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Performance Evaluation of Adaptive Robotic Assembly Systems Using Sensor Fusion and Reinforcement Learning

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Abstract: Modern manufacturing facilities have robotic assembly systems that need high precision, flexibility, and durability to manage the changing operating environments. Control methods that are traditional, using fixed parameters, can often fail to ductilely control performance in the face of sensor noise, disturbances and environmental uncertainties. This paper does a performance analysis of an adaptive assembly system of a robot which combines sensor fusion and control enhanced with reinforcement learning. The sensor fusion system employs a Kalman filter-based sensor fusion system, which involves the fused data of both the vision and force sensors to provide precise state estimation. The PID controller is an adaptive controller under the control architecture with a reinforcement learning module to optimize control activities and enhance system adaptability. The experiments was carried out as simulation experiments within a MATLAB/Simulink environment (with a robotic manipulator model with disturbances like sensor noise and external factors). The suggested solution was tested using accuracy of the tracking of a trajectory, ability to reject disturbances and convergence of learning. Experimental findings indicate that the adaptive PID with the reinforcement learning is very effective in enhancing the tracking performance and disturbance recovery as opposed to the conventional PID which includes the use of a static PID and the adaptive PID. The results reveal the possibilities associated with the combination of sensor fusion and learning-based control to improve the reliability and efficiency of intelligent robotic assembly systems.

Keywords: *Adaptive Robotics, Sensor Fusion, Reinforcement Learning, Industrial Automation, Robotic Assembly, Intelligent Manufacturing.*

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I. INTRODUCTION

Under Industry 4.0 and 5.0 robotics is considered a crucial element of contemporary manufacturing and allows automation, precision, and productivity to be applied in tasks like assembly, inspection, and handling materials [1-3] . The combination of digital technologies and AI has made manufacturing a dynamic and interconnected process, but the issues of misalignment of parts and the inability to detect parts because of noise and environmental changes remain [4]. Also, variable industrial situations present uncertainties such as changing payloads, external disturbances, and so on, and thus the traditional fixed controllers are not as effective [5]. To solve this, sensor fusion algorithms combine the information of two or more sensors (vision, force, tactile) to improve the precision and strength of perception with the help of filtering methods like Extended Kalman Filter [6]. These processes can be highly effective in enhancing reliability in robotic manipulation processes. The latest developments include machine learning, reinforcement learning, edge computing, and IIoT, which is used to support the intelligent and real-time operations of robots [710]). Multimodal sensor fusion based on deep learning is more effective in improving perception precision and flexibility of operation in multifaceted settings [1114], whereas reinforcement learning is more effective in improving decision-making and self-directed actions in dynamic exercises [15].

II. RELATED WORK

➢ *Adaptive Robotic Control in Industrial Automation*

Adaptive control of robots in the industry is a topic that has attracted increased interest in recent years. Adaptive control is now a key field of research in industrial robotics as manufacturing systems grow more and more flexible, precise and autonomous in decision-making. Conventional robotic control techniques that rely on hard parameters can fail in the current industrial world where the dynamics of the system can be altered by different loads, uncertainties or disturbances in the environment. To solve those problems, scholars have investigated data-driven and adaptive control tools that can modify the control parameters dynamically. Combined data-driven and disturbance rejection-based hybrid control methods have been shown to be more stable and robust in highly structured industrial systems, including tower crane tasks and robotic manipulators [22].

The latest progress in the field of artificial intelligence has also been used to create intelligent control systems that can study the dynamics of nonlinear systems and modify the control strategies to fit the situation. Complex dynamic processes have been examined by Ai-based computational models and enhanced predictative power of adaptive control structures [27]. Moreover, digital modeling and AI-based simulation methods have been used to measure the work of the system in various conditions of operation, which made it possible to develop more credible and strong control algorithms [28]. The above advances underscore the increased relevance of the adaptive and intelligent control methodologies in contemporary industrial automation.

