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VARIOUS SCHEDULING TECHNIQUES USED IN HUMAN-ROBOT COLLABORATIVE SYSTEM STRATEGIES FOR ALLOCATION AND OPTIMIZATION OF TASKS

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Abstract. This paper explores scheduling techniques used in Human-Robot Collaborative (HRC) systems to allocate and optimize tasks. The objective is to enhance productivity and efficiency by leveraging the strengths of both humans and robots. The study examines three main task distribution models in HRC: human-centric task allocation, human-robot task allocation, and robot-centric task allocation. Human-centric task allocation prioritizes human capabilities and preferences, while human-robot task allocation aims to strike a balance between humans and robots, considering their complementary skills. Robot-centric task allocation focuses on maximizing the utilization of robots for enhanced performance. Additionally, the paper discusses other task distribution models, including project management models, lean manufacturing models, and scheduling algorithms. Project management models aid in planning and managing complex projects, while lean manufacturing models optimize workflow and resource allocation. Scheduling algorithms provide efficient strategies for task scheduling and allocation. By considering these models, researchers and practitioners can make informed decisions when allocating and optimizing tasks in HRC systems. Ultimately, the utilization of appropriate scheduling techniques contributes to improved collaboration, productivity, and efficiency between humans and robots in HRC systems.

Keywords: HRC (Human-Robot Collaboration), Collaborative robotic systems, Collaborative work, Task scheduling and coordination, Resource allocation and utilization, Workflow optimization.

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1 Introduction

Scheduling strategies for optimization and task allocation in Human-Robot Collaborative (HRC) systems encounter numerous fundamental problems. For starters, job complexity emerges because of considering human and robot skills, preferences, and expertise. To assign duties efficiently, this complexity needs comprehensive analysis and decision-making. Second, coordination and task dependency pose difficulties in managing task interdependencies and assuring smooth collaboration among people and robots. Task scheduling and coordination become crucial to getting desired results (Liang et al., 2021; Mokhtarzadeh et al., 2020; Lee et al., 2022).

Another difficulty is resource use, where managing the allocation and usage of resources such as workers, robots, and equipment is critical for boosting production and decreasing idle time. Real-time adaptability and responsiveness are required in HRC systems to interact with changing environments and fluctuating objective needs. Scheduling methods must adapt and respond fast to alter job distribution and enhance performance.

Finally, safety issues are crucial in HRC systems. It is essential to provide safe job allocation and execution, including human safety and collision avoidance. Solving these shortcomings is critical for the effective adoption of scheduling strategies in HRC systems, which will eventually improve cooperation, safety, and productivity in human-robot interactions (Proia et al., 2022). Several actions may be taken to address the major issues related to scheduling strategies in Human-Robot Collaborative (HRC) systems (Li et al., 2023).

Conducting a thorough examination of the current job scheduling methods applied to HRC systems. This entails researching numerous techniques, algorithms, and models used in the subject to comprehend their strengths, limits, and applicability.

An examination of the job scheduling strategies chosen and used by various types of manufacturers. Custom manufacturing, engineer-to-order, manufacturing job shop manufacturing, and other similar areas are included. Recognizing the various requirements and restrictions that each type of manufacturer faces may offer insights into the scheduling approaches that are often used in their respective sectors.

Exploring scheduling strategies used in different industries including project management, lean manufacturing, and different scheduling algorithms outside of the HRC domain. These domains frequently have proven to schedule methodologies that might provide useful insights and potential solutions for HRC systems (Parsa & Saadat, 2021; Tram & Raweewan, 2021).

Evaluating the suitability of scheduling approaches used in other sectors with the special needs and limits of HRC systems. Determine the similarities and contrasts across the areas, as well as the transferability and adaptation of scheduling strategies from one domain to another. This study aids in the selection and modification of scheduling methods from other domains to meet the specific requirements of HRC systems.

2 Related Work

There have been several attempts to optimize task allocation and optimization. One of these methods, detailed in Dalle Mura & Dini (2019) used a genetic algorithm to build HRC workplaces while accounting for ergonomic and economic concerns. It assigns humans and robots to workstations depending on their expertise.

Other techniques, such as those in (Wesskamp et al., 2019; Michalos et al., 2018), make use of simulation models. In Wesskamp et al. (2019) processes are evaluated for their appropriateness for people and robots, with the final assignment established through simulation, taking ergonomic, economic, and safety factors into account. In Michalos et al. (2018) an algorithm develops alternative schedules based on a CAD model, designing layouts, and assessing them for cost, cycle time, and ergonomics using a simulation model.

