Multi-objective collaborative assembly line design problem with the optimization of ergonomics and economics

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ABSTRACT

Manufacturing systems are socio-technical systems, with explicit interactions between humans and technologies in shared workspaces. These shared workspaces could also be called hybrid collaborative manufacturing systems, that involve workers as well as technological equipment and combine the benefits of human workers and new Industry 4.0 technologies, such systems are particularly useful in a context requiring flexibility and adaptability. Furthermore, the new Industry 5.0 approach has the objective to shift toward more human-centric and resilient manufacturing systems. The key problems to solve in the design of collaborative manufacturing systems are the combinatorial assembly line balancing problem and the equipment selection problem. An efficient and sustainable line requires a cost-effective choice of equipment while improving the ergonomics and the safety of workers. Both decisions of balancing workload and the assignment of equipment impact the ergonomics of a collaborative system and present conflicting criteria. To this end, we propose a multi-objective approach, the objectives are the optimization of the investment costs and the ergonomics with a fatigue and recovery criterion. We propose to linearize the fatigue and recovery to formulate a new Mixed Integer Linear Programming formulation. We developed an exact multi-objective solving algorithm based on the ϵ-constraint to obtain the trade-off between these objectives. We conducted numerical experiments with different instances from the literature with promising results for instances with up to 45 operations. Finally, we discuss insightful managerial conclusions and future research perspectives.

KEYWORDS
Assembly Line Balancing Problem; Assembly Line Design Problem; Equipment selection; Ergonomics; Industry 4.0; Industry 5.0; Multi-objective optimization

1. Introduction

The current industrial context is characterized by a growing extensive use of modern technologies and digital equipment in manufacturing systems, we are currently referring to this change as Industry 4.0, which is an extension of past trends in automation. Although advanced assistive

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technologies are increasingly used in production systems, human workers will remain an essential element for greater flexibility and productivity (Sgarbossa et al. 2020; Neumann et al. 2021). Recently, the European Commission start a complementary approach, called Industry 5.0, with more human-centric, sustainable, and resilient systems (Commission 2021).

Industry 5.0 goes beyond the efficiency and productivity of manufacturing systems and reinforces the role and contribution of workers while respecting the global production limits of the planet. Industry 5.0 is a transformative vision of the European Industry that complements "Industry 4.0" approach by a new vision for the industry toward more green, human-centric and resilient manufacturing systems. This new approach shift from a technology-centered approach to resilient and sustainable growth and expands the corporate environment and social responsibility (Commission 2021). The keyword that could summarize this approach is resilience, through the development of innovative technologies and workplaces in a human-centered way.

Collaborative hybrid systems with humans-machines interacting and operating in harmony could benefit from the advantages and strengths of both components, increasing the performance and flexibility of manufacturing systems (Hashemi-Petroodi et al. 2020). However, such systems require taking into account both the ergonomics of the workers to avoid work-related musculoskeletal disorders (MSDs) as well as the manufacturing system performance measures (Abdous et al. 2023).

With the digital transition and Industry 4.0, a wide range of new technological equipment accession in manufacturing systems, among them, intelligent automation devices (IAD), intelligent gripping, power amplifying assist devices, collaborative robot (cobot) that interact with workers in a shared workspace, mobile robot, mobile robot manipulators, assistive exoskeleton technology, and many more. The main two benefits of advanced equipment in manufacturing systems are the enhancement of performance and ergonomics. In Manufacturing systems, decisions are made for the configuration of the system and the level of automation, particularly for assembly line systems (Dolgui et al. 2022), where assembly lines are manufacturing systems designed for the final assembly of products. Future workers or Operator 4.0 (Romero et al. 2020) will be assisted with collaborative cyber-physical systems, with advanced human-machine interaction technologies. Future collaborative manufacturing systems with a human workforce would achieve a human-automation symbiosis (Romero et al. 2020).

Several decisions have to be made in the design of collaborative manufacturing systems, including the combinatorial optimization problem of assigning different operations to be performed for every workstation referred to in the literature as the Assembly Line Balancing Problem (ALBP), and the equipment selection problem. The associated combinatorial problem with the equipment selection is the so-called Assembly Line Design Problem (ALDP). The ALDP link the assignment of tasks to a workstation with an equipment selection problem, such that the assembly task is equipment-dependent. Since ALDP is most of the time a long-term strategic problem involving massive investment costs, the objective function usually optimizes a cost-oriented objective (Boysen et al. 2022; Weckenborg et al. 2022). Investment may contain costs related to the purchase and maintenance of equipment and spare parts. This paper proposes a contribution to the development of analytical and mathematical models to solve complex decision problems that arise in the design stage of modern assembly lines, and to gain insights into the integration of human operators and technology with a human-centric modern Industry 5.0 approach.

In this work, we propose a bi-objective approach for the Collaborative Assembly Line Design Problem. The first objective is the total investment costs, and the second is the ergonomics of workers with fatigue and recovery. In the sequel, Section 2 presents a literature review of the existing literature related to our work. In Section 3, we develop our new Mixed Integer Linear Programming (MILP) model. In Section 4, we describe the ϵ-constraint algorithm to obtain the Pareto front, and in Section 5 we present numerical experiments conducted to illustrate the results. Finally, we highlight the managerial insights of this work in Section 6 and a conclusion and future research perspectives in Section 7.

2. Literature review

In the literature, Assembly Line Balancing Problems (ALBP) are widely studied, with many works that focused on the ALDP with equipment choice (Boysen et al. 2022). However, the introduction of ergonomics into the assembly system is recent in the literature (Battini et al. 2016; Otto and Battaïa 2017; Finco et al. 2020). In their review, Boysen et al. (2022) highlights the recent interest in ergonomic aspects in practice and research in the context of repetitive tasks in assembly lines.

Ergonomics in assembly systems should be further studied, particularly with some recent contributions that promote a systematic approach considering ergonomics in new Industry 4.0 production systems (Kadir et al. 2019; Neumann et al. 2021). In the next Subsection, we present some related works regarding the ALDP literature, while in Subsection 2.2, we present works that integrate ergonomics into the assembly line problems.

2.1. *Assembly line design problem*

The articles investigating the problem of equipment choice mainly consider the optimization of criteria related to the costs, such as in Bukchin and Tzur (2000), when authors addressed the questions when only one equipment is allowed to minimize total equipment costs and developed a branch and bound algorithm and a heuristic for the problem. Later, Bukchin and Rubinovitz (2003) extended the model of Bukchin and Tzur (2000) for parallel workstations. Recent works by Barutçuoğlu and Azizoğlu (2011) developed a branch and bound algorithm that used powerful lower bounds and reduction mechanisms to solve the ALDP. Öncü Hazir et al. (2015) presented a detailed review of works that address cost and profit-oriented objectives for assembly line design and balancing problems.

The ALDP presents conflicting objectives, such as economics-oriented objectives related mainly to investment costs, and ergonomics improvement which may require significant investment in specialized equipment. In the literature, the ALDP was considered in a multi-objective approach in several articles. Rekiek et al. (2001) propose a multi-objective method for assembly line design with the optimization of cost, the authors proposed a multiple objective grouping genetic algorithm. Pekin and Azizoglu (2008) consider a bi-criteria assembly line design problem and generate the set of efficient solutions with a branch and bound algorithm. Oesterle et al. (2019) considered the assembly line balancing and equipment selection problem and compare several solving approaches. Delorme et al. (2014) proposed a detailed review of the multi-objective approach for the design of assembly lines.

Other optimization problems that consider equipment selection are the transfer line balancing and the robotic assembly lines, these types of lines are fully automated in the majority of cases. In transfer lines, each workstation is equipped with a machining tool (multi-spindle) that performs machining operations by block. The problem considers the optimization of the number of workstations and the investment cost on the transfer lines along with the assignment of the blocks of operations to execute (Delorme et al. 2012; Essafi et al. 2012; Battaïa et al. 2014; Lahrichi et al. 2021).

