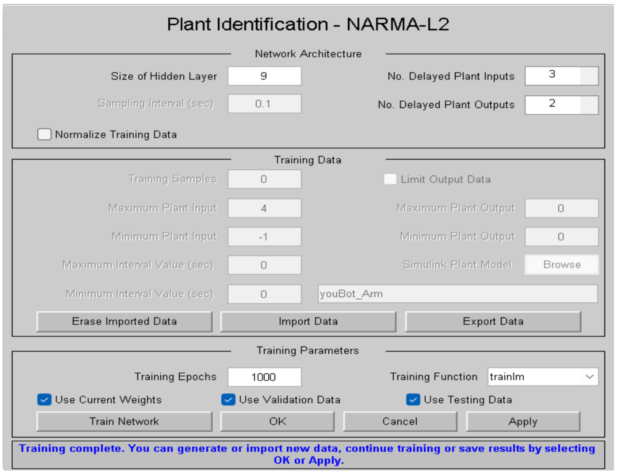
4. Results and Discussion

This section depicts and explains the methodology phases results, including: the NARMA-L2 controller, ANFIS, and FOPID results based JOA.

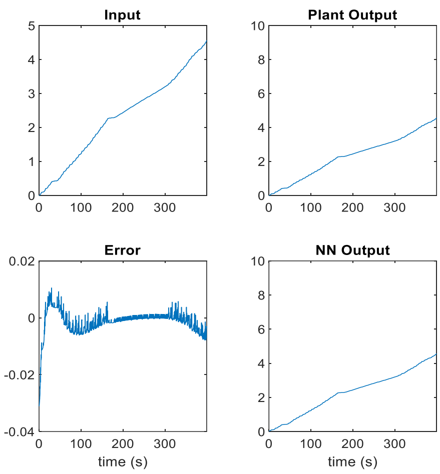
4.1. NARMA(L2)-FO(ANFIS)PD-I based Jaya Optimization Algorithm

This section discusses the NARMA-L2-based plant identification after importing MATLAB output data MAT. Variables depends on training, validation, and testing were experimented on performance, training state, regression and X(2Y) graph as depicts in Fig. 13. part (a).

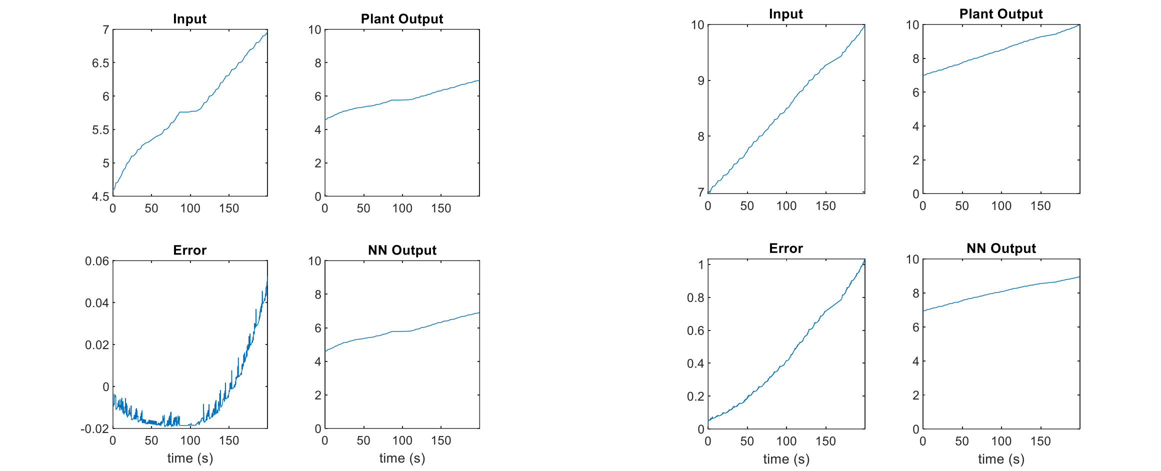
NARMA-L2 based variables configuration, The NARMA-L2 controller is established by configuring the hidden layer to comprise nine neurons, with each neuron corresponding to a sampling period of approximately 0.1 seconds for every three input values. Two output plants were subsequently subjected to training, and their behavior was estimated within the RACB Simulink file. This configuration relied on four crucial elements: a maximum input constraint of four units and a minimum constraint of 4^{-1} during the 1000 training epochs. These constraints were expressed as part of the trainim membership function, which considered weights derived from validation and testing data, both of which were stored in a .MAT file with dimensions of N*1 for reference as in Fig. 13. part (b) Training data-based NARMA-L2, Fig. 13. part (c) Validation data-based NARMA-L2, and Fig. 13. part (d) Testing data-based NARMA-L2.



