

Integrating collaboration scenarios and workforce individualization in collaborative assembly line balancing

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ABSTRACT

Integrating collaborative robots into assembly lines represents a significant opportunity for industries to execute tasks autonomously or support human workers in response to the advancements of Industry 4.0. Human-robot collaboration (HRC) is an appropriate solution to enhance the productivity of manual systems compared to traditional robots. However, to ensure the success of HRC implementation, it is necessary to investigate the production systems, considering several influencing factors. Workforce diversity can be mentioned as one of the factors since workers may possess different skills and experience levels, as well as varying levels of fatigue. Therefore, creating a realistic and effective optimization model that includes workforce diversity is crucial. This study proposes a mathematical model to optimize a human-robot collaborative assembly line performance to minimize the cycle time. The model integrates several collaborative scenarios (i.e. sequential, simultaneous, supportive and all possible combinations), and the workforce differences are considered in terms of skill level and fatigue, allowing the flexible selection of collaboration scenarios across the assembly line and assigning workers and cobots to stations based on individual characteristics. Finally, the proposed model is applied in a case study to provide results and some managerial insights for practitioners.

1. Introduction

Collaborative robots (cobots) are recognized as a key pillar of Industry 5.0 (Kadir et al., 2018). According to the International Federation of Robotics (IFR) definition (International Federation of Robotics, 2020), cobots are designed to work alongside humans in industrial settings, enhancing productivity, efficiency, and safety. This stands in contrast to traditional industrial robots, which typically function in isolation behind safety barriers, while cobots are intended to collaborate with human workers directly. Hence, cobots represent pivotal advancements in the industry, embodying flexibility, safety, and affordability (Keshvarparast et al., 2021, 2023b).

Cobots can provide a solution to enhance the throughput of manual systems, such as assembly systems, without reducing their flexibility (Boschetti et al., 2021). In such a context, collaborative assembly systems have the potential to enhance production systems by effectively adapting to new designs or product volumes (Takata and Hirano, 2011). Therefore, researchers and practitioners have recently focused on Collaborative Assembly Lines (CAL). In CAL, cobots and workers can

share the same stations, yielding the advantages of manual and automated assembly at low costs (Weckenborg and Spengler, 2019) and benefiting from cobots accuracy and fatigue resistance (Ferreira et al., 2021). Cobots can perform repetitive tasks, reducing physical strain on human workers and allowing them to focus on more complex and value-added activities. In the collaboration between humans and cobots, there are different scenarios, depending on how they work together to perform the assembly tasks: independent, sequential, simultaneous, and supportive (Fig. 1). Workers and cobots contribute differently depending on the scenario, and each scenario can impact different aspects of the assembly line, including time, efficiency, and cost. Therefore, selecting the most appropriate scenario represents an important aspect of CAL design.

Moreover, to successfully implement cobots in manufacturing systems, it would be interesting to consider different human factors such as physical and ergonomic level, mental workload, skills, and age in the design and balancing of manufacturing systems with the evaluation of their effect, as well as of the cobot, on the worker's fatigue and production system efficiency (Zheng et al., 2023). Besides human factor

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consideration, workforce diversity and differences among workers should be considered since the workforce may differ regarding skills, age, gender, and anthropometry measures. Hence, individualization is necessary because consideration of the human factor itself may not respond to all workforce requirements in production systems (Katirae et al., 2019, 2021a, 2024). Workforce diversity can impact production system output (Buzacott, 2002) or influence task operation time due to the worker's capabilities, skills, and experiences (Miralles et al., 2007; Battaia and Dolgui, 2013). Further, it is necessary to investigate the proper collaboration strategy between the cobot and the worker according to the task it is asked to execute (El Zaatari et al., 2019).

Previous studies in CAL have typically considered only one collaboration scenario, and, to the best of the authors' knowledge, no studies have analyzed all collaboration scenarios and their combination together. Besides, no studies have considered the workforce as a unique resource (intended as workforce individualization) in CAL with different collaborative scenarios. Therefore, to address the gaps above, namely flexibility, workforce individualization, and collaboration scenarios, a novel single-objective mathematical model is developed for CAL balancing. The objective of the proposed model is to minimize cycle time, as this is considered to directly affect production efficiency, cost reduction, and throughput maximization. A shorter cycle time leads to faster task completion, reduced idle time, and better utilization of resources, thereby enhancing the overall productivity of the assembly line (Goyal et al., 2022). This study evaluates the worker's fatigue through energy expenditure and the required rest allowance (RA). Further, the cycle time incorporates RA calculated for each worker individually while optimizing the line. Finally, this model allows the flexible selection of collaboration scenarios across the assembly line and assigns workers and cobots to stations based on individual characteristics that influence RA calculations. The proposed model enables a comprehensive study of cobot use, various collaboration scenarios, and the effects of workers' age. The results obtained from applying the model in a case study provide practitioners and researchers information to find a relation between workforce differences and productivity, a relation between cobot implementation and RA, and a relation between collaboration scenarios and RA. This research highlights the significance of addressing these factors to offer improved industry solutions.

The remainder of this article is organized as follows. Section 2 provides an overview of the literature on the collaborative assembly line and the contribution of the study. Section 3 presents the problem description and the model formulation. Section 4 presents an application of the proposed model in a case study. Managerial insights are provided in Section 5. Finally, Section 6 reports conclusions, limitations, and the future research agenda.

2. Research background

In this section, we aim to review recent contributions regarding CAL. To establish context, we initially introduce both the traditional assembly line and the concept of CAL. Following this introduction, section 2.1 introduces various CAL scenarios. Section 2.2 investigates relevant studies that consider and integrate the workforce in CAL problems,

emphasizing the importance of incorporating workers' features in strategic and tactical decisions. Finally, section 2.3 outlines this study's contribution and novel insights.

The Simple Assembly Line Balancing Problem (SALBP), introduced by Baybars (1986), consists of assigning tasks to workstations considering the task precedence and task processing time. In traditional Assembly Line Balancing Problems (ALBPs), tasks are often performed manually by workers, leading to significant workers' physical strain and fatigue. Physical fatigue can adversely affect workers' health, productivity, and overall efficiency of assembly lines (Katirae et al., 2021b). Furthermore, in traditional ALBPs, tasks are often assigned only according to strategic decisions such as cycle time, task precedence constraint, and available space, neglecting the worker's capabilities and differences. The shift towards mass customization and emphasis on worker's well-being are driving the transformation of manufacturing processes. Hence, while still relevant in specific contexts, the traditional manual assembly line may not meet these evolving needs. Manufacturers are exploring new production methods and technologies to meet the demands of mass customization and address worker's well-being. Robotics, automation, and artificial intelligence are being integrated into manufacturing processes, allowing for greater flexibility and customization while reducing the need for repetitive manual labor. For example, cobots are designed to work alongside human workers, enhancing productivity and safety (Bragança et al., 2019). Therefore, introducing the CAL serves as a solution to increase flexibility and decrease the physical workload for human workers (Boschetti et al., 2021). In CAL, although the cobot is integrated into the assembly systems to help workers, the importance of workers cannot be neglected since they are still the most flexible resources and perform various tasks in a shorter time than the cobots (Mao et al., 2024). Therefore, the workforce should be considered in CALs to provide a more holistic understanding of an individual's contributions. Designing a CAL was introduced by Matthias et al. (2011) for the first time when they proposed a framework with a particular focus on safety as a crucial performance criterion.

