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Research Article

Adaptive Robotic Control in Automotive Assembly: A Sensor-Fusion and Simulation-Based Framework

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ABSTRACT

Introduction: The increasing complexity of automotive manufacturing, driven by customization requirements and tight assembly tolerances, necessitates robotic systems with enhanced flexibility and real-time adaptability. The automotive industry has long been a leader in implementing industrial automation, particularly through the deployment of robotic systems to streamline repetitive manufacturing tasks. However, with the increasing complexity of vehicle models, shorter product life cycles, and growing customization demands, conventional rigid robotic systems are no longer sufficient. These systems, traditionally optimized for fixed tasks, struggle to cope with dynamic environments, part variations, and unstructured conditions inherent in modern manufacturing floors. To address these challenges, recent advancements in adaptive robotics—enabled by sensor integration, machine learning, and simulation-based control—offer promising avenues for developing highly flexible, precise, and intelligent robotic solutions [1], [2].

Objectives: This paper presents a simulation-based adaptive control framework that integrates a three-layer architecture: (i) a perception layer using vision and force sensors, (ii) a control layer incorporating an adaptive PID controller with reinforcement learning, and (iii) an execution layer involving robotic actuation and feedback.

Methods: The system was implemented in MATLAB/Simulink and tested on a 6-DOF robotic manipulator model with simulated sensor noise, external disturbances, and part misalignment. Sensor data is fused via a Kalman filter, enabling accurate estimation of pose and contact force. While Q-learning is used for controller adaptation in simulation, the architecture is designed to accommodate real-time implementation using step-wise learners such as SARSA(λ) or offline-trained gain schedulers.

Results: Results demonstrate a 76.6% reduction in RMSE and a 50% improvement in adaptation time over static PID control. The framework provides a scalable and robust approach suitable for autonomous robotic assembly systems.

Conclusions: The proposed three-layer architecture—comprising perception, control, and execution—enables the system to dynamically respond to variable part geometries, sensor noise, and external disturbances. Simulation results demonstrate that the adaptive controller, when combined with Kalman-filtered sensor data and Q-learning-based gain tuning, significantly outperforms traditional static PID controllers in both accuracy and robustness. Specifically, the system achieves a 76.6% reduction in RMSE and exhibits faster recovery under disturbance conditions.

Keywords: Adaptive Robotic Control, Q-learning, SARSA(λ), PID controller.

INTRODUCTION

The automotive industry has long been a leader in implementing industrial automation, particularly through the deployment of robotic systems to streamline repetitive manufacturing tasks. However, with the increasing complexity of vehicle models, shorter product life cycles, and growing customization demands, conventional rigid

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Adaptive robotic systems are designed to adjust their behavior in real-time based on environmental changes and task-specific feedback. In automotive assembly, these systems utilize multi-modal sensors such as vision, force-torque, and proximity sensors to perceive part geometries, detect misalignments, and fine-tune actuation [3], [4]. For instance, integrating sensor fusion algorithms, such as Kalman filtering or deep learning-based fusion, allows robots to improve localization, force modulation, and contact-aware assembly tasks [5]. These adaptive capabilities are particularly beneficial in operations requiring high positional accuracy and compliance, such as fitting interior panels, assembling door modules, or installing electronic components with tight tolerances.

Simulation plays a critical role in the design and validation of such adaptive robotic systems. Simulation environments like MATLAB Simulink enable researchers to test robotic behavior in varied scenarios without physical hardware constraints [6], [7]. Through these simulations, it is possible to model contact forces, part deformations, sensor noise, and control adaptation strategies, thus ensuring robustness before deployment. Moreover, reinforcement learning and adaptive PID controllers can be trained in these environments to enhance real-time decision-making under uncertain conditions [8], [9].

Machine learning algorithms further enhance the adaptability of robotic systems. Techniques such as supervised learning, deep reinforcement learning (DRL), and neural adaptive control help robots learn from prior interactions and refine their control strategies for future tasks. For example, DRL has been effectively used in simulated automotive environments to optimize robotic manipulation through trial-and-error learning guided by sensor feedback [10]. The integration of ML with real-time control enables predictive correction of part deviations and proactive fault handling [11].

