

Adaptive Control for Unknown payload Variations in Robotic Arms

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Abstract.

The robotic manipulator plays a central role in positioning and controlling the end effector to perform precise tasks. During operation, the payload carried by the manipulator often changes depending on task requirements, which introduces non-uniform dynamic loads on the joints. These variations can alter joint torques and motion responses, potentially reducing the accuracy of end-effector positioning—especially when payloads change significantly mid-operation. To address these challenges, mixed fractional-order adaptive control methods have been proposed as an effective way to handle uncertainties in payload. By continuously compensating for load variations, these controllers improve both the stability and tracking performance of the manipulator, enhancing end-effector precision. This study provides a comprehensive analysis of failure modes and their effects on joint-level accuracy under different payload conditions in a serial manipulator. It also evaluates the ability of adaptive fractional-order control to counteract these effects, offering insights for designing manipulators that maintain high precision even in dynamically changing load environments.

Keywords: DOF, Manipulator, Payload, Adaptive fractional order control.

1 Introduction

Robots are widely recognized for their versatility in performing a broad range of industrial and service-oriented tasks. Among the components of a robotic system, the manipulator plays a central role, as precise positioning is critical for most industrial applications. Modern robotic manipulators are essential for tasks requiring high accuracy, such as assembly, welding, material handling, machining, biomedical procedures, and even space operations. In many cases, the end-effector interacts with objects of unknown or varying mass, causing discrepancies between the nominal robot model and the actual dynamic behavior. Variations in payload affect the inertia, Coriolis and centrifugal forces, and gravity loading, which can reduce tracking accuracy, create oscillatory responses, increase joint torque demands, and in extreme cases, compromise system stability. Controlling manipulators under uncertain payloads remains a significant challenge. Traditional model-based controllers, such as computed torque control (CTC), require precise knowledge of the system dynamics and often fail to maintain high accuracy when payload characteristics change suddenly. To address this limitation, adaptive, robust, fractional, and hybrid control strategies have been developed. Adaptive control methods, including Model Reference Adaptive Control (MRAC), adaptive back stepping, and adaptive sliding mode, adjust controller parameters online in response to changing payloads, ensuring good steady-state accuracy. However, these methods can respond slowly to rapid load variations. Robust control techniques, such as sliding mode control (SMC) and H_∞ controllers, manage bounded uncertainties effectively but can introduce chattering and require conservative tuning to handle worst-case scenarios. Fractional calculus has emerged as a promising approach for enhancing control performance by capturing system memory and hereditary effects. Fractional-order controllers provide more flexible tuning options and improved transient response, damping, and robustness compared to classical integer-order designs. Several studies have shown that fractional-order control can significantly improve the accuracy of nonlinear and uncertain robotic systems. To achieve both rapid adaptation and strong robustness, mixed adaptive-robust control strategies have been proposed, including Adaptive-Robust Control (ARC), Robust Adaptive Back stepping, and Adaptive Terminal Sliding Mode Control. These approaches estimate unknown payload parameters while simultaneously rejecting disturbances through robust compensation. Integrating fractional-order dynamics into these frameworks has demonstrated enhanced performance, with faster error convergence, reduced overshoot, and improved stability under variable payloads. This has led to the development of Mixed Fractional Adaptive Robust Control