2.1. Collaborative assembly line scenarios

According to El Zaatari et al. (2019), the collaboration between humans and cobots in assembly systems can be categorized into four scenarios depending on how robots and humans collaborate to accomplish tasks: independent, sequential, simultaneous, and supportive. Therefore, workers and cobots have different contributions depending on the scenario type, as shown in Fig. 1 (Keshvarparast et al., 2023a). In a sequential scenario, a human worker and a cobot carry out two distinct tasks on the same workpiece in a consecutive manner. In contrast, in a simultaneous scenario, the human worker and the cobot simultaneously perform two jobs on the same workpiece. In an independent scenario, a human worker and a cobot perform two tasks separately on two different workpieces, while in the supportive scenario, a human operator and a cobot interactively perform a single task on a single workpiece, which supports each other (usually physical support) to conduct a task (Zhang et al., 2021). Previous studies in CAL have considered only one

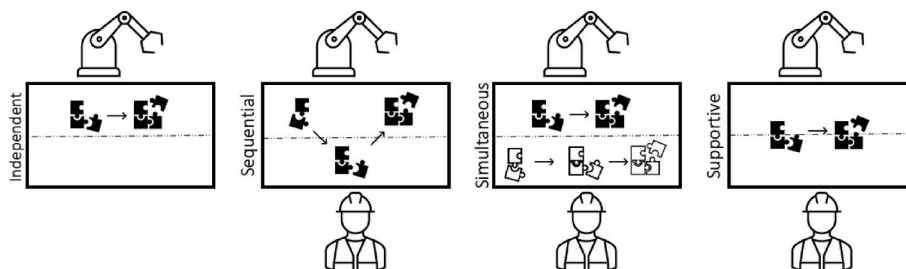


Fig. 1. Collaboration scenarios (Keshvarparast et al., 2023a).

collaboration scenario, for example, an independent scenario (Koltai et al., 2021), a sequential scenario (Abdous et al., 2020, 2022), a simultaneous scenario (Almasarwah et al., 2022), or a supportive scenario (Li et al., 2021). Few studies have considered two collaboration scenarios simultaneously (Boschetti et al., 2021; Dalle Mura and Dini, 2023; Li et al., 2023).

2.2. Workforce integration in CAL

Several studies have investigated the integration of the workforces and their differences in worker fatigue and experience for the traditional ALBPs (i.e., Katirae et al., 2021b; Katirae et al., 2021c; Katirae et al., 2023). Although cobots can perform some tasks, workers still play an essential role due to their flexibility. The advantages of human presence in CAL result in greater flexibility, particularly in handling and joining complex components and the reliable execution of process aims (Stadnicka and Antonelli, 2019).

Modern industries have a diverse array of jobs that require the flexibility of human operators, while some others can be performed by cobots (Javaid et al., 2022). The cobots facilitate a fair allocation of tasks among the resources in industrial applications (Calzavara et al., 2023). Hence, to provide efficient and successful collaborative assembly operations, it is essential to establish an optimal division of jobs between human operators and the cobots. For this purpose, Salunkhe et al. (2023) proposed a design methodology that assessed the human cognitive and physical levels of human-robot collaboration and operator skill requirements. Furthermore, Calzavara et al. (2023) developed a multi-objective optimization model for task allocation in collaborative robot systems. Their model aimed to address productivity and the worker's well-being by minimizing the following objectives: (1) make-span, (2) the worker's energy expenditure, and (3) average mental workload. The first objective was to meet the necessary criteria for high productivity standards. The second and third objectives involved creating a work environment that prioritized the needs and well-being of the workers, aligning with human-centred principles as recommended by the Industry 5.0 paradigms.

Several recent studies have focused on optimizing and balancing CAL operations, integrating ergonomic considerations, and leveraging advanced technologies like cobots and exoskeletons. For example, Weckenborg and Spengler (2019) studied this problem considering ergonomics. They aimed to identify cost-efficient system configurations that assign collaborative robots and human workers to the stations. They considered the task processing time and energy expenditure per resource, including robots and humans. Their findings underscore cobots as cost-effective for automating manual tasks. Weckenborg et al. (2022) extended this approach with a mixed-integer programming model integrating ergonomic and economic factors. They highlighted cobots and exoskeletons as beneficial tools in assembly line operations that improve cost and energy expenditure. Regarding this issue, Dalle Mura and Dini (2019, 2022) addressed the assembly line balancing problem, considering job rotation and human-robot collaboration to improve workers' ergonomic levels. Their multi-objective model minimized implementation costs while improving worker ergonomics and energy load balance, demonstrating the cobot's potential to reduce physical strain from heavy component handling and burdensome activities. Steck and Mokhtarzadeh (2022) developed a mixed-integer linear programming model to optimize cycle time and ergonomic risks through cobot deployment in assembly lines, using energy expenditure to evaluate ergonomic risk. Keshvarparast et al. (2022) introduced a bi-objective optimization model for CALs to minimize human operators' cycle time and physical workload, considering differences in experience and physical capabilities. By developing a new integer linear programming model, Rahman et al. (2023) addressed a sustainable assembly line balancing problem, including human operators, robots, and human-robot collaboration. Their model minimized cycle time, ergonomic risks, and energy consumption, assessing ergonomic risks such as

lifting and twisting for human workers. In general, occupational ergonomic risk is influenced by both the physical demands of a task and the environmental aspects of the workplace, such as noise. For example, assessing noise levels can aid in mitigating potential health risks for workers related to hearing injuries. In this regard, Dalle Mura and Dini (2023) have recently introduced a software tool that measured the noise exposure level during the evaluation process, aiming to mitigate ergonomic risk and improve workplace conditions. In a recent study, Mao et al. (2024) developed mixed-integer programming to address human-robot collaboration assembly line balancing problems with multi-type robots. Their study has focused on the impact of interaction between humans and cobots on selecting collaboration scenario modes. They consider workers to be homogeneous resources who have no differences from each other.

These studies collectively highlight advancements in CAL optimization, emphasizing ergonomic improvements and integrating advanced technologies to enhance efficiency and worker well-being. However, some aspects still need to be considered as research gaps, discussed in Section 2.3.

2.3. Contribution of this study

Despite some studies examining and optimizing cobots in assembly lines, researchers have yet to consider the characteristics of collaboration scenarios and their potential impact on an assembly system in optimization models. The importance of collaboration scenarios has not been adequately emphasized in previous studies. However, in this study, the main aim is to consider several combinations of the collaboration scenario, including supportive, sequential, and simultaneous, as well as all possible combinations. Additionally, the lack of consideration of resource diversity in previous studies could create a gap between the optimized solution and real-world situations. This discrepancy arises mainly because each worker possesses unique characteristics. For example, Weckenborg et al. (2022) have considered the energy expenditure of each task as an input parameter without consideration of workforce diversity, while in this study, the energy expenditure is a variable that can be changed from one worker to another according to the worker's age, body weight, and gender (according to the formula from e Silva et al., 2016). Therefore, the main contributions of this study are as follows: (1) Respecting workforce ergonomic level by integrating the individualized rest allowance (RA) into the model; (2) Investigating the relation between cobot implementation and RA; (3) Investigating the relation between different collaboration scenarios and RA; and, finally, (4) Understanding the relation between workforce age and required RA and cobot implementation.

3. Model description

To address workforce individualization in the CAL optimization model and better understand the relation between collaboration scenarios and workforce differences, we propose a single objective Mixed Integer Non-Linear mathematical model (MINLP). This model aims to enhance the productivity of the CAL by considering the cycle time as the objective function. In this study, we consider worker differences in terms of (1) experience, which is measured by the worker's task processing time (T_p), and (2) the worker's fatigue level, which is evaluated through the required RA for each worker. Further, we examine seven CAL scenarios: sequential (SE), simultaneous (SI), and supportive (SU), as well as their combinations SE-SI, SE-SU, SI-SU, and SE-SI-SU. Finally, in our model, non-linearity arises due to the calculation of cycle time in all possible collaboration scenarios and the dynamic rest allowance calculation formula for diverse workers. Since solving a non-linear model can be challenging, we employ a linearization approach to transform the non-linear model into a linear one. Consequently, the final model is a linear Mixed-Integer Problem (MIP), as shown in the following sections.

3.1. Model assumptions

The assumptions of the model are summarized as follows.

- The assembly line is exclusively committed to manufacturing a single product, and the task precedence relations are known in advance.
- Workers have different skill/experience levels, which results in different task times.
- Each task time and required energy expenditure are deterministic and known in advance.
- The required energy expenditure for each task is known.
- Each worker is considered individually in terms of his/her energy expenditure.
- The physical demand on workers for jobs given to workers and cobots in supportive mode is negligible.
- Each station has one worker or one worker and one cobot.
- The number of stations is deterministic and known.
- The number of available cobots is limited, and their performance may vary.
- Cobots can perform only some types of tasks (not all tasks).
- Task times vary according to the worker or the cobot selected and the collaborative scenario.
- Allocating all available resources to the production line is mandatory.
- Sequential, simultaneous, and supportive collaboration modes can guarantee a harmonized assembly line.