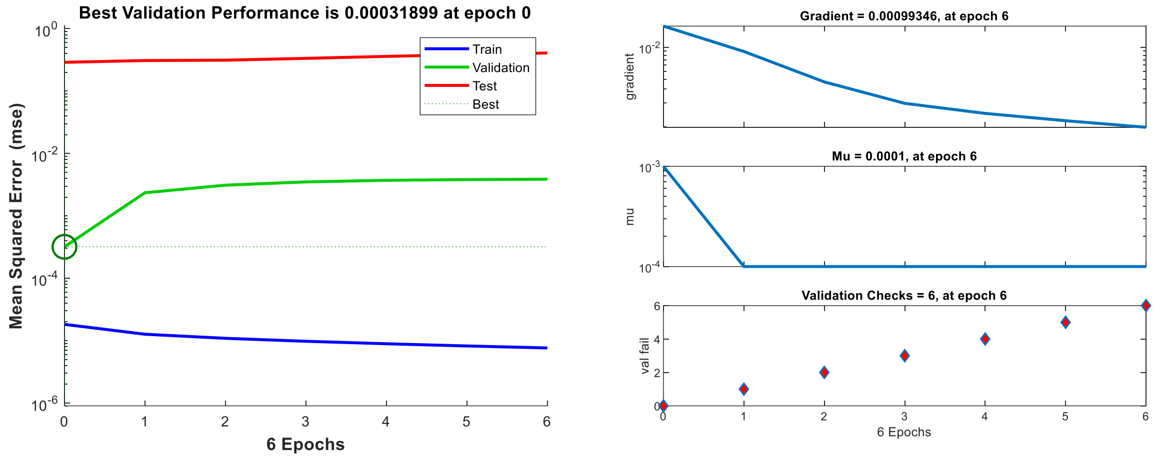
(a) NARMA-L2 based variables configuration