In Raatza et al. (2020) attempted to make the deployment of Human-Robot Collaboration (HRC) workplaces easier by concentrating on task scheduling, capabilities, and time assumptions. They applied their method to the construction of a gearbox at Lenze SE, a German manufacturer of automation systems. A Genetic Algorithm (GA) was employed to develop two schedules, one targeted at boosting manufacturing volume and the other at enhancing ergonomics. The first schedule was chosen by Lenze because of its shorter cycle time and lesser safety risk.

While robots may take longer than people to complete some subprocesses, parallelization considerably decreased cycle time, leading to a 23% increase in productivity over the manual method Raatza et al. (2020). However, it was emphasized that greater direct collaboration between humans and machines, as demonstrated in the second schedule, might boost efficiency even more.

According to the study, this job scheduling strategy is especially advantageous for Small and Medium Enterprises (SMEs) since it does not need costly simulations or substantial specialist expertise. When integrated with hardware selection, the GA optimizes scheduling based on a company's worldwide objectives and the strengths of collaborators, providing an ideal solution for HRC workspaces (Raatza et al., 2020).

While these models can be effective, there might be other methods to implement this, ultimately offering more comprehensive solutions for optimizing Human-Robot Collaboration (HRC) workspaces.

3 Problem Statement

In the context of Human-Robot Collaborative (HRC) systems, effective task allocation poses multifaceted challenges. Balancing human and robot capabilities, coordinating task dependencies, and efficient resource utilization are critical for enhanced productivity.

Additionally, real-time adaptability, safety, and seamless integration of scheduling methods are imperative. To address these challenges, a comprehensive approach is proposed: Analyzing Current Methods: Investigate existing scheduling techniques, algorithms, and models in HRC systems to understand their strengths and limitations.

Industry-Specific Insights: Examine scheduling strategies employed by different manufacturers to glean insights applicable to diverse manufacturing types.

Cross-Domain Exploration: Explore scheduling methodologies from industries like project management and lean manufacturing, assessing their adaptability to HRC systems.

Transferability Evaluation: Evaluate the feasibility of transferring strategies from other domains to HRC systems, considering unique requirements.

By undertaking these steps, the aim is to enhance the efficiency, safety, and productivity of task allocation in HRC systems.

4 Task Distribution Models in HRC

Human-robot collaboration (HRC) Task Distribution Models encompass a sophisticated framework for efficiently assigning tasks to both human and robotic agents in collaborative settings. These models aim to enhance operational efficiency and coordination by meticulously considering multifaceted task attributes, the cognitive proficiencies of human workers, the technical capabilities of robots, and the equilibrium of workloads. The application of task distribution techniques in HRC settings leads to improved performance, heightened adaptability, and the alleviation of human labor through judicious task allocation among the pertinent agents (Hans-Jürgen, 2020).

The domain of Human-Robot Collaboration (HRC) Task Distribution Models employs a diverse range of methodologies to effectively partition tasks among human and robot entities. Priority-based scheduling mechanism allocates tasks based on their priority levels, ensuring that tasks with utmost significance are addressed foremost. In parallel, deadline-driven scheduling ensures tasks are apportioned in accordance with their temporal constraints to meet time-sensitive requirements. Load balancing methodologies ensure a fair and equitable distribution of responsibilities across both human and robot agents, forestalling undue strain on any single entity.

Task dependency analysis is employed to decipher intricate task interdependencies, guiding the sequencing and allocation of tasks. Additionally, optimization algorithms are invoked to ascertain the optimal task allocation strategy, hinging on variables such as time, cost, and resource utilization. Real-time scheduling mechanisms dynamically allocate assignments in concordance with their priority and responsiveness mandates. Moreover, heuristic-based systems leverage rule-based or experiential paradigms to rationally distribute tasks based on accumulated knowledge (Pupa et al., 2022).

Human-Robot Collaboration Task Distribution (HRC Task Distribution)

$$HRC\_Task\_Distribution = f(TC, HA, RA, WC, PD, LB, TD, TA, OA, RS, HS) \quad (1)$$

Where: HRC_Task_Distribution: Represents the orchestrated task distribution strategy within the Human-Robot Collaboration context.

f(): Signifies a function amalgamating an array of intrinsic and contextual factors.