Meanwhile, the convergence of robotics and high-tech computing infrastructures is speeding up the development of smart manufacturing. Distributed processing architectures and edge computing enable robots to compute nearer to the source and make decisions as quickly as possible and control in real-time. Industrial IoT (IIoT) systems are becoming a common method to interconnect robotic systems, sensors, and data analytics systems to facilitate intelligent manufacturing environments [19]. With these architectures, robots can work with a higher degree of responsiveness and coordination in very automated production systems.

➢ *Sensor Fusion in Robotic Systems*

Robotic perception plays a critical role in industrial automation today, as the manipulation, assembly, and sorting of objects requires the use of such sensors to manipulate them within the environment with high accuracy, but noise and environmental variability tend to affect single-sensor methods, resulting in the use of multi-sensor fusion methods to achieve a higher degree of accuracy. Recent developments in deep multimodal data fusion help robots to combine visual, tactile, and motion data to provide improved perception and decision-making [16], and systems that use computer vision have been shown to be useful in tasks such as object classification and pick-and-place tasks [17] despite the limitation in the presence of occlusions and changes in lighting. To address them, more sophisticated fusion techniques include graph-based Kalman filtering can be used to enhance effective multi-object tracking in dynamical scenes [18], and the combination of more sensors including vision, inertial, and force measurements can also be intended to enhance the accuracy of localization and the stability of the system [25], so that effective robotic functionality can be achieved in complex and uncertain environments.

➢ *Research Gap*

Despite the major strides in the adaptive robotic control, sensor fusion and reinforcement learning, a number of research gaps exist. Majority of the research on robotics mainly dwells on formulation of control algorithms, perception systems or learning systems in robots. Although these contributions are of value, there is scarcity of research on systematic performance analysis of adaptive robotic assembly systems, which incorporate sensor fusion and reinforcement learning methods. Specifically, there exists no in-depth research comparing the impact of multi-sensor perception and learning-based control integration on the performance of the system in the realistic industrial environment of sensor noise, environmental disturbances, and uncertainties in the tasks. Thus, the adaptive robotic assembly systems require a closer examination of the performance to be on the position to comprehend the benefits and shortcomings of integrating sensor fusion and reinforcement learning in industrial robotic systems.

III. SYSTEM ARCHITECTURE

The suggested adaptive robotic assembly system is based on the combination of perception, sensor fusion, adaptive control, and reinforcement learning to enhance the robustness and accuracy of industrial assembly processes. The architecture has a layered architecture which comprises of perception layer, sensor fusion module, control and learning layer and execution layer. This modularity of design allows the effective combination of sensing, decision-making and motion control units into the robot system.

➢ *Robotic Assembly System Overview*

The robotic assembly system is composed of a 6-DOF industrial robotic manipulator, an assembly workstation, sensing modules, as well as a control unit that makes decisions and plans the motion. The robot engages with the parts on the assembly table and is also involved in tasks like positioning, inserting and aligning parts. A high-level robotic system coupled with smart sensing have been demonstrated to enhance the efficiency and flexibility of automation in the modern factory settings [16]. Robotic manipulation using vision is applicable in various automated sorting and assembly processes that involve counting and precise localization and detection of objects [17], [23].