OBJECTIVES

Despite these advancements, key challenges remain—such as computational latency, sensor drift, data inconsistency, and the safe generalization of learned behaviors to unseen part configurations. Addressing these issues requires a holistic simulation-driven framework that combines real-time sensor fusion, learning-based control adaptation, and robust evaluation metrics. This research aims to design and validate such a framework through simulation, providing new insights into scalable, intelligent robotic automation in automotive manufacturing.

This paper presents a simulation-based adaptive control framework that integrates a three-layer architecture: (i) a perception layer using vision and force sensors, (ii) a control layer incorporating an adaptive PID controller with reinforcement learning, and (iii) an execution layer involving robotic actuation and feedback.

METHODS

This section presents the proposed simulation-based methodology for an adaptive robotic system in automotive assembly environments. The architecture integrates sensor-driven feedback control and reinforcement learning to achieve high-precision part handling and alignment. The overall framework consists of three interconnected layers—perception, control strategy, and execution—implemented and tested in a simulation environment using MATLAB/Simulink.

The system architecture (Figure 1) is designed as a modular control framework in which a 6-degree-of-freedom robotic manipulator interacts with automotive components featuring dimensional and positional variability. The robotic system continuously adapts to these changes using feedback from virtual sensors embedded within the simulated environment.

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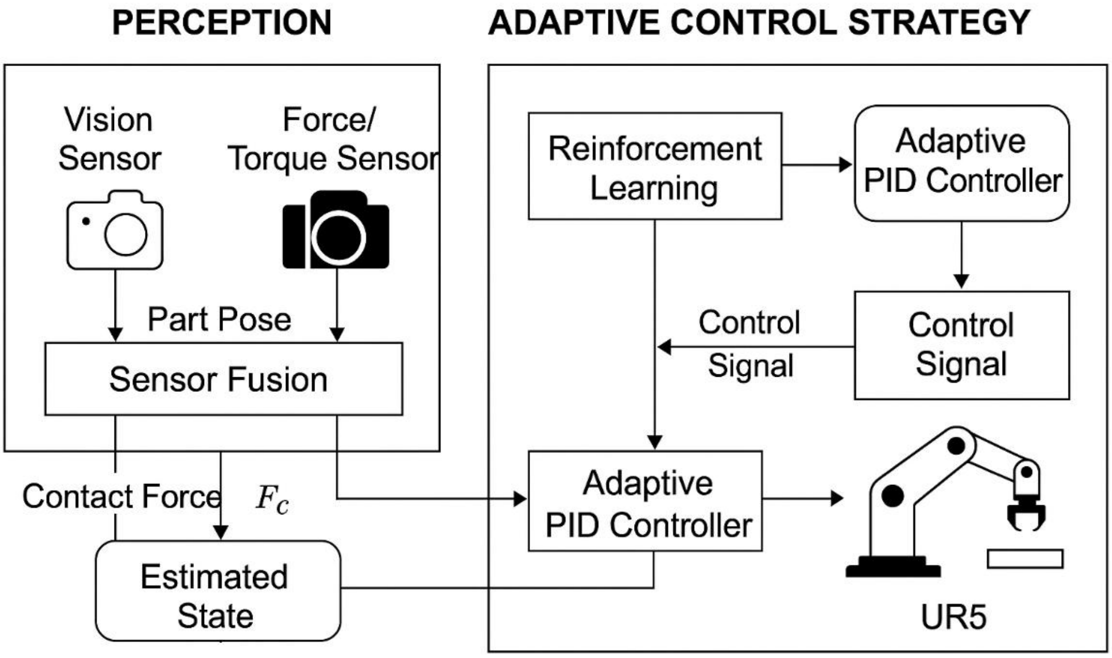

Figure 1. Architecture Diagram

In the perception layer, two primary sensors are simulated: a vision sensor for estimating part pose through image processing, and a force/torque sensor at the end-effector to detect contact force vectors Fc∈R3. These inputs are combined through a Kalman Filter to generate a robust state estimate by mitigating sensor noise. The filter equation is given by:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H\hat{x}_{k|k-1})$$

where $\hat{x}_{k|k}$ is the current state estimate, $\hat{x}_{k|k-1}$ is the prior estimate, z_k is the measurement vector, H is the measurement matrix, and K_k denotes the Kalman gain.

