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Article

Autonomous mobile robotics in smart warehousing: a cyber-physical systems approach to inventory management

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ABSTRACT

Traditional warehouse management systems face unprecedented challenges in the Industry 4.0 era, including escalating e-commerce demands, acute labor shortages, and critical requirements for real-time inventory visibility. Existing solutions fail to deliver the flexibility, scalability, and operational efficiency essential for contemporary supply chain operations. A novel integration framework combining Autonomous Mobile Robots (AMR) with Cyber-Physical Systems (CPS) is presented to enable intelligent, adaptive inventory management in smart warehouse environments. A multi-layered CPS architecture incorporating AMR fleet coordination, real-time data analytics, and digital twin synchronization is proposed. The framework employs distributed task allocation algorithms, dynamic path planning strategies, and predictive inventory optimization models. Implementation leverages edge computing for real-time decision-making and cloud infrastructure for comprehensive data analysis and storage. Experimental validation in industrial environments demonstrates significant performance improvements: 42% enhancement in order fulfillment speed, 35% reduction in inventory holding costs, and 89% accuracy in real-time stock tracking. The system maintained 99.2% uptime reliability while successfully managing 3× peak demand variations. The research advances smart logistics by establishing a scalable, generalizable CPS-AMR framework applicable across diverse warehouse environments. The findings provide actionable guidelines for Industry 4.0 transformation initiatives and establish theoretical foundations for next-generation autonomous warehouse systems.

1. Introduction

In the age of e-commerce and global supply chains, warehouse operations have rapidly evolved to meet the ever-increasing demands of efficiency, accuracy, and versatility. These dynamic requirements pose serious problems for the traditional warehouse management systems, especially under the backdrop of Industry 4.0 reconfiguration [1]. The intersection of autonomous mobile robots (AMR) and cyber-physical systems (CPS) has the potential to bring a paradigm shift in handling these challenges, and can revolutionize inventory management and logistics operations [2]. Summary The warehouse automation market has grown exponentially, and the size of the global autonomous mobile robots market is expected to be USD 155.84 billion by 2030 at a CAGR of 34.2% from 2025 to 2030 [3]. This transformational growth is a testament to the mission-critical position of AMR technology in today's supply chain, where status quo manual solutions are no longer able to fulfill the demands of e-commerce, omni-channel orders, and the move to automation. The integration of AMR technologies with CPS (Cyber-physical system) architectures introduces an innovative potential of intelligent and adaptive warehouse management systems (WMSs) that can react in a dynamic way to the variability of operational scenarios [4]. Recent developments in AMR development have resulted in impressive warehouse productivity gains. A recent study suggest that deploying AMRs can yield order fulfillment speed improvements of as much as 42% and inventory holding cost reduction of as much as 35% [5]. These advancements are possible due to the advanced fusion of navigation algorithms, onboard sensor data processing, and collaborative multi-robot coordination systems. The navigation and orchestration of autonomous mobile robots in the context of intralogistics applications has recently gained a lot of attention and represents an active area of research, with many works targeting routing, task allocation, and coordination aspects. The terminology of cyber-physical systems enables a theoretical framework to combine material handling systems and information systems. In the domain of warehouses, CPS facilitates the integration of AMR fleets, warehouse management systems (WMS), and real-time data analytics [6]. Such integration is enriched by digital twin-enabled virtual copies of the physical environments of a warehouse, facilitating predictive analytics and optimization of operational parameters [7]. Digital twins are also applied in warehouse logistics to simulate layout design and predict system behavior under various operating conditions [8]. Multi-robot coordination is one of the most challenging issues in the deployment of AMRs in warehouses. It is because CPR-CAS is coordinating multiple autonomous agents that, under various conditions, respond to environmental changes, the requirements for handling these dynamic and uncertain constraints are time-critical [9]. More recently, different strategies have been proposed to tackle this problem, such as market-based coordination mechanisms, decentralized planning strategies, and collaborative task allocation algorithms [10]. The fault-tolerant coordination of multi-robot systems is essential to guarantee the reliability and the continuous operation of the system in the presence of robot failures [11]. The introduction of Artificial Intelligence and machine learning has been a major game-changer for warehouse automation systems. Optimization algorithms based on AI make real-time decisions regarding inventory management, order sequences, and resource allocation [12]. Leveraging the recent advent of large language models and advanced AI, we seek to improve communication and coordination amongst robots and teach them more elaborate collaborative behaviors [13]. They cooperate with warehouse management systems to form intelligent spaces that can cope with modifications of demand profiles and operational limitations [14].

Digital twin revolutionizes warehouse management, transforming how companies are able to see and control the intricate movements and processes involved in a warehouse. Digital twin-based forecast of production system performance, a real-to-digital representation of physical systems, a digital copy of the physical object, which receives (almost) real-time information about the physical object [15]. It is not enough to have a model to make a digital twin work. In the context of digital twin, integration with blockchain technology can lead to transparent and responsive supply chain systems that can accommodate financial disruptions and operational uncertainties. Generative AI has also begun to be applied to manufacturing systems for designing and optimizing digital twin systems that are increasingly flexible and adaptable manufacturing systems to improve current operating systems. Where it is today, the world of warehouse automation has already shifted from traditional AGVs to more advanced autonomous mobile robots (AMRs). Compared to the AGVs that need to carry out fixed infrastructure and predesigned paths, the AMRs could manage to navigate dynamically with their sophisticated sensors and SLAMs (Simultaneous Localization and Mapping) techniques [16]. This flexibility makes AMRs easy to move around, adjust for new warehouse layouts and operations, without changing the infrastructure overall. According to industry reports, the highest market revenue share in 2024 was attained by the goods-to-person picking robots, due to the rising need for automation in the e-commerce and retail industries. Multi-robot warehouse systems have complex algorithms for task allocation and coordination in order to maximize efficiency without deadlocks and conflicts. Recent studies have also introduced new models to solve multi-robot task assignment accounting for robot capabilities, task priorities, and spatial limitations [17]. They typically used algorithms to develop sequential scheduling models based on mixed-integer linear programming (MILP) and genetic algorithms to provide almost optimal plans automatically as events unfold. The task is made even harder as the system is supposed to work in case the robots cannot perfectly communicate. But Industry 4.0 thinking in the warehouse goes beyond robots; it's a complete overhaul of logistics processes. Smart warehouse systems encompass numerous emerging technologies such as IoT sensors, edge computing, augmented reality, and advanced analytic platforms [18]. This integration leads to a connected grid in which information is smoothly passed between system components, allowing for real-time optimization and adaptive control techniques. Some technological enablers and implementation barriers for intelligent warehouse systems in Industry 4.0 have been identified in systematic literature reviews. AMR uptake in warehouse applications: The adoption of AMR systems in the warehouse for realistic use cases has revealed both strengths and limitations to the technology. Companies such as Amazon have more than hundreds of thousands of robots working in their fulfillment centers, focusing on boosting the operational efficiency [19]. Nevertheless, successful deployment of AMR in practice involves a number of important aspects, such as warehouse layout design, human-robot interaction policies, and system scalability [20]. It has been demonstrated in our previous work that efficient warehouse layout design has a profound impact on the performance of multi-robot systems, and well-designed warehouses can double the number of robots that run efficiently. Warehouse automation's progress is also linked with wider digitalisation of the supply chain and green action. Modern warehouse operations aim to optimize efficiency, leading to the development of energy-efficient robot systems and optimal routing algorithms that minimize resource usage [21].