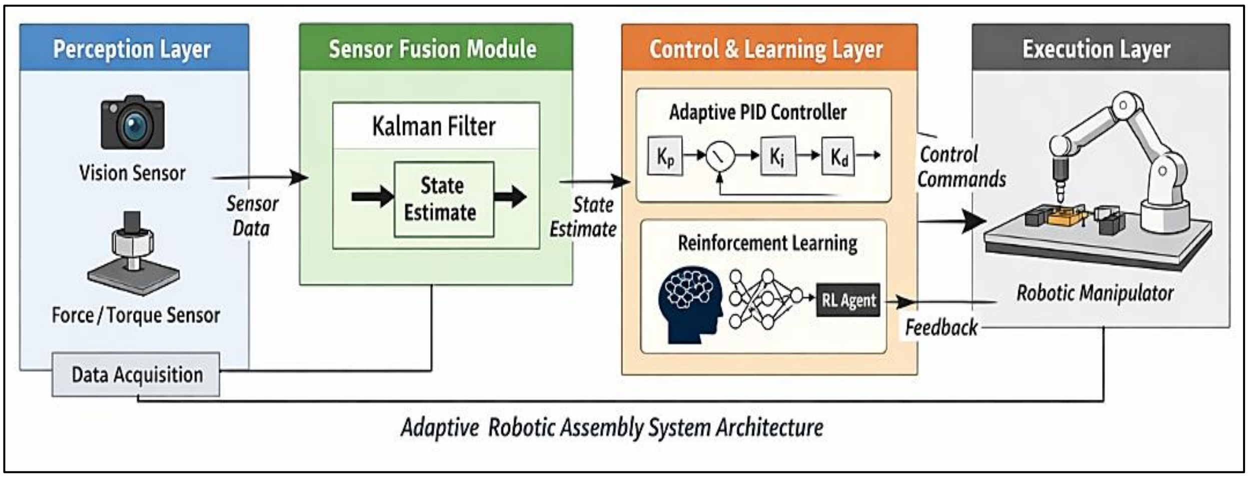


Fig 1 Overall Architecture of the Adaptive Robotic Assembly System

➢ *Perception Layer*

The perception layer gathers the environmental information with the help of several sensors so that the state estimation was made. The perception module in the proposed system will consist of a vision sensor and force/torque sensor.

Vision sensors are applied in the detection of the position and orientation of assembly components. Computer vision algorithms take pictures that are captured and analyze them to determine the position of objects found in the workspace. The use of vision-based robotic systems in automated sorting and assembly systems has gained popularity because they can adjust to different object positions and orientation [17], [24].

The sensor of force on the robot end-effector is used to measure the interaction forces when components are in contact with the robot end-effector. The measurements are necessary to identify the force of insertion and avoid undue contact during the assembly process. Multi-sensory sensor systems enhance the effectiveness of robotic perception systems [16].

➢ *Sensor Fusion Module*

To enhance the accuracy of perception, sensor outputs of the vision sensor and the force sensor are combined through sensor fusion algorithm based on Kalman filter. Sensor fusion is the process where measurements of various sources are used to come up with a more accurate estimate of the system state.

Kalman filter state prediction model is given as

$$x_k = Ax_{k-1} + Bu_{k-1} + w_k$$

Where $x_k$represents the system state vector and $u_k$denotes the control input.

The measurement update is defined as

$$z_k = Hx_k + v_k$$

Where $z_k$represents sensor measurements and $H$is the observation matrix. Kalman filtering techniques have been widely applied in robotic perception and multi-object tracking systems for improved state estimation accuracy [18], [25].

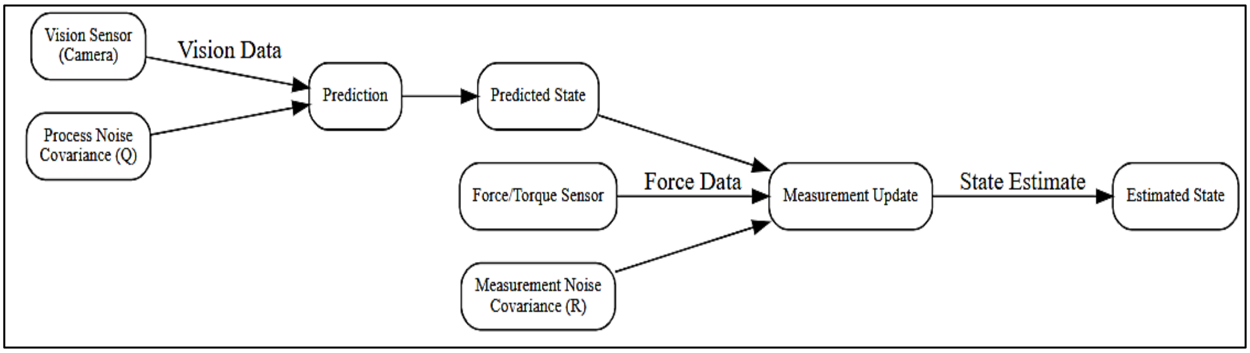


Fig 2 Sensor Fusion Framework Combining Vision and Force Sensor Data.

