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Multi-disciplinary Optimization for Designing Human-Robot Collaborated Work-Cell for Low-Volume and High-Variant Production

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Abstract. Human–robot collaboration solutions have gradually become popular, in which some tasks are performed by robots and others by humans. Designing such a production cell requires simultaneous consideration of human-centered factors, machine-focused mechanical design, and system engineering in the early planning stages. However, different objectives often conflict (e.g., speeding up a robot can improve productivity while compromising energy efficiency), and the same variables can affect multiple models and simulations simultaneously (e.g., a machine where humans and robots collaborate can influence both the operator's working posture and the robot's cycle time). Therefore, multidisciplinary tools and multi-level optimization are needed to model, simulate, and optimize elements such as production flows, robotics, and human operators to balance objectives related to cycle time, energy consumption, and worker well-being. In this paper, we formulate an approach that integrates different simulation tools and a bi-level optimization framework to balance worker well-being, cycle time, and energy consumption. We demonstrate this approach through a real industrial case of designing a work cell for elevator pipe assembly in a grain conveying system, where ABB RobotStudio is used for robotic simulation and IPS IMMA for human simulation. IBM ILOG CPLEX Optimization Studio is employed for the top-level task allocation optimization, and a set of results is presented based on data extracted from the lower-level robot-centered optimization. The results show that our approach can effectively balance different objectives by incorporating detailed information from different levels of the work cell design.

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1 Introduction

Manufacturing has evolved from manual craftsmanship to mechanized mass production and, more recently, to advanced intelligent systems [1]. The automation transformation continues to advance, increasingly penetrating small and medium-sized enterprises (SMEs) specializing in Low-Volume and High-Variant (LVHV) production. This trend persists although manual labor offers significant adaptability and allows for quick adjustments to changes in product design and customer requirements [2, 3]. The shift is driven not only by the need to balance demands for efficient productivity and high-quality output but also by rising labor costs, increasing concerns over working conditions, and the emergence of advanced technologies such as artificial intelligence and collaborative robotics [2, 4]. Given the substantial investment and complexity required for full automation in an LVHV context, human-robot collaboration (HRC) presents a more practical and feasible solution. However, realizing these solutions remains complex, as the early design phase may demand various simulations and optimizations for different purposes, even with comprehensive guides for investment decisions and reference designs for workstations [4, 5].

In industry, the manufacturing system design process often follows a top-down approach. Productivity, frequently the initial objective, is defined at a high level and is usually represented with cycle time. To achieve this objective, overall workflows are broken down and sub-processes are assigned to different workstations. This necessitates determining decision variables at lower levels, such as process times, parallel execution of tasks by multiple robots, and buffer sizes and locations. For such cases, Discrete Event Simulations (DESs) are commonly employed to simulate flow lines and facilitate system design. Optimization techniques, including linear, integer, or mixed-integer programming and metaheuristics, are then applied to obtain high-quality scheduling solutions.

When automating a series of manual operations where manual operations cannot be fully automated, robots and human operators are often planned to work together within a shared workstation. This type of collaboration requires decisions on task allocation between the robot and the operator. The general principle is to assign tasks that could lead to work-related musculoskeletal disorders to the robot, using simulations to verify feasibility under constraints like layout space, cycle time, and safety guidelines. However, even simple manual tasks can pose risks to employees if equipment design details—such as the height of a worktable or the stopping position of a cylinder—are not considered, as these factors influence the operator's working postures. To evaluate the short- and long-term impacts on operator well-being, digital human modeling and simulation are required for ergonomic analysis and for optimizing working conditions, taking human diversity into account.

Modern production systems must frequently balance multiple objectives that reside in different disciplines, such as cycle time, human well-being, equipment selection, and energy consumption. A single simulation or optimization with a single simulation method cannot cover all these aspects, especially when a key performance indicator is affected by variables at different system levels. For example, the final productivity of a cell can be influenced by the raw material arrival pattern, machine availability, and operator behavior. Hybrid modeling and simulation enable the combination of different factors—such as process, equipment, factory, and human elements—within a production system for comprehensive analysis [6]. Coupled with bi-level optimization, which explores and solves two hierarchically related problems, this represents a promising approach in both theory and application [7].

In this paper, we propose a methodology that integrates multi-disciplinary modeling and bi-level optimization to design a workstation where a robot and a human collaborate to produce elevator pipes. The goal is to balance objectives related to productivity (represented by cycle time), operator ergonomics, and robotic energy consumption. The paper is structured as follows:

Section 2 reviews background and related work, Section 3 introduces the methodological framework, and Section 4 presents the use case. A set of preliminary results is shown and explained in Section 5, and the paper concludes with discussions and conclusions in Section 6.

