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Dynamics, Control Strategies, and Robotics: A Review of Intelligent Mechanical Systems

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Abstract

Today's engineers employ intelligent mechanical systems that mix mechanical structures and complex control algorithms with robotic technology to help create machines that can function independently and adapt to unknown environments. These technologies are used in smart manufacturing, industrial automation, self-driving vehicles, and healthcare robots. It is difficult to develop automatic controls, operate a robot in real time, and even to model them due to their nonlinear dynamics and unpredictable operating conditions. Therefore, many researches have found to be used to develop better dynamic modelling and smart control to make better system both stability, accuracy and adaptability. The current study of intelligent mechanical systems cover robotics integration, control methodology, and system dynamics. We discuss previous and new methods to study mechanical and robotic systems. Other control techniques that are currently under investigation are adaptive, fuzzy logic, neural-network-based, proportional-integral-derivative (PID) and reinforcement learning. This paper explores the application of robotics to put smart mechanical systems in many different settings. The emphasis is laid on significant research challenges, technical constraints and future research prospects for intelligent robots and autonomous mechanical systems.

Keywords: Intelligent mechanical systems; Robotics integration; Adaptive & AI-based control; Nonlinear system dynamics; Autonomous systems & smart applications.

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1. Introduction

Intelligent mechanical systems combine mechanical parts, sensor technology, control algorithms, and AI to make operation possible without human intervention in modern engineering. These systems are used in a variety of different fields, including robotics, industry, medicine, and self-driving cars. In turn, when automation and robots are ubiquitous, we require additional mechanical systems that are flexible and perform well in difficult and uncertain circumstances. Smart control strategies [1] have contributed to improving robot performance, mobility, and reliability. Mechanical systems are studied for their mechanical properties — how they work, how stable, how accurately they move. Robotic systems are characterized by nonlinear dynamics, uncertain parameters, and external disturbances that prevent us from accurately modeling and designing controls. Newton-Euler and Lagrangian formulations have been widely used to describe the dynamics of robotic systems; these approaches, however, may struggle to adequately capture intricate nonlinear interactions as observed in the real environment. Therefore, modern control approaches have been introduced to be more flexible and robust. Control tactics are critical to ensure robotic systems perform as they should perform to within the limit as per their functionality. Simplistic and reliable controllers like proportional-integral-derivative (PID) controllers are also widely adopted and used for industrial applications. However, more recent robotic algorithms require more sophisticated controls that can account for uncertainties and nonlinearities. Fuzzy logic, neural networks, and hybrid algorithms are smart control systems which have demonstrated good performance in improving flexibility and precision of systems in [2]. For instance, in terms of performance of varied control schemes available for robotic manipulators, the hybrid fuzzy–neural controller was the most suitable for robot control [3].

The intelligent mechanical systems are composed of many different parts which work together to enable sensing, decision making and interaction with the environment, as represented by figure 1. Cameras, LiDAR (light detection and ranging), inertial measurement units, etc. sensor modules gather information regarding the environment and physical entities of the system so that information can be detected and dynamically modelled such as the system behaviour. The control algorithm uses the goals of the job and the dynamic model for the tasks to determine what control inputs are required. AI and ML techniques make systems work better by allowing them to make decisions which are more flexible, find the best paths to traverse, avoid obstacles and find out what is best to do. The robotic system is capable of moving by issuing control signals to actuators. This enables autonomous robots to perform complex missions in highly dynamic environments.

AI methods have accelerated the pace of intelligent robotic systems in recent years. Soft computing, such as neural networks, fuzzy systems, evolutionary algorithms, and swarm intelligence, has been a popular method for handling uncertainties and nonlinearities in the design of robotic control and motion systems [4]. These AI-driven solutions enable robotic systems to perform complex jobs with minimal oversight, learn from data, and respond to environmental changes. To this end, robotic and mechanical systems were added as artificial intelligence (AI) and their integration has been viewed as one of the key research topics for modern automation.

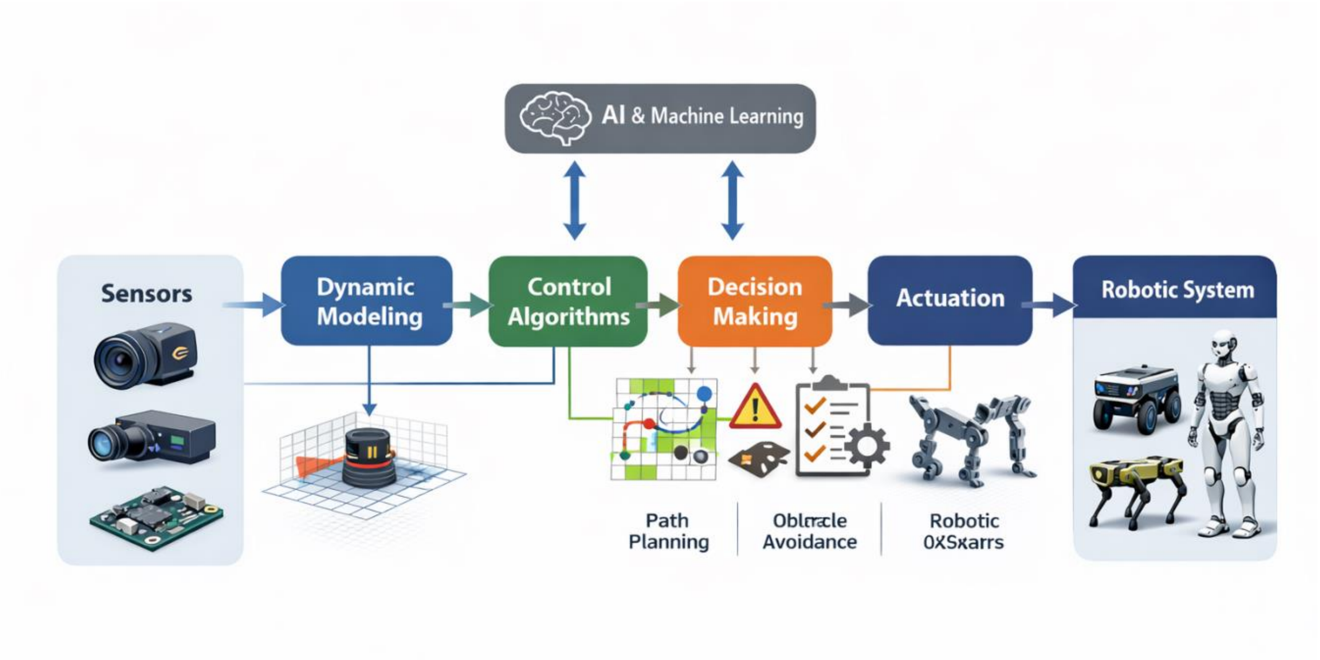


Figure 1: Design of an intelligent mechanical system with information on sensor technology, dynamic modeling, control algorithm, AI-based decision making, and actuation, with regard to robot platforms for autonomous devices such as mobile robots, quadrupedal robots, humanoid systems

