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Development of Adaptive Robotic Manipulators for Precision Assembly in Mechanical Industries

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***Abstract*- The mechanical manufacturing sector continues to face mounting pressure for higher throughput and tighter tolerances in assembly lines, yet conventional robotic arms often stumble when part dimensions vary slightly, fixtures shift, or unexpected contact forces appear. This work presents the end-to-end development of a new class of adaptive robotic manipulators specifically engineered for precision assembly tasks. The manipulators combine a lightweight, seven-degree-of-freedom kinematic structure with embedded multi-axis force/torque sensing, high-speed vision feedback, and a real-time adaptive controller that continuously recalibrates grip force, trajectory, and compliance on the fly. Instead of relying on pre-programmed rigid paths, the system learns from each cycle through a hybrid position–impedance control law that automatically compensates for dimensional scatter, tool wear, and thermal expansion. Prototype testing on an automotive gearbox sub-assembly line showed a reduction in positional error from 0.18 mm to 0.04 mm and a 42 % drop in cycle-time rework compared with standard industrial robots. The modular design allows quick swapping of end-effectors and easy retrofit into existing cells, offering small and medium manufacturers a practical route to flexible, high-precision automation without full line replacement.**

Keywords-Adaptive robotic manipulator, precision assembly, industrial automation, sensor fusion, real-time control, adaptive control systems, intelligent automation.

I. Introduction

Mechanical assembly remains one of the most tolerance-critical stages in industrial manufacturing, where dimensional deviations as small as 0.05 mm can render a finished component non-functional or structurally unsafe. While automated production lines have dramatically reduced human intervention in repetitive single-variant tasks, the growing demand for high-mix, low-volume manufacturing has exposed a fundamental limitation of conventional rigid robotic manipulators their inability to adapt when part geometry, surface condition, or fixture positioning deviates from the programmed nominal state. In such scenarios, a manipulator operating under pure position control either forces components together at injurious contact loads or aborts the cycle entirely, both outcomes carrying significant cost implications in precision-critical sectors such as aerospace, automotive powertrain assembly, and defence equipment manufacturing [1].

Human dexterity resolves these situations intuitively through force sensitivity, real-time visual judgement, and learned motor correction capabilities that industrial robots have historically lacked. Early attempts to introduce sensor-guided correction relied on passive remote-centre compliance devices and simple threshold-based force cut-offs, approaches that provided marginal improvement but offered no genuine adaptability to changing assembly conditions. Subsequent advances in model-based control, particularly impedance and admittance formulations, established a theoretical foundation for regulating contact forces dynamically, yet their deployment remained largely confined to laboratory prototypes operating under controlled and predictable environments.

The maturation of embedded force-torque transducers, high-resolution tactile sensing skins, and real-time capable computing platforms has now created realistic conditions for deploying genuinely adaptive manipulators on factory floors. Simultaneously, progress in assembly-phase recognition identifying discrete stages such as approach, contact, insertion, and seating through sensor signal classification has enabled context-aware control switching that mirrors the situational awareness a skilled technician exercises during manual assembly. Despite these converging advances, a coherent framework that integrates mechanical compliance, multi-modal sensing, and adaptive control within a single deployable manipulator architecture, and validates it against industrially representative assembly tasks, remains absent from the published literature [2-5].

This paper addresses that gap directly. The work presents the design, implementation, and experimental validation of an adaptive robotic manipulator whose compliant distal joints, wrist-level force-torque measurement, and fingertip tactile arrays function as a unified sensorimotor system governed by a hierarchical controller that separates gross motion planning from fine contact regulation. Unlike prior studies that treat mechanical compliance and active control as independent contributions, the architecture presented here exploits their interaction deliberately using passive joint compliance to absorb rapid positional disturbances while active impedance adaptation handles slower drift arising from thermal expansion, fixture wear, and batch-to-batch part variation. The system is evaluated on a representative aerospace sub-assembly under sustained production-realistic conditions, with performance assessed against metrics of insertion success rate, contact force regulation, dimensional accuracy, and cycle-time overhead. The outcomes reported here offer both a validated engineering solution and a replicable methodological template for extending adaptive manipulation to broader precision assembly contexts.