2 Background and Related Work

Designing a Human-Robot Collaboration (HRC) workstation often begins with allocating available resources and tasks between the human and the robot. Numerous studies have focused on configuring stations to balance workloads and improve productivity [8]. For instance, the study in [9] formulated available resources and constraints into a mixed-integer linear programming model to address assembly line balancing problems with HRC. Similarly, a method with assessing assembly complexity and workload is introduced in [10] to inform a new task allocation model for optimizing cycle time, workload variance, and assembly complexity.

Solving the task and resource allocation problem requires various types of data, such as precedence relations between tasks, human and robotic process times, and the type of collaboration required for each task. However, there is often a lack of precise data, with many inputs relying on rough estimations [11]. An example is from [10], in which they evaluated whether a collaborative robot could complete a task based solely on physical characteristics and task descriptions but without any simulation or physical experiment.

Simulating a robot in a virtual cell can verify automation feasibility and provide precise data on process time and energy consumption for specific tasks [12]. Beyond supplying fundamental data for allocation, this approach unlocks the potential for better overall solutions by incorporating detailed design considerations. For example, optimizing a robot's path plan can reduce the time required for a task, thereby improving the station's overall cycle time [13].

Meanwhile, when human-robot collaboration is involved, modeling and simulating human operations by motion capture data based simulations also become necessary. Such simulations in combination with motion capture can evaluate the risk of musculoskeletal disorders and assess the operator's physical well-being when performing repetitive tasks [14]. Various ergonomic assessment methods exist, such as Rapid Entire Body Assessment, Rapid Upper Limb Assessment (RULA) and Arm Force Field. To overcome the limitations of traditional observation, motion capture data can be used to enhance the precision and reliability of these evaluations [15] .

Facilitated by advanced human and robot modeling and simulation, additional objectives can be incorporated when designing the workstation, such as minimizing the total ergonomics score to improve operators' well-being and reducing the robot's energy consumption for sustainability [16]. However, this integration can lead to more complex optimization problems, as a top-level objective may be influenced by variables or solutions from different system levels. Although metaheuristic algorithms can be utilized to handle the complexities (e.g., split-based Non-Dominated Sorting Genetic Algorithm II (NSGA-II) in [17]), bi-level optimization techniques appear more suitable for workstation design to achieve optimal objective values [18] with considering the hierarchical relations in task allocation and robot-centered optimization.

The major contribution of this paper is to propose a methodology for designing an HRC workstation that integrates human and robotic modeling and simulation within a bi-level multidisciplinary multi-objective optimization framework. This integrated approach generates solutions for task allocation, equipment layout, and robotic running speed, balancing multiple objectives across different levels of the system hierarchy.

3 Methodology

This study employs a multi-disciplinary approach combining hybrid simulation and bi-level optimization to design an automated manufacturing workstation for tasks previously performed

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entirely by human operators. The methodology begins with an analysis of high-level design requirements and constraints, such as the total budget, target productivity, layout dimensions, and future scalability of the workstation. These initial parameters are then used to inform the subsequent development of robotic and human simulations. During this phase, the requirements are applied flexibly to guide decisions on lower-level details, including the number of workers, robots, and essential equipment, while identifying and resolving potential hidden contradictions—for instance, between a target productivity and an unrealistic budget.

The human modeling and simulation phase involves breaking down human operations, whether discrete or continuous, into a sequence of discrete, atomized tasks. This decomposition allows for detailed observation and ergonomic evaluation. To mitigate subjective bias, multiple ergonomic assessment methods are typically employed, with a final conclusion derived through a consensus mechanism, such as a majority vote or unanimity rule. Beyond identifying potential safety and health risks, this process yields critical data, including: (1) the process time for a human to complete each atomized task, and (2) an assessment of the necessity (e.g., for simple but risky tasks like heavy lifting) and feasibility (e.g., for complex, low-precision tasks like part bolting) of automating each individual task.

Concurrently, a virtual robotic work cell is constructed to visually represent the potential physical workstation. This simulation serves several key purposes: (1) to verify the feasibility of using a robot or required machine to perform an atomized task, (2) to validate the overall process flow within the cell, (3) to determine the optimal shapes and locations of equipment, and (4) to explore safe and efficient human-robot collaboration methods.