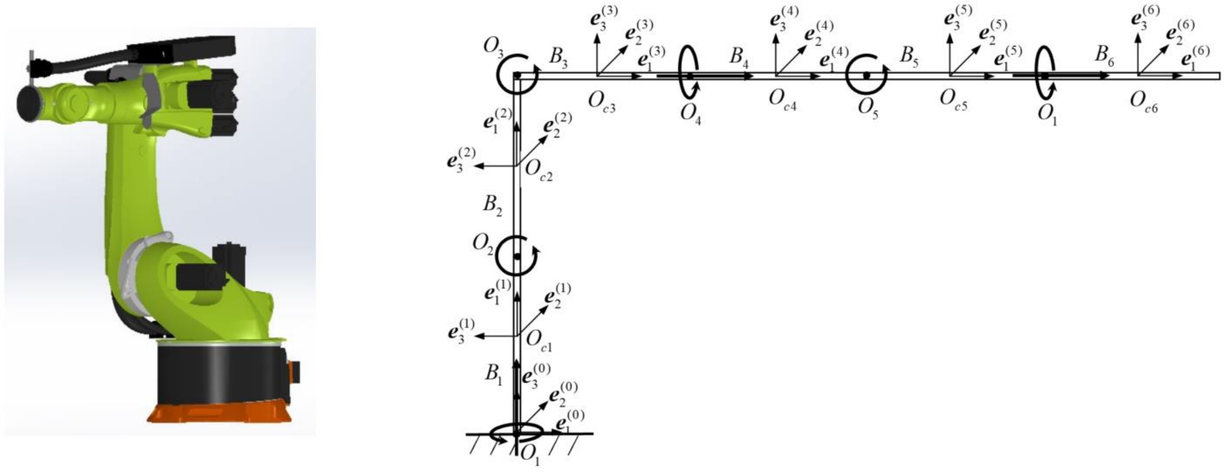
Despite these advances, the majority of modern robotics research focuses on a specific topic, such as control algorithms, robotic kinematics, or AI approaches. However, few comprehensive evaluations simultaneously include the integration of robotics, control strategy, and system dynamics. Furthermore, new research has tended to focus solely on control ways, rather than providing a balanced view of how the various approaches contribute to the development of intelligent mechanical systems. This work attempts to establish a complete understanding of intelligent mechanical systems by focusing on three domains: system dynamics, system control techniques, and robotic integration.

2. Advanced Intelligent Systems Dynamics

Accurate dynamic modeling and analysis are vital to the construction of intelligent mechanical systems. Existing robotic systems work in the presence of complex mechanical interactions, nonlinear dynamics, and parameter uncertainty. The need for advanced dynamic modeling that helps robots to become more self-regulated, precise, and flexible is becoming more prevalent. Conventional rigid-body modeling techniques fall short of modern robotic applications like variable structure, rapid motion, and flexible materials. Researchers have therefore investigated complex modeling frameworks including continuum mechanics, multibody dynamics, nonlinear dynamic analysis models and have applied hybrid physics–data-driven modeling techniques.

2.1 Multibody Dynamics of Robotic Systems

Multibody dynamics is a basic framework that simulates mechanical systems comprised of diverse and interconnected stiff or flexible bodies. In robotics, many links are joined together via joints in a complex kinematic chain, used to build manipulators, mobile robots, and parallel machines. The dynamic response of these systems is determined by the interaction between link masses, joint torques, inertia properties, and external forces. The design structure and multibody dynamic characteristic of a standard industrial robot manipulator used in smart mechanical systems are presented in Figure 2. Left (a) illustrates the image of an interactive multi-degree-of-freedom (DOF) industrial robotic arm that is commonly used in fabrication processes such as assembly, welding, and material handling. These robotic manipulators consist of several moving joints and associated links facilitating a variety of spatial dynamics. Right image (b) shows the kinematic modeling and dynamic model of the robot using a multibody framework. The joints Oi are the rotational degrees of freedom between nearby links, each link is represented as a rigid body Bi. The coordinate frames are e_1, e_2, and e_3. Three dimensions describe movement of the links connected to each body and its direction along which the joint is connected. This approach facilitates forming the equations of motion of the robot with traditional dynamic formulas, including the Lagrangian and Newton-Euler methods. For trajectory planning, control design, and dynamic simulations of intelligent robotics, systematic study of dynamic interaction between links, joint torques, and inertia is facilitated by modeling of the robot as a multibody system.



(a) (b)

Figure 2: Industrial robotic manipulator and its multibody dynamic model: (a) physical structure of a multi-DOF industrial robot arm; (b) multibody representation showing links, joints, and coordinate frames used for kinematic and dynamic modeling

Multibody dynamic modeling allows engineers to build the equations of motion that govern these complex and interconnected systems. Two of the leading methods to arrive at these equations are the Lagrangian formulation and the Newton-Euler formulation. For real-time control, the Newton-Euler method is computationally efficient, by employing recursive propagation for determination of forces and torques on each link. The Lagrangian approach produces concise mathematical models of motion by developing dynamic equations from the system's energy (kinetic and potential).

Trajectory planning, dynamic modeling, motion optimization, and controller design are all heavily influenced by these models. Because joint coupling and inertia effects have a great impact on motion precision, accurate multibody dynamic models are crucial for high-speed industrial manipulators to achieve precise movements. Many complex controllers depend extensively on reliable dynamic models derived from multibody system analysis [5].

2.2 Robotic Dynamics' Nonlinearities

Robotic systems naturally demonstrate nonlinear dynamic behavior due to a multitude of mechanical and operational factors. Unlike simple mechanical systems which can easily be modeled linearly, robotic manipulators and mobile robots exhibit nonlinear interactions among joints, actuators, and external environments. Friction in joints and transmission systems is a typical cause of nonlinearity. Nonlinear torque disturbances caused by friction also influence motion accuracy and energy efficiency. Backlash is a common nonlinear phenomenon in gear transmissions, which is triggered by mechanical clearance between interlocking gears. Backlash creates oscillations, motion delays, and less accurate positioning.

The dynamic properties of the nonlinear movement of robotic manipulators, especially during actuator–joint contact, are also presented in Figure 3. The figure presents a common industrial robotic arm, a simplified dynamic model of a single joint, and consists of the robotic link, speed reducer, and permanent magnet synchronous motor (PMSM). In functioning robotic models, the motor generates electromagnetic torque T_e transferred to the robotic arm via a gear reduction mechanism which results in the load torque T_l. The symbols θ_m and θ_l are the angular positions of both the motor and load, respectively. Many mechanical transmission components, such as gear reducers and other mechanical transmission parts, induce nonlinear behaviors between the motor and the robotic joint; for example, friction, backlash, and elastic coupling. Nonlinear effects on the dynamic behavior and control performance of robotic systems are of pivotal interest, particularly when executing precision or high-velocity work. Hence, dynamic modeling of the actuator–joint system can be precise in developing resilient control strategies that can endure disturbances and sustain stable dynamics for intelligent robotic systems.

Structural vibrations in high-velocity robots pose a major source of nonlinear dynamics. Lightweight robotic arms that enable quick operations often experience flexible vibrations due to reduced stiffness and inertia coupling between joints. These vibrations can cause tracking issues and inconsistent behavior if not properly controlled. These nonlinearities are the targets of increasingly sophisticated modeling and control strategies to mitigate with intelligent model and control strategies. Artificial neural networks and fuzzy logic controllers can be used to approximate nonlinear functions and mitigate unknown disturbances in robotic dynamics. Such methods of controlling, for instance, have been shown to be more robust with lower trajectory tracking errors in nonlinear robotic systems [6]. Hybrid fuzzy-neural control architectures have been suggested to improve system stability and adaptability in unpredictable operating settings [3].

