Analysis of the Development of Control Algorithms for Artificial Intelligence-Based Manipulator Robots on Industrial Environment

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Abstract
Robot manipulators are one of the key components in industrial automation, especially in assembly, object removal, and precision operation tasks. However, the main challenge in its implementation is the ability to adapt to a dynamic and unstructured work environment. This study aims to analyze the development of an artificial intelligence-based (AI)-based control algorithm on robot manipulators, with an initial approach using the inverse kinematics (IK) method, Pixy2 visual sensor, and PID control. The system was tested in a controlled environment and showed an average position error of only 1–4 mm, with relatively low and stable power consumption. However, this approach still relies on static environmental conditions and system parameters that must be calculated manually. To improve flexibility and adaptability, the Deep Reinforcement Learning (DRL) method was identified as a more advanced AI solution. DRLs allow the system to learn from experience and respond to environmental changes autonomously, but with the consequent greater power requirements due to high computing loads and dynamic motor control. The results of the analysis show that the integration of DRLs can improve the intelligence and independence of manipulator robots, but requires more complex electrical system planning and energy management. In conclusion, the IK approach is suitable for systems with limited resources and structured environments, while DRLs are more suitable for dynamic and complex industrial scenarios with adequate power infrastructure support.

Keywords: *Robot Manipulator, Inverse, Power Consumption, Artificial Intelligence, DRL, Industry, Control*

Introduction

Robotics has become an essential element in modern industry, particularly in the automation of manufacturing processes. One type of robot that is widely used in the industrial sector is the robot manipulator, which is designed to perform tasks such as object removal, assembly, welding, and other precision operations (Zhang et al., 2020). Along with the increasing demands of productivity and efficiency, robot manipulators are now expected to be able to work faster, smarter, and more accurately.

The challenges in controlling manipulator robots in industrial environments are complex. Robots must be able to adapt to changes in the environment, such as shifts in object positions, task variations, and frequent disruptions and uncertainties in the production process (Lee et al., 2019). Traditional approaches, such as mathematical model-based control, tend to be less flexible and inefficient in dynamic and unstructured industrial scenarios.

In response to these limitations, the development of artificial intelligence (AI)-based control algorithms is a promising alternative. Artificial intelligence, especially in the form of machine learning and deep learning, allows robots to learn from past data and experiences, as well as adapt autonomously to changing conditions (Sadeghi et al., 2021). The application of AI is expected to improve speed, accuracy, and reduce errors due to operational uncertainty.

However, the effectiveness of AI-controlled manipulator robots is highly dependent on reliable and efficient electrical system support. Electrical components such as servo motors, actuators, current and voltage sensors, and power distribution systems are integral parts of the robot's operations. AI-based control systems require a stable power supply and intelligent energy management system in order to operate optimally, especially when handling dynamic loads and high-precision movements. In addition, AI hardware such as graphics processing units (GPUs), microcontrollers, and edge computing modules that are often used in AI systems on robots require proper electrical configuration to avoid overheating or excessive power consumption.

In the context of Industry 4.0, the integration between robotics, AI, and electrical systems technology is becoming increasingly crucial. Technologies such as the Internet of Things (IoT) allow real-time monitoring of electrical conditions, while big data analytics help in the prediction of energy needs and power consumption efficiency (Lu, 2019). Electrical sensors embedded in manipulator robots also play a role in detecting overcurrent, voltage disturbances, and alerting the system to potential failures that can hinder operations (Nguyen et al., 2020).

Despite this, the implementation of manipulator robots in industry still faces major challenges, especially in the aspects of electrical system resilience and efficiency in work environments that are not always structured and dynamic (Kim & Lee, 2021). The reliability of the electrical system is the main determinant in maintaining the continuity of the robot's work, because even a small disruption in the power system can result in downtime and production losses.

Based on this background, this research focuses on the analysis of the development and application of artificial intelligence-based control algorithms for robot manipulators in industrial environments, which is specifically associated with the role of the electrical system as the main support. The main focus is on answering how AI can be used to improve the efficiency, flexibility, and adaptive capabilities of robots, as well as how electrical systems need to be designed to support robotic intelligence in a sustainable manner. The research will also identify the challenges of integration between artificial intelligence and electrical systems, as well as develop technical recommendations to improve the performance and reliability of manipulator robots in the modern industrial sector.

Research Objectives

The purpose of the material in this journal is to:

1. To determine the effect of the application of artificial intelligence algorithms on improving the performance of manipulator robots in dynamic and unstructured industrial environments.
2. To find out the most effective artificial intelligence methods to apply in the control of manipulator robots, in particular in terms of adaptation to changes in the environment and tasks.

Literature Review

2.1 Robot Manipulators and the Complexity of Industrial Environments

Robot manipulators have become a vital element in modern industrial automation processes, especially on production lines that demand high accuracy, speed, and efficiency. The industrial environment, which is often unstructured and capricious, presents a major challenge to conventional control systems (Zhang et al., 2020). In such a situation, a control system is needed that is not only capable of executing commands, but also able to adapt in real-time to changing conditions.

2.2 Electrical System

The effectiveness of manipulator robots controlled by artificial intelligence (AI) relies heavily on reliable and efficient electrical systems. Components such as servo motors, electric actuators, current and voltage sensors, inverters, and power distribution systems play an important role in supporting the robot's operations. These systems require a stable power supply and adaptive energy management, especially when robots handle heavy loads or perform high-precision movements. Power System Reliability: According to Hassan et al. (2021), the reliability of electrical systems is crucial because components such as servo motors are highly sensitive to voltage fluctuations and harmonic disturbances. In addition, the speed and torque regulation of the motor requires the support of intelligent power electronics, such as PWM-based driver motors as well as feedback from current and voltage sensors.

2.3 Artificial Intelligence in Robot Control Systems

Artificial Intelligence (AI), particularly through machine learning and deep reinforcement learning approaches, provides a new paradigm in the robot manipulator control system. AI allows robots to learn system patterns and behavior from data, not just based on physical models. Sadeghi et al. (2021) state that this approach is very effective in dealing with the uncertainty and variability of tasks. The deep Q-learning algorithms and policy gradient applied to the control system allow the robot to make decisions based on value evaluation and prediction of the outcome of a particular action, without the need for complex physical modeling (Wang et al., 2022).

2.4 Integration of AI with Sensors and IoT in Industry 4.0

In the Industry 4.0 ecosystem, robot manipulators are increasingly integrated with smart sensors and the Internet of Things (IoT). According to Lee et al. (2019), this integration enables real-time data-driven decision-making through industrial data networks. By combining AI algorithms and sensors, robots can access environmental data, recognize objects, and adjust actions quickly, improving production efficiency and reducing downtime. Chen et al. (2021) added that the combination of computer vision, deep learning, and adaptive control systems has succeeded in creating manipulator robots that are capable of operating in uncertain conditions, such as handling objects of unknown shapes and sizes.

Research Methodology

Tool System Design:

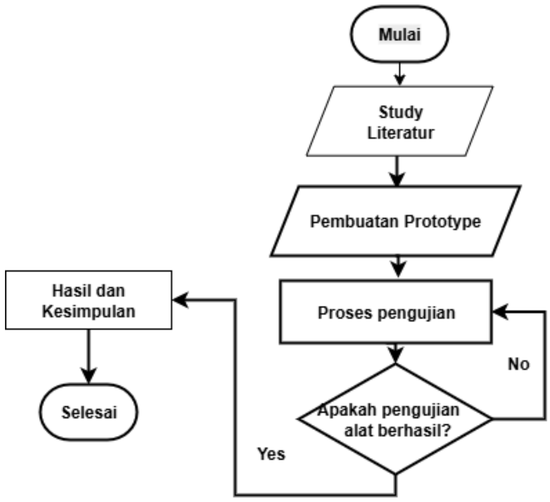

Figure 1. Flowchart

Description of the research stages:

1. Start of Research: An initial stage that includes the formulation of the problem and the exploration of basic ideas regarding the development of intelligent control algorithms for robot manipulators, taking into account the challenges in a dynamic and complex industrial environment.
2. Literature Study: A literature review is conducted to understand core concepts such as robot manipulators, conventional control systems, artificial intelligence (AI), machine learning, and their implementation in the robotics manufacturing and automation industries.
3. Problem Identification: Identify technical and operational problems that often arise in the control of robots in the industrial sector, such as environmental uncertainty, limitations in adaptation of conventional systems, and the need for flexible and intelligent control.
4. Formulation of Objectives: Determine the main objectives of the research, which is to design, develop, and analyze an artificial intelligence-based control algorithm capable of improving the flexibility, accuracy, and work efficiency of manipulator robots in industrial environments.
5. Control System Design: Designing an AI-based control system architecture, including system block diagrams, control logic flows, and technology selection such as position and force sensors, machine learning-based controls (e.g. *reinforcement learning*), and computing platforms.
6. Algorithm Implementation: Apply algorithm design in the simulation or prototype of a manipulator robot, either through direct programming or integration with an industrial-based test environment (e.g. 6-arm DOF robot).
7. System Testing: Conducting tests on system response, motion accuracy, adaptation to disturbances, and the ability of the system to learn from previous experiences, both through simulation and physical testing.
8. Result Analysis: Analyze the performance of the algorithm from the aspects of movement accuracy, response speed, calculation efficiency, and adaptability in real or semi-real industrial scenarios. It is also compared to conventional control methods as a baseline.
9. Conclusions and Recommendations: Conclude the effectiveness of the development of AI-based control algorithms for manipulator robots and provide suggestions for

further development, such as IoT integration, multi-robot collaboration, or the use of lighter AI models for real-time efficiency.

Results And Discussion

4.1 Description of Robot Manipulators

This study uses a prototype of the arm manipulator robot shown in Figure 4. The robot has three links with four degrees of freedom, and all joints are rotating. This prototype was developed from previous research [16].

As a control system, an Arduino Mega 2560 microcontroller is used. This microcontroller functions to transmit signals from the computer to the robot, receive sensor data, and execute control commands to drive the motor on the robot.

The kinematic structure of the manipulator is described using Denavit–Hartenberg (DH) parameters, namely α_i (link twist), a_i (link length), d_i (joint offset), and θ_i (joint angle) [1, 17]. The values of the DH parameter for this robot have been specified in the previous reference [16].

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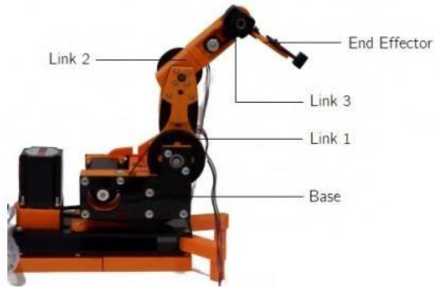

Figure 2. Pixy2 Camera Sensor Module Display

4.2 Sensor Systems and Kinematic Parameters

Figure 4 shows the display of the Pixy2 camera sensor module used in this study as a tool to detect the position of objects based on a specific color. The camera is integrated with a robotic control system to provide real-time visual feedback.

The kinematic structure of the robot manipulator used is determined based on the Denavit–Hartenberg (DH) parameter. Table 2 presents the DH parameters for the manipulator robots shown in Figure 4. This robot has three links with three rotational joints. The parameter α_i indicates the angle of twist between links, a_i is the length of the link, d_i is the offset, and θ_i is the angle of rotation in each joint.

Table 1. Parameters of DH robot manipulator

Link (i)	α_i	a_i	d_i	θ_i
1	α_1	l_1	0	θ_1
2	0	l_1	0	θ_2
3	0	l_1	0	θ_3

The main object of this study is to conduct inverse kinematics (IK) analysis and develop an end-effector positioning system with the help of visual feedback from the Pixy2 camera. The research is focused on two-dimensional motion on a flat plane, which is tailored to the system's capabilities and practical objectives.

The image shows the electrical connection network between the Pixy2 camera and the Arduino Mega 2560 microcontroller. The connection is made through the ICSP pin using a flat cable. The position of the camera against the manipulator can also be seen in Figure 6. In the testing phase, the system is tested to recognize and determine the position of the object based on a specific identification color placed on a flat plane (as shown in Figure 6), and moves the robotic arm to respond to the object's position.

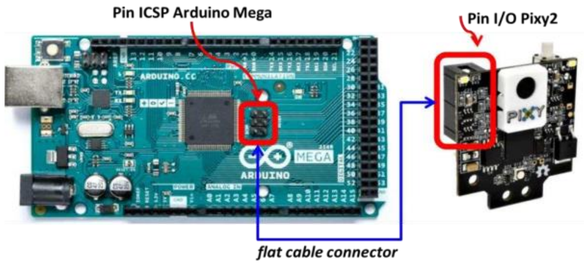

Figure 3. Display of the Pixy2 Camera Sensor Module

4.3 Inverse Kinematics (IK) Analysis

The analysis of inverse kinematics (IK) on the prototype of the robot arm in this study was carried out using an analytical approach based on the schematic of the kinematic system shown in Figure 7 [1, 16–18]. This analysis is limited only to two-dimensional movements in a flat plane, with a global coordinate framework (X_0, Y_0). In Figure 7, the angle θ_i expresses the orientation of the i-link (with *i* = 1, 2, 3), while (x_3, y_3) is the position of the end-effector in global coordinates.

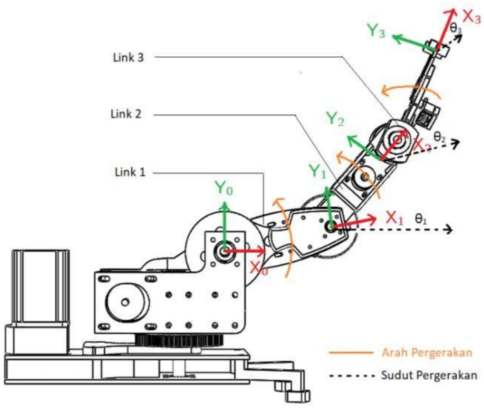

Figure 4. Configuration of the Robot Used in the IK Analysis

The IK problem in this context is formulated as follows: in order to achieve the target position of the end-effector at the coordinates (x_3, y_3), the system must be able to determine the orientation angle values of each link, i.e. θ_1, θ_2, and θ_3. Based on the geometry of the robotic arm in Figure 7, the IK solution can be obtained analytically through several calculation steps [17–19].

First, the variable Φ is defined as the total sum of the orientation angles of all links, i.e.:

$$\boldsymbol{\Phi = \theta_1 + \theta_2 + \theta_3} \quad (2)$$

Second, the coordinate projection (x_2, y_2), which is the position of the second link end to the global coordinate system, is determined, using end-effector position information and the length of the third link (l_3). The formula is:

$$\mathbf{x_2 = x_3 - l_3 \cos(\Phi)} \quad (3)$$
$$\mathbf{y_2 = y_3 - l_3 \sin(\Phi)} \quad (4)$$

Third, after obtaining the position of the second link projection, the angular value θ_2 can be calculated using the following formula:

$$\boldsymbol{\theta_2 = \cos^{-1} ((x_2^2 + y_2^2 - l_1^2 - l_2^2) / (2l_1l_2))} \quad (5)$$

Then, the angle θ_1 is calculated based on the values obtained:

$$\boldsymbol{\theta_1 = \tan^{-1}(y_2 / x_2) - \tan^{-1}((l_2 \sin \theta_2) / (l_1 + l_2 \cos \theta_2))} \quad (6)$$

Finally, the angle θ_3 is calculated as:

$$\boldsymbol{\theta_3 = \Phi - \theta_1 - \theta_2} \quad (7)$$

By applying the steps in equations (2) to (7), the orientation angle values for each link (θ_1, θ_2, and θ_3) required for the end-effector to reach the desired position (x_3, y_3) are obtained.

4.3.1 Visual System Integration and Its Impact on Power Consumption

In this study, the IK solution was integrated with the Pixy2 camera, which is used to detect the position of objects based on color. This camera provides real-time position feedback and is used as the target coordinate input in the IK algorithm. This integration allows the end-effector to move automatically and precisely based on visual information. However, the use of visual systems such as Pixy2 and real-time IK computing has a direct impact on the power load of robotic systems. IK computing that continuously processes trigonometric calculations and sensor readings requires a stable power supply and efficient power management, especially when combined with servo motor control or an electric actuator that drives the robotic arm. The high-precision movement, resulting from the results of the IK calculations, will force the servo motor to work intensively with variable torque and speed settings according to the target coordinates. This causes fluctuations in power consumption, especially when the motor holds a certain position (holding torque), accelerates, or brakes suddenly. Therefore, electrical systems need to be designed with the peak load capacity, voltage stability, and cooling in the power driver components.

4.3.2 Optimization of Energy Consumption with Adaptive Control

To maintain energy efficiency, an AI-based control approach can be applied in conjunction with an IK algorithm to regulate power-on-demand, i.e. the system only activates power at certain actuators when needed. In addition, the PWM (*Pulse Width Modulation*) based driver motor allows for efficient power regulation by adjusting the duty cycle according to the angular commands of the IK algorithm. The use of power monitoring modules and current/voltage sensors can also be added to monitor the performance of the electrical system during operation. This data is useful for detecting anomalies, estimating component life, and preventing damage due to overload or overheating.

Table 2. Robotic Arm System Power Calculation

Yes	Component	Voltage (V)	Current (A)	Power (Watts) = V × A	Information
1	Servo Motor 1	5	2.0	10.0	First link drive motor
2	Servo Motor 2	5	1.8	9.0	Second link drive motor
3	Servo Motor 3	5	1.5	7.5	Third-link drive motor (end-effector)
4	Pixy2 Camera	5	0.3	1.5	Visual sensor of target detection
5	Microcontroller (ESP32/Arduino)	5	0.4	2.0	IK algorithm processing unit and sensor input
6	Current and Voltage Sensors	5	0.1	0.5	Monitoring the Electrical System
7	Motor Driver (PWM)	12	0.6	7.2	Torque and speed control module
	Total Power	—	—	37.7 Watts	Estimated total system power consumption

4.4 Deep Reinforcement Learning (DRL) Analysis

In a complex and ever-changing industrial environment, robot manipulators are required to work intelligently and flexibly. One of the most effective artificial intelligence methods for robot control is Deep Reinforcement Learning (DRL). This method combines *deep learning* with reinforcement *learning*, allowing robots to learn from trial and error. Unlike conventional methods such as PID or inverse kinematics (IK) which require complex mathematical calculations, DRLs are able to make their own decisions based on environmental conditions, without the need for reprogramming when there are changes. For example, if an object changes position or a sensor glitch occurs, the DRL system can remain adaptable.

DRL algorithms such as DQN, PPO, and SAC have proven to be effective in robotic tasks such as object retrieval, assembling, and visual tracking. DRLs can also be combined with cameras or visual sensors to improve the accuracy and work efficiency of the robot. DRLs also have challenges such as the need for big data, long training time, and adequate computing devices. Therefore, DRLs are suitable for the development of advanced robotic systems or through simulation in advance. From the results of this study, the IK-based and PID-based systems have shown good performance with small errors. But if it is replaced with DRLs, the system will become more adaptive and smart, especially for uncertain environments.

The results of the manipulator control system test in this study show that an approach based on inverse kinematics (IK) algorithms and visual sensors is quite effective for detecting and directing end-effectors towards the target object. However, the system still relies on manual calculations of the target position (x_3, y_3) and the kinematic parameters of the robotic arm.

For example, in Case I with a position target of 130 mm, the results of the IK calculation produce the angular orientation value:

$\theta_1 = 20{,}61°$

$\theta_2 = 107{,}73°$

$\theta_3 = -98{,}33°$

And in Case II with a target of 220 mm, it was obtained:

$\theta_1 = 8{,}45°$

$\theta_2 = 73{,}23°$

$\theta_3 = -51{,}67°$

These values are obtained through analytical equations:

$$\theta_2 = \cos^{-1}\left(\frac{x_2^2 + y_2^2 - l_1^2 - l_2^2}{2l_1 l_2}\right)$$

$$\theta_1 = \tan^{-1}\left(\frac{y_2}{x_2}\right) - \tan^{-1}\left(\frac{l_2 \sin\theta_2}{l_1 + l_2 \cos\theta_2}\right)$$

$$\theta_3 = \phi - \theta_1 - \theta_2$$

The system works either in testing, with an average position error of only 1–4 mm, or in an error percentage of 0.0045% – 0.023%. However, such accuracy is only achieved under structured environmental conditions (fixed objects, stable light, flat working planes).

1. Power Requirements of Computing system

   Training and execution of DRL algorithms requires compute-intensive components, such as GPUs, edge AI devices, or high-powered embedded computers. These components require a stable power supply and adequate cooling, as power consumption can reach 15–50 watts or more, depending on the device used. Compared to IK or PID-based systems that only require lightweight microcontrollers (such as Arduino/ESP32) with low power consumption (around 1–2 watts), DRL systems have a larger energy footprint.

2. Motorcycle Activities are More Dynamic and Varied

   Because DRLs generate control based on adaptive decision-making, the movements of servo motors or actuators become more diverse and not necessarily linear as in IK systems. This causes non-constant fluctuations in electrical power, as the motor can work under conditions of acceleration, quick correction, or sudden braking. The electrical system must be able to provide peak power when the motor load is high, as well as efficient when the load is light.

3. Energy Management and Sensor Monitoring

   DRL-based systems should be equipped with power consumption monitoring sensors, both for energy efficiency and safety purposes. Current, voltage, and temperature sensor data can be used as feedback to prevent overload or overheat on critical components such as driver motors and visual processing modules.

4.4.1 Comparison with the Potential of Deep Reinforcement Learning (DRL)

In comparison, Deep Reinforcement Learning (DRL) offers a more flexible approach. DRL does not require explicit IK calculation because the system learns directly through interaction. This means that the system doesn't need to know the link length or the initial position of the object—the DRL just needs data from the sensor (e.g., the position of the object from the camera), then take action, evaluate the results (rewards), and refine the strategy.
To illustrate, in the same scenario as Case I and II:

1. The DRL will map the coordinates of the object (x, y) from the camera directly to the motor rotation action (θ_1, θ_2, θ_3) through the learning process.
2. After thousands of iterations of simulations or real experiments, the DRL will find the optimal policy that is able to move the robot towards the target with minimal errors without the need for an IK formula.

The following is an example of the learning structure of DRL in a manipulator system:

1. State(s): the position of the object (x, y), the current position of the end-effector, or the camera feedback.
2. Action (a): change in the angle of the joint ($\Delta\theta_1$, $\Delta\theta_2$, $\Delta\theta_3$).
3. Reward (r): negative of the remaining distance between the end-effector and the target (the closer, the positive reward increases).
4. Policy (π): the optimal strategy learned to choose the action from each condition.

Table 3. Electrical Load Power Analysis Table Robot Manipulator Control System

Component	IK + PID (Conventional)	DRL (Deep Reinforcement Learning)	Comparative Analysis
Control Unit (Controller)	Microcontroller (Arduino, ESP32) 5V / 0.4A = 2W	Embedded PC (Jetson Nano / Raspberry Pi 4) 5V / 3A = 15W	DRLs require higher computing devices so that power consumption is greater.
Servo Motor 3 Axis	3 × 5V / 1.5A = 22.5W	3 × 5V / varies between 1.5–2A = ~27W	DRLs produce dynamic control, so motor consumption fluctuates and tends to be higher.
Sensor Visual	Pixy2 Camera 5V/0.3A=1.5W	Camera + Processing Module (CSI + VPU) 5V / 0.8A = 4W	DRL systems generally require a higher resolution camera and additional visual computing.
Current/Voltage Sensor	5V/0.1A = 0.5W	5V/0.1A = 0.5W	Same in both systems, it is used for power monitoring.
Motor Driver (PWM)	12V/0.6A = 7.2W	12V/0.8A=9.6W	DRL motor drivers handle loads more dynamically,

Component	IK + PID (Conventional)	DRL (Deep Reinforcement Learning)	Comparative Analysis
			requiring more power.
Total Power Consumption	33.7 Watt	56.1 Watts	DRLs require ±66% more power than IK systems for adaptive performance.

The choice between the IK and DRL systems is not only considered in terms of control intelligence, but also from the efficiency and electrical capacity available. DRL systems are suitable for complex and flexible applications, but must be supported by a reliable and energy-efficient power system. For systems with limited power limits (such as portable systems), the IK approach is more suitable.

Conclusion

Based on the results of the study, it can be concluded that the robot manipulator control system using an analytics-based inverse kinematics (IK) approach integrated with the Pixy2 visual sensor is able to provide fairly accurate and efficient performance in a structured work environment. The system shows a very small average position error, which is between 1 to 4 mm, or about 0.0045% to 0.023%, with relatively low power consumption and stable electrical loads. This makes the IK approach particularly suitable for industrial applications that have fixed conditions, such as unchanged object positions and consistent lighting.

IK-based systems still have limitations in dealing with environmental dynamics, such as changes in the position of objects or interference in visual sensors. To address this, the Deep Reinforcement Learning (DRL) approach offers a more adaptive and intelligent solution. DRLs allow robot manipulators to learn from experience and make decisions autonomously, even when environmental conditions change unexpectedly. Nonetheless, the use of DRLs has an impact on significantly increasing power consumption, mainly due to the need for high-power computing devices and more dynamic motor control. Comparative analysis shows that the power consumption of DRL-based systems can be up to 66% higher than IK systems.

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