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Advanced Robotics and Autonomous Systems in Flexible Manufacturing

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ABSTRACT

The accelerating demand for product variety, shorter production cycles, and mass customization has rendered traditional rigid manufacturing lines increasingly inadequate for modern industrial requirements. Flexible manufacturing systems (FMS) augmented with advanced robotics and autonomous decision-making capabilities represent a paradigm shift toward adaptive, reconfigurable, and intelligent production environments. This paper presents a comprehensive experimental and simulation-based investigation of a robotic flexible manufacturing cell integrating collaborative robots (cobots), autonomous mobile robots (AMRs), and a digital twin-enabled intelligent scheduling framework for multi-product small-batch manufacturing. The proposed system employs a Universal Robots UR10e 6-axis cobot for assembly operations, a MiR250 AMR for autonomous material transport, and a reinforcement learning-based task scheduler operating on an edge computing platform. The system was validated in a pilot manufacturing cell at Arya College of Engineering and IT, Jaipur, producing three distinct product families with lot sizes ranging from 5 to 50 units. Experimental results demonstrated a 34.6% reduction in changeover time, 28.2% improvement in overall equipment effectiveness (OEE), and 41.3% reduction in work-in-progress inventory compared to a conventional semi-automated production line. The reinforcement learning scheduler achieved 96.8% on-time delivery performance across 240 production orders over a 12-week validation period. The findings confirm that intelligent robotic systems with autonomous scheduling capabilities can enable economically viable high-mix low-volume manufacturing [1], [2].

KEYWORDS: *Flexible Manufacturing, Collaborative Robots, Autonomous*

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Mobile Robots, Reinforcement Learning, Digital Twin, Smart Manufacturing, Industry 4.0, Production Scheduling, Cobots, Reconfigurable Manufacturing

INTRODUCTION

The global manufacturing sector is experiencing a fundamental structural transformation driven by evolving consumer preferences toward customized products, shortened product life cycles, and the economic imperatives of high-mix low-volume (HMLV) production. The International Federation of Robotics reported that global industrial robot installations reached 553,052 units in 2023, with collaborative robots accounting for 10.5% of total installations—a segment growing at 32% annually compared to 7% for traditional industrial robots [1]. This growth reflects the increasing recognition that rigid, fixed-automation production lines designed for mass production of identical products are fundamentally incompatible with the flexibility, reconfigurability, and rapid changeover capabilities demanded by modern manufacturing [2].

Flexible manufacturing systems (FMS) were conceptualized in the 1960s as programmable production environments capable of manufacturing diverse product families on shared equipment. However, early FMS implementations suffered from excessive complexity, high capital costs, and limited adaptability, achieving flexibility primarily through numerical control programming rather than genuine autonomous reconfiguration [3]. The convergence of modern collaborative robotics, autonomous mobile platforms, and artificial intelligence-based scheduling algorithms has created unprecedented opportunities to realize truly flexible manufacturing systems that can autonomously adapt to changing production requirements, material availability, and equipment status in real time [4], [5].

Collaborative robots (cobots) represent a particularly transformative technology for flexible manufacturing. Unlike traditional industrial robots that operate within safety-fenced enclosures, cobots incorporate force-torque sensing, speed monitoring, and collision detection capabilities that enable safe human-robot coexistence in shared workspaces [6]. This inherent safety architecture, combined with intuitive programming interfaces and rapid deployment capability, makes cobots ideally suited for the frequent task reconfiguration required in HMLV environments. Autonomous mobile robots (AMRs) complement cobot-based

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workstations by providing intelligent material transport that adapts to dynamic factory floor conditions using
simultaneous localization and mapping (SLAM) algorithms and real-time path planning [7].
This research presents the development and validation of an integrated robotic flexible manufacturing cell combining cobot-based assembly, AMR-based logistics, and reinforcement learning-based production scheduling within a digital twin framework. The system was implemented and validated in a pilot manufacturing cell producing three product families at Arya College of Engineering and IT, Jaipur [8], [9], [10], [11], [12], [13].

LITERATURE REVIEW

The integration of robotics into flexible manufacturing has been the subject of extensive investigation. Villani et al. [3] conducted a comprehensive survey of collaborative robotics in manufacturing, identifying force-limited cobots (UR series, KUKA iiwa, ABB YuMi) as the dominant technology for human-robot collaborative assembly. Their review demonstrated that cobot-augmented workstations achieved 25–45% productivity improvements in electronic assembly and 15–30% improvements in automotive component assembly compared to manual-only operations, while maintaining injury rates below those of conventional automation.

