



Optimization of human-aware logistics and manufacturing systems: A survey on the Human-Aware Models

Thibault Prunet^{a,b,*}, Nabil Absi^a, Valeria Borodin^{a,c}, Diego Cattaruzza^d

^a Mines Saint-Etienne, Univ. Clermont Auvergne, CNRS, UMR 6158 LIMOS, Center CMP, Departement SFL, F-13541 Gardanne, France

^b CERMICS, Ecole des Ponts, Marne-la-Vallée, France

^c IMT Atlantique, LS2N-CNRS, La Chantrerie, 4, rue Alfred Kastler, F-44307 Nantes cedex 3, France

^d Univ. Lille, CNRS, Centrale Lille, Inria, UMR 9189 - CRISTAL - Centre de Recherche en Informatique Signal et Automatique de Lille, F-59000 Lille, France

ARTICLE INFO

Keywords:

Optimization
Human factors
Ergonomics
Manufacturing
Logistics

ABSTRACT

Historically, Operations Research (OR) discipline has mainly been focusing on economic concerns. Since the early 2000s, human considerations are gaining increasing attention, pushed by the growing societal concerns of sustainable development on the same terms as the economic and ecological ones. This paper is the second part of a work that aims at reviewing the efforts dedicated by the OR community to the integration of human aspects into logistics and manufacturing systems. A focus is put on the models proposed to represent and quantify human characteristics, their practical relevance, and the complexity induced by their integration with mathematical optimization models. In this paper, the techniques used in the OR literature to represent the human considerations encountered in logistics and manufacturing systems are surveyed. The existing Human-Aware Models (HAM) are classified and reviewed by domain. Particular attention is paid to the field validity of each method, its relevance to specific use cases, the required data collection, and its usability within mathematical optimization models. Since the surveyed HAMs rely on concepts originating from different related scientific disciplines (e.g., ergonomics, occupational medicine), a brief introduction of these fields of study is proposed together with a work of contextualization that is carried out during the analysis.

Contents

1.	Introduction	2
2.	Definition of key concepts and related background	3
2.1.	Human-related concepts	3
2.2.	Related background	3
3.	Skills and learning	4
3.1.	Skills	4
3.1.1.	Qualifications	4
3.1.2.	Skill levels	5
3.1.3.	Skill improvement via training	5
3.2.	Learning	6
3.2.1.	Organizational learning	6
3.2.2.	Individual learning	6
3.2.3.	Forgetting	7
4.	Fatigue and breaks	7
4.1.	Energy expenditure	7
4.2.	Rest allowance	8
4.3.	Fatigue effect and rate modifying activities	8
4.4.	Learning forgetting fatigue recovery model	9
4.5.	Meal breaks	9
4.6.	Hours of service regulations	9

* Corresponding author.

E-mail address: thibault.prunet@enpc.fr (T. Prunet).

4.7.	Work-stretch duration.....	10
5.	Work-related musculo-skeletal disorders: Risk assessment methods.....	10
5.1.	Whole body.....	10
5.2.	Manual handling.....	11
5.3.	Working posture.....	12
5.4.	Repetitive movements.....	12
6.	Cognitive and psychosocial human factors.....	13
6.1.	Motivation and boredom.....	13
6.2.	Satisfaction and work preferences.....	13
6.3.	Psychosocial and organizational factors.....	13
6.4.	Cognitive risk factors.....	14
7.	Perceptual and environmental factors.....	14
7.1.	Noise exposure.....	14
7.2.	Visual considerations.....	14
7.3.	Heat exposure.....	15
7.4.	Vibration exposure.....	15
8.	Additional considerations.....	15
8.1.	Anthropometric considerations.....	15
8.2.	Biomechanical considerations.....	15
8.3.	Heterogeneity of the workforce.....	16
8.4.	Health states.....	16
8.5.	Human errors.....	16
8.6.	Hazard exposure.....	17
8.7.	Equity.....	17
8.8.	Total cost function.....	17
8.9.	Expert opinions/collaborations.....	17
9.	Future research directions.....	18
9.1.	Under-represented areas of study.....	18
9.2.	Development of new HAMs.....	18
10.	Conclusions.....	18
	Declaration of competing interest.....	19
	Acknowledgments.....	19
	References.....	19

Preamble

Given the large volume of material reviewed, which does not enable the authors to present a substantive analysis in a single paper, the current literature review has been split into two separate papers (parts), that are highly connected. We refer to the present paper as the *second part*, and to its twin paper (Prunet et al., 2024) as the *first part*. Although an introduction is present in both parts, the scope definition, the positioning within the landscape of the related literature, and the methodology applied to collect the relevant material are only discussed in detail in the first part. Then, the retrieved corpus is studied and discussed by adopting three different points of view:

- *Application area*, where we discuss how human factors are treated in each class of problem within the logistics and manufacturing communities. This work is presented in the first part, Sections 4–6. The results of the material collection are provided with tables in these sections.
- *Human factors*, where we discuss which human factors are investigated. For each factor, we study the *Human-Aware Models* used to model and quantify it, and the advantages and limitations of such models. This is done in the second part, Sections 3–8.
- *Mathematical optimization*, where we discuss the integration of human-aware considerations within optimization models. The study focuses on the impact on the models, in terms of objective function, constraints, parameters, and the associated complexity burden. This is done in the first part, Section 7.

As an illustration, let us consider a paper addressing an assembly line balancing problem that account for the ergonomic risk related to awkward posture by enforcing a maximal exposure limit for each workstation. The paper would be discussed with respect to its *application* as an assembly line in Prunet et al. (2024) Section 5.2, in terms of

human factor as studying awkward postures in Section 5.3, and in terms of *mathematical optimization* for implementing threshold constraints in Prunet et al. (2024) Section 7.2. Then, future research directions are discussed in both parts of the work. Note that, in the current paper (the second part), we often refer to the areas of application within logistics and manufacturing, without explicit definitions of the mentioned concepts. The reader is referred to the first part (Prunet et al., 2024) for this information.

1. Introduction

This article is part of a review work that studies the integration of human-aware considerations in optimization models that address applications in logistics and manufacturing. In this paper, we present the models and methods found in the collected material that integrate a *Human Factor (HF)* (i.e., a characteristic or behavior that is typically human) into a decision-support model. A model that expresses and quantifies a HF is called a *Human-Aware Model (HAM)*. The present paper aims at providing an overview of available methods to integrate a HF in an OR work. In the first part of this work (Prunet et al., 2024), we already introduced the scope of the review, and the main motivations of this work, as such we are only proposing a brief introduction in this section. An interested reader is referred to Prunet et al. (2024) for a more substantial contextualization of the work.

Motivation. Historically, the main factor that has driven the development of OR is related to the optimization of the performance criteria of a production or service system, and especially the maximization of profit. Human considerations have often been overly simplified by strong assumptions, for instance, by considering a homogeneous workforce, or a constant productivity rate for the human labor. However, recent advances in computing power and the academic development of OR, allow the OR community to address more challenging problems, with a more accurate representation and modeling of constituent parts

that impact the key performance indicators. Furthermore, the growing global concern of the different stakeholders for the *sustainability* of production and service systems, leads to an increased pressure on the decision-makers to account for the ecological and social implications of their decisions. Regarding the social aspects of sustainability, these concerns have led to the development of various legislative regulations and guidelines on working conditions, especially applied to industrial systems that still rely heavily on manual labor, in an environment prone to occupational diseases and injuries. As a consequence, more and more OR research works integrate HFs with their models. The present work gives an overview of the literature on the integration of HFs into decision models and provides a holistic study of this topic.

Structure of the paper. In the current paper, we focus on the quantitative models found in the literature to represent HFs in decision problems. We present the main HAMs found in the literature, and derive some insights on their respective industrial and ergonomic relevance, the ease of use, and the related difficulties. First, Section 2 introduces some key concepts related to human-aware modeling, and introduces the background related to *Human Factors and Ergonomics (HF/E)*. Sections 3 to 8 review the different HAMs found in the collected material. In Section 3, we study the topics of employee *skills* and *learning*, both individual and collective. Section 4 studies the modeling of human fatigue, and the mechanisms to recover from this fatigue with rest breaks. In Section 5, we review the Work-related Musculoskeletal Disorder (WMSD) risk assessment methods, mainly coming from works on HF/E. In Section 6, we introduce the cognitive and psychosocial HFs that are studied in the OR literature, and Section 7 focuses on perceptual and environmental factors. Section 8 presents more transverse considerations, that do not focus on a single HF. Finally, we discuss future research directions in Section 9 and conclude this paper in Section 10.

2. Definition of key concepts and related background

2.1. Human-related concepts

In this review, we deal with concepts and tools coming from HF/E, as a scientific discipline. To avoid any source of confusion, we provide a taxonomy and convention that we will adopt throughout this paper. We will refer to:

- **Human Factors and Ergonomics (HF/E):** as a scientific discipline that studies the interactions between a human operator and his/her work system, focusing on the improvement of the working conditions. HF/E research frameworks usually identify four critical elements in human-system interactions: *physical* related to the human body, *mental* related to the task cognitive complexity, *perceptual* related to the human perceptions (e.g., hearing, sight, etc.) and *psychosocial* related to the interactions with colleagues and management (Salvendy and St, 2022).
- **Operations Research (OR):** as a scientific discipline that aims at providing better decisions by the analysis and modeling of complex systems, and the development of efficient decision-support algorithms based on advanced mathematical methods. A typical OR study involves optimizing the performances of a work system through the following steps: 1. the observation and analysis of a work environment, 2. the development of a simplified mathematical model for this environment, 3. the design of an efficient algorithm to solve the problem, and 4. the industrial evaluation of the returned solution.
- **Work-related Musculoskeletal Disorder (WMSD):** as an injury or a disease that affects the body's structural systems (i.e., the bones, tissues, nervous or circulatory systems), caused by a work situation. Examples of WMSDs include (but are not limited to) low back pain, carpal tunnel syndrome, tendinitis, or trigger finger. WMSDs encompass a large portion of work-related injuries, but some do not affect the musculoskeletal system (e.g., hearing loss, excessive heat exposure).

- **Ergonomic Risk (ER):** referring to the additional risk factor of developing WMSD, or any other occupational accident, disease, or injury, for an employee due to a specific work situation. This concept is found under different names in the literature, without a clear difference: ergonomic load, ergonomic workload, ergonomic burden, ergonomic strain, etc.
- **Risk Factors:** as workplace situations that cause wear and tear for the body, and increase the ergonomic risk for the employee. These include repetition, awkward posture, lifting, noise, work stress, etc.
- **A Human Factor (HF):** as a characteristic or behavior that is typically human. This can be a factor affecting the individual performance of workers and the ability to perform tasks (e.g., fatigue, learning, forgetting), the safety of workers (e.g., work-related injuries, awkward postures), the interests of workers (e.g., satisfaction, motivation), or any other real-life human characteristic that would interact with the optimization of a production or service system.
- **A Human-Aware Model (HAM):** as a quantitative model that explicitly translates a HF into a mathematical expression, which can then be used in an optimization problem (e.g., in a constraint or as an objective function). In other words, the concept of HAM is the transposition of HF/E methods to an OR context. A typical HAM can be expressed as a function mapping the different states of a human system to a set of real numbers, which can be interpreted as the "ergonomic score" of the states. For instance, the NIOSH equation is a HAM that evaluate the ergonomic risk related to manual handling. Based on a set of criteria (e.g., weight, handling posture, duration), a score can be computed for each handling task that need to be scheduled in a shift and used as an input for a related optimization problem.

It is brought to the reader's attention that these definitions are consistent with those introduced in Prunet et al. (2024), which provides more details on the scope of the work, and a comprehensive contextualization of these key concepts.

2.2. Related background

In this section, we introduce some concepts and methodologies, mostly coming from HF/E, that relate to the sections of this paper. These concepts are general methodologies and analysis frameworks that appear in different contexts.

Methods from different disciplines. The set of HAMs presented in this paper is very heterogeneous. First, there are several works focusing on mathematical modeling, or the development of solution approaches, that disregard the modeling of HFs: The most common example in the collected material is when a research work aims at minimizing the ER, or balancing it among the employees, without clearly defining what this quantity represents exactly. These works are still of interest to the community since the human-related solution approaches are also a meaningful line of research. In the context of this paper, they are, however, mostly out of scope since they use a purely abstract model to represent HFs. In this case, we refer to these works as using *implicit metrics*. In the vast majority of the research works included in the collected material, the authors use a defined model to quantify a HF. This HAM can originate from different disciplines, as we define the scope to include all works modeling human characteristics, without restriction on the method. The discipline that we need to investigate for HAMs is HF/E, and unsurprisingly, a lot of HAM comes from this discipline, for example, most WMSD risk assessment methods (see Section 5), some works on fatigue (see Section 4), cognitive, psychosocial and perceptual aspects (see Sections 6 and 7).

Human Factors and Ergonomics (HF/E). This concept refers to a scientific discipline that aims at understanding the interactions among humans and the other elements of a production or service system, and at optimizing the human well-being and overall system performances.¹ Despite these common goals, one should note that HF/E is already multidisciplinary, and can be tackled from different points of view. A risk assessment method might be built upon work from:

- Biomechanics with the study of the body as a mechanical system, subjected to stress;
- Epidemiology with the statistical analysis of the prevalence of certain conditions in working conditions;
- Occupational medicine with the different regulations on working conditions;
- Physiology with the study of the human body as a biological system;
- Psychology as mental disorders and conditions are major risk factors in the development of WMSD;
- Psychophysics when studying the sensations and perceptions;
- Anthropometry, as the science concerned with the measurement of human physical properties.

Each of these disciplines (among others) interacts with HF/E. It is therefore not surprising that the methodologies used by an ergonomist may be very diverse. An interested reader is directed to the work of Bridger (2018) for a comprehensive introduction on HF/E.

Common methodologies. There are some methodologies that are frequently used in HF/E and found in several HAMs. HF/E is a broad subject, but there are two main classes of tools used in the discipline: ergonomics checklists and task analysis (Bridger, 2018). An ergonomics checklist is a list of items and considerations to check when assessing a work environment, to ensure that the investigation is performed thoroughly and completely, and does not merely reflect the area of expertise of the investigator. The task analysis consists of an observation of the concerned tasks, and the interactions between the operator and its production or service system, to get a complete understanding of the task. A useful tool for the task analysis is a *semi-structured interview*, which is performed with an operator performing the task, to learn more about the perceived difficulty and exertion linked to its components, and the adaptation mechanisms developed by the workforce. In this paper, the methods borrowed from HF/E are mainly *risk assessment methods*, designed to be comprehensive and easy to use for a practitioner that is not necessarily trained in HF/E, whereas a complete task analysis requires a fair amount of previous knowledge and experience. These methods are often based on an *index* that quantifies the risk level, which is computed with the support of a *worksheet*, i.e., a concise summary of the method consisting of all the steps of the computation, as well as illustrations to help the practitioner to evaluate some aspects of the tasks (e.g., the different postural factors). An example of such a worksheet is presented for the Rapid Entire Body Assessment method (REBA) in Section 5.3, to assess the postural ER of a work situation. In the scope of this work, the index of a risk assessment method is often interpreted through the lens of a *three color system*, where the task is labeled depending on the value of the index:

- The green zone corresponds to a low value of the index, which indicates that the task presents an acceptable level of risk, and no corrective action is required.
- The yellow zone corresponds to a medium value of the index, which indicates an uncertain level of risk, that can be acceptable under some conditions. In this case, it is recommended to monitor the situation and train the concerned employees on the safety procedures.

- The red zone corresponds to a high value of the index. In this case, the work situation presents a clear level of risk, and corrective actions are required.

Evaluation of the advantages of a ham. In the rest of this paper, we present the HAMs found in the collected material. For each of them, we try to briefly introduce the background on which they rely and present some thoughts on the use of this HAM in decision models. When discussing the advantages of a given HAM, several aspects are accounted for, including:

- The validity of the method, i.e., if it measures what it is supposed to, and with which level of accuracy. We pay particular attention to the fact that the HAM has, or has not, actually been tested with an epidemiological analysis in a real-life context, and its reliability concerning the identification of hazardous situations.
- The amount of literature on the topic, as it is an important factor when choosing a HAM. This is especially true for the amount of OR works on the topic, which makes it easier to get an overview of the method used in decision models.
- The ease of use, since some HAMs are easier than others to integrate into decision models.
- The required data collection, which is an important criterion for an OR practitioner. The frameworks borrowed from HF/E often require extensive data collection on the studied tasks, and employees, to be applied to a real case. In this case, practical use is more complicated, especially if the task analysis requires extensive knowledge and experience in HF/E.
- The mathematical properties of the HAM, which are of crucial importance for the integration in an optimization model. This is especially true for the risk assessment methods since the risk does not often vary linearly with the input.

3. Skills and learning

In this section, we discuss the topics related to *skills* and *competences*, and the associated HAMs. This includes the modeling of human skills, their applications, and the evolution of the skill set of an individual via *training* or *learning*. Skills and learning have found numerous applications in the OR literature. The size of this research stream does not allow us to perform an exhaustive analysis of all concerned documents. All the main topics and insights retrieved from the collected material are however presented in this section. Interested readers are referred to other reviews on these topics, e.g., De Bruecker et al. (2015) study workforce planning with skills, Glock et al. (2019b) review the application of learning curves in operation management, and Grosse et al. (2015) provide a meta-analysis of existing learning curve models. This section covers two main topics. First, we focus on *skills*, as the competencies of employees in Section 3.1. Then we consider *learning*, as the autonomous improvement of the skills of employees in Section 3.2. Note that we make the distinction between *autonomous learning*, where the repetition of a given task improves the proficiency at performing this task, and *induced learning*, where training takes place, and the competence improvement comes from an exogenous source. The former is studied in Section 3.2 dedicated to learning, while the latter is studied in Section 3.1 dedicated to skills.

3.1. Skills

In this section, we first present the main approaches to deal with employee skills, namely as *qualifications* and *proficiency levels*, then address the skill improvement (i.e., training).

3.1.1. Qualifications

The simplest way to deal with skills in the literature is to consider the compatibility between employees and tasks. Shuib and Kamarudin

¹ The International Ergonomics Association (IEA). <https://iea.cc/what-is-ergonomics/> Access: September 20, 2022.

(2019) and Kandakoglu et al. (2020) highlight, that in an industrial environment, this skill compatibility modeling is often used to reflect *qualifications*, where employees do have or are qualified for different jobs, rather than *skills* that are often modeled with more sophisticated approaches.

Models. Basically, each worker has a set of tasks he/she is allowed to perform, and this is enforced by a hard compatibility constraint. Koltai and Tatay (2013) provide an analytical introduction to this HAM.

Fields of application. Among all existing papers considering this HAM, one can cite early works such as Stewart et al. (1994) for workforce sizing, or (Cai and Li, 2000) for work scheduling. This HAM is a very common feature in workforce assignment or scheduling problems, and is now included in a large number of papers jointly with other more complicated features (Van den Bergh et al., 2013), where the use of qualifications is not the main contribution. Several papers in the collected material make a substantial modeling effort to focus their contribution on industrial applications. Manavizadeh et al. (2013) study an assembly line balancing problem with a relevant distinction between permanent and short-term workers. Othman et al. (2012) make a distinction between skills, that can be improved through training, and personality traits that are also required for some tasks, but cannot be modified. Asensio-Cuesta et al. (2012a) study a job rotation problem with several real-life aspects, considering explicitly physical characteristics and soft skills (e.g., meticulous, self-control). Shuib and Kamarudin (2019) study a workforce planning problem with soft compatibility constraints in a power plant, and Kandakoglu et al. (2020) integrate skills into a model dedicated to hospital planning. Katirae et al. (2022) study an assembly line balancing problem where they model *trainers* (i.e., experienced employees) and classical employees. The most challenging tasks are only feasible by the classical employees if a trainer is assigned to the same workstation.