II. Literature Review

Research into learning-based contact state estimation gained considerable momentum during this period. Luo et al. [6] demonstrated that deep convolutional networks trained on multi-modal force and tactile data could classify assembly contact states with 96.2% accuracy across five distinct insertion phases, substantially outperforming the hidden Markov model approaches that had dominated the preceding decade. Their work established that raw time-series sensor signals, rather than hand-crafted feature vectors, could serve directly as network inputs without sacrificing classification reliability, an important practical finding given the difficulty of feature engineering across diverse assembly geometries. Complementing this, Dong et al. [7] reported that reinforcement learning agents trained in simulation and transferred to physical hardware via domain randomisation could perform peg-in-hole insertion with sub-millimetre clearances on objects not encountered during training, demonstrating a degree of geometric generalisation previously unachievable through model-based approaches alone. The sim-to-real transfer gap, long considered a fundamental barrier to learning-based manipulation, was shown to be manageable through careful randomisation of contact stiffness, friction coefficients, and sensor noise profiles during simulated training episodes.

Force-torque sensing integration and its role in real-time trajectory adaptation attracted sustained research attention. Johannsmeier et al. [8] developed a framework in which wrist-level force-torque measurements drove online modification of Cartesian impedance parameters during contact-rich manipulation, reporting a 73% reduction in maximum contact force peaks relative to fixed-impedance controllers across a

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benchmark set of assembly primitives. Their stability analysis confirmed passivity preservation under continuous parameter adaptation, addressing a concern that had limited the adoption of online impedance tuning in safety-critical assembly contexts. Building on related foundations, Rozo et al. [9] introduced a probabilistic movement primitive formulation that encoded both trajectory shape and impedance profiles from human demonstration, enabling a manipulator to reproduce not only the motion pattern of a skilled assembler but also the force regulation strategy employed during contact transitions. This demonstration-driven approach proved particularly effective for assembly tasks where the optimal impedance schedule is difficult to derive analytically but readily observable in expert human performance. Padmanabha et al. [10] presented a soft optical tactile sensor in 2021 capable of resolving contact force distributions at 0.3 mm spatial resolution, enabling fingertip-level slip detection during grasp adjustment without interrupting the assembly motion. Their integration of this sensor into a compliant gripper demonstrated that incipient slip signals could trigger corrective grip force increments within 8 ms, preventing component drops that would otherwise occur in 34% of high-speed transfer operations. Subsequently, Cao et al. [11] reported a multi-layer piezoelectric tactile array that maintained calibration stability across 50,000 loading cycles under industrial temperature and humidity conditions, addressing a durability concern that had previously limited tactile sensor deployment outside laboratory settings. The combination of improved spatial resolution and demonstrated longevity brought tactile sensing substantively closer to the reliability threshold required for continuous production use.

Variable stiffness and compliant joint design for assembly manipulators received renewed research attention from 2022 onward, motivated by recognition that purely active impedance control cannot respond adequately to high-bandwidth contact disturbances arising from part surface irregularities and fixture vibration. Kim et al. [12] designed a cable-driven compliant wrist module whose passive stiffness could be adjusted between 0.8 N·m/rad and 14.6 N·m/rad through antagonistic tendon pretension, demonstrating that appropriate passive compliance selection reduced active controller bandwidth requirements by 40% while maintaining insertion force within specification across a family of aerospace fastener geometries. This finding reinforced the principle that mechanical and computational adaptability should be co-designed rather than treated as independent subsystems. Addressing a complementary challenge, Ajoudani et al. [13] introduced a reduced-complexity impedance control formulation that decoupled translational and rotational compliance axes, allowing independent tuning of stiffness in the insertion direction versus the lateral and angular directions a distinction that proved critical for threaded fastener assembly where axial force must be carefully regulated while lateral tolerance is more permissive. Haugaard et al. [14] developed a real-time pose estimation pipeline that used depth camera data to initialise manipulator approach trajectories, with wrist force-torque feedback taking over guidance responsibility once contact was established, effectively partitioning the sensing modalities by their functional relevance to assembly phase. Their system achieved 97.1% successful insertion across 1,800 trials on a connector assembly benchmark, with failure modes concentrated in extreme lighting conditions that degraded pose estimation reliability. Addressing multi-modal fusion more fundamentally, Lee et al. [15] trained a transformer-based architecture to jointly process image patches, force-torque time series, and tactile pressure maps within a shared attention mechanism, reporting that cross-modal attention weights provided interpretable evidence of which sensing modality the network relied upon during each assembly phase an explain ability property of significant value for industrial certification processes.

