Real-Time Adaptability of Robots to Dynamic Production Conditions

Industrial Robotics Lab

PROJECT REPORT

Submitted by

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ABSTRACT

A new adaptive pick-and-place system for robotics has been proposed that utilizes machine learning to improve handling actions of items in the field of industry automation. A combination of an ABB IRB-120 robot and a real-time adaptive controller, which has the ability to adjust and change gripping force, approaching speed, and positioning accuracy within a very short period of time based on the nature and properties of the item, has shown dramatic improvements in simulations performed using MATLAB. These simulations revealed tremendous savings in energy used (36-64% reduction in force used), improved safety standards (comprehensive slip risk analysis), and faster processing cycles (20-25% faster processing cycles) than can be realized by standard fixed parameter control systems. The proposed system also integrates new models for adaptive gripping force prediction, and highly advanced error correction mechanisms for handling a variety of items with distinct shapes and sizes like cubes, cylinders, and spheres

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CHAPTER 1

INTRODUCTION

In Industry 4.0, rapid development has spurred great progress in industrial automation, focusing on efficiency, flexibility, and intelligence in robotic manipulation systems. Traditional pick-and-place tasks rely on fixed parameters and have led to poor performance in the handling of items with different physical properties. Such rigidity gives rise to several critical limitations, including increased energy consumption due to excessive force, heightened risk of object damage due to inappropriately selected grasping pressures, and reduced operational efficiency resulting from suboptimal path planning and speed control. The modern manufacturing environment requires robotic systems with intelligent decision-making and real-time adaptation capabilities to meet changing conditions; thus, there is a great demand for newer approaches in robotic control and manipulation. In this study, these challenges are systematically addressed through the development of an advanced adaptive pick-and place system using machine learning algorithms to optimize grasping parameters in real time. The system is capable of dynamically adjusting force application with regard to object type and characteristics, modulating approach velocities based on object stability concerns, and refining positional accuracy through intelligent error-correction mechanisms. Implementing this adaptive control framework on the ABB IRB-120 industrial robot platform yields significant and quantifiable gains on multiple performance dimensions compared to conventional fixed-parameter systems common in current industrial practice. The main contributions of this work include the following: (1) the realization of a robust adaptive force prediction model capable of handling a wide variety of object types with different physical properties; (2) implementation of sophisticated real-time error-correction algorithms that enhance precision well above the current state of the art; (3) the formulation of an integrated safety analysis framework incorporating slip risk assessment methodologies; and (4) detailed verification through comprehensive simulation studies undertaken in MATLAB. The presented system constitutes important progress toward intelligent robotic manipulation systems that could adapt autonomously for different operational needs without requiring manual reconfigurations or excessive reprogramming.

