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HUMAN-CENTERED DESIGN SOLUTIONS FOR ERGONOMIC WORKING ENVIRONMENTS

Ph.D. School Director: Prof. Daria Battini

Supervisor: Prof. Daria Battini
University of Padova
Co-supervisor: Prof. W. Patrick Neumann
Toronto Metropolitan University (Canada)
Co-supervisor: Ph.D. Serena Finco
University of Padova

Ph.D. Candidate: Nicola Berti

Human-centered design solutions for ergonomic working environments

by

Nicola Berti

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Department of Management and Engineering
University of Padova – Italy

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Abstract

The latest industrial paradigms are driving research and innovation to facilitate the transition to a sustainable, human-centered and resilient industry. In the manufacturing context, workers' diversity in terms of experience, productivity, and physical capacities represents a significant challenge for companies, especially those characterized by high staff turnover and manual processes with high workload and poor ergonomics.

In seeking to address such challenges, this research adopts a human-centric perspective for the development of new human-oriented solutions for ergonomic and sustainable work environments. To speed up technical data collection, a new high-tech ergonomic platform was developed to progress the occupational risk assessment and training session of the workforce in real time. Furthermore, this research proposes a multi-objective job rotation scheduling model to achieve multiple job assignment objectives simultaneously considering different sociotechnical factors: worker experience, physical capacity and limitations, safety risks related to the postural position, noise levels, vibration exposure and boredom of workers.

The implementation of the model in real environments can be supported by a new digital ergonomic platform that can collect data on worker efficiency, postural risk and task performance, and allow workers to participate in the measurement of perceived fatigue and boredom. The proposed model aims to find the most appropriate assignment of jobs and flexible individual rest-break plan for each worker. A methodological framework was also defined to help collect data from the workplace and the workforce and to improve the development of safe and inclusive workplaces. The solution proposes a structured method to support workforce diversity management and workforce involvement.

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Nicola

“There should be no boundaries to human endeavor. We are all different.

However bad life may seem, there is always something you can do,

and succeed at. While there is life, there is hope.”

Stephen Hawking

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Introduction

One of the biggest management challenges for companies today is the inclusion of individual characteristics of workers during production process decisions to obtain more realistic planning and scheduling outcomes. Defining the recovery time based on operator’s age and gender (Finco et al., 2019), considering the maximum weights that workers can lift in manual handling of loads ((ISO 11228-1, 2003), Lifting index - NIOSH (Waters et al., 1993)) and the physical limitations, impairments or disabilities, according to individual work exemptions, are only few examples of crucial aspects that managers need to consider when progressing daily work plans. Furthermore, the phenomenon of workforce ageing is recently affecting most of the Organization for Economic Cooperation and Development (OECD) member countries, due to the general ageing of their populations and a higher average retirement age of the workforce. The European population is projected to grow from 507.2 million in 2013 to 522.8 million in 2060, with the percentage of seniors (65 years or older) forecast to grow by 10% (Eurostat, 2019). Following this international trend, the MAIA project (MAIA Project, 2019, Models and Methods for an Active Ageing workforce: an International Academy) has begun investigating the interaction of an aging industrial workforce with a range of contextual multilevel factors such as culture, workforce demographics, technology type, company policies, and organizational design to develop new design principles and create human-centric assembly and production workspaces suitable for aging workforce conditions, by researching and advancing productivity, quality, and safety paradigms.

The increasing percentage of ageing operators in manufacturing areas, due to the postponement of retirement age, contributed to enhancing the level of physical and cognitive disparity among workers (Calzavara et al., 2020).

On the industrial side, companies increasingly outsource segments of their production to rationalize core production toward a greater reliance on automation and information technology (Mathiassen, 2006). These actions result in fewer and more similar work tasks and a general move toward less varying exposure levels in those tasks. This suggests that jobs will show fewer opportunities for variation and recovery through discretionary or unplanned breaks and a greater occurrence of repeated short-cycle operations. In such a context, repetitive tasks and hazardous postures can negatively impact the well-being of workers, causing work-related muscle disorders (WRMSDs). This trend has been confirmed by a recent report of the European Agency for Safety and Health at Work (Jan et al., 2019), which states that more than half of the EU workforce reports WRMSD, especially located in the shoulders, neck, and upper extremities. Furthermore, WRMSDs cause about 90% absenteeism and injuries. Additionally, strong seasonality and the current spread of e-Commerce lead companies to deal with sudden high peaks of market demand through constant operator turnover. Consequently, workers are not equally skilled and work-related injuries can arise if tasks are not performed correctly from an ergonomic point of view. During production peaks, companies often hire temporary workers that are assigned to easy and standardized tasks, thus leaving a smaller selection of tasks for long-term employees (Neumann et al., 2006). Therefore, both groups of workers might experience a limited variation in biomechanical exposures during these periods.

New goals for workforce management arise dealing with this diversity challenge: Find the best match between worker capacities and limitations with the most suitable set of assignable jobs. A "one size fits all" approach is unlikely to be successful anymore, given the inherent heterogeneity in the demographics and capabilities of workers. In this sense, company employers must increase their awareness of workforce diversity management in job scheduling decisions. In addition, new industrial paradigms are shifting the focus of companies on societal values and worker wellbeing to reinforce the role and contribution of industry to society. In this regard, the integration of sociotechnical aspects during the definitions of work arrangements can bring great advantages in achieving a higher degree of flexibility in workforce management, embracing the new human-centric industrial paradigms for the development of inclusive, ergonomic, and more resilient work environments against any disruptive and unpredictable event.

Research purpose

To pursue a sustainable development of the society, the European Commission stated that economic, environmental and social aspects should be equally considered in short- and long-term goals of governments, institutions and companies toward the satisfaction of human needs and aspirations (Breque et al., 2021; Renda et al., 2022). Following this perspective, this research aims to promote the integration of sociotechnical aspects in operational and strategic decisions in manufacturing companies, to enhance sustainable development both from economic and social perspectives. Although economic and environmental aspects have already been widely discussed, the social dimension has been often neglected so far (Trost et al., 2022). In particular, according to the Global Reporting Initiative (2018) standard, which defines the "triple bottom line" approach that promotes sustainability in three domains (i.e., distinguishes between the economic, environmental and the social dimension of sustainability), this research focuses on economic and social sustainability, aiming to guarantee the health condition of workers, employee satisfaction, but also allowing companies to improve economic performance. In fact, social and economic dimensions of sustainability are deeply connected since an insufficient consideration of employee-related social aspects can lead to increased physical and mental exhaustion, and therefore to a decrease in performance (David, 2005).

Monitoring workers' performance and efficiently managing workers' job assignment are essential activities to rapidly react to unforeseen events and sudden changes of market demand. Resilience and flexibility have become fundamental assets to ensure business stability against disruptive events. Moreover, the latest industrial paradigms provided a new vision for the future of work in smart resilient manufacturing systems (Romero & Stahre, 2021). This research contributes to the development of resilient approaches to help companies face unpredictable events (e.g., it helps with workforce turnover, with the integration of new temporary employees, or manage job re-assignment based on workers' capacities and limitations, through flexible and human-oriented work arrangement). Furthermore, this research also considers the new central role of the operator, who gains control of the work process (Romero et al., 2016). A human-oriented perspective was adopted to manage workforce diversity (i.e., technical factors and individual characteristics such as anthropometric characteristics, physical limitations, skills and capacities) but also to actively include and integrate workers' perspective in operational and strategic decisions.

In this sense, this research moves a step forward in the conciliation between operations management, which primarily focuses on firm profitability, often neglecting issues with any ethical implications, human resource management, which focuses more on selecting and developing people in order to fit them to the system and the integration of human factors in manufacturing work field, on adapting the system design in order to fit it to the people (Neumann et al., 2006). Therefore, the dissertation should provide practitioners and scholars with a better understanding of new methods and approaches to manage workforce diversity in the manufacturing industry and the development of flexible work plans by answering the following research questions.

- RQ1: "Do current workforce management methodologies include the characteristics of workers and their individual perspective for the development of flexible work plans?"
- RQ2: "How has the latest technological advancement shaped occupational risk assessment methods to create a safe and inclusive workplace?"
- RQ3: "What are the implications of adopting a human-oriented perspective in defining the workforce rotation strategy?"

Dissertation outline

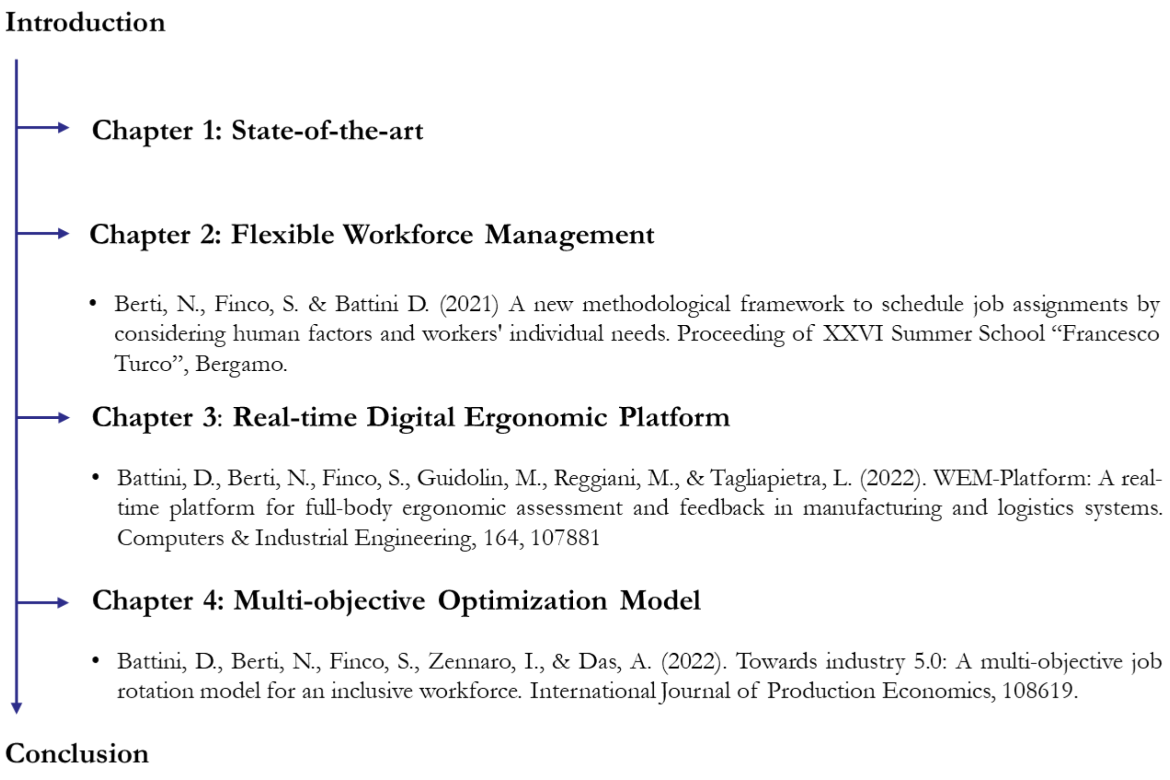


Figure I.1: Dissertation outline

The dissertation is organized into five main parts as follows:

I. **Theoretical background**: After a first introduction of the context, motivations, and objective of the study, Chapter 1 provides an overview of existing job rotation scheduling models which include human factors and sociotechnical aspects. Consequently, a review of the literature is provided in the context of occupational risk assessment methods, with a particular focus on postural risk assessment approaches. Finally, a survey of the methods available to proactively reduce postural risks at work is presented.

II. **Methodological framework**: Based on the findings of the state-of-the-art, Chapter 2 describes a new methodological framework to integrate sociotechnical aspects and human factors into scheduling decisions to progress flexible work arrangements based on the workforce profile.

III. **New ergo-digital platform**: A new technological solution to perform occupational risk assessment and workforce training time in real-time is proposed in Chapter 3. The technological platform is described and validated with another commercial system. Finally, the new solution is tested for real and laboratory test cases.

IV. **New mathematical model**: starting from the technical data collected from the in-house ergo-platform, Chapter 4 proposes a new multi-objective job rotation scheduling model to include productive, ergonomic, and social aspects in the definition of flexible work plans and the most suitable job rotation strategy given workforce profile. Therefore, a numerical application is proposed to test the applicability of the model.

V. **Conclusions and future directions**: The last chapter aims to summarize all the main results and provide managerial insight to practitioners. In conclusion, practical applications and the implications of the findings for company management are reported. In addition, a critical examination of the work and its results is conducted. Finally, limitations and future perspectives are provided to suggest relevant future research directions.

Summary of papers

This section reports the presented and published contributions for conferences and international journals that I produced during my Ph.D. research activity.

- Berti, N., Finco, S., Battini, D. (2021). A new methodological framework to schedule job assignments by considering human factors and workers' individual needs. Proceedings of the XXVI Summer School 'Francesco Turco'. AIDI – Industrial Systems Engineering.

- Battini, D., Berti, N., Finco, S., Guidolin, M., Reggiani, M., & Tagliapietra, L. (2022). WEM-Platform: A real-time platform for full-body ergonomic assessment and feedback in manufacturing and logistics systems. Computers & Industrial Engineering, 164, 107881.
- Berti, N., Finco, S., Guidolin, M., Reggiani, M. & Battini, D. (2022). Real-time postural training effects on single and multi-person ergonomic risk scores. IFAC-PapersOnLine, 55(10), 163-168.
- Berti, N., Finco, S., Zennaro, I., Battini, D. Towards a flexible work scheduling: a multi-objective job rotation model and real case application. XXII International Working Seminar on Production Economics, Innsbruck, Austria, February 2022
- Battini, D., Berti, N., Finco, S., Zennaro, I., & Das, A. (2022). Towards industry 5.0: A multi-objective job rotation model for an inclusive workforce. International Journal of Production Economics, 108619.

Hereafter, the contributions that are not included in this dissertation are as follows.

- Berti N., Finco S., Battini D., Battaïa O. Minimizing human fatigue and make-span in a dual resource constrained job shop scheduling problem, Proceedings of the 21st International Working Seminar on Production Economics, February 2020, Innsbruck, Austria
- Katiraee N., Battini D., Berti N., Calzavara M., Finco S. (2020) The workforce ageing phenomenon: statistics, policies and practices. Proceedings of the XXV Summer School “Francesco Turco” – Industrial Systems Engineering.
- Berti, N., Finco, S., Battaïa, O., Delorme, X. (2021). Ageing workforce effects in Dual-Resource Constrained job-shop scheduling. International Journal of Production Economics, 237, 108151.
- Berti, N., Finco, S. (2022). Digital Twin and Human Factors in Manufacturing and Logistics Systems: State of the Art and Future Research Directions. IFAC-PapersOnLine, 55(10), 1893-1898.

1

State-of-the-art

Introduction

This chapter investigates the literature background related to the job rotation scheduling problem (JRSP), and the mathematical models able to include sociotechnical factors for the creation of flexible and inclusive work arrangements, which consider the characteristics and limitations of individual operators. Eventually, to promote safe, inclusive, and ergonomic workplaces, a collection of some of the most famous methods for evaluating occupational risks in the workplace is reported and described, according to the technical standards of the International Organization for Standardization. In this analysis, both qualitative and quantitative techniques are considered to include the perspective of workers in the assessment of workplace risks. Furthermore, to reduce occupational risk related to hazardous postures, the focus of the analysis shifts to enabling technologies that can monitor the postural risk of workers and provide real-time corrections to awkward behavior.

1.1 Job rotation scheduling model

Job rotation scheduling (JRS) strategies have been introduced in manufacturing and logistics (M&L) systems since the 1980s with the aim of improving workforce flexibility and performance (Padula et al., 2017). JRS has received considerable research attention, especially on economic aspects and system productivity. It was only in the last decade that those worker-related social aspects began to appear in production planning strategies and JRS (Trost et al., 2022). The initial concern was to prevent work-related Musculoskeletal Disorders (WMSD) or other diseases caused by prolonged exposure of operators to high safety risk factors (Leider et al., 2015). The aim was to avoid excessive exposure to the same set of jobs characterized by heavy loads, vibrations, awkward postures or repetitive movements performed during the work activity (A. Otto & Battaïa, 2017; A. Otto & Scholl, 2013; Padula et al., 2017).

In contrast to workforce rotation strategies, which mainly focus on worker assignment throughout several rotation periods, the Job-Shop Scheduling Problem (JSP) represents another classic scheduling problem that focuses on job assignment. Dealing with a JSP means scheduling a set of jobs on a set of machines, subject to the constraint that each machine can progress only one job at a time (Applegate & Cook, 1991). The aim of the JSP is to minimize the total completion time of the jobs in queue to the shop floor. In this sense, workforce assignment respecting industry needs and personal features becomes a secondary objective, unless the number of workers is less than the total number of machines, as described in the literature concerning the Resource-constrained JSP and on its applications considering workforce skills and limitations (Berti et al., 2021). The literature review process was based on the guidelines outlined by Otto & Battaïa (2017). As shown in Table 1.1, this literature survey was carried out first by defining appropriate keywords, then filtering the results, analyzing the literature and finalizing the results according to other literature reviews existing on similar topics (Mehdizadeh et al., 2020; Moussavi et al., 2019; A. Otto & Battaïa, 2017). The scope of this review was to investigate contributions that consider the integration of sociotechnical aspects, such as occupational risks and workforce diversity, to propose optimization models or algorithms on the job rotation scheduling problem. Therefore, the articles were filtered according to the following selection criteria.

- Articles had to be written in English and published in peer-reviewed journals.
- Articles had to investigate the job rotation scheduling problem (i.e., they had to contain a sufficiently precise description of the objective function and constraints).

- Articles had to contain an explicit measure of the physical occupational risks.

Focusing the research of the literature only on the keyword ‘job rotation scheduling’, the investigation reached a restricted subset of 54 suitable articles; however, to avoid possible missing results, the list of keywords adopted for this survey was intentionally enlarged, as reported in Table 1.1.

Table 1.1: Keyword categories used for the literature search

Group 1	**Group 2**
‘Job rotation’ AND (model* OR formul* OR optimiz* OR approach* OR algorithm* OR program* OR problem* OR schedul*)	Ergonom* OR ‘human factor*’ OR ‘manual handl*’ OR ‘occupation* disorder’ OR 'occupation* disease’ OR ‘musculoskeletal disorder*’ OR ‘musculoskeletal disease*’ OR ‘upper extremity disorder*’ OR ‘upper extremity disease*’ OR ‘low back pain’ OR postur* OR ‘application* force*’ OR ‘exposure* force*’ OR vibration* OR fatigue OR ‘energy expenditure’ OR noise OR boredom OR repet*

The search then provided 200 hits, which were subsequently analyzed. The documents identified in the search were evaluated by reading the abstracts and then the full text. Irrelevant papers were discarded according to selection criteria and through an information clustering technique implemented using VOSviewer (Figure 1.1). As a result, 45 articles were selected and analyzed. Finally, 18 articles were defined that are suitable for the purpose of this analysis.

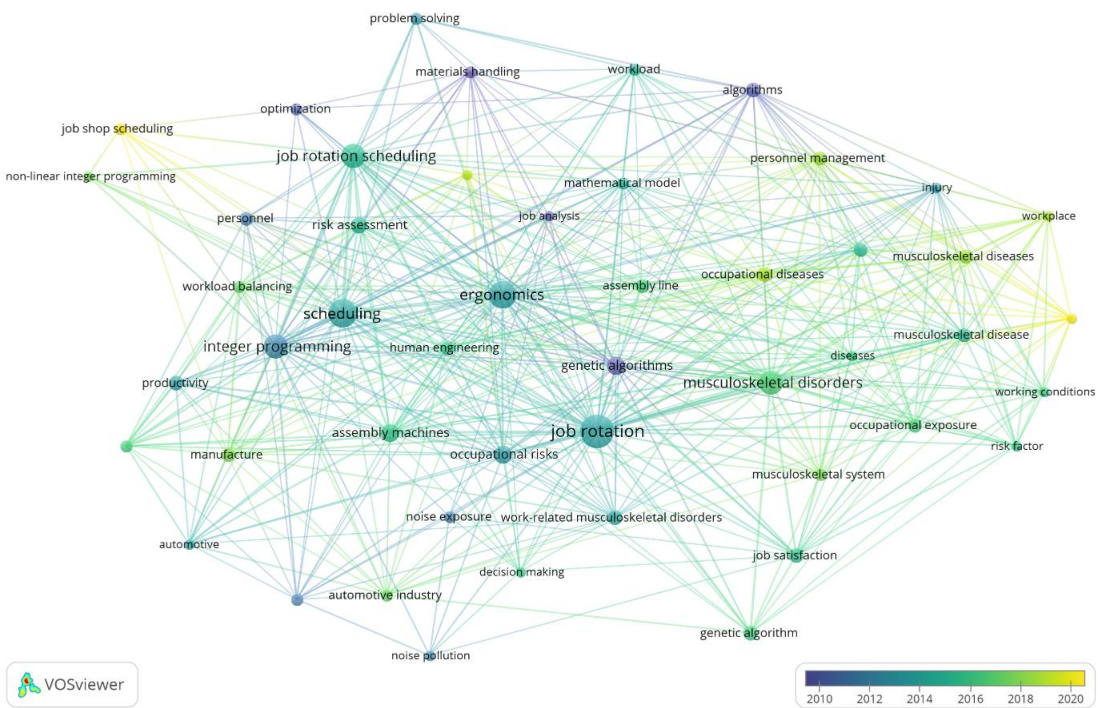


Figure 1.1: Keyword map made with VOSviewer (colors are related to the publication year)

Regarding the existing mathematical models on JRS, the contribution of Carnahan et al. (2000) can be considered the pioneer in including HF and ergonomics in JRS since they proposed the first mathematical contribution to minimize the ergonomic load for the worker most exposed through the Job Severity Index (JSI). They developed both Linear Programming (LP) and Genetic Algorithm (GA) methods to find over 400 unique solutions to the rotation plan, involving eight rotation periods within the same work shift. Asensio-Cuesta et al. (2012a) introduced a fitness function based on the Occupational Repetitive Actions Index (OCRA) (Occhipinti, 1998) to avoid the repetition of the worker's job and increase the variability of the risk level to which workers are exposed. The authors proposed a GA to find the best feasible solutions corresponding to the fitness function with the lowest value, considering the penalties for the incompatibilities between jobs and the physical, mental and communication abilities of workers. Asensio-Cuesta et al. (2012b) used 39 different criteria to develop a multi-criteria GA to generate job rotation schedules considering ergonomic movements of workers, physical skills and individual competence. Suitable rotation plans are obtained in acceptable computational time to reduce MSD risk factors, diversifying movements, and including the disability of the worker, limitations, and other medical considerations.

Otto & Scholl (2013) developed a smoothing heuristic capable of providing initial solutions as input for the tabu search procedure. Furthermore, they demonstrated the NP-hard nature of the dynamic model and state that the reduction of computational times is a potential improvement when the estimation of individual safety risks is considered in the proposed tabu search algorithm. Mossa et al. (2016) proposed a model to maximize the production rate in work environments characterized by high repetition frequency. The authors adopted the OCRA method in car seat assembly line workstations to determine task acceptability and balance workloads and safety risk among workers. Song et al. (2016) developed a hybrid GA for the minimization of WMSD considering muscle fatigue, working height, and the NIOSH (National Institute of Occupational Safety and Health) lifting index, but neglecting physical and psychological factors such as motivation, personal preferences, and fatigue, which the authors consider as limitations of their research. Yoon et al. (2016) estimated the perceived workload in three automotive assembly lines through the Rapid Entire Body Assessment Index (REBA) (Hignett & McAtamney, 2000) to avoid successively workload in the same body regions. The authors proposed a classification of the workstations into high- and low-loading groups to ensure WMDS risk prevention and defined job rotation schedules according to the daily cumulative REBA score for each worker. Furthermore, Digiesi et al. (2018) developed a model to reduce the safety risk of workload within acceptable limits while ensuring productivity goals. The capacity of the model has been tested on four manual assembly workstations for five different scenarios, with the objective of minimizing the coefficient of variation of the RULA risk index weighted for the entire workforce.

Despite their usefulness, postural ergonomic indexes cannot precisely discriminate the repetitive use of body parts, for this reason, their adoption is often matched with specific assessment tools like NIOSH Lifting Equation, JSI and OCRA (Yoon et al., 2016). Sana et al. (2019) considered both RULA, NIOSH and OCRA risk indexes as ergonomic constraints of their multi-objective optimization model. Due to the level of complexity, the authors adopt a GA to efficiently find the set of Pareto solutions within a reasonable computing time. Hochdörffer et al. (2018) created a short-term staff planning system for multiple rotation rounds based on the Balanced Ergonomic Qualification preserving job rotation (BEQR) method. They proposed a heuristic approach to generate workday rotation plans to guarantee balanced workload distribution, qualification preservation, and fair schedule plans along with workforce characteristics. Asensio-Cuesta et al. (2019) created an algorithm based on game theory to design job rotation schedules according to job competencies and worker preferences. Four different scenarios are presented to evaluate the capacity of the method. The results are then compared based on the fitness score achieved, and the final conclusions are drawn based on preferences, competencies, and ergonomic perspectives. Moussavi et al. (2019) adopted an in-house ergonomic method to include five main parameters in the proposed model for job rotation, to simultaneously balance daily physical workload and prevent consecutive high workloads in task assignments. Work posture, repetition, force, material handling, and energy consumption are detailed in 20 parameters adopted to avoid rotation schedules with consecutive high workload assignments and repetitiveness for the same criterion along with daily activity.

Due to the high complexity of the problem and its NP-hard nature, most of the resolution algorithms proposed in literature to solve the JRS problem are genetic algorithms. Diego-Mas (2020) presented an evolutionary GA to develop cyclic rotation among a small number of workstations. The proposed algorithm defines how to group jobs and the rotation sequence that workers must perform to prevent musculoskeletal pain, balance the cumulative effect of fatigue, and minimize repetitive movement. Mehdizadeh et al. (2020) defined an updated and complete review of previous JRSP models and proposed a fatigue-failure mathematical model to quantify the risk profile of workers. The authors develop three different scenarios to analyze the results obtained based on the defined objective function (i.e., minimize the worst assignment, minimize the average worker risk, or evenly distribute the workload among the workforce). Ayough et al. (2020) addressed the integration of behavioral factors (i.e., learning, forgetting, motivation, and boredom) and human aspects for a U-shaped cell design in the classical line balancing and sequencing problem, and compared the results obtained with a static case where no human factors were included. Botti et al. (2021) developed a bi-objective model chasing the trade-off between optimal person-job fit and maximum movement turnover. In their formulation, they adopt the OCRA index to define the level of exposure of workers to occupational risk. The model is tested for six workstations with eight operators aged between 19 and 57 years, finding 10 non-dominated solutions belonging to the Pareto front.

Finally, among the most recent contributions in JRS problem, Assunção et al. (2022) developed a genetic algorithm to quickly provide to the team leaders suitable job rotation plans for the assembly line of an automotive industry, considering simultaneously the occupational risk score, the diversity of exposure risk in terms of force, posture and manual material handling and the homogeneity of the workforce team. Most of the articles cited in this survey considered only a few established safety risk measurement methods. The literature highlights that the diversity and heterogeneity aspects of workers are currently a source of interest in studies on mathematical models and approaches that deal with the exposure of safety risks in the JRS problem; however, individual characteristics are rarely considered in job rotation mathematical models. Relatedly, substantive research has been conducted in Job Rotation Scheduling approaches incorporating human factors (as reported in Table 1.2). However, joint effects are scarcely studied in this literature.

Table 1.2 Notation: N/I: Not Included; JSI: Job Severity Index; TWA: Time-Weighted Average (OSHA); EAWS: European Assembly Worksheets (Schaub et al., 2013); LI: Lift Index; HAV: Hand-Arm Vibration; IP: Integer programming model; MILP: Mixed integer linear programming model.

Table 1.2: Published works on Job Rotation Scheduling with human factors consideration.

Reference	Human factors involved	Workers' Features	Worker participation	Recovery and fatigue aspects	Duration of the rotation period	Model & Method
(Costa & Miralles, 2009)	Job repetitiveness; Skills improvement	Task-worker incompatibilities	N/I	N/I	Consideration of Different Rotation Schemes	MILP - Heuristic decomposition method
(Azizi et al., 2010)	Skills improvement	Worker's learning and forgetting rate; Individual	N/I	N/I	Consideration of different rotation schemes	SAMED-JR algorithm; Metaheuristic
(Asensio-Cuesta et al., 2012a)	Job repetitiveness (OCRA); Postural risk (OCRA)	Worker' s restrictions	N/I	Recovery period multiplier (OCRA)	N/I	(Fitness function) - Genetic algorithm
(Asensio-Cuesta et al., 2012b)	Ergonomic criteria; Physical skill criteria	Competence criteria; Physical limitations of workers	N/I	Cumulative fatigue effects	N/I	(Fitness function); Genetic algorithm
(Moreira & Costa, 2013)	Job repetitiveness; Skills improvement	Infeasible task-worker pairs; Variability of execution time	N/I	N/I	Consideration of different rotation schemes	Mixed IP - Metaheuristic and Hybrid Algorithm
(A. Otto & Scholl, 2013)	Postural risk (EAWS)	N/I	N/I	N/I	N/I	Mixed IP - Tabu Search Approach - Heuristic
(Mossa et al., 2016)	Job repetitiveness (OCRA); Postural risk (OCRA)	Individual risk limits	N/I	Recovery period multiplier (OCRA)	N/I	MINLP
(Song et al., 2016)	Postural risk (NIOSH LI)	N/I	N/I	Rodgers Muscle Fatigue Analysis	N/I	Non linear; Hybrid Genetic Algorithm
(Yoon et al., 2016)	Postural risk (REBA)	N/I	N/I	N/I	N/I	Non-linear
(Digiesi et al., 2018)	Postural risk (RULA)	Individual postural risk threshold	N/I	N/I	N/I	MINLP
(Hochdörffer et al., 2018)	Postural risk (EAWS)	Permanent or temporary impairments	N/I	N/I	Consideration of Different Rotation Schemes	IP Linear; Heuristic
(Asensio-Cuesta et al., 2019)	Risk exposure	Physical / psychological limitations	Worker' s job preference and competence lists	Accumulated fatigue	Consideration of different rotation schemes	(Fitness function); Gale-Shapley algorithm
(Moussavi et al., 2019)	Job repetitiveness; Postural risk (SES); Energy consumption	N/I	N/I	N/I	Consideration of different rotation schemes	MILP; Optimal solution
(Sana et al., 2019)	RULA, OCRA, NIOSH LI	Worker' s restrictions	Worker' s preferences	Recovery period multiplier (OCRA)	N/I	Multi-objective ILP; Genetic algorithm
(Diego-Mas, 2020)	Force load postures, movement score	Mental and communication skills, temporal disabilities	Worker' s preferences	Cumulative fatigue effects	N/I	(Fitness function); Evolutionary algorithm
(Mehdizadeh et al., 2020)	Postural risk: Low back (LiFFT tool), Upper extremities (DUET tool)	N/I	No worker preference	N/I	Consideration of different rotation schemes	IP - Heuristic
(Adem & Dağdeviren, 2021)	Work environment (HAV).	N/I	Skill level; Day-off preferences	N/I	N/I	Linear – Branch & Bound; Non linear – Program-Baron
(Botti et al., 2021)	Job repetitiveness (OCRA); Postural risk (OCRA)	Functional capacity, competencies, technical skills	Relational skills and mental capacities; Person-job fitness	Recovery period multiplier (OCRA)	N/I	Bi-objective ILP model; Pareto front

1.2 Occupational Risk Assessment

Following the definition proposed by the International Ergonomics Association (IEA): "Ergonomics (or human factors), is ... concerned with the understanding of interactions among humans and other elements of a system, … in order to optimize human well-being and overall system performance." (IEA Council, 2000). Integration of human factors in manufacturing and logistics is widely suggested in the literature, both from the initial workplace design (Battini et al., 2011) and during operational and strategic decisions (Sgarbossa et al., 2020). According to the National Institute of Occupational Safety and Health (2018) and the European Union Statistical Office (Eurostat, 2021), work-related Musculoskeletal Disorders (WRMSD) are one of the main causes of pain and disability suffered by blue collar workers. Such injuries can result from repetitive motions and excessive loads carried during job execution. To detect and reduce the appearance of such musculoskeletal disorders, engineers and ergonomists have developed assessment methods for quantifying the risk of WRMSD to reduce the exposure of workers to hazardous environments and tasks. These tools can be divided into three main categories: self-reports, observational methods, and direct/instrument-based methods (David G. C., 2005).

1.2.1 Qualitative methods

Qualitative methods are based on subjective evaluations based on verbal estimation provided by the workforce on the performance of the work activity. The advantages of these techniques lie in the lower initial costs compared to other techniques (i.e., cost of the tools and instruments used to conduct the analysis) and the shorter amount of time needed to understand the use of qualitative methods in the industrial context. Whenever there is limited knowledge about complex operations processes in which human factors are included, qualitative methods can be used to gather relevant information by interviewing workplace parties who are most familiar with the processes of interest: workers and managers (Trautrims et al., 2012). Nevertheless, qualitative methods might be influenced by a high level of subjectivity, which can bring to distort analyses that can vary according to the qualitative opinion of each worker.

1.2.1.1 Self-reports

Self-reports are methods adopted to collect data on risk exposure in the workplace to physical and psychosocial factors by adopting tools such as interviews, questionnaires, and work diary. They are low-cost approaches and, lately, data collection can also be performed with semi-automatic tools such as self-evaluation methods, video records of the work activity and web-based questionnaire (David G. C., 2005). They are commonly adopted to involve workers during ergonomic improvements in their workplace and are easy to use. However, there are some limitations to their adoption. Workers involved in these evaluations can have a personal perspective on the proposed questions, which can be interpreted differently from everyone else. Then the information and data collected can be imprecise and unreliable. For these reasons, large sample sizes are normally required to ensure the representativeness of the acquired data. This is one of the main concerns of self-report methods and the reason why they are often used as a support for other risk assessment methods. As a recent example of the adoption of the qualitative method, Winkelhaus and Grosse (2020) suggest using qualitative interviewing to examine human factors in critical logistics processes, such as the warehouse system. Despite the subjective perspective of the method, qualitative interviews with workers can be beneficial in understanding the relationship between design, work environment, and the physical and psychosocial factors of the operators that influence their work, to improve worker health and optimize organizational performance.

1.2.2 Semi-quantitative methods

Self-assessment tools collect data on risk exposure using questionnaires, checklists, or interviews that workers themselves complete. These reports are based on workers' perceptions and feelings, which can lead to imprecise and subjective analyses. To overcome this limit, observational methods allow analysts to make postural evaluations based on direct observations or video recording of the tasks under examination. These methods are often semi-quantitative since they need both simple judgment information and quantitative information to obtain the risk assessment. The main difference between semi-quantitative and quantitative methods relies on the level of independence of the method to assess the risk of a posture, or an activity, without human involvement, such as the methods described later in Section 3.1. The most used and widely known observational methods follow international standard ergonomic indexes, such as the Occupational Repetitive Actions (OCRA) (Occhipinti, 1998), NIOSH lifting equation (National Institute of Occupational Safety and Health Lifting Index) (Waters et al., 1993) and Job strain index (JSI) (Moore & Garg, 1995). Job Strain Index (JSI) (Moore & Garg, 1995), for noisy workplaces: Daily Noise Dosage (DND) (NIOSH, 1998; OSHA, 1993), and general risk assessment tools: the Ergonomic Assessment Worksheet (EAWS) (Schaub et al., 2013) and the energy expenditure method (Garg et al., 1978).

1.2.2.1 OCRA

The Occupational Risk Assessment Method (OCRA) (Occhipinti, 1998) was designed to be a concise exposure index to assess occupational risk factors associated with work-related musculoskeletal disorders and repetitive movements of the upper extremities. It is based on the relationship between the daily number of actions performed during repetitive tasks and the number of recommended actions calculated based on a constant that refers to the optimal work condition. Compared to the other indexes, the OCRA method proposes an integrated assessment of the contribution of the main occupational risk factors (e.g., repetitiveness, force, posture and lack of recovery). The index is the result of the ratio of the number of technical actions carried out effectively performed during the shift (A_e) to the number of recommended technical actions (A_r). The number of recommended technical actions per each repetitive task in the work shift is computed as in Equation (1.1):

$$A_r = \sum_i^n \left[CF * \left(F_f x * F_p x * F_a x\right) * Dx\right] * F_r \tag{1.1}$$

where CF represents a frequency constant of the technical action per minute [CF=30 actions/minute], $F_f x, F_p x, F_a x$ are the multiplier factors for the force, posture and additional elements [0;1], D is the duration of each repetitive task [min] and F_r is the multiplier factor which describes the risk factor related to the lack of recovery period [0;1]. Once the OCRA index has been computed as the ratio:

$$OCRA = {}^{A_e}\!/_{A_r} \tag{1.2}$$

If the value of the index is less than 0.75 the current situation is acceptable, the value of OCRA index in the range between 0.75 and 4 represents a borderline situation, while if the value exceeds 4, actions need to be taken to improve the working conditions.

According to ISO standard 11228-3:2007(E) (ISO, 2007), simplified ergonomic methods can be adopted in the initial ergonomic analysis due to their simplicity and short computational time. Simplified methods that can rapidly provide safety risk evaluations, especially for static tasks, are the Rapid Upper Limb Assessment (RULA) (McAtamney & Nigel Corlett, 1993), the Rapid Entire Body Assessment (REBA) (Hignett & McAtamney, 2000), the Ovako Working posture Assessment System (OWAS) (Karhu et al., 1977) and most recently the Postural Ergonomic Risk Assessment (PERA) (Chander & Cavatorta, 2017).

1.2.2.2 OWAS

The Ovako Working Posture Analysing System (OWAS) (Karhu et al., 1977) represents an ergonomic method for the identification of operator discomfort caused by poor working postures. It can be used both as a daily work routine method and for the evaluation of workplace redesign, based on a set of criteria defined by experienced workers and ergonomic experts. The method relies on sampling work postures, which can be gathered by direct observations or photographic material. The procedures are then evaluated according to the OWAS classified system. This method was developed in a steel company in collaboration with experienced steel workers and work-study engineers. After each of the postures have been rated, they are re-classified into four categories according to the results. Each category, starting from the first and up to the fourth, represents the increasing necessity of considering an imminent change, if the posture belongs to the fourth category, or considering further analysis soon or during the next regular check (Figure 1.2).

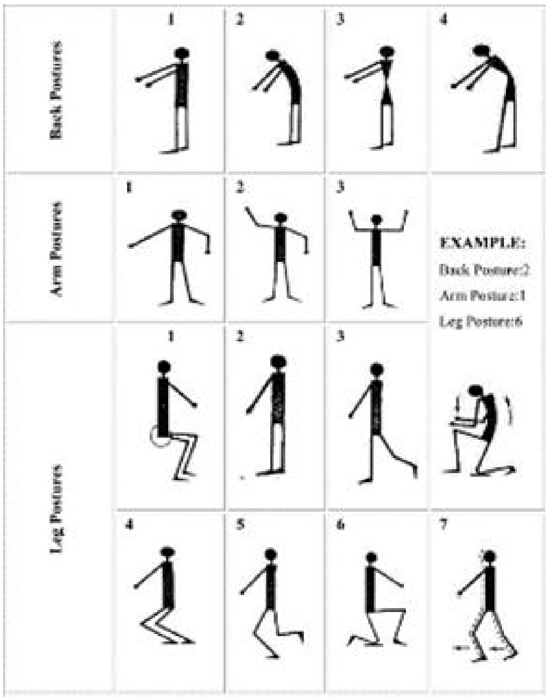


Figure 1.2: List of items classified by OWAS (Karhu et al., 1977)

Finally, the OWAS method provides one single-digit score for each part of the body, starting from the back, arms, legs, and the loads carried during the activity. These four digits are used as input for the table that includes all possible combinations of digits and their corresponding risk (Figure 1.3).

		BACK	1			2			3			4		
		ARMS	1	2	3	1	2	3	1	2	3	1	2	3
LEGS LOAD	1	1	1	1	1	2	2	3	1	2	2	2	3	4
		2	1	1	1	2	2	3	1	2	2	3	3	4
		3	1	1	1	3	3	4	1	3	3	3	4	4
	2	1	1	1	1	2	2	2	1	1	1	2	2	2
		2	1	1	1	2	2	2	1	1	1	2	3	3
		3	1	1	1	3	3	3	1	1	1	3	4	4
	3	1	1	1	1	2	2	3	1	1	2	2	3	3
		2	1	1	1	2	3	3	1	1	3	3	3	3
		3	1	1	1	3	3	3	2	2	3	3	4	4
	4	1	2	2	2	3	3	3	3	4	4	4	4	4
		2	2	2	2	3	4	4	3	4	4	4	4	4
		3	2	2	3	3	4	4	3	4	4	4	4	4
	5	1	2	2	2	3	3	4	4	4	4	4	4	4
		2	2	2	2	3	4	4	4	4	4	4	4	4
		3	2	2	3	3	4	4	4	4	4	4	4	4
	6	1	1	1	1	2	3	4	1	2	4	4	4	4
		2	1	1	1	2	3	4	1	2	4	4	4	4
		3	1	1	1	3	4	4	1	2	4	4	4	4
	7	1	1	1	1	2	2	2	1	1	1	2	2	2
		2	1	1	1	3	3	3	1	1	1	3	3	3
		3	1	1	2	3	4	4	1	1	2	4	4	4

Figure 1.3: Risk indices per body posture calculation (Louhevaara and Suurnäkki, 1992)

1.2.2.3 RULA

Rapid Upper Limb Assessment (RULA) (McAtamney & Nigel Corlett, 1993) represents a posture, force, and muscle use assessment tool widely adopted in the literature to perform ergonomic investigations of workplaces, where the upper limbs of the worker are mainly involved in the progression of the job. The RULA method adopts diagrams of body postures and joint angles based on previous studies in the literature with three scoring tables to provide an assessment of exposure to risk factors. It aims to be a method to rapidly screen the working population for exposure to upper limb disorders related to work. RULA was developed without the need for special equipment, with the aim of being a method that was easy to use to report discomfort to the operator's body parts. Its development starts with the activity of recording the working posture, by observing the operator during several work cycles to detect the posture that needs to be assessed. The scoring system is then adopted, and finally, the scale of action levels provides a guide to the level of risk and a roadmap to conduct a more detailed assessment. The scoring system for the method varies from 1 to 7 (Figure 1.4) where number 1 reports the range of movements or working postures with minimal risk factor (i.e., acceptable work conditions), while the higher the score, the more extreme postures and risk factors that characterize the body segment. A score of 3 or 4 determines the need to conduct a further investigation with possible required changes. A grand score of 5 or 6 points out that the working postures are not within a suitable range of motion, so investigations are required soon, and changes need to be made in short term. A total score of 7 denotes immediate changes in activity performed to reduce excessive loading of the musculoskeletal system and the risk of injury to the operator.

RULA is one of the most popular observational methods in the industrial field and is cited by the ISO standard (ISO 11228-3, 2007) (E) as one of the simplified methods for fast EPR analysis of mainly static tasks; however, it also presents some limitations to its adoption. The system represents each segment of the body in the sagittal plane; then, when abduction occurs, the scoring system to be adopted is not reported on the diagram. In fact, only one side of the body (i.e., the right side or the left side) can be evaluated at a time; the evaluation does not include an overall score for the whole body. Furthermore, the postural assessment of the fingers and thumbs is not included in the RULA score, although the force exerted by the fingers is part of the evaluation procedure.

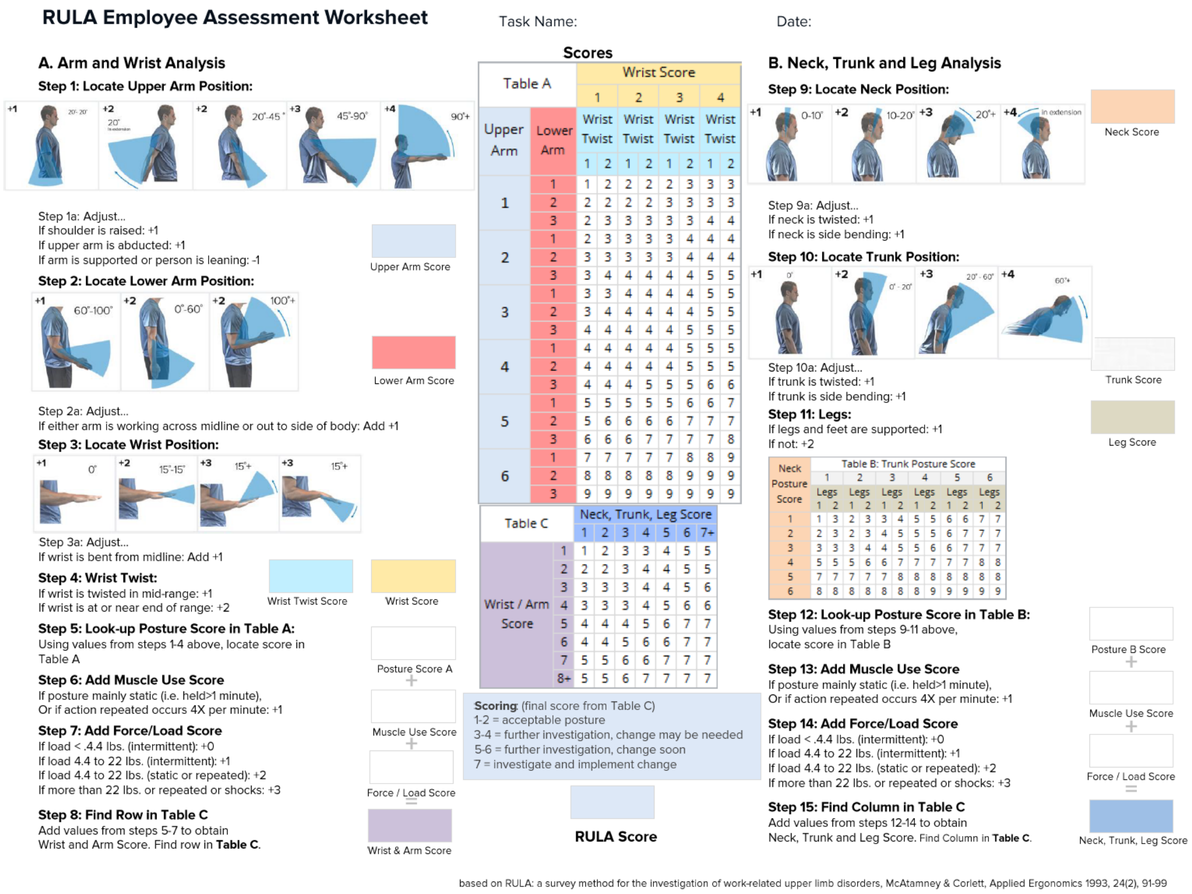


Figure 1.4: RULA worksheet (illustration from Ergo-plus.com)

1.2.2.4 REBA

Rapid Entire Body Assessment (REBA) (Hignett & McAtamney, 2000) was developed as a field tool for practitioners to detect the risk of musculoskeletal injury associated with recorded postures. Its development was inspired from several techniques including NIOSH (Waters et al., 1993), Rated Perceived Exertion (Borg et al., 1985), OWAS, Body Part

Discomfort Survey (Corlett & Bishop, 1976) and RULA. Compared to RULA, the REBA method includes static and dynamic postural loading factors, human-load interface (i.e., coupling score) and the concept of gravity-assisted upper limb position (Figure 1.5). Moreover, it aims to compensate for the high generality in performing a postural analysis method deriving from OWAS, which can provide low detailed results due to its wide range of use, and the need of highly detailed information regarding specific parameters of the posture that are required to progress NIOSH. In summary, the REBA method is an analysis system that gives an action level with an indication of urgency without the need of sophisticated equipment. Its risk scores can range from 1 to 15, divided into 5 levels of action of ergonomic intervention, where the risk score of 1 represents a negligible risk level with no necessary action or further evaluation, while a score between 11 and 15 implies a very high-risk level and immediate interventions in the posture analyzed.

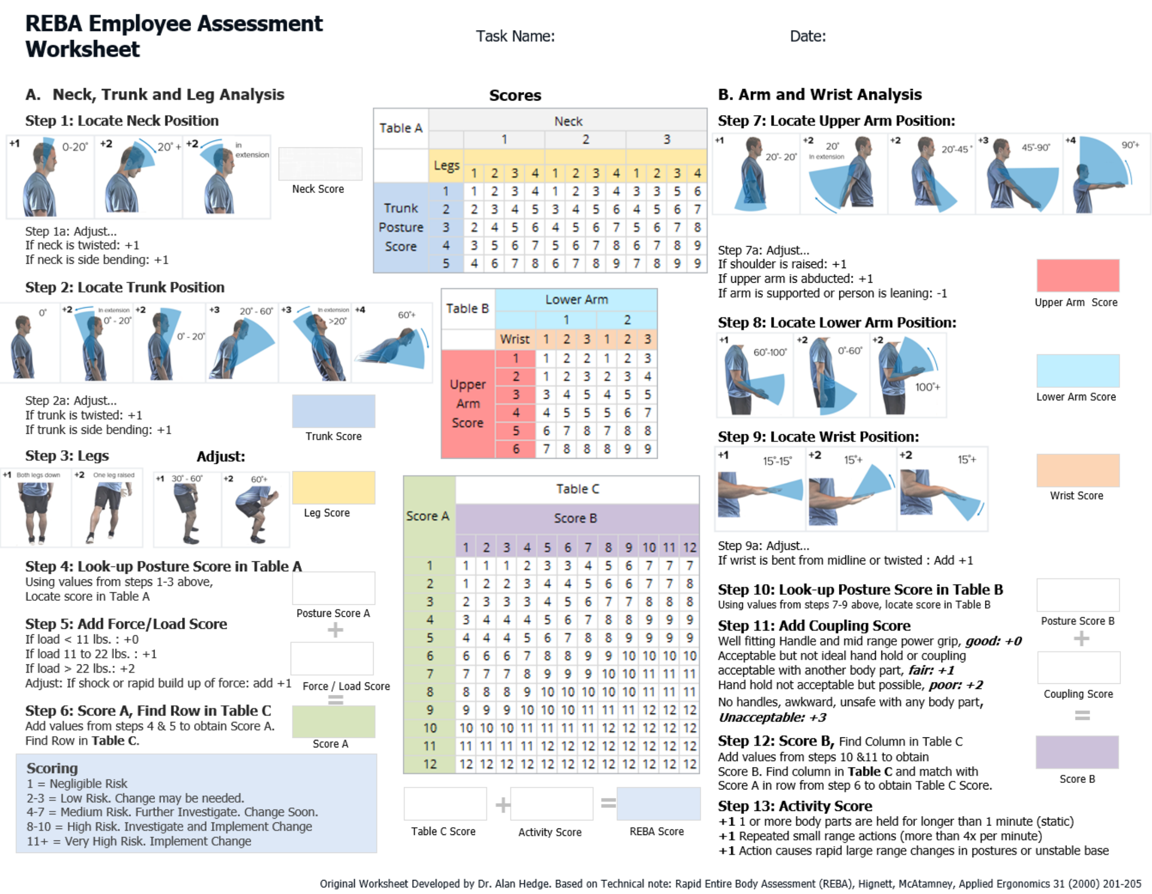


Figure 1.5: REBA worksheet (illustration from Ergo-plus.com)

RULA and REBA are two similar methods for detecting and identify harmful postures. RULA is more suitable for intensive hand-arm activities, such as sitting assembly work. At the same time, REBA evaluates the entire body and is more appropriate when both upper and lower extremities are involved, such as during picking or construction activities. Generally, several snapshot observations are taken to assess the most critical work position and posture. Nowadays, the possibility that RULA and REBA scores are influenced by the subjectivity of the evaluator is minimized thanks to automation of posture risk assessment, which allows one to have precise results in short time.