➢ *Control and Learning Layer*

Control and learning layer translates the control commands to the robotic manipulator and enhances the performance of the system by optimizing the system using learning.

A PID controller is adaptive and it regulates the robot motion. The proportional, integral and derivative gains are dynamically varied by the controller to reduce the tracking error and enhance disturbance rejection. Adaptive control methods have been shown to be more robust in industrial control systems that are prone to uncertainties and disturbances [22].

To increase flexibility a reinforcement learning (RL) module is attached to the controller. The RL agent acquires the best control strategies by interacting with the robotic environment. We define the update rule as the Q-learning update rule as follows. Q(s,a) is the action-value function, ais the learning rate and gis the discount factor. Edge AI platform reinforcement learning makes it possible to make real-time decisions about robots in smart manufacturing settings [21].

$$Q(s,a) = Q(s,a) + \alpha[r + \gamma \max Q(s',a') - Q(s,a)]$$

Where $Q(s,a)$ represents the action-value function, α is the learning rate, and γ is the discount factor. Reinforcement learning combined with edge AI platforms enables real-time robotic decision-making in smart manufacturing environments [21].

➢ *Execution Layer*

The execution layer translates control commands to physical movements of the robotic manipulator. The robot will move on a predefined path to arrive at the required assembly position and reduce the tracking error between the target and the actual assembly positions.

The error on the trajectory is termed as

$$e(t) = r(t) - x(t)$$

Where $r(t)$ is the desired trajectory and $x(t)$ is the actual robot position. Continuous monitoring of the tracking error allows the controller to adjust control signals and maintain precise positioning during assembly operations.

IV. ADAPTIVE CONTROL AND LEARNING STRATEGY

The framework suggested to enhance the precision and quality of robotic assembly tasks incorporates an adaptive PID controller and a reinforcement learning (RL) unit. The controller controls the robot motion by the real-time sensor feedback, and the RL mechanism can optimize the system performance parameters by controlling the control parameters. Sensor fusion gives trustworthy state estimations that augment the stability of control and also the learning.

➢ *Adaptive PID Controller*

An adaptive proportional-integral-derivative (PID) controller is used to control the movement of the robotic manipulator. The adaptive controller also works differently to conventional PID controllers which have set gains, it dynamically changes its parameters according to the behavior of the system and its performance on the tracking. Adaptive control techniques have been extensively applied in industrial robots to enhance disturbance rejection as well as stability in unpredictable working conditions [22].

The control input applied to the robot actuators is defined as

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt}$$

Where:

Symbol	Description
$u(t)$	control input signal
$e(t)$	tracking error
K_p	proportional gain
K_i	integral gain
K_d	derivative gain

The tracking error is calculated as

$$e(t) = r(t) - x(t)$$

Where $r(t)$ is the desired trajectory and $x(t)$ is the measured robot position. The adaptive controller adjusts the gain parameters according to the observed system error to maintain stable trajectory tracking during assembly operations.

➢ *Reinforcement Learning Mechanism*

In order to increase adaptability, a reinforcement learning mechanism is coupled with the adaptive control system. Reinforcement learning helps the controller to acquire optimal action in the environment by interacting with the environment and feedback in form of rewards. Learning-driven control mechanisms have demonstrated high capabilities in enhancing the robotic decision-making and adaptability in intelligent manufacturing systems [21].

Q-learning algorithm has been applied to control actions optimum in this work. The rule of Q-value updating has the form of

$$Q(s,a) = Q(s,a) + \alpha[r + \gamma max\, Q(s',a') - Q(s,a)]$$

Where:

Parameter	Description
$Q(s,a)$	action value function
α	learning rate
r	reward
γ	discount factor
s	current state
a	action

These sensor-based information is included in the state representation like position error and the force feedback. Reward function helps in discouraging actions that increase tracking error and also discourages excessive force when assembling.