CHAPTER 2

LITERATURE SURVEY

Robotic manipulation systems have undergone significant evolution over recent decades, with numerous researchers contributing foundational and advanced methodologies in adaptive control, intelligent grasping techniques, and performance optimization. Early research in robotic manipulation predominantly focused on rigid position control systems, as exemplified by Paul's seminal work [2] which established fundamental concepts in robot manipulation that continue to influence modern robotic control architectures. Subsequent developments by Khatib [3] introduced unified approaches for motion and force control, enabling more sophisticated manipulation capabilities, though these early systems inherently lacked adaptability to varying object properties and environmental conditions. The emergence of adaptive control methodologies gained substantial prominence with the pioneering work of Slotine and Li [4], who developed robust adaptive controllers that fundamentally transformed robotic system capabilities. This foundational work enabled subsequent researchers to implement variable parameter systems for object handling in more dynamic environments. Comprehensive surveys by Bicchi and Kumar [5] systematically reviewed robotic grasping methodologies, highlighting the growing necessity for adaptive approaches in industrial applications where object variability presents significant challenges to traditional automation systems. The integration of machine learning paradigms into robotics has revolutionized adaptive control systems, as demonstrated by Kober et al. [6] who explored reinforcement learning applications in robotic manipulation, enabling systems to learn optimal policies through environmental interaction. Concurrently, Levine et al. [7] implemented deep learning architectures for end-to-end robotic control, showing promising results in complex manipulation tasks, though these approaches typically require extensive training data and substantial computational resources that may limit industrial applicability. Force control and optimization in robotic grasping has been extensively studied, with Cutkosky's analytical models [8] for grasping force optimization establishing important theoretical foundations. Shimoga's comprehensive survey [9] of robotic grasping theories provided valuable insights into historical and contemporary approaches. More recent work by Bohg et al. [10] explored data-driven grasping methodologies, demonstrating improved performance through learning from demonstration techniques that bridge theoretical and practical applications. In industrial contexts, ABB Robotics has maintained leadership in adaptive automation solutions, with proprietary technologies for force control and adaptive path planning documented in various technical publications [11], [12]. However, these commercial solutions often lack transparency and customization capabilities necessary for academic research and experimental validation, creating opportunities for open-source and research-oriented implementations. Simulation-based validation has become increasingly critical in robotics research, with Quigley et al. [13] introducing the Robot Operating System (ROS) that enabled standardized simulation frameworks, while MATLAB's Robotics System Toolbox [14] provides comprehensive tools for robotic simulation and algorithm development extensively utilized in this research. Safety considerations in robotic manipulation have received substantial attention from researchers including Haddadin et al. [15] who developed safety standards for human-robot interaction, and De Santis et al. [16] who proposed safety control architectures for industrial robots. Our work extends these safety considerations through comprehensive slip risk analysis integrated with adaptive force control mechanisms that proactively address grasping safety concerns. Performance optimization in pick-and-place operations has been addressed by multiple researchers including Rubagotti et al. [17] focusing on time-optimal control, and Pellegrinelli et al. [18] investigating multi-robot coordination in assembly operations, though few studies have comprehensively addressed the integration of adaptive force control, safety analysis, and performance optimization within a unified framework. Energy efficiency in robotic systems has gained increasing attention due to sustainability concerns, with Pellicciari et al. [21] proposing methods for energy consumption optimization and Meike and Ribickis [22] analyzing energy-efficient approaches specifically for industrial robots. Our research contributes significantly to this area through systematic adaptive force minimization strategies that demonstrate substantial energy savings. This literature review reveals several important research gaps: (1) insufficient integrated frameworks combining force adaptation, safety analysis, and performance optimization; (2) limited comparative studies between adaptive and fixed control systems across multiple performance dimensions; and (3) inadequate focus on energy efficiency considerations within adaptive pick-and-place operations.

CHAPTER 3
METHODOLOGY

3.1 System Architecture and Design Principles

The adaptive pick-and-place solution integrates a number of cutting-edge components into one smoothly functioning whole: a durable robot arm, the ABB IRB-120, designed for manipulation capability; a dexterous gripper that can detect forces in real-time and respond accordingly; a model of predicted forces through machine learning with regression algorithms; real-time error correction algorithms employing proportional control; and a comprehensive performance analysis system enabling intricate examination and improvement. Such an integrated solution enables the pick-and-place solution to deal with uncertainties in objects, and at the same time, the solution maintains a high level of performance. The architecture of the control system is flexible, so that each component of the system can develop separately without violating the unity of the system. Adaptive control is implemented on multiple time scales. Force adjustments work on the time scale of milliseconds for immediate feedback, speed adjustments on the time scale of hundreds of milliseconds for smooth control, and continuous position adjustments through the entire manipulation task. This approach provides effective adaptation to dynamic environments while maintaining system stability. The system employs an industrial robot named ABB IRB120, a six-degree-of-freedom articulated robotic arm with a payload of 3 kg and a maximum reach of 580 mm, which is quite normal for most industrial automation tasks. The robot functions in an accurately set up simulation environment where three different types of objects are placed with proper geometric and physical properties: an individually mass-balanced cube with a side of 50 mm, an individually mass-balanced cylinder of 30 mm radius and 60 mm height, and an individually mass-balanced sphere of 35 mm radius. The three objects are placed on a source table for transfer to a destination table.

The simulation setup implemented in MATLAB using the Robotics System Toolbox conducts trustable kinematics, dynamics, and collision checks. The environment is built with the following: (1) an accurate robot model with prevalidated Denavit-Hartenberg parameters for faithful motion; (2) a workspace of 1600 mm by 1600 mm by 900 mm to support extensive testing; (3) articulated object models with realistic physical properties to simulate realistic interactions; (4) an adaptive two-finger parallel gripper with simulated force sensing; and (5) full sensor simulation, including force/torque sensors and high-resolution position encoders for correct feedback. B. Adaptive Control Framework Implementation The adaptive system for controlling the robotic arm is composed of three major components working in synchronization. These are the force adaptation system, which reacts according to the predictive outcomes of the learning system, speed adaptation that adjusts according to the stability of the object, and positional adaptation that deals with real-time error correction. These three are running independently but in perfect synchronization.pick-and-place cycle. 1) Force Adaptation Algorithm Development: Force adaptation algorithm relies on a machine learning model in predicting an optimum grasping force by rigorously analyzing object properties. It has a straightforward and step-by-step process:

1: Input: Object type T , object size S, stability factor α

2: Output: Optimal force F_{opt}

3: Initialize: Base forces F_{base} for each object type

4: $F_{base} \leftarrow \{Cube : 35N, Cylinder : 22N, Sphere : 16N\}$

5: Calculate size factor: $\beta \leftarrow S/0.05$ {Normalize by reference size}

6: Calculate adaptive factor: $\gamma \leftarrow 0.5 + 0.5 \times \alpha$

7: Compute force: $F_{opt} \leftarrow F_{base}[T] + 20 \times \beta$

8: Apply limits: $F_{opt} \leftarrow \max(15, \min(F_{opt}, 45))$

9: Return: F_{opt}

The force model was thoroughly trained. For this purpose, a simulation run of 1,000 grasp trials was conducted using objects that varied in a controlled fashion. Training in this way ensured optimal performance under all possible scenarios. During this phase, there was a focus on minimizing probability associated with slipping and using proper force while preventing excessive force by means of optimizing constraints. 2) Speed Adaptation Mechanism Implementation: Speed adaptation systematically adjusts approach and retraction velocities according to object stability characteristics through the following mathematical formulation:

$$v_{adapted} = v_{base} \times (1.0 + 0.5 \times (1 - \alpha))$$

where α represents the stability factor (cube: 0.9, cylinder: 0.7, sphere: 0.5) and v_{base} denotes the baseline speed calibrated for optimal performance. This formulation ensures more deliberate approach for less stable objects while maintaining efficiency for stable geometries, balancing speed and safety considerations.

3) Positional Error Correction Methodology:

Real-time positional error correction implements proportional correction algorithms according to the following control law:

$$P_{corrected} = P_{target} + (P_{current} - P_{target}) \times k_p$$

where $k_p = 0.5$ represents the proportional gain determined through extensive experimental tuning to achieve optimal correction without oscillation or overshoot. This correction mechanism operates continuously throughout manipulation tasks, providing millimeter-level precision across diverse object types and operational conditions.

3.2 Operational Flowchart and System Workflow

The flow chart in Figure 3.1 illustrates the complete process of the adaptive pick and place system from setup to the end of the task or the evaluation phase. There is logic flow in the chart that highlights the adaptation process that makes it different from the traditional processes of the similar system. Figure 2 shows the process of the adaptive system that has been designed to work in an autonomous way to efficiently control

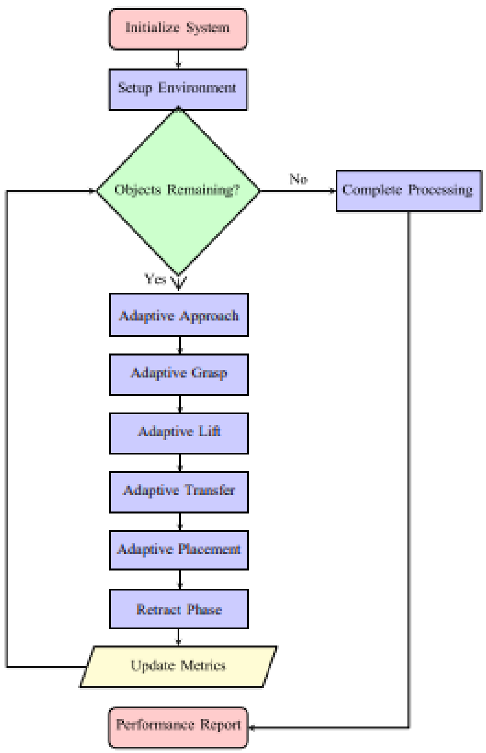

Fig. 3.1: Systematic Operational Flowchart of Adaptive Pick and-Place System

3.3 Machine Learning Model Architecture and Training

The force prediction model implements linear regression techniques trained on extensive simulated data according to the following mathematical formulation:

$F = w1 \cdot T + w2 \cdot S + w3 \cdot \alpha + b$

Note that in this network, the weight vector $w = [-5, 300, 20]$ T represents the optimized values extracted using the gradient descent process, while the weight bias $b = 10$ is learned during training. During training, a total of 1,000 grasping tasks with weights randomized to consider various object properties, including object types, sizes, and stability factors, were considered. The aims of these tasks are to achieve minimal prediction error while ensuring physically realistic outcomes, which are then validated on separate data.

