*Proceeding Paper*

# Robust Control Approaches and Trajectory Planning Strategies for Industrial Robotic Manipulators in the Era of Industry 4.0: A Comprehensive Review [†]

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**Abstract:** This article presents a comprehensive review of control approaches for industrial robotic manipulators, focusing on research conducted from 2020 onwards. The efficient functioning of robotic arms and successful task completion necessitate effective control strategies. Addressing real-world challenges, such as dynamic system variations due to environmental changes and unknown disturbances, remains crucial. To tackle these challenges, robust control strategies, including PID, H∞, and Model Predictive Control, are thoroughly surveyed. Commercially employed trajectory planning techniques for manipulators are also extensively discussed. Ultimately, the paper concludes by providing valuable insights into prospective areas for future research, with the aim of enhancing the capabilities and performance of control strategies for industrial robotic manipulators. This study offers valuable knowledge to advance the field of robotic automation in Industry 4.0, fostering the development of efficient and intelligent manufacturing processes.

**Keywords:** industrial robots; collaborative robots; trajectory planning; robust control; industry 4.0

## 1. Introduction

Robotic arms play a pivotal role in the modern industrial landscape. Being an important component of industry 4.0, they are of great importance in various industries and their integration is necessary to realize the concept of a smart factory. The significance of robotic arms is paramount and their control strategies hold even greater importance as they ensure their proper functioning. There are many studies that have focused on the control of industrial robotic arms in the past. Some delved into the control strategies for a specific industrial application such as welding [1], assembly [2] or material handling [3], while others classified control strategies based on different criteria, such as kinematic configuration, end-effector type and payload capacity. Additionally, there are studies which extensively discussed one aspect of control in robotic arms such as trajectory control [4]. In recent years, there is a rapid increase in use of intelligent control strategies for industrial robotic arms [5] and it is driven by the need for adaptability to dynamic environments, increased flexibility to perform various tasks, handling unknown disturbances and ensuring safety. This review explores the control strategies for the industrial robotic manipulators, with focus on the research work done from 2020 onwards. The review discusses the robust control strategies and highlights different aspects of control, including trajectory planning, trajectory tracking, convergence and stability, while considering the need for adaptability, flexibility, and challenges like environmental changes and unknown disturbances. This study offers valuable knowledge to advance the field of robotic

automation in Industry 4.0, fostering the development of efficient and intelligent control strategies for manufacturing processes.

Different control strategies can be used for robotic manipulators, whereas the choice depends on the application, operating conditions and other application specific requirements. For instance, classical PID and a linear MPC controller are compared in [6] on a 5 DOF RV-2AJ Mitsubishi robotic arm for three distinctively defined reference trajectories. The study argues that MPC is faster and requires less control effort, whereas PID has greater precision. It is also worth mentioning that the choice of controllers to some extent is dictated by the dynamics of the system. In real-world scenarios, system dynamics can vary due to changes in environment and unknown disturbances. Therefore, robust controllers are needed to handle uncertainties, parameter variations, external disturbances and unmodeled dynamics.

Following the introduction, the second section of the article highlights some of the robust control strategies. Afterwards, the article explores the trajectory planning techniques for robotic manipulators. Section 4 discusses the trajectory tracking methods, whereas convergence and stability in control of robotic manipulators is discussed in Section 5. Finally, valuable insights into prospective areas for future research are provided in Section 6, with the aim to enhance the capabilities and performance of control strategies for industrial robotic manipulators. Section 7 concludes the article.