The Robotic Assembly Line Balancing Problem (RALBP) extends the ALBP with the additional assignment of robots as equipment. Rubinovitz et al. (1993) investigated the RALBP when the purpose was to balance the workload with respect to the production rate and to allocate the most efficient robot that offers different specializations. Likewise, Borba et al. (2018)

proposed exact and heuristic algorithms for the RALBP, when the exact method includes a MILP and a branch-bound-remember with specific dominance rules. Recent contributions integrated social and sustainability criteria with the RALBP (Zhang et al. 2019; Zhou and Wu 2020). The main contributions of the RALBP are recently reviewed, discussed, and classified in the comprehensive literature review by Chutima (2022).

2.2. *Ergonomics in lines balancing problems*

In the last decades, many ergonomics criteria and risk analyses were developed to improve the safety of workers in assembly lines (Boysen et al. 2022). Attempts were made to include industrial ergonomics assessment tools in the ALBP. In the literature, works tried to introduce ergonomics issues mainly focusing on fully manual assembly lines to mitigate the risks and reduce MSDs. Most articles in the literature consider the ergonomics with a risk assessment criteria, such as the occupational repetitive actions index (OCRA) (Otto and Scholl 2011; Baykasoglu et al. 2017; Tiacci and Mimmi 2018), with OCRA being a method of evaluating the musculoskeletal load of the upper limbs. Other works consider a customized general ergonomics assessment risk, such as environment, postural, and physical load (Choi 2009; Özcan Mutlu and Özgörmüş 2012; Bautista et al. 2016).

Alternatively, quantitative and biomechanical models are used in some articles with the assembly line balancing problems, e.g., in the work of Carnahan et al. (2001) with physical fatigue of grip strength, in Abdous et al. (2018b, 2023) with general fatigue and recovery criteria; energy expenditure and rest allowance (Battini et al. 2016; Finco et al. 2020), and vibration exposure (Finco et al. 2019, 2021).

Motivated by recent developments of cobot, Weckenborg and Spengler (2019) used quantitative energy expenditure (Battini et al. 2016) as ergonomics criteria for the design and balancing of assembly lines. Thereafter, Weckenborg et al. (2022) extended their work with a multi-objective modeling approach with the consideration of collaborative robots and exoskeletons, and proposed a Pareto optimal frontier for decision-makers. Recently, Abdous et al. (2020) studied a new Cobotic Assembly Line Design Problem with ergonomics.

In their review of the literature on works integrating the ergonomics in assembly lines, Otto and Battaïa (2017) emphasized the non-linearity of the majority of ergonomic criteria, and the lack of an efficient method to include them in a low computational cost with the assembly line balancing problem. Furthermore, they stated that most articles in the literature consider metaheuristics and heuristics without information about the gap to the optimal solution. Contributions including the safety of workers and ergonomics are recent, and they are not numerous and only focus on fully manual assembly lines, ergonomics in assembly line design problems is underrepresented in the literature.

To the best of our knowledge, only two articles in the literature contribute to the modeling and solving approach of multi-objective ALDP with the consideration of ergonomics and economics criteria (Abdous et al. 2020; Weckenborg et al. 2022). In this article, we aim to include ergonomics with the collaborative assembly line design problem, with a possible Human-Machine collaboration in shared workspaces. Furthermore, we provide an exact multi-objective algorithm to obtain the set of efficient solutions and to provide decision-makers with a set of alternative solutions.

3. Modeling approach

In this work, we attempt to provide designers and engineers with decision support to design collaborative assembly lines with Human-Machine cooperation. The collaborative Assembly

Line Design Problem consists of the assignment of operations to workstations and the selection of one equipment to assign to each workstation with the optimization of both ergonomics and economics. We assume that a human worker is present in each workstation with a set of non-collaborative or collaborative equipment to choose from.

The assignment of operations to workstations must respect the technological constraints between operations, and the takt time is denoted T. Decision variables x_{jk} are used for the assignment of the operation $j \in V$ to a workstation $k \in W$, with V the set of operations and W the set of workstations.

The decision variables y_{ik} are used for the assignment of equipment $i \in E$ to workstation k, with E the set of equipment alternatives. An equipment $i \in E$ is composed of one or many components, that could be either classical, collaborative, or both. Possible components could be non-collaborative, such as manual tools, classical automation machines, power amplifying assist devices, etc. The equipment components could be collaborative, such as cobot, mobile robot, intelligent exoskeleton, mobile robot manipulator, etc. Equipment could also be composed of a set of collaborative and non-collaborative components. For example, equipment $i_1 \in E$ is composed of an exoskeleton, while other equipment $i_2 \in E$ is composed of a gripping device and advanced collaborative equipment, such as cobot.

Equipment i influences the processing time t_{ij} of operation j and/or the physical load, defined with $Fload_{ij}$. Operation time or processing time t_{ij} is defined with a deterministic predetermined time and set as the standard time in which a worker should complete a given operation j with equipment i. $Fload_{ij}$ represents the physical load of operation j when executed with the equipment i. The objectives are the minimization of investment costs and the optimization of ergonomics with a fatigue and recovery model.

3.1. *Ergonomics and economics objectives*

3.1.1. Ergonomics with fatigue and recovery model

We use the fatigue and recovery model developed by Ma et al. (2015), this model was first used as a criterion for evaluating ergonomics in assembly lines in Abdous et al. (2020) and in Abdous et al. (2023).

The fatigue depends on the external load magnitude ($Fload_{ij}$), repetitiveness, duration of the load, and the equipment present in the workstation. Furthermore, fatigue depends on workers' characteristics such as fatigability α, recovery rate R, and MVC or maximum voluntary contraction, defined as the maximum force capacity of workers without fatigue. At the end of the execution of operations, the idle time allows recovery and reduces the fatigue level. We refer to Abdous et al. (2023) for the integration of this fatigue and recovery model in assembly line balancing problems.

The level of muscular capacity after one takt time in an assembly line is represented in the following equation:

$$F_k = 1 + (\mathrm{e}^{-\sum_{i \in E} \sum_{j \in V} I_{ij} y_{ik} x_{jk}} - 1)\mathrm{e}^{-R(T - \sum_{i \in E} \sum_{j \in V} t_{ij} y_{ik} x_{jk})} \quad \forall k \in W \tag{1}$$

With I_{ij} the integral of load of operation j executed with the equipment i during the exertion period t_{ij}, the integration by part allows aggregating operations assigned to a given workstation.

$$I_{ij} = (\frac{\alpha}{MVC}) \int_{t}^{t+t_{ij}} Fload_{ij}(u)du \tag{2}$$

We assume in this work an average worker's characteristics: α and R represent average workers, in the 50th percentile of the working population. This assumption considers that operators belong to the 50% percentile of the population with average physical characteristics. Most of the time in the design stage of assembly lines, workers' characteristics are not available, the consideration of a percentile of the working population is a reasonable assumption in the design stage of assembly lines. In this article, we choose the average values of α and R obtained from the regression studies by (Ma et al. 2015; Liu et al. 2018).

In the practice, the calculation of $Fload$ can be obtained by a professional ergonomist with several methods. $Fload$ can be assessed with the objective measures of the forces with surface electromyography (EMG), we refer to Choung et al. (2016); Ashok et al. (2018) for applications of EMG in the context of assembly lines task's load evaluation. Another method is the computer-aided ergonomics and digital human models as in Duffy et al. (2007); Ma et al. (2011). Greig et al. (2018) developed a tool that could be considered as a digital human simulation tool to compute the operation's physical load or $Fload$ for light assembly lines. Furthermore, the assessment of $Fload$ is also possible with a rating of perceived effort on a scale such as the Borg scale. A high correlation was found between perceived effort estimation with the Borg scale and the EMG for different force levels. This method is fast and could be applied easily in industrial configuration (Hampton et al. 2014).

