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Ergonomic design of Human-Robot collaborative workstation in the Era of Industry 5.0

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ABSTRACT

The increasing adoption of collaborative robots to support job execution in manufacturing has catalyzed companies' attention to safety and well-being issues. Sharing the human-centric perspective and harmonious human–machine collaboration concepts emphasized by Industry 5.0, the design phase of a collaborative workstation must integrate both psychological and physical risk evaluations to provide a safe and inclusive work environment suitable for a diversified workforce. Accelerating the pre-deployment phase to quickly reconfigure workstation design and assess its impact on workload balancing and task sequencing during the deployment of assembly lines still represents a challenging task considering the available software tools. This research proposes a new mathematical model to accelerate the design of ergonomic human-robot collaborative workstations based on task alternatives and the combined consideration of postural assessment and fatigue analyses for each of them to design an ergo-friendly collaborative environment. Surface electromyography analysis is jointly adopted with postural risk assessment measured with inertial measurement units and developed by a digital ergonomic platform to determine the optimal workplace configuration for tools, equipment, and resources to promote physical well-being while considering station productivity. Experimental tests are performed to investigate arm muscles and postural risk assessment for different configurations of workstation design and collaborative human-robot job progression. Experimental results demonstrate the feasibility, and the advantages of the proposed approach compared to existing simulation software to quickly generate and assess alternative scenarios and find a trade-off between ergo-quality levels and system performance. The final discussion offers valuable information for decision-makers and practitioners to facilitate the integration of human factors throughout the early stages of ergo-friendly workspace design, while effectively managing the complexity generated by resource allocation and collaborative robots.

1. Introduction

Manufacturing systems are transitioning to more flexible and sustainable workspaces where technology can help workers progress their jobs safely and more efficiently (European Commission 2021, 2022). Close collaboration between workers and machines represents the opportunity to improve workplace resilience, enabling the development of human-orientated working environments, especially where operators' competencies are difficult to completely replace (Battaïa et al., 2018). Industry 4.0 initially promoted the development of collaborative workstations, characterized by the coexistence of operators and machines (Frank et al., 2019). However, research on workplace design has been massively constrained by strong barriers to practical implementation, due to safety issues related to the proximity of collaborative robots (or "cobots") to workers (Gualtieri et al., 2021). Consequently, research interest in developing new methods to enhance the reliability of automated machines involved in collaborative activities has grown, to test the safe adoption of collaborative robots, and to demonstrate the benefits they can provide to workforce safety and well-being (Keshvarparast et al., 2023a). Aiming to settle the trust between humans and machines, Industry 5.0 shifted research and innovation to a sustainable, human-centric, and resilient paradigm (Neumann et al.,

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2021; Xu et al., 2021). Therefore, researchers and practitioners reconsidered the central role of the design of the human operator in collaborative workplaces, with the aim of including human factors (HFs) and socio-technical aspects related to workforce diversity (Battini et al., 2022a; Lu et al., 2022).

Correct integration of HFs in the initial design process has important consequences in successive stages of assembly line deployment (Battini et al., 2011). The definition of the workplace design phase can become costly and time-consuming due to the continuous feedback loop within the design process before final implementation. Human Digital Models (HDM) are often adopted to simulate the performance of manufacturing systems considering HFs to forecast real efficiency (Wolf et al., 2020); however, anytime small adjustments are needed after the workplace design phase is completed, a new round of simulation is required to determine the implications of the implemented changes in the real layout application (Azzi et al., 2012). Therefore, the design process of collaborative assembly lines with multiple workstations and different resources can follow a recursive path, like the workflow described in the framework proposed by Michalos et al. (2018) on collaborative assembly workstations. This approach can eventually get stuck within iterations of the long-term design process, from strategic to operational decisions related to task scheduling and sequencing (Fig. 1).

Consequently, the assembly line design process might take a long time to complete, as well as huge amounts of resources for the continuous adjustments between consecutive decision steps. Therefore, it became extremely important to reduce the time of the pre-deployment phase to pay more attention to operative decisions such as line balancing, task sequencing or scheduling, during daily work activities.

Collaborative workplace design currently represents a time-consuming work activity due to the multiple iterations required to find the optimal ergonomic and human-friendly design solution, each time small changes are made in the workstation or workplace design. Software available for the development of Human Digital Models can partially address the high degree of complexity behind the vast possibilities of differently placing resources, elements, and objects within the workspace. The amount of time required to design alternative workspaces, and the computational effort needed to evaluate them are still improvable and open to more efficient solutions. Furthermore, the literature research proposed in this article highlighted only few previous works on ergonomic workplace design that quantitatively determine and integrate into a mathematical approach both occupational risk and the associated fatigue developed during work execution.

Aiming to challenge the time-consuming design approaches with conventional HDM software and to integrate both postural and fatigue assessments, this paper proposes a mathematical model to efficiently perform the ergonomic design of a human-robot collaborative workstation during the pre-deployment phase. The main goal of this work is to jointly reduce design process time and support the creation of resilient and flexible collaborative workplaces. One of the main novelties of the presented model concerns the integration of both safety and productivity aspects into a unique formulation to cover the gap in human-oriented workstation design. To validate the model, an experimental laboratory test of human-robot collaboration (HRC) has been set up and the execution of assembly tasks performed jointly by humans and cobots has been investigated. Occupational risk assessment during test progression was evaluated with widely recognized postural assessment methods coupled with muscular fatigue detection determined by surface electromyography sensors (s-EMG).

The remainder of this paper is organized as follows. Section 2 provides a theoretical background on previous collaborative workstation design approaches, focusing on the methods adopted to integrate human factors and ergonomic principles in HRC workstation design. Section 3 presents the definition of the problem while Section 4 describes the proposed mathematical model. Section 5 outlines the description of the experimental tests performed. Finally, Section 6 comments on the results obtained, and Section 7 discusses the importance of the ergo-friendly design process and concludes this work by pointing out current limitations and future research agenda.

2. Related works

Collaboration between humans and robots represents one of the most investigated research topics of recent years, exploiting the flexibility of machines to allow workers to maintain their performance level for longer. The issue of safety in the design phase, however, is still much debated to find a compromise between the performance required by the company and the well-being of the operator. In this section, we will discuss these topics focusing on collaborative workstation design.

2.1. *Collaborative workplace design for manufacturing systems*

The integration of new industrial resources that interact with humans, designed to help workers in task progression, has generated new challenges for the industrial designers of collaborative workstations (Keshvarparast et al., 2023b). Cobots are entities with embedded sensors that capture robots and environment working conditions enabling precise movements to avoid the entities surrounding the robot (Liu et al., 2024).

Industry 4.0 promoted the adoption of robots able to work close to workers, exploiting robot features, and helping repetitive and strenuous task progression; however, huge limitations on the safety and wellness of the workforce were initially raised toward the proximity of the two resources (Gualtieri et al., 2021). The adoption of international standards in HRC allows companies to rely on a safe workstation design process toward a more interactive working context to express cobots' full potential and the ability to work near human operators. The adoption of international standards, such as ISO 10218–1 and ISO 10218–2, provides coverage of safety prescriptions for industrial robot systems and workplaces discussing the safety requirements. Furthermore, ISO/TS 15066:2016 supplements the requirements for collaborative robot system applications of prior international standards, providing additional safety requisites for workspace design and collaboration in proximity to the cobot.

Nevertheless, the list of risk factors to be considered in human-robot collaboration cannot be limited only to physical safety. Psychosocial, environmental, ethical and cyber risk are equally valuable factors

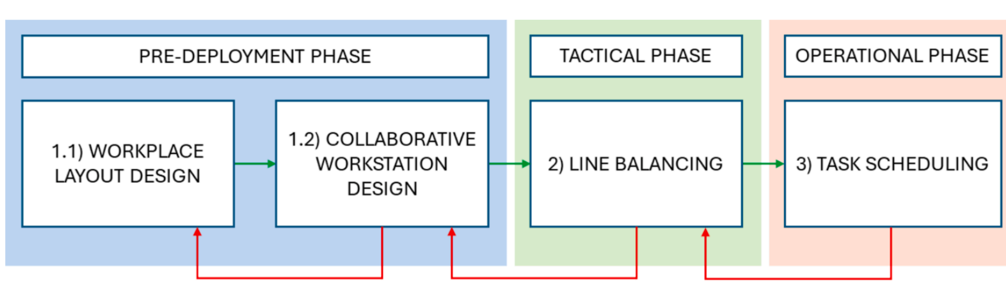

Fig. 1. Recursive loop of collaborative assembly line for strategic, tactical, and operational decisions.

although they are still less investigated during the design phase of collaborative workplaces; however, they can potentially produce safety-related risks for the operator (Berx et al., 2022).

Aiming to show perfect compliance with regulations and safety standards, ergonomic assessment of workstations is often validated with methodological frameworks through the adoption of a Digital Human Model (DHM) (Chang & Wang, 2007), such as Dassault Systems safe work model, including in Catia and Delmia software (Delmia, Ergonomics), and Jack model available on Siemens/Tecnomatix products (Jack, Siemens) to integrate ergonomic evaluation in industrial setting (Peruzzini et al., 2020). Andronas et al. (2023) provided a recent example of the adoption of DHM in the design of collaborative setups that exploited the ErgoToolkit, an ergonomics evaluation software extension of DELMIA, to assess worker's postures to quantify risk and discomfort to plan collaborative robot movements of the collaborative robots accordingly and validate them in a simulation environment. Likewise, Ulutas and Yetkin (2024) adopted Jack Siemens to investigate and compare the physical workload of different collaborative design scenarios for gear pump assembly workstations.

The adoption of simulations to evaluate alternative scenarios provides an immediate graphical overview of the design of the workstation and the related risk assessment; however, such solutions demonstrate a low degree of flexibility in designing adjustments. They are extremely time-consuming, since, for every little variation, new simulations are required to assess workplace risk. Recent solutions to cope with the expensive design process include the adoption of virtual reality (VR) and augmented reality (AR) that can help experts and workers progress through the design phase iteratively in a virtual environment (Chu et al., 2025); however, the technological setup still needs to be virtually created, as well as the software libraries containing all the items and resources.

Further complexity arises when the analysis evolves from the collaborative workstation design process toward the assembly line design. Different layouts, resources, and items can be allocated in several workstations with diverse shapes and layouts (e.g., straight lines or U-shaped human-robot collaborative systems), creating a variety of solutions companies must consider (Nourmohammadi et al., 2024).

To demonstrate the novelty that this research brings to the existing literature, we conducted literature research on the Scopus database using the following set of keywords. TITLE-ABS-KEY ("Workstation design" OR "Workplace design" OR "Human-centred design" AND "Collaborative robot" OR "Human-robot collaboration"), limiting the research until August 2024. We carefully reviewed 68 documents to find the suitability for this work.

The selection of works was carried out excluding off-topics, research focusing on dynamic task allocation, and pure theoretical studies on the workplace, workspace layout, and system design without any real application (i.e., case study or laboratory test). Similar works were found in research performing analysis on alternative workstation design and multi-criteria decision-making systems, considering several design variables such as the industrial robot variant, industrial robot position, industrial robot gripper design, material position, workstation equipment position, and anthropometric database (Ore et al., 2017, Tsarouchi et al., 2017). As a result of this review, Table 1 reports relevant work on collaborative workstation design in manufacturing applications.

As reported in Table 1, most of the previous literature developed methodological frameworks to integrate human factors and ergonomics within the HRC workstation design process; however, few of them quantitatively jointly determine occupational risk and the associated fatigue developed during work execution. The adoption of software for this purpose is still preferred to the development of mathematical approaches (Ore et al., 2017, Tsarouchi et al., 2017). Tsarouchi et al. (2017) progressed an alternative workplace layout where the parameters related to both active resources (e.g., robots and humans) and passive resources (e.g., working tables) were reported in a 3D simulation environment in existing Tecnomatix libraries. Therefore, the alternatives generated with the simulation tool were selected, visualized and evaluated to determine the most suitable criteria for the design of an HR work cell; however, the displacement of tools belonging to the workbench was neglected, since each passive resource was already considered with its attached tools (e.g., grippers, screwdrivers), without questioning their alternative displacement on the workbench. Ore et al. (2017) propose a framework for the design of collaborative workstations before making investment decisions. They adopted an HRC simulation software to test the combination of six workstation variables that generate 512 scenarios (i.e., different HRC workstation designs) to be evaluated with the RULA risk index. The results of this research emphasize the impact that many variables can have on the computational time required to find optimal solutions. The authors demonstrate that the greater the number of admissible values for each variable, the

Table 1
Comparison of collaborative workplace design methods and human factors integration.