TC: Encompasses Task Characteristics, encompassing aspects like task complexity and nature.

HA: Encompasses Human Abilities, encompassing their cognitive and skill-based attributes.

RA: Encompasses Robot Abilities, embodying their technical capabilities and potential for automation.

WC: Encompasses Workload Considerations, orchestrating an even-handed distribution of tasks.

PD: Signifies the Priority-driven Scheduling scheme.

TD: Conveys the Deadline-driven Scheduling paradigm.

TA: Denotes the Task Dependency Analysis strategy. OA: Represents the Optimization Algorithms employed for discerning optimal allocations.

RS: Stands for the Real-time Scheduling approach.

HS: Represents the Heuristic-based Systems utilized for intelligent allocation.

This holistic formulation underscores the systematic integration of disparate factors to achieve effective cooperation, augmented efficiency, and elevated performance within Human-Robot Collaboration systems.

4.1 Human Centric Task Allocation

Human-centric task allocation represents a paradigm shift in task assignment methodologies within the manufacturing domain. This revolutionary technique places paramount emphasis on harnessing human capabilities, knowledge, and preferences to optimize collaboration between human workers and robotic systems (Dianatfar et al., 2019). The core framework is mathematically encapsulated within the Human-Centric Task Allocation (HCT) formula:

$$HCT = \sum(w_{\text{cap}} \cdot C + w_{\text{knowledge}} \cdot K + w_{\text{preferences}} \cdot P) \tag{2}$$

In this formulation, HCT embodies the holistic integration of human capabilities (C), knowledge (K), and preferences (P), duly weighted by coefficients w_cap, w_knowledge, and w_preferences. This systematic approach aligns task allocation to amplify human contributions, adhering to the tenets of human-centered design principles. The outcome manifests in tasks expertly tailored to maximize human involvement, thus engendering elevated overall productivity. The formula encompasses not only human aptitudes but also their availability, experience, and preferences, harmoniously interwoven with the capabilities of robotic systems (Ranz et al., 2017).

For specific contexts such as custom manufacturing, characterized by intricate tailoring to individual client needs, the HCT framework assumes pivotal significance. The Task Allocation formula in this domain can be succinctly presented as:

$$\text{Task\_Allocation} = H + R \tag{3}$$

In this equation, 'H' signifies tasks designated to humans, encompassing cognitive tasks such as decision-making, problem-solving, and customization. Conversely, 'R' pertains to tasks delegated to robots, encompassing repetitive or physically demanding actions. This deliberate segregation capitalizes on human ingenuity for intricate tasks, while seamlessly integrating robotic precision for tasks necessitating repetition or high precision. This synergy culminates in manufacturing efficiency that steadfastly upholds product quality (**?**).

Transitioning to the realm of job shop production, characterized by diverse item processing requirements, HumanCentric Task Allocation proves its mettle. The Job Allocation formula assumes the form:

$$\text{Job\_Allocation} = \sum(w_{\text{talents}} \cdot T + w_{\text{expertise}} \cdot E + w_{\text{availability}} \cdot A) \tag{4}$$

This formula meticulously assesses human talents (T), expertise (E), and availability (A), weighted by coefficients w_talents, w_expertise, and w_availability. The meticulous balancing of these factors ensures that adept individuals are entrusted with roles commensurate with their expertise, thereby optimizing production and minimizing lead times. For engineer-to-order enterprises, which hinge on crafting bespoke, innovative products, the significance of Human-Centric Task Allocation endures. The Design Allocation equation emerges as:

$$\text{Design\_Allocation} = \sum (w_{\text{talents}} \cdot T + w_{\text{experience}} \cdot E) \tag{5}$$

This expression focalizes on human engineers' talents (T) and experience (E), harmonized by coefficients w_{talents} and $w_{\text{experience}}$. Through judicious task assignments informed by human strengths, this approach streamlines the design process, fostering seamless human-robot collaboration. Engineer-to-order manufacturers can consistently deliver customized, high-quality products punctually (Johannsmeier & Haddadin, 2017). By incorporating these precise formulas and principles, Human-Centric Task Allocation becomes a beacon guiding manufacturing endeavors. This scientific approach assures optimal task distribution, synergizing human ingenuity with robotic capabilities, to orchestrate manufacturing processes characterized by efficiency and innovation (Fansen et al., 2021).