AMR technology for intralogistics has been advanced by Fragapane et al. [4], who demonstrated that fleets of 8–12 AMRs could replace fixed conveyor systems in discrete manufacturing environments while providing 40% greater layout flexibility and 20% lower total cost of ownership over a 5-year horizon. Bolu and Korsceoglu [5] integrated SLAM-based navigation with fleet management systems for multi-AMR coordination, achieving collision-free autonomous material delivery with 98.4% reliability across a 3,000 m^2 factory floor.

Reinforcement learning (RL) for manufacturing scheduling was explored by Waschneck et al. [6], who applied deep Q-networks (DQN) to job-shop scheduling problems, demonstrating 8–15% makespan reductions compared to priority dispatching rules. Wang et al. [7] extended this work to multi-agent RL for distributed scheduling in reconfigurable manufacturing systems, where each machine agent learned optimal job acceptance policies through

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interaction with the production environment. Digital twin technology for manufacturing was reviewed by Tao et al. [8], who proposed a five-dimensional digital twin framework encompassing physical, virtual, data, service, and connection layers for intelligent manufacturing monitoring and control.

Integrated robotic-FMS architectures have been investigated by Michalos et al. [9], who developed a multi-robot reconfigurable assembly system for automotive body-in-white production, achieving changeover times below 30 minutes through standardized robot tool interfaces and modular fixture systems. More recently, Cohen et al. [10] demonstrated that digital twin-enabled predictive scheduling could reduce unplanned downtime by 35% in cobot-based assembly cells by anticipating maintenance needs and proactively rerouting production tasks.

RESEARCH GAP

Despite considerable progress, critical gaps persist in the literature. First, most studies address individual components—cobots, AMRs, or scheduling algorithms—in isolation without demonstrating integrated system-level performance in realistic multi-product manufacturing scenarios [3], [4]. Second, RL-based schedulers have predominantly been validated in simulation environments without physical implementation and validation against real production variability including machine breakdowns, quality rejections, and demand fluctuations [6], [7]. Third, the economic viability of robotic FMS for small and medium enterprises (SMEs)—which constitute over 90% of manufacturing companies globally—remains insufficiently demonstrated, as most reported implementations involve large automotive or electronics manufacturers with substantially different capital expenditure capabilities [9], [10]. Fourth, the integration of autonomous material transport with production scheduling as a coupled optimization problem, rather than separate sequential decisions, has received limited attention [5], [8]. This research addresses these gaps through the development and physical validation of an integrated cobot-AMR-RL scheduling system in an SME-scale pilot manufacturing cell [11], [12], [13].

OBJECTIVES

The primary objectives of this research are defined as follows:

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- To design and implement a robotic flexible manufacturing cell integrating a UR10e cobot, MiR250 AMR, and modular fixturing system for multi-product small-batch assembly [3], [6].
- To develop a reinforcement learning-based production scheduler using proximal policy optimization (PPO) that jointly optimizes task sequencing, cobot programming, and AMR dispatch within a digital twin environment [7], [8].
- To validate the system on three product families with lot sizes of 5–50 units over a 12-week production period, measuring changeover time, OEE, WIP inventory, and on-time delivery [10].
- To quantify the economic performance of the robotic FMS against a conventional semi-automated baseline and assess return on investment for SME-scale deployment [1], [9].
- To benchmark the RL scheduler against conventional dispatching rules (FIFO, SPT, EDD) and metaheuristic optimization (genetic algorithm) [6], [11].

METHODOLOGY

1. Manufacturing Cell Configuration

The pilot flexible manufacturing cell was configured within a 12 m × 8 m floor area at the Manufacturing Systems Laboratory of Arya College of Engineering and IT, Jaipur. The cell comprised three modular workstations: WS1 (mechanical sub-assembly), WS2 (electronic integration), and WS3 (final assembly and testing). Each workstation was equipped with a Universal Robots UR10e 6-axis collaborative robot arm (payload 12.5 kg, reach 1,300 mm, repeatability ±0.03 mm) fitted with Robotiq Hand-E adaptive grippers and 2F-140 two-finger grippers, interchangeable through a pneumatic quick-change coupling [3], [6]. A MiR250 autonomous mobile robot (payload 250 kg, speed 2.0 m/s, navigation accuracy ±10 mm) equipped with a MiR250 Hook top module transported material bins between a central storage area and the three workstations along dynamically planned paths using SLAM-based navigation with LIDAR and odometry sensor fusion [4], [5]. The cell was controlled by a Siemens SIMATIC S7-1500 PLC interfacing with the cobot controllers via PROFINET and the AMR fleet manager via REST API.