We define the objective function as $F = Min_{k \in W}\{F_k\}$, we would refer to F as the "fatigue level", which refers to the ergonomics of the worker in the critical workstation after one takt time (Abdous et al. 2023). A workstation k is critical when the fatigue level is minimal compared to other workers: $Min_{k \in W}\{F_k\}$. The optimization of the fatigue level of the critical workstations would result in an overall better work-rest schedule in all workstations. Thus the ergonomics objective is expressed as in Equation (3).

$$Maximize\{F\} \tag{3}$$

Figure 1 represents the evolution of the fatigue level in a workstation k after one takt time for two different cases. The assembly tasks are performed during working time, afterward, in recovery time, the operator recovers from fatigue. We assume that the worker is fully recovered at the beginning (i.e. 100%) and the final $F_k(\%)$ represents the fatigue level after one takt time in the workstation k. The blue curve shows the evolution of fatigue level when the workstation k is equipped with equipment i_1, while the red curve shows the evolution of fatigue level with another equipment i_2. This example shows that equipment influences the level of fatigue after one takt time when a worker executes the same set of tasks, as well as the total processing time and thus the recovery time.

3.1.2. Economics investment costs

The second objective is an economic objective, mainly related to the total investment costs of equipment. This economic objective is expressed in Equation (4). The aim is to minimize the total costs of equipment.

$$Minimize\ \{C\} = \sum_{i \in E} \sum_{k \in W} C_i y_{ik} \tag{4}$$

3.2. *Mixed-integer nonlinear programming*

For the formal definition, we use the following notations:
ALDP parameters:

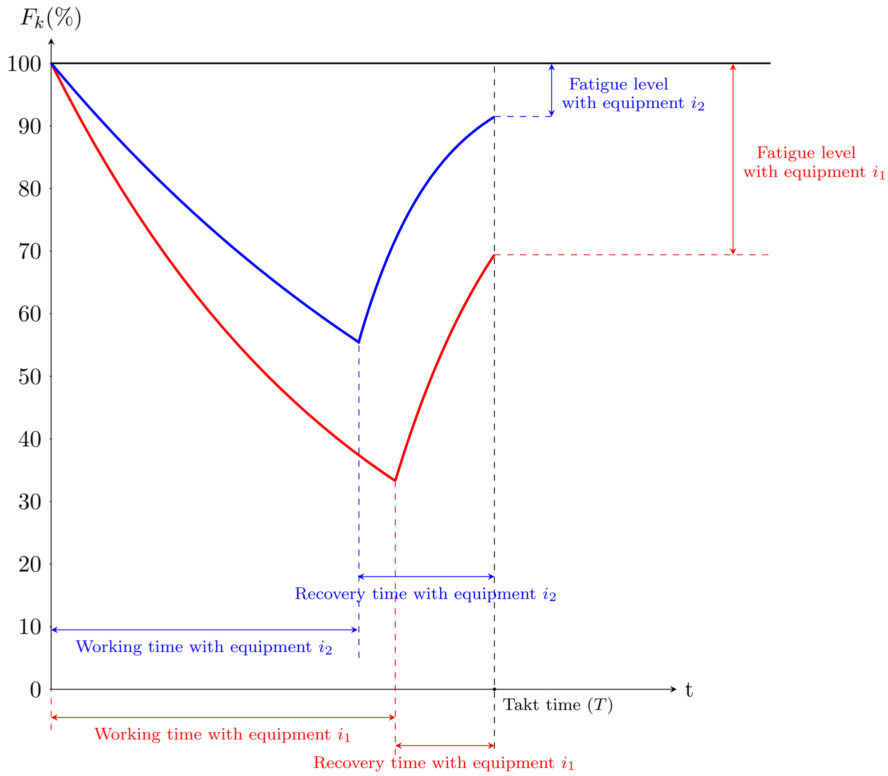

Figure 1.: Evolution of the fatigue level for a worker in the workstation k in the case of use of equipment i_1 and in another case with the use of another equipment i_2

$V = \{1, .., n\}$: Set of operations
$E = \{1, .., r\}$: Set of equipment
$W = \{1, .., m\}$: Set of workstations
T: Takt time $[s]$
t_{ij}: deterministic time of operation j or processing time when executed with the equipment i $[s]$
P: Set of precedences between operations ($(h, g) \in P$ if operation h precedes operation g)
$C_i \in \mathbb{N}$: Cost of equipment i
Ergonomics parameters:
$MVC = 100\%$: Maximum voluntary contraction
$Fload_{ij}$: Operations load (intensity) of operation j when performed with the equipment i
I_{ij}: Integral of load of operation j executed with equipment i
$\alpha = \frac{1}{60}$: Worker fatigability $[s^{-1}]$
$R = \frac{1}{60}$: Worker recovery rate $[s^{-1}]$
Decision variables:

$$x_{jk} = \begin{cases} 1 & \text{if operation } j \text{ is assigned to the workstation } k \\ 0 & \text{Otherwise} \end{cases}$$

$$y_{ik} = \begin{cases} 1 & \text{if equipment } i \text{ is assigned to workstation } k \\ 0 & \text{Otherwise} \end{cases}$$

Ergonomics constraints:
Constraint (5) ensures the bounding of the fatigue level.

$$F \leq 1 + (\mathrm{e}^{-\sum_{i \in E} \sum_{j \in V} I_{ij} y_{ik} x_{jk}} - 1)\mathrm{e}^{-R(T - \sum_{i \in E} \sum_{j \in V} t_{ij} y_{ik} x_{jk})} \quad \forall k \in W \tag{5}$$

Unicity constraints:
Unicity constraint (6) ensures that each operation j is assigned to only one workstation k. (7) guarantees that for each workstation, exactly one equipment is to be chosen out of a set of alternatives.

$$\sum_{k \in W} x_{jk} = 1 \quad \forall j \in V \tag{6}$$

$$\sum_{i \in E} y_{ik} = 1 \quad \forall k \in W \tag{7}$$

Takt time:
Constraint (8) guarantees that the working time of any workstation k is at most equal to the takt time T.

$$\sum_{i \in E} \sum_{j \in V} t_{ij} x_{jk} y_{ik} \leq T \quad \forall k \in W \tag{8}$$

Precedence:
Constraint (9) ensures respecting the technological order of operations.

$$\sum_{k \in W} k x_{hk} \leq \sum_{k \in W} k x_{gk} \quad \forall (h, g) \in P \tag{9}$$

Finally, (10) defines the type of variables.

$$x_{jk}, \ y_{ik} \in \{0, 1\} \tag{10}$$

The MO-MINLP, defined with (3) – (10) combines the challenges of handling nonlinearities, the multi-objective aspects, and the combinatorial explosion of integer variables. We remind that the ALDP is an NP-hard combinatorial problem (Scholl 1995). To tackle the problem, we propose different linearizations in the following subsections.

3.3. *Linearization of the ergonomics constraint (5)*

We introduce two decision variables such that $\sigma_{jk} = \sum_{i \in E} I_{ij} x_{jk} y_{ik}$ and $\pi_{jk} = \sum_{i \in E} t_{ij} x_{jk} y_{ik}$ in order to linearize the product $x_{jk} y_{ik}$. The variable σ_{jk} will take the value I_{ij} when the equipment i is used in workstation k. The sum $\sum_{i' \in E \ | \ I_{ij} \leq I_{i'j}} y_{i'k}$ and $\sum_{i' \in E \ | \ I_{ij} \leq I_{i'j}} (Max_{q \in E} \{I_{qj}\} - I_{i'j}) \, y_{i'k}$ improve the linear relaxation and present more tight constraints. Similarly, the variable π_{jk} will take the value t_{ij} when the equipment i is used in workstation k.