4.2 Human Robot Allocation

Human-Robot Task Allocation is a pivotal process encompassing the strategic assignment of responsibilities within collaborative environments, harmoniously capitalizing on the synergies between human operatives and robotic entities. This orchestration serves as a linchpin for optimizing productivity, efficiency, and safety, empowered by the distinct proficiencies of both humans and collaborative robots.

The formula for Human-Robot Task Allocation is represented as:

$$HRTA = \sum (w_{\text{human}} \cdot H + w_{\text{robot}} \cdot R) \tag{6}$$

Where: - $HRTA$: Symbolizes the orchestrated Human-Robot Task Allocation strategy. - $\sum$: Represents the summative amalgamation of diverse tasks. - w_{human}: Reflects the weightage assigned to human-centric tasks. - H: Encompasses tasks delegated to human operatives. - w_{robot}: Represents the weightage attributed to tasks entrusted to robotic entities. - R: Encompasses tasks earmarked for robotic execution.

Mass Production Manufacturer: Within the confines of mass production realms products are manufactured in substantial volumes and the orchestration of task allocation assumes paramount significance. Human-robot task allocation could be depicted as:

$$\begin{aligned} HRTA_{\text{Mass Production}} &= w_{\text{human}} \cdot (Decision + \text{QualityControl} \\ &+ \text{Troubleshooting}) + w_{\text{robot}} \cdot (Assembly + \text{Packaging} + \text{MaterialHandling}) \end{aligned} \tag{7}$$

For enterprises entailing batch production characterized by customization, the task allocation dynamic could be articulated as:

$$\begin{gathered} HRTA_{\text{Batch Production}} = w_{\text{human}} \cdot (Customization + \text{Inspection} + \text{ProblemSolving}) \\ + w_{\text{robot}} \cdot (MaterialPreparation + RepetitiveAssembly) \end{gathered} \tag{8}$$

Make-to-Order Manufacturer: In the context of enterprises crafting bespoke solutions based on customer requisites, the underlying formula could be conveyed as:

$$\begin{aligned} HRTA_{\text{Make-to-Order}} = w_{\text{human}} \cdot (Customization + Design + CustomerInteraction) \\ + w_{\text{robot}} \cdot (MaterialHandling + AutomatedInspections) \end{aligned} \tag{9}$$

Assemble-to-Order Manufacturer: For establishments dealing in assemble-to-order paradigms, catering to a spectrum of product variants, the task allocation dynamic finds expression as:

$$\begin{aligned} HRTA_{\text{Assemble-to-Order}} = & w_{\text{human}} \cdot (Customization + FinalAssembly + QualityAssurance) \\ & + w_{\text{robot}} \cdot (StandardizedAssembly) \end{aligned} \tag{10}$$

This holistic paradigm shift underscores the seamless fusion of human expertise and robotic precision, epitomizing the pioneering realm of collaborative manufacturing. By adroitly capitalizing on the strengths of each agent, industries materialize a future deeply rooted in efficient, innovative, and adaptive production methodologies. In the dynamic contexts of mass production, batch production, make-to-order, and assemble-to-order, formula-driven allocation strategies propel manufacturing into an era of enhanced productivity, versatility, and excellence (Ali et al., 2022; Malik & Bilberg, 2019).

4.3 Robot Centric Task Allocation

Robot-Centric Task Allocation is a methodical paradigm characterized by the strategic distribution of tasks and responsibilities within a collaborative framework, groun- ded in the inherent capabilities and efficiency of robotic systems. This approach is intricately crafted to harness the utmost potential of robots and their specialized competencies, thereby fostering an amplification of productivity, precision, and expeditiousness. Within the domain of continuous process manufacturing, where products perpetuate in an uninterrupted cascade, the efficacy of robot-centric task allocation models assumes salience.

These models ingeniously apportion tasks to robots that are primed for uninterrupted operation, ensuring an unceasing production continuum. Tasks involving material handling, assembly, and quality inspection are astutely entrusted to robots, capitalizing on their predisposition for rapidity and unwavering repetition. In parallel, human operatives are strategically assigned roles necessitating decision-making acumen, maintenance expertise, or supervisory oversight. This astute choreography substantiates manufacturing efficiency and substantiates the bedrock of consistency Lamon et al. (2019).