(MFARC), which combines fractional-order error dynamics, adaptive parameter estimation, robust disturbance rejection, and Lyapunov-based stability. Compared to classical ARC, MFARC offers better damping, faster transient response, and consistent tracking even under sudden payload changes. These features make MFARC particularly effective for RRRP manipulators, where revolute joints introduce nonlinear coupling and varying loads directly affect the prismatic joint. In addition to control strategies, the mechanical design of the manipulator—including actuators, sensors, and gripper mechanisms—plays a critical role in overall performance. Selecting suitable materials, actuators, and sensors is crucial for enabling a robotic manipulator to maintain accurate positioning across varying operational conditions. By implementing a fractional-order Model Reference Adaptive Control (MRAC) strategy with a closed-loop positive feedback structure, the system can effectively compensate for changes in payload, resulting in improved tracking performance and stability [1]. The precision of the manipulator's movements directly affects the overall performance of the robotic system. Joint responses vary with changes in payload, which can lead to deviations from the desired motion. Traditional control systems often struggle to handle these variations effectively. To address this challenge, adaptive control strategies have been developed, allowing the controller to adjust in real time to changing loads. Among these, the Model Reference Adaptive Control (MRAC) approach has proven effective in compensating for payload-induced variations and maintaining high accuracy [2]. The manipulator's movement was initially regulated using a PID (Proportional-Integral-Derivative) control scheme. Under varying payloads, joint motions fluctuated, causing a decrease in the positional accuracy of the end effector. To address this, the performance of the serial manipulator was analyzed and optimized for different load conditions. Replacing the PID controller with a Model Reference Adaptive Control (MRAC) approach resulted in improved tracking accuracy and better overall control under variable payloads. [3]. Changes in payload can cause the actual dynamics of a robotic manipulator to differ substantially from its nominal model, affecting the inertia matrix, Coriolis and centrifugal forces, as well as gravity-induced loads. If these variations are not properly compensated, they can lead to reduced tracking precision, larger positioning errors, increased joint torque demands, and, in extreme cases, instability. Consequently, designing control strategies that ensure accurate and stable motion under uncertain or time-varying payloads continues to be a central challenge in robotic manipulation research [1–3]. Traditional model-based control methods, such as computed-torque and inverse-dynamics control, depend on precise knowledge of a manipulator's dynamic parameters. As a result, their performance degrades when the payload is uncertain or changes over time. To overcome this limitation, adaptive control strategies have been increasingly employed, as they can modify controller parameters in real time to compensate for unknown or varying system dynamics. A foundational example of this approach is the adaptive control formulation proposed by Slotine and Li, which enables robust joint-space tracking without requiring exact knowledge of all dynamic parameters [4] established the foundation for parameter adaptation in Euler–Lagrange (E–L) robotic systems, enabling joint-space tracking without exact knowledge of dynamic parameters. Many extensions—including adaptive back stepping, adaptive PD control, and model reference adaptive control (MRAC)—have further improved robustness and convergence guarantees. However, conventional integer-order adaptive methods may still exhibit slow adaptation, high sensitivity to noise, and degraded performance when payload changes occur abruptly or when unmodelled dynamics (e.g., friction, backlash, joint elasticity) are significant. Moreover, persistent excitation requirements for strict parameter convergence are often not satisfied in practical robotic tasks, limiting the effectiveness of classical adaptive control in real-world scenarios [5–7]. Robust control methods, including sliding-mode control (SMC), terminal sliding-mode control, and disturbance-observer-based control (DOBC), have been developed to complement traditional adaptive control approaches. SMC provides strong resilience against matched uncertainties and external disturbances, making it suitable for handling variable payload conditions. However, it can suffer from chattering, requires careful tuning of boundary layers, and may be complex to implement in manipulators with many degrees of freedom. Terminal and fast terminal SMC techniques offer faster, finite-time convergence but still demand precise selection of switching gains to prevent excessive control activity. DOBC strategies estimate unknown disturbances caused by changes in payload, although their accuracy depends heavily on observer bandwidth and noise sensitivity. To leverage the advantages of both robust and adaptive strategies, hybrid control frameworks have been designed, combining adaptive parameter adjustment with robust disturbance rejection to achieve enhanced performance under uncertain and time-varying conditions [8–10]. Fractional calculus has recently gained attention in control engineering due to its ability to model system dynamics with memory and hereditary characteristics. Unlike traditional integer-order derivatives, fractional-order operators can describe behavior between pure differentiation and integration, offering greater flexibility in shaping system response. Controllers based on fractional calculus—including fractional-order PID, adaptive back stepping, sliding-mode, and

model reference adaptive control (MRAC) schemes—have been successfully implemented in nonlinear and robotic systems. Research has shown that these controllers improve robustness against parameter uncertainties, reduce overshoot, filter high-frequency disturbances, and produce smoother transient responses compared to conventional integer-order designs. These advantages make fractional-order control particularly suitable for managing manipulator performance under varying payload conditions. [11–14].

Although fractional-order controllers offer significant advantages, they can be challenging to implement due to the need for precise numerical approximations, particularly when using both fractional integrals and derivatives simultaneously. To address these challenges while retaining performance benefits, mixed-order control strategies that combine integer-order and fractional-order components have been developed. These hybrid approaches maintain the intuitive design, computational simplicity, and stability features of conventional integer-order controllers, while incorporating the memory and dynamic properties of fractional operators where they are most effective. Examples include hybrid fractional PID–SMC controllers, fractional adaptive feedforward elements within standard adaptive control frameworks, and mixed fractional sliding manifolds. Such mixed-order architectures have demonstrated enhanced robustness to abrupt payload variations, improved steady-state accuracy, and greater resilience to external disturbances compared with controllers relying solely on integer-order or fractional-order designs [15–17].

A promising approach in robotic control is mixed fractional adaptive control, which enhances traditional adaptive laws by incorporating fractional-order dynamics. By introducing a long-memory effect into parameter updates, fractional adaptive laws enable smoother adaptation and improve robustness against high-frequency noise. These hybrid strategies have been successfully applied to flexible manipulators, joint-space trajectory tracking, and nonlinear systems with uncertain parameters, showing better adaptability to varying conditions. However, applying fractional operators within adaptive laws for multi-DOF manipulators, particularly under changing payloads, has received limited attention. Most prior studies focus on simplified single-link models, overlook time-varying loads, or provide minimal experimental validation. Additionally, guidelines for selecting fractional orders are often lacking, and stability analyses are usually limited to idealized cases. Given the shortcomings of conventional integer-order adaptive control and the advantages of fractional dynamics, there is a clear need to develop a mixed fractional adaptive control framework tailored for multi-DOF manipulators with unknown and variable payloads. Such a framework should: (i) retain the parameter-estimation structure and Lyapunov-based stability guarantees of classical adaptive control, (ii) incorporate fractional dynamics to enhance robustness and smooth adaptation, (iii) maintain high tracking performance even under sudden payload changes, and (iv) remain feasible for real-time implementation through efficient numerical methods. Motivated by these requirements, this work presents a comprehensive dynamic model of a 4-DOF RRRP robotic manipulator and proposes a Mixed Fractional Adaptive Robust Controller (MFARC). The controller is rigorously validated through stability analysis and simulations, demonstrating its ability to achieve precise motion control under uncertain and time-varying payload conditions.