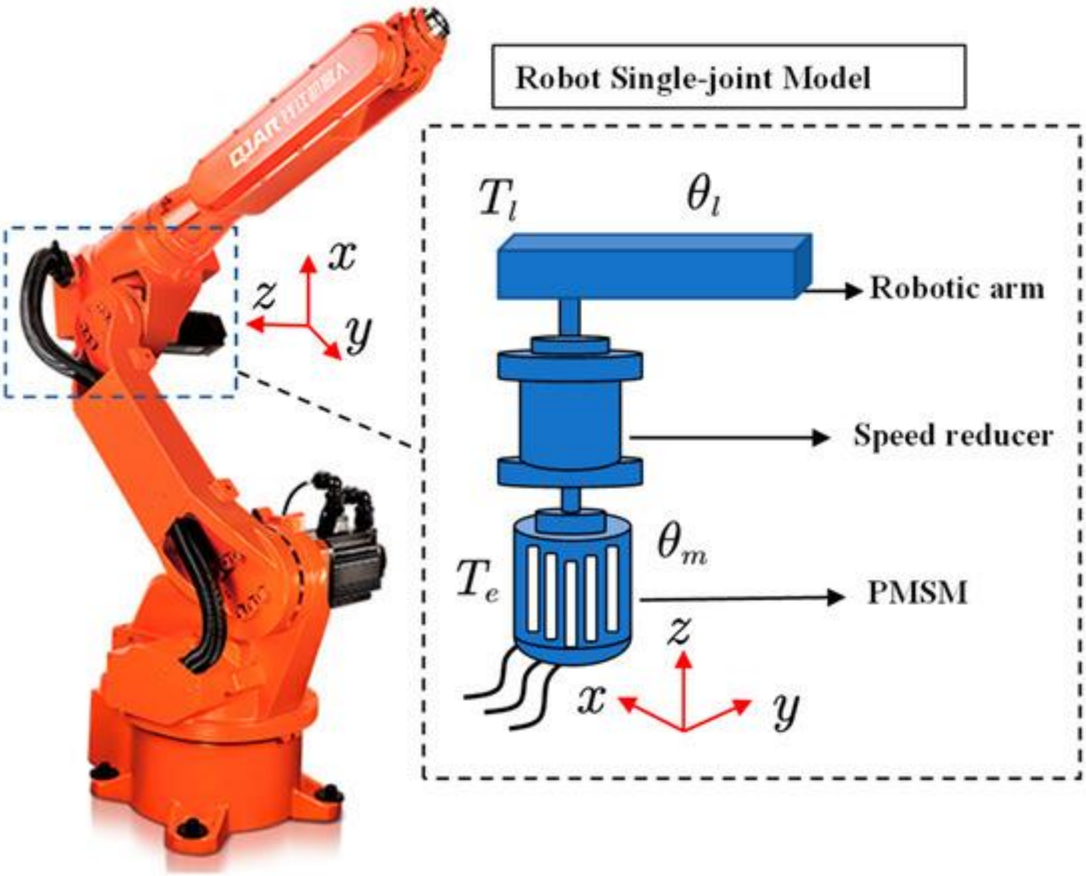


Figure 3: Single-joint dynamic model of an industrial robotic manipulator showing the actuator-transmission-link structure, including the PMSM motor, speed reducer, and robotic arm used to analyze nonlinear joint dynamics

2.3 Flexible and Soft Robotics

Normally, classical robotic systems are simulated using rigid-body dynamics, which assumes that each link is totally rigid. While this assumption simplifies mathematical modeling, it is unsuitable in modern applications when soft polymers, compliant mechanisms, or lightweight structures are used. Flexible robotics refers to systems with elastic deformation in their linkages during movement. Examples include space manipulators, extended robotic arms, and lightweight collaborative robots. The structural flexibility of these systems causes additional dynamic effects, such as distributed deformation along connections and bending vibrations. Soft Robotics is a growing field that uses materials such as silicone, elastomers, and polymers to build robots. These soft robots are especially useful for applications that require safe interactions with humans, medical devices, or bio-inspired movements. Their deformation is described using continuum mechanics principles, whereas standard rigid-body robots can be represented using discrete joint coordinates. As a result, these systems are studied using a variety of modeling techniques, including distributed parameter models (DPM), Cosserat rod theory, and finite element analysis (FEA). Soft robotic systems frequently necessitate complex control algorithms due to their high levels of nonlinearity and structural unpredictability. In flexible robotics, hybrid intelligent control frameworks that include fuzzy logic alongside neural networks have shown favorable outcomes in terms of motion precision and stability [7].

As comparison to the rigid-body robotic structures under consideration in this section, Figure 4 presents the flexible and soft robotic systems along actuation mechanism. A flexible continuum robotic arm with wire-rope actuation system and flexible tube, which bends and deforms along its length is presented in subfigure (a). Due to their mobility in constrained locations, such structures are widely used in minimally invasive surgical instruments and inspection robotic systems. A small, flexible manipulator with multiple channels for actuation, sensing, and tool manipulation (indicating its adjustable-to-manipulation capability) is shown in the subfigure (b) to be integrated into the endoscopic platform. And these systems, unlike conventional rigid manipulators, show distributed deformation, therefore require a continuum mechanics model rather than discrete stiff-body kinematics. Mechanical actuation platforms for flexible robotic constructions with cable driven or transmission systems are depicted in the subfigures (c) and (d). For these systems, motor motion is turned into a controllable flexible robotic arm deformation. To achieve the correct amount of motion in flexible and soft robotic system we need complex modeling and sophisticated control algorithms because of the complex interplay of the structure elasticity, cable tension and actuator's dynamics which induce high nonlinearity [8].

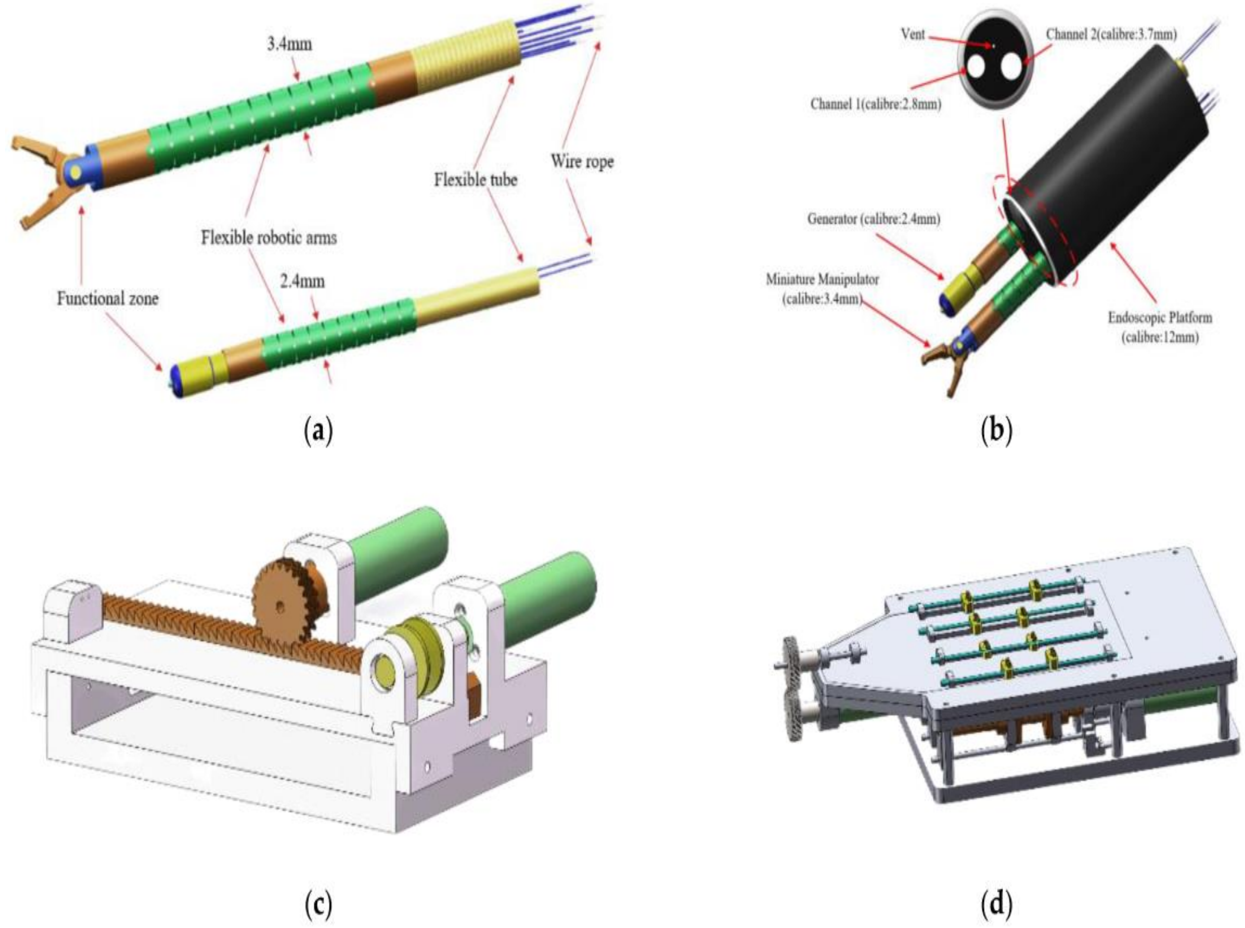


Figure 4: Examples of flexible and soft robotic systems: (a) flexible continuum robotic arm with wire-driven actuation, (b) miniature flexible manipulator integrated into an endoscopic platform, and (c-d) mechanical actuation systems used to control flexible robotic structures [8]