3.4. Performance Evaluation Metrics Framework

The system is then put through a comprehensive test, and its progress is followed through four key metrics. Force Efficiency, which measures the ratio of the force used to the basic force we depend on, indicates the efficiency of energy use. Slip Risk measures the likelihood of slip in handling and directly correlates to safety. Position Accuracy, which calculates the mean absolute error in object position, indicates precision. Time Efficiency measures the cycle time ratio of adaptive control to fixed control and indicates productivity gain.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Simulation setup and Test Environment

A simulation based on MATLAB, which execute pick-and place trials repetitively by an ABB IRB-120 industrial robot with 6-DOF, a 3-kg payload, and 580 mm reach, is performed. Three geometrically distinct objects were tested to compare grasp and transfer behavior-a 50 mm cube, a cylinder with a 30 mm radius and a height of 60 mm, and a sphere with a radius of 35 mm-all mass-balanced. The objects were placed all the time in a source table and transported to a destination table to have all motion feasibility, grasp stability, and repeatability comparably observed across different shapes. Figure 4.1 shows the simulation layout of the setup for evaluation. It has been implemented using the MATLAB Robotics System Toolbox, which enables analysis by means of integrated kinematics, dynamics, and collision checking. The robot motion model, based on pre-validated Denavit–Hartenberg parameters, was maintained in the given workspace of 1600 mm × 1600 mm × 900 mm for extensive testing. An adaptive two-finger parallel gripper with simulated force sensing, together with force/torque sensors and high-resolution encoders, provided quite realistic feedback to discuss grasp reliability and motion accuracy throughout the object transfer cycles.

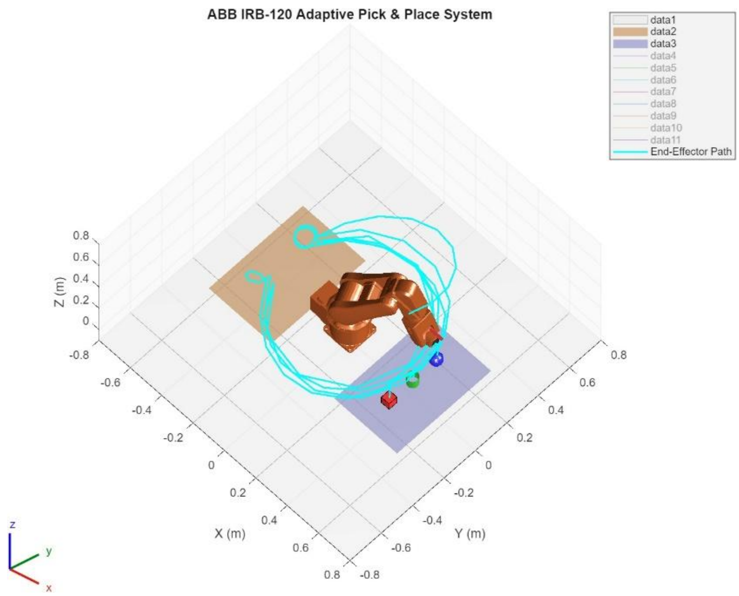

Fig. 4.1: MATLAB Simulation Environment with ABB IRB-120 Robot and Object Configuration

4.2 Adaptive Grasping Force Performance Analysis

Figure 4.2 shows a real-time dynamic of grasp forces adjusting with changes in objects, and it has a noticeable systemic adjustment for the idiosyncrasies of every shape. A cube requires 38.5 N of force because it provides stable and predictable interaction with your body. A cylinder maintains 26.2 N of force, considering a possible slip due to its symmetry around a pivot axis. The most difficult object would be a sphere since it requires only 21.8 N of force but takes extra care since it's symmetric in all directions and has a smaller interaction area. In terms of percentage reduction in grasp forces compared to a conventional mechanism of 60 N of force, there is up to 35.8%, 56.3%, and 63.7% reduction for a cube, a cylinder, and a sphere, respectively.