Source	Research objective	Safety features	Cycle time analysis	Methodology	Application
Ore et al., 2017	Optimization method and HRC simulation demonstrator software	Posture (RULA)	MTM (Methods-Time Measurement)	Software	Industrial case study
Tsarouchi et al., 2017	A multi-criteria decision-making framework to compute alternative layouts and task allocations.	Average human muscle strain (AMS) percentage	Real data from the case study	Software (Tecnomatix Siemens)	Industrial case study
Mateus et al., 2019	A method to determine the complexity of tasks in HRC design	Posture (RULA)	MOST (Maynard operation sequence technique)	Theoretical framework	Test case application
Gualtieri et al., 2020	Case study on collaborative workstation re-design (16 alternative scenarios)	Posture (RULA, OCRA checklist); Force (NIOSH LI)	Censored data from the case study – Average task time	Theoretical framework	Industrial case study
Ore et al., 2020	Decision-making method for HRC workstation design process	Posture (RULA)	MTM	Theoretical framework	Industrial case study
Andronas et al., 2023	Human-robot collaborative design for high-payload industrial robot arms	Posture, force (AAWS method)	Real data from the case study	Software (ErgoToolkit DELMIA)	Industrial case study
Cella et al., 2023	Collaborative cell layout for a static production environment	Posture (RULA)	–	Theoretical framework	Simulation
Ulutas & Yetkin, 2024	Human-centred workplace design with simulation software	Posture (RULA), Load (NIOSH)	–	Software (Tecnomatix Siemens)	Simulation
Chu et al., 2025	Prototype to iteratively adjust the workstation setup design	Posture (RULA)	–	VR and AR adoption	Usability study
This paper	Optimization of resource allocation and equipment position in HRC workstation design	Posture (REBA), fatigue (s-EMG sensors)	MOST	Mathematical model	Experimental test cases in the laboratory

greater the chance of finding an optimal result; however, the process requires longer simulation times (Ore et al., 2017).

Therefore, one of the main problems still lies in the exponential computational time related to the huge amount of data generated during the development and assessment of feasible scenarios. The complexity of combinatorial problems related to resource allocation and all possible permutations of materials, items, equipment, collaborative robots, and tools has been largely recognized in workstation design as one of the main issues (Fechter et al., 2018). Therefore, hybrid solutions or heuristic algorithms are often adopted instead of proprietary simulation solutions, such as CAD, CAM, and CAE software, to reduce computational complexity.

2.2. Integration of human factors in collaborative workplace design

The impact of HFs on the design phase of manufacturing operations and industrial system performance has been widely addressed in the literature (Battini et al. 2011, Kolus et al., 2018, Sgarbossa et al., 2020, Neumann et al., 2021, Battini et al., 2022b). Integration of worker postures and muscular fatigue analyses can provide valuable information for the ergonomic design of workstations, as well as increase the sustainability of manufacturing companies (Realyvásquez Vargas et al., 2021). The postural analysis and the consequent quantification of the risk exposure for hazardous postural behavior during work activity can be determined with a set of ergonomic assessment methods. Among the widely spread ergonomic indexes adopted for this purpose, are the NIOSH lifting equation (Dempsey, 2002), the Ovako Working Posture Assessment System (OWAS, Karhu et al., 1977), the Occupational Risk Assessment OCRA (Occhipinti, 1998), the Rapid Upper Limb Assessment (RULA, McAtamney & Corlett, 1993) and the Rapid Entire Body Assessment (REBA, Hignett & McAtamney, 2000). These latest indexes are mentioned in the International Standard (ISO 11228) as rapid methods for fast ergonomic analysis.

On the other hand, muscular fatigue analysis aims to quantify the impact of dynamic physical workload on operators during continuous manual labor (De Luca, 1984). Researchers have contributed significantly to the development of biomechanical models to estimate fatigue accumulation over time. The learning-forgetting fatigue-recovery (LFFR) model proposed by Jaber et al. (2013) estimates fatigue and recovery trends by an exponential curve, where fatigue and recovery are static and predetermined to match the work preference of an operator. Objective evaluation measures the physical attributes to evaluate fatigue over consistent muscle force exertion through continuous monitoring of physiological indicators (e.g. heart rate, breathing rate, skin temperature) to observe the decline of physical state as inferred from fatigue (Mehta and Agnew, 2012).

Nevertheless, monitoring physiological indicators poses limitations, including requiring operator-specific analyses of the fatigued and non-fatigued physiological state and dealing with inference from external factors (e.g., stress, mental fatigue) that could impact the physiological indicators. This limitation has led researchers to evaluate localized muscular fatigue by intrinsic measurement of the myoelectric signal from within the muscle using surface electromyography (sEMG) (De Luca, 1984). As such, the properties of myoelectric signals can be used as fatigue indicators that remain unaffected by external factors and depend on the muscle strength of the target muscle.

To mitigate and reduce the presence of HFs, cobots have been introduced to stabilize production performance by supporting workers during task progression (Gualtieri et al., 2021). However, the workstation design concept of "one size fits all" is no longer suitable considering the increasing heterogeneity of the human workforce in terms of physical attributes and psychosocial attitudes (Neumann et al., 2021). Consequently, collaborative workstations need specific methods and approaches to effectively integrate human-orientated design principles in advanced HRC workplaces (Li et al., 2023).

The research conducted in the literature highlights the rare integration of HFs and ergonomic principles in the collaborative workstation design phase. The flexibility that cobots can guarantee enables them to dynamically change their behavior in real time according to workers' features. This characteristic is specially adopted in dynamic task assignments (i.e., an operational managerial decision), where cobots can change working patterns according to the psychophysical values of their partners. As an example of the integration of HFs into operational decisions, Busch et al. (2017) demonstrated that cobots positively impact worker body postures, comfort, and acceptance during collaborative task execution in a laboratory setting. Gualtieri et al. (2020) analyze operator physical risk with OCRA and RULA indexes and demonstrate that the reduction of work-related biomechanical overload and ergonomic risk does not affect the cycle time and HRC productivity. Finally, Rinaldi et al. (2023) investigated HRC for large components in the aerospace industry, demonstrating important economic benefits related to productivity and efficiency without affecting postural risk scores, calculated with the OWAS index.

The literature demonstrates that HRC allows one to reduce occupational risks; however, considering static ergonomics alone leaves unaffected a significant area of dynamic operator well-being (Keshvarparast et al., 2021). Therefore, a collaborative workstation must optimize the impact of the operator's workload over time, such as fatigue, alongside postural ergonomics in operational decisions and in the design process of workstations. A recent paper by Chand et al. (2023) developed a mathematical model for the evaluation of localized muscular fatigue evaluation using sEMG technologies considering the effects of an operator, type of operation, load weight, and number of repetitive operations in manufacturing task. Yaacoub et al. (2023) proposed a physics-based digital human simulator to predict the fatigue caused by each task; therefore, they could assign physically demanding tasks to cobots. Chand and Lu (2023) used their previously developed fatigue model to provide a scheduling model for a human-robot collaborative assembly line with two objective functions: cycle time and fatigue level. Buerkle et al. (2023) used an incremental learning approach to detect the fatigue level based on EMG signals and proposed a Mondrian Forest model to predict fatigue level. They used this approach and increased the workload until the level at which workers needed the cobot to perform the task happened, and they evaluated their model accuracy under both conditions. Zheng et al. (2023) proposed a video-based AI approach to estimate the fatigue level of workers performing tasks. Consequently, optimizing the task assignment to the worker and the cobot based on the fatigue level of the worker, Sotirios et al. (2022) proposed a framework to assess the mental fatigue of workers caused by working near a cobot. Their study was different from all other studies because, in other studies, researchers were looking to use cobots to decrease the physical fatigue of workers. However, they wanted to evaluate the mental fatigue caused by cobot.

Vermin et al. (2024) considered the fatigue of workers in an HRC picking system and proposed a bi-objective mathematical approach to optimize a job-shop scheduling problem. However, the fatigue model they used was an energy expenditure model and not a median frequency (MF)-based method. Finally, Yao et al. (2024) proposed a new multi-modal AI-based approach to assess the fatigue level of workers in real time. Consequently, based on the online fatigue level of workers, they used a deep reinforcement learning approach to assign the next task to a human or cobot.

Although recent literature demonstrates an increased interest in adaptive cobot behavior based on human muscle activity, especially in dynamic task reallocation based on the perceived worker's fatigue (Yao et al., 2024), the integration of both postural and fatigue assessment in workplace design and the joint adoption of postural assessment and fatigue analyses in the collaborative human-robot design process has been rarely addressed. The work proposed by Chand et al. (2023) introduced in the literature regarding fatigue assessment is a methodology and a mathematical approach for evaluating fatigue levels during dynamic tasks in an assembly system. The authors attempted to apply this approach to allocate fatiguing tasks to cobots within a human-robot collaborative assembly system.

Therefore, this article proposes a mathematical model to jointly quantify and minimize the postural occupational risks and accumulation of fatigue associated with each task performed by humans, cobots, or both in a collaborative assembly process.

3. Problem definition

The design process of manufacturing systems, such as assembly lines, has several steps that range from macroscale to microscale design. The accuracy level of the design process and its details increases as much as the analysis goes from the macro-level to the micro-level. The design phase of an assembly line starts with estimating the task time and ergonomic scores, which are directly related to the location of entities in the workstation. The number of possible configurations to allocate one resource in the workstation increases as much as the number of available places. Hence, several trade-offs between locations may arise based on ergonomic scores and on the performance level of the activity that involves each location. Fig. 2 shows an example of trade-off selection for a collaborative workstation. In this example, Task 1 requires Object A and Task 2 requires Object B. Three locations can accommodate large objects, including Objects A and B. Locations 1 and 3 are within the reach of the worker and both at an ergonomic height. Location 2 is behind the worker on the pallet, which requires the worker to bend the knee to grab the object. Therefore, both task times and ergonomic indexes for Locations 1 and 3 are lower than for Location 2.

Consider that Location 3 is temporarily unavailable. If only one of the two tasks is assigned to this workstation, the respective object could be placed in Location 1, which has a better task time, and ergonomic score compared to Location 2. However, if both tasks are assigned to the same workstation, one of the two objects must be placed at Location 2. This means that one of the tasks will have a higher task time and ergonomic score than initially estimated. The situation could be even more complicated on a collaborative assembly line, considering all three locations are available. If both tasks were assigned to the station, they could be performed normally, with the objects placed in Locations 1 and 3. However, if a cobot is assigned to this station and is located on the left side, the cobot requires free space for movement, making the left side of the station unavailable. Therefore, one of the objects must be placed in Location 2. In the worst-case scenario, if Location 2 is already occupied, the proposed task allocations and workstation design will become impossible to implement in the real world due to space limitations.

Current solutions to implement collaborative workstation layout design typically rely on simulation tools and software; however, these tools are not generative. All feasible solutions should be designed and tested manually inside the software by the company workplace designer, leading to a time-consuming activity, since the number of possible solutions in a complex system is almost infinite. Therefore, this research develops a linear mixed integer multi-objective model to tackle the challenge of placing all entities within the available places in a human-robot collaborative workstation. The main objective of this study is to propose a mathematical model to dynamically design a collaborative workstation layout. When designing a collaborative workstation, both the productivity and ergonomic aspects of the design are important. Since cobots can improve the ergonomic aspects of a workstation and reduce the physical load on workers, this study will consider not only the operation time but also the postural index and the fatigue level of workers. Dealing with such a problem means connecting the locations of objects with task time and ergonomic indexes, and, to do that, task alternatives and activity segmentation need to be introduced. The task alternatives concept ensures that all possible designs for the workstation are evaluated, which leads to overcoming one of the major shortcomings of current simulation approaches. However, due to the high number of alternatives for each task, it is not feasible to assess task time, postural ergonomics, and fatigue levels for each alternative without a practical approach. To address this challenge, a segmentation approach based on the Maynard Operation Sequence Technique (MOST) (Zandin, 2002) is proposed for the first time in this study.

In the next subsections, task alternatives and the segmentation approach will be discussed, followed by a detailed explanation of the methods used to evaluate the postural index and the fatigue level. Fig. 3 reports a graphical description of the process adopted to compute alternative workplace design.

3.1. Task alternatives

Different methods of performing a single task are called task alternatives. The variations between these alternatives are not dependent on the workers or the way they execute the task but are related to the positioning of the objects and tools involved. For example, the task time and posture index for placing an object on a workbench is directly influenced by the object's position (see Location 1 and Location 2 in Fig. 2). Using task alternatives creates an opportunity to incorporate task

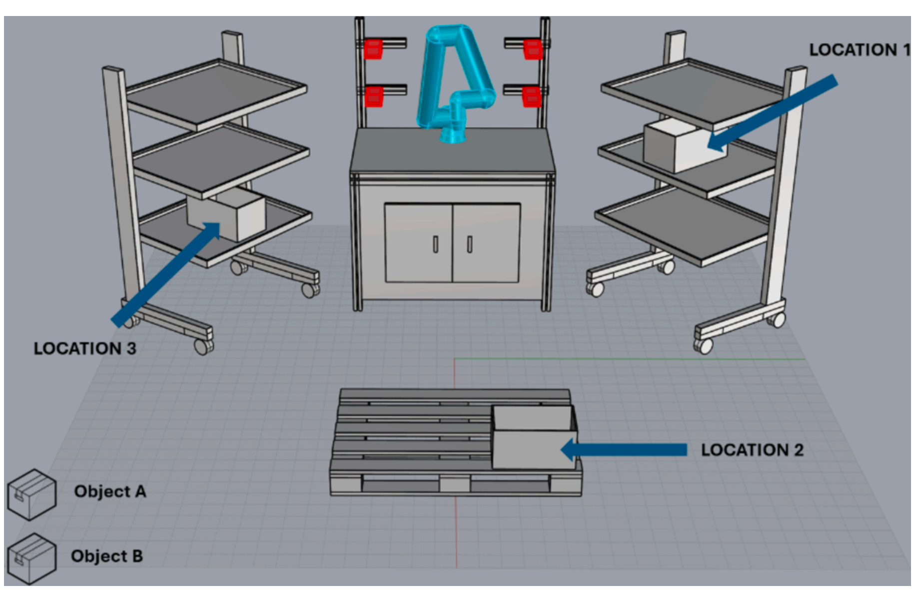

Fig. 2. Illustrative example of workspace, including three possible locations and two objects.