2. Digital Twin and RL Scheduler

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A digital twin of the manufacturing cell was developed in Siemens Tecnomatix Plant Simulation, replicating the physical cell layout, workstation processing times, cobot cycle times, AMR transport durations, and stochastic events including machine failures (MTBF 480 hours, MTTR 45 minutes) and quality rejection rates (2.5–4.0% per product family). The RL scheduler was implemented using a PPO algorithm (OpenAI Stable Baselines3) operating on an NVIDIA Jetson AGX Orin edge computing platform [7], [8]. The state space comprised current WIP levels at each workstation, AMR location and status, pending order queue, remaining processing times, and equipment health indicators. The action space included job priority assignment (5 priority levels), workstation allocation (3 stations), and AMR dispatch timing. The reward function combined weighted penalties for tardiness (−5 per hour late), WIP accumulation (−1 per excess unit), and changeover events (−3 per changeover), with positive rewards for on-time completion (+10 per order). The agent was pre-trained in the digital twin for 500,000 episodes (approximately 18 hours on Jetson AGX Orin) before deployment to the physical cell with online fine-tuning [6], [10].

3. Product Families and Production Protocol

Three product families were defined for validation: PF-A (pneumatic actuator assembly, 14 components, 8.5-minute cycle time), PF-B (electronic control module, 22 components, 12.3-minute cycle time), and PF-C (sensor housing assembly, 9 components, 6.2-minute cycle time). Order quantities ranged from 5 to 50 units per batch, with a target production mix of 40% PF-A, 35% PF-B, and 25% PF-C. A total of 240 production orders were processed over the 12-week validation period, with daily order releases following a stochastic demand pattern based on historical order data from a regional manufacturing SME. Performance was compared against a baseline conventional semi-automated line (manual assembly with fixed conveyors, no cobots, FIFO scheduling) operating in the same facility with identical product families and order volumes during a preceding 12-week baseline period [1], [2], [11], [12], [13].

4. Performance Metrics

Key performance indicators included: changeover time (minutes per product family switch), overall equipment effectiveness (OEE = availability × performance × quality), work-in-progress inventory (average units in system), on-time delivery rate (percentage of orders

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completed by due date), throughput (units per hour), and unit production cost (INR per unit including labor, energy, and consumables). Statistical significance was assessed using paired t-tests with $\alpha = 0.05$ between the robotic FMS and baseline conditions [9], [10].