Linear constraints for operation load:

$$I_{ij}\left(x_{jk}+\sum_{i'\in E:\ I_{ij}\leq I_{i'j}} y_{i'k}-1\right)\leq \sigma_{jk} \quad \forall i\in E,\ \forall j\in V,\ \forall k\in W \tag{5a}$$

$$\sigma_{jk}\leq Max_{q\in E}\left\{I_{qj}\right\} \ -\sum_{i'\in E\ \mid\ I_{ij}\leq I_{i'j}} \left(Max_{q\in E}\left\{I_{qj}\right\}-I_{i'j}\right) y_{i'k} \quad \forall i\in E,\ \forall j\in V,\ \forall k\in W \tag{5b}$$

To include the fatigue and recovery of workers into ALDP, we introduce a lower bound $\underline{F}$ that represents the workstation with the lowest fatigue level among workstations. Hence, Equation (5c) is valid for all $k\in W$.

$$\underline{F}\leq 1+(\mathrm{e}^{-\sum_{j\in V}\sigma_{jk}}-1)\mathrm{e}^{-R(T-\sum_{j\in V}\pi_{jk})} \quad \forall k\in W \tag{5c}$$

We introduce a decision variable z_{lk} for the recovery time with $U=\{0,1,..,T\}$ the set of discrete possible recovery time.

The set U of possible recovery time could go from 0 when the worker works all the takt time and could be equal to T when the worker is idle all the takt time.

$$z_{lk}=\begin{cases}1 & \text{if recovery time of workstation } k \text{ is equal to } l\text{, with } l\in U\\ 0 & \text{Otherwise}\end{cases}$$

We develop (5c) to obtain the following constraint:

$$\sum_{j\in V}\sigma_{jk}\leq \sum_{l\in U\ \mid\ l<\mathcal{D}} \ln\left(\frac{1}{(\underline{F}-1)\mathrm{e}^{Rl}+1}\right) z_{lk}+\sum_{j\in V}\sum_{l\in U|l\geq\mathcal{D}} I_{ij}z_{lk} \quad \forall k\in W \tag{5d}$$

In the case when the value of recovery time l is inferior to the value $\mathcal{D}=\frac{1}{R}\ln\left(\frac{1}{1-\underline{F}}\right)$, the logarithm function specifies a bound on the load in workstations to respect the lower bound $\underline{F}$ on the fatigue level. In the case when the value of the recovery exceeds $\mathcal{D}$, no matter which load value is assigned to workstations, the fatigue level will respect the bound $\underline{F}$, a maximum load $\sum_{j\in V} I_{ij}$ can be used as a bound on the load.

To define the value of the recovery time, constraint (5e) ensures that the idle time l in workstation k is equal to the difference between the takt time and working time. Constraint (5f) ensures the uniqueness of the idle time in every workstation k. (5g) defines the type of variables.

$$T-\sum_{j\in V}\pi_{jk}=\sum_{l\in U} l z_{lk} \quad \forall k\in W \tag{5e}$$

$$\sum_{l\in U} z_{lk}=1 \quad \forall k\in W \tag{5f}$$

$$\pi_{jk} \in \mathbb{N}; \sigma_{jk} \geq 0, z_{lk} \in \{0,1\} \tag{5g}$$

3.4. *Linearization of the takt time constraint (8)*

The tandem of constraints (8a) and (8b) guarantee that the variable π_{jk} takes the time t_{ij} when we have a given set of equipment i assigned to the workstation k. Similarly, $\sum_{i' \in E \ | \ t_{ij} \leq t_{i'j}} y_{i'k}$ and $\sum_{i' \in E \ | \ t_{ij} \leq t_{i'j}} \left(Max_{q \in E}\left\{t_{qj}\right\} - t_{i'j}\right) y_{i'k}$ improve the linear relaxation with tight constraints.

$$t_{ij}\left(x_{jk} + \sum_{i' \in E: \ t_{ij} \leq t_{i'j}} y_{i'k} - 1\right) \leq \pi_{jk} \quad \forall i \in E, \ \forall j \in V, \ \forall k \in W \tag{8a}$$

$$\pi_{jk} \leq Max_{q \in E}\left\{t_{qj}\right\} - \sum_{i' \in E: \ t_{ij} \leq t_{i'j}} \left(Max_{q \in E}\left\{t_{qj}\right\} - t_{i'j}\right) y_{i'k} \quad \forall i \in E, \ \forall j \in V, \ \forall k \in W \tag{8b}$$

Takt time:
Constraint (8) is transformed into (8c).

$$\sum_{j \in V} \pi_{jk} \leq T \quad \forall k \in W \tag{8c}$$

3.5. *Collaborative Assembly Line Design Problem: CALDP*

3.5.1. CALDP-MO

The MO-MINLP defined in Subsection 3.2 is a multi-objective optimization problem, with the simultaneous consideration of two conflicting objectives. The MOO could be referred to as CALDP-MO which means Collaborative Assembly Line Design Problem CALDP, and refer to the ALDP as the collaboration between human workers and machines. CALDP-MO is formulated as:

$$Minimize\{C\}; \ Maximize\{F\}$$

$$s.t. \quad (5) - (10)$$

The set denoted $\mathcal{X}$ is the feasible set of decisions that solutions must satisfy. A solution $s^1 \in \mathcal{X}$ dominates another solution $s^2 \in \mathcal{X}$ if $C(s^1) \leq C(s^2)$ and $F(s^1) \geq F(s^2)$, with the strict inequality holds at least once. The non-dominated set of the entire space $\mathcal{X}$ is denoted as the Pareto-optimal set or simply Pareto front which is the optimal solution to the MOO problem. We may also refer to the Pareto front as the efficient set (Ehrgott 2005). To handle the non-linearity, we define two Mixed Integer Linear Programming (MILP) formulations. The first is a decision problem denoted CALDP-F, and the second is a minimization problem denoted CALDP-C.

3.5.2. CALDP-F

We transform the CALDP-MO into a MILP decision problem defined with the set of constraints: $\{(5a),(5b),(5d),(5e),(5f),(5g),(6),(7),(8a),(8b),(8c),(9),(10),(11)\}$. Constraint (11) ensures that the total investment costs does not exceed an upper parametric cost level $\overline{C}$.

$$\sum_{i\in E}\sum_{k\in W} C_i y_{ik} \leq \overline{C} \tag{11}$$

Decision problems attempt to answer the question of whether or not a feasible solution exists with an objective function value (in the case of maximization) exceeding a particular value defined in the set of constraints (Scholl 1995). In our case, a solution of the CALDP-F will only give a better level of ergonomics than the $\underline{F}$ without exceeding the parametric bound on the budget $\overline{C}$. To obtain the trade-off between the design cost and the level of ergonomics, we propose in the following Section a multi-objective exact algorithm.

3.5.3. CALDP-C

This optimization problem is defined with the economics objective function (4) that minimize the investment cost of equipment, and the set of constraints: $\{(5a),(5b),(5d),(5e),(5f),(5g),(6),(7),(8a),(8b),(8c),(9),(10),(11)\}$.

4. Multi-objective solving approach

4.1. *ϵ-constraint algorithm*

The ϵ-constraint algorithm is a generic method that solves a multi-objective optimization problem by solving the single-objective version of the problem iteratively. Multiple works in the literature have explored this method to find a Pareto front for bi-objective integer programming problems (Sáez-Aguado and Trandafir 2018). Furthermore, the epsilon-constraint algorithm was successfully used for multi-objective algorithms with ALBP with ergonomics consideration (Weckenborg et al. 2022).

We design the ϵ-constraint algorithm to get efficient solutions with the two objectives, the total cost of equipment and the fatigue level. The principle is to set bounds on cost and ergonomics and solve the decision problem CALDP-F and the minimization problem CALDP-C, the following steps describe the algorithm:

- **Step 1**: Iteratively solve CALDP-F with a bound on the budget. The optimal level of ergonomics is obtained by an adapted version of the Iterative Dichotomic Search (IDS) algorithm (Abdous et al. 2023).
- **Step 2**: we fix the level of ergonomics obtained in **Step 1** as bound, and we optimize the cost by solving the CALDP-C. This step is performed with the ϵ-constraint algorithm and allows us to obtain an efficient point.

We used the pseudo-code in Algorithm 1 to describe the distinct steps of the algorithm.

First, we fix the maximum possible budget, corresponding to: $C^{max} = mMax_{i\in E}\{C_i\}$ (i.e., the most expensive equipment is assigned to all m workstations) and then the parametric bound take the value $\overline{C} = C^{max}$; the lower bound on the budget corresponding to: $C^{min} = mMin_{i\in E}\{C_i\}$ (i.e., the less expensive equipment is assigned to all m workstations).