Advantages. The main advantage of modeling skills as qualifications is the convenient modeling of such aspects with compatibility constraints. In the nowadays literature, this HAM is part of the definition of classical problems (e.g., workforce scheduling or planning), and does not make a significant contribution to the human-aware literature on its own.

3.1.2. Skill levels

The other way to model skills is through *skill levels*. It reflects more accurately what a skill actually is, i.e., an indicator of proficiency at a given task, instead of qualification. This approach is usually used in more recent works compared to qualifications.

Models. Skill levels can be modeled in optimization problems with different perspectives by considering variations in the processing times, in the quality rates, or in the costs incurred when performing a task. These approaches are not exclusive and are sometimes used in association with qualifications. With *skill-dependent task times*, the processing time of a given task varies depending on the assigned operator. Often, processing times are modeled through a two-entries parameter matrix task/skill level, but there exist more sophisticated models, where the processing time of a task depends on several skill-related parameters (Marichelvam et al., 2020; Lanzetta et al., 2016). With *skill-dependent quality level*, an error rate or quality rate depends on the skill level of the operator assigned to the task. It is indeed a reasonable hypothesis that for complex tasks, where the operator skills have a significant impact, not only the processing time, but also the quality might be impacted. This is most often represented with a parameter matrix with two entries: operator and task. With *skill-dependent cost*, the wage of an operator depends on his/her skill levels. It is indeed a reasonable assumption that a better-performing employee, or a very versatile one with a larger skill set, is associated with a higher wage.

Fields of application. The skill-dependent task times are used extensively in various areas of logistics and manufacturing. Some examples include Akyol and Baykasoğlu (2019), Polat et al. (2016), Samouei and Ashayeri (2019), which study assembly line balancing with the task duration depending on the skill levels of workers, or (Nanthavanij et al., 2010; Azizi et al., 2010) for job rotation. Another common application area is flowshop scheduling (Gong et al., 2020; Costa et al., 2014), where only the setup time varies, or (Marichelvam et al., 2020) where the task duration depends on multiple factors (age, skills, learning and forgetting). Lanzetta et al. (2016) develop a new model to compute the task duration with the consideration of various factors such as skills, motivation, or environment, and Kiassat and Safaei (2019) study the effect of imprecise skill level evaluation in workforce rotation frameworks. Another approach uses stochastic task times, where the expected processing time and variance are different for each operator (Egilmez et al., 2014; Hong, 2018). Finally, Matusiak et al. (2017) study an order picking problem in a warehouse with a focus on picker skills. They apply statistical regression methods to explore historical data on the route duration, based on the characteristics of the given routes. They identify several categories of skill sets and assign them to workers (e.g., agile worker, quick driver, tall or strong person).

Concerning skill-dependent quality, Norman et al. (2002) present an early work on workforce planning in cell manufacturing accounting for skill-related errors. The objective is to maximize the profit, including skill-dependent productivity and quality output of employees. Training can be scheduled to improve workforce skills at the expense of an additional cost. McDonald et al. (2009) study another workforce assignment problem, where the quality level depends on the skill of the employee performing the task. Salehi et al. (2018) and Tang et al. (2006) tackle the issue of varying skill-dependent quality levels with fuzzy logic, respectively on assembly and disassembly lines.

Skill-dependent costs are mostly used in tactical workforce-related problems, where the size and composition of the workforce are decision variables. In this case, wages, as well as hiring/firing/training costs, are integrated into the objective function. Norman et al. (2002) study a cell formation problem in workforce planning, where the productivity and quality depend on the employee skill level, which can be improved by training. In Aryanezhad et al. (2009), Mehdizadeh et al. (2016), the cell formation is integrated with workforce planning, and a total cost function integrates skill-dependent wages, as well as training cost and, for the first one, hiring and firing costs. In Zhang and Gen (2011), the financial aspect is integrated as a parameter for each task, depending on the operator performing the task.

Advantages. This HAM is fairly easy to consider from a pure modeling perspective. However, the integration into mathematical models increases their complexity, since the processing time (resp. quality or cost) of a task is no longer a fixed exogenous parameter. The modeling accuracy depends on the specific work. In the collected material, skill level models range from theoretical studies that use abstract skill definitions and randomly generated parameters, to more applied studies that put substantial efforts into the skill identification, or skill-related time (resp. quality) estimation.

3.1.3. Skill improvement via training

When modeling skills, their improvement often comes with training where an employee “learns” new skills, or improves them. There is a clear distinction between *learning via training*, which is induced learning from an exogenous source, and *autonomous learning*, which presupposes that an individual gets better at a task by repeating it. With the latter one, learning is endogenous to the concerned individual and is usually modeled through learning curves (see Section 3.2).

Models. The most straightforward model for training is via the scheduling of training periods for employees to improve their skills. During training an employee is unavailable for productive tasks. Other interesting models include McDonald et al. (2009), who present an assembly cell worker assignment problem with training, where a trained worker needs to be assigned to each task he/she is trained for at least once in the planning horizon for skill retention. In Sueer and Tummaluri (2008), autonomous learning is considered for skill improvement: To improve from one level to another on a specific skill, an employee needs to work a given number of consecutive weeks on tasks requiring this skill. After these training periods, he/she has a given probability to improve his/her skill level on each additional period working with it. Bordoloi and Matsuo (2001) and Gans and Zhou (2002) provide other examples of stochastic skill transition, where the composition of the workforce is modeled with a Markov chain, accounting for skill improvement, hiring, firing, and leaving.

Fields of application. Training is mostly integrated into workforce planning and human resources planning, where such tactical decisions are available. In Fowler et al. (2008), Aryanezhad et al. (2009), training is a part of the HR strategy, alongside hiring and firing, to develop a workforce meeting the skill set requirements. Othman et al. (2012) model skills with a distinction between technical skills and personality traits, which work in the same way to determine the requirements of a task. However, only technical skills can be improved through training. Wirojanagud et al. (2007) and Fowler et al. (2008) integrate a general cognitive ability level for each worker, that affects the training time required to pass from one skill level to another. Stewart et al. (1994), Hopp et al. (2004), Olivella and Nembhard (2017) study different cross-training strategies and establish a comparison between them.

Advantages. Most of the time, the variation of proficiency is modeled via learning. Usually, training is considered together with sufficiently long time horizons, where it is reasonable to take such tactical decisions. Considering training periods results in a modeling that is simpler than using learning curves. However, the resulting model is less accurate.

3.2. Learning

Learning has been extensively studied in the collected material, and the amount of literature available on this topic is abundant. The interested reader is referred to the reviews published on the topic (Anzanello and Fogliatto, 2011; Glock et al., 2019b; Jaber et al., 2022). In this section, we make the distinction between *i. organizational learning* where the productivity of an industrial system increases due to a general improvement of processes, and *ii. individual learning* that corresponds to the improvement of an employee's performances due to the repetition of the same task. Both phenomena are modeled using *learning curves*, but they differ in terms of application problems.

3.2.1. Organizational learning

The early work on learning focuses on organizational learning, where a production system increases its productivity rate as time goes on as a consequence of both the cognitive process of learning from employees and the operational improvement from the firm.

Models. Organizational learning, as well as individual learning, is modeled with *learning curves (LC)*. Many models exist, and an interested reader is referred to the reviews highlighted at the beginning of Section 3.2 for additional information. An LC gives a mathematical expression of a task duration depending on the time spent on similar tasks, or its position in a schedule. The seminal work of Wright (1936) was the first to introduce a learning curve, displayed in Eq. (1).

$$y_x = y_1 x^{-b} \quad (1)$$

In this formula, y_x is the cumulative average time to produce the x th unit, y_1 the production time for the first unit, and b the learning exponent, computed as $b = \log(LR)/\log(2)$ with LR the learning rate of the curve. Although it is still broadly used by the community, this LC presents several flaws that limit its suitability to model realistically the learning phenomenon, especially because the duration of tasks converges asymptotically to zero. Several other LC models have been developed to address this issue. The most common LCs follow a log-linear behavior similar to the one developed by Wright (1936), yet with more sophisticated mechanisms to better reflect real-life considerations. Other options include exponential models (Levy, 1965) or hyperbolic models (Mazur and Hastie, 1978). Jaber and Bonney (2003) propose a formulation with a *plateau effect*, and De Jong (1957) addresses the problem with an irreducible minimal task duration, which corresponds to the asymptotic behavior of the curve. Jaber and Guiffrida (2004) develop a learning curve model that accounts for error rates in addition to processing time. Jaber and Sikstrom (2004) and Grosse et al. (2015) study different classical LC models and draw a comparison between them.

There are also some works that propose linear versions of learning curves to better fit optimization methods. For example, Valeva et al. (2017) study the workforce planning problem with a linearization of a hyperbolic learning curve and stochastic demand. Hewitt et al. (2015) propose a linearization method that can be used with different curve models. Cavagnini et al. (2020) study a workforce planning problem, where the learning rate is uncertain. Finally, some works develop models to consider learning without proper LCs, for instance Przybylski (2018) study parallel machine scheduling, with learning based on a proper Riemann integral.

Fields of application. Organizational learning has been first integrated into lot sizing models, to account for the improvement of the production processes over time (Muth and Spremann, 1983; Smunt, 1987; Elmaghraby, 1990). Organizational learning effects are also extensively studied in production scheduling, especially in single machine scheduling where several authors analyzed mathematically different versions of the problem, partly because polynomial algorithms exist for a large variety of them (Biskup, 1999; Cheng and Wang, 2000; Mosheiov, 2001). Research on single machine scheduling with organizational learning is still ongoing, as many papers are still publishing studies with more and more sophisticated approaches, for example, Pei et al. (2017) with serial batching and fatigue effects. Flowshop scheduling problems have also been considered with organizational learning (Wang and Xia, 2005; Amirian and Sahraeian, 2015; Pargar and Zandieh, 2012). There are attempts to integrate organizational learning with other families of problems, although less frequently. For instance, Otto and Otto (2014) study assembly line balancing with a different learning curve for each task, Zanoni et al. (2012) apply them to the vendor-managed inventory problem. Interesting applications include Kazemi et al. (2016b) who study the EOQ with learning and forgetting. The parameters of the learning and forgetting functions are modeled with fuzzy parameters and estimated through semi-structured expert interviews.

Advantages. Learning curves are an interesting class of HAMs that model an important phenomenon affecting the system productivity. Important work has been carried out to develop accurate LCs, with the integration of various features to adapt to specific applications. LCs have furthermore been field-validated by numerous studies in psychology or HF/E (Glock et al., 2019b). LCs integrate well in optimization models, but often present some non-linearities that should be addressed. Organizational learning may lack some precision compared to individual learning. However, the process is much easier to implement as the inputs can be easily inferred from historical data.

3.2.2. Individual learning

In this section, we study the learning process of individual employees, instead of the general improvement of processes studied in Section 3.2.1. As employees are different individuals, it is a natural hypothesis to suppose that the learning process changes from one to another. This justifies the consideration of individual LCs.

Models. The difference in modeling between individual and organizational learning lies in the fact that the parameters that determine the expression of the LC depend on a given employee. Some works study the impact of the workforce heterogeneity on the solutions provided by optimization models within a learning context (Shafer et al., 2001; Nembhard and Shafer, 2008), and show that individual modeling might have a significant impact on solutions, and is therefore interesting to integrate into optimization models.

Fields of application. Individual learning is especially studied in workforce assignment models, where the impact is significant. Nembhard (2001) present an early work on the topic, which integrates individual learning rates. More recent works include Sayin and Karabati (2007), Nembhard and Bentefouet (2014), which use more sophisticated models with several competencies subject to learning. Individual learning parameters have also been used in machine scheduling (Anzanello and Fogliatto, 2010; Janiak and Rudek, 2010), or assembly lines (Bukchin and Cohen, 2013). Lot sizing is also an important application, especially to compute the Economic Order Quantity (EOQ) (Kazemi et al., 2015, 2016a). Jaber and Peltokorpi (2020) study group learning, the effect of which depends on the group size, in the context of lot sizing, and Lohmann et al. (2019) study the grouping of workers with a similar learning profile to increase productivity. In vehicle routing, Battini et al. (2015) compare daily routing optimization, versus a fixed routing plan where the drivers benefit from a learning effect, being assigned to the same route each day. In Ulmer et al. (2020), the driver familiarity with the different routes is integrated into the routing model. Dar-El et al. (1995) account for motor and cognitive components of the learning process based on experimental data. The integration of motor and cognitive components has been updated in a more sophisticated approach by Jaber and Glock (2013), with a focus on assembly lines, and more recently by Peltokorpi and Jaber (2020). Korytkowski (2017) proposes a new model to assess the performances of multi-skilled workers depending on learning, forgetting, experience, and competencies. Finally, Şenyiğit et al. (2020) study the effect of the OCRA parameters (see Section 5.4) on the learning rate in machine scheduling.

Advantages. See Section 3.2.1 for a general discussion on learning curves. The modeling of individual learning instead of organizational learning enables a finer granularity in modeling the heterogeneity of the workforce in terms of initial capacities, as well as learning capabilities. However, individual modeling requires extensive personal data collection, which may be challenging depending on the legislation.

3.2.3. Forgetting

Forgetting is commonly associated with learning. Learning models are used to represent the proficiency an employee acquires by repeating the same task. In this context, forgetting designs the deterioration of performance due to the assignment of the employee to different tasks.

Models. The most common learning and forgetting HAM found in the collected material is the *Learning Forgetting Curve Model* (LFCM), developed by Jaber and Bonney (1996). The model is composed of the LC of Wright (1936) and an analogous power-form term for forgetting. This model is further refined to account for other effects, for instance with the *Learning Forgetting Fatigue Recovery Model* (presented in Section 4.4) that also accounts for fatigue and recovery. However, various other learning and forgetting curve models are found in the collected material, but not developed further in this review, for example, the S-shape forgetting function (Teyarachakul et al., 2011).

Fields of application. The consideration of forgetting, in association with learning, is present since the early work on the topic, for instance, on lot sizing models (Muth and Spremann, 1983; Elmaghraby, 1990). Learning and forgetting are also found in other families of problems, especially in the scheduling literature, with single machine scheduling (Lai and Lee, 2013), parallel machine scheduling (Nembhard and

Bentefouet, 2012), or flowshop scheduling (Li et al., 2018a). Interesting applications include Stratman et al. (2004) who estimate the shadow cost of learning and forgetting in hiring workers for short-term activities.

Advantages. The integration of forgetting completes the study of the learning process. Generally, it shares the advantages of LCs with organizational and individual learning (see Sections 3.2.1 and 3.2.2). However, it also allows for more accurate modeling in problems with a long time horizon, where forgetting aspects play an important role in the correct evaluation of the employees' knowledge to perform a task.

4. Fatigue and breaks

In this section, we discuss the HAMs related to the fatigue of employees and the topic of *rest breaks*, which refer to activities that reduce the fatigue level. Fatigue is indeed an important factor affecting both the injury rate and employees' performances (Yung et al., 2020). A reader interested in this topic is referred to Xu and Hall (2021) for a dedicated review, with a focus on work-rest and shift scheduling. This section covers the following topics: *energy expenditure* in Section 4.1, *rest allowance* in Section 4.2, *fatigue effect and rate modifying activities* in Section 4.3, *learning forgetting fatigue recovery model* in Section 4.4, *meal breaks* in Section 4.5 and *work-stretch duration* in Section 4.7.

4.1. Energy expenditure

Metabolic Energy Expenditure (EE) is based on physiological measurements and is used to determine the maximum task intensity that can be performed continuously by an individual without accumulating excessive fatigue. EE is often associated with rest allowance (see Section 4.2) in decision models, where an appropriate rest time is computed after a work period depending on the EE of this period.

Models. The most common method applied to compute EE was developed by Garg et al. (1978), originally for material handling applications. The model developed by Garg et al. (1978) assumes that a job can be divided into elementary tasks and that the EE of the job is the sum of the EE of its elementary components. The elementary tasks include maintaining a standing posture, walking, lifting, etc. Tables are used to compute the EE of the different tasks depending on their characteristics (speed of walking, carried load, etc.). Other computation methods for the EE include the definition of Wu and Wang (2001), which is based on the heart rate when performing a task, and computes the corresponding productivity, error rate, and maximum work duration. This HAM is for example used in Zhao et al. (2019). It is also common in the literature that the EE is used as a general concept (i.e., the metabolic energy consumption associated with a task), without details on the method of computation.

Fields of application. EE is a commonly considered aspect in manual order picking in warehouses. Calzavara et al. (2017, 2019a) aim at finding the optimal rack layout among several options (full pallets, half pallets with or without pullout systems). Battini et al. (2016b), Diefenbach and Glock (2019) study the storage assignment with EE while reducing overall walking time and ER, Diefenbach and Glock (2019) integrate as well the layout design of the picking zone into their decision model. Another important area of application for EE is assembly line balancing. Battini et al. (2016a) propose a method to compute EE with tables using the predetermined motion capture system: The range of feasible movements in an assembly situation is decomposed into elementary movements (e.g., reach, grasp), and the EE is associated with each of them, based on Garg et al. (1978). The advantage of such a system is the ease of use, where a quick observation of a work situation is sufficient to get a somewhat accurate measurement. Their model is tested on an industrial case of a high-pressure cleaner manufacturer, and applied in other works (Battini et al., 2017a). Al-Zuheri et al. (2013, 2016) associate EE with other biomechanical

HAMS for assembly lines. Other areas of application include workforce scheduling (Dewi and Septiana, 2015), work-rest scheduling (Zhao et al., 2019), vehicle routing (Rattanamanee et al., 2015), or lot sizing (Battini et al., 2017c). Interesting applications include Zhang et al. (2018) who use a 3D simulation software (IGRIP/ERGO) to compute the EE according to Garg et al. (1978).

Advantages. EE presents several advantages for an OR practitioner, explaining their popularity in the collected material. In terms of validity, it is a common methodology in HF/E, and is therefore soundly validated by empirical data and studies. In terms of the integration into mathematical models, EE has the important advantage of being linear, which is uncommon for HAMS based on HF/E works. Indeed, an elementary movement is associated with an energy value, and the total energy consumption of an individual corresponds to the sum of the EE for all elementary movements in the work shift. The drawback of this linearity is that the method lacks some refinement in assessing the ER based on fatigue.

4.2. Rest allowance

The Rest Allowance (RA) is an interesting concept originating from HF/E, that is especially suited for scheduling problems. The basic idea is that a rest break is required after a period of physical exhaustion, for instance, a period of manual work for an employee. The length of this RA is set to enable full recovery and depends on the length and intensity of the work period it follows.

Models. The most common computation method for RA is introduced by Price (1990), with the idea of providing workers an additional rest time depending on their EE. The value of the rest allowance is computed using a simple function of the EE. If the average value of EE for a work period exceeds a given threshold, then the risk is excessive, and a break should be scheduled to enable recovery (Price, 1990). Other methods are found in the literature to compute the RA. For instance, Battini et al. (2017b) compute the RA based on the OWAS index (see Section 5.3). Calzavara et al. (2019b) propose another analytical computation method where the input parameters are measured using a heart monitoring system. The processing time of a task can be adapted to take into account this additional rest, as it is shown in Eq. (2) where RA is the rest allowance, T is the nominal task time, and $\hat{T}$ is the corrected one.

$$\hat{T} = T \cdot (1 + RA) \quad (2)$$

To integrate this corrected task time into an existing model, the most straightforward solution is to compute beforehand the corrected task times, and use the corrected duration as inputs, instead of the original ones. In this way, the rest breaks are not scheduled explicitly, but accounted for implicitly in the task duration.