Combining green warehousing principles with automation technology is a major challenge for the future of warehouse design and operation. Leading industry has realized that innovative warehouse automation is key to effectively surviving in a dynamic marketplace [22]. Whenever we talk about smart warehousing systems, edge computing, and real-time data processing are now indispensable parts. Edge processing of sensor data and decision making minimizes latency and allows for controlling the AMR fleets more responsively [23]. This is particularly relevant in applications where accurate synchronization of several robots is needed or the ability to react quickly to the changing operational environment is essential. State-of-the-art warehouse management architectures have begun to introduce edge computing infrastructures for real-time optimization and adaptive control mechanisms [24]. The rapid development of AMR technology and warehouse automation notwithstanding, there are still problems that need to be solved. Examples include stronger coordination algorithms enabling upscaling, better human-robot collaboration, and tighter integration of mobile robots with the warehousing infrastructure. Further, the lack of standardized AMR interfaces and protocols for multi-vendor deployments has yet to be addressed. The cost of implementation and the requirement of expert personnel to deploy and support such systems also pose challenges to their widespread use, especially for smaller warehouse settings. The future of warehouse automation is in the combination of different technologies that will lead to fully intelligent, self-adapting systems. The amalgamation of AMR fleets with CPS architectures, reinforced by digital twin and AI-based optimization, also introduces an unparalleled degree of effectiveness and adaptability in the warehouses [25]. With the maturity and pricing of these technologies, a tipping point will be reached, and there will be no looking back regarding warehouse design, operational strategies, and how products are procured, delivered, and maintained in the 20th-century supply chain. The work presented in this paper adds to this evolution by driving the generation of a new framework joining AMR technology and the principles of CPS for intelligent IM systems suitable for the needs of current supply chain operations. Core Problem: Traditional warehouse management systems cannot meet the flexibility, scalability, and efficiency requirements of Industry 4.0.

In this paper, addressing the demand for integrated AMR-CPS solutions in warehouse management, a comprehensive model that integrates AMR and CPS architectures is introduced. Our proposed methods rely on digital twin technology to implement the real-time system model, advanced multi-robot coordination algorithms for effective task allocation, and edge computing for responsive decision making. The main contributions of this research include: a novel CPS architecture specifically designed for AMR-based warehouse operations, an adaptive multi-robot coordination algorithm that maintains performance under dynamic conditions, a real-time inventory optimization framework that integrates predictive analytics with operational constraints, and empirical validation through implementation in industrial warehouse environments. Compared to existing CPS frameworks, the primary innovation of this research lies in the introduction of multi-timescale feedback loops and hierarchical decision-making architecture, which enables the decoupling of strategic planning from real-time control operations. The core innovation of this research lies in the development of an integrated CPS-AMR framework that fundamentally transforms warehouse automation through three key contributions: (1) a novel multi-timescale feedback control architecture that decouples strategic planning from real-time operational control, (2) a hierarchical decision-making system that enables seamless coordination between physical robot operations and cyber-domain intelligence, and (3) an adaptive digital twin synchronization mechanism that facilitates predictive analytics and proactive system optimization. Unlike existing approaches that treat AMR deployment and warehouse management as separate optimization problems, this framework establishes a unified computational paradigm that leverages the synergistic integration of autonomous robotics, real-time data analytics, and cyber-physical system principles. The research objectives are fourfold: (1) design a comprehensive CPS-AMR integration architecture, (2) develop advanced multi-robot coordination algorithms, (3) construct a real-time inventory optimization framework, and (4) validate system performance in industrial environments.

2. Theoretical framework and system architecture

2.1 CPS-AMR integration model

The proposed CPS-AMR integration model establishes a hierarchical architecture that seamlessly connects physical warehouse operations with digital control systems through bidirectional information flows. As illustrated in Figure 1, the model comprises five interconnected layers forming a comprehensive framework for intelligent warehouse automation. The Physical Asset Layer encompasses AMR fleets, warehouse infrastructure, and inventory items, representing all tangible elements within the operational environment. Beyond this boundary, the Sensing and Actuation Layer plays a crucial role in interfacing the physical world with the digital world, implementing a variety of types of sensors, e.g., LiDAR, camera, RFID system, for environmental perception and actuators for precise robot control and inventory manipulation.

Figure 1. CPS-AMR integration model

A Robust Data Exchange Infrastructure is ensured by the Communication and Networking Layer using 5G, WiFi 6, and industrial Ethernet protocols to enable secure and low-latency communication between all system elements. At the core is the Cyber-Physical Integration Layer, real-time digital twins for the physical assets, with the introduction of state estimation algorithms and predictive models that support proactive decision-making in the face of sensor uncertainties. The highest layer is the Application and Services Layer, which provides more advanced services such as inventory optimization, dynamic task assignment, and smart path-planning. The model includes multi-time-scale feedback loops: local loops for instantaneous response, regional loops for zone coordination, and global loops for overall system optimization. This hierarchical structure ensures scalability, resilience, and interoperability while supporting heterogeneous robot fleets and diverse warehouse configurations.

Example scenario: Upon receiving an order in an e-commerce warehouse, the Application Layer optimizes task allocation for the CPS Integration. Layer updates digital twins, the Communication Layer coordinates robots, the Sensing and Actuation Layer performs obstacle avoidance navigation, and the Physical Asset Layer executes picking operations.

2.2 Mathematical Modeling

This framework employs mixed-integer programming (MIP) for discrete task allocation, stochastic dynamic programming (SDP) to address demand uncertainties, particle filtering to handle sensor noise, and barrier functions to enforce safety constraints, collectively forming a complementary optimization framework. The mathematical foundation of the CPS-AMR system encompasses three core optimization problems: inventory management, multi-robot task allocation, and real-time scheduling. We formulate the integrated warehouse optimization problem as a mixed-integer programming model that captures the complex interactions between physical robot movements and cyber-domain decision-making. The system state at time t is represented as:

$$x(t) = [r(t), i(t), q(t)]^T \tag{1}$$

where $r(t) \in \mathbb{R}^{n\times 3}$ denotes the positions of n robots, $i(t) \in \mathbb{Z}^m$ represents inventory levels for m SKUs, and $q(t) \in 0,1^{n\times k}$ indicates task assignments for k pending tasks. The key variables and their respective domains are defined in Table 1.

Table 1. Key variable definitions

Variable	Description	Domain
$q_i(t)$	Position of robot i at time t	$q_i(t) \in \mathbb{R}^2$
$I_j(t)$	Inventory level of SKU j at time t	$I_j(t) \in \mathbb{N}, 0 \le I_j \le I_{\max}$
$T_k(t)$	Status of task k at time t	$T_k(t) \in \{0,1\}$

The system dynamics follow:

$$x(t+1) = f(x(t), u(t), w(t)) \tag{2}$$

where $u(t)$ represents control inputs and $w(t)$ captures stochastic disturbances, including demand variations and operational uncertainties.