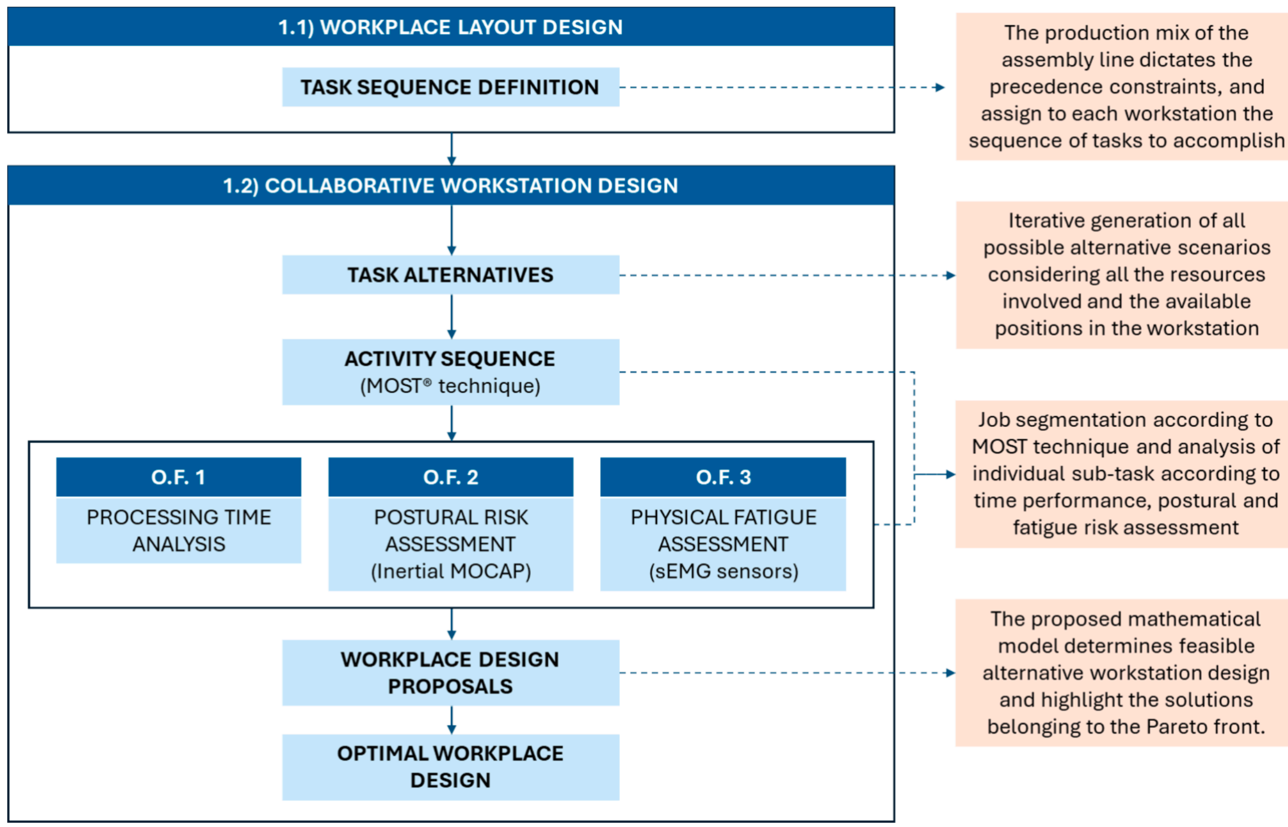

Fig. 3. Flowchart of the key steps of the proposed methodological approach to determine optimal workplace design.

time, postural index, and fatigue level into the proposed mathematical model. Since the location of each entity involved in a task alternative is known, the calculation of task time, postural index, and fatigue level will be accurate, eliminating the need for rough estimations. By selecting the best alternative for each task, the overall task time, postural ergonomic index, and fatigue level for the workstation can be evaluated. Therefore, the first step in preparing data to optimize the layout of a collaborative workstation is to identify the possible alternatives for each task.

In a collaborative workstation, apart from cobots, three other types of entity need placement within the workstation: tools, small objects (e.g. screws, pins), and big parts. Collectively, we refer to this set of entities as E, where $E = \{E^C, E^T, E^{SP}, E^{BP}\}$. In each workstation and surrounding environment, there are several possible locations for entities. In this study, these locations are represented by sets L^C (locations for cobots), L^T (locations for tools), L^{SP} (locations for small objects), and L^{BP} (locations for big parts). The number of alternatives for each task is directly related to the location of the entities involved in performing that task. In this way, all available locations in a workstation should be labelled (see Fig. 4).

Each entity can only be placed in respective possible locations. For example, the cobot can only be placed at locations 4, 5, and 6 on level 2. Similarly, small parts can only be positioned in locations 4, 5, and 6 on levels 3 and 4. However, if the cobot is positioned in a location, no small

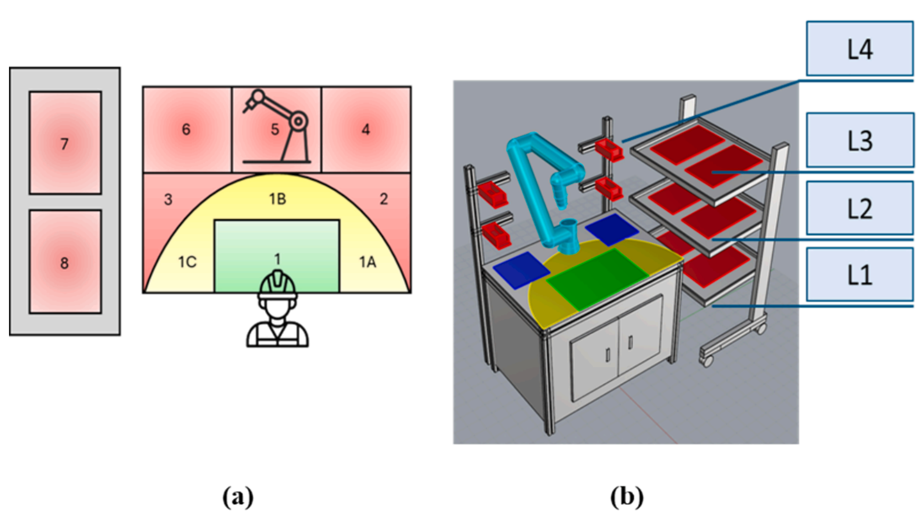

Fig. 4. (a) Golden zone and all the locations available for resource allocation in the workstation; (b) One possible configuration of the HRC workstation with different height levels.

parts can be placed in other levels of the same location (i.e., since the cobot needs all the height of the reserved location to work properly). Additionally, some locations can potentially accommodate multiple entities; hence, we introduce a maximum capacity for each location. For instance, in locations 1A, 1B, 1C, 2, and 3 on level 2, all the tools can be grouped in one location or placed separately in various positions.

Supposing that task *i* involves a big part and a tool, and there are 6 different locations for big parts and 5 different locations for tools in the workstation, there will be 30 (equal to 6*5) different alternatives for performing task *i*. However, if the task is performed by a cobot and there are 3 different locations available for the cobot, the number of alternatives increases up to 90 (i.e., 6*5*3 different scenarios). Therefore, the number of alternatives for each task is directly related to the number of entities involved in performing the task and the number of possible locations for each entity.

A quick calculation for a small case reveals that the number of possible alternatives for all tasks on a workstation can easily reach thousands. Evaluating task time, postural ergonomics, and fatigue levels for each of these alternatives individually is not feasible in a real-world case study. This limitation has prevented previous studies from developing a comprehensive mathematical model for designing collaborative workstations. However, in this study, we have addressed this challenge for the first time using a segmentation approach based on the MOST standard.

3.2. Maynard operation sequence technique (MOST)

Starting from the main tasks of assembly operation, the task decomposition was performed according to the framework proposed by Mateus et al. (2019), where the disaggregation of the work continues until the function level and the tools needed to perform singular tasks are specified. MOST represents a standard for the task decomposition phase. The method performs task segmentation into several activities and sub-activities and provides standard time to calculate task time for a predefined set of tasks (Zandin, 2002). Therefore, the first step of the procedure clusters the tasks into the three available task categories in MOST: "General Move", "Controlled Move" and "Tool Use". The category represents tasks that are performed with the help of machinery such as milling, grinding, and shaping machines; therefore, such a category of tasks is not related to human-robot collaborative systems; hence, its sub-activities are not included in this study. Fig. 5 reports an example of the "General Move" classification presented in Basic MOST.

MOST evaluates a sequence of activities to determine the standard time needed to execute the task according to a set of pre-defined task durations based on its characteristics. The sequence of activities is usually fixed. For example, in "General Move", the usual sequence of activities is A B G A B P A, where A refers to "Action Distance", B refers to "Body Motion", G refers to "Gain Control", and P refers to "Placement". Furthermore, each activity has its index, which shows the exact category of the task in the data cards, as shown in Fig. 5. For example, grasping a light object is a "Gain Control" action with an index of 1, or positioning an object with care is a "Placement" activity with an index of 6. To demonstrate the computation of MOST for one task, we hereafter report one example belonging to the "General Move".

Example: *a worker gets one screw from a bin located within reach and puts it with care in a hole located on the object that is within reach. The object is small and within close range of the worker (less than 5 cm from his/her hands).*

In this example, first, the worker needs to move their hand to the bin, therefore, it is an "Action Distance" activity. Since the bin is within reach, according to Fig. 4(a), the index of this action will be 1. Therefore, this action will be a A_1. The initial hand position should always be a comfortable and natural posture at the workstation, ready to begin operations. Fig. 6 shows the action.

The next action is to get the screw out from the bin. Getting objects is a "Gain Control" activity, and based on Fig. 5, its index is 3. Therefore, the action will be G_3. The next action will be moving the screw to the location of the object, which is an "Action Distance" activity. Since the object is within reach, the index will be 1. Therefore, this action will be aa A_1. Fig. 7 shows the action.

The next activity consists of putting the screw inside the hole, which is a "Placement" activity with index 6. Therefore, this action will be an P_6. Finally, the last action will be moving the hand to the initial position, which is an "Action Distance" activity. However, since the distance between the object and the initial position of the hands is less than 5 cm, based on Fig. 5, the index will be zero. Therefore, this action will be aa A_0. Fig. 8 shows the action.

All the actions involved in this example can be written as follows:

$A_1B_0G_3A_1B_0P_6A_0$

Because there was no body movement activity in this example, the indexes belonging to B are equal to zero. To calculate the task time for this set of activities, it is needed to sum all the indexes and multiply it by 10, which is equal to 110-*time measurement units* (TMU). Since each TMU

BasicMOST® System		General Move		A B G A B P A	
Index x 10	A Action Distance	B Body Motion	G Gain Control	P Placement	Index x 10
0	≤ 2 in. (5 cm)			Pickup Toss	0
1	Within Reach		GRASP: Light Object Light Objects Simo	PUT: Lay Aside Loose Fit	1
3	1 – 2 Steps	Sit or Stand Bend and Arise 50% occ.	GET: Light Objects Non-Simo Heavy or Bulky Blind or Obstructed Disengage Interlocked Collect	PLACE: Loose Fit Blind or Obstructed Adjustments Light Pressure Double Placement	3
6	3 – 4 Steps	Bend and Arise		POSITION: Care or Precision Heavy Pressure Blind or Obstructed Intermediate Moves	6
10	5 – 7 Steps	Sit or Stand with Adjustments			10
16	8 – 10 Steps	Stand and Bend Bend and Sit Climb On or Off Through Door			16

Fig. 5. General Move data card (MOST, Zandin, 2002).

