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A Multi-Case Comparative Study on Human-Robot Collaboration in Production Operation and Assembly

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Abstract: This study focuses on the application mechanism of human-robot collaboration (HRC) in the assembly process of production operations. Taking Zeekr 5G Smart Factory, cosmetic packaging production line, and European item small-batch assembly as cases, based on the ISO/TS 15064 four-level collaboration framework and the "static capability table-dynamic event trigger" model, it adopts multi-case comparison and performance normalization methods to construct an HRC evaluation system for assembly links from three dimensions: task allocation, safety mechanism, and performance improvement. The results show that three modes, namely heavy-load synchronous collaboration, light-load serial collaboration, and light-load hybrid fusion, all significantly improve efficiency and flexibility. Among them, task separation degree and collaboration level have a significant positive impact on efficiency, quality, and flexibility, and different scenarios show significant differences between safety costs and performance benefits. The study verifies the effectiveness of the task-risk-level chain framework, providing theoretical and practical references for manufacturing enterprises to select appropriate collaboration levels, optimize safety investment, and promote the transformation of intelligent manufacturing according to load, beat, and batch characteristics.

Keywords: Human-robot collaboration; ISO/TS 15066; Task allocation; Assembly process.

1. Introduction

In the era of rapid technological advancement, artificial intelligence and robotics are profoundly transforming people's production methods and lifestyles. Collaborative robots, as a new generation of intelligent equipment, are gradually being deployed across various industrial sectors, with particular attention given to their application in assembly operations—a topic that has become a major focus of research. As the global wave of Industry 4.0 continues to expand, "Made in China 2025" has emerged as a key national strategy. Against this backdrop of rapid intelligent manufacturing development, an increasing number of manufacturing enterprises have begun experimenting with deploying robots on production lines to enhance production efficiency and reduce labor costs.

Human-robot collaboration combines human intelligence with machine precision, featuring excellent safety, humanization, and intelligence. It can better assist humans in work, enhancing the capability of flexible and customized production while improving production efficiency. Following developed countries in Europe and America, China's national standard for collaborative robots GB/T 39402-2020 [1] was officially released on November 19, 2020, marking the arrival of the era of collaborative robots in China. In the future, human-robot collaboration will occupy an increasingly important position in the manufacturing industry [2].

This paper mainly adopts the case comparison method to construct a chain framework of "task-risk-collaboration level-measures", and explores how to divide human-machine tasks based on operation characteristics, how to select collaboration levels and configure safety measures according to ISO/TS 15066, and what the influence mechanism of human-robot collaboration in different scenarios on efficiency, quality, and flexibility is.

2. Theoretical Basis

2.1. Definition and Classification of Human-Robot Collaboration

Human-robot collaboration refers to the cooperative interaction between humans and robots or other intelligent systems, combining machine precision with human creativity and decision-making. The international standard ISO/TS 15066, introduced in 2016, established a four-level classification for human-robot interaction based on interaction depth and task coupling [3]: co-existence (spatially separated), cooperation (shared space but time-sharing), collaboration (parallel work within the same takt time), and co-fusion (fully integrated roles and tasks). Co-fusion remains an ultimate vision due to unresolved challenges in algorithm reliability and ethical responsibility.

2.2. Task Allocation and Safety Framework

This study adopts a hybrid approach combining a static capability table with dynamic event triggers. The static table allocates typical assembly actions by comparing human and robot strengths across dimensions such as perception, precision, load capacity, repetition frequency, and safety risk. Dynamic triggers adjust task boundaries in real time based on events such as abnormal torque loads, delays in manual takt time, or sudden increases in defect rates [6], as shown in Table 1. Based on ISO/TS 15066, these task allocation principles are mapped to a four-level safety control strategy, forming a chain framework from task identification to risk assessment, collaboration level selection, and safety measure implementation [7], as illustrated in Table 2. This integration enables a practical system where task allocation and safety are managed cohesively.