We call the Iterative Dichotomic Search (IDS) algorithm to obtain the optimal fatigue level with a fixed bound on the budget $\overline{C}$. The Iterative Dichotomic Search algorithm was originally proposed in (Abdous et al. 2018a, 2023). IDS computes an initial upper bound on the fatigue level $\overline{F}$:

$$\overline{F} = Min_{j \in V} \left\{ Max_{i \in E} \left\{ 1 + (\mathrm{e}^{-I_{ij}} - 1)\mathrm{e}^{-R(T - t_{ij})} \right\} \right\} \tag{12}$$

Algorithm 1 ϵ-constraint algorithm

$S = \varnothing$; $i \longleftarrow 0$
Set $\overline{C} \longleftarrow C^{max}$
while $(C^{min} \leq \overline{C})$ **do**
  $\underline{F_i} \longleftarrow IDS(\overline{C})$ ▷ Call the IDS algorithm with $\overline{C}$
  Set $\underline{F} \longleftarrow \underline{F_i}$ in constraint (5d)
  $C_i \longleftarrow$ Solve CALDP-C
  $S \longleftarrow S \cup \{(\underline{F_i}, C_i)\}$
  Decrease the bound on the budget by 1 unit: $\overline{C} \longleftarrow C_i - 1$
  $i \longleftarrow i + 1$
end while
return S ▷ return the Pareto set S

The initial upper bound $\overline{F}$ represents the theoretical optimal level of ergonomics that we can obtain. The initial lower bound $\underline{F}$ could be obtained with a solution known beforehand or by solving the problem denoted $ALDP - 1$ without consideration of the fatigue level and defined with the constraints: $\{(6), (7), (8a), (8b), (8c), (9), (10), (11)\}$. IDS use a dichotomy to iteratively improves the value of the $\underline{F}$ to quickly reduce the search space while Cplex is used for solving the MILP decision problem CALDP-F in each iteration. Solving the CALDP-F brings two possible results, either we find a better solution to update the $\underline{F}$, otherwise, no possible feasible solution exists and we update the upper bound $\overline{F}$. The optimal fatigue level is found when the distance between the $\underline{F_i}$ and $\overline{F_i}$ in a given iteration i is less than a small fixed precision.

Second, to find the efficient point, we solve the CALDP-C with $\underline{F}$ representing the level of ergonomics, obtained from the output of the IDS algorithm.

The ϵ-constraint stopping condition is defined with $\overline{C} \leq C^{min}$ when the parametric bound on the budget is below the minimum possible cost.

4.2. *Example of using the epsilon-constraint algorithm*

We provide an example using the epsilon-constraint algorithm. In Figure 2, we present the initial search space, the fatigue level to maximize is represented in percentage (%) on the x-axis. The cost function is to be minimized on the y-axis, the cost is assumed in this example to be between 0 and 100 cost units (i.e., k€). We represent the maximum possible budget: C^{max} (respectively minimum C^{min}), with $\overline{C} = C^{max}$. The initial upper and lower bound on the ergonomics are represented respectively with $\overline{F_0}$ and $\underline{F_0}$. The resulting initial search space is represented by the hashed area.

Firstly, the IDS divides the initial space and sets a target F^{target} and tries to find a solution on the right side of the search area to improve the initial lower bound by solving the CALDP-F. If a solution exists, the algorithm updates the initial search area and repeats the same procedure with the new search space. Otherwise, if no solution is found, we update the upper bound $\overline{F_0}$ with the value of the F^{target} to reduce the search area.

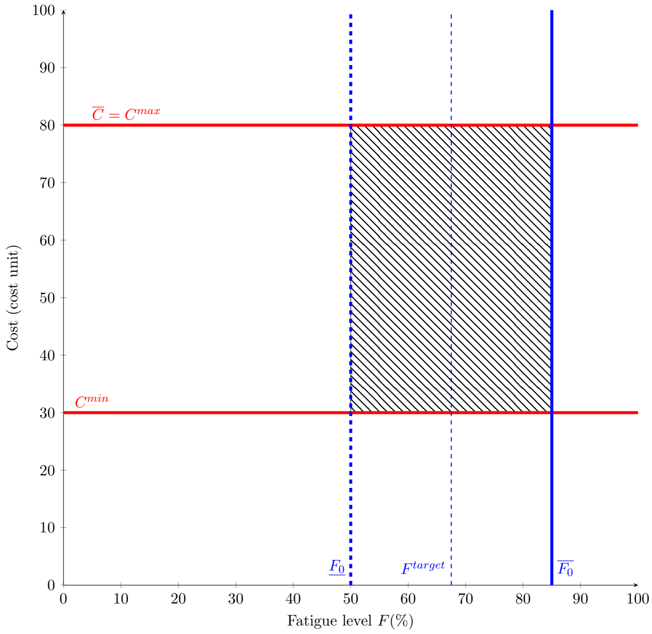

Figure 2.: Example of the first search space

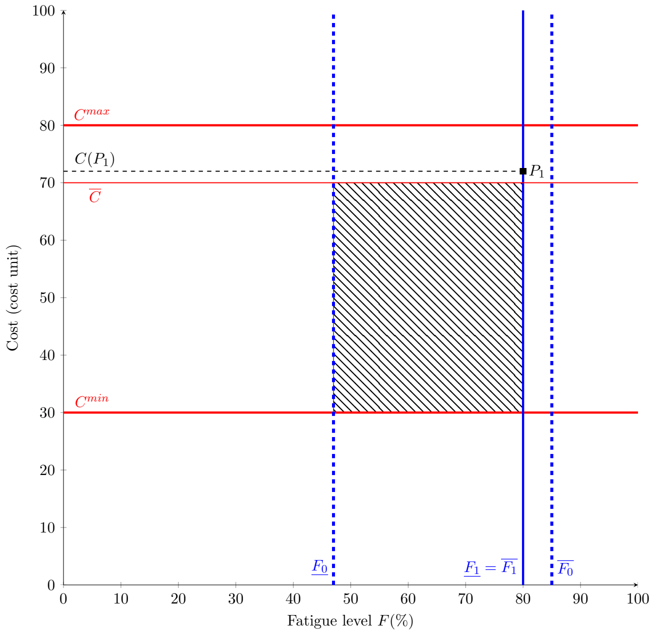

Figure 3.: Example of the second search space

Secondly, we present the evolution of the search space in Figure 3. From the first step, the IDS algorithm provides the optimal fatigue level (80% in this example). Then, we solve the CALDP-C with the optimal level of the ergonomics to obtain $C(P_1)$ that represents the optimal cost, and hence the first efficient point P_1 is obtained. Since P_1 is an efficient point, we update the $\overline{F_1}$ to exclude the dominated space.

Then, the ϵ-constraint updates the bound on the cost, $\overline{C} = C(P_1) - 1$ and we solve the ALDP-1 to update the search space $(\underline{F_0}, \overline{F_1}, \overline{C}, C^{min})$ as represented with the hashed area in Figure 3.

The same procedure described above is repeated, with the call of the IDS on the new search area. The ϵ-constraint stopping condition is defined with $\overline{C} \leq C^{min}$ when the parametric bound on the budget is below the minimum possible cost.

5. Numerical experiments

We implemented the IDS algorithm and the ϵ-constraint in C++. We used Cplex V12.6 as a MILP solver with default parameters. We use in our experiments a single node of a cluster with 4 CPUs: Intel(R) Xeon(R) CPU E5-2660, 2.60GHz, and 65 Gbit of RAM. For the IDS algorithm, we fix a precision of 10^{-5}. We fix a time limit to keep the algorithm's running time compatible with the practical industrial application. The time limit is 3600s for each call of the solver for ALDP-1, CALDP-F, and CALDP-C.

In the next Subsection, we present the instances that are used as a benchmark for the numerical experiments, and in Subsection 5.2 we discuss the results.