➢ *Integration with Sensor Fusion*

The adaptive control and learning modules use the right state information that is provided by sensor fusion framework as indicated in Section 3. Sensor fusion is a fusion of vision and force sensor data based on a Kalman filter that provides an estimate of the robot state.

Trustworthy state estimation enhances the adaptive controller performance through minimizing uncertainties in measurements and noise. It has been demonstrated that multi-sensor fusion methods considerably improve the accuracy of perception and the robustness of the system of robots in dynamic conditions [16], [18], [25].

The given framework allows the robotic system to be adapted to disturbances and deviations of the environment with the help of sensor fusion and learning-based control, preserving the stability of assembly performance.

V. SIMULATION SETUP

To analyze the efficiency of the suggested adaptive robotic assembly system, simulation experiments were carried out. The simulation environment represents real-life assembly conditions such as sensor noises, disturbances, and uncertain parameters.

➢ *Simulation Environment*

The implementation of the simulation was done through the MATLAB/Simulink which offers functions of modeling the robot dynamics and control program. The simulated assembly processes included component positioning and insertion and were modelled using a six-degree-of-freedom (6-DOF) robotic manipulator model.

The simulated vision and force sensors send sensor inputs to the robotic system which is then processed by the sensor fusion module and then utilized by the adaptive control system.

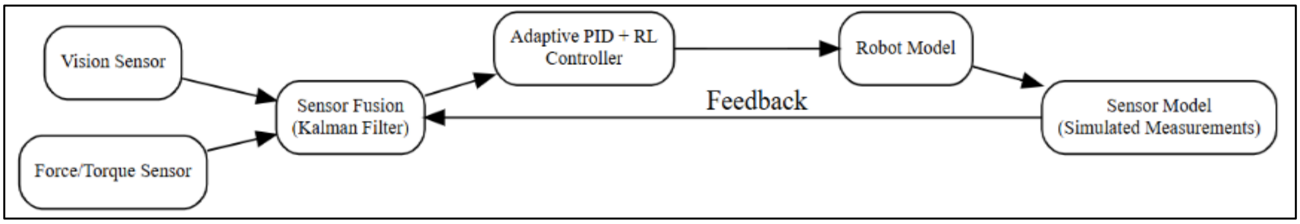


Fig 3 Simulation Framework of the Proposed Adaptive Robotic Assembly System Integrating Sensor Fusion, Adaptive PID Control, and Reinforcement Learning

➢ *Disturbance Scenarios*

In order to test the strength of the suggested control strategy, the following disturbance scenarios were implemented in the process of simulation:

- Sensor Noise – Gaussian noises that are applied to vision and force sensor readings.
- External Forces – forces during the action of contact with the robotic end-effector.
- Part Misalignment – motion of assembly parts.
- Parameter Uncertainty – robot dynamic parameter variation.

These disturbances replicate natural conditions found in the manufacturing environment where robotics systems have to have reliable behaviour despite uncertainty conditions associated with the environment.

➢ *Evaluation Metrics*

The operation of proposed robotic assembly system is judged on the basis of various quantitative measures which measure tracking accuracy, adaptability and robustness. Root Mean Square Error (RMSE) is the measure of the difference between the wanted path and the real position of the robot and is given by

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(r_i - x_i)^2}$$

Where r_i is the desired reference position, x_i is the measured robot position, and N is the total number of samples. Reduced values of RMSE imply high tracking accuracy. Adaptation time is the interval in which the controller takes to rebound the disturbances and get the system to a steady state. Disturbance rejection is used to gauge the capability of the system to remain in a stable configuration in the face of external perturbation and to control stability measures the overall stability of the control system under the sustained operation of robots. These measures are an overall appraisal of the accuracy, robustness, and reliability of the system.