Fields of application. In the collected material, the corrected task time with RA is used, for instance, in order picking problems (Battini et al., 2016b), or in assembly line balancing problems (Battini et al., 2017a; Finco et al., 2020b). Battini et al. (2017c) and Condeixa et al. (2020) use the RA as a cost in a total cost function (see Section 8.8): The worker fatigue is converted into a rest allowance, which is seen as a paid rest time for the employees, and therefore integrated into the cost structure. They study respectively lot sizing and reverse logistics. El Mouayni et al. (2020) develop a new simulation-based assessment method for the rest allowance, based on assembly lines, taking into account various effects (e.g., fatigue, learning, reliability).

Advantages. Since the RA is based on EE, it has the same level of modeling accuracy and field verification. Moreover, it is very convenient to use the RA in decision models, as it can be easily converted into quantities that are commonly used in objective functions (time or cost). It is then fairly easy to integrate this into the objective function, which minimizes the total cost of the production or service system. In

such a case, the two conflicting objectives (monetary and human) are aggregated homogeneously. This avoids the common pitfall of multi-objective optimization concerning the tuning of the parameters related to the preferences of the decision maker (see Prunet et al. (2024), *Multi-objectives*). The use of the RA as an input of human-aware task times in decision models is also an interesting use case that easily fits the OR methodologies.

4.3. Fatigue effect and rate modifying activities

Fatigue effect is a common family of HAMS used to integrate fatigue into decision models. This effect is based on a simple hypothesis: The performance of an individual in a work situation decreases over the time spent without a break. To restore the productivity level, a rest break needs to be scheduled. Since breaks modify the productivity rate, they are called *Rate Modifying Activities (RMA)* (Lodree et al., 2009).

Models. The function modeling the fatigue effect is called the *decay function*. During a break, the productivity level increases up to its initial value according to another function, called the *recovery function*. A model for fatigue effects and RMA is characterized by these two functions, several examples are found in the collected materials.

An early model is introduced by Bechtold (1979), which is the basis of a number of more refined models introduced afterwards. The author develops a simple model for the fatigue effect and RMA, based on linear functions for both decay and recovery.

Another very common model for the fatigue effect is a position-dependent or time-dependent effect. Mosheiov (2005) provides a seminal work on the topic, with a model characterized by a simple linear decay function, and a recovery RMA of fixed duration, which fully restores the productivity to its initial level. In this case, the processing time of a task depends either on its starting time or on its position in the sequence of tasks. Note that this model is originally applied to machines instead of human operators, where the RMAs correspond to maintenance activities. The main difference with the model of Bechtold (1979) is the point of view. In the time-based fatigue effect, the decay function is applied directly to jobs instead of to the productivity of an individual. This difference has a significant impact on decision models: If no RMA is scheduled during the time required to complete a set of jobs, the total completion time is constant with the model of Bechtold (1979), no matter the order, while this is not the case with position-dependent or time-dependent effects.

Fields of application. The model of Bechtold (1979) is extensively used in the early work on work-rest scheduling (Bechtold, 1991; Bechtold and Thompson, 1993; Bechtold et al., 1984). In these works, the decay and recovery functions are characterized by a set of parameters for each employee, as the workforce is considered heterogeneous, and the goal is to find the best work-break schedule, where all employees take their break simultaneously. Concerning time-dependent effect, (Lodree and Geiger, 2010) introduce the concept with human fatigue, and propose an analytical study of this HAM in the scheduling theory. This is used, for instance, by Zhu et al. (2017), who study scheduling with interruption, fatigue effects, and rest breaks. Wang et al. (2020) study a position-based fatigue effect with interruptible jobs, but also include an additional *promotion effect* to model motivation and boredom (see Section 6.1), which increases productivity when there is a switch between different jobs. Interesting applications include Jamshidi and Seyyed Esfahani (2014), who integrate the impact of fatigue on error rate in a work-rest scheduling problem, instead of task time/productivity. Yan et al. (2019) study fatigue in vehicle routing, where the driver efficiency is modeled by a linear piecewise efficiency curve: At the beginning of the shift the efficiency increases due to the driver adaptation, then there is a stable plateau, and after some time it decreases with fatigue.

Advantages. One of the main advantages when working with fatigue effects is the existing body of literature on the topic. The available models work analogously when applied to machines, where the literature is abundant. Therefore, they integrate well into the scheduling theory. Another advantage is the ease of use, these models propose reasonably accurate modeling of fatigue with a moderate requirement on input parameters. Since they affect productivity, the parameters characterizing the decay and recovery functions can be inferred with statistical regressions, which require data, but are not too time or competence-intensive.

4.4. Learning forgetting fatigue recovery model

The *Learning Forgetting Fatigue Recovery Model* (LFFRM) is a HAM developed by Jaber et al. (2013) to account simultaneously for learning/forgetting and fatigue/recovery. These two effects share similarities in the way they affect the work rate of human operators (see Section 3.2 for more details on the learning and forgetting mechanisms). Indeed, during a continuous work period, performances improve due to learning, but at some point, muscular fatigue has a negative effect. During a break period, muscular recovery happens, resetting the level of fatigue. However, at the same time, forgetting might occur.

Model. The learning/forgetting process is computed using the learn-forget curve model developed by Jaber and Bonney (1996). More details about this model can be found in the dedicated Section 3.2. The fatigue/recovery process is represented using the model developed by Konz (1998), which extends the fatigue effect model of Bechtold (1979) by using exponential-based decay and recovery functions, instead of linear ones.

Fields of application. The LFFRM is used for example in assembly lines (Ostermeier, 2020) or production planning (Givi et al., 2015b). The model introduced by Givi et al. (2015a) extends the LFFRM to also model human reliability and error rate with respect to worker learning/forgetting and fatigue level. Petronijevic et al. (2019) use the LFFRM in a simulation/optimization-based approach for a scheduling problem with variable work rate and error rate, computed according to Givi et al. (2015a). Finally, the fatigue/recovery aspect of the model can also be found in the work of Glock et al. (2019c), which uses it in addition to biomechanical models to find the optimal box size for an industrial packaging process.

Advantages. The LFFRM is a HAM composed of two different HAMs, its advantages are therefore a mix of the advantages of both models it is based on. Both effects integrate well into the scheduling theory and have seen extensive attention from the community, providing a sound basis for the LFFRM. Moreover, this model presents a complete and rather sophisticated method for individual performance modeling. This sophistication enables a finer estimation of the individual performances, however, it brings the complexity of both methods, i.e., more parameters to compute/estimate and more complex computations. Since both effects are linked together, the empirical estimation of the parameters becomes more complicated. However, both effects integrate similarly into a decision model with time-dependent task duration, which has the advantage of integrating two complementary HF's without increasing too much the complexity of the models.

4.5. Meal breaks

Probably the most basic way to model breaks is with *meal breaks*. The idea is very simple: A break should be scheduled for every shift so that employees can get a meal.

Models. Most of the time the length of the meal break is predefined, and there is a time window in which the break can be scheduled. This is enforced by hard time window constraints. Another common HAM is the consideration of breaks, not specifically dedicated to meals, but modeled in the same way: Several breaks of a fixed length need to be scheduled, each in its corresponding time window.

Fields of application. Meal breaks are easy to model, and have thus been widely used in the early workforce scheduling literature (Thompson, 1990; Brusco, 2008; Brusco and Jacobs, 2000). It has also been used in vehicle routing, where drivers must be back at the depot for their meal break (Kim et al., 2006; Benjamin and Beasley, 2010; Coelho et al., 2016). Some works have different rules concerning the positioning of the meal break, adapted to a specific application case: Chen et al. (2013) study a work-rest scheduling problem with Chinese meal break rules. The modeling of rest breaks with time windows is often used in early works on work-rest scheduling (Mehrotra et al., 2000; Topaloglu and Ozkaran, 2003; Aykin, 1998), where the shifts must include one meal break, plus one (or several) other rest breaks that are modeled in the same way. Note that this is mostly found in early works, since the state-of-the-art studies on work-rest scheduling often use more sophisticated rules for break placement, like the work-stretch duration (see Section 4.7). However, this HAM is still found in recent works, often when the authors focus on other real-life aspects of the problem (Bonutti et al., 2017; Gérard et al., 2016).

Advantages. The main advantage of meal breaks is their ease of use and integration into decision models. Modeling meal breaks does not need any parameters apart from the legislation, or the managerial policy of a company. The modeling is very straightforward and fits without much effort in a large variety of logistics and manufacturing problems without adding too much complexity since time windows are a very common way to model constraints in decision problems. However, this approach is a bit "rough" and does not allow the models much flexibility when deciding how to schedule breaks, which makes sense for meal breaks that should take place around lunch time, but may not be the most efficient way to integrate other rest breaks into a model.

4.6. Hours of service regulations

Another common way to model breaks is through work-stretch duration or regulation frameworks, especially in vehicle routing. The main idea is to schedule breaks according to a set of rules, for example, a maximum duration of a work period without a break, a minimum break duration during a shift, etc. In general, the work periods between two breaks do not have a fixed length, and the objective is to schedule work and rest periods in the best possible way. When the set of rules directly comes from legislation, we call this HAM *Hours of Service regulations* (HOS) otherwise, we call it *work-stretch duration*. In this section, we discuss HOS breaks.

Models. The working and driving times of truck drivers are regulated in several countries. These regulations differ from one country to another, but the underlying idea remains the same, and the modeling is similar: They impose restrictions on driver driving and working times on road transportation, reaching from single driving periods up to several weeks. These rules are modeled with forward/backward constraints.

Fields of application. In the collected material, they appear only in Vehicle Routing Problems (VRP), mostly due to recent regulations that force companies to schedule the rest breaks in the routing plans of truck drivers (Kok et al., 2010). Due to this obligation, the topic has seen substantial interest from the community. Goel (2009) is the first work, to our best knowledge, that integrates these regulatory frameworks into the VRP over a one-week planning horizon. In the EU, the working time of truck drivers is regulated by the European Community (EC) Regulation No 561/2006,² which entered into force in April 2007. Since the EU regulations impose the logistics companies to schedule

² The European Community (EC) regulation No 561/2006 of 15 March 2006. <https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A32006R0561> Access: September 20, 2022.

the breaks in their routing plans, they are the most studied in the context of this survey (Kok et al., 2010; Prescott-Gagnon et al., 2010; Wen et al., 2011). Other countries have followed the example of the EU and produced their own set of rules for truck driver work times. The periods and duration differ from one legislation to another, but the underlying idea stays the same, and the modeling is similar. Goel (2012) studies the Australian regulations,^{3,4} Mayerle et al. (2020) the Brazilian ones,⁵ in association with lunch break. Rancourt et al. (2013) and Rancourt and Paquette (2014) study a VRP with the US driving hours regulations.⁶ Some works also study this problem generically, without choosing a specific set of regulations to apply to driver schedules. For instance, Brandao and Mercer (1997) is one of the first papers, where the regulations related to working hours are integrated into a VRP, although in a very simple way with only a maximal working time per day. Other general examples include Erera et al. (2008), Ceselli et al. (2009), Min and Melachrinoudis (2016). Another interesting application is the work of Bowden and Ragsdale (2018), which studies a VRP with hours of service regulations, and enforces additional constraints to account for the sleepiness of drivers, and to ensure an acceptable level of alertness during the driving periods. Goel and Vidal (2014) provide a computational comparison of different regulations, in the scope of the vehicle routing problem.

Advantages. There is no real advantage *per se* for this HAM: It models a regulation on truck driver hours of service if a company is concerned by the regulations when planning routes. One alternative would either not use optimization methods, or use simpler HAMs like meal breaks time windows (see Section 4.5) for break placement. Despite being simpler, time windows are much more restrictive if used to enforce these regulations, because they are not suited for them, which would lead to a net loss of performance for the resulting solutions.

4.7. Work-stretch duration

Work-stretch duration is used to integrate rest breaks in planning while giving more freedom to the decision models. The mechanism is very similar to HOS regulations, but the application differs since there is no transportation decision.

Models. In *work-stretch duration*, the length of a work period is not fixed, and a set of rules is used as a guideline on when to schedule rest breaks. This HAM is similar to HOS regulations, except that the set of rules does not come from enforced legislation, but from a managerial policy of the concerned company. The break rules are modeled with forward-backward constraints with, for example, a maximum work duration without break, a minimum break time to be scheduled during a shift, or a minimum duration between the shift beginning and the first break.

³ The Australian National Transport Commission Guidelines for managing heavy vehicle driver fatigue of August 2007. <https://s3-ap-southeast-2.amazonaws.com/cdn-nrpp/wp-content/uploads/sites/4/2017/03/11223238/05-Guidelines-Fatigue-August07.pdf> Access: September 20, 2022.

⁴ The Australian National Law Act of 2012 on Heavy Vehicle. <https://www.legislation.qld.gov.au/view/pdf/inforce/2017-07-01/act-2012-021> Access: September 20, 2022.

⁵ The Brazilian regulation No. 13.103 on Labor laws for truck drivers of the March 2015. http://www.planalto.gov.br/ccivil_03/_ato2015-2018/2015/lei/13103.htm Access: September 20, 2022.

⁶ The Federal Motor Carrier Safety Administration regulation No. 49 CFR Parts 385, 386, 390 and 395 about Hours of Service of Drivers. <https://www.govinfo.gov/content/pkg/FR-2011-12-27/pdf/2011-32696.pdf> Access: September 20, 2022.

Fields of application. The break rules are applied to shift scheduling or work-rest scheduling problems, often with additional side constraints. Gärtner et al. (2001) is one of the first papers to study work-stretch duration in shift scheduling. Widl and Musliu (2014) study the problem from an analytical perspective, and propose theoretical insights on the modeling of such breaks. Rekik et al. (2008) compare different break placement strategies including break time windows or work stretch duration, and study their impact on solutions. Thompson and Pullman (2007) compare a priori break scheduling with real-time dynamic scheduling. Finally, several works in the collected material study a workforce scheduling problem in a contaminated area with chemical or nuclear hazards (Janiak and Kovalyov, 2006, 2008; Sawik, 2010), where each work period should be followed by a rest period, which duration is not fixed, but depends exponentially on the work period duration.

Advantages. The main advantage of work-stretch duration is the flexibility allowed to both the break placement rules and the decision model. Indeed, this HAM is much more flexible than time windows, and allows more efficient solutions to be found. This is illustrated by the works that study the comparison of different methods (e.g., Rekik et al. (2008)). However, this flexibility comes at a cost in terms of problem complexity. These constraints are more complicated to handle for classical solution approaches than time windows. Moreover, since the set of rules is mostly defined by company policies, fatigue is accounted for implicitly, and the method lacks the human modeling accuracy of, for instance, fatigue effect and RMA (see Section 4.3).

5. Work-related musculo-skeletal disorders: Risk assessment methods

The HAMs presented in this section consist in assessing the risk of the apparition of Work-related Musculo-Skeletal Disorders (WMSD) for the operators. They are mostly based on epidemiological, physiological, or biomechanical considerations and their practical relevance has been studied within HF/E. However, they are based on field techniques and methodologies that are mostly unfamiliar to a typical OR practitioner. An interested reader is referred to Takala et al. (2010) for a systematic evaluation of observational risk assessment methods. These HAMs have been classified in a number of categories, introduced in the following subsections, depending on which risk they assess: *Whole body* in Section 5.1, *manual handling* in Section 5.2, *posture* in Section 5.3, and *repetitive movements* in Section 5.4.

5.1. Whole body

In this section, we present the methods found in the collected material that estimate the risk of WMSD for the body as a whole, and focus neither on a specific body region nor a specific work situation. The *European Assembly Worksheet (EAWS)* is the main HAM in this category, but some works using other models are presented as well.

Models. The EAWS, introduced by Schaub et al. (2012), is a risk assessment framework designed to assess the ER as a whole. It was created to be a self-sufficient ergonomic evaluation method for assembly work that captures a large variety of risk factors (e.g., postures, action forces, manual handling, repetitive movements of the upper limbs). Moreover, the EAWS fits the EU regulatory frameworks dealing with machining in manufacturing, namely the EU machinery directive No. 2006/42/EC⁷ and the EU general framework No. 89/391/EEC.⁸ The EAWS is based

⁷ The Directive No. 2006/42/EC of the European Parliament and Council on machinery usage. <https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2006:157:0024:0086:fr:PDF> Access: September 20, 2022.

⁸ The European Council Directive No. 89/391/EEC of 12 June 1989 on the introduction of measures to encourage improvements in the safety and health of workers at work. <https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A31989L0391> Access: September 20, 2022.

on a worksheet that consists of four sections (plus a general one) for the evaluation of working postures, action forces, manual handling, and repetitive movements of the upper limbs. The first three sections are based on physiological and biomechanical criteria and are combined into a *whole body* exposure score. The fourth section is based on medical and epidemiological criteria and represents the *upper limbs* exposure score. The overall risk score is the maximum value between these two intermediate scores. Depending on the value of this score the recommended action is determined by a traffic light evaluation system. A detailed presentation of the computation for each of the sections of the EAWS can be found in Schaub et al. (2012).

Some works study the whole body exposure with other HAMs. For instance, Asensio-Cuesta et al. (2012a) study the job rotation problem, and use 29 criteria to assess the physical and cognitive demands of a job. The employees are also given capability scores on these criteria, and an assignment job/operator is only feasible in case of compatibility.

Fields of application. The EAWS is mostly used in assembly-related problems, as it was created for such context. Otto and Scholl (2013), Hochdörffer et al. (2018) study the job rotation problem in an automotive assembly line through industrial case studies. Hochdörffer et al. (2018) also account for the aging workforce, which is more prone to WMSD but is more experienced. Hence, the resulting problem is to retain the workforce skills and reduce the ER of aged workers. Whole body assessment is also used to study the assembly line balancing problem (Otto and Scholl, 2011).

Advantages. The main advantage of the EAWS is its completeness, as it assesses the impact of a work situation on different body regions, and accounts for a large set of coupling factors that increase the ER, providing a flexible HAM that can adapt to a large variety of work situations. This completeness is an advantage since a single worksheet is required for the evaluation, but it also means that in specific situations, when the workload is focused on a specific body region, other risk estimation methods are more suited. Overall, the EAWS is adapted to jobs with diverse tasks and requirements, e.g., assembly work. Regarding the validity, the different sections of the worksheet are based on well-established works and methods from HF/E with diverse backgrounds (i.e., medicine, biomechanics, physiology). Finally, an advantage of the EAWS is its consistency with several legislative requirements, especially in machinery work (Schaub et al., 2012).

5.2. Manual handling

Manual handling, and especially lifting tasks, represents an activity that has a significant risk of developing WMSDs (Moore and Garg, 1995), and is, therefore, a topic that has seen particular attention from the scientific community. In this section, we focus on the two main HAMs related to manual handling found in the collected material: the NIOSH equation and the JSI. Some other assessment methods have been seldom used, like the *Lifting Fatigue Failure Tool (LiFFT)* used in the work of Mehdizadeh et al. (2020) for a job rotation scheduling problem or an in-house assessment method for intra-hospital patient transportation in von Elmbach et al. (2019).

Models. The NIOSH lifting equation has originally been developed by the American National Institute for Occupational Safety and Health (NIOSH) as a guideline for safe work practices in manual handling in 1981,⁹ and updated in 1991 (Waters et al., 1993). The NIOSH equation is now part of the ISO 11228 standard,¹⁰ the European standard UNI EN

1005-2:2009,¹¹ and the US standards No. 29 CFR Part 1910¹² (Caballini and Paolucci, 2020; Otto et al., 2017). The NIOSH equation is based on biomechanical, physiological and psychophysical criteria (Waters et al., 2007). This is achieved by computing a *Recommended Weight Limit (RWL)* for the task, based on the handling posture and quality of the grip. A recommended course of action is then determined via a traffic light system, depending on the ratio between the RWL and the actual weight carried. Waters et al. (2016) extend the NIOSH equation to consider a whole shift instead of a single task by penalizing the succession of high-risk tasks. This improves the accuracy of the method, at the expense of additional non-linearities.