3.2. Model elements

The following notations are used to model the CAL balancing problem.

Sets, indexes, and parameters:	
I	Set of tasks, $i, j = \{1, \dots, I\}$
H	Set of workers, $h = \{1, \dots, H\}$
C	Set of cobots, $c = \{1, \dots, C\}$
R	Set of resources, $R = C \cup H, r = \{1, \dots, R\}$
S	Set of stations, $s = \{1, \dots, S\}$
TP	Set of tasks precedencies
T_{ir}	Completion time of task i when assigned to only one resource r (cobot or worker)
T_{ihc}^c	Completion time of task i when assigned to worker h and cobot c in supportive mode
e_i	Energy required for performing task i
ETR	Rest Energy-Time ratio (1.86 kcal/min)
$MAEE_h$	Maximum Acceptable Energy Expenditure for worker h
UB	A very large positive number
Decision Variables:	
X_{irs}	$= \begin{cases} 1 & \text{if task } i \text{ is assigned to resource } r \text{ in station } s \\ 0 & \text{Otherwise} \end{cases}$
W_{ijr}	$= \begin{cases} 1 & \text{if task } j \text{ should be done after task } i \text{ by resource } r \\ 0 & \text{Otherwise} \end{cases}$
Other Variables:	
Z_{ihcs}	$= \begin{cases} 1 & \text{if task } i \text{ is assigned to worker } h \text{ and cobot } c \text{ in supportive mode in station } s \\ 0 & \text{Otherwise} \end{cases}$
Y_{rs}	$= \begin{cases} 1 & \text{if resource } r \text{ is assigned to station } s \\ 0 & \text{Otherwise} \end{cases}$
δ_s	$= \begin{cases} 1 & \text{if worker } h \text{ assigned to station } s \text{ needs rest} \\ 0 & \text{Otherwise} \end{cases}$
ST_i	= Start time of task i
FT_i	= Finish time of task i
CTS_s	= Cycle Time for station s
CT	= Cycle Time
RA_s	= Rest allowance for the assigned worker in workstation s
TRA_s	= Rest allowance time for the assigned worker in workstation s
r_{ih}	= Rest allowance for each task i and worker h in workstation s
N_s	= The value of the numerator

3.3. Mixed-integer nonlinear mathematical model

The objective function of the proposed mathematical model is to minimize the Cycle Time (CT), as shown by equation (1). Since the ergonomic aspect of this problem can be translated through the rest allowance formula, cycle time is considered an appropriate objective function for this study.

$$\text{Objective Function:} \quad \text{Minimize CT} \quad (1)$$

Subject to:

$$Z_{ihcs} \leq \frac{X_{ihc} + X_{ics}}{2} \quad \forall i \in I, h \in H, r \in R, c \in C, s \in S \quad (2)$$

$$\sum_r \sum_s X_{irs} - \sum_h \sum_c \sum_s Z_{ihcs} = 1 \quad \forall i \in I \quad (3)$$

$$X_{irs} \leq Y_{rs} \quad \forall i \in I, r \in R, s \in S \quad (4)$$

$$\sum_s Y_{rs} = 1 \quad \forall r \in R \quad (5)$$

$$\sum_h Y_{hs} = 1 \quad \forall s \in S \quad (6)$$

$$\sum_c Y_{cs} \leq 1 \quad \forall s \in S \quad (7)$$

$$\sum_r \sum_s X_{irs} \bullet s - \sum_h \sum_c \sum_s Z_{ihcs} \bullet s \leq \sum_r \sum_s X_{jrs} \bullet s - \sum_h \sum_c \sum_s Z_{jhcs} \bullet s \quad \forall (i, j) \in TP \quad (8)$$

$$\sum_i \sum_j W_{ijr} = \sum_i \sum_s X_{irs} - 1 \quad \forall r \in R \quad (9)$$

$$W_{ijr} \leq \frac{\sum_s X_{irs} + \sum_s X_{jrs}}{2} \quad \forall i, j \in I, h \in H \quad (10)$$

$$W_{ijr} + W_{jir} \leq 1 \quad \forall i, j \in I, r \in R \quad (11)$$

$$\sum_j W_{ijr} \leq 1 \quad \forall i \in I, r \in R \quad (12)$$

$$\sum_i W_{ijr} \leq 1 \quad \forall j \in I, r \in R \quad (13)$$

$$ST_j \geq FT_i, \forall (i, j) \in TP \quad (14)$$

$$ST_j \geq FT_i - UB \bullet \left(1 - \sum_h W_{ijr}\right) \quad \forall i, j \in I \quad (15)$$

$$FT_i \geq ST_i + \sum_h \sum_c \sum_s Z_{ihcs} \bullet T_{ihc}^c + \left(\sum_r \sum_s X_{irs} \bullet T_{ir} \right) \left(1 - \sum_h \sum_c \sum_s Z_{ihcs} \right) \quad \forall i \in I \quad (16)$$

$$CTS_s \geq FT_i - ST_j - UB \bullet \left(1 - \left(\sum_r X_{irs} - \sum_h \sum_c Z_{ihcs} \right) \right) - BigM \bullet \left(1 - \left(\sum_r X_{jrs} - \sum_h \sum_c Z_{jhcs} \right) \right) \quad \forall i, j \in I, s \in S \quad (17)$$

$$RA_s = \max \left\{ 0; \frac{\sum_i \sum_h X_{ihcs} \bullet e_i - MAEE_h}{\sum_i \sum_h X_{ihcs} \bullet T_{ih} - MAEE_h - ETR} \right\} \quad \forall s \in S \quad (18)$$

$$CT \geq CTS_s + RA_s, \forall s \in S \quad (19)$$

$$X_{irs}, W_{ir}, Z_{ihcs}, Y_{rs} \in \{0, 1\} \quad (20)$$

$$FT_i, ST_i, SCT_s, CTS_s, CT, RA_s \in \mathbb{R}^+ \quad (21)$$

Equation (2) ensures task i will be performed in supportive mode if task i is assigned to a worker and cobot together. Equation (3) ensures that each task should be assigned to exactly one resource, except in supportive mode, in which tasks will be assigned to a human and cobot together. Equation (4) ensures that task i can be assigned to resource r in station s only if resource r is already assigned to station s . Equation (5) ensures that each resource will be assigned to only one station. Equation (6) guarantees that one worker will be assigned to each station, and Equation (7) ensures that at most one cobot can be assigned to each station. Equation (8) enforces that all task precedence relations will be respected. Therefore, if tasks i and j have a precedence relation, task j can only be assigned to the same station as task i or the following stations.

Equations (9)–(13) are designed to determine task sequencing (W_{ijr}) and ensure the correct sequencing between tasks assigned to each resource. Equation (9) guarantees that the number of sequencing relations between tasks is equal to the sum of tasks assigned to a resource minus one. Since in a series sequencing, the number of arcs is one unit less than the number of nodes, the number of sequences should be one unit lower than the number of tasks assigned to a resource. Equation (10) ensures that a sequencing relation between tasks i and j can be equal to one only when tasks i and j are assigned to the same resource. Equation (11) ensures that there will not be any sequencing loop between the two tasks. Equations (12) and (13), respectively, guarantee that task i can only have a sequencing relation with at most one task ahead and one task before it.

Equations (14)–(17) are intended for calculating ST , FT , and CTS to obtain the cycle time. Equation (14) ensures that if tasks i and j have a precedence relation, the start time of task j should be equal to or greater than the finish time of task i . Equation (15) ensures that if tasks i and j have a sequencing relation, the start time of task j should be equal to or greater than the finish time of task i . Equation (16) calculates the FT for each task. However, given that in supportive mode, variable X_{irs} for both the worker and the cobot will be equal to one, the calculation of FT needs to distinguish the supportive mode from others. Therefore, FT_i will be equal to ST_i plus two different parts. The first part belongs to the task completion time in the supportive scenario, and the second part belongs to the task completion time for other scenarios. This second part makes Equation (16) a non-linear equation, which involves multiplying two binary variables. The next step is calculating CTS for each station. To calculate it, it is necessary to subtract the ST of the first task that started in a station from the FT of the last task that finished in the same station. Equation (17) calculates the CTS based on this approach. To ensure that two tasks are assigned to a single station, using a large constant (big-M) provides the relaxation of the equation if they are not assigned to the same station.