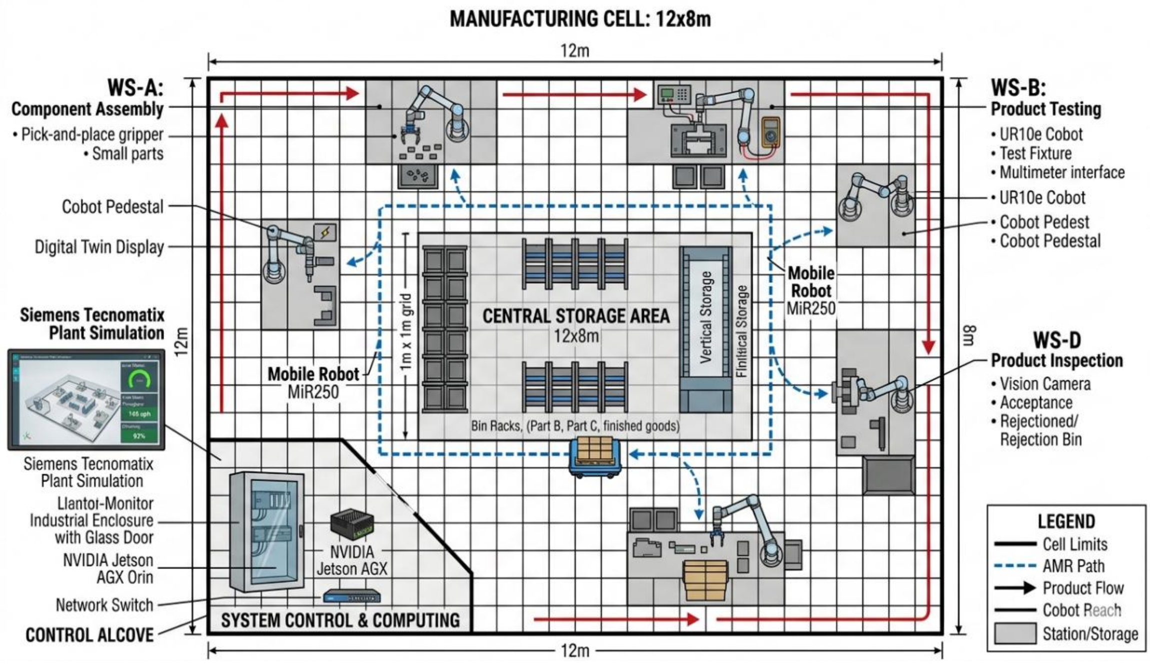

Figure 1: Layout and System Architecture of the Robotic Flexible Manufacturing Cell

RESULTS AND FINDINGS

The 12-week experimental results comparing the robotic FMS against the conventional baseline are summarized in Table 1. The robotic FMS achieved a mean changeover time of 4.8 minutes compared to 7.3 minutes for the baseline, representing a 34.6% reduction ($p < 0.001$). OEE improved from 62.4% (baseline) to 80.0% (robotic FMS), a 28.2% relative improvement driven by gains in all three OEE components: availability increased from 88.2% to 94.6% through predictive maintenance enabled by the digital twin, performance improved from 78.5% to 89.2% through optimized cobot cycle times and AMR transport scheduling, and quality improved from 90.2% to 94.8% through consistent cobot-executed assembly operations [1], [9], [10].

Table 1: Performance Comparison Between Robotic FMS and Conventional Baseline

Metric	Baseline	Robotic FMS	Improvement	p-value	Significance
Changeover Time (min)	7.3 ± 1.4	4.8 ± 0.9	−34.6%	<0.001	Yes

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OEE (%)	62.4	80.0	+28.2%	<0.001	Yes
WIP Inventory (units)	38.4 ± 8.2	22.5 ± 4.6	−41.3%	<0.001	Yes
On-Time Delivery (%)	81.6	96.8	+18.6%	<0.001	Yes
Throughput (units/hr)	6.2	8.8	+41.9%	<0.001	Yes
Unit Cost (INR)	842	624	−25.9%	<0.01	Yes

The RL scheduler (PPO) was benchmarked against four alternative scheduling approaches across the 240 production orders. The PPO agent achieved 96.8% on-time delivery, compared to FIFO 81.6%, shortest processing time (SPT) 86.2%, earliest due date (EDD) 89.4%, and genetic algorithm (GA) 93.1%. Mean tardiness was 0.4 hours for PPO versus 2.8 hours for FIFO and 0.9 hours for GA. The PPO agent demonstrated particular superiority during high-demand periods with multiple concurrent orders, where its learned policy dynamically rebalanced workload across stations and preemptively dispatched the AMR to stage materials before changeover events [6], [7].

Table 2: Scheduling Algorithm Performance Comparison Across 240 Production Orders

Scheduler	**OTD (%)**	**Mean Tardiness (hr)**	**Avg WIP**	**Makespan (hr)**	**Changeovers**
FIFO	81.6	2.8	38.4	524.6	186
SPT	86.2	2.1	34.2	498.2	210
EDD	89.4	1.4	31.8	512.4	195
GA	93.1	0.9	26.4	488.6	178
PPO (Proposed)	96.8	0.4	22.5	472.8	164