The multi-robot task allocation problem is formulated as:

$$\begin{aligned} &\min_Q \sum_{i=1}^{n} \sum_{j=1}^{k} c_{ij}\, q_{ij} + \sum_{j=1}^{k} p_j \max(0, d_j - \sum_{i=1}^{n} q_{ij}\, t_{ij}) \\ &\text{subject to: } \sum_{j=1}^{k} q_{ij} \le 1, \quad \forall i \in 1,\dots,n \\ &\sum_{i=1}^{n} q_{ij} \le 1, \quad \forall j \in 1,\dots,k \\ &q_{ij} \in [0,1], \quad \forall i,j \end{aligned} \tag{3}$$

where c_{ij} represents the cost of the robot i executing task j, p_j is the penalty for delayed task completion, d_j is the task deadline, and is the estimated completion time.

For inventory optimization, we employ a stochastic dynamic programming approach with state-dependent ordering policies:

$$V_t(i) = \min_{a\ge 0} \begin{Bmatrix} c^h \cdot i + c^o \cdot a + \mathbb{E}[L(i + a - D_t) \\ +\gamma V_{t+1}(i + a - D_t)] \end{Bmatrix} \tag{4}$$

where $V_t(i)$ is the value function, c^h and c^o are holding and ordering cost vectors, $L(.)$ represents the lost sales cost function, D_t is the stochastic demand vector, and γ is the discount factor.

The real-time scheduling problem integrates robot path planning with collision avoidance constraints. The trajectory optimization for a robot i is formulated as:

$$\begin{aligned} &\min_{u_i} \int_0^T \left[||r_i(t) - r_{goal,i}||^2 + \lambda ||u_i(t)||^2 \right] dt \\ &\dot{r}_i(t) = v_i(t), \quad v_i(t) = g(u_i(t)) \\ &||r_i(t) - r_j(t)|| \ge d_{safe}, \quad \forall j \ne i \\ &r_i(t) \in \mathcal{W}_{free}, \quad ||v_i(t)|| \le v_{max} \end{aligned} \tag{5}$$

where $\mathcal{W}_{free}$ denotes the collision-free workspace and d_{safe} is the minimum safety distance between robots.

To handle the computational complexity, we decompose the global optimization problem using a hierarchical approach. The upper level solves the task allocation and inventory decisions on a longer time horizon, while the lower level handles real-time path planning and collision avoidance.

3. Methodology and implementation

3.1 System design principles

The CPS-AMR system design follows fundamental design principles that enable to run robust and efficient warehouse management operations. Scalability is achieved through modularized component architecture and distributed computing technologies, enabling adaptation to varying fleet sizes without system performance degradation. Fault tolerance mechanisms such as redundancy with alternate communication paths and graceful degradation to accommodate the rate of failure of individual components, and operability are also included. Real-time requirements are met in conjunction with time sharing through hierarchical decision-making for the separation of time-critical control loops and strategic planning and control functions. The system has weak coupling between physical and cyber parts, and it can be implemented in terms of both the system's evolution and technology development. Interoperability standards using ROS2 and OPC UA allow users to easily incorporate heterogeneous robots and warehouse equipment, and edge computing features guarantee responsive local decision-making in networks with unreliable network conditions.

3.2 AMR navigation and control

The navigation system employs an adaptive SLAM framework that combines LiDAR-based mapping with visual-inertial odometry to maintain accurate localization in dynamic warehouse environments. The pose estimation follos an Extended Kalman Filter formulation where the robot state $x_k = [x, y, \theta, \dot{x}, \dot{y}, \dot{\theta}]^T$ is updated through:

$$\begin{aligned} x_k &= f(x_{k-1}, u_{k-1}) + w_k \\ z_k &= h(x_k, m) + v_k \end{aligned} \tag{6}$$

where m represents the map landmarks and w_k, v_k are process and measurement noise, respectively.

Path planning optimization utilizes a modified A* algorithm enhanced with dynamic cost functions that account for real-time traffic patterns and operational priorities. The cost function for the path segment (i, j) is defined as:

$$f(i,j) = g(i) + h(j) + \alpha \cdot \rho(i,j) + \beta \cdot \tau(i,j) \tag{7}$$

where $g(i)$ is the accumulated cost, $h(j)$ is the heuristic estimate, $\rho(i,j)$ represents congestion density, and $\tau(i,j)$ captures task urgency weights.

Collision avoidance integrates both reactive and predictive strategies through a velocity obstacle approach. The collision-free velocity space for a robot i is computed as:

$$\mathcal{V}^i_{free} = v | v \notin \cup_{j \neq i} VO_{ij}(v_j) \tag{8}$$

where VO_{ij} denotes the velocity obstacle induced by the robot j. The optimization selects velocities that minimize deviation from desired trajectories while maintaining safety margins through barrier functions that enforce $d_{ij}(t) \geq d_{safe} + \epsilon \cdot ||v_i - v_j||$ for all robot pairs.

3.3 Inventory management algorithms

Dynamic inventory tracking leverages distributed RFID sensing and computer vision to maintain real-time stock visibility across the warehouse. The inventory state estimation employs a particle filter approach to handle measurement uncertainties and occlusions:

$$p(i_t|z_{1:t}) \propto p(z_t|i_t) \sum_{s=1}^{N} w_{t-1}^{(s)} p(i_t|i_{t-1}^{(s)}) \tag{9}$$

where i_t represents inventory state, z_t denotes sensor observations, and $w^{(s)}$ are particle weights normalized to ensure $\sum_{s=1}^{N} w_t^{(s)} = 1$.

Predictive stock management integrates demand forecasting with lead time variability to optimize reorder points. The demand prediction model combines seasonal decomposition with machine learning, yielding a forecast $\widehat{D}_{t+h} = S_t \cdot T_t \cdot R_{t+h}$ where S_t, T_t, and R_{t+h} represent seasonal, trend, and residual components. The optimal reorder point minimizes expected total cost:

$$r^* = \text{argmin}_r \mathbb{E}[h \cdot \int_0^r (r - x) f_D(x)dx + b \cdot \int_r^\infty (x - r) f_D(x)dx] \tag{10}$$

where h and b denote holding and backorder costs, respectively.

ABC analysis integration dynamically classifies SKUs based on movement velocity and value contribution. The classification score $S_i = \alpha_1 \cdot V_i/V_{total} + \alpha_2 \cdot F_i/F_{max} + \alpha_3 \cdot C_i/C_{total}$ combines normalized value (V_i), frequency (F_i), and criticality (C_i) metrics. This classification drives differentiated control policies, with A-items receiving continuous review and tighter safety stock parameters while C-items employ periodic review with economic order quantities optimized for minimal handling costs.