1.2.2.5 PERA

Postural Ergonomic Risk Assessment (PERA) (Chander & Cavatorta, 2017) contributes to fill the gap in risk assessment methods that do not consider cyclical work in their metrics. This method was recently developed and is suitable for evaluating short cyclic assembly work, with a detailed analysis of every task in the work cycle. PERA is also in compliance with (ISO 11226:2000, 2018) and EN 1005-4 and with the European Assembly Worksheet (EAWS) (Schaub et al., 2013) to ensure industrial relevance. The method progresses to seven main steps starting from work cycle segmentation, task posture, and force analysis categorization in terms of risk and finally score calculation. Three main parameters are considered in the PERA methods, which are: posture, force, and duration (Figure 1.6).

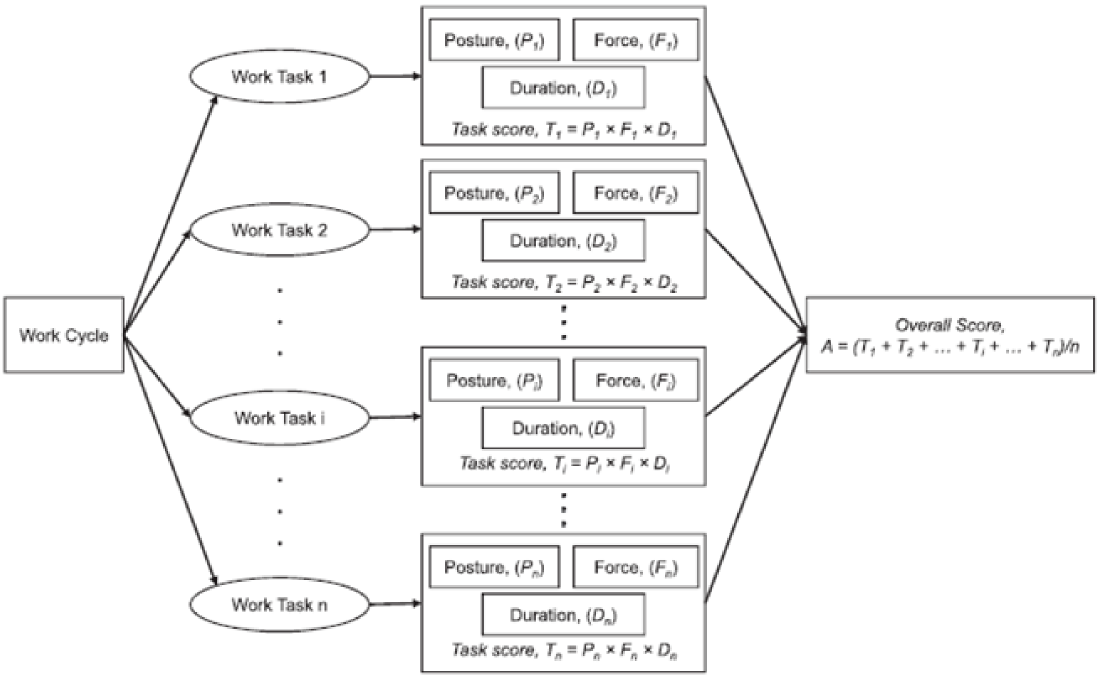


Figure 1.6: Overall PERA score of the work cycle (Chander & Cavatorta, 2017)

The score for each activity is progressed with a cube method which multiplies the single score for each of these parameters, such as:

$$T_i = posture_i * force_i * duration_i \tag{1.3}$$

while the overall work cycle score is calculated as the average value of the scores obtained from the analysis of a single task:

$$A = {}^{\sum T_i}/_{n} \tag{1.4}$$

PERA has a risk classification of three levels starting with the lower level, achieved with an overall score of less than 4, a medium risk level if the risk score is between 4 and 7 and finally a high-risk level whenever the risk score overcomes the value of 7.

1.2.3 Energy expenditure

Energy expenditure represents another valuable method to assess safety risk assessment of activities that involve the entire operator's body for their progression (Garg et al., 1978). It allows detecting the set of activities that lead workers to perform strenuous physical effort and identifying the root causes of the overcoming of workers' abilities (Ilmarinen & Tuomi, 1992). The maximum threshold an individual can achieve during job execution, without perceiving fatigue effects, is represented by the Maximum Acceptable Energy Expenditure (MAEE) (Saltin & Astrand, 1967). This limit was initially established at 33% of the maximum aerobic capacity of an individual, which represents the maximum amount of energy an individual can spend during job execution; however, technological devices today can help to better estimate this threshold by monitoring body activity in real time. Recently, the introduction of smart technologies in the manufacturing work field has allowed the adoption of new tools and instruments, such as heart rate devices, to measure worker effort in real time (Battini et al., 2022). When MAEE is exceeded, accumulated fatigue arises and physical stress occurs (Konz, 2000).

To avoid deterioration of the physical capacity of workers, rest breaks can help workers recover from fatigue accumulation. In this sense, the rest allowance (RA), which is the time needed for adequate rest after executing static or dynamic exertion (Rohmert, 1973), began to be introduced within mathematical models. The literature reports several ways to evaluate RA (El ahrache & Imbeau, 2009). However, some of these methods require data on the maximum voluntary contraction or endurance time, which require specific tools and competencies to correctly perform data collection (e.g., electromyography (EMG) sensors). Moreover, they cannot be easily collected in the industrial work field, so laboratory data are considered. The formulation of RA defined by Price (1990) represents a good compromise between the accuracy of the output and the difficulty in obtaining input data to evaluate the amount of time each worker should rest to fully recover from fatigue.

In Price (1990), MAEE is assumed to be 4.3 kcal/min, and it represents 33% of the maximum aerobic capacity of a healthy man (40 years old, 1.75 m and 70 kg). According to Price (1990), RA is defined as Equation (1.5):

$$RA = max\left\{0; \frac{EE - ET_{\max}}{ET_{\max} - ET_R}\right\} \tag{1.5}$$

where:

- EE: Mean energy expenditure. It is the mean rate of work that can be considered during a defined period. It is defined as the ratio of the total amount of energy expended in executing a job on the execution time.
- $ET_{\max}$: MAEE; 4.3 $Kcal/min$ represents the value assumed for a 40-year-old worker who works 8 hours continuously.
- ET_R: Energy expenditure during rest. It represents the relaxation rate of 1.86 kcal/min if the worker is in a standing position or 1.64 kcal/min if the worker is sitting.

1.2.3.1 Energy expenditure of the ageing workforce

Following Price (1990) formulation, MAEE is set on the average value of a 40-year-old healthy man. Considering the high level of heterogeneity that characterizes the manufacturing industry, this assumption could underestimate the need for ageing workers to have more rest to fully recover from fatigue. Furthermore, MAEE has been shown to be affected by sex, age, body weight, and body height (Wu & Wang, 2002). Consequently, MAEE must be adapted to workers according to their personal characteristics. In fact, according to Price's formulation, RA occurs if energy expenditure exceeds the threshold value of 4.3 kcal/min for every worker. To better fit the RA to the physical features of each individual, Finco et al. (2019) modified the Price (1990) formulation as Equation (1.6):

$$RA = max\left\{0; \frac{EE - MAEE}{MAEE - ET_R}\right\} \tag{1.6}$$

where MAEE varies according to the age and body weight (BW) of the worker as defined in the formula provided by De Souza Silva et al. (2016):

$$MAEE = 0.0016[(60 - 0.55 * AGE) * BW] \tag{1.7}$$

In Figure 1.7 the variation of MAEE according to the age of the worker. The older the age, the lower the MAEE, expressed in Watt. For this reason, for older workers, a longer period of time is needed because they often exceed their maximum threshold during work.

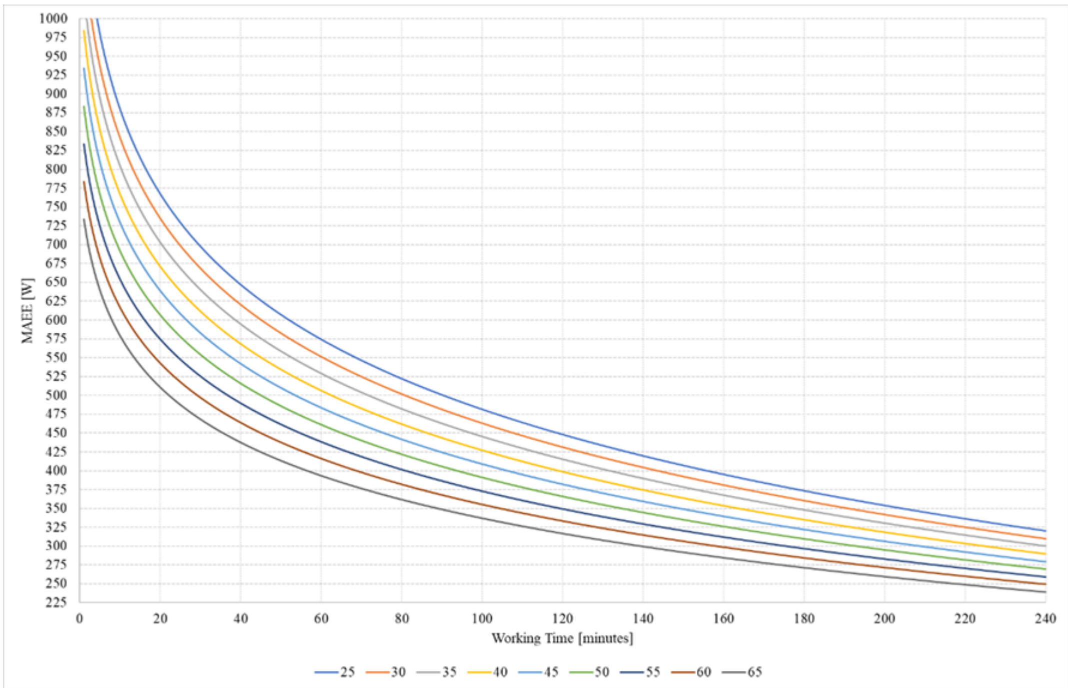


Figure 1.7: Male's worker maximum acceptable energy expenditure (Finco et al., 2019)

1.3 How to reduce postural risk

Occupational risk assessment analyzes are often progressed late in the process and are often initiated reactively from employee reports of symptoms, disorders, or disabilities (Eliasson et al., 2019). Proactive risk management can anticipate risk assessment by moving risk assessment of potential hazards in earlier stages, even before symptoms such as work-related pain have already emerged. Traditional work techniques adopt ergonomist or safety experts to progress workers' training, resulting in time-consuming and resource intensive analyses. Biofeedback training represents an effective and efficient training method, as it promotes worker self-training (Lind & Rose, 2016). Therefore, there is the potential to apply extrinsic direct feedback training in combination with cost-effective movement tracking of workers to assess risks associated with physical loads (Lind et al., 2020). Furthermore, the latest technological advancements fostered by Industry 4.0 allow research and industrial sectors to develop new approaches and methods for conducting postural risk assessment and training for the workforce.

Providing real-time feedback to workers during work activities requires a system that is capable of rapidly assessing their posture and quickly giving feedback to correct their behavior in real-time, ultimately avoiding the risk of WRMSD. Recently, Kadir et al. (2019) analyzed the interaction between Industry 4.0 systems and human factors and highlighted that wearable and handheld devices lead to improvements in ergonomic feedback. Depending on the application sector, different technologies have emerged in the literature that seek to correct worker behavior. The construction field has been extensively researched due to the dangerous positions that workers assume during the progression of the task. In this sector, the feedback intervention has yielded the best results in terms of training and posture correction for trunk position (Yan et al., 2017, 2018), especially in lifting activities, but also for the lower back, legs and joint angles (Valero et al., 2016). The presence of many obstacles in the workplace means that it is not always easy to monitor the performance of workers.

Virtual reality (VR) and immersive reality (IR) represent solutions to achieve posture monitoring wherever other technologies cannot work (Akanmu et al., 2020; Daria et al., 2018; Simonetto et al., 2022; Sivanathan et al., 2014). Another sector monitors the effect of feedback on caregivers and nurses during work activities and during the training phase. Researchers have tested wearable devices and garments with real-time auditory biofeedback or vibrotactile intervention (Doss et al., 2018; Kamachi et al., 2020; Owlia et al., 2019), prototypes of systems that educate student trainees' lifting behaviors (Bootsman et al., 2019) by providing improved movement strategies for spine postures or posture rehabilitation, and real-time feedback provision for correct training (Alahakone & Senanayake, 2010).

Moving into the manufacturing sector, the literature contains several examples of wearable devices and prototypes of systems that advance training techniques through real-time feedback intervention. Some of these systems can progress the full body assessment and provide feedback to workers during dedicated actions or movements such as lifting activities (Delpresto et al., 2013) as well as (and mainly) during daily work through visual (Z. Li et al., 2020; T. B. Otto et al., 2017) and vibrotactile stimuli (Lins et al., 2018; Mgbemena et al., 2018). However, most of the activities carried out by the workforce in industrial contexts involve the upper bodies; therefore, most of the relevant literature focuses only on upper extremity movements. Here, optical motion capture (MOCAP) systems are adopted to track body movements in static activities (e.g., workers do not need to leave their workstations to progress the overall task). In this case, the feedback provision is mainly actuated through visual graphical interfaces on the monitors (Kim et al., 2018) or directly projected on the job (Mengoni et al., 2018).

Wearable devices become necessary to track body movements in the workplace whenever the progression of tasks requires the displacement of workers. Recent smart garment prototypes have been developed to advance vibrotactile feedback intervention in general manufacturing activities (Cerqueira et al., 2020), picking simulations (Lind et al., 2020), and automotive assembly tasks (Raso et al., 2018). Real-time postural feedback intervention and postural risk assessment are rarely progressed together by the same software or platform (Lim & D'Souza, 2020).

In a pioneering contribution, Vignais et al. (2013) developed a promising system to perform both a real-time postural risk assessment and feedback provision. Arroyave-Tobón & Osorio-Gómez (2017) give a similar example: they provide visual real-time feedback along with a postural risk assessment through head-mounted displays (HMDs) of users. The continuous advancement in automation has created the opportunity to involve collaborative robots to support worker activities. Busch et al. (2017) provided evidence that robot behavior can lead workers toward posture correction through real-time posture analysis and visual feedback correction. Manghisi et al. (2020) proposed an automatic software tool for ergonomic postural risk monitoring with a visual graphical user interface focusing mainly on upper body assessment. The authors adopt visual and acoustic feedback as their feedback intervention method.

Table 1.3 provides a summary of the works, highlighting the type of intervention provided to the worker and the system adopted to interact with the user. It should be noted that most of the contributions collected in Table 1.3 based the feedback intervention of their systems and prototypes on the joint angle thresholds adopted in the observational methods reported in Section 1.2.2.

Table 1.3 Notations: Application sector: M: Manufacturing; C: Construction; H: Healthcare; R: Rehabilitation; MMH: Manual material handling; real-time feedback: I: Interface visual; A: Auditory; H: Haptic; V: Vibration; VR: Virtual Reality; AR: Augmented Reality.

Table 1.3: Published works on feedback intervention and real-time ergonomic assessment

Reference	***Motion capture system***	***Application sector***	***Body Parts Analyzed***	***Real-time feedback***	***Feedback threshold based on***	***Real-time ergonomic indexes***
(Vignais et al., 2013)	Inertial (7 IMUs)	MMH	Upper	I (AR) - A	RULA	*RULA*
(Delpresto et al., 2013)	Markerless	M	Full	I	NIOSH	-
(Busch et al., 2017)	Markerless	M	Full	I	REBA	-
(Yan et al., 2017)	Inertial (2 IMUs)	C	Trunk	I - A	ISO 11226:2000	-
Arroyave et al. (2017)	Markerless	M	Upper	I (AR)	RULA	*RULA*
Otto et al. (2017)	Accelerometers	M	Full	I	RULA; REBA	-
(Yan et al., 2018)	Inertial (2 IMUs)	C	Trunk	I - A	OWAS	-
(Mengoni et al., 2018)	Markerless	M	Upper	I	RULA	*RULA*
(Kim et al., 2018)	Inertial (1 IMU)	M	Trunk	I - V	Customized	-
Lins et al. (2018)	Markerless	M	Upper	V	OWAS	-
(Raso et al., 2018)	Strain sensors	MMH	Upper	I - H	EAWS	-
(Owlia et al., 2019)	Inertial (2 IMUs)	H	Trunk	A	Customized	-
(Doss et al., 2018)	Accelerometers	H	Trunk	A	Customized	-
(Mgbemena et al., 2018)	Markerless	M	Upper	I	RULA	-
(Bootsman et al., 2019)	Inertial (2 IMUs)	H	Trunk	A - V	Customized	-
(Cerqueira et al., 2020)	Inertial (4 IMUs)	M	Upper	V	RULA; LUBA	-
(Kamachi et al., 2020)	Inertial (2 IMUs)	H	Trunk	A	Customized	-
(Lind et al., 2020)	Inertial (3 IMUs)	MMH	Upper	V	Customized	-
(Akanmu et al., 2020)	Inertial (19 IMUs)	C	Full	I (VR)	ISO 11226:2000; PERA	-
(Manghisi et al., 2020)	Markerless	M	Upper	A - V	RULA	*RULA*
(Zhao et al., 2021)	Markerless	C	Full	V	OWAS	-

Conclusion

Based on the literature review in the research field of job rotation scheduling models, I can conclude that only few previous works have progressed postural risk assessment and feedback intervention at the same time. A recent review proposed by Stefana et al. (2021) reported that a limited number of studies evaluated and improved safety risk factors using feedback strategies. Most of the existing research provides feedback on the calculation of an ergonomic index (Vignais et al., 2013), and only a few evaluate multiple ergonomic indexes in real time (Akanmu et al., 2020; Cerqueira, Moreira, et al., 2020; T. B. Otto et al., 2017).

Evaluating multiple risk indexes at the same time means collecting personal data from the workforce, comprising historical medical data, to avoid job assignment that can threaten the safety of operators. Privacy issue can arise from personal data collection, and benefits cannot be those expected from the company. The assignment performed on individual profile and recovery time according to the characteristics of the workforce could give the impression to the workers that they are not treated fairly and differently by their employer. The consequences and the main impact of job rotation strategies have been already investigated in literature (Foroutan et al., 2021), however, job rotation strategies are extremely useful in contexts where strenuous workload or high repetition of the same set of activities can become hazardous for the employees.

For this reason, and to contribute to the current state-of-the-art, my research aims to first provide a tool to help managing the complexity generated from the introduction of multiple sociotechnical aspects within operational decisions. Then, a new digital platform and a new model are provided to help data collection and to integrate all the new data collected in real-time to make quick decisions, respectively.

2

Flexible Workforce Management

Introduction

Based on literature findings on job rotation scheduling problem, rare contributions can jointly include both social and technical aspects regarding workforce participation in operational decisions and worker safety and well-being in an industrial context. For this reason, in this chapter, I propose a new methodological framework to integrate sociotechnical aspects and human factors into the scheduling decision process. The methodological approach defines a step-by-step procedure to progress inclusive and flexible work arrangements based on individual characteristics, preferences, and perspectives of the workforce. For this reason, to help company managers develop human-oriented scheduling work plans, this framework aims to be a useful tool to promote task allocation decisions with greater awareness of worker diversity.

2.1 Framework structure

The methodological framework proposed in this chapter integrates anthropometric and ergonomic measures during the job scheduling decision process, and defines steps needed to define a worker-oriented and flexible scheduling of jobs. Each task is classified in the framework according to three drivers: physical stress, occupational risk, and execution time. Based on the characteristics of each activity and worker, this framework proposes a step-by-step procedure that can help practitioners select the most suitable worker for each task assignment, with the aim of reaching flexible scheduling by an inclusive workforce. In addition, another key aspect of the following method is represented by the procedure for the introduction of new employees into the workplace. It is extremely important to immediately profile new workers to understand the characteristics of the workforce and define the training needed for new workers from both a quality and ergonomic perspective.

The novelty of this approach, compared to the existing literature, is related to the progression of a step-by-step framework that can demonstrate a singular deficiency in risk propension. In some previous work, job risk indexes were defined starting from the average score progressed by a group of workers. This approach is surely faster, but it can also penalize less-skilled operators, from an ergonomic viewpoint, due to the scarce or absent training phase or by neglecting individual risk propensity for certain activities. However, with this approach, the main obstacle is related to the need for an accurate occupational risk assessment for each operator, which can be time and cost consuming. Furthermore, another main problem with the integration of workforce diversity in mathematical models and methods is the difficulty in evaluating the differences between workers involved in the manufacturing system.

For this reason, this research aims to propose a new framework to involve the perspectives of the workforce and the maintenance of healthcare care through occupational risk prevention. The procedure proposed by this framework consists of the integration of different inputs derived from three main analyses:

- Job analysis defines the characteristics of each job and the common risks related to its execution, also related to workstation design.
- The analysis involves the perception of workers and their health status. It also considers the operator-job fitness according to individual preference and aptitude.
- Ergo-time analysis is progressed with the inertial MOCAP system to assess ergonomic postural risk and physical effort from the heart rate monitoring device. This analysis also

provides the execution time of the job and helps to determine the level of experience of each operator.

The main objective of this framework concerns the individualization of the different quantifiable aspects related to the personal profile of the workforce to perform the job scheduling and workload balancing decision in several workplaces. This new methodology aims to describe the data integration process, starting from the initial data acquisition phase followed by the quantification of the safety risks and concluding with managerial insight from the JRSP solution approach. The procedure consists of eight steps to be executed, some in parallel and some in sequence, to finally obtain an effective worker-oriented job rotation and job assignment solution (Figure 2.1).

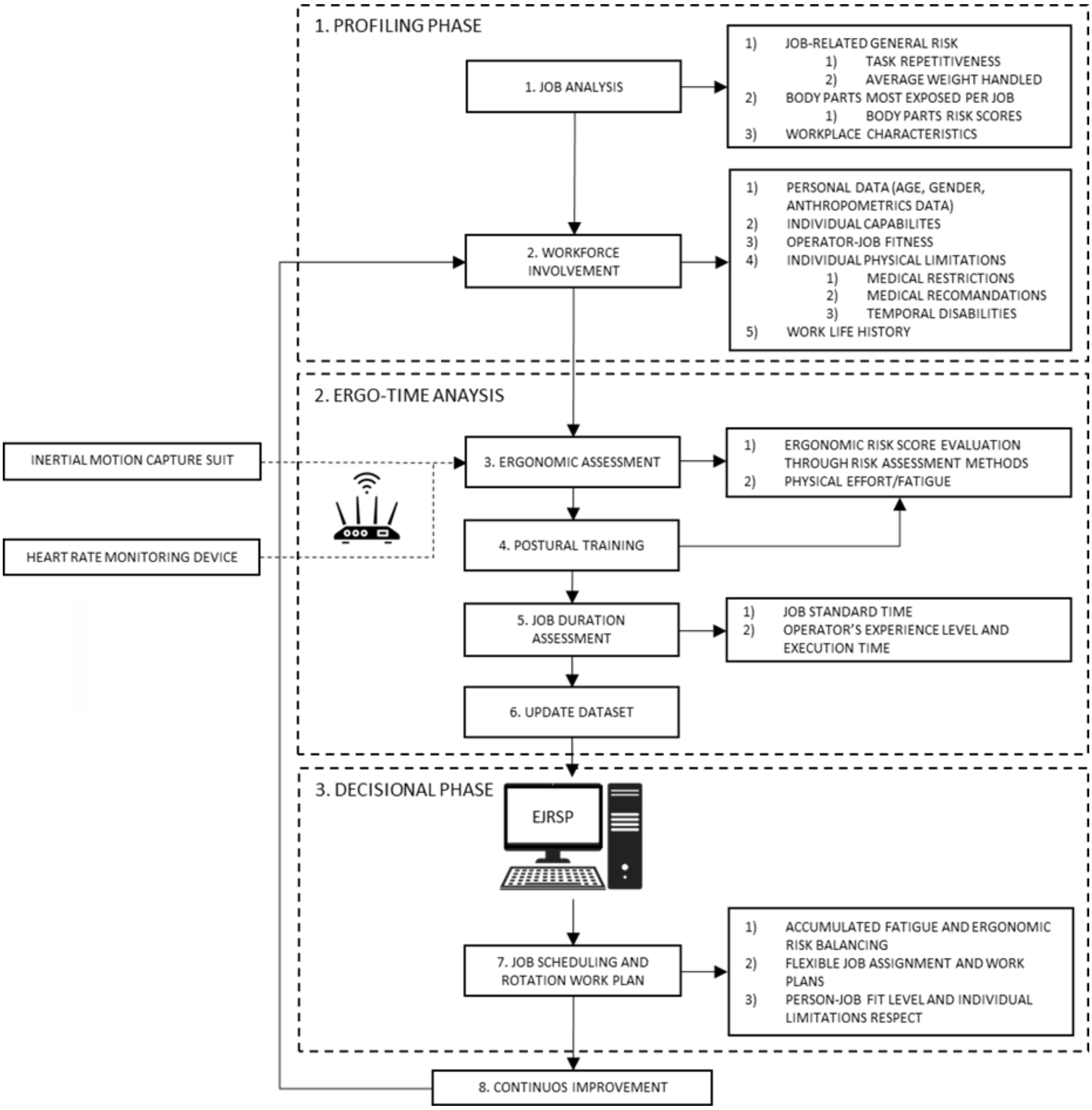


Figure 2.1: Methodological Framework

2.1.1 Profiling phase

The profiling phase deals with the initial collection of workforce data. In this phase, workers are involved to collect, for each job, some insight about the job description and physical attitude. Moreover, this phase aims to create updated profiles for each job and operator. Step 1 reports an exhaustive description of the job depending on its characteristics, such as the repetitiveness of actions, or the part of the body that is more exposed to musculoskeletal risk, the noise level, and vibration exposure during the progression of the job. Step 2 involves the operator's opinion and perception about the personal health condition and the preference for job assignment preference (e.g., which work plan fits the capabilities of most operators in terms of competence, skills, and attitude). Another important aspect is related to the skills developed in the workforce. For this reason, skills are collected in the matrix where a binary parameter specifies whether a worker can perform a particular job or not. In phase 2, the subjective workload assessment is measured according to the NASA Task Load Index (Hart & Staveland, 1988). In this way, the mental demand is also measured, as well as the frustration of performing such kinds of task. In addition, from the point of view of the workforce, it is also possible to highlight shared opinions and evaluations on the part of the body, involved in the completion of the job, the most exposed to risk. Workers can provide subjective feedback according to the Borg C10 scale and in such a way they can also provide a quick measure of physical and muscular fatigue (Morishita et al., 2013). However, in this case, scores assigned to each task are influenced both by workstation design and by the sequence of activities to be performed in job execution and, for this reason, different scenarios are created.

The most innovative aspect of the profiling phase concerns the collection of past, temporary, or permanent physical limitations of workers and operators' perceptions to perform improved values of job-operator fitness (Botti et al., 2021). In fact, it has been shown that each worker's life history has certainly an impact on future work ability, especially for older workers (Fischer & Martinez, 2013). In this way, the rotation of jobs can better fit the physical and cognitive level of the worker. For this reason, the integration of sociotechnical data from the workforce involvement phase and the quantitative and qualitative information collected in this framework represent novelty and is useful in completing the data set with all the necessary data as input for the model to solve JRSP and to find optimal solutions, depending on the objectives of the company and the desired performance.

In addition to the job-operator fitness score, physical restrictions and possible chronic diseases must be collected for each part of the body of each worker. These data are collected from occupational medicine practitioners, but also directly from the opinions of the workforce through questionnaire and self-evaluation approaches, developed to capture in advance possible incoming musculoskeletal disorders or to avoid an aggravation of global health status. These methods can help companies assess the actual health condition of the workforce and the proneness to permanent or temporal injuries. This information becomes useful in avoiding job assignment, which can foster consequences such as absenteeism of the workforce and the relative costs that arise.

2.1.2 Ergo-time phase

Thanks to the rapid technological advancement fostered by the fourth industrial revolution, which bases its principles on data collection, new devices are continuously introduced into the market at accessible and more affordable prices (Menolotto et al., 2020). To perform a precise evaluation of working posture and define relative postural risks during work progression, smart technologies such as MOCAP systems are also currently being adopted in the manufacturing field. The integration of these technologies allows us to save time and costs during posture assessment during the worker training phase. The amount of data needed to perform a postural risk assessment for each operator is collected during the initial postural assessment. The execution of each job is performed using a MOCAP system, which consists of several IMUs placed throughout the body. Data are collected and processed by a software platform capable of calculating postural risk in real time through the most suitable international indicator for the job analyzed. In addition, direct feedback is given to the worker since they can see the monitor in front of their workplace and easily understand which part of the body is the most stressed from an ergonomic point of view.

Ergo-time analysis starts with an ergonomic evaluation (Step 3) to assess the initial level of ergonomic experience of each worker. In fact, due to the strong turnover effect, new employees can perform the same job in several ways, depending on their attitude and level of experience. This step assesses whether the worker needs to perform postural training with a real-time feedback intervention and suggestions from some practitioners, with the aim of educating the operator to behave with proper movements to reduce postural risk. It is assumed that after the postural training session (Step 4) the job risk score is reduced to the lowest level due to the training activity performed. Furthermore, in this phase, the amount of accumulated physical fatigue and stress for each worker can be monitored for further analysis (e.g., in the form of energy expenditure consumption, heart rate, oxygen consumption). Heart rate monitoring systems are today easily affordable and reliable devices to monitor the heart rate of the worker. For example, they can be adopted to calculate energy expenditure for individuals (Li et al., 1993). In this way, postural risk can be smothered together with physical effort in the job scheduling activity. This information reflects the fact that different operators can process the same job progressing with different amounts of fatigue, depending on the age and physical condition of the worker. In this phase, ergonomic data are collected for each task, each worker, and each part of the body involved. Since the threshold limit on the postures changes according to the type of activity they are performing, in this phase ergonomic experts are involved. Step 4 does not collect performance data. For this reason, Step 5 performs a job duration assessment to provide information about the level of experience of each worker compared to the standard time of job completion. This information can be displayed both as the real job duration per each operator or by the incidence of experience and the worker's ability compared to the standard completion time of job completion. Once the level of experience of the workforce, the duration of the job, the postural risk score and the physical effort values have been collected, the data set of the workforce is updated (Step 6) with all the information from the profile phase (Step 1 and Step 2) and from the ergo-time analysis (from Step 3 to Step 5).

2.1.3 Decisional phase

Once the data acquisition process is completed and ergonomic indicators, attesting the risk proneness related to work for each worker, are finally progressed, the integration phase (Step 7) in the JRSP can be initialized. According to the type of activity, the appropriate ergonomic index is selected; for example, in picking activities, the NIOSH index may be the most suitable one. Additionally, supplemental constraints are included in the model to consider the physical and cognitive limits of each worker. In particular, constraints related to fatigue, as well as those related to mental demand, are always included.

Since the data required in the model can be collected easily and faster, the model can be applied each time new workers are involved, and new tasks are introduced in the manufacturing field. This approach can ensure a balanced workload to the workforce depending on individual physical characteristics and flexible work plans to smooth and balance the risk exposure. Physical limitations, collected and constantly updated with the continuous improvement phase (Step 8), will ensure feasible job rotation schedules by the restrictions imposed on operators who cannot perform some activities, avoiding the appearance of physical impairments and musculoskeletal disorders.

2.2 Practical application

The methodological framework proposed in this chapter includes many sociotechnical factors in the analysis, which can be difficult to collect for all real applications. For this reason, in this section, a simplified application of the proposed structure is presented and described, which only includes a fraction of the aspects in the methodological framework.

For this application, the initial profiling phase starts to collect information on the workforce regarding individual physical limitations, to avoid strenuous job assignment, which can increase the chance of developing musculoskeletal disorders or injuries. Information on age and gender of workers are gathered to adopt the formulas developed by Finco et al. (2019) that calculate energy consumptions and recovery times for workers of different age and gender. The duration of the task is calculated according to the individual expertise of the workers and adjusted with the ergo-time analysis performed with the adoption of a digital system. In addition, participation in the workforce is required to determine the similarity between different jobs according to the previous experience of the workers in each task progression. Digital sensors can be adopted to collect information related to workplace risks, such as noise and vibration levels, for each area where jobs are performed. On the contrary, the formulas designed by Finco et al. (2020) can be adopted to estimate the exposure to vibrations in manufacturing systems.

In ergo-time analysis, the digital real-time platform for full-body ergonomic assessment and feedback developed by Battini et al. (2022), and presented in the next chapter, can be used to calculate ergonomic parameters from wearable worker sensors. The platform was validated with laboratory tests. It uses sensors that provide workers' input data to the final model for targeting and assigning jobs appropriate to the worker. The work of Finco et al. (2019, 2020) and Battini et al. (2022) is consistent with the methodological approach described in this chapter (Berti et al., 2021).

Lastly, the goal of the decisional phase of the proposed framework is based on data collected in previous steps to calculate flexible and human-centric work plans based on the characteristics of the workers. Figure 2.2, derives from and extends the overall structure of the framework and shows how the new optimization model can be seen as the culminating step of a whole human-centric methodology.

Theoretical logic also finds support from the new international standards published by ISO in 2022 (ISO 25550, 2022), which provide specific requirements and guidelines to achieve an age-inclusive workforce. ISO directs attention to making available options for flexibility in job assignments and working arrangements to accommodate age-related factors. Such options include flex-time, job sharing, job redesign, swapping shifts, allowing time to adapt to new tasks and flexibility in rest breaks during working shifts. Such facilitations in work conditions are envisaged to benefit older workers potentially and especially and may also help workers with health problems work consistently and stay longer in the workforce. Recent academic literature is beginning to develop worker-inclusive decision-making tools and flexible, human-centric job scheduling models. Some stress the need to involve the worker in the individual data collection phase and in the decision-making phase to develop more work-inclusive solutions (Finco et al., 2020; Sgarbossa et al., 2020; Vijayakumar et al., 2022).

Recent works in job rotation scheduling already include HF (i.e., occupational risks related to postures and fatigue, experience/skill levels) in both long- and short-term decisions (i.e., Mehdizadeh et al., 2020; Mossa et al., 2016). However, they often neglect to consider worker attributes and ignore various complexities of worker involvement in input data estimation.

Conclusion

Based on the theoretical fundamentals discussed earlier and inspired by the concepts shared by Industry 5.0 vision, this framework proposes a new human-centric guide to collect information useful for solving a multi-objective Job Rotation Scheduling problem. The final model, which will be detailed in the final chapter of this dissertation, breaks new ground by jointly considering a variety of realistic shop floor sociotechnical factors in JRS: ergonomic postural scores, vibration and noise risk constraints (respecting international standards threshold values), worker experience in performing jobs, and individual physical limitations. Furthermore, workers' opinion is considered to define a similarity score between jobs, which can be useful in finding solutions to minimize worker boredom. As an extension of the current framework, learning and forgetting curves can be included to better detail the effect that frequent rotation periods can have on workers’ performance and skills.

Moreover, the environmental parameters such as temperature, humidity and light conditions can provide additional insights to the current version of the methodological framework.

The level of automation of the company can also be interesting data to collect to detail with more precision supplementary the level of information related to the technology with which the workforce must deal, to predict the impact on the performance and level of usability.

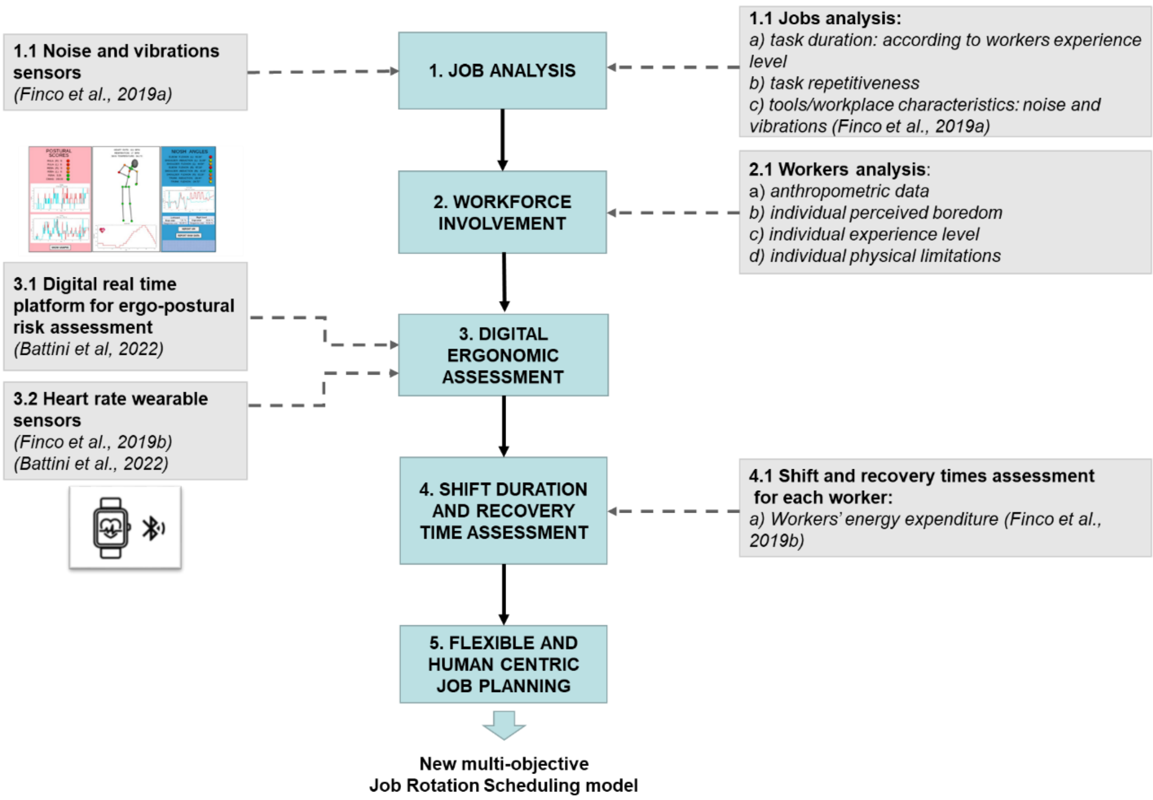


Figure 2.2: Theoretical-based methodological framework supporting the implementation of the new JRS model (derived from Berti et al., 2021)

3

Real-time digital ergonomic platform

Introduction

This chapter first provides a brief overview of direct measurement systems to integrate Section 1.2 on occupational risk assessment methods and approaches. Then, starting from the literature survey reported in Section 1.3 on the available systems and prototypes able to provide real-time feedback to users based on the assumed posture, it presents a new digital platform to simultaneously progress real-time postural risk assessment and training session. A benchmark analysis is also provided to highlight the innovation of the digital platform compared to some of the most well-known and adopted software and ergonomic risk analysis tools. The results of the platform were tested and validated with commercial software, and finally it was adopted to progress risk assessment in a real industrial case and for some single- and multi-person risk assessment and training session in the laboratory of the department.

3.1 Postural Risk Assessment in Industry 4.0

The so-called ‘Smart Factory’ resulting from digitalization and Industry 4.0 can be beneficial for all actors involved in improving and performing the manufacturing process, with several tools already developed and continually improved. In the last decade, thanks to technological advancement, new postural assessment methods based on the latest technologies have surpassed traditional approaches by providing more accurate and objective measurements in real-time. Furthermore, collected data can be shared between product and safety managers, as well as ergonomists, to positively impact worker well-being (Romero et al., 2016). Additional tools such as activity trackers, heart rate devices, or smartwatches that were initially developed for other purposes (e.g., leisure or sports) are receiving more attention and are increasingly being used to assess the state of workers' well-being in production or logistics processes. The monitoring systems adopted for this purpose exploit inertial sensors, depth cameras, reflective markers, and wearable medical devices. Recently, Menolotto et al. (2020) conducted a systematic review on motion capture systems in different industrial applications. They divided MOCAP technologies into two main categories: Inertial measurement units (IMU) and camera-based systems.

3.1.1 Inertial MOCAP

Inertial measurement units (IMUs) are portable devices that are commonly used in manufacturing contexts because of their small size. In fact, they have gained increasing attention in the manufacturing panorama because of their ability to collect data from machines and workers as well. IMUs are sensors that can be adapted to capture postures and movements during a typical working day. IMUs are small and portable devices that combine information obtained from multiple electromechanical sensors (i.e., accelerometers, gyroscopes, and magnetometers) to estimate the spatial orientation of an object using recursive sensor fusion algorithms. In recent years, their high accuracy has earned them a great deal of attention in the field of ergonomics. In particular, they have been used to provide real-time posture data or feedback based on one or more existing ergonomic assessment tools (Alberto et al., 2018). Some studies have evaluated postural risk on site (e.g., Yan et al., 2017) while others have tested the inertial system they developed under laboratory conditions; in some cases, they have reported substantial differences between these and real work environments (Vignais et al., 2013). Filippeschi et al. (2017) conducted an exhaustive survey of IMU-based motion-tracking methods; they placed a particular focus on human motion-tracking in the upper extremities in different applications. Battini et al. (2014) created a full-body system based on inertial sensors featuring integrated compensation for magnetic interference and long wireless connection. They used it to evaluate the ergonomics of manual material handling in warehouse environments where all parts of the body are used while performing work activities. In a recent example of IMU adoption to progress a real-time ergonomic assessment, Giannini et al. (2020) estimated four different ergonomic indexes, namely NIOSH (Snook & Ciriello, 1991), REBA, and JSI, by performing a body-tracking activity on a worker in real-time.

For this research, two IMU-based MOCAP suits (MTw Awinda [Xsens] and G4 MOCAPSUIT [Synertial]) were adopted for the tests reported in this research (they are reported in Figure 3.1). The MTw Awinda has 17 IMUs. The system includes a shirt with trunk and shoulder where IMUs are placed on special straps, one headband, two hand bands, and 11 strips for the rest of the body. It provides data up to 60 Hz; furthermore, the external antenna of the Awinda station enables an indoor wireless range of 20 m and an outdoor range of 50 m. The G4 MOCAPSUIT has 29 IMUs, 14 of which are used to capture the angles and positions of the wearer's fingers. This inertial suit links all IMUs, which are cabled, to a master device that sends data to the software wirelessly over Wi-Fi. A main limitation of this suit is the connection cables, which can limit the movements of the wearer.

Figure 3.1: Inertial suits of the Department Ergo lab

3.1.2 Marker-based MOCAP

Marker-based optical MOCAP exploits active or passive markers, properly displaced in specific parts of the human body, that can actively contribute to monitor human movements by emitting light at a high frequency, or by being passive (i.e., using a retro-reflecting surface that reflects the infrared emission the cameras produce). A bunch of cameras detects the position of each marker in its own two-dimensional (2D) field of view, whereas the relative position and orientation of cameras enable one to triangulate the location of markers in the 3D space of action (Tian & Duffy, 2011). Active markers are light-emitting diodes (LEDs) that typically emit their own light, one at a time, at a high frequency. In contrast, passive markers are small plastic spheres coated with a retroreflective material to reflect the light that is generated near the camera lens by an infrared emitter (Ceseracciu et al., 2014). As an example of passive marker-based adoption for a study of intralogistics processes, Feldmann et al. (2019) designed one of the largest reference systems in Europe with 39 passive markers and 38 Vicon cameras. The markers reflect the camera's LED signals, so that the position of each marker in a 3D space can be calculated using Vicon Nexus® software (Oxford Metrics, Oxford, UK).

3.1.3 Markerless MOCAP

Markerless MOCAP, or camera-based devices, were successfully used for human activity tracking and gesture, or posture classification, through the adoption of various technologies (e.g., RGB, infrared, depth, or optical cameras, mostly coming from the gaming industry (Microsoft Kinect and Xbox 360) (Menolotto et al., 2020). Markerless body-tracking technologies may suffer from some technical issues that could possibly decrease the accuracy of the captured data, such as the influence of lighting conditions in the environment and self-occlusions (in postures such as crossing arms, trunk bending, trunk lateral flexion and trunk rotation), especially when applied in the real work environment (Plantard et al., 2017). Nguyen et al. (2013) adopted the first markerless solution to monitor the postures and movements of an operator during manual manufacturing processes. Haggag et al. (2013) investigated the application of Kinect for real-time RULA to aid in ergonomic analysis for assembly operations in industrial environments. More recently, Bortolini et al. (2020) developed a camera-based technology called Motion Analysis System (MAS), which assesses four international ergonomic indexes: OWAS, REBA, NIOSH, and EAWS using a network of four depth cameras. Manghisi et al. (2020) adopt a single camera to perform real-time data capturing and processing to provide the worker with feedback to improve posture during training session.

3.2 WEM-Platform

The WEM-Platform represents a digital in-house developed system able to provide direct visual real-time feedback to three different users: Worker, Ergonomist, and operation Manager. It differs from the other available system for its capacity to progress in real-time a wide number of postural risk assessment methods based on international standards, for its capacity to progress postural risk analysis to multiple people in the workplace, for its flexibility to collect raw data from different types of hardware, and finally for the possibility of incorporating additional sensors and tools into the system.

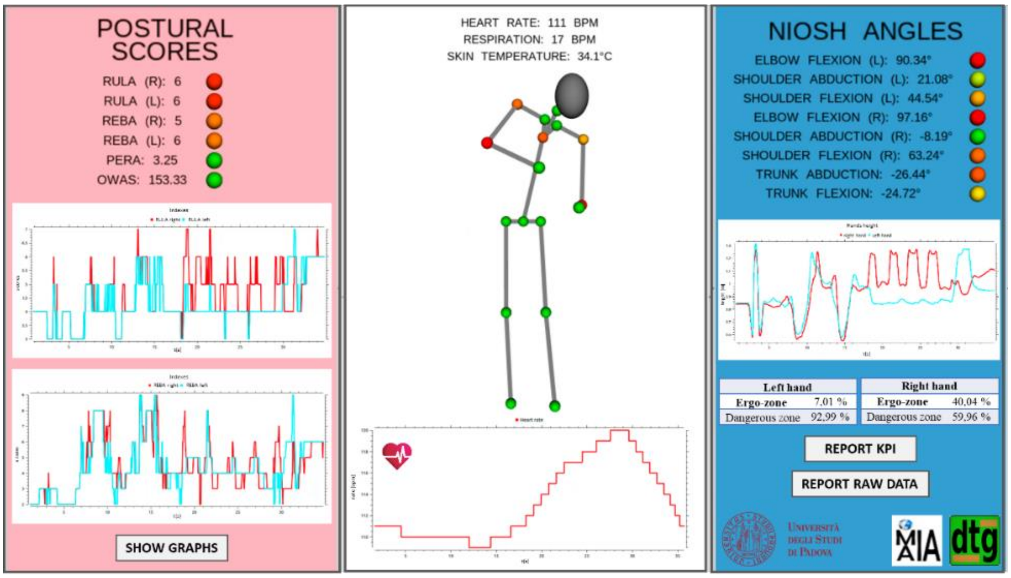


Figure 3.2: WEM-Platform Guided User Interface

The graphical user interface (GUI) of WEM-Platform is divided into three colored areas: pink, white, and blue (Figure 3.2). The pink area is primarily oriented toward ergonomists and safety managers, the white area toward the worker, and the blue area toward the operation manager. Real-time visual feedback is provided through both a real-time chart progression of heart rate values and ergonomic scores and colored dots. Traffic light colors for the feedback provision are adopted:

- Green dots define postures that do not need to be further analyzed, since they do not point out any possible damage to the safety of the user.
- Yellow dots warn experts and workers that there might be a possible risk arising from the current position.
- Red dots alert users that current posture represents a severe risk to worker well-being and needs improvement.

To avoid sudden color changes when repetitive movements are performed, two additional color scales were introduced in the transition between green and yellow and between yellow and red. In these cases, orange and light green appear to signal changing situations. In such a way, the transition from a right to a wrong posture is also evaluated according to a continuous transition instead of a discrete way. Figure 3.2 shows the division of the graphical user interface into three colors.

Pink area: The left side of the screen is dedicated to the ergonomist, or to the safety expert of the company, who wants to know the ergonomic scores and highlight the points when they reach critical values during the process. All the indexes that allow experts to rapidly evaluate the current situation through the real-time computation of ergonomic indexes are grouped together in this section. The high postural risk score highlighted by the red light is mainly due to the awkward position of the worker's trunk, which is bent and twisted during activity. In particular, the right side of the worker's body is suffering more due to the raised shoulder and the abducted position of the right upper arm. While the RULA and REBA indexes depict severe postural risk for static posture of the worker, the OWAS and PERA indexes, which are time-weighted scores, outline low risk values for the entire assembly activity performed until the last captured frame. The reason for these scores is attributable to the previous frames analyzed by the platform, which are characterized by postures with lower postural risk values. Whenever ergonomists need more details, they can open a separate page by tapping the button marked 'Show graphs' to access the real-time evolution of all ergonomic indexes during the cycle time. Figure 3.3 and Figure 3.4 report an example of RULA and REBA charts for the whole assembly process.

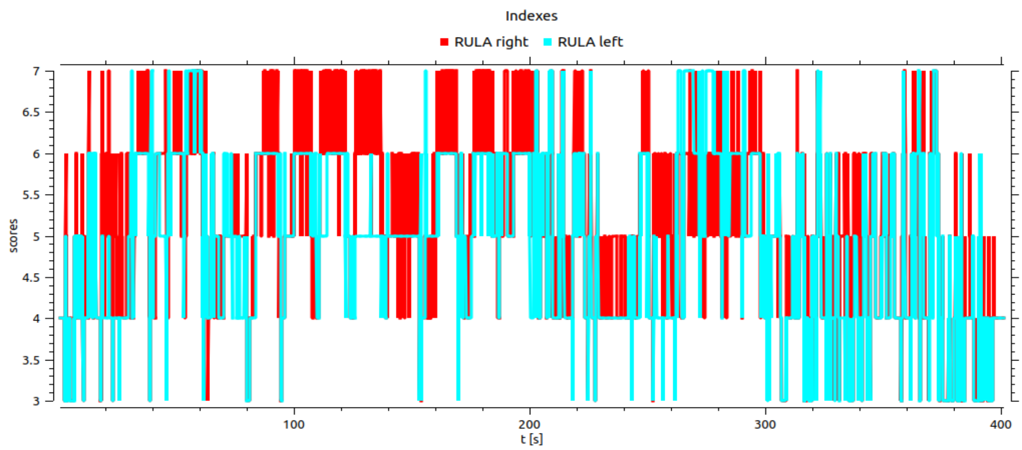


Figure 3.3: RULA scores for the assembly process

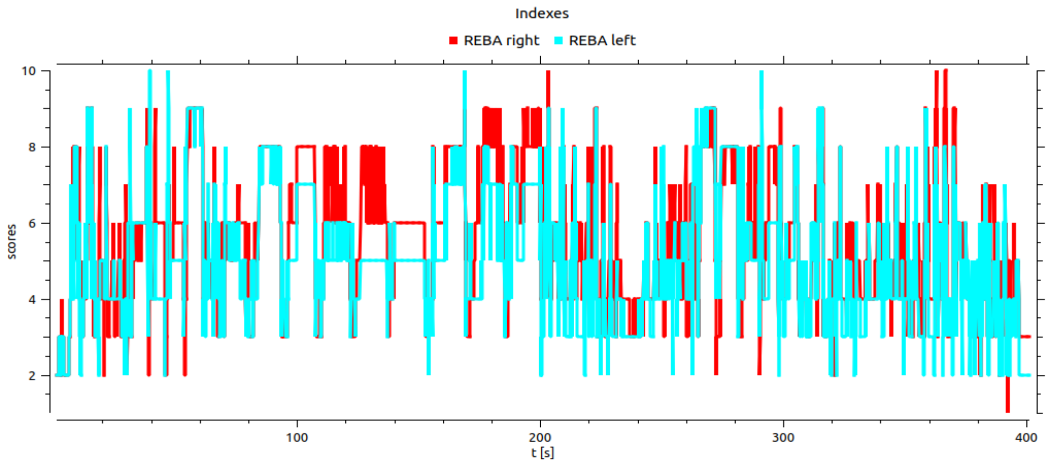


Figure 3.4: REBA scores for the assembly process

This visual feedback can provide quick evidence to experts about the high percentage of time the worker spends in wrong postures during the assembly process. This information is designated for the ergonomist, but can also benefit the worker, who can visually interpret the overall risk.