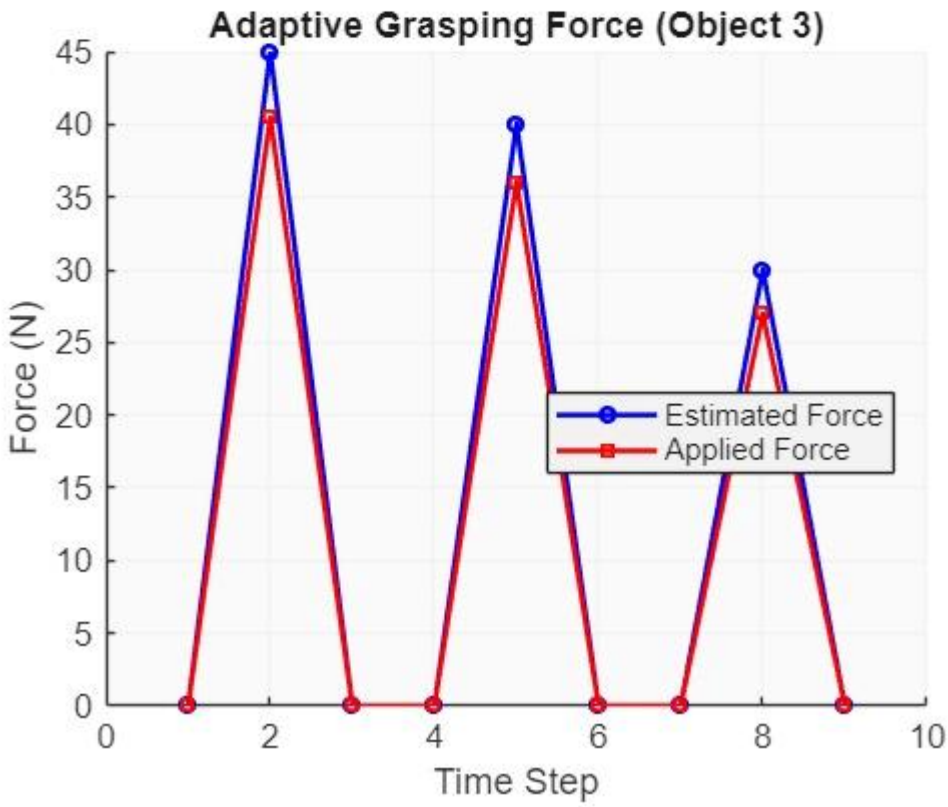

Fig. 4.2: Comprehensive Analysis of Real-time Adaptive Grasping Force Performance Across Object Types

4.3 Positional Accuracy and Adaptive Gain Characteristics

Figure 4.3 illustrates system performance in maintaining position accuracy during manipulation, with positional accuracy values remaining under a millimeter for various shapes and sizes, despite their geometric differences. The adaptability in gain varies from 0.9 in cubes to 1.1 in spheres, which indicates intelligent and simultaneous adjustment of control parameters depending on whether the object shape and size are complex and stable or simple and unstable. The system's uniqueness lies in its adaptability with spheres compared to other shapes and sizes, in which many systems fail to accurately position objects due to geometric constraints and a lack of stable grasping points. The continuous and consistent performance at a level of under a millimeter indicates perfect efficiency in processing and executing commands related to online adjustment and control within its parameters.