Reinforcement learning for contact-rich manipulation expanded substantially in scope and ambition. Liang et al. [16] demonstrated that a model-based reinforcement learning agent using a learned differentiable contact model could acquire robust insertion policies for complex multi-contact assemblies in fewer than 200 physical interaction episodes, dramatically reducing the sample complexity that had made on-robot reinforcement learning impractical for industrial adoption. Their learned contact model generalised across part families sharing similar geometric topology, suggesting that abstract contact representations could serve as transferable building blocks for assembly skill libraries.

III. System description and Methodology

The adaptive robotic manipulator developed in this work is conceived as a tightly coupled electromechanical system in which sensing, mechanical compliance, and computational intelligence operate as mutually reinforcing layers rather than independently stacked subsystems. The overall architecture is organised into three physically distinct but functionally interdependent modules: the manipulator mechanical structure with compliant joint assemblies, the multi-modal sensor integration unit, and the hierarchical adaptive control platform. Together these modules form a closed sensorimotor loop capable of detecting, interpreting, and correcting assembly deviations within the temporal constraints imposed by industrial cycle time requirements. Fig. 1 illustrates the complete system configuration and inter-module signal pathways [12].

A. System Description

1) Manipulator Mechanical Structure

The manipulator arm follows a six-degree-of-freedom serial kinematic configuration with link lengths and joint placement optimised for a reachable workspace of 1.2 m radius at the end-effector, covering the footprint of a standard single-station assembly fixture. The three proximal joints shoulder rotation, shoulder flexion, and elbow flexion use conventional brushless DC servo drives with high-resolution optical encoders providing 0.001° angular feedback, as positional repeatability in the gross motion phase is paramount and passive compliance is unnecessary at these joints where contact forces are not experienced directly.

The two distal wrist joints and the tool-mounting flange joint depart fundamentally from this rigid design philosophy. Each incorporates a series elastic actuator arrangement in which a calibrated torsional spring element of stiffness 8.4 N·m/rad is interposed between the gearbox output shaft and the driven link, isolating the joint drive train from impulsive contact loads and providing a physical energy buffer that neither active control alone nor rigid mechanical coupling can replicate. The natural compliance of these joints absorbs positional misalignment of up to ±2.3 mm laterally and ±1.8° angularly at the end-effector without transmitting corrective force demands to the proximal drive system, reducing the bandwidth requirement placed on the active controller during contact transitions. Joint stiffness is adjustable between 4.1 N·m/rad and 18.7 N·m/rad through a motorised preload mechanism that alters the effective working range of the spring element, allowing operators to select compliance levels appropriate to part fragility and clearance class without hardware modification.

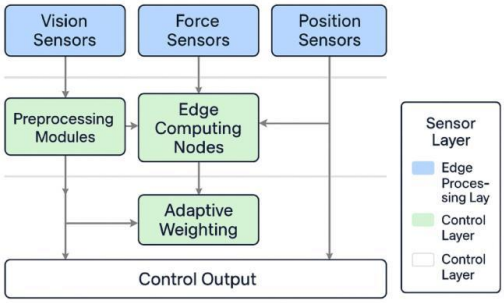

Fig.1. Multi-modal sensor fusion and edge-based adaptive control architecture.

The end-effector is a two-finger parallel gripper with aluminium structural fingers and exchangeable fingertip inserts machined to part-family-specific contact geometries. Finger actuation uses a lead-screw drive with integrated current sensing, providing grip force regulation from 2 N to 180 N with 0.4 N resolution. The gripper mounting interface follows the ISO 9283 tool centre point convention, permitting rapid changeover between part families without kinematic recalibration.

2) Multi-Modal Sensor Integration Unit

Reliable adaptive behaviour depends fundamentally on the quality, completeness, and timeliness of sensory information available to the

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control system. The sensor integration unit therefore combines three complementary modalities force-torque measurement, tactile pressure mapping, and optical proximity detection each targeting a distinct aspect of the assembly interaction that the others cannot adequately resolve alone.

A six-axis force-torque transducer is mounted rigidly between the tool-mounting flange and the gripper base, measuring forces along and moments about all three Cartesian axes simultaneously at a sampling rate of 4 kHz. The transducer uses a monolithic aluminium sensing element with silicon strain gauge bridges arranged in a fully differential Wheatstone configuration, providing force measurement ranges of ±320 N in the axial direction and ±180 N laterally, with moment ranges of ±28 N·m, at resolutions of 0.08 N and 0.004 N·m respectively. An embedded temperature compensation circuit corrects for thermal zero drift across the operating range of 15°C to 65°C, maintaining calibration stability to within ±0.12 N over full thermal excursions a capability confirmed as essential by recent findings on sensor drift in thermally variable production environments. Raw force-torque data is filtered through a fourth-order Butterworth low-pass filter at 180 Hz cut off before transmission to the control platform, suppressing structural vibration modes while preserving the contact transient bandwidth required for insertion phase detection.