White area: The central part of the screen represents an overall evaluation of the current worker's posture; It is dedicated to the worker because by looking at the virtual representation of his body, he can receive immediate feedback on his personal parameters and incorrect postures assumed during the execution of the task. Here, the information provided includes the instant value of heart rate and its time progression (Figure 3.5), breathing rate, and skin temperature. In this way, workers can check their health status by comparing heart rate during task execution with their maximum achievable value based on their physical characteristics. Skin temperature is used to monitor general working conditions since high values for a long period represent a warning to ergonomists and operations managers and a decrease in safety for the entire working team (particularly during the current post-Covid-19 emergency period). Finally, critical situations or specific cases of fatigue overexertion can be detected from the value of the breathing rate. Figure 3.5 shows a heart rate trend: There is just a pick over 130 bpm for a relatively short period, and consequently, the assembly process under study is not critical from a physical effort point of view. Furthermore, a representation of the operator's body with 17 colored dots provides real-time visual feedback to the worker, who can visually understand which parts of the body do not assume a correct position in current working posture.

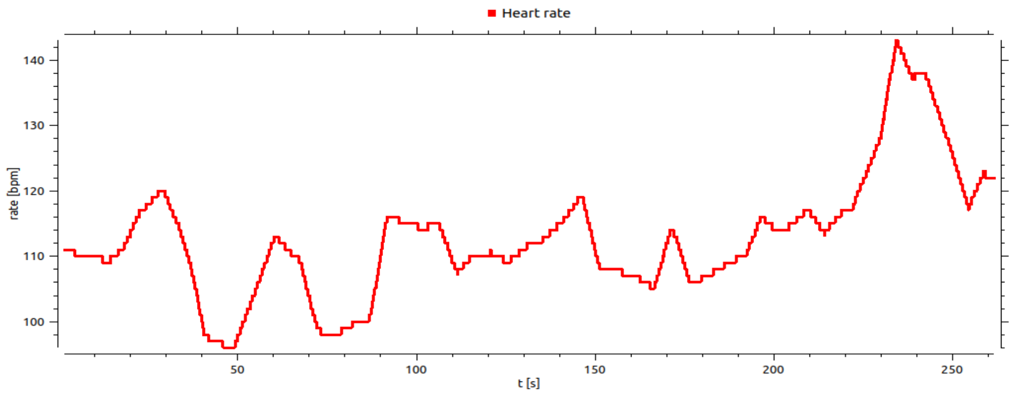


Figure 3.5: Heart rate value graph related to the assembly process

Blue area: The right side of the screen is dedicated to the worker's feedback intervention and helps the operation manager understand which movements must be carefully analyzed and improved. The area reports the NIOSH angle values and allows the operation manager to immediately understand when a task needs to be modified or enhanced to limit overexertion in lifting, overexertion in pushing or pulling objects, or overexertion in holding, carrying, or turning objects. Angle values are related to ISO 11226:2000. Three angles are dedicated to the assessment of posture of the right and left arms and two angles to the posture of the trunk. The platform adopts the same visual feedback intervention previously described for ergonomic indexes. The hand height chart (Figure 3.6) is dynamically progressed together with the percentage of time spent in dangerous positions, or in the ergo-zone, to help operation managers evaluate the amount of time that the worker's hands are active during the assembly process in real time.

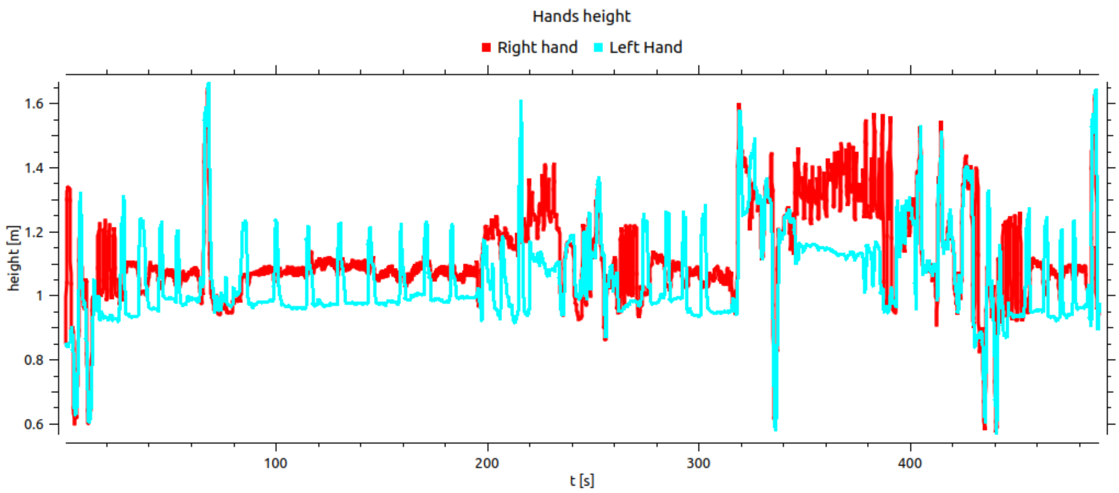


Figure 3.6: Hand height throughout the assembly process

During the training activity, by tapping the button ‘Report KPI’, or automatically at the end of the session, the WEM-Platform can print a report with the three performance KPIs related to the tracked activity. The KPI is strongly affected by the dexterity and capabilities of the worker. The segmentation of each activity is performed manually by the worker at the end of the progression of each task by pressing a button on the monitor. In the final report, the number of assembled products is reported. Additionally, a spaghetti chart and an overall hand height graph give a complete overview of the movements of the worker in the workspace along the horizontal and vertical planes.

To conclude, the button ‘Report raw data’ allows the user to obtain a report with all the positions and orientations of each joint of the body along the three axes; this can be used to perform additional evaluations. The spaghetti chart of the laboratory test case is represented in Figure 3.7. The graph obtained refers to the pelvic position. When considering the graphical output, one can conclude that the working area for this case is limited near the workbench.

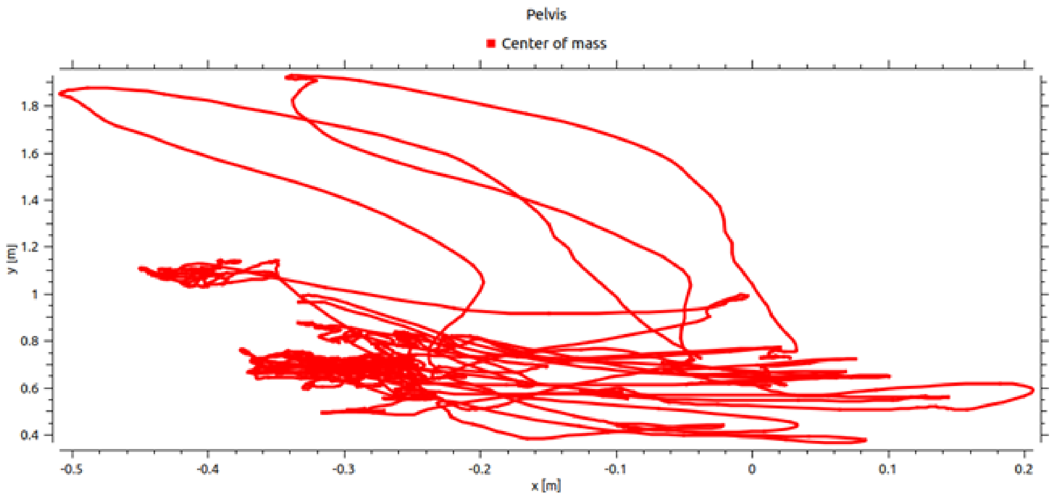


Figure 3.7: Spaghetti chart movement

The assembler concentrates all body movements within the workspace, avoiding any movements far from the assembly workbench. This is not a surprising output for this application since parts and components of the final object were intentionally placed near the worker. Only a few components, which are easily detectable in Figure 3.7, represent some exceptions by performing slightly far-reaching routes to grab the heaviest components from the rear rack.

3.2.1 System benchmark

To better understand and highlight the differences between the existing in-house developed systems and commercial software, and the WEM-Platform, in this section, I propose a benchmark analysis which first describes the main competitors of the platform and then points out the main differences that justify the creation of this new tool.

- Jack Siemens is a human modeling and simulation tool that enables improving the ergonomics of product design by performing ergonomic analysis of virtual products and virtual work environments. It includes ergonomic analysis tools which can perform static and real-time fatigue analysis, low back analysis, material handling limits, energy expenditure, NIOSH, OWAS, RULA and static strength prediction.
- ViveLab Ergo is a commercial software that helps design risk-free working conditions and processes for people working in the fields of occupational safety and engineering. It replaces paper-based methods performing automated ergonomic analyzes by identifying health-damaging effects of movements and postures by seven built-in analyses: RULA, OWAS, NASA-OBI, ISO 11226:2000, EN 1005-4, reachability zone, spaghetti diagram.
- Captiv-VR is a commercial software proposed by TEA-ergo to assess the risk of musculoskeletal disorders through postural analysis. This software aims to reduce the time dedicated to performing postural risk assessment; however, it does not provide any tools for training in real-time of the operator but focuses mainly on the post-processing motion analysis captured with the software hardware. Furthermore, the software enables the integration of additional sensors to enrich occupational risk assessment for the operator, similarly to what ViveLab Ergo does with ergonomic design of workstation.
- Vignais et al. (2013) are among the pioneers in real-time postural index assessment adopting an inertial motion capture system. In their research, they used a head-mounted display to provide visual feedback to the user, according to the RULA risk score. The computation of the index was made in real-time, as well as the feedback intervention.
- Battini et al. (2014) introduced an innovative full-body system for real-time ergonomics evaluations of manual material handling in warehouse environments. The system consists of 17 IMUs, placed in a full-body suit that operates at an inertial update rate of 500 Hz. The system can collect data and process them in real-time to compute the RULA, OCRA, OWAS, and NIOSH Lift Index.

- Bortolini et al. (2020) developed the Motion Analysis System (MAS), which is an architecture based on a Wi-Fi network with up to four depth cameras connected each one via USB port to dedicated PCs. They adopted Microsoft Kinect v.2™ depth cameras for the movement tracking. The cameras have two parallel sensors for a best depth evaluation: a color RGB sensor and an IR depth sensor. They evaluated four ergonomic indexes: OWAS, REBA, NIOSH, and EAWS. Markerless technology is adopted to acquire at 30 fps and store the information which is processed by the system to assess operator productivity and ergonomic performance.
- Manghisi et al. (2020) created the ErgoSentinel tool. Based on previous work by Manghisi et al. (2017) on the K2RULA tool, the authors exploited multithread programming to allow their new tool to monitor in real-time operators and serve both as a postural warning and as a training system. Visual feedback and acoustic warning are adopted to perform a postural training of the operator in real-time based on the RULA index score achieved by the worker. Data capture is carried out with a single Microsoft Kinect ® V2 camera.

Despite the literature and software market offering systems that are willing to perform an automated postural risk assessment, not all solutions are able to process data in real time. Most of the available solutions compute the acquired data in a post-processing analysis to obtain the final scores. This is an alternative that may suit the risk assessment of a workstation, which can be done even after data acquisition; however, real-time postural training sessions with feedback intervention need real-time computation of ergonomic indexes to assess user posture and provide prompt feedback. Although automatic and objective occupational risk monitoring is fundamental for recognizing hazardous work activities, to date, intervening in people's behavior and bad habits occurs only at the end of an ergonomic expert's analysis and risk assessment.

For this reason, WEM-Platform differs from other solutions because it provides real-time index computation and feedback intervention, as the solution proposed by Manghisi et al. (2020), but with a set of indexes which is wider and more complete (i.e., RULA index analyses only upper limbs of system user, while the integration of other indexes with data coming from other sensors such as the heart rate monitoring device, can give a complete overview of the current health situation of the worker in real-time). In fact, another great feature of the platform lies in its scalability to capture input data from different systems. It can collect raw data from different hardware, thus not only coming from inertial units, and it can support additional analyses which can be integrated into the current version of the system.

3.2.2 Platform Validation

The validation of the results obtained from the platform was progressed with some laboratory tests. For this purpose, WEM-Platform continuously computed the data captured from the assembly process of a bedside table, for a cycle time equal to 7 minutes. The workstation consisted of an assembly station, with front and rear racks adapted to store all parts involved in the assembly process.

The assembly process started by selecting the required components from the lowest level of the rear rack. To validate the software, 10 frames were sampled (Figure 3.8) from the assembly process. The frames chosen represent activities characterized by a high level of repeatability during the assembly activity. The aim of this validation test is to compare the results obtained in real time from the WEM-Platform with those obtained by computing ergonomic indexes with traditional post-processed video-recording evaluation.

Figure 3.8: Set of postures for software validation

The results for the proposed platform are very promising: The two scores for almost all the time frames evaluated, as reported in Figure 3.9, are close together. Only a few cases showed that the scores evaluated by the WEM-Platform were higher than those calculated manually.

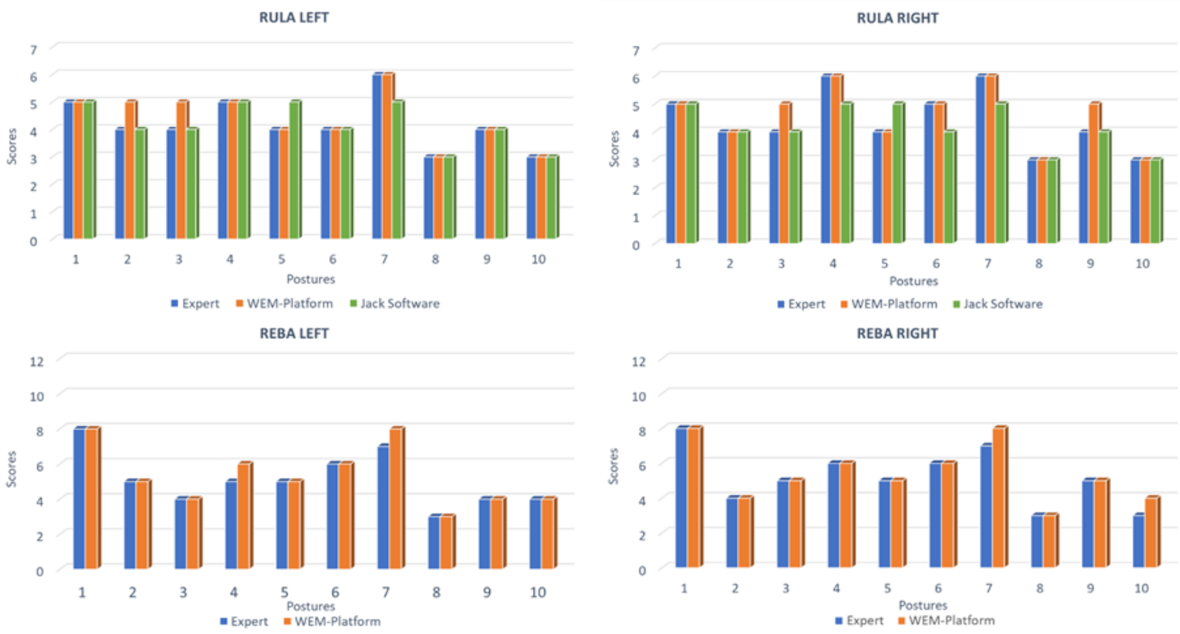


Figure 3.9: Validation for RULA and REBA Ergonomics Indexes: Comparison of WEM-Platform results, experts and, when available, Siemens Jack

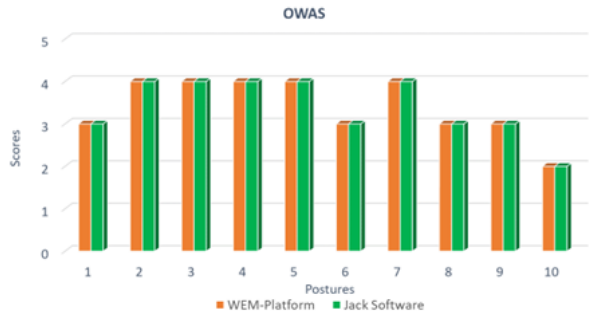


Figure 3.10: OWAS risk assessment: results from WEM-Platform and Siemens Jack

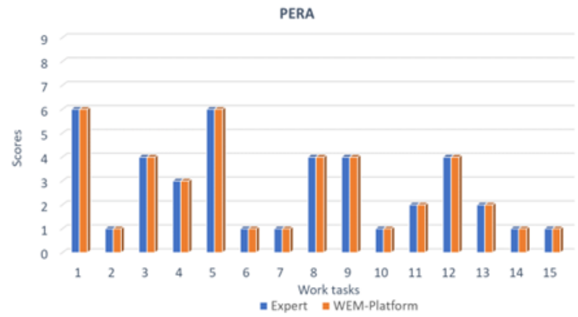


Figure 3.11: PERA risk assessment: results from the WEM-Platform and expert evaluation

These discrepancies occurred especially when the joint angles were close to an index threshold. Indeed, while the observer may mistakenly classify the angle, with high precision in the joint angle estimation of the inertial suit, the angle falls into the right range. In fact, a few degrees can have a significant impact on the final score. For the validations of the RULA and OWAS scores, the WEM-Platform outputs were compared with the results obtained with the Siemens Jack software. Figure 3.12 shows the graphical interface of the Jack software during the analysis of the first posture in Figure 3.8.

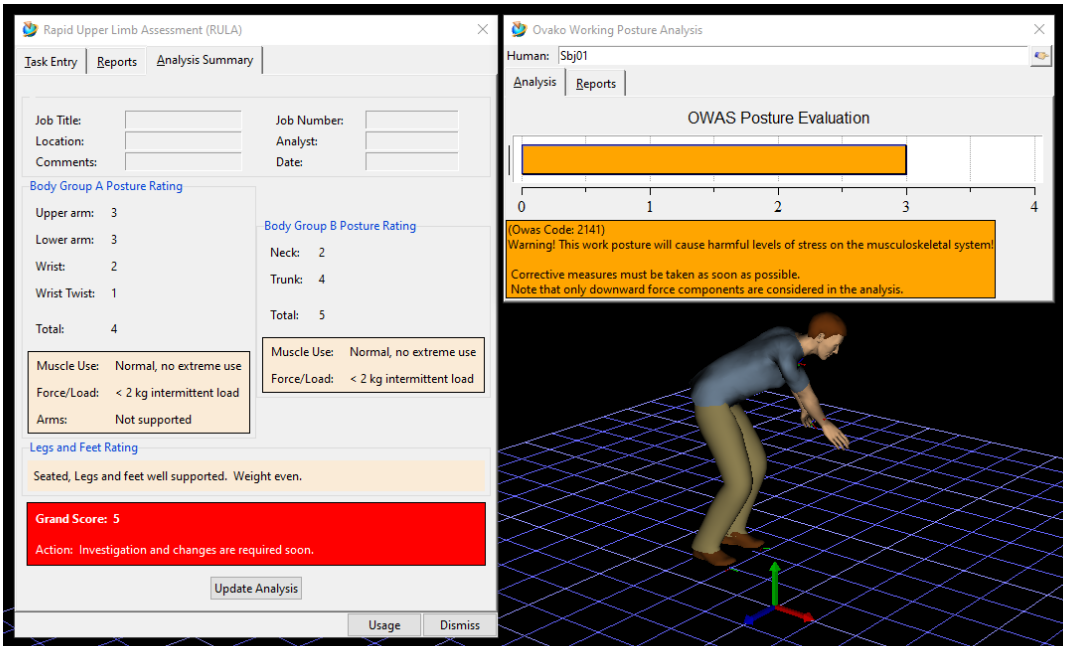


Figure 3.12: Posture validation through Jack Siemens software benchmark

As shown in Figure 3.9, both ergonomic expert and Siemens software agreed mainly with the RULA index score proposed by the WEM-Platform. Jack software evaluates ergonomic postural risk with a single grand score, which does not refer to a specific side of the body, as WEM-Platform does. For this reason, Figure 3.9 reports the same value of the Siemens Jack analysis for both the right and left sides of the operator's body. In some postures, the WEM-Platform performs slightly higher risk scores compared to other assessments. The higher score provided by the WEM-Platform is mainly due to the computation of some joint angles that are not stated in the RULA index progression (i.e., a raised shoulder, an abducted upper arm, a bent wrist from the midline, etc.). For this reason, a range of movements was introduced to state whether to perform a scoring adjustment based on the ergo zone of the volunteer relative to the maximum threshold reached. For the OWAS index, Figure 3.10 shows that WEM-Platform output and Jack software scores are in complete agreement. The higher risk score for the first proposed postures is mainly related to the position of the trunk and legs. On the contrary, in the last frames of Figure 3.10, the operator performs less awkward postures, resulting in lower OWAS scores. Although for both RULA and OWAS scores a benchmark between WEM-Platform and Siemens Jack software postural evaluation toolkit can be progressed, the validation of REBA and PERA scores relies only on the expert's assessment. Figure 3.9 reports the comparison between the REBA score, assessed on both sides of the operator's body, provided by the WEM-Platform and the expert's estimates. Similarly, Figure 3.11 reports WEM-Platform output and expert scores for each work task, as required by the analysis of the

PERA index. Task segmentation is performed manually by recognizing tasks characterized by distinct postures or work content, as reported by Chander & Cavatorta (2017). The score values presented for the activities analyzed are usually low due to the small force needed for their progression. However, awkward postures or long durations still clearly affect some tasks.

3.3 Single-person postural risk assessment

This section describes some practical applications of the WEM-Platform in real and laboratory test cases to evaluate the accuracy of the results obtained from the system and to test the efficacy of the feedback intervention to improve the postural behavior of the operator.

3.3.1 Postural risk assessment in a real case

The system was adopted in a real scenario to test the performance of postural risk assessment in a work environment. The operator performing the assembly activities could be considered a young but experienced worker. The inertial suit adopted in this test was the Xsens Awinda inertial suit with 17 IMUs. The data collected from the platform was progressed in real time and converted to ergonomic scores, which were displayed to the observers through the guided user interface, as described in Section 3.1. As an example, the RULA scores for the right and left sides of the worker's body are reported in Figure 3.13 and Figure 3.14.

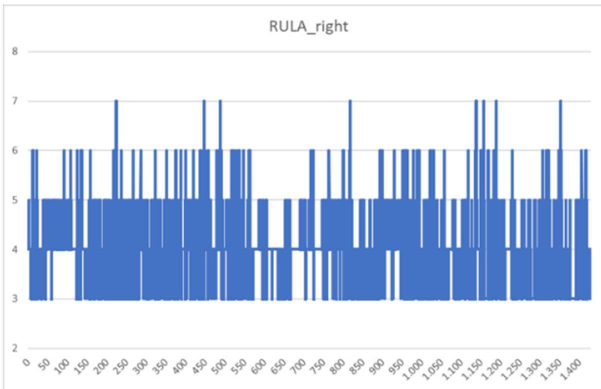


Figure 3.13: RULA scores for the right side of the worker’s body

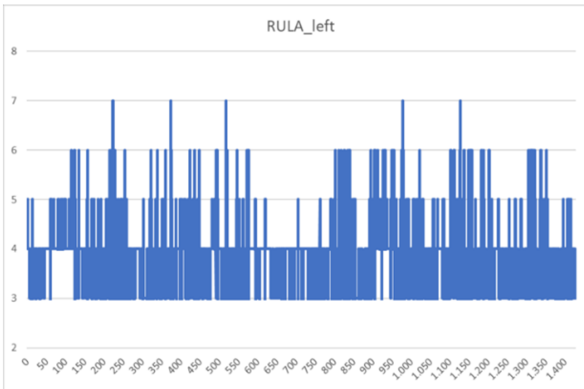
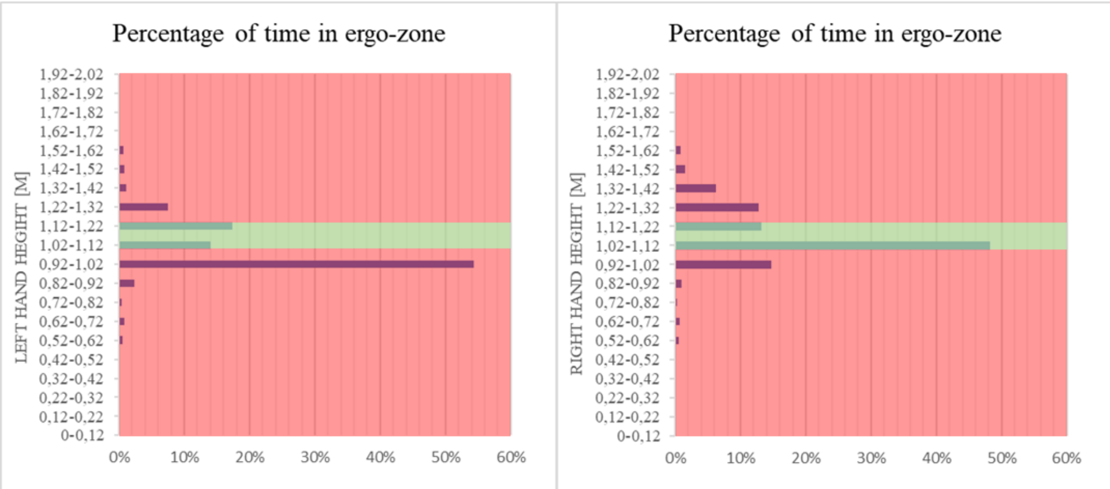


Figure 3.14: RULA scores for the left side of the worker’s body

The results obtained from the WEM-Platform test showed that the worker performed on average posture risk, which was below the maximum threshold, however, few peaks of awkward postures were analyzed with the company, and solutions were proposed to smooth the risk in those hazardous situations. Furthermore, the platform calculated the percentage of time the operator's hands spent within the ergo-zone and the percentage of time spent in dangerous positions and plotted the results in Figure 3.15. The graphs highlight that the left hand, which was not the operator's favorite hand, was out of the ergo zone for the highest percentage of time. This is imputable to the fact that the operator was used to use his favorite arm to accomplish the assigned tasks, which may be progressed in parallel with both arms, to increase the percentage of time of the left arm inside the ergo-zone.



Left hand	
Ergo-zone	31,36 %
Dangerous zone	68,64 %

Right hand	
Ergo-zone	61,44 %
Dangerous zone	38,56 %

Figure 3.15: Percentage of time hands spent in ergo-zone (green) and in dangerous zone (red).

3.3.2 Training effects on inexperienced worker

The laboratory tests presented hereafter aim to investigate the influence and the benefits of the adoption of WEM-Platform feedback on the postural behavior of an inexperienced worker during an assembly process. Therefore, the same drawer assembly process was performed by an operator without and with WEM-Platform feedback. Due to the small dimension of the assembled object, the operator can work in front of the workbench. The laboratory setup is represented by a standard 1-meter-high workbench.

During these two scenarios (i.e., assembly activities with and without feedback intervention), the WEM-Platform processes the data collected by an inertial MOCAP suit and computes in real time the scores of RULA, REBA, and OWAS.

Figure 3.16: Workplace layout for the postural training session

Time performance is also considered an indicator of the efficiency of assembly activity. Only the RULA, REBA and OWAS indexes were adopted for this analysis because of their suitability for the assembly activities. However, additional safety risk indexes can be integrated into the analysis depending on the industrial context analyzed. As an example, for multi-person postural risk assessment on multi-manned workstations of automotive assembly lines, the platform could be extended with the European Assembly Worksheet (EAWS) (Schaub et al., 2013) designed for the automotive industrial sector.

In the first scenario, the operator performs the drawer assembly activity without previous training experience or external feedback intervention. For this scenario, the WEM-Platform calculates the RULA, REBA, and OWAS risk index during the assembly task, but no visual feedback is provided to the operator during the progression of the activity.

In the second scenario, the same operator repeats the drawer assembly task. However, in this case, the operator received feedback from the WEM-Platform during the activity. The WEM-Platform constantly monitors the operator’s posture and assesses the postural risk scores of RULA, REBA, and OWAS in real time. In addition, a virtual representation of the posture of the trainee is shown on the workbench monitor to provide the operator with intuitive visual feedback while performing the assembly activity.

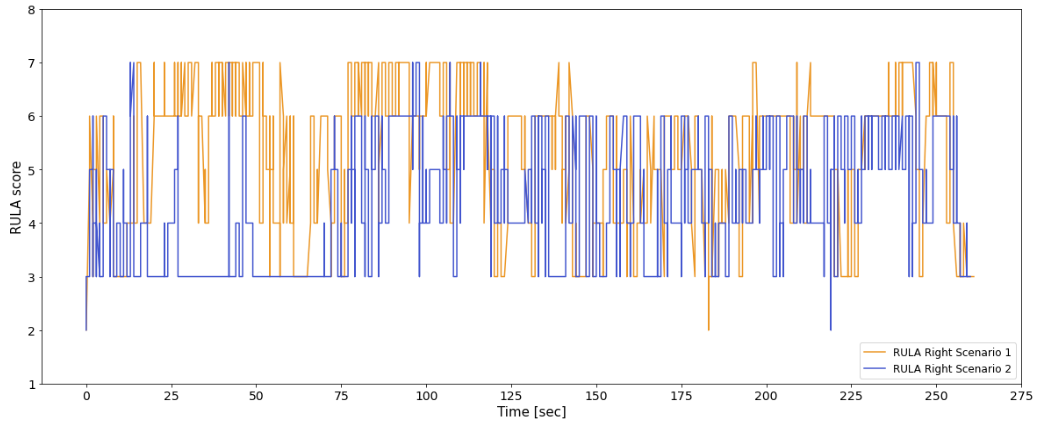


Figure 3.17: RULA index scores progressed in the two scenarios

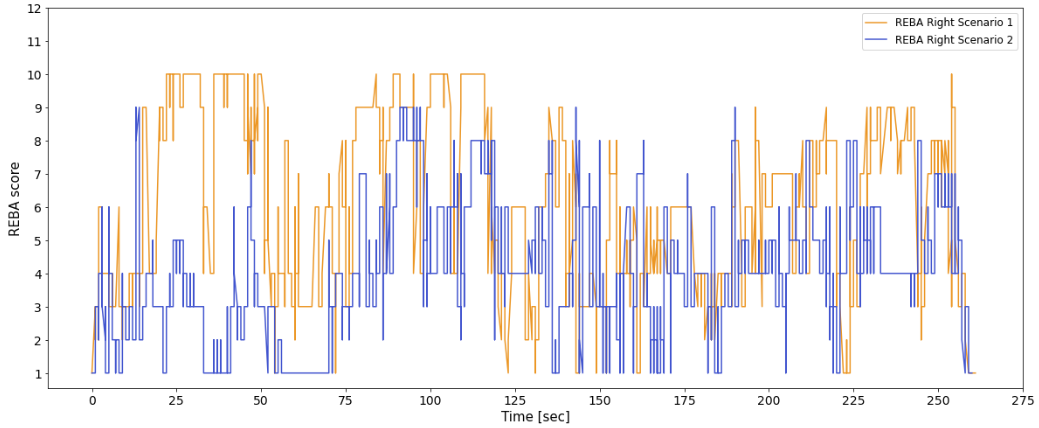


Figure 3.18: REBA index scores progressed in the two scenarios

The results of the postural risk assessment performed in this analysis highlight the postural improvement of the operator in drawer assembly activity. Table 3.1 provides the RULA, REBA, and OWAS index scores for both sides of the worker's body. Improvement in postural behavior between the first and second scenarios is significant for all ergonomic index scores. The REBA index for the right side has the highest score improvement, corresponding to 34,3% of the initial value.

Table 3.1: Impact of the feedback intervention on the inexperienced worker

Index	Side	Without feedback from WEM-Platform	With feedback from WEM-Platform	Δ %
RULA	Right	5.32	4.39	-17.5%
	Left	5.44	4.66	-14.3%
REBA	Right	6.1	4.01	-34.3%
	Left	6.09	4.17	-31.5%
OWAS	-	149.37	112.74	-24.5%
Time [sec]	-	260	261	0.4%

Table 3.1 shows that the greatest improvements are achieved on the right side of the body. The reduction in the REBA score for both sides of the body is considerable, although the total assembly time did not increase.

3.4 Multi-person postural risk assessment

To test the scalability of the WEM-Platform for the simultaneous real-time postural risk assessment of two people collaborating on the same activity, two multi-person work scenarios were designed and tested in the Department Ergo-laboratory. The analysis focuses on multi-person ergonomic assessment in materials picking and in assembly activities performed in a multi-manned workstation.

3.4.1 Multi-manned assembly workstation

In production sites, especially for medium and large product assembly lines, a group of workers can be employed at the same workstation to simultaneously perform different operations on the same product (Fattahi et al., 2011). A multi-manned assembly line is a type of production line where tasks are simultaneously performed on the same individual product by groups of workers in multi-manned workstations. The literature already provides models and solutions to multi-manned assembly line balancing problems to reduce the number of operators involved in the workstations or minimize the cycle time (Roshani & Giglio, 2017).

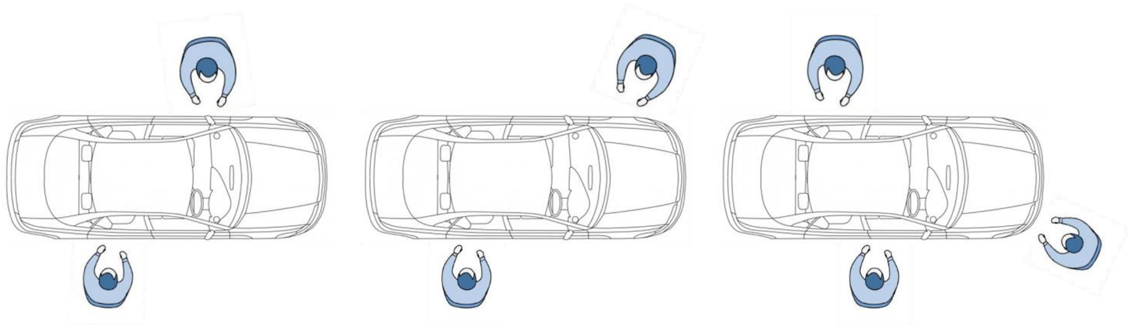


Figure 3.19: A configuration of assembly line with multi-manned workstations

The group of operators involved in these workplaces can have different levels of experience and different anthropometric characteristics. Dealing with such heterogeneity can be challenging for companies, which need advanced solutions to consider the individuality of the operator during the training phase and the assignment of the job. Postural training sessions are effective countermeasures against the onset of WMSD; however, the effectiveness of the training phase also depends on the level of experience of the trainee (Denadai et al., 2021).

3.4.2 Laboratory test case

In the test case presented here, two volunteers were recruited to carry out the activities.

- Operator #1: inexperienced worker with no previous experience in the product assembly process and not previously trained by the WEM-Platform (male, 30 y/o, 187 cm tall).
- Operator #2: experienced worker in the assembly process under study and previously trained by the WEM-Platform (male, 27 y/o, 174 cm tall).

Both participants have voluntarily participated in the study and signed a written consent to participate in laboratory tests. In detail, the activities studied are:

- Scenario 1: Activity of picking up three large sheets and placing them on a shelf at three different heights.
- Scenario 2: Assembly activity of a medium-size cart performed on a multi-manned workstation.

Scenario 1 was designed to analyse the effect that the anthropometric characteristics of different operators may have on risk indexes. During the activity, each operator moves three large metal sheets from a 1-meter-high workbench. He picks up the first one and walks about 2 meters to the rack to place the metal sheet at the ground level (i.e., 15 cm from the ground). He then goes back to take the second one and place it at the middle level (i.e., at the same height as the workbench). Finally, he picks up the last one and places it on the upper level of the rack (i.e., about 2 m. from the ground). This analysis aims to determine how the difference in height between the two operators can affect their posture risk scores while working in the same workplace. In this sense, the two volunteers have a height difference of almost 15 cm.

The second scenario analyses a multi-person postural risk assessment for a cart assembly activity in a multi-manned workstation. The process consists of assembling two shelves, initially placed on a pallet close to the workstation, at different heights on the cart. Each shelf is fixed with two bolts on both sides of the cart. Due to the dimensions of the object, which can be considered a medium-sized product (150 x 93 x 70 cm), it was not possible to proceed with its assembly on the workbench. For this reason, assembly activity was carried out in front of the workbench, where two monitors displayed their postural risk assessment to both workers in real time (Figure 3.20).

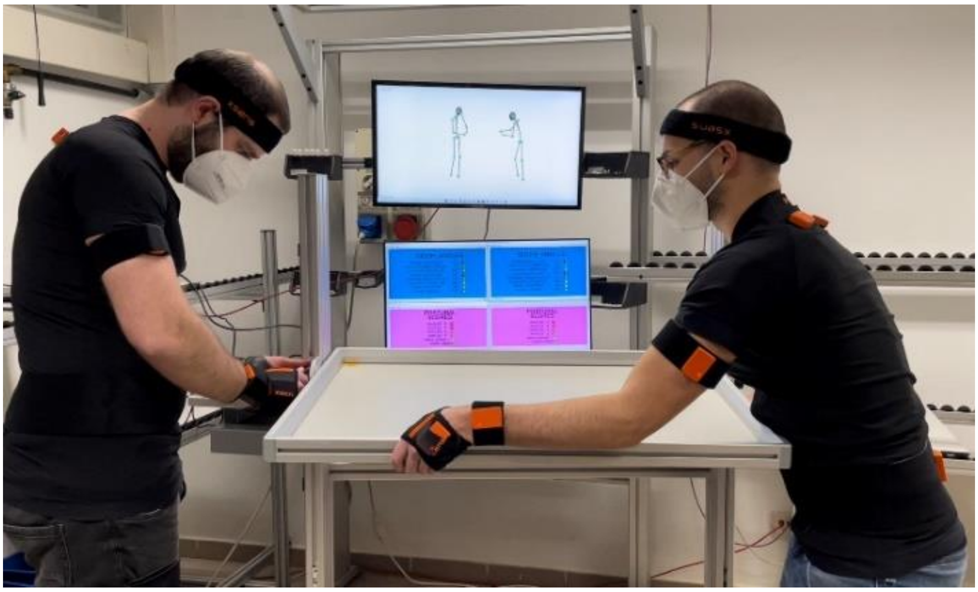


Figure 3.20: Multi-person postural real-time risk assessment

The analysis performed in Scenario 1 aims to test whether anthropometric characteristics affect ergonomic index scores. The results reported in Table 3.2 confirm initial expectations, especially for the REBA index time average values.

Despite the greater experience in the assembly activity of Operator #2, his risk score increased due to the hazardous postures maintained while moving the metal sheets. Regarding the RULA index (Figure 3.21), there is a slight difference between the postural risks of the operators.

Table 3.2: Postural risk assessment scores for multi-person pick-and-place activity

Index	Side	Scenario 1	
		Operator #1	Operator #2
RULA	Right	4.44	4.23
	Left	4.43	4.36
REBA	Right	3.42	4.82
	Left	3.49	4.93
OWAS	-	138.79	149.3
Time [sec]	-	36	

Although the value represents a warning for operator safety (i.e., a RULA index score greater than 4 requires the implementation of some actions to reduce the value for this activity), the RULA index itself does not provide other helpful information on the anthropometric differences between the two operators.

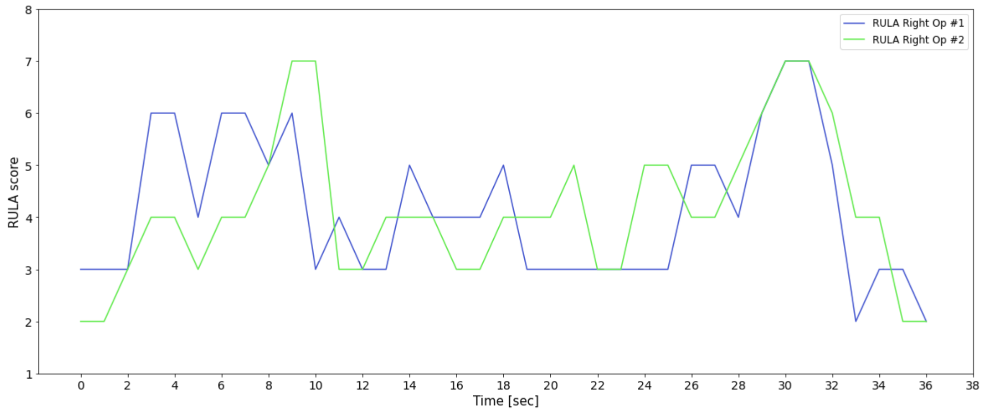


Figure 3.21: RULA index for pick-and-place activity (Scenario 1)

In contrast, Figure 3.22 reports the REBA index, which clearly indicates that there are only a few cases throughout the duration of the activity where the postural risk of Operator #1 exceeds that of his shorter colleague.

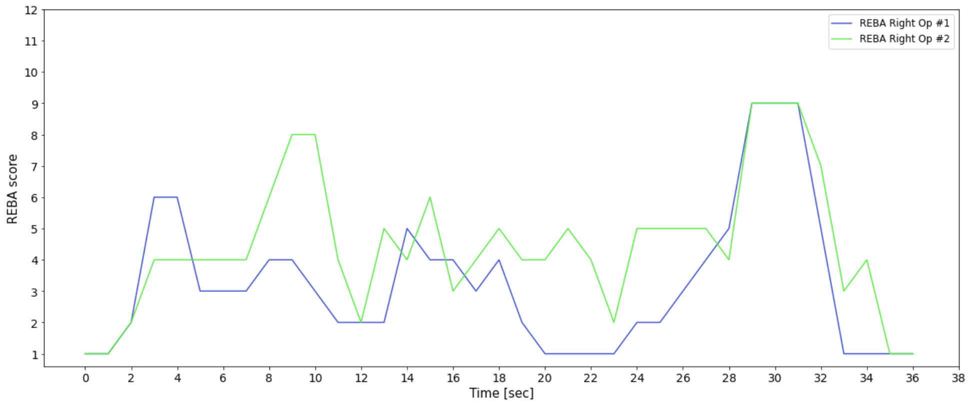


Figure 3.22: REBA index for pick-and-place activity (Scenario 1)

In the second scenario, the WEM-Platform was adopted to assess multi-person postural risk for two operators. Table 3.3 reports the results of this scenario, which involves two workers collaborating on a cart assembly task. Throughout the duration of the activity, the WEM-Platform provides visual feedback in real time through two monitors placed on a nearby work bench (Figure 3.20). The monitors show the digital representation of the operators, the NIOSH angles, together with the RULA, REBA and OWAS risk index scores. The analysis aims to highlight the postural risk assessment of Operator #1 working together with an experienced operator. In a multi-manned assembly workstation, the activities performed by each operator may differ depending on product precedence constraints and task scheduling decision. Therefore, it is fundamental to monitor the behavior of both operators to highlight individual postural risk scores.

Table 3.3: Postural risk assessment of assembly activity in multi-manned workstation

Index	Side	Scenario 2	
		Operator #1	Operator #2
RULA	Right	4.54	4.24
	Left	4.92	4.12
REBA	Right	5.38	5.49
	Left	5.92	4.49
OWAS	-	205.21	145.43
Time [sec]	-	288	

The computation of risk indexes in real time allows the ergonomist to immediately detect uncomfortable postures during the progression of the activity. The scores reported in Table 3.3 show that Operator #2 completes the activity with a lower average risk value. Furthermore, Figure 3.23 and Figure 3.24 show that Operator #1 usually exceeds Operator #2 scores for both the RULA and REBA indicators. In conclusion, the expertise of Operator #2 allowed him to achieve a lower average risk compared to the inexperienced worker.

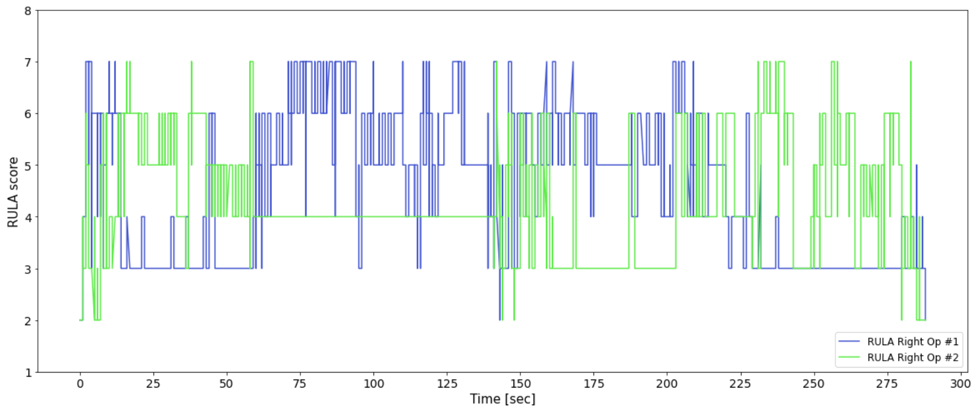


Figure 3.23: RULA index for multi-manned assembly station (Scenario 2)

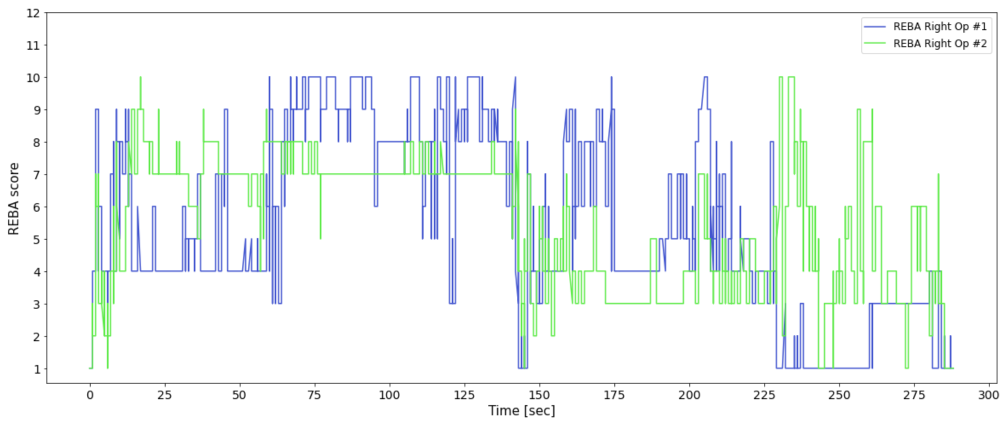


Figure 3.24: REBA index for multi-manned assembly station (Scenario 2)

Conclusion

Human motion data capturing has recently become one of the most interesting research topics and one of the greatest opportunities for manufacturing companies to monitor workers for safety purposes, besides focusing on performance aspects. Therefore, discussions can arise about trust, employee rights, privacy, and trade unions. Complaints could arise if the human tracking system also performs a time tracking by recording employee attendance and absences from the production workstation. In the same way, tracking by collecting data on how employees spend their time during a work shift could also limit workers' privacy. Finally, biological and physical data tracking could open the company to legal concerns with the General Data Protection Regulation 2016 (Regulation EU on GDPR, 2016), which governs the processing of personal data.

Violating regulations could leave companies open to Human Resource (HR) complaints and lawsuits. Finally, monitoring every moment of an employee's workday can damage employee morale. Employees may resent the intrusion and lack of trust, and this could lead to employee stress and burnout. Several limitations exist to the real implementation of environments where data are constantly monitored in real-time, even if the technologies and the methodological approaches are ready for this implementation. However, by correctly understanding the benefits on workers' wellbeing and safety of such systems, it is possible to work toward more focused and efficient data collection, according to the different industrial contexts, employment contracts and labor relationship.

4

Multi-objective job rotation scheduling model

Introduction

This chapter presents a new mathematical model to solve the job rotation scheduling problem considering system productivity, operator safety and boredom level. This model represents one of the first attempts to include such different objective functions in a single mathematical formulation. In fact, previous contributions aim to keep workforce safety as a constraint of the model and not as an objective. To calculate the risk level of the worker at each workstation, during the preliminary phase of field data collection, the WEM-Platform can be adopted to speed up ergonomic assessment. In this problem formulation, REBA index score was chosen because of its suitability to the characteristics of the jobs performed in the shop floor for this application test case. However, the risk index can be easily replaced with another method available among the list of indexes of the WEM-Platform assessment tool (e.g., the RULA index might be more suitable whether jobs are more static and can be performed mainly with the upper limbs of the workers).

4.1 Research gap

While past works on JRS have indeed been useful and knowledge-building, they have a singular lacuna: they mainly consider a single aspect at a time. Most of the prior works neglect to address the combinatorial effect that multiple parameters might have on the JRS model performance and results. For example, in a human-centric working space, body postures, tool vibrations, and noise should be jointly considered to better define a sustainable and human-centric job rotation schedule. Similarly, there is little research on flexible shift duration times and different rest breaks developed to match the characteristics of individual workers. A notable exception is the study by Tharmmaphornphilas & Norman (2004), which investigates the effects that the frequency of intervals and break positioning can have on safety risk reduction by assessing the evaluation of the proper time length for rotating workers. However, they consider workers with similar attributes. Recent works in job rotation scheduling already include HF (i.e., occupational risk linked to postures and fatigue, experience/skill levels) related to long- and short-term decisions (i.e., Mehdizadeh et al., 2020; Mossa et al., 2016). However, they often neglect to consider worker attributes and ignore various complexities of worker involvement in input data estimation.

Based on the theoretical fundamentals discussed in Section 1.1, this research proposes a new human-centric approach for solving a multi-objective job rotation scheduling problem. The proposed model breaks new ground in jointly considering a variety of realistic shop floor sociotechnical factors in JRS: ergonomics postural scores, vibration and noise risk constraints (respecting international standards threshold values), workers’ experience in performing jobs and individual physical limitations. Furthermore, workers' opinion is considered to define a similarity score between jobs, useful in finding solutions to minimize worker boredom. Finally, the number of shifts, as well as the break time between each shift, is optimally scheduled, as they strongly influence productivity and worker well-being. The duration of rest breaks is flexible because differences related to age and gender are considered. Improving on previous job rotation scheduling models (e.g., Hochdörffer et al., 2018; Song et al., 2016; Yoon et al., 2016), the assumption made for this contribution is that break time between shifts is an opportunity for operators to recover, contingent on worker individual characteristics (age and gender, for example).

In summary, this research model presents a new human-centric job rotation scheduling approach. The model aims to make the worker (and inferentially the production system) more resilient to variability in ergonomic workloads and minimize boredom risks in human intensive working environments. The model is inspired by Industry 5.0 human-centric priorities and is grounded in previous research. More specifically, it seeks to maximize throughput while customizing job rotation schedules to match individual worker attributes.

4.2 Workplace Risk Factors

This section investigates the most common risks in the manufacturing field that can represent a threat to the safety and well-being of the workforce. Excess exposure to vibrations and noise can lead to diseases that endanger the health condition and workability of workers, which can bring the negative effects of prolonged exposure lifelong. For this reason, the main international standards that determine the maximum threshold for exposure to noise and vibration are investigated and introduced in the mathematical model developed in this research.

4.2.1 Vibration exposure

Manufacturing workplaces are often characterized by the presence of tools and machines that produce vibrations that are transferred to workers in proximity or directly using production tools. Prolonged vibration exposures can lead to adverse effects that can be localized in a specific part of the body, or they can interest the whole body, leading to harmful effects on the physical health of workers (McCallig et al., 2010). Vibrations can be transmitted directly from the tool to the hand-arm system, which can cause diseases in the upper extremities limbs of the body, called hand-arm vibration syndrome (HAVS) (Bovenzi et al., 2019). In contrast, when the whole body is exposed to vibrations, whole-body vibration (WBV) disorders can arise. Since vibration values depend on several aspects such as the frequency, magnitude and duration, several international standards have been developed to provide guidelines and policies to correctly estimate vibration exposure. Among the standards developed, two of the most widespread regulations are ISO 5349-1, 2001 and ISO/TR 18570, 2017. ISO 5349-2, 2001 defines that the daily vibration exposure duration requires an evaluation of the exposure duration associated with each work phase. During a workday, workers can use different tools to progress their work, but only some of them transmit vibrations to workers. Measurement of the vibration level of a tool must be performed with instruments according to 2017, measuring it in all three directions. In ISO 5349-1, 2001 the first measure to evaluate for each of the three axes (x, y, and z) is the root mean square (r.m.s.) frequency-weighted acceleration.

Then, the total vibration value for a generic tool a_{hv} is defined as:

$$a_{hv} = \sqrt{a_{hvx}^2 + a_{hvy}^2 + a_{hvz}^2} \tag{4.1}$$

Equation (4.1) defines the vibration level produced by a vibrating tool that integrates the vibration values along the x, y and z axes in a single value. Following ISO 5349-1, 2001 the daily exposure through the total vibration value and its daily exposure duration is expressed as:

$$A(T_0) = a_{hv}\sqrt{\frac{T}{T_0}} \tag{4.2}$$

where T represents the total daily exposure to a_{hv} and T_0 represents the equivalent working time. However, when several tools are used during a working day, the daily vibration exposure is determined using the following equation:

$$A(T_0) = a_{hv}\sqrt{\frac{1}{T_0}\sum_{i=1}^{n} a_{hvi}^2 T_i} \tag{4.3}$$

where the vibration value a_{hvi} and the duration T_i of the adoption of each tool is considered. T_0 represents the shift time. Taking into account a typical workday of 8 h, ISO 5349-1, 2001 defines a threshold value of 2.50 m/s^2 and a maximum limit exposure of 5.00 m/s^2 of daily vibration exposure $A(T_0)$. If the daily exposure is less than 8 h, according to Equation (4.2), the threshold and the maximum acceptable vibration value increase, as reported in Table 4.1. For example, for an exposure period of 30 min, the acceptable level of vibration can be high (20.00 m/s^2) if compared to the acceptable value related to 8 h.

Table 4.1: Vibration limits according to ISO 5349-1, 2001

Total daily exposure [hours]	Threshold value [m/s^2]	Maximum limit exposure [m/s^2]
8	2.50	5.00
6	2.89	5.77
4	3.54	7.07
2	5.00	10.00
1	7.07	14.14
0.5	10.00	20.00

4.2.2 Noise Exposure

There is certified evidence that workers exposed to noise in the workplace ($L_{Aeq8hr} \geq 80\ dBA$) have an increased risk of accident (Picard et al., 2008). Hearing loss caused by exposure to work-related noise is called occupational noise-induced hearing loss (NIHL) (Morata, 2012). The most effective means of preventing NIHL is to eliminate the noise hazard (NIOSH, 1996). According to the study by Tak et al. (2009), the manufacturing industry in the United States had the highest number of workers exposed to hazardous workplace noise exposure (estimated number of exposed workers, 5.7 million or 25% of all workers exposed to hazardous workplace noise), followed by construction (4.5 million) and retail trade (2.1 million). In manufacturing industry, mechanics and repairers of vehicles and mobile equipment showed the highest prevalence (82%) of exposure to hazardous workplace noise exposure. When employees experience sounds that exceed those listed in Table 4.2, feasible administrative or engineering controls must be used. If such controls do not reduce the sound levels within the levels of Table 4.2, personal protective equipment shall be provided and used to reduce the sound levels within the levels of the table.

Table 4.2: Permissible noise exposure according to the OSHA standard (OSHA 1910.95)

Duration per day [hours]	Sound level [dBA]
8	90
6	92
4	95
3	97
2	100
$1^1/_2$	102
1	105
$^1/_2$	110
$^1/_4$ *or less*	115

4.3 Mathematical model

In this section, the new multi-objective job rotation scheduling model is presented. The aim is to maximize the throughput of the manufacturing system and to minimize the maximum level of boredom and safety risk in the work team, considering workers' differences in terms of age, gender, experience levels, and physical limitations according to specific jobs. Daily exposures to noise and vibration from tools are also considered additional constraints.

4.3.1 Notation

Sets and indices:

- W Set of workers, indexed by i
- J Set of jobs, indexed by j
- K Set of shifts, indexed by k

Parameters:

- N_j Nominal execution time for job *j* [seconds]
- α_{ij} Level of experience of worker *i* in executing job *j*
- β_{ij} Physical limitation for worker *i* in performing job *j*
- RA_{ij} Rest allowance for worker *i* in executing job *j*
- $s_{ijj'}$ Level of similarity defined by the worker *i* between jobs *j* and *j'*
- T_k Time for shift *k* [seconds]
- B_k Break time for shift *k* [seconds]
- E_j Safety risk score for job *j*
- L_j Noise level for job *j* [seconds]
- a_j Acceleration value for job *j* $\left[{}^{m}/{}_{s^2}\right]$
- a_{lim} Maximum acceleration value $\left[{}^{m}/{}_{s^2}\right]$
- D Workday duration [seconds]
- $z_{j(min)}$ Minimum required throughput for job *j* [pcs]
- $z_{j(max)}$ Maximum required throughput for job *j* [pcs]
- UB Big number

Decision variables:

- x_{ijk} 1 if worker *i* is assigned to job *j* during shift *k*; 0 otherwise
- $x_{ij'(k+1)}$ 1 if worker *i* is assigned to job *j'* during shift *k+1*; 0 otherwise

Variables:

- z_{ijk} The throughput obtained by worker i for job *j* during shift *k*
- z_{max} Total throughput
- E_i Safety risk to the worker *i*
- E_{max} Maximum safety risk
- S_i Job similarity level for worker *i*
- S_{max} Maximum similarity level

The following assumptions are included in the model.

- The set of jobs and workers is fixed.
- In a working day, the same job can be assigned at least once to the same worker.
- The number of jobs is larger than the number of operators, so at least one job will be assigned to each operator in each period. This assumption reflects common reality in industry. In fact, due to the variety of products, the number of jobs is generally higher than the number of workers.
- A minimum quantity of product is required for each job.
- For each job, a maximum number of products is defined to avoid higher inventory costs.
- Each worker must complete the assigned job according to his/her physical capacity, limitations, and experience level. The time required to perform a job can be lower than or greater than the nominal execution time, depending on the level of experience.
- For each job, data on noise and vibration levels, ergo-postural risks, and nominal execution time are known.
- Each worker is directly involved in defining the level of similarity among jobs and, consequently, the perceived boredom.
- The recovery time (RA) required for each job varies according to the worker. It considers the energy expenditure required to perform the job and the maximum acceptable energy expenditure of each worker according to Finco et al. (2019).
- A suitable and dynamic rotation for the worker is guaranteed daily according to the characteristics of the workers.
- All parameters are deterministic and constant.

4.3.2 Model Formulation

The objective functions (O.F.) of the mathematical model can be defined as follows:

$$\textit{O.F.1: Maximize } z_{max} \tag{4.4}$$

$$\textit{O.F.2: Minimize } S_{max} \tag{4.5}$$

$$\textit{O.F.3: Minimize } E_{max} \tag{4.6}$$

Subject to:

$$\sum_{j} x_{ijk} = 1 \ \forall \ i = 1,..,W; k = 1,..,K \tag{4.7}$$

$$\sum_{i}\sum_{k} x_{ijk} \geq 1 \ \forall \ j = 1,..,J \tag{4.8}$$

$$\sum_{i} x_{ijk} \leq 1 \ \forall \ j = 1,..,J; k = 1,..,K \tag{4.9}$$

$$z_{j\_min} \leq \sum_{i}\sum_{k} z_{ijk} \leq z_{j\_max} \ \forall \ j = 1,..,J \tag{4.10}$$

$$0 \leq z_{ijk} \leq \frac{T_k - \max\left(0; T_k RA_{ij} - B_k\right)}{\alpha_{ij}\beta_{ij}N_j} x_{ijk} \ \forall \ i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{4.11}$$

$$\sum_{k}\sum_{j}\sum_{i} z_{ijk} \leq \ z_{max} \tag{4.12}$$

$$\mathrm{S_i} = \frac{\sum_{k=1}^{K-1}\sum_{j=1}^{J}\sum_{j\prime=1}^{J} x_{ijk}x_{ij\prime(k+1)}s_{ijj\prime}}{K-1} \ \forall \ i = 1,..,W \tag{4.13}$$

$$S_{max} \geq \mathrm{S_i} \ \forall \ i = 1,..,W \tag{4.14}$$

$$E_i = \frac{1}{D}\sum_{j}\sum_{k} E_j[T_k - \max\left(0; T_k RA_{ij} - B_k\right)]x_{ijk} \ \ \forall \ i = 1,..,W \tag{4.15}$$

$$E_{max} \geq \mathrm{E_i} \ \forall \ i = 1,..,W \tag{4.16}$$

$$\frac{1}{D}\sum_{j}\sum_{k} a_j^2[T_k - \max\left(0; T_k RA_{ij} - B_k\right)]x_{ijk} \leq a_{lim}^2 \ \ \forall \ i = 1,..,W \tag{4.17}$$

$$\sum_{j}\sum_{k} \frac{\alpha_{ij}\beta_{ij}N_j}{L_j} x_{ijk} \leq 1 \ \forall \ i = 1,..,W \tag{4.18}$$

$$x_{ijk} \in \{0,1\} \ \forall \ i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{4.19}$$

$$z_{ijk} \in \mathbb{N} \ \forall \ i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{4.20}$$

$$z_{max} \in \mathbb{N} \tag{4.21}$$

$$S_i, E_i \ \in \mathbb{R} \ \forall \ i = 1,..,W \tag{4.22}$$

$$S_{max}, E_{max} \in \mathbb{R} \tag{4.23}$$

Where O.F.1, hence the first objective function, maximizes the daily throughput. The second objective function, O.F.2, minimizes boredom (based on the worker's perceived level of similarity between jobs). Finally, the third objective function, O.F.3, minimizes safety risk. Constraint (4.7) states that each worker in each rotation shift must perform only one job. Constraint (4.8) guarantees the execution of all jobs at least once during a working day, while constraint (4.9) defines that each job must be executed by a maximum of one worker in each rotation shift. Constraint (4.10) guarantees the respect of the minimum and maximum throughput for each job j, constraint (4.11) quantifies the throughput for job j obtained by worker i in rotation shift *k.* Constraint (4.11) considers the level of experience of worker i in performing job $j,$ as well as the rest allowance and some physical limitations. Moreover, it evaluates whether to assign an extra amount of time, which is set as the maximum value between 0, and the difference between rest time ($T_k RA_{ij}$), defined as the product between the rotation shift length and the percentage of recovery time required for executing the job, and the beak time (B_k).

Constraint (4.12) quantifies the total daily throughput. Constraint (4.13) evaluates the average value of the similarity score for the worker *i* involved, while constraint (4.14) quantifies the maximum similarity level between workers. Constraints (4.15) and (4.16) evaluate the safety risk for each worker and the maximum safety risk score between workers to create a highly flexible model that can be applied to any type of occupational risk score. Constraints (4.17) and (4.18) ensure respect for vibration (Finco et al., 2020) and daily exposure to noise according to ISO5349-1:2001 and NIOSH. Finally, the constraints set (4.19)-(4.23) define the variable type.

The model proposed here is not linear due to constraints (4.11) and (4.13). However, it can be linearized by adding additional constraints and variables, and thus a Mixed Integer Linear Programming (MILP) model can be obtained. Going in-depth of the linearization approach, constraint (8) can be replaced as follows:

$$0 \leq z_{ijk} \leq \frac{T_k x_{ijk} - R_{ijk}}{\alpha_{ij}\beta_{ij}N_j} \; \forall\, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{4.24}$$

The following additional constraints are included in the model:

$$R_{ijk} \geq 0 \; \forall \, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{4.25}$$

$$R_{ijk} \geq (T_k RA_{ij} - B_k) x_{ijk} \; \forall \, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{4.26}$$

$$R_{ijk} \leq (T_k RA_{ij} - B_k) x_{ijk} + UB(1 - \varphi_{ijk}) \; \forall \, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{4.27}$$

$$R_{ijk} \leq 0 + UB\varphi_{ijk} \; \forall \, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{4.28}$$

$$\varphi_{ijk} \in \{0,1\} \; \forall \, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{4.29}$$

$$R_{ijk} \in \mathbb{R} \; \forall \, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{4.30}$$

Where R_{ijk} assumes the maximum value between zero (no rest) and the rest time to assign to a worker in case the break time is not enough to cover the physical fatigue spent in performing the job. Constraints (4.25) - (4.28) set the value of R_{ijk} for each worker, *i*, each job, *j*, and each shift, *k*. Finally, constraints (4.29) and (4.30) define the type of variable.

Considering constraint (4.13) the non-linearity is due to the product between two Boolean variables. For this reason, an additional set of Boolean variables must be included in the final model and constraint (4.13) must be replaced as follows:

$$\mathrm{S_{ik}} = \sum_{j=1}^{J} \sum_{j'=1}^{J} \gamma_{ijj'k(k+1)} s_{ijj'} \; \forall \, i = 1,..,W; \; k = 1,..,K \tag{4.31}$$

Moreover, the following additional constraints must be included:

$$\gamma_{ijj'k(k+1)} \leq x_{ijk} \; \forall \, i = 1,..,W; j = 1,..,J; j' = 1,..,J; k = 1,..,K-1 \tag{4.32}$$

$$\gamma_{ijj'k(k+1)} \leq x_{ij'(k+1)} \forall \; i = 1,..,W; j = 1,..,J; j' = 1,..,J; k = 1,..,K-1 \tag{4.33}$$

$$\gamma_{ijj'k(k+1)} \geq 0 \; \forall \, i = 1,..,W; j = 1,..,J; j' = 1,..,J; k = 1,..,K-1 \tag{4.34}$$

$$\gamma_{ijj'k(k+1)} + 1 - x_{ijk} - x_{ij'(k+1)} \geq 0 \; \forall \, i = 1,..,W; j = 1,..,J; j' = 1,..,J; \quad k = 1,..,K-1 \tag{4.35}$$

$$\gamma_{ijj'k(k+1)} \in \{0,1\} \; \forall \, i = 1,..,W; j = 1,..,J; j' = 1,..,J; k = 1,..,K-1 \tag{4.36}$$

Where $\gamma_{ijj'k(k+1)}$ is the Boolean variable representing the product between x_{ijk} and $x_{ij'(k+1)}$. The constraint set (4.32) - (4.35) is required to set the value of $\gamma_{ijj'k(k+1)}$ which can assume a value equal to 1 in case both x_{ijk} and $x_{ij'(k+1)}$ assume a value of 1 or equal to 0 in case of both or one Boolean variable among x_{ijk} and $x_{ij'(k+1)}$ assume a 0 value. Finally, the constraint (4.36) sets the type of variables.

4.4 Multi-objective solution procedure

Since the model is multi-objective, the ε-constraint algorithm was adopted to obtain the set of optimal solutions, thus the 3D Pareto's front. With the ε-constraint algorithm, the multi-objective problem is reduced to a single object, by adding the constraints that represent the remaining objective functions (Haimes Yv et al., 1971), Table 4.3 presents the pseudocode.

Table 4.3: ε-constraint pseudo-code

Algorithm: ε-constraint algorithm of the JRS model

1: $\mathrm{S} = \emptyset; \gamma \leftarrow 0$
2: Set
$\overline{\mathrm{E}} \leftarrow \mathrm{E}_{\mathrm{lim}}$
3: **while** ($\overline{\mathrm{E}} \geq \mathrm{E}_{\mathrm{min}}$) **do**
4: Set: $\overline{\mathrm{S}} \leftarrow \mathrm{S}_{\mathrm{lim}}$
5: **while** ($\overline{\mathrm{S}} \geq \mathrm{S}_{\mathrm{min}}$)) **do**
6: Set $\mathrm{Z}' \leftarrow$ solve JRS-S
7: Set $\mathrm{S}_{\gamma} \leftarrow$ solve JRS-E
8: Set $\mathrm{E}_{\gamma} \leftarrow$ solve JRS-T
9: $\mathrm{P} \leftarrow \mathrm{P} \cup \{(\mathrm{E}_{\gamma}; \mathrm{S}_{\gamma}; \mathrm{Z}')\}$
10: Decrease the bound on the budget by 1 unit: $\overline{\mathrm{E}} \leftarrow \mathrm{E}_{\gamma} - 1$
11: Decrease the bound on the budget by 1 unit: $\overline{\mathrm{S}} \leftarrow \mathrm{S}_{\gamma} - 1$
12: $\gamma \leftarrow \gamma + 1$
13: end while
14: **return** S (return the Pareto set S)

Furthermore, in this specific case, the ε-constraint algorithm consists of two steps:

Step 1: An upper bound of both ergonomics and similarity is set equal to $\bar{E}$ and $\bar{S}$ respectively. They represent the maximum ergonomic and similarity value that can be computed by considering jobs with the higher ergonomic score and similarity. Then, the mathematical model, denoted as JRS-HF (Job Rotation Scheduling - Human Factor) is solved by considering $E_{max} \geq \bar{E}$ and $S_{max} \geq \bar{S}$, constraints {(4.7)-(4.10);(4.12)-(4.36)} and O.F.1. JRS-HF defines a solution with respect to the fixed value of the ergonomic postural score and similarity.

Step 2: the optimal value of Z', thus the throughput, obtained in Step 1 is fixed as a bound and the model is solved by minimizing the ergonomic safety score and similarity. In this way, the non-dominated point with respect to the fixed $\bar{Z}$ can be obtained.

Finally, the algorithm decreases the ergonomic postural score and the similarity score by 1 and returns to Step 1. The stopping condition is reached when the upper bound of throughput is reached. It corresponds to the situation related to the highest worker performance while performing the job according to their cognitive and physical abilities.

4.5 Computational analysis

In this section, the multi-objective job rotation scheduling model is applied to a numerical case. The data adopted in this case are collected from a production line of a multinational company, which is a world leader in the production of integrated technologies for industrial automation and mobile operating machines. The assembly workstations of the company have already adopted enabling technologies belonging to the Industry 4.0 paradigm, such as the integrated system for production control and advanced product movement systems. Due to the large amount of data needed for the application of the proposed model, it was not possible to find a case study in the literature on job rotation scheduling problems to perform a benchmark analysis because none of them considers such as a huge number of parameters related to noise exposure, vibration level, safety risk, and worker boredom in the same case study.

4.5.1 Dataset generation

In the following numerical case, ten different jobs are considered (data are reported in Table 4.4). Each job represents the entire production process of a water pump and includes different tasks such as pre-assemble, assembly, quality control, and packaging. Depending on the type of product, the job can be performed using automatic, semi-automatic or manual tools, leading to different values of vibration level and noise exposure.

In this company, since the entire worker's body is involved in the progression of the job with variable cycle time (see Table 4.4), the Rapid Entire Body Assessment (REBA) (Hignett & McAtamney, 2000) was chosen as the index to assess the ergonomic score. In a real case study, the ergo-digital tool named WEM-Platform (Battini et al., 2022) can be adopted to rapidly assess the postural risk related to each job, depending on the ergonomic method that more suits the characteristics of the job analyzed. The platform considers the entire set of body movements needed to perform the job, asking workers to wear the suit while performing the job. Moreover, the energy expenditure required to perform each job can also be calculated based on the same ergo-digital platform software (Battini et al., 2022). Finally, this input was used to evaluate the rest allowance (RA) for each worker when the worker is involved in the job for a rotation shift (according to the formulas provided by Finco et al. (2019)). Jobs execution times range from 10 to 28 minutes. J1 and J2 refer to basic products, while J8, J9, and J10 refer to complex products that require a higher level of experience.

Furthermore, according to the management guidelines for each job, the minimum and maximum number of products to be produced in a day is established. Jobs J1 and J5 are entirely executed manually and, for this reason, acceleration and noise exposure values are respectively set as 0 m/s^2 (i.e., there is no vibration) and 100,000 minutes (i.e., there is no exposure to hazards noise exposure). The remaining jobs present both vibration and noise exposure. The higher the acceleration value (a), the higher the vibration exposure (Finco et al., 2020). The lower the time-exposure limit (L), the higher the noise exposure. Finally, energy expenditure varies in the range of 3.2 kcal/min to 4.3 kcal/min. Jobs requiring higher values of energy expenditure refer to special models of water pumps that involve large and heavy parts that need to be lifted and moved manually.

Table 4.4: Jobs features

	J1	**J2**	**J3**	**J4**	**J5**	**J6**	**J7**	**J8**	**J9**	**J10**
T *[minutes]*	10	12	15	15	17	19	21	25	27	28
Z_{min} *[pcs/day]*	5	5	5	5	1	1	1	1	1	1
Z_{max} *[pcs/day]*	40	40	25	25	25	25	20	20	20	20
a *[m/s^2]*	0	3.54	4.25	5.45	0	4.97	4.25	3.63	1.23	1.17
L *[minutes]*	100000	525	1250	2480	100000	1460	2780	3230	630	720
E *[REBA]*	5.5	5.9	4.6	4.2	3.7	5.4	6.4	3.5	4.7	3.8
EE [kcal/minute]	4.3	3.8	3.7	3.9	4.2	3.4	3.2	3.6	4.1	3.9

The job can be performed by six workers whose characteristics are reported in Table 4.5. Two out of six workers (e.g., W5 and W6) can be considered ageing workers (Cloostermans et al., 2015) as they are older than 45 years. Also, they have a long experience. W1 is a young worker in his first job, so he has no experience. W2 and W4 have low levels of experience since they have worked in the company for only a year. Following Finco et al. (2019), the Maximum Acceptable Energy Expenditure (MAEE) for each worker is provided and then used to define the rest allowances required for each worker while performing each job.

Table 4.5: Workers' attributes

	W1	W2	W3	W4	W5	W6
Age	23	31	37	42	52	58
Experience	Very low	Low	High	Low	Very high	Very high
MAEE [kcal/min]	4.8	4.7	4.4	4.2	3.8	3.5
Physical limitations	-	-	J1	J2, J7	J2, J6, J7	J2, J5, J9

Table 4.6 reports the RA values. As can be seen, W1, W2, and W3 do not have RA, since the energy expenditure to execute each job is always lower than their MAEE.

Table 4.6: Rest Allowance for a working day of eight hours (resp. six hours)

	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
W1	0	0	0	0	0	0	0	0	0	0
W2	0	0	0	0	0	0	0	0	0	0
W3	0	0	0	0	0	0	0	0	0	0
W4	0.05 (0.04)	0	0	0	0	0	0	0	0	0
W5	0.26 (0.21)	0	0	0.06 (0.05)	0.21 (0.17)	0	0	0	0.16 (0.13)	0.06 (0.05)
W6	0.49 (0.40)	0.19 (0.16)	0.13 (0.11)	0.25 (0.20)	0.43 (0.35)	0	0	0.07 (0.06)	0.37 (0.30)	0.25 (0.20)

Finally, according to the physical limit of the workers, W1 and W2 can perform all the jobs even if they have a low level of experience. W3, W4, W5 and W6 cannot perform some tasks, as they require a great deal of physical effort or were assessed as potentially hazardous activities according to their individual limitations (i.e., they correspond to a high ergonomic score). Depending on the experience of each worker, the time required to execute each job can be greater or lower than the nominal time. Finally, workers are directly involved in the short-term decision process by providing their perceived similarity score among jobs.

4.5.2 Scenario generation

The following three scenarios are considered to analyze how the workday duration, the rotation shifts and breaks length time influence throughput, ergonomics, and similarity scores:

- Scenario 1 (S1): two rotation shifts (RS) and a break (B).
- Scenario 2 (S2): three rotation shifts (RS) and two breaks (B).
- Scenario 3 (S3): four rotation shifts (RS) and three breaks (B).

For each scenario, two different working days (WD) durations were considered, which are equal, respectively, to 6 hours/day (Case A) and 8 hours/day (Case B). In Case A, workers are involved 6 days/week, while in Case B, they work 5 days/week. According to Finco et al. (2019), in Case A, the RA for each worker is reduced because their MAEE is higher, and the hourly throughput could be higher due to the lower rest that some workers can have. Furthermore, the maximum vibrations and noise exposure change according to Section 4.2. Then, for each case, the following shift and break time intervals have been considered (Table 4.7).

Table 4.7: Details of working and break shift durations for the three work-schedule scenarios

Scenario	Case A (WD duration: 6 hours)	Case B (WD duration: 8 hours)
S1	RS: 172 min/rotation shift B: 15 minutes/break	RS: 232 min/ rotation shift B: 15 minutes/break
S2	RS: 113 min / rotation shift B: 10 min / break	RS: 153 min / rotation shift B: 10 min / break
S3	RS: 86 min/ rotation shift B: 5 min / break	RS: 116 min/rotation shift B: 5 min / break

4.6 Results Discussion

The main results of this analysis are discussed in this subsection. All scenarios for both cases (Case A and Case B) were analyzed for a total of six different cases. Furthermore, additional investigations were carried out on the impact of different safety risk scores and similarity values on the Pareto front. The CPLEX 22.1.0.0 version of the solver was used to obtain the set of optimal solutions.

Figure 4.1 and Figure 4.2 report the set of feasible solutions and the non-dominated points for each case and scenario. As demonstrated by Otto & Scholl (2013), job rotation is an NP-hard problem. Consequently, for the case study discussed here, the higher the number of rotation shifts, the higher the computational time required to get the entire optimal set of feasible results. In fact, in the case of two rotation shifts, the computational time was on average equal to 195 seconds for both Case A and Case B; while in the case of four rotation shifts, the computational time was on average equal to 12500 seconds.

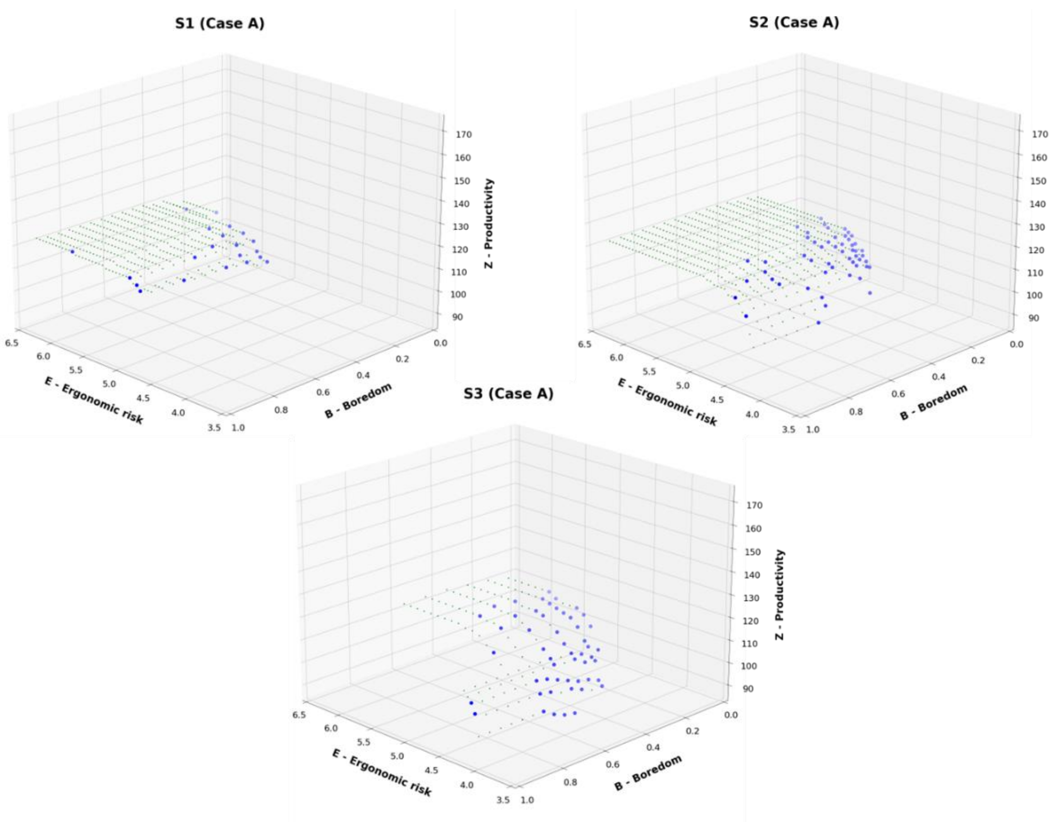


Figure 4.1: Feasible set of solutions for different numbers of rotation shifts (Case A: 6 hours/day)

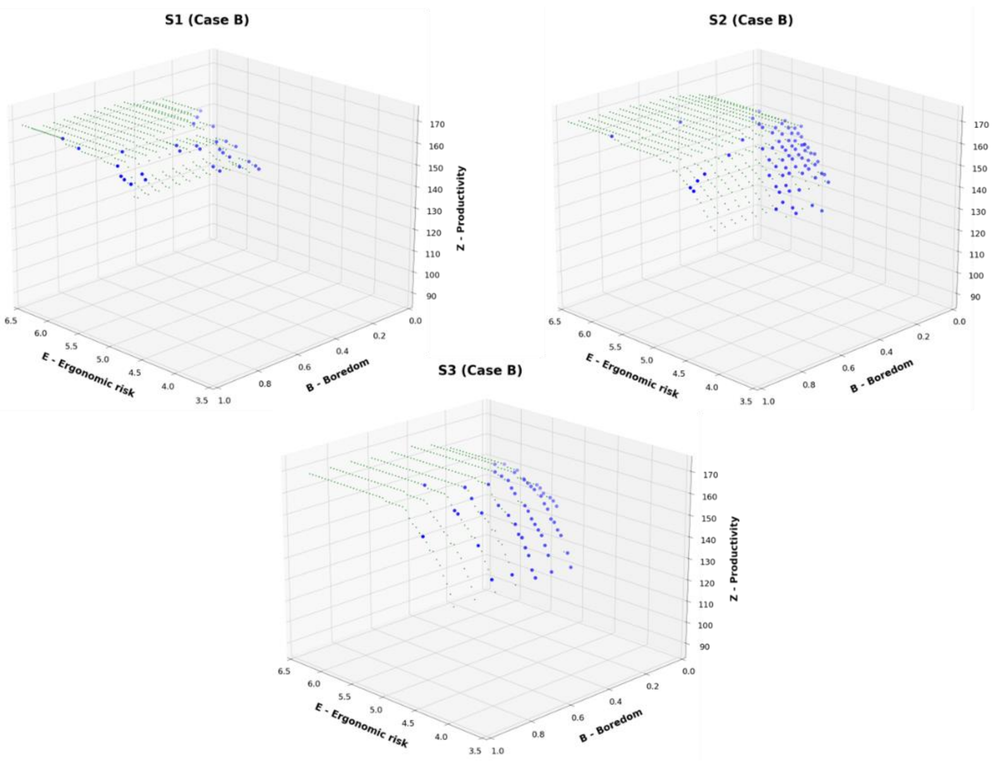


Figure 4.2: Feasible set of solutions for different numbers of rotation shifts (Case B: 8 hours/day)

By comparing Case A and Case B, the hourly productivity decreases slightly by 1% for Case A (resp. 1% for Case B) in S2 and by 6% for Case A (resp. 2% for Case B) in S3. The main cause can be attributed to the different RA values required for older workers to cover the physical effort spent performing the job. In S1, they can use only one available break, but an additional amount of time is needed to cover all physical fatigue. By increasing the number of rotation shifts, a double benefit is achieved.

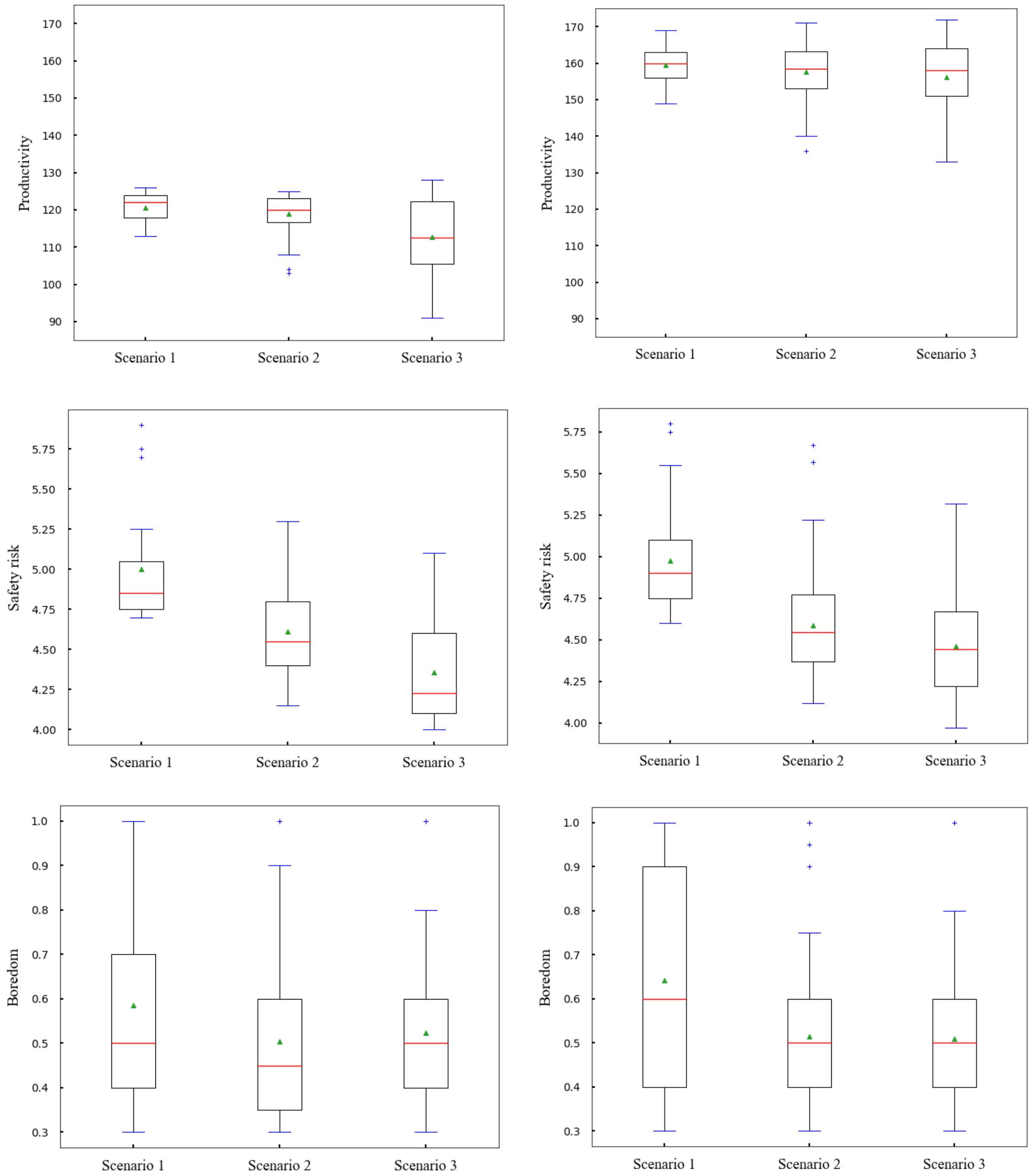
1) Ageing workers can rest more, but an additional period of recovery time is still necessary for some of them to fully recover from fatigue.
2) Ageing workers can also perform a high physical job for a shorter period. Finally, for the specific case study, ageing workers are also those who have more experience, and their experience can positively contribute to smoothing the extra recovery time assigned to them.

Furthermore, by focusing on the comparison between scenarios, the same considerations can be raised for both Case A and Case B. The higher the number of rotations, the lower the maximum scores of safety risks and boredom. Coming to the details, by considering the non-dominated point, Case A (resp. Case B) presents a safety risk range that is 4.7-5.90 (resp. 4.6-5.80) for S1, 4.15-5.3 (resp. 4.12-5.60) for S2, and 4.00-5.10 (resp. 3.97-5.32) for S3. For the specific case study, the range is always in the safety risk of a medium level, but very close to the lower limit. Consequently, for this specific application case, the selection of one non-dominated solution may not be considered influenced by the ergonomic score. However, in case some jobs are classified as hazardous activity from an ergonomic point of view, the choice of the best non-dominated point could be that one presenting an ergonomic score in a medium-risk area.

Moving to the boredom aspect, the higher the number of rotation shifts, the higher the chance to diversify jobs assignment to the same workers, and consequently, the similarity level can decrease since job variations increases. The boredom score range decreases by increasing the number of rotations shifts for both Case A and Case B. By focusing on non-dominated solutions, the boredom range varies for Case A (resp. Case B) as follows: 0.3-1.0 (resp. 0.3-0.1) for S1, 0.3-0.9 (resp. 0.3-0.75) for S2 and, finally, 0.3-0.8 (resp. 0.3-0.8) for S3. The choice of one non-dominated point by focusing on boredom aspects can be conducted by managers in collaboration with the workers involved in the production process. In fact, according to Jeon et al. (2016), some workers might prefer to perform similar jobs during the work day, while others suggest that greater variability leads to greater motivation. However, for the case study investigated here, greater boredom also leads to a slightly higher value of productivity.

Table 4.8: Comparison analysis of Pareto front non-dominated solutions

Case A **Case B**



The box plots reported in Table 4.8, which represent the values obtained from the non-dominated solutions per each objective function, can provide additional information on the results. First, the outcomes that emerge mostly are related to the safety risk scores of the Pareto front solutions, which decrease the mean values as long as the number of rotation periods increases (results are reported in Table 4.9). In particular, the results obtained state that the average reduction of safety risk from the initial situation with two rotation periods per day (Scenario 1) decreased by 8% for both Case A (6 hours/day) and Case B (8 hours/day), when an additional rotation period is introduced (Scenario 2).

Table 4.9: Safety risk performance for the analyzed scenarios

Safety risk (**Case A**)	Scenario 1	Scenario 2	Scenario 3	Δ(S1-S2)	Δ(S1-S3)
Average	5	4.61	4.36	-8%	-13%
First quartile (Q1)	4.75	4.4	4.1	-7%	-14%
Median (Q2)	4.85	4.55	4.25	-6%	-13%
Third quartile (Q3)	5.05	4.8	4.6	-5%	-9%
Interquartile range (IQR)	0.3	0.4	0.5	2%	5%
Upper whisker	5.25	5.3	5.1	-	-
Lower whisker	4.7	4.15	4	-	-
Safety risk (**Case B**)	Scenario 1	Scenario 2	Scenario 3	Δ(S1-S2)	Δ(S1-S3)
Average	4.98	4.59	4.46	-8%	-10%
First quartile (Q1)	4.75	4.37	4.22	-8%	-11%
Median (Q2)	4.9	4.545	4.445	-7%	-9%
Third quartile (Q3)	5.1	4.77	4.67	-6%	-8%
Interquartile range (IQR)	0.35	0.4	0.45	2%	3%
Upper whisker	5.55	5.22	5.32	-	-
Lower whisker	4.6	4.12	3.97	-	-

Moreover, when the job rotation strategy includes 4 rotation periods (Scenario 3), compared to the scenario with only two rotation periods (Scenario 1), the reduction of the final throughput is limited to 13% for Case A and 10% for Case B (results are reported in Table 4.10). This result is predictable since the application of job rotation strategies, especially considering a higher number of rotation periods, primarily aims to increase the variety of the movements accomplished by the worker in executing daily work activity, and consecutively, they aim to reduce the exposure of the same parts of the body to high repetitions, hence decreasing the chance of developing occupational disorders.

Also, interesting comments can be made on productivity results. In fact, the average value of productivity does not decrease drastically as the number of rotation periods increases. The total throughput of the system depends on the skills of the operators, which impact the task time needed to perform the activity, but also on the rest-break time, which can affect the available time between rotation periods, when scheduled breaks are not enough to recover from accumulated fatigue. Consequently, one may expect that as the number of rotation periods increases, the chance of rest increases as well, and productivity can be affected by this scheduling decision, which prioritizes the reduction of safety risks on productivity. However, the results obtained state that the average reduction in total throughput from the initial situation with 2 rotation periods per day (Scenario 1), only by 1% for both Case A (6 hours/day) and Case B (8 hours/day), when an additional rotation period is introduced (Scenario 2).

Table 4.10: Productivity performance for the analyzed scenarios

Productivity (**Case A**)	Scenario 1	Scenario 2	Scenario 3	Δ(S1-S2)	Δ(S1-S3)
Average	120.6	118.9	112.8	-1%	-6%
First quartile (Q1)	118	116.75	105.5	-1%	-11%
Median (Q2)	122	120	112.5	-2%	-8%
Third quartile (Q3)	124	123	122.25	-1%	-1%
Interquartile range (IQR)	6	6.25	16.75	0%	9%
Upper whisker	126	125	128	-	-
Lower whisker	113	108	91	-	-
Productivity (**Case B**)	Scenario 1	Scenario 2	Scenario 3	Δ(S1-S2)	Δ(S1-S3)
Average	159.48	157.61	156.25	-1%	-2%
First quartile (Q1)	156	153	151	-2%	-3%
Median (Q2)	160	158.5	158	-1%	-1%
Third quartile (Q3)	163	163.25	164	0%	1%
Interquartile range (IQR)	7	10.25	13	2%	4%
Upper whisker	169	171	172	-	-
Lower whisker	149	140	133	-	-

Furthermore, when the job rotation strategy includes 4 rotation periods (Scenario 3), compared to the scenario with only two rotation periods (Scenario 1), the reduction of the final performance is limited to 6% for Case A and 2% for Case B. Finally, the level of boredom was positively affected by the adoption of the job rotation strategy with a higher number of rotation periods, already starting from the adoption of three rotation periods (results are reported in Table 4.11).

Table 4.11: Boredom performance for the analyzed scenarios

Boredom (**Case A**)	Scenario 1	Scenario 2	Scenario 3	Δ(S1-S2)	Δ(S1-S3)
Average	0.59	0.50	0.52	-14%	-11%
First quartile (Q1)	0.4	0.35	0.4	-13%	0%
Median (Q2)	0.5	0.45	0.5	-10%	0%
Third quartile (Q3)	0.7	0.6	0.6	-14%	-14%
Interquartile range (IQR)	0.3	0.25	0.2	-2%	-14%
Upper whisker	1	0.9	0.8	-	-
Lower whisker	0.3	0.3	0.3	-	-
Boredom (**Case B**)	Scenario 1	Scenario 2	Scenario 3	Δ(S1-S2)	Δ(S1-S3)
Average	0.64	0.51	0.52	-20%	-21%
First quartile (Q1)	0.4	0.4	0.4	0%	0%
Median (Q2)	0.6	0.5	0.5	-17%	-17%
Third quartile (Q3)	0.9	0.6	0.6	-33%	-33%
Interquartile range (IQR)	0.5	0.2	0.2	-33%	-33%
Upper whisker	1	0.75	0.8	-	-
Lower whisker	0.3	0.3	0.3	-	-

In the following subsections, the investigation focuses on how ergonomics risk scores, perceived boredom and workforce attributes can influence the decision process. The analysis is carried out only for Case A, since similar considerations could be made for Case B.

4.6.1 Influence of safety risk scores

Initially, three sets of safety risk values E1, E2, and E3 are randomly generated. They present a mean value and a standard deviation, respectively, equal to 4.5(+/-0.9), 5.9(+/-2.1), 6.2(+/-1.8); in the last case, some jobs are critical, since they have an ergonomic score close to the critical threshold value (i.e., a score equal to 8 for REBA).

Figure 4.3 depicts the Pareto front by assuming a fixed boredom value equal to 0.5 and varying the value of the safety risk score from E1 to E3. As shown in

Figure 4.3, S2 and S3 present a larger Pareto front for both E2 and E3, while they present a more closed Pareto front for E1. In the last case (E1), since the ergonomic score difference is very slight (e.g., minimum value 3.70 and maximum value 4.35) the choice of the best rotation strategy should be one that guarantees higher throughput.

Moving to the E2 and E3 cases, the ergonomic score gap increases, as well as the throughput, with a difference between the extremal points, which is equal, respectively, to 25% for the ergonomic risk and the 16% for the throughput. However, in all cases, the safety risk never assumes a critical value and, consequently, the optimal point could be selected considering the one that provides higher throughput. Focusing on S1, it has four non-dominated points, and the maximum achievable production exceeds the minimum one by 4% while the ergonomics risk improves from 4% (S1) to 13.45% (S3).

Finally, when comparing E1, E2 and E3 in 4.3, maximum throughput is always achievable when considering S3. Furthermore, for E3 the same throughput is obtained for both S1, S2 and S3, however, S3 provides a lower safety risk with a slight difference of 2% compared to S2. Consequently, in this application case, a higher number of rotation shifts leads to lower daily safety risk postural scores without influencing performance.

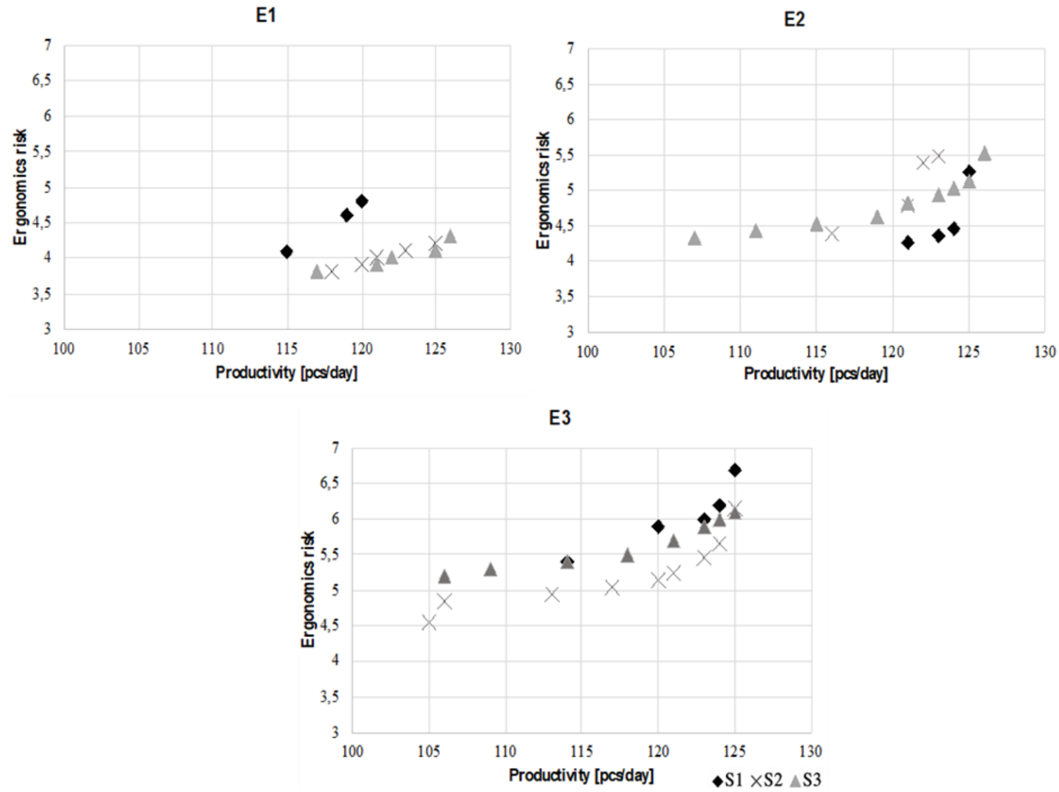


Figure 4.3: Productivity and safety risk values for three rotation period strategies (S1, S2, S3) by varying the ergonomic scores of the postural job (E1, E2, E3).

4.6.2 Influence of job boredom values

In this section, the effects of perceived boredom between workers are investigated. In the specific case, the following scenarios are designed: (1) perceived boredom by all workers is close to 0.6 (B1), which is around a medium level (i.e., workers evaluated the similarity between different couples of jobs in the same way, by assigning scores closer to 0.6 on a scale 0-1), (2) perceived boredom is negligible (B2) (i.e., workers consider jobs as totally different between them; hence, on average, the similarity scores assigned from each worker to the couples of jobs are close to zero), (3) perceived boredom is very high for all workers (B3) (i.e., workers evaluated jobs as very similar, so the similarity scores for all the couples of jobs are close to 1). This analysis aims to investigate the values assumed by productivity and boredom scores for three cases (B1, B2, B3) differentiated for three job rotation strategies (i.e., scenario 1, scenario 2, scenario 3). For this purpose, a hypothetical constant ergonomic score of 5 is assumed and Figure 6 depicts the Pareto fronts for each scenario, varying only boredom levels (B1, B2, B3).

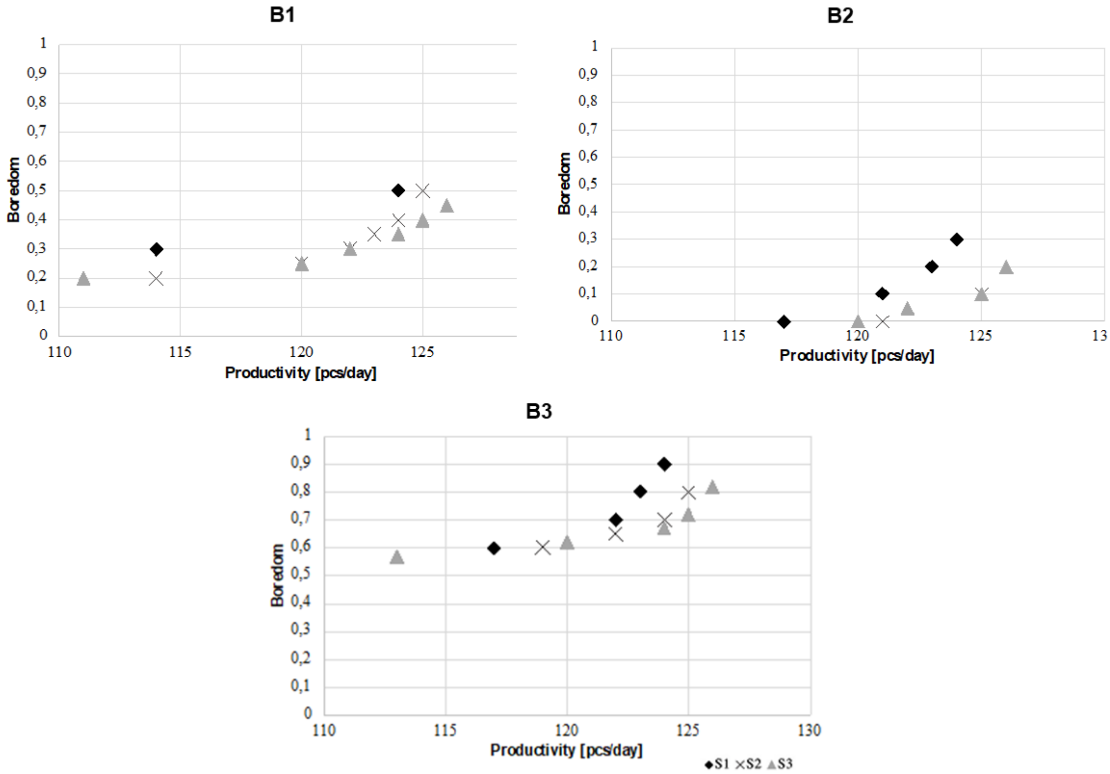


Figure 4.4: Productivity and boredom values considering for the three rotation period strategies by varying the perceived boredom: medium level of boredom (B1), negligible boredom (B2), and high level of boredom (B3).

The first results presented in Figure 4.4 (B1) show the case where all workers evaluated the couple of jobs with similar scores. In other words, all workers involved in the job rotation strategy evaluated the degree of similarity between different couples of jobs by assigning similar scores (e.g., all workers agreed that the degree of similarity between the couple of jobs can be described with a score that is almost the same for all workers). The results obtained for the highest level of productivity demonstrate that there are few differences amongst the optimal solutions for the three rotation strategies analyzed (S1, S2, S3). In particular, the solutions obtained with S3 dominate the solutions of S1 and S2 for the highest productivity value. Not surprisingly, the job rotation strategy with fewer rotation periods (S1) brought the highest level of boredom. However, due to the same job similarity scores, the boredom value was barely reduced even with the other job rotation strategies (S2, S3). Considering the same level of job similarity for every operator does not allow to progress the job assignment trying to match workers' previous assignments and workers' individual perceived level of similarity. However, the general trend of all scenarios highlights that the productivity level increases and the boredom score decreases when job rotations are more frequent. An exception related to low boredom values can be highlighted. In this case, the solution provided by the second scenario

(S2) dominates those obtained by S1 and S3, providing greater productivity compared to S3 with a lower level of boredom than S1. In the second case presented in Figure 4.4 (B2), the level of similarity between jobs was evaluated by workers near zero (e.g., the degree of similarity between a couple of jobs was evaluated as totally different). The results obtained show that the scenario with three rotation shifts (S3) leads to the highest productivity. Furthermore, one can notice that the results obtained with two and three rotation shifts tend to overlap for higher production values, while in the other cases the distinction between S2 and S3 is more prominent. Similarly to the first case, the scenario with two rotation shifts (S2) offers the highest productivity amongst the solutions with the lowest value of boredom. Finally, Figure 4.4 (B3) proposes the case in which workers assess the jobs as very similar. In this third case, the degree of similarity between couple of different jobs is close to the unit value, and boredom levels are the highest obtained so far in this analysis. Fewer rotation shifts lead to the highest boredom value (S1). This is the only case where three rotation shifts (S3) lead to the best results for both the lowest level of boredom and the highest productivity. In last case, the scenario with three rotation shifts outperforms the others for almost every value of productivity and boredom.

4.6.3 Influence of workers' attributes

Finally, in this subsection, the investigation focuses on how performance can be influenced by the characteristics of workers. The age and level of experience are the two drivers that directly influence the execution time and thus the performance (see Equation (4.11)). Consequently, also in that case, three new sets of RA and experience values have been randomly generated, and the following scenarios have been analyzed:

- Young working team with low experience levels (YWT): All workers are not older than 40 years, so the contribution of recovery time determined by RA is negligible, as the maximum acceptable energy expenditure level of young workers is high and is rarely reached during the execution of the job (Finco et al., 2019). However, workers are not highly skilled and fully trained, and an additional amount of time compared to the nominal job duration is required to obtain a final product.
- Aged Working Team with high experience levels: (AWT): all workers are older than 40 years. Consequently, RA can occur for some jobs according to the physical effort required (Finco et al., 2019). In this case, the workers are highly skilled, and consequently, the higher RA needed can be smoothened by their greater experience, thus achieving a lower execution time.

- Mixed working team with high experience level (MWT): young and ageing workers are jointly involved and the whole team is highly skilled.

Figure 4.5 reports the set of feasible solutions and non-dominated points by considering three rotation shifts. Even if young people do not necessarily need rest, their inexperience in executing jobs leads to lower productivity. The maximum value, which is 112 pcs/day, is achieved for a lower level of boredom and a higher value of safety risk (see Figure 4.5 YWT). For the AWT scenario (see Figure 4.5 AWT), the higher productivity is equal to 148 items/day, but in this case, it is also obtained considering the higher value of the ergonomic score. However, the case that corresponds to the lowest risk score (a safety risk score of 3.6) can be achieved with a higher boredom value and daily productivity equal to 110 pcs/day, which is close to the maximum daily throughput obtained for case YWT. Finally, the MWT scenario (see Figure 4.5 MWT) presents a maximum daily productivity of 139 pcs/day. The maximum throughput value is achieved with a boredom score of 0.3 and a safety risk value of 5.85. Consequently, MWT, which also represents a common scenario in several manufacturing companies, guarantees a proper balance among the three drivers included as objective functions and supports the idea that heterogeneous working teams can benefit system productivity.

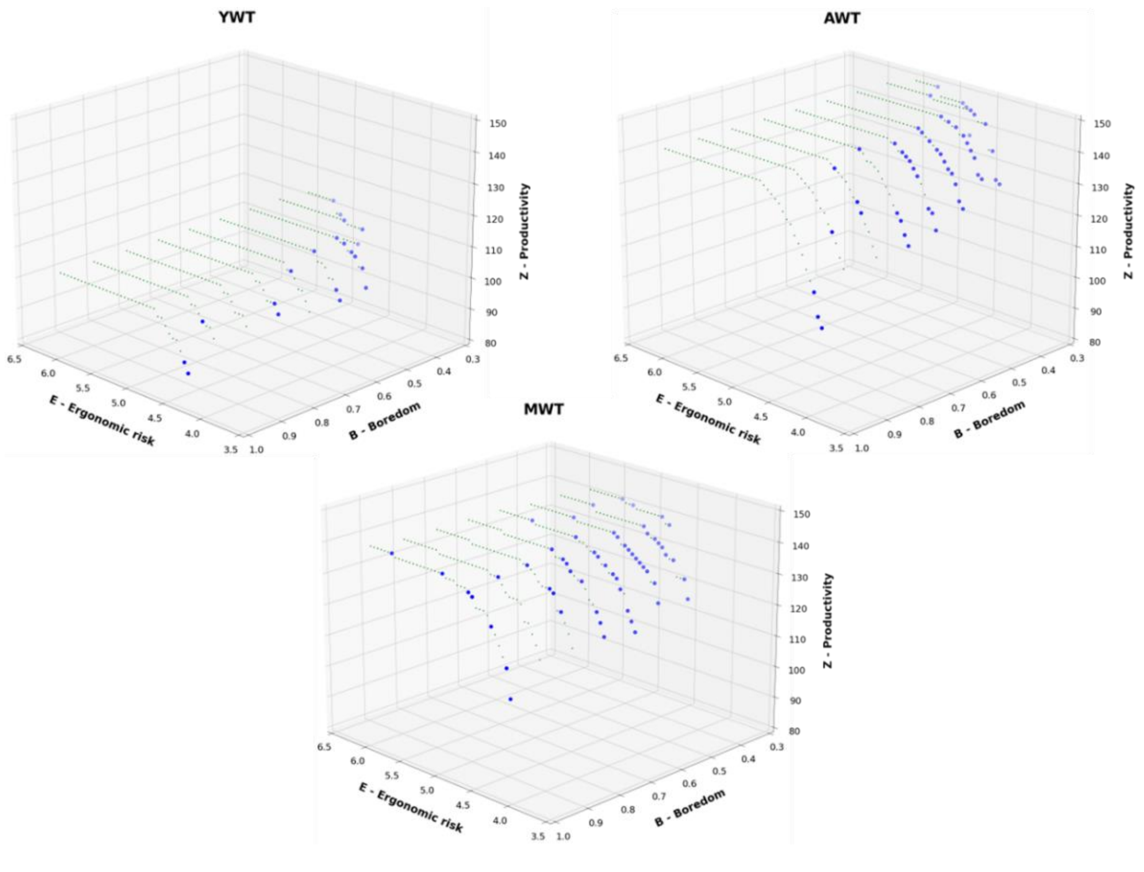
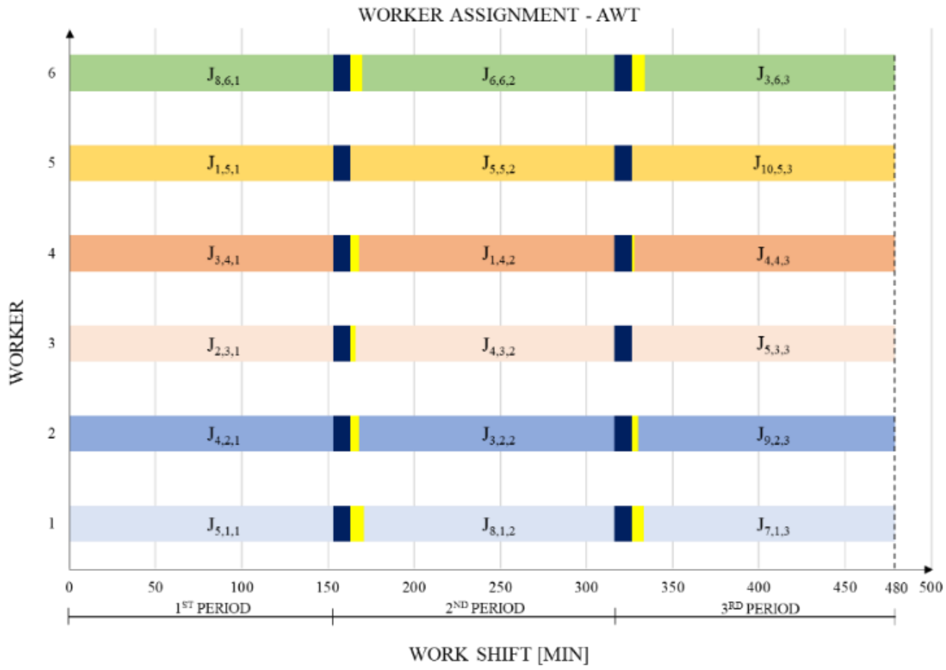


Figure 4.5: Feasible set of solutions by varying workers' experience and age

To conclude this subsection, some final considerations are raised by considering one single solution belonging to the Pareto 3D front of scenario AWT. The analyzed solution maximizes throughput of up to 141 pieces per day, while reaching a dangerous safety risk of 5.35 and a boredom level of 0.3. Figure 8 shows the flexible job rotation scheduling solution obtained with three rotation shifts (Scenario 2) and 8 hours/day (Case B) as reported in Figure 4.6.



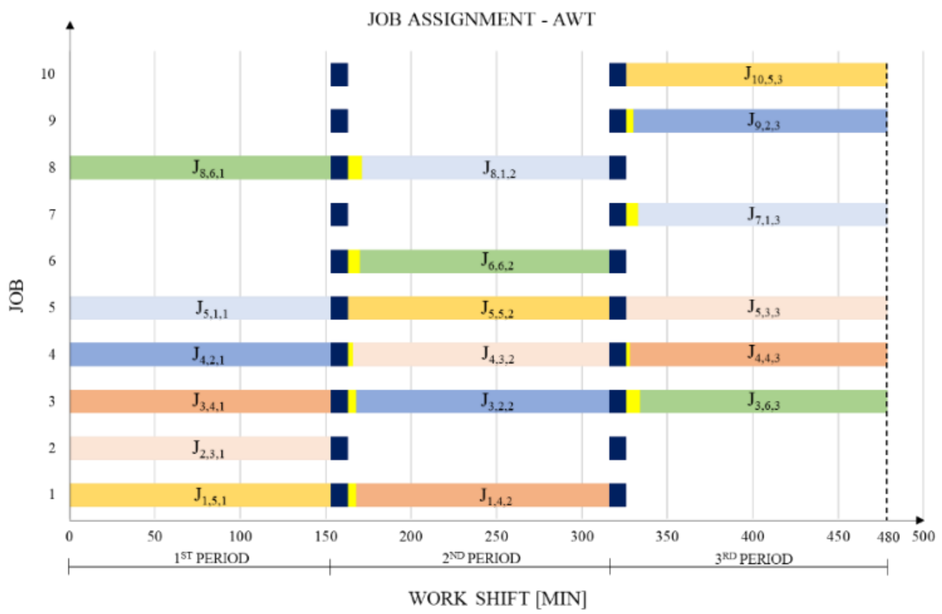


Figure 4.6: Gantt chart of a flexible working schedule with 3 rotation shifts, 8 hours/day (Case B) and an aged work team (AWT).

In the proposed charts, different colors are associated with different workers, fixed breaks between rotation periods are reported in blue, and the additional recovery times for each operator are reported in yellow. The recovery time portion was calculated considering the value of the rest allowance for each individual operator as reported in Equation (8). Older workers are more likely to need a longer recovery time, often exceeding the duration of the break. The solution analyzed aims to maximize system throughput; however, safety/health risks may arise due to a lack of adequate recovery time. Therefore, older workers may experience strenuous work periods that are not sustainable for a prolonged period.

Conclusion

The multi-objective job rotation scheduling model proposed in this chapter demonstrates the benefits of occupational risk reduction, when adopting a job rotation strategy. Amongst the most relevant results, the test case application of the model highlighted that the higher the number of rotation periods, the higher the benefits of frequent job rotation periods. Nevertheless, when rotation periods increase in number, the complexity increases, as well as the computational time to find optimal solutions. This effect is well depicted in Figure 4.1 (i.e., Scenario 3, Case A) and Figure 4.2 (i.e., Scenario 3, Case B), where test case whit 3 rotation periods were applied. In these cases, the number of solutions belonging to the Pareto front are fewer than the other scenarios because some of them overcome the maximum time limit imposed for the ε-constraint algorithm. For this reason, as a future perspective of this work, a metaheuristic algorithm will be developed, enabling the reduction of the computational time and the determination of the breakeven point between the number of rotation periods and the effective benefits of job rotation, without penalize much the productivity of the company. Other limitations of the current mathematical model can be addressed in the next future, such as the impact of frequent job rotation periods on jobs nominal duration, which is also related to the learning and forgetting curves of operators, and on workplace conditions that are equals in the scenarios analyzed but that can change according to the work area where jobs are executed. Furthermore, the higher the number of parameters considered in the analysis, the higher the complexity of the final analysis. Hence, a more detailed sensitivity analysis can help to provide more information regarding the effects that each factor has on the results.

Conclusions

This dissertation presents a novel approach to include, assess, and integrate sociotechnical aspects in job rotation scheduling models. Starting from the analysis of the models and methods that progress the job rotation strategy, including ergonomics aspects and human factors, few contributions have been found on a method that can jointly consider both technical and social aspects to carry out flexible work arrangements, considering workforce diversity. For this reason, in this research, a new multi-objective mathematical model was developed, improving in this way the current state-of-the-art. Furthermore, another research gap was highlighted on the lack of a methodological approach that can guide the collection and adoption of the information needed to develop a suitable work assignment based on the profile of the workforce and individual characteristics. Therefore, a methodological framework was designed aiming to be a useful tool for workforce management, to increase the resilience of the company against unforeseeable events, by providing a guide to rapidly react to workforce shortage or to high turnover rate, considering the introduction of new temporary personnel in a flexible work environment, able to accept workers with different characteristics. Finally, to improve the assessment of postural risk and the quality of the training session, a new ergonomic digital platform was designed. It allows postural risk assessment to accelerate through the computation of real-time ergonomic indexes and to provide on-site feedback to trainees during the training session to reduce their postural risk. Both the ergonomic digital platform and the multi-objective job rotation scheduling model have been tested and validated with numerical examples coming from data collected in real industrial case studies. The results of this research aim to increase managers' awareness in managing workforce diversity when making operational and strategical decisions. The achievement of a higher degree of flexibility in workforce management is consistent with new human-centric industrial paradigms for the development of more resilient work environments against disruptive events. Furthermore, the application of a human-oriented job rotation scheduling model, which include sociotechnical aspects of the workforce and workplace, enables the development of safe and ergonomic work environments, which support workers' inclusion. Increasing social sustainability in the company, considering workers' perspective in operational decisions, demonstrated a positive impact on both workers' performance and morale, sharing positive benefits also on economic sustainability.

Theoretical and managerial insights

The latest industrial paradigms are driving research and innovation to facilitate the transition to a sustainable, human-centered, and resilient industry. In the manufacturing context, workers' diversity in terms of experience, productivity, and physical capacity represents a significant challenge for companies, especially those characterized by high staff turnover and manual processes with high workload and poor ergonomics. The management of workforce diversity is increasingly gaining interest in manufacturing companies due to the complexity related to the development of flexible and suitable work plans based on the profile of available workers. The first chapter of my research investigates the state-of-the-art on job rotation scheduling problem, with the aim of answering the first research question.

RQ1: *"Do current workforce management methodologies include the characteristics of workers and their individual perspective for the development of flexible work plans?"*

Relatedly, substantive research has been conducted on job rotation scheduling approaches that incorporate human factors. The integration of human factors in operational decision processes has gained growing interest in the last decade (Sgarbossa et al., 2020; Neumann et al., 2021), however, joint effects of socio-technical aspects are scarcely included in literature. Despite the fact that human factors need to be integrated as soon as possible in the design of the system, as a method to prevent worker injuries and absenteeism (Battini et al., 2011), workers' individual limitations and perspectives on job scheduling decisions have only started to be recently included in models and frameworks.

This research proposes a methodological approach to guide the collection and the integration of such aspects, promoting the development of flexible and inclusive work plans, based on the profile, limitations, and preferences of the workers (Berti et al., 2021). It also includes the adoption of industry 4.0 sensor-based technologies to progress the collection of technical data to be integrated into scheduling decisions. Following this technological paradigm, this research brought to the development of a new ergo-digital platform with several potential applications to increase the performance and quality of postural risk assessment and worker training. To investigate the impact that the latest technologies have had on the manufacturing work field, I conducted a survey on the current software and systems to answer the second research question.

RQ2*: 'How has the latest technological advancement shaped occupational risk assessment methods to create a safe and inclusive workplace?'*

The adoption of new technologies in manufacturing work field has enhanced the development of new risk assessment and training methods. Data collection can generate insightful information for product and safety managers, as well as ergonomists, to positively impact worker well-being (Romero et al., 2016). Providing real-time postural risk assessment and feedback to workers during work activities requires a system that is capable of rapidly assessing their posture and promptly giving feedback to correct their behavior in real time.

WEM-Platform (Battini et al., 2022) represents a new solution that combines postural risk assessment with feedback intervention to overcome previous systems with a wider set of risk indices compared to existing solutions, capable of providing insightful information to ergonomists, safety risk experts and operational managers on workplace risks and worker behavior. Merging technical information collected from the workplace with real-time tools with social aspects, related to workforce diversity and individual characteristics, allows the progression of human-oriented scheduling decisions, which can jointly achieve the productive and efficiency target within ergonomic and inclusive workplaces. Consequently, this research proposes a new multi-objective optimization model to assign jobs to workers by considering multiple sociotechnical factors and three distinct objectives: worker productivity, job ergo-quality level, and worker perceived boredom. The results of the model optimize multiple objective functions that encompass efficiency and psychological factors.

The mathematical formulation proposed in this research led to results that can justify the adoption of a human-oriented perspective on managerial decisions. In particular, the results obtained from the multi-objective job rotation scheduling model answer the third research question:

RQ3: *"What are the implications of adopting a human-oriented perspective in defining the workforce rotation strategy?"*

Adopting a human-oriented approach to make scheduling decisions and develop flexible work arrangements, based on sociotechnical aspects related to the profile and workplace of workers, can help develop a more inclusive and ergonomic workplace (Battini et al., 2022). Flexibility in work arrangements has recently emerged as a top-rated job trait for manufacturing workers. Flexible job scheduling approaches that include such factors would foster workforce motivation and inclusiveness in moving toward the Industry 5.0 factory of the future. Following the principles shared by the emergent Industry 5.0 paradigms, this research proposes a new multi-objective job rotation scheduling model which incorporates multiple sociotechnical factors and maximizes throughput, while minimizing boredom and ergonomics risks.

The results suggest that different rotation strategies can affect system productivity, safety risk level, and operator boredom, depending on rotation frequency. The numerical results show that flexible job rotation plans can provide workers with opportunities to enrich their capabilities by acquiring experience in a variety of tasks in a short period of time, while reducing perceived boredom and increasing motivation and satisfaction. These results are also supportive of and align well with the recent and new ISO 25550:2022 for the age-inclusive workforce. The correct computation of rest times during the day can lead to different breaks for each worker considering individual worker attributes. In fact, the number of shifts, as well as the break time between each shift, is optimally scheduled, as they strongly influence productivity and worker well-being. Improving previous job rotation scheduling models (e.g., Hochdörffer et al., 2018; Song et al., 2016; Yoon et al., 2016), the proposed mathematical model assumes break time between shifts as an opportunity for operators to recover, contingent on worker individual characteristics.

The proposed model also translates the Industry 5.0 principle of placing the well-being of the worker central to the production process into meaningful and practical task-related insights and recommendations. Human-centered focus can help managers make better decisions about improving inclusion and resilience in the workforce. The increased operational flexibility enabled by job re-assignment and re-planning can help management protect operations against unforeseen worker shortages or absenteeism. Furthermore, the resilience of the system can increase against disruptive events or unpredictable market demand due to the possibility to redistribute or hire new staff and introduce new employees in an inclusive workplace capable of considering their physical characteristics and attitudes when progressing flexible work arrangements, ensuring the full and safe operational status of quick workers. The model provided can also be easily adapted to different work applications and contexts. It can develop sustainable and less hazardous job rotation plans by providing a set of optimal solutions based on the predominance of particular and possibly differently weighted human-oriented factors.

In summary, this research presents a new human-centric job rotation scheduling approach whose model aims to make the worker (and inferentially the production system) more resilient to variability in ergonomic workloads and minimize boredom risks in human-intensive working environments. The model is inspired by the new human-centric Industry 5.0 paradigm and is grounded in previous research.

Generalization of Results

Enduring competitive advantage is seen as a goal for investments in digital, resilient and sustainable manufacturing systems (Breque et al., 2021; Renda et al., 2022). As such systems evolve, new paradigms emerge to guide and shape the manufacturing industry. A significant dynamic in this regard is the progressive movement of Industry 4.0 toward Industry 5.0 paradigm, relaxing the focus on efficiency and productivity to embrace and reinforce the role and the contribution of industry to society. The sharper focus on societal value and worker wellbeing also manifests in the well-known ESG (Environment, Social and Governance) paradigm that adds people and the planet in equal proportion to traditional productivity goals (Duque-Grisales & Aguilera-Caracuel, 2021; Gbejewoh et al., 2021). In the era of Industry 4.0, disruptive technologies such as artificial intelligence, collaborative robotics, blockchain, Internet of Things, and digital twins have been the main paradigms for developing competitive and efficient manufacturing systems. However, these benefits did not come without consequences, especially in encounters related to human-machine conflicts. Choi et al. (2022) highlight worker welfare, health problems, and worker satisfaction as concerns of note in this regard. Industry 5.0 seeks to ameliorate and reconcile these human-machine frictions by specifically directing research and innovation to a sustainable, human-centric, and resilient paradigm (Neumann et al., 2021).

Conceptually, the concepts shared by Industry 5.0 paradigm complement, rather than replace, Industry 4.0, while the latter is largely technology driven, the former is primarily values-oriented (Xu et al., 2021). However, the transition between the two paradigms poses interesting challenges. Notwithstanding technological advances, labor-intensive manufacturing and logistics systems still see tasks being performed manually even when experiencing high levels of perceived fatigue and boredom. In these contexts, advanced and intelligent human-machine interaction technologies of Industry 4.0 (Frank et al., 2019; Romero et al., 2020) may be difficult to fully implement. Reasons could range from limitations imposed by high manual task content, movement and space restrictions, individual worker attributes, low flexibility material handling systems, and worker hesitancy with new technology (Dornelles et al., 2022; Neumann et al., 2021). Throughput and system efficiency could be strongly influenced by human and work environment factors that impact worker satisfaction, motivation and physical stress (Digiesi et al., 2009). Therefore, differences in spatial working conditions, nature of the task, and individual worker characteristics would likely restrict a standardized approach to the physical implementation and installation of advanced technologies, affect the actual extent of use of such technologies by the individual worker and result in performance differences from similar investments in technology.

Nevertheless, this research did not examine the interaction between human factors and advanced technology, which is a much-researched area as evident from the above-mentioned sites. Instead, it speaks directly towards the Industry 5.0 focus on worker well-being by developing ways in which finer-grain individual worker attributes can be tracked and incorporated effectively in work planning decisions. Workforce diversity finds reflection in individual capabilities, physical capacities, technology acceptance level, gender, age and more. It becomes a strategic imperative to actively identify, measure and consider diversity in work policies to enhance the satisfaction and the wellbeing of the workforce. In manual manufacturing and logistics systems, operating factors such as repetitiveness of tasks, unsafe or awkward postures, and exposure to noise and vibration, can negatively affect the well-being of workers to different degrees, depending on individual worker characteristics.

Deteriorated performance results with consequent efficiency reductions and greater absenteeism (David, 2005). Careful consideration of worker diversity in determining work policy would result in a more resilient system. A worker whose specific capabilities and conditions have been systematically matched with task requirements and task schedules would be a better and more robust performer relative to performances obtained from a random or uniform allocation of tasks to the worker. Similarly, following the Covid-19 pandemic in 2020, Romero and Stahre (2021) introduced the notion of the “resilient operator 5.0” in order to make “human operators more resilient against a range of influencing factors”. In the long run, productivity and efficiency can be best achieved by explicitly incorporating human factors in process design and operation. A ‘one size fits all workers’ approach is unlikely to be successful given the inherent heterogeneity in workforce demographics and capabilities.

Limitations and future directions

The proposed research is deeply related to the new human-centric perspective and the paradigm of ESG (Environment, Social and Governance) paradigm, also shared among the main concepts of Industry 5.0, for the creation of an ethical, sustainable and resilient work environment. This research topic has raised debates among researchers and practitioners about the novelties it brought in the manufacturing work field, compared to the previous concept of Industry 4.0. However, Industry 4.0 was notoriously a technology-driven approach, while new paradigms seem to favor the human-centered and human-oriented development of inclusive and ergonomic solutions to help diversity management within manufacturing companies. The model proposed in this research represents a first step towards the adoption of a more human-oriented approach, which enables the inclusion of sociotechnical aspects during the progression of job scheduling decisions. The future perspectives of this work involve the development of alternative solutions for the proposed job rotation scheduling model, which can integrate additional social aspects to include the participation in scheduling decisions. However, the inclusion of social aspects increases subjective and qualitative information, which can distort the accuracy of suitable job arrangements.

For this reason, the inclusion of a weighted method in the model may be a solution to consider sociotechnical contributions to final scheduling decisions. Moreover, as already mentioned in the literature review, job rotation scheduling is an NP-hard problem and as jobs and operators increase in number, the linear programming model decreases in its capability to provide optimal solutions in reasonable time. For this reason, a metaheuristic approach can reduce the computational time for large instances. Additionally, the model can be tested in other industrial sectors, such as, for example, healthcare systems for the management of nurses’ workload. Furthermore, the pursuit of increased worker involvement and improved work schedule flexibility could involve performing different rotation frequencies and different working days length for different workers, based on workers’ individual experience, age and physical limitations. Future research will finally consider the effect of different shapes of learning curve and training costs to accelerate the learning process in different jobs.

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A new methodological framework to schedule job assignments by considering human factors and workers' individual needs

Berti N., Finco S., Battini D.

Department of Management and Engineering, University of Padova, Stradella San Nicola 3, 36100, Vicenza, Italy (nicola.berti.5@phd.unipd.it, serena.finco@unipd.it, daria.battini@unipd.it)

Abstract: One of the biggest management challenges for companies consists in including workers' features during production process decisions to obtain more realistic planning and scheduling outcomes. The increasing percentage of ageing operators in manufacturing areas, due to the postponement of retirement age, contributes to enhance the level of both physical and cognitive disparity among workers. Moreover, workers could present physical limitations that restrict the execution of certain tasks. Strong seasonality and the current spread of e-commerce lead companies to face sudden high peaks of market demand through constant operators' turnover. Consequently, workers are not equally skilled and work-related injuries can arise whether tasks are not performed correctly by an ergonomic viewpoint. In such a context, Industry 4.0 tools and real-time monitoring systems have gained higher attention since they can be adopted for training purpose and also such as data collector for every single worker in order to propose ad hoc job rotation solutions. In this paper, we propose a new methodological framework that integrates anthropometric and ergonomics measures during the scheduling decision process and defines all steps needed to define a worker-oriented and flexible scheduling of assembly tasks or job assignment. Each task is categorized in the framework according to three drivers: physical stress, ergonomic risk and execution time. According to the variability of each of them among workers, we propose a step-by-step procedure that can help practitioners to select the most suitable worker in executing each task aiming to reach flexible scheduling by an inclusive workforce.

Keywords: Methodological framework, Ergonomics, Operator 4.0, Mocap system, Occupational Safety

1. Introduction

In this particular period, as the world grapples with COVID-19, it is paramount to consider how the pandemic situation is going to change the market scenario for companies. Numerous enterprises, that previously were not used to cope with unpredictable peaks of demands, have been challenged to satisfy market needs with different volumes or additional services. Several specific business models found some benefits from the pandemic and their market area has increased. Moreover, several companies have experienced an increment in labor turnover and the need to fast train new and not expert workers, also by using virtual training sessions and fast methods to re-scheduling the jobs according to different scenarios. As a consequence, companies need to modify their level of flexibility by rapidly increasing the staffing level, to take the opportunities that derive from unpredictable events. On one hand, the human workforce remains the most flexible resource that allows pursuing this aim, but on the other hand, fast workforce turnover might lead to unwanted work-related consequences due to scarce attention to the initial training phase. According to the European Agency for Safety and Health at Work (EU-OSHA) and the International Labour Organization (ILO), workers musculoskeletal disorders (MSDs) impact 15% of all the work-related causes of years of life lost or lived with disabilities (DALY) both for the European countries and worldwide. Work-related injuries and illnesses produce a loss of 3.9% of all work-years globally and 3.3% of those in the EU, which correspond to 476 billion costs for EU countries (EU-OSHA, 2017a). In addition, according to EC 2017, the working-age population is expected to rise by 9.4% in the following 40 years. The ageing workforce phenomenon is causing significant production system changes since older employees are more exposed to MSDs and cognitive decline (Gonzalez and Morer, 2016). The new forthcoming ISO 314 on Ageing Society will soon support EU companies to provide inclusive working environments, able to support an active ageing involvement by developing flexible and individualized working plans.

The lack of knowledge about workforce characteristics, especially whenever workforce turnover is high, may lead to suboptimal job assignment, and consecutively to high probability to incur in health-related injuries and musculoskeletal disorders.

In this context, a high workforce's diversity needs to be managed within manufacturing fields, in terms of experience level, individual qualifications, age-related personal physical limitations and personal risk propensity. For this reason, just some practitioners and academics have started to include anthropometric and workers' physical and cognitive features during operational processes (Sgarbossa et al., 2020). The main reason is due to some practical limitations that exist. In fact, data must be properly collected and workers must be completely involved before the task assignment phase.

For this reason, in this work, a new methodological framework aims to integrate various aspects of employees that need to be considered in managerial decisions when job assignment is performed. In particular: Section 2 provides a literature review on job rotation scheduling problem (JRSP) analysing how previous works measured and integrated diversity aspects of the workforce in their model or approaches; Section 3 introduces the new step by step methodological framework with a complete description of the diversity aspects it considers. Finally, Section 4 and Section 5 explain the possible limitations of the implementation of the methodological framework and describes the benefits and their relevance to the industry, also providing some further research development.

2. Literature review

Amongst all the studies of the existing literature that propose solutions both for workload balancing and risk prevention, assembly line balancing and job rotation scheduling problem are the strategies of most interest. The first approach deals with task-to-station assignment in assembly lines while the second one defines worker-to-station assignment. An exhaustive survey about different algorithms and models adopted in literature, aiming to reduce and balance physical ergonomic risks by considering ergonomic aspects, is performed by Otto and Battaïa (2017). Concerning the studies that adopt a job rotation strategy, two macro-categories can be outlined: field studies and line-balancing studies. In particular, field studies focus their attention on the effectiveness of job rotation as an intervention strategy for worker MSDs risk management, in various workplaces (Yoon et al, 2016). Of the existing literature on this subject, the present study reviewed only works regarding ergonomic risks reduction generated by flexible work plans through job rotation strategies adoption, by including workforce diversity aspects. The research has been performed in the Scopus database comprising papers until the end of March 2021. The keywords adopted for the research are "job rotation" and "ergonomic" which results into 141 hits. The query considered only "Title, abstract and keywords" and has been limited to papers written in English and published in Journals or Conference proceedings.

2.1. Workforce diversity in job rotation scheduling

The adoption of job rotation programs started at the beginning of the 1980s such as a strategy to reduce costs and time and, in the meanwhile, mitigate continuous exposure to the same risk factors due to repetitive mansions (Padula et al., 2017). According to the survey proposed by Otto and Battaïa (2017), physical ergonomic risks are much more integrated into present mathematical models and algorithms in comparison to psychological and psychosocial ergonomic risk factors, which are mostly absent in the ergonomic measurement methods currently adopted by companies. Job rotation strategies aim to prevent the arise of possible injuries or diseases for workers that repetitively perform the same actions during the entire work shift, involving the same group of muscles and joints of the body. In literature, the problem that most suits this goal is called the ergonomic job rotation scheduling problem (EJRSP) and was firstly introduced by Carnahan et al. (2000). Its main goal is to balance ergonomic risks between operators by minimizing the workload of the worker most exposed to ergonomic risks.

Carnahan et al. (2000) presented a basic model to assign jobs, each one characterised by period-specific ergonomic risk points measured through the Job severity Index (JSI), to the workforce to mitigate ergonomic risks. Otto and Scholl, (2013) extended previous works on EJRSP by considering the possibility to include individual aspects for each worker, replacing general ergonomic points with dynamic and individual values (EJRSP-Ind). Workforce's individuality is considered in the research of Asensio-Cuesta et al. (2012) which defined a set of "vetoed assignments" to avoid incompatibilities between workers' capabilities and physical, mental and/or communication demand of jobs. The identification of the physical limit of the workforce is often carried out by the Occupational Health and Safety Department of each company, in charge of capturing and preventing the possible onset of accidents and occupational diseases. Recently, Diego-Mas (2020) includes medical advice in the developed algorithm to progress job rotation considering individual limitations.

Much more attention to the workforce profiling phase should be paid in the case of aged operators' presence in the manufacturing system. For this purpose, Boenzi et al. (2015) developed an age-related model for JRSP where age-performance profiles of operators are considered during job assignment for overall system performance maximization with an ergonomic perspective. Finally, Finco et al. (2019) investigated the effect of gender and age on threshold limits of fatigue exposure for heterogeneous workers and they considered the individual physical threshold limit in a job rotation model (Finco et al. 2020). Recently, Berti et al. (2021) proposed a new Dual-resource-Constrained Job Shop scheduling problem including ageing and fatigue.

2.2. Estimation of ergonomic risks

The analysis of workload and physical ergonomic risks depends both on job and workplace characteristics. The intensity, frequency and duration of the exertion can strongly impact the workload risk estimation. In the case of job rotation strategy, the most frequent adopted risk assessment methods are reported in Table 1. Amongst all of them, the Occupational Repetitive Action tool (OCRA) (Occhipinti, 1998) is adopted to evaluate jobs with a large number of repetitive actions. Such as example, Asensio-Cuesta et al. (2012) propose a genetic algorithm to balance the level of risk generated by high repetitive manual tasks with the OCRA ergonomic assessment method, to obtain job rotation schedules to prevent work-related injuries.

Rapid posture assessment methods perform faster evaluations of working posture. Recently, Digiesi et al. (2018) recognised that literature concerning JRSP presents a lack of studies that incorporate Rapid Upper Limb Assessment (RULA) (McAtamney & Corlett, 1993). For this reason, the authors proposed a mixed-integer programming approach to balance ergonomic risks in JRSP with RULA-based ergonomic constraints.

Furthermore, such as an extension of the upper body assessment, the Rapid Entire Body Assessment, (REBA) (Hignett and McAtamney, 2000) incorporates also legs risk evaluation. REBA method is adopted in Yoon et al. (2016) for the classification of each job, considering the average risk value performed by individual worker. In the presence of jobs where particular attention must be paid to lifting activities, the NIOSH lifting equation (Waters et al., 1993) is adopted to evaluate trunk risk assessment. Finally, with a particular focus on the automotive sector, the Ergonomic Assessment Work Sheet (EAWS) (Schaub et al., 2013) provides separated ergonomic risk assessment on the whole-body posture and awkward hand movements.

The novelty of our approach, in comparison to the existing literature, is related to the progression of a step-by-step framework that can evidence singular deficiency regarding risk tendency. In some prior works, job risk indexes were defined starting from the average score progressed by a group of workers. This approach is surely faster, but it can also penalize less skilled operators, from an ergonomic viewpoint, due to the scarce or absent training phase or by neglecting individual risk propensity for certain activities. On the other hand, with our approach, the main obstacle is related to the need of an accurate ergonomic risk assessment for each operator, which can be considered as much time and cost consuming. Moreover, another main problem of workforce diversity integration in mathematical models and methods consists in the difficulty to evaluate the differences among the workers involved in the manufacturing system.

For this reason, we aim to propose a new framework to involve workforce's perspectives and healthcare maintenance through ergonomic risk prevention.

Reference	Measurement of ergonomic risks	Values of ergonomic risk index determined with	Individual qualification profile	Individual physical limitations
Carnahan et al. (2000)	JSI-Diff	Randomly generated from task characteristic	-	✓
Asensio-Cuesta et al. (2012)	OCRA	On field observations and ergonomic analysis	-	✓
Otto and Scholl (2013)	EAWS	2 Random data sets, uniform distribution	-	✓
Mossa et al. (2016)	OCRA	On field observations, ergonomic risk analysis	✓	-
Yoon et al. (2016)	REBA	Ergonomic analysis, 2 video camcorders report	-	-
Song et al. (2016)	NIOSH	Job ergonomic assessment with NIOSH Lifting Equation	-	✓
Hochdörffer et al. (2018)	EAWS	Colour scheme ergonomic risk assessment per each workstation	✓	✓
Digiesi et al. (2018)	RULA	Ergonomic risk assessment and experts' evaluation of obtained results	✓	-
Sana et al. (2019)	NIOSH OCRA RULA	Ergonomic risks scores are available or can be estimated by author's assumption	✓	✓
Botti et al. (2020)	OCRA	Videotaping analysis, ergonomic specialists' risk assessment	✓	✓

Table 1: Ergonomic risks methods adopted in job rotation models

3. Method

3.1. New Methodological framework

The trend that can be outlined from the proposed literature review highlights that workers' diversity and heterogeneity aspects are currently a source of interest in studies on mathematical models and approaches that cope with ergonomic risks exposure in JRSP. The procedure proposed by this framework consists of the integration of different inputs derived from three main analyses: 1) Job analysis defines the characteristics of each job and the common risks related to its execution, also related to workstation design; 2) Workforce profiling analysis involves workers' perception and health state. It also considers the operator-job fitness according to individual preference and aptitude; 3) Ergo-time analysis is progressed with the inertial Motion Capture (MOCAP) system to assess ergonomic postural risk and also physical effort from heart rate monitoring device. This analysis also provides job execution time and helps to determine the experience level of each operator.

The main objective of this framework concerns the individualisation of the different quantifiable aspects related to the personal profile of the workforce to perform job scheduling and workload balancing decision in several workplaces. This new methodology aims to describe data integration process, starting from initial data acquisition phase followed by the ergonomic risks quantification and concluding with managerial insight coming from EJRSP solution approach. The procedure consists of 8 steps to

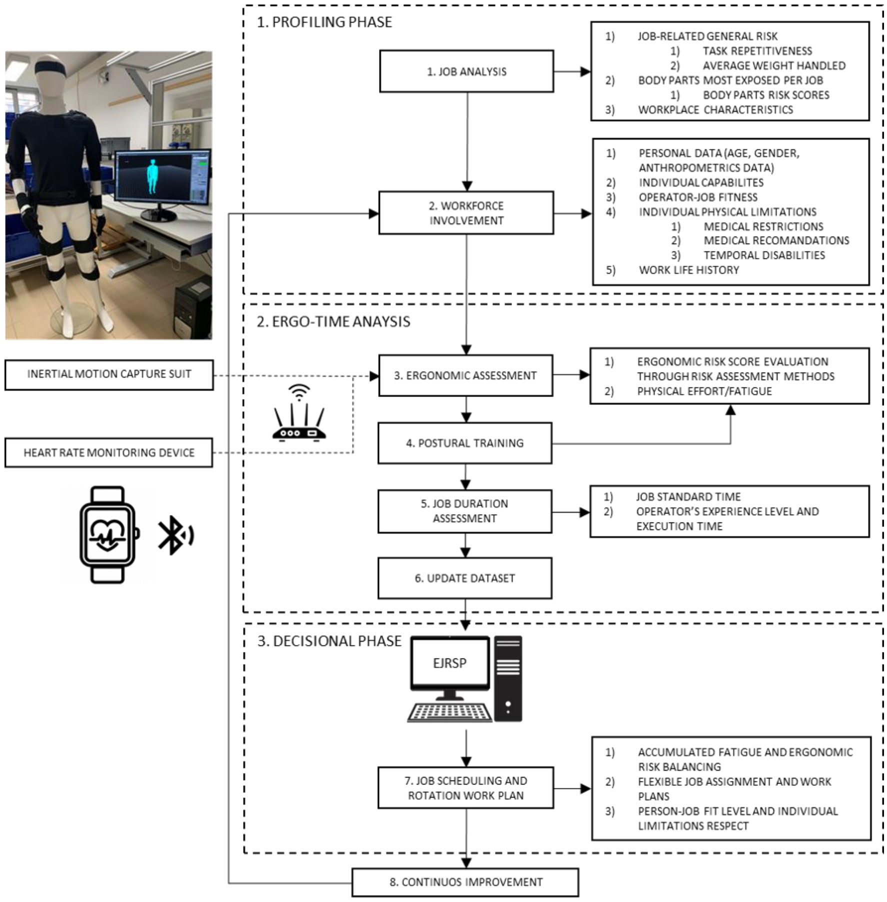

Figure 1: Methodological framework for assessing a worker-oriented ergonomic job rotation scheduling problem

be executed some in parallel and some in sequence to finally obtain an effective worker-oriented job rotation and job assignment solution.

3.2. Profiling phase (Step 1 and Step 2)

The profiling phase deals with the initial workforce data collection. In this phase, workers are involved to collect, for each job, some insights about the job description and physical attitude. Moreover, this phase aims to create updated profiles of each job and operator. Step 1 reports an exhaustive description of the job depending on its characteristics, like the repetitiveness of actions or the part of the body that are more exposed to musculoskeletal risk. Furthermore, Step 2 involves the operator's opinion and perception about the personal health condition and job assignment preference (e.g., which work plan fits most operator's capabilities in terms of competence, skills and attitude). Another important aspect is related to the workforce's developed abilities. For this reason, skills are collected in the matrix where a binary parameter specifies whether a worker can perform a particular job or not. In phase 2, the subjective workload assessment is measured according to the NASA Task Load Index (Hart and Staveland, 1988). In this way, also the mental demand is measured as well as the frustration in performing such kind of tasks. Moreover, starting from the workforce's viewpoint, it is also possible to highlight shared opinion and evaluation on part of the body, involved in job completion, most exposed to risk. Workers can provide subjective feedback according to the Borg C10 scale and is such a way they are able to also provide a quick measure of the physical and muscular fatigue (Morishita et al., 2013). However, in this case, scores assigned to each task are influenced both by workstation design and also by the sequence of activities to be performed in job execution and for this reason different scenario are created.

The most innovative aspect about the profiling phase concerns the collection of past, temporary or permanent physical limitations of workers and operators' perceptions to perform improved values of job-operator fitness (Botti et al., 2020). In fact, it has been demonstrated that each worker's life history has certainly impact on future work ability, in particular for older workers (Fischer and Martinez, 2013). In such a way, job rotation can better fit the worker's physical and cognitive level. For this reason, the integration of data coming from workforce's involvement phase and quantitative and qualitative information collected in this framework, represent our novelty and it is useful in completing the dataset with all data necessary as input for the model to solve EJRSP and to find optimal solutions, depending on company objectives and desired performance.

In addition to the job-operator fitness score, physical restrictions and possible chronic diseases for each part of the body of each worker must be collected. These data are collected from occupational medicine practitioners, but also directly from the workforce's opinions through questionnaire and self-evaluation approaches, developed to capture in advance possible incoming musculoskeletal disorders or to avoid an aggravation of the global health status. These methods can help the company to judge the actual health condition of the workforce and the proneness to permanent or temporal injuries. This information becomes useful to avoid job assignment that can foster consequences such as workforce absenteeism and the relative arising costs.

3.3. Ergo-time analysis (from Step 3 to Step 6)

Thanks to the quick technology advancement fostered by the fourth industrial revolution, which bases its principles on data collection, new devices are continuously introduced in the market at accessible and more affordable prices. To perform a precise evaluation of working posture and to define relative postural risks during work progression, smart technologies like MOCAP systems are currently adopted also in the manufacturing field. The integration of these technologies allows us to save time and costs during posture assessment during the worker's training phase. The amount of data needed to perform ergonomic risks evaluation for each operator are collected during the initial postural assessment. The execution of each job is performed wearing a MOCAP system which consist in several IMUs placed in the whole body. Data are collected and processed by a software platform able to calculate in real-time the ergonomic risks through the most suitable international indicator for the job analysed. Moreover, direct feedbacks to worker are given since they can see the monitor in front of their working place and easily understand which part of body is majorly stressed by an ergonomic point of view.

The ergo-time analysis starts with an ergonomic assessment (Step 3) to evaluate the initial level of ergonomic experience of each worker. In fact, due to the strong turnover effect, new employees can perform the same job in several manners, depending on their attitude and experience level. This step assesses whether the worker needs to perform postural training with real-time feedback intervention and some practitioners' suggestions, aiming to educate the operator to behave with proper movements to reduce postural ergonomic risk. We assume that after the postural training session (Step 4) job risk score is reduced to the lowest level, thanks to the training activity performed. Furthermore, in this phase, the amount of accumulated physical fatigue and stress for each worker can be monitored for further analysis (e.g., in the form of energy expenditure consumption, heart rate, oxygen consumption). Heart rate monitoring systems are nowadays easily affordable and reliable devices to monitor the worker's heart rate. For example, they can be adopted to calculate energy expenditure for individuals (Li, Deurenberg, and Hautvast, 1993). In such a way, postural risk can be smothered together with physical effort in job scheduling activity. This information reflects the fact that different operators can process the same job progressing different amount of fatigue, based on the age and the physical condition of the worker. In this phase, ergonomic data are collected for each task, each worker and each part of the body involved. Since threshold limit on the postures changes according to the type of activity they are performing, in this phase ergonomic experts are involved. Step 4 does not collect data about performances. For this reason, Step 5 carries out a job duration assessment to provide information about the experience level of every worker in comparison to the standard time of job completion. This information can be displayed both such as the real job duration per each operator or by the incidence of experience and worker's ability in comparison to the standard time of job completion. Once the workforce's experience level, job duration, postural risk score and physical effort values have been collected, the workforce dataset is updated (Step 6) with all the information coming from the profiling phase (Step 1 and Step 2) and from the ergo-time analysis (from Step 3 to Step 5).

3.4. Decisional phase and continuous improvement (Step 7 and Step 8)

Once the data acquisition process is completed and ergonomic indicators, attesting the work-related risk proneness for each worker, are finally progressed, the integration phase (Step 7) in the EJRSP can be initialised. In our case, the proposed EJRSP model is bi-objective, where productivity must be maximized by minimizing the ergonomic risk of each worker. According to the type of activity the appropriate ergonomic index is selected, for example, in picking activities NIOSH is selected. Moreover, additional constraints are included in the model aiming to consider physical and cognitive limits of each worker. In particular, the constraint related to the fatigue, as well as that one related the mental demand, are always included.

Since data required in the model can be collected easily and in a faster way, the model can be applied each time new workers are involved as well as new tasks are performed. Our approach can ensure a balanced workload to the workforce depending on the individual physical characteristics and flexible work plans to smooth the fatigue accumulated and the risk exposure. Physical limitations, collected and constantly updated with continuous improvement phase (Step 8), will ensure feasible job rotation schedules by the restrictions imposed to operators that cannot perform some activities, avoiding the arise of physical impairments and musculoskeletal disorders.

4. Relevance to industry

The framework presented in this work should be considered as a starting point for individual and personal flexible and dynamically generated working plans and job rotation schedules. Other operator's features can be further added to the framework, like psychosocial and psychological characteristics of the workforce as well as the learning and forgetting effects. However, as stated in Section 2.1, physical aspects are nowadays much more integrated into the current measurements progressed by companies because data are directly collectable and exploitable. For this reason, this work aims to exploit the initial postural assessment and, eventually, the training phase to collect data and further information on the workforce to obtain the most suitable work plan for everyone depending on physical conditions and job-operation fit.

The information in the system needs to be constantly updated concerning the ergonomic level reached by the workforce with the experience matured in the working field. For this reason, the training process is not only progressed once, at the beginning of operator's work experience but also repeated (Step 8), since the profile of operators can differ in terms of gained experience level or capabilities, but also for health status deterioration or due to high workforce turnover. According to current legislation, occupational medicine carries out medical examinations on an annual basis. This time window can be too wide to pursue risk detection on the workforce on a wide range. For this reason, constant workforce assessment sessions can support risk evaluation and investigation both on operators' viewpoint and on workplace design. The solutions obtained from the EJRSP model, starting with all the information collected in the previous framework steps, must respect all the ergonomic and physical constraints outlined during the framework. From this set of solutions, managers can determine which one fits best the current objectives of the company. Whenever critical or unexpected periods arise, ergonomic aspects can be considered momentarily secondary in comparison to daily production performance.

The strongest weakness of this framework resides in one of its major strength: workforce viewpoint integration. The high reliance on qualitative measurements, collected in the workforce integration phase, provides additional information to perform flexible and individual work plans based on operators' health status. On the other hand, qualitative measurements, as well as ergonomic self-assessments, are subjected to personal evaluation, which could lead to imprecise and precautionary assessments of the self-condition. To mitigate this problem, historical data of past operators' work plans can be considered to avoid the risk of repetitive assignment to jobs that could urge the same parts of the body, allowing to naturally spread the stress in a uniform condition.

Furthermore, data collection in manufacturing fields is highly restricted from privacy rights. Workers' rejection of being profiled trough their personal data might leads the framework to neglect a part of the profiling phase, reducing work plans individualisation effect and benefits. From a practical viewpoint, the implementation of this framework starts with whom most perceives positive benefits from the individualisation of personal work plan and later spread among the rest of workforce. Such as other successful strategies, this framework pursues a bottom-up approach, driven by the forecasted benefits of personal and human-oriented job scheduling activity.

5. Conclusions

There is conflicting evidence about how the workforce's diversity management, in terms of age, gender and personality, can lead to increase workers' commitment or might foster conflicts that can damage the cohesiveness within a group (Bassett-Jones, 2005). Sometimes, the workforce is intentionally assumed homogeneous in terms of efficiency and quality (e.g., concerning operators' gender or capabilities) to respect current regulations and territorial anti-discrimination laws, as reported both in Otto and Scholl, (2013) and in Hochdörffer et al., (2018).

The choice to consider a heterogeneous workforce concerning gender, age and capabilities, represents a challenge to the management that can embrace diversity aspects such as a risky business to enhance overall company performance. Moreover, as defined in Sgarbossa et al. (2020) considering human factors leads to more reliable, efficient and safe workplaces. The novelty of the new methodological framework proposed in this paper is related to the possibility to rapidly profile each worker considering personal features for the execution of jobs dependently on the current level of qualification of each worker and on the health status in which the operator behaves. The integration of ergonomic features together with fatigue workload and job-operator fitness function represents an overall analysis of the health condition that allows monitoring and evaluating the risk related to the operator's wellbeing during job execution.

Future research on this framework will evaluate the feasible job rotation schedules obtained as output from the optimal model or from heuristic approaches adopted to solve EJRSP. The impact that each quantitative and qualitative variable considered in this framework on final results will be evaluated with various scenario analyses based on real-case application.

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WEM-Platform: A real-time platform for full-body ergonomic assessment and feedback in manufacturing and logistics systems

Daria Battini [a], Nicola Berti [a], Serena Finco [a,*], Mattia Guidolin [a], Monica Reggiani [a], Luca Tagliapietra [b]

[a] *Department of Management and Engineering, University of Padova, Stradella San Nicola 3, 36100 Vicenza, Italy*
[b] *Henesis s.r.l., Strada Budellungo 2, 43123 Parma, Italy*

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A B S T R A C T

This article presents a new real-time full-body ergonomic platform: the Workforce Ergonomics and Management Platform (WEM-Platform). It provides ergonomic assessments in industrial and logistics environments based on motion capture using an inertial suit and an activity tracker. The platform also provides visual feedback to the workers involved in assembly, manufacturing, and picking operations. This innovative platform makes it possible to evaluate a set of ergonomic indexes (RULA, REBA, OWAS and PERA) and provide visual feedback in real-time to workers regarding posture and physical fatigue metrics. The graphical user interface (GUI) and the software were developed in house and support a variety of inertial suits, depth cameras, and activity tracker devices. The article discusses the WEM-Platform architecture, its state-of-the-art design, and crucially, its validation via rigorous laboratory testing.

1. Introduction

Despite the opportunities automation and Industry 4.0 solutions have created, several tasks and activities are still performed manually in industrial settings. Manufacturing contexts – characterized by complex products comprising hundreds of different parts and a high variety of assembly, lifting, and handling tasks – require a high level of flexibility that robots have not yet achieved (Zennaro, Finco, Battini, & Persona, 2019). In addition, humans have cognitive and physical skills that are very difficult to replicate (Sgarbossa, Grosse, Neumann, Battini, & Glock, 2020). In such contexts, tasks repetitiveness, hazardous or awkward postures, heavy loads and other ergonomic risks can negatively impact workers' well-being, causing Work Related Musculoskeletal Disorders (WRMSDs). According to Luttmann et al. (2003), WRMSDs refer to all health problems of the locomotor apparatus and all forms of ill-health disorders or injuries induced by work circumstances and performances.

Consequently, it is necessary to sustain workers' physical and cognitive well-being by reducing ergonomic risk through human-oriented production systems and workplaces design (Berti, Finco, Battaïa, & Delorme, 2021). This is confirmed by a recent report of the European Agency for Safety and Health at Work (EU-OSHA, 2019), which states that more than half of the EU workforce reports WRMSDs, especially located in the shoulders, neck, and upper limbs. Moreover, WRMSDs cause about 90% of absenteeism and injuries.

There are two main consequences related to WRMSDs: 1) they directly affect workers' well-being, and 2) productivity decreases due to absenteeism or higher turnover rates (Battini, Faccio, Persona, & Sgarbossa, 2011). Aiming to limit the negative consequences of WRMSDs, several tools, new prototypes or equipment and ergonomics analysis techniques have been developed to support the ergonomics assessment necessary to evaluating workers' body postures (Lowe, Dempsey, & Jones, 2019; Mgbemena, Tiwari, Xu, Prabhu, & Hutabarat, 2020; Takala et al., 2010). At the same time, academics and practitioners have placed more emphasis on the need to design safe and proper work environments, including implementing more robust safety practices and human-oriented workplace design solutions (Sgarbossa et al., 2020). Postural training for the workforce plays a strategic role in this objective. In fact, it permits workers to evaluate and correct poor postures assumed while performing tasks, as well as provide feedback when they are incorrectly executed (Cerqueira, Da Silva, & Santos, 2020).

The so-called 'Smart Factory' resulting from digitalization and Industry 4.0 can be beneficial for all actors involved in improving and performing the manufacturing process, with several tools already

* Corresponding author.
E-mail address: serena.finco@unipd.it (S. Finco).

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developed and being continuously improved. Recently, Kadir, Broberg, and da Conceicao (2019) analyzed the interaction between Industry 4.0 systems and human factors, and they highlighted that wearable and handheld devices lead to improvements in ergonomic feedback. Moreover, collected data can be shared among product and safety managers as well as ergonomists to positively impact workers' well-being (Romero, Stahre, Wuest, Noran, Bernus, Fast-Berglund, & Gorecky, 2016). By focusing on some devices which are commonly used in manufacturing contexts the inertial measurement units (IMUs) gain higher and higher attention to collect data from machines and workers too. IMUs are sensors that can be adapted to capture postures and movements during a typical working day. IMUs are small and portable devices that combine information obtained from multiple electromechanical sensors (i.e., accelerometers, gyroscopes, and magnetometers) to estimate the spatial orientation of an object using recursive sensor fusion algorithms. In recent years, their high accuracy has earned them a great deal of attention in the field of ergonomics. In particular, they have been used to provide real-time posture data or feedback based on one or more of the existing ergonomic assessment tools (Alberto, Draicchio, Varrecchia, Silvetti, & Iavicoli, 2018). Some studies have evaluated ergonomic risks on site (e.g., Yan, Li, Li, & Zhang, 2017) while others have tested the IMUs system they developed in laboratory conditions – in some cases, they have reported substantial differences between these and real work environments (Vignais et al., 2013). Most of the existing research provides feedback calculating only a single ergonomic index (Vignais et al., 2013), and only a few evaluate multiple ergonomic indexes in real time (Otto, Campos, & de Souza, 2017; Cerqueira et al., 2020; Akamnu et al., 2020). Moreover, additional tools such as activity trackers, heart rate devices, or smartwatches that were initially developed for other purposes (e.g., leisure or sports) are getting more attention and are increasingly used to evaluate the status of workers' well-being in production or logistics processes.

Starting from these initial considerations, this article presents an innovative ergonomics digital platform based on an inertial suit, an activity tracker device, and a distributed software the authors developed that provides a real-time ergonomic assessment, posture feedback to workers and productivity Key Performance Indicators (KPIs). Moreover, additional details of the worker involved in the activity (e.g., skin temperature and heart and respiration rate) are provided to continuously monitor each worker's personal health status.

In its current state, the platform evaluates four ergonomic risk indexes: RULA, REBA, OWAS, and PERA. They have been selected for their versatility and extensive use in manual assembly environments. Moreover, their computation is mainly based on the postures assumed in performing tasks requiring only a few additional information to be manually added in the software. For these reasons, they represent an appropriate ergonomic index set to be computed in real-time from the joint angles provided by an inertial suit, as presented, or from other sensors such as depth cameras. The platform is a multi-purpose tool since it can be adopted both in postural training sessions and workstation design evaluation. In fact, it permits to easily understand if the worker is performing the task ergonomically and which human muscle districts are affected by wrong postures. Moreover, it supports a real-time assessment of ergonomics risk parameters, indispensable to evaluate the ergo-quality design of the workplace by ergonomists and industrial engineers.

The main novelty of the WEM-Platform consists in both capturing postures and computing several ergonomic indexes in real-time. In fact, according to the state of the art provided in Section 2, the real-time concept is usually related to the data capturing phase only, while the ergonomic risk evaluation is generally made in a post-processing phase.

Finally, the platform not only provides information for ergonomic postures and risks but also computes in real-time productive KPIs. They are available to all actors involved in improving the production process, including workers, ergonomists, and safety managers. The focus on final stakeholders' needs inspired the name WEM-Platform: workforce, ergonomics, and management.

The remainder of this article is organised as follows. In Section 2, we analyze existing motion-capture technologies and demonstrate the novelty of our solution. We also give a brief description of the ergonomic indexes included in the WEM-Platform. In Section 3, we present the methodological framework we use in our platform. Section 4 describes the hardware and software architecture we developed for the real-time evaluation of postures and ergonomic indexes during production and handling activities (e.g., manual assembly and picking). In Section 5, we validate the ergonomics platform with a laboratory case study related to a medium-size bed-side table assembly process and discuss the main outcomes of this study. We conclude with Section 6, suggesting opportunities for future research.

2. Literature review

In this section, we describe the existing methods to conduct ergonomic assessments of working conditions (Section 2.1.), the different MOtion CAPture (MOCAP) systems used to track human movements (Section 2.2), and the existing research providing ergonomic assessment and feedback to workers using MOCAP systems and activity trackers (Section 2.3).

2.1. Ergonomic assessment in production systems

Engineers and ergonomists have developed assessment methods for WRMSDs risk quantification to reduce workers' exposure to hazardous environments and tasks. These tools can be divided into three main categories: self-reports, observational methods, and direct/instrument-based methods (David, 2005). Self-assessment tools collect data on risk exposure using questionnaires, checklists, or interviews that worker themselves fill out. These reports are based on workers' perceptions and feelings, which can lead to imprecise and subjective analyses. To overcome this limit, observational methods allow analysts to make postural evaluations based on direct observations or videorecording the tasks under examination. The most used and widely known observational methods follow international standard ergonomic indexes, such as the Occupational Repetitive Actions (OCRA) (Occhipinti, 1998), NIOSH lifting equation (National Institute of Occupational Safety and Health Lifting Index) (Waters, Putz-Anderson, Garg, & Fine, 1993) and Job strain Index (JSI) (Steven Moore & Garg, 1995).

According to the ISO standard 11228-3:2007(E) (ISO, 2007), simplified ergonomics methods can be adopted in the initial ergonomics analysis due to their simplicity and short computational time. Simplified methods that can rapidly provide ergonomic risk evaluations, especially for static tasks, are the Rapid Upper Limb Assessment (RULA) (McAtamney & Corlett, 1993), the Rapid Entire Body Assessment (REBA) (Hignett & McAtamney, 2000), the Ovako Working posture Assessment System (OWAS) (Karhu, Kansi, & Kuorinka, 1977) and, most recently, the Postural Ergonomic Risk Assessment (PERA) (Chander & Cavatorta, 2017). Since one of our main research objectives is a real-time ergonomic risk evaluation through workers' postures, we have incorporated these four indexes into the WEM-Platform.

In particular, the OWAS score analyses the position of both upper and lower body parts. It provides one single-digit score for each part of the body, starting from the back, arms, legs and the loads carried during the activity. These four digits are used as an input for the table that includes all possible digit combinations and their corresponding ergonomic risk. OWAS classifies action risk into four categories ranging from 1 = no risk to 4 = high risk.

RULA and REBA are two similar methods for screening and identifying harmful postures. RULA is more suitable for intensive hand-arm activities, such as sitting assembly work. At the same time, REBA evaluates the entire body and is more appropriate when both upper and lower body are involved, such as during picking or construction activities. Generally, several snapshot observations are collected to evaluate the most critical working position and posture. Nowadays, the possibility that RULA and REBA scores are influenced by the subjectivity of the evaluator is minimized thanks to the automation of the posture risk assessment, which allow to have precise outcomes in short time.

RULA worksheet evaluates position deviation in six body regions (upper arm, forearm, wrist, neck, trunk, and legs) from their neutral position as well as the carried weight carried and the type of movement (static or dynamic). The final score varies from 1 to 7, where 1 describes a work situation without risk and 7 highlights the necessity to act via immediate adjustments.

REBA worksheet evaluates the same body regions as RULA, but it also includes grips and coupling in the analyses. The final score ranges from 1 to 5. As long as the score is lower than 3, minor corrections are necessary. Conversely, a score ranging from 4 to 7 requires corrective actions. Whenever the score exceeds 7 points, corrective interventions need to be implemented as soon as possible, as the repetitiveness of the analysed work posture can cause ergonomics diseases over time.

Finally, PERA (Chander & Cavatorta, 2017) analyses each work task, particularly in the case of short cyclic assembly works. The method progresses seven main steps starting from work cycle segmentation, task posture and force analysis categorization in terms of risk and finally the score computation.

As Chander and Cavatorta (2017) demonstrated that, even though it is simpler, PERA can deliver the same evaluation as the European Assembly Worksheets (EAWS) (Schaub, Caragnano, Britzke, & Bruder, 2013).

All the presented ergonomic indexes can be automatically computed when technology is available to stream real-time collected data. However, it is not sufficient to stream data in real-time to perform real-time index progression and evaluation. With this purpose, we provide an overview of the main literature results concerning the use of technologies that are able to perform real-time ergonomic assessment and feedback intervention in the next section.

2.2. Background literature on MOCAP systems

In the last decade, thanks to technological advancements, direct methods have surpassed prior approaches by providing objective measurements in real-time. Both static and dynamic body posture assessments have progressed, now at the point where they can prevent critical situations. The monitoring systems adopted for this purpose exploit inertial sensors, depth cameras, reflective markers, and wearable medical devices. Battini, Persona, and Sgarbossa (2014) created a full-body system based on inertial sensors featuring integrated compensation of magnetic interference and long wireless connection. They used it to evaluate the ergonomics of manual material-handling in warehouse environments in which all parts of the body are in use while executing the activities. The system gives feedback to the ergonomists using it after post-processing the collected data.

More recently, Menolotto, Komaris, Tedesco, O'Flynn, and Walsh (2020) conducted a systematic review on MOCAP systems in different industrial applications. They divided MOCAP technologies into two main categories: IMUs and camera-based systems. IMUs are mainly composed of accelerometers and gyroscopes; they are usually adopted to reconstruct the position or orientation of the limb they are attached to. In many cases, a three-axis magnetometer is integrated into an IMU tracking system to correct mis-orientation of the sensors due to time-varying biases and noise interference. Filippeschi et al. (2017) conducted an exhaustive survey of IMU-based motion-tracking methods; they placed particular focus on upper limb human motion-tracking in different applications. In a recent example of IMU adoption to progress a real-time ergonomic assessment, Giannini, Bassani, Avizzano, and Filippeschi (2020) estimated four different ergonomic indexes – NIOSH (Snook & Ciriello, 1991), REBA, and JSI – beginning with body-tracking a worker in real time. Like IMUs, camera-based sensors can detect human body position and orientation through various technologies (e.g., RGB, infrared, depth, or optical cameras) (Menelotto et al., 2020). These systems can track the position and orientation of limbs without any sensors – they can even adopt certain markers (e.g., marker-based MOCAP) captured by a fleet of cameras. Markers can actively contribute to body monitoring by emitting light at a high frequency or by being passive (using a *retro*-reflecting surface that reflects the infrared emission the cameras produce). Bortolini, Faccio, Gamberi, and Pilati (2020) adopted camera-based technology in their Motion Analysis System (MAS), which assesses four international ergonomic indexes: OWAS, REBA, NIOSH, and EAWS using a network of four depth cameras.

Although automatic and objective ergonomic risk-monitoring is fundamental for recognising hazardous working activities, thus far, intervening in people's conduct and bad habits only occurs at the end of an ergonomic specialist's analysis and risk assessment.

2.3. Applying MOCAP systems to ergonomic assessment and real-time feedback

Providing real-time feedback to workers during working activities requires a system that is capable of rapidly assessing their posture and promptly giving feedback to correct their behavior in real-time, ultimately avoiding the risk of WRMSDs. Depending on the application sector, different technologies in pursuit of this objective have emerged in the literature. The construction field has been heavily researched due to the dangerous positions assumed by workers during task progression. In this sector, feedback intervention has yielded the best results in terms of training and posture correction for trunk position (Yan et al., 2017, 2018), especially in lifting activities, but also for the lower back, legs, and joint angles (Valero, Sivanathan, Bosché, & Abdel-Wahab, 2016). The presence of many obstacles in the workplace means it is not always easy to monitor workers' performance. Virtual reality (VR) and immersive reality (IR) represent solutions to achieve posture-monitoring wherever other technologies cannot work (Akanmu, Olayiwola, Ogunseiju, & McFeeters, 2020; Battini et al., 2018; Simonetto, Arena, & Peron, 2022; Sivanathan, Abdel-Wahab, Bosche, & Lim, 2014). Another sector with a great deal of work monitors the effect of feedback on caregivers and nurses during work activities and during the training phase. Researchers have tested wearable devices and garments with real-time auditory biofeedback or vibrotactile intervention (Doss, Robathan, Abdel-Malek, & Holmes, 2018; Kamachi, Owlia, & Dutta, 2019; Owlia, Ng, Ledda, Kamachi, Longfield, & Dutta, 2018), prototypes of systems that educate student trainees' lifting behaviours (Bootsman et al., 2020) by providing improved movement strategies for spine postures or for posture rehabilitation, and real-time feedback provision to correct training (Alahakone & Senanayake, 2010).

Moving into the manufacturing sector, the literature contains several examples of wearable devices and prototypes of systems that progress training techniques through real-time feedback intervention. Some of these systems can progress full body assessment and provide feedback to workers during dedicated actions or movements such as lifting activities (Delpresto, Duan, Layiktez, Moju-Igbene, Wood, & Beling, 2013) as well as (and mainly) during daily work through visual (Otto et al., 2017; Zhang et al., 2021) and vibrotactile stimuli (Lins, Fudickar, Gerka, & Hein, 2018; Mgbemena, Oyekan, Hutabarat, Xu, & Tiwari, 2018). Nevertheless, most of the activities progressed by the workforce in industrial contexts involve workers' upper bodies; thus, most of the relevant literature focuses only on upper limb movements. Here, optical MOCAP systems are adopted to track body movements in static activities (e.g., workers do not need to leave their workstations to progress the overall task). In this case, feedback provision is mainly actuated through visual graphical interfaces on monitors (Kim, Lorenzini, Kapıcıoğlu, & Ajoudani, 2018) or directly projected into the workplace (Mengoni, Ceccacci, Generosi, & Leopardi, 2018). Wearable devices become necessary to track body movements in the work field whenever task progression requires workers' displacement. Recent prototypes of smart garments have been developed to progress vibrotactile feedback intervention in general manufacturing activities (Cerqueira et al., 2020), picking simulations (Lind et al., 2020), and automotive assembly tasks (Raso, Emrich, Burghardt, Schlenker, Gudehus, Strter, & Loos, 2018).

Real-time postural feedback intervention and ergonomic risk assessment are rarely progressed together by the same software or platform (Lim & D'Souza, 2020). In a pioneering contribution, Vignais et al. (2013) developed a promising system to perform both real-time ergonomic risk assessment and feedback provision. Arroyave-Tobón and Osorio-Gómez (2017) give a similar example – they provide visual real-time feedback alongside an ergonomic risk assessment through users' head-mounted displays (HMDs). Continuous automation advancement has created the opportunity to involve collaborative robots to support workers' activities. Busch, Maeda, Mollard, Demangeat, and Lopes (2017) provided evidence that robot behavior can lead workers toward posture correction through real-time posture analysis and visual feedback correction. Manghisi et al. (2020) proposed an automatic software tool for ergonomic postural risk-monitoring with a visual graphical user interface focusing mainly on upper body assessment. The authors adopt both visual and acoustic feedback as their feedback intervention method.

Few prior works have progressed ergonomic risk evaluation and feedback intervention at the same time, and a recent review of past literature reported that a limited number of studies assessed and improved ergonomic risk factors using feedback strategies (Stefana, Marciano, Rossi, Cocca, & Tomasoni, 2021).

Table 1 contains a selection of papers that implement a platform or a system able to provide real-time feedback intervention, and, in some cases, real-time ergonomic risk index progression. In particular, the literature shows that feedback intervention is often adopted in three main application sectors: medical, construction, and industrial. Table 1 shows that there is often a correlation between the analyzed body part and the application sector. In particular, analyses of healthcare workers' posture focus their feedback intervention on trunk wellness, whereas in the manufacturing context, legs and lower back are often neglected due to the characteristics of assembly activities. Moreover, Table 1 highlights that different devices are adopted to provide feedback intervention based on the application context. For example, graphical user interfaces are widely adopted in the manufacturing research field, particularly at assembly workstations. In contrast, audio and haptic feedback are preferred in manual material-handling activities due to workers' continuous displacement.

The literature reveals that feedback intervention is often triggered by thresholds set based on ergonomic indexes or international standards. However, the healthcare sector prefers to adopt thresholds based on customised values determined by an individual's maximum flexion or extension measurements. Only four of the works contained in Table 1 (Arroyave-Tobón & Osorio-Gómez, 2017; Manghisi et al., 2020; Mengoni et al., 2018; Vignais et al., 2013) develop systems that simultaneously provide real-time feedback to users and display ergonomic indexes to ergonomists for on-site risk assessment. Finally, many previous works evaluate the ergonomic risk through a single ergonomic score (RULA) and by performing an upper limb evaluation, neglecting

Table 1
List of published works concerning feedback intervention and real-time ergonomic assessment.

Paper	Motion capture stem	Application sector	Body part analyzed	Real-time feedback	Feedback threshold based on	Real-time ergonomic indexes
Vignais et al. (2013)	Inertial (7 IMUs)	MMH	Upper	I (AR) - A	RULA	RULA
Delpresto et al. (2013)	Marker-less	M	Full	I	NIOSH	–
Busch et al. (2017)	Marker-less	M	Full	I	REBA	–
Yan et al. (2017)	Inertial (2 IMUs)	C	Trunk	I - A	ISO 11226:2000	–
Arroyave-Tobón and Osorio-Gómez (2017)	Marker-less	M	Upper	I (AR)	RULA	RULA
Otto et al. (2017)	Accelerometers	M	Full	I	RULA REBA	–
Yan, Li, Zhang, and Rose (2018)	Inertial (2 IMUs)	C	Trunk	I - A	OWAS	–
Mengoni et al. (2018)	Marker-less	M	Upper	I	RULA	RULA
Kim et al. (2018)	Inertial (1 IMU)	M	Trunk	I - V	Customized	–
Lins et al. (2018)	Marker-less	M	Upper	V	OWAS	–
Raso et al. (2018)	Strain sensors	MMH	Upper	I - H	EAWS	–
Owlia et al. (2018)	Inertial (2 IMUs)	H	Trunk	A	Customized	–
Doss et al. (2018)	Accelerometers	H	Trunk	A	Customized	–
Mgbemena et al. (2018)	Marker-less	M	Upper	I	RULA	–
Bootsman, Markopoulos, Qi, Wang, and Timmermans (2019)	Inertial (2 IMUs)	H	Trunk	A - V	Customized	–
Cerqueira et al. (2020)	Inertial (4 IMUs)	M	Upper	V	RULA LUBA	–
Kamachi et al. (2019)	Inertial (2 IMUs)	H	Trunk	A	Customized	–
Lind et al. (2020)	Inertial (3 IMUs)	MMH	Upper	V	Customized	–
Akanmu et al. (2020)	Inertial (19 IMs)	C	Full	I (VR)	ISO 11226:2000 PERA	–
Manghisi et al., 2020	Marker-less	M	Upper	A - V	RULA	RULA
Zhao, Obonyo, & Bilén, 2021	Marker-less	C	Full	V	OWAS	–

Application Sector: M: Manufacturing; C: Construction; H: Healthcare; R: Rehabilitation; MMH: Manual material handling;
Real-time feedback: I: Interface visual; A: Auditory; H: Haptic; V: Vibration; VR: Virtual Reality; AR: Augmented Reality.

total body assessments.

For these reasons, we aim to progress the existing literature by providing an in-house-developed ergonomic platform that can evaluate four ergonomic indexes and give feedback to workers in real time. Despite the available solutions, which mainly assess upper limb postures, the digital platform we propose can be adopted within several industrial contexts to perform full body evaluations of workers' posture and health status. The WEM-Platform's user-friendly visual interface can provide real-time feedback to three actors during the analysis: the ergonomist and safety expert, the operation manager, and the worker. These stakeholders have different knowledge about ergonomic risk – consequently, we provide them with the right tools to evaluate the risk of executing tasks to define future improvements (see Figs. 1, 2 and 3).

3. Methodological framework

Fig. 4 conveys the methodological framework of the WEM-Platform. The platform collects two main types of input data: 1) real-time data provided by devices monitoring the users (currently, an inertial MOCAP system and an activity tracker), and 2) static data assessed offline and manually introduced by the ergonomists and operation managers in a specific toolbox of the GUI software. The static data represent the features concerning the job to be performed and the worker's physical characteristics. At the beginning of the setup phase, the worker's anthropometric physical properties such as age, gender, weight, and height are entered into the system. Moreover, job characteristics need to be specified both in the initial phase and during the training session, as the job segmentation adopted for the postural evaluation of each activity is still manually estimated. Workplace layout and components features are defined during the offline phase, whereas task duration and frequency must be specified during the training session. In this way, the ergonomist can determine the length of each activity for which online postural assessment is being evaluated.

Real-time data are collected for the entire duration of the training session. The real-time data consist of heart rate, breathing rate, and skin temperature; these are collected through an activity tracker, whereas the joint angles and positions are collected with the MOCAP system. The

Fig. 2. MOCAP suits used in the laboratory tests: (a) Mtw Awinda, (b) G4 MOCAPSUIT, and (c) the Aidlab activity tracker.

platform is designed to work independently of the type of MOCAP system used for the postural assessment. However, the precision of the output will be affected by the quality of the data received from the MOCAP system. The data are directly integrated into the ergonomic platform that outputs the four ergonomic indexes' values, a representation of the human posture, and the posture scores according to the NIOSH. Once the assembly or logistic process begins, the platform can

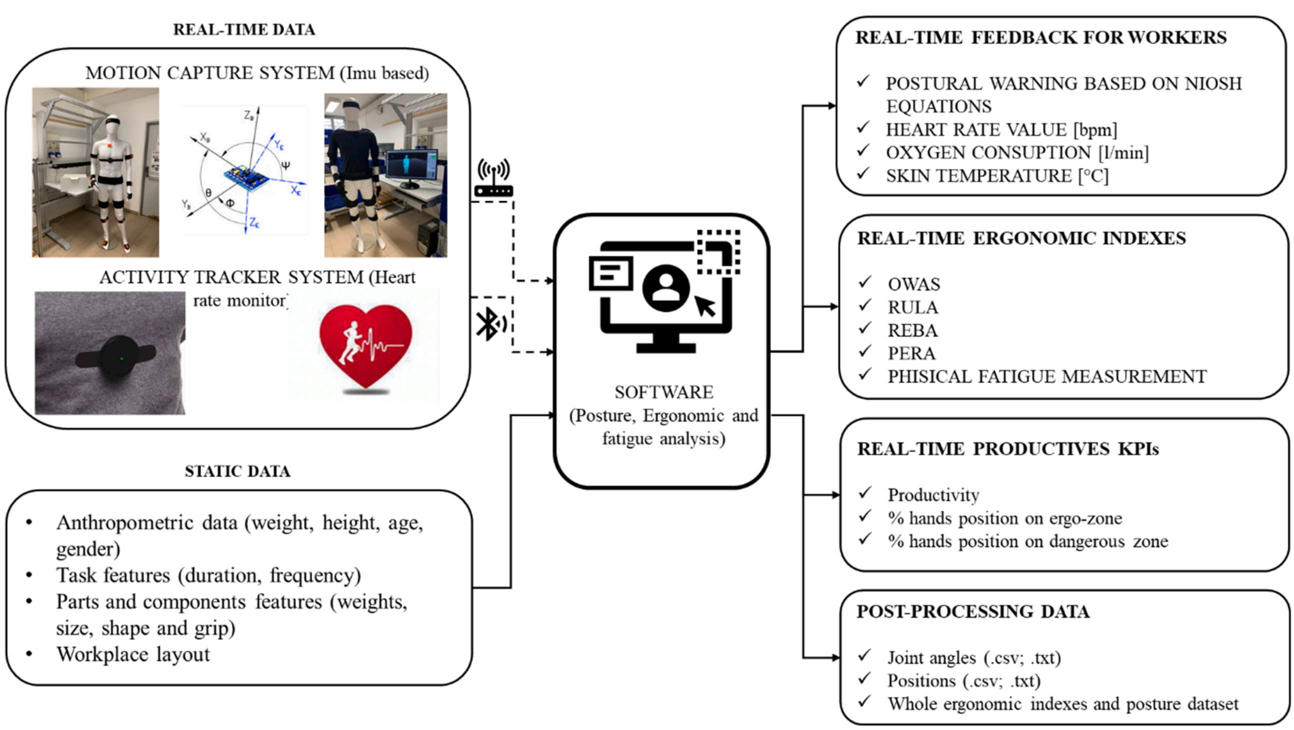


Fig. 1. The integrated methodological framework of the WEM-Platform.

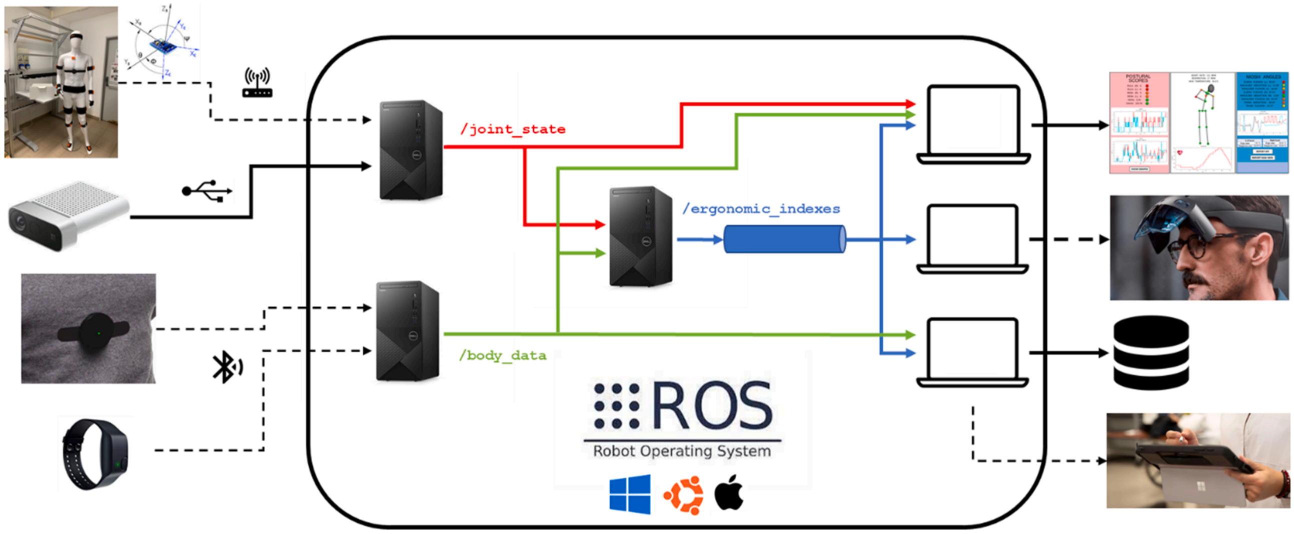


Fig. 3. Modular, extendable, and reconfigurable architecture based on ROS in the current version of the WEM-Platform.

Fig. 4. The assembled bedside table.

process all the data in real time and thus directly provide the output.

Four are the output of the WEM-Platform.

In the first output, the real-time visual feedback for the worker is displayed online during the whole production process. A representation of human body and a table containing all the main joint angles created according to the ISO 11226 allows workers to see their heart rate, breathing rate, and skin temperature as well as their posture. In this way, workers can see incorrect postures and adjust and change their movements until they reach a correct state.

In the second output, real-time ergonomic indexes (RULA, REBA, OWAS, and PERA) are continuously computed and reported to the ergonomist through visual dashboards to evaluate workers' posture. Both current values and graphs of time trends are provided for each of the four indexes.

In the third output, three KPIs are determined in real-time to monitor workers' efficiency, production rate, and walking path. Here, a hip movement spaghetti chart and a hand height chart during the production process are given.

Finally, the last output is defined at the end of the training activity. It is a summary report automatically created with post-processed information for additional insights.

4. Hardware and software architecture

4.1. Hardware

Our software is not dependent upon a particular hardware device if it is able to produce the required input data. The software design allows the user to adopt different MOCAP technologies to collect postures and process the output in real-time. We used two IMU-based MOCAP suits (MTw Awinda [Xsens] and G4 MOCAPSUIT [Synertial]) and an activity tracker [Aidlab]) in our laboratory tests (Fig. 5). The MTw Awinda has 17 IMUs. The system includes a shirt with trunk and shoulder IMUs placed on special straps, one headband, two hand bands, and 11 strips for the rest of the body. It provides data up to 60 Hz; further, the external antenna of the Awinda station enables an indoor wireless range of 20 m and an outdoor range of 50 m.

The G4 MOCAPSUIT has 29 IMUs, 14 of which are used to capture the wearer's finger angles and positions. This inertial suit links all the IMUs, which are cabled, to a master device that sends data to the software wirelessly over Wi-Fi. A main limitation of this suit is the connecting cables, which can limit the wearer's movements. The Aidlab activity tracker is extremely light (46 g) and integrates five sensors: ECG, heart rate, skin temperature, respiration, and a microphone. It sends data to the WEM-Platform via a Bluetooth 4.0 + connection.

4.2. Software

The inputs driving the WEM-Platform come from heterogeneous acquisition systems. In the current scenario, joint angles are estimated using different IMU-based MOCAP suits that are wirelessly connected to the central platform. At the same time, an affordable activity tracker provides data through a Bluetooth connection. Future scenarios will require integrating new devices working on different operating systems and connected through other communication channels.

To keep the project stable and long-lasting despite the progress in sensors, processors, and networks and the changes in final user requirements, we have based the WEM-Platform on the Robot Operating System (ROS) (Quigley, Conley, Gerkey, Faust, Foote, Leibs, & Ng, 2009), the de facto standard for developing robotic software. ROS provides a set of open-source libraries and tools for developing software modules that communicate with each other in a loosely coupled, multiprocess, distributed environment.

Briefly, a ROS-based system is composed of nodes, which are processes that perform a computation from running algorithms to interfacing with sensors or actuating devices. Nodes communicate with each

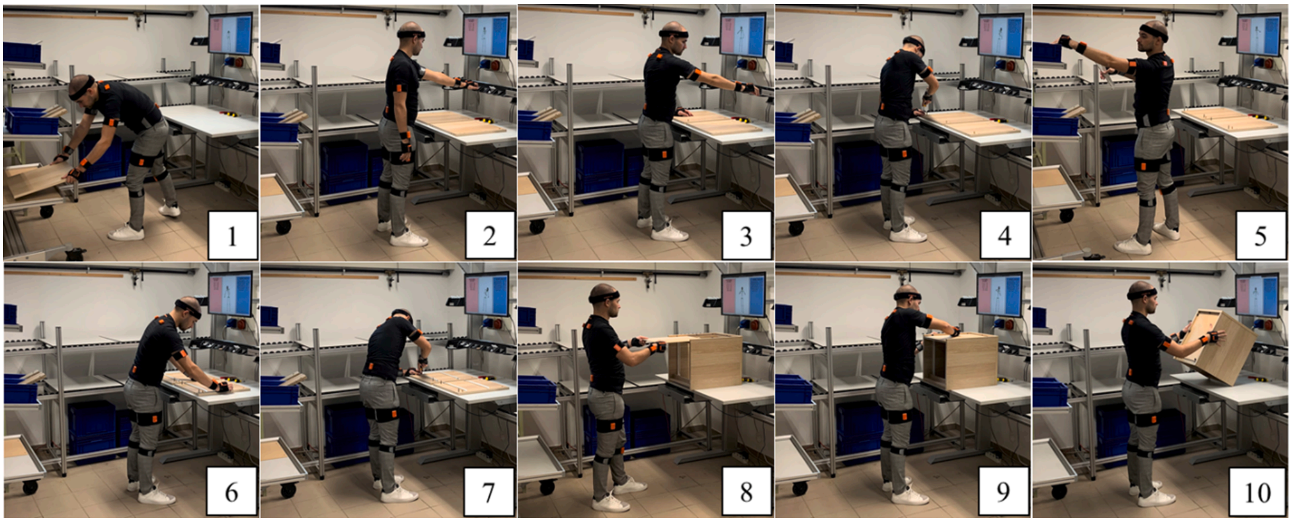


Fig. 5. Postures collected for WEM-Platform score validation.

other using a publish/subscribe model (i.e., a node that produces data publishes them on a named topic). ROS takes charge of distributing the data only to nodes that previously subscribed to this topic. While ROS is more complicated and features many other concepts, it is not necessary to include them in the background description for the WEM-Platform.

A Windows computer running a ROS-based executable program, ROS Node, reads the data from the MOCAP suit through proprietary SDK software and distributes it to other nodes. The worker's pose is published as a standard *sensor_msgs/JointState* message in the */joint_angles* topic, whereas data from the Aidlab tracker is published as a custom message in the */body_data* topic. Another ROS node implements the real-time computation of the ergonomic indexes; this node subscribes to the */joint_angles* and */body_data* topics and publishes an */ergonomic_indexes* topic. Finally, we have implemented several ROS nodes that subscribe to the previous topics and provide the most suitable data representation based on the users' needs.

ROS adoption will support developing a platform that can evolve into a complex network of sensors, devices, drives, and algorithms that run concurrently on distributed systems. Indeed, using ROS as the base software architecture allows us to move the node's execution to another computer, eventually running a different operating system without any change in the code implementation. Another property of ROS, coming from publisher/subscriber, is that a change in the ROS node publisher of a topic does not affect the other nodes of the architecture. Therefore, if a camera instead of a MOCAP suit estimates the joint angles, or if multiple sensors replace the simple Aidlab tracker, this does not change the implementation of the other ROS nodes.

5. Application, validation, and discussion

Here, we describe the laboratory tests we used to validate our platform. We use both MOCAP suits and the activity tracker described in Section 4.1.

A volunteer (male, 27 years old, 175 cm tall, weighing 70 kg) is involved in the assembly process of a bedside table (Fig. 4). We evaluate the assembly process only for the bedside table frame, as we assume the drawers are sub-assembled components. The worker is very familiar with the components as well as the whole assembly process.

The participant executes the assembly process within the cycle time of 7 min; our WEM-Platform continuously executes for the entire analysis. The workplace is composed of an assembly station with front and rear racks adapted to store all the parts involved in the assembly process. We have intentionally placed all the components on shelves at different heights. Moreover, the drawers are on a conveyor system since they were assembled at another station. The assembly process starts by picking the required components from the lowest level of the rear rack.

To validate our software, we selected 10 frames (Fig. 5) of the assembly process. Here, we compared the results obtained in real-time from the WEM-Platform with those obtained by computing ergonomic indexes with traditional post-processed videorecording evaluation. The frames represent activities characterized by a high level of repeatability during the assembly activity. Consequently, we have been able to analyze a higher number of postures based only on this small sample.

The results for the proposed platform are very promising – the two scores for almost all the evaluated time frames, as reported in Fig. 6, are close together. In only a few cases were the scores evaluated by the WEM-Platform higher than the ones that were manually calculated. This discrepancy happens when the joint angles are close to an index threshold. Indeed, while the observer may wrongly classify the angle, with the high precision in the joint angle estimation of the inertial suit, the angle falls into the right range. Indeed, a few degrees can have a remarkable impact on the final score.

For the validations of RULA and OWAS, we compared WEM-Platform outputs with the results from both an expert and the Siemens Jack software. Fig. 8 shows the graphical interface of Jack software during the analysis of the first posture in Fig. 5. As shown in Fig. 6, both the ergonomic expert and Siemens software mostly agreed with the RULA ergonomic assessment proposed by the WEM-Platform.

Jack software evaluates ergonomic postural risk with one single grand score, which does not refer to a specific side of the body, as WEM-Platform does. For this reason, Fig. 6 reports the same value from the Siemens Jack analysis for both the right and left sides of the operator's body. In a few postures, the WEM-Platform performs slightly higher risk scores in comparison to other assessments. The higher score provides by the WEM-Platform is mainly due to the computation of some joint angles which are not stated in RULA index progression (i.e., a raised shoulder, an abducted upper arm, a bent wrist from the midline, etc.). For this reason, we introduced some range of movements to state whether to perform a scoring adjustment, based on the volunteer's ergo-zone in relation to his maximum reached threshold.

For the OWAS index, Fig. 7a shows that our outputs and Jack software scores are in complete agreement. The higher risk score for the first proposed postures is mainly related to trunk and legs position. On the contrary, in the last frames of Fig. 5, the operator performs less awkward postures resulting in lower OWAS scores. Whilst for both RULA and OWAS scores we could also perform a benchmark between WEM-Platform and Siemens Jack software postural evaluation toolkit, REBA and PERA scores validation rely only on the expert's assessment. Fig. 6

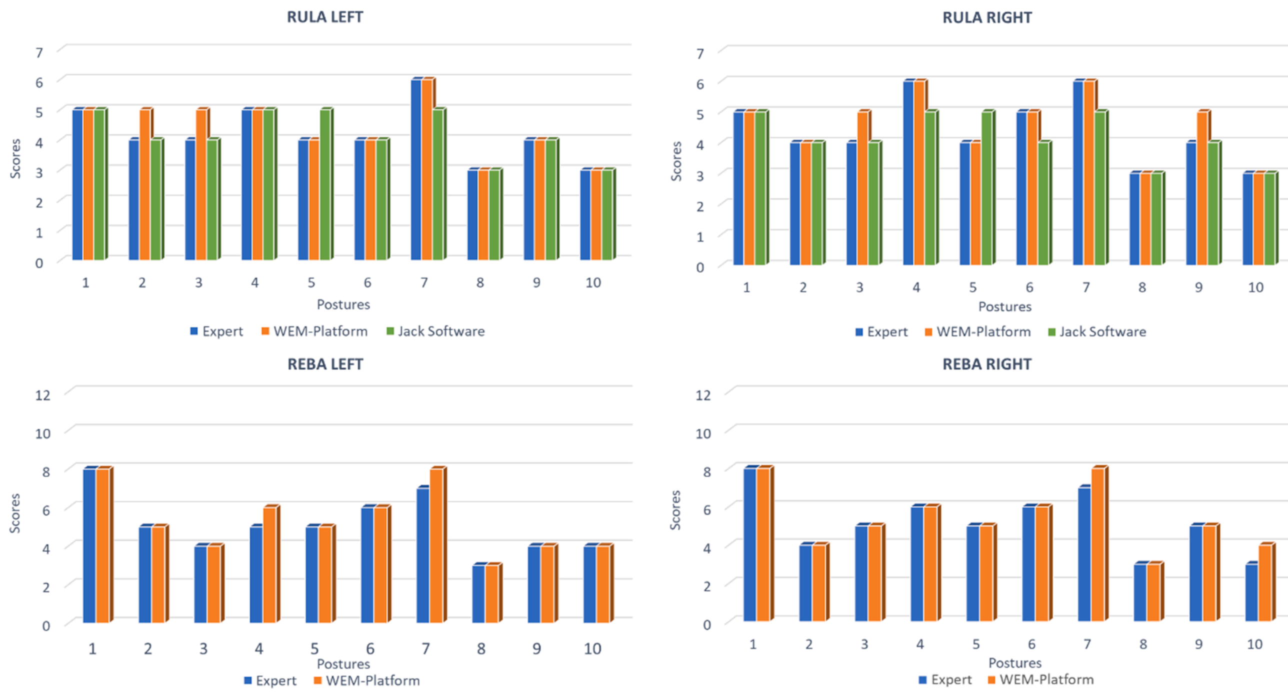


Fig. 6. WEM-Platform validation for RULA and REBA ergonomic indexes: Comparison of WEM-Platform results, experts and, when available, Siemens Jack evaluations.

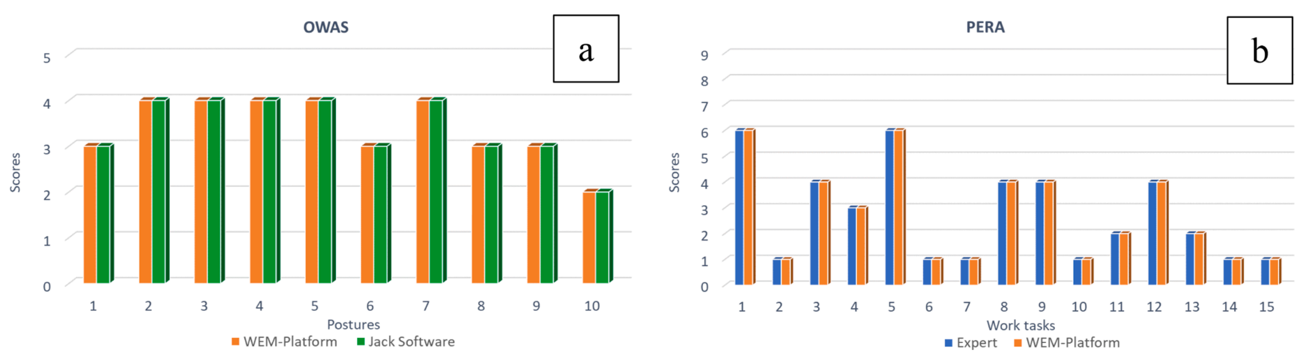


Fig. 7. a: OWAS ergonomic risk assessment: results from WEM-Platform and Siemens Jack; b: PERA ergonomic risk assessment: results from WEM-Platform and expert evaluation.

reports the comparison between REBA score, assessed for both side of operator's body, provided by the WEM-Platform and expert's estimation. Likewise, Fig. 7b reports our output and expert scores per each work task, as required by the PERA index analysis. Task segmentation is manually performed by recognizing tasks characterized by distinct postures or work content, as reported in Chander and Cavatorta (2017). The score values presented for the analyzed activities are usually low due to the scarce force needed for their progression. However, awkward postures or long durations are still clearly affecting a few tasks.

The goal of our platform is to provide direct visual real-time feedback to three different users: the worker, the ergonomist, and the operation manager. For this reason, the main screen is divided into three coloured areas: pink, white, and blue. The pink area is mainly oriented to the ergonomists and safety managers, the white area to the worker, and the blue area to the operation manager. The real-time visual feedback is provided both through a real-time chart progression of the heart rate values and ergonomics scores and by coloured dots. We used traffic light colours for feedback provision:

- Green dots represent postures that do not need to be further analyzed since they do not have ergonomic risks.
- Yellow dots warn experts and workers that there might be a possible risk arising from the current posture.
- Red dots alert users that the current posture represents a severe risk for the worker's wellbeing and needs improvement.

To avoid sudden colour changes when repetitive movements are performed, we introduce two additional scales of colours into the transition between green and yellow and between yellow and red. In these cases, orange and light green colours appear to signal changing situations. In such a way, we evaluate the transition from a right to a wrong posture according to a continuous transition instead of a discrete way.

Fig. 9 shows the division of the graphical user interface into the three colours:

- Pink area: the left side of the screen is dedicated to the ergonomist, who wants to know the ergonomics scores and see when they reach a critical value during the process. We group together all the indexes that allow experts to rapidly evaluate the current situation through the real-time computation of ergonomic indexes. For example, the frame in Figs. 10a and 10b represents a worker tightening a screw. The high postural risk score highlighted by the red traffic light is

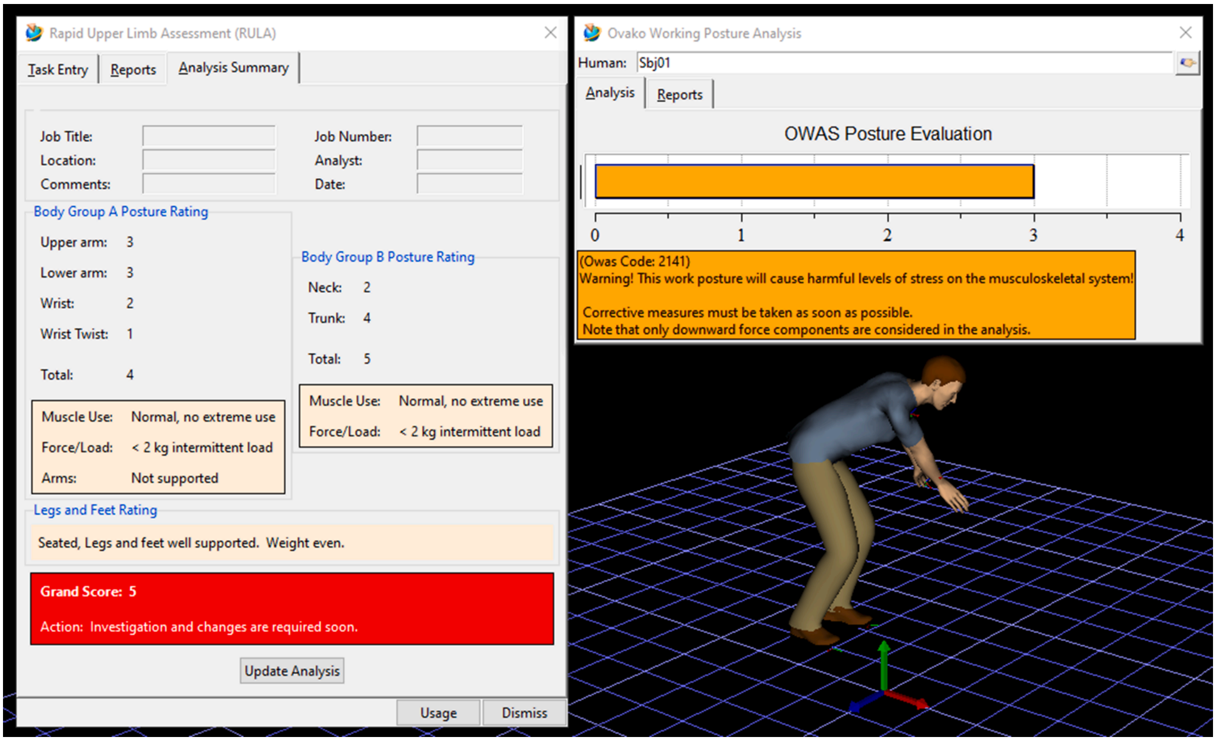


Fig. 8. Validation of RULA and OWAS ergonomic indexes with Siemens Jack Task Analysis Toolkit software through post-progressed ergonomic assessment.

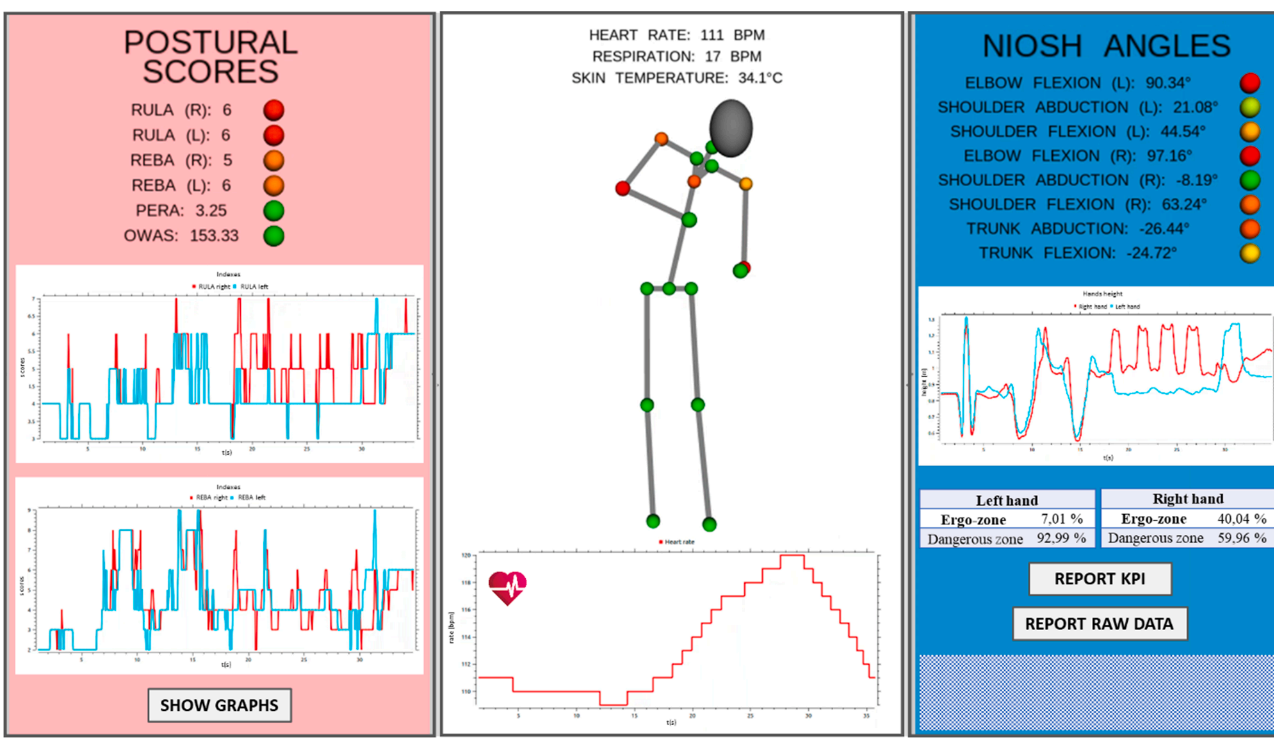


Fig. 9. Graphical user interface of the WEM-Platform (we have obscured the logos on the bottom-right part of the screen to preserve anonymity during the revision process).

mainly attributable to the awkward position of the worker's trunk, which is both bent and twisted during the activity. In particular, the right side of the worker's body is suffering more due to the raised shoulder and abducted right upper arm position. Whilst the RULA and REBA indexes depict severe ergonomic risk for the worker's static posture, the OWAS and PERA indexes, which are time-weighted scores, outline low risk values for the whole assembly activity performed until the last captured frame. The reason for these scores is attributable to the previous frames analyzed by the platform, which are characterized by postures with lower ergonomic risk values. These seem to balance the current ergonomic risk of the posture depicted in Fig. 9. For this reason, the platform reports a green time-weighted risk score for the overall activity the worker performs. For clarity's sake, we intentionally avoid crowding the screen with real-time graphs, which might divert both workers' and experts' focus. Whenever ergonomists need more detail, they can open a separate page by tapping the button marked 'Show graphs' to access the real-time evolution of all ergonomic indexes during the cycle time. In Figs. 10a and 10b, we report the RULA and REBA graphs for the whole assembly process. As can be seen, both graphs present a swinging trend that mainly resides in the upper part of the graphs This visual feedback can provide quick evidence to experts regarding the high percentage of time the worker spends in wrong postures during the assembly process. This information is designated for the ergonomist, but it can also benefit the worker, who can visually interpret the overall risk. For this reason, only these two graphs are shown on the main screen together with the worker's visual feedback.

- White area: the central part of the screen represents an overall evaluation of the current worker's posture; it is dedicated to the worker because by looking at the representation of their body, they can receive immediate feedback on their personal parameters and on the wrong postures assumed during the task execution. Here, the provided information includes the instant value of the heart rate and its time progression (Fig. 11), breathing rate, and skin temperature. In such a way, the worker can check his/her health status by comparing the heart rate during tasks execution with his/her maximum achievable value according to his/her physical features. Skin temperature is used to monitor the general working conditions since high values for a long period represent a warning for ergonomists and operation managers and a decline in safety for the whole working team (particularly during the current post-Covid emergency period). Finally, critical situations or specific cases of fatigue overexertion can be detected from the breathing rate value. Fig. 11 shows a heart rate trend: there is just a pick over 130 bpm for a relatively short period and, consequently, the assembly process under study is not critical from a physical effort point of view.

Moreover, a representation of the operator's body with 17 coloured dots provides real-time visual feedback to the worker, who can visually understand which body parts do not assume a correct position in the current working posture.

Blue area: the right side of the screen is dedicated to the worker's feedback intervention and helps the operation manager to understand which movements need to be carefully analyzed and improved. The area reports the NIOSH angle values and permits the operation manager to immediately understand when a task needs to be modified or enhanced to limit overexertion in lifting, overexertion in pushing or pulling objects, or overexertion in holding, carrying, or turning objects. We adopt the angle values related to the ISO 11226:2014. In particular, we have dedicated three angles to right and left arm posture assessment and two angles to trunk posture. The platform adopts the same visual feedback intervention previously described for the ergonomic indexes. The hand height chart is dynamically progressed together with the percentage of time spent in dangerous positions, or in the ergo-zone, to help operation managers evaluate the amount of time the worker's hands are active during the assembly process in real time.

At any moment during the training activity by tapping the button 'Report KPI' or automatically at the end of the session, the WEM-Platform will print a report with the three performance KPIs related to the tracked activity. Productivity KPI is strongly affected by a worker's dexterity and capabilities. The segmentation of each activity is manually performed by the worker at the end of the progression of each task by pressing a button on the monitor. In the final report, the number of assembled products is reported. Moreover, a spaghetti chart and an overall hand height plot give a complete overview of the worker's movements in the workspace along the horizontal and vertical planes. Fig. 12 highlights the KPIs related to the percentage of time spent within the ergo-zone and the percentage of time spent in dangerous positions.

To conclude, the button 'Report raw data' allows the user to obtain a report with all the positions and the orientations of each joint of the body along the three axes; this can be used to perform additional evaluations.

The spaghetti chart of the laboratory test case is represented in Fig. 13. The graph obtained refers to the pelvis position. By considering the graphical output, we can conclude that the working area for this case is limited near the workbench. The assembler concentrates all his body movements within the workplace, avoiding any movements far from the assembly workbench. This is not a surprising output for this application since we intentionally placed all the parts and components near the worker. Only a few components, which are easily detectable in Fig. 13, represent some exceptions by performing slightly far routes to grab the heaviest components from the rear rack.

In addition, both hand heights are represented in Fig. 14. According to the ergonomic standards, hand height for assembly operations should remain between 900 and 1200 mm. In our test case, this standard is respected most of the time. We highlight only some peaks that refer to when the participant picked up screws from the front of the workbench, inserted drawers into the final structure of the bedside table and picked up certain parts in the rear rack. From this analysis, we can conclude that components in the rear rack should be placed higher up to ensure a better hand working area. Furthermore, the height of the left hand was slightly lower than 900 mm for a limited amount of time. However, this was not a problem, as the hand did not do any work during this time, and the assembler placed it in alignment with his body. Finally, we can note two similar values for both hands for a reduced amount of time. In this

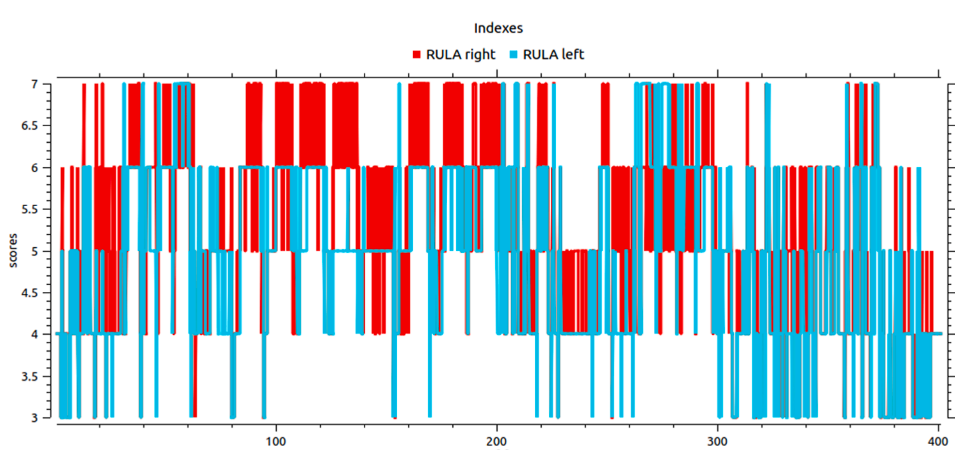


Fig. 10a. RULA scores for the assembly process.

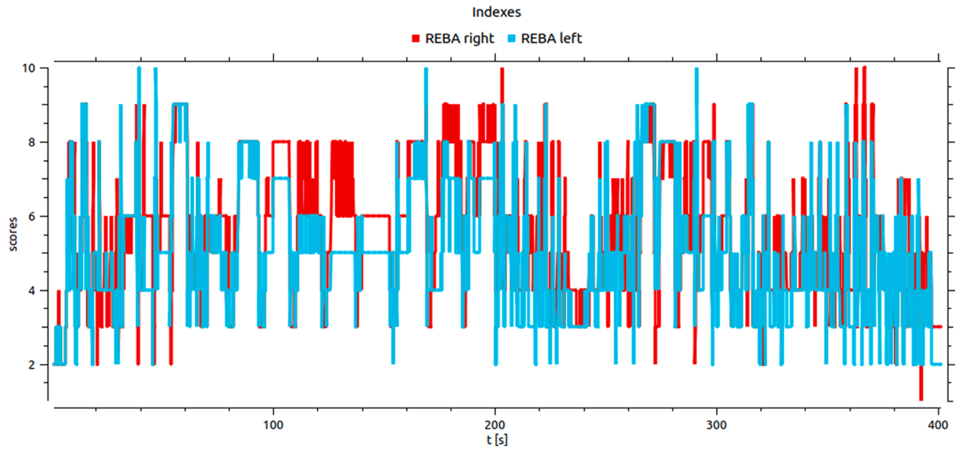


Fig. 10b. REBA scores for the assembly process.

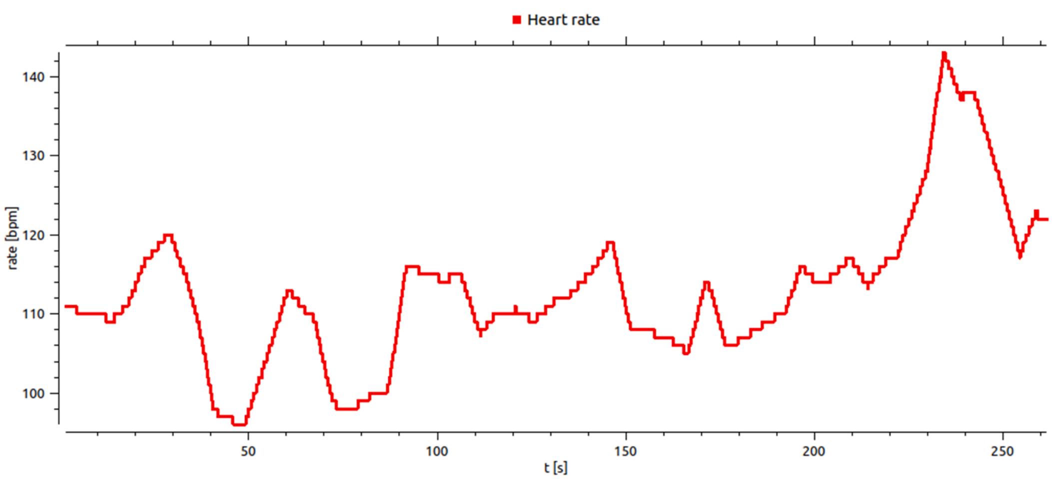
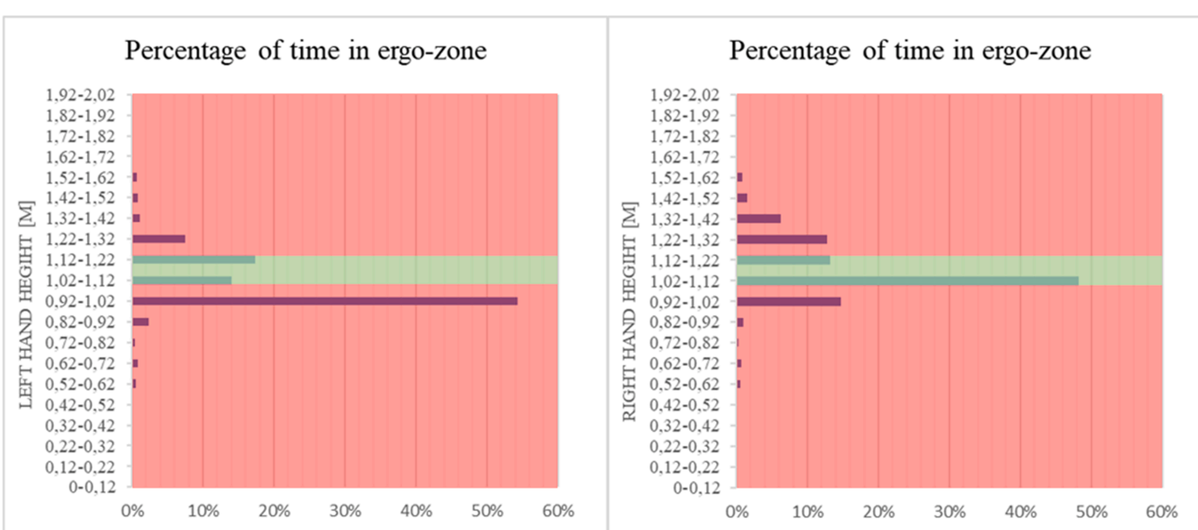


Fig. 11. Heart rate value graph related to the assembly process.



Left hand	
Ergo-zone	31,36 %
Dangerous zone	68,64 %

Right hand	
Ergo-zone	61,44 %
Dangerous zone	38,56 %

Fig. 12. Percentage of assembly time the hands spend in the ergo-zone (green) and in dangerous positions (red).

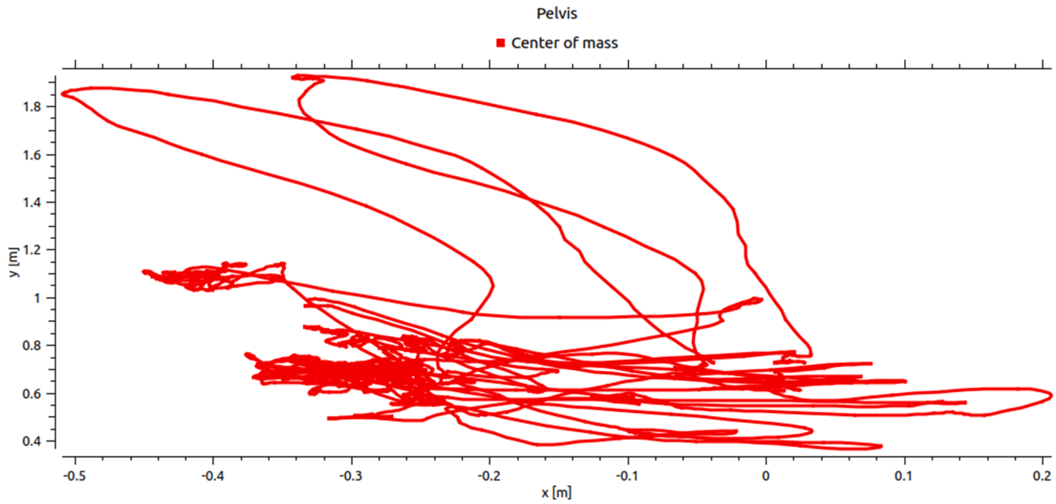


Fig. 13. Spaghetti chart movement.

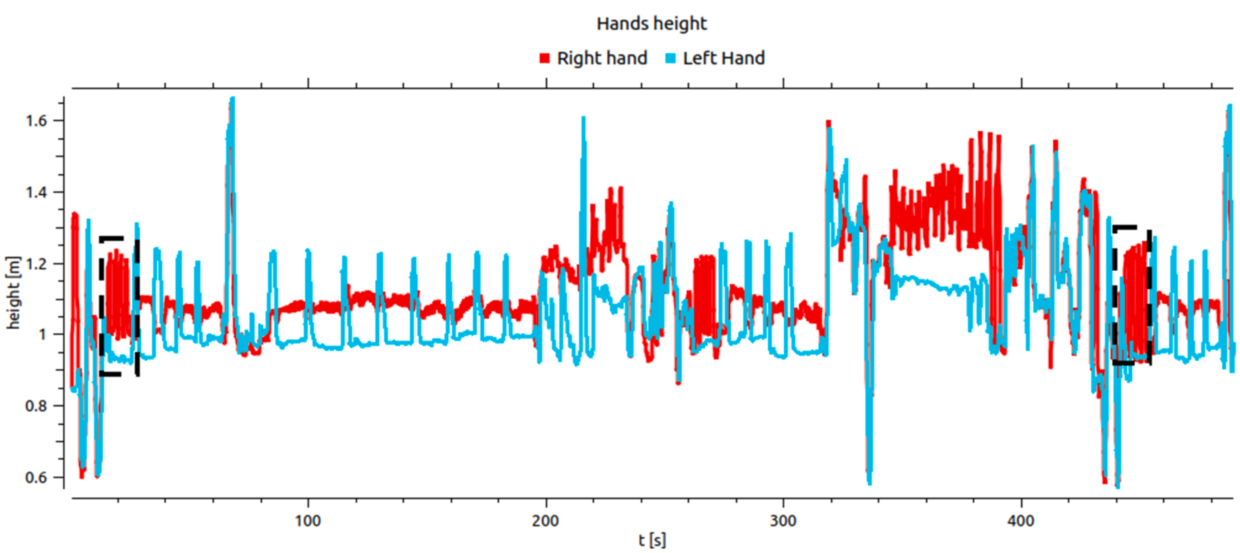


Fig. 14. Hand height throughout the assembly process.

case, aiming to measure the productivity, we asked the assembler to put the right hand in the same position for a couple of seconds in order to understand how the assembly process starts each time. For this example, he has completed a product and started another one.

6. Conclusions

In this article, we present our new WEM-Platform, which provides real-time ergonomic analysis to experts (ergonomists and operation managers) and visual feedback to workers, enabling all stakeholders to learn correct postures through real-time postural training. Moreover, our platform enables offline analysis because the final report with all the data, ergonomic indexes, and postures can be downloaded to allow for data post-processing.

The WEM-Platform aims to reduce several existing gaps in current technology. It is a multi-purpose platform; thus, it can be applied in several contexts in which human workers execute manual jobs (e.g., picking, assembly, construction, general production systems). It computes four ergonomic risk indexes and eight NIOSH angles – this is a step forward from the existing literature, which generally evaluates just one or two ergonomic indexes that are mainly based on upper limbs instead of on the full body (Stefana et al., 2021). Moreover, our platform couples ergonomic postural scores and fatigue measures in one unique instrument. Referencing Sgarbossa et al. (2020), we can now close the gap between ideal and real production systems' models and methods. Through the WEM-Platform, we can easily derive ergonomic risk values, postures, heart rate and respiration values in order to improve workplace design, balance assembly/production lines, and introduce job rotation strategies (Finco, Calzavara, Sgarbossa, & Zennaro, 2020; Finco, Zennaro, Battini, & Persona, 2020).

Finally, the WEM-Platform can easily be used in real industrial contexts since it respects the recent EU General Data Protection Regulation (GDPR) (2016). Personal data protection is ensured at every stage, and users can request and directly obtain the removal of their collected data. An agreement with the workers involved in the capturing and analysis processes is always signed.

As further research, to reduce some limits of WEM-Platform current version, the following points will be addressed:

- Integration of depth cameras as a tool to collect posture data
- Estimation of more complex ergonomic indexes (e.g., OCRA)
- Workers' vibrotactile feedback to immediate alert in case of high ergonomic risk levels

- Workers' visual feedback with augmented reality tools to avoid obstruction of the workplace by the screen.

Moreover, by using the WEM-Platform, a real-time resource assignment and scheduling process as well as a workstation re-design can be accomplished by following a digital-twin approach. In fact, collected data can directly drive real-time models to improve safety and efficiency.

CRediT authorship contribution statement

Daria Battini: Conceptualization, Methodology, Writing – review & editing, Supervision. **Nicola Berti:** Conceptualization, Methodology, Validation, Resources, Data curation, Writing – original draft, Writing – review & editing. **Serena Finco:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing. **Mattia Guidolin:** Conceptualization, Methodology, Software, Validation, Resources, Data curation, Writing – original draft, Writing – review & editing. **Monica Reggiani:** Conceptualization, Methodology, Software, Writing – review & editing, Supervision. **Luca Tagliapietra:** Conceptualization, Methodology, Software.

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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Towards industry 5.0: A multi-objective job rotation model for an inclusive workforce

Daria Battini [a,*], Nicola Berti [a], Serena Finco [a], Ilenia Zennaro [a], Ajay Das [b]

[a] *Department of Management and Engineering, University of Padova, Stradella San Nicola 3, 36100 Vicenza, Italy*
[b] *Loomba Department of Management, Zicklin School of Business, Baruch College, New York, USA*

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ABSTRACT

The new Industry 5.0 paradigm complements the well-known Industry 4.0 approach by specifically driving research and innovation to facilitate the transition to sustainable, human-centric and resilient industry. In the manufacturing context, workers' diversity in terms of experience, productivity and physical capacity represents a significant challenge for companies, especially those characterized by high staff turnover and manual processes with high workload and poor ergonomics. In seeking to address such challenges, this research adopts a human-centric perspective to define new flexible job arrangements by developing a new multi-objective job rotation scheduling model. The proposed model is unique in that it aims to achieve multiple job assignment objectives by simultaneously considering different socio-technical factors: workers' experience, physical capacity and limitations, postural ergonomic risks, noise and vibration exposure, and workers' boredom. The model's implementation in real environments can be supported by new sensor-based technologies that collect data on workers' efficiency, ergonomic scores and task performance and enable workers to participate in measuring perceived fatigue and boredom. The primary goal of our model is to find the most appropriate assignment of job and individual-flexible rest-break plan for each worker. The authors test the model application in an industrial setting. Useful managerial insights emerge and prescriptive recommendations are provided.

1. Introduction

Enduring competitive advantage is seen as a goal for investments in digital, resilient and sustainable manufacturing systems (European Commission 2021 and 2022). As such systems evolve, new paradigms emerge to guide and shape manufacturing industry. A significant dynamic in this regard is the progressive movement of Industry 4.0 to Industry 5.0 transcending efficiency and productivity to emphasize and reinforce the role and the contribution of industry to society. The sharper focus on societal value and worker wellbeing also manifests in the well-known ESG (Environment, Social and Governance) paradigm that adds people and the planet in equal proportion to traditional productivity goals (Duque-Grisales and Aguilera-Caracuel, 2021; Gbejewoh et al., 2021). In the Industry 4.0 era, disruptive technologies such as artificial intelligence, robotics, blockchain, 3D printing, Internet of Things, and digital twins have been the main paradigms in developing competitive and efficient manufacturing systems. However, these benefits did not come without consequences, especially in encounters related to human-machine conflicts. Choi et al. (2022) highlight worker welfare, health problems, and worker satisfaction as concerns of note in this regard. Industry 5.0 seeks to ameliorate and reconcile such human-machine frictions by specifically directing research and innovation to a sustainable, human-centric, and resilient paradigm (Neumann et al., 2021). Conceptually, Industry 5.0 complements, rather than replaces Industry 4.0 – while the latter is largely technology driven, the former is primarily focused on values (Xu et al., 2021). However, the juxtaposition of the two paradigms poses interesting challenges. Notwithstanding technology advances, labor-intensive Manufacturing and Logistics (M&L) systems still see tasks being performed manually even when experiencing high levels of perceived fatigue and boredom. Consider, for instance, complex product assembly systems or job shop operations in which tasks are carried out by shop floor operators; or distribution centers in which a high proportion of picking, storing and packing activities are performed manually by humans; or waste collection and recycling services in municipalities. In these contexts, Industry 4.0 smart and advanced human-machine interaction technologies (Frank et al., 2019; Dornelles et al., 2022; Romero et al., 2019) may be difficult to implement and benefit from, fully. Reasons could range from

* Corresponding author.
E-mail address: daria.battini@unipd.it (D. Battini).

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limitations imposed by high manual task content, movement and space restrictions, individual worker attributes, low flexibility material handling systems and worker hesitancy with new technology (Dornelles et al., 2022; Neumann et al., 2021). Throughput and system efficiency could be strongly influenced by human and work environment factors that impact worker satisfaction, motivation and physical stress (Digiesi et al., 2009; Katiraee et al., 2021a; Simonetto et al., 2022). Thus, differences in spatial working conditions, nature of task, and individual worker characteristics would likely a) constrain a standardized approach to physical implementation/installation of advanced technologies, b) affect the actual extent of use of such technologies by the individual worker, and c) result in performance differentials from similar investments in technology. Our research does not however examine the interaction between HF and advanced technology – a much researched area as evident from the above-mentioned sites.

Instead, it speaks directly to the Industry 5.0 focus on worker well-being by developing ways in which finer grain individual worker attributes can be tracked and incorporated effectively in work planning decisions. Workforce diversity finds reflection in individual capabilities, physical capacities, technology acceptance level, gender, age, and more. It becomes a strategic imperative to actively identify, measure and considers diversity in work policies in order to a) enhance the satisfaction and the wellbeing of the workforce (Katiraee et al., 2021a) and b) achieve improved performance by better matching work policy and practice decisions with the diversity among individual worker qualities. In manual M&L systems, operating factors such as task repetitiveness, hazardous or awkward postures, and noise and vibration exposure can negatively affect worker well-being to different degrees, depending on individual worker characteristics. Deteriorated performance results with consequent efficiency reductions and greater absenteeism (David, 2005). These effects are seen to be more pronounced for ageing workers employed in labor-intensive jobs (Bogataj et al., 2019; Berti et al., 2021a). Careful consideration of worker diversity in determining work policy would result in a more resilient system. A worker whose specific capabilities and conditions have been systematically matched with task requirements and task schedules would be a better and more robust performer, relative to performances obtained from a haphazard or uniform allocation of tasks to worker. Relatedly, following the Covid pandemic disruption in 2020, Romero and Stahre , (2021) introduced the notion of the “resilient operator 5.0” in order to make “human operators – being the most agile and flexible resource in a manufacturing system while simultaneously the most fragile one – more resilient against a range of influencing factors”.

In the longer run, productivity and efficiency can best be achieved by explicitly incorporating human factors in process design and operation. A ‘one size fits all workers’ approach is unlikely to be successful given the inherent heterogeneity in workforce demographics and capabilities. Consequently, we propose a new multi-objective optimization model to assign jobs to workers by considering (simultaneously) different socio-technical factors and three distinct objectives: worker productivity, job ergo-quality level and worker perceived boredom. The model input is unique in that it simultaneously employs workers’ anthropometric data, workers’ physical limitations, experience levels, job ergonomic risks, fatigue and recovery, and perceived boredom. The model outcomes are also unique in that it optimizes multiple objective functions encompassing efficiency and psychological factors. Anthropometric data (age and gender, for instance) are used to assign tasks appropriately.

The rest of the paper is organized as follows. Section 2 provides the theoretical background to our research while section 3 describes a new flexible multi-objective JRS model. Section 4 provides the computational experimentation of the model and a numerical application with insights related to the impacts of different break lengths and workers’ attributes on the objective functions. Section 5 concludes the study and discusses future steps and research opportunities.

2. Theoretical background

This section provides a review of closely related literature and builds a theoretical precursor for the methodology introduced in Section 3.

2.1. Human factors consideration in job rotation scheduling

Job Shop Scheduling and Job Rotation Scheduling (JRS) strategies have been introduced in M&L systems starting from the 1980s aiming to improve workforce flexibility and performance (Padula et al., 2017). JRS has received considerable research attention, especially concerning economic aspects and system productivity. It was just in the last decade though those worker-related social aspects began to appear in production planning strategies and JRS (Trost et al., 2022). The initial concern was to prevent Worker Musculoskeletal Disorders (WMSDs) or other diseases caused by the prolonged exposure of operators to high ergonomic risk factors (Leider et al., 2015). The aim was to avoid excessive exposure to the same set of jobs characterized by heavy loads, vibrations, awkward postures or repetitive movements performed during the work activity (Otto and Scholl, 2013; Otto and Battaïa, 2017; Padula et al., 2017). Carnahan et al. (2000) a pioneer in including human factors and ergonomics in JRS, developed the first mathematical contribution to worker ergonomic load minimization by considering the Job Severity Index. They developed both Linear Programming (LP) and Genetic Algorithm (GA) methods to find over 400 unique solutions to the rotation plan, involving 8 rotation periods within the same work shift. Asensio-Cuesta et al. (2012a) introduced a fitness function based on the Occupational Repetitive Actions index (OCRA, Occhipinti, 1998) to avoid the worker’s job repetition and increase the variability of the risk level that workers are exposed to. The authors proposed a GA to find the best feasible solutions corresponding to the fitness function with the lowest value, considering the penalties for the incompatibilities between jobs and workers’ physical, mental and communication capabilities. Asensio-Cuesta et al. (2012b) employed 39 different criteria to develop a multi-criteria GA to generate job rotation schedules considering workers’ ergonomic movements, physical skills and individual competence. Otto and Scholl (2013) developed a smoothing heuristic able to provide initial solutions as input for the tabu search procedure. Mossa et al. (2016) proposed a model for the maximization of production rate in work environments characterized by high repetition frequency. The authors adopted the OCRA score method to car seat assembly line workstations to determine task acceptability and to balance workloads and ergonomic risk among workers. Song et al. (2016) developed a hybrid GA for the minimization of WMSDs considering muscle fatigue, working height and the NIOSH (National Institute for Occupational Safety and Health) Lifting Index, but neglecting physical and psychological factors such as motivation, personal preferences and fatigue, which are considered by the authors as limitations of their research. Yoon et al. (2016) estimated the perceived workload in three automotive assembly lines through Rapid Entire Body Assessment index (REBA) (Hignett and McAtamney, 2000) to avoid successively workload in the same body regions. Furthermore, Digiesi et al. (2018) developed a model to reduce the ergonomic risk of the workload within acceptable limits while ensuring productivity goals by minimizing the weighted Rapid Upper Limb Assessment index (RULA). Table 1 shows published works on JRS with human factors consideration.

While past work on JRS has indeed been useful and knowledge building, they have a singular lacuna – they consider a single aspect at a time. The majority of the work neglects to address the combinatorial effect that multiple parameters might have on JRS model performance and results. For instance, in a human-centric working space, body postures, tools’ vibration, and noise should be jointly considered to better define a sustainable and human-centric job rotation schedule. Similarly, there is scant investigation about flexible shift duration times and different rest break schedules developed to match individual workers’ attributes. A notable exception is the study by Tharmmaphornphilas and

Table 1
Published works on Job Rotation Scheduling with human factors consideration.

Authors (year)	Human factors involved	Workers' Features	Workers' involvement	Recovery and fatigue aspects	Rotation period length	Model & Method
Costa and Miralles (2009)	Job repetitiveness Skills improvement	Task-worker incompatibilities	N/I	N/I	Consideration of Different Rotation Schemes	MILP - Heuristic decomposition method
Azizi et al. (2010)	Skills improvement	Worker's learning and forgetting rate Individual motivation and boredom slopes	N/I	N/I	Consideration of different rotation schemes	SAMED-JR algorithm Metaheuristic
Asensio-Cuesta et al. (2012a)	Job repetitiveness (OCRA) Postural risk (OCRA)	Worker's restrictions	N/I	Recovery period multiplier (OCRA)	N/I	(Fitness function) - Genetic algorithm
Asensio-Cuesta et al. (2012b)	Ergonomic criteria Physical skill criteria	Competence criteria Workers' physical limitations	N/I	Cumulative fatigue effects	N/I	(Fitness function) Genetic algorithm
Moreira and Costa (2013)	Job repetitiveness Skills improvement	Infeasible task-worker pairs Variability of execution time	N/I	N/I	Consideration of different rotation schemes	Mixed IP - Metaheuristic and hybrid algorithm
Otto and Scholl (2013)	Postural risk (EAWS)	N/I	N/I	N/I	N/I	Mixed IP - Tabu search approach - Heuristic
Mossa et al. (2016)	Job repetitiveness (OCRA) Postural risk (OCRA)	Individual risk limits	N/I	Recovery period multiplier (OCRA)	N/I	MINLP
Song et al. (2016)	Postural risk (NIOSH LI)	N/I	N/I	Rodgers Muscle Fatigue Analysis	N/I	Non linear Hybrid genetic algorithm
Yoon et al. (2016)	Postural risk (REBA)	N/I	N/I	N/I	N/I	Non linear
Digiesi et al. (2018)	Postural risk (RULA)	Individual ergonomic risk threshold	N/I	N/I	N/I	MINLP
Hochdörffer et al. (2018)	Postural risk (EAWS)	Permanent or temporary impairments	N/I	N/I	Consideration of Different Rotation Schemes	IP Linear Heuristic
Asensio-Cuesta et al. (2019)	Risk exposure	Physical/Psychological limitations	Worker's job preference and competence lists	Accumulated fatigue	Consideration of different rotation schemes	(Fitness function) Gale-Shapley algorithm
Moussavi et al. (2019)	Job repetitiveness Postural risk (SES) Energy consumption	N/I	N/I	N/I	Consideration of different rotation schemes	MILP Optimal solution
Sana et al. (2019)	RULA, OCRA, NIOSH LI	Worker's restrictions	Worker's preferences	Recovery period multiplier (OCRA)	N/I	Multi-objective ILP Genetic algorithm
Diego-Mas (2020)	Force loads, postures, movements score	Mental and communication skills, temporal disabilities	Worker's preferences	Cumulative fatigue effects	N/I	(Fitness function) Evolutionary algorithm
Mehdizadeh et al. (2020)	Postural risk: Low back (LiFFT tool), Upper extremities (DUET tool)	N/I	No workers' preference	N/I	Consideration of different rotation schemes	IP - Heuristic
Adem and Dağdeviren (2021)	Working environment (HAV)	N/I	Skill level Day-off preferences	N/I	N/I	Linear – Branch & Bound Non linear – Program-Baron solver
Botti et al. (2021)	Job repetitiveness (OCRA) Postural risk (OCRA)	Functional capacities and senses, competencies and technical skills	Relational skills and mental capacities Person-job fitness	Recovery period multiplier (OCRA)	N/I	Bi-objective ILP model Pareto frontier

N/I: Not Included; JSI: Job Severity Index; TWA: Time-Weighted Average (OSHA); EAWS: European Assembly Worksheets (Schaub et al., 2013); LI: Lift Index; HAV: Hand-Arm Vibration; IP: Integer Programming model; MILP: Mixed Integer Linear Programming model.

Norman (2004) which researches the effects that the frequency of intervals and break positioning can have on ergonomic risk reduction, by assessing the evaluation of the proper time length for rotating workers. However, they consider workers with similar attributes.

2.2. Theoretical foundation and methodological framework

Our new JRS model rests its conceptual and theoretical foundation on three central studies: Berti et al., (2021b), Finco et al., (2019a), and Battini et al., (2022).

Berti et al. (2021b) proposed a methodological framework that integrates anthropometric and ergonomics measures during the job scheduling decision process, and defines steps needed to define a worker-oriented and flexible scheduling of jobs. Each task is categorized in the framework according to three drivers: physical stress, ergonomic risk and execution time.

The Berti et al. (2021b) framework is compatible with the formulas developed by Finco et al. (2019b) that calculate energy consumptions and recovery times for workers of different age and gender and with Finco et al. (2019a), that estimate vibrations exposure in manufacturing systems. Finally, Battini et al., 2022 developed a digital real-time platform for full-body ergonomic assessment and feedback to calculate ergonomics parameters from wearable workers sensors. The platform is validated using laboratory tests, using sensor provided workers' input data for targeting and assigning jobs appropriate to the worker. Finco et al. (2019a; 2019b) and Battini et al. (2022) works are consistent with the methodological approach described in Berti et al. (2021b). Fig. 1 below derives from and extends Berti et al. (2021b), and shows how our new optimization model can be seen as the culminating step of a whole human-centric methodology.

Our theoretical logic also finds support from the new international standards published by ISO in 2022 (ISO 25550–2022), which provide specific requirements and guidelines to achieve an age-inclusive workforce. ISO directs attention to making available options for flexibility in job assignments and working arrangements to accommodate age-related factors. Such options include flex-time, job sharing, job redesign,

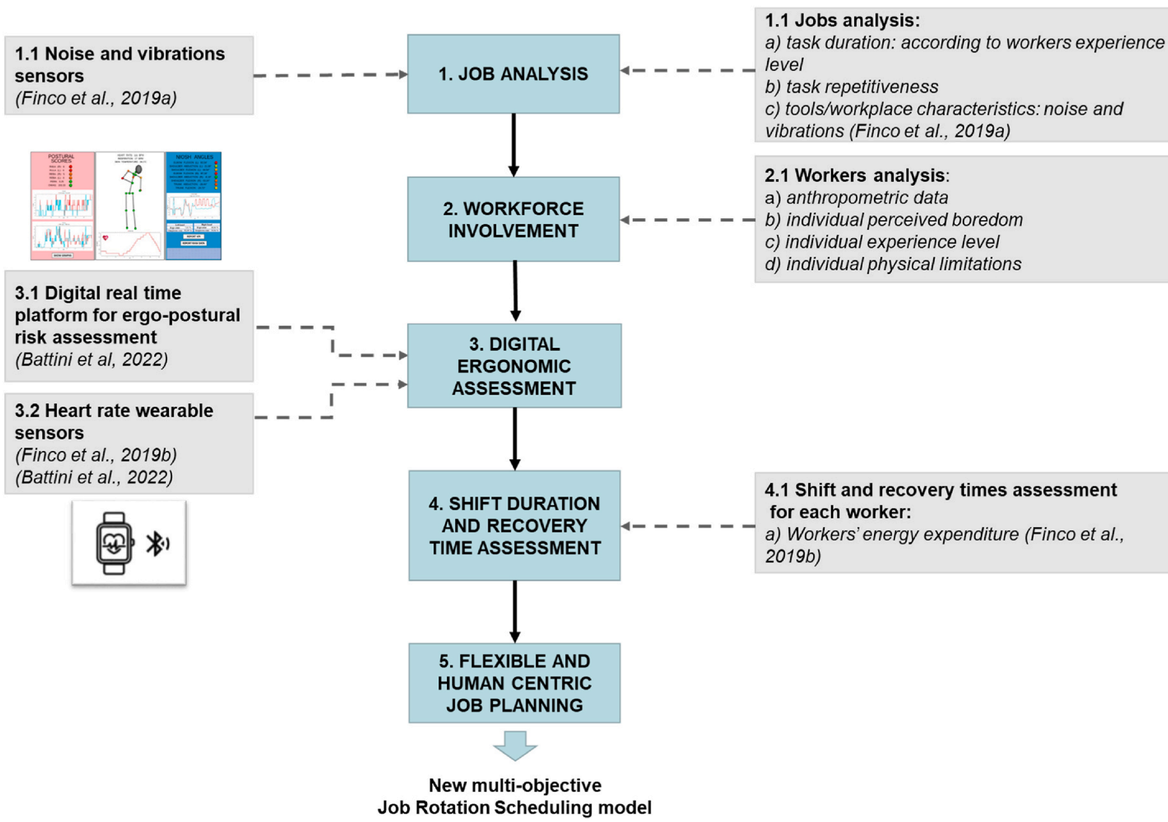

Fig. 1. Theory-based methodological framework supporting the implementation of new JRS model (derived from Berti et al., 2021b).

swapping shifts, allowing time to adapt to new tasks as also flexibility in rest breaks during working shifts. Such facilitations in work conditions are envisaged to potentially and especially benefit older workers and may also help workers with health problems to work consistently and stay longer in the workforce. Recent academic literature is beginning to develop worker-inclusive decision-making tools and human-centric and flexible job scheduling models. Some stress the need to involve the worker in the individual data collection phase as well as in the decision-making phase in order to develop more work-inclusive solutions (Sgarbossa et al., 2020. Finco et al., 2020a, 2020b; Vijayakumar et al., 2022; Katiraee et al., 2021b). Others stress the need to better manage expert workers and involve them in mentoring and training rookies (Katiraee et al. 2021c).

Recent works in job rotation scheduling already include HF (i.e., ergonomic risks linked to postures and fatigue, experience/skill levels) in both long and short-term decisions (i.e. Mehdizadeh et al., 2020 and Mossa et al., 2016). However, they often neglect to consider worker attributes and ignore various complexities of worker involvement in input data estimation.

Based on the theoretical fundamentals discussed earlier and the Industry 5.0 vision presented in the first section, this research proposes a new human-centric approach for solving a multi-objective Job Rotation Scheduling problem. Our model breaks new ground in *jointly* considering a variety of realistic shop floor socio-technical factors in JRS: ergonomics postural scores, vibration and noise risk constraints (by respecting international standards threshold values), workers' experience in performing jobs and individual physical limitations. Further, workers' opinion is considered to define a similarity score among jobs, useful in finding solutions to minimize worker boredom. Finally, the number of shifts, as well as the break time among each shift, are optimally scheduled since they strongly influence productivity and workers' well-being. Rest break durations are flexible since age- and gender-related differences are taken into account. Improving on previous job rotation scheduling models (e.g., Hochdörffer et al., 2018; Song et al., 2016; Yoon et al., 2016), we assume that the break time between shifts is an opportunity for operators to recover, contingent on worker individual characteristics (age and gender, for example). In summary, our research model presents a new human centric job rotation scheduling approach. The model aims to make the worker (and inferentially the production system) more resilient to variability in ergonomic workloads, and minimize boredom risks in human intensive working environments. The model is motivated by Industry 5.0 human centric priorities and is grounded in past research. More specifically, our model seeks to maximize throughput while customizing job rotation schedules to match individual worker attributes.

3. Problem definition and mathematical model

In this section, a new multi-objective job rotation scheduling model is presented. It maximizes the manufacturing system throughput and minimizes the maximum level of boredom and ergonomic risk in the work team, by considering workers' differences in terms of age, gender, experience levels, and physical limitations according to specific jobs. Daily exposures to noise and tools vibration are also considered additional constraints.

Table 2 reports all the indices, parameters and decision variables we will use in the sequel.

The following assumptions are included in the model:

1) The set of jobs and workers is fixed.
2) In a working day, the same job can be assigned at least once to the same worker.
3) The number of jobs is larger than the number of operators, so at least one job will be assigned to each operator in each period. This assumption reflects common reality in industry. In fact, due

Table 2
List of all indices, parameters, variables and decision variables.

Indices	
I	Index for Workers
J	Index of jobs
K	Index for shifts
Parameters	
W	Number of workers
J	Number of jobs
K	Number of shifts
UB	Big number
T_j	Nominal execution time for job j [seconds]
α_{ij}	Level of experience of worker i in executing job j
β_{ij}	Physical limitation for worker i in executing job j
RA_{ij}	Rest allowance for worker i in executing job j
$s_{ijj'}$	The level of similarity defined by worker i between jobs j and j'
T_k	Time for the shift k [seconds]
B_k	Break time for shift k [seconds]
E_j	Ergonomic risks score for job j
L_j	Noise level for job j [s]
a_j	Acceleration value for job j [$m/_{s^2}$]
a_{lim}	Maximum acceleration value [$m/_{s^2}$]
T_0	Workday duration [seconds]
z_{j_min}	Minimum required throughput for job j
z_{j_max}	Maximum required throughput for job j
Variables	
z_{ijk}	Throughput obtained by worker i for job j during shift k
z_{max}	Total throughput
E_i	Ergonomic risk for worker i
E_{max}	Maximum ergonomic risk
S_i	Job similarity level for worker i
S_{max}	Maximum similarity level
Decision variable	
x_{ijk}	Boolean variable that assumes a value 1 if worker i is assigned to job j during shift k, 0 otherwise

to the variety of products, the number of jobs is generally higher than the number of workers.
4) A minimum quantity of product is required for each job.
5) For each job, a maximum number of products is defined to avoid higher inventory costs.
6) Each worker must complete the assigned job according to his/her physical capacity, limitations and experience level. The time required to perform a job can be lower or higher than the nominal execution time depending on the level of experience.
7) For each job, data concerning noise and vibration levels, ergo-postural risks, and nominal execution time are known.
8) Each worker is directly involved in defining the level of similarity among jobs and, as a consequence, the perceived boredom.
9) The recovery time (RA) required for each job varies according to the worker. It considers the energy expenditure required to perform the job and the maximum acceptable energy expenditure of each worker according to Finco et al. (2019b).
10) A dynamic and suited rotation for the worker is guaranteed daily according to the characteristics of the workers.
11) All parameters are deterministic and constant.

The objective functions (O.F.) of the mathematical model can be defined as follows:

$$O.F.1: \ Maximize\ z_{max} \tag{1}$$

$$O.F.2: \ Minimize\ S_{max} \tag{2}$$

$$O.F.3: \ Minimize\ E_{max} \tag{3}$$

Subject to:

$$\sum_j x_{ijk} = 1 \ \forall\, i = 1,..,W; k = 1,..,K \tag{4}$$

$$\sum_i \sum_k x_{ijk} \geq 1 \ \forall\, j = 1,..,J \tag{5}$$

$$\sum_i x_{ijk} \leq 1 \ \forall\, j = 1,..,J; k = 1,..,K \tag{6}$$

$$z_{j\_min} \leq \sum_i \sum_k z_{ijk} \leq z_{j\_max} \ \forall\, j = 1,..,J \tag{7}$$

$$0 \leq z_{ijk} \leq \frac{T_k - \max(0; T_k RA_{ij} - B_k)}{\alpha_{ij}\beta_{ij}T_j} x_{ijk} \ \forall\, i=1,..,W; j=1,..,J; k=1,..,K \tag{8}$$

$$\sum_k \sum_j \sum_i z_{ijk} \leq z_{max} \tag{9}$$

$$S_i = \frac{\sum_{k=1}^{K-1} \sum_{j=1}^{J} \sum_{j'=1}^{J} x_{ijk} x_{ij'(k+1)} s_{ijj'}}{K-1} \ \forall\, i = 1,..,W \tag{10}$$

$$S_{max} \geq S_i \ \forall\, i = 1,..,W \tag{11}$$

$$E_i = \frac{1}{T_o} \sum_j \sum_k E_j \left[T_k - \max(0; T_k RA_{ij} - B_k)\right] x_{ijk} \ \forall\, i = 1,..,W \tag{12}$$

$$E_{max} \geq E_i \ \forall\, i = 1,..,W \tag{13}$$

$$\frac{1}{T_0} \sum_j \sum_k a_j^2 \left[T_k - \max(0; T_k RA_{ij} - B_k)\right] x_{ijk} \leq a_{lim}^2 \ \forall\, i = 1,..,W \tag{14}$$

$$\sum_j \sum_k \frac{\alpha_{ij}\beta_{ij}T_j}{L_j} x_{ijk} \leq 1 \ \forall\, i = 1,..,W \tag{15}$$

$$x_{ijk} \in \{0,1\} \ \forall\, i=1,..,W; j=1,..,J; k=1,..,K \tag{16}$$

$$z_{ijk} \in \mathbb{N} \ \forall\, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{17}$$

$$z_{max} \in \mathbb{N} \tag{18}$$

$$S_i,\ E_i \in \mathbb{R} \ \forall\, i = 1,..,W \tag{19}$$

$$S_{max},\ E_{max} \in \mathbb{R} \tag{20}$$

where O.F. 1, hence the first objective function, maximizes the daily throughput. The second objective function, O.F. 2, minimizes boredom (based on the worker's perceived similarity level between jobs). Finally, the third objective function, O.F.3, minimizes ergonomic risk. Constraint (4) states that each worker in each rotation shift must perform only one job. Constraint (5) guarantees the execution of all jobs at least once during a working day, while constraint (6) defines that each job must be executed by a maximum of one worker in each rotation shift. Constraint (7) guarantees the respect of the minimum and maximum throughput for each job j, constraint (8) quantifies the throughput for job j obtained by worker i in rotation shift k. Constraint (8) considers the level of experience of worker i in executing job j, as well as the rest allowance and some physical limitations. Moreover, it evaluates whether to assign an extra amount of time, which is set as the maximum value between 0, and the difference between rest time ($T_k RA_{ij}$), defined as the product between the rotation shift length and the percentage of recovery time required for executing the job, and the beak time (B_k).

Constraint (9) quantifies the total daily throughput. Constraint (10) evaluates the average value of the similarity score for the worker i involved, while constraint (11) quantifies the maximum similarity level between workers. Constraints (12) and (13) evaluate the ergonomic risk for each worker and the maximum ergonomic risk score between workers to create a highly flexible model which can be applied to any kind of ergonomic risk score linked to postural job evaluation.

Constraints (14) and (15) ensure the respect for vibration (Finco et al., 2019a) and daily exposure to noise in accordance with ISO5349–1:2001 and NIOSH. Finally, the constraints set (16)–(20) define variable type.

The model proposed here is not linear due to constraints (8) and (10). However, it can be linearized by adding additional constraints and variables, and thus a Mixed Integer Linear Programming (MILP) model can be obtained. Going in-depth of the linearization approach, constraint (8) can be replaced as follows:

$$0 \leq z_{ijk} \leq \frac{T_k x_{ijk} - R_{ijk}}{\alpha_{ij}\beta_{ij}T_j} \ \forall\, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{21}$$

The following additional constraints are included in the model:

$$R_{ijk} \geq 0 \ \forall\, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{22}$$

$$R_{ijk} \geq \left(T_k RA_{ij} - B_k\right) x_{ijk} \ \forall\, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{23}$$

$$R_{ijk} \leq \left(T_k RA_{ij} - B_k\right) x_{ijk} + UB\left(1 - \varphi_{ijk}\right) \ \forall\, i = 1,..,W; j = 1,..,J; k = 1,.., K \tag{24}$$

$$R_{ijk} \leq 0 + UB\varphi_{ijk} \ \forall\, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{25}$$

$$\varphi_{ijk} \in \{0,1\} \ \forall\, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{26}$$

$$R_{ijk} \in \mathbb{R} \ \forall\, i = 1,..,W; j = 1,..,J; k = 1,..,K \tag{27}$$

where R_{ijk} assumes the maximum value between zero (no rest) and the rest time to assign to a worker in case the break time is not enough to cover the physical fatigue spent in performing the job. Constraints (22)–(25) set the value of R_{ijk} for each worker, i, each job, j, and each shift, k. Finally, constraints (26) and (27) define the type of variable.

Considering constraint (10) the non-linearity is due to the product between two Boolean variables. For this reason, an additional set of Boolean variables must be included in the final model and constraint (10) must be replaced as follows:

$$S_{ik} = \sum_{j=1}^{J} \sum_{j'=1}^{J} \gamma_{ijj'k(k+1)} S_{ij(j+u)} \ \forall\, i = 1,..,W;\ k = 1,..,K \tag{28}$$

Moreover, the following additional constraints must be included:

$$\gamma_{ijj'k(k+1)} \leq x_{ijk} \ \forall\, i = 1,..,W; j = 1,..,J; j' = 1,..,J; k = 1,..,K-1 \tag{29}$$

$$\gamma_{ijj'k(k+1)} \leq x_{ij'(k+1)} \ \forall\, i = 1,..,W; j = 1,..,J; j' = 1,..,J; k = 1,..,K-1 \tag{30}$$

$$\gamma_{ijj'k(k+1)} \geq 0 \ \forall\, i = 1,..,W; j = 1,..,J; j' = 1,..,J; k = 1,..,K-1 \tag{31}$$

$$\gamma_{ijj'k(k+1)} + 1 - x_{ijk} - x_{ij'(k+1)} \geq 0 \ \forall\, i = 1,..,W; j = 1,..,J; j' = 1,..,J; k = 1,..,K-1 \tag{32}$$

$$\gamma_{ijj'k(k+1)} \in \{0,1\} \ \forall\, i = 1,..,W; j = 1,..,J; j' = 1,..,J; k = 1,..,K-1 \tag{33}$$

where $\gamma_{ijj'k(k+1)}$ is the Boolean variable representing the product between x_{ijk} and $x_{ij'(k+1)}$. Constraints set (29)–(32) is required to set the value of $\gamma_{ijj'k(k+1)}$ which can assume a value equal to 1 in case both x_{ijk} and $x_{ij'(k+1)}$ assume a value of 1 or equal to 0 in case of both or one Boolean variable among x_{ijk} and $x_{ij'(k+1)}$ assume a 0 value. Finally, the constraint (33) sets the type of variables.

Since the model is multi-objective, we applied the ε-constraint algorithm to obtain the set of optimal solutions, thus the 3D Pareto's front. With the ε-constraint algorithm, the multi-objective problem is reduced to a single object, by adding the constraints that represent the remaining objective functions. Fig. 2 presents the pseudocode.

Moreover, in this specific case, the ε-constraint algorithm consists of two steps:

Algorithm: ε-constraint algorithm of the JRS model

$S = \emptyset; \gamma \leftarrow 0$
Set : $\bar{E} \leftarrow E_{lim}$
while ($\bar{E} \geq E_{min}$) **do**
Set: $\bar{S} \leftarrow S_{lim}$
while ($\bar{S} \geq S_{min}$)) **do**
Set $Z' \leftarrow$ solve JRS-S
Set $S_\gamma \leftarrow$ solve JRS-E
Set $E_\gamma \leftarrow$ solve JRS-T
P← P ∪ $\{(E_\gamma; S_\gamma; Z')\}$
Decrease the bound on the budget by 1 unit: $\bar{E} \leftarrow E_\gamma - 1$
Decrease the bound on the budget by 1 unit: $\bar{S} \leftarrow S_\gamma - 1$
$\gamma \leftarrow \gamma + 1$
end while
return S (return the Pareto set S)

Fig. 2. ε-constraint pseudo-code.

Step 1. an upper bound of both ergonomics and similarity is set equal to $\bar{E}$ and $\bar{S}$ respectively. They represent the maximum ergonomic and similarity value which can be computed by considering the jobs with the higher ergonomic score and similarity. Then, the mathematical model, denoted as JRS-HF (Job Rotation Scheduling - Human Factor) is solved by considering $E_{max} \geq \bar{E}$ and $S_{max} \geq \bar{S}$, constraints {(4)–(7); (9)–(33)} and O.F. 1. JRS-HF defines a solution by respecting the fixed value of ergonomic postural score and similarity.

Step 2. the optimal value of Z', thus the throughput, obtained in Step 1 is fixed as a bound and the model is solved by minimizing the ergonomic postural score as well as the similarity. In this way, the non-dominated point with respect to the fixed $\bar{Z}$ can be obtained.

Finally, the algorithm decreases the ergonomic postural score and the similarity score by 1 and goes back to Step 1. The stopping condition is reached when the upper bound of throughput is reached. It corresponds to the situation related to the highest worker performance while performing the job according to their cognitive and physical abilities.

4. Test-case and managerial insights

4.1. Test case description

In this section, we apply the model to a numerical case inspired by a real industrial scenario. Ten different jobs are considered (the data are reported in Table 3). Each job represents the entire production process of a water pump and includes different tasks such as preassembly, assembly, quality control, and packaging. According to the type of product, the job can be performed by using automatic, semi-automatic, or manual tools, which lead to different values of vibrations and noise exposure. In this company, since worker's whole body is involved in job progression with variable cycle time (see Table 3), we decide to compute the Rapid Entire Body Assessment (REBA) as the index to assess ergonomic score. In our case, the value of this index is always lower than the threshold value for each job, referring to the urgent necessity to implement changes in the workplace design - which is set to 8 for REBA. The ergonomic score for each job, defined through the REBA index (Hignett and McAtamney, 2000), was computed by using the ergo-digital platform described in Battini et al. (2022). The platform considers the whole set of body movements needed to execute the job, asking workers to wear the suit while executing the job. Next, the energy expenditure required to perform each job was calculated based on the ergo-digital platform software (Battini et al., 2022). Finally, this input was then used to evaluate the rest allowance (RA) for each worker in case he/she

Table 3
Jobs features.

	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
T *[minutes]*	10	12	15	15	17	19	21	25	27	28
Z_min *[pcs/day]*	5	5	5	5	1	1	1	1	1	1
Z_max *[pcs/day]*	40	40	25	25	25	25	20	20	20	20
a $[m/_{s^2}]$	0	3.54	4.25	5.45	0	4.97	4.25	3.63	1.23	1.17
L *[minutes]*	100000	525	1250	2480	100000	1460	2780	3230	630	720
E *[REBA]*	5.5	5.9	4.6	4.2	3.7	5.4	6.4	3.5	4.7	3.8
EE [kcal/minute]	4.3	3.8	3.7	3.9	4.2	3.4	3.2	3.6	4.1	3.9

is involved in the job for a rotation shift (according to the formulas provided by Finco et al., 2019b). Jobs execution times vary from 10 to 28 min. In particular, J1 and J2 refer to basic products, while J8, J9, and J10 refer to complex products that require a higher experience level. Moreover, according to managerial guidelines for each job, the minimum and maximum number of products to produce in a day are set. Jobs J1 and J5 are entirely executed manually and, for this reason, acceleration and noise exposure values are respectively set as 0 $m/_{s^2}$ (e.g., there is no vibration) and 100,000 min (e.g., there is no hazards noise exposure). The remaining jobs present both vibration and noise exposure. The higher the acceleration value (a), the higher the vibration exposure (Finco et al., 2019a). The lower the time-exposure limit (L), the higher the noise exposure. Finally, energy expenditure varies in the range of 3.2 kcal/min to 4.3 kcal/min. Jobs requiring higher values of energy expenditure refer to water pump special models involving heavy and large parts that need to be lifted and moved manually.

The job can be performed by six workers whose features are reported in Table 4. Two out of six workers (e.g., W5 and W6) can be considered ageing workers (Cloostermans et al., 2015) since they are more than 45 years old. Also, they have long experience. W1 is a young worker in his first job, so he has no experience. W2 and W4 have low levels of experience since they have worked in the company for just a year. Following Finco et al. (2019b), the Maximum Acceptable Energy Expenditure (MAEE) for each worker is provided and then used to define the rest allowances required for each worker while performing each job. Table 5 reports the RA values. As we can see, W1, W2, and W3 do not have RA since the energy expenditure for executing each job is always lower than their MAEE. Finally, according to the physical limit of the workers, W1 and W2 can perform all jobs even if they have low experience level. W3, W4, W5, and W6 cannot perform some jobs since they require high physical effort or were assessed as potentially hazardous activities according to their individual limitations (i.e., they correspond to a high ergonomic score).

Depending on the experience of each worker, the required time to execute each job can be higher or lower than the nominal time. The experience percentage (α_{ij}) for each worker and each job is presented in Table A1 in the appendix section.

Finally, workers are directly involved in the short-term decision process by providing their perceived similarity score among jobs (details are presented in Figure A2 in the Appendix section).

We consider the following three scenarios to understand how the working day duration and the rotation shifts and breaks length time influence throughput, ergonomics, and similarity scores.:

Table 4
Workers' attributes.

	W1	W2	W3	W4	W5	W6
Age	23	31	37	42	52	58
Experience	Very low	Low	High	Low	Very high	Very high
MAEE [kcal/min]	4.8	4.7	4.4	4.2	3.8	3.5
Physical limitations	–	–	J1	J2, J7	J2, J6, J7	J2, J5, J9

- Scenario 1 (S1): two rotation shifts (RS) and a break (B)
- Scenario 2 (S2): three rotation shifts (RS) and two breaks (B)
- Scenario 3 (S3): four rotation shifts (RS) and three breaks (B)

For each scenario, we also consider two different working days (WD) durations which are equal, respectively, to 6 h/day (Case A) and 8 h/day (Case B). In Case A workers are involved 6 days/week, while in Case B they work 5 days/week. According to Finco et al. (2019), 2019b in Case A, the RA for each worker is reduced since their MAEE is higher, and the hourly throughput could be higher due to the lower rest that some workers can have. Furthermore, the maximum vibrations and noise exposure change according to Section 2.1. Then, for each case the following shifts and breaks time lengths have been considered:

Details of each scenario are reported in Table 6.

The rotation shifts and breaks time values defined above represent the nominal times; in fact, according to Equation (8) workers could require more rest according to their individual attributes (Table 4).

To obtain the set of optimal feasible solutions, we apply the ε -constraints algorithm by assuming the ergonomic risk score and boredom value as constraints, and maximizing throughput.

4.2. Results analysis

In this subsection, the main outcomes of our analysis are discussed. We provide an analysis of all scenarios for both cases (Case A and Case B). Then, we investigate how the ergonomic risk score and the similarity among tasks influence the Pareto front, thus the throughput. The CPLEX 22.1.0.0 version of the solver was used to obtain the set of optimal solutions.

Fig. 3 and Fig. 4 report the set of feasible solutions and the non-dominated points for each case and scenario. As demonstrated by Otto and Scholl (2013), job rotation is an NP-hard problem. Consequently, for the case study discussed here, the higher the number of rotation shifts, the higher the computational time required to get the whole optimal set of feasible results. In fact, in the case of two rotation shifts, the computational time was on average equal to 195 s for both Case A and Case B; while in the case of four rotation shifts, the computational time was on average equal to 12500 s.

By comparing Case A and Case B, the hourly productivity increases by 5% for S1, while it decreases by 5% for S2 and 3.5% for S3. The main cause is related to the different RA values required for older workers to cover the physical effort spent in performing the job. In S1 they can use the break, but an additional amount of time is needed to cover all physical fatigue. By increasing the number of rotation shifts, a double benefit is achieved: 1) ageing workers can rest more, but an additional period of recovery time is still necessary for some of them to fully recover from fatigue; 2) a high physical job can be executed also by ageing workers for a lower period of time. Finally, for the specific case study, ageing workers are also those possessing greater experience, and their experience can positively contribute to smoothing the extra recovery time assigned to them.

By focusing on the comparison between scenarios, the same considerations can be done for both Case A and Case B. The higher the number of rotations, the lower maximum values of both ergonomics

Table 5
Rest Allowance for a working day of 8 h (resp. Six hours).

	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
W1	0	0	0	0	0	0	0	0	0	0
W2	0	0	0	0	0	0	0	0	0	0
W3	0	0	0	0	0	0	0	0	0	0
W4	0.05 (0.04)	0	0	0	0	0	0	0	0	0
W5	0.26 (0.21)	0	0	0.06 (0.05)	0.21 (0.17)	0	0	0	0.16 (0.13)	0.06 (0.05)
W6	0.49 (0.40)	0.19 (0.16)	0.13 (0.11)	0.25 (0.20)	0.43 (0.35)	0	0	0.07 (0.06)	0.37 (0.30)	0.25 (0.20)

Table 6
Details of working and break shift durations for the three work-schedule scenarios.

Scenario	Case A (WD duration: 6 h)	Case B (WD duration: 8 h)
S1	RS: 172 min/rotation shift B: 15 min/break	RS: 232 min/rotation shift B: 15 min/break
S2	RS: 113 min/rotation shift B: 10 min/break	RS: 153 min/rotation shift B: 10 min/break
S3	RS: 86 min/rotation shift B: 5 min/break	RS: 116 min/rotation shift B: 5 min/break

risks and boredom. Going in-depth, by considering the non-dominated point, Case A (resp. Case B) presents an ergonomics risks range which is 4.75–5.90 (resp. 4.65–5.80) for S1, 4.20–5.30 (resp. 4.15–5.60) for S2, and 4.00–5.10 (resp. 4.00–5.40) for S3. For the specific case study, the range is always in the orange (medium-level) ergonomic risk area and is very close to the lower bound. Consequently, for this specific application case, the selection of one non-dominated point cannot be considered as influenced by the ergonomic score.

However, in case some jobs are classified as hazardous activity from an ergonomic point of view, the choice of the best non-dominated point could be that one presenting an ergonomic score in a medium risk area.

Moving to the boredom aspect, the higher the number of rotation shifts, the higher the chance to assign diversified jobs to the same workers and consequently the similarity level decreases since job variations increases. The boredom score range decreases by increasing the number of rotations shifts for both Case A and Case B. By focusing on non-dominated points, the boredom range varies for Case A (resp. Case B) as follows: 0.3–1.0 (resp. 0.3–0.85) for S1, 0.3–0.8 (resp. 0.3–0.75) for S2 and, finally, 0.3–0.65 (resp. 0.30–0.70) for S3. The choice of one

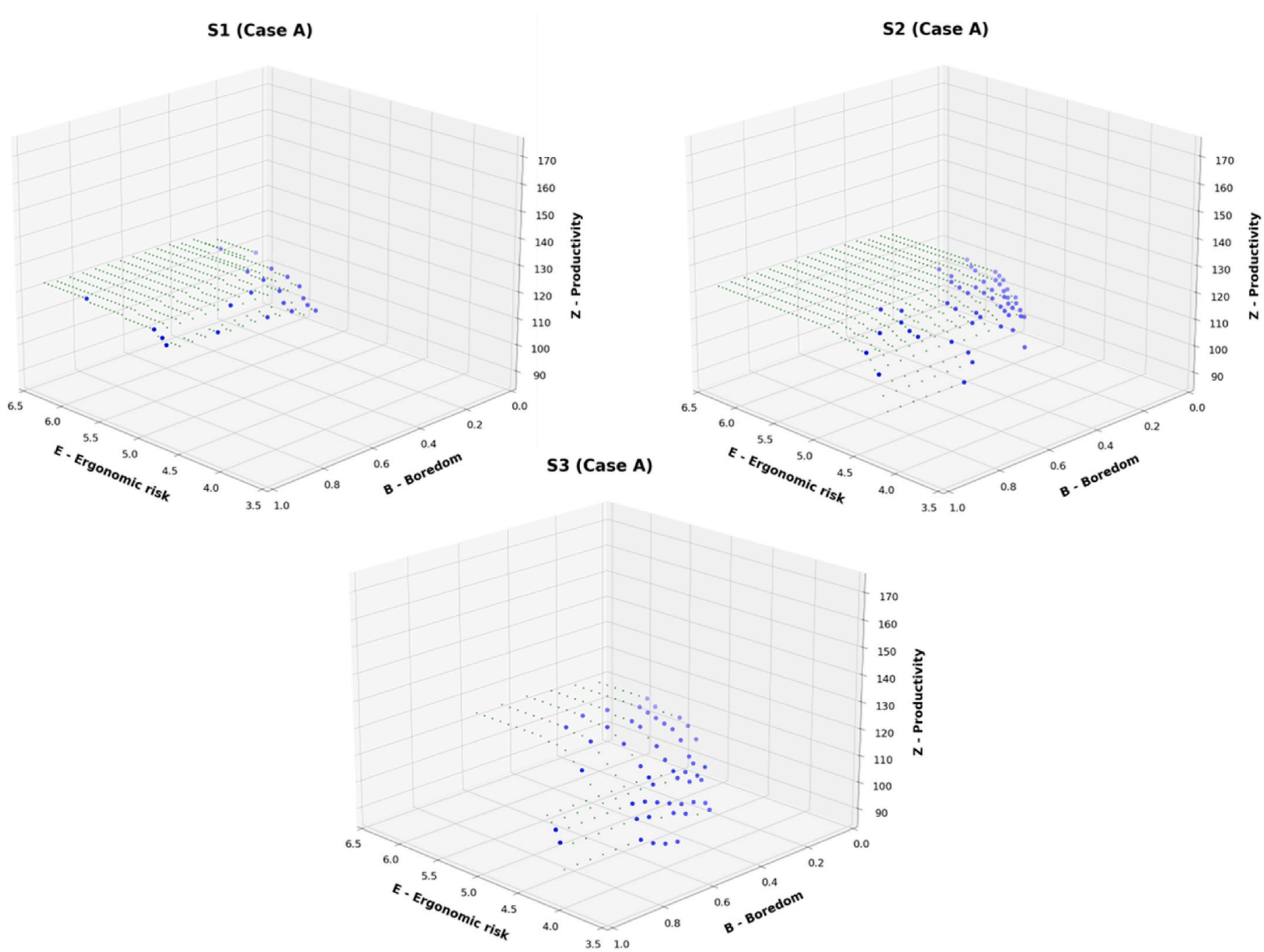

Fig. 3. Feasible set of solutions by varying the number of rotation shifts with 6 h/day (Case A).

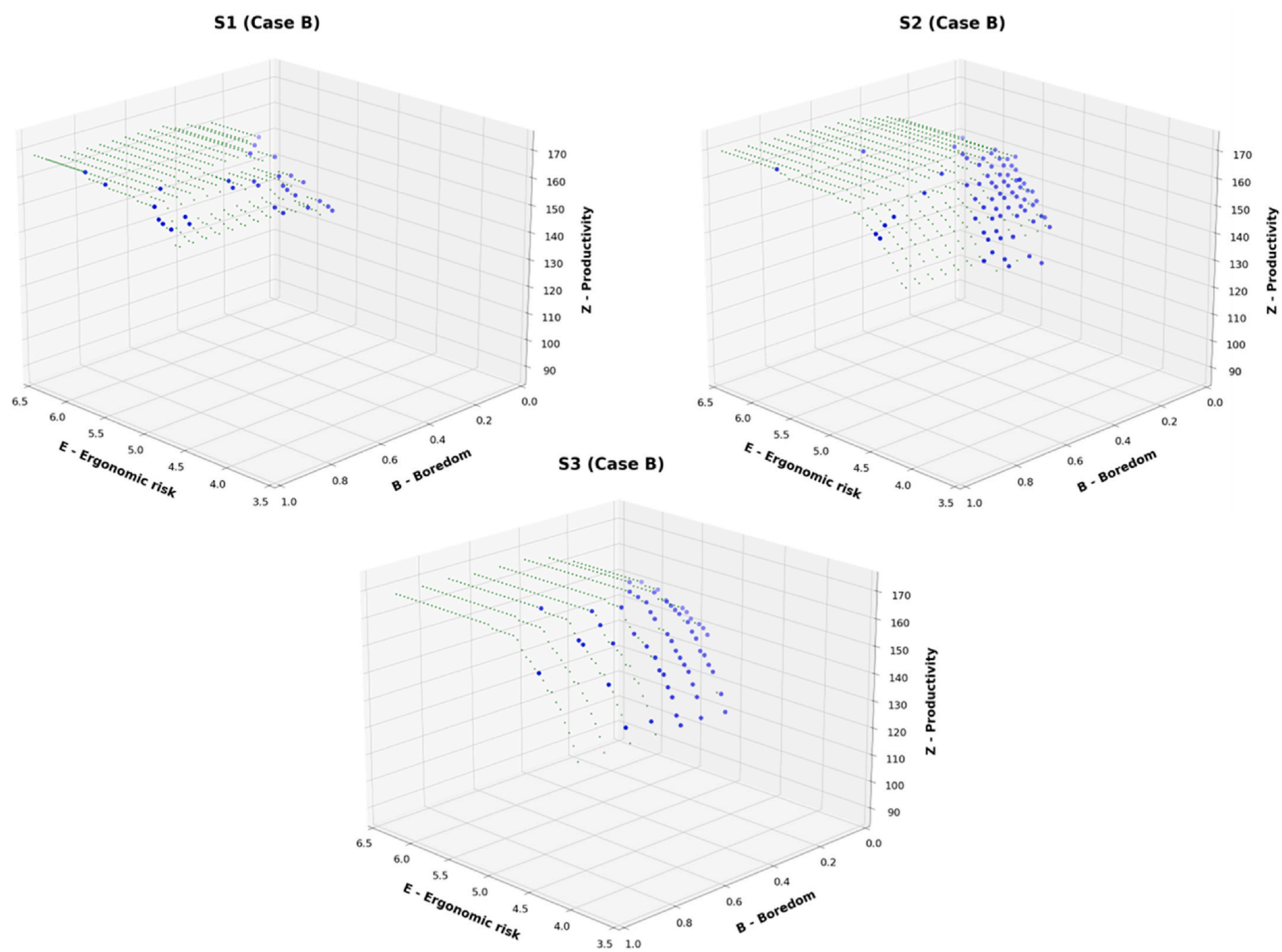

Fig. 4. Feasible set of solutions by varying the number of rotation shifts with 8 h/day (Case B).

non-dominated point by focusing on boredom aspects can be conducted by managers in collaboration with the workers involved in the production process. In fact, according to Jeon and Jeong (2016), some workers prefer to execute similar jobs during the work day, while others suggest that greater variability leads to higher motivation. However, for the case study here investigated, higher boredom also leads to a slightly higher value of productivity.

In the next subsections, we investigate how ergonomics risk scores, perceived boredom, and workforce attributes influence the decision process. The analysis is carried out only for Case A since similar considerations could be made for Case B.

4.3. Influence of jobs' ergonomics risk scores values

We randomly generate three sets of the ergonomic risk values E1, E2, E3, presenting a mean value and a standard deviation, respectively, equal to 4.5(±0.9), 5.9(±2.1), 6.2(±1.8); in the last case, some jobs are critical since they have an ergonomic score close to the critical threshold value (i.e., a score equals to 8 for REBA). Fig. 5 depicts the Pareto front by assuming a fixed boredom value equals to 0.5 and varying the ergonomic risk score value from E1 to E3. As shown in Fig. 5, S2 and S3 present a larger Pareto front for both E2 and E3, while they present a more closed Pareto front for E1. In the last case (E1), since the ergonomic score difference is very slight (e.g., minimum value 3.70 and maximum value 4.35) the choice of the best rotation strategy should be the one that guarantees the higher throughput. Moving to E2 and E3 cases, the ergonomic score gap increases as well as the throughput with a difference between the extremal points which is equal respectively to 25% for the ergonomics risk and the 16% for the throughput. However, in all cases, the ergonomic risk never assumes a critical value, and, consequently, the optimal point could be selected by considering the one that provides higher throughput. Focusing on S1, it has four non-dominated points and the maximum achievable production exceeds the minimum one by 4% while the ergonomics risk improves from 4% (S1) to 13.45% (S3). Finally, comparing E1, E2, and E3 in Fig. 5, we can see that the maximum throughput is always achievable when S3 is considered. Moreover, for E3 the same throughput is obtained for both S1, S2 and S3 however S3 provides a lower ergonomic risk with a slight difference of 2% compared to S2. Consequently, in this application case, a higher number of rotation shifts leads to lower daily ergonomics risk postural scores without influencing the throughput.

4.4. Influence of job's boredom values

In this section, we investigate the effects of the perceived boredom between workers. In the specific case, we generate the following scenarios: (1) perceived boredom by all the workers is closed to 0.6 (B1) that is around a medium level, (i.e., workers evaluated the similarity between different couples of jobs in the same way, by assigning scores closer to 0.6 on a scale 0–1), (2) perceived boredom is negligible (B2) (i.

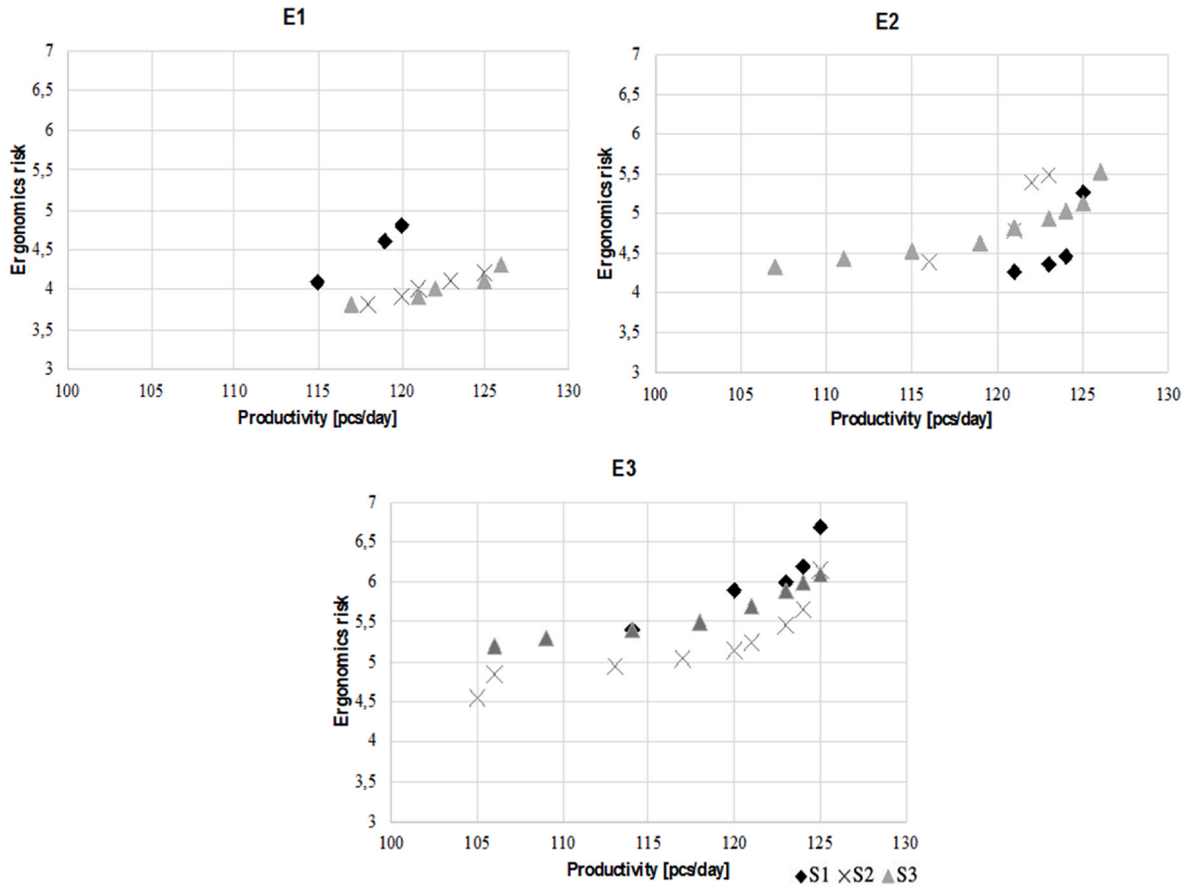

Fig. 5. Productivity and ergonomics risk values for three rotation period strategies (S1, S2, S3) by varying ergonomic scores of the postural job (E1, E2, E3).

e., workers consider jobs as totally different between them, hence, on average, the similarity scores assigned from each worker to the couples of jobs are close to zero), (3) perceived boredom is very high for all the workers (B3) (i.e., workers evaluated jobs as very similar, so the similarity scores for all the couples of jobs are close to 1). This analysis aims to investigate the values assumed by productivity and boredom scores for three cases (B1, B2, B3) differentiated for three job rotation strategies (i.e., scenario 1, scenario 2, scenario 3). For this purpose, we assume a hypothetical constant ergonomic score equals 5, and we determine in Fig. 6 the Pareto fronts for each scenario, by varying only boredom levels (B1, B2, B3).

The first results presented in Fig. 6 (B1) depict the case where all workers evaluated the couple of jobs with similar scores. In other words, all the workers involved in the job rotation strategy evaluated the degree of similarity between different couples of jobs by assigning similar scores (e.g., all workers agreed that the degree of similarity between the couple of jobs can be described with a score which is almost the same for all the workers). The results obtained for the highest level of productivity demonstrate that there are few differences amongst the optimal solutions for the three rotation strategies analyzed (S1, S2, S3). In particular, the solutions obtained with S3 dominate the solutions of S1 and S2 for the highest productivity value. Not surprisingly, the job rotation strategy with fewer rotation periods (S1) brought the highest level of boredom. However, due to the same job similarity scores, boredom value was barely reduced even with the other job rotation strategies (S2, S3). Considering the same level of job similarity for every operator does not allow to progress the job assignment trying to match workers' previous assignments and workers' individual perceived level of similarity. However, the general trend of all scenarios highlights that the productivity level increases, as well as the boredom score decreases, when job rotations are more frequent. We can highlight only one exception related to low boredom values. In this case, the solution provided by the second scenario (S2) dominates those obtained by S1 and S3, by providing greater productivity compared to S3 with a lower level of boredom than S1. In the second case presented in Fig. 6 (B2), the level of similarity between jobs was evaluated by the workers near zero (e.g., the degree of similarity between couple of jobs was evaluated as totally different). The results we obtained show that the scenario with three rotation shift (S3) leads to the highest productivity. Furthermore, one can notice that the results obtained with two and three rotation shifts tend to overlap for higher production values, while in the other cases the distinction between S2 and S3 is more prominent. Similarly, to the first case we presented, the scenario with two rotation shifts (S2) offers the highest productivity amongst the solutions with the lowest value of boredom. Finally, Fig. 6 (B3) proposes the case in which workers evaluate jobs as very similar. In this third case, the degree of similarity between couple of different jobs is close to the unit value, and boredom levels are the highest we have noticed so far in this analysis. Fewer rotation shifts lead to the highest boredom value (S1). This is the only case where three rotation shifts (S3) lead to the best results for both the lowest level of boredom and the highest productivity. In the last case, the scenario with three rotation shifts outperforms the others for almost every value of productivity and boredom.

4.5. Influence of workers' attributes

Finally, in this subsection, we investigate how performance can be influenced by the characteristics of workers. The age and level of experience are the two drivers that directly influence the execution time and thus the performance (see Equation (8)). Consequently, also in that

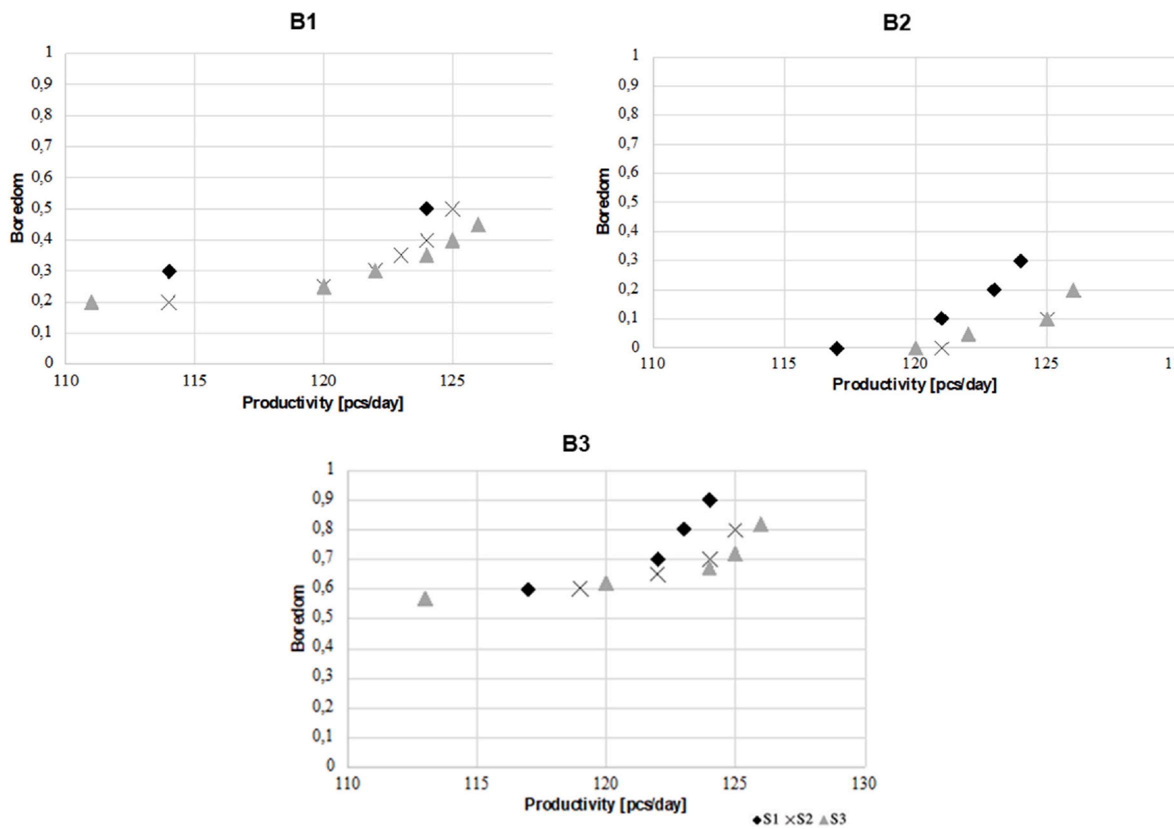

Fig. 6. Productivity and boredom values considering for the three rotation period strategies by varying the perceived boredom: medium level of boredom (B1), negligible boredom (B2) and high level of boredom (B3).

case, three new sets of RA and experience values have been randomly generated, and the following scenarios have been analyzed:

- Young working team with low experience levels (YWT): All workers are no more than 40 years old, so the contribution of recovery time determined by RA is negligible, since the maximum acceptable energy expenditure level of young workers is high and is rarely reached during job execution (Finco et al., 2019a). However, workers are not highly skilled and fully trained and an additional amount of time compared to the nominal job duration is required to obtain a final product.
- Aged Working Team with high experience levels: (AWT): all workers are older than 40 years. Consequently, RA can occur for some jobs according to the physical effort required (Finco et al., 2019b). In this case, the workers are highly skilled and, consequently, the higher RA needed can be smoothened by their greater experience thus achieving a lower execution time.
- Mixed working team with high experience level (MWT): young and ageing workers are jointly involved and the whole team is highly skilled.

Fig. 7 reports the set of feasible solutions and non-dominated points by considering three rotation shifts. As we can see, even if young people do not necessarily require rest time, their inexperience in executing jobs leads to lower productivity. The maximum value, which is equal to 112 pcs/day, is achieved for a lower level of boredom and the higher value of ergonomic risk (see Fig. 7 YWT). For the AWT scenario (see Fig. 7 AWT), the higher productivity is equal to 148 items/day, but in this case it is also obtained by considering the higher value of ergonomic score. However, the case which correspond to the lowest ergonomics score (an ergonomics score of 3.6) can be achieved with a higher boredom value and daily productivity equal to 110 pcs/day, which is close to the maximum daily throughput obtained for case YWT. In brief, we demonstrate that Thus, experienced worker productivity, which includes also rest breaks, exceeds that of inexperienced younger workers who can work longer hours without rest breaks.

Finally, the MWT scenario (see Fig. 7 MWT) presents a maximum daily productivity of 139 pcs/day. The maximum throughput value is achieved with a boredom score equals to 0.3 and an ergonomic risk value of 5.85. Consequently, MWT, which also represents a common scenario in several manufacturing companies, guarantees a proper balance among the three drivers we have included as objective functions and supports the idea that heterogeneous working teams can benefit system productivity.

To conclude this subsection, we raise some final considerations regarding one single solution belonging to the Pareto 3D front of Scenario AWT. The solution we analyzed maximizes throughput up to 141 pieces per day, while reaching a hazardous ergonomic risk of 5.35 and a boredom level of 0.3. Fig. 8 shows the flexible job rotation scheduling solution obtained with three rotation shifts (Scenario 2) and 8 h/day (Case B) as reported in Fig. 7. In the proposed charts, different colors are associated to different workers, fixed breaks between rotation periods are reported in blue, and the additional recovery time for each operator are reported in yellow. The portion of recovery time was calculated considering the value of the rest allowance of each individual operator as reported in Equation (8). Older workers are more likely to need a longer recovery time, often exceeding the duration of the break. The solution analyzed aims at the maximization of system throughput; however, safety/health risks may arise due to lack of adequate recovery time. Older workers may thus experience strenuous work periods that are not sustainable for a prolonged period of time.

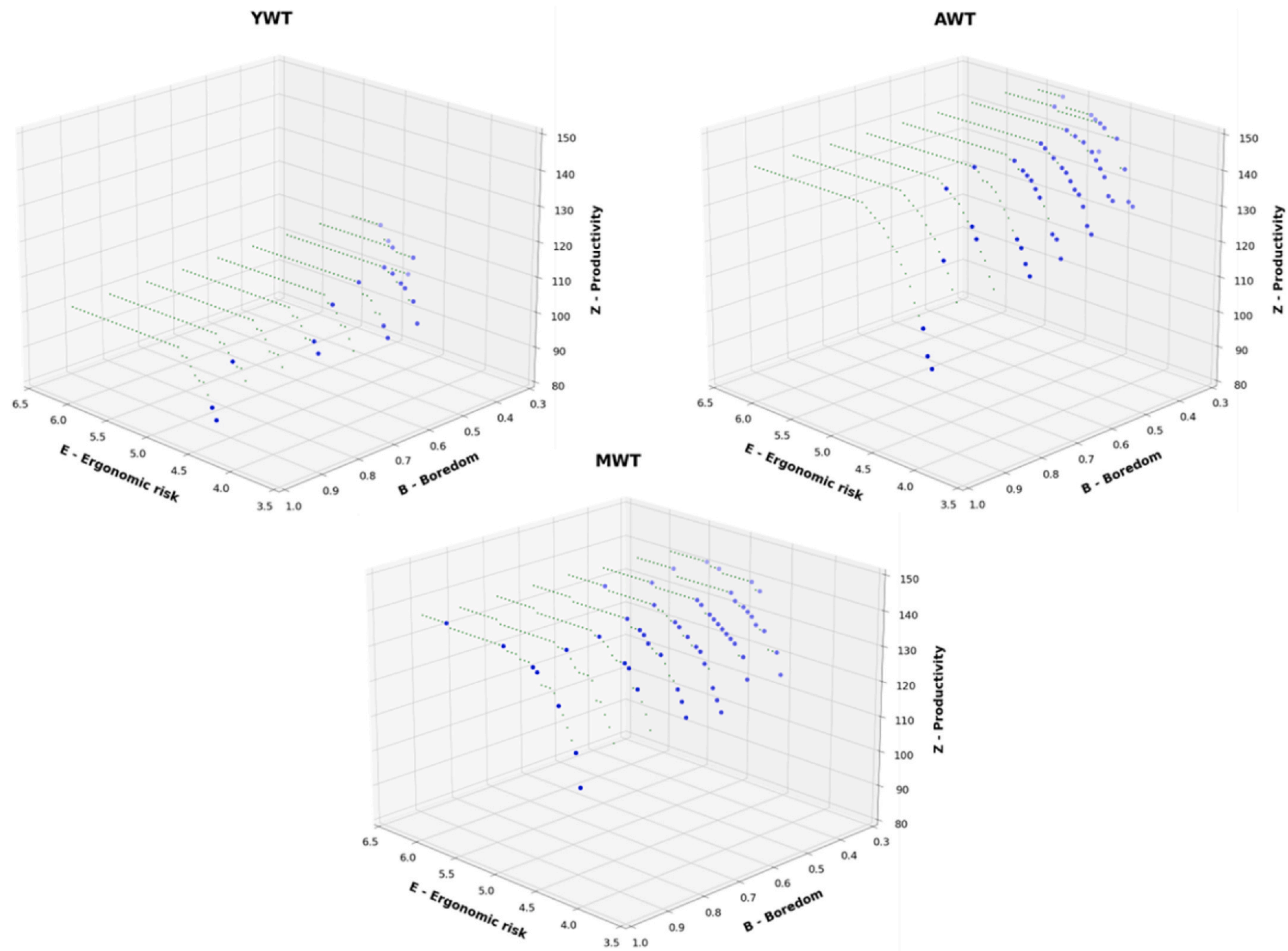

Fig. 7. Feasible set of solutions by varying workers' experience and age.

5. Conclusions and future research

Integration of human factors in operational decision processes has gained growing interest in the last decade (Sgarbossa et al., 2020). Relatedly, substantive research has been conducted in Job Rotation Scheduling approaches incorporating human factors (as reported in Table 1). However, joint effects are scarcely studied in this literature. Following emergent Industry 5.0 paradigms, we propose a new multi-objective job rotation scheduling model which explicitly incorporates multiple socio-technical factors and maximizes throughput, while minimizing boredom and ergonomics risks. Workers' characteristics such as age, gender, experience, individual physical limitations and perceived boredom are considered as important human elements in the design and scheduling of work. In addition, constraints are included to reflect the vibration and noise exposure of tools in the workplace according to ISO5349–1:2001 and the NIOSH method. The model is not linear, and, consequently, a linear formulation has been proposed. The results suggest that different job rotation schedules can affect system productivity, ergonomic risk level, and operator boredom, based on the rotation frequency and number and length of the rest times. Flexible job scheduling approaches that include such factors would foster workforce motivation and inclusiveness in moving towards the Industry 5.0 factory of the future. Flexibility in work arrangements has recently emerged as a top-rated job trait for manufacturing workers. A 2022 survey of over 19, 000 manufacturing and warehouse workers in the USA revealed that flexibility in work schedule figures as a key factor in job retention, especially when compensation and job security may already be competitive (Employbridge, 2022). Our numerical results show that flexible job rotation plans can provide workers with opportunities to enrich their capabilities by acquiring experience in a variety of tasks in short time, while reducing perceived boredom and raising motivation and satisfaction. These results are also supportive of, and align well with the recent and new ISO 25550–2022 for age-inclusive workforce. We note that the correct computation of rest times during the day can lead to different breaks for each worker (as shown in Fig. 8, the yellow bars are differentiated for each worker), considering individual worker attributes. As a consequence, our model directly moves Industry 5.0 concept into practice. We translate the Industry 5.0 principle of placing the well-being of the worker central to the production process into meaningful and practical task-concerned insights and recommendations. Our human-centric focus can help managerial decisions on improving inclusiveness and resilience in the workforce. We offer tangible ways to maximize productivity while attending to, and optimizing opportunities and constraints inherent in worker profiles and capabilities. We attend to concerns of workers with specific needs or physical limitations. The increased operational flexibility enabled by job re-assignment and re-planning can help management protect operations against unforeseen worker shortages or absenteeism. The model provided here can be easily adapted to different work contexts. It can develop sustainable and less hazardous job rotation plans by providing a set of optimal solutions

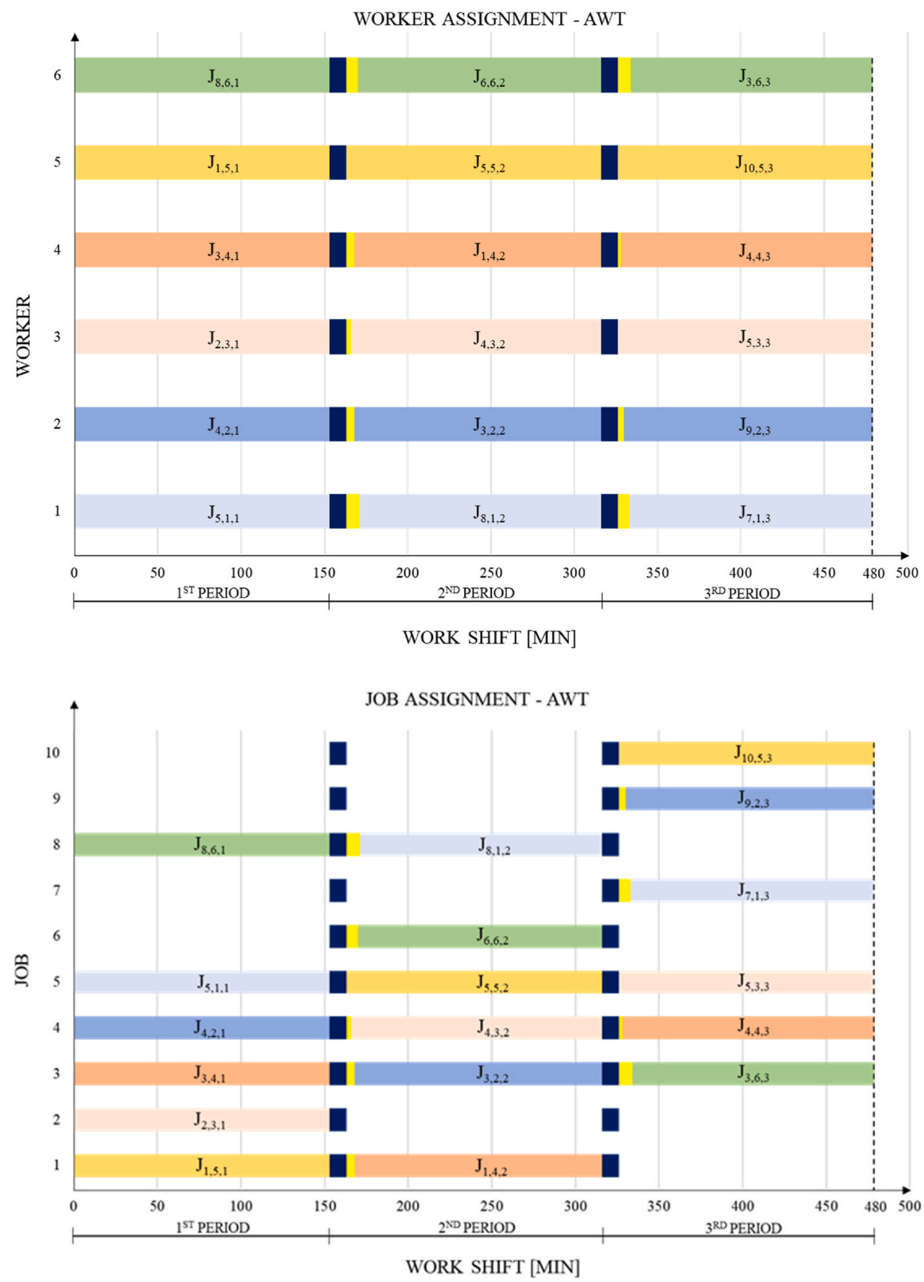

Fig. 8. Example of a flexible working schedule with 3 rotation shifts, 8 h/day (Case B) and an aged work team (AWT).

based on the predominance of particular, possibly differently weighted human-oriented factors.

The future perspectives of this work involve the development of alternative solutions for the proposed model. As we have already mentioned in the literature review, job rotation scheduling is an NP-hard problem and as jobs and operators increase in number, the linear programming model decreases in its capability to provide optimal solutions in reasonable time. For this reason, we intend to develop a metaheuristic approach to reduce computational time for large instances and test the method in other industrial sectors. Furthermore, the pursuit of increased worker involvement and improved work schedule flexibility could involve performing different rotation frequencies and different working days length for different workers, based on workers' individual experience, age and physical limitations. Future investigations will finally take in consideration the effect of different learning curve shapes and the training costs to accelerate the learning process in different jobs.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix

Table 1.A
Level of experience for each worker and job.

	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
W1	1.25	1.25	1.25	1.25	1.25	1.25	1.25	1.25	1.25	1.25
W2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2
W3	-	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
W4	1.2	-	1.2	1.2	1.2	1.2	-	1.2	1.2	1.2
W5	0.9	-	0.9	0.9	0.9	-	-	0.9	0.9	0.9
W6	0.9	-	0.9	0.9	-	0.9	0.9	0.9	-	0.9

W1 similarity scores

	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
J1	1	0	0.5	1	0.5	0.3	0.2	0.4	0.3	1
J2	0	1	0.3	0.7	0.5	0.8	0.2	0.3	0.5	0.5
J3	0.5	0.3	1	0.2	0.3	0.5	0.6	0.7	0.8	0.2
J4	1	0.7	0.2	1	0.4	0.5	0.8	0.9	0.1	0.4
J5	0.5	0.5	0.3	0.4	1	0.2	0.4	0.5	0.8	0.9
J6	0.3	0.8	0.5	0.5	0.2	1	1	0.5	0.6	0.8
J7	0.2	0.2	0.6	0.8	0.4	1	1	1	0.5	0.5
J8	0.4	0.3	0.7	0.9	0.5	0.5	1	1	0.5	1
J9	0.3	0.5	0.8	0.1	0.8	0.6	0.5	0.5	1	1
J10	1	0.5	0.2	0.4	0.9	0.8	0.5	1	1	1

W4 similarity scores

	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
J1	1	0.4	0.5	1	0.5	0.3	0.2	0.4	0.3	1
J2	0.4	1	0.3	0.7	0.5	0.8	0.2	0.3	0.5	0.5
J3	0.5	0.3	1	0.2	0.3	0.5	0.6	0.7	0.8	0.2
J4	1	0.7	0.2	1	0.4	0.5	0.8	0.9	0.1	0.4
J5	0.5	0.5	0.3	0.4	1	0.2	0.4	0.5	0.8	0.9
J6	0.3	0.8	0.5	0.5	0.2	1	1	0.5	0.6	0.8
J7	0.2	0.2	0.6	0.8	0.4	1	1	1	0.5	0.5
J8	0.4	0.3	0.7	0.9	0.5	0.5	1	1	0.5	1
J9	0.3	0.5	0.8	0.1	0.8	0.6	0.5	0.5	1	0.8
J10	1	0.5	0.2	0.4	0.9	0.8	0.5	1	0.8	1

W2 similarity scores

	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
J1	1	0.4	0.5	1	0.5	0.3	0.2	0.4	0.3	1
J2	0.4	1	0.3	0.7	0.5	0.8	0.2	0.3	0.5	0.5
J3	0.5	0.3	1	0.2	0.3	0.5	0.6	0.7	0.8	0.2
J4	1	0.7	0.2	1	0.4	0.5	0.8	0.9	0.1	0.4
J5	0.5	0.5	0.3	0.4	1	0.2	0.4	0.5	0.8	0.9
J6	0.3	0.8	0.5	0.5	0.2	1	1	0.5	0.6	0.8
J7	0.2	0.2	0.6	0.8	0.4	1	1	1	0.5	0.5
J8	0.4	0.3	0.7	0.9	0.5	0.5	1	1	0.5	1
J9	0.3	0.5	0.8	0.1	0.8	0.6	0.5	0.5	1	1
J10	1	0.5	0.2	0.4	0.9	0.8	0.5	1	1	1

W5 similarity scores

	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
J1	1	0.1	0.6	1	0.4	0.4	0.4	0.3	0.1	0.9
J2	0.1	1	0.2	0.8	0.6	0.7	0.3	0.4	0.6	0.6
J3	0.6	0.2	1	0.3	0.4	0.6	0.5	0.6	0.9	0.3
J4	1	0.8	0.3	1	0.5	0.5	0.8	1	0.2	0.5
J5	0.4	0.6	0.4	0.5	1	0.3	0.5	0.4	0.9	0.7
J6	0.4	0.7	0.6	0.5	0.3	1	0.9	0.6	0.7	0.9
J7	0.4	0.3	0.5	0.8	0.5	0.9	1	1	0.6	0.4
J8	0.3	0.4	0.6	1	0.4	0.6	1	1	0.5	0.8
J9	0.1	0.6	0.9	0.2	0.9	0.7	0.6	0.5	1	1
J10	0.9	0.6	0.3	0.5	0.7	0.9	0.4	0.8	1	1

W3 similarity scores

	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
J1	1	0.3	0.5	1	0.5	0.5	0.2	0.4	0.2	1
J2	0.3	1	0.3	0.7	0.5	0.8	0.2	0.3	0.5	0.5
J3	0.5	0.3	1	0.2	0.3	0.5	0.7	0.7	0.8	0.2
J4	1	0.7	0.2	1	0.6	0.5	0.8	0.9	0.1	0.4
J5	0.5	0.5	0.3	0.6	1	0.2	0.4	0.5	0.8	0.7
J6	0.5	0.8	0.5	0.5	0.2	1	1	0.5	0.6	0.8
J7	0.2	0.2	0.7	0.8	0.4	1	1	1	0.5	0.4
J8	0.4	0.3	0.7	0.9	0.5	0.5	1	1	0.6	1
J9	0.2	0.5	0.8	0.1	0.8	0.6	0.5	0.6	1	1
J10	1	0.5	0.2	0.4	0.7	0.8	0.4	1	1	1

W6 similarity scores

	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
J1	1	0.1	0.6	0.9	0.4	0.4	0.4	0.3	0.2	0.8
J2	0.1	1	0.2	0.8	0.6	0.7	0.3	0.4	0.6	0.6
J3	0.6	0.2	1	0.3	0.4	0.6	0.5	0.6	0.9	0.3
J4	0.9	0.8	0.3	1	0.5	0.4	0.9	1	0.2	0.5
J5	0.4	0.6	0.4	0.5	1	0.3	0.5	0.4	0.9	0.8
J6	0.4	0.7	0.6	0.4	0.3	1	0.9	0.6	0.7	0.9
J7	0.4	0.3	0.5	0.9	0.5	0.9	1	1	0.6	0.4
J8	0.3	0.4	0.6	1	0.4	0.6	1	1	0.5	0.9
J9	0.2	0.6	0.9	0.2	0.9	0.7	0.6	0.5	1	1
J10	0.8	0.6	0.3	0.5	0.8	0.9	0.4	0.9	1	1

Fig. 1.A. Values of similarity scores used for the case study.

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Daria Battini holds a Ph.D. in Industrial Engineering and she graduated cum laude at the University of Modena and Reggio Emilia. She teaches and conducts research in the field of industrial system design and management, supply network mapping, modelling and optimization, inventory management and product/process traceability. She published more than 110 scientific papers, published in International ISI journals or in proceeding of International conferences Peer Reviewed. She is an Editorial Board Member of the International Journal of Production Economics and she is a member of the IFAC Technical Committee 5.2. (Manufacturing Modelling for Management and Control).

Nicola Berti graduated at the University of Padova in Management Engineering. Currently, he is enrolled at the third year of Ph.D. Course in Mechatronics and Product Innovation Engineering (Industrial plants and Logistics Curricula) at the Department of Management and Engineering in Vicenza. The topic of his research concerns the development of new human-centered design solutions and methods for ergonomic working environments considering workforce's diversity, in terms of anthropometric characteristics, workforce's ageing-related risks and individual physical limitations.

Finco Serena is Assistant Professor at the University of Padova. She holds a joint PhD in Industrial Engineering and she graduated at the University of Padova in Innovation Product Engineering. Her researches are mainly related to industrial and logistic system

design and modelling with a particular focus on the integration of ergonomics principles in assembly systems design and balancing techniques. She is also involved in European and Italian projects.

Ilenia Zennaro is an Assistant Professor and researcher in the Department of Management and Engineering at the University of Padua. Her research interest includes industrial and logistics systems design, management and modelling, and sustainability of industrial plants. In particular, on the design and on the improvement of warehousing and assembly systems and on maintenance management and on transportation, considering sustainability aspects.

Ajay Das is a Professor in the Operations Management group at Baruch College, NYC, NY. His research currently engages innovation, technology, risk, and quality in operations and supply chains. Ajay has published extensively in journals such as the Journal of Operations Management, Decision Sciences Journal, IJPR, IJOPM, IJPE, and other scholarly research outlets. He is the current Editor-in-Chief of IJISM, a niche journal for supply chain integration research.