Following the development of the human and robotic models, a bi-level optimization framework is implemented to balance the objectives of cycle time, robotic energy consumption, and ergonomics. A key variable linking the two optimization levels is the process time for individual robotic tasks, which is determined by the robot's path running time. This time, along with the associated energy consumption, is directly influenced by the robot's speed settings and the via/target locations in its path program. The target location, where the robot interacts with equipment, is often linked to equipment parameters (e.g., height, stop position) that also affect human operator postures, thereby serving as a bridge between ergonomic and automation analyses.

The overall workstation cycle time is an emergent property resulting from task allocation between human and robot, the task execution sequence, and the precise process time of each task. The first-level (lower-level) optimization involves detailed robotic-centered (and human) simulation, with decision variables focused on robotic path programming. The outputs of this level, which comprises ergonomics scores, energy consumption, and precise process times for each task, serve as inputs to the second-level (upper-level) optimization. This upper level focuses on task allocation to optimize the system-wide objectives of cycle time, total energy consumption, and aggregate ergonomics score.

The general framework of this methodology is illustrated in Figure 1. The final optimal task allocation decision, derived from this bi-level process, ultimately defines the level of automation for the workstation, situating it between the extremes of fully manual operation and complete automation.

4 Case Study

This case study involves designing a workstation to automate the assembly of parts for a grain conveyor system. The initial goal for the cell is to assemble elevator pipes, which have five variants of different sizes and weights, with future scalability planned to include pipe connectors and rolling axes. The tasks involved are loading, gluing, assembling, bolting, and unloading sub-