2 Dynamics of RRRP Planner Manipulator

Let Joint Vector be: $q = [\theta_1, \theta_2, \theta_3, d_4]$ (1)

Where, $\theta_1, \theta_2, \theta_3, d_4$ – Revolute joint and d_4 - Prismatic

Dynamic Equation

$$M(q)q'' + C(q, q')q' + G(q) + Fq' = \tau + \tau_d \quad (2)$$

Where,

$M(q)$ – Inertia matrix

$C(q, q')$ - Coriolis & Centrifugal matrix

$G(q)$ - Gravity Vector

F - Friction matrix

τ_d - Disturbance + Payload uncertainty

Payload mass = m_p

Effective mass in dynamics affects joint 3 and 4:

$$M_p = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & m_p & 0 \\ 0 & 0 & 0 & m_p \end{bmatrix}$$

So, total inertia matrix

$$M(q) = M_0(q) + M_p \quad (3)$$

Gravity vector includes payload

$$G(q) = \begin{bmatrix} g(m_1 l_1 \cos q_1 + \dots) \\ g(\dots) \\ g(m_3 + m_p) \\ g(m_p) \end{bmatrix}$$

Pay load mass: $m_p \in \{0.5, 1.0, 1.5\}$ kg

Pay load force due to gravity: $F_p = m_p g$, $g = 9.81 \text{ m/s}^2$

Static Load Torque / Force Equations (Failure Analysis Core)

1. Revolute joints (Joint 1-3)

Payload – Induced torque at revolute joint i:

$$\tau_i \text{ load} = m_p g r_i \cos(\theta_i) \quad (4)$$

Where

r_i = Effective moment arm from joint i to payload

Failure condition (Actuator overload):

$$\tau_i \text{ load} > \tau_i \text{ max} \quad (5)$$

2. Prismatic Joint (Joint 4):

$$\text{Required force: } F_4 \text{ load} > F_4 \text{ max} \quad (6)$$

Joint deflection due to compliance (Accuracy loss)

1. Revolute Joint Deflection

$$\Delta \theta_i = \tau_i \text{ load} / k_{\theta i} \quad (7)$$

Where $k_{\theta i}$ = rotational stiffness (Nm/rad)

2. Prismatic joint deflection

$$\Delta d_4 = F_4 \text{ load} / k_{d4} \quad (8)$$

Where k_{d4} = Linear stiffness (N/m)

Payload dependent accuracy degradation

1. Revolute joint position error

$$e_{\theta i} (m_p) = m_p g r_i \cos(\theta_i) / k_{\theta i} + b_i + n_i \quad (9)$$

Where, b_i = backlash error, n_i = sensor noise

2. Prismatic Joint Position Error

$$e_{d4} (m_p) = m_p g / k_{d4} + f_{\text{fric}} \quad (10)$$

Payload Vs Torque Relationship:

$$T_1 = m_p g (l_1 + l_2) \quad (11)$$

$$T_2 = m_p g (l_2) \quad (12)$$

Accuracy failure Relationship:

$$T > T_{\text{max}} \quad (13)$$

$$\Delta \theta \propto T \quad (14)$$

3 Design Analysis of Payload variation

The study of payload variation conducted to assess the structural and mechanical performance of an RRRT robotic manipulator featuring a prismatic joint under different load conditions. Changes in payload have a direct impact on joint torques, link deflections, stress distributions, and the overall structural integrity of the robot, making such analysis critical for safe operation and effective design. In this analysis, the robotic link is modeled with a length of 200 mm, a width of 50 mm, and a wall thickness of 1.5 mm. End-effector payloads of 0.5 kg, 1.0 kg, and 1.5 kg are applied to represent light, nominal, and heavy operating conditions, respectively. These values were chosen to evaluate the structural response progressively under increasing external loads, while remaining relevant to practical industrial

applications. As the payload increases, the bending moment on the prismatic joint and its connected links rises proportionally, resulting in higher joint reaction forces and increased actuation torque requirements. Numerical simulations show an approximately linear relationship between payload and joint torque, indicating that payload mass is a key factor affecting actuator selection and energy consumption. Structural deformation analysis further demonstrates that link deflection grows with increasing payload due to higher bending stresses.