Equation (18) calculates the Rest Allowance (RA) for each station

where e_i is the energy required for performing task i which is fixed and task dependent (Garg et al., 1978) and $MAEE_h$ varies according to the workers' age, gender, and body weight of the worker as defined in the formula by (e Silva et al., 2016). Finally, Equation (19) calculates the cycle time by adding the RA and CTS of each station together to find the total time required for completing tasks in each station. In the next section, we provide the linearization of non-linearity.

3.4. Linearization of the non-linearities

Equations (16) and (18) are non-linear in our mathematical model. For this reason, this section shows how to linearize them.

By splitting equation (16) and applying the big-M method to one of the parts, we can easily linearize the binary-to-binary nonlinearity.

$$FT_i \geq ST_i + \sum_r \sum_s (X_{irs} \bullet T_{ir}) - UB \bullet \sum_h \sum_c \sum_s Z_{ihcs} \quad \forall i \in I \quad (16a)$$

$$FT_i \geq ST_i + \sum_h \sum_c \sum_s (Z_{ihcs} \bullet T_{ihc}^c) \quad \forall i \in I \quad (16b)$$

In the case where task i is assigned to both a human and a cobot in supportive mode, equation (16b) is used to calculate the FT_i , while equation (16a) is relaxed due to the presence of the big-M term (UB). On the other hand, if task i is not assigned to resources in the supportive mode, the variable Z_{ihcs} for task i will be equal to zero, resulting in the relaxation of equation (16b) and the big-M term in equation (16a). Furthermore, equation (18) is non-linear due to the division of the two decision variables. In this study, since each worker is assigned to each station, the RA is indexed by s to reduce the complexity of the model linearization. Equation (18) can be written as (22) to start the linearization. Where TRA_s is RA_s expressed in terms of time for the assigned worker in workstations and defined as:

$$TRA_s = \max \left\{ 0; \frac{\sum_i \sum_h X_{ihcs} \bullet (e_i - t_{iw} \bullet MAEE_w)}{\sum_h Y_{hs} \bullet MAEE_h - ETR} \right\} \quad \forall s \in S \quad (22)$$

In equation (22), although the value for the $MAEE_h$ is known, it is considered a decision variable since workers can be reassigned among workstations in each iteration and the solver decides which tasks and workers should be assigned to each workstation. Hence, two steps need to be taken to linearize the TRA_s . First, we define another variable named N_s :

$$N_s = \max \left\{ 0; \sum_i \sum_w X_{iws} \bullet (e_i - t_{iw} \bullet MAEE_w) \right\} \quad \forall s \in S \quad (23)$$

As Equation (23) reports, the N_s is equal to the numerator of Equation (22). Thus, starting from the mathematical approach adopted by Finco et al. (2020), the following additional equations (23a) to (23j) are required for linearizing constraint (23). Constraints set (23a)–(23e) allows selecting the maximum value for N_s . UB corresponds to the big-M, while γ_s is the additional Boolean variable that leads to choosing the higher value that N_s can assume. Furthermore, as can be seen by equation (23e), another additional variable r_{ihcs} is defined, which indicates the amount of rest allowance in each workstation for each task and each worker. Therefore, in addition to the applied Equations by Finco et al. (2020), the following Equations (23f) to (23i) are needed to define the additional variable r_{ihcs} .

$$N_s \geq 0 \quad \forall s \in S \quad (23a)$$

$$N_s \geq \sum_i \sum_h X_{ihcs} \bullet (e_i - t_{ih} \bullet MAEE_h) \quad \forall s \in S \quad (23b)$$

$$N_s \leq UB \bullet \gamma_s \quad \forall s \in S \quad (23c)$$

$$N_s \leq \sum_i \sum_h x_{ihs} \bullet (e_i - t_{ih} \bullet MAEE_h) + UB \bullet (1 - \gamma_s) \quad \forall s \in S \quad (23d)$$

$$N_s = \sum_i \sum_h r_{ihs} \bullet (MAEE_h - ET_R) \bullet t_{ih} \quad \forall s \in S \quad (23e)$$

$$r_{ihs} \leq UB \bullet x_{ihs} \quad \forall i \in I, h \in H, s \in S \quad (23f)$$

$$r_{ihs} \leq RA_s \quad \forall i \in I, h \in H, s \in S \quad (23g)$$

$$r_{ihs} \geq RA_s - UB \bullet (1 - x_{ihs}) \quad \forall i \in I, h \in H, s \in S \quad (23h)$$

$$r_{ihs} \in \mathbb{R}^+ \quad \forall i \in I, h \in H, s \in S \quad (23i)$$

$$\gamma_s \in \{0, 1\} \quad \forall s \in S \quad (23j)$$

$$N_s \in \mathbb{R}^+ \quad \forall s \in S \quad (23k)$$

Constraints (23a) to (23k) result in RA_s linearization. Adding constraints (23a) to (23k) to the model and replacing equation (18) with them leads to solving the proposed model.

Equation (19) can be written as follows (19a):

$$CT \geq CTS_s + TRA_s, \quad \forall s \in S \quad (19a)$$

4. Case study and results discussion

In this section, the mathematical model proposed in section 3 is applied to a real case study aiming to investigate how cobots' implementation affects the cycle time from several points of view. We used Gurobi Python API on a standard computer with an AMD Ryzen 7 4800H processor to solve the model, operating at 2.90 GHz and 16 GB of RAM. The studied case is taken from [Katirae et al. \(2023\)](#), and it consists of a sub-assembly system for customized minibuses. The precedence graph has 43 tasks and 51 task precedencies, as illustrated in [Fig. 2](#). Workers can execute all tasks while cobots can perform on average 17 out of 43 tasks (40%) in SE and SI collaboration scenarios and 8 out of 43 tasks (18.6%) in SU scenario. Further, there is no time difference between SE and SI scenarios, and the task time could be higher or lower than the manual execution mode. Finally, in the SU scenario, the task time is always lower than in manual mode.

To derive preliminary insights and general consideration, we initially assume to have four stations and four workers aged 26, 38, 45, and 58, respectively, according to the data provided by [Katirae et al. \(2023\)](#). The workers are male, with body weights ranging from 66 to 80

kg. According to the worker's age and weight, the MAEE for these workers ranges between 3.12 kcal/min and 5 kcal/min. Differences in workforce experience are also considered, as they significantly influence task times, resulting in task time variability among workers based on their experience levels. Unlike the fixed number of available workers, which remains four, the number of cobots available is variable from 0 to 4. For the first part of our analysis, we are interested in 1) investigating how the RA and the number of cobots influence the cycle time and 2) how collaboration scenarios affect cycle time. Finally, we investigate the effects of workforce composition on cycle time and cobot implementation. In such a way, we provide some insights about cobots and tasks to stations assignment.

4.1. Impact of RA and number of cobots

As previously stated, in absence of RA, the physical pressure on workers could be higher than their capacity, and performing tasks repeatedly in these circumstances can bring different physical risks for workers. Therefore, considering RA when designing and balancing assembly lines is crucial to make the working environment more ergonomic for workers and reach a more sustainable assembly line ([Otto and Battaia, 2017](#)). This model is solved to examine how cycle time in manual and CAL is affected by workforce individualization in terms of energy expenditure and RA. To investigate how energy expenditure and the related RA affect the cycle time, we propose two approaches and apply them to an entirely manual assembly line and the seven possible collaboration scenarios between humans and cobots, as presented in [Table 1](#).