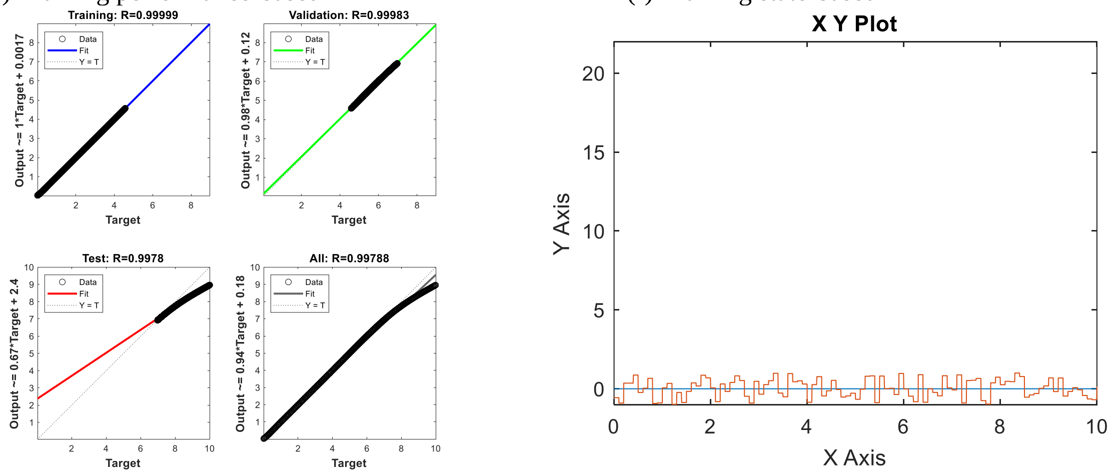
(b) Training data-based NARMA-L2



(c) Validation data-based NARMA-L2 (d) Testing data-based NARMA-L2



(e) Training performance-based NARMA-L2 (f) Training state-based NARMA-L2



(g) Training regression-based NARMA-L2 (h) $X(2Y)$ graph-based NARMA-L2

Fig. 13. NARMA-L2 model design configuration on MATLAB

In the performance evaluation, the mean square error (MSE) was initially trained, achieving its best validation result during epoch 0, with an MSE value of 0.00031899. As the training stage commenced, the primary objective was to minimize error generation to its lowest possible level. However, during the subsequent testing stage, it became evident that the error was comparatively higher, with a magnitude of 10^{-1}, in contrast to the $10^{-3.5}$ observed during the critical validation stage. This discrepancy highlights the importance of addressing and mitigating the error during the testing phase to enhance overall system performance as in Fig. 13. part (e) Training performance-based NARMA-L2, Fig. 13. part (f) Training state-based NARMA-L2, Fig. 13. part (g) Training regression-based NARMA-L2, and Fig. 13. part (h) X(2Y) graph-based NARMA-L2.

Table 3 presents the training progress for NARMA-L2 controller, the initial value at 0 based on epoch unit while stopped value at 6, and the target value is 1000 repeated in epoch, 5 sec were applied for elapsed time based on 1.82e-05 to performance as initialization, 7.63e-06 considered as stopped value, 0.0186 for gradient as initializing, 0.000993 illustrated for stopped value, while the outcome of Mu, 0.001 as initial, 0.0001 for stopped value, and target based on both, 1e-10, 1e+10, in gradient, and Mu, respectively. the initialization, stopped, and target values were applied for 0, 6, and 6 based NARMA-L2 controllers.

Fig. 14. discusses the RACBs mechanics motions based JOA parameters, five elements were applied for variables based on NARMA(L2)-FO(ANFIS)PD-I, lower and upper boundaries were experimented in 0 to 0.5 ranges, 1000 is considered as the size of population, while the maximum number of iterations were supposed as 3000. The NARMA-L2 controller plays a pivotal role in harnessing the power of neural networks to significantly reduce the probability of errors occurring during RACB motions at the end-effector. It is particularly crucial to ensure robust timing, which is of utmost significance in verifying the execution of tasks within the initial 20 seconds of handling a cube. Additionally, the utilization of FOPID based ANFIS has proven to be highly effective. This approach not only enhances the speed of arm motion but also demonstrates remarkable improvements in both pivot and wrist equipment operations. Furthermore, it contributes to the refinement of conveyor belt functionality, rectifying issues related to directivity and precision in handling tasks, thus optimizing the overall performance of the system.

Table 3. Training progress based NARMA-L2 controller

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	6	1000
Elapsed Time	-	00:00:05	-
Performance	1.82e-05	7.63e-06	0
Gradient	0.0186	0.000993	1e-10
Mu	0.001	0.0001	1e+10
Validation Checks	0	6	6

