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RECENT ADVANCES IN ROBOTIC MANIPULATOR MODELING AND INTELLIGENT CONTROL: CHALLENGES AND FUTURE RESEARCH DIRECTIONS

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ABSTRACT

Robotic manipulators have become a cornerstone of modern automation, playing a critical role in industrial production, healthcare systems, space exploration, and intelligent service robotics. These systems are typically composed of multiple interconnected rigid links and actuated joints, forming multi-degree-of-freedom (multi-DOF) structures capable of performing complex spatial tasks with high precision and repeatability. Over the past decades, significant research efforts have been directed toward improving the modeling accuracy and control performance of robotic manipulators, particularly as applications demand higher speed, adaptability, and autonomy in uncertain environments. Traditionally, robotic manipulator modeling has been based on rigid-body dynamics derived from first principles, primarily using the Euler–Lagrange and Newton–Euler formulations. These approaches provide a physically interpretable representation of system dynamics by capturing inertia, Coriolis and centrifugal forces, gravitational effects, and joint interactions. While these classical methods are mathematically rigorous and widely adopted, they are often computationally intensive and highly sensitive to parameter uncertainties such as friction, payload variation, and manufacturing tolerances. As robotic systems become more complex, especially in multi-DOF configurations, these limitations significantly affect real-time implementation and control accuracy.

Keywords: Robotic arm, challenges, modeling, Euler, degree of freedom, classical method

1. INTRODUCTION

Robotic manipulators have become a cornerstone of modern automation, playing a critical role in industrial production, healthcare systems, space exploration, and intelligent service robotics. These systems are typically composed of multiple interconnected rigid links and actuated joints, forming multi-degree-of-freedom (multi-DOF) structures capable of performing complex spatial tasks with high precision and repeatability. Over the past decades, significant research efforts have been directed toward improving the modeling accuracy and control performance of robotic manipulators, particularly as applications demand higher speed, adaptability, and autonomy in uncertain environments (Hopko et a., 2022).

Traditionally, robotic manipulator modeling has been based on rigid-body dynamics derived from first principles, primarily using the Euler–Lagrange and Newton–Euler formulations. These approaches provide a physically interpretable representation of system dynamics by capturing inertia, Coriolis and centrifugal forces, gravitational effects, and joint interactions (Johnson et al., 2019).

While these classical methods are mathematically rigorous and widely adopted, they are often computationally intensive and highly sensitive to parameter uncertainties such as friction, payload variation, and manufacturing tolerances. As robotic systems become more complex, especially in multi-DOF configurations, these limitations significantly affect real-time implementation and control accuracy. Figure 1 presents the diagram of robot arm (Joosse et al., 2021).

Figure 1: Robot arm description (Joosse et al., 2021)

In parallel with advancements in modeling, control strategies for robotic manipulators have evolved from conventional linear controllers to more intelligent and adaptive systems. The Proportional–Integral–Derivative (PID) controller remains one of the most widely used methods due to its simplicity and ease of implementation. However, its performance is limited in nonlinear, time-varying, and strongly coupled systems such as multi-DOF robotic arms (Layne, 2023). To overcome these challenges, researchers have introduced advanced control techniques including sliding mode control, adaptive control, fuzzy logic systems, and neural network-based controllers. These approaches aim to enhance robustness, reduce tracking error, and improve system stability under dynamic operating conditions (Jost et al., 2021).

More recently, intelligent optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and hybrid learning-based methods have gained significant attention in robotic control design (Mitchell et al., 2020). These techniques are primarily used to optimize controller parameters, improve convergence speed, and enhance system adaptability without requiring precise mathematical models. Among these, PSO-based PID tuning has become particularly popular due to its balance between computational efficiency and optimization capability, making it suitable for real-time robotic applications (Muller et a., 2024).

Despite these advancements, several critical challenges remain unresolved in robotic manipulator modeling and control. One of the major challenges is the inherent nonlinear coupling between joints in multi-DOF systems, which leads to complex dynamic interactions that are difficult to decouple using classical control techniques (Rubagotti et a., 2022; Slajpah et a., 2021). Additionally, actuator saturation, sensor noise, external disturbances, and payload variations further degrade system performance. Another key issue is the trade-off between model accuracy and computational complexity, as highly accurate models are often too computationally expensive for real-time implementation (Sanders et al., 2023).