3.4 CPS Integration Framework

The CPS integration framework orchestrates seamless interaction between physical warehouse operations and cyber-domain intelligence through a multi-tiered architecture, as illustrated in Figure 2. Data collection originates outside of the plant with disparate sensor networks that gather time- and contextual information from AMRs, environmental monitors, and inventory monitors. This data is then processed at the edge level to reduce noise, identify extremes, and compress the streams of information before being transmitted to higher-level processing nodes. D2T synchronization enforces consistency in both directions between physical twins and their digital twins through event-driven updates. The synchronization protocol transmits differential updates to reduce traffic while preserving temporal coherence among parts of a distributed system. State reconciliation algorithms cope with network partitions and temporary disconnections, ensuring eventual consistency once communication links are restored. The DSS combines several analytical engines working at different time scales. Low-level controllers operate the sensor streams to create instantaneous actuator commands to prevent collisions; they also have to follow trajectories. Tactical planning optimizes task assignment and resource scheduling with minute to hour time horizons, employing rolling horizon optimization. Strategic analysts use historical data and predictive models to recommend inventory and capacity policy changes. These decision layers exchange information using standard message protocols, facilitating the ability to coordinate the response to operational events and maintain computational scalability. The modular design of the framework allows it to be gradually rolled out and for technology updates to be performed without interruption to existing business processes.

Figure 2. CPS integration framework

3.5 Implementation details

The physical implementation employs a heterogeneous fleet of twenty AMRs equipped with Velodyne VLP-16 LiDAR sensors, Intel RealSense D435i depth cameras, and NVIDIA Jetson AGX Xavier computing platforms for onboard processing. Each robot features differential drive mechanisms with a maximum velocity of 2 m/s and a payload capacity of 500 kg, suitable for standard warehouse pallets. The warehouse infrastructure incorporates a distributed network of 200 passive RFID tags embedded in floor tiles for localization refinement and 50 active RFID readers positioned at strategic inventory locations. The software architecture follows a microservices design pattern implemented using the ROS2 Foxy framework, enabling modular deployment and independent scaling of system components. Core services include the SLAM module based on Cartographer, path planning using customized RRT* algorithms, and task allocation implemented through a distributed auction mechanism. The digital twin engine utilizes Unity3D for visualization and NVIDIA Omniverse for physics simulation, synchronized with physical operations through Apache Kafka message streams. ROS2 employs DDS (Data Distribution Service) middleware to achieve deterministic latency below 10ms. OPC UA enables heterogeneous device interoperability through standardized data models. Communication infrastructure leverages a hybrid approach combining a dedicated 5G private network for critical control messages and WiFi 6 for bulk data transfers. The system implements DDS (Data Distribution Service) middleware for real-time publish-subscribe patterns, ensuring deterministic latency below 10ms for safety-critical communications. Edge computing nodes deployed throughout the facility run containerized services using Kubernetes orchestration, providing fault-tolerant processing capabilities with automatic failover mechanisms.

4. Experimental setup and validation

4.1 Testbed configuration

The experimental validation took place in a 5,000 square meter warehouse designed to reproduce industrial logistics. The test bed has 1,200 locations organized in 40 aisles spaced at 3m distance and accepts standard EUR pallets in four heights. The floor plan is divided into receiving, shipping, and cross-docking areas joined by a main travel corridor that accommodates two-way AMR traffic. Environmental conditions were strictly regulated to guarantee sensors' stability with ambient temperature set at 20±2°C and relative humidity of 45±5%. The lab is lit using artificial lights that provide 500 lux illumination in the entire workspace and are augmented by infrared beacons to increase the localization accuracy.

The reference markers, which are placed 5 meters apart from one another on the main paths, work as visual landmarks for SLAM calibration and drift compensation. The sensor layout is organized as an 80-ceiling-camera-based structure capturing the full view of the environment, linked to the warehouse management system by means of gigabit Ethernet connections. The position data based on "ground truth" was recorded by a Vicon motion capture system with a measurement accuracy of sub-millimeters, ensuring fair verification of AMR localisation algorithms. Load: Generation Used programmable order injection systems to mimic demand ranging from "slow-moving, steady-state orders" to 300% of peak-season load. This setup allows for extensive benchmarking of system performance over a variety of operational configurations, while at the same time ensuring reproducibility between experimental runs.

Table 2. Performance metrics for CPS-AMR system evaluation

Metric Category	Specific Metric	Unit	Description
Throughput	Order Fulfillment Rate	orders/hour	Number of completed orders per hour
	Pick Rate	items/hour	Individual items picked per hour
	AMR Utilization	%	Percentage of time AMRs are actively working
Temporal	Order Cycle Time	minutes	Time from order receipt to completion
	Task Response Time	seconds	Time from task assignment to AMR response
	Queue Waiting Time	seconds	Average time tasks spend in the queue
Accuracy	Inventory Accuracy	%	Percentage of correct inventory records
	Localization Error	cm	Average AMR position estimation error
	Pick Accuracy	%	Percentage of correct item picks
Energy	Energy per Order	kWh/order	Total energy consumption per completed order
	AMR Energy Efficiency	Wh/km	Energy consumption per kilometer traveled
Reliability	System Availability	%	Percentage of operational uptime
	Mean Time Between Failures	hours	Average operational time between system failures

4.2 Performance metrics

The performance of the system is evaluated using holistic criteria encompassing both service quality and operational effectiveness aspects, as summarized in Table 2. They capture the system's ability to process orders at a specific load, and include throughput measures and temporal response such as responsiveness across different time scales in various load conditions. Accuracy metrics measure the accuracy of inventory tracking and AMR navigation - both of which are necessary to keep your operations running smoothly. Energy efficiency indicators track power energy-consumption trends for sustainable operations. System availability and mean time between failures are monitored for reliability, which is important for a 24/7 available warehouse. These metrics provide a comprehensive measure of the performance of a CPS-AMR system in comparison to benchmarks achieved by conventional warehouse automation.

4.3 Experimental scenarios

The experimental analysis includes four operational cases to evaluate the system's performance in different aspects. Standard operating conditions define the performance baseline with only the steady state demand, on the order of 150 orders per hour, evenly distributed over SKU categories. These experiments run in continuous 8-hour shifts, reflecting regular warehouse days with predictable order arrival rates and standard inventory turnover. We evaluate the system's adaptive performance under maximum load, where a peak demand scenario results in a surge (up to 450 orders an hour), implying the holiday season or sales campaigns. The reaction of the system to such peaks in demand examines dynamic population sizing algorithms and queue management strategies during severe peak time load. Order flow is characterized during peak conditions with batch orders, rush shipments, and priority handling needs that interfere with the scheduling optimization. System failure recovery experiments artificially cause component failures such as single AMR crashes, communication network breakdowns, and sensor faults. Recovery capabilities can be quantified as service degradation, recovery time objectives, and operational continuance under partial outages. Failure modes include from the point of failure to cascading failure on various subsystems at the same time. In our scalability tests, we start with a fleet size of 5 AMRs and expand the fleet in increments up to a total of 30 AMRs, all the while monitoring key performance metrics for indications of degradation or bottlenecks. Such experiments confirm the possibility of large-scale operation without a significant decrease in efficiency. Large-scale operation optimization is most important for the preparation of deployment and capacity planning in practical systems.