The *Job Strain Index (JSI)* is a risk assessment method first developed by Ayoub et al. (1978) for lifting injury, which has been validated through field studies (Ayoub et al., 1983; Liles et al., 1984). The index computes, for a given task, the ratio between the lifted weight and the maximum safe lifting weight for a given individual. Compared to the NIOSH equation, the JSI accounts for the physical characteristics of the individual performing the task (e.g., gender, age), and extrapolates to a whole shift in a time-average manner.

Fields of application. The NIOSH equation is commonly used with warehousing applications, which is unsurprising since they involve a notable amount of manual handling activities. Otto et al. (2017) compare the standard and linearized versions of the NIOSH equation, to balance the ER between picking zones. (Marvel et al., 2001) study the storage assignment decision, and a recommended weight limit is computed for each storage slot, depending on its height. Assembly line balancing is another common application, where the NIOSH equation is combined with other WMSD risk assessment methods to compute a holistic estimation of the ER of tasks, then balanced among workstations (Bautista et al., 2016a,b; Sana et al., 2019). The HAM is also used in workforce scheduling (Caballini and Paolucci, 2020), workforce assignment (Gebennini et al., 2018) or lot sizing (Andriolo et al., 2016). (Mateo et al., 2020) study a problem based on the newspaper printing industry, and use the NIOSH equation to compute a weight limit on a newspaper batch that is manually fed to the machines.

Concerning the JSI, it is used exclusively in relation to job rotation scheduling with the objective of minimizing the highest ER among all employees. In Carnahan et al. (2000), Tharmmaphornphilas and Norman (2004), the heterogeneity of the workforce is fully considered, and different working groups are constituted depending on their gender and lifting capacities. Tharmmaphornphilas and Norman (2007) and Carnahan et al. (2000) use the equations developed in Liles et al. (1984) to convert the JSI into lost days due to injuries, enabling the homogeneous integration of the ER in the objective function. Tharmmaphornphilas and Norman (2004) are interested in determining the optimal duration of a rotation in a job rotation schedule while accounting for the ER computed with the JSI.

Advantages. The NIOSH equation is a comprehensive and field-validated risk assessment method for manual handling tasks, based on biomechanical, physiological, and psychophysical criteria. The main advantage of this HAM is its widespread use in regulations and guidelines for handling work. It is, however, important to note that the NIOSH equation in its original form presents several non-linearities (especially concerning the frequency of the lifting tasks). The usual way to handle them is by making some assumptions and linear approximations (see

⁹ The National Institute for Occupational Safety and Health (NIOSH) Technical report No. 81-122 on the work practices for manual lifting of March 1981. <https://www.cdc.gov/niosh/docs/81-122/pdfs/81-122.pdf> Access: September 20, 2022.

¹⁰ The International Organization for Standards (ISO) standard 11228-1:2021 on manual handling. <https://www.iso.org/fr/standard/76820.html>.

¹¹ The European standard No. UNI EN 1005-2:2009 on manual handling of machinery and component parts of machinery. <https://www.boutique.afnor.org/en-gb/standard/nf-en-10052-a1/safety-of-machinery-human-physical-performance-part-2-manual-handling-of-ma/fa160747/32231>.

¹² The Occupational Safety and Health Administration (OSHA) final rule of the ergonomic program No. 29 CFR Part 1910 of November 2000. <https://www.govinfo.gov/content/pkg/FR-2000-11-14/pdf/00-28854.pdf> Access: September 20, 2022.

e.g., Otto et al. (2017) for more details), which reduce the modeling accuracy of the method. The JSI presents the advantage of being individualized. Its reliability is also validated by field studies. The other advantage is that the JSI is linear since it is computed as a time-average sum, and therefore it does not take into account the succession of high-intensity tasks. However, its computation requires anthropometric data on the individual performing the task, which can be complicated to obtain a priori.

5.3. Working posture

In this section, we present the WMSD risk assessment methods that focus on posture-related risks. The repetition of awkward postures is a major risk factor for the development of WMSDs (Bridger, 2018). There are mainly three postural risk assessment methods found in the collected material namely, the OWAS, the RULA, and the REBA. They are similar in their definition and computation, but differ in the body region they focus on.

Models. The *Ovako Working posture Assessment System (OWAS)* is a comprehensive postural assessment method developed by Karhu et al. (1977). It has been designed for a direct application in Ovako, a Finnish metal bars and profiles manufacturer, being thus focused on industrial applications. The OWAS is designed to be comprehensive and easy to use for untrained professionals, with non-ambiguous results even if it leads to some simplifications (Karhu et al., 1977). It assesses postures on the whole body by dividing it into three segments (back, arms and legs), with an additional factor corresponding to the weight of the handled load, if applicable. Based on expert opinions, a course of actions is recommended depending on the index value.

The *Rapid Upper Limb Assessment (RULA)* is a worksheet-based risk assessment method developed by McAtamney and Corlett (1993). It provides a quick risk assessment for the upper part of the body (upper limb, neck, and trunk), based on previous works on postural assessment, and fulfill the requirements of the European directive No. 90/270/EEC on the minimum safety and health requirements for work with display screen equipment.¹³ The RULA is based on a survey of the literature on postural risk assessment at the time of development (1993). A score is computed with the aid of a worksheet for each body segment, depending on the working angle of the segment on its sagittal plane, and the level of flexion or extension (McAtamney and Corlett, 1993). The overall score is adjusted by an additional score depending on muscle and force use. This score provides a guideline to assess the ER associated with the working postures.

The *Rapid Entire Body Assessment (REBA)* is a concise, worksheet-based, postural assessment method. It has been designed by a team of UK ergonomists (Hignett and McAtamney, 2000), to cover a large variety of working postures, especially those found in healthcare or other service industries. The REBA is intended as an extension of the RULA to account for the whole body and to address some of the flaws of the RULA, especially an improved definition of neutral postures (Madani and Dababneh, 2016). The computation of the REBA and RULA indexes are similar. The REBA divides the body into different segments, which are scored independently according to their movement planes. The scoring system considers additional risk factors as coupling scores in the computation: muscle activity, static or dynamic postures, repetition, handling, etc, and a corresponding risk level is given with a traffic light system.

¹³ The European Council directive No. 90/270/EEC on the minimum safety and health requirements for work with display screen equipment of May 1990. <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:31990L0270> Access: September 20, 2022.

Fields of application. In the collected material, postural risk assessment methods are often applied to assembly line balancing problems. Examples are found with the OWAS (Cheshmehgaz et al., 2012), the RULA (Bautista et al., 2016a,b), and the REBA (Bortolini et al., 2017). Interestingly, Cheshmehgaz et al. (2012) use a simplified version of the OWAS index to compute an “accumulated risk of postures” index, which has the particularity to increase quadratically with successive high-risk scores on the same body part, in order to favor posture changes during a shift. This idea of favoring posture change to mitigate the risk is also found in job rotation problems (Yoon et al., 2016; Sana et al., 2019). Unsurprisingly, warehousing is another important application of posture-related risk, as the order picking operations involve the repetition of awkward postures (Battini et al., 2017b; Gajsek et al., 2021). Calzavara et al. (2019a) study different rack layouts (i.e., full pallets on the floor, and half pallets on the floor and upper shelf) from the economic and ergonomic perspectives for order pickers, where ergonomic inputs are measured using a motion capture system. In some studies, the postural risk assessment methods are used in conjunction with other WMSD methods to get a holistic estimation of the ER, for instance, the NIOSH equation (Rinaldi et al., 2022), the OCRA (Bautista et al., 2016a), or the energy expenditure (Gajsek et al., 2021).

Advantages. The validity and pertinence of the OWAS have already been acknowledged (Battini et al., 2017b). The method is well suited for warehousing applications, as it considers the whole body and the different loads of material handling. However, the method lacks precision for complex activities, as several important body segments are not considered (neck, wrist), and only with static postures. Thus, the OWAS appears to provide a simplified and easy-to-use postural evaluation for most assembly activities. The RULA provides a comprehensive risk assessment method and is usable with only minimal formation. As with the other observational methods, the ease of use comes at a cost in terms of modeling accuracy. The RULA has been field-validated (McAtamney and Corlett, 1993) and presents the advantage of compliance with several regulations and guidelines. The REBA is very similar to the RULA, it is actually a more recent method that has been designed to address some of the flaws of the RULA index, especially the consideration of the whole body. Overall, the indexes computed with the two methods present a high correlation with each other in experimental studies. The REBA appears to be more suited for static and dynamic postures, with a large variety, whereas the RULA is more suited to seated work involving only the upper body (Madani and Dababneh, 2016). According to Madani and Dababneh (2016), the comparison between these three methods shows that overall none of them is better at assessing the ER than the others.

5.4. Repetitive movements

In this section, we present the HAMs related to repetitive handling movements, which are an important risk factor for the development of WMSDs (Bridger, 2018). The Operational Repetitive Actions (OCRA) index is the main HAM identified in this category.

Model. The OCRA index (Occhipinti, 1998) is a concise evaluation index designed to assess the risk of WMSDs for repetitive handling movements with a low load and a high frequency, based on epidemiological data. The OCRA index is the recommended evaluation method for repetitive actions by the ISO 11228-3 standard,¹⁴ as well as the European NF-EN 1005-5:2007 standard.¹⁵ The score is computed

¹⁴ The International Organization for Standardization (ISO) standard No. 11228-3:2007 on manual handling of low loads at high frequency. <https://www.iso.org/fr/standard/26522.html>.

¹⁵ The European standard No. NF-EN 1005-5:2007 on the safety of machinery. <https://www.boutique.afnor.org/en-gb/standard/nf-en-10055/safety-of-machinery-human-physical-performance-part-5-risk-assessment-for-r/fa104409/29388>.

separately for each hand. The final index is a ratio between the actual frequency of repetitions compared to the recommended one that depends on several factors. The recommended maximum frequency accounts for various risk factors (e.g., applied forces, postures, vibrations, or break frequency). For the general multitask model, a time-average aggregation is used, and a recommended course of actions is advised with a traffic light system based on the norm ISO 11228-3.

Fields of application. The OCRA index is designed for highly repetitive tasks. It is therefore not surprising that it is used in works related to assembly lines (Akyol and Baykasoglu, 2019; Zhang et al., 2020; Bautista et al., 2016b), and in job rotation scheduling problems (Mossa et al., 2016; Asensio-Cuesta et al., 2012b; Botti et al., 2020). Interesting applications include (Botti et al., 2017), which use the OCRA index to assign the different tasks in a hybrid manual/automated assembly line. Anzanello et al. (2014) apply the method in combination with learning to schedule tasks depending on their complexity. Şenyiğit et al. (2020) study the effects of the different OCRA parameters in a production scheduling context. They perform a statistical analysis on industrial data from a Turkish electrical appliance manufacturing plant, and the results show a statistically significant positive correlation between the OCRA index and the processing time.

Advantages. The OCRA index is a major risk assessment method used in assembly line optimization. It covers a large range of risk factors in this field (Şenyiğit et al., 2020) and complies with the recommendations of national and international standards. Moreover, the OCRA is rather accurate as it takes into account the cumulative ER over a whole shift, and accounts for side of the body separately. The drawback is the non-linearity of the method. Another limitation of this HAM is the lack of anthropometric input, since the index is computed for a workstation, and does not take into account the characteristics of the individual performing the work. Concerning the ease of implementation, the method requires some data collection to compute the different multipliers (especially the posture-related one), but provides good accuracy considering the number of inputs required.

6. Cognitive and psychosocial human factors

This section studies both the cognitive and psychosocial impacts of work on employees. Despite not being much studied in the OR literature, cognitive and psychosocial human factors have a strong impact on employees' health and performance and are large fields of study within HF/E (Bridger, 2018). This section covers the HAMS related to *motivation and boredom* in Section 6.1, *satisfaction and work preferences* in Section 6.2, *psychosocial and organizational factors* in Section 6.3 and *cognitive ER* in Section 6.4.

6.1. Motivation and boredom

Since boredom can be seen as a lack of motivation, they are treated together in this section. Boredom is often neglected in the literature, despite being a common complaint among employees and a cause of performance loss and high turnover (Fisher, 1993).

Models. Despite its importance, boredom is not easy to model, as it strongly depends on the considered individual and situation. Common modeling approaches include a varying productivity rate depending on the sequence of tasks (Wang et al., 2020), or the minimization of the maximal number of consecutive periods with the same task assignment among the employees (Bhadury and Radovilsky, 2006). Azizi et al. (2010) develop a new framework to take into account boredom, as well as learning/forgetting. Productivity increases with learning, then decreases due to boredom after some time, and a change of task induces a forgetting effect, but also a recovery of the boredom level. The model developed in Azizi et al. (2010) is extended by Azizi et al. (2013) with a focus on boredom. Three different models are presented, from a linear one easy to integrate into a mathematical model to a probabilistic Bayesian network.

Fields of application. Boredom is mostly applied to job rotation problems (Ayough et al., 2020; Azizi et al., 2010; Bhadury and Radovilsky, 2006), which is unsurprising considering that boredom reduction is one of the pursued goals when implementing a job rotation organization. Othman et al. (2012) study a workforce planning problem, where employees are clustered in homogeneous categories depending on their skills and personality traits. Boredom is then modeled as a multiplier affecting the processing time of the tasks depending on the employee category, and the time spent since the start of the shift. Wang et al. (2020) study a machine scheduling problem, where both fatigue and boredom affect the processing time of a task.

Advantages. The study of boredom is useful to integrate an important factor of performance variation in decision models (Fisher, 1993). The added complexity depends on the chosen model, but the tuning of boredom-related parameters might be a challenging task, considering the individual nature of motivation.

6.2. Satisfaction and work preferences

Employee satisfaction is shown to be an important factor of success for an organization (Taris and Schreurs, 2009). This factor is often ignored in workforce planning and scheduling models, despite the heterogeneity of employee preferences in terms of workload, task assignment, or shift types. An interested reader is referred to Larco Martinelli (2010) for a detailed study of the interactions between individual performance and job satisfaction in operations management.

Models. Employee preferences are most of the time simply modeled by a preference matrix, giving a score for an assignment employee/task (or employee/shift in longer planning horizons). The objective is to maximize the sum of preferences and thus the overall satisfaction (Brusco, 2015; Lazzarini and Pistolesi, 2018; Cheng and Kuo, 2016). Another way to model employee satisfaction is by considering their preferences in shift types and work duration. For instance, in Topaloglu and Ozkaran (2004) the employees have preferred lower and upper bounds for their workload during the planning horizon, as well as preferences on the shift types they work, weekends off, and the maximum number of consecutive workdays.

Fields of application. Employee preferences are mostly used in shift scheduling problems, where employees have shift preferences (Pan et al., 2010; Cheng and Kuo, 2016; Soriano et al., 2020), but other applications are found in workforce planning (Ruiz-Torres et al., 2015; Doan et al., 2022) or vehicle routing (Knust and Schumacher, 2011; Khaitan et al., 2022). Equity is often considered when dealing with preferences. Knust and Schumacher (2011) study a truck driver scheduling problem, and consider their preferences in terms of working time with a soft constraint on lower and upper bounds, but also their preferences related to the truck they are assigned to, or the number of truck changes for a driver in a working week.

Advantages. Employee satisfaction is challenging to model, and mostly tackled by shift preferences. This modeling has the advantage of being easy to integrate in decision models, and to provide a sound basis for equity computation.

6.3. Psychosocial and organizational factors

Psychosocial and organizational ergonomics are the major fields of study in HF/E and have been profusely studied (Bridger, 2018). In the OR literature, the organizational policy of a company constitutes a major concern, being mainly oriented to rationalizing and optimizing the quantitative management of operations. Organizational ergonomics has, however, not been studied much in the collected material.

Models. The modeling of psychosocial and organizational factors is mainly done using *ad hoc* problem definition, and no clear model appears.

Fields of application. The main topic of study relates to work team composition. Schultz et al. (2010) study the correlation between the productivity of employees working at nearby stations and show that, to some extent, employees tend to adapt their work pace to adapt it to their coworkers' pace, creating a regression to the mean of the processing times. Azadeh et al. (2017) study the team constitution in cell manufacturing, identify several decision-making styles (decisive, flexible, hierarchic, integrative, and systemic), and try to assign workers to cells accordingly. In Cheng and Kuo (2016), Anoshkina and Meisel (2020), one of the objectives is to maximize the team consistency between days, trying not to change the work team composition too often. Some studies deal with managerial policies, often in workforce planning and assignment problems (Fini et al., 2017; Shahbazi et al., 2019). Celano et al. (2004) study a U-shaped assembly line, and the different organizational strategies available to deal with line interruptions or bottlenecks.

Advantages. The works presented in this section focus on innovative problem definitions rather than the development of quantitative human-aware models. They present the advantage of modeling interesting industrial considerations.

6.4. Cognitive risk factors

The topic of the cognitive demand of task processing is not studied much in the collected material, although it can have a significant impact on workers' fatigue and is a major field of study within HF/E (Bridger, 2018).

Models. Several cognitive HAMs are used in the collected material. Dewi and Septiana (2015) use the NASA-TLX model, which is a widely used questionnaire-based assessment method of perceived cognitive workload. Li et al. (2018b) model the cognitive ER with the subjective workload assessment technique, which evaluates job difficulty by giving a 1–3 score to the three different criteria: time load, psychological effort load, and psychological stress load. Finally, Fini et al. (2017) study a workforce assignment problem applied to construction work, and develop a model accounting for the brain resource requirement of a task, which affects the productivity level.

Fields of application. Cognitive ER is applied to various problems, including shift scheduling (Dewi and Septiana, 2015), facility layout (Li et al., 2018b), workforce assignment (Fini et al., 2017) or assembly line balancing (Kara et al., 2014). Considering the low number of applications, no general trend emerges.

Advantages. Cognitive ER presents the advantage of integrating an often neglected aspect in optimization problems, even for the ones including human factors. Similarly to the physical ER assessment methods, several options exist for the integration within mathematical models depending on the specific HAM considered (i.e., constraint, objective, parameters).

7. Perceptual and environmental factors

Perceptual ergonomics deals with the perceptions of individuals in relation to their environment (e.g., hearing, sight, etc.), and is a major topic of study within HF/E (Bridger, 2018). However, this human aspect has not seen much attention from the OR community compared to physical-related factors. A reasonable explanation would be that physical risk factors are a more obvious source of work-related injuries and discomfort for an OR practitioner. Another probable explanation would be that perceptual risk factors are not particularly suited to integrate into the mainstream problems studied in the optimization of logistics and manufacturing systems. In this section, we study *noise exposure* in Section 7.1, *visual considerations* in Section 7.2, *heat exposure* in Section 7.3, and *vibration exposure* in Section 7.4.

7.1. Noise exposure

Noise nuisance in the industry is a widespread phenomenon, and more than 35% of the manufacturing operators are exposed to a daily noise level of 90dBA, according to the US National Institute of Occupational Safety and Health (see footnote 16). The main reported risks associated with exposure to high noise levels are direct hearing impairment and hearing loss (Irle et al., 1998). This exposure has also been linked to other serious physiological or psychological situations, including lack of concentration, drowsiness, or heart disease (Szalma and Hancock, 2011).

Models. The main model used to quantify noise exposure is the *Daily Noise Dosage (DND)*, a standard derived from NIOSH recommendations¹⁶ and OSHA guidelines¹⁷ on worker safety concerning noise exposure. For a given task, a maximum exposure duration is computed using the measured noise level. Then the DND score of the task corresponds to the ratio between the actual exposure duration, and its recommended maximum duration. The total exposure over a shift is the sum of these DND scores over the shift. A recommended course of action is derived from this score. Note that a short exposure to a high noise level may not be hazardous as the time of exposition is a key parameter in this context.

