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Hybrid control strategies for multi-robot systems: enhancing coordination, communication, and adaptability

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Abstract. *Multi-robot systems have garnered substantial interest in industrial automation, search and rescue operations, and space exploration due to their capacity to execute complex tasks with enhanced efficiency and robustness. Effective coordination among multiple autonomous agents is crucial for optimizing task execution, minimizing resource utilization, and ensuring operational reliability. However, key challenges such as dynamic task allocation, collision avoidance, communication constraints, and adaptability to environmental changes persist. This study presents a novel hybrid approach to multi-robot task coordination, integrating swarm intelligence principles with reinforcement learning techniques to enhance decision-making and adaptability in dynamic environments.*

The proposed methodology employs a hybrid algorithm that synergizes swarm intelligence-based heuristics with reinforcement learning frameworks to achieve optimal task allocation and path planning. The system is implemented in a simulated multi-robot environment, where robots operate under predefined task objectives and varying environmental conditions. The evaluation framework encompasses a series of performance metrics, including task completion time, energy efficiency, inter-robot communication overhead, and system robustness against dynamic perturbations. Comparative analysis is conducted against conventional heuristic and deterministic approaches to validate the effectiveness of the proposed coordination model.

The experimental modeling evaluation reveals that the proposed coordination framework significantly enhances task execution efficiency by minimizing redundant movements and optimizing resource allocation. Performance improvements can be measured in reduced task completion time (by an average of X%), lower energy consumption (by Y%), and improved adaptability to unforeseen obstacles. Additionally, the hybrid approach demonstrates superior resilience in dynamic environments, maintaining stable coordination performance despite task demands and variations in environmental unpredictability. Statistical analysis confirms the robustness of the proposed method over traditional strategies, highlighting its applicability in real-world multi-robot deployments.

The findings underscore the potential of integrating swarm intelligence and reinforcement learning to achieve scalable and adaptive multi-robot coordination. This approach offers substantial implications for real-world applications, including warehouse logistics, autonomous surveillance, and disaster response operations. Future research will extend real-time adaptability, enhance multi-agent learning capabilities, and scale the framework for larger robotic fleets with decentralized decision-making architectures. Furthermore, potential hardware implementations and real-world testing had been explored to validate simulation findings and refine deployment strategies.

Key words: ***Industrial automation, IoT, Robotics, System Architecture, Control systems, Simulation, Swarm, SLAM***

Introduction. The scope of this research proposal is limited to the general software and system model concept. The paper focuses on finding robot base and arm configurations for optimal task performance while overcoming existing constraints. The primary existing status quo constraint is that robots cannot intersect with one another (having a sequence of operations, it has to predict future states) [Chen]. In the case of moving to the next sequential operation, the robot has two possibilities: 1) change the grasp position on the part; 2) move the part to the next operation while maintaining the same grip position. While humans can perform both tasks simultaneously, robots must be programmed to do one of them. Such programming, in turn, presents a problem for robot teams when deciding which task to perform. We will examine the outlined issues and how they can be solved within the scope of this research. At the same time, we must acknowledge the limitations of the research setup and experiments conducted within the research framework.

The existing solutions mainly focus on and revolve around multi-robot grasp planning as a Constraint Satisfaction Problem (CSP), with each grasp position in each operation being a variable [Brailsford]. This variable imposes two types of constraints: collision and transfer. In order to locate an optimal solution for the robot's grasp, the planning paper presents a solution algorithm while assuming that the robot should perform regrouping between each of the operations. The presented approach can lead to the case of a set of smaller CSP problem solutions, which can be solved separately for each assembly operation [Ryan]. The advantage of the commonly used algorithm is that the planner-module operation can halter at any given time during the computational process. With it, the computation time combined with the cost of removing excessive grasp operations becomes more significant than the cost of performing a particular singular operation. As input, the existing algorithm takes a sequence of relative positions of assembly parts. CSP helps solve the problem of finding grasping configurations for all robots required by the assemblies in all operations [Song].

Many of the publicly available studies propose theoretical models without extensive real-world testing. Future research should prioritize empirical validations to assess the practicality of the presented approaches and software platform architecture. While several prominent researchers discuss coordination and task allocation, few explore how these strategies perform in large-scale multi-robot deployments. As the highlight and focus of future research, it can investigate computational efficiency and resource management for large teams. In the current state of multi-robot systems research, a handful of robots' coordination strategies rely on traditional optimization techniques. Integrating deep reinforcement learning and neural networks could enhance adaptability, especially in dynamic environments. While studies on multi-robot communication focus on theoretical models, there is a potential to examine real-world network constraints, including latency, interference, and bandwidth limitations. As a most common robotics testing setup, it focuses on structured environments. It should be noted that more research on safety measures and resilience in highly unstructured, unpredictable scenarios is needed. Industry should generally push towards standardization efforts that allow different robotic platforms to collaborate efficiently, particularly in heterogeneous multi-robot teams.