The first approach (approach A) follows [Finco et al. \(2020\)](#), adding RA after designing or balancing an assembly line. They designed the assembly line without considering RA in the model and added the necessary RA to the calculated cycle time to include fatigue aspects. For this approach, we calculate the cycle time by running the same model with two changes. First, removing Equation (18), and second, changing Equation (19) to Equation (24):

$$CT \geq CTS_s, \quad \forall s \in S \quad (24)$$

After optimizing the modified model, by using Equation (18), we manually calculate the RA for each station based on the assigned tasks. Finally, by adding the computed RA for each station to CTS_s , we determine the station time of each station and, consequently, the cycle time for the entire assembly line.

The second approach (approach B) incorporates RA according to the mathematical model proposed in section 3. This method allows us to

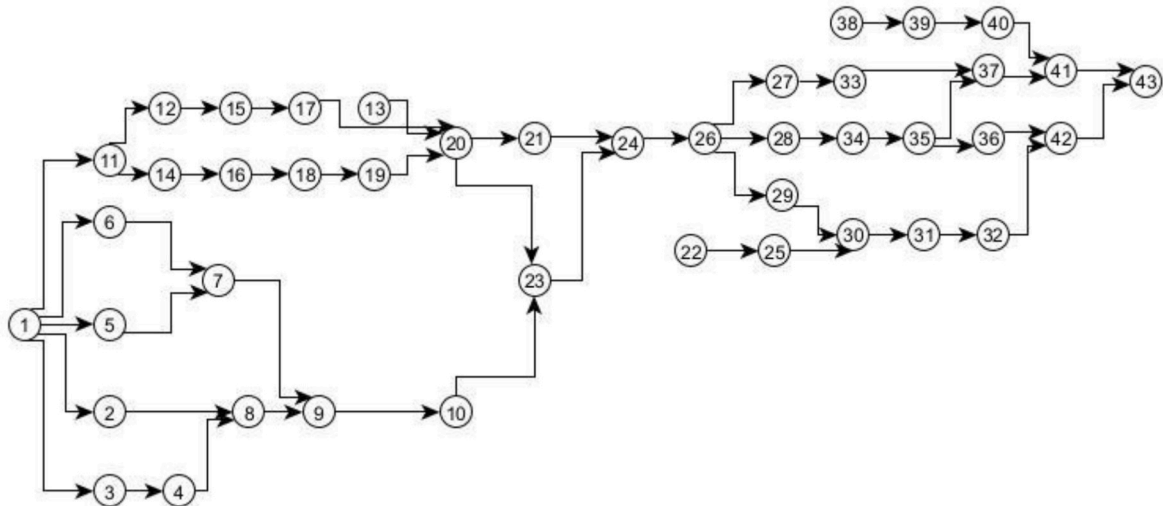


Fig. 2. Task Precedencies (data taken from [Katirae et al., 2023](#)).

Table 1

Cycle time [min/piece] comparison of approaches A and B for different collaboration scenarios considering different number of cobots.

Cobots	Approach	Manual	Collaboration scenarios						
			SE	SI	SU	SE-SI	SE-SU	SI-SU	SE-SI-SU
1	A	57.81	57.01 (-1.38%)	49.93 (-13.63%)	55.31 (-4.32%)	49.71 (-14.01%)	54.81 (-5.19%)	49.42 (-14.51%)	49.42 (-14.51%)
	B	55.04	53.83 (-2.29%)	46.27 (-15.93%)	52.49 (-4.63%)	45.92 (-16.57%)	52.08 (-5.38%)	44.97 (-18.3%)	44.97 (-18.3%)
	A-B	2.77 (4.79%)	3.18 (5.58%)	3.66 (7.33%)	2.82 (5.10%)	3.79 (7.62%)	2.73 (4.98%)	4.45 (9.00%)	4.45 (9.00%)
2	A	57.81	56.47 (-2.32%)	45.39 (-21.48%)	52.99 (-8.34%)	45.25 (-21.73%)	52.79 (-8.68%)	44.51 (-23.01%)	44.33 (-23.32%)
	B	55.04	53.23 (-3.29%)	41.26 (-25.04%)	50.27 (-8.67%)	40.83 (-25.82%)	49.57 (-9.94%)	39.52 (-28.2%)	39.21 (-28.76%)
	A-B	2.77 (4.79%)	3.24 (5.47%)	4.13 (9.10%)	2.72 (5.13%)	4.42 (9.77%)	3.22 (6.10%)	4.99 (11.21%)	5.12 (11.55%)
3	A	57.81	55.17 (-4.57%)	42.72 (-26.1%)	50.89 (-11.97%)	42.19 (-27.02%)	50.25 (-13.08%)	41.07 (-28.96%)	40.83 (-29.37%)
	B	55.04	52.82 (-4.03%)	39.76 (-27.76%)	49.16 (-10.68%)	39.09 (-28.98%)	48.57 (-11.76%)	37.83 (-31.27%)	37.48 (-31.9%)
	A-B	2.77 (4.79%)	3.35 (4.26%)	3.96 (6.93%)	2.73 (3.40%)	4.10 (7.35%)	2.68 (3.34%)	4.24 (7.89%)	3.35 (8.20%)
4	A	57.81	54.13 (-6.37%)	40.87 (-29.3%)	50.38 (-12.85%)	40.56 (-29.84%)	49.51 (-14.36%)	39.89 (-31%)	39.71 (-31.31%)
	B	55.04	52.51 (-4.6%)	39.25 (-28.69%)	48.91 (-11.14%)	38.44 (-30.16%)	48.17 (-12.48%)	37.28 (-32.27%)	36.91 (-32.94%)
	A-B	2.77 (4.79%)	3.32 (2.99%)	2.62 (3.96%)	2.97 (2.92%)	3.12 (5.23%)	1.34 (2.71%)	3.61 (6.54%)	2.80 (7.05%)

A: Adding RA after optimization; B: Optimization with RA in the model. SE=Sequential, SI=Simultaneous, SU=Supportive, SE-SI=Sequential-Supportive, SE-SU=Sequential-Supportive, SI-SU=Simultaneous-Supportive, SE-SI-SU=Sequential-Simultaneous-Supportive.

assess the impact of integrating RA into the optimization of assembly line design.

Table 1 and Fig. 3 show optimal cycle times obtained for both manual and collaborative scenarios for approaches A and B, varying the number of cobots. Moreover, Table 1 shows the percentage improvement of approach B with respect to approach A and the cycle time percentage differences with respect to a manual assembly line. Hence, approach B reduces cycle times for manual assembly lines and CAL scenarios (i.e. SE, SI, SU, SE-SI, SE-SU, SI-SU, SE-SI-SU). Table 1 shows that, in a manual assembly line, approach B reduces the cycle time from 57.81 min/piece to 55.04 min/piece, resulting in a 4.79% improvement (this is in line with Finco et al., 2020). The most significant improvement can be seen with two cobots across the SE-SI-SU scenario, resulting in an 11.55% improvement or a 5.12-min/piece reduction (highlighted in green in Table 1). Conversely, the slightest improvement occurred with four cobots available, limited to the SE-SU scenario, showing a 2.71% improvement or a 1.34-min/piece reduction (highlighted in red in Table 1).

This analysis highlights the benefits of incorporating individualized RA into the optimization process for manual and CAL scenarios, enhancing productivity. The effectiveness of this approach is related to the model's capacity to include various factors, such as task energy requirements and workers' physical characteristics. Focusing on the number of cobots, Table 1 and Fig. 3 show that including cobots in the assembly line enhances productivity. Due to a cycle time reduction, the productivity improvement aligns with expectations since the number of operational resources increases. In all studied scenarios, there is a cycle time improvement of at least 1.38% for approach A and 2.2% for approach B. The maximum improvement observed in approach A is 31.31%, and in approach B is 32.94%, related to the SE-SI-SU scenario.

The productivity improvement has a plateau beyond a certain point (i.e. three cobots) because not all tasks can be automated by cobots. Adding more than three or four cobots in this case study does not significantly influence cycle time. To clarify this issue, Table 2 and Fig. 4

present each cobot's idle time to cycle time ratio for the seven CAL scenarios by considering approach B (which leads to lower cycle time values).