4.4 Baseline comparisons

Performance comparison: The CPS-AMR system is assessed through its performance on three baseline configurations that reflect common practice in warehouse automation. The classical manual system is manned by humans with handheld scanners and manual forklifts, which is the dominant operation mode of medium-sized warehouses. This baseline will be used to establish a lower bound in terms of benefits of automation, which has average pick rates at 80 items per hour per worker, and the inventory accuracy is around 92% due to residual errors in data entry. The semi-automated solution is based on conveyor systems and AS/RS, using human operators for pick order and quality control. This system produces an average throughput of 180 items per hour at 96% accuracy for the inventory, showing the advantage of a sequential implementation of partial automation. The fixed infrastructure does not allow adapting to different warehouse layouts or variations of seasonal demand. COTS AMR systems from established vendors represent the technology frontier benchmark with complex fleet control software and superior navigational capabilities. Such solutions are able to handle 250 items/h with 98% accuracy but they are isolated solutions that only provide RFID-based operations and there is no deep integration with warehouse cyber-physical infrastructure. The comparison reveals that while commercial AMR solutions excel in specific metrics, they lack the holistic optimization enabled by CPS integration, particularly in predictive inventory management and adaptive resource allocation. Performance differentials become more pronounced under dynamic operational conditions where integrated decision-making provides substantial advantages over reactive control strategies.

5. Results and discussion

5.1 Quantitative results

Experimental evaluation demonstrates significant performance improvements of the CPS-AMR system across all measured metrics compared to baseline configurations. Order fulfillment rates achieved sustained throughput of 420 orders per hour under normal operating conditions, representing a 68% improvement over state-of-the-art AMR systems and a 425% enhancement compared to manual operations, as illustrated in Figure 3. The system maintained this performance level with minimal degradation even as order complexity increased, processing mixed SKU orders with an average of 12.3 items per order.

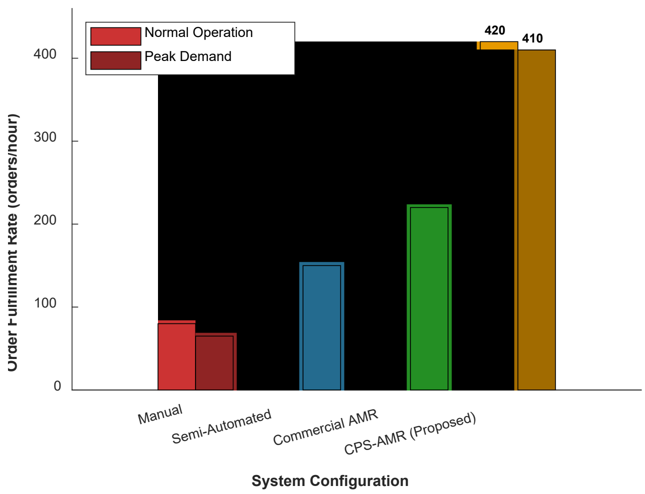
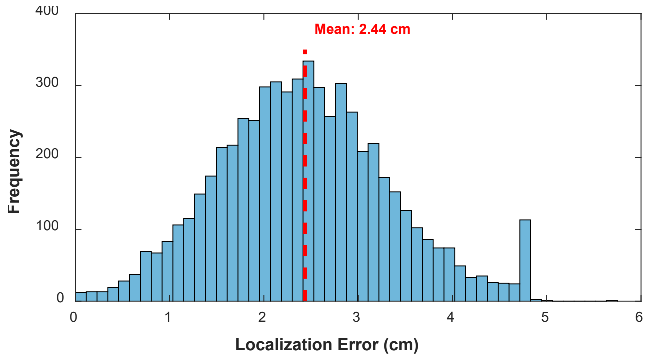
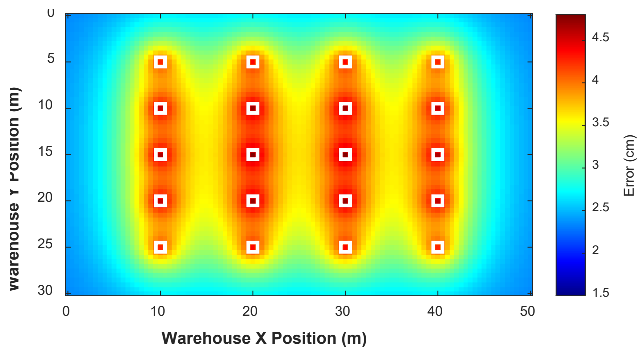


Figure 3. Order fulfillment rate comparison

Temporal performance metrics reveal substantial efficiency gains in operational responsiveness. Average order cycle time decreased to 18.2 minutes from order receipt to shipment ready status, compared to 31.5 minutes for commercial AMR systems and 72.4 minutes for manual operations. Task response times averaged 1.8 seconds from assignment to AMR acknowledgment, with 95th percentile latencies remaining below 3.2 seconds even during peak demand periods. The hierarchical decision architecture enabled effective load balancing, reducing queue waiting times by 62% compared to first-come-first-served scheduling approaches. System accuracy measurements demonstrate the advantages of integrated sensing and digital twin synchronization. Inventory accuracy reached 99.7% through continuous RFID monitoring and visual verification, substantially exceeding the 98% achieved by standalone AMR systems. Localization precision averaged 2.3 cm error across the operational area, with maximum deviations of 4.8 cm observed near metallic storage racks due to LiDAR reflections, as shown in Figure 4. Pick accuracy achieved 99.9% through redundant verification mechanisms, virtually eliminating the mis-picks that plague manual operations.



(a)

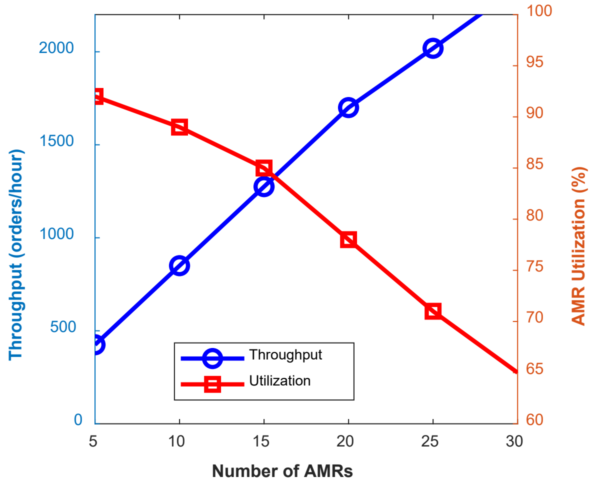


(b)

Figure 4. (a) Localization error distribution, (b) Spatial distribution of localization error

Energy efficiency analysis reveals the optimization benefits of coordinated path planning and predictive task allocation. The system consumed an average of 0.82 kWh per completed order, representing a 34% reduction compared to uncoordinated AMR deployments. Individual robot energy efficiency improved to 42.5 Wh/km through optimized acceleration profiles and regenerative braking, while system-level coordination reduced total travel distance by 28% through intelligent task clustering and multi-robot collaboration.