## 2. Robust Control

Robust controllers are designed to effectively maintain performance by handling model uncertainties, parameter variations, external disturbances, and unmodeled dynamics. Control strategies lacking robustness often rely on accurate knowledge of system parameters. However, in real-world scenarios, system dynamics can vary due to factors such as environmental changes or unknown disturbances. As Ulusoy et al. [7] and Liu et al. [8] have used linear PID by ignoring coupled dynamics, thus lacking robustness. The authors in [9], on the other hand, have proposed an adaptive neural control based on a simple structured PID-like control. The authors used radial basis function neural networks to estimate uncertainties and determine PID gains through a direct Lyapunov method. The proposed method can deal with nonlinear dynamics of robotic systems and model uncertainty. Furthermore, the proposed methodology demonstrates robustness against external disturbances with the ability to achieve auto-tuning of the PID gains. Another application of robust algorithms can be found in [10] in which the H∞ controller and the fuzzy logic (FL) compensator work together to achieve robustness. The strategy can handle un-modelled dynamics and resolve parametric uncertainty, but require a high level of mathematical ability due to computational complexity. Similarly, Parkash et al. [11] has proposed adaptive backstepping neural controller for a robot manipulator with dynamic uncertainties and demonstrated the controller performance using a 4 DOF Barrett WAM Arm. Whereas Carlucho et al. [12] has developed an adaptive controller based on data-driven MPC which utilizes a model derived by a NN, considering the environmental disturbances to control a manipulator working with unknown payloads. Similarly, Kang et al. [13] has worked on a NN-based MPC of a 2 DOF robotic manipulator with unknown dynamics and input constraints to improve the model estimation accuracy. Taken together, these studies suggest that robust controllers offer effective solutions to address the challenges posed by the uncertainties, disturbances, and unmodeled dynamics and overall improve control performance in real-world scenarios.

## 3. Trajectory Planning

Trajectory planning is a crucial aspect of robotic systems which involves determining the optimal path and motion profiles to be followed in order to accomplish a specific task. The need for trajectory planning arises from the complexity of robotic tasks and the desire

for precise and efficient execution. By planning a well-defined trajectory, robots can navigate through their workspace with improved accuracy, safety and optimized motion.

In this regard, ref. [14] has proposed a manipulator trajectory planning method which is based on a radial basis function (RBF) neural network, implemented on a 6-DOF robotic arm showing that the proposed method can improve the trajectory tracking accuracy and motion efficiency. However, the study in [15] proposes a soft actor–critic (SAC) based deep reinforcement learning path planning algorithm for multi-arm manipulators with periodically moving obstacles. Neural networks estimate the future location of moving obstacles in SAC. Further to improve estimation for periodic signals, Prianto et al. [15] suggested other deep learning algorithms like RNN. Whereas, for the optimized trajectory, ref. [16] has used a combination of simulated annealing algorithm and neural network learning while the PID control algorithm is used to reduce errors. The neural network and PLC control system are combined to optimize the servo motor.

As far as collision avoidance is concerned, ref. [17] has developed Path Planning and Collision Checking Network (PPCNet) framework which is end-to-end learning based and uses deep neural networks to find a real-time solution for path-planning and collision-checking. Kinova Gen3 robot is used to examine the proposed framework. The neural network and PLC control system are combined to optimize the servo motor. However, the challenges are posed by slowness and complexity in path planning. To cater the issue, ref. [18] has proposed an approach based on Q-learning and neural network. This is a hybrid path planning method which uses KNN to determine the location of starting point, obstacle and target. Then Q-learning algorithm is used to reach the target cell and avoid obstacles. Finally, a trained neural network is used to obtain the joints angles of the robotic arms. These diverse range of trajectory planning methods discussed are important for the intelligent operations of autonomous robotic arms. Overall, it can be inferred that the ongoing evolution, in which intelligent algorithms and autonomous decision making are incorporated for path planning, is revolutionizing various industries and enabling robots to do complex tasks with greater precision, efficiency and speed without any human intervention.

### 4. Trajectory Tracking

After planning the trajectory, next comes trajectory tracking. Trajectory tracking focuses on controlling the robot's motion in real-time to closely follow the predefined or planned trajectory. Not all control systems have both trajectory planning and trajectory tracking. It depends on the requirements and application. However, both can be incorporated to achieve robust, safe, optimized and accurate motion control. Nubert et al. [19] has combined Robust MPC and NN control to achieve safe and fast tracking of KUKA LBR4+ robotic arm. Whereas, ref. [20] has achieved excellent position tracking performance under non-linear interference, by developing a Friction Compensation Controller (FCC) that integrated Time Delay Estimation (TDE) and an Adaptive Fuzzy Logic System (AFLS). Wang et al. [21], on the other hand, has used Baxter robot to validate RBF-NN-based controller to track the reproduced motion accurately. Similarly, for satisfactory tracking performance with superior anti-disturbance capability, Cheng et al. [22] has proposed a generalized saturated adaptive controller based on backstepping control, singular perturbation decoupling and neural networks. The proposed method was successfully tested on a 2-DOF flexible-joint robot with bounded torque inputs.