Here, it can be seen that the cobots' idle time to cycle time ratio increases significantly with adding more cobots. For instance, with four cobots and using the supportive collaboration scenario, the idle time to cycle time ratio can reach up to 96%, which means the cobot is almost entirely idle. These analyses demonstrate that increasing the number of cobots does not necessarily lead to significant improvements. The main reason is that not all tasks can be executed by cobots, and even those that can be are not always performed efficiently. For example, cobots are generally more efficient at material handling than at tasks requiring complex movements, such as screwing or hammering. Consequently, with the addition of more cobots, the same tasks are distributed among a larger number of cobots, resulting in fewer tasks assigned to each cobot and increased idle time for each.

As far as the effect of the seven collaboration scenarios on RA is concerned, Table 1 and Fig. 3 show that in the SE-SI-SU scenario, where all possible collaboration scenarios are combined, the difference between approaches A and B is higher than when only one or a combination of two scenarios are considered. For example, when two cobots are available, the percentage cycle time difference between approaches A and B is 11.5% in the SE-SI-SU scenario. At the same time, this value is decreased to 5.13% with the SU scenario. This cannot be classified as either an advantage or a disadvantage. However, it suggests that considering the SE-SI-SU scenario makes the model more capable of reducing the RA and decreasing the cycle time. Furthermore, Table 1 and Fig. 3 demonstrate that with the same number of cobots, considering the SE-SI-SU scenario in the model leads to a more significant reduction in cycle time. For example, with three cobots available, the cycle time is 37.48 min/piece in the SE-SI-SU scenario; however, in the case of using the SE scenario, the cycle time is 52.82 min/piece. The difference between these two scenarios is more than 15 min/piece, highlighting the significance of considering the SE-SI-SU collaboration scenario in the

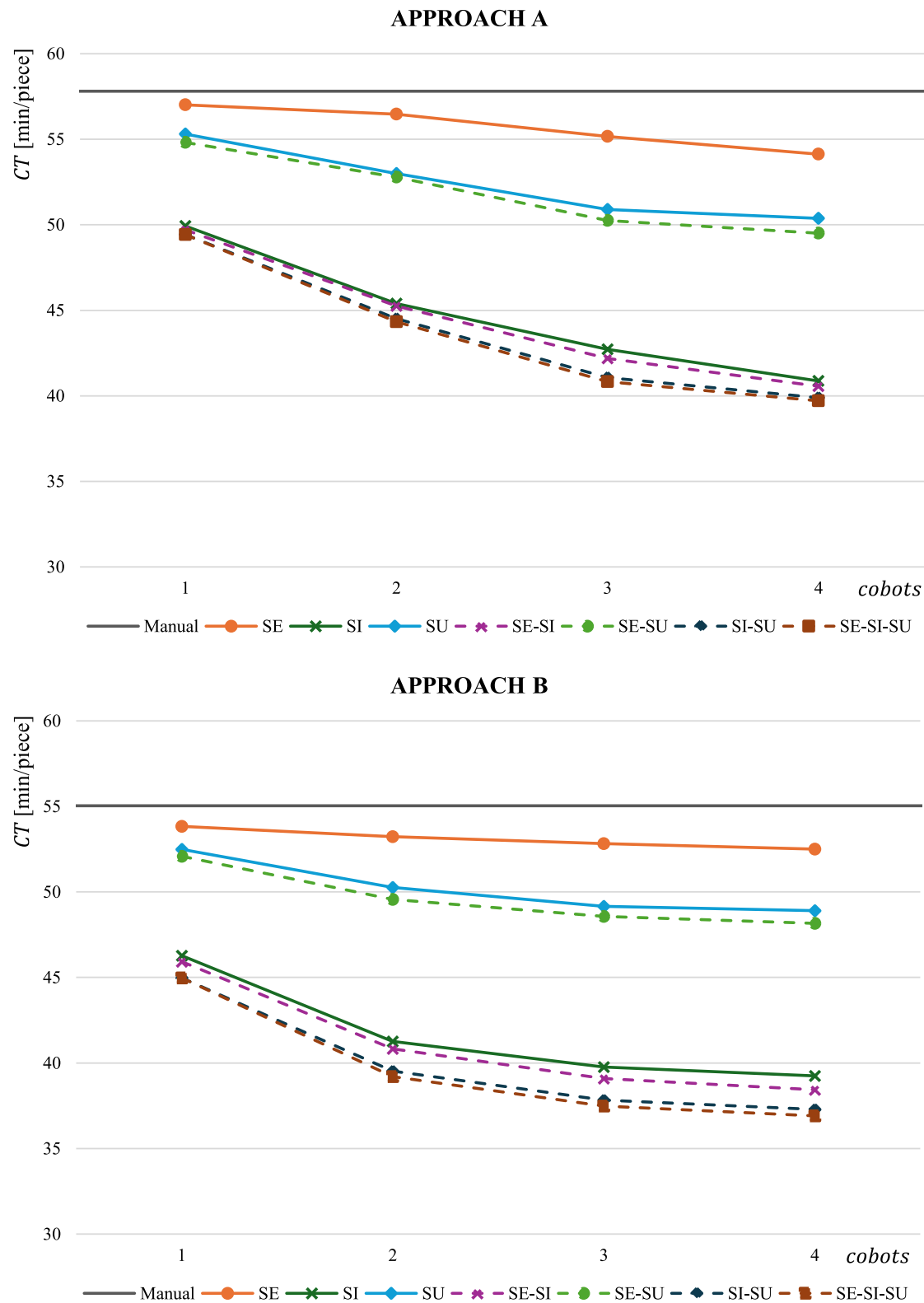


Fig. 3. Cycle time for manual and collaborative scenarios for approaches A and B with different numbers of cobots.

Table 2

Cobot's idle time to cycle time ratios: Percentage Analysis for Cobots in all seven collaboration scenarios (considering approach B).

Number of cobots	Cobots	Collaboration Scenarios						
		SE	SI	SU	SE-SI	SE-SU	SI-SU	SE-SI-SU
1	C	64%	27%	51%	25%	47%	21%	21%
2	C1	61%	34%	57%	31%	52%	25%	25%
	C2	72%	24%	52%	23%	55%	21%	21%
	Ave	67%	29%	55%	27%	54%	23%	23%
3	C1	69%	43%	71%	37%	75%	36%	35%
	C2	81%	36%	64%	41%	61%	34%	32%
	C3	74%	44%	76%	43%	68%	39%	37%
	Ave	75%	41%	70%	40%	68%	36%	35%
4	C1	82%	54%	81%	50%	85%	47%	46%
	C2	71%	49%	94%	46%	91%	41%	39%
	C3	92%	43%	84%	42%	82%	42%	40%
	C4	89%	64%	96%	61%	91%	58%	56%
	Ave	84%	53%	89%	50%	87%	47%	45%