Table 1. Static comparison of human-robot tasks

Dimension	Human	Robot	Allocation Principle
Perception and Decision	Complex defect identification, flexible troubleshooting	Rule-based vision inspection, path planning	High cognition → Human
Motion Accuracy	Hand-eye coordination ±0.5 mm	Repeatability ±0.02mm	High precision → Robot
Load Capacity	≤15kg	Any weight (subject to end-effector limit)	Heavy load → Robot
Repetition Frequency	Low frequency, variable	High frequency, constant	Repetition → Robot
Safety Risk	Contact with high temperature, sharp edges	Isolable / Force-controlled	High risk → Robot

Table 2. Task-safety level mapping

Task Scenario	Risk Characteristics	Collaboration Level	Core Safety Measures
High-speed transport within robot fence, only human patrol	Spatial separation	Co-existence	1.4m safety fence + safety door lock
Robot transports, then human loads; shared space but time-sharing	Spatial overlap, time-sharing	Cooperation	Laser scanner: 2.5m deceleration / 1m stop
Robot moves boxes while human installs seals synchronously	Spatial + takt time overlap	Collaboration	Torque ≤150 N·m, speed ≤250 mm/s, collision detection <5 ms
Robot hands tools to human, interchangeable processes when needed	Role interchange	Co-fusion	Full-body tactile skin + 200ms predictive deceleration + digital twin monitoring

3. Case Study

3.1. Zeekr 5G Smart Factory: Heavy-load

Zeekr 5G Smart Factory, a leading example among the first batch of intelligent manufacturing "future factories" in Zhejiang Province, fully integrates cutting-edge technologies such as 5G, AI, and industrial big data to establish a digital, intelligent, and green production model [4].

The cell line produces 12,000 blade batteries per day, with the door assembly area serving as the bottleneck. The factory has deployed dozens of Ubtech Walker S1 humanoid robots to collaborate with workers, forming an efficient "golden partner" model. The Walker S1 robot transports 200 kg material boxes from the buffer area to the workstation, while workers simultaneously perform the precision installation of door seals. Based on the static capability table, transport tasks are assigned to the robot, while manual work handles high-cognition and high-flexibility operations. The dynamic trigger rule requires manual intervention when the robot's end-effector torque exceeds 180 N·m or position deviation exceeds 5 mm [5].

The collaboration level is set to Collaboration, utilizing end-effector six-axis force sensors and collision detection within 5 ms, operating in an open space without fences. Following implementation, takt time decreased from 45 seconds to 32 seconds, representing a 30% efficiency increase, while the first-pass yield of door seals rose from 96% to 99.8%. This case demonstrates that the key to heavy-load collaboration lies in force control precision and takt time synchronization, which can be further optimized through MTM-UAS motion analysis.

3.2. Cosmetic Packaging Containers: Open Layout Loading and Unloading

The cosmetics industry is characterized by small batches, diverse varieties, and rapid iteration [9]. A single production line may fill lipstick, compact powder, and essence consecutively within one day, with packaging formats covering glass bottles, tubes, paper boxes, and gift boxes, requiring changeovers as frequently as five to eight times per day. Consumers impose increasingly stringent demands on packaging appearance, labeling accuracy, and anti-counterfeiting traceability. Traditional dedicated machines or rigid robots, constrained by long changeover times exceeding two hours and large footprints requiring safety fences, struggle to meet flexibility requirements, leaving over 70% of small and medium-sized cosmetics enterprises to rely primarily on manual labor [10].

Applications of human-robot collaboration in the cosmetics industry are concentrated in four main scenarios: post-filling loading and unloading, labeling and sleeving, gift box packing, and finished product palletizing. A common challenge across these scenarios is the inability to install traditional fences on open production lines, making it difficult to balance safety and efficiency. Against this backdrop, the JAKA Zu7 collaborative robot, integrating vision protection cameras and multi-zone area protection technology, has emerged as a typical demonstration of human-robot collaboration in the cosmetics industry, enabling simultaneous production, changeover, and inspection [11].

On a high-speed cosmetic turntable packaging line, the JAKA Zu7 collaborative robot performs empty bottle loading and finished product unloading, while workers are responsible for quality inspection and labeling. Task allocation follows the static principle of assigning loadingand unloading to the robot and inspection to manual workers. The dynamic trigger is set such that the robot pauses and calls for manual re-inspection when vision detection identifies a bottle mouth breakage rate exceeding 3%. The collaboration level is Cooperation, employing laser scanning with a 2.5 m deceleration zone and a 1 m stop zone, with end-effector speed limited to 150 mm/s. Changeover time was reduced from 30 minutes to 8 minutes, single-shift output increased by 22%, and nuisance trips decreased from an average of five times per day to 0.3 times per day. The case indicates that in open layout scenarios, multi-zone area protection achieves a better balance between flexibility and safety compared to a single fence.