Fields of application. Application problems include job rotation, where the noise exposure is balanced among operators (Asawarungsaengkul and Nanthavanij, 2008; Rerkjirattikal and Olapiriyakul, 2021). Tharmaphornphilas and Norman (2004) use different risk factors (including noise exposure computed with the DND) in the application case of a sawmill, and try to determine the optimal length of the job rotation interval. Production scheduling is another important field of application (Kaya et al., 2020; Fu et al., 2020; Peng et al., 2022), where some authors make the distinction between *working* and *idle* machines in terms of noise emission (Lu et al., 2019). Interesting applications include Razavi et al. (2014), who study a design and worker assignment problem in a press shop, where the objective cost function integrates the potential purchase of noise isolation material, personal equipment, or noise source reduction.

Advantages. Noise exposure is the most studied “non-physical” ergonomic risk factor in the collected material. The DND presents the advantage of complying with several regulations and relying on a sound HF/E basis. The mathematical model is linear, and the required data is not too difficult to collect (i.e., the noise level on the different workstations).

7.2. Visual considerations

Visual considerations have not met great attention from the OR literature. Some works still try to integrate this HF with various modeling approaches.

Models. The modeling of visual factors is mainly done using *ad hoc* problem definition and models.

Fields of application. Al-Araidah et al. (2017) study a warehousing storage assignment problem, where the time to get visual contact with

¹⁶ The US National Institute for Occupational Safety and Health revised criteria for a recommended standard on noise exposure of 1998. <https://www.cdc.gov/niosh/docs/98-126/pdfs/98-126.pdf> Access: September 20, 2022.

¹⁷ The Occupational Safety and Health Administration guideline No 29 CFR 1910.95(b)(1) for noise enforcement (Appendix A) of 19 December 1983. <https://www.osha.gov/enforcement/directives/cpl-02-02-035> Access: September 20, 2022.

the items is accounted for, depending on the item position with respect to the picker visual field. In the vehicle routing literature, some authors study the visual attractiveness of the routes (Raghavendra et al., 1992; Hollis and Green, 2012). Pistolesi and Lazzerini (2019) study a problem related to the design of assembly lines, where operators work simultaneously on the product and visual fields of the employees are considered in the way they should not work on the same face of the product simultaneously.

Advantages. The works presented in this section focus more on innovative problem definitions rather than the development of quantitative human-aware models. They present the advantage of modeling interesting industrial considerations.

7.3. Heat exposure

It is not surprising that working in hot or cold climates is a risk factor for occupational injuries. In the collected material, only the case of hot temperatures is studied. Heavy physical work in the heat imposes conflicting demands on the cardiovascular system and is a risk factor for several occupational conditions: heat hyperpyrexia, heat exhaustion, heat syncope, or hyperventilation (Bridger, 2018).

Models. The estimation of the heat-related risk is not straightforward without actually measuring the body temperature of the individual (Lee, 1980). The *Heat Stress Model* is the main HAM found in the collected material to quantify heat exposure. This model has been introduced by Chan et al. (2012) in an empirical study, where individuals rated subjectively the stress and discomfort felt during an activity. Then multiple regression analyses are applied to infer this result from explanatory variables including environment factors (temperature, humidity, work duration, air pollution) and individual factors (age, resting heart rate, body fat, drinking and smoking habits).

Fields of application. If the protection against climatic conditions is not possible, or not efficient, the use of a work-rest schedule is recommended.¹⁸ Heat tolerance is thus often integrated into work-rest scheduling problems. Yi and Chan (2015) and Yi and Wang (2017) study such problems, with an application to construction workers in Hong-Kong, under heat stress conditions. Yi and Chan (2015) consider the weather conditions with a multi-scenario framework simulated by a Monte-Carlo approach, and the best work-rest schedule over the given scenarios is chosen. Heat exposure is also studied in production planning by Korkulu and Bona (2021), where a rest allowance is computed based on heat exposure.

Advantages. This HAM is very situational, since it is only relevant for specific applications. It presents the advantages of being linear and validated by a field study. However, it requires an extensive collection of personal data, which may be challenging to get with respect to the concerned legislation.

7.4. Vibration exposure

In the manufacturing industry, tools and machines may produce a high level of vibration exposure. This leads to the adoption of awkward postures or the use of excessive force as a coping mechanism by the operators. The consequence is the potential apparition of WMSDs. According to Krajnak (2018), workers in the manufacturing sector have a 74% chance of being exposed to vibrations. In 2015, 12.5% of them missed workdays due to pathologies associated with excessive exposure to vibrations.

Models. Some works in the collected material use the ISO 5349-1 standard,¹⁹ which defines a threshold for vibration exposure over a work shift. This HAM computes an exposure score based on the duration and vibration value of the tool used during the shift. Note that this is not linear with respect to the different tasks.

Fields of application. Working with an implicit metric, Kaya et al. (2020) study a machine scheduling problem embedded in a decision support system. Multiple criteria are considered, including vibrations. Finco et al. (2020a) study the design of an assembly line with both an objective of minimizing the equipment cost and the vibration exposure of employees, based on the ISO 5349-1 standard.

Advantages. This HAM is suited to specific applications, where vibration is an important risk factor. The modeling is non-linear, but requires little data collection. It presents the advantage of being based on an existing standard.

8. Additional considerations

In this section, we present a number of additional considerations, namely *anthropometric considerations* in Section 8.1, *biomechanical considerations* in Section 8.2, the *heterogeneity of the workforce* in Section 8.3, *health states* in Section 8.4, *human errors* in Section 8.5, *hazard exposure* in Section 8.6, *equity* in Section 8.7, *total cost functions* in Section 8.8, and *expert opinions and collaborations* in Section 8.9.

8.1. Anthropometric considerations

Anthropometry is the science of measuring the human body (Bridger, 2018). Anthropometric data are used extensively in HF/E, especially to specify the dimensions of workspaces and equipment. In the context of the optimization of manufacturing and logistical systems, anthropometry is used either to account for the physical heterogeneity of the workforce or to ensure that a task is designed to be comfortable for a large majority of the employees. When designing a task or a workstation to be suitable for the general working population, a common HF/E methodology using anthropometric data is to consider that it should fit 95% of the target population (depending on the age, gender, etc.) (Bridger, 2018). In the collected material, Al-Araidah et al. (2017) study order picking with vehicles, where items to pick are clustered so that the picker should be able to safely pick all items of a cluster within one stop of the vehicle. This is done by considering that 95% of the picker population should be able to do so without awkward postures. Mateo et al. (2020) address a problem arising in the printing industry, where the aim is to find an optimal batch size for a stack of paper, accounting for both economic and ergonomic considerations. The size of this stack is determined so that its weight and height are safe to handle by hand for the employees, based on anthropometric data on hand size. Huang and Pan (2014) study a job rotation problem, where an RGB-D camera is used to measure the anthropometric characteristics of the different employees. These data are then used to better assign tasks to employees.

8.2. Biomechanical considerations

The human body is a mechanical system. Its movements obey physical laws, and mechanical stress can occur on different body parts, especially articulations. This stress can ultimately lead to injuries, and a large part of the ER assessment methods presented in this paper (see Section 5) are based, to some extent, on biomechanical considerations. In this section, we present some works where a biomechanical method

¹⁸ The National Institute for Occupational Safety and Health (NIOSH) revised criteria for a recommended standard on occupational exposure to heat and hot environments in 2016. <https://www.cdc.gov/niosh/docs/2016-106/pdfs/2016-106.pdf> Access: September 20, 2022.

¹⁹ The International Organization for Standardization (ISO) standard No 5349-1:2001 on mechanical vibration <https://www.iso.org/standard/32355.html>.

is used directly in the modeling. Some works optimize over a large number of criteria, some of them being related to biomechanics. This is done, for example, by [Moussavi et al. \(2019\)](#), who study an assembly line balancing problem and use an in-house ER assessment method from the case company consisting of 20 criteria. Some of them are determined by biomechanical analysis of a video recording of the working postures. [Diego-Mas et al. \(2009\)](#) study a job rotation problem with 45 objective criteria grouped into 4 categories: movements, general capacities, mental capacities, and communication capacities.

Another method employed is the working posture analysis from a biomechanical point of view with a specialized software. For instance, [Glock et al. \(2019a\)](#) study a design problem related to the order picking area with rotating pallets. The authors perform field measurements on the working postures in the company under study and use them as input for the model of the software *4D Watbak*. These data are used to compute the peak compressive force active on the L4/L5 intervertebral joint, used as a risk measure for low back injuries. [Glock et al. \(2019c\)](#) investigate the industrial packaging process with the consideration of fatigue and recovery using the LFFRM model (see Section 4.4). The fatigue and recovery parameters are computed using *4D Watbak* with data on the different working postures and handled weights. In [Braun et al. \(1996\)](#), another biomechanical software is used to design workstations. [Carnahan et al. \(2001\)](#) use a biomechanical model to compute the grip strength fatigue in the context of an assembly line balancing problem.

8.3. Heterogeneity of the workforce

Considering the workforce heterogeneously is pertinent when modeling HFs since employees have different physical capabilities and personality traits. In the collected material, few research works integrate this aspect into their model. Indeed, taking into account heterogeneity increases substantially the complexity of the mathematical models (see [Prunet et al. \(2024\)](#), *Heterogeneous workforce*). Moreover, it requires the collection of personal data to be used in case studies. This can be delicate depending on the context, as the collection of personal data is regulated in several countries. The heterogeneous workforce is, however, used extensively in works related to skills, due to the differences between employees when skills are considered in an optimization model. The modeling of a heterogeneous workforce is also found, more seldom, in studies related to learning curves when employees are modeled individually. Other applications include works related to risk assessment methods when some parameters are individual-dependent, and cognitive HAMS accounting for the differences in terms of preferences, personalities or motivation levels. Sometimes only basic differences are accounted for, like age and gender ([Marichelvam et al., 2020](#); [Efe et al., 2018](#)), which constitute the first level of granularity in anthropometry ([Bridger, 2018](#)). An interested reader is directed to the first part of this review ([Prunet et al., 2024](#)) for a more substantial analysis, and to [Katirae et al. \(2021\)](#) for a dedicated review on the topic.

8.4. Health states

An interesting way to work with the risk of WMSDs is through health states. In this HAM, an employee can be in three different health states ([Sobhani et al., 2017](#)):

- Healthy, which is the normal state characterizing the health of an employee with no ergonomic problem.
- In-pain, when the employee stays at work, but has some pain due to poor ergonomic conditions.
- Injured, when the employee is absent from work due to a work-related injury.

These states are modeled through a Markov chain with given transition probabilities between them. The transition probabilities depend on several work-related risk factors, i.e., factors that are associated with an increased likelihood of occupational disease of physical (e.g., high repetitiveness, handling of heavy loads) or psychosocial (e.g., job control, overtime) nature. Most of the time, a logistic regression from epidemiological data is performed to compute the transition probabilities between the different health states and the impact of the different risk factors on them. Then the steady-state probability for an employee to be in a given health state can be computed. This is used to estimate the performance loss, mainly due to an increased error rate for in-pain employees, as well as a decreased productivity level. A model based on such a defined Markov chain integrates health states into a total cost function, accounting for performance loss and other indirect costs of poor working conditions: injury leave costs, increased insurance costs, hiring, training, and firing costs for short-term employees, and costs related to a high turnover rate. [Sobhani et al. \(2017\)](#) present in detail the described health state model, with an application on a serial production system. However, a rougher version of this model has been used earlier by [Sobhani et al. \(2015\)](#) in an investigation of the performances of a manufacturing system considering ergonomic risk factors. The model is applied successfully to the vendor-buying inventory model in [Sobhani et al. \(2019\)](#), also accounting for a varying error rate of an employee depending on his/her health state. [Sobhani and Wahab \(2017\)](#) study the impact of poor working conditions and work-related ill health effects on the carbon emissions of a manufacturing system.

8.5. Human errors

The error rate of a manual task is affected by HFs. The error rate and quality level are common considerations in OR. However, it is not always clear if the errors originate from the machines or the human operators. The topic related to the modeling of human errors appears in the collected material. An error rate is linked to the skill level (see Section 3.1), the fatigue level (see Section 4) or health states (see Section 8.4). It also relates to learning curves (see Section 3.2), where the quality improves over time. For instance, [Givi et al. \(2015a\)](#) improve the learning forgetting fatigue recovery model (see Section 4.4) by adding a quality learning curve. This model is used by [Givi et al. \(2015b\)](#), and the same idea of a quality learning curve is developed by [Jeang and Rahim \(2019\)](#) for a lot sizing problem. In [Jaber and Bonney \(2003\)](#), [Mosheiov and Sidney \(2003\)](#), the authors use an adaptation of the Wright learning curve to account for human errors, where the underlying idea is that errors need a rework, and thus an additional term on the task processing time. An extensive analysis of human errors in the kitting and feeding processes in assembly is performed by [Caputo et al. \(2017a,b\)](#), who introduce a detailed taxonomy and classification of errors. The classification process is detailed into an event tree accounting for all possible sources of errors and an estimation of the probability for each event. The aim is to compute the overall cost due to human errors in the kitting process. [Khan et al. \(2012, 2014\)](#) use a simpler classification of the human errors between type I (false positive) and type II (false negative) to model the inspection process of the customer in a two-level supply chain. This is also studied in [Shin et al. \(2018\)](#), [Gilotra et al. \(2020\)](#), where both error types are modeled through random variables with known probability density functions. [Khanna et al. \(2017\)](#) use the same model with rework times taken into account when errors occur. Other models of human errors are found in the collected material, e.g., [Zhao et al. \(2019\)](#) study manual order picking, where the error rate depends on the employee workload. In [Jamshidi and Seyyed Esfahani \(2014\)](#), the error rate increases for an employee when he/she reaches his exhaustion limit. [Sheikhalishahi et al. \(2019\)](#) study an open shop scheduling problem with preventive maintenance and human errors, modeled with the Human Error Assessment and Reduction Technique (HEART). Finally, the error rate is modeled with fuzzy numbers in [Salehi et al. \(2018\)](#).

8.6. Hazard exposure

An aspect that is not treated much so far is hazard exposure. Obviously, a lot of situations can expose workers to some kind of hazard, for example, repetitive actions (see Section 5.3) or material handling (see Section 5.2). Works in the literature focus specifically on chemical or nuclear hazard exposure, which is often subject to work regulations. This is modeled in Janiak and Kovalyov (2006, 2008), Sawik (2010) in the context of workforce scheduling in a contaminated area. In these works, the exposure level increases over time during a work period, and each work period must be followed by a rest period whose length depends exponentially on the exposure duration. Villeda and Dean (1990) also study a workforce scheduling problem in a toxic environment, where each job has an hourly exposure rate, and the daily exposure level for a worker should not exceed a threshold limit defined by the OSHA regulations.

8.7. Equity

Equity among employees is a legitimate concern when trying to optimize human well-being in a production or service system. From an OR perspective, this theme is rather common in the form of sharing the workload among different assembly lines/machines/work teams in order to get better utilization of the resources (e.g., to minimize the cycle time or the makespan). Therefore considering worker equity as a HAM fits well in classical optimization models, with a shift of interpretation between balancing workload between machines to balancing workload between employees. Karsu and Morton (2015) present a review of equity and balance in OR, including a taxonomy and an analysis of the different equity metrics and their modeling implications. Usually, the quantity that is balanced is the workload (Sadeghi et al., 2018; Pistolesi and Lazzerini, 2019; Yilmaz, 2020), or the ER quantified by a risk assessment method (von Elmbach et al., 2019; Moussavi et al., 2019; Bautista et al., 2016a). It is also quite common to find equity considerations in works related to the shift scheduling problem, expressed in terms of the number or the placement of days off (Prot et al., 2015; Nishi et al., 2014; Shuib and Kamarudin, 2019). There are also some interesting applications in vehicle routing, for example in Lehuédé et al. (2020), Matl et al. (2019), where the authors compare the resulting schedules obtained with different resources to be balanced among drivers (e.g., number of customers, route duration, load).

8.8. Total cost function

A total cost function is a useful way to integrate HF's into optimization models. The general idea is to convert a HF in a cost, and thus to consider it homogeneously in the objective function. This is done instead of using a weighted sum of different objective functions that requires the intervention of the decision-maker to fine-tune the weights. More details on the mathematical impact of such a formulation can be found in (Prunet et al. (2024), *Multi-objective optimization*).

The most obvious place to work with total cost functions is in problems related to the Human Resource decisions about the workforce, i.e., hiring, firing, and training costs. This is especially the case when considering the training costs, related to non-productive time during the training of an employee to a new skill. This is found, for example, in Gans and Zhou (2002), Othman et al. (2012), McDonald et al. (2009). In some works, the different skills are also accounted for in the wages of employees (Moon et al., 2009). Kim et al. (2013) also consider a cost for holding the skilled employees, consisting of their wages during periods, where there is an overcapacity of the workforce and employees are not laid off. Another classical term in total cost functions relates to human errors. A higher error rate has a financial impact due to a higher scrap rate or to wages and machine times that were unproductive after the quality check (Givi et al., 2015b).

An interesting approach to consider HF's in a financial objective function is to model fatigue and break time with the rest allowance (see Section 4.2). The more exhaustive a task, the more time an employee needs to rest to keep the ER at a reasonable level. However, this unproductive rest time is part of the total working time of the employee, and should thus be counted as an additional wage cost. This is described by Battini et al. (2017b), who propose a model to estimate the additional cost due to poor ergonomic conditions via a lessened availability of the workforce due to injuries or absenteeism. They also include costs related to injuries and sick leaves. Additional working time can also be due to boredom, leading to lower productivity, and thus an additional overtime cost (Azizi et al., 2010). Zhang et al. (2019) account in their model for an additional cost for unplanned downtime due to safety issues. It is computed based on the wages of unplanned idle workers.

Health states (see Section 8.4) also provide an interesting model for the indirect cost of poor working conditions. In the model proposed by Sobhani et al. (2015, 2017), Sobhani and Wahab (2017), a Markov chain is used to determine the steady state of the number of injured employees and consequent sick leaves. This value is then used to compute the indirect costs of such leaves. It accounts for performance loss, injury leave costs, increased insurance costs, hiring, training, and firing costs for replacing the injured employees with short-term workers, and, finally, to compensate for the higher turnover rate linked to the degraded working conditions. Finally, an interesting approach is to consider the cost of additional protections that lower the ER. Kara et al. (2014) account for the personal protection equipment to reduce the ER. This is also the case of Razavi et al. (2014) to lower noise exposure, by considering protective equipment to lower the emission level of a source, and isolation materials to reduce its diffusion. Cui et al. (2020) study a coal production problem and account for the investment cost in terms of social benefits.

8.9. Expert opinions/collaborations

Several methods presented in this paper require extensive data collection and/or parameter tuning for the models to be applied in a real-life case. These data have to be collected by a field investigation that is time-consuming and often requires knowledge and know-how that are out of the skill set of most OR academics. To tackle this issue, the simplest approach is to work in collaboration with HF/E practitioners: The two disciplines are indeed strongly connected in their applications. Yet true multidisciplinary research is seldom encountered in the literature, despite the important benefits both sides can gain from a mutual understanding. Ryan et al. (2011) provide a very insightful discussion on the interactions between HF/E and OR.