The formula for Robot-Centric Task Allocation in Continuous Process Manufacturing:

$$\begin{aligned} RCTA_{\text{Continuous\_Process}} = w_{\text{robot}} \cdot (MaterialHandling + Assembly + QualityInspection) \\ + w_{\text{human}} \cdot (DecisionMaking + Maintenance + SupervisoryRoles) \end{aligned} \tag{11}$$

w_robot: This is the weight assigned to tasks intended for robotic execution. It indicates the importance of robots in performing specific tasks. Material Handling, Assembly, and Quality Inspection: These are the tasks that robots are assigned in the continuous process manufacturing setting. They include activities like moving materials, assembling components, and conducting quality checks.

w_human: This signifies the weight attributed to tasks that are designated for human workers. It reflects the significance of human involvement in certain aspects of the manufacturing process. Decision Making, Maintenance, and Supervisory Roles: These tasks are entrusted to human workers in the continuous process manufacturing context.

They involve making decisions, conducting maintenance activities, and overseeing the overall process. For contract manufacturers, entities who extend their manufacturing prowess on behalf of external stakeholders, the virtues of robot-centric task allocation manifest conspicuously.

Within these models, tasks are judiciously delegated to robots, grounded in their intrinsic efficiency, repeatability, and cost-effectiveness. Robots emerge as paragons of precision, accuracy, and high-volume operations – encompassing domains like assembly, packaging, or rigorous testing. In tandem, human operatives pivot towards tasks demanding the nuance of customization, the rigor of quality control, or the finesse of customer communication.

This symphony underpins the capacity of contract manufacturers to robustly fulfill production mandates, sans compromise to the benchmarks of quality (Müller et al., 2016).

The formula for Robot-Centric Task Allocation for Contract Manufacturers

$$\begin{aligned} RCTA_{\text{Contract}} &= w_{\text{robot}} \cdot (Assembly + Packaging + Testing) \\ &+ w_{\text{human}} \cdot (Customization + QualityControl + CustomerCommunication) \end{aligned} \tag{12}$$

w_robot: This weight indicates the priority of tasks suited for robotic execution, considering their efficiency and capabilities. Assembly + Packaging + Testing: These tasks are assigned to robots within the context of contract manufacturing. They encompass activities like product assembly, packaging, and quality testing.

w_human: This weight signifies the importance of tasks intended for human workers. It reflects the value of human involvement in specific facets of the manufacturing process.

Customization, Quality Control, and Customer Communication: These tasks are reserved for human workers in the contract manufacturing realm. They include customization of products, quality control checks, and interactions with customers. Within the context of lean manufacturing principles, a philosophy dedicated to waste reduction and operational efficiency maximization, robot-centric task allocation introduces renewed dynamism. Robots are entrusted with tasks tethered to repetitive operations, attenuating variability and accelerating cycle times.

This strategic alliance capitalizes on the alacrity and precision intrinsic to robots, thus ushering in streamlined manufacturing processes. Human workers, in turn, are adroitly assigned tasks demanding problem-solving prowess, acumen in process enhancement, and finesse in intricate decision-making. This harmonious interplay seamlessly dovetails with the ethos of continual improvement, thereby enhancing the efficacy of lean manufacturing principles. Through the prism of robot-centric task allocation, superfluous tasks are extricated, rendering resource allocation at its zenith of optimization.

$$\begin{aligned} RCTA_{\text{Lean\_Manufacturing}} &= w_{\text{robot}} \cdot (RepetitiveOperations) \\ &+ w_{\text{human}} \cdot (ProblemSolving + ProcessImprovement + DecisionMaking) \end{aligned} \tag{13}$$

w_robot: This weight signifies the significance of tasks tailored for robots' capabilities in the context of lean manufacturing, focusing on minimizing waste and optimizing efficiency. Repetitive Operations: This task category is assigned to robots in the context of lean manufacturing. It comprises tasks that are repetitive in nature and can be efficiently executed by robots.

w_human: This weight reflects the priority of tasks intended for human workers, aligning with lean manufacturing principles. Problem Solving + Process Improvement + Decision Making: These tasks are earmarked for human workers in the realm of lean manufacturing. They encompass activities such as addressing problems, refining processes, and making informed decisions to enhance overall efficiency (Antoniuk et al., 2020).

These formulations succinctly encapsulate the quintessence of robot-centric task allocation across diverse industrial scenarios. Through such strategic orchestration, industries adroitly harness the innate strengths of both robots and human workers, culminating in an epoch characterized by heightened efficiency, precision, and sustainable growth.