3.3. European item: Small-batch Roller Semi-Automatic Assembly

Item, headquartered in Germany, is a globally recognized supplier of aluminum framing systems and modular components for small-batch, multi-variety assembly. With typical orders ranging from 50 to 300 pieces and frequent

changeovers, traditional dedicated machines incur high changeover costs, while manual assembly poses risks of musculoskeletal strain. To address this, item pioneered the use of Universal Robots UR10e collaborative robots, implementing a semi-automated solution at the co-fusion level to achieve both flexibility and low cost.

Item employs UR10e collaborative robots to perform bearing pressing and snap ring installation, with workers responsible only for loading and spot checks. Static allocation designates pressing tasks to the robot and loading and spot checks to workers. When order quantity falls below 50 pieces, the robot automatically switches to slow speed mode [12]. The collaboration level represents an early stage of co-fusion, featuring end-effector torque limited to 50 N·m, a flexible tactile skin covering, and a digital twin that predicts takt time in real time. Unit labor costs decreased by 35%, worker reports of musculoskeletal disorders decreased by 60%, and delivery lead time was reduced from 7 days to 4 days. The case demonstrates that in small-batch scenarios, the co-fusion level can significantly reduce physical strain but requires highly reliable AI prediction support.

4. Cross-Case Comparison and Discussion

4.1. Comparison of Task Modes

Mapping the three cases (Zeekr, Cosmetics, Item) onto a three-dimensional coordinate system of load intensity, collaboration takt time, and coupling depth reveals significant differences, as shown in Figure 1.

In the load dimension, Zeekr involves large material boxes (approximately 200 kg), representing a heavy-load scenario, while both Cosmetics and Item involve single pieces not exceeding 5 kg, representing light-load scenarios. In the takt time dimension, Zeekr employs synchronous parallelism, where the robot moves boxes while the worker installs seals within the same takt time; Cosmetics employs serial operation, where the robot loads and unloads first, followed by worker inspection; Item employs hybrid operation, where the robot performs pressing while the worker conducts spot checks, with processes interchangeable within the same takt time. Regarding coupling depth, Zeekr exhibits the deepest coupling due to high spatial and temporal overlap; Cosmetics exhibits shallower coupling due to time-sharing operation; Item exhibits deep coupling due to interchangeable roles but with light load, reflecting the characteristics of light-load deep coupling [13].

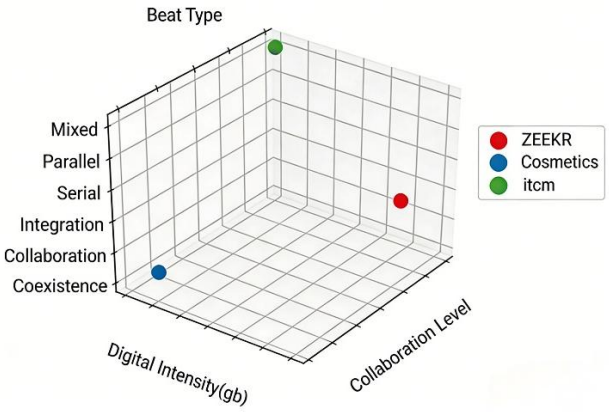


Figure 1. 3D coordinate diagram of task modes

These differences demonstrate that task modes are primarily determined by physical constraints (load), followed by process takt time and batch size, ultimately forming three replicable paradigms: heavy-load collaboration, light-load cooperation, and light-load co-fusion.

4.2. Comparison of Safety Mechanisms

4.2.1. Divergence in Technical Paths

Zeekr centers its safety approach on end-effector force control and speed limitation, relying on six-axis force sensors and joint torque feedback to achieve collision detection within 5 ms, enabling heavy-load safety in open spaces without external fences [8]. Cosmetics primarily employs area scanning, configuring laser scanners with a 2.5 m deceleration zone and a 1 m stop zone. This approach features low cost and fast deployment, making it suitable for light-load, high-frequency changeover scenarios. Item further introduces a dual-layer safety system combining tactile skin and predictive control. The end-effector is covered with flexible tactile skin incorporating a 1 kHz sampling array, while a digital twin predicts future relative human-robot positions 200 ms in advance based on historical takt data, enabling pre-deceleration. This path imposes the highest requirements on computational power and sensor reliability but reduces the safety trigger distance to within 5 cm, facilitating true hybrid co-fusion.