Furthermore, most intelligent control strategies rely heavily on simulation-based validation, with limited experimental verification on physical robotic platforms (Stasevych and Zvarych, 2023). This creates a gap between theoretical developments and practical deployment. There is also an increasing need for scalable control frameworks that can be generalized across different robotic configurations without extensive retuning or redesign (Story et al., 2022).

In response to these challenges, recent research has shifted toward hybrid and data-driven approaches that integrate physics-based modeling with machine learning and optimization techniques (Vora et al., 2023). Concepts such as digital twins, reinforcement learning-based control, and adaptive intelligent systems are emerging as promising directions for next-generation robotic manipulators (Arjaya et al., 2024). These approaches aim to achieve real-time adaptability, improved robustness, and higher levels of autonomy in complex and uncertain environments (Mathew et al., 2022).

This study, therefore, presents a comprehensive review of recent advances in robotic manipulator modeling and intelligent control strategies, with a particular focus on their strengths, limitations, and applicability to multi-DOF systems. It further identifies key challenges and outlines future research directions necessary for the development of more intelligent, efficient, and adaptive robotic systems capable of meeting the demands of modern industrial and technological applications.

2. Working Components of a Robotic Arm

A robotic arm is a complex electromechanical system designed to replicate the motion and functionality of a human arm for tasks such as manipulation, assembly, and automation. Its operation depends on the coordinated interaction of several key components, each responsible for specific functions that collectively enable precise motion, control, and task execution. Figure 1 presents the robot components (Rarz et a., 2022).

(a) Robot controller Arduino

(b) Gripper

(c) Robot servomotor

Figure 2: Selected component of robot arm (Rarz et a., 2022).

The **base** serves as the foundation of the robotic arm, providing structural support and stability during operation. It anchors the system to a fixed surface and often houses the primary rotation mechanism, allowing the arm to swivel horizontally (Ali et al., 2023). A stable base is essential for maintaining accuracy, especially when handling varying payloads or performing high-speed movements. The **links and joints** form the mechanical structure of the arm. Links are the rigid segments that connect different parts of the arm, while joints provide the necessary degrees of freedom by enabling rotational or linear motion between links. In a multi-degree-of-freedom robotic arm, multiple joints work together to achieve complex spatial positioning and orientation of the end-effector (Eendi et al., 2024). **Actuators,** typically in the form of electric servo motors, are responsible for driving the motion of the joints.

They convert electrical energy into mechanical movement, providing the torque required for positioning and movement. The performance of the robotic arm largely depends on the actuator's power, speed, and precision. The **end-effector** is the functional component attached to the final link of the robotic arm. It interacts directly with the environment and varies depending on the application, such as grippers for picking objects, welding tools, or sensors (Jahanshahi et al., 2024). Its design determines the type of tasks the robot can perform. **Sensors**play a crucial role in feedback and control by monitoring parameters such as position, velocity, force, and environmental conditions. This information is transmitted to the control system to ensure accurate and adaptive operation. Finally, the **controller** acts as the brain of the robotic arm, processing input signals, executing control algorithms, and coordinating all components to achieve desired motion and task objectives. Together, these components enable efficient, precise, and intelligent robotic operation. Types of robot arm in figure 3.

Figure 3: Types of robot arm (Jahanshahi et al., 2024).

2.1 Robotic Manipulator Modeling Approaches

Robotic manipulator modeling is a fundamental aspect of robotics research, as it provides the mathematical and computational foundation required to understand, predict, and control the motion of multi-degree-of-freedom (multi-DOF) robotic systems (Zhang et al., 2023). Over the years, various modeling approaches have been developed, ranging from classical physics-based formulations to modern data-driven and hybrid techniques. This section reviews these approaches in detail, highlighting their principles, strengths, and limitations in the context of modern intelligent robotic systems. Figure 4 presents the three main robot arm modeling approaches.