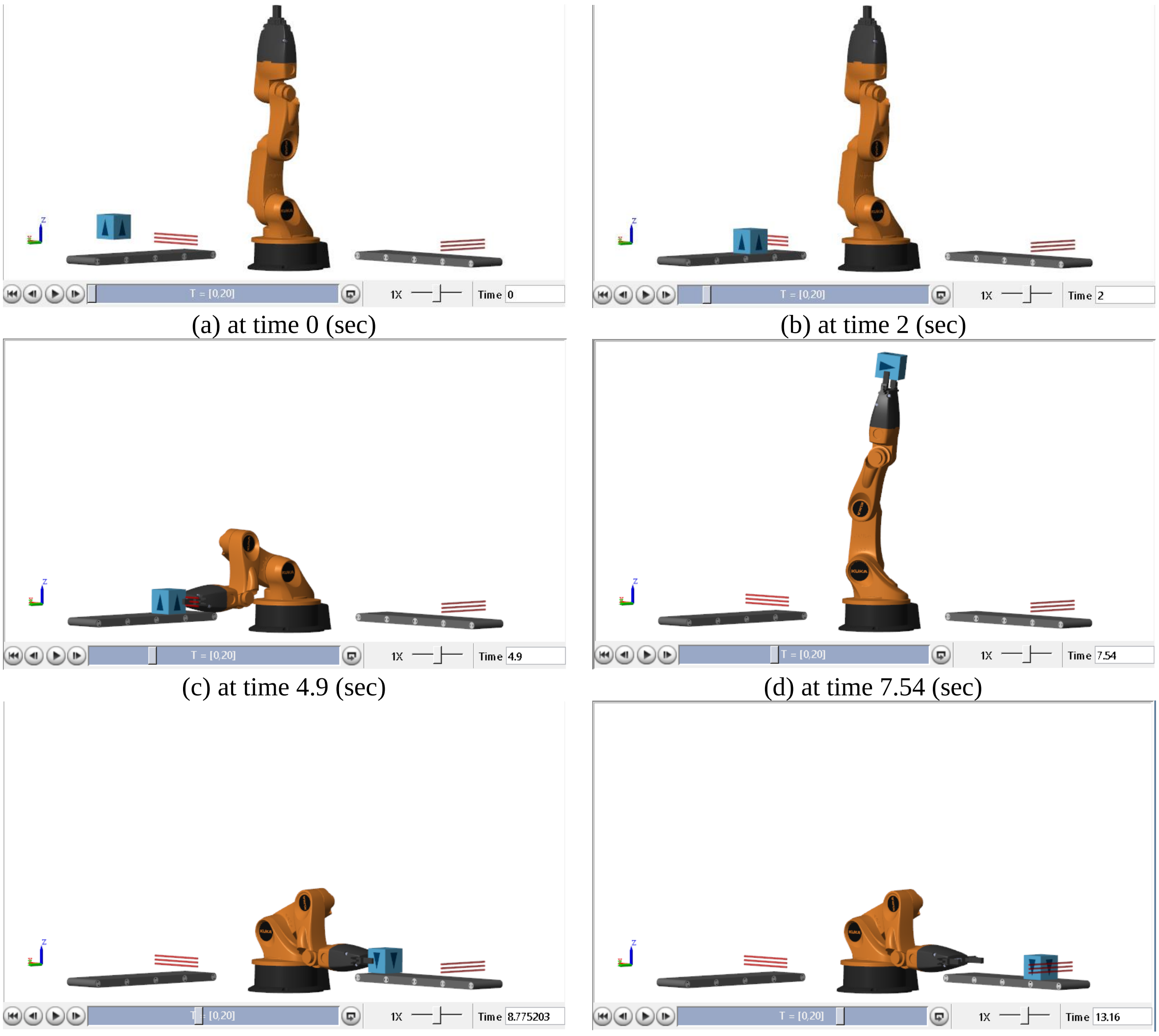
As shown in Table 4, the values had a significant impact on evaluating the selection of the best gains and the criteria based on the optimized JOA. Various values were tested to achieve the optimal solution considering both the trade-off and critical value. These values were determined based on the NARMA(L2)-FO(ANFIS)PD-I criteria obtained from the introduced algorithm. The selection, formulation, and evaluation of these considerations are illustrated in Fig. 15.

The proposed algorithm (JOA) operates by leveraging the probability of reconstruction to anticipate the optimal values for addressing a specific calculation problem in the NARMA(L2)-FO(ANFIS)PD-I controller gains. The algorithm relies on a probability distribution, with 60% allocated to upper bounds, which correspond to the gains employed when the RACBs motion follows a positive cosine wave pattern (used for manipulating the cube on the right).

The remaining 30% is dedicated to lower gains, which correspond to the RACBs behavior during a negative sine wave pattern (employed for handling the cube on the left). Table 4 presents the NARMA(L2)-FO(ANFIS)PD-I criteria, which are dependent on JOA. The table showcases a set of criteria, including K_p_joint, K_i_motor, K_d_sensor, λ_gear, and μ_N which are specifically related to the motions of RACBs.