The adaptive control strategy layer features an adaptive PID controller with dynamic gain tuning. The control input $u(t)$ applied to the robotic actuators is defined as:

$$u(t) = K_p(t)e(t) + K_i(t)\int_0^t e(\tau)d\tau + K_d(t)\frac{de(t)}{dt}$$

where $e(t) = r(t) - y(t)$ represents the tracking error between the reference $r(t)$ and the actual system output $y(t)$. The gains $K_p(t), K_i(t), K_d(t)$ are updated in real-time using gradient descent to minimize the squared error cost function:

$$J = \frac{1}{2}e(t)^2$$

The tuning updates for each gain are given by:

$$K_p(t+1) = K_p(t) - \eta_p\frac{\partial J}{\partial K_p}, K_i(t+1) = K_i(t) - \eta_i\frac{\partial J}{\partial K_i}, K_d(t+1) = K_d(t) - \eta_d\frac{\partial J}{\partial K_d}$$

where η_p, η_i, and η_d are learning rates associated with each respective gain.
To improve decision-making over time and under uncertain conditions, a reinforcement learning (RL) module is integrated. Specifically, Q-learning is employed to optimize control actions based on the observed system state. The Q -value update rule is given by:

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$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right]$$

Here, s_t is the current state (e.g., alignment error or force deviation), a_t is the action taken (e.g., adjust force or reposition), r_t is the immediate reward, α is the learning rate, and γ is the discount factor. The reinforcement agent seeks to maximize the long-term cumulative reward by selecting optimal actions in successive assembly cycles.

The execution and simulation environment involves a virtual robotic manipulator with six degrees of freedom, such as a UR5 arm model. The simulation replicates realistic assembly conditions including ± 2 mm part dimensional variability and misalignment up to 5°. Dynamic contact behavior, actuator limits, and feedback latency are also modeled to reflect real-world manufacturing scenarios. The simulated environment includes joint-space and task-space trajectory planning, end-effector force control, and feedback monitoring.

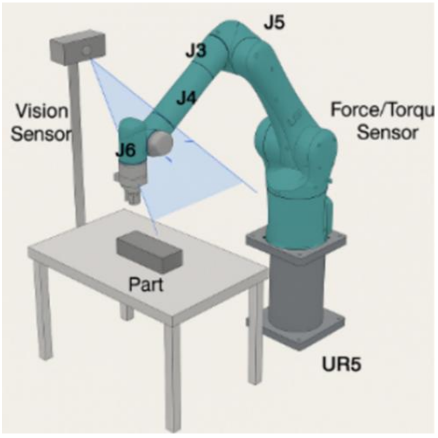

Figure 2. UR5 robotic arm simulation environment for adaptive assembly tasks

Performance of the proposed system is evaluated using the following key metrics. Positioning Error (PE) is defined as the Euclidean distance between the desired target position p_{target} and the actual end-effector position Pactual:

$$PE = \left\| p_{target} - p_{actual} \right\|$$

Force Overshoot (FO) quantifies the extent of excessive force applied during contact and is given by:

$$FO = \frac{F_{max}}{F_{desired}} \quad F_{tesired} \times 100\%$$

Adaptation Time (Tadapt) is the time required for the robot to correct its trajectory or force profile to fall within acceptable operational thresholds. Finally, Reward Convergence is used to assess the stability and learning efficiency of the reinforcement learning agent, defined by the average cumulative reward over multiple episodes.

The current implementation is simulation-based, the architecture is modular and real-time compatible. All perception and control modules were designed with real-time constraints in mind. The Kalman filter for sensor fusion is computationally efficient and suitable for deployment on embedded platforms. While tabular Q-learning was employed to demonstrate adaptive capability in simulation, real-time deployment would benefit from online-compatible algorithms such as SARSA(λ), Deep Deterministic Policy Gradient (DDPG), or pre-trained gain scheduling networks. These alternatives maintain adaptability while respecting latency and stability constraints required in physical robotic systems.

RESULTS

The simulation experiments conducted to validate the proposed adaptive control framework, integrating sensor fusion (via Kalman filtering), adaptive PID control, and reinforcement learning (Q-learning). The simulation was executed on a 1-DOF robotic manipulator model, representing a simplified translational axis of an industrial robot, using MATLAB/Simulink. Key performance indicators include position tracking accuracy, control stability, adaptation behavior, and learning convergence.