VI. RESULTS AND DISCUSSIONS

To test the proposed adaptive robotic assembly framework, a series of simulation experiments were conducted to measure the performance of the system based on the accuracy of tracking, ability to reject disturbances, and convergence of reinforcement learning. The findings were contrasted with traditional control methods such as the use of a stationary PID controller and adaptive PID controller. The experiments were carried out in MATLAB/ Simulink with the robotic manipulator model in Section 5. The assessment criteria will be the capability of the planned controller to act in a steady state and to follow the required trajectory in case of varied disturbance conditions.

➢ *Tracking Accuracy*

Accuracy of tracking is the capability of the robotic manipulator to trace the intended path during the assembly tasks. Three control strategies were compared in terms of their performance:

- Static PID controller
- Adaptive PID controller
- Adaptive PID combined with reinforcement learning (Adaptive PID + RL)

The tracking performance was measured by Root Mean Square Error (RMSE) measure as presented in Section 5.3. Small values of RMSE are associated with a more precise tracking of the trajectory.

The simulation findings reveal that the fixed PID controller has greater tracking errors because the gain settings are not adjustable to respond to dynamically changing conditions in the system. The adaptive PID controller enhances the precision of the tracking when the control gains are modified as per the system feedback. The adaptive PID + RL controller performs best and is able to continuously learn the best control actions through reinforcement learning. Control techniques based on learning have been shown to be more adaptive and more accurate with regards to robotic systems that run in uncertainties.