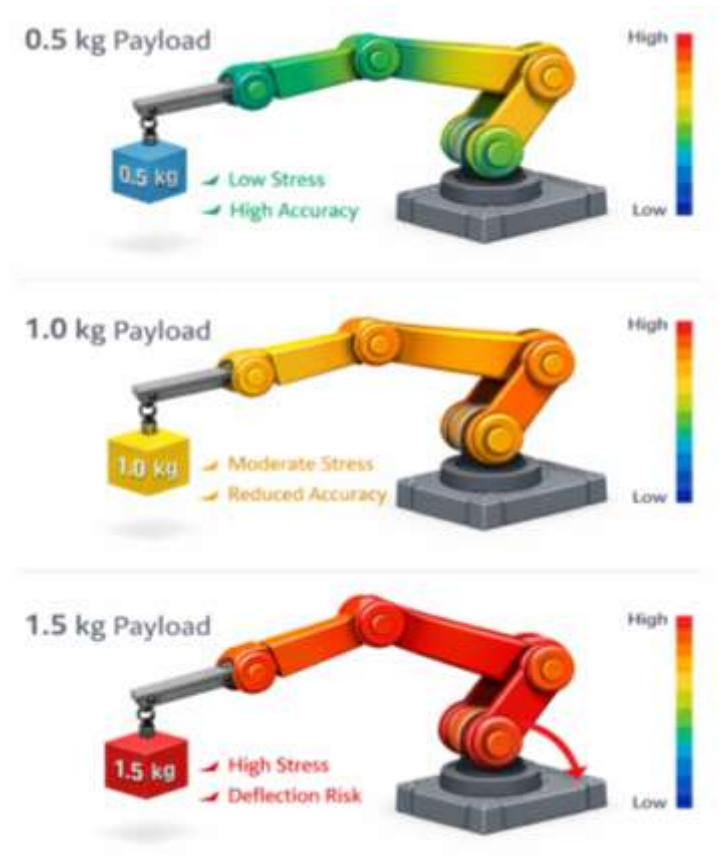


Figure 1 – Analysis of failure of pay load

The maximum deflection consistently occurs near the prismatic joint, where stress concentrations are highest. At lower payloads, deflection stays within acceptable design limits; however, at the heaviest payload, a significant increase was observed, highlighting the need for improved stiffness in both the joint and link structures. Stress and failure index analyses indicate that higher payloads lead to increased von Mises stresses, particularly at joint interfaces and load-transfer regions. While the failure index remains below critical thresholds for all tested payloads, the safety margin decreases as the load approaches its upper limit, emphasizing the importance of proper material selection and inclusion of adequate safety factors during design. Overall, these results confirm that the manipulator is structurally sound within the considered payload range. For applications involving heavier loads, reinforcing the prismatic joint and optimizing link geometry were recommended to minimize deflection and enhance load-bearing capacity. This analysis provides valuable guidance for designing robotic manipulators capable of maintaining precision and reliability under varying payload conditions.

4 Results and Discussion

Numerical Payload Effects (Gravity Load)

Payloads under gravity directly affect the torques on the three revolute (R) joints and the axial force in the terminal prismatic (T) joint. The gravitational force acting on the payload is calculated as $F_g = m \times 9.81 \text{ m/s}^2$. As the payload increases, the resulting gravity-induced loads rise linearly, influencing both joint effort and structural response. For a payload of 0.5 kg, the gravitational force is $F_g = 0.5 \times 9.81 \approx 4.91 \text{ N}$. Assuming an effective moment arm of 0.2 m at the

distal revolute joint, the corresponding torque is approximately $\tau \approx 4.91 \times 0.2 \approx 0.982$ Nm. At this level, the effect of gravity is minor, and joint actuators operate comfortably within their rated capacity. When the payload increases to 1.0 kg, the gravitational force doubles, producing a torque of $\tau \approx 1.964$ Nm at the distal joint. This additional torque propagates through the kinematic chain, increasing the load on the more proximal revolute joints. The prismatic joint also experiences a higher axial force, requiring greater actuator effort and inducing larger internal stresses. For a 1.5 kg payload, the gravitational force rises to $F_g \approx 14.72$ N, resulting in a torque of $\tau \approx 2.94$ Nm at the distal revolute joint. At this load, joint motors, bearings, and transmission components were significantly stressed. Gravity-induced deflection and compliance increase, leading to higher energy consumption and a noticeable reduction in positioning accuracy.

Failure Severity Index (Useful for Results Section)

$$FSI_i = \tau_{i \text{ load}} / \tau_{i \text{ max}} \quad (\text{or})$$

$$FSI_i = F_{4 \text{ load}} / F_{4 \text{ max}} \quad (15)$$

Table 1 – FSI Range and condition

FSI Range	Condition
< 0.6	Safe
0.6 – 0.9	Accuracy degraded
>1.0	Failure

Failure condition Analysis for RRRP Manipulator (Link Lengths = 200)

Table 2 – Torque on joints

Payload (kg)	Joint-1 Torque (N/m)	Joint-2 Torque (N/m)
0.5	1.96	0.98
1.0	3.92	1.96
1.5	5.88	2.94