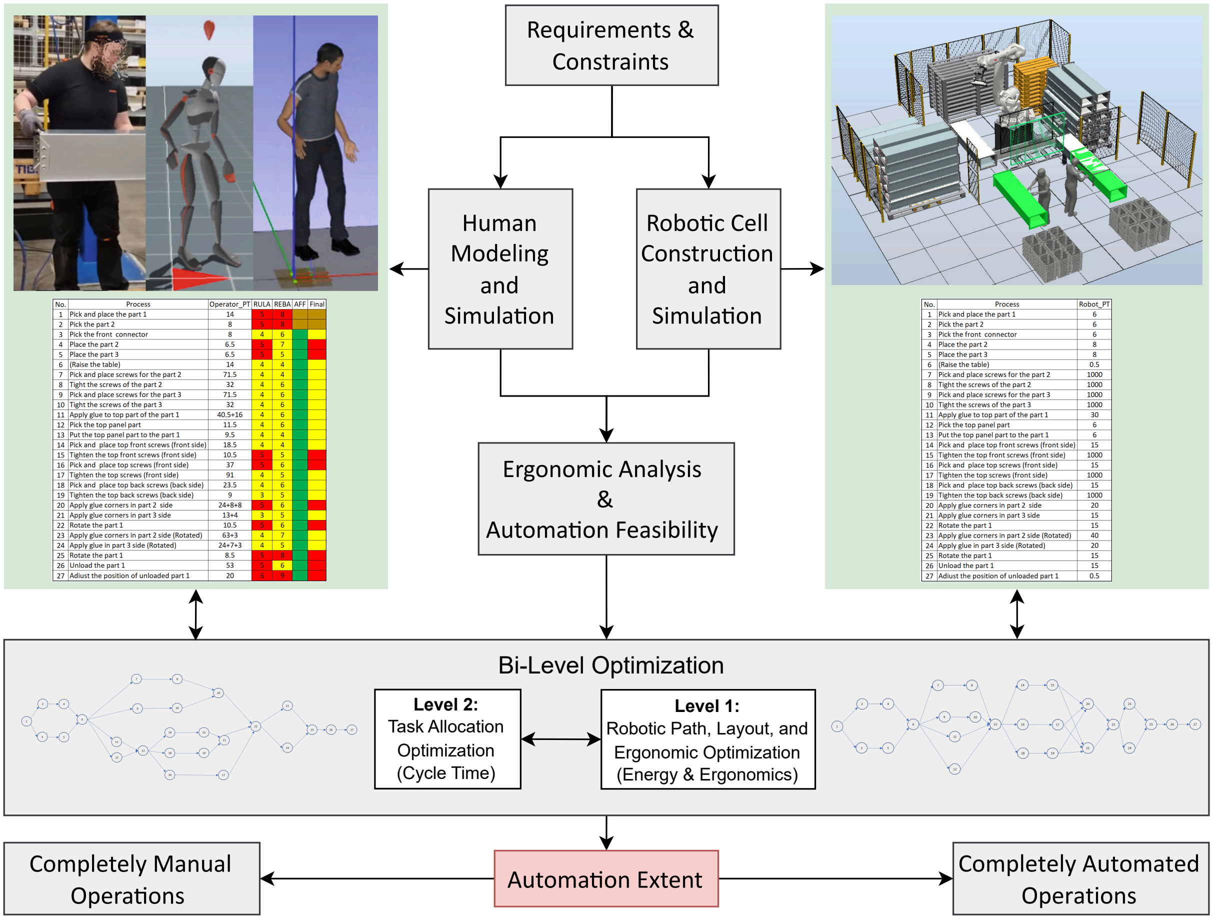

Figure 1: Framework of a hybrid simulation and bi-level optimization methodology

assemblies or final parts, all of which are currently performed manually. A set of demonstration data for process time, ergonomics score, and energy consumption per task is provided in Table 1, and the manufacturing process precedence is illustrated in Figure 2.

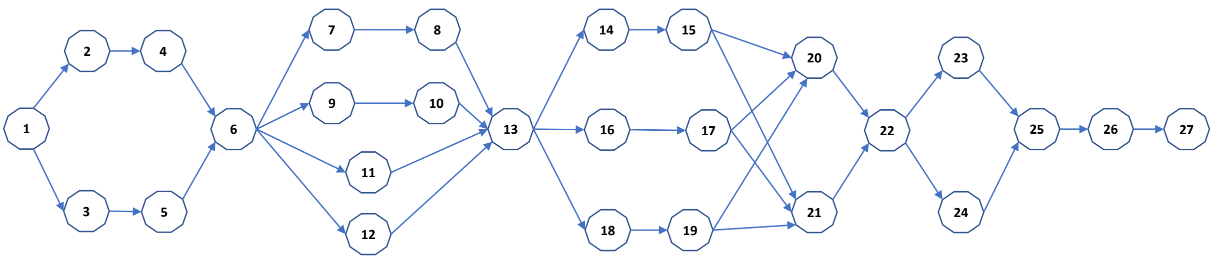

Figure 2: The precedence of the 27 tasks to assemble the elevator pips in the study case

Although integrated platforms for human and robot simulation exist, we performed the simulations in separate software environments at the industrial partner's request. For task allocation, We utilized the solver developed in [9]; for ergonomic analysis, we began by recording a worker's movements using Xsens MVN Awinda motion capture technology and subsequently integrated this data with digital human modeling in IPS IMMA (left side of Figure 3). After evaluat-

Table 1: A set of intermediate objective values for task allocation optimization

No.	Task Description	HPT[1]	RPT[2]	ES[3]	EC[4]
1	Pick and place Part 1	14	6	5	9
2	Pick Part 2	8	6	5	12
3	Pick front connector	8	6	4	10
4	Place Part 2	6.5	8	5	12
5	Place Part 3	6.5	8	5	15
6	(Raise the table)	14	0.5	1	2
7	Pick and place screws for Part 2	71.5	1000	5	1000
8	Tight screws of Part 2	32	1000	4	1000
9	Pick and place screws for Part 3	71.5	1000	4	1000
10	Tight screws of Part 3	32	1000	4	1000
11	Apply glue to top of Part 1	56.5	30	5	15
12	Pick top panel	11.5	6	5	8
13	Put top panel to Part 1	9.5	6	5	10
14	Pick and place top front screws	18.5	15	5	25
15	Tighten the top front screws	10.5	1000	3	1000
16	Pick and place top screws	37	15	3	25
17	Tighten the top screws	91	1000	3	1000
18	Pick and place top back screws	23.5	15	4	30
19	Tighten the top back screws	9	1000	3	1000
20	Apply glue on Part 2 corners	40	20	5	8
21	Apply glue on Part 3 corners	17	15	5	8
22	Rotate Part 1	10.5	15	4	12
23	Glue on Part 2 corners (rotated)	66	40	5	8
24	Glue in Part 3 (rotated)	34	20	5	6
25	Rotate Part 1	8.5	15	5	12
26	Unload Part 1	53	15	5	18
27	Adjust position of Part 1	20	0.5	6	8

[1] HPT: Human Process Time of handling the task
[2] RPT: Robot Process Time of handling the task
[3] ES: Ergonomics Score of human handling the task
[4] EC: Energy Consumption of robot handling the task

ing each task separately by three different methods, the most limiting ergonomics evaluation method, RULA, was selected. In order to represent the accumulation of risk across the different tasks, an accumulative calculation of RULA was used for the ergonomics score objective (see from [15]). Beyond obtaining ergonomics scores, the key findings were: (1) bolting and certain gluing tasks should remain manual, because some part precision requirements and awkward angles for glue application make their automation difficult; and (2) to improve visual and manual operation conditions, the shared fixtures used by the human and robot at different times should be rotatable and able to stop at predefined positions to avoid manual, heavy-lifting part flipping.