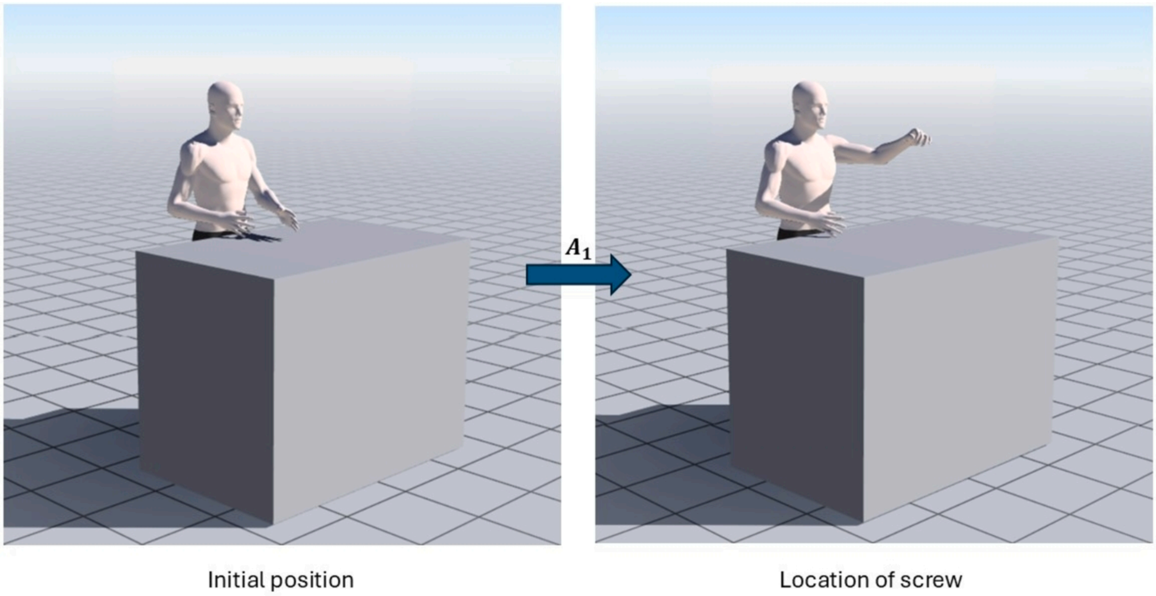

Fig. 6. Simulation of the “Moving hand” task from the initial position to the target location to pick a screw.

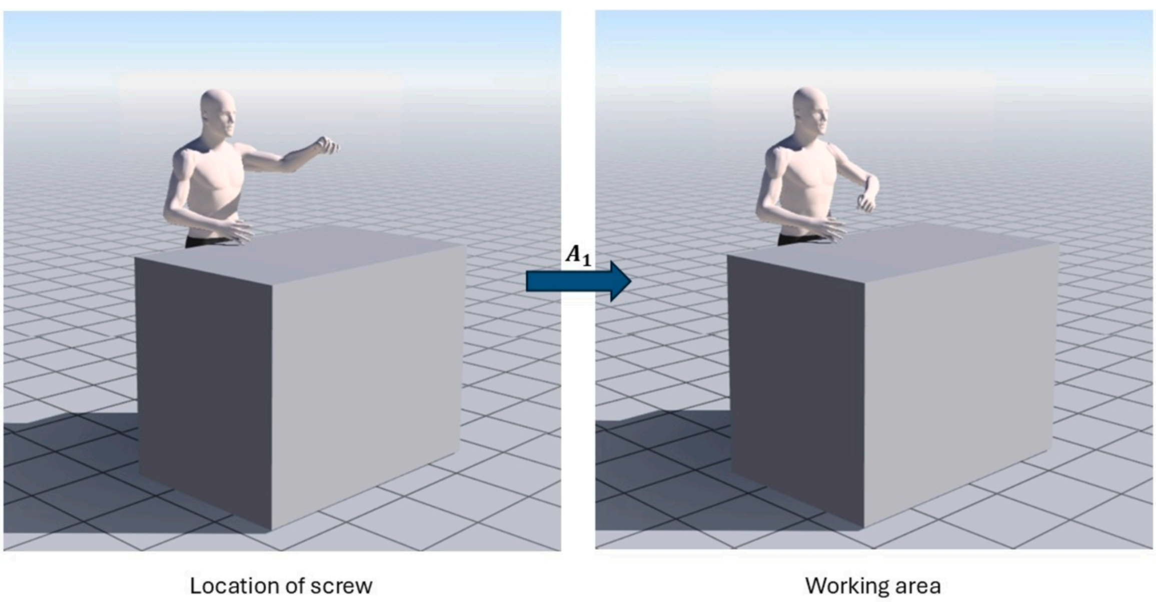

Fig. 7. Simulation of the “Moving hand” task from the location of the screw to the working area.

equals 0.036 s, the task time for this task will be nearly 4 s. In this study, based on the location of each entity, the actions needed for performing the task will be determined and task time will be estimated.

3.3. Ergonomic assessment

Calculating the postural ergonomic index scores for each alternative of a task needs separate experiments; however, due to the high number of alternatives for each task, it is not time efficient. In addition, one should design and implement all the existing alternatives for performing the experiments, which is again not cost-efficient. Nevertheless, the MOST standard can help solve these two problems. Considering that each task, based on the MOST standard, is a combination of a sequence of several activities and that the postural ergonomic index will not change for each activity (i.e., grasping a tool from a shelf will always lead to the same risk index score, except if the tool is moved to another location), it is possible to evaluate the postural ergonomic index of each single activity. In this way, the MOST standard creates an opportunity to generalize the postural ergonomic index evaluation based on specific activities. For example, consider the MOST activity “Body Motion: Bend and Arise”. It is irrelevant in which task the worker performs this action. The postural ergonomic risk index for this action will be the same anywhere it is performed (i.e., considering the same workplace layout). Since each task is a sequence of activities, the maximum postural ergonomic index between activities in a task will be the postural ergonomic index for that specific task.

When evaluating postural ergonomics, several indexes can be used to assess the physical strain on workers during different tasks. Common postural ergonomic indexes include the Rapid Upper Limb Assessment (RULA, McAtamney & Corlett, 1993), which focuses on upper body postures, and the Rapid Entire Body Assessment (REBA, Hignett & McAtamney, 2000), which evaluates the entire body and is particularly

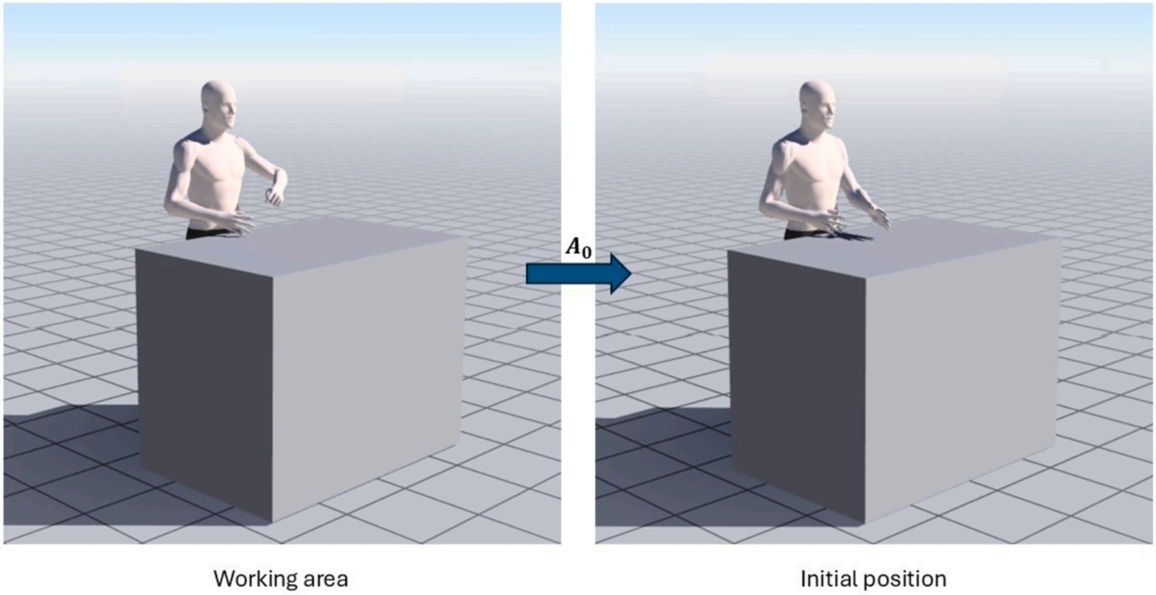

Fig. 8. Simulation of the “Moving hand” task from the working area to the initial position.

suited for tasks involving a range of complex body movements. Additionally, the Ovako Working Posture Analysis System (OWAS, Karhu et al., 1977) is used to assess the physical workload based on working postures. In our case, since the worker performs a variety of body motions, REBA is a better fit, providing a comprehensive assessment of the ergonomic risks involved. However, the mathematical model we propose is versatile and remains functional even if other postural indexes, such as RULA or OWAS, are used instead, allowing for flexibility based on the specific requirements of different workstations. In this study, a single REBA score was assessed and assigned to each activity within a task. The REBA index score for each task is determined by the maximum REBA score among all activities within that task.

Unlike other activities, the “Action Distance” activity is directly related to the location of the object. For example, in the previous case, the bin could be in Location 4 – Level 4 or in Location 2 – Level 3 (as shown in Fig. 4(b)). The same “Action Distance” activity yields different REBA scores based on the object’s location, and this variation was considered in this study. However, for other activities, the primary location of entities does not affect the REBA score, so a segmentation approach is not necessary for evaluating their postural ergonomic index.

3.4. Fatigue assessment

Repetitive tasks create fatigue in the muscles involved. To quantify the amount of fatigue, electromyography (EMG) sensors are used widely in literature. However, analyzing the signals coming from sensors

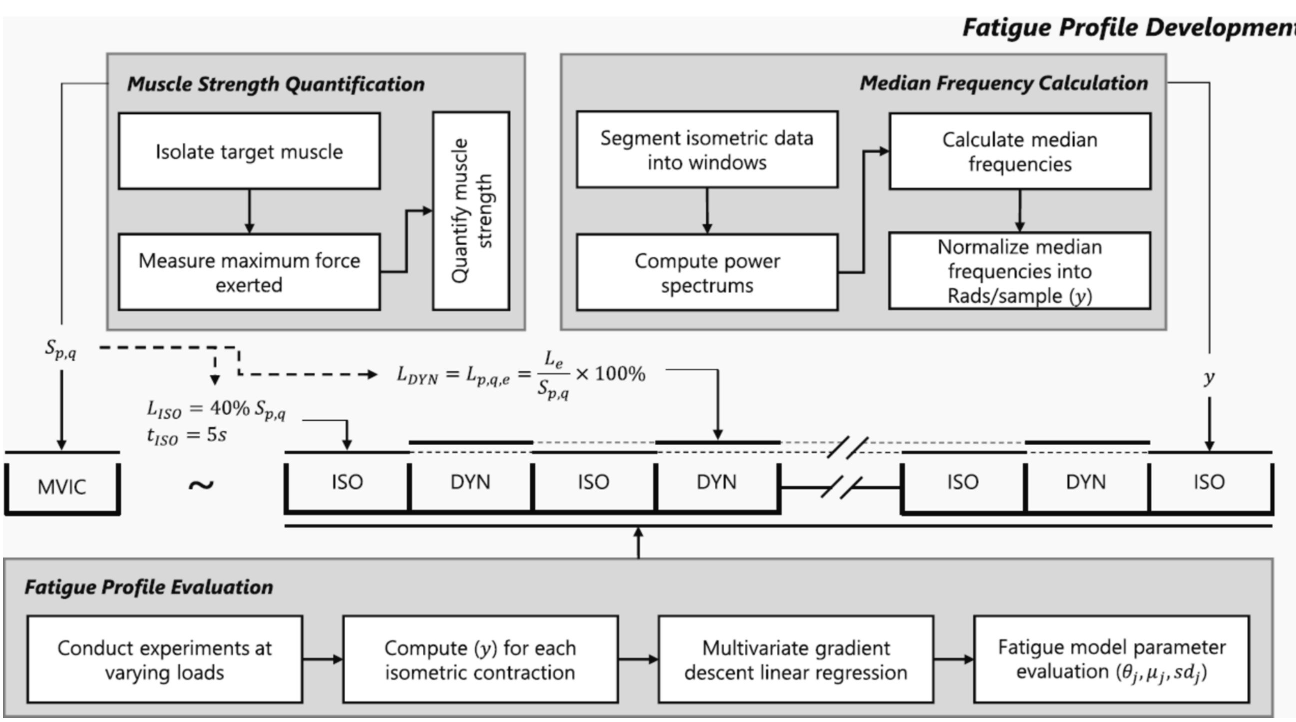

Fig. 9. Fatigue profile assessment and relevant components required (Chand et al., 2023).

represents a great challenge, especially in the manufacturing field for two reasons; first, most of the tasks involve several muscles in the worker's body, and second, performing tasks in the same way is impossible for human beings. For several years, researchers were only able to evaluate fatigue levels in static actions, such as lifting an object to a certain height, or in repetitive actions like cycling, where the trajectory of movements is always consistent and reach a certain location. However, recently, Chand et al. (2023) proposed a novel approach that makes evaluating fatigue possible for complex tasks in manufacturing systems. They proposed a multi-variable linear equation to calculate fatigue levels for different task types based on workload, base muscle strength, and the maximum possible number of repetitions for workers. Fig. 9 shows the steps and framework for this approach.

Their experiments had two important outcomes. First, workers with the same base muscle strength for the same type of task show the same fatigue pattern. Second, there is a nearly linear relationship between fatigue and the number of repetitions divided by the maximum possible repetitions for a worker before experiencing full fatigue. With the help of these two results, assessing the fatigue for each task becomes possible with their new proposed fatigue model. In addition, the outcome of their proposed formula will be a percentage, zero shows a worker with enough rest, and 100 % shows a fully fatigued worker who cannot perform the next repetition.