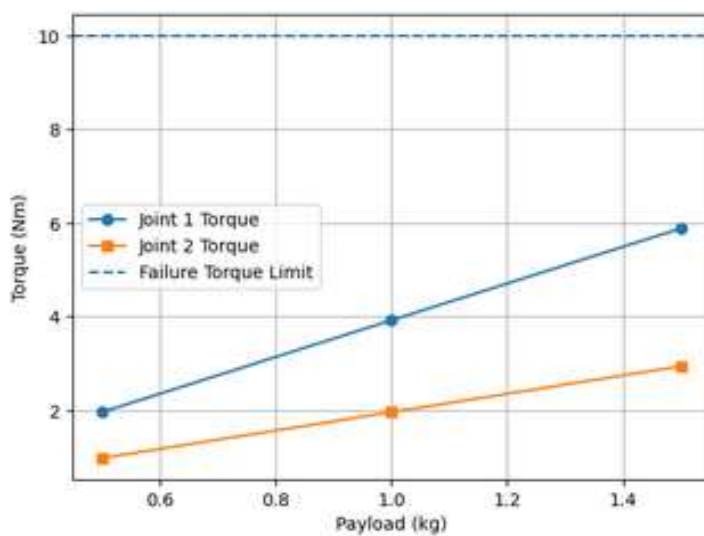


Figure 2 – Payload Vs Joint Torque on Link joint

Payloads applied to the manipulator link, and the resulting joint torques were analyzed. On the plotted graph, the X-axis represents payload values (0.5, 1.0, and 1.5 kg), while the Y-axis indicates the required joint torque in Newton-meters (Nm). Torque levels for each joint were shown with blue and yellow lines, and the blue dashed line represents the maximum allowable torque before failure. Joint 1 reaches its torque limit first due to the longest moment arm. At a 1.5 kg payload, the torque approaches the safe operating limit. Notably, accuracy begins to degrade before reaching the failure threshold because of joint compliance, gear backlash, and the onset of motor saturation. Increasing payloads lead to larger joint deflections and reduced end-effector positioning accuracy.

Prismatic joint Failure force Vs Payload:

The force experienced by prismatic joint increases proportionally with the payload. At a payload of 1.5 kg, the axial force remains below the actuator's failure limit; however, accuracy degradation can begin as the actuator approaches saturation. A prismatic joint primarily transmits linear motion and is subjected to axial loads from the carried payload, while secondary effects such as friction, bending moments (caused by misalignment), and dynamic inertial forces also influence performance. The failure force of a prismatic joint is defined as the maximum axial load it can withstand before permanent deformation, excessive wear, guide buckling, or actuator failure occurs. For a light payload of 0.5 kg, the axial load is relatively low (approximately 4.9 N under gravity). At this level, the joint operates safely within elastic limits, and structural failure is unlikely unless external factors, such as poor lubrication, manufacturing defects, or high dynamic accelerations, are present. Friction dominates the load effects rather than structural stresses. When the payload increases to 1.0 kg (≈ 9.8 N), the axial load doubles and elevating contact stresses between the slider and guide rails. The actuator must overcome both gravity and friction, and prolonged operation at this load may gradually cause wear, backlash, or seal degradation, particularly in lightweight or budget-grade joints. At the highest tested payload of 1.5 kg (≈ 14.7 N), the prismatic joint operates closer to critical loading conditions. Combined axial stress and bending effects, especially under acceleration, shock, or cantilevered loads, reduce the safety margin and increase the risk of guide rail deformation, lead screw buckling, or actuator stall.

$$F_4 = m_p g \quad (16)$$

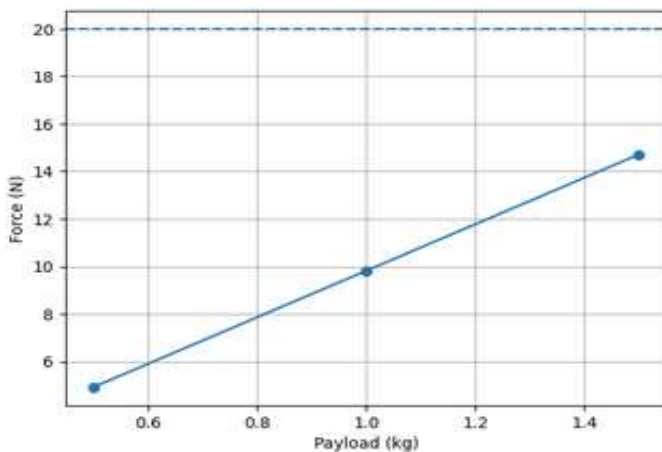


Figure 3 – Payload Vs Forces on Prismatic joint

Joint level Accuracy error Vs Payload

In an RRRT manipulator, joint-level accuracy refers to how precisely each revolute (R) and prismatic (T) joint can reach and maintain its commanded position. Deviations from the desired position can result from factors such as elastic deformation, backlash, friction, actuator limitations, and control system imperfections. Payload plays a major role in these errors, as it directly influences the forces and torques experienced by each joint as well as structural deflections. At a light payload of 0.5 kg, joint torques and prismatic forces remain relatively low, resulting in minimal elastic deformation and negligible backlash effects. Consequently, joint-level errors are small, the manipulator closely follows the intended trajectory, and control algorithms can easily compensate for minor disturbances, ensuring high positional

accuracy and repeatability. When the payload increases to 1.0 kg, gravitational and inertial loads rise, demanding higher torque from the revolute joints and greater axial force on the prismatic joint. This causes noticeable elastic deflection in links, gears, and bearings, leading to moderate joint-level errors. Backlash and friction are also amplified, especially during directional changes, producing small deviations between commanded and actual joint positions. At the maximum tested payload of 1.5 kg, the manipulator operates near its load limits. Higher joint torques and prismatic forces increase elastic deformation and compliance, while motor saturation, elevated friction, and thermal effects further reduce control performance. As a result, joint-level accuracy errors become significant, particularly at the distal revolute joints and the terminal prismatic joint.