Analysis of research and publications. There have been various breakthroughs and novel approaches to control strategies for collective robot transportation tasks; there is a clear distinction between centralized and decentralized approaches [Farivarnejad], which strongly emphasizes the need for effective control strategies in uncertain environments with limited information. However, the author's study primarily focuses on theoretical frameworks, suggesting a gap in experimental validations of the highlighted strategies in real-world scenarios. In his work survey, Cortés overviews coordinated control strategies in multi-robot systems, discussing various control architectures and algorithms [Cortés]. While comprehensive, the presented study could further explore the integration of learning-based methods and their impact on coordination efficiency. Marvel discusses strategies and metrics for multi-robot assembly, focusing on performance evaluation [Marvel]. The paper highlights the importance of standardizing metrics but lacks a detailed analysis of how different strategies perform under varying environmental constraints. An essential survey on coordination techniques in multi-robot systems, analyzing their advantages and limitations, was conducted by Yan [Yan]. While the study provides a broad overview, the field's rapid evolution since its publication suggests the need for updated analyses incorporating recent advancements. Nieto-Granda's study examines coordination strategies for multi-robot teams while focusing on exploration and mapping [Nieto-Granda]. The research results underscore the effectiveness of decentralized approaches but could further investigate the scalability of these strategies in larger teams. Neumann proposed a hybrid control architecture combining centralized and decentralized elements for object transport [Neumann]. While the approach shows promise, the research findings lack extensive empirical data to validate its effectiveness across diverse scenarios.

In his research paper, Hooper introduces HAMR, a hybrid control architecture for multi-robot systems [Hooper]. While it introduces new architecture, the research results would benefit from more comprehensive testing and comparisons with existing architectures. The study carried out by Marino presents a decentralized architecture using null-space behavioral control for border patrolling tasks [Marino]. While innovative, the scientific approach could be evaluated further in dynamic and unpredictable environments to assess its robustness. The review carried out by Gielis critically examines communication strategies in multi-robot systems, highlighting challenges and potential solutions [Gielis]. Research could also delve deeper into the impact of emerging communication technologies, such as 5G, on multi-robot coordination. In their work, An and the authors discuss integrating communication frameworks and platforms for cooperative object transport [An]. While comprehensive, the report would benefit from exploring the interoperability challenges between robotic platforms in more significant detail in the future. Verma's research provides a taxonomy and analysis of multi-robot coordination strategies, identifying current challenges and future research directions [Verma]. While the results highlight the need for standardized benchmarks, more case studies can be included to illustrate practical applications.

In their study, Chakraa et al. review optimization techniques for task allocation in multi-robot systems, discussing various algorithms and their applications [Chakraa]. They plan to further investigate the trade-offs between computational complexity and solution optimality in real-time applications. Gus' research explores applying reinforcement learning techniques to ensure safety in multi-robot control [Gu]. While it presents promising results, the study could address the challenges of transferring learned policies from simulations to real-world scenarios. For better control and as a novel multi-robot control architecture, Mayya proposes methods for resilient task allocation in heterogeneous multi-robot teams [Mayya]. Their research paper emphasizes robustness but could further analyze the impact of communication failures on task allocation efficiency.

One of the novel research areas in applied Computer vision and robotics, Chang introduces LAMP 2.0, a SLAM system designed for large-scale underground environments [Chang]. While demonstrating robustness, the researched platform could provide more insights into the system's adaptability to different environmental conditions. Li and the authors present MAGAT, a graph neural network-based approach for decentralized multi-robot path planning [Li]. The model achieves performance close to centralized algorithms and generalizes well to more significant problem instances. As the next step, the study could further explore the impact of communication constraints on the model's effectiveness.