5 Other Task Distribution Models

Other Task Distribution Models encompass additional approaches used for allocating and distributing tasks in various contexts (Choudhury & Biswal, 2009). These models offer alternative strategies that may be applicable in specific scenarios or industries, addressing unique requirements and objectives. While not exhaustive, these models broaden the range of options available for effective task distribution in different collaborative settings.

When choosing an alternative distribution model for a specific application, there are several factors that users need to consider. Firstly, they should assess the project's unique requirements and constraints to determine the model's suitability. Factors such as project complexity, resource availability, and task interdependencies play a crucial role in model selection. Secondly, the scalability and flexibility of the chosen model should be evaluated, to ensure it can accommodate future growth and adapt to changing circumstances.

Additionally, the ease of implementation and integration with existing systems is important for a smooth transition. Users should also consider the computational complexity and efficiency of the model, as it can impact overall performance. Finally, the level of control and visibility provided by the model, including the ability to monitor progress and make adjustments, should be taken into account. By considering these factors, users can make informed decisions when selecting an appropriate task distribution model that aligns with their specific requirements and optimizes task allocation and management.

5.1 Project Management Models

Project management models provide a systematic approach to organizing and coordinating project tasks, ensuring efficient resource allocation, meeting deadlines, and achieving desired outcomes. In this section, we will explore key models like the Gantt Chart, Critical Path Method (CPM), and Program Evaluation and Review Technique (PERT). These models optimize task scheduling and project execution, playing a vital role in successful project management (Zhang et al., 2018).

Gantt Chart: The Gantt Chart is a widely used project management tool that visually represents project schedules. It displays project activities as horizontal bars on a timeline, indicating the start and end dates of each task. Gantt Charts provide a clear overview of task dependencies, milestones, and resource allocation, facilitating effective planning and tracking of project progress.

Critical Path Method (CPM): The Critical Path Method is a project management technique that identifies the critical path, the longest sequence of dependent activities, in a project schedule. By analyzing the critical path, project managers can determine the tasks that directly impact project duration. CPM helps identify bottlenecks, optimize resource allocation, and ensure timely completion of the project (Das et al., 2020).

Program Evaluation and Review Technique (PERT): PERT is a probabilistic project management technique that incorporates uncertainty and risk analysis into project scheduling. It involves estimating activity durations based on three estimates: optimistic, pessimistic, and most likely. PERT uses these estimates to calculate the expected duration of activities and overall project completion time. PERT enables project managers to account for uncertainties and make informed decisions regarding project scheduling and resource allocation Zhang et al. (2018).

5.2 Lean Manufacturing Models

Lean manufacturing models are renowned for their focus on efficiency, waste reduction, and continuous improvement within manufacturing processes. These models aim to eliminate non-value-added activities and streamline operations, resulting in increased productivity and customer satisfaction (Trebuna et al., 2023). In this section, we will delve into the key lean manufacturing models, including the Kanban System and Just-In-Time (JIT), and explore their significance in optimizing production flow and resource utilization.

Kanban System: The Kanban System is implemented to optimize production. This lean manufacturing model emphasizes visual control and just-in-time replenishment, minimizing inventory and reducing lead times. Collaborative robots are strategically placed at different production stages to assist human workers. For example, in the soldering stage, a human worker places components on a circuit board, while a robot inspects placement accuracy using a camera system. If deviations are detected, the robot alerts the worker for rework. When components are correctly placed, a Kanban card signals the next stage (Trebuna et al., 2023).

At the component placement stage, the collaborative robot efficiently places components based on the pre-programmed design and verifies alignment with sensors. After completing the component placement, a Kanban card initiates the quality inspection stage. This Kanban System with collaborative robots ensures smooth and uninterrupted production, aligning manufacturing with customer demand while enhancing efficiency and flexibility.

The quality inspection stage involves both human workers and collaborative robots. The robots use advanced vision systems to inspect the board for defects, ensuring that components are correctly placed and soldered. Human workers conduct additional checks and perform more intricate inspections. If any issues are detected, the Kanban card triggers the board to be sent back for rework.

Finally, the Kanban card for the packaging stage is initiated. Collaborative robots handle the packaging process, placing the assembled electronic devices into appropriate containers. The robots ensure that the devices are carefully placed to prevent damage during transportation.

In this example, the Kanban System orchestrates the movement of work-in-progress items through different stages of production, with collaborative robots seamlessly integrating with human workers to ensure accuracy, quality, and efficiency.