The other way for an operations researcher to estimate the missing parameters is through expert estimation from a seasoned industrial practitioner. This is the case, for example, in the work of Anzanello et al. (2014), who studies a machine scheduling problem applied to a footwear industrial case with learning and task complexity accounted for. The complexity value of the different tasks is defined by an expert rating. Zhang et al. (2019) study a workforce assignment problem with a focus on the safety of the employees. They take into account the task complexity and the strength and weakness of the different employees to optimize the assignment. The used parameters are estimated by an expert in an industrial case study in a company working in the iron and steel industry. In Lazzerini and Pistolesi (2018), the workforce assignment accounts for the risk sensitivity of the employees toward the different tasks. Each task has a risk level, and a set of prevention strategies can be used by employees to cope with it, allowing the decision-maker to compute the carefulness of the employees. The risk level of different tasks and the mitigation level of the prevention strategies are assessed by an expert rating.

Other forms of collaboration include the use of structured or semi-structured interviews as inputs in mathematical models. Indeed, these

techniques are part of the skill set of an ergonomist but are hardly replicable for an OR academic. Larco et al. (2017) study a storage-related problem in warehousing, where the discomfort rating of the different tasks is computed using statistical regressions from the employee opinions. Kazemi et al. (2016b) study a production planning problem with learning and forgetting effects. The learning and forgetting parameters are estimated based on semi-structured interviews. In Tiacci and Mimmi (2018), the ER is computed using the OCRA index (see Section 5.4), and some of the task parameters are estimated using the worker perception of the task using a 1-10 scale.

9. Future research directions

The analysis of the collected material highlights numerous research gaps in the literature, as well as promising research directions. In this section, we present research opportunities that are focused on HAMs. The interested reader is referred to the first part of this study (Prunet et al., 2024) for additional insights from the literature and research directions focusing on applications. Section 9.1 highlights under-represented areas of study and Section 9.2 provides research directions for the development of new HAMs.

9.1. Under-represented areas of study

Further work on cognitive and psychosocial ergonomics. In the collected material of this review, the topics of cognitive and psychosocial ergonomics are very rarely studied. Indeed, when applying HF/E methodologies, the work focuses mostly on physical risk factors for the development of WMSD and injuries. However, in the HF/E literature, cognitive and psychosocial ergonomics are major fields of studies (Stanton et al., 2004), and major risk factors for the development of work-related injuries and conditions. These HFs are perhaps less straightforward to consider and model for an OR practitioner, compared to physical ones, however further research in this direction would help to reduce the gap between OR and HF/E. Moreover, cognitive and psychosocial ergonomics are linked to the management and organization of the work, which somehow relates to a large number of topics studied in OR.

Job satisfaction. This is an important factor for both employee performance, and ergonomic risk (Larco Martinelli, 2010), yet the topic is not studied much in the literature. Satisfaction is mainly modeled through shift preferences, and implicitly in job rotation models. More works should study the impact of job satisfaction on decision models. For instance, the integration of goal-setting theory (Locke and Latham, 2002; Larco Martinelli, 2010) in optimization models presents an interesting direction for future research.

Long-term impact of human factors. More works should study the long-term impact of human factors in the optimization of logistics and manufacturing systems. Indeed, most studies focus on short-term impacts (i.e., on a work shift), which do not account for certain effects. For instance, poor ergonomics leads to injuries and sick leave, which has an economic impact. For instance, the work of Sobhani et al. (2015, 2017) on health states account for indirect costs, such as injury leave costs, increased insurance costs, hiring, training, and firing costs for short-term employees, and costs related to a high turnover rate. This kind of models is useful to highlight that improving working conditions may also have a positive impact on the company revenue.

Data-driven models. An interesting direction for future research would be the integration of real-time data (e.g., heartbeat, posture with motion capture, etc.) into optimization models. These problems could be solved by online optimization, where, for example, the assignment of tasks to employees changes dynamically depending on the fatigue level of operators. To the best knowledge of the authors, no such models have been studied in the optimization literature. Another possibility to integrate real data could be the adaptation of the instructions for operators based on their fatigue levels or skill levels (Peltokorpi et al., 2023).

9.2. Development of new HAMs

New ergonomic risk assessment methods. A large number of ER assessment methods come from HF/E. They are therefore designed to fit the needs of ergonomic practitioners expressed in forms that are not necessarily common and convenient for OR researchers. Indeed, these methods are designed to be accurate in their assessment of the risk level, and easy to use for an ergonomist, for example, a concise and comprehensive pen-and-paper worksheet that can be easily applied to a field study. However, this is quite far from the needs of an optimization practitioner, for several reasons:

- They are designed to evaluate an existing work situation, whereas OR mostly focus on prescriptive analysis, on how to design a system to optimize some objective functions.
- Since they evaluate existing situations, they require extensive data collection on-site. Yet, most OR researchers do not have the knowledge and experience to perform such a field study. Without collaboration with ergonomists, it will be difficult to validate the models with real-life data.
- Most of the time their models do not have convenient mathematical properties for optimization models, such as convexity or linearity.

An interesting line of study would be to design new methods for risk estimation or adapt existing ones to overcome these downsides. For example, the work of Battini et al. (2016a) uses motion capture systems to provide tables that translate basic elementary movements in their energy expenditure equivalent, in the context of assembly work. Obviously, there is always a risk of accuracy loss in the risk modeling by avoiding field studies, however, a trade-off between accuracy and ease of use can be made in the design of risk estimation methods.

Refinement of learning curve models. Learning is probably the most studied topic in this literature review. However, a lot of optimization works on the topic use simple learning curve models, whose limitations have been highlighted (Anzanello and Fogliatto, 2011; Glock et al., 2019b). Two promising research directions appear from the study of the learning literature. First, the development of more refined models, to account for multiple factors and close the gap between theory and field studies. For instance, Jaber et al. (2021) adjust learning curve models to account for the *cognitive interference*, an effect borrowed from psychology that model the limited working memory when learning by repeating a task. Second, the integration of modern learning curve models into optimization problems, to better estimate individual performances in optimization models by taking advantage of the more refined models.

Integrated models. An interesting direction for future research is the development of HAMs that integrate several HFs. Indeed, most HAMs focus on a single HF, yet decision problems often integrate several HFs. It is always possible to combine different HAMs in a model, but their quantitative values may not be comparable if they come from different theories. The development, and tuning, of integrated models prevent this drawback. For instance, the LFFRM (see Section 4.4) accounts for both learning/forgetting and fatigue/recovery to estimate the productivity of an individual.

10. Conclusions

In this second part of our literature review work, the conducted study focuses on human-aware models for human factors. From the large corpus of literature related to logistics and manufacturing optimization, we extracted the existing methods used to represent and quantify HFs. We propose a map of identified human aspects to better locate their integration points into optimization models. For each of them, we provide a comprehensive list of HAMs, which enable the quantification of the inherently fuzzy human characteristics.

With the whole review work (first and second parts), we presented a broad picture of the integration of optimization models with Human-Aware Modeling in the scope of logistics and manufacturing. We believe that this topic will gain importance in the coming years, both in the academic literature and in industrial applications. The increasing number of regulations on working conditions, as well as the pressure on stakeholders to tend toward more sustainable systems, are pushing more and more decision-makers and planners to account for human aspects in their models. Therefore an increasing number of OR academics and practitioners are interested in this topic, which share goals and methods with other scientific disciplines they do not necessarily have a background in. We believe that this work will help to bridge this gap, by providing interested researchers and practitioners a guide of the suitable HFs to integrate into their work, and the corresponding HAMs.

Some HAMs have been more thoroughly studied than others. Historically, the performance assessment models (e.g., learning) and the hard operative constraints (e.g., skills compatibility) are predominant in the literature. Recent developments focus more on the integration of HF/E within OR with the aim of improving employee welfare and safety at work. Increased collaboration between the two disciplines has led to the creation of new research directions, and overall improved accuracy in the modeling of human characteristics, especially related to WMSD risk assessment. However, there are still many research gaps and interesting directions to follow for future work. The development of human-aware optimization has the potential to leverage working conditions in real-life applications, but also economic objectives with more accurate modeling of some human-related aspects of a system, and the reduction of indirect costs from poor ergonomic conditions in a workplace (e.g., sick leave, absenteeism). This aligns with the societal aspirations of our society, with *decent working conditions* being one of the goals of the United Nations 2030 Agenda of sustainable development.²⁰ To conclude this work, we introduce this declaration from the former General Secretary of the United Nations Kofi Annan:

Health and safety at work is not just sound economic policy, it is a basic human right.

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.

Acknowledgments

We kindly thank the two anonymous reviewers for their careful reading of the paper and their valuable comments that allowed to highly improve the quality of the manuscript. This work has been supported by the French National Research Agency through the AGIRE project under the grant ANR-19-CE10-0014.²¹ This support is gratefully acknowledged.

References

- Akyol, S.D., Baykasoglu, A., 2019. ErgoALWABP: A multiple-rule based constructive randomized search algorithm for solving assembly line worker assignment and balancing problem under ergonomic risk factors. *J. Intell. Manuf.* 30 (1), 291–302, Place: Dordrecht Publisher: Springer WOS:000456588800022.
- Akyol, S., Baykasoglu, A., 2019. A multiple-rule based constructive randomized search algorithm for solving assembly line worker assignment and balancing problem. *J. Intell. Manuf.* 30 (2), 557–573.

²⁰ The resolution A/RES/70/1 of the seventieth general assembly of the United Nations of 21 October 2015 on the 2030 Agenda of sustainable development. <https://sdgs.un.org/2030agenda> Access: September 20, 2022.

²¹ <https://anr.fr/Projet-ANR-19-CE10-0014>

- Al-Araidah, O., Dalalah, D., Azeez, M.A.-A., Khasawneh, M.T., 2017. A heuristic for clustering and picking small items considering safe reach of the order picker. *Eur. J. Ind. Eng.* 11 (2), 256–269, Place: Geneva Publisher: Inderscience Enterprises Ltd WOS:000397842000006.
- Al-Zuheri, A., Luong, L., Xing, K., 2013. Prediction and analysis impact of operational design of a manual assembly system with walking workers on performance. *Int. J. Comput. Integr. Manuf.* 26 (6), 540–560, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000319325400005.
- Al-Zuheri, A., Luong, L., Xing, K., 2016. Developing a multi-objective genetic optimisation approach for an operational design of a manual mixed-model assembly line with walking workers. *J. Intell. Manuf.* 27 (5), 1049–1065, Place: Dordrecht Publisher: Springer WOS:000382682400010.
- Amirian, H., Sahraeian, R., 2015. Augmented epsilon-constraint method in multi-objective flowshop problem with past sequence set-up times and a modified learning effect. *Int. J. Prod. Res.* 53 (19), 5962–5976.
- Andriolo, A., Battini, D., Persona, A., Sgarbossa, F., 2016. A new bi-objective approach for including ergonomic principles into EOQ model. *Int. J. Prod. Res.* 54 (9), 2610–2627.
- Anoshkina, Y., Meisel, F., 2020. Interday routing and scheduling of multi-skilled teams with consistency consideration and intraday rescheduling. *EURO J. Transp. Logist.* 9 (3).
- Anzanello, M., Fogliatto, F., 2010. Scheduling learning dependent jobs in customised assembly lines. *Int. J. Prod. Res.* 48 (22), 6683–6699.
- Anzanello, M.J., Fogliatto, F.S., 2011. Learning curve models and applications: Literature review and research directions. *Int. J. Ind. Ergon.* 41 (5), 573–583, Place: Amsterdam Publisher: Elsevier WOS:000295242700019.
- Anzanello, M., Fogliatto, F., Santos, L., 2014. Learning dependent job scheduling in mass customized scenarios considering ergonomic factors. *Int. J. Prod. Econ.* 154, 136–145.
- Aryanezhad, M., Deljoo, V., Mirzapour Al-E-Hashem, S., 2009. Dynamic cell formation and the worker assignment problem: A new model. *Int. J. Adv. Manuf. Technol.* 41 (3), 329–342.
- Asawarungsangkul, K., Nanthavanij, S., 2008. Heuristic genetic algorithm for workforce scheduling with minimum total worker-location changeover. *Int. J. Ind. Eng.-Theory Appl. Pract.* 15 (4), 373–385, Place: Cincinnati Publisher: Univ Cincinnati Industrial Engineering WOS:000207714000005.
- Asensio-Cuesta, S., Diego-Mas, J., Canós-Darós, L., Andrés-Romano, C., 2012a. A genetic algorithm for the design of job rotation schedules considering ergonomic and competence criteria. *Int. J. Adv. Manuf. Technol.* 60 (9), 1161–1174.
- Asensio-Cuesta, S., Diego-Mas, J., Cremades-Oliver, L., González-Cruz, M., 2012b. A method to design job rotation schedules to prevent work-related musculoskeletal disorders in repetitive work. *Int. J. Prod. Res.* 50 (24), 7467–7478.
- Aykin, T., 1998. A composite branch and cut algorithm for optimal shift scheduling with multiple breaks and break windows. *J. Oper. Res. Soc.* 49 (6), 603–615.
- Ayoub, M.M., Bethea, N.J., Deivanayagam, S., Asfour, S.S., Bakken, G.M., 1978. Determination and Modeling of Lifting Capacity. *Tech. Rep. PB88237805*, Texas Tech Univ., Lubbock. Inst. for Biotechnology.; National Inst. for Occupational Safety and Health, Cincinnati, OH., Num Pages: 287. URL <https://ntrl.ntis.gov/NTRL/dashboard/searchResults/titleDetail/PB88237805.xhtml>.
- Ayoub, M.M., Selan, J.L., Liles, D.H., 1983. An ergonomics approach for the design of manual materials-handling tasks. *Hum. Factors* 25 (5), 507–515. <http://dx.doi.org/10.1177/001872088302500505>, Publisher: SAGE Publications Inc.
- Ayough, A., Zandieh, M., Farhadi, F., 2020. Balancing, sequencing, and job rotation scheduling of a U-shaped lean cell with dynamic operator performance. *Comput. Ind. Eng.* 143, 106363, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000525872600003.
- Azadeh, A., Ravanbakhsh, M., Rezaei-Malek, M., Sheikhalishahi, M., Taheri-Moghaddam, A., 2017. Unique NSGA-II and MOPSO algorithms for improved dynamic cellular manufacturing systems considering human factors. *Appl. Math. Model.* 48, 655–672, Place: New York Publisher: Elsevier Science Inc WOS:000403994400037.
- Azizi, N., Liang, M., Zolfaghari, S., 2013. Modelling human boredom at work: Mathematical formulations and a probabilistic framework. *J. Manuf. Technol. Manag.* 24 (5), 711–746.
- Azizi, N., Zolfaghari, S., Liang, M., 2010. Modeling job rotation in manufacturing systems: The study of employee's boredom and skill variations. *Int. J. Prod. Econ.* 123 (1), 69–85.
- Battini, D., Calzavara, M., Otto, A., Sgarbossa, F., 2017a. Preventing ergonomic risks with integrated planning on assembly line balancing and parts feeding. *Int. J. Prod. Res.* 55 (24), 7452–7472, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000423135100012.
- Battini, D., Calzavara, M., Persona, A., Sgarbossa, F., 2017b. Additional effort estimation due to ergonomic conditions in order picking systems. *Int. J. Prod. Res.* 55 (10), 2764–2774.
- Battini, D., Delorme, X., Dolgui, A., Persona, A., Sgarbossa, F., 2016a. Ergonomics in assembly line balancing based on energy expenditure: A multi-objective model. *Int. J. Prod. Res.* 54 (3), 824–845, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000370669400012.
- Battini, D., Faccio, M., Persona, A., Røpke, S., Zanin, G., 2015. Routing strategy in a distribution network when the driver learning effect is considered. *Int. J. Logist. Syst. Manag.* 21 (3), 385–411.