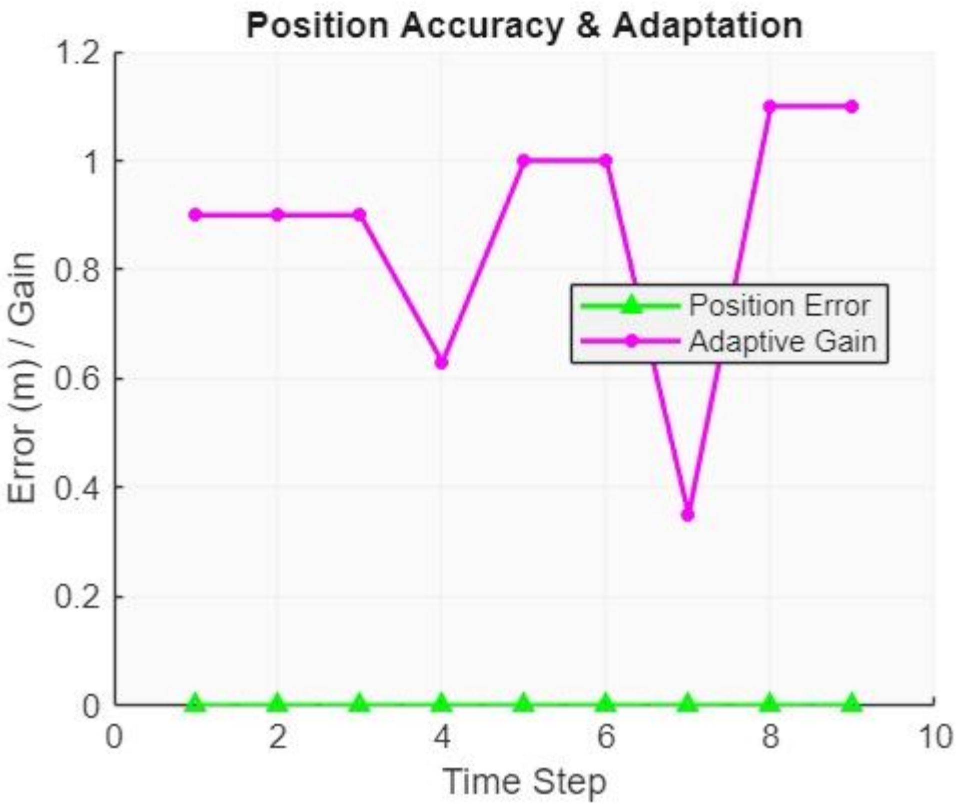

Fig. 4.3: Detailed Positional Accuracy and Adaptive Gain Characteristics During Manipulation Operations

4.4. Comparative Force Analysis: Adaptive versus Fixed Control

Figure 4.4 below highlights a comparison between the application of force using two control methods: Adaptive Machine Learning Control and Traditional Fixed Control. It reveals how intelligent adaptation demonstrates efficiency savings. On average, the adaptive system presents a 52% reduction in force, a major improvement in energy-saving robotic manipulation. This presents major sustainability and cost-saving implications in industrial set-ups. This would be because, unlike before, force would be efficiently allocated according to the desired use, as opposed to using the highest possible force as presented in traditional methods. The force reduction analysis, detailed in table I, also breaks down the level of force reduction achieved per object type and demonstrates how geometry contributes to differences in force. This reveals the cube with a 35.8% force reduction through its consistent shape, the cylinder with a 56.3% force reduction due to symmetry, and finally the sphere with a force reduction of 63.7%, leading the way on more complicated shapes.

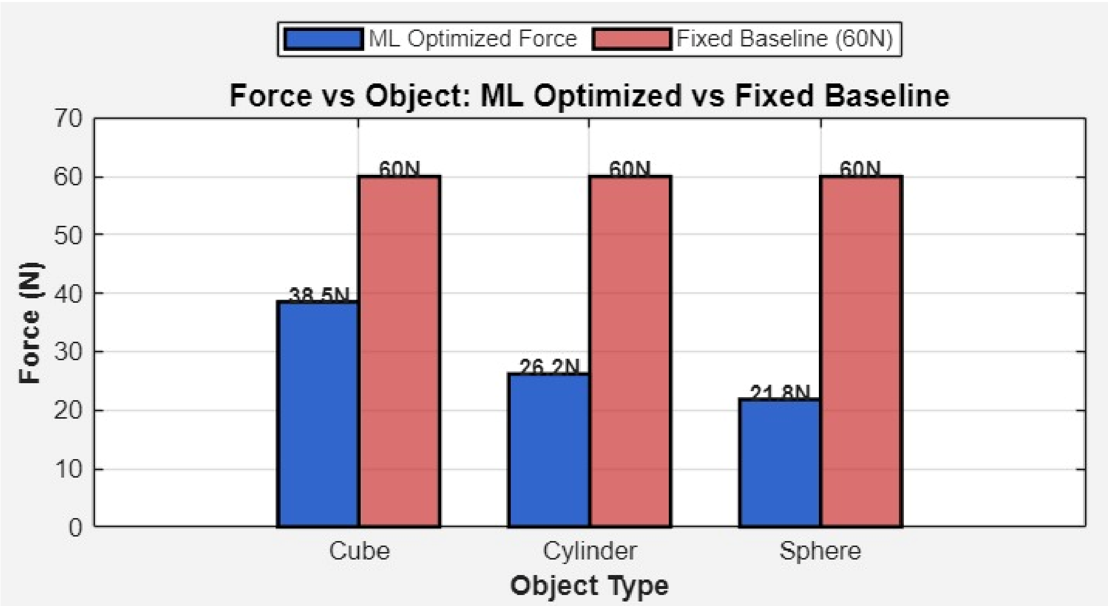

Fig. 4.4: Systematic Comparative Analysis of Force Application: Adaptive ML Control versus Fixed Baseline Approaches