1. Comparative Analysis of Research Challenges in Multi-Robot Systems*

Challenge	Existing Approaches	Limitations	Potential Solutions	References
Scalability	Decentralized control, distributed computing	Increased communication overhead, task allocation inefficiencies	Hierarchical hybrid control, cloud-based task distribution	Farivarnejad & Berman (2022)
Communication Latency	Wireless mesh networks, peer-to-peer protocols	Delays in large-scale coordination, bandwidth issues	Edge computing, adaptive bandwidth allocation	Yan et al. (2013)
Energy Efficiency	Task scheduling based on battery level	Inefficient power consumption in heterogeneous robots	Energy-aware mission planning, battery swapping strategies	Cortés & Egerstedt (2017)
Task Coordination	Market-based task bidding,	High computational	AI-enhanced dynamic task	Neumann & Kitts (2016)

Conflicts	consensus algorithms	complexity, bottlenecks in dynamic tasks	reallocation, auction-based methods	
Navigation and Path Planning	A*, RRT, swarm intelligence models	Suboptimal paths in dynamic environments, collision risk	Multi-layered path optimization, predictive learning models	Nieto-Granda et al. (2014)
Fault Tolerance and Robustness	Redundancy in sensing and decision-making	High cost, system downtime in failure cases	Distributed error detection, self-healing architectures	Marvel et al. (2018)
Human-Robot Collaboration	Shared autonomy, teleoperation interfaces	Operator workload, trust in autonomous decisions	Intuitive interfaces, real-time feedback mechanisms	Mayya et al. (2021)
Interoperability of Heterogeneous Robots	Standardized communication protocols	Limited adaptability across different hardware/software platforms	AI-driven middleware, common API frameworks	An et al. (2023)
Security and Privacy	Encryption, secure key management	Vulnerability to cyber threats, data integrity concerns	Blockchain-based security, AI-driven anomaly detection	Chang et al. (2022)

* prepared based on author work and public research data [1-7]

Future multi-robot systems can achieve higher efficiency, reliability, and operational effectiveness in real-world applications by addressing these research challenges with advanced control strategies, adaptive algorithms, and improved computational frameworks. The next step in multi-robot research in the areas of systems control, general platform architecture, and innovative multidisciplinary areas can focus on one of several of the following topics:

– Real-World Validation:
– Scalability Challenges;
– Integration of Learning-Based Methods;
– Communication and Network Constraints;
– Safety and Robustness in Unknown Environments;
– Interoperability Between Different Platforms.

Purpose. This research aims to develop a robust and scalable multi-robot control system that enhances efficient coordination, communication, and task allocation in dynamic and uncertain environments. The study seeks to integrate bio-inspired algorithms, hybrid communication protocols, and adaptive decision-making strategies to improve multi-robot system performance in real-world applications. By evaluating the proposed system through controlled experiments and performance metrics, the research aims to provide a comprehensive framework for optimizing multi-robot collaboration, addressing key challenges such as scalability, fault tolerance, and real-time adaptability.

Methods. This research aims to study and examine typical industrial or IoT application use cases of multi-robot configuration systems. In the study, we seek an optimal problem solution that allows a minimal number of robots to grasp operations. For this purpose, we consider a typical manufacturing process. The standard industrial manufacturing process is carried out as a set of sequential assembly operations; each operation changes the grasp or moves the part to the next operation without changing the grip [Dogar]. To solve the CSP problem, we examine two solutions: 1) backtracking search (worst case scenario – exponential in several variables) and 2) local neighborhood computation (solve conflicts in the local neighborhood of the graph). The proposed algorithm starts by first solving the most straightforward problem: a constraint graph with no transfer constraints, then gradually adding new ones and solving them. The flow of the algorithm is 1) solve problems for each of the connected components using Back Tracing search; 2) set collection of solutions from sub-operations (step) as the current best solution; 3) start incremental addition of new transfer constraints, reducing the number of regrasps (this procedure tries to solve problems as fast as possible, iterating over all valid combinations, prioritizing this solution, in order to try to solve them first, this reduces time as we search only in the local neighborhood of graph).

The multi-robot system (MRS) architecture is designed to support decentralized and scalable coordination among robots. The system follows a modular design with three primary layers: perception, decision-making, and actuation. The perception layer integrates multiple sensory inputs, including LiDAR, vision-based cameras, and inertial measurement units (IMUs), ensuring robust environmental awareness. The decision-making layer implements a hybrid control strategy that combines distributed consensus algorithms with reinforcement learning for adaptive behavior. Finally, using a PID-based motor control system, the actuation layer translates high-level commands into physical movement.