2.4 Modeling Techniques: Classical Mechanics vs Data-Driven Modeling

Historically, physics-based analytics, particularly classical mechanics, have been used to simulate robotic dynamics. One well-liked approach is the Lagrangian method, which provides equations of motion that accurately characterize the behavior of robotic systems. This formulation provides a thorough physical understanding of the system's dynamics based on generalized coordinates and the energy correlations. Strong analytical models for complex robotic systems are more challenging to build because to uncertainties about the system features, frictional effects, and external disturbances. In real-world applications, these uncertainties may lead to modeling errors that reduce control efficacy.

Recent research has shown that some of these constraints can be addressed with data-driven modeling tools. They use a machine learning approach to directly extract behavior from empirical data. Artificial neural networks, Gaussian process models, and reinforcement learning techniques are frequently used in this field to represent nonlinear robotics dynamics. Physics-informed machine learning, a branch of machine learning that applies a scientific approach where well-structured physics and data-driven learning meet established physical laws, is one of the most prominent and well-liked methods in this field. In order to create a physical model that is more precise and physically consistent, physics-informed neural networks (PINNs) can incorporate physical factors like conservation laws into the training process. Furthermore, soft computing techniques like neural networks, fuzzy logic systems, evolutionary algorithms, and swarm intelligence applications show a lot of promise for modeling intricate robotic systems and enhancing control efficiency in ambiguous circumstances [4].

3. Modern Control Strategies

Advanced control algorithms that can manage nonlinear dynamics, uncertainties, and variable environments are necessary for modern intelligent mechanical applications. The foundations of robotic control systems were established by traditional systems, including PID controllers and linear optimum control methods. However, the increasing complexity of contemporary robotic platforms necessitated the development of advanced and adaptable controls. This encompasses intelligent control methodologies, including neural network control, fuzzy logic control, reinforcement learning-based control, and model predictive control, in addition to robust and optimal control methods. These strategies significantly improve the autonomy, flexibility, and performance of robotic systems that operate in unpredictable and dynamic environments.

3.1 Classical vs. Modern Control Approaches

Traditional controlling techniques still appear in industrial robotics with respect to these two aspects of the applications were due to ease, consistency and stability of classical control systems. Proportional–Integral–Derivative (PID) controller is the best control algorithm that is used in robotic systems while controlling positions, velocities, torque. PID controllers vary control inputs in response to the proportional, integral and derivative terms of the tracking error. PID controllers are useful for a wide range of industrial applications although, their effectiveness diminishes when dealing with highly nonlinear robot systems or systems with uncertain parameters. Linear Quadratic Regulator (LQR) is a classical control method that is quite fundamental and thus one type of advanced control technique that minimizes a quadratic cost function that reflects the performance of the system while reducing the control effort. Whereas LQR controllers allow stable and optimal operation of linear systems, but require accurate mathematical models and thus may not yield the best results for systems with very nonlinear dynamics.

Fortunately, there are a number of powerful control methods that can overcome this restriction, including adaptive control, robust control, and optimal nonlinear control. When the system's dynamics or external factors change in real-time, adaptive control approaches modify the controller parameters to adapt to these changes. Sliding mode control and other resilient active controllers are suggested to keep the system stable in the face of external perturbations and modeling biases. Robotic control systems and mobile robots' dynamic ability and trajectory tracking accuracy have been greatly enhanced by advanced controllers such as adaptive, sliding mode, fuzzy logic, neural network, and model predictive control, according to recent research on robotic control approaches [9]. The present methods outperform the conventional linear control systems in terms of robustness and flexibility.

3.2 Intelligent Control Techniques

Through utilizing artificial intelligence concepts for intelligent control through the design of the approach, the intelligent control approach can enhance the control system’s flexibility, learning potential, and resilience. These techniques are highly useful in robotics, since these cope with uncertainty of the operational environment and nonlinear dynamic nature of robotic systems.

- **Control of Neural Networks**

Artificial neural networks (ANNs) are now a potent tool for controlling intricate robotic systems, approximating nonlinear functions, and learning from data. These neural network controllers can reduce uncertainties and simulate unknown system dynamics without requiring an exact analytical model. In robotic manipulators, neural networks are widely used for trajectory tracking, adaptive control, and inverse dynamics control. Neural networks are able to generate accurate control signals although some characteristics of the system cannot be determined by inferring the nonlinear relationship between control inputs and system outputs. Neural network-based control systems and other control techniques based on neural network control strategies have attained high precision for precise trajectory tracking control and nonlinear robotic dynamics approximation. Such controllers may also lead to the enhancement of precision in robotic motions and the improvement of motion fidelity and robustness for complex robotic systems via adaptive reduction of model uncertainty and external disturbances [3]. Recently, research on the efficiency and adaptability of complex neural networks such as deep neural networks and spiking neural networks (SNNs) has been focused on robotic trajectory tracking. Experimental results showed that in terms of trajectory accuracy and error reduction, the neural network-based controllers outperformed fuzzy-based and conventional PID controllers [10].

- **Control of Fuzzy Logic**

One such widely used robotic intelligent control method is fuzzy logic control (FLC). Fuzzy controllers use linguistic principles and approximate reasoning to deal with uncertainty and imprecision in system measurements, in contrast to classical controllers that rely on exact mathematical models. An accumulation of if-then rules, which also resemble human reasoning, characterizes the behavior of fuzzy logic systems. This methodology is especially beneficial for robotic systems where it has been difficult to acquire accurate models or with unclear or inconsistent sensor readings.

Fuzzy controllers have been utilized effectively since the beginning in a variety of robotic systems, such as collaborative multi-robot systems, mobile robot navigation, and manipulator control. These controllers are capable of maintaining stable control performance while effectively managing the system's nonlinear dynamics and uncertainties. Fuzzy neural network-based controllers can significantly increase the trajectory tracking accuracy and robustness of robotic manipulators under uncertain dynamic settings [11]. Because of their capacity to handle uncertainty and approximate nonlinear dynamics, they have been thoroughly studied for robotic systems (e.g., hybrid intelligent control method based on neural networks and fuzzy logic). These controllers enhance trajectory tracking accuracy and resilience in robotic manipulators by fusing the reasoning powers of fuzzy systems with the learning capabilities of neural networks [12].

- **Reinforcement Learning–Based Control**

Reinforcement learning (RL) has emerged as a powerful approach for designing autonomous robotic control systems. With Reinforcement Learning, robots learn the best control strategies by learning by trial and error in their environment. As part of this process, the robot gets the inputs based on an incentive or penalty and gradually comes to own the control actions with improvement over time with a view of maximizing its effectiveness. In this way, the major advantage of reinforcement learning is that it is independent of explicit system models. Control policies are learned instantly by the robot during interaction with the environment. This type of knowledge is particularly beneficial for complicated robotic systems in which accurate dynamic models are difficult to obtain.

Deep reinforcement learning methods apply neural networks to reinforcement learning (RL) algorithms for robotics to help them acquire skills in complex behavior, such as manipulation, locomotion, and autonomous navigation. It has been found that control techniques based on reinforcement learning can have positive results in adapting robots to a dynamic and even unpredictable environment. Adaptive robotic controllers based on reinforcement learning and deep neural networks have been applied to make precise trajectory planning and motion control for industrial robots [13]. In robotic manipulators, reinforcement learning has been successfully employed, enabling robots to create approaches to control without explicit kinematic and dynamic models [14].