- Battini, D., Glock, C., Grosse, E., Persona, A., Sgarbossa, F., 2016b. Human energy expenditure in order picking storage assignment: A bi-objective method. *Comput. Ind. Eng.* 94, 147–157.
- Battini, D., Glock, C.H., Grosse, E.H., Persona, A., Sgarbossa, F., 2017c. Ergo-lot-sizing: An approach to integrate ergonomic and economic objectives in manual materials handling. *Int. J. Prod. Econ.* 185, 230–239, Place: Amsterdam Publisher: Elsevier Science Bv WOS:000395222400020.
- Bautista, J., Alfaro-Pozo, R., Batalla-García, C., 2016a. Maximizing comfort in assembly lines with temporal, spatial and ergonomic attributes. *Int. J. Comput. Intell. Syst.* 9 (4), 788–799, Place: Paris Publisher: Atlantis Press WOS:000379938400016.
- Bautista, J., Batalla-García, C., Alfaro-Pozo, R., 2016b. Models for assembly line balancing by temporal, spatial and ergonomic risk attributes. *European J. Oper. Res.* 251 (3), 814–829.
- Bechtold, S., 1979. Quantitative models for optimal rest period scheduling: A note. *Omega* 7 (6), 565–566.
- Bechtold, S., 1991. Optimal work-rest schedules with a set of fixed-duration rest periods. *Decis. Sci.* 22 (1), 157–170.
- Bechtold, S., Janaro, R., Sumners, D., 1984. Maximization of labor productivity through optimal rest-break schedules. *Manage. Sci.* 30 (12), 1442–1458, Place: Linthicum Hts Publisher: Inst Operations Research Management Sciences WOS:A1984AAP4000004.
- Bechtold, S., Thompson, G., 1993. Optimal scheduling of a flexible-duration rest period for a work group. *Oper. Res.* 41 (6), 1046–1054, Place: Linthicum Hts Publisher: Operations Research Soc Amer WOS:A1993MR00300004.
- Benjamin, A., Beasley, J., 2010. Metaheuristics for the waste collection vehicle routing problem with time windows, driver rest period and multiple disposal facilities. *Comput. Oper. Res.* 37 (12), 2270–2280.
- Van den Bergh, J., Belien, J., De Bruecker, P., Demeulemeester, E., De Boeck, L., 2013. Personnel scheduling: A literature review. *European J. Oper. Res.* 226 (3), 367–385, URL <https://www.sciencedirect.com/science/article/pii/S0377221712008776>.
- Bhadury, J., Radovitsky, Z., 2006. Job rotation using the multi-period assignment model. *Int. J. Prod. Res.* 44 (20), 4431–4444.
- Biskup, D., 1999. Single-machine scheduling with learning considerations. *European J. Oper. Res.* 115 (1), 173–178.
- Bonutti, A., Ceschia, S., De Cescio, F., Musliu, N., Schaerf, A., 2017. Modeling and solving a real-life multi-skill shift design problem. *Ann. Oper. Res.* 252 (2), 365–382.
- Bordoloi, S.K., Matsuo, H., 2001. Human resource planning in knowledge-intensive operations: A model for learning with stochastic turnover. *European J. Oper. Res.* 130 (1), 169–189, Place: Amsterdam Publisher: Elsevier Science Bv WOS:000167031900014.
- Bortolini, M., Faccio, M., Gamberi, M., Pilati, F., 2017. Multi-objective assembly line balancing considering component picking and ergonomic risk. *Comput. Ind. Eng.* 112, 348–367.
- Botti, L., Calzavara, M., Mora, C., 2020. Modelling job rotation in manufacturing systems with aged workers. *Int. J. Prod. Res.*
- Botti, L., Mora, C., Regattieri, A., 2017. Integrating ergonomics and lean manufacturing principles in a hybrid assembly line. *Comput. Ind. Eng.* 111, 481–491, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000410468600040.
- Bowden, Z.E., Ragsdale, C.T., 2018. The truck driver scheduling problem with fatigue monitoring. *Decis. Support Syst.* 110, 20–31, Place: Amsterdam Publisher: Elsevier Science Bv WOS:000433273000003.
- Brandao, J., Mercer, A., 1997. A tabu search algorithm for the multi-trip vehicle routing and scheduling problem. *European J. Oper. Res.* 100 (1), 180–191, Place: Amsterdam Publisher: Elsevier Science Bv WOS:A1997XG48100013.
- Braun, W., Rebollars, R., Schiller, E., 1996. Computer aided planning and design of manual assembly systems. *Int. J. Prod. Res.* 34 (8), 2317–2333.
- Bridger, R.S., 2018. Introduction to Human Factors and Ergonomics. CRC Press, OCLC: 987376231.
- Brusco, M.J., 2008. An exact algorithm for a workforce allocation problem with application to an analysis of cross-training policies. *IIE Trans.* 40 (5), 495–508, Place: Philadelphia Publisher: Taylor & Francis Inc WOS:000254486200001.
- Brusco, M., 2015. A bicriterion algorithm for the allocation of cross-trained workers based on operational and human resource objectives. *European J. Oper. Res.* 247 (1), 46–59.
- Brusco, M.J., Jacobs, L.W., 2000. Optimal models for meal-break and start-time flexibility in continuous tour scheduling. *Manage. Sci.* 46 (12), 1630–1641, Place: Linthicum Hts Publisher: Inst Operations Research Management Sciences WOS:000166263400009.
- Bukchin, Y., Cohen, Y., 2013. Minimising throughput loss in assembly lines due to absenteeism and turnover via work-sharing. *Int. J. Prod. Res.* 51 (20), 6140–6151, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000327867500010.
- Caballini, C., Paolucci, M., 2020. A rostering approach to minimize health risks for workers: An application to a container terminal in the Italian port of Genoa. *Omega-Int. J. Manag. Sci.* 95, 102094, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000534416300011.
- Cai, X., Li, K., 2000. Genetic algorithm for scheduling staff of mixed skills under multi-criteria. *European J. Oper. Res.* 125 (2), 359–369.
- Calzavara, M., Glock, C., Grosse, E., Persona, A., Sgarbossa, F., 2017. Analysis of economic and ergonomic performance measures of different rack layouts in an order picking warehouse. *Comput. Ind. Eng.* 111, 527–536.
- Calzavara, M., Glock, C., Grosse, E., Sgarbossa, F., 2019a. An integrated storage assignment method for manual order picking warehouses considering cost, workload and posture. *Int. J. Prod. Res.* 57 (8), 2392–2408.
- Calzavara, M., Persona, A., Sgarbossa, F., Visentin, V., 2019b. A model for rest allowance estimation to improve tasks assignment to operators. *Int. J. Prod. Res.* 57 (3), 948–962, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000460630300018.
- Caputo, A.C., Pelagagge, P.M., Salini, P., 2017a. Modeling errors in parts supply processes for assembly lines feeding. *Ind. Manag. Data Syst.* 117 (6), 1263–1294, Place: Bingley Publisher: Emerald Group Publishing Ltd WOS:000407077300014.
- Caputo, A.C., Pelagagge, P.M., Salini, P., 2017b. Modelling human errors and quality issues in kitting processes for assembly lines feeding. *Comput. Ind. Eng.* 111, 492–506, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000410468600041.
- Carnahan, B.J., Norman, B.A., Redfern, M.S., 2001. Incorporating physical demand criteria into assembly line balancing. *IIE Trans.* 33 (10), 875–887, Place: Dordrecht Publisher: Kluwer Academic Publ WOS:000168971700005.
- Carnahan, B.J., Redfern, M.S., Norman, B., 2000. Designing safe job rotation schedules using optimization and heuristic search. *Ergonomics* 43 (4), 543–560, Place: London Publisher: Taylor & Francis Ltd WOS:000086519100008.
- Cavagnini, R., Hewitt, M., Maggioni, F., 2020. Workforce production planning under uncertain learning rates. *Int. J. Prod. Econ.* 225, 107590, Place: Amsterdam Publisher: Elsevier WOS:000532795300024.
- Celano, G., Costa, A., Fichera, S., Perrone, G., 2004. Human factor policy testing in the sequencing of manual mixed model assembly lines. *Comput. Oper. Res.* 31 (1), 39–59, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000185555500003.
- Ceselli, A., Righini, G., Salani, M., 2009. A column generation algorithm for a rich vehicle-routing problem. *Transp. Sci.* 43 (1), 56–69, Place: Catonsville Publisher: Inform WOS:000263720200006.
- Chan, A.P., Yam, M.C., Chung, J.W., Yi, W., 2012. Developing a heat stress model for construction workers. *J. Facil. Manage.* 10 (1), 59–74. <http://dx.doi.org/10.1108/14725961211200405>, Publisher: Emerald Group Publishing Limited.
- Chen, S., Shen, Y., Su, X., Chen, H., 2013. A crew scheduling with Chinese meal break rules. *J. Transp. Syst. Eng. Inf. Technol.* 13 (2), 90–95.
- Cheng, C.-H., Kuo, Y.-H., 2016. A dissimilarities balance model for a multi-skilled multi-location food safety inspector scheduling problem. *IIE Trans.* 48 (3), 235–251, Place: Philadelphia Publisher: Taylor & Francis Inc WOS:000375232400004.
- Cheng, T., Wang, G., 2000. Single machine scheduling with learning effect considerations. *Ann. Oper. Res.* 98 (1), 273–290.
- Cheshmehgazi, H., Haron, H., Kazemipour, F., Desa, M., 2012. Accumulated risk of body postures in assembly line balancing problem and modeling through a multi-criteria fuzzy-genetic algorithm. *Comput. Ind. Eng.* 63 (2), 503–512.
- Coelho, L.C., Gagliardi, J.-P., Renaud, J., Ruiz, A., 2016. Solving the vehicle routing problem with lunch break arising in the furniture delivery industry. *J. Oper. Res. Soc.* 67 (5), 743–751. <http://dx.doi.org/10.1057/jors.2015.90>.
- Condeixa, L., Silva, P., Moah, D., Farias, B., Leiras, A., 2020. Evaluating cost impacts on reverse logistics using an economic order quantity (EOQ) model with environmental and social considerations. *CEJOR Cent. Eur. J. Oper. Res.*
- Costa, A., Cappadonna, F.A., Fichera, S., 2014. Joint optimization of a flow-shop group scheduling with sequence dependent set-up times and skilled workforce assignment. *Int. J. Prod. Res.* 52 (9), 2696–2728, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000334051300013.
- Cui, Z., Zhang, J., Wu, D., Cai, X., Wang, H., Zhang, W., Chen, J., 2020. Hybrid many-objective particle swarm optimization algorithm for green coal production problem. *Inform. Sci.* 518, 256–271.
- Dar-El, E., Ayas, K., Gilad, I., 1995. A dual-phase model for the individual learning process in industrial tasks. *IIE Trans.* 27 (3), 265–271. <http://dx.doi.org/10.1080/07408179508936740>, Publisher: Taylor & Francis.
- De Bruecker, P., Van den Bergh, J., Belien, J., Demeulemeester, E., 2015. Workforce planning incorporating skills: State of the art. *European J. Oper. Res.* 243 (1), 1–16, Place: Amsterdam Publisher: Elsevier WOS:000349592500001.
- De Jong, J.R., 1957. The effects of increasing skill on cycle time and its consequences for time standards. *Ergonomics* 1 (1), 51–60. <http://dx.doi.org/10.1080/00140135708964571>, Publisher: Taylor & Francis.
- Dewi, D., Septiana, T., 2015. Workforce scheduling considering physical and mental workload: A case study of domestic freight forwarding. *Procedia Manuf.* 4, 445–453.
- Diefenbach, H., Glock, C.H., 2019. Ergonomic and economic optimization of layout and item assignment of a U-shaped order picking zone. *Comput. Ind. Eng.* 138, UNSP 106094. Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000500375600004.
- Diego-Mas, J.A., Asensio-Cuesta, S., Sanchez-Romero, M.A., Artacho-Ramirez, M.A., 2009. A multi-criteria genetic algorithm for the generation of job rotation schedules. *Int. J. Ind. Ergon.* 39 (1), 23–33, Place: Amsterdam Publisher: Elsevier WOS:000263007600004.
- Doan, M.P., Fondreville, J., Botta-Genoulaz, V., Ribeiro, J.F.F., 2022. Impact of flexible work contracts and multi-skilled agents on a multi-objective workforce planning problem. *Int. J. Prod. Res.* 60 (5), 1650–1665. <http://dx.doi.org/10.1080/00207543.2020.1867922>, Publisher: Taylor & Francis.

- Efe, B., Kremer, G.E.O., Kurt, M., 2018. Age and gender based workload constraint for assembly line worker assignment and balancing problem in a textile firm. *Int. J. Ind. Eng.-Theory Appl. Pract.* 25 (1), 1–17. Place: Cincinnati Publisher: Univ Cincinnati Industrial Engineering WOS:000431221200001.
- Egilmez, G., Erenay, B., Süer, G., 2014. Stochastic skill-based manpower allocation in a cellular manufacturing system. *J. Manuf. Syst.* 33 (4), 578–588.
- El Mouayni, I., Etienne, A., Lux, A., Siadat, A., Dantan, J.-Y., 2020. A simulation-based approach for time allowances assessment during production system design with consideration of worker's fatigue, learning and reliability. *Comput. Ind. Eng.* 139, 105650. Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000509784000098.
- Elmaghraby, S., 1990. Economic manufacturing quantities under conditions of learning and forgetting (EMQ/LaF). *Prod. Plan. Control* 1 (4), 196–208.
- von Elmbach, A.F., Scholl, A., Walter, R., 2019. Minimizing the maximal ergonomic burden in intra-hospital patient transportation. *European J. Oper. Res.* 276 (3), 840–854. Place: Amsterdam Publisher: Elsevier Science Bv WOS:000463121000004.
- Erera, A., Karacik, B., Savelsbergh, M., 2008. A dynamic driver management scheme for less-than-truckload carriers. *Comput. Oper. Res.* 35 (11), 3397–3411. Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000255671800002.
- Finco, S., Abdous, M.-A., Calzavara, M., Battini, D., Delorme, X., 2020a. A bi-objective model to include workers' vibration exposure in assembly line design. *Int. J. Prod. Res.*
- Finco, S., Battini, D., Delorme, X., Persona, A., Sgarbossa, F., 2020b. Workers' rest allowance and smoothing of the workload in assembly lines. *Int. J. Prod. Res.* 58 (4), 1255–1270. Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000469115800001.
- Fini, A.A.F., Akbarnezhad, A., Rashidi, T.H., Waller, S.T., 2017. Job assignment based on brain demands and human resource strategies. *J. Constr. Eng. Manag.* 143 (5), 04016123. Place: Reston Publisher: Asce-Amer Soc Civil Engineers WOS:000398563900015.
- Fisher, C., 1993. Boredom at work: A neglected concept. *School of Business Discussion Papers* 46.
- Fowler, J.W., Wirojanagud, P., Gel, E.S., 2008. Heuristics for workforce planning with worker differences. *European J. Oper. Res.* 190 (3), 724–740. Place: Amsterdam Publisher: Elsevier Science Bv WOS:000256902800010.
- Fu, Y., Li, Z., Chen, N., Qu, C., 2020. A discrete multi-objective rider optimization algorithm for hybrid flowshop scheduling problem considering makespan, noise and dust pollution. *IEEE Access* 8, 88527–88546.
- Gajsek, B., Dukic, G., Kovacic, M., Brezocnik, M., 2021. A multi-objective genetic algorithms approach for modelling of order picking. *Int. J. Simul. Modell.* 20 (4), 719–729.
- Gans, N., Zhou, Y.P., 2002. Managing learning and turnover in employee staffing. *Oper. Res.* 50 (6), 991–1006. Place: Catonsville Publisher: Informs WOS:000179794700007.
- Garg, A., Chaffin, D.B., Herrin, G.D., 1978. Prediction of metabolic rates for manual materials handling jobs. *Am. Ind. Hygiene Assoc. J.* 39 (8), 661–674.
- Gärtner, J., Musliu, N., Slany, W., 2001. Rota: A research project on algorithms for workforce scheduling and shift design optimization. *AI Commun.* 14 (2), 83–92.
- Gebennini, E., Zeppetella, L., Grassi, A., Rimini, B., 2018. Optimal job assignment considering operators' walking costs and ergonomic aspects. *Int. J. Prod. Res.* 56 (3), 1249–1268. Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000429228100014.
- Gérard, M., Clautiaux, F., Sadykov, R., 2016. Column generation based approaches for a tour scheduling problem with a multi-skill heterogeneous workforce. *European J. Oper. Res.* 252 (3), 1019–1030.
- Gilotra, M., Pareek, S., Mittal, M., Dhaka, V., 2020. Effect of carbon emission and human errors on a two-echelon supply chain under permissible delay in payments. *Int. J. Math., Eng. Manag. Sci.* 5 (2), 225–236.
- Givi, Z.S., Jaber, M.Y., Neumann, W.P., 2015a. Modelling worker reliability with learning and fatigue. *Appl. Math. Model.* 39 (17), 5186–5199. Place: New York Publisher: Elsevier Science Inc WOS:000357228100015.
- Givi, Z.S., Jaber, M.Y., Neumann, W.P., 2015b. Production planning in DRC systems considering worker performance. *Comput. Ind. Eng.* 87, 317–327. Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000360772100030.
- Glock, C.H., Grosse, E.H., Abedinnia, H., Emde, S., 2019a. An integrated model to improve ergonomic and economic performance in order picking by rotating pallets. *European J. Oper. Res.* 273 (2), 516–534. Place: Amsterdam Publisher: Elsevier Science Bv WOS:000452345600009.
- Glock, C.H., Grosse, E.H., Jaber, M.Y., Smunt, T.L., 2019b. Applications of learning curves in production and operations management: A systematic literature review. *Comput. Ind. Eng.* 131, 422–441. Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000468710600034.
- Glock, C.H., Grosse, E.H., Kim, T., Neumann, W.P., Sobhani, A., 2019c. An integrated cost and worker fatigue evaluation model of a packaging process. *Int. J. Prod. Econ.* 207, 107–124. Place: Amsterdam Publisher: Elsevier Science Bv WOS:000454973200008.
- Goel, A., 2009. Vehicle scheduling and routing with drivers' working hours. *Transp. Sci.* 43 (1), 17–26. Place: Catonsville Publisher: Informs WOS:000263720200003.
- Goel, A., 2012. A mixed integer programming formulation and effective cuts for minimising schedule durations of Australian truck drivers. *J. Sched.* 15 (6), 733–741. Place: New York Publisher: Springer WOS:000314524100005.
- Goel, A., Vidal, T., 2014. Hours of service regulations in road freight transport: An optimization-based international assessment. *Transp. Sci.* 48 (3), 391–412. URL <http://pubsonline.informs.org/doi/abs/10.1287/trsc.2013.0477>.
- Gong, G., Chiong, R., Deng, Q., Han, W., Zhang, L., Lin, W., Li, K., 2020. Energy-efficient flexible flow shop scheduling with worker flexibility. *Expert Syst. Appl.* 141, UNSP 112902. Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000496334800026.
- Grosse, E., Glock, C., Müller, S., 2015. Production economics and the learning curve: A meta-analysis. *Int. J. Prod. Econ.* 170, 401–412.
- Hewitt, M., Chacosky, A., Grasman, S., Thomas, B., 2015. Integer programming techniques for solving non-linear workforce planning models with learning. *European J. Oper. Res.* 242 (3), 942–950.
- Hignett, S., McAtamney, L., 2000. Rapid entire body assessment (REBA). *Appl. Ergon.* 31 (2), 201–205. URL <http://www.sciencedirect.com/science/article/pii/S0003687099000393>.
- Hochdörfer, J., Hedler, M., Lanza, G., 2018. Staff scheduling in job rotation environments considering ergonomic aspects and preservation of qualifications. *J. Manuf. Syst.* 46, 103–114.
- Hollis, B., Green, P., 2012. Real-life vehicle routing with time windows for visual attractiveness and operational robustness. *Asia-Pac. J. Oper. Res.* 29 (4).
- Hong, S., 2018. The effects of picker-oriented operational factors on hand-off delay in a bucket brigade order picking system. *OR Spectrum* 40 (3), 781–808.
- Hopp, W., Tekin, E., Van Oyen, M., 2004. Benefits of skill chaining in serial production lines with cross-trained workers. *Manage. Sci.* 50 (1), 83–98.
- Huang, S.-H., Pan, Y.-C., 2014. Ergonomic job rotation strategy based on an automated RGB-D anthropometric measuring system. *J. Manuf. Syst.* 33 (4), 699–710. Place: Oxford Publisher: Elsevier Sci Ltd WOS:000348883200023.
- Irle, H., Hesse, J.M., Strasser, H., 1998. Physiological cost of energy-equivalent noise exposures with a rating level of 85 dB(a): Hearing threshold shifts associated with energetically negligible continuous and impulse noise. *Int. J. Ind. Ergon.* 21 (6), 451–463. URL <http://www.sciencedirect.com/science/article/pii/S0169814196000820>.
- Jaber, M.Y., Bonney, M., 1996. Production breaks and the learning curve: The forgetting phenomenon. *Appl. Math. Model.* 20 (2), 162–169. URL <https://www.sciencedirect.com/science/article/pii/0307904X9500157F>.
- Jaber, M., Bonney, M., 2003. Lot sizing with learning and forgetting in set-ups and in product quality. *Int. J. Prod. Econ.* 83 (1), 95–111.
- Jaber, M.Y., Givi, Z.S., Neumann, W.P., 2013. Incorporating human fatigue and recovery into the learning-forgetting process. *Appl. Math. Model.* 37 (12), 7287–7299. Place: New York Publisher: Elsevier Science Inc WOS:000321535500012.
- Jaber, M.Y., Glock, C.H., 2013. A learning curve for tasks with cognitive and motor elements. *Comput. Ind. Eng.* 64 (3), 866–871. Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000315832300013.
- Jaber, M., Guifrida, A., 2004. Learning curves for processes generating defects requiring reworks. *European J. Oper. Res.* 159 (3), 663–672.
- Jaber, M.Y., Peltokorpi, J., 2020. The effects of learning in production and group size on the lot-sizing problem. *Appl. Math. Model.* 81, 419–427. Place: New York Publisher: Elsevier Science Inc WOS:000521509900025.
- Jaber, M.Y., Peltokorpi, J., Glock, C.H., Grosse, E.H., Pusic, M., 2021. Adjustment for cognitive interference enhances the predictability of the power learning curve. *Int. J. Prod. Econ.* 234, 108045. URL <https://www.sciencedirect.com/science/article/pii/S0925527321000219>.
- Jaber, M.Y., Peltokorpi, J., Smunt, T.L., 2022. The lot size problem and the learning curve: A review of mathematical modeling (1950's-2020). *Appl. Math. Model.* 105, 832–859. Place: New York Publisher: Elsevier Science Inc WOS:000798858900003. URL <https://www.webofscience.com/wos/woscc/full-record/WOS:000798858900003>.
- Jaber, M.Y., Sikstrom, S., 2004. A numerical comparison of three potential learning and forgetting models. *Int. J. Prod. Econ.* 92 (3), 281–294. Place: Amsterdam Publisher: Elsevier Science Bv WOS:000225395300007.
- Jamshidi, R., Seyyed Esfahani, M.M., 2014. Human resources scheduling to improve the product quality according to exhaustion limit. *TOP* 22 (3), 1028–1041. <http://dx.doi.org/10.1007/s11750-013-0310-z>.
- Janiak, A., Kovalyov, M., 2006. Scheduling in a contaminated area: A model and polynomial algorithms. *European J. Oper. Res.* 173 (1), 125–132.
- Janiak, A., Kovalyov, M., 2008. Scheduling jobs in a contaminated area: A model and heuristic algorithms. *J. Oper. Res. Soc.* 59 (7), 977–987.
- Janiak, A., Rudek, R., 2010. A note on a makespan minimization problem with a multi-ability learning effect. *Omega* 38 (3), 213–217.
- Jeang, A., Rahim, A., 2019. Lot size determination for finite horizon under the effect of productivity and quality learning process. *Int. J. Syst. Sci.: Oper. Logist.* 6 (3), 193–236.
- Kandakoglu, A., Sauré, A., Michalowski, W., Aquino, M., Graham, J., McCormick, B., 2020. A decision support system for home dialysis visit scheduling and nurse routing. *Decis. Support Syst.* 130.
- Kara, Y., Atasagun, Y., Gokcen, H., Hezer, S., Demirel, N., 2014. An integrated model to incorporate ergonomics and resource restrictions into assembly line balancing. *Int. J. Comput. Integr. Manuf.* 27 (11), 997–1007. Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000341924400004.