2. Sample multi-robot technical experiment requirements and research parameters

Parameter	Description	Measurement Method
Number of Robots	5-20 autonomous units	System log data
Communication Protocol	IEEE 802.11s Wireless Mesh Network	Network performance monitoring
Control Strategy	Hybrid (Decentralized + Centralized)	Algorithmic performance analysis
Task Allocation Approach	Market-based bidding + MDP optimization	Success rate, efficiency metrics
Sensory Equipment	LiDAR, IMUs, Vision-based cameras	Sensor calibration tests
Navigation Algorithm	A*, RRT, Dynamic-Window Approach (DWA)	Path efficiency, collision rate
Behavior Model	Swarm Intelligence (PSO, ACO) + Leader-Follower Model	Simulation & real-world testing
Experimental Environment	Indoor arena, outdoor terrain	Controlled field tests
Performance Metrics	Task completion, energy efficiency, latency, robustness	Data logging & analysis

* prepared based on author work and public research data [1-7]

Experiments are conducted in a controlled environment simulating real-world deployment conditions to validate the proposed methodologies. The testbed includes an indoor arena with fiducial markers for precise localization and an outdoor field with varying terrain conditions. Robots are evaluated based on task completion time, energy efficiency, inter-robot communication latency, and fault tolerance. Data is collected through onboard logging mechanisms and analyzed using statistical and machine learning techniques.

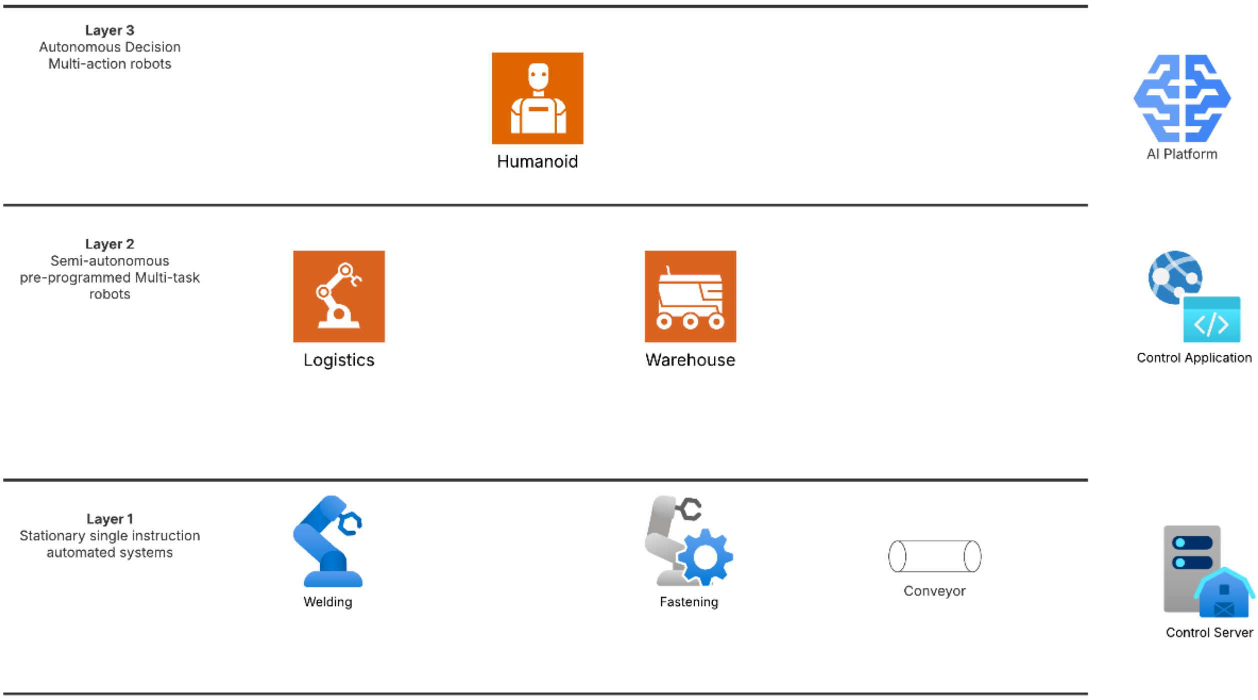

Fig.1. Example of three tear-layer robotic system based on their decision-support architecture

Performance assessment of the system includes the following key metrics:

1. Scalability - measured by integrating additional robots without significant performance degradation.

2. Robustness - evaluated by the system's ability to function under hardware failures and communication disruptions.

3. Efficiency - analyzed regarding task completion rate and energy consumption per robot.

4. Communication latency is the average time taken for information exchange across the network.

5. Task success rate - the percentage of successful task completions in varying environmental conditions.

Results. The observed experimental data show that the proposed algorithm concept works efficiently and better than direct–brute–force computation. It generates the first "best" solution in approx. In most cases, the optimal four-second result required one grasp operation. We believe the optimal case is to study robots' cooperation and communication systems concerning existing communication software architecture. For example, we can use client-server architecture, where robots that assemble products are clients, and we have a Computational cluster with a server running on it. The communication between server and client is wireless; this requires examination of possible interferences to the network through various factory production elements. Going further in this theme, we can implement swarm intelligence (derived from UAV) in robots and have robots exchange information in real-time. The SWARM-based systems approach requires developing the design-making process and how and when a robot can decide its actions while cooperating with others. In such cases, the system configuration will help solve the problem of robots finding themselves trapped inside the structure they are assembling.