3.3 Model Predictive Control (MPC)

One of the most popular control methodologies for autonomous systems and robotics is Model Predictive Control (MPC), which is based on optimization. The core principle of Model Predictive Control (MPC) is to solve an optimization problem in order to ascertain the best order of inputs for the control, which is based on making short-term predictions about the system's future motion. Being able to explicitly incorporate system constraints like actuator limitations, safety thresholds, and obstacle avoidance is a major advantage of MPC. For robotic systems operating in confined spaces, this feature makes MPC ideal.

Model Predictive Control (MPC) has seen widespread use in domains like trajectory tracking, robotic manipulation, and autonomous vehicle navigation. In order to improve the overall stability and efficiency of the system, MPC provides the capability to continuously adjust predictions using real-time data from sensors to derive more effective control actions. Model Predictive Control (MPC) and machine learning have been the subject of numerous recent investigations on ways to enhance robotic systems' decision-making and adaptability. Improved trajectory planning and collaborative activity in human-robot interaction environments have been achieved through the use of reinforcement learning in conjunction with Model Predictive Control (MPC) [15].

In order to attain stability, accuracy, and adaptability in unpredictable and dynamic environments, modern robotic systems employ a variety of control algorithms. Innovative robotics technology has led to the emergence of intelligent and optimization-driven control methodologies like neural network control, fuzzy logic control, reinforcement learning, and model predictive control as popular controllers, despite the fact that classical controllers, particularly PID and LQR, are widely used in industrial applications. Each strategy has advantages in terms of resilience, computing requirements, and adaptability when used in intelligent mechanical systems. Table 1 provides a comparative overview of common robotics control systems, including their fundamental concepts, advantages, drawbacks, and limits, as well as typical application areas.

Table 1: Comparison of Classical and Intelligent Control Strategies in Robotic Systems

Control Strategy	**Principle**	**Advantages**	**Limitations**	**Typical Robotics Applications**	**References**
PID Control	Uses proportional, integral, and derivative feedback to minimize the error between desired and actual system output.	Simple structure, easy implementation, widely used in industrial systems.	Limited performance for nonlinear systems and uncertain environments.	Industrial manipulators, motor speed control, actuator regulation.	[9]
LQR / Optimal Control	Minimizes a quadratic cost function involving state errors and control effort to achieve optimal system performance.	Provides mathematically optimal control and good stability for linear systems.	Requires accurate system modeling and linearization assumptions.	Aerospace robotics, balancing robots, robotic manipulators.	[9]
Neural Network Control	Uses artificial neural networks to approximate nonlinear system dynamics and generate adaptive control signals.	Strong capability for nonlinear function approximation and adaptive learning.	Requires training data and computational resources.	Robot trajectory tracking, adaptive robotic manipulators.	[10, 12]
Fuzzy Logic Control	Employs rule-based reasoning with linguistic variables to control	Handles uncertainty and noisy sensor data effectively.	Designing rule bases can be complex and application dependent.	Mobile robot navigation, manipulator control, multi-robot coordination.	[4, 11]

	systems under uncertainty.				
Reinforcement Learning Control	Learns optimal control policies through interaction with the environment using reward-based learning.	Enables autonomous learning without explicit system models.	Training can be computationally expensive and requires exploration.	Autonomous navigation, robotic manipulation, adaptive robots.	[13, 14]
Model Predictive Control (MPC)	Predicts future system states using a model and optimizes control inputs over a finite prediction horizon.	Handles constraints and optimizes performance in real time.	Computational complexity can limit real-time implementation.	Autonomous vehicles, robot trajectory tracking, collision avoidance.	[9, 15]

4.Robotics and Integration

In a very simple version, modern dynamics and control methods have been integrated into them, leading to a very powerful robot that is capable of autonomous actions, working together with humans and interacting with their tough environments intelligently. The current robotics incorporates mechanical engineering, robust control algorithms, cutting-edge sensor technology, artificial intelligence, and other advanced principles to develop intelligent systems that can perceive the environment around them, and make decisions and adapt based on their behavior. This section aims to research fundamental aspects of robotic incorporation, such as bio-inspired robotic systems, human-robot collaboration, autonomous robotic platforms, and sensory fusion approaches for intelligent environmental awareness.

4.1 Autonomous Robotic Systems

An important development in robotics of today is the autonomous robotic system. These systems are capable of sensing the environment around them and using sophisticated sensor technology, onboard computation, and control algorithms to make decisions almost immediately. Some autonomous robots are unmanned aerial vehicles (UAVs), unmanned ground vehicles (UGVs), or humanoid or service robots, and classified according to their operational location. Drones, also called unmanned aerial vehicles (UAVs), are widely used in various fields such as delivery, infrastructure inspection, environmental monitoring, and surveillance. Advanced navigation algorithms, sensor fusion and control systems that can regulate flight behaviour in changing circumstances are necessary. Recent surveys also suggest that LiDAR combined with vision-based sensing technologies are crucial for fast autonomous flight and obstacle avoidance systems for modern UAVs [16].

Similarly, unmanned ground vehicles (UGVs) are a sort of autonomous earth mobile robot that is employed in areas such as logistics, exploration, military, and disaster response. These robots are frequently used in difficult areas and depend on sophisticated vision and navigation algorithms for a safe journey that considers changing surroundings. The contribution of advanced sensors, manipulators and intelligent control algorithms in UGV systems are studied under such a view, which makes UGV systems to be equipped with advanced sensors, manipulators or intelligent control algorithms for autonomy and operation in risky/unstructured environments [17]. Humanoid robots are a large category of autonomous robots capable of modeling human-like posture and movement. They are robots that have advanced dynamic modelling, perception and control models to perform functions such as moving/manipulating objects, moving and navigating as well as interpersonal interaction. The development of humanoid robot platforms is inspired by the need for robots working in human-centric task areas: for instance manufacturing, health, and services. Today's autonomous robots are characterized by mechanical systems, artificial intelligence, high-performance sensing technology, etc. - to perform complex tasks with very low human involvement (Muktadir and his colleagues, 2022). As robotics technology progresses, there are robots that are capable of completing complex tasks in industrial, service and research domains [17].

4.2 Human Robot Collaboration (HRC)

Human-robot collaboration (HRC) has received much attention in modern robotics, especially under the context of Industry 4.0/5.0 and intelligent manufacturing. Conventional industrial robots, which operate in different environments, are designed to create safety with human workers — that’s what the cobot (i.e. collaborative robot) is. Collaborative robotic systems incorporate advanced sensing technology, safety control algorithms, and human-centric motion planning for safer human-robot communication. Robots’ behaviour can be altered when in contact with humans in the workplace due to a number of safety-relevant applications such as force control, collision detection, and vision-based monitoring.

For industrial efficiency and safety enhancement, more and more attention has been drawn to find out about the growing demand for human-robot collaboration frameworks for striking the right balance between robot automation and human cognitive abilities [18]. For example, a recent (in Industry [19]) paper explores human-robot collaboration which is “a dynamic cooperation of humans and robots to accomplish tasks while sharing operational roles, decision-making, and workspace.” In order to ensure safe physical contact, flexible behaviors, and effective task coordination between humans and robots, these collaborative systems tend to have complex control and perceptual strategies.

4.3 Bio-Inspired Robotic Systems

In current robotics, human-robot collaboration (HRC) has been a well-researched area, particularly in the context of Industry 4.0/5.0 and smart manufacturing. Unlike more classical industrial robots, which work across environments, cobots (collaborative robots) are intended to work within safe working relationships with people, like we see with robots in industry. For human-robot friendly interaction, collaborative robotic systems consist of advanced sensing technology, safety management algorithms, and human-centre oriented motion systems.