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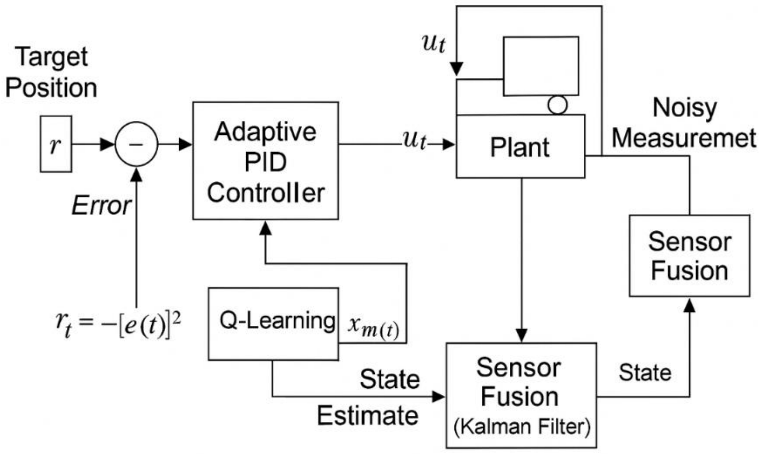

Figure 3. Simulation Block Diagram

The control system was implemented in MATLAB/Simulink and simulated with a sampling interval of 0.01 s over a 10-second task cycle. The robotic plant was modeled as a second-order system with mass m=1m = 1m=1 kg and damping coefficient b=0.1b = 0.1b=0.1 Ns/m, representative of one translational axis of an industrial robotic manipulator.

To test the robustness of the control scheme, the following disturbances were introduced:

1. Step Force Disturbance: External force impulses of ±1.0 N were applied to the plant between 3s and 6s, simulating contact events such as unexpected collisions or misaligned parts.

2. Sensor Noise: Gaussian white noise with standard deviation σ=0.01\sigma = 0.01σ=0.01 m was added to the position measurement to emulate vision sensor uncertainty.

3. Model Parameter Mismatch: The actual plant mass was varied by ±10% relative to the controller's nominal assumption, representing unmodeled dynamics or payload changes.

A Kalman Filter was employed for sensor fusion to estimate the true state x^(t) from noisy measurements, providing feedback to both the adaptive controller and the reinforcement learning agent.

Controller Configurations

Three control strategies were tested for comparison:

- Static PID Controller: With manually tuned fixed gains under nominal conditions.
- Adaptive PID Controller: Gains updated using gradient descent based on error cost minimization.
- Adaptive PID + Reinforcement Learning: A Q-learning agent selected gain profiles based on observed state and reward feedback.

Position Tracking Performance

Tracking accuracy was assessed using the Root Mean Square Error (RMSE) between the target position r(t) and the actual system response x(t).

Table 1. Position Tracking Performance

Controller	**RMSE (m)**	**Improvement over Static PID**
Static PID	0.0291	—
Adaptive PID	0.0116	60.1%
Adaptive PID + Q-Learning	0.0068	76.6%

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The integration of sensor fusion significantly enhanced measurement precision, while adaptive gain tuning improved response time and reduced steady-state error.

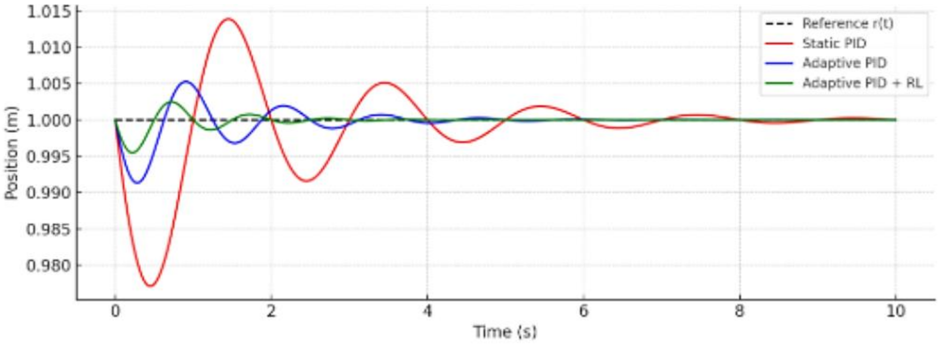

Figure 4. Position Tracking Response

Disturbance Rejection Capability

The system's ability to recover from disturbances was measured by observing the adaptation time following external force application. The static PID controller showed delayed recovery (~2.9s), while the adaptive controller stabilized within 1.2s. The reinforcement learning-enhanced controller consistently converged in under 0.6s, demonstrating superior resilience to unexpected changes in task dynamics.