The virtual workstation was constructed using ABB RobotStudio for robotics and equipment simulation (right side of Figure 3). Payload requirements, with one product variant exceeding 50 kg, necessitated the use of an industrial robot instead of a preferred collaborative robot. The major equipment includes a gluing gun, tables and frames for gluing and part flipping, a vacuum gripper, and a large rotating table with fixtures. In addition to equipment positions, locations for material inflow and outflow, as well as pallet placement, are critical to the workflow. In this

Figure 3: Human and Robot Modeling and simulation in IPS IMMA and ABB RobotStudio

proposed design phase, initial robotic programs were designed for the robot to perform tasks among the equipment prototypes. The decision variables in the current setting include eight equipment locations and two variables for the speed and acceleration settings in the robotic program. The exploration of this decision space is controlled by an optimizer, such as NSGA-III; once a solution is generated, it is sent and configured into the simulation cell via a custom-developed software add-in. Simultaneously, the location of the rotating table, particularly its height (z-direction), communicates with the dataset of results from IPS IMMA for ergonomic analysis. The electricity consumption and running time (i.e., the process time) for the robot to execute each task, obtained from the robot simulation, along with the ergonomics scores from the human simulation, are gathered as intermediate objectives. These values are subsequently used to optimize the task allocation and calculate the final objective values.

To utilize the workload balancing tool, an initial task sequence is established based on the natural process flow of manufacturing the product. At this level of optimization, the decision variables are represented by binary values indicating whether each individual task is performed by the human or the robot. For tasks mandated for human performance, the process time for the robot is set to a prohibitively large value. The outputs of this optimization include the workstation's cycle time, the robot's total energy consumption, the overall ergonomics score, and a Gantt chart. The Gantt chart visualizes the optimal schedule, detailing the allocation and sequence of each atomized task, while the other three outputs constitute the final objective values for the system.

The configuration of the ABB RobotStudio add-in for the low-level optimization is currently ongoing. Consequently, the task allocation optimization has been conducted only once, using a single set of intermediate objective values with estimated robot energy consumption data (see Table 1). Ideally, the data in Table 1 should be updated for each solution explored during the low-level, human-and-robot-related optimization. This is necessary for two reasons: (1) changes to the robot's running speed and the equipment layout, which influence the robot's travel distance, will alter the process time and energy consumption data for each robotic task; and (2) modifications to the equipment used by the operator can require re-evaluation of human performing the tasks, which can lead to updated process times and ergonomics scores. To balance the objectives of productivity, ergonomics, and energy consumption, we employ the epsilon-constraint method for Pareto front generation within a mixed-integer programming model, implemented using the

IBM ILOG CPLEX Optimization Studio solver.

5 Results and Analysis

An optimization was performed using the process precedence from Figure 2 and the data from Table 1, yielding the results presented in Figure 4. To narrow down the solutions, we applied preference-based filters with the following bounds: 450 ≤ Cycle Time ≤ 460, 30 ≤ Ergonomics Score ≤ 60, and 150 ≤ Robot Energy Consumption ≤ 200, to filter the obtained solutions. This identified six optimal solutions that are suitable for further decision-making analysis.