In this study, since actions are fully dynamic and not static, traditional approaches cannot be used to calculate fatigue levels. Instead, the new fatigue model proposed by Chand et al. (2023) was utilized to evaluate the fatigue level for each task. The fatigue level of each task alternative is determined by summing the fatigue levels caused by each activity within that alternative. This approach is consistent with the linear fatigue behavior described by Chand et al. (2023). Therefore, the fatigue level for each activity must first be calculated, which was done in this study using s-EMG. For more details on the new fatigue model and assessment approach, refer to Chand et al. (2023). Section 5 consists of a detailed description of the implemented case study and the data collection procedure, focusing specifically on the postural index and fatigue level.

4. Mathematical model

In this study, to optimize the layout of a workstation, a new multi-objective mathematical model is proposed. The first objective function minimizes the total operation time for producing the product. The second objective function minimizes the average postural ergonomic index (REBA score) of the worker, while the third objective function minimizes the fatigue level of the worker. In a collaborative workstation, tasks can be assigned to the worker, the cobot, or to the collaboration of the worker and the cobot. Based on the task assignment, there are four different collaboration scenarios: independent, sequential, simultaneous, and supportive (Keshvarparast et al., 2023a). To decrease the complexity of the proposed mathematical model, tasks in this study can only be performed in sequential and supportive scenarios. Moreover, tasks that are assigned to the cobot report the fatigue level and REBA risk score for the worker equal to zero. Other assumptions used in the proposed model are listed below:

- One cobot is available to be allocated for each workstation.
- In the previous design step (i.e., workplace layout design phase, see Fig. 1), tasks were assigned to the workstation and not yet to the worker or cobot. Therefore, the mathematical model will assign tasks to cobots and workers at the same time during the collaborative workstation design step.
- Each location has a limited capacity, which cannot be exceeded.
- Since tasks cannot be performed in parallel, the operation time can be calculated by summing the chosen alternatives for each task. Therefore, precedence relation constraints are not involved.
- There is at least one alternative available for each task.
- The speed of the cobot follows Directive 2006/42/EC on specific requirements for the design and construction of machinery (European Commission, 2024).

4.1. Model's notations

In the following, the model notations and formulation are presented.

Sets and Indexes:

I	Set of Tasks; $i = 1, 2, \cdots, I$
A_i	Set of alternatives for task i; $a = 1, 2, \cdots, A_i$
E^C	Set of Cobots available for locating in the workstation;
E^T	Set of tools available for locating in the workstation;
E^{SP}	Set of small parts available for locating in the workstation;
E^{BP}	Set of big parts available for locating in the workstation;
E	Set of all entities available; $E = \{E^C \cup E^T \cup E^{SP} \cup E^{BP}\}$;
L^C	Set of locations where Cobot can be located;
L^T	Set of locations where Tools can be located;
L^{SP}	Set of locations where small parts can be located;
L^{BP}	Set of locations where big parts can be located;
L	Set of all locations available; $L = \{L^c \cup L^T \cup L^{SP} \cup L^{BP}\}$;

Parameters:

$T_{i,a}$	Task time of task i for alternative a
$P_{i,a}$	Posture index of task i for alternative a
$F_{i,a}$	Fatigue level of task i for alternative a
Cap_l	Capacity Location l for locating different entities
$W_{i,a,e,l}$	$\begin{cases} 1 = iftoperformtaskiinalternativeaentityeshouldbelocatedinlocationl \\ 0 = Otherwise \end{cases}$
$\gamma_{i,a}$	$\begin{cases} 1 = ifworkerperformtaskiinalternativea \\ 0 = Otherwise \end{cases}$

Variables:

$X_{i,a}$	$\begin{cases} 1 = iftaskiperformedinalternativea \\ 0 = Otherwise \end{cases}$
$Y_{e,l}$	$\begin{cases} 1 = ifentityeassignedtolocationl \\ 0 = Otherwise \end{cases}$

4.2. Objective Functions

Three primary objective functions are considered in this mathematical model. The first objective function, Equation (1), minimizes the operation time for the entire workstation, ensuring maximum efficiency in task completion. The second objective function, Equation (2), minimizes the average REBA risk score for tasks assigned to workers, a critical aspect for the well-being and health of workers. To calculate it, the sum of the posture indexes of the tasks performed by the worker should be divided by the number of tasks performed by the worker. The third objective function, Equation (3), minimizes the fatigue level of the workers after completing all assigned tasks.

$$OF1 : MinimizeOperationTime = \sum_i^I \sum_a^{A_i} X_{i,a} \times T_{i,a} \tag{1}$$

$$OF2 : MinimizeAverageofPostureErgonomicscore = \frac{\sum_i^I \sum_a^{A_i} X_{i,a} \times P_{i,a}}{\sum_i^I \sum_a^{A_i} X_{i,a} \times \gamma_{i,a}} \tag{2}$$

$$OF3 : MinimizeFatigueLevel = \sum_i^I \sum_a^{A_i} X_{i,a} \times F_{i,a} \tag{3}$$

As can be seen, equation (2) is a non-linear equation. In section 4.1, a series of formulations are used to turn the non-linearity of equation (2) into a linear equation.

4.3. Constraints

In this model, four different groups of constraints are incorporated into the mathematical model. The first group of constraints belongs to the location of objects. The respective constraints ensure that all entities only assign allowable locations to that specific kind of entity. The second group of constraints belongs to the capacity of each location to ensure there will not be any additional assignment to a location beyond its capacity. The third group of constraints belongs to the alternative selection for each task and the relationships that need to be respected. Finally, a boundary for the REBA score will be the last group of constraints.

4.3.1. Location constraints:

The first set of constraints in the proposed mathematical model relates to the locations of entities within the workstation, to ensure a proper and valid allocation of entities. Equations (4) to (7) guarantee that each entity present in the workstation is assigned to only one location. Furthermore, they enforce that each entity can only be placed in the locations designated for its corresponding category. For instance, considering the position of the cobot Equation (4) ensures that the cobot will be assigned to a single location, which can be any of the predefined locations for the cobot (i.e., left, center, or right side of the station). Similarly, equations (5) to (7) handle the allocation of tools, small objects, and big parts following the same perspective.

$$\sum_{l}^{L^c} Y_{e,l} = 1, \forall e \in E^c \tag{4}$$

$$\sum_{l}^{L^T} Y_{e,l} = 1, \forall e \in E^T \tag{5}$$

$$\sum_{l}^{L^{SP}} Y_{e,l} = 1, \forall e \in E^{SP} \tag{6}$$

$$\sum_{l}^{L^{BP}} Y_{e,l} = 1, \forall e \in E^{BP} \tag{7}$$

4.3.2. Capacity constraints:

In this study, locations were divided into different zones to avoid unnecessary complexity caused by several locations that do not have meaningful differences. Some zones are smaller, such as the worker's reaching area on the workbench, and some other zones are larger, such as shelves around the workbench. Therefore, it is reasonable to consider that each zone has a different capacity for containing entities. However, this scenario is not applicable to all types of entities. In fact, the cobot is a special entity that should be singularly located in one possible spot. Equation (8) shows compliance with the assumptions raised for this model and it guarantees that at most one cobot can be assigned to the workstation. Equations (9) to (11) ensure that the number of tolls, small objects, and big parts assigned to each location will not exceed the capacity of the respective zone.

$$\sum_{e}^{E^C} Y_{e,l} \leq 1, \forall l \in L^C \tag{8}$$

$$\sum_{e}^{E^T} Y_{e,l} \leq Cap_l, \forall l \in L^T \tag{9}$$

$$\sum_{e}^{E^{SP}} Y_{e,l} \leq Cap_l, \forall l \in L^{SP} \tag{10}$$

$$\sum_{e}^{E^{BP}} Y_{e,l} \leq Cap_l, \forall l \in L^{BP} \tag{11}$$

4.3.3. Alternative choosing constraints:

The third group of constraints is the "alternative choosing" constraints. These constraints are critical in determining the optimal configuration of entities for each task within the workstation. Equation (12) ensures that, for each task, only one alternative configuration should be chosen. An alternative configuration specifies the locations where each entity related to the task should be placed. In other words, it defines the location of cobots, tools, small objects, or big parts required to execute the task in that specific alternative.

However, it is possible that two chosen alternatives for two tasks could not be feasible simultaneously. For example, suppose we have Task 1 and Task 2, and each task has multiple alternative configurations. For Task 1, Alternative 1 requires the cobot to be positioned on the right side of the table, while for Task 2, Alternative 3 specifies that the cobot should be on the left side. Therefore, these two alternatives cannot be selected at the same time because they present two different configurations of resources that are not coherent. Equations (13) to (16) guarantee the feasibility of selecting all the alternatives simultaneously for all tasks. The purpose of these constraints is to ensure that the chosen alternatives for different tasks do not conflict with each other.

$$\sum_{a}^{A_i} X_{i,a} = 1, \forall i \in I \tag{12}$$

$$W_{i,a,e,l} \times X_{i,a} \leq W_{i,a_i,e,l} \times Y_{e,l} \forall i \in I, a \in A_i, e \in E^c, l \in L^c \tag{13}$$

$$W_{i,a,e,l} \times X_{i,a} \leq W_{i,a_i,e,l} \times Y_{e,l} \forall i \in I, a \in A_i, e \in E^T, l \in L^T \tag{14}$$

$$W_{i,a,e,l} \times X_{i,a} \leq W_{i,a_i,e,l} \times Y_{e,l} \forall i \in I, a \in A_i, e \in E^{SP}, l \in L^{SP} \tag{15}$$

$$W_{i,a,e,l} \times X_{i,a} \leq W_{i,a_i,e,l} \times Y_{e,l} \forall i \in I, a \in A_i, e \in E^{BP}, l \in L^{BP} \tag{16}$$

4.3.4. Boundary for REBA score constraints

The REBA method is used to assess occupational risk and avoid musculoskeletal disorders (MSD). It adopts a table to report the risk related to the postures assumed by the worker, assigning a cumulative score to each joint angle of the worker's entire body. Based on the REBA method, tasks that report a REBA risk score higher than 7 are considered high-risk tasks. Therefore, equation (17) makes sure that any tasks with a REBA risk score higher than 7 will not be assigned to workers (i.e., they will be automatically assigned to the cobot).

$$\gamma_{i,a} \times X_{i,a} \leq 7 \forall i \in I, a \in A_i \tag{17}$$

4.4. Linearization

To linearize the proposed model, several steps are required. First, a new variable *REBAve* will replace the objective function,

$$OF2 : MinimizeAverageofPostureErgonomicscore = REBAve \tag{18}$$

and the equation (2) will move to constraints.

$$\frac{\sum_{i}^{I}\sum_{a}^{A_i} X_{i,a} \times P_{i,a}}{\sum_{i}^{I}\sum_{a}^{A_i} X_{i,a} \times \gamma_{i,a}} = REBAve \tag{19}$$

In Equation (19), the denominator is equal to the number of tasks assigned to workers. Therefore, it is an integer variable and could be replaced by a new variable, Z. The equation (19) will be replaced by equations (20) and (21).

$$\sum_{i}^{I}\sum_{a}^{A_i} X_{i,a} \times P_{i,a} = REBAve \times Z \tag{20}$$

$$Z = \sum_{i}^{I}\sum_{a}^{A_i} X_{i,a} \times \gamma_{i,a} \tag{21}$$

Until now, the division non-linearity changed to a multiplication non-linearity. The non-linearity is based on multiplying a non-negative variable by an integer variable. Therefore, it is needed to use a special method to turn an integer variable into a binary variable. To use this method, the integer variable must have an upper bound. In this model, the upper bound for Z will be equal to the number of all the tasks, so that $Z \in \{0, 1, 2, \cdots, I\}$. Therefore variables $Z_j^{'}$ for $j = 0, 1, \cdots, I$ will be introduced to this model. In this way, variable Z, could be written as:

$$Z = \sum_{j=0}^{I} j \times Z_j^{'} \tag{22}$$

By replacing equation (22) in equations (20) and (21), these two equations will be:

$$\sum_i^I \sum_a^{A_i} X_{i,a} \times P_{i,a} = REBAve \times \sum_{j=0}^I j \times Z_j' = \sum_{j=0}^I j \times REBAve \times Z_j' \tag{23}$$

$$\sum_{j=0}^I j \times Z_j' = \sum_i^I \sum_a^{A_i} X_{i,a} \times \gamma_{i,a} \tag{24}$$

The non-linearity of a non-negative variable multiplied by an integer variable in equation (20) turns into a non-linearity based on multiplying a binary variable in a non-negative variable, which can be linearized. To linearize equation (23), a new dummy variable will be used, $S_j = REBAve \times Z_j'$. Therefore, equation (23) will be replaced by equations (25) to (28).

$$\sum_i^I \sum_a^{A_i} X_{i,a} \times P_{i,a} = \sum_{j=0}^I j \times S_j \tag{25}$$

$$S_j \leq REBAve, \forall j = \{0, 1, \cdots, I\} \tag{26}$$

$$S_j \leq BigM \times Z_j', \forall j = \{0, 1, \cdots, I\} \tag{27}$$

$$S_j \geq REBAve - BigM(1 - Z_j'), j = \{0, 1, \cdots, I\} \tag{28}$$

Therefore, to linearize the proposed mathematical model, equation (2) should be replaced by equation (18) as the new objective function, and equations (24) to (28) should be added as new constraints to equations (4) to (17).