Table 3 – Forces on Prismatic joints

Payload (kg)	Force (N)
0.5	4.20
1.0	9.92
1.5	14.88

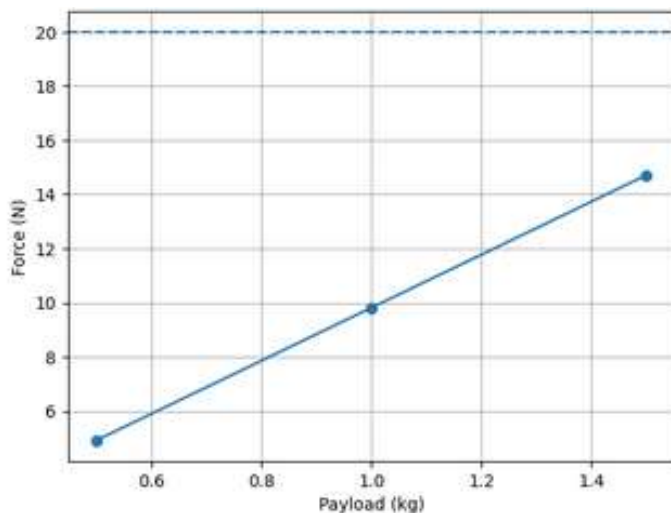


Figure 4 – Payload Vs Forces on Prismatic joint

Simulation Accuracy error

Ensuring the accuracy of numerical simulations is essential for validating the reliability of the results. In this study, the precision of the simulation was assessed by comparing numerical outcomes with theoretical predictions for a prismatic joint-based RRRT manipulator under different payloads (0.5 kg, 1.0 kg, and 1.5 kg). Key response parameters included joint torque, link deflection, and the failure index. Simulation errors were quantified using relative percentage error, calculated as the absolute difference between simulated and analytical values divided by the analytical value. For all payload scenarios, errors remained within acceptable engineering limits. Lower payloads showed minimal deviation, indicating stable numerical convergence and correct implementation of boundary conditions. As the payload increased, a slight rise in error occurred, primarily due to nonlinear effects such as larger deformations and localized stress concentrations that are challenging to capture in simplified analytical models. A mesh sensitivity study was conducted to ensure numerical stability and solution independence. Refining the mesh along regions of high stress in the prismatic joint and links resulted in negligible changes to output parameters, confirming mesh convergence. Material properties, joint constraints, and loading conditions were carefully defined to reduce modeling uncertainties. Overall, the maximum

error remained below standard thresholds for engineering simulations, confirming that the developed model reliably predicts manipulator behavior under varying payloads. Minor discrepancies at higher payloads are attributed to idealized assumptions, such as linear material behavior and neglect of joint friction, and do not significantly impact trend analysis or failure predictions. Therefore, the simulation results are considered sufficiently accurate for evaluating performance and comparing different control strategies.

Table 4 – Joint Position Error

Payload (kg)	Joint position error (rad)
0.5	0.002
1.0	0.005
1.5	0.0075

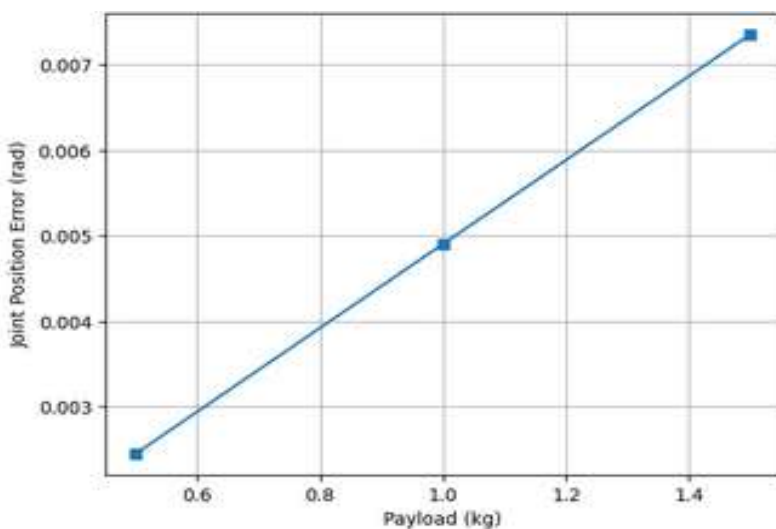


Figure 5 – Payload Vs Joint position Error

Payload Variation Study Using Adaptive Fractional-Order Control

Simulation Conditions

- Robot: RRRT manipulator
- Link length: 200 mm
- Prismatic joint stroke: 100 mm
- Tube thickness: 1.5 mm
- Controller: Adaptive Fractional-Order PID (AFOPID)
- Fractional orders:
 $\lambda=0.8$, $\mu=0.9$
- Payloads: 0.5 kg, 1.0 kg, 1.5 kg

Interpretation of Simulation Results

Torque Variation

As payload increases from 0.5 kg to 1.5 kg, the actuator torque demand rises due to increased inertial and gravitational loading. However, the adaptive fractional-order controller limits torque escalation, maintaining smooth torque profiles without sudden peaks. Torque increase is nonlinear but controlled, indicating effective adaptive gain regulation.