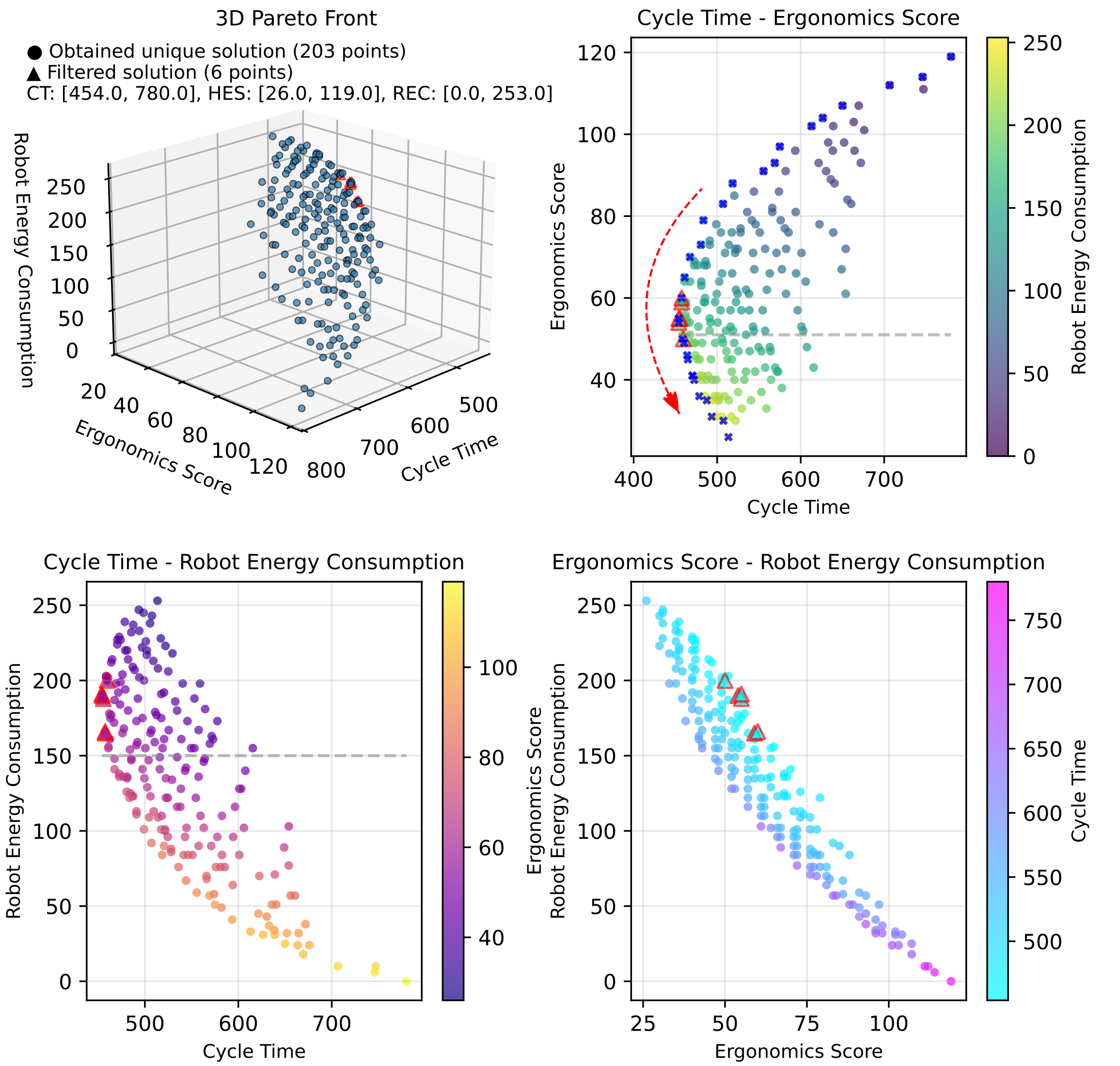

Figure 4: Tasks allocation results with a given demo set of Human Process Time, Robot Process Time, Human Ergonomics Score and Robot Energy Consumption value of each task

The optimization results are presented in Figure 4. The cycle time is determined by the allocation and sequencing of tasks between the human and robot. The ergonomics score represents the cumulative score of all tasks performed by the human operator in a cycle, while the robot energy consumption is the total from all tasks completed by the robot. The objectives are minimizing all three indicators. From the bottom-right plot in Figure 4, it is evident that the objectives of human ergonomics score and robot energy consumption are conflicting, as they exhibit opposite trends with increasing cycle time. However, when consider the relation between cycle time and ergonomics score, the trade-off trend changes from cooperating to conflicting with the ergonomics score dropping to a certain level according to the top-right figure. The relation among cycle time and robot energy consumption is similar to that of cycle time and ergonomics score according to the bottom-left figure. The trade-off relations are more clear from observing the height of bar plots in Figure 5, which illustrate the cycle time and the total working time of the human and robot in different solutions. The order of the solution indexes in Figure 5 is along the dashed line direction from the blue marked solutions in the top-right plot in Figure 4 with a decreasing ergonomics score.