For position control, the study in [23] has investigated four different control strategies for a 2-DOF robotic arm and successfully applied them using an Alternating Current Brushless Permanent Magnet Motor (ACBPMM) and three-phase multilevel inverter having 27 levels of voltage per phase to drive the first link. The study has provided a base for position control of robotic arm with multiple DOFs using AC motors and multi-level inverters. Nonetheless, the challenge of tracking error arises when there are discrepancies between the desired trajectory and the actual trajectory followed by a system. To that end, Hu et al. [24] has proposed the dynamic surface control (DSC) based on nonlinear

disturbance observer (NDO) with interval type-2 fuzzy neural network (IT2FNN) which performed better compared to the adaptive DSC with neural network (NN) approximator and type-1 fuzzy (T1F) approximator in converging the tracking error to a sufficiently small value. Furthermore, in order to improve trajectory tracking accuracy, an adaptive fuzzy sliding mode control (AFSMC) was used in [25], which allowed to compensate parametric uncertainties, bounded external disturbances and constraint uncertainties. However, ref. [26] has investigated Wavelet Neural Network (WNN) with adaptive fuzzy sliding model control and Lyapunov method to train a 2-DOF robotic arm for high tracking accuracy. In light of these advancements, it is evident that trajectory tracking is crucial for the industrial robotic arms where precise and accurate task execution is required while ensuring high-quality output and reducing errors in manufacturing processes.

## 5. Convergence ad Stability

Stability in control systems refers to the property of a system to remain bounded and achieve a balanced state over time, even in the presence of disturbances or uncertainties. Convergence, on the other hand, is behavior of a system in which certain variables or parameters tend to approach a specific value or reach a desired goal. In this context, Trans et al. [27] has used Radial Basis Function Neural Network (RBSFNN) along with Sliding Mode Control using Neural Network (SMC-NN) and Lyapunov training method for a two joint robotic manipular which can guarantee a finite-time convergence and stability. Similarly, the study in [28] has used the Radial Basis Function Neural Networks (RBFNNs) control for a three link industrial robot manipulators under various environments to guarantee the stability of the system and the convergence of the weight adaptation. These studies point to the fact that the advanced techniques like neural networks and sliding mode control are contributing to achieve stability and convergence, enhancing performance, reliability, efficiency and safety in intelligent industrial operations under diverse environments.

## 6. Future Directions

In the light of research works studied, it is evident that these approaches provide robust control and are significant to deal with model uncertainties, environmental changes and unknown disturbances. However, future research is still required to continually advance control systems for industrial robotic manipulators in regards of robustness, intelligence and automation. This section discusses different areas which can be explored for future research to contribute in enhancing the field.

- Current robust control strategies often rely on offline tuning of control parameters or the assumption of known system dynamics. Future research can focus on developing online adaptive control algorithms that can continuously adapt the control parameters and adjust the control strategy based on real-time measurements and system feedback.
- Development of advanced Prognosis Health Management systems for industrial robotic arms based on real-time monitoring and adaptive control techniques [29].
- The use of multiple robots in collaborative tasks is increasing to enhance productivity and flexibility [30]. Thus, need for effective coordination strategies arises. Future research can explore techniques that consider the coordination and cooperation of multiple robots. This can involve developing control algorithms for collision-free motion and communication protocols.
- Soft robotics is another emerging area. Future research can focus on integrating robust control, trajectory planning, and trajectory tracking algorithms for soft robotics to achieve more adaptive and compliant robot behavior. This can lead to advancements in fields such as robot-assisted surgery, human-robot collaboration, and assistive robotics.

## 7. Conclusions

In this article the significance of control strategies for industrial robotic manipulators in the context of the modern industrial landscape is discussed. The importance of robust control methods to handle uncertainties, parameter variations, external disturbances, and unmodeled dynamics has been highlighted. Additionally, works on trajectory planning techniques to ensure accurate and efficient execution of robotic tasks, including neural networks, deep reinforcement learning, and optimization algorithms, are reviewed. Trajectory tracking methods, such as robust MPC, adaptive control, and neural network-based controllers, are also mentioned in relation to achieving precise motion control and position tracking. The review also touches upon the topics of convergence and stability and concludes by providing valuable insights into prospective areas for future research.

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