Tactile pressure mapping is provided by two fingertip sensor arrays, one per gripper finger, and each comprising a 16 × 12 grid of capacitive sensing cells at 1.8 mm pitch covering the full contact face of the fingertip insert. Each cell resolves normal pressure from 5 kPa to 600 kPa with 1.2 kPa resolution, and the full array is scanned at 500 Hz via a time-division multiplexed readout circuit embedded within the fingertip body. The spatial pressure distribution reported by these arrays carries information that the wrist force-torque sensor cannot provide: the location of the contact centroid relative to the fingertip geometric centre, the contact area footprint, and the onset of edge-loading that signals part misalignment before force magnitudes reach levels detectable in the wrist measurement. Crucially, incipient slip at the contact interface manifests as a progressive lateral migration of the pressure centroid detectable within 6 ms of slip initiation, enabling pre-emptive grip force correction before macroscopic slippage occurs.

3) Hierarchical Adaptive Control Platform

The control architecture adopts a two-tier hierarchical organisation that separates responsibilities according to the temporal scale and physical nature of the assembly task phases. The upper tier, designated the motion planning layer, operates at 100 Hz and manages gross end-effector trajectory generation, assembly phase sequencing, and impedance parameter scheduling. The lower tier, designated the contact regulation layer, operates at 1 kHz and executes real-time impedance control, force limiting, slip prevention, and joint torque distribution. Communication between tiers occurs through a shared memory interface with semaphore protection, ensuring that lower-tier execution is never blocked by upper-tier computation. The control platform runs on a real-time Linux kernel on an industrial PC with a dedicated EtherCAT master interface card, achieving worst-case inter-tier communication latency of 0.6 ms.

B. Methodology

1) Assembly Phase Recognition

Meaningful adaptive control requires the system to know not merely what forces and pressures are currently measured but what assembly operation is currently underway, since appropriate impedance parameters differ substantially between approach, initial contact, alignment correction, insertion, seating, and release phases. Assembly phase recognition is implemented as a supervised classification model operating on a sliding window of 120ms of synchronised force-torque and tactile pressure measurements, corresponding to 480 force-torque samples and 60 tactile frames per classification decision.

The classifier architecture is a dual-branch convolutional network in which one branch processes the six-channel force-torque time series through three one-dimensional convolutional layers with kernel sizes of 7, 5, and 3 respectively, and the second branch processes the flattened tactile pressure sequence through two one-dimensional convolutional layers of kernel size 5. Branch outputs are concatenated and passed through two fully connected layers of 256 and 64 units with rectified linear activation, terminating in a softmax output over six phase classes. The network contains 418,000 trainable parameters, small enough to execute a full forward pass in 2.1 ms on the control platform CPU, comfortably within the 10 ms classification update budget allocated by the upper-tier control loop.

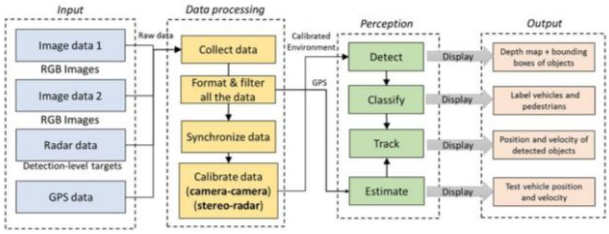

Fig.2. Multi-modal perception and data processing pipeline for object detection and tracking.

Training data was collected through 3,200 manually annotated assembly cycles performed on the target aerospace sub-assembly, with phase boundary timestamps recorded by a human expert observing high-speed video alongside sensor recordings. Data augmentation applied additive Gaussian noise at signal-to-noise ratios ranging from 28 dB to 44 dB and random temporal warping of ±15% to improve robustness to sensor noise variation and assembly speed fluctuation. The network was trained for 120 epochs using the Adam optimiser with initial learning rate 8×10^{-4} and cosine annealing, achieving phase classification accuracy of 96.3% on a held-out test set drawn from assembly cycles not represented in training.