5.1. *Benchmark*

Instances from the literature do not present all the data necessary for numerical experimentation. Hence, we generate a dataset to validate the approach experimentally. The starting benchmark is ALBP instances composed of instances from two separate benchmarks, the first is the widely used dataset of Scholl (Scholl 1993) and the second benchmark is the Otto dataset (Otto et al. 2013).

We selected 21 instances from the Scholl dataset, with a number of tasks ranging from 7 to 148. From the Otto dataset, we selected 6 instances with 20 operations and 4 instances with 50 operations. For each instance, we selected from the corresponding benchmark the minimum number of workstations m for each instance, and the corresponding optimal takt time T.

For each instance from the 31 starting instances, we generated the missing information according to the following procedure:

- We generate a static operation load (i.e., $\int_t^{t+t_{ij}} Fload_{ij}(u)du = Fload_{ij}.t_{ij}$, cf. Equation (2)) corresponding to basic manual equipment. The operation load $Fload_{ij}$ is expressed in percentage, following a statistical beta distribution between [2%,60%] with statistical parameters specified by making values between 2% and 30% more likely and values further from 30% less likely. The beta law seems to represent the distribution of load in manual lines as it was observed in real data from industrial lines (Finco et al. 2020; Abdous et al. 2018). Operation physical load is expressed in percentage.
- Then, we generate more sophisticated equipment that impacts a subset of operations by reducing the processing time and/or the load of operations. Sophisticated equipment could impact up to 60% of operations of an instance. For each operation of the subset impacted by the sophisticated equipment, the reduction of processing time is defined according to a uniform distribution law in the range [1%, 30%] (i.e., the reduction of the processing time could be up to 30% of the processing time of the basic equipment). Similarly, for each operation of the subset, the reduction of the load is defined according to a uniform distribution law in the range [1%, 50%].
- We generate a cost C_0 for the basic manual or non-collaborative equipment, then we generate the cost of sophisticated equipment that evolves exponentially and could be up to $10C_0$ (i.e., 10 times the cost of basic equipment (Gorlach and Wessel 2008)). Equipment is expensive depending on the proportion of operations that it influences and the magnitude of reduction of the physical load and/or the processing time. Equipment are collaborative if the costs are superior to $2C_0$. Manual tools could be economically justifiable, but expose

the workers to heavy load and low fatigue levels while more advanced equipment reduces the load and time execution (Krüger et al. 2009). However, advanced equipment raises the cost over-proportionally and causes the cost to increase exponentially (Gorlach and Wessel 2008).

For each of the 31 instances from the benchmark, we generate 9 instances with 2 to 10 equipment following the procedure described above. A total of 279 instances are tested in our numerical experiment.

5.2. *Results analysis*

The ϵ-constraint algorithm is described in the ideal situation when we obtain the Pareto front. However, in cases when we exceed the time limit, we update the search space with the best-known values and we compute the gap to assess the quality of the approximation. The gap is computed with the hypervolume metric (Zitzler and Thiele 1999) of the remaining search space that we have not entirely covered with the algorithm.

We conducted the experiment on the 279 instances, and we present in Table 1 averages statistics, e.g., in the second line (Mertens): n represents the number of operations, the remaining values represent the average results of the 9 Mertens instances with 2 to 10 equipment; The average total time in second (Avg tot time [s]) to obtain the set of solutions; The average number of solutions (Avg nb sol) in the set of solutions; The average gap in % (Avg gap (%)); The last column presents the average % of efficient solutions in a set of solution.

The results can be divided into 3 categories, according to the average gap (%). The first category of instances that are solved optimally. The second category of instances where the average gap is less than or equal to 10%, and the third category of instances with an average gap higher than 10%. Instances in Table 1 are ordered according to the increasing value of the average gap (%).

5.2.1. Optimally solved instances

We succeed to solve all instances with less than 25 operations and up to 10 equipment (47% of the benchmark). The average number of points in the set of Pareto front is 6.5 points with an average computation time to obtain the whole front of 583s. The average computation time to obtain each efficient point is 78s.

We represent in Figure 4 the Pareto front for the instance Otto n=20_9 with 20 operations and 8 possible equipment. The Pareto front presents 9 efficient points and the average time to obtain an efficient point is 17s.

We present in Table 2, depending on the number of equipment, the average total time to obtain the Pareto front (Avg tot time [s]), and the average number of solutions on the front (Avg nb sol). The increase in the number of equipment seems to have a limited effect on the complexity of the problem and the number of efficient points beyond 3 equipment. The number of operations is the characteristic that makes an instance more challenging.

Table 1.: Numerical results of the ϵ-constraint algorithm

Instance	n	Avg Tot time [s]	Avg nb sol	Avg gap (%)	Avg Opti pt (%)
Instances solved optimally					
Mertens	7	18.03	4.44	0	100
Bowman	8	0.47	2.89	0	100
Jaeschke	9	9.29	2.89	0	100
Jackson	11	24.90	5.11	0	100
Mansoor	11	37.25	4.78	0	100
Otto n=20_9	20	1460.67	7.56	0	100
Otto n=20_10	20	1657.00	8.33	0	100
Otto n=20_372	20	713.80	8.22	0	100
Otto n=20_385	20	316.47	8.22	0	100
Otto n=20_47	20	1130.68	10.56	0	100
Otto n=20_417	20	1304.44	10.78	0	100
Mitchell	21	41.65	6.78	0	100
Roszieg	25	161.76	7.67	0	100
Instances with Avg gap (%) $\leq$ 10%					
Gunther	35	2306.40	6.44	0.03	96.55
Buxey	29	2531.08	6.44	0.03	96.55
Sawyer	30	2805.34	7.11	0.05	81.25
Arcus1	83	4381.22	2.22	2.43	0
Wee-Mag	58	2669.98	1.89	3.66	5.88
Heskiaoff	28	6470.88	6.89	3.81	50.94
Kilbridge	45	3823.85	5.67	9.72	47.06
Lutz1	32	3095.84	4.00	9.92	63.89
Instances with Avg gap (%) > 10%					
Hahn	53	2131.70	4.22	11.36	76.32
Otto n=50_85p5	50	1304.91	2.44	19.68	0
Lutz3	89	1392.26	2.00	36.29	22.22
Otto n=50_51	50	771.06	1.56	37.40	0
Arcus2	111	12107.50	3.11	39.45	0
Otto n=50_6	50	1162.10	2.22	59.72	0
Otto n=50_7	50	1627.46	2.67	68.94	0
Tonge	70	451.75	1.11	70.13	0
Mukherje	94	1036.85	1.67	81.23	0
Barthold	148	727.76	1.44	94.65	0

Table 2.: Results of instances solved optimally according to the number of equipment

Equipement	Avg tot time [s]	Avg nb sol	Avg % sol in the convex hull
2	198.15	3.32	95.13
3	229.25	3.88	91.24
4	696.19	6.12	71.78
5	725.81	7.93	65.99
6	333.32	8.18	65.19
7	564.10	6.71	61.05
8	956.48	8.71	59.19
9	1016.06	8.71	62.65
10	654.77	7.42	66.01

We compute in the last column the average percentage of solutions in the convex hull (Avg % sol in the convex hull), the overall average percentage of solutions in the convex hull is 70.91%. A large proportion of solutions are in the convex hull and thus not dominated by any convex combinations of solutions. Points on the convex hull are more difficult to obtain since they are not optimal solutions to a weighted sum problem.