When dealing with a mathematical model, a single objective function often leads to a unique outcome aligned with the desired objective. However, in problems involving multiple conflicting objectives, achieving a singular outcome that satisfies all objectives becomes challenging, leading to suboptimal solutions for some variables. To address this challenge, this study adopts the ε-constraint algorithm (Abdous et al., 2023). This algorithm helps find non-dominant points, forming the Pareto front—a set of optimal solutions where no point is better across all considered optimization objectives. The Pareto front visualizes trade-offs between conflicting objectives, aiding decision-makers in evaluating solutions based on preferences and constraints.

5. Experimental test case

In the literature on human-robot collaborative systems, there are no available case studies or databases that provide real-world data on task time, postural score, and fatigue levels. This lack of data makes it challenging for researchers to develop and validate their solutions for designing effective collaborative workstations and prevents them from showcasing their potential in this field. To address this gap, this study conducted an experimental test campaign in a laboratory setting and compiled all the collected information into an online database for future research purposes. As mentioned in Section 2, the scarcity of studies proposing innovative approaches for designing human-robot collaborative workstations contrasts sharply with the significant benefits that cobots can bring to manufacturing environments. The case study chosen in this study is a bookshelf with dimensions of 91 cm (L) × 29.5 cm (W) × 91 cm (H). Assembling this bookshelf required 62 tasks with 67 task precedence relations, as shown in Fig. 10.

This bookshelf presents several characteristics that make it an ideal candidate for evaluating a human-robot collaborative system. First, its size and weight are sufficient to cause worker fatigue during repetitive tasks. Second, the variety in component sizes, especially the inclusion of large parts, enables a thorough assessment of different factions within the collaborative framework.

The experiment was conducted in a university laboratory, where a dedicated workstation was set up for assembly operations. The collected data were categorized according to each elementary task investigated, including task execution times, repetition numbers, zones, postural ergonomic scores, and fatigue levels. The workstation setup, illustrated in Fig. 4(b), comprised four levels with distinct zones for each one. We employed the segmentation approach and task alternatives described in Section 3.1 to assess task time, postural index, and fatigue level. For instance, based on the location and position of objects within the workstation, we conducted an "action distance" activity to measure the postural index. This methodology enabled us to create a comprehensive database of all possible actions in a collaborative workstation. Additionally, we ensured that our database covered all the categories outlined in the MOST standard, making it robust and valuable for both future research and industrial applications. All experiments were performed by a 34-year-old man, 174 cm in height.

All the experiments have been conducted once entirely manually and once with the assistance of cobots. This approach facilitated the collection of necessary data for designing an ergo-friendly workstation. The cobot was programmed to perform specific gripping and positioning movements to aid the operator. The experimental phase concluded with the preparation of data for input into a mathematical model, aiming to optimize the placement of cobots, tools, and objects within the workspace.

REBA score:

In this study, the occupational risk assessment of postures adopted by the worker during the collaborative task progression was monitored using an inertial motion capture system (Xsens MVN Awinda), while real-time scores were computed through the WEM-Platform (Battini et al., 2022b). A systematic calibration process was conducted to ensure accurate spatial references, requiring the operator to perform specific poses and movements. Fig. 11 shows an example of WEM-Platform risk assessment of four different activities performed during collaborative task execution.

To determine the REBA risk score for each task, a comprehensive set of experiments was designed based on the activities outlined in the

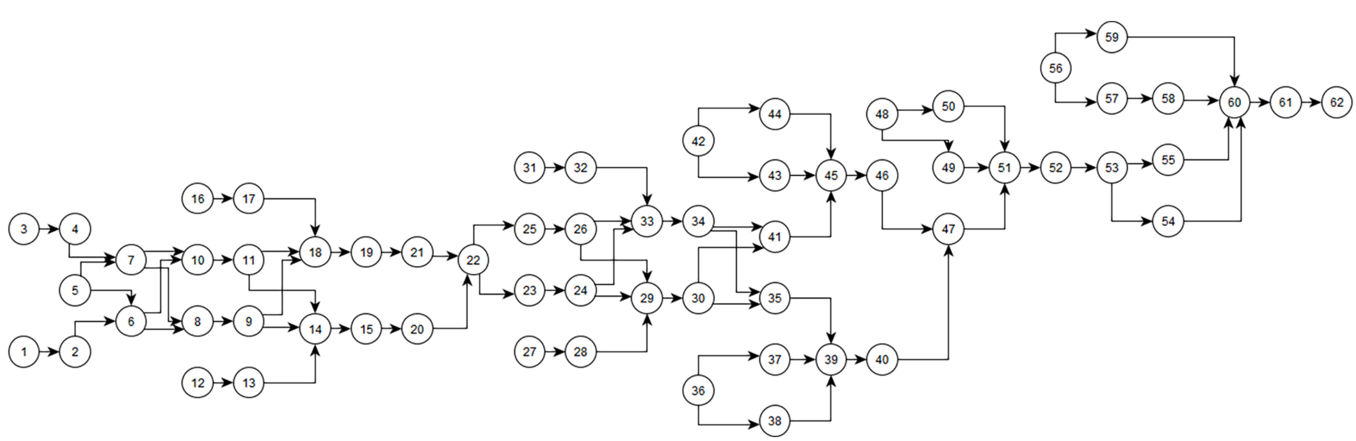

Fig. 10. Task precedence relations (PERT chart) for the assembling bookshelf.

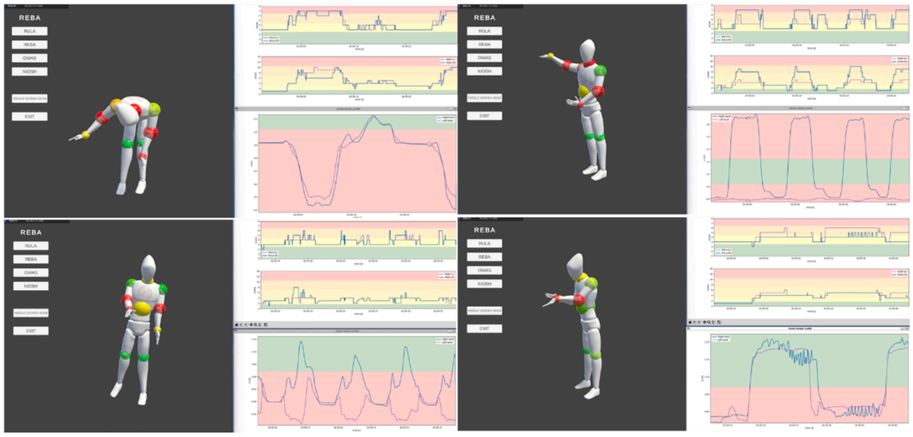

Fig. 11. REBA postural scores computed in real-time with the WEM-Platform (Battini et al., 2022b).

MOST standard. Various activities, including screwing, hammering, and different types of "Body Motions" and "Action Distance" activities to reach different zones, were repeated ten times each. Throughout these experiments, body postures were recorded using motion capture sensors and analyzed by the WEM-Platform. The platform provided a REBA risk score for each activity, enabling the evaluation of risk levels for different task alternatives based on the position of entities in the workstation.

Fatigue assessment:

In this case study, four distinctive tasks could stimulate fatigue and were repeated several times throughout the assembly process: (i) moving plates (both small and big), (ii) screwing, (iii) hammering, and (iv) rotating the heavy semi-assembled parts on the assembly table. Other tasks, such as adjusting parts on the table or collecting hardware, had a negligible fatigue effect on workers, equal to zero. An experiment with surface electromyography (s-EMG) equipment designed to validate the analytical approach introduced by Chand et al. (2023). The chosen task was lifting an object. Since lifting an object for an exact height is possible, it was possible to calculate the Median Frequency (MF) based on the traditional approach and the Chand et al. (2023) proposed one. The result of our validation shows that for different weights the new approach estimates the MF with a high accuracy. Therefore, for other tasks, this approach was used to assess the fatigue level caused by each task.

6. Numerical results and managerial insights

Since the proposed model has three distinct objective functions that contrast with each other, the ε-constraint algorithm was employed for its resolution. Consequently, the outcome, instead of a single optimal solution, will be a set of non-dominant solutions, each representing a different design for the human-robot collaborative workstation. The proposed mathematical model has been used to optimize the design of the collaborative workstation. By considering ε equal to 0.1 in the ε-constraint method, 13 non-dominant solutions have been found. Fig. 12 shows the Pareto front of the bookshelf case study. These 13 non-dominant solutions of the collaborative workstation mean that no single solution outperforms others in all criteria simultaneously. Therefore, each one represents an optimal solution considering the trade-offs between operation time, posture, and fatigue. Since each solution has two variables X and Y, where $X_{i,a}$ designates the assignment of an alternative a to each task i, and $Y_{e,l}$ assigns the entity e to the specific location l, each solution provides a set of alternatives for task assignment and entity placement, dictated by the model's constraints. Consequently, these solutions offer unique configurations for the assembly of the bookshelf.

The first graph displays individual solutions, while the subsequent figure seamlessly connects them, forming a surface that effectively represents the Pareto frontier. For a more comprehensive understanding, the graphical representation is shown in a tabular format. Table 2 employs a color-coded scheme, with green indicating the best values and

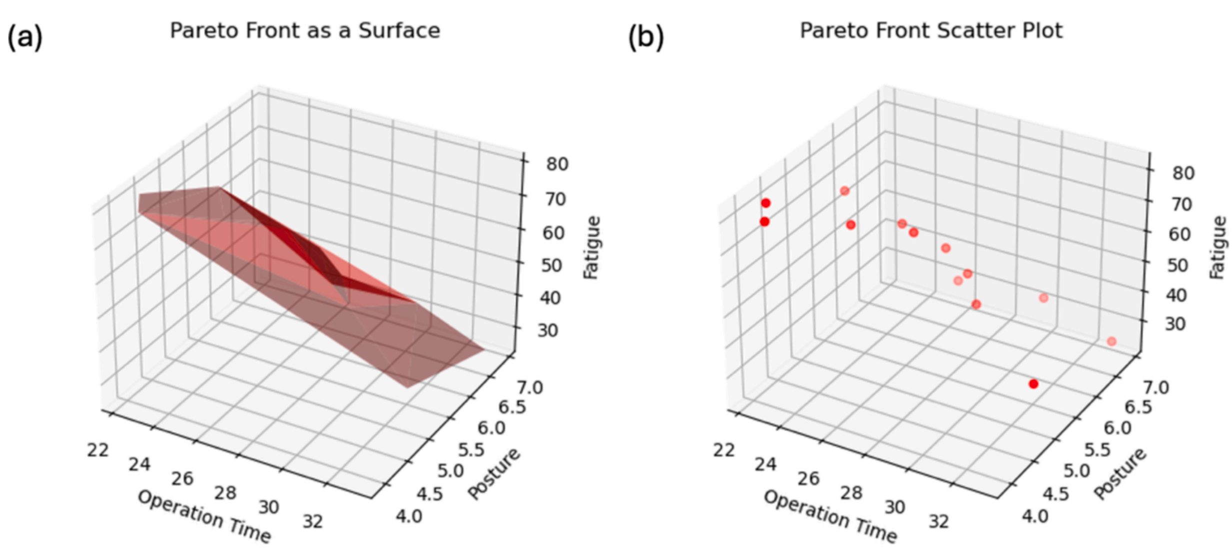

Fig. 12. Pareto frontier (Operation time: minutes/pc; Posture: REBA score; Fatigue: intensity of fatigue (percentage of full fatigue)).

Table 2
Scores list of the scenarios belonging to the Pareto front.

Solutions	Objective functions Operation time (min/pc)	Posture (REBA)	Fatigue (%)
1	22.3	4.47	81.06
2	22.5	6.79	67.39
3	23.1	4.21	81.06
4	24.5	6.73	69.23
5	25.1	6.56	60.7
6	26.4	5.91	64.62
7	26.8	6.24	53.76
8	26.9	5.98	40.02
9	27.9	5.71	47.83
10	29.7	5.42	41.66
11	30.1	5.88	24.92
12	31	5.37	29.59
13	31.2	5.18	27.64

red highlighting the worst ones. The solutions have been sorted by operation time to better show the trade-offs between the three objective functions. Among all the 13 non-dominant solutions, except for solutions 1 and 3, the cobot has been installed in the workstation in all other solutions.

Solutions 1 and 3:

Solutions 1 and 3 have the highest fatigue level among all the non-dominant solutions. In addition, solution 1 has the lowest operation time and the second-lowest REBA score. Meanwhile, solution 3 has the second-lowest operation time and the lowest REBA score. Both solutions are manual workstations. Therefore, all the tasks are performed by the worker, which leads to the highest possible fatigue level. However, in such scenarios all of the tasks, except for the screwing activity that is performed faster by cobots in comparison to workers, are made faster, hence decreasing the operation time but increasing the fatigue level. Also, since there is no cobot stationed in the workstation, more ergonomic spaces are available in the workstation that can accommodate different parts.