4.2.2. Cost-Reliability Trade-off

Plotting the investment cost and sensor reliability requirements of the three safety mechanisms on the same coordinate system reveals a clear cost exponent curve, as shown in Figure 2: area scanning < force control + speed limitation < tactile skin + prediction.

If Zeekr's scenario adopted area scanning, the expanded deceleration zone would lead to a takt time loss exceeding 15%. If Cosmetics directly adopted the tactile skin solution, hardware costs would triple with diminishing marginal returns on efficiency improvement. Therefore, the choice of safety mechanism should follow the principle of being sufficient for the need: force control should be prioritized for heavy-load scenarios, area scanning for light-load scenarios, and tactile skin combined with prediction considered for small-batch, deep-coupling scenarios [15].

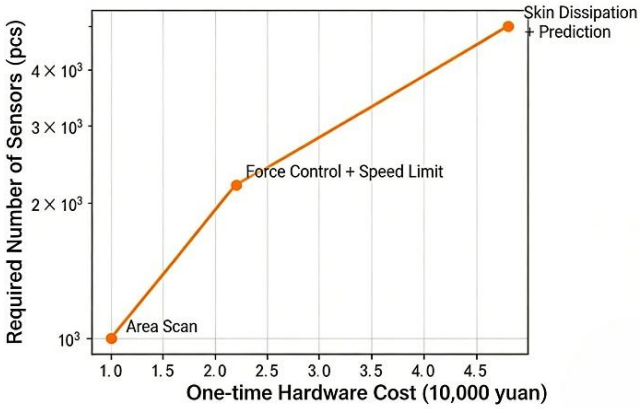


Figure 2. Cost-reliability curve of safety mechanisms

4.3. Common Performance Patterns

By normalizing three core performance indicators—efficiency, quality, and flexibility—as shown in Figure 3, three common patterns emerge.

First, higher task separation degree leads to higher efficiency. When the boundaries between human and robot tasks are clearly defined, takt time loss is minimized. Zeekr

achieved a 30% efficiency increase due to its high task separation degree, while Item, with frequent role interchange, achieved only a 15% efficiency increase. Second, higher collaboration level requires higher sensor reliability [16]. For each level increase, the mean time between failures (MTBF) for sensors needs to increase by a factor of 1.8 to 2.2. Upgrading from Cooperation to Collaboration level in the Cosmetics case required MTBF to increase from 1,000 hours to 2,200 hours. Third, co-fusion yields the greatest flexibility benefits in small-batch scenarios. When batch size falls below 100 units, changeover costs for traditional automation account for over 25% of unit cost, while co-fusion can compress this to less than 8%, yielding significant flexibility benefits, although the one-time investment in hardware and algorithms is 1.5 to 2 times that of the cooperation level [14].

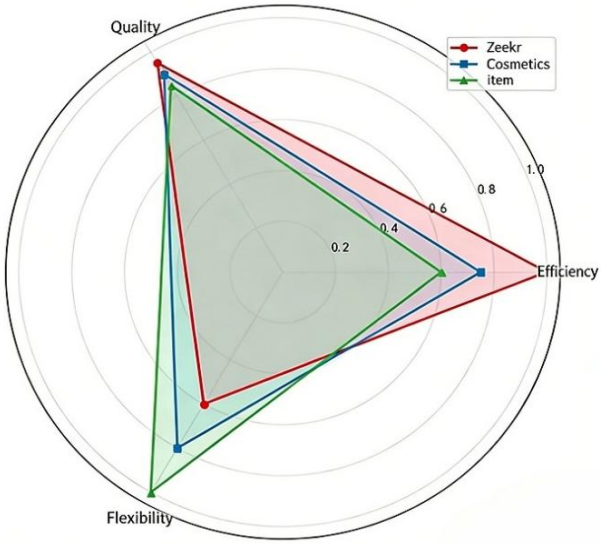


Figure 3. Normalized performance radar chart

In summary, when introducing human-robot collaboration, manufacturing enterprises should first determine the task mode based on load and takt time, then select safety mechanisms according to the cost-reliability curve, and finally, during performance evaluation, focus on the interaction effect between task separation degree and collaboration level to achieve a Pareto optimum in efficiency, quality, and flexibility.