Note that, instances from the Otto dataset present more solutions and seem to be more challenging than instances from the Scholl dataset. This conclusion is consistent with the results

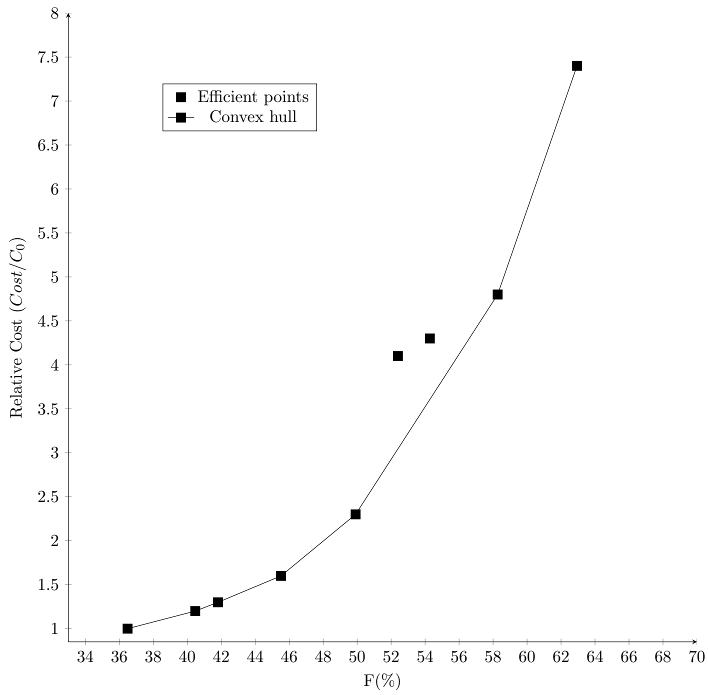

Figure 4.: Pareto front, Otto n=20_9 with 8 possible equipment

from the literature for the Simple Assembly Line Balancing Problem (SALBP) (Otto et al. 2013).

5.2.2. Instances with an approximation of the Pareto Front

The second category of instances has an average gap in percentage inferior or equal to 10%. This category represents 22.5% of the benchmark. It took on average 4350s to obtain the set of solutions. On average, we get 5.17 points in the set of solutions with 55.3% which are proven as efficient. In Arcus1, the average gap is equal to 2.43% with 0% of efficient solutions, which means that we are close to the efficient points, but we fail to find any.

The third category of instances represents 30.5% of the benchmark and has an average gap in percentage more significant than 10%. The average gap in this category is 56.6% with an average total computation time of 1982s, which is less than instances of the second category. The time limit is fixed for an iteration of the solver, instances of this category exit the procedure after fewer iterations which explains this relatively low average total computing time but exit with a larger remaining search space which justifies the higher average gap (%). The average point in the set of solutions is 2.11; we only found an average of 9.85% of efficient solutions, which is less than the average of the other categories. This is due to the behavior of the ϵ-constraint with some challenging instances: a first feasible solution is obtained, then in the solving of $CALDP - C$, proved to be feasible also with the lowest possible budget, we then stop the algorithm with only one point in the set of solutions.

Similarly to instances solved optimally, the number of equipment seems to have less effect on the computation time compared to the number of operations. Only small differences could be observed in the results when the number of equipment increased. The operation number n seems to have more influence over the performance of the solving approach.

To understand how the time limit influences the results, we considered the 9 Kilbridge instances from the second category and the 9 Lutz3 instances from the third category with 7200s as a time limit for each call of the solver. We choose these two instances since they are only partially solved with a time limit of 3600s. We can observe that for Kilbridge instances, the average gap decreases to 8.92% (a 0.8 percentage points improvement), with 52.30% of optimal points in the Pareto fronts (a 5.24 percentage points improvement). For Lutz3, the average gap decreases to 35.79% (only a 0.5 percentage points improvement) and the average percentage of optimal points in the Pareto fronts remains constant at 22.22%. Hence, doubling the computational time limit slightly increases the quality of the results but generating the whole Pareto front is still out of reach.

To sum up, we succeed to provide the Pareto front for all instances with less than 25 operations and up to 10 equipment, for instances from the second category; we provide a good approximation with a large proportion of solutions proven efficient. However, with n larger than 45, the approach does not guarantee a good approximation of the Pareto front, and the performance varies according to the instance.

6. Managerial insights

Decision-makers should evaluate the advantages of new Industry 4.0/5.0 technologies implementation with the consideration of their specific effect on ergonomics and the associated investment costs, a target fatigue level comes with economic investments, largely associated with equipment costs. The modeling and numerical results of this paper aim to support decision-makers in the design stage of assembly lines to choose the best possible alternative from a set of solutions.

An investment in equipment leads to an improvement in fatigue level, we refer to Figure 5 to illustrate this point. The example proposed several trade-offs, which are associated with different levels of fatigue and different economic costs. The example of Figure 5 represents the Pareto front with 3 workstations, we present in Table 3 the cost of equipment, the variation rate of cost, and fatigue level for each point in the Pareto front with P_1 as reference. Recall that C_0 to C_2 represent the costs of non-collaborative equipment, and the costs C_3 to C_7 are the costs of collaborative equipment, that could impact positively productivity and ergonomics, but are more expensive than non-collaborative equipment.

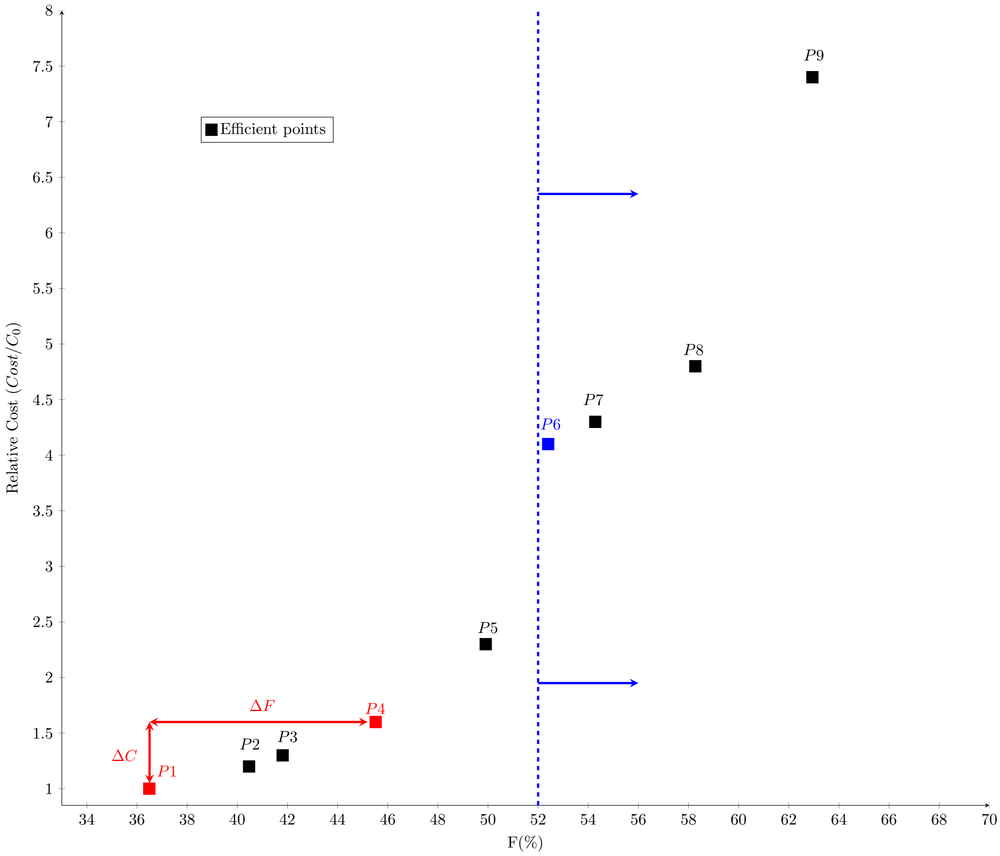

Figure 5.: Pareto font illustrating the variation rate between cost and fatigue level (Otto n=20_9 with 8 possible equipment and 3 workstations)

Table 3.: Cost of equipment assigned to workstations and variation rate of cost and fatigue level with P_1 as a reference; collaborative equipment are specified in bold (Otto n=20_9 with 8 possible equipment and 3 workstations)

	Cost of Equipment	$\frac{\Delta C}{C(P_i)}$	$\frac{\Delta F}{F(P_i)}$
P1	C_0-C_0-C_0	–	–
P2	C_1-C_0-C_0	18.9%	9.8%
P3	C_2-C_0-C_0	24.2%	12.7%
P4	C_1-C_2-C_0	35.6%	19.8%
P5	C_1-**C4**-**C3**	56.3%	26.9%
P6	C_1-C_0-**C7**	75.6%	30.4%
P7	C_1-C_1-**C7**	76.9%	32.8%
P8	**C4**-C_1-**C7**	79.0%	37.4%
P9	**C7**-**C4**-**C7**	86.5%	42.0%

In Figure 5, we observe a high level of elasticity of fatigue level at a relatively low levels of cost (e.g., between P_1 and P_2 and between P_1 and P_4). In the first solutions (e.g., P_1, P_2 and P_3), a non-collaborative equipment is added in a targeted way to workstations at risk (i.e., C_1 in solution P_2 and C_2 in solution P_3). On the other side of the curve (e.g., between P_5 and P_9), more expensive and collaborative equipment (e.g., C_4 and C_7 for solution P_9) are used which leads to high levels of relative costs, but the relative gains in terms of ergonomics are also significant. The decision-maker has thus a large range of trade-offs to consider.