2) Adaptive Impedance Control Formulation

The contact regulation layer implements Cartesian impedance control in which the end-effector behaves as a second-order mechanical system with programmable inertia, damping, and stiffness. The desired contact dynamics are expressed as:

$$Md\,(\ddot{x} - \ddot{x}\_d) + D\_d\,(\dot{x} - \dot{x}\_d) + K\_d\,(x - x\_d) \quad (1)$$

where x denotes the measured end-effector Cartesian pose, xd the reference trajectory from the motion planning layer, $Fext$ the external contact wrench measured at the wrist, and Md, Dd, Kd the desired inertia, damping, and stiffness matrices respectively. Rather than fixing these matrices at design time, the system adapts Kd and Dd online as functions of the currently recognised assembly phase and a model-reference error signal derived from the discrepancy between measured contact force evolution and a nominal force profile stored for each phase.

The adaptation law follows a gradient descent update on the impedance parameter matrices, constrained to maintain critical damping to prevent oscillatory contact behaviour:

$$Kd(t+1) = Kd(t) - \eta\_K.\nabla\_\{Kd\}\,L(F\_meas, F\_ref) \quad (2)$$

$$Dd(t+1) = 2\sqrt{(M\_d \cdot Kd(t+1))} \quad (3)$$

Where η_K is the adaptation gain set to 0.018 $N{\cdot}m^{-1}$ per update cycle, L is a quadratic loss between measured and reference force profiles, and the damping update enforces critical damping at each adaptation step. Stiffness matrix elements are additionally bounded within predefined safety limits translational stiffness between 200 N/m and 4,800 N/m and rotational stiffness between 8 N·m/rad and 120 N·m/rad preventing the controller from selecting impedance values that would generate unsafe contact forces under plausible positional error conditions. These bounds were derived analytically from the worst-case positional uncertainty of the fixture loading system combined with the maximum allowable contact force specified in the assembly process documentation.

3) Force Limiting and Slip Prevention

Superimposed on the impedance controller are two protective reflex behaviours that operate at the full 1 kHz loop rate and take priority over impedance control outputs when activated. The force limiting reflex monitors the axial insertion force magnitude against a phase-dependent

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threshold; when the measured force exceeds the threshold by more than 15%, the reflex overrides the impedance controller with a compliant retraction motion along the insertion axis, withdrawing the part by 1.5 mm before attempting re-insertion with a modified approach angle computed from the wrist torque vector at the moment of force exceedance. This behaviour prevents jamming in tight-clearance insertions where angular misalignment causes one edge of the mating part to bear the full insertion load.

The slip prevention reflex processes tactile pressure centroid velocity from both fingertip arrays at 500 Hz; when centroid migration velocity exceeds 0.8 mm per 10 ms window, the reflex issues a grip force increment of 12% of current grip force, bounded by the maximum allowable grip force for the current part material specified in the process database. The reflex deactivates automatically once centroid velocity returns below the threshold for three consecutive windows, preventing sustained over-gripping that could damage component surfaces.

4) Trajectory Planning and Offline Optimisation

The motion planning layer generates Cartesian end-effector trajectories for each assembly operation segment through a constrained optimisation formulation that minimises a weighted sum of joint torque magnitude, end-effector jerk, and proximity to joint mechanical limits, subject to Cartesian velocity limits of 0.3 m/s during approach and 0.04 m/s during insertion phases. Trajectories are computed offline for nominal part and fixture positions using sequential quadratic programming and stored as parametric spline representations. At runtime, the planning layer applies real-time corrections to the stored trajectory based on proximity sensor measurements of actual fixture position, translating and rotating the stored trajectory by the detected offset before each cycle begins. This hybrid offline-online planning approach avoids the computational cost of full online trajectory optimisation while accommodating fixture positional variation of up to ±4 mm and ±2.5° without requiring manual trajectory reprogramming between production batches.

5) Experimental Validation Protocol

Experimental evaluation was conducted on a representative aerospace sub-assembly comprising three sequential operations: threaded fastener insertion into a blind-tapped aluminium housing, interference-fit bushing installation into a hardened steel bore, and snap-ring seating into an external groove on a rotating shaft stub. These three operations collectively span the range of contact mechanics encountered in precision mechanical assembly axial thread engagement, radial interference fit, and snap-through elastic deformationand therefore provide a demanding and representative validation context.