Solution 2:

Since the screwing tasks can be performed by cobots slightly quicker than humans, in solution 2, all the screwing tasks have been assigned to the cobot. Therefore, its operation time is better than that of solution 3, which does not have any cobots, but it is still slightly higher than that of solution 1, because the presence of a cobot in the workstation caused some of the locations within reach to become unavailable. Consequently, some objects need to be located far away from the worker; therefore, the operation time is slightly higher than solution 1. Solution 2 has the highest average REBA score among all 13 non-dominant solutions for two reasons. First, screwing is a physically demanding task (higher fatigue) with a low REBA score; therefore, performing screwing tasks by the cobot will cause the REBA scores of the other tasks performed by the worker to have a higher average. Second, the cobot needs a free area for movement; therefore, some of the locations with a low REBA score will be unavailable, and the REBA score for performing other tasks will increase.

Solutions 4 to 10, 12, and 13:

Cobot can perform two types of tasks in this case study: screwing and object movements. Since the cobot performs the same tasks slower than the worker, from solution 4, where a small portion of tasks are assigned to the cobot, to solution 13, where all the object movement tasks are assigned to the cobot, the operation time increases. Also, the fatigue level is reduced because workers perform fewer tasks. The average REBA score also decreases since tasks with a high REBA score have been assigned to the cobot. However, these are the general trends that are not necessarily always true. For example, solution 6 has a higher operation time and a lower average REBA score than solution 5, which aligns with the general trend. However, the fatigue level of solution 6 is higher than solution 5, which is not aligned with the mentioned trend. The reason behind this behavior lies in the different characteristics of screwing tasks and object movements. Solution 5 has a higher portion of the screwing task, which leads to a lower fatigue level but a higher average REBA score than Solution 6.

Solution 11:

Solution 11 has the lowest fatigue level but not the highest operation time or the lowest average REBA score. The reason behind it is that all the possible screwing and object movement tasks are assigned to the cobot. Therefore, since the screwing tasks will be performed quicker when performed by the cobot, solution 11 has a lower operation time than solutions 12 and 13. Also, as it is mentioned, the REBA score for screwing tasks is low; therefore, by performing all the screwing tasks by cobot, these tasks that help the average REBA score to some degree are removed from the calculations, and the average REBA score increases slightly regarding the solutions 9, 10, 12, and 13.

6.1. Layout analysis

To be more specific about the optimal design of an ergo-friendly collaborative workstation, three out of thirteen solutions have been analyzed in detail, and the assigned locations for each entity are demonstrated in separate tables.

Solution 1:

Solution 1 from the Pareto front has the lowest cycle time of all the non-dominant solutions, and the ε-constraint approach was provided for this case study. This solution achieves optimal values for cycle time (22.3 min/pc) and the second lowest average of the REBA score (4.47) but sacrifices worker fatigue (81.06 %). This scenario represents the manual assembly solution, where all the tasks are assigned to the human worker according to an ergonomic design of the workplace and favorable postures. All the small objects are located on level 3, and other parts are located on level 2 (See Table 3).

Solution 8:

Solution 8 from the Pareto front provides a good balance between posture (5.98) and fatigue (40.02 %) values and an acceptable operation time (26.9 min/pc). This configuration assigns multiple tasks to cobots, relieving operators from physically demanding activities. In this solution, all handling of big objects is assigned to the cobot; therefore, to maintain the postural score as low as possible, the model chose a position with better posture (See Table 4).

Solution 11:

Solution 11 from Pareto front implements the cobot on the left side of the workstation, minimizes human worker fatigue (24.92 %) but compromises cycle time (30.1 min/pc) and posture (5.88). Physically demanding tasks are assigned to the cobots; therefore, workers's fatigue is significantly reduced. Although the layout configuration leads to an overall slowdown in task execution times, mainly due to cobot speed limits in shared environments with humans, this solution could be a good choice for manufacturing systems where the fatigue level of workers is very important for their management. Therefore, by sacrificing productivity and postural scores to a certain level, the fatigue level decreased to the lowest possible level. In this solution, all handling and screwing tasks are assigned to the cobots, and other tasks are assigned to humans (See Table 5).

Table 3
Location and nature of the entities corresponding to Solution 1.

Entity	Location	Entity	Location
Cobot		Object 3	Z4-L3
Screwdriver	Z1A-L2	Object 4	Z5-L3
Hammer	Z1C-L2	Object 5	Z6-L3
Object 1	Z4-L3	Small Plates	Z8-L2
Object 2	Z5-L3	Big Plates	Z7-L2

Table 4
Location and nature of the entities corresponding to Solution 8.

Entity	Location	Entity	Location
Cobot	Left	Object 3	Z4-L3
Screwdriver	Z1A-L2	Object 4	Z4-L4
Hammer	Z1A-L2	Object 5	Z4-L4
Object 1	Z5-L4	Small Plates	Z8-L2
Object 2	Z4-L3	Big Plates	Z7-L2

Table 5
Location and nature of the entities corresponding to Solution 11.

Entity	Location	Entity	Location
Cobot	Left	Object 3	Z4-L3
Screwdriver	Z2-L2	Object 4	Z5-L4
Hammer	Z2-L2	Object 5	Z4-L3
Object 1	Z4-L4	Small Plates	Z7-L3
Object 2	Z5-L4	Big Plates	Z7-L2

6.2. Selecting a single solution

The multi-objective method provides a range of options belonging to the Pareto optimal solution. Only after a careful analysis of each alternative, it is possible to select the optimal layout configuration for each specific case. Several approaches assist in selecting a non-dominant design for implementation, and one such method is the upper/lower bound approach. This approach involves establishing thresholds for specific objectives, providing the opportunity to identify a single solution for implementation. For example, consider a system whose highest acceptable operation time is 26 min/pc, since they have a minimum number of products that should respect it. Five of the solutions have an operation time higher than 26 min/pc, therefore, we can put them aside (See Table 6).

Next, the system expresses that a fatigue level higher than 0.7 is not acceptable for this system. Two of the remaining solutions have a fatigue level higher than 0.7. The remaining three solutions are shown in Table 7.

In case there is no other boundary or excluding criteria, all three solutions could be selected for implementation in the workspace. However, the best solution would be the one with the lowest REBA score, i.e., solution 5. This solution fulfills the requirements of management and has the lowest REBA score among the remaining ones.

6.3. Managerial insights

The results of this study offer several critical managerial insights for the design and implementation of human-robot collaborative workstations in manufacturing environments. By employing a multi-objective optimization approach using the ε-constraint algorithm, the study provides a set of 13 non-dominant solutions, each representing a unique configuration of task assignments and resource allocations. These solutions reflect different trade-offs between operation time, worker posture, and fatigue levels, offering decision-makers a versatile framework to optimize both productivity and ergonomics.

Table 6
New Pareto table with boundary of 26 min/pc for operation time.

Nodes	Objective functions Operation time (min/pc)	Posture (REBA)	Fatigue
1	22.3	4.47	81.06
2	22.5	6.79	67.39
3	23.1	4.21	81.06
4	24.5	6.73	69.23
5	25.1	6.56	60.7

Table 7
New Pareto table with boundary of 26 min/pc for operation time and 0.7 for Fatigue level.

Nodes	Objective functions Operation time (min/pc)	Posture (REBA)	Fatigue
2	22.5	6.79	67.39
4	24.5	6.73	69.23
5	25.1	6.56	60.7

1. Tr**ade-offs in design Considerations:** The set of non-dominant solutions illustrates that there is no single best configuration that excels in all criteria simultaneously. For instance, solutions 1 and 3, which are fully manual, show the lowest operation times and favorable postural scores but result in the highest fatigue levels due to the physical demands placed solely on human workers. Conversely, solutions that incorporate cobots, such as solutions 8 and 11, show significant reductions in worker fatigue but at the cost of increased operation time due to the slower speed of cobots. This highlights the need for a balanced approach where management can prioritize productivity and worker well-being depending on the specific requirements of the operational environment
2. Strategic **use of Cobots:** The findings suggest that cobots can be strategically employed to handle physically demanding tasks, such as screwing and object movement, to alleviate worker fatigue and improve ergonomic conditions. For example, solution 11, which assigns all heavy lifting and repetitive tasks to the cobot, achieves the lowest fatigue level (24.92 %). This insight is particularly valuable for manufacturing systems that prioritize worker safety and health, indicating that investments in cobots could reduce occupational risks and long-term health costs
3. Flexibility in **layout and task Assignment:** The detailed layout analysis of select solutions (e.g., solutions 1, 8, and 11) demonstrates that optimal workstation design is highly dependent on the specific configuration of task assignments and resource placements. Managers can use these insights to create flexible layouts that adapt to varying production needs while maintaining ergonomic standards. For instance, solution 8, which offers a balanced performance across all criteria, assigns tasks and objects based on their ergonomic impact, ensuring both efficiency and worker comfort
4. **Decision Support for Implementation:** The multi-objective optimization framework provides a structured decision-making tool for selecting the most suitable workstation configuration. Managers can utilize the Pareto frontier and the subsequent trade-off analysis to choose a layout that best aligns with their operational constraints and objectives. By setting specific boundaries for each objective (e.g., operation time, posture, and fatigue), as demonstrated in the filtering process, management can narrow down the options to those that meet predefined criteria, facilitating a more informed and strategic implementation.

7. Conclusion

Finding the optimal balance between workers and collaborative robots remains one of the most challenging aspects of collaborative manufacturing. Traditional collaborative workstation design approaches primarily focus on safe interactions and the functional placement of parts and tools within shared spaces to increase cobot efficiency, often neglecting the needs of workers. In this pioneering study, based on recent laboratory experiments, we propose a novel approach for ergo-friendly collaborative workstation design that integrates assessments of workers' postural and fatigue levels. This human-centric approach not only considers workstation productivity as an objective but also prioritizes the ergonomic well-being of workers by minimizing postural strain and fatigue. Unlike previous simulation approaches that could only evaluate a limited set of pre-designed configurations, our unique method enables the consideration of all possible workstation layouts and selects the optimal one. We developed a mathematical model to maximize assembly line productivity while jointly minimizing postural occupational risks and fatigue accumulation for all tasks performed by humans and cobots in a collaborative assembly process. The model systematically generates and evaluates every potential workstation layout by solving the combinatorial problem of resource allocation across all available locations, ensuring both design feasibility and layout performance.

The proposed model focuses on the initial workplace design that precedes tactical and operational decisions in the assembly line design process represented in Fig. 1. Anytime industrial practitioners, company managers and decision-makers need to deal with collaborative workplace design must consider that:

- Assessing a multi-objective design in the pre-deployment phase, and not later during assembly line deployment, can help companies avoid losses and costs for possible future changes.
- Finding the optimal design, degree of collaboration and task assignment represent challenging tasks since the three objective functions move in opposite directions.
- Investigating one factor at a time during design phase (i.e., only postures, or only fatigue) does not represent a sufficient solution, since these factors can be strictly correlated and deserve to be investigated simultaneously to highlight possible conflicts (e.g., productivity and ergonomics).
- Operative task execution may bring some unexpected outcomes during the deployment phase in real-world scenarios. Indeed, small adjustments can be made to the optimal workspace design according to the product mix and to the characteristics of the human labor involved in task accomplishment. Nevertheless, the aim of this research is not only to provide a useful and efficient tool to speed up the pre-deployment phase, but a tool that can also support companies to quickly check whether small adjustments to the collaborative workstation layout can be integrated safely in the operational phase.
- Adopting the proposed mathematical model ensures speed and effectiveness; however, it does not exclude the possibility of validating the optimal collaborative design with simulations to ensure the flexibility and inclusiveness of the collaborative workplace. Therefore, the proposed design method can be applied when sensors are not all available and some input data could come from simulation software, such as Jack Siemens.

7.1. Limitations and future perspectives

Despite the rapid computational generation of alternative workplace layout represents the primary objective of this work, the main limitation lies in the less-efficient initial generation of alternative solutions (i.e., first task of the workflow presented in Fig. 3). The combinatorial problem iterates the computation of all possible alternative layouts, which can eventually include unfeasible scenarios, that slow down the design process due to the additional feasibility-check required by the mathematical model before the development non-dominated solutions belonging to the efficient Pareto front. Therefore, one possible future perspective of this work concerns the integration of the combinatorial approach adopted to develop initial alternative scenarios within the mathematical model that individuates the optimal set of solutions to reduce the total computational time and provide faster workplace design solutions.

Future research will also explore the impact of task and resource numbers on computational processing time, evaluating alternative algorithms to accelerate the design process, and integrating workstation design with assembly line balancing. This will let us address strategic and tactical managerial challenges more cohesively and efficiently.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT/GPT-4 to improve the English writing. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Ali Keshvarparast: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nicola Berti:** Writing – original draft. **Saahil Chand:** Writing – original draft. **Mattia Guidolin:** Writing – review & editing, Software. **Yuqian Lu:** Writing – review & editing, Conceptualization. **Olga Battaia:** Writing – review & editing, Conceptualization. **Xun Xu:** Supervision, Conceptualization. **Daria Battini:** Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

All data related to the case study, including the fatigue and ergonomic assessments are publicly available via (https://researchdata.cab.unipd.it/id/eprint/1226).

References

Abdous, M. A., Delorme, X., Battini, D., & Berger-Douce, S. (2023). Multi-objective collaborative assembly line design problem with the optimisation of ergonomics and economics. *International Journal of Production Research, 61*(22), 7830–7845.

Andronas, D., Kampourakis, E., Papadopoulos, G., Bakopoulou, K., Kotsaris, P. S., Michalos, G., & Makris, S. (2023). Towards seamless collaboration of humans and high-payload robots: An automotive case study. *Robotics and Computer-Integrated Manufacturing, 83*, Article 102544.

Azzi, A., Battini, D., Faccio, M., & Persona, A. (2012). Sequencing procedure for balancing the workloads variations in case of mixed model assembly system with multiple secondary feeder lines. *International Journal of Production Research, 50*(21), 6081–6098.

Battaïa, O., Otto, A., Sgarbossa, F., & Pesch, E. (2018). Future trends in management and operation of assembly systems: From customized assembly systems to cyber-physical systems. *Omega, 78*, 1–4.

Battini, D., Faccio, M., Persona, A., & Sgarbossa, F. (2011). New methodological framework to improve productivity and ergonomics in assembly system design. *International Journal of industrial ergonomics, 41*(1), 30–42.

Battini, D., Berti, N., Finco, S., Zennaro, I., & Das, A. (2022a). Towards industry 5.0: A multi-objective job rotation model for an inclusive workforce. *International Journal of Production Economics, 250*, Article 108619.

Battini, D., Berti, N., Finco, S., Guidolin, M., Reggiani, M., & Tagliapietra, L. (2022b). WEM-Platform: A real-time platform for full-body ergonomic assessment and feedback in manufacturing and logistics systems. *Computers & Industrial Engineering, 164*, Article 107881.

Berx, N., Decré, W., Morag, I., Chemweno, P., & Pintelon, L. (2022). Identification and classification of risk factors for human-robot collaboration from a system-wide perspective. *Computers & Industrial Engineering, 163*, Article 107827.
Buerkle, A., Al-Yacoub, A., Eaton, W., Zimmer, M., Bamber, T., Ferreira, P., & Lohse, N. (2023). An Incremental Learning Approach to Detect Muscular Fatigue in Human–Robot Collaboration. *IEEE Transactions on Human-Machine Systems*.
Busch, B., Maeda, G., Mollard, Y., Demangeat, M., & Lopes, M. (2017). In *September). Postural optimization for an ergonomic human-robot interaction* (pp. 2778–2785). IEEE.
Cella, C., Zanchettin, A. M., & Rocco, P. (2023). In *October). Digital technologies for the design of human-robot collaborative cells* (pp. 438–443). IEEE.
Chand, S., McDaid, A., & Lu, Y. (2023). Dynamic muscle fatigue assessment using s-EMG technology towards human-centric human-robot collaboration. *Journal of Manufacturing Systems, 68*, 508–522.
Chand, S., & Lu, Y. (2023). Dual task scheduling strategy for personalized multi-objective optimization of cycle time and fatigue in human-robot collaboration. *Manufacturing Letters, 35*, 88–95.
Chang, S. W., & Wang, M. J. J. (2007). Digital human modeling and workplace evaluation: Using an automobile assembly task as an example. *Human Factors and Ergonomics in Manufacturing & Service Industries, 17*(5), 445–455.
Chu, C. H., Pan, J. K., & Chen, Y. W. (2025). Ergonomic workplace design based on real-time integration between virtual and augmented realities. *Robotics and Computer-Integrated Manufacturing, 92*, Article 102859.
De Luca, C. J. (1984). Myoelectrical manifestations of localized muscular fatigue in humans. *Critical reviews in biomedical engineering, 11*(4), 251–279.
Dempsey, P. G. (2002). Usability of the revised NIOSH lifting equation. *Ergonomics, 45* (12), 817–828.
European Commission (2021). Directorate-General for Research and Innovation. Breque, M., De Nul, L., Petridis, A. *Industry 5.0: towards a sustainable, human-centric and resilient European industry*, Publications Office, 2021. European Commission 2021, https://data.europa.eu/doi/10.2777/308407.
European Commission (2022). Directorate-General for Research and Innovation, Renda, A., Schwaag Serger, S., Tataj, D., et al., *Industry 5.0, a transformative vision for Europe: governing systemic transformations towards a sustainable industry*, Publications Office of the European Union, https://data.europa.eu/doi/10.2777/17322.
European Commission (2024). Machinery (MD) - Directive 2006/42/EC. https://single-market-economy.ec.europa.eu/single-market/european-standards/harmonised-standards/machinery-md_en.
Fechter, M., Seeber, C., & Chen, S. (2018). Integrated process planning and resource allocation for collaborative robot workplace design. *Procedia CIRP, 72*, 39–44.
Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics, 210*, 15–26.
Gualtieri, L., Palomba, I., Merati, F. A., Rauch, E., & Vidoni, R. (2020). Design of human-centered collaborative assembly workstations for the improvement of operators' physical ergonomics and production efficiency: A case study. *Sustainability, 12*(9), 3606. https://doi.org/10.3390/su12093606
Gualtieri, L., Rauch, E., & Vidoni, R. (2021). Emerging research fields in safety and ergonomics in industrial collaborative robotics: A systematic literature review. *Robotics and Computer-Integrated Manufacturing, 67*, Article 101998.
Hignett, S., & McAtamney, L. (2000). Rapid entire body assessment (REBA). *Applied Ergonomics, 31*(2), 201–205.
ISO 10218-1:2011 Robots and Robotic Devices – Safety Requirements for Industrial Robots – Part 1: Robots. Geneva, Switzerland: International Organization for Standardization.
ISO 10218-2:2011 Robots and Robotic Devices – Safety Requirements for Industrial Robots – Part 2: Robot Systems and Integration. Geneva, Switzerland: International Organization for Standardization.
ISO/TS 15066:2016 Robots and Robotic Devices – Collaborative Robots. Geneva, Switzerland: International Organization for Standardization.
Jaber, M. Y., Givi, Z. S., & Neumann, W. P. (2013). Incorporating human fatigue and recovery into the learning–forgetting process. *Applied Mathematical Modelling, 37* (12–13), 7287–7299.
Karhu, O., Kansi, P., & Kuorinka, I. (1977). Correcting working postures in industry: A practical method for analysis. *Applied ergonomics, 8*(4), 199–220.
Keshvarparast, A., Battini, D., Battaia, O., & Pirayesh, A. (2023a). Collaborative robots in manufacturing and assembly systems: Literature review and future research agenda. *Journal of Intelligent Manufacturing*, 1–54.
Keshvarparast, A., Katiraee, N., Finco, S., & Battini, D. (2021). Cobots implementation in manufacturing systems: literature review and open questions. ... *Summer School Francesco Turco. Proceedings*.
Keshvarparast, A., Katiraee, N., Pirayesh, A., Battaia, O., & Berti, N. (2023b). Integrated Resource Optimization in a Multi-Product Separated Line Collaborative Assembly Line Balancing Problem (MPSLC-ALBP). *IFAC-Papers OnLine, 56*(2), 713–718.
Kolus, A., Wells, R., & Neumann, P. (2018). Production quality and human factors engineering: A systematic review and theoretical framework. *Applied Ergonomics, 73*, 55–89.
Li, S., Zheng, P., Liu, S., Wang, Z., Wang, X. V., Zheng, L., & Wang, L. (2023). Proactive human–robot collaboration: Mutual-cognitive, predictable, and self-organising perspectives. *Robotics and Computer-Integrated Manufacturing, 81*, Article 102510.
Liu, L., Guo, F., Zou, Z., & Duffy, V. G. (2024). Application, development and future opportunities of collaborative robots (cobots) in manufacturing: A literature review. *International Journal of Human–Computer Interaction, 40*(4), 915–932.
Lu, Y., Zheng, H., Chand, S., Xia, W., Liu, Z., Xu, X., & Bao, J. (2022). Outlook on human-centric manufacturing towards Industry 5.0. *Journal of Manufacturing Systems, 62*, 612–627.
Mateus, J. C., Claeys, D., Limère, V., Cottyn, J., & Aghezzaf, E. H. (2019). A structured methodology for the design of a human-robot collaborative assembly workplace. *The International Journal of Advanced Manufacturing Technology, 102*, 2663–2681.
McAtamney, L., & Corlett, E. N. (1993). RULA: A survey method for the investigation of work-related upper limb disorders. *Applied Ergonomics, 24*(2), 91–99.
Mehta, R. K., & Agnew, M. J. (2012). Influence of mental workload on muscle endurance, fatigue, and recovery during intermittent static work. *European Journal of Applied Physiology, 112*, 2891–2902.
Michalos, G., Kousi, N., Karagiannis, P., Gkournelos, C., Dimoulas, K., Koukas, S., & Makris, S. (2018). Seamless human robot collaborative assembly–An automotive case study. *Mechatronics, 55*, 194–211.
Neumann, W. P., Winkelhaus, S., Grosse, E. H., & Glock, C. H. (2021). Industry 4.0 and the human factor–A systems framework and analysis methodology for successful development. *International Journal of Production Economics, 233*, Article 107992.
Nourmohammadi, A., Fathi, M., & Ng, A. H. (2024). Balancing and scheduling human-robot collaborated assembly lines with layout and objective consideration. *Computers & Industrial Engineering, 187*, Article 109775.
Occhipinti, E. (1998). OCRA: A concise index for the assessment of exposure to repetitive movements of the upper limbs. *Ergonomics, 41*(9), 1290–1311.
Ore, F., Hansson, L., & Wiktorsson, M. (2017). Method for design of human-industrial robot collaboration workstations. *Procedia Manufacturing, 11*, 4–12.
Ore, F., Jiménez Sánchez, J. L., Wiktorsson, M., & Hanson, L. (2020). Design method of human–industrial robot collaborative workstation with industrial application. *International Journal of Computer Integrated Manufacturing, 33*(9), 911–924.
Peruzzini, M., Grandi, F., & Pellicciari, M. (2020). Exploring the potential of Operator 4.0 interface and monitoring. *Computers & Industrial Engineering, 139*, Article 105600.
Realyvásquez Vargas, A., Maldonado-Macías, A. A., & García-Alcaraz, J. L. (2021). *Postural and Fatigue Analyses for Ergonomic Workstations Design as an Integrated Approach to Sustainable Workplaces. New Perspectives on Applied Industrial Ergonomics*. Springer, Cham. https://doi.org/10.1007/978-3-030-73468-8_13.
Rinaldi, M., Caterino, M., & Fera, M. (2023). Sustainability of Human-Robot cooperative configurations: Findings from a case study. *Computers & Industrial Engineering*, Article 109383.
Sotirios, P., Fabio, F., & Francesco, M. (2022, June). A Methodological Framework to Assess Mental Fatigue in Assembly Lines with a Collaborative Robot. In International Conference on Flexible Automation and Intelligent Manufacturing (pp. 297-306). Cham: Springer International Publishing.
Sgarbossa, F., Grosse, E. H., Neumann, W. P., Battini, D., & Glock, C. H. (2020). Human factors in production and logistics systems of the future. *Annual Reviews in Control, 49*, 295–305.
Tsarouchi, P., Michalos, G., Makris, S., Athanasatos, T., Dimoulas, K., & Chryssolouris, G. (2017). On a human–robot workplace design and task allocation system. *International Journal of Computer Integrated Manufacturing, 30*(12), 1272–1279.
Ulutas, B., & Yetkin, B. N. (2024, March). A Human-Robot Collaboration Workstation Design to Assess Worker Physical Workload with JACK Software. In International Scientific-Technical Conference Manufacturing (pp. 43-56). Cham: Springer Nature Switzerland.
Vermin, B. L., Abbink, D., & Schulte, F. (2024). Bi-objective job-shop scheduling considering human fatigue in cobotic order picking systems: a case of an online grocer. *Procedia Computer Science, 232*, 635–644.
Wolf, A., Miehling, J., & Wartzack, S. (2020). Challenges in interaction modelling with digital human models–A systematic literature review of interaction modelling approaches. *Ergonomics, 63*(11), 1442–1458.
Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception. *Journal of Manufacturing Systems, 61*, 530–535.
Yaacoub, A., Thomas, V., Colas, F., & Maurice, P. (2023). A Probabilistic Model for Cobot Decision Making to Mitigate Human Fatigue in Repetitive Co-Manipulation Tasks. *IEEE Robotics and Automation Letters*.
Yao, B., Li, X., Ji, Z., Xiao, K., & Xu, W. (2024). Task reallocation of human-robot collaborative production workshop based on a dynamic human fatigue model. *Computers & Industrial Engineering, 189*, Article 109855.
Zandin, K. B. (2002). *MOST work measurement systems*. CRC Press.
Zheng, H., Chand, S., Keshvarparast, A., Battini, D., & Lu, Y. (2023). In *August). Video-Based Fatigue Estimation for Human-Robot Task Allocation Optimisation* (pp. 1–6). IEEE.