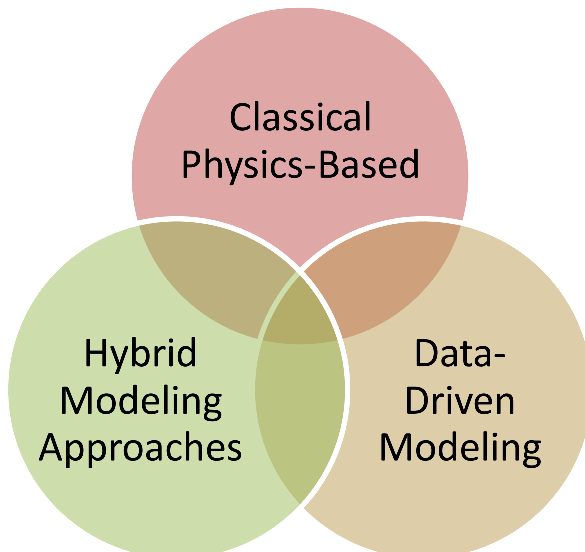

Figure 4: Robot modeling approaches (Jahanshahi et al., 2024)

2.1.1 Classical Physics-Based Modeling

Classical physics-based modeling forms the foundation of robotic manipulator analysis and is widely used due to its strong theoretical grounding in mechanics. The Euler–Lagrange formulation is one of the most prominent approaches, where the system dynamics are derived from energy relationships, enabling a structured representation of the robot's motion based on kinetic and potential energy (Liu et al., 2024). This method is particularly useful for multi-DOF systems because it systematically captures the interaction between joint movements and link dynamics. The Newton–Euler method, on the other hand, is a recursive formulation that focuses on force and torque propagation through the robotic structure, making it computationally efficient and suitable for real-time dynamic analysis (Wang et al., 2023). In addition, the Denavit–Hartenberg (DH) representation provides a standardized geometric framework for describing the spatial relationships between adjacent links and joints, forming the basis for kinematic modeling in most robotic systems. Collectively, these classical methods provide accurate and interpretable models that are essential for understanding robotic motion, although they often require precise system parameters (Wu et al., 2023; Zeng et al, 201).

2.1.2 Data-Driven Modeling Techniques

Data-driven modeling techniques have emerged as powerful alternatives to classical approaches by leveraging experimental data to learn system behavior without requiring explicit physical equations.

Machine learning-based system modeling utilizes algorithms that identify patterns and relationships in input-output data to approximate the dynamics of robotic manipulators (Wang et al., 2018). Neural network approximations, in particular, have gained significant attention due to their ability to model highly nonlinear relationships and generalize across different operating conditions. These networks can learn complex mappings between joint inputs and outputs, making them suitable for adaptive control and prediction tasks (Guochun et al., 2025). Reinforcement learning approaches further extend this capability by enabling robots to learn optimal control policies through interaction with the environment, gradually improving performance based on reward feedback. While these techniques offer high flexibility and adaptability, they often require large datasets and significant training effort, and their lack of physical interpretability remains a key limitation.

2.1.3 Hybrid Modeling Approaches

Hybrid modeling approaches aim to combine the strengths of classical physics-based models with modern data-driven techniques to achieve improved accuracy, adaptability, and robustness. Physics-informed neural networks represent one such approach, where physical laws and constraints are embedded into the learning process of neural networks, ensuring that predictions remain consistent with known system dynamics while benefiting from data-driven flexibility. This integration helps reduce the dependency on large datasets while maintaining physical interpretability (Zhou et a., 2024). Digital twin frameworks represent another advanced hybrid approach, where a virtual replica of the robotic system is created to mirror its real-time behavior. This virtual model continuously updates using sensor data from the physical system, enabling real-time monitoring, prediction, and optimization. Digital twins are particularly valuable in intelligent manufacturing environments, as they allow simulation, diagnostics, and control optimization without disrupting physical operations. Together, hybrid approaches represent a promising direction for next-generation robotic manipulator modeling, bridging the gap between theoretical rigor and practical adaptability (Tang et al., 2024).