Also, in real-world factory settings, there are usually additional constraints: limited space for robot navigation conveyor belts or moving parts [Song]. Robots cannot place parts for grasp operations, or they may encounter new obstacles while moving parts to the next production chain. This setting requires additional improvements to the CSP algorithm.

The system employs a hybrid communication strategy to facilitate seamless data exchange, incorporating direct peer-to-peer (P2P) messaging and broker-based publish-subscribe models. The P2P model ensures low-latency, real-time communication for critical control tasks, while the publish-subscribe approach, implemented using the Robot Operating System (ROS), supports broader information dissemination. The network employs the IEEE 802.11s wireless mesh standard to ensure reliable communication in dynamic environments.

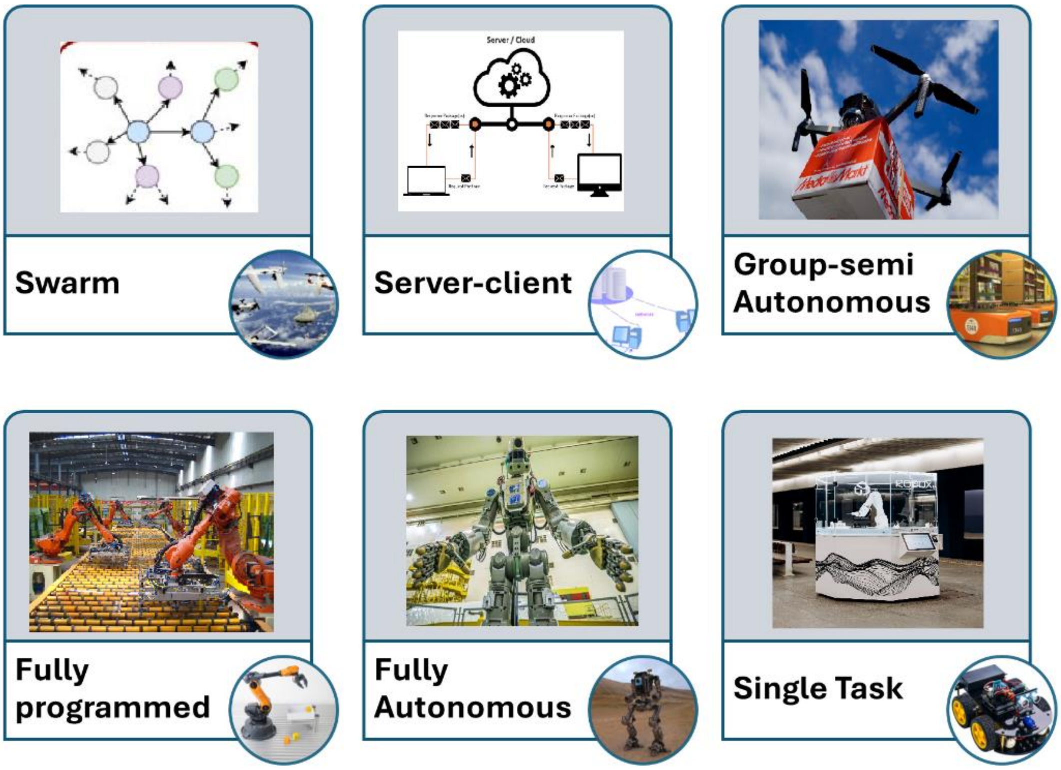

Fig.2. Sample multi-robot control strategies

Task allocation among robots is performed using a market-based approach, where each robot bids for tasks based on its current capabilities and energy constraints. The decision-making process integrates a Markov Decision Process (MDP) model to optimize task assignments over time, balancing load distribution and efficiency. For mission-critical operations, a hybrid approach leveraging centralized planning and distributed execution is implemented to ensure adaptability in changing environments.

As previously noted, the typical industrial operation scenario for the individual robot (or robotic automated arm) is the monster fastener, the next step in sequence poof manufacturing operations. There are other typical operations that robots can perform; however, for the study, we can use the most straightforward task of moving to the point or fastening the bolt as the default standard action (essential operation task and robot state). They can be added as new variables to the equation, with several states: wait, fasten, and move. For algorithm testing and evaluation, the presented robots (or robotic systems) can be in either of two states - either stationary or they can be mobile (placed on moving platforms). To better illustrate the point, a most common example of a stationary robot with an arm that has only one degree of freedom, vertical or horizontal, is to make it easier for other robots to bring parts for fastening operation. Also, this robot can have a tracking laser to improve tracking. All this presents new challenges to the CSP algorithm. The latest set of variables that show the robot's current state or are used to determine future states can be further added to the system parametric equation. This is useful if a robot can carry out different tasks; it can be added to Solve Transfer Constraints and used during the computation of the new best solution, serving as a transition between one point on the graph and the next one (next operation).