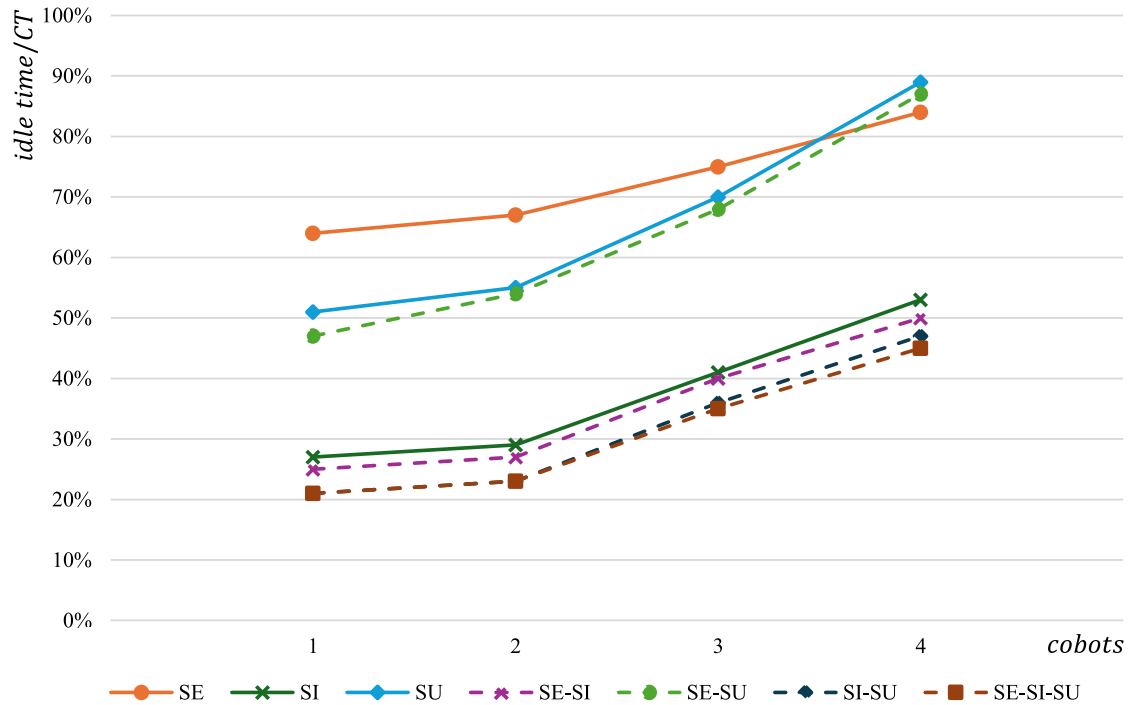


Fig. 4. Idle time to cycle time ratio with different numbers of cobots and collaborative scenarios (considering approach B).

model.

Lastly, Table 2 reveals that in the SE-SI-SU scenario, the cobots' idle time to cycle time ratio is lower than that of other collaboration scenarios. The most important reason behind this result is the simultaneous scenario, which allows parallel working. When humans and cobots work simultaneously, the idle time for the cobot and the worker is reduced compared to other scenarios. However, since not all tasks can be performed by a cobot simultaneously with a worker, considering the SE-SI-SU scenario provides opportunities to assign tasks to cobots in a way that

minimizes idle time as much as possible.

4.2. Relation between workforce age with RA and implementing cobots

The main aim of this section is to assess the impact of worker's age on RA and the implementation of cobots. To achieve this, we consider five sets of workers, each composed of four workers, as shown in Table 3. Workers set 2 includes workers aged 26, 38, 45, and 58, as introduced in Section 4. In workers set 1, we replaced the aged worker (58 years old)

Table 3

Workers' features and sets.

Worker		W1	W2	W3	W4	W5	W6	W7	W8
Age		30	28	26	45	60	55	58	64
$MAEE_h$ [kcal/min]		5.11	5	4.83	3.38	3.15	3.01	2.95	2.79
Workers set	1	*	*	*	*				
	2		*	*	*	*			
	3			*	*	*	*		
	4				*	*	*	*	
	5					*	*	*	*

with a younger one, while in workers sets 3, 4, and 5, we progressively replaced one, two, and three younger workers, respectively, with aged workers. In this study, we define aged workers as those older than 55, as noted by [Katirae et al. \(2024\)](#). These aged workers have a lower MAEE, and therefore they require higher RA for the same tasks compared to younger workers. However, the aged workers experience cannot be underestimated, as it often results in a shorter task processing time ([Boenzi et al., 2015](#)).

[Table 4](#) presents the results for the five workers sets varying the number of available cobots for the SE-SI-SU scenario, which has shown to be the best performing cycle time reduction. First, it reports that a higher number of aged workers within a workers set correlates with increased cycle times, given the same number of available cobots. However, this increment can be mitigated by adding more cobots to the line (from manual to cobotic). For instance, for workers set 1, with no aged workers, the cycle time for manual assembly stands at 52.13 min/piece, while the cycle time for a SE-SI-SU scenario with four cobots is 35.64 min/piece, marking a 31.63% reduction due to cobot integration. Conversely, for workers set 5, which includes four aged workers, the cycle time for manual assembly is 64.68 min/piece, and for the SE-SI-SU scenario with four cobots, it is 40.09 min/piece, equating to a 38.02% reduction. This enhancement is attributed to the cobots' ability to perform some tasks with aged workers, thereby reducing the RA and cycle time. Simultaneously, due to the experience of aged workers, they may complete some tasks more efficiently, reducing the time required. Therefore, time reduction depends on the contribution of cobots and the worker's experience.

Furthermore, when comparing different workers sets, particularly the homogeneous ones from an age perspective (sets 1 and 5), the difference between the two approaches A and B is less pronounced than other workers sets (sets 2, 3 and 4). This is because, in homogeneous workers sets, assigning workers to stations and tasks is less critical. In contrast, in sets with diverse workers' age profiles, it is crucial to avoid assigning physically demanding tasks to workers with lower MAEE. As a result, omitting RA from the model (approach A) can lead to significant deviations from the optimal outcome.

To better demonstrate the interconnections between workers' age

and RA characteristics and the implementation of cobots in the assembly line, [Fig. 5](#) shows the resources to stations assignment for all four existing workstations, including different numbers of cobots and workers sets, for both approaches A and B. The investigation focuses only on configurations with one, two, and three cobots since when four cobots are available, each station is equipped with one cobot, which prevents the investigation of the relationship between cobots and aged workers.

Results show that, in most cases, approach A assigns the existing cobots to the young workers. Pairing a young worker with a cobot at a station allows tasks to be completed in a shorter time, thus reducing the cycle time without considering RA. Nevertheless, for each workers set, the cycle time is always defined by the station with the aged worker. The older the worker, the higher the RA will be assigned to cover the effort spent executing the tasks. Moving to approach B, the cobots are assigned to aged workers more than in approach A, aiming to reduce the RA and the final cycle time. Thus, approach B performs better since it jointly considers experience, age and the effort required to execute tasks.

However, it should not be assumed that all aged workers are assigned to a station with a cobot. It is interesting to note that, in a heterogeneous workers set, a cobot can work with a young worker instead of an aged one. For example, considering the case of three cobots, in workers set 3 with two aged workers, two cobots are assigned to the two young workers, leaving one aged worker working without a cobot. This could be due to the experience of aged workers, who can perform tasks faster than younger ones. Further, the aged worker executes tasks with a lower physical effort than others. Therefore, although the general trend is to assign cobots to aged workers, this is not always the case. Thus, approach B for optimizing resource assignment is still recommended to obtain the most effective allocation of human resources and cobots.

5. Managerial insights

The case study provided interesting results that can be used as a starting point for some preliminary managerial insights, summarized in [Table 5](#). Of course, the considerations presented here are case-related, but they can be an inspiration for further cases.

Table 4

Cycle time [min/piece] for different workers sets and number of available cobots for SE-SI-SU scenario.

Workers Set	Approach	Manual	SE-SI-SU Scenario			
			One cobot	Two cobots	Three cobots	Four cobots
1	A	53.09	45.62 (−14.07%)	40.11 (−24.45%)	37.58 (−29.21%)	36.55 (−31.15%)
	B	52.13	44.21 (−15.19%)	38.39 (−26.36%)	36.2 (−30.56%)	35.64 (−31.63%)
	A-B	0.96	1.41	1.72	1.38	0.91
2	A	57.81	49.42 (−14.51%)	44.33 (−23.32%)	40.83 (−27.64%)	39.71 (−29.58%)
	B	55.04	44.97 (−18.3%)	39.21 (−28.76%)	37.48 (−31.9%)	36.91 (−32.94%)
	A-B	2.77	4.45	5.12	3.35	2.8
3	A	61.47	51.16 (−16.77%)	46.14 (−24.94%)	43.07 (−29.93%)	41.31 (−32.8%)
	B	58.11	47.28 (−18.64%)	42.21 (−27.36%)	39.28 (−32.4%)	38.09 (−34.45%)
	A-B	3.36	3.88	3.93	3.79	3.22
4	A	63.29	53.52 (−15.44%)	47.49 (−24.96%)	43.74 (−30.89%)	41.05 (−35.14%)
	B	61.24	50.14 (−18.13%)	43.87 (−28.36%)	41.01 (−33.03%)	39.13 (−36.1%)
	A-B	2.05	3.38	3.62	2.73	1.92
5	A	65.81	53.93 (−18.05%)	47.51 (−27.81%)	43.61 (−33.73%)	41.11 (−37.53%)
	B	64.68	52.38 (−19.02%)	45.49 (−29.67%)	42.18 (−34.79%)	40.09 (−38.02%)
	A-B	1.13	1.55	2.02	1.43	1.02