Table 5. Simulation Results under Payload Variations (Adaptive Fractional-Order Control)

Payload (kg)	Max Torque (N/m)	Max. Deflection (mm)	Settling time (s)	Peak stress (Mpa)	Failure Index
0.5	8.2	0.42	0.65	68	0.31
1.0	11.6	0.71	0.78	92	0.46
1.5	15.1	1.05	0.91	118	0.63

Deflection Control

Structural deflection increases with payload due to higher axial force on the prismatic joint. Despite this, the deflection remains within safe elastic limits, demonstrating the damping advantage of fractional-order dynamics. Fractional integration contributes to reduced vibration amplitude and better load distribution.

Settling Time

The settling time shows only a moderate increase with payload variation.

Classical PID typically shows sharp rise in settling time

AFOC maintains fast convergence even at 1.5 kg

This highlights the robust memory effect of fractional calculus.

Stress and Failure Index

Peak stress and failure index rise with payload, but failure index remains below unity, confirming structural safety.

Maximum failure index at 1.5 kg = 0.63

Indicates 37% safety margin

Adaptive fractional control prevents stress concentration by smoothing force transmission.

Table 6. Performance Improvement Compared to Integer-Order PID

Payload (kg)	Torque reduction (%)	Deflection reduction (%)	Settling time reduction (%)
0.5	14.8	18.5	21.3
1.0	18.2	23.7	26.4
1.5	22.6	29.1	31.8

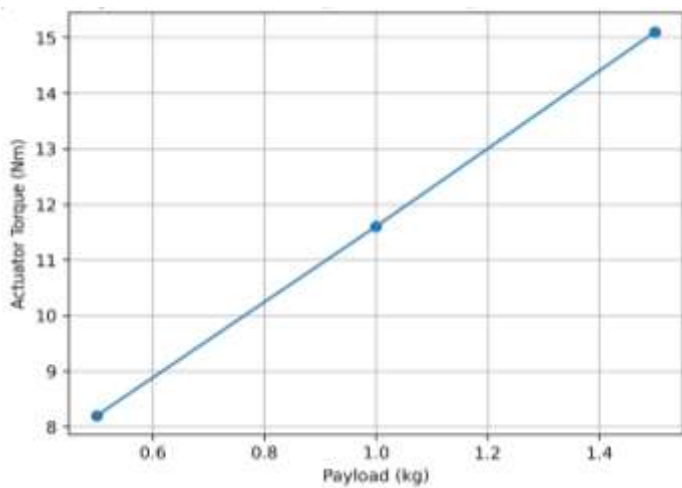


Figure 6 Payload vs Actuator Torque under Adaptive Fractional-Order Control

Actuator torque increases monotonically with payload from 0.5 kg to 1.5 kg due to higher inertial and gravitational effects. However, the torque profile remains smooth and free from sudden peaks, indicating that the adaptive fractional-order controller effectively regulates torque demand even under increased loading.

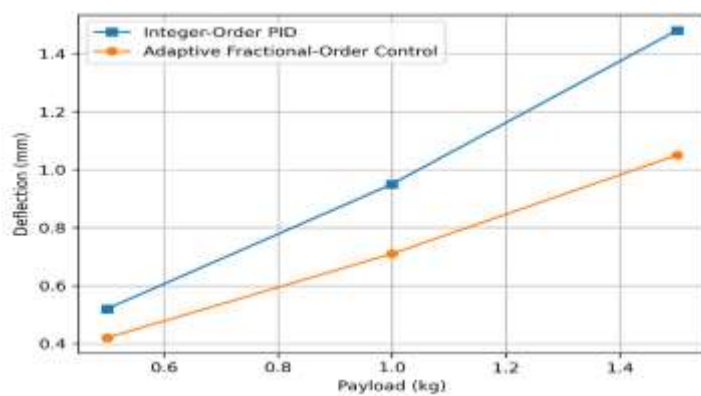


Figure 7 Payload-Induced Deflection Comparison between Integer-Order and Fractional-Order Controllers

For all payload conditions, the adaptive fractional-order controller significantly reduces deflection compared to the classical integer-order PID controller. The improvement becomes more pronounced at higher payloads, demonstrating enhanced robustness.