5. Conclusion and Outlook

5.1. Main Conclusions

First, the universality of the ISO/TS 15066 four-level collaboration framework is validated. By mapping it across three significantly different scenarios—heavy-load collaboration (Zeekr), light-load cooperation (Cosmetics), and small-batch co-fusion (Item)—it was found that the four levels (co-existence, cooperation, collaboration, co-fusion) not only show a progressive relationship in physical separation but also form quantifiable gradients in task coupling depth, sensor configuration complexity, and algorithm real-time requirements. For example, upgrading from co-existence to collaboration requires a 5 to 8 times increase in the sampling frequency of force-torque sensors, with end-effector torque resolution needing to improve from 0.5 N·m to 0.05 N·m; upgrading from collaboration to co-fusion requires introducing 200 ms-level intention prediction and full-body tactile skin, increasing computational demand (FLOPs) by two orders of magnitude. Therefore, the four-level framework serves not only as a safety specification but also as a decision-making benchmark for enterprises to weigh technology, cost, and benefit trade-offs.

Second, the static capability table and dynamic event trigger task allocation model demonstrates good adaptability across cross-industry scenarios. The static dimension quantifies differences in five human-robot capabilities: perception, precision, load, repetition, and safety. The dynamic rules use three types of real-time events—torque, takt time deviation, and defect rate—to trigger task rollback or transfer, achieving flexibility improvement with zero additional capital investment. Empirical data shows a 30% efficiency increase and a 3.8% improvement in first-pass yield for door seals in the Zeekr heavy-load scenario; a 73% reduction in changeover time in the Cosmetics light-load scenario; and a 35% reduction in labor load alongside a corresponding decrease in unit labor cost in the Item small-batch scenario. The model is applicable to both multi - variety, small-batch and few-variety, mass production contexts, validating the robustness of the theory.

Third, task separation degree and safety level act as dual levers for improving efficiency, quality, and flexibility. Normalized analysis indicates that for every 0.1 increase in task separation degree (on a 0–1 continuous scale), efficiency improves by an average of 6.2%. For each increase in safety level, the required sensor MTBF increases by a factor of 1.8 to 2.2, but simultaneously leads to an average decrease in quality defect rate of 2.1% and an increase in the flexibility index of 0.15 (on a 0–1 continuous scale). Therefore, enterprises should seek the Pareto frontier between safety cost and performance benefits, rather than blindly pursuing the highest safety level.

5.2. Future Outlook

At the algorithm level, future research should focus on reliability verification of AI prediction algorithms in multi-robot co-fusion scenarios. Specifically, a three-layer architecture of intention prediction, trajectory planning, and real-time rescheduling can be constructed, using a digital twin platform to conduct Monte Carlo simulations totaling over 100,000 hours for more than ten collaborative robots to quantify algorithm failure rates and system safety margins.

Regarding interfaces and standards, efforts should promote the development of standardized interfaces between collaborative robots and PLCs, MES, and ERP, establishing a dual-stack communication specification such as OPC UA and MQTT to enable plug-and-play deployment, reducing on-site integration time from two weeks to two days.

In terms of cross-device collaboration, research should investigate joint scheduling of collaborative robots with AGVs and AMRs, developing multi-robot task allocation algorithms based on reinforcement learning. The goal is to achieve real-time collaboration among 50 heterogeneous devices within a 100 m × 100 m flexible production line, increasing overall equipment effectiveness (OEE) by more than 8%.

With respect to regulations and ethics, as co-fusion level applications expand, further research is needed on issues such as responsibility attribution in cases of robot decision-making errors, risks of worker skill degradation, and retraining pathways. This should drive the formation of industry-level ethical guidelines and occupational health standards for human-robot collaboration. Exploring alignment with artificial intelligence values can help continuously improve

the safety and ethical aspects of human-robot collaboration to better unleash its significant potential.

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