- Karhu, O., Kansil, P., Kuorinka, I., 1977. Correcting working postures in industry: A practical method for analysis. *Appl. Ergon.* 8 (4), 199–201.
- Karsu, O., Morton, A., 2015. Inequity averse optimization in operational research. *European J. Oper. Res.* 245 (2), 343–359, Place: Amsterdam Publisher: Elsevier Science Bv WOS:000355360900001.
- Katirae, N., Calzavara, M., Finco, S., Battaia, O., Battini, D., 2022. Assembly line balancing and worker assignment considering workers' expertise and perceived physical effort. *Int. J. Prod. Res.* Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000884665800001, URL <https://www.webofscience.com/wos/woscc/full-record/WOS:000884665800001>.
- Katirae, N., Calzavara, M., Finco, S., Battini, D., Battaia, O., 2021. Consideration of workers' differences in production systems modelling and design: State of the art and directions for future research. *Int. J. Prod. Res.* 59 (11), 3237–3268.
- Kaya, B., Adem, A., Dağdeviren, M., 2020. A DSS-based novel approach proposition employing decision techniques for system design. *Int. J. Inf. Technol. Decis. Making* 19 (2), 413–445.
- Kazemi, N., Abdul-Rashid, S.H., Shekarian, E., Bottani, E., Montanari, R., 2016a. A fuzzy lot-sizing problem with two-stage composite human learning. *Int. J. Prod. Res.* 54 (16), 5010–5025, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000380165700017.
- Kazemi, N., Olugu, E., Abdul-Rashid, S., Ghazilla, R., 2016b. A fuzzy EOQ model with backorders and forgetting effect on fuzzy parameters: An empirical study. *Comput. Ind. Eng.* 96, 140–148.
- Kazemi, N., Shekarian, E., Cárdenas-Barrón, L., Olugu, E., 2015. Incorporating human learning into a fuzzy EOQ inventory model with backorders. *Comput. Ind. Eng.* 87, 540–542.
- Khaitan, A., Mehlatat, M.K., Gupta, P., Pedrycz, W., 2022. Socially aware fuzzy vehicle routing problem: A topic modeling based approach for driver well-being. *Expert Syst. Appl.* 205, 117655, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000832959800006, URL <https://www.webofscience.com/wos/woscc/full-record/WOS:000832959800006>.
- Khan, M., Jaber, M.Y., Ahmad, A.-R., 2014. An integrated supply chain model with errors in quality inspection and learning in production. *Omega-Int. J. Manag. Sci.* 42 (1), 16–24, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000325953500003.
- Khan, M., Jaber, M.Y., Gufrida, A.L., 2012. The effect of human factors on the performance of a two level supply chain. *Int. J. Prod. Res.* 50 (2), 517–533, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000303582300014.
- Khanna, A., Kishore, A., Jaggi, C., 2017. Inventory modeling for imperfect production process with inspection errors, sales return, and imperfect rework process. *Int. J. Math., Eng. Manag. Sci.* 2 (4), 242–258.
- Kiassat, C., Safaei, N., 2019. Effect of imprecise skill level on workforce rotation in a dynamic market. *Comput. Ind. Eng.* 131, 464–476, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000468710600037.
- Kim, K., Kim, T.-S., Lim, D.-E., Park, H.M., 2013. Managing the supply and demand uncertainty in workforce recruitment: Planned or just-in-time acquisition. *J. Oper. Res. Soc.* 64 (11), 1654–1663, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000325757800009.
- Kim, B.-I., Kim, S., Sahoo, S., 2006. Waste collection vehicle routing problem with time windows. *Comput. Oper. Res.* 33 (12), 3624–3642.
- Knust, S., Schumacher, E., 2011. Shift scheduling for tank trucks. *Omega* 39 (5), 513–521.
- Kok, A.L., Meyer, C.M., Kopfer, H., Schutten, J.M.J., 2010. A dynamic programming heuristic for the vehicle routing problem with time windows and European community social legislation. *Transp. Sci.* 44 (4), 442–454, Place: Hanover Publisher: Informa WOS:000284307000002.
- Koltai, T., Tatay, V., 2013. Formulation of workforce skill constraints in assembly line balancing models. *Optim. Eng.* 14 (4), 529–545.
- Konz, S., 1998. *Work/rest: Part II the scientific basis (knowledge base) for the guide.* *Int. J. Ind. Ergon.*
- Korkulu, S., Bona, K., 2021. Development of a lot-sizing model to prevent heat stress and work-related musculoskeletal disorders. *Promet-Traffic Transp.* 33 (6), 871–882, Place: Zagreb Publisher: Svcenliste U Zagrebu, Fakultet Prometnih Znanosti WOS:000755146800009, URL <https://www.webofscience.com/wos/woscc/full-record/WOS:000755146800009>.
- Korytkowski, P., 2017. Competences-based performance model of multi-skilled workers with learning and forgetting. *Expert Syst. Appl.* 77, 226–235.
- Krajnak, K., 2018. Health effects associated with occupational exposure to hand-arm or whole body vibration. *J. Toxicol. Environ. Health. Part B, Crit. Rev.* 21 (5), 320–334.
- Lai, P.-J., Lee, W.-C., 2013. Single-machine scheduling with learning and forgetting effects. *Appl. Math. Model.* 37 (6), 4509–4516, Place: New York Publisher: Elsevier Science Inc WOS:000316706300071.
- Lanzetta, M., Rossi, A., Puppato, A., 2016. Modelling activity times by hybrid synthetic method. *Prod. Plan. Control* 27 (11), 909–924.
- Larco, J.A., de Koster, R., Roodbergen, K.J., Dul, J., 2017. Managing warehouse efficiency and worker discomfort through enhanced storage assignment decisions. *Int. J. Prod. Res.* 55 (21), 6407–6422, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000412561900013.
- Larco Martinelli, J., 2010. *Incorporating Worker-Specific Factors in Operations Management Models.* Number: EPS-2010-217-LIS. URL <https://repub.eur.nl/pub/21527/>.
- Lazzerini, B., Pistolesi, F., 2018. Multiobjective personnel assignment exploiting workers' sensitivity to risk. *IEEE Trans. Syst., Man, Cybern.: Syst.* 48 (8), 1267–1282.
- Lee, D.H.K., 1980. Seventy-five years of searching for a heat index. *Environ. Res.* 22 (2), 331–356, URL <https://www.sciencedirect.com/science/article/pii/0013935180901462>.
- Lehuédé, F., Péton, O., Tricoire, F., 2020. A lexicographic minimax approach to the vehicle routing problem with route balancing. *European J. Oper. Res.* 282 (1), 129–147.
- Levy, F.K., 1965. Adaptation in the production process. *Manage. Sci.* 11 (6), B-136, Num Pages: B-154 Publisher: INFORMS. URL <https://pubsonline.informs.org/doi/abs/10.1287/mnsc.11.6.B136>.
- Li, X., Jiang, Y., Ruiz, R., 2018a. Methods for scheduling problems considering experience, learning, and forgetting effects. *IEEE Trans. Syst., Man, Cybern.: Syst.* 48 (5), 743–754, Conference Name: IEEE Transactions on Systems, Man, and Cybernetics: Systems.
- Li, J., Tan, X., Li, J., 2018b. Research on dynamic facility layout problem of manufacturing unit considering human factors. *Math. Probl. Eng.* 2018, 6040561, Place: London Publisher: Hindawi Ltd WOS:000423573600001.
- Liles, D.H., Deivanayagam, S., Ayoub, M.M., Mahajan, P., 1984. A job severity index for the evaluation and control of lifting injury. *Hum. Factors* 26 (6), 683–693. <http://dx.doi.org/10.1177/001872088402600608>, Publisher: SAGE Publications Inc.
- Locke, E.A., Latham, G.P., 2002. Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *Am. Psychol.* 57, 705–717, Place: US Publisher: American Psychological Association.
- Lodree, E.J., Geiger, C.D., Jiang, X.C., 2009. Taxonomy for integrating scheduling theory and human factors: Review and research opportunities. *Int. J. Ind. Ergon.* 39 (1), 39–51, Publisher: Elsevier. URL <https://www.cabdirect.org/cabdirect/abstract/20093022460>.
- Lodree, Jr., E., Geiger, C., 2010. A note on the optimal sequence position for a rate-modifying activity under simple linear deterioration. *European J. Oper. Res.* 201 (2), 644–648.
- Lohmann, M., Anzanello, M.J., Fogliatto, F.S., da Silveira, G.C., 2019. Grouping workers with similar learning profiles in mass customization production lines. *Comput. Ind. Eng.* 131, 542–551, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000468710600044.
- Lu, C., Gao, L., Pan, Q., Li, X., Zheng, J., 2019. A multi-objective cellular grey wolf optimizer for hybrid flowshop scheduling problem considering noise pollution. *Appl. Soft Comput.* 75, 728–749.
- Madani, D.A., Dababneh, A., 2016. Rapid entire body assessment: A literature review. *Am. J. Eng. Appl. Sci.* 9 (1), 107–118, URL <http://thescpub.com/abstract/10.3844/ajeassp.2016.107.118>.
- Manavizadeh, N., Hosseini, N.-S., Rabbani, M., Jolai, F., 2013. A simulated annealing algorithm for a mixed model assembly U-line balancing type-I problem considering human efficiency and just-in-time approach. *Comput. Ind. Eng.* 64 (2), 669–685.
- Marichelvam, M.K., Geetha, M., Tosun, O., 2020. An improved particle swarm optimization algorithm to solve hybrid flowshop scheduling problems with the effect of human factors - A case study. *Comput. Oper. Res.* 114, UNSP 104812. Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000499768500017.
- Marvel, J.H., Shell, R.L., Weckman, G.R., 2001. An application of heuristic algorithms for determining inventory location in a distribution warehouse. *Int. J. Ind. Eng.-Theory Appl. Pract.* 8 (1), 5–15, Place: Cincinnati Publisher: Univ Cincinnati Industrial Engineering WOS:000168224400001.
- Mateo, M., Tarral, M., Rodríguez, P., Galera, A., 2020. Ergonomics as basis for a decision support system in the printing industry. *CEJOR Cent. Eur. J. Oper. Res.* 28 (2), 685–706.
- Matl, P., Hartl, R.F., Vidal, T., 2019. Workload equity in vehicle routing: The impact of alternative workload resources. *Comput. Oper. Res.* 110, 116–129, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000474309800009.
- Matusiak, M., de Koster, R., Saarinen, J., 2017. Utilizing individual picker skills to improve order batching in a warehouse. *European J. Oper. Res.* 263 (3), 888–899.
- Mayerle, S., De Genaro Chiroli, D., Neiva de Figueiredo, J., Rodrigues, H., 2020. The long-haul full-load vehicle routing and truck driver scheduling problem with intermediate stops: An economic impact evaluation of Brazilian policy. *Transp. Res. Part A: Policy Pract.* 140, 36–51.
- Mazur, J., Hastie, R., 1978. Learning as accumulation: A reexamination of the learning curve. *Psychol. Bull.* 85 (6), 1256–1274.
- McAtamney, L., Corlett, N., 1993. RULA: A survey method for the investigation of work-related upper limb disorders. *Appl. Ergon.* 24 (2), 91–99.
- McDonald, T., Ellis, K., Van Aken, E., Patrick Koelling, C., 2009. Development and application of a worker assignment model to evaluate a lean manufacturing cell. *Int. J. Prod. Res.* 47 (9), 2427–2447.
- Mehdizadeh, E., Daei Niaki, S., Rahimi, V., 2016. A vibration damping optimization algorithm for solving a new multi-objective dynamic cell formation problem with workers training. *Comput. Ind. Eng.* 101, 35–52.

- Mehdizadeh, A., Vinel, A., Hu, Q., Schall, M.C., Gallagher, S., Sesek, R.F., 2020. Job rotation and work-related musculoskeletal disorders: A fatigue-failure perspective. *Ergonomics* 63 (4), 461–476. Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000512519000001.
- Mehrotra, A., Murphy, K., Trick, M., 2000. Optimal shift scheduling: A branch-and-price approach. *Naval Res. Logist.* 47 (3), 185–200.
- Min, H., Melachrinoudis, E., 2016. A model-based decision support system for solving vehicle routing and driver scheduling problems under hours of service regulations. *Int. J. Logist. Res. Appl.* 19 (4), 256–277. <http://dx.doi.org/10.1080/13675567.2015.1075475>, Publisher: Taylor & Francis.
- Moon, I., Logendran, R., Lee, J., 2009. Integrated assembly line balancing with resource restrictions. *Int. J. Prod. Res.* 47 (19), 5525–5541.
- Moore, J.S., Garg, A., 1995. The strain index: A proposed method to analyze jobs for risk of distal upper extremity disorders. *Am. Ind. Hygiene Ass. J.* 56 (5), 443–458.
- Mosheiov, G., 2001. Scheduling problems with a learning effect. *European J. Oper. Res.* 132 (3), 687–693.
- Mosheiov, G., 2005. A note on scheduling deteriorating jobs. *Math. Comput. Modelling* 41 (8), 883–886, URL <https://www.sciencedirect.com/science/article/pii/S0895717705001500>.
- Mosheiov, G., Sidney, J., 2003. Scheduling with general job-dependent learning curves. *European J. Oper. Res.* 147 (3), 665–670.
- Mossa, G., Boenzi, F., Digiesi, S., Mummolo, G., Romano, V., 2016. Productivity and ergonomic risk in human based production systems: A job-rotation scheduling model. *Int. J. Prod. Econ.* 171, 471–477.
- Moussavi, S.E., Zare, M., Mahdjoub, M., Grunder, O., 2019. Balancing high operator's workload through a new job rotation approach: Application to an automotive assembly line. *Int. J. Ind. Ergon.* 71, 136–144, Place: Amsterdam Publisher: Elsevier Science Bv WOS:000466999800018.
- Muth, E.J., Spremann, K., 1983. Learning effects in economic lot sizing. *Manage. Sci.* 29 (2), 264–269.
- Nanthavanij, S., Yaoyuenyong, S., Jeenanunta, C., 2010. Heuristic approach to work-force scheduling with combined safety and productivity objective. *Int. J. Ind. Eng.-Theory Appl. Pract.* 17 (4), 319–333, Place: Cincinnati Publisher: Univ Cincinnati Industrial Engineering WOS:000286014300006.
- Nembhard, D., 2001. Heuristic approach for assigning workers to tasks based on individual learning rates. *Int. J. Prod. Res.* 39 (9), 1955–1968.
- Nembhard, D.A., Bentefouet, F., 2012. Parallel system scheduling with general worker learning and forgetting. *Int. J. Prod. Econ.* 139 (2), 533–542, URL <http://www.sciencedirect.com/science/article/pii/S0925527312002162>.
- Nembhard, D., Bentefouet, F., 2014. Selection policies for a multifunctional workforce. *Int. J. Prod. Res.* 52 (16), 4785–4802.
- Nembhard, D.A., Shafer, S.M., 2008. The effects of workforce heterogeneity on productivity in an experiential learning environment. *Int. J. Prod. Res.* 46 (14), 3909–3929, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000256997600009.
- Nishi, T., Sugiyama, T., Inuiguchi, M., 2014. Two-level decomposition algorithm for crew rostering problems with fair working condition. *European J. Oper. Res.* 237 (2), 465–473.
- Norman, B.A., Tharmmaphornphils, W., Needy, K.L., Bidanda, B., Warner, R.C., 2002. Worker assignment in cellular manufacturing considering technical and human skills. *Int. J. Prod. Res.* 40 (6), 1479–1492, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000175277300010.
- Occhipinti, E., 1998. OCRA: A concise index for the assessment of exposure to repetitive movements of the upper limbs. *Ergonomics* 41 (9), 1290–1311.
- Olivella, J., Nembhard, D., 2017. Cross-training policies for team cost and robustness. *Comput. Ind. Eng.* 111, 79–88, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000410468600008.
- Ostermeier, F.F., 2020. The impact of human consideration, schedule types and product mix on scheduling objectives for unpaced mixed-model assembly lines. *Int. J. Prod. Res.* 58 (14), 4386–4405, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000480779200001.
- Othman, M., Bhuiyan, N., Gouw, G., 2012. Integrating workers' differences into workforce planning. *Comput. Ind. Eng.* 63 (4), 1096–1106.
- Otto, A., Boysen, N., Scholl, A., Walter, R., 2017. Ergonomic workplace design in the fast pick area. *OR Spectrum* 39 (4), 945–975.
- Otto, C., Otto, A., 2014. Extending assembly line balancing problem by incorporating learning effects. *Int. J. Prod. Res.* 52 (24), 7193–7208.
- Otto, A., Scholl, A., 2011. Incorporating ergonomic risks into assembly line balancing. *European J. Oper. Res.* 212 (2), 277–286, Place: Amsterdam Publisher: Elsevier WOS:000290084300006.
- Otto, A., Scholl, A., 2013. Reducing ergonomic risks by job rotation scheduling. *OR Spectrum* 35 (3), 711–733.
- Pan, Q.-K., Suganthan, P., Chua, T., Cai, T., 2010. Solving manpower scheduling problem in manufacturing using mixed-integer programming with a two-stage heuristic algorithm. *Int. J. Adv. Manuf. Technol.* 46 (9), 1229–1237.
- Pargar, F., Zandieh, M., 2012. Bi-criteria SDST hybrid flow shop scheduling with learning effect of setup times: Water flow-like algorithm approach. *Int. J. Prod. Res.* 50 (10), 2609–2623, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000304824400004.
- Pei, J., Liu, X., Pardalos, P., Migdalas, A., Yang, S., 2017. Serial-batching scheduling with time-dependent setup time and effects of deterioration and learning on a single-machine. *J. Global Optim.* 67 (1), 251–262.
- Peltokorpi, J., Hoedt, S., Colman, T., Rutten, K., Aghezzaf, E.-H., Cottyn, J., 2023. Manual assembly learning, disability, and instructions: an industrial experiment. *Int. J. Prod. Res.* 61 (22), 7903–7921. <http://dx.doi.org/10.1080/00207543.2023.2195957>, Publisher: Taylor & Francis.
- Peltokorpi, J., Jaber, M.Y., 2020. A group learning curve model with motor, cognitive and waste elements. *Comput. Ind. Eng.* 146, 106621, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000548931200046.
- Peng, Z., Zhang, H., Tang, H., Feng, Y., Yin, W., 2022. Research on flexible job-shop scheduling problem in green sustainable manufacturing based on learning effect. *J. Intell. Manuf.* 33 (6), 1725–1746.
- Petronijevic, J., Etienne, A., Dantan, J.-Y., 2019. Human factors under uncertainty: A manufacturing systems design using simulation-optimisation approach. *Comput. Ind. Eng.* 127, 665–676, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000460708800050.
- Pistolesi, F., Lazzarini, B., 2019. TeMA: A tensorial memetic algorithm for many-objective parallel disassembly sequence planning in product refurbishment. *Ieee Trans. Ind. Inform.* 15 (6), 3743–3753, Place: Piscataway Publisher: Ieee-Inst Electrical Electronics Engineers Inc WOS:