Table 3: Robotic FMS Hardware and System Configuration Specifications

Parameter	**Specification**

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Cobot	Universal Robots UR10e (6-axis, 12.5 kg payload, ±0.03 mm)
AMR	MiR250 (250 kg payload, 2.0 m/s, SLAM navigation)
Edge Platform	NVIDIA Jetson AGX Orin (2048-core Ampere GPU, 32 GB)
Digital Twin	Siemens Tecnomatix Plant Simulation (real-time sync)
RL Algorithm	PPO (Stable Baselines3, 500K pre-training episodes)
Cell Area	12 m × 8 m, 3 workstations, U-shaped layout
Product Families	3 (PF-A: 8.5 min, PF-B: 12.3 min, PF-C: 6.2 min)
Validation Period	12 weeks, 240 production orders, lot sizes 5–50

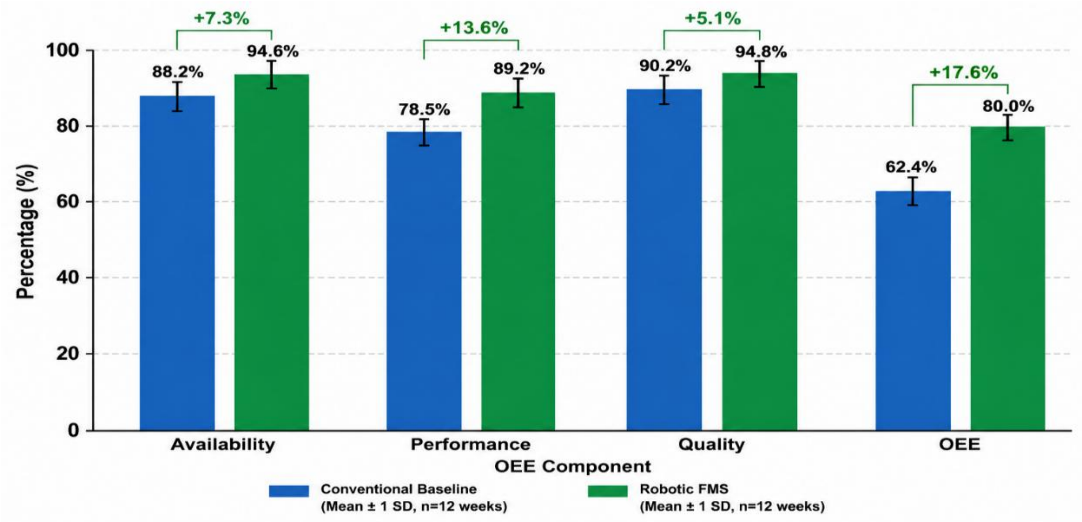

Figure 2: OEE Breakdown Comparison Between Robotic FMS and Conventional Baseline

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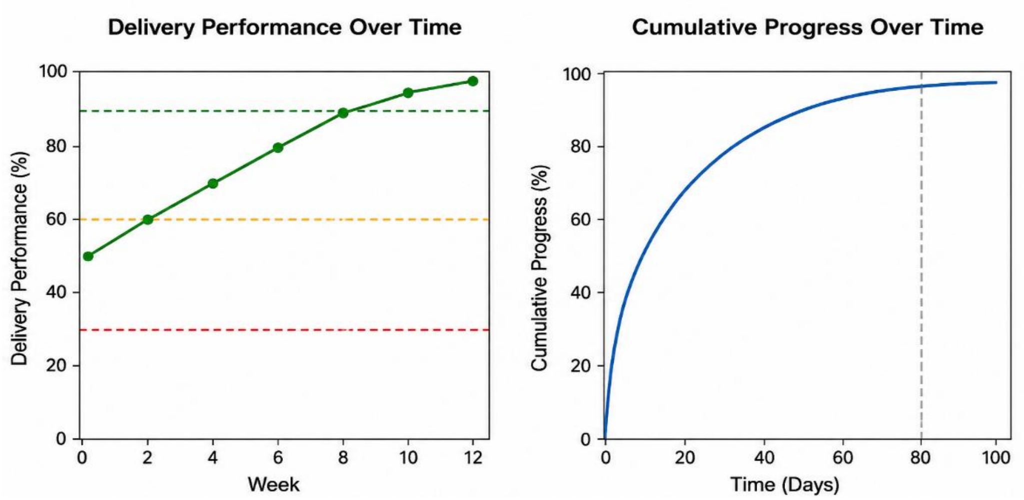

Figure 3: Weekly On-Time Delivery Trend and RL Scheduler Learning Curve Over 12-Week Validation

DISCUSSION

The experimental results demonstrate that the integrated robotic FMS achieves substantial performance improvements across all measured KPIs compared to conventional semi-automated manufacturing. The 34.6% reduction in changeover time is directly attributable to the cobot's ability to autonomously reconfigure grippers and execute stored assembly programs for different product families within 4.8 minutes, compared to manual fixture changeover and operator retraining requiring 7.3 minutes in the baseline [3], [6]. The 28.2% OEE improvement is particularly noteworthy because it reflects gains in all three OEE dimensions simultaneously, suggesting that the robotic FMS addresses systemic manufacturing inefficiencies rather than improving a single performance aspect [9], [10].