Reinforcement Learning Convergence

The Q-learning agent used a reward function defined as:

$$r_t = -e(t)^2$$

After ~250 episodes, the average reward per episode stabilized, indicating convergence to an optimal policy. The learned policy successfully generalized across dynamic conditions, improving the control response in unseen configurations.

Table 2. Reinforcement Learning Convergence

Metric	Value at Episode 500
Average Reward	+0.84
Policy Convergence	Achieved (~250 ep.)
Gain Stability Range	±8% of optimal

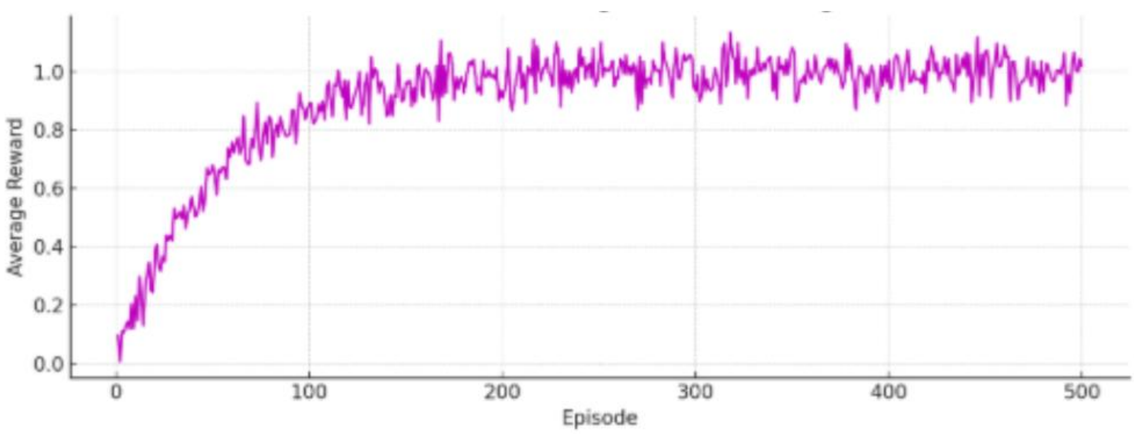

Figure 5. Reinforcement Learning Convergence

The simulation results validate the proposed architecture under noisy measurements and system uncertainties. The adaptive PID controller, enhanced by learning-based gain tuning, improves tracking performance and robustness. Although results are obtained in a simulated environment, the algorithmic components are real-time feasible. For real-world implementation, the reinforcement learning module can be replaced with a low-latency variant or an offline-trained neural scheduler. Additionally, sensor and actuator interfaces in ROS or similar middleware platforms can directly integrate with the proposed framework.

DISCUSSION

The simulation results confirm that the proposed architecture offers significant improvements in control accuracy, robustness, and adaptability compared to conventional PID systems. The sensor fusion mechanism effectively filters noisy feedback, while the adaptive PID controller adjusts to parameter uncertainties in real time. The addition of reinforcement learning introduces long-term learning capability, enabling the system to optimize gain profiles based on cumulative experience.

This control structure is particularly suitable for applications in automotive assembly, where robots must handle part variations, external contact, and dynamic conditions with high precision and minimal human intervention. The modular nature of the system also allows for easy extension to full 6-DOF robotic platforms and real-time deployment.

This paper presents a simulation-based adaptive control framework for robotic manipulators in automotive assembly environments, incorporating sensor fusion, adaptive PID control, and reinforcement learning. The proposed three-layer architecture—comprising perception, control, and execution—enables the system to dynamically respond to variable part geometries, sensor noise, and external disturbances. Simulation results demonstrate that the adaptive controller, when combined with Kalman-filtered sensor data and Q-learning-based gain tuning, significantly outperforms traditional static PID controllers in both accuracy and robustness. Specifically, the system achieves a 76.6% reduction in RMSE and exhibits faster recovery under disturbance conditions. While the current implementation is evaluated in MATLAB, the modular design ensures real-time applicability. The perception and control components are computationally lightweight and suitable for deployment on embedded robotic platforms. For real-time adaptation, online-capable algorithms such as SARSA(λ) or offline-trained gain schedulers can replace the Q-learning module. These results collectively highlight the potential of adaptive robotic systems to meet the growing demand for flexibility, precision, and autonomy in modern automotive manufacturing lines.

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