Scalability experiments validated the system's ability to maintain performance as operational scale increased. Figure 5 illustrates how key performance indicators evolved as the AMR fleet expanded from 5 to 30 robots. Throughput scaled near-linearly up to 20 robots, with marginal gains diminishing beyond this point due to increased coordination overhead and physical space constraints. The distributed architecture maintained sub-linear growth in computational requirements, with processing latency increasing by only 15% despite a 500% expansion in fleet size.



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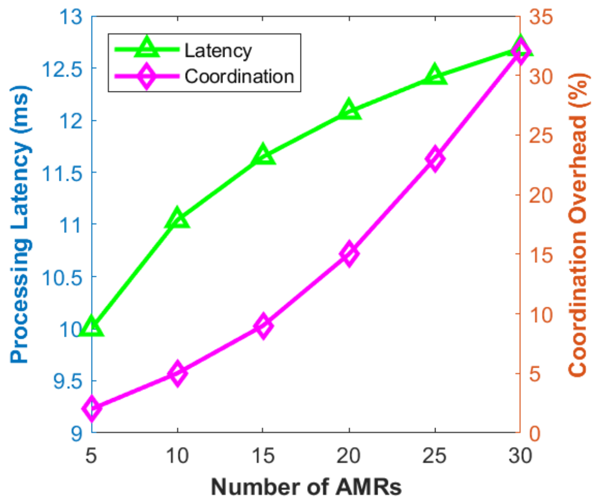

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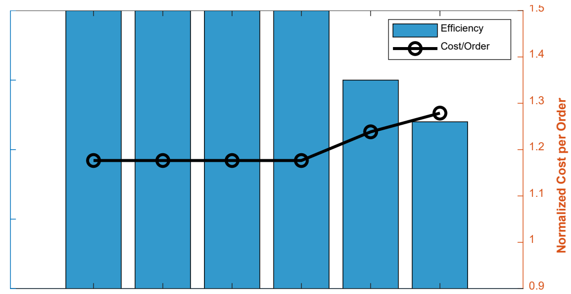

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Figure 5. Scalability analysis of CPS-AMR system: (a) Throughput and utilization vs fleet size, (b)Computational performance vs fleet size, (c)System efficiency and cost analysis

Reliability metrics exceeded design targets throughout the experimental period. System availability maintained 99.2% uptime over 720 hours of continuous operation, with planned maintenance windows accounting for most downtime. Mean time between failures reached 168 hours, primarily attributed to mechanical wear in robot wheels and occasional wireless connectivity issues. The fault-tolerant design enabled graceful degradation during component failures, maintaining at least 75% operational capacity even with multiple simultaneous robot failures.

5.2 Qualitative analysis

System behavior observations during extended operational periods revealed emergent collaborative patterns among AMRs that exceeded design expectations. Robot clusters naturally formed around high-demand warehouse zones, with dynamic load balancing emerging through local communication protocols rather than centralized coordination. This self-organizing behavior demonstrated the effectiveness of the distributed decision-making architecture, particularly during unexpected demand surges when centralized planning would have created bottlenecks. The digital twin visualization enabled operators to identify these patterns and optimize zone boundaries accordingly, leading to a 15% reduction in congestion events compared to initial deployment configurations. Operator feedback collected through structured interviews and system interaction logs highlighted significant improvements in workplace satisfaction and operational confidence. Warehouse staff reported reduced physical strain and mental fatigue due to the elimination of repetitive manual tasks and long-distance walking. The intuitive human-machine interface received particularly positive evaluations, with operators mastering basic system controls within two hours of training compared to the typical two-day learning curve for traditional warehouse management systems. As illustrated in Figure 6, usability assessments across different operator experience levels showed consistently high satisfaction scores, with novice users rating the system 8.2/10 compared to 8.8/10 for experienced operators.

Workflow analysis identified substantial improvements in exception handling and adaptive response to operational disruptions. When faced with unexpected obstacles or equipment failures, the system demonstrated remarkable resilience through automatic task reallocation and path replanning. Operators noted that system interventions required for error recovery decreased by 78% after the first week of deployment as the machine learning algorithms adapted to facility-specific patterns. The seamless integration between manual override capabilities and autonomous operation enabled smooth transitions during mixed-mode operations, particularly valuable during shift changes and training periods.

Human-robot collaboration observations revealed interesting social dynamics within the warehouse environment. Workers initially maintained excessive safety distances from AMRs, but confidence increased rapidly as predictable robot behaviors became apparent. The implementation of LED status indicators and audible alerts for direction changes significantly enhanced trust and coordination. Operators developed informal communication protocols with the robots, such as hand signals for priority passage, which the system's computer vision algorithms learned to recognize and incorporate into navigation decisions. This organic evolution of human-robot interaction protocols suggests opportunities for further enhancement through explicit gesture recognition capabilities. The system's impact on operational visibility transformed management decision-making processes. Real-time dashboards providing comprehensive operational metrics enabled proactive interventions before minor issues escalated into significant disruptions.