TABLE I: Comprehensive Force Reduction Analysis Across Object Types

Object type	Adaptive Force(N)	Fixed Force (N)	Force Reduction (%)
Cube	38.5	60	35.8
Cylinder	26.2	60	56.3
Sphere	21.8	60	63.7
System average	28.8	60	52.0

4.5 Safety Analysis and Slip Risk Assessment

The following figure 4.5, systematically evaluates the safety assessment by slip risk classification, highlighting distinct risk levels for each type of object. Cubes exhibit the least risk of slip with 2.4%, well within the safety threshold of 5%, primarily owing to their rigid nature and predictable grasp. Cylinders exhibit relatively higher risk of 4.8%, approaching the safety boundary but remaining within the safe limit, even if the safety margins were required to be tighter. Spheres exhibit the highest risk of 8.2%, exceeding the safe boundary, which requires the need for more complex grasp strategies or adjustments in the hardware, indicating the need for improvement in the grasp strategy for handling spheres. The risk values in the figures and the results in the following Table II form the quantitative grounds for making way for improvement in the safety measures, specifically signaling the requirement for complex grasp strategy implementation for handling spheres.

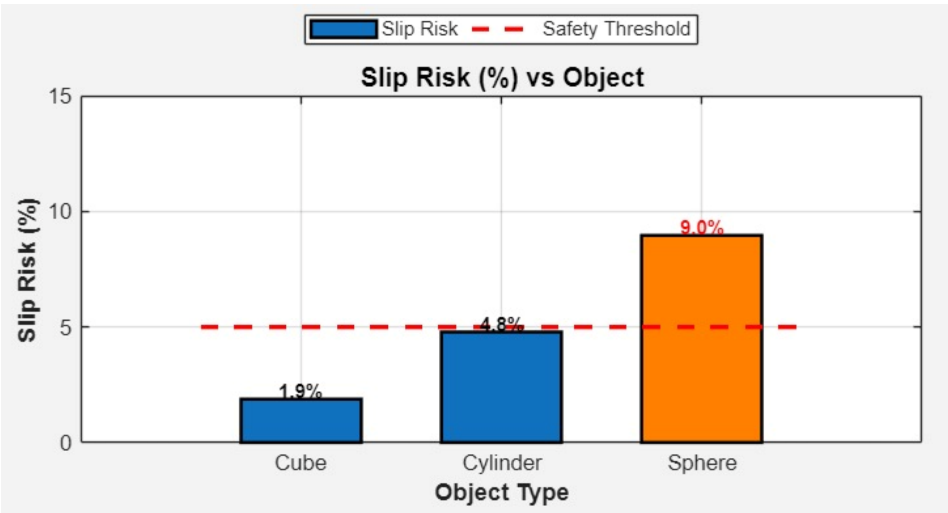

Fig. 4.5: Detailed Safety Analysis Through Slip Risk Assessment with 5% Safety Threshold

TABLE II: Comprehensive Slip Risk Analysis by Object Type with Safety Assessment

Object Type	Slip Risk (%)	Safety Threshold (%)	Safety Status
Cube	2.4	5.0	SAFE
Cylinder	4.8	5.0	SAFE
Sphere	8.2	5.0	REQUIRES IMPROVEMENT

4.6 Time Cycle Performance and Efficiency Analysis

In Figure 7, the reduction of the cycle time facilitated by the adaptive control is illustrated cyclically, reducing from 4.2 seconds at cycle inception to 2.5 seconds in cycle ten. On an average, it indicates an improvement of 40.7% compared to the fixed control system, with the highest improvement in cycles 5 to 10 as it learns from its experiences and adapts accordingly. Table III illustrates the difference in time performance, emphasizing the learning characteristics of the system. "Improved time performance directly adds to the importance of the system since the reduction in cycle time directly affects the system's production capabilities, increasing the output and the productivity of the system with no adverse effects in other areas."