Just-In-Time (JIT) Manufacturing: Just-In-Time manufacturing is a lean approach that focuses on producing and delivering goods precisely when they are needed, minimizing waste and inventory. This strategy aims to streamline production processes, reduce lead times, and enhance efficiency by aligning production with customer demand. JIT is built on the idea of delivering the right quantity of items, at the right time, to the right place. The JIT philosophy requires a well-orchestrated coordination between various stages of the supply chain, from suppliers to production and distribution. By minimizing inventory levels and eliminating non-value-added activities, JIT helps companies achieve cost savings, improved quality, and enhanced responsiveness to market fluctuations (Gupta & Garg, 2012).

Collaborative robots, often referred to as cobots, seamlessly integrate into the JIT approach by providing a dynamic and responsive solution to various manufacturing tasks. Their ability to work alongside human operators, automate repetitive tasks, and respond swiftly to changing demands aligns well with the JIT principles. Now, let's explore how collaborative robots contribute to a Just-In-Time manufacturing environment through a specific example.

In an automotive assembly plant practicing Just-In-Time manufacturing, collaborative robots enhance the efficient production of cars. Consider the task of installing doors on car bodies:

- **Door Delivery and Real-Time Demand:** Collaborative robots receive doors from suppliers and store them based on real-time demand signals. This minimizes excess inventory and ensures doors are ready precisely when needed.

- **Seamless Installation and Quality Control:** Collaborative robots work alongside human workers to fetch and position doors for installation. Equipped with vision systems, the robots ensure proper alignment, minimizing defects.

By integrating collaborative robots, benefits include optimized resource utilization, reduced waste, flexibility to adapt to demand changes, and an overall more efficient assembly process. This aligns with the principles of Just-In-Time manufacturing.

5.3 Scheduling Algorithms

Scheduling algorithms occupy a pivotal role in orchestrating task sequencing and resource allocation across diverse domains, ranging from intricate manufacturing processes to intricate project management endeavors. Within this realm, these algorithms furnish structured methodologies for discerning the optimal sequence for task execution, thereby ensuring the judicious utilization of resources while attaining stipulated performance benchmarks. Within this discourse, we shall delve into several salient scheduling algorithms, encompassing Flexible Job Shop Scheduling (FJSP), Round Robin, Critical Ratio (CR), and Parallel Scheduling. Each algorithm proffers distinct strategies and evaluation criteria for task prioritization and scheduling, characterized by their unique attributes and contextual considerations.

Flexible Job Shop Scheduling (FJSP): is a manufacturing optimization problem where jobs with multiple operations must be scheduled on machines while considering various constraints, such as machine availability and processing times, to minimize makespan or other performance metrics.

This paper Yu et al. (2021); Johnson et al. (2022) approach using Double DQN to tackle the dynamic Flexible Job Shop Scheduling Problem in robot assembly cells. The solution combines a centralized training phase with decentralized scheduling policies, minimizing agent communication for efficiency. Notably, it outperforms heuristic rules in scenarios with high job arrival rates and extended time windows, consistently achieving shorter makespans. While validated through a conveyor case study, its design principles are broadly applicable to various Flexible Job Shop Scheduling Problem settings.

Where the main goal is to minimize the makespan, which is the maximum completion time among all operations, and can be expressed as:

$$\min\left\{\max\left\{C_{ij}^{T}\right\}\right\} \tag{14}$$

$$\text{Subject to: } C_{ij}^{T} \text{ for all } i, j. \tag{15}$$

Operation Sequence Constraint: Each job's operations must be completed in the correct order. The completion time of each operation should be greater than or equal to the completion time of the previous operation of the same job.

$$1 \leq 2 \leq \ldots \leq O \quad C_{ij}^{1} \leq C_{ij}^{2} \leq \ldots \leq C_{ij}^{O} \tag{16}$$

Machine Constraint: Each machine can process only one operation at a time. This constraint ensures that at any time step, a machine is working on only one operation.

$$\sum(m_{ijk}, m_{ijk'}) \leq 1 \quad \text{for all } i, j, k \quad \delta(m_{ijk}, m_{ijk'}) \leq 1 \quad \text{for all } k \quad \text{(Kronecker delta)} \tag{17}$$

Job Conflict Constraint: The completion time of an operation must be greater than or equal to the completion time of the previous operation on the same machine. This prevents conflicts between operations of different jobs on the same machine.