Moreover, when the ergonomics score is held constant at a certain level, the robot's energy consumption decreases as the cycle time increases, as shown by the color gradient along the gray dashed line in the top-right plot in Figure 4. Conversely, with fixed robot energy consumption, the ergonomics score decreases as the cycle time increases, evident from the color change along the gray dashed line in the bottom-left plot. There are many details in a single, and we use a Gantt chart in Figure 6 to illustrate the task orders and their beginning time from the solution that is marked by the blue star in Figure 5. It is an optimal one with a minimum cycle time of 454 seconds, although the robot works less time and has idle time in a production cycle.

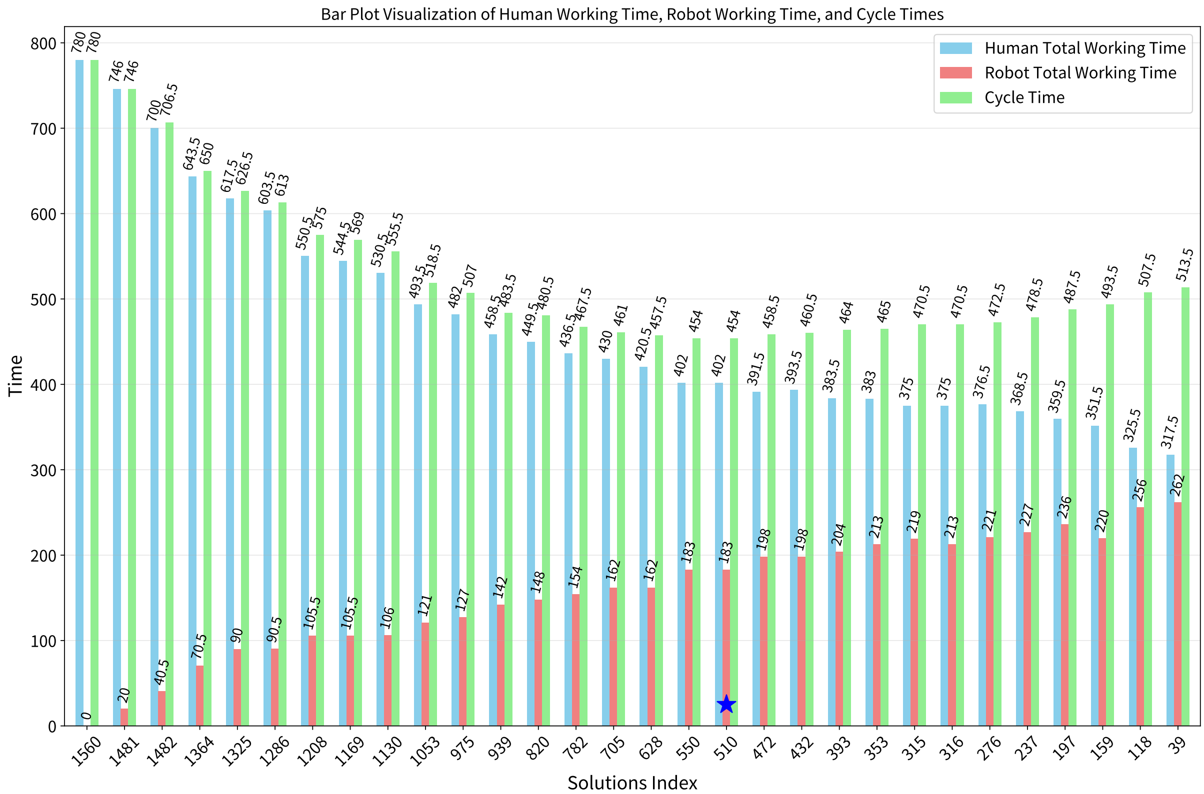

Figure 5: Cycle time and the total working time of robot and human from a series of solutions

From the results in Figure 4, no solution achieves a total ergonomics score of zero, indicating that a fully automated solution, where the robot performs all tasks, is not present. This is a direct result of constraints from the incapability of the robot to perform some specific tasks.