The safety applications of robots that allow robots to adapt their functions in response to human presence in the workplace include force control, collision detection, as well as vision-based supervision and vision monitoring. This brings greater significance for the development of an appropriate level of human-robot collaboration approaches for achieving the trade-off between the automation of robotics and human cognition, as there is a focus in industrial science on enhancing industrial efficiency and safety to introduce human and robot collaboration to the market, there is increasingly a demand for a harmonizing human-robot collaboration mechanism that considers robot automation and human cognition in a way that ensures robots can integrate this human-robot cooperation [18]. For example, in a recent research article in Industry [19] human-robot collaboration is explored as the dynamic cooperation of humans and robots in a way that enables them to work together to accomplish a task and simultaneously share operational and decision-making tasks and workspace resources. To ensure safe physical contact, adaptable behaviours and appropriate task coordination between humans and robots, such cooperative environments necessitate complex governing mechanisms and perceptual protocols of these collaborative systems.

4.4 Sensory Fusion in Intelligent Robotic Systems

Robots must be able to perceive stimuli with strong capabilities for autonomous operation and efficient engagement with their environment. Modern intelligent robot systems rely on multimodal sensory fusion to merge data from different sensors into a true scene visual representation. Common sensors such as LiDAR sensors, IMUs (inertial measurement units), visual cameras, and touch sensors found in the AI robot perception system are employed in this investigation. LiDAR sensors produce high-resolution three-dimensional coordinate measurements vital to mapping and obstacle classification. The acceleration and angular velocity of the IMU sensors are measured to support robots to know their orientation and movement. Visual information used to interpret objects, location data, and scene information is provided by vision systems. Integration of alternative sense modalities allows robots to perform tasks ranging from simultaneous localization and mapping (SLAM) to autonomous navigation and environmental awareness [18]. According to recent publications, the incorporation of multimodal sensors significantly improves the robustness and functionality of robotic perception systems, allowing for the self-driving robot to operate more efficiently and adapt to complex and dynamic environments [22]. Additionally, developments in embodied intelligence and brain-inspired decision modes and navigation systems are enabling robots to combine sensory data and cognitive decision processes, which helps them to move and engage with environments like biological animals [23]. Figure 5 develops a multimodal sensor fusion framework applied on autonomous robotic systems for environment vision and navigation. It consolidates information from different sensors; an RGB camera, pseudo-LiDAR, accelerometer, gyroscope, and so on, into one environment representation [24]. The raw sensor data are processed in the first level — images, point clouds, accelerometer, and rotation measurements. In the second level, the camera and LiDAR data are transformed into two-dimensional occupancy grids; inertial sensors send orientation information. Data is combined to create a full view of the environment, which is further utilized by a path planning module via neural network to figure out the optimal command directions for navigation. Such control actions are executed by the robotic system to provide autonomous, unassisted movement through the environment and to avoid hazards from occurring.

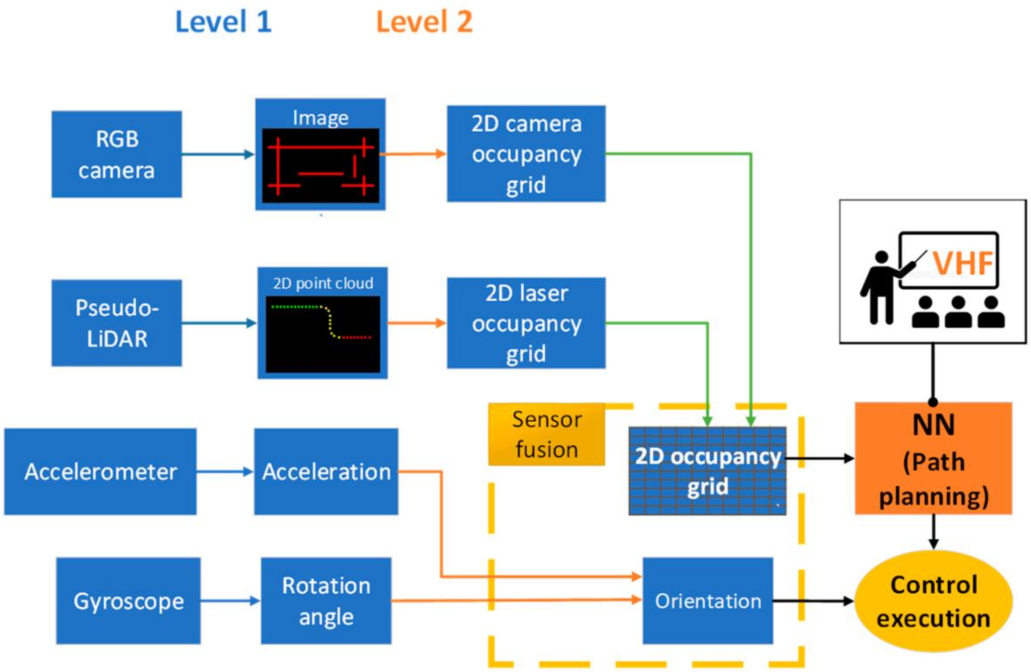


Figure 5: Integrating camera, LiDAR and inertial sensor data in the sensor fusion architecture to produce occupancy grids as well as orientation estimates for neural network based path planning and control execution for autonomous robotic navigation [24]

Table 2: Main robotic systems and enabling technologies in intelligent mechanical systems are compared by their vital technological characteristics of sensing, essential technological elements, and typical application areas

Robotics System	Key Technologies	Typical Sensors	Applications	References
Unmanned Aerial Vehicles (UAVs)	Flight control, autonomous navigation, trajectory planning	LiDAR, cameras, IMU, GPS	Environmental monitoring, aerial inspection, mapping	[16]
Unmanned Ground Vehicles (UGVs)	Autonomous navigation, obstacle avoidance, path planning	LiDAR, radar, vision sensors, IMU	Logistics, military operations, disaster response	[17]
Collaborative Robots (Cobots)	Human–robot interaction, safety monitoring, adaptive control	Force sensors, vision systems, proximity sensors	Smart manufacturing, assembly tasks	[18]
Bio-inspired Robots	Biomimetic locomotion, gait optimization, adaptive control	IMU, tactile sensors, vision	Search and rescue, terrain exploration	[20]
Sensor Fusion Systems	Multimodal perception, SLAM, environmental mapping	LiDAR, cameras, IMU, MEMS sensors	Autonomous navigation, robotic perception	[22]

5.Emerging Trends and Applications

Robotics, AI, sensor technologies, and computational models are all fields that are changing quickly and will likely change the way intelligent mechanical systems work in the future. Robotic platforms are becoming more autonomous, adaptable, and efficient in a wide range of uses thanks to robots that can work on their own and change their minds on the fly. Digital twin technologies, micro- and nano-robotics systems, and long-lasting robotic systems that use little energy are some of the new areas of attention. These improvements not only make systems work better, but they also allow for predictive analysis, real-time optimization, and manufacturing methods that are better for the environment. As intelligent robotics gets better, these solutions will have a big effect on smart factory systems, healthcare improvements, and self-driving robot platforms in the future.

5.1 Digital Twins in Intelligent Mechanical Systems

A novel approach to the construction, monitoring, and tuning of smart mechanical systems is the emerging digital twin technology. A digital twin is a real-time electronic virtual version of a system, which is created by data gathered from sensors built into a real-world system and is updated on actual physical data. Because of this instant real-time synchronization, engineers are able to inspect the operating situation, simulate what happens and predict possible breakdowns of the system. Digital twins can be utilized by researchers and engineers to model system dynamics and to confirm control strategies in robotic and smart mechanical devices independently of the operational performance. Using sensor data, dynamic models and machine learning algorithms, digital twin systems could act like highly advanced robots to recommend operating systems. Such functional potential is extremely beneficial to system design verification, performance improvement, and predictive maintenance.