Cobots	WS	Station	APPROACH A				APPROACH B			
			1	2	3	4	1	2	3	4
1	1	Resources								
			W4	W2	W1 C1	W3	W3	W2	W4 C1	W1
	2	Resources								
			W4	W3 C1	W2	W5	W4	W2	W5 C1	W3
	3	Resources								
			W6	W4 C1	W3	W5	W5	W3	W6 C1	W4
	4	Resources								
			W5	W4 C1	W6	W7	W7	W4	W6 C1	W5
	5	Resources								
			W6	W7 C1	W8	W5	W8	W6	W7 C1	W5
2	1	Resources								
			W4	W1 C2	W2 C1	W3	W2	W4 C1	W1 C2	W3
	2	Resources								
			W4	W2 C2	W3 C1	W5	W4	W3 C1	W5 C2	W2
	3	Resources								
			W6	W3 C1	W5 C2	W4	W4	W6 C1	W5 C2	W3
	4	Resources								
			W7	W4 C1	W5 C2	W6	W4	W7 C1	W6 C2	W5
	5	Resources								
			W7	W8 C1	W5 C2	W6	W7	W5 C2	W8 C1	W6
3	1	Resources								
			W4	W2 C2	W1 C3	W3 C1	W4	W1 C2	W2 C1	W3 C3
	2	Resources								
			W5	W2 C3	W4 C1	W3 C2	W3	W2 C2	W4 C1	W5 C3
	3	Resources								
			W6	W3 C1	W4 C3	W5 C2	W5	W4 C2	W6 C3	W3 C1
	4	Resources								
			W7	W4 C1	W5 C2	W6 C3	W7	W6 C2	W4 C1	W5 C3
	5	Resources								
			W8	W5 C2	W6 C1	W7 C3	W6	W8 C2	W5 C1	W7 C3

Fig. 5. Resources assignment for SE-SI-SU scenario with different numbers of cobots and workers sets (WS).

Table 5
Summary of the case study results and suggested managerial insights.

Category	Results summary	Managerial insight
Optimization approach	The preferable approach is B, which includes workers' RA during tasks assignment (Table 1 and Fig. 3)	Utilizing Approach B is beneficial due to the integration of workforce individualization into the model in terms of the worker's RA, which leads to less workers' fatigue and more productivity.
Cobots implementation	Having three cobots out of four workstations reduces cycle time and alleviates workers' physical fatigue, while adding a fourth cobot does not provide additional value (Figs. 3 and 4)	When assigning cobots to workstations, it should be considered the best balance between productivity gains, time performance and workers' benefits. The number of tasks a cobot can execute has an influence on the effectiveness of cobots implementation.
Collaboration scenarios	The preferable collaboration scenario is the SE-SI-SU scenario, which minimizes the cycle time (Fig. 3). The SI scenario brings results similar to SE-SI-SU, while the SE scenario is less impactful (Fig. 3).	Focusing more on the SE-SI-SU and SI scenarios in the design and balancing of assembly lines can lead to lower cycle times and higher productivity. Implementing the most appropriate scenario highly depends on the task types and the possibility of performing them in SE, SI and SU scenarios.

Further, the mathematical model presented here allows us to include both technological (i.e., collaborative scenarios, number of cobots), environmental (i.e., number of workstations, assembly line layout) and human (i.e., experience, age) variables to minimize the cycle time of CALs. We have demonstrated how integrating all these variables could influence the cycle time by achieving lower values compared to models adopting a hierarchical approach (i.e., considering variables in different steps of the assembly line design process). Furthermore, according to the obtained results, we can say that it is impossible to assume a priori only one collaborative scenario, and including all possible scenarios should be preferable to achieve a lower cycle time. Finally, an interesting point arises for the workers and cobots to station assignments since it is influenced by the variability among workers involved in the assembly. Both experience and age affect the choice to assign a worker and a cobot to a station. The inexperience of a younger worker (thus, the higher time required to execute a task) could be reduced by assigning a cobot to the same station. Conversely, the higher experience of an aged worker (thus, the less time to execute a task) can balance the higher RA required to reduce fatigue after performing the assigned tasks. On the other hand, for lower variability among workers (i.e., similar experience and age), cobots are generally assigned to aged workers to minimize the RA and, thus, the cycle time as much as possible.

In summary, considering the collaborative scenarios of cobots and the individual characteristics of workers is crucial for optimizing CAL design and layout. By integrating this information into decision-making processes, managers can make informed decisions to enhance efficiency, ergonomics, and overall performance in assembly operations.

6. Conclusions, limitation, and future research

Although cobots have been used in industries for several years, researchers initially focused on ensuring safety (Gualtieri et al., 2020). Consequently, developing a mathematical model for optimizing a human-robot collaborative assembly line is a relatively recent endeavour. In addition, the lack of real case studies for implementing cobots in real-life scenarios has left significant gaps in the literature. Thus, in this paper, we have developed a mathematical model to optimize the CAL performance by minimizing cycle time and considering different collaborative scenarios, workforce features (experience, age and consequently, MAEE) and cobots features (different times to perform the same task). Further, we applied the proposed model to a case study to investigate 1) how workforce and cobots features (i.e. age, RA and the number of cobots) influence the tasks to stations assignment and, thus, the cycle time (Table 1, Table 2, Figs. 2, Figure 3, Figure 5), 2) which collaboration scenario performs better (Table 1 and Fig. 2). The analysis was conducted through a case study, so the results are specific to this case. While some findings align with existing literature and previous studies, others were unexpected. For instance, cobots were expected to be assigned primarily to aged workers; however, the study revealed that cobots could also be assigned to younger workers in the presence of aged workers, leaving them to perform tasks independently

(Fig. 5). This result may be attributed to the experience of the aged workforce in performing tasks effectively on their own.

This study, however, has some limitations. First, as already mentioned, the obtained results are case-related. Further applications of the model would be helpful to understand better its suitability to solve the design and the balancing of CALs. Moreover, this would lead to more robust insights for researchers and practitioners. However, the need to increase the number of tested cases also leads to another limitation of this study, which is the model's scalability. The complexity of the model and its NP-hard nature, along with the extensive computations required to test several instances, call for the development of proper meta-heuristics approaches. Moving to the model formulation, in its current stage, it considers the energy expenditure and RA (equation (18)). However, other postural ergonomic assessments could be used to better measure the worker's physical workload and pressure. Finally, our research is focused on the study of CAL time performance without considering the cost of the assembly line, including the cost of the resources (cobots and workers) and equipment costs.

According to the limitations highlighted, there are several areas for potential future research. In the future, the proposed model should be tested with more cases, and efficient metaheuristic methods should be developed tailored to handle its complexity, especially with large-scale problem instances. The model can also be expanded, including an ergonomic evaluation that goes beyond the energy expenditure and RA concepts by integrating other postural ergonomic assessments, such as RULA (Rapid Upper Limb Assessment), REBA (Rapid Entire Body Assessment), or OCRA (Occupational Repetitive Actions) to provide a different understanding of the physical workload on workers. In this work, we highlight that the closer the number of cobots to the number of workstations, the more idle time is assigned to each cobot, but this insight is strictly connected to the number of tasks that cobots can execute. Thus, it could be interesting to investigate how the number of tasks that cobots can execute could influence the choice of the number of cobots to install in the assembly line.

Finally, future studies could integrate a more comprehensive analysis of the cost-effectiveness of implementing cobots in the assembly lines by comparing the investment costs related to the installation of the cobots and the savings they can provide in terms of performance improvement.

CRedit authorship contribution statement

Ali Keshvarparast: Writing – original draft, Validation, Supervision, Methodology, Investigation, Conceptualization, Data curation. **Niloofer Katirae:** Writing – original draft, Validation, Supervision, Methodology, Investigation, Conceptualization, Data curation. **Serena Finco:** Writing – review & editing, Validation, Supervision, Methodology. **Martina Calzavara:** Writing – review & editing, Validation, Supervision, Methodology.

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Data availability

No data was used for the research described in the article.

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