$$C_{ij}(k-1) + p_{ij}(k-1) \leq C_{ijk} \quad \text{for all } i, j, k \tag{18}$$

$$C_{ij'}^{k} + p_{ij'}^{k} \leq C_{ijk} \quad \text{for all } i, j, j', k \tag{19}$$

Planning Horizon Constraint: Operations must finish within the planning horizon, T.

$$C_{ij}^{T} \leq T \quad \text{for all } i, j \tag{20}$$

Round Robin algorithm assigns a fixed time quantum TQ to each task within a cyclic trajectory. Tasks are allotted execution intervals adhering to the stipulated quantum before being preempted and shifted to the queue's rear. In paper Yu et al. (2021) a decentralized DQN-MARL method for solving multi-agent task scheduling in Human-Robot Collaboration (HRC) environments. It frames HRC assembly as an assembly chessboard game, with defined rules. The DQN-MARL algorithm combines traditional DQN reinforcement learning with a cooperative and correlated equilibrium model. Case studies on height-adjustable desk assembly show its effectiveness, outperforming other machine learning algorithms like DQN-SARL, naive Nash-Q learning, and dynamic programming (DP). Which can be used for round-robin algorithm which is architect of parity among tasks, Round Robin teeters on potential inefficacies in instances of varying task execution durations.

Knowing that tasks are assigned a fixed time quantum TQ for execution. Mathematical consider the waiting time W_i for each task i:

$$\text{If } C_i > T_i : W_i = (C_i - T_i) - A_i \tag{21}$$

$$\text{If } C_i \leq T_i : W_i = 0 \tag{22}$$

Where C_i is the completion time of task i, T_i is the execution time of task i, and A_i is the arrival time of task i

Critical Ratio (CR): It is predicated upon the calculus of slack time and processing time ratios, unveils its prioritization rubric. Tasks are sequenced based on their critical ratio, where elevated ratios equate to escalated urgency. CR harbors the aim of optimizing resource utilization while curtailing project duration by targeting tasks endowed with minimal scheduling flexibilities.

Based on Tung et al. (2022) a unique bilevel optimization strategy for robot kitting, demonstrates its efficacy in lowering work duration and eliminating idle times for a furniture assembly task. This methodology beat a generic whole-kit assembly (Whole Assembly) and a human-designed just-in-time method (Single Task) in terms of task completion speed and user satisfaction on several subjective criteria in comparative user research.

Based on user input, the study also shows the opportunity for additional research in two critical areas. The first step is to investigate online estimations of human job length to improve idle time reduction, and the second step is to incorporate human-related parameters into the optimization framework. Furthermore, the study intends to explore which elements contribute the most to the efficiency and usability of kitting tray designs.

The algorithm prioritizes tasks based on their critical ratio. Let's consider the critical ratio CR_i for each task i:

$$CR_i = \frac{S_i}{P_i} \tag{23}$$

Where S_i is the slack time of task i and P_i is the processing time of task

Parallel Scheduling: Parallel scheduling algorithms are cast in the mold of task allocation across multiple processors or resources to bolster holistic system performance. This breed of algorithms takes into consideration a tapestry of facets, spanning task interdependencies, resource availability, and communication overhead, to judiciously allocate tasks and harness the tenets of parallelism inherent in the system.

These scheduling algorithms represent quintessential components within the tapestry of efficient resource allocation and systematic task sequencing. Their amalgamation into various operational landscapes is predicated upon a discerning evaluation of distinct operational parameters, cementing their significance as cardinal tools within the ambit of multifaceted industrial orchestration.

6 Conclusion

In conclusion, this study focused on scheduling techniques in Human-Robot Collaborative (HRC) systems for task allocation and optimization. It explored various task distribution models in HRC, including human-centric, human-robot, and robot-centric approaches. Additionally, other models such as project management, lean manufacturing, and scheduling algorithms were examined. The study identified challenges related to task complexity, dependency, resource utilization, real-time adaptation, and safety considerations. By analyzing existing methods, understanding manufacturer preferences, exploring techniques from other fields, and considering compatibility, researchers can develop tailored scheduling strategies for HRC systems.

This research contributes to enhancing collaboration, productivity, and safety in human-robot interactions. Further research can build upon these findings to address remaining challenges and improve the efficiency of scheduling techniques in HRC systems.

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