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

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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

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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,

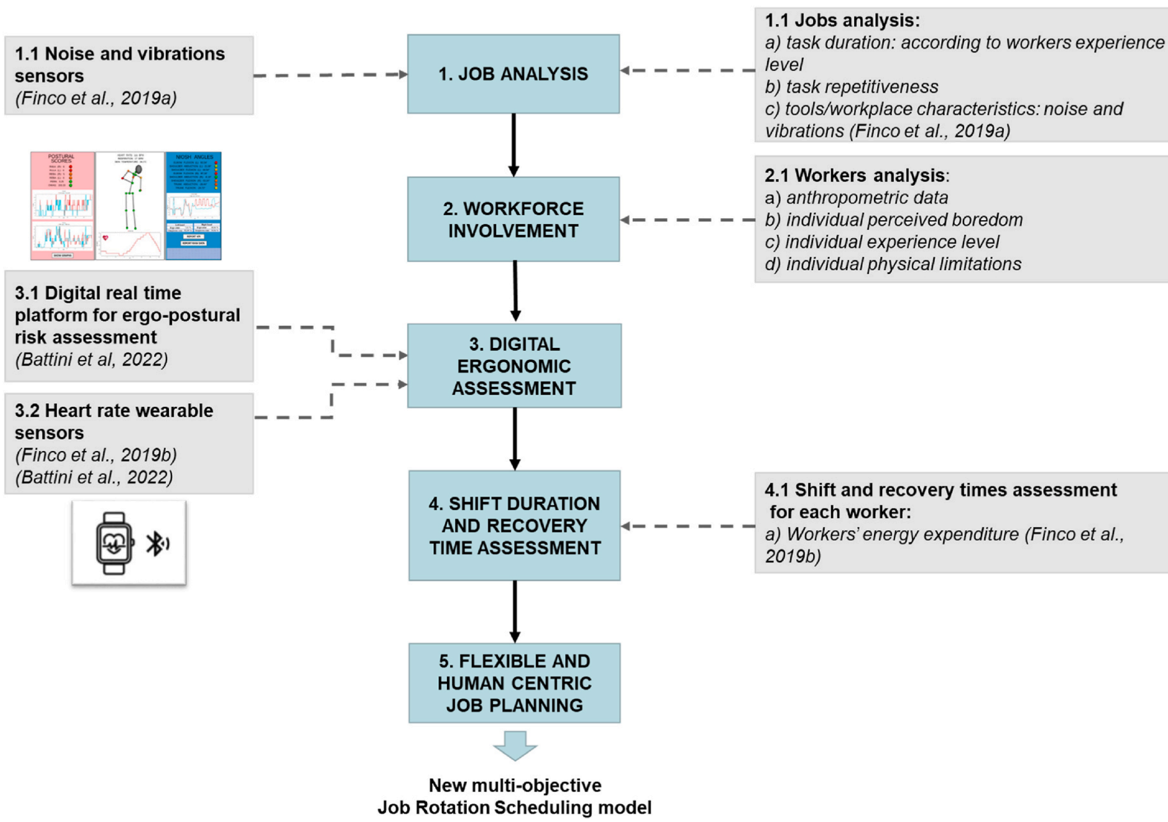

Fig. 1. Theory-based methodological framework supporting the implementation of new JRS model (derived from Berti et al., 2021b).

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:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