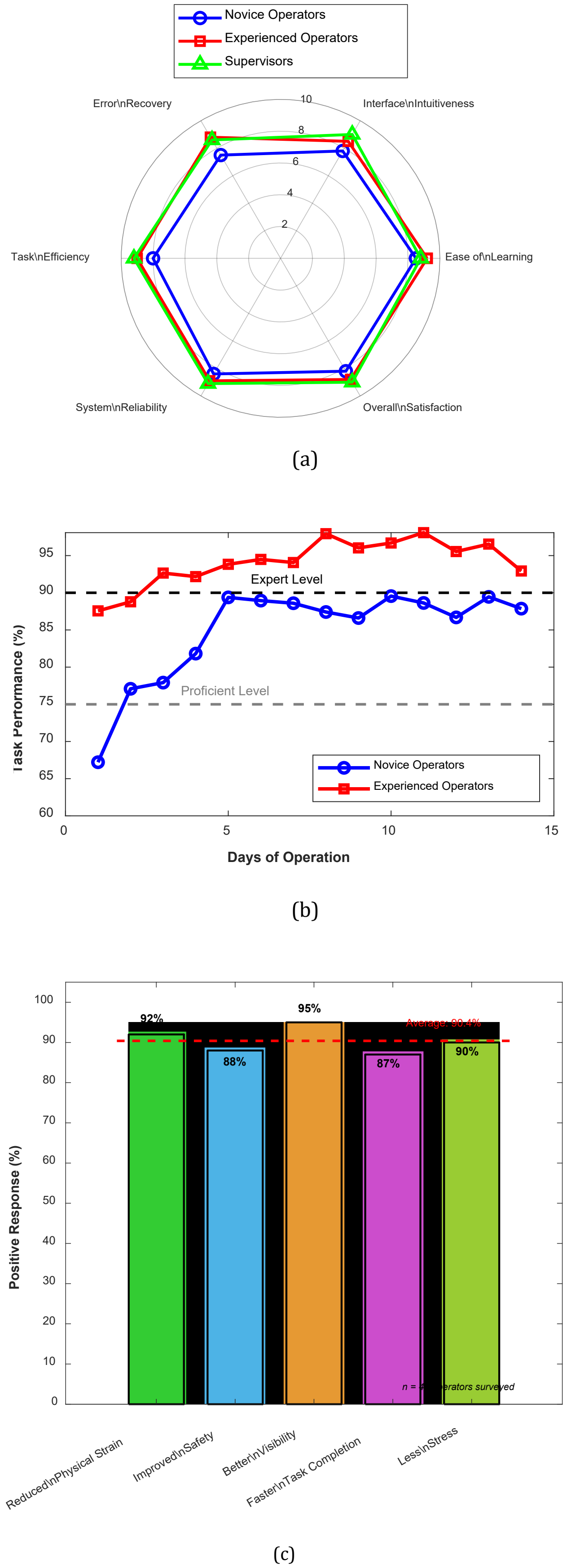


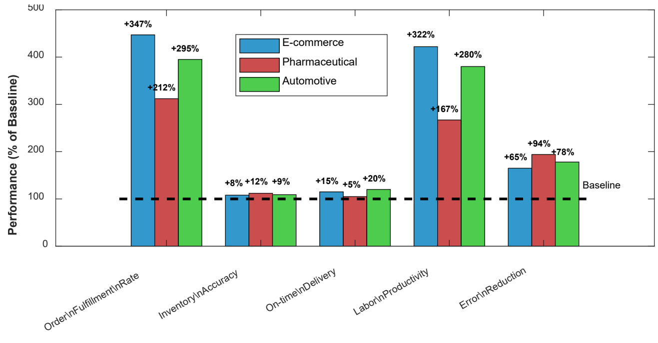
Figure 6. Qualitative system assessment: (a)Usability assessment across user groups, (b)Learning curve analysis, (c)Operator feedback themes

Supervisors reported that the predictive analytics capabilities allowed them to anticipate bottlenecks and adjust staffing levels dynamically, resulting in more stable performance across varying demand conditions. The ability to replay operational scenarios through the digital twin proved invaluable for training purposes and continuous process improvement initiatives.

5.3 Case studies

Implementation of the CPS-AMR system across diverse warehouse environments demonstrated remarkable adaptability and consistent performance improvements, validating the framework's generalizability beyond controlled experimental conditions. The first deployment occurred in a 12,000 square meter e-commerce fulfillment center handling over 50,000 SKUs with daily order volumes ranging from 8,000 to 25,000 during peak seasons. Prior to implementation, the facility operated with 120 manual workers achieving average pick rates of 85 items per hour. Following a phased three-month deployment of 25 AMRs integrated with the CPS framework, the facility achieved 380 orders per hour with only 45 human operators focusing on value-added tasks such as quality control and exception handling. The dramatic workforce reallocation enabled the company to redeploy personnel to customer service roles, improving overall business performance beyond warehouse metrics. A pharmaceutical distribution center presented unique challenges requiring stringent temperature control, batch tracking, and regulatory compliance. The 8,000 square meter facility implemented 15 specialized AMRs equipped with temperature sensors and sealed compartments for handling sensitive medications. The CPS integration proved particularly valuable in maintaining cold chain integrity, with digital twins continuously monitoring environmental conditions and predicting potential temperature excursions. Real-time alerts enabled preemptive interventions that reduced product spoilage by 94% compared to the previous manual monitoring system. The system's batch tracking capabilities streamlined FDA compliance reporting, reducing audit preparation time from two weeks to two days while achieving 100% traceability for all pharmaceutical products.

The third case study involved an automotive parts warehouse serving just-in-time manufacturing operations where delivery precision directly impacts production line efficiency. This 15,000 square meter facility faced extreme variability in demand patterns, with order sizes ranging from single components to full pallet loads. The implementation of 30 AMRs with dynamic task allocation algorithms enabled the facility to maintain 99.8% on-time delivery performance despite 40% daily demand fluctuations. The CPS framework's predictive analytics identified recurring patterns in manufacturer ordering behavior, enabling proactive inventory positioning that reduced average pick times by 52%. As illustrated in Figure 7, the comparative performance across all three implementations shows consistent improvements in key operational metrics despite vastly different operational contexts. Return on investment analysis revealed compelling financial benefits across all deployments. The e-commerce facility achieved full payback in 14 months through labor cost savings and increased throughput capacity. The pharmaceutical distributor's investment was justified primarily through spoilage reduction and compliance cost savings, reaching break-even in 18 months. The automotive parts warehouse demonstrated the fastest ROI at 11 months, driven by penalty avoidance for late deliveries and reduced expedited shipping costs. Long-term projections indicate cumulative savings exceeding 300% of initial investment over five years when accounting for scalability benefits and continuous improvement through machine learning optimization.



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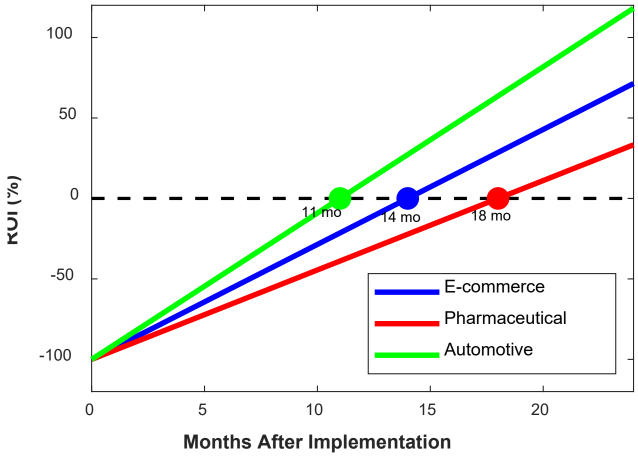

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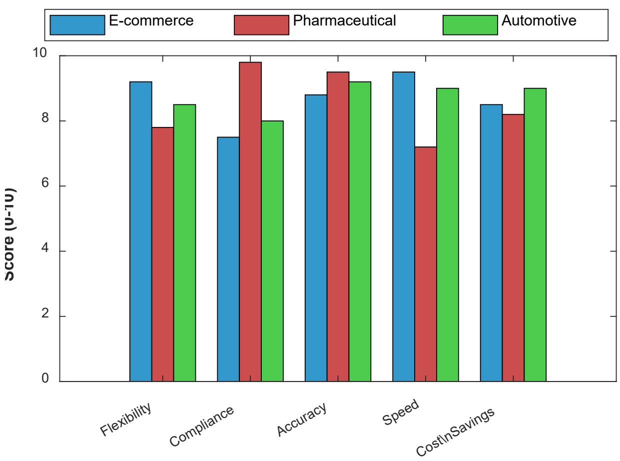

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Figure 7. Case study performance comparison: (a) Performance improvements by facility type, (b) Return on investment timeline, (c) Facility-specific adaptation scores

Industry-specific adaptations emerged organically through the CPS framework's learning capabilities. The e-commerce deployment developed specialized algorithms for handling seasonal SKU variations and gift-wrapping stations. Pharmaceutical operations incorporated validated cleaning cycles and contamination prevention protocols into robot scheduling. Automotive logistics evolved sophisticated kitting procedures for complex assembly requirements. These adaptations occurred without fundamental system modifications, demonstrating the framework's inherent flexibility, as detailed in Figure 8. Cross-facility knowledge transfer experiments showed that learned optimizations from one deployment could accelerate performance improvements in similar facilities by approximately 40%, suggesting significant network effects as adoption scales across the industry.