Table 4. The selection and evaluation of NARMA(L2)-FO(ANFIS)PD-I criteria based JOA

NARMA(L2)-FO(ANFIS)PD-I Criteria				
K_p_joint	**K_i_motor**	**K_d_sensor**	**λ_gear**	**μ_N**
0.4074	0.3156	0.3724	0.1898	0.2135



(a) at time 0 (sec)
(b) at time 2 (sec)
(c) at time 4.9 (sec)
(d) at time 7.54 (sec)
(e) at time 8.7752 (sec)
(f) at time 13.16 (sec)

Fig. 14. RACB mechanics explorer demo based arm motions on MATLAB

5. Study Implications

The study's implications can be synthesized into the following key points:

- Enhancing RACB manufacturing outcomes: By implementing a robust integrated evaluation and selection approach for the Jaya optimization algorithm in the global RACB market, this study offers a promising avenue for improving RACB development. The results demonstrate the superior performance of the proposed JOA integrated approach, surpassing traditional RACB motions through the gains selection process.
- Overcoming challenges in RACB optimization: The NARMA(L2)-FO(ANFIS)PD-I controller was subjected to comprehensive testing across the four main RACB motions and various angles. The findings revealed the inherent complexities in selecting the most effective method due to the diverse parameter influences (as shown in Table 4). Consequently, caution is advised against advocating for specific optimization algorithms. To address this challenge, the study presents a novel evaluation and selection framework through JOA integration.
- Accounting for complex interactions and nonlinear effects: RACBs encounter a multitude of interactions with components such as joints, motors, gears, and sensors during real-world missions. These interactions often involve unknown factors with nonlinear effects that cannot

be captured by conventional motion equations. Hence, it is crucial for researchers to acknowledge the significance of these factors. The study highlights this importance through the diverse outcomes observed in joints, motors, gears, and sensors. Notably, the study pioneers the development of weighted criteria for the five FOPID controller gains, tailored specifically to the four RACB motions (refer to Table 4).

- Recommendation for future advancements: Building upon the selection outcomes, this study suggests leveraging adaptive neuro-fuzzy controllers within the developed JOA evaluation and selection algorithm to address the challenges. By incorporating the NARMA-L2, ANFIS, and FOPID-based JOA, this approach enables the selection of optimized values for all RACB motions, leading to enhanced RACB performance and improved end-effector capabilities.

The study exhibits a range of both advantages and limitations:

Advantages:

- Comprehensive Methodology: The study employs a comprehensive methodology that integrates multiple control techniques, including NARMA-L2, ANFIS, and FOPID. This inclusive approach allows for a nuanced optimization process.
- Adaptability Emphasized: By incorporating adaptive control techniques like ANFIS, the study endows the RACB system with the ability to respond to dynamic conditions and uncertainties, making it well-suited for volatile industrial environments.
- Enhanced Performance Focus: The study aims to augment the overall performance of RACB systems by addressing critical issues such as non-linearity, energy efficiency, and safety. The expected outcome is heightened operational efficiency and diminished costs.
- Safety Priority: The study underscores the importance of safety in RACB operations, particularly in industrial scenarios. This emphasis on safety measures is essential to prevent accidents and ensure the well-being of workers.
- Applicability in Real-world Scenarios: The study's application in MATLAB Simulink enhances its relevance to actual RACB systems, making it potentially implementable in practical industrial environments.

Limitations:

- Complexity Challenge: The integrated approach, involving a combination of various control techniques and optimization methods, can be intricate to execute and fine-tune. It may necessitate substantial expertise and computational resources.
- Resource Demands: The utilization of machine learning techniques such as ANFIS can consume significant computational resources, rendering it unsuitable for systems with limited computing capabilities.
- Data Prerequisites: The efficacy of machine learning-based methods, notably ANFIS, is contingent upon the availability of high-quality data. Collecting and processing such data can be daunting in industrial settings.
- Generalizability Constraints: The findings of the study may be specific to the studied RACB system and the industrial context, constraining their applicability to other systems or industries.
- Overfitting Concerns: The study should address the issue of overfitting in machine learning models to ensure that the proposed control strategies possess robust applicability to diverse situations.
- Practical Implementation Complexity: While the study offers theoretical and simulation-based outcomes, the practical implementation of the proposed control strategies in actual industrial

RACB systems may encounter additional complexities and necessitate validation in real-world settings.