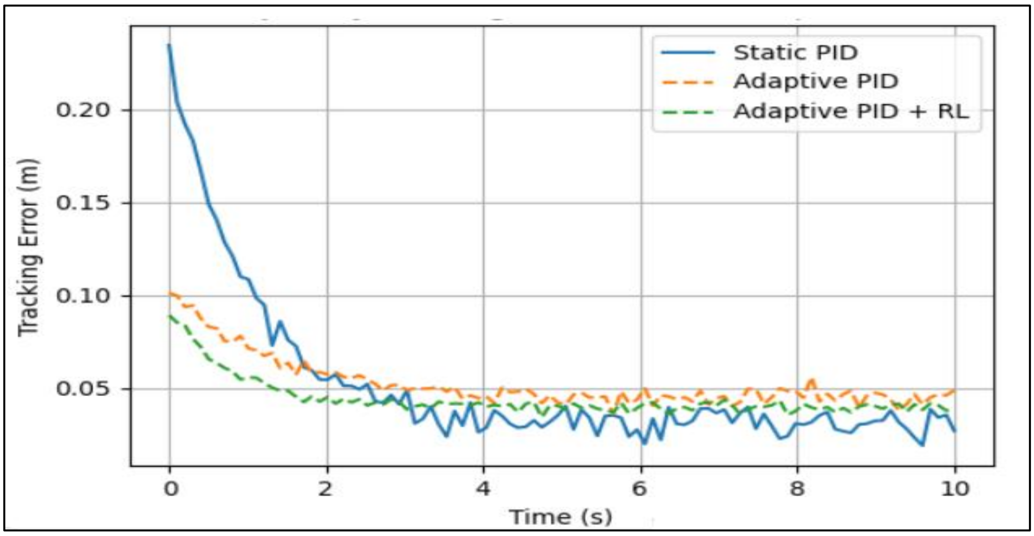


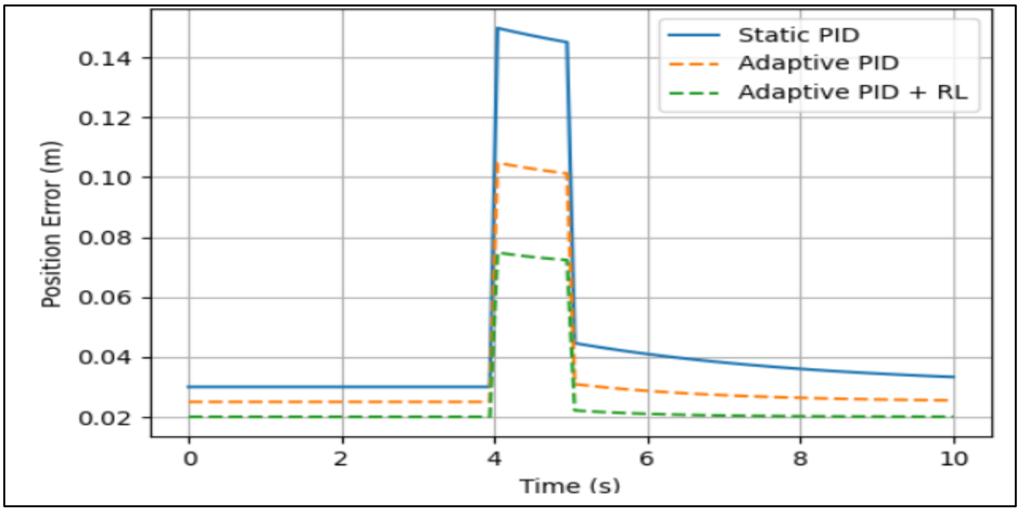
Fig 4 Trajectory Tracking Performance Comparison Between Static PID, Adaptive PID, and Adaptive PID + RL Controllers

- ➢ *Disturbance Rejection Performance*

The ability to reject disturbance is fundamental to robotic assembly systems in real manufacturing conditions whereby uncertainty factors of sensor noise, external forces and misalignment of parts can exist. In order to test the strength of the control system, disturbances were added to the simulation environment such as:

- Gaussian sensor noise
- External force disturbances applied to the robot end-effector
- Component misalignment in the assembly task

The response of the system was viewed in the form of deviation and time needed to get the controller back on the desired path. With disturbances, the static PID controller also had slower recovery and greater deviations. The adaptive PID controller was more robust as it alters its control parameters as a response to the disturbances. Adaptive PID + RL controller was the most disturbance rejection controller and stabilized the system quickly and the tracking error was minimized. Adaptive control schemes of robotic manipulation tasks have also been reported to have improved disturbance rejection performance similarly.



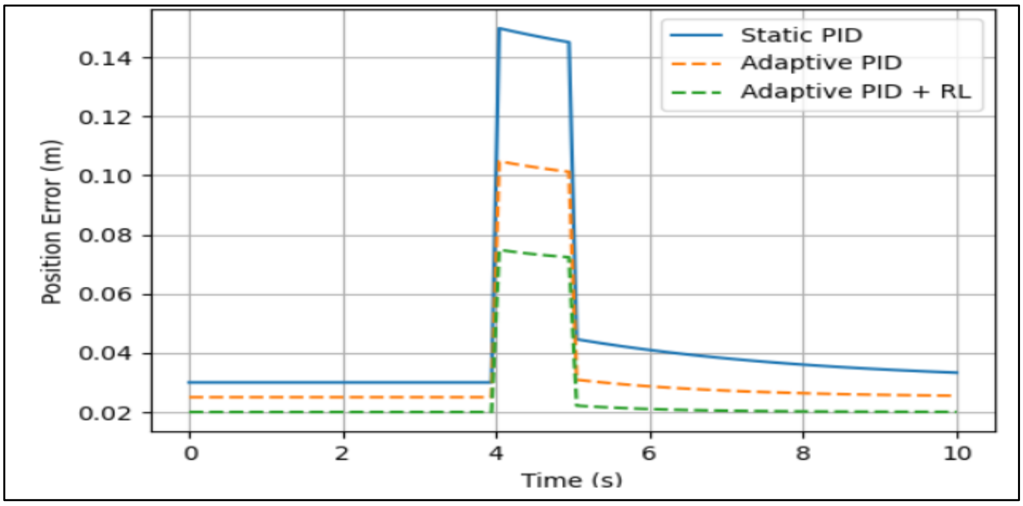


Fig 5 System Response Under Disturbance Conditions Comparing Different Control Strategies.