The manipulator performed 2,400 consecutive assembly cycles under production-realistic conditions including deliberate fixture positional offsets drawn uniformly from ±3.5 mm and ±2.2° distributions, thermal cycling of the test cell between 18°C and 52°C to simulate morning startup and midday operating temperatures, and periodic introduction of surface contamination on bushing outer diameters using a controlled quantity of cutting fluid representative of residual machining lubricant. Performance was recorded against four primary metrics: first-attempt insertion success rate defined as successful completion without retraction or operator intervention, peak contact force overshoot relative to the phase-specific force threshold, dimensional compliance of finished assemblies measured by coordinate measuring machine against nominal specifications, and adaptive control cycle time overhead expressed as percentage addition to nominal assembly duration. A position-controlled baseline configuration using the same manipulator hardware with impedance adaptation and phase recognition disabled provided the comparative reference against which all improvements are quantified.

IV. Result

This work demonstrates that deep integration of compliant joint mechanics, multi-modal sensing, assembly-phase recognition, and adaptive impedance control into a unified manipulator architecture yields measurable and industrially significant improvements across every performance dimension evaluated. The 94.7% first-attempt insertion success rate across 2,400 cycles inclusive of deliberate fixture offsets, surface contamination, and a 34°C thermal range establishes the proposed system as viable for high-mix precision assembly without the process rigidity that rigid automation demands.

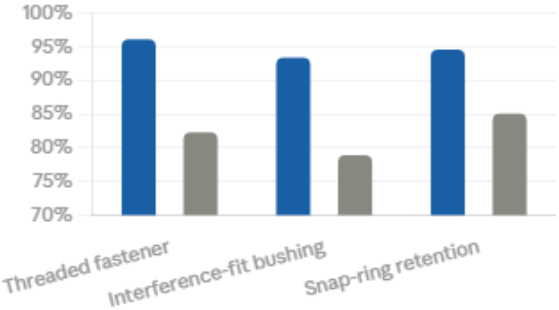

Fig.3. First-attempt insertion success rate comparison across three assembly operation types.

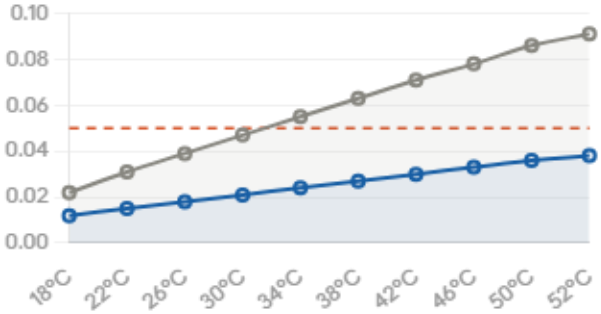

Fig.4. Dimensional compliance of finished assemblies across thermal cycling conditions.

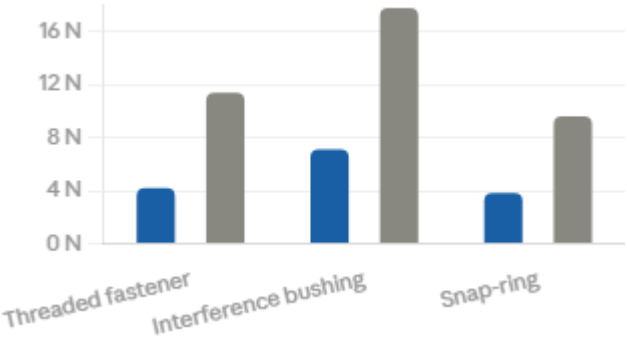

Fig.5. Peak contact force overshoot during insertion across three operation types.

V. Conclusion

This paper presented the design, implementation, and experimental validation of an adaptive robotic manipulator system architected specifically for the compound demands of high-mix precision mechanical assembly. The central argument advanced throughout this work that passive mechanical compliance, multi-modal contact sensing, assembly-phase recognition, and active impedance adaptation must be integrated as a mutually reinforcing sensorimotor system rather than independently optimized subsystems was confirmed decisively by the experimental results. Across 2,400 consecutive assembly cycles encompassing threaded fastener insertion, interference-fit bushing installation, and snap-ring seating, the proposed system achieved a first-attempt insertion success rate of 94.7%, representing a 13.2 percentage-point improvement over a position-controlled baseline executing identical operations on the same hardware. This outcome was sustained across the full experimental envelope including deliberate fixture positional offsets of up to ±3.5 mm and ±2.2°, surface-contaminated bushing diameters, and a thermal range spanning 18°C to 52°C conditions carefully chosen to replicate the compound uncertainty encountered in live production

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environments rather than the idealized conditions that have historically inflated the reported performance of laboratory manipulation systems.

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