- Cost Evaluation: The incorporation of advanced control methods and optimization techniques may entail supplementary costs, necessitating a thorough assessment of anticipated benefits.
- The study presents a promising avenue for optimizing RACB motions in industrial settings. Nevertheless, it encounters challenges related to intricacy, resource demands, and the requirement for practical validation. Addressing these limitations and thoughtfully considering the advantages will guide future research endeavors and potential industrial applications stemming from the study's findings.

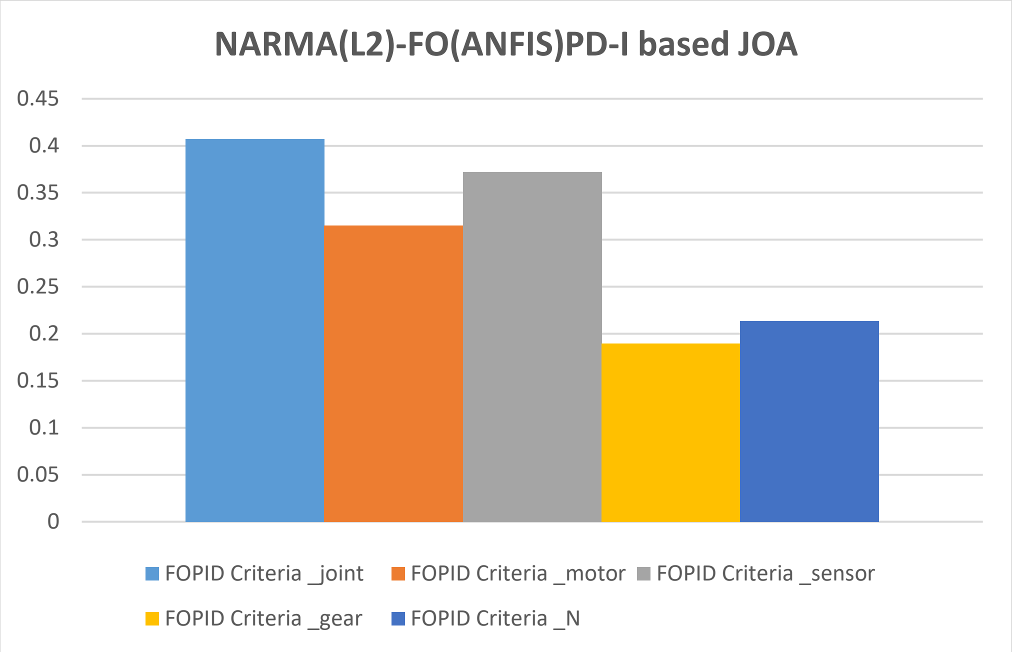


Fig. 15. Statistical assessment of the JOA algorithm utilizing the NARMA(L2)-FO(ANFIS)PD-I criteria