- *Reinforcement Learning Convergence*

The quality of the reinforcement learning module was demonstrated through the convergence of the reward function of the training process. The reinforcement learning algorithms progressively boost the control performance by modifying the policy according to the feedback of the rewards. The reward role in this paper was intended to reduce tracking errors of trajectories and the unnecessary forces of contact when the assembly process occurs.

The learning performance was measured based on the values of rewards achieved in the repeated training episodes. The values of the rewards grow and ultimately stabilize as the learning process continues meaning that the controller has learnt an optimal control strategy. Convergence behavior of reinforcement learning has been significantly applied in the context of robotic control to measure the stability of a policy.

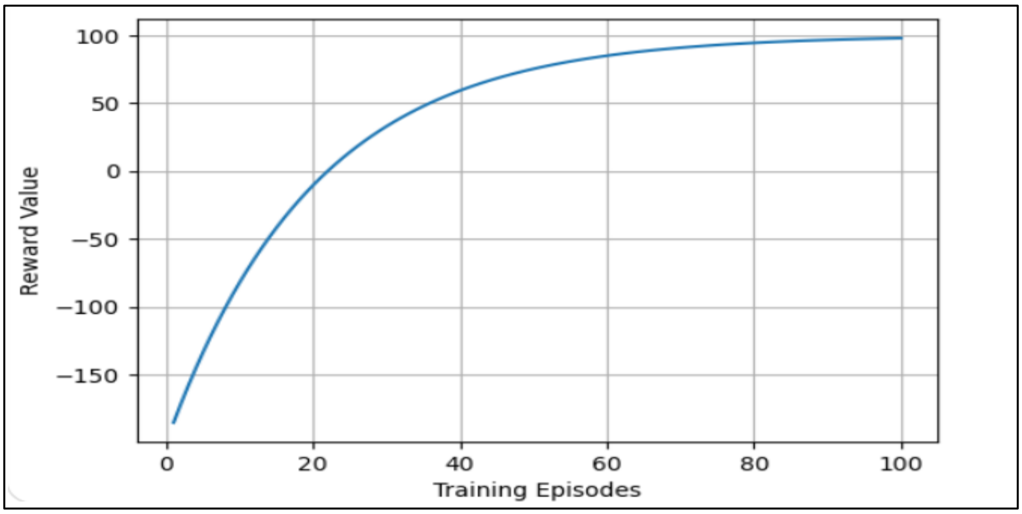


Fig 6 Reinforcement Learning Convergence Showing Reward Improvement Over Training Episodes

- *Discussion*

The simulation findings indicate that adaptive control when used in combination with reinforcement learning, both enhance the performance of robotic assembly systems in uncertain conditions. Adaptive PID + RL method is superior to the static and adaptive PID controllers in that it has a higher tracking error, lower steady-state error, and faster disturbance recovery because the control actions are updated continuously under the influence of the environmental feedback. It also shows better disturbance rejection and stable convergence which has indicated the usefulness of learning-based control and sensor fusion in achieving robustness and adaptability within the way the modern robotic systems operate.

VII. CONCLUSION

This paper presented a performance evaluation of an adaptive robotic assembly system that integrates sensor fusion and reinforcement learning with adaptive PID control. The proposed framework utilizes a Kalman filter–based sensor fusion module to obtain reliable state estimates from vision and force sensors, enabling accurate perception of the robotic environment. Simulation experiments conducted in MATLAB/Simulink demonstrated that the adaptive PID + RL controller significantly improves trajectory tracking accuracy and disturbance rejection compared with conventional static PID and adaptive PID controllers. The reinforcement learning module allows the control system to adapt to dynamic conditions by learning optimal control strategies during operation. The results indicate that integrating sensor fusion with learning-based control can enhance the robustness and adaptability of robotic assembly systems. Future work will focus on implementing the proposed framework on a real robotic platform and exploring advanced deep reinforcement learning techniques for more complex industrial applications.

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