In virtual twin system, which is used in intelligent manufacturing context, to assist a factory manager with managing robots and scheduling and real-time assignments of tasks to shopfloor workers, a recently published research also emphasizes the importance of digital twin technology for better human robot collaboration [25]. In order to eliminate the operational risk and improve the operational efficiency, digital twins enable engineers to design the manufacturing process in the industrial factory and compare with the alternative control systems before introducing. On the other hand, in order to detect anomalies and predict equipment failures, digital twin systems can integrate with current sensor data to dynamically model its own devices. This predictive capability significantly reduces the downtime for maintenance and service of industrial robotic systems. In pursuit of all-to-autonomous monitoring-in-the-loop decision-making for intelligent mechanical systems, as Industry 4.0 technologies continue to advance, digital twins are being integrated with edge computing platforms and the power of AI.

5.2Micro and Nano-Robotics

Micro- and nano-robotics are fast evolving study topics that focus on robotic devices with minuscule dimensions. These small robotic devices are used to execute extremely precise operations in fields such as biomedical engineering, targeted medicine administration, and micro-assembly. The governing physical dynamics at the micro- and nanoscales differ dramatically from those observed in ordinary macroscale robotic systems. Surface forces (electrostatic, van der Waals, and viscous) dominate in these conditions, with gravity forces playing minor roles. As a result, simulating micro-robots' dynamic behavior requires the use of particular physical frameworks that take into account these major surface interactions.

Micro-robots often function by a variety of actuation mechanisms, including magnetic actuation, electrostatic forces, chemical propulsion, and optical manipulation. These techniques can help with precise motion control in fluidic or biological systems where traditional mechanical actuators are ineffective. Furthermore, numerous micro-robotic systems use minuscule sensors in conjunction with advanced imaging technologies to navigate and position themselves in complex environments.

The perceptual performance of micro- and nano-robot platforms has significantly improved because to recent sensing technologies, especially micro-electromechanical systems (MEMS). For robots working in confined places, MEMS sensors provide small, energy-efficient ways to monitor acceleration, pressure, and environmental stimuli [22]. Personalized therapeutic methods and minimally invasive surgical systems are only two examples of the new opportunities in medical robotics made possible by the combination of strong control algorithms and micro-scale sensors.

5.3 Sustainability and Energy-Efficient Robotics

Today's robotic systems are designed and operated with sustainability in mind. Reducing the potential harm that industrial automation might cause to the environment is now seen as a crucial concern as the rate of industrial automation in industrial systems rises daily. Robotic systems that are energy-efficient aim to use less energy while still producing and performing at high levels. Developing energy-efficient control strategies is one way to achieve sustainable robotics. Energy savings are made possible by sophisticated control algorithms, especially model predictive control and adaptive optimization techniques, which optimize actuator movement and remove needless mechanical effort. In robotic manipulators, trajectory optimization algorithms produce motion paths that reduce joint torque and energy consumption. Optimizing mechanical design is essential for sustainable robotics. High-performance actuation technologies and lightweight robotic frameworks can drastically lower operating energy needs. Additionally, energy generated during robotic joint braking or deceleration can be recovered and reused by regenerative energy systems.

According to the analysis of intelligent manufacturing systems, human-robot cooperation improves production efficiency while reducing energy consumption and operational waste [18]. AI-based robotics systems can change their performance based on human input, resulting in more flexible and effective manufacturing techniques. Furthermore, emerging applications integrating digital twins and AI-based optimization techniques are likely to improve the long-term viability of robotic systems. The goal of these methods is to achieve the desired goal of minimizing energy expenditure related to the maintenance or control of a robotic plant. By simulating the robot's performance prior to operation, the engineer can develop an energy-efficient management approach and improve the performance of the robotic plant through improved manufacturing processes.

6. Challenges and Future Directions

Intelligent mechanical systems have been built, but in terms of fully autonomous and adaptive robotic systems still there are several challenges and issues to be solved. As robotics integrates new AI algorithms with AI-powered sensors, adaptive control strategies, and generalizability of the platform, concerns emerged with regard to computing efficiency, system generalization, and ethical safety for robotic systems. Such questions need to be dealt with in order for intelligent robotic systems to work safely in real-life environment. However, computational overhead is still one of the most challenging problems that faces intelligent mechanical systems today. All of the above means that high-order control approaches such as deep neural networks, reinforcement learning, or model predictive control need extensive computing effort to process high-dimensional data from sensors on a single device, making advanced optimization in the heat of the moment. But for most robotic systems, hardware capabilities of embedded computation, memory and energy are limited so they perform only at such limited levels. Smart mobile robots and drones must achieve perception, localization and controls with small processors on board to remain highly mobile and energy efficient by being mobile. Herein, we have the compromise between “robotic algorithm robustness,” the more robustness of the algorithm, and “effective on-the-fly.” Efficient algorithms, effective routing of neural networks (such as neural network topology) and edge-computing architectures that can perform a more intelligent control and perception tasks with lower computation requirement are considered the most critical aspects during recent progress [22]. Herein, we will study hardware software co-design, neuromorphic computing and optimised machine learning models to achieve performance in a small power environment on a practical level considering the robot serving as our research protocol in our pipeline, as a base case.

The biggest challenge that arises is generalizability of intelligent robotic solutions. Most of the machine learning-based control methods are made from raw laboratory data in the laboratory setting. However, despite their impressive capability in the test datasets, it still becomes nearly certain that these models would fail in practical situations where both environmental conditions are complex and difficult. Under these types of changing lighting conditions, noise from sensors, unexpected obstacles & environment disturbances, severely degrading the performance of systems is a constant. This phenomenon, which has been known as the reality gap, provides some context for the daunting task taking place in transforming taught models from simulation or laboratory environments into the real environment. In particular, the research on autonomous navigation and perception systems highlights the necessity of using multimodal sensing and adaptive learning techniques to guarantee the system's overall robustness in challenging contexts [23]. Further research on domain adaptation, transfer learning, self-supervised learning, and simulation-to-reality training frameworks for appropriate generalization of intelligent robotic systems is then anticipated in later stages. And, while these technical issues have become increasingly obvious as we approach the future of AI, they are also related with ethical and safety concerns, which will only grow as robotic systems gain more degrees of control and interact much more autonomously with humans.

Classical control is largely deterministic, that is, an order of magnitude of the actions of the system can be predicted with a high degree of accuracy given to them by instruction. For these days, a large proportion of AI-based control systems work almost as a probabilistic algorithm, where machine learning algorithms are involved. These are not machines that learn structures we impose on our bodies. While these methods could offer benefits to enhance the adaptability of the systems, probabilistic decision making also induces uncertainty, which can lead to safety risks as these systems transition to the autonomous vehicles, automated health care operations, and industrial automation. Since this is a domain where security has to be preserved, we should build sound systems around safety and decision-making, and robust fault detection in order to enhance secure cooperation between human and robot [18]. We will mainly focus on explainable artificial intelligence, formal verification of robotic control algorithms, and safety-oriented control systems that ensure system resilience to uncertainty.

7.Conclusion

In order to enable autonomous, adaptive mechanical technologies, this review has recommended a comprehensive study of intelligent mechanical systems that focuses on system dynamics, complex control mechanisms, and robotic embedding. In 21st-century engineering technologies such as industrial automation, self-driving fleets, medical robots, and smart manufacturing environments, intelligent mechanical systems are becoming increasingly crucial. Thanks to a combination of mechanical design, sensor technology, computer intelligence, and sophisticated control algorithms, these systems can more readily complete difficult tasks with greater accuracy, agility, and performance. High-level dynamic modeling techniques for accurate simulation of complicated robotic system behavior were the first focus of the review. Newton-Euler and Lagrangian formulas are examples of old modeling tools that are still widely used in the research of robotic system mobility and system stability.Due to the complexity of the modern robotic platforms with a wide range of dynamic features, including flexible forms, fast manipulators, and soft robotic systems, there are also new advanced modeling techniques, such as multibody dynamics, nonlinear dynamic analysis, and continuum mechanics.