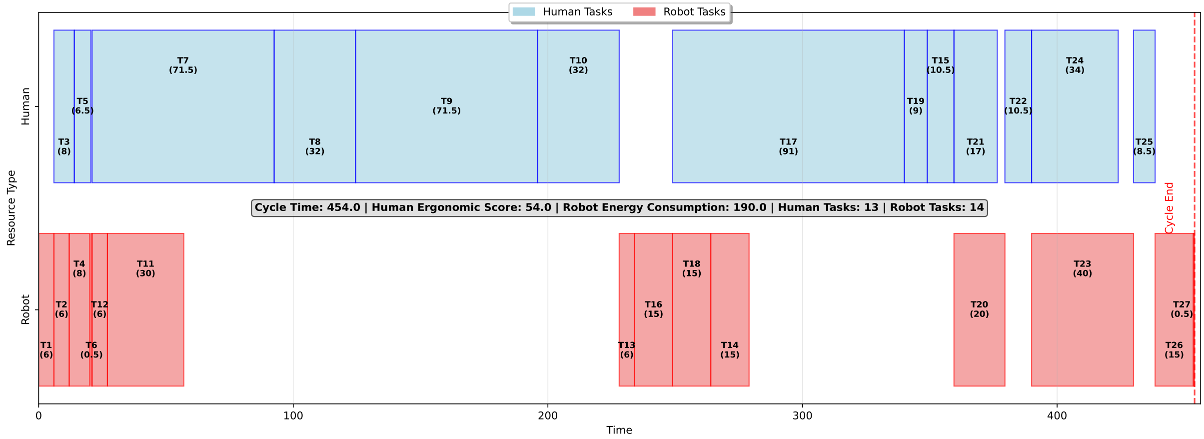

Figure 6: Gantt chart for showing the details of task arrangement within a cycle time of a specific solution

In contrast, several solutions exhibit an energy consumption of zero, which corresponds to a fully manual workstation where all tasks are performed by the human operator. Thus, the automation level of any given solution can be summarized from its final ergonomics score and energy consumption values.

6 Discussion

The desired robotic cell in this use case originally is for many product variants, even though the their production volume is low. But when solving this specific industrial problem, only the product variant with the largest and heaviest specifications was selected for analysis, based on the premise that it would present the worst-case scenario for worker well-being and energy consumption. However, this assumption requires further validation, as the ergonomics scores and energy consumption for performing the same task across different product variants may follow similar patterns but are likely to exhibit distinct quantitative differences.

The precedence relations between tasks are mandatory constraints for the task allocation optimization. While these relations are typically provided by process engineers for a given product, the introduction of additional resources in a new workstation, such as more robots or operators, creates opportunities for task parallelization. This, in turn, enables the optimization of the precedence relations themselves, which would subsequently influence the task allocation. For the present case study, the precedence relations were fixed to isolate the allocation problem.

In robotic simulation, equipment selection is a critical determinant of whether a task can be finished by a robot or not. The construction of simulation models for both robot and human can remain flexible, if equipment selection is not constrained when defining the initial requirements and constraints for designing a workstation. In the studied case, for example, a robot using a handheld glue gun may be unable to seal corners on a part placed on a standard table. However, this task becomes feasible if the robot instead manipulates the part itself, bringing it into contact with a stationary, fixture-mounted glue gun. This highlights the need for integrated equipment selection within the robotic simulation and optimization loop.

Finally, the analysis revealed a non-intuitive relationship: when one of the two objectives on total ergonomics score and total energy consumption is held constant on a certain level, the other one shows a decreasing trend with increasing cycle time. This observed trade-off merits further exploration of the underlying task allocations in the solution set to provide a conclusive explanation. But with 27 tasks in each solution, listing or overlapping all the Gantt charts from many solutions is not intuitive for visualization and analyses. Meanwhile, the observation and analysis reside on a preference direction that is a horizontal line decided by a similar level of objective values. It is necessary to further explore more combinations of the visualization methods of presenting the data and handling the preference in a given direction.

7 Conclusion and Future Work

Through a case study on designing a human-robot collaborative workstation for manufacturing grain conveyor pips, this paper has presented a methodology that integrates cross-disciplinary simulation with bi-level optimization with a main focus on the level for task allocation. This approach successfully balances the competing objectives of cycle time, accumulated ergonomics score, and total energy consumption. The current implementation has yielded an initial set of results from the upper-level task allocation optimization. These outputs provide not only a detailed load balancing plan but also the execution sequence of each task, the ergonomics score for every manual operation, and the electricity consumption for each automated task, thereby offering a comprehensive foundation for decision-making. This study also demonstrates the needs of methods and tools for visualizing the results with complex structure (many tasks involved in a solution) for given preference expressions from decision makers.

The potential of the first-level optimization, which encompasses detailed human and robotic modeling, extends beyond its current application. It could be developed to provide optimal machine layout, robotic program configurations, and practical guidelines for human operators working with the equipment. Our future work will focus on this lower-level optimization, primarily through the continued development of the software add-in for automated robot simulation and optimization. Concurrently, with the aim of scaling the workstation to accommodate other products, we will also explore and formalize a generalizable framework for the design of such adaptable human-robot collaborative cells.

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