6. Conclusion

The literature has extensively documented the significance of RACBs in industrial operations. Previous studies have emphasized the importance of RACBs, prompting numerous researchers to develop techniques and models related to RACB movements. However, when it comes to RACB motions, various challenges have emerged, including the availability of multiple evaluation criteria, the existence of trade-offs, variations in critical values, and the relative importance of each NARMA(L2)-FO(ANFIS)PD-I criterion for each RACB motion. This research aims to tackle these challenges by evaluating and selecting the Jaya optimization algorithm for four specific RACB motions: joints, motors, gears, and sensors. Importance criteria weights for each motion are determined using the former, while the latter employs these weights in the Jaya optimization algorithm selection process. Both methods hold significance, as they contribute to identifying the most optimized values for each RACB motion. This contribution is particularly valuable for the implementation of reliable RACB industrial explorations. The robustness of this approach is demonstrated through two evaluation approaches: the NARMA-L2 controller and ANFIS. However, this work has certain limitations. Firstly, the selection procedure for the Jaya optimization algorithm during RACB motions is performed statically, without considering the dynamic nature of simultaneous motion execution. Future research should address this issue by incorporating the dynamically changing environment and the need for continuous synchronization between different motions. Additional limitations to be addressed include the use of a uniform evaluation approach across all motions, without considering interrelationships between them or across motions. Future research can investigate the impact of each criterion on others using a double-input-double-output-ANFIS and develop evaluation laboratory modeling to measure the influence of criteria on weighting values. Furthermore, the evaluation and selection process lack a precise measurement of conflicts or trade-offs among criteria for each motion. In addition, the PC speed parameters were simulated and done in MSI Crosshair Core i7-11750H with Nvidia GeForce RTX 3050 Ti Laptop GPU 16GB dedicated RAM with percentage usage of 3% CPU, 33% GPU, 72% Memory, 3% Disk, 3018 RPM Fan 1, 2666 RPM Fan 2, 31% SSD, 71°C CPU Temperature, 562 MHz GPU Clock, 810 MHz VRAM Clock, and 46°C GPU Temperature with MATLAB R2022a. The implications of this study for enhancing the manufacturing outcomes of RACBs within the global industrial market are significant and hold great potential for future research. The following are specific implications:

a) Gaining a Competitive Edge: The findings of this study can offer RACB manufacturers a competitive advantage. By optimizing RACB motions to strike a balance between conflicting factors like energy efficiency, precision, and throughput, manufacturers can present systems that surpass competitors in terms of versatility and efficiency.

b) Adaptability to Market Dynamics: RACB systems, designed with a profound understanding of trade-offs and conflicts among criteria, can be more adaptable to the dynamic needs of the industrial market. Manufacturers can customize their offerings to meet precise customer requirements and swiftly adapt to shifting market demands.

c) Enhanced Energy Efficiency: As global concerns regarding energy efficiency persist, the insights from this study can aid manufacturers in developing RACBs that not only conserve energy but also maintain high levels of performance. This is especially critical as sustainability becomes a central consideration in industrial operations.

d) Prioritizing Safety and Compliance: The study's emphasis on safety considerations can lead to RACB designs that prioritize worker safety and align with industry regulations. This approach can reduce accidents, minimize downtime, and mitigate potential legal issues, ultimately enhancing the overall dependability of RACBs in manufacturing environments.

e) Informed Resource Allocation: Manufacturers can make well-informed decisions regarding the allocation of resources. For example, if safety and precision are of paramount importance, investments can be directed towards advanced sensors and control systems, ensuring that resources are optimally utilized to achieve specific objectives.

f) Exploring New Markets: With RACBs capable of accommodating user preferences and diverse market requirements, manufacturers can venture into new markets and industries. The ability to offer versatile and adaptable RACB solutions can open doors to previously unexplored sectors.

g) Proactive Risk Management: Understanding the trade-offs among criteria empowers manufacturers to proactively identify and mitigate risks associated with RACB operations. This proactive approach can prevent costly incidents and minimize downtime.

h) Continuous Enhancement: Manufacturers can implement continuous improvement processes guided by the insights from this study. By regularly reviewing and optimizing RACB designs and control strategies, they can maintain a competitive edge and remain at the forefront of technological advancements.

i) Global Adoption: The study's findings can stimulate the global adoption of RACBs across various industries. When RACBs offer enhanced performance, efficiency, and safety, they become appealing solutions for manufacturers worldwide.

In future research, scholars can delve further into the practical implementation of the study's insights, developing real-world applications and case studies to demonstrate the tangible benefits of optimizing RACB motions. Furthermore, exploring the economic and environmental impacts of these optimizations can further validate the advantages of the proposed approach. By considering these implications and integrating them into future research and development endeavors, manufacturers can position themselves as leaders in the RACB market, delivering solutions that align with the evolving requirements of the global industrial sector.

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