The capabilities of conventional analytical models are being expanded with data-driven and physics-informed analysis approaches thanks to advancements in machine learning techniques, which can not only simulate complex nonlinear behaviors in highly uncertain environments or model under complex uncertainty environments. The paper examined several control techniques and dynamic modeling in intelligent mechanical systems. Due to their dependability, simplicity of use, and suitability for industrial applications, classical controllers (PID, LQR) have been the norm for industrial control system decision-making. Because robotic control systems are becoming increasingly complicated, innovative control approaches such as adaptive control, robust control, neural network control, fuzzy logic control, reinforcement learning control, and model predictive control are very effective. By greatly enhancing the system's functionality, tolerance, and ability to adapt to nonlinear and uncertain settings, these advanced control methods improve the system's overall performance. Robots can learn through data analysis, adapt to their surroundings, and carry out difficult jobs on their own with very little assistance or interaction from humans thanks to AI algorithms integrated into control systems. We included robotics technologies for intelligent mechanical systems in the current investigations, with a primary focus on bio-inspired robotics, human-robot cooperation, autonomous robotic platforms, and multimodal sensing fusion. UAVs, UGVs, and humanoid robots make up autonomous systems, which show how sophisticated dynamics and clever control methods enable robots to function autonomously in difficult settings.

On the other hand, collaborative robots and human-robot interaction frameworks are transforming the current industry by enabling safe and effective human-machine cooperation. Similarly, bio-inspired robotic systems and advanced sensor fusion technologies are progressively enhancing robot mobility, perception, and environmental adaptability to function in less rigid environments. On the other hand, intelligent mechanical systems will have even more capabilities owing to emerging technical trends e.g., digital twin technology, micro- and nano-scale robotics, energy efficient robotic systems, etc.

Data generation and analytics capabilities offered by digital twins also support the real-time synchronization of virtual models and physical systems, allowing for higher precision in robotic behavior optimization and predictive analytics. Micro- and nano-robotics develop these large-scale robotic applications in biomedical and micro-manufacturing where surface forces dominate system dynamics. However, for energy saving and sustainable production, energy-efficient control mechanisms and sustainable robotics are widely considered as necessary. Although there are several progressors available, there are still limitations of embedded robotic systems, implementing machine learning models in real-world systems, and safety for probabilistic AI-based controls. These barriers will be explored in multiple studies covering powerful computing architectures, robust learning algorithms, explainable artificial intelligence, safety-aware control frameworks, etc. Ultimately, the autonomous systems of the future will likely rely on the continuous application of robotics technologies and smart control techniques and dynamic modeling to evolve the control paradigm further. Emerging intelligent mechanical systems for more optimal autonomy, reliability, and flexibility will necessarily involve physics/modeling, AI, advanced sensing/scenarios, and cooperative robotics architectures. The end result will be a new type of intelligent and sustainable robotic technology with a huge potential that could bring about change in industries, healthcare, transportation and exploration fields.

References

[1]. Abbas, A.K., et al., *Review of intelligent control systems with robotics.* Indonesian Journal of Electrical Engineering and Informatics (IJEEI), 2022. **10**(4): p. 734-753.

[2]. Tai, K., et al., *Review of recent type-2 fuzzy controller applications.* Algorithms, 2016. **9**(2): p. 39.

[3]. Chao, F., et al., *Type-2 fuzzy hybrid controller network for robotic systems.* IEEE transactions on cybernetics, 2019. **50**(8): p. 3778-3792.

[4]. Kim, Y.-T., I. Kobayashi, and E. Kim, *Soft Computing in Advanced Robotics*. 2014: Springer.

[5]. Mahdi, S.M., et al., *Comprehensive review of control techniques for various mechanisms of parallel robots.* IEEE Access, 2025.

[6]. Hu, J., *Research on robot fuzzy neural network motion system based on artificial intelligence.* Computational Intelligence and Neuroscience, 2022. **2022**(1): p. 4347772.

[7]. Khoobjou, E. and A.H. Mazinan, *On hybrid intelligence-based control approach with its application to flexible robot system.* Human-Centric Computing and Information Sciences, 2017. **7**(1): p. 5.

[8]. Sun, L. and X. Chen, *Flexible continuum robot system for minimally invasive endoluminal gastrointestinal endoscopy.* Machines, 2024. **12**(6): p. 370.

[9]. Tinoco, V., et al., *A review of advanced controller methodologies for robotic manipulators: V. Tinoco et al.* International Journal of Dynamics and Control, 2025. **13**(1): p. 36.

[10]. Marrero, D., J. Kern, and C. Urrea, *A novel robotic controller using neural engineering framework-*

based spiking neural networks. Sensors, 2024. **24**(2): p. 491.

[11]. Kong, L., et al., *Adaptive fuzzy control for coordinated multiple robots with constraint using impedance learning.* IEEE transactions on cybernetics, 2019. **49**(8): p. 3052-3063.

[12]. Lewis, F.L., *Neural network control of robot manipulators.* IEEE Expert, 2002. **11**(3): p. 64-75.

[13]. Kunal, K., et al., *AI-Driven Intelligent Control Strategies for Industrial Robotics: A Reinforcement Learning Approach.* International Journal of Basic and Applied Sciences, 2025. **14**(2): p. 429-440.

[14]. Solovyeva, E.B. and A. Abdullah, *Controlling system based on neural networks with reinforcement learning for robotic manipulator.* Информационно-управляющие системы, 2020(5 (108)): p. 24-32.

[15]. Caregnato-Neto, A., et al., *ARMCHAIR: integrated inverse reinforcement learning and model predictive control for human-robot collaboration.* International Journal of Social Robotics, 2025: p. 1-17.

[16]. Ren, Y., et al., *A Survey on LiDAR-based autonomous aerial vehicles.* IEEE/ASME Transactions on Mechatronics, 2025.

[17]. Muktadir, M., et al., *Uncrewed Ground Vehicles (UGVs) and Nature-Inspired Designed Robot DIGIT and SPOT: A Review.* American Journal of Engineering and Applied Sciences, 2022. **15**(4): p. 274-287.

[18]. Rodriguez-Guerra, D., et al., *Human-robot interaction review: Challenges and solutions for modern industrial environments.* Ieee Access, 2021. **9**: p. 108557-108578.

[19]. Langås, E.F., M.H. Zafar, and F. Sanfilippo, *Exploring the synergy of human-robot teaming, digital twins, and machine learning in Industry 5.0: a step towards sustainable manufacturing.* Journal of Intelligent Manufacturing, 2025: p. 1-24.

[20]. Azeez, S., R.K. Mandava, and N.S. Naik, *A Novel Review on Quadruped Robots Design Variants, Gait Modulation, and Motion Planning Schemes.* Journal of Field Robotics, 2025. **42**(7): p. 3615-3693.

[21]. Singh, S., et al., *Bio-Inspired robotics: kinematic and gait analysis of quad and Hexa-Legged systems.* Journal of Robotics and Control (JRC), 2025. **6**(2): p. 757-768.

[22]. Zhou, X., et al., *MEMS: The sensory nervous system for embodied AI robots.* SmartBot, 2025. **1**(3): p. e70004.

[23]. Bai, Y., et al., *A review of brain-inspired cognition and navigation technology for mobile robots.* Cyborg and Bionic Systems, 2024. **5**: p. 0128.

[24]. Ušinskis, V., et al., *Sensor-fusion based navigation for autonomous mobile robot.* Sensors, 2025. **25**(4): p. 1248.

[25]. Langås, E.F., M.H. Zafar, and F. Sanfilippo, *Exploring the synergy of human-robot teaming, digital twins, and machine learning in Industry 5.0: a step towards sustainable manufacturing.* Journal of Intelligent Manufacturing, 2026. **37**(3): p. 999-1022.