3. Intelligent Control Strategies for Robotic Manipulators

Intelligent control strategies for robotic manipulators have evolved significantly in response to the increasing complexity, nonlinearity, and coupling effects present in multi-degree-of-freedom (multi-DOF) systems. Unlike traditional control approaches, intelligent control methods aim to enhance system adaptability, robustness, and precision under varying operational conditions such as payload changes, external disturbances, and parameter uncertainties. This section provides a comprehensive review of classical, robust, adaptive, and optimization-based control strategies widely adopted in modern robotic manipulators (Makarova et a., 2024).

3.1 Classical Control Methods

Classical control methods form the foundation of robotic manipulator control systems and are widely implemented in industrial applications due to their simplicity and reliability. The Proportional–Integral–Derivative (PID) control system remains the most commonly used approach because of its straightforward structure and ease of implementation (Habor et a., 2021). It regulates system behavior by continuously correcting errors between desired and actual outputs, making it suitable for a wide range of robotic applications (Bai et al., 2024). However, its performance is often limited in highly nonlinear and time-varying environments. To address multi-DOF systems, multi-loop decentralized PID control is commonly employed, where each joint of the robotic manipulator is controlled independently using a dedicated PID loop. This structure simplifies control design and reduces computational complexity, but it may suffer from inter-joint coupling effects that degrade overall system performance.

3.2 Robust Control Techniques

Robust control techniques are designed to maintain system stability and performance in the presence of uncertainties and disturbances. Sliding Mode Control (SMC) is a widely studied robust control method that ensures system trajectories converge to a predefined sliding surface, providing strong robustness against parameter variations and external disturbances. However, it may introduce chattering effects, which can negatively impact mechanical components. H-infinity control is another robust control strategy that focuses on minimizing the worst-case system response under uncertainty (Amy et al., 2024). It provides a systematic framework for handling disturbances and model inaccuracies, making it suitable for safety-critical robotic applications. Despite their effectiveness, robust control techniques often require complex mathematical formulations and may be difficult to tune for practical implementation (Sochima et al., 2025).

3.3 Adaptive and Intelligent Control

Adaptive and intelligent control methods have been developed to overcome the limitations of fixed-parameter controllers by enabling real-time adjustment based on system behavior. Fuzzy logic control utilizes linguistic rules and fuzzy sets to handle uncertainty and approximate reasoning, making it effective in systems where precise mathematical models are difficult to obtain. Neural network control leverages learning capabilities to approximate nonlinear system dynamics and improve control performance through training, allowing robots to adapt to changing environments (Tange et al., 2024). Adaptive PID control enhances traditional PID structures by continuously adjusting controller gains based on system feedback, improving performance under varying operating conditions. These methods collectively enhance flexibility and robustness, although they may require significant computational resources and careful design to ensure stability (Sochima et a., 2025).

3.4 Optimization-Based Control Techniques

Optimization-based control techniques have gained significant attention in robotic manipulators due to their ability to automatically tune controller parameters for improved performance. Particle Swarm Optimization (PSO)-based PID tuning is one of the most widely used approaches, where a swarm of candidate solutions is iteratively optimized to minimize tracking error and improve system response. This method enhances convergence speed and reduces manual tuning effort. Genetic Algorithm (GA) approaches similarly apply evolutionary principles such as selection, crossover, and mutation to optimize controller parameters, offering strong global search capabilities (Guochun et al., 2025). Hybrid optimization strategies combine multiple optimization techniques or integrate optimization with adaptive control methods to achieve improved performance, robustness, and convergence

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reliability. These approaches are particularly effective in complex multi-DOF robotic systems where traditional tuning methods are insufficient.

4. Challenges in Robotic Manipulator Systems

Robotic manipulator systems, particularly multi-degree-of-freedom configurations, face a wide range of challenges that limit their performance in real-world applications. Figure 5 presents the challenges of robot manipulator.

4.1 Nonlinear Coupling between Multiple Joints

Nonlinear coupling between multiple joints remains one of the most fundamental challenges in robotic manipulator systems. In multi-DOF configurations, the motion of one joint directly influences the dynamic behavior of others due to shared inertia, Coriolis effects, and interlinks dependencies. This coupling makes independent joint control difficult and introduces unexpected system interactions, especially during fast or high-precision movements. As a result, achieving accurate trajectory tracking requires advanced control strategies capable of compensating for these interdependent dynamics (Wang et al., 2018; Amy et al., 2024).

4.2 Payload Variation and System Uncertainty

Robotic manipulators often operate under varying payload conditions, which significantly alter the system's mass distribution and dynamic response. These variations introduce uncertainty in model parameters, leading to degraded controller performance when using fixed-parameter designs. In practical applications such as pick-and-place or assembly tasks, payload changes occur frequently, making robustness a critical requirement (Wu et a., 2023). Failure to account for these uncertainties can result in tracking errors, oscillations, or instability.

Figure 5: Challenges of robotic manipulator system

4.3 Actuator Saturation and Physical Constraints

Actuator saturation is a critical limitation in robotic systems, particularly in servo-based manipulators where torque, speed, and angular limits are strictly defined. When control signals exceed these physical limits, the system experiences nonlinear distortion, reduced responsiveness, and potential instability. These constraints are especially problematic in high-speed or high-load operations, where aggressive control inputs are required but cannot be fully executed due to hardware limitations (Zeng et al., 2018).

4.4 Sensor Noise and Communication Delays

Sensor noise and communication delays introduce significant challenges in closed-loop robotic control systems. Noisy sensor readings reduce the accuracy of feedback signals, leading to incorrect control actions (Stasevych et al., 2023). Similarly, communication delays between sensors, controllers, and actuators degrade system responsiveness and may induce oscillatory behavior. These issues are more pronounced in distributed or networked robotic systems, where real-time synchronization is essential.

4.5 Computational Limitations in Real-Time Control

Real-time control of robotic manipulators requires fast computation of dynamic equations and control laws. However, advanced algorithms such as optimization-based or learning-based controllers are often computationally expensive. In embedded systems with limited processing power, this creates a trade-off between control accuracy and computational feasibility. Ensuring real-time performance while maintaining high control precision remains a major research challenge (Vora et al., 2023).

4.6 Stability Issues in Decentralized Multi-Loop Systems

Decentralized multi-loop control structures are widely used in robotic manipulators, where each joint is controlled independently. While this simplifies controller design, it introduces stability challenges due to ignored inter-joint coupling effects (Mathew et al., 2022). Without proper coordination mechanisms, local control actions may conflict, leading to degraded global stability and performance. Ensuring stability in such decentralized systems requires careful controller tuning and sometimes additional coordination strategies (Arjaya et al., 2024).

5. Comparative Analysis of Existing Approaches

This section provides a structured comparison of existing robotic manipulator modeling and control approaches, highlighting their fundamental differences in terms of modeling philosophy, adaptability, computational demand, and performance robustness (Raza et a., 2022). The comparison is essential for understanding the trade-offs involved in selecting appropriate methods for multi-DOF robotic systems, especially under varying operational conditions such as uncertainty, nonlinearity, and real-time constraints. The analysis focuses on classical, data-driven, and intelligent control paradigms, emphasizing their relative strengths and limitations in practical applications.

Table 1: Comparative Analysis of Robotic Modeling and Control Approaches

Approach Category	**Typical Methods**	**Strengths**	**Limitations**
Classical Modeling	Euler–Lagrange, Newton–Euler, DH	High physical interpretability, strong	Computationally intensive, sensitive to parameter

	method	theoretical foundation, widely validated	uncertainty, limited adaptability
Data-Driven Modeling	Neural networks, system identification, machine learning models	High adaptability, can model nonlinear systems without explicit equations	Requires large datasets, low interpretability, generalization issues
Hybrid Modeling	Physics-informed neural networks, digital twins	Combines physics accuracy with learning flexibility, improved robustness	Complex design, high computational and implementation cost
Classical Control	PID, multi-loop PID	Simple structure, easy implementation, low computational cost	Poor performance in nonlinear and time-varying systems
Robust Control	Sliding Mode Control, H-infinity control	High disturbance rejection, strong stability guarantees	Chattering effects, complex tuning, implementation difficulty
Intelligent Control	Fuzzy logic, neural control, adaptive PID	Handles uncertainty, improves adaptability and performance	Requires design expertise, higher computational demand
Optimization-Based Control	PSO-PID, GA-PID, hybrid optimization	Improved tuning, better tracking performance, reduced error	Computational overhead, convergence sensitivity

The comparative analysis clearly shows that no single approach is universally optimal for all robotic applications. Classical methods provide strong theoretical reliability but lack adaptability, while data-driven and intelligent approaches offer superior flexibility at the cost of increased complexity. Hybrid and optimization-based methods represent a balanced compromise, making them increasingly popular in modern robotic systems.

6. Future Research Directions

This section outlines emerging research directions that are expected to shape the future development of robotic manipulator modeling and control systems. These directions are driven by the increasing demand for higher autonomy, adaptability, and intelligence in robotic applications, particularly in complex and uncertain environments.

6.1 AI-Driven Robotic Control Systems

Artificial intelligence is expected to play a central role in next-generation robotic systems. AI-driven controllers will enable robots to learn from experience, adapt to changing environments, and make autonomous decisions without relying solely on pre-defined mathematical models. This shift will significantly enhance system flexibility and operational intelligence.

6.2 Reinforcement Learning for Real-Time Adaptation

Reinforcement learning is emerging as a powerful tool for robotic control, allowing systems to learn optimal actions through continuous interaction with their environment. This approach eliminates the need for explicit modeling and enables real-time adaptation to dynamic conditions, making it highly suitable for complex multi-DOF manipulators.

6.3 Digital Twin-Enabled Robotics

Digital twin technology is becoming increasingly important in robotics, providing a real-time virtual representation of physical systems. This enables continuous monitoring, predictive analysis, and performance optimization without interrupting physical operations. It also enhances fault detection and system reliability.

6.4 Multi-Objective Optimization of Control Systems

Future robotic systems will require simultaneous optimization of multiple performance criteria such as accuracy, energy efficiency, stability, and actuator stress. Multi-objective optimization techniques will be essential for balancing these competing requirements and achieving optimal overall system performance.

6.5 Edge Computing and Embedded Intelligent Control

Edge computing enables real-time execution of control algorithms directly on robotic hardware, reducing latency and improving responsiveness. This is particularly important for time-sensitive applications where centralized computation may introduce unacceptable delays.

6.6 Human-Robot Collaborative Systems

Human-robot collaboration represents a rapidly growing research area where robots operate safely and efficiently alongside humans in shared environments. This requires advanced perception, adaptive control, and intelligent decision-making systems capable of ensuring safety while maintaining high productivity.

7. CONCLUSION

Robotic manipulator modeling remains a fundamental research area that directly influences the accuracy, efficiency, and reliability of robotic control systems across industrial automation, healthcare, space exploration, and intelligent service applications. This review examined the evolution of manipulator modeling techniques, highlighting the strengths and limitations of classical physics-based approaches, including the Euler–Lagrange and Newton–Euler formulations, as well as emerging data-driven and hybrid modeling methods. While analytical models provide strong physical interpretability and remain the foundation of robot dynamics, their dependence on accurate system parameters and computational complexity limits their effectiveness in highly nonlinear and uncertain operating environments.

Recent advances in machine learning and deep learning have introduced powerful alternatives capable of learning complex nonlinear dynamics directly from data, thereby improving modeling accuracy and adaptability. However, purely data-driven methods often require large training datasets, exhibit limited interpretability, and may struggle to generalize beyond the conditions represented in the training data. Consequently, hybrid approaches that integrate physical knowledge with data-driven learning have emerged as a promising direction, combining the interpretability of analytical models with the adaptability of artificial intelligence.

Future research should focus on developing computationally efficient, robust, and interpretable hybrid modeling frameworks that support real-time implementation, online adaptation, and uncertainty-aware decision-making. Such models will play a crucial role in enabling the next generation of intelligent robotic manipulators capable of operating safely, accurately, and autonomously in dynamic and unstructured environments.

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