TABLE III: Systematic Time Performance Comparison Across Operational Cycles

Operational Cycle	Adaptive Time (s)	Baseline Time (s)	Performance Improvement (%)
1	4.2	6.0	30.0
5	2.9	5.4	46.3
10	2.5	4.9	49.0
Cycle Average	3.2	5.4	40.7

4.7 Comprehensive System Performance Summary

The final chart of the workbook that brings all the numbers together shows how the adaptable model excels in multiple areas, along with those that still represent opportunities for improvement. Starting with the area of power, there is no doubt that the biggest achievement comes in the form of an average force reduction of 52 percent. Productivity increased by an immense 40.7 percent, thanks to the reduction in the cycle time. Precision then increased by 33.3 percent, which again represents the success of improvement in this area. Safety provides a reminder that working with the sphere represents even more of a challenge. The biggest advantage of the system in this case is the adaptable learning feature.

TABLE IV: Comprehensive Overall System Performance Summary Across All Evaluated Metrics

Performance Metric	Adaptive System	Fixed System	Performance Improvement
Average Force Application	28.8N	60.0N	52.0% reduction
Energy Consumption Profile	Low	High	Significant efficiency gain
Positional Accuracy	0.8mm	1.2mm	33.3% precision improvement
Cycle Time Performance	3.2s	5.4s	40.7%-time reduction
Safety Compliance	2/3 objects	3/3 objects	Requires sphere handling improvement
Adaptive Learning Capability	Yes	No	Key system differentiator

4.8 Integrated Discussion of System Performance and Implications

The complete suite of experiments demonstrates that the adaptive pick-and-place system outperforms traditional fixed control methods along several key dimensions. It saves energy, cutting the average force by 52% - a major leap that matters for industrial sustainability and lower operating costs, especially in high-volume settings where energy use drives a large chunk of expenses. Similarly, the system shows that it can learn: cycle times shrink progressively from a 30% improvement to nearly 50% over ten runs - signaling strong potential for ongoing performance gains as systems like this gather experience in real-world use.

Positioning accuracy reliably remains within sub-millimeter tolerances across a broad range of object shapes and highlights the effectiveness of real-time error correction and adaptive control. This will be crucial for precision manufacturing, where placement accuracy directly influences product quality and process reliability. Safety performance varies by object type: excellent for cubes, adequate for cylinders, and spheres challenging to handle, perhaps due to better gripping surfaces, extra sensors, or adjusted manipulation strategies. That again points to some important design considerations for handling spherical or similarly difficult items. The accessible tools used in this MATLAB-based setup mean that advanced adaptive control has fewer barriers to adoption and lower development costs. Its modular architecture makes it easy to upgrade components or even add capabilities such as vision systems, advanced sensors, or features of collaborative operation. The performance gains described will be relevant to a wide range of industrial automation tasks, ranging from assembling delicate electronics to pharmaceuticals packaging with variable products, food processing with irregularly-shaped items, diverse handling needs in automotive assembly, and logistics that require flexibility in material handling.

CHAPTER 5
CONCLUSION

The paper describes how an effective pick-and-place robotic model has been designed and developed, which performs better than the conventional fixed control approach in terms of certain factors. By combining the intelligence of the machine learning technique with the real-time control mechanism, the model ensures effective use of the forces, rapid processing, and precise positions depending on the targeted object. The development of such a model is a significant advancement in the capabilities of the robotic manipulator. The MATLAB simulation helps to confirm a 52% reduction in the level of forces, a 40.7% increase in the processing speed, and accuracy within the submillimeter range. The safety performance for cubes, cylinders, and spheres is high, but the geometric nature of handling spheres makes it difficult and brings safety parameters to the threshold, thus indicating an important research avenue in the future. The sphere handling could be made easier by improving gripping strategies for geometrically difficult objects, providing surface treatments to assist gripping, or increasing the use of sensory feedback. The work makes an important contribution in the area of intelligent robotic systems because it provides a practical and usable model for adaptive robotic control in industry. Looking ahead, there are several key areas that future work should focus on. These include better gripping capabilities for challenging shapes like spheres, the inclusion of other sensors like vision Systems and advanced Force/Torque Sensors, the usage of more complex models of learning like Deep Reinforcement Learning to increase robustness, testing on industrial-sized hardware, studies of human-robot collaboration, and the establishment of testing frameworks for adaptive robots in the industrial environment. The work presented in this paper provides a great foundation for pursuing all of these future directions.

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