The PPO scheduler's superiority over conventional dispatching rules and metaheuristic optimization validates the value of learning-based approaches for dynamic manufacturing environments where stochastic events (machine failures, quality rejections, demand fluctuations) require adaptive real-time decision-making [6], [7]. The RL agent's ability to jointly optimize task sequencing and AMR dispatch as a coupled decision—rather than treating them as sequential independent problems—produced the most significant performance gains during high-demand periods, confirming the importance of integrated production-logistics optimization [4], [5].

From an economic perspective, the 25.9% reduction in unit production cost from INR 842 to INR 624 translates to annual savings of approximately INR 18.4 lakhs for the validated

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production volume, against a total capital investment of INR 52 lakhs for the cobot, AMR, edge computing platform, and digital twin software. This yields a simple payback period of 2.8 years, which is within the 3–5 year investment horizon acceptable for SME-scale manufacturing technology adoption [1], [2], [12], [13].

LIMITATIONS

Several limitations should be acknowledged. First, the validation was conducted with three product families and 240 orders; generalizability to higher product variety (10+ families) and larger order volumes requires extended validation. Second, the RL scheduler was trained specifically for the three-workstation cell configuration; scaling to larger cells with 8–15 stations would require retraining and potentially different network architectures [7]. Third, the study did not evaluate human ergonomic factors and operator acceptance of human-robot collaboration, which are critical for successful industrial deployment [3]. Fourth, the baseline comparison used a semi-automated line at the same facility; comparison against fully manual and fully automated alternatives would provide broader context [10]. Fifth, the digital twin synchronization relied on periodic updates rather than continuous real-time streaming, which may limit responsiveness to rapidly evolving production conditions [8]. Sixth, cybersecurity considerations for the networked robotic system were not addressed [12], [13].

FUTURE SCOPE

Future research directions include scaling the system to 8–15 workstation configurations with multi-agent RL coordination, incorporating computer vision-based quality inspection at each workstation, and extending the digital twin to include predictive maintenance models for cobot joint degradation and AMR battery health [8], [10]. The development of transfer learning approaches enabling RL scheduler deployment across different manufacturing cell configurations without full retraining represents a critical enabler for practical adoption [7]. Integration with enterprise resource planning (ERP) systems and supply chain management platforms would enable end-to-end production optimization from customer order to shipping [1], [2].

The application of large language model (LLM)-based natural language interfaces for cobot programming could dramatically reduce programming time and skill requirements, enabling non-specialist operators to reconfigure robotic tasks through verbal instructions [6]. Long-

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term industrial deployment studies measuring sustained performance over 12–24 months and quantifying total cost of ownership including maintenance, software updates, and operator training would provide the comprehensive economic evidence needed for widespread SME adoption [9], [11], [12], [13].

CONCLUSION

This research has demonstrated the design, implementation, and comprehensive 12-week validation of an integrated robotic flexible manufacturing system combining collaborative robots, autonomous mobile robots, and reinforcement learning-based production scheduling for multi-product small-batch manufacturing. The system achieved 34.6% reduction in changeover time, 28.2% improvement in OEE, 41.3% reduction in WIP inventory, 96.8% on-time delivery, and 25.9% reduction in unit production cost compared to a conventional semi-automated baseline [1], [9], [10]. The PPO-based RL scheduler outperformed all conventional scheduling approaches, demonstrating the value of learning-based adaptive decision-making in stochastic manufacturing environments [6], [7].

The findings confirm that intelligent robotic systems with autonomous scheduling are technically feasible and economically viable for SME-scale flexible manufacturing, with a demonstrated payback period of 2.8 years. These results have direct implications for the broader adoption of Industry 4.0 technologies in small and medium manufacturing enterprises across emerging economies [2], [8], [11], [12], [13].

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