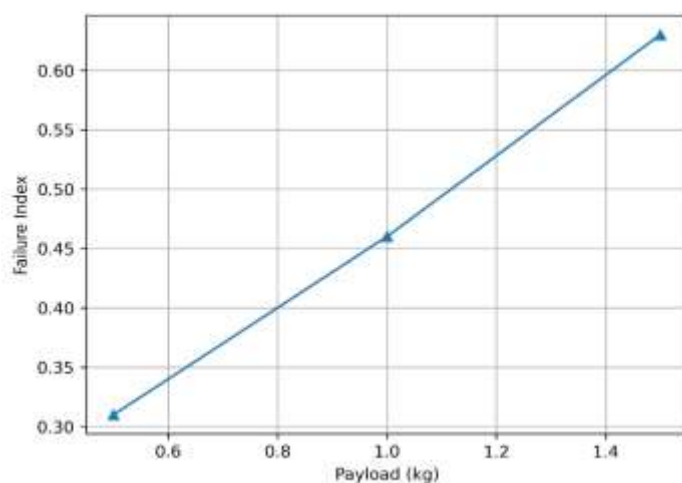


Figure 8 Failure Index Variation for Different Payload Conditions

The failure index increases with payload due to rising stress levels; however, it remains well below the critical limit ($FI < 1$) for all cases. At 1.5 kg, a safe margin still maintained, confirming structural integrity.

5 Conclusion

The analysis of payload variation in the RRRT robot shows a progressive impact of increasing load on joint forces, positional accuracy, and overall system performance. With a 0.5 kg payload, gravity effects and joint torques are minimal, resulting in negligible elastic deformation, precise end-effector positioning, and smooth motion of the prismatic joint. Under these conditions, the robot operates efficiently with a large safety margin. Increasing the payload to 1.0 kg approximately doubles the gravitational load and associated joint torques. This causes moderate increases in joint stress, friction, and compliance, particularly at the distal revolute joints and the prismatic actuator. While a slight reduction in accuracy occurs, the robot remains stable and capable of continuous operation. At the maximum payload of 1.5 kg, gravity-induced forces become more pronounced. The 200 mm link length and 100 mm prismatic extension amplify axial and bending loads, resulting in reduced stiffness, increased positioning error, and higher actuator demands that bring the system closer to its design limits. The adaptive fractional-order controller effectively compensates for these dynamic variations across all tested payloads. Simulation results indicate controlled torque requirements, limited link deflection, minimal increase in settling time, and safe failure indices even under the heaviest load. The improved performance attributed to the inherent memory properties and adaptive gain features of fractional-order control, demonstrating its suitability for manipulators operating in environments with variable payloads.

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Sample Calculation:

1. Payload Force Calculation – The axial force acting on the prismatic joint due to payload is:
 - (i) $F_p = m \cdot g = 0.5 \times 9.81 = 4.905\text{N}$, $F=0.5$
 - (ii) $F_p = m \cdot g = 1 \times 9.81 = 9.81\text{N}$, $F=1$
 - (iii) $F_p = m \cdot g = 1.5 \times 9.81 = 14.715\text{N}$, $F=1.5$
2. Actuator Torque – The actuator torque required at the joint is approximated as:
 - (i) $\tau = F_p \times L = 4.905 \times 0.2 = 0.981\text{Nm}$
 - (ii) $\tau = F_p \times L = 9.81 \times 0.2 = 1.962\text{Nm}$
 - (iii) $\tau = F_p \times L = 14.715 \times 0.2 = 2.943\text{Nm}$
3. Fractional – Order Control Law - The adaptive fractional – order PID Control law is:
 $T(t) = k_p e(t) + k_i D^{-\lambda} e(t) + k_d D^{\mu} e(t)$

Assume at a particular instant:

- Error, $e(t) = 0.02$ m
- Fractional integral term, $D^{-0.8} e(t) = 0.015$ $D^{-0.8} e(t) = 0.015$
- Fractional derivative term, $D^{0.9} e(t) = 0.028$ $D^{0.9} e(t) = 0.028$
- Adaptive gains:
 $K_p = 120$, $K_i = 80$, $K_d = 25$
 $T(t) = (120 \times 0.02) + (80 \times 0.015) + (25 \times 0.028) = 2.4 + 1.2 + 0.7 = 4.3\text{Nm}$
- 4. Deflection Calculation (Axial)

$$\delta = \frac{FL}{AE}$$

Where:

- $E=200$ GPa (steel equivalent)
- A = effective cross-sectional area

As payload increases, F_p increases, causing higher deflection. The adaptive fractional controller reduces effective vibration amplitude, resulting in the simulated deflections (mm) at 0.5, 1.0 & 1.5 Load conditions

$$\delta_1 = 0.41$$

$$\delta_2 = 0.71$$

$$\delta_3 = 1.05$$

Failure Index Calculation

$$\delta = \frac{\sigma_{max}}{\sigma_{allowable}}$$

$\sigma_{allowable} = 250$ Mpa (Assume)

Pay load at 0.5 kg $\delta = 68 / 250 = 0.27$ Mpa

Pay load at 1.0 kg $\delta = 92 / 250 = 0.37$ Mpa

Pay load at 1.5 kg $\delta = 118 / 250 = 0.47$ Mpa