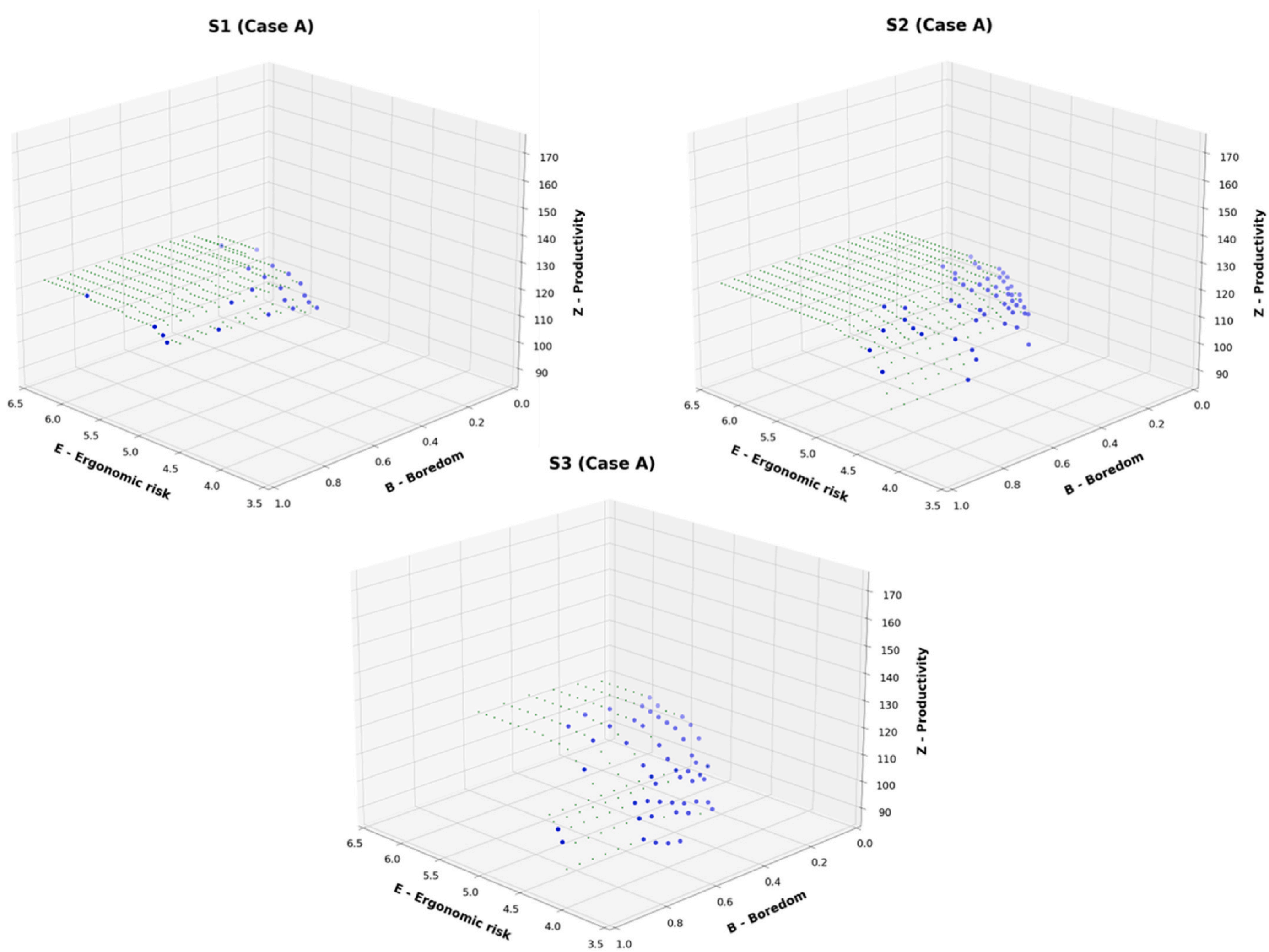

Fig. 3. Feasible set of solutions by varying the number of rotation shifts with 6 h/day (Case A).