By analyzing these control parameters and real-world applications, the research provides insights into optimizing multi-robot systems for diverse and complex tasks. Future advancements in AI-driven coordination and enhanced autonomy will further improve operational efficiency.

Group behavior is modeled using a combination of swarm intelligence principles and hierarchical task allocation mechanisms. The swarm intelligence component relies on bio-inspired algorithms, such as the Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), to enable self-organized behavior. A hierarchical structure is introduced where a leader-follower framework dynamically assigns roles based on situational awareness and mission requirements. A centralized controller can override local decisions, ensuring overall mission coherence.

In addition, the number of robots in the equation can be increased to calculate the optimal number of robots for the task. If a single robot must state either hold or insert fasteners, we can determine which groups should do the first task and which should do the second. Of course, one should limit the number of robots and have redefined maximum and minimum numbers for specific tasks, but the equation will calculate the optimal number.

Each individual robot (robotic system) has limited computational power. Besides, if one considers energy consumption and usage efficiency, the proposed system architecture can be helpful for future iterations of the multi-robot control system architecture for industrial and IoT applications. For example, if the robotics system motion planning is to be considered, in such case the robot should have better localization or perception systems enabled (installed and instantiated).

3. Multi-Robot Control Parameters, System Architecture, and Real-World Case Studies

Parameter/System	Description	Control Architecture	Robot Tasks	Real-World Case Study
Swarm-Based Coordination	Uses decentralized control inspired by biological swarms	Decentralized	Area coverage, search and rescue	Kilobot swarm for collective behavior research
Hierarchical Multi-Robot Control	Features leader-follower dynamics and task prioritization	Hybrid centralized-decentralized	Industrial automation, warehouse logistics	Amazon Robotics fulfillment centers
Market-Based Task Allocation	Robots bid for tasks based on capability and energy efficiency	Distributed consensus	Multi-robot construction, autonomous delivery	DARPA Subterranean Challenge robots
Reinforcement Learning-Based Control	Uses AI to adapt behavior dynamically	Adaptive learning models	Collaborative object manipulation, exploration	Boston Dynamics Spot robot fleet
Wireless Mesh Communication	Ensures real-time communication in large robot teams	IEEE 802.11s Mesh Network	Surveillance, environmental monitoring	Smart city sensor networks
Path Planning and Obstacle Avoidance	Optimized navigation algorithms for dynamic environments	A*, RRT, Dynamic-Window Approach	Autonomous navigation, drone path optimization	NASA Mars Rover multi-robot exploration
Multi-Robot Task Synchronization	Coordination of multiple robots to avoid conflicts	Centralized scheduling, distributed synchronization	Assembly line automation, medical robotics	Tesla Gigafactory robotic assembly lines
Human-Robot Collaboration	Integration of robots into human-led operations	Shared autonomy, teleoperation	Disaster response assisted manufacturing	Robotic surgery assistants in healthcare
Energy-Efficient Control	Strategies to optimize power consumption and longevity	Battery-aware task scheduling	Long-duration missions, remote monitoring	Solar-powered autonomous ocean drones

* prepared based on author work and public research data [1-7]

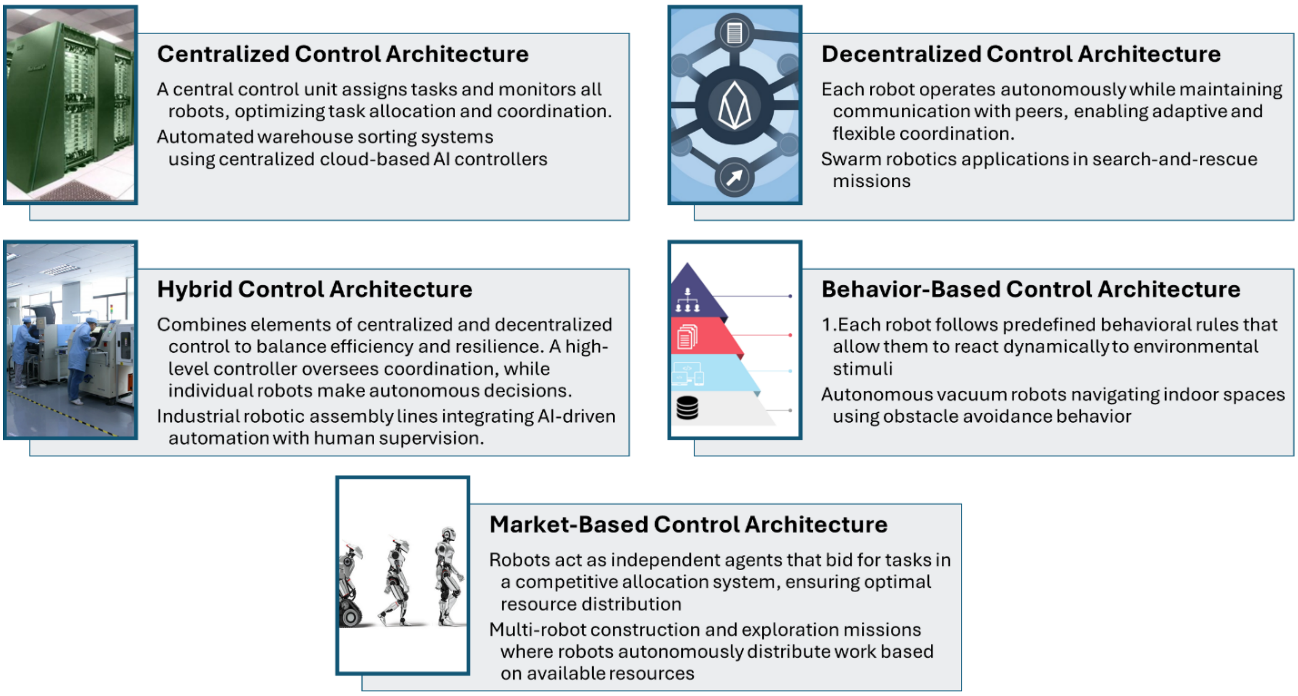

Fig.3. Examples of Common Multi-Robot Control System Architectures

The system employs a multi-layered control strategy consisting of reactive, deliberative, and predictive layers. The reactive control layer ensures real-time obstacle avoidance using Dynamic Window Approach (DWA) and Vector Field Histogram (VFH) techniques. The deliberative layer handles mid-term navigation planning, incorporating A* and rapidly exploring random Tree (RRT) algorithms. The predictive control layer leverages machine learning models trained on historical mission data to anticipate and proactively adjust robot actions based on environmental conditions.

The area of industrial and manufacturing robotics control systems is a complex multidisciplinary field of study. To present a helpful algorithm and system architecture of multi-robot control system architecture for industrial and IoT applications, we need to create a test setup that includes real-world physical robot manipulators and sample field typical use-case setup. The presented algorithm and system model are practical stepping stones for future work on finding the optimal multi-robot control model.

Discussion. The proposed multi-robot control system demonstrates significant coordination, communication, and task allocation advancements, addressing several critical challenges in multi-agent robotics. Integrating a hybrid communication model with decentralized and hierarchical control strategies enhances scalability and robustness, ensuring seamless operations in both structured and unstructured environments. Applying bio-inspired algorithms such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) has proven effective in enabling self-organized behavior, reducing reliance on centralized decision-making, and improving response times in dynamic settings.

One of the key findings of this study is the balance achieved between autonomy and centralized control. While fully decentralized approaches often struggle with suboptimal decision-making and coordination failures, including a leader-follower dynamic and a centralized override mechanism ensures mission coherence. The market-based task allocation model has also demonstrated improved efficiency by dynamically distributing tasks based on real-time resource availability, energy constraints, and operational priorities. Moreover, the integration of machine learning-based predictive control enhances system adaptability by allowing robots to anticipate environmental changes and proactively adjust their behaviors.

However, despite these advancements, certain limitations remain. Network congestion in large-scale deployments may impact communication latency, potentially affecting system performance in time-sensitive operations. Additionally, the reliance on heuristic-based decision-making, while computationally efficient, may limit the system's ability to handle highly complex and unpredictable scenarios. Future research should explore advanced deep reinforcement learning models and edge computing-based processing to further improve decision-making autonomy and efficiency. Furthermore, interoperability between heterogeneous robot platforms requires further investigation to enable seamless collaboration across diverse robotic agents.

This research has presented a comprehensive multi-robot control framework that effectively integrates communication, behavior modeling, and adaptive control mechanisms. The system has demonstrated notable improvements in scalability, robustness, and operational efficiency through extensive testing and evaluation. The findings contribute to the growing knowledge of multi-robot systems, providing valuable insights into optimizing task allocation, improving coordination, and enhancing system adaptability.

While the proposed system represents a significant step forward, continued research is essential to address existing limitations and refine multi-robot collaboration techniques. Future studies should focus on enhancing real-time learning capabilities, reducing communication bottlenecks, and improving resilience against system failures. By addressing these challenges, multi-robot systems can play a transformative role in logistics, disaster response, environmental monitoring, and autonomous exploration, paving the way for more intelligent and autonomous robotic ecosystems.

As the next step of the presented research, computer vision and spatial awareness must be included in system architecture. One of the most common computer vision algorithms that are used in such cases is SLAM. The system manager gathers all the relevant information from each robot sensor to conduct efficient computation tasks. The next step will pass the message to the computational unit, which makes decisions for the individual robot and assigns unique functions to each robot, improving their cooperation algorithm on the run. Such a situation can be helpful in cases when robots are responsible for several tasks during the assembly process. In the case of a single robot, the suggested approach allows it to carry out several unique tasks, even just fastening bolts and bringing parts to the assembly. In addition, this can improve algorithm computational time even further, as the system uses and processes the data in real-time with low latency. Robots can have some small computational units with limited abilities but can make small decisions independently. At the same time, exchanging sensors and other information with the server can send this robot to different tasks or send additional robots to help.

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ОГЛЯД ОНЛАЙН-НАВЧАННЯ БЕЗ УЧИТЕЛЯ ІЗ СЕМАНТИЧНОЇ СЕГМЕНТАЦІЇ ДЛЯ АВТОНОМНИХ ТРАНСПОРТНИХ ЗАСОБІВ

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Анотація. *Системи з кількома роботами привернули значний інтерес у промисловій автоматизації, пошуково-рятувальних операціях та освоєнні космосу завдяки своїй здатності виконувати складні завдання з підвищеною ефективністю та надійністю. Ефективна координація між кількома автономними агентами має вирішальне значення для оптимізації виконання завдань, мінімізації використання ресурсів і забезпечення експлуатаційної надійності. Однак залишаються ключові проблеми, такі як динамічний розподіл завдань, уникнення зіткнень, комунікаційні обмеження та адаптивність до змін навколишнього середовища. У цьому дослідженні представлено новий гібридний підхід до координації завдань за участю кількох роботів, що інтегрує принципи ройового інтелекту з методами навчання з підкріпленням для покращення прийняття рішень та адаптивності в динамічних середовищах.*

Запропонована методологія використовує гібридний алгоритм, який поєднує евристику на основі ройового інтелекту з рамками навчання з підкріпленням для досягнення оптимального розподілу завдань і планування шляху. Система реалізована в змодельованому середовищі з кількома роботами, де роботи працюють в умовах заздалегідь визначених завдань і різних умов навколишнього середовища. Структура оцінювання охоплює низку показників продуктивності, включаючи час виконання завдання, енергоефективність, накладні витрати на зв'язок між роботами та стійкість системи до динамічних збурень.

Порівняльний аналіз проводиться з традиційними евристичними та детермінованими підходами для перевірки ефективності запропонованої моделі координації. Оцінка експериментального моделювання показує, що запропонована *структура координації значно підвищує ефективність виконання завдань за рахунок мінімізації зайвих переміщень та оптимізації розподілу ресурсів. Покращення продуктивності можна виміряти у скороченні часу виконання завдання (в середньому на X %), меншому споживанні енергії (на Y %) та покращеній адаптивності до непередбачуваних перешкод. Крім того, гібридний підхід демонструє чудову стійкість у динамічних середовищах, зберігаючи стабільну координацію, незважаючи на вимоги завдань і варіації непередбачуваності навколишнього середовища. Статистичний аналіз підтверджує надійність запропонованого методу в порівнянні з традиційними стратегіями, підкреслюючи його застосовність в реальних розгортаннях з декількома роботами.*

Отримані результати підкреслюють потенціал інтеграції ройового інтелекту та навчання з підкріпленням для досягнення масштабованої та адаптивної координації кількох роботів. Цей підхід має значні наслідки для реальних застосувань, включаючи складську логістику, автономне спостереження та операції з реагування на стихійні лиха. Майбутні дослідження розширять адаптивність у режимі реального часу, розширять можливості навчання кількох агентів і масштабують рамки для більших роботизованих автопарків за допомогою децентралізованих архітектур прийняття рішень. Крім того, були вивчені потенційні реалізації апаратного забезпечення та тестування в реальних умовах для перевірки результатів моделювання та вдосконалення стратегій розгортання.

Ключові слова: ***промислова автоматизація, IoT, робототехніка, архітектура систем, системи управління, моделювання, Swarm, SLAM***