The choice of the ideal configuration in terms of collaborative or non-collaborative equipment assigned to each workstation depends on the strategic choices and the available budget. For decision-makers, and depending on their operational constraints such as available budget or risk analysis, they could benefit from the approach of this paper to choose the appropriate solution from the Pareto front. For example, with a managerial target of a fatigue level higher than 52%, illustrated with the dashed line in Figure 5, the suitable solution is P_6 since it's the solution that respects the constraint on the ergonomics and presents the minimal costs.

For example, comparing the case of a manual non-collaborative equipment (P_1) and the mixture of non-collaborative equipment and collaborative equipment (e.g., P_6), an additional cost of 75% leads to a 30% of improvement in the fatigue level. This clearly shows that investment could lead to a significant improvement of ergonomics and that a mixture of non-collaborative equipment and collaborative equipment is a relevant managerial choice, which allows a significant gain in terms of ergonomics but implies investing in appropriate equipment. We observe that starting from P_5, the use of collaborative equipment increases the cost significantly. The extensive use of collaborative equipment significantly improves ergonomics with a 42% variation rate between P_1 and P_9 (only P_9 uses the collaborative equipment in all workstations). The investment required to achieve this gain is up to 86% higher than a production line fully equipped with the least expensive non-collaborative equipment.

Even if the investment costs seem important, we can compare them with the cost that could be induced by some post-design changes in the assembly line to reduce MSDs. We present in Figure 6 the design stage alternatives and post-design alternatives solutions. The post-design points correspond to the assignment of tasks of P_1 since this solution is the solution that would have been chosen without equipment alternatives. We varied the equipment in each workstation as a manager would do on an existing line to improve ergonomics. Overall, we can observe the impossibility to achieve the fatigue level of the best solutions obtained in the design phase: five points in the design phase are better than any solutions in the post-design phase, and the difference between the best solution in the design stage and the one in the post-design is 13.19 percentage points. In addition, a post-design investment will always be expensive without reaching an optimal level of ergonomics. If we set a threshold on the level of fatigue at 40%, we observe that the cost is twice more. Similarly, if we set a threshold on the level of fatigue at 49%, the cost is 3 times more. Hence, the post-design investment could cost up to 3 times the cost in the design stage. This comparison clearly shows that the investment in the design stage is the best option and that post-design investment is expensive and does not achieve optimal fatigue levels.

More generally, the number of efficient solutions in the Pareto front remains low, which is practical for decision-makers and managers to study and compare each alternative before choosing and implementing a specific solution. For example, an investment in collaborative equipment could be used in a targeted way which will improve the ergonomics of the line and help reach the target level of ergonomics while respecting the constraints on the budget.

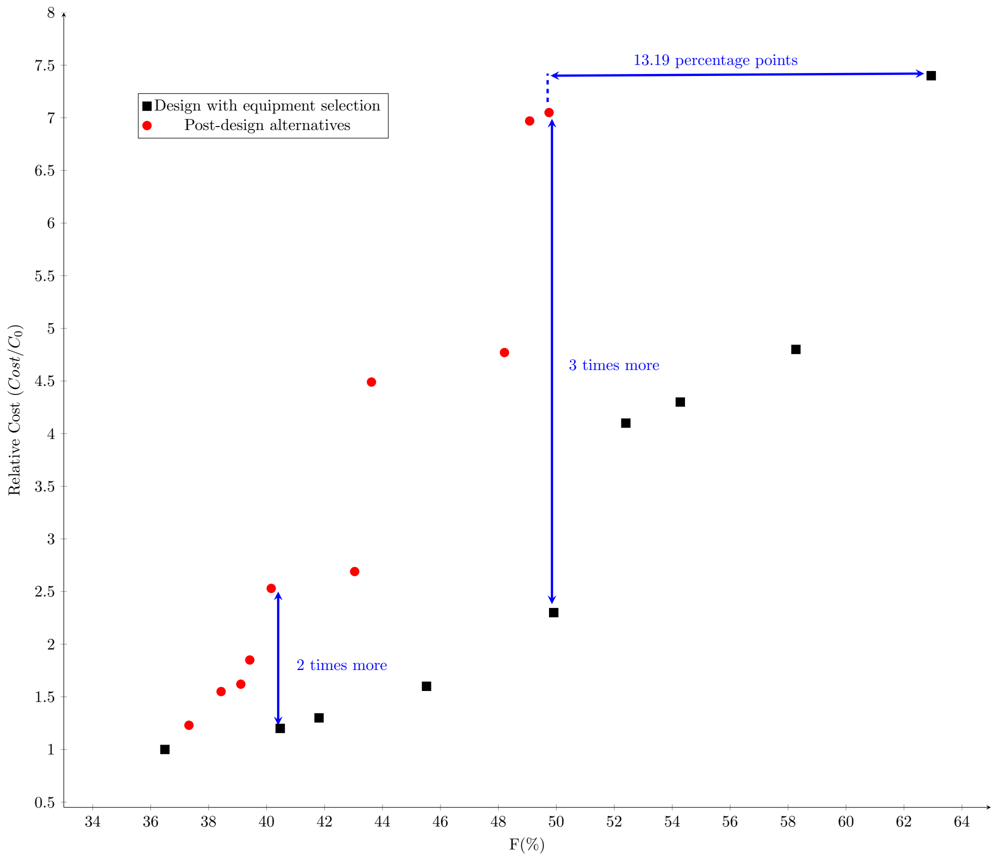

Figure 6.: Comparison of solutions in design stage with post-design solutions (Otto n=20_9 with 8 possible equipment)

7. Conclusion and future works

The paper presents a multi-objective approach for the early design phase of collaborative assembly lines, with consideration of ergonomics and investment costs, where decision-makers may have different choices between these objectives. Therefore, we propose a new MILP formulation for the multi-objective problem and a solving approach with an ϵ-constraint algorithm that we test on different instances from the literature. In our approach, collaborative advanced equipment such as cobots, exoskeletons, mobile robots, and other advanced Industry 4.0/5.0 technologies collaborate with human workers in the same workplaces. In such an environment, the consideration of ergonomics as a performance lever is important. In addition, we also optimize an economics criterion with equipment costs.

This work is among the first contributions to developing a modeling and solving approach for the collaborative assembly line balancing and equipment selection problems with the joint consideration of cost and ergonomics. We obtain interesting results with instances of small and medium sizes. The problem is NP-hard, large size instances of the problem are challenging with an optimal solving method. A perspective to this work to solve challenging instances is the development of a multi-objective metaheuristic, with the use of the algorithm proposed in this approach to provide information about the bounds and the gap. Another interesting perspective could be the comparison of the solving approach with the generic bi-objective Branch-and-Bound algorithm for assembly line problems introduced in Cerqueus and Delorme (2019).

The proposed approach could be adapted to another optimization problem, which is the assembly line balancing problem with the assignment of workers considering workers' characteristics, this problem is usually tactical or operational. This perspective would be interesting in the case where we seek to improve the ergonomics for a specific group of workers, such as aging workers. Another perspective of this work could be the variation of the number of workstations and workers in each workstation, the cost function could include both the cost of workstations and the cost of workers.

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