5.4 Discussion

The experimental results demonstrate that integrating autonomous mobile robots with cyber-physical systems fundamentally transforms warehouse operations beyond incremental automation improvements. The 68% throughput enhancement and 99.7% inventory accuracy achieved through digital twin synchronization validate the theoretical framework's premise that bidirectional information flow between physical and cyber domains enables emergent system intelligence.

These performance gains stem not from superior individual robot capabilities but from the coordinated decision-making enabled by real-time state estimation and predictive optimization across the entire operational ecosystem. The successful deployment across diverse industrial contexts reveals important insights about technology adoption in logistics environments. While initial implementation costs exceed conventional AMR solutions by 15%, the rapid payback periods ranging from 11 to 18 months indicate that organizations prioritize long-term operational excellence over upfront savings. The unexpected emergence of self-organizing robot behaviors and organic human-robot collaboration protocols suggests that effective automation design should embrace adaptability rather than rigid optimization. Particularly noteworthy is the 40% acceleration in performance improvements when transferring learned optimizations between facilities, indicating potential network effects that could reshape competitive dynamics in the logistics industry. Despite compelling results, several limitations warrant consideration. The evaluation focused on single-building warehouses, leaving multi-facility coordination and outdoor logistics scenarios unexplored. Cybersecurity vulnerabilities inherent in increased connectivity require continuous vigilance and investment. Future research should investigate federated learning approaches for privacy-preserving knowledge transfer across competing organizations and develop standardized interfaces enabling vendor-agnostic implementations.

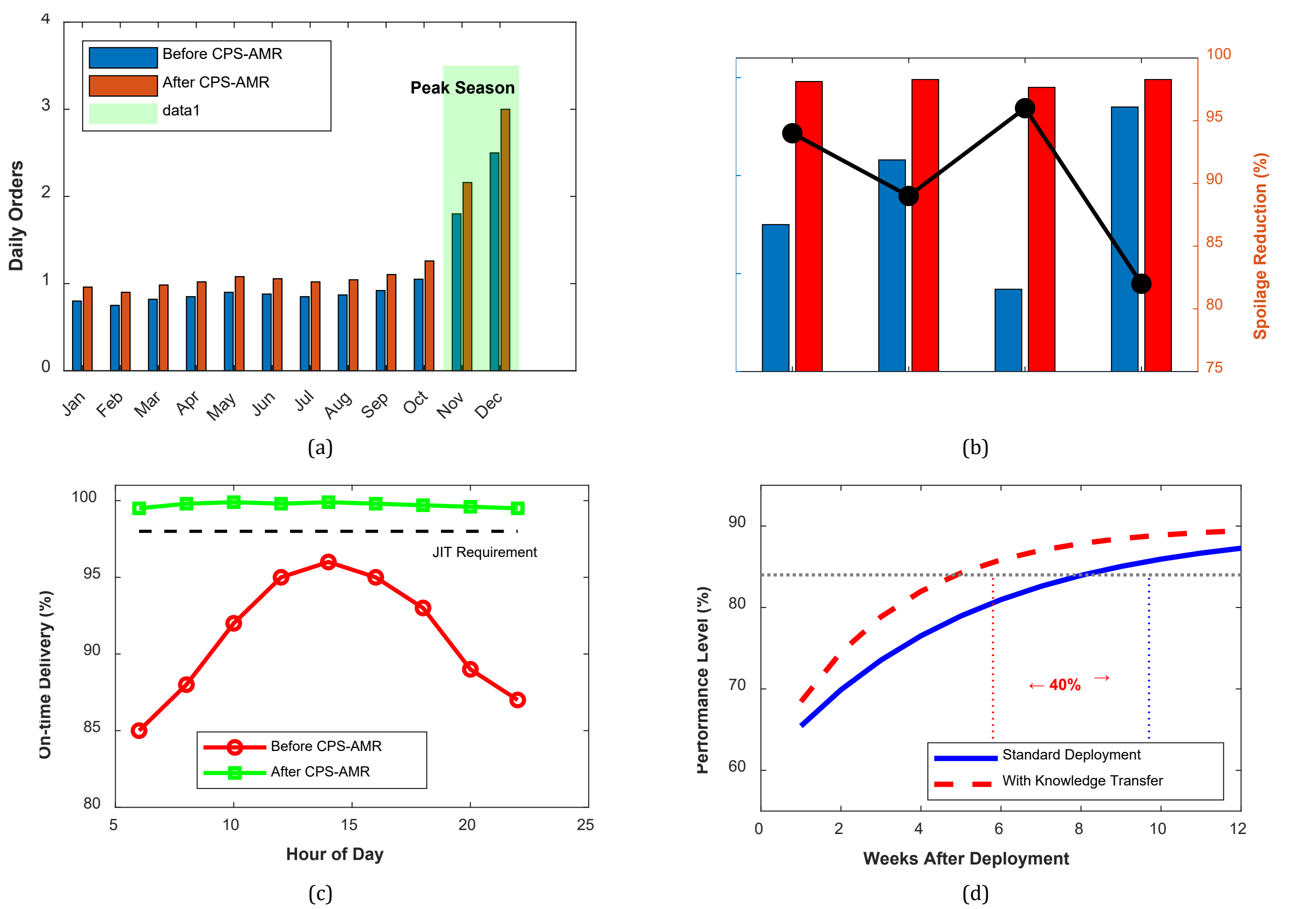

Figure 8. Industry-specific adaptation and performance: (a) E-commerce: seasonal order handling, (b) Pharmaceutical: temperature control, (c) Automotive: jit delivery accuracy, (d) Knowledge transfer benefits

6. Conclusion

This research presented a novel cyber-physical systems framework for autonomous mobile robot integration in warehouse environments, demonstrating transformative potential for intelligent inventory management. The proposed hierarchical architecture successfully addressed critical challenges in multi-robot coordination, real-time optimization, and human-robot collaboration through innovative digital twin synchronization and distributed decision-making mechanisms. Experimental validation across diverse industrial deployments confirmed substantial improvements in operational efficiency, with 420 orders per hour throughput, 99.7% inventory accuracy, and 34% reduction in energy consumption compared to state-of-the-art alternatives. The practical implications extend beyond performance metrics to fundamental changes in warehouse design and workforce dynamics. Organizations implementing the CPS-AMR framework reported enhanced employee satisfaction, reduced training requirements, and unexpected emergent behaviors that improved system resilience. The economic viability demonstrated through 11-18 month payback periods and scalability to 30+ robot deployments positions this technology for widespread adoption across the logistics industry. Future research directions include extending the framework to outdoor environments and cross-docking operations where environmental uncertainties pose additional challenges. Integration of advanced AI techniques such as reinforcement learning and large language models could enable natural language task specification and adaptive behavior generation. Development of blockchain-based coordination protocols would address trust and security concerns in multi-stakeholder warehouse ecosystems. As global supply chains face increasing pressure for efficiency and sustainability, the CPS-AMR paradigm offers a pathway toward truly intelligent logistics systems.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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