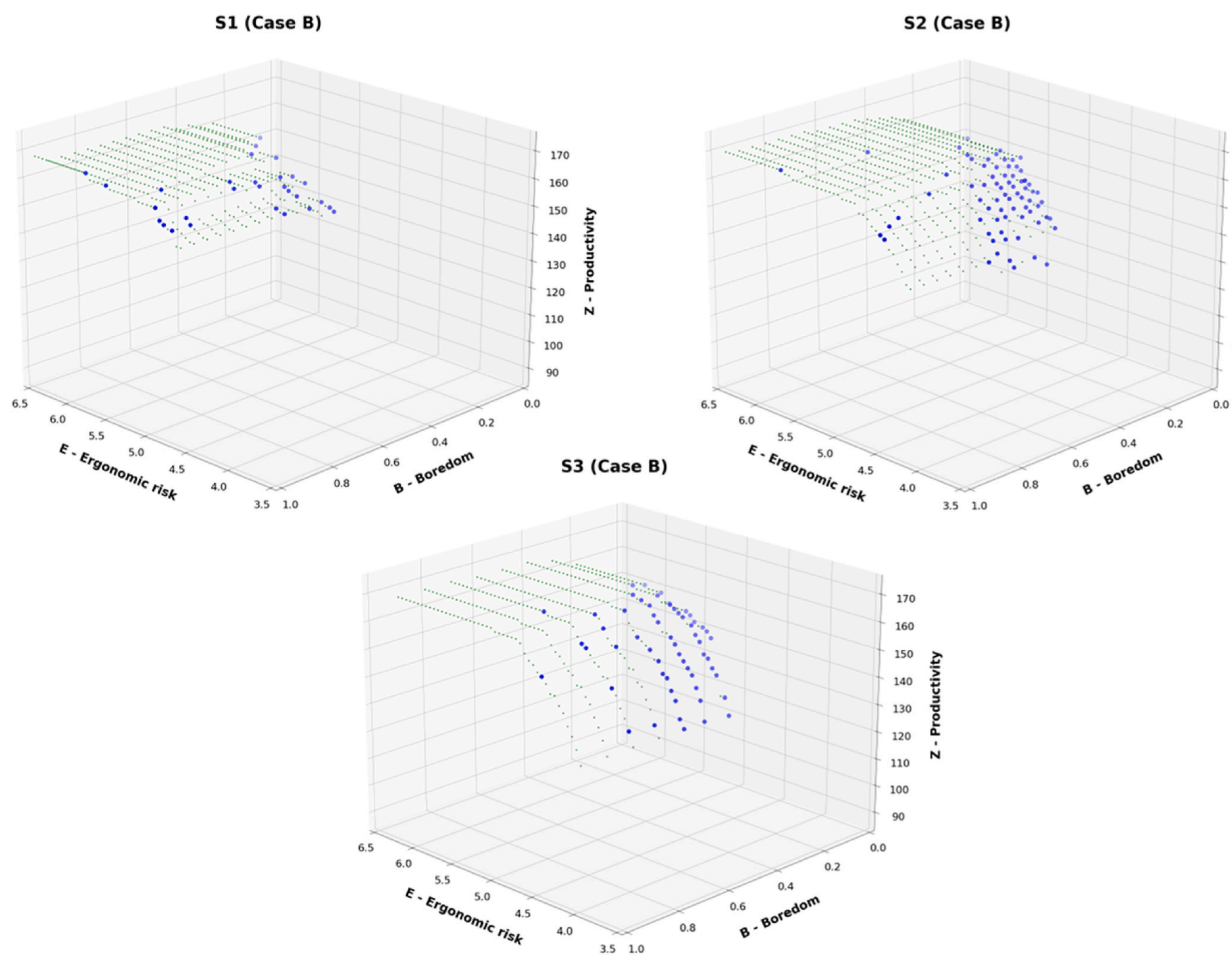

Fig. 4. Feasible set of solutions by varying the number of rotation shifts with 8 h/day (Case B).

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($\pm$0.9), 5.9($\pm$2.1), 6.2($\pm$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.

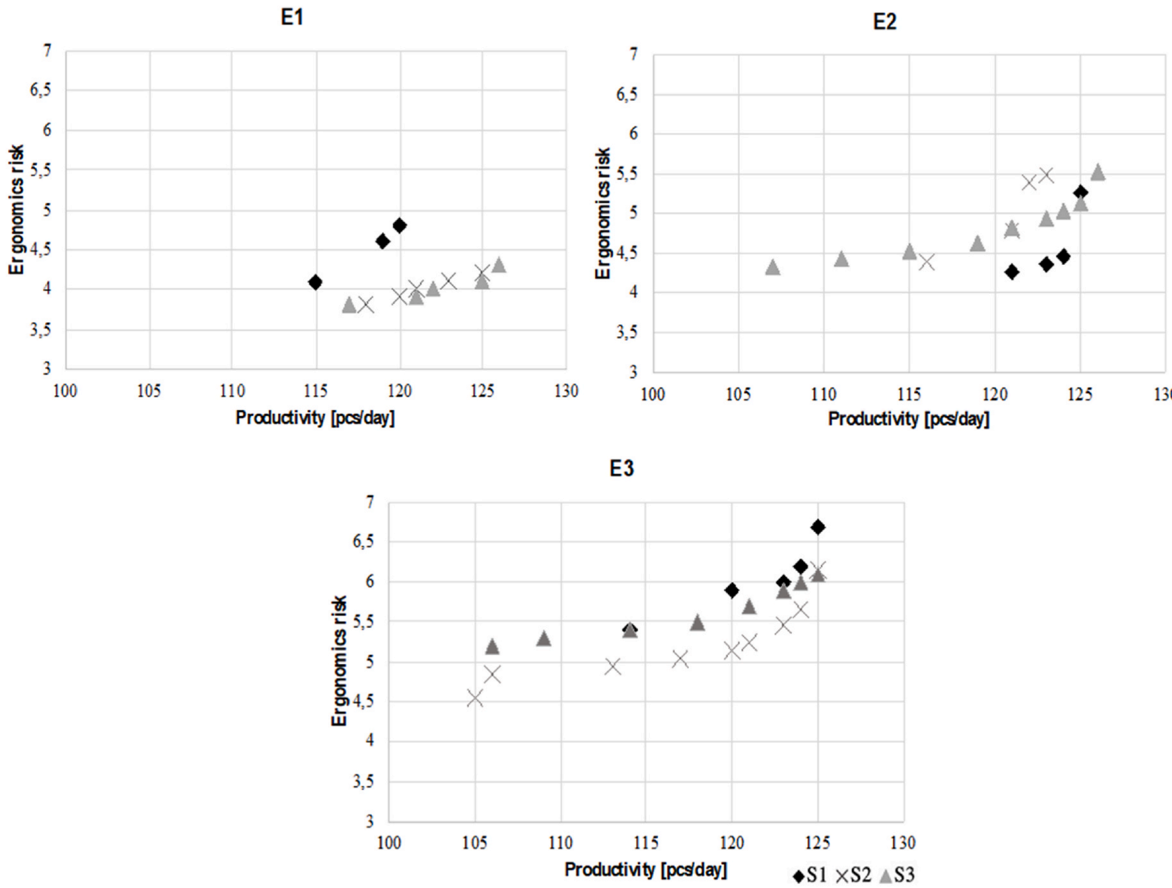

Fig. 5. Productivity and ergonomics risk values for three rotation period strategies (S1, S2, S3) by varying ergonomic scores of the postural job (E1, E2, E3).

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

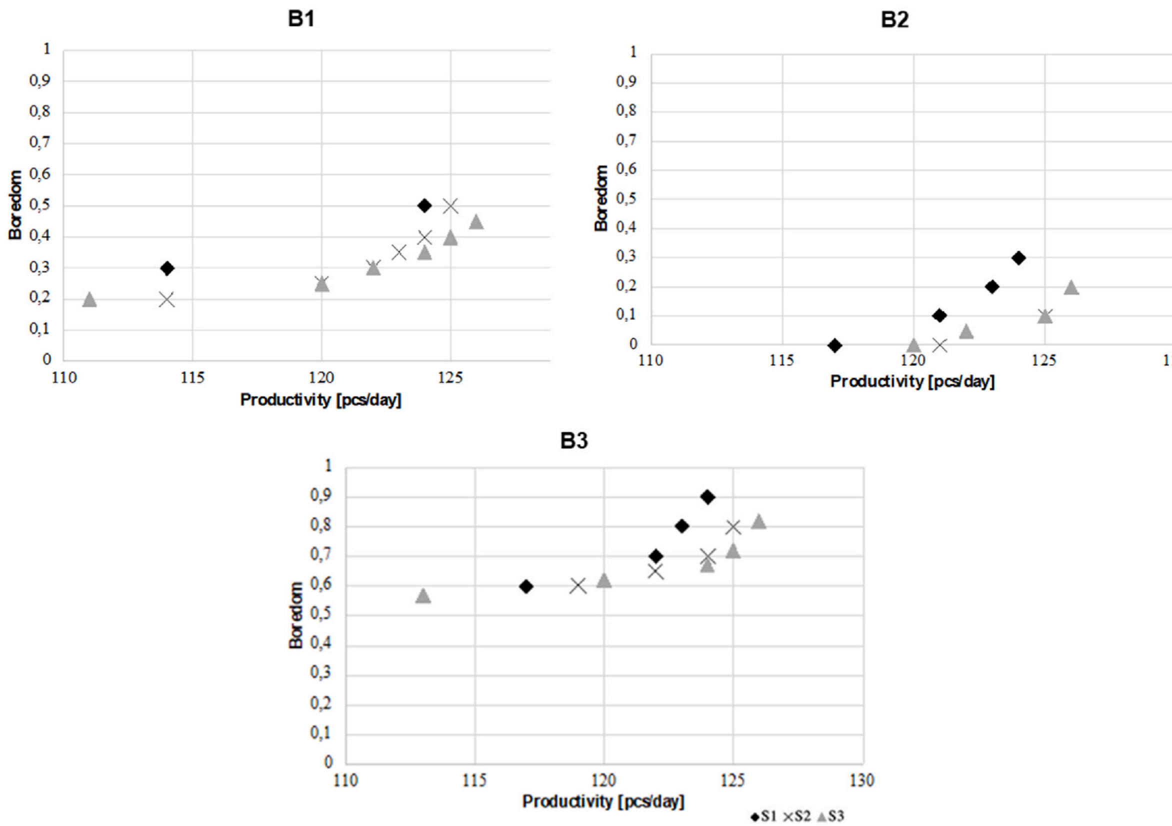

Fig. 6. Productivity and boredom values considering for the three rotation period strategies by varying the perceived boredom: medium level of boredom (B1), negligible boredom (B2) and high level of boredom (B3).

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.

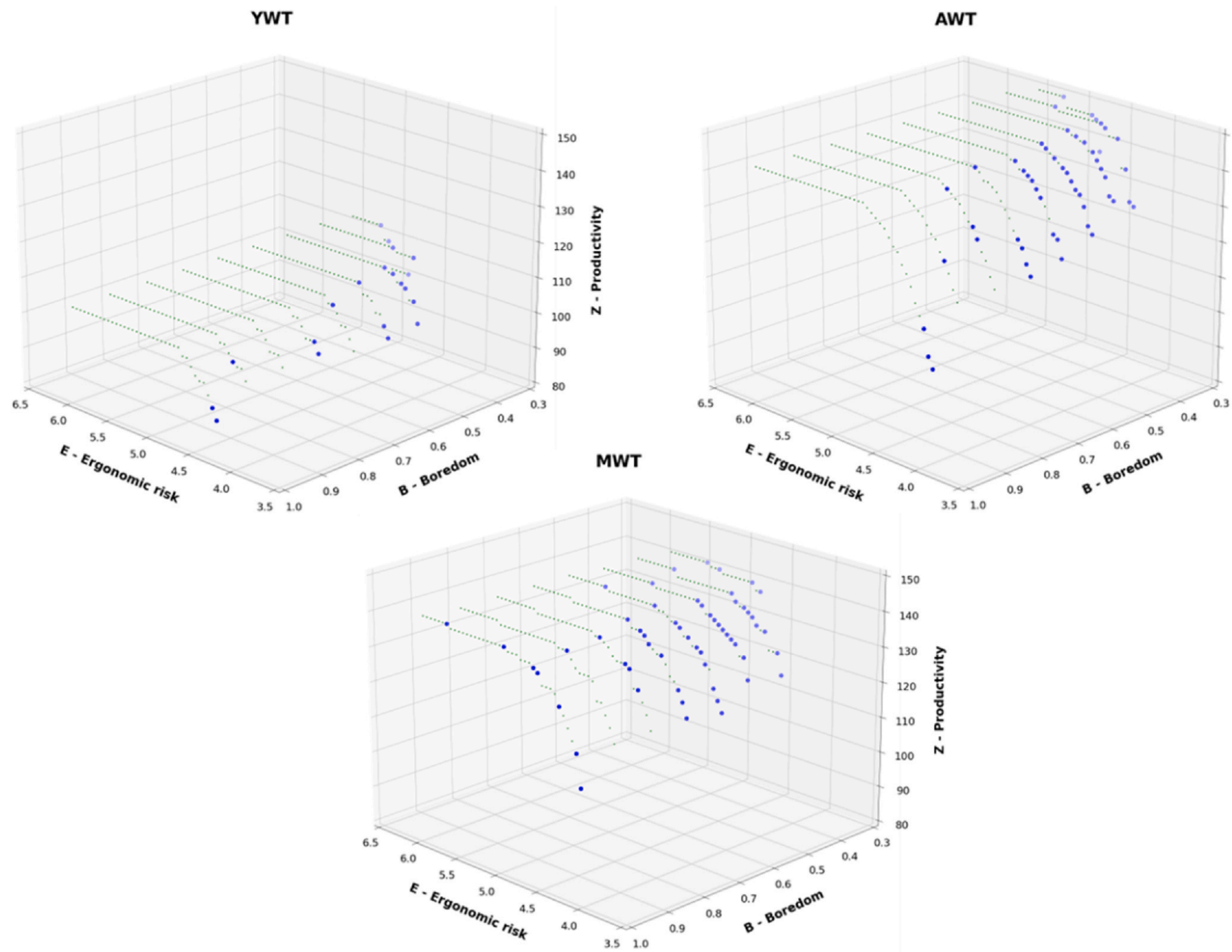

Fig. 7. Feasible set of solutions by varying workers' experience and age.

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

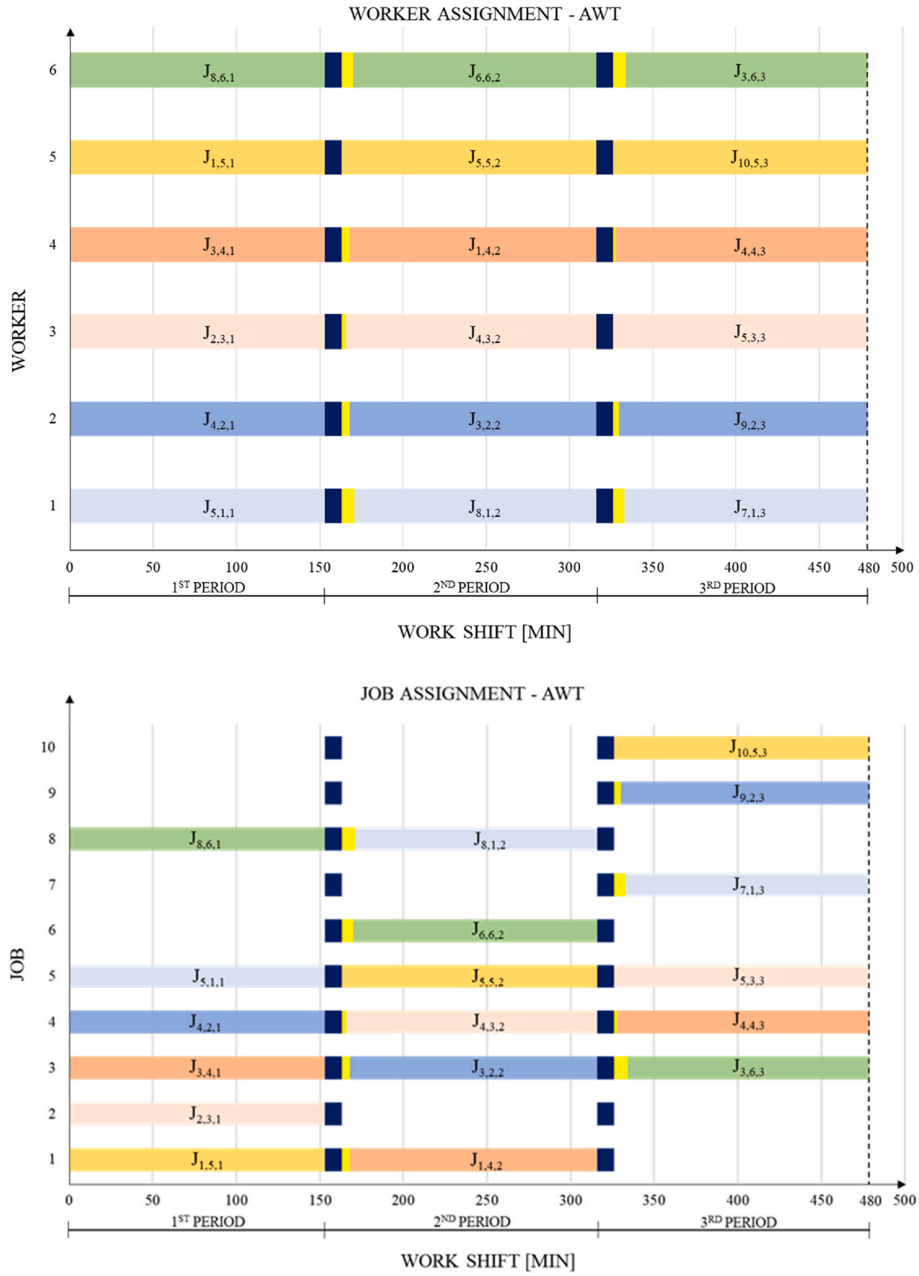

Fig. 8. Example of a flexible working schedule with 3 rotation shifts, 8 h/day (Case B) and an aged work team (AWT).

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.

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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

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

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

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

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

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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