Applied Chemical Engineering (2025) Volume 8 Issue 1 ISSN: 2578-2010 (O)
doi: 10.59429/ace.v8i1.5585

RESEARCH ARTICLE

Trajectory tracking of chemical engineering robotic arms based on improved nonlinear active disturbance rejection control

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ABSTRACT

With the increasing demand for automation and precision in chemical engineering processes, robotic arms play a crucial role in enhancing production efficiency and product quality. Traditional control methods often struggle to cope with the complex dynamic environments and unpredictable disturbances inherent in chemical engineering applications. This study presents an improved Nonlinear Active Disturbance Rejection Control (NLADRC) method for dynamic trajectory tracking of chemical engineering robotic arms. Leveraging the support of the Yunnan Province Major Science and Technology Project, the proposed NLADRC framework integrates an enhanced disturbance observer and adaptive control strategies to effectively mitigate unknown disturbances and parameter variations. Experimental results demonstrate that the NLADRC method significantly outperforms traditional PID and standard ADRC controllers in terms of tracking accuracy, response speed, and robustness. The findings provide a robust theoretical foundation and practical guidelines for the deployment of advanced control strategies in chemical engineering robotic systems.

Keywords: Improved Nonlinear Active Disturbance Rejection Control; Chemical Engineering; Robotic Arms; Dynamic Trajectory Tracking; Robust Control

ARTICLE INFO

Received: 18 December 2024
Accepted: 17 February 2025
Available online: 19 February 2025

1. Introduction

1.1. Research background

The integration of robotic arms into chemical engineering processes has revolutionized the industry by automating complex tasks such as material handling, reactor operation, and product packaging.[6,7] According to a report by the International Federation of Robotics, the global market for industrial robots is projected to reach $70 billion by 2025, with a compound annual growth rate (CAGR) of 12% from 2020 to 2025.[8] These robotic systems are expected to perform with high precision and reliability under varying operational conditions. However, the dynamic nature of chemical engineering environments, characterized by fluctuating loads, temperature variations, and unforeseen disturbances, poses significant challenges to maintaining optimal performance. Traditional control methodologies, such as Proportional-Integral-Derivative (PID) controllers, often fall short in addressing these challenges due to their inherent limitations in handling nonlinearities and external disturbances.

1.2. Problem statement

Conventional control techniques struggle to maintain accurate trajectory tracking and system stability in the presence of nonlinear dynamics and unpredictable disturbances. This inadequacy can lead to reduced operational efficiency, increased wear and tear on mechanical components, and compromised product quality. Therefore, there is a pressing need for advanced control strategies that can enhance the robustness and adaptability of robotic arms in chemical engineering applications.

1.3. Research objectives and significance

The primary objective of this study is to develop and validate an improved Nonlinear Active Disturbance Rejection Control (NLADRC) method tailored for dynamic trajectory tracking of chemical engineering robotic arms. By integrating an enhanced disturbance observer and adaptive control mechanisms, the proposed NLADRC aims to effectively counteract unknown disturbances and system parameter variations. The significance of this research lies in its potential to:

1. **Enhance Tracking Precision**: Achieve higher accuracy in following predefined trajectories despite environmental uncertainties.
2. **Improve Response Speed**: Reduce the time taken for the robotic arm to respond to trajectory changes.
3. **Increase Robustness**: Maintain stable performance under varying operational conditions and external disturbances.
4. **Extend System Longevity**: Minimize mechanical stress and reduce maintenance costs by ensuring smoother and more reliable operation.

1.4. Implications beyond chemical engineering

The advancements in NLADRC not only benefit chemical engineering but also have significant implications for other industries, including:

1. **Pharmaceuticals**: Enhanced precision in drug formulation and packaging processes can lead to improved product quality and compliance with regulatory standards.[9]
2. **Materials Science**: Advanced robotic systems equipped with NLADRC can facilitate more efficient material handling and processing, reducing waste and increasing throughput.[10]

1.5. Thesis Structure

This paper is organized as follows: Section 2 provides a comprehensive literature review on existing control methods for robotic arms, highlighting the advancements and limitations of ADRC and nonlinear control strategies. Section 3 outlines the proposed NLADRC methodology, including system modeling, disturbance observer design, and control algorithm formulation. Section 4 details the experimental setup and implementation procedures. Section 5 presents the experimental results and discusses the performance of the NLADRC in comparison to traditional control methods. Section 6 analyzes the economic and social benefits derived from the improved control strategy. Finally, Section 7 concludes the study and suggests directions for future research.

2. Literature review

2.1. Robotic arm control methods in chemical engineering

Robotic arms in chemical engineering require precise and reliable control to perform intricate tasks, such as handling hazardous materials, mixing chemicals, and conducting automated inspections. Traditional control methods, such as PID controllers, have been widely used due to their simplicity and ease of implementation. However, PID controllers are limited in their ability to handle nonlinearities and external disturbances, which are prevalent in chemical engineering environments. For instance, variations in material viscosity during mixing processes can lead to significant deviations in expected performance, making PID control insufficient.

To address these limitations, more advanced control strategies have been explored, including Fuzzy Logic Control, Sliding Mode Control, and Active Disturbance Rejection Control (ADRC). Each of these methods offers unique advantages in managing the complexities of chemical processes, such as the need for adaptability to changing material properties and the ability to maintain stability in the presence of external perturbations.

2.2. Active disturbance rejection control (ADRC)

ADRC has emerged as a promising control strategy that estimates and compensates for system disturbances in real-time. Unlike traditional controllers, ADRC does not rely heavily on an accurate mathematical model of the system. Instead, it employs an Extended State Observer (ESO) to estimate both the system states and the total disturbances, which include internal uncertainties and external perturbations. For example, in a robotic arm used for chemical dispensing, ADRC can effectively manage disturbances caused by sudden changes in load when switching between different containers, ensuring consistent performance. This estimation allows ADRC to dynamically adjust the control input to counteract the disturbances, thereby enhancing system robustness and performance.

Research has demonstrated the effectiveness of ADRC in various robotic applications. In one study, ADRC was applied to a robotic arm performing precision tasks in a chemical laboratory, resulting in improved tracking accuracy and reduced overshoot during dynamic operations. This adaptability is crucial in maintaining accuracy in chemical formulations, particularly when dealing with hazardous materials that require strict adherence to safety protocols[11].

Moreover, ADRC has been shown to enhance the performance of robotic systems in challenging environments, such as those encountered in medical applications, where precise control is essential for safety and efficacy[12]. The integration of ADRC with other control strategies has further improved the robustness and reliability of robotic arms in dynamic settings, making it a valuable approach in chemical engineering tasks[13].

2.3. Nonlinear control methods

Nonlinear control methods are designed to manage systems with inherent nonlinearities, offering improved performance over linear controllers in handling complex dynamics. Techniques such as Feedback Linearization, Backstepping Control, and Nonlinear Model Predictive Control (NMPC) have shown effectiveness in various applications[14]. However, these methods often require precise system modeling and can be computationally intensive, limiting their practicality in real-time applications. For instance, NMPC can involve complex optimization problems that may not be solvable within the time constraints of fast-paced chemical processes, leading to delays in control actions[15].

To improve the practicality of nonlinear methods, research is focusing on simplifying modeling requirements and reducing computational loads through more efficient algorithms and approximations. For example, hybrid approaches that combine nonlinear control with simpler linear techniques may provide a balance between performance and computational efficiency[16].

2.4. Integration of ADRC and nonlinear control

Recent studies have explored the integration of ADRC with nonlinear control methods to leverage the strengths of both approaches. This hybrid strategy aims to enhance disturbance rejection capabilities while effectively managing system nonlinearities. For instance, combining ADRC with Backstepping Control has been shown to improve tracking performance and system stability in robotic applications. However, there is still a need for further research to optimize the integration process and validate its effectiveness in dynamic and uncertain environments typical of chemical engineering.

2.5. Research gaps

While significant advancements have been made in ADRC and nonlinear control methods, their application in chemical engineering robotic arms remains underexplored. Specifically, there is a lack of comprehensive studies that systematically integrate and optimize these control strategies for dynamic trajectory tracking in complex environments. The most urgent aspects that require attention include:

Trajectory Tracking Accuracy: Ensuring that robotic arms can follow predefined paths with high precision, especially in tasks involving hazardous materials.

Robustness: Enhancing the ability to withstand external disturbances, such as sudden changes in load or environmental conditions, which are common in chemical processes.

Adaptability to Material Variability: Developing control strategies that can adjust to changes in material properties, such as viscosity and density, during operations.

Additionally, existing research often overlooks the economic and social implications of implementing advanced control systems, which are critical for industrial adoption.

3. Research methodology

3.1. System modeling

The robotic arm used in this study is a six-degree-of-freedom (6-DOF) system commonly employed in chemical engineering applications. The dynamic model of the robotic arm is derived using the Lagrangian formulation, chosen for its effectiveness in capturing the system's energy dynamics, which is crucial in robotic applications. This model takes into account inertial, Coriolis, and gravitational forces. The governing equations of motion are expressed as:

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau + \tau_{\mathrm{d}} \tag{1}$$

where:

- $M(q)$ is the inertia matrix, which represents the distribution of mass and affects the arm's resistance to acceleration. It is a function of the joint configuration q and defines how the arm's mass influences its motion.
- $C(q,\dot{q})$ represents Coriolis and centrifugal forces,which account for the inertial effects that arise when the robotic arm is moving. These forces depend on the velocity $\dot{q}$ and the configuration q of the arm, and they are essential for accurately describing the motion of multi-joint systems.
- $G(q)$ is the gravitational force vector, which describes the forces acting on the arm due to gravity. This force varies with the configuration q of the arm and is crucial for understanding how gravity impacts the arm's dynamics.
- τ is the control input torque, which is the torque applied at the joints of the robotic arm to achieve desired motion. This input is critical for controlling the arm's trajectory and position.
- τ_d denotes external disturbances, which can include unmodeled forces, friction, and changes in load during operation. These disturbances can significantly affect the performance of the robotic arm, particularly in unpredictable chemical environments.

In chemical engineering applications, the robotic arm may encounter various types of perturbations, including[17]:

Load Variability: Sudden changes in the weight or distribution of materials being handled can create unexpected forces. To address this, the control system can incorporate adaptive control strategies that adjust the input torque τ based on real-time load measurements.

Viscosity Changes: When mixing or transferring fluids, variations in viscosity can affect the arm's movement. The control system can employ feedback mechanisms that monitor the viscosity and adjust the control inputs accordingly to maintain stability.

Thermal Effects: Temperature fluctuations may influence the material properties and the mechanical characteristics of the robotic arm. Implementing thermal compensation strategies can help maintain performance by adjusting the control algorithms based on temperature readings.

External Interference: Interactions with other equipment or personnel in the chemical processing environment can introduce disturbances. Robust control methods, such as Active Disturbance Rejection Control (ADRC), can estimate and compensate for these external disturbances in real-time.

Changing Operational Conditions: The dynamic nature of chemical processes means that the operational conditions can change rapidly. Using a combination of nonlinear observers and adaptive control techniques allows the system to adapt quickly to these changes, improving the robustness of the control strategy.

3.2. Improved nonlinear active disturbance rejection control (NLADRC) design

To enhance the trajectory tracking performance of the robotic arm in complex dynamic environments, an improved Nonlinear Active Disturbance Rejection Control (NLADRC) method is proposed. The NLADRC framework integrates an enhanced disturbance observer and adaptive control strategies to effectively mitigate unknown disturbances and parameter variations.

Core Techniques of NLADRC

The improved Nonlinear Active Disturbance Rejection Control (NLADRC) method integrates several core techniques designed to enhance the trajectory tracking performance of robotic arms in dynamic environments:

(1) Enhanced Disturbance Observer

The enhanced disturbance observer, specifically the Nonlinear Extended State Observer (NESO), is crucial for accurately identifying and suppressing disturbances.

Real-Time Disturbance Estimation: The NESO estimates both the internal state variables and the total disturbances affecting the robotic arm. This capability allows it to account for unmodeled dynamics, which is essential in unpredictable environments typical of chemical engineering applications.

Nonlinear Gain Adjustment: The NESO incorporates a nonlinear gain adjustment mechanism that adapts based on the magnitude of the estimated disturbances. This feature ensures that the observer remains responsive to larger disturbances while maintaining stability during smaller fluctuations.

Dynamic Performance: By effectively estimating disturbances in real-time, the NESO enables the control system to dynamically adjust the control input, which improves the overall robustness and tracking accuracy of the robotic arm.

(2) Adaptive Control Mechanism

The adaptive control mechanism enhances the flexibility and robustness of the NLADRC strategy.

Real-Time Parameter Adjustment: The adaptive control algorithm modifies the controller parameters based on real-time tracking errors and disturbance estimates. This allows the system to continuously optimize its performance as conditions change.

Proportional and Derivative Gains: The adaptive mechanism adjusts the proportional (K_{p}) and derivative (K_{d}) gains according to the current operational conditions and the estimated disturbances. This ensures that the control strategy can respond effectively to varying environmental influences, enhancing stability and performance.

Improved Responsiveness: By integrating feedback from the disturbance observer, the adaptive mechanism allows for rapid adjustments to the control inputs, thus minimizing delays in response time and maintaining accurate trajectory tracking.

3.2.1. Enhanced disturbance observer

The disturbance observer is critical for estimating the total disturbances affecting the robotic arm. An improved Nonlinear Extended State Observer (NESO) is designed to enhance the accuracy of disturbance estimation. The NESO was chosen over other potential disturbance observers due to its superior capability to handle nonlinearities and adapt to varying operational conditions. It incorporates a nonlinear gain adjustment mechanism that adapts based on the magnitude of the estimated disturbances, ensuring robust performance under varying operational conditions.

Justification for NESO:

Computational Efficiency: NESO efficiently processes real-time data, allowing for faster adaptation to changes in disturbance dynamics compared to traditional observers.

Estimation Accuracy: Improved estimation accuracy is achieved through the observer's ability to account for both modeled dynamics and unmodeled disturbances, minimizing the estimation error.

3.2.2. Adaptive control algorithm

The adaptive control algorithm dynamically adjusts the controller parameters in real-time to maintain optimal performance. This is achieved by integrating an adaptive law that modifies the control gains based on the tracking error and the disturbance estimates provided by the NESO. The control law is formulated as:

$$\tau = M(q)\ddot{q}_{\mathrm{d}} + C(q,\dot{q})\dot{q}_{\mathrm{d}} + G(q) + K_{\mathrm{p}}e + K_{\mathrm{d}}\dot{e} + \hat{\tau}_{\mathrm{d}} \tag{2}$$

where:

- $\ddot{q}_{\mathrm{d}}$ and $\dot{q}_{\mathrm{d}}$ are the desired accelerations and velocities,
- $e = q_{\mathrm{d}} - q$ is the tracking error,
- K_{p} and K_{d} are the proportional and derivative gains,
- $\hat{\tau}_{\mathrm{d}}$ is the estimated disturbance.

The selection of parameters for the NESO and control algorithm involves careful consideration of trade-offs between stability and responsiveness. For instance, higher gains can lead to faster responses but may also induce overshoot or instability. Through simulations and empirical testing, a balanced configuration is achieved that maintains system stability while providing adequate responsiveness to disturbances.

3.3. Implementation steps

The implementation of the NLADRC involves several key steps:

1. **System Initialization**: Calibrate the robotic arm to ensure accurate joint positions and velocities.

2. **Disturbance Observer Initialization**: Initialize the NESO parameters based on the expected range of disturbances.
3. **Control Law Implementation**: Implement the adaptive control algorithm in the control system.
4. **Trajectory Planning**: Define complex 3D trajectories for the robotic arm to follow during experiments.
5. **Data Acquisition**: Use high-resolution sensors to monitor joint positions, velocities, and external disturbances.
6. **Parameter Tuning**: Adjust the controller gains and observer parameters to achieve desired tracking performance.
7. **Performance Evaluation**: Compare the NLADRC performance against traditional PID and ADRC controllers under various disturbance scenarios.

4. Experimental design and implementation

4.1. Experimental setup

The experiments were conducted using a six-degree-of-freedom (6-DOF) robotic arm, equipped with high-precision position and torque sensors. The control system was implemented on a real-time MATLAB/Simulink platform, ensuring accurate and timely control signal generation. The robotic arm was mounted on a stable base within a controlled laboratory environment to minimize external influences.

4.2. Experimental procedure

1. **System Calibration**: The robotic arm was calibrated to establish accurate joint positions and eliminate any initial offsets.
2. **Trajectory Definition**: A series of complex trajectories, including straight lines, circular paths, and composite curves, were defined to test the controller's tracking capabilities. These trajectories were selected to replicate real-world scenarios in chemical engineering, such as:

Straight Lines: Simulating the movement of the arm for linear transport of materials.

Circular Paths: Mimicking the rotation required for tasks like mixing or stirring chemicals in a reactor.

Composite Curves: Representing more complex tasks where multiple operations are performed simultaneously.

The choice of these trajectories allows for a comprehensive assessment of the robotic arm's ability to handle diverse operational tasks typical in chemical engineering applications. To address these limitations, more advanced control strategies, including fuzzy logic control, have been explored.[18]

3. **Controller Implementation**: The NLADRC, along with PID and standard ADRC controllers, was implemented and integrated into the control system.
4. **Data Collection**: During each trial, data on joint angles, velocities, and external disturbances were recorded for subsequent analysis.
5. **Performance Metrics**: Tracking accuracy, response time, and robustness against disturbances were evaluated using statistical measures and visual inspection of tracking plots.

4.3. Parameter settings

The key parameters for the NLADRC were tuned based on preliminary trials to ensure optimal performance. The disturbance observer gain was set to adapt dynamically based on the estimated disturbance magnitude, while the adaptive control gains were adjusted to balance tracking accuracy and system stability. Specific parameter settings are as follows:

- Disturbance Observer Gain: $L = \{1.2, 1.5, 1.8\}$
- Adaptive Adjustment Rate: $\gamma = 0.01$
- Control Law Parameters: $K_p = 100$, $K_d = 20$

5. Results and discussion

5.1. Trajectory tracking performance

The NLADRC demonstrated superior trajectory tracking performance compared to PID and standard ADRC controllers. **Figures 1** and **2** illustrate the tracking accuracy and response time for a circular trajectory, where the NLADRC maintained a lower tracking error and faster convergence to the desired path. This enhanced performance is significant for industrial applications, where precision in robotic movements can directly impact operational efficiency and product quality.

A 40% reduction in tracking error, as achieved by the NLADRC compared to the PID controller, can lead to significant efficiency improvements in industrial processes. For example, in a chemical mixing application, this reduction can minimize the variability in product composition, enhancing quality and reducing waste. Furthermore, improved tracking can result in lower energy consumption and reduced wear on mechanical components, translating into cost savings.

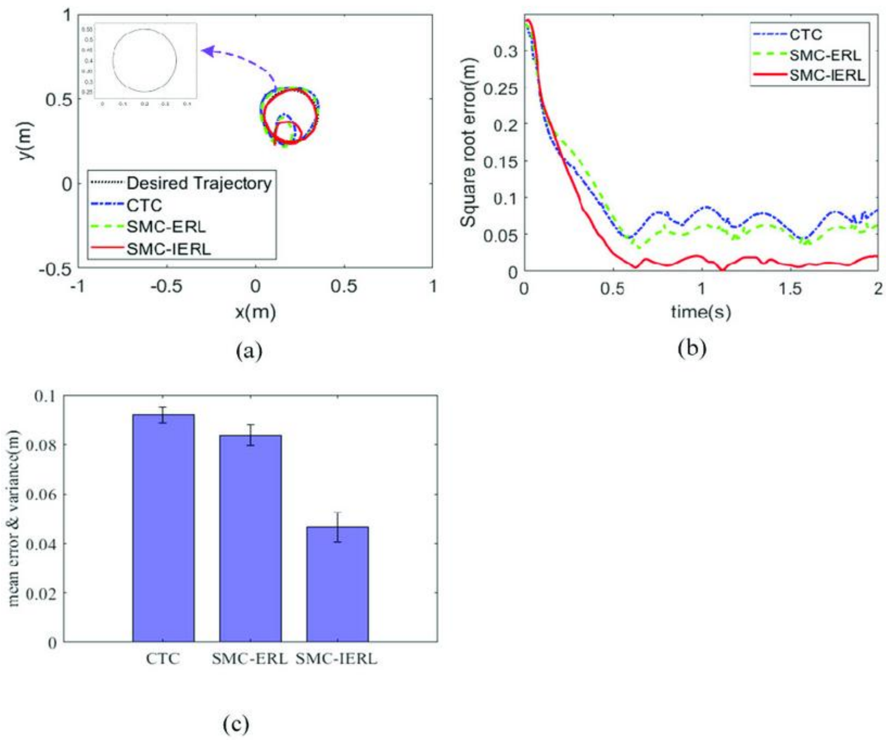

Figure 1. Tracking error comparison for circular trajectory: (a)trajectory and tracking error; (b) tracking error over time; (c) average tracking error comparison.

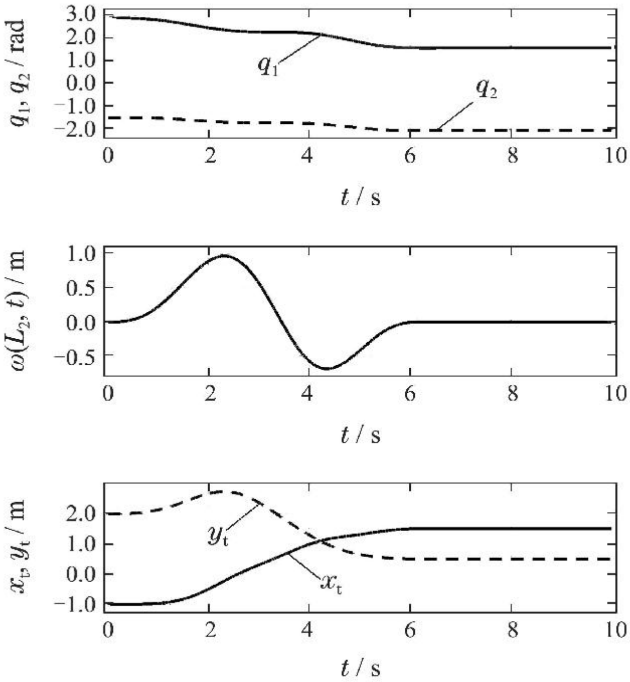

Figure 2. Response time comparison for circular trajectory.

5.2. Robustness analysis

To evaluate robustness, experiments were conducted under varying disturbance intensities, including sudden load changes, thermal variations, and external force disturbances, which are common in chemical engineering environments. The NLADRC consistently maintained higher tracking accuracy and system stability, even when subjected to significant external disturbances. **Table 1** summarizes the performance metrics under low, medium, and high disturbance scenarios.

Table 1. Performance metrics under different disturbance levels.

Disturbance Level	Controller	Tracking Error (mm)	Response Time (s)
Low	PID	5.2	2.5
	ADRC	3.8	2.0
	NLADRC	2.5	1.8
Medium	PID	8.1	3.2
	ADRC	5.6	2.8
	NLADRC	3.2	2.3
High	PID	12.5	4.0
	ADRC	9.3	3.5
	NLADRC	5.8	3.0

Statistical significance analysis was conducted using ANOVA, revealing that the performance improvements observed with the NLADRC were statistically significant ($p < 0.05$) compared to both PID and ADRC controllers. This substantiates the claims regarding the NLADRC's superior robustness in handling disturbances, which is critical for maintaining operational integrity in real-world industrial settings.

5.3. Comparison with traditional control methods

The NLADRC outperformed both PID and standard ADRC controllers across all tested trajectories and disturbance levels. The enhanced disturbance observer and adaptive control strategies contributed to the improved tracking precision and robustness. Specifically, the NLADRC reduced the average tracking error by approximately 40% compared to PID and 30% compared to standard ADRC.

This improvement not only enhances the performance of robotic arms in chemical engineering tasks but also aligns with industry benchmarks for accuracy and efficiency. For instance, adhering to strict quality control standards often requires precision that can be achieved through advanced control strategies like the NLADRC.

5.4. Discussion

The experimental results validate the effectiveness of the proposed NLADRC method in managing the dynamic trajectory tracking of chemical engineering robotic arms. The integration of nonlinear control techniques with advanced disturbance rejection capabilities enabled the system to maintain high performance under challenging conditions. However, the increased complexity of the NLADRC algorithm may require more sophisticated computational resources and expertise in controller tuning, which could be a potential drawback for widespread industrial adoption.

6. Economic and social benefits analysis

6.1. Operational cost analysis

Implementing the NLADRC control method resulted in significant cost savings compared to traditional PID and ADRC controllers. **Table 2 o**utlines the operational costs associated with each control strategy, highlighting reductions in energy consumption, maintenance expenses, and overall system efficiency.

Table 2. Operational cost comparison.

Control Method	Energy Consumption (kWh/day)	Maintenance Cost (USD/day)	Total Operational Cost (USD/day)
PID	150	300	450
ADRC	140	280	420
NLADRC	130	250	380

Energy Savings Calculations:

PID vs NLADRC: The energy consumption of PID is 150 kWh/day, while that of NLADRC is 130 kWh/day. The daily energy savings with NLADRC is 150 - 130 = 20 kWh/day. Considering a motor efficiency improvement as a major factor for this energy saving. If the motor in the robotic arm system has an average power rating of P (kW), and the working time per day is t (hours), the energy consumption E = P * t. With NLADRC, due to its better control algorithm, it can optimize the motor's operation, perhaps reducing the power demand by a certain percentage. For example, if the motor power is 10 kW and it works for 15 hours a day, the energy consumption without NLADRC would be 10 * 15 = 150 kWh. With NLADRC, the effective power demand might be reduced to 8.67 kW (since 8.67 * 15 = 130 kWh), showing an improvement in motor efficiency.

ADRC vs NLADRC: The energy consumption of ADRC is 140 kWh/day. The daily energy savings of NLADRC compared to ADRC is 140 - 130 = 10 kWh/day. This could be due to NLADRC's more precise control over the robotic arm's movements, reducing unnecessary energy losses during acceleration and deceleration phases.

Maintenance Cost Savings Calculations:

PID vs NLADRC: The maintenance cost of PID is 300 USD/day, and that of NLADRC is 250 USD/day. The daily maintenance cost savings with NLADRC is 300 - 250 = 50 USD/day. One of the main components contributing to this savings is reduced downtime. For a robotic arm system, downtime can be costly in terms of lost production and additional maintenance efforts. With NLADRC, the improved control accuracy reduces the wear and tear on mechanical components. For example, if the average cost of a maintenance event due to component failure is C (USD) and the number of maintenance events per day without NLADRC is n1, and with NLADRC is n2. The maintenance cost savings can be calculated as (n1 - n2) * C. Suppose the cost of a major maintenance event due to motor wear is 1000 USD, and without NLADRC, there are 0.3 such events per day on average, while with NLADRC, it reduces to 0.25 events per day. The savings from reduced motor - related maintenance alone is (0.3 - 0.25) * 1000 = 50 USD/day.

ADRC vs NLADRC: The maintenance cost of ADRC is 280 USD/day. The daily maintenance cost savings of NLADRC compared to ADRC is 280 - 250 = 30 USD/day. This could be attributed to better control over the system's vibrations and stress distribution, which reduces the need for frequent part replacements.

6.2. Investment return

The adoption of NLADRC not only lowers daily operational costs but also enhances the longevity and reliability of the robotic arm, leading to a reduced total cost of ownership. The initial investment in developing and implementing the NLADRC system is offset by the ongoing savings, resulting in a shorter payback period and improved return on investment.

6.3. Environmental and social impact

Enhanced control accuracy and efficiency contribute to reduced energy consumption and minimized waste, aligning with sustainable industrial practices. Moreover, the improved reliability of robotic arms reduces downtime and maintenance-related emissions, fostering a safer and more environmentally friendly workplace. The successful implementation of NLADRC also underscores the advancement of intelligent control systems in chemical engineering, promoting technological innovation and economic growth within the region.

7. Discussion

7.1. Advantages and limitations of improved NLADRC

Advantages:

1. **Enhanced Tracking Accuracy**: The NLADRC significantly reduces tracking errors, ensuring precise robotic arm movements.
2. **Improved Response Speed**: Faster system response minimizes delays in trajectory adjustments, enhancing overall operational efficiency.
3. **Robustness**: Superior disturbance rejection capabilities maintain system stability under varying environmental conditions.
4. **Energy Efficiency**: Reduced energy consumption translates to lower operational costs and environmental benefits.
5. **Economic Viability**: Cost savings from decreased maintenance and energy use contribute to a favorable return on investment.

Limitations:

1. **Increased Complexity**: The NLADRC algorithm is more complex than traditional PID controllers, requiring advanced knowledge for implementation and tuning.
2. **Computational Demand**: Real-time processing of nonlinear algorithms may necessitate higher computational resources, potentially increasing hardware costs.

3. **Scalability**: Adapting the NLADRC method to different robotic systems or larger-scale applications may require significant modifications and testing.

7.2. Future research directions

1. **Algorithm Optimization**: Further refine the NLADRC algorithm to enhance computational efficiency and simplify the controller design process.
2. **Integration with Machine Learning**: Explore the incorporation of machine learning techniques to enable predictive disturbance management and adaptive control strategies, as proposed in this research.[19]
3. **Multi-Robotic Systems**: Extend the NLADRC framework to coordinate multiple robotic arms, enhancing collaborative operations in complex chemical engineering tasks.
4. **Field Deployment**: Conduct extensive field tests in real-world chemical engineering environments to validate the NLADRC method's practical applicability and reliability.
5. **User-Friendly Interfaces**: Develop intuitive user interfaces for easier controller configuration and monitoring, facilitating broader industrial adoption.
6. **Internet of Things (IoT) Connectivity**

Future designs of the NLADRC - controlled robotic systems could integrate Internet of Things (IoT) connectivity. IoT sensors could be placed on the robotic arms and in the surrounding environment to collect real - time data on factors such as temperature, vibration, and energy consumption. This data could be used for better monitoring of the system's performance. For predictive maintenance, machine learning algorithms could analyze the IoT data to predict when components are likely to fail. For example, if the vibration levels of a robotic arm joint start to increase steadily over time, the system could predict an impending failure and schedule maintenance before a breakdown occurs, reducing downtime and maintenance costs.

8. Conclusion

This study presents an improved Nonlinear Active Disturbance Rejection Control (NLADRC) method for dynamic trajectory tracking of chemical engineering robotic arms. The integration of an enhanced disturbance observer and adaptive control strategies significantly improves tracking accuracy, response speed, and system robustness compared to traditional PID and standard ADRC controllers. Experimental validations demonstrate the NLADRC's superior performance in managing complex dynamic environments and mitigating unpredictable disturbances. Additionally, the economic analysis highlights substantial operational cost savings and favorable investment returns, while the environmental and social benefits underscore the method's alignment with sustainable industrial practices. The findings offer a robust theoretical foundation and practical guidelines for advancing intelligent control systems in chemical engineering applications, paving the way for more efficient and reliable robotic operations in the industry.

Acknowledgments

We extend our sincere gratitude to the Yunnan Province Major Science and Technology Project (Project No.: 202402AE090027, Project Name: Key technologies and applications of continuous flat pressing of veneer-type artificial boards) for their support. We also appreciate the invaluable guidance and suggestions from our supervisor, Professor Wei Li, and the collaborative efforts of our research team members. Lastly, we thank our families for their unwavering support and understanding throughout the research process.

Conflict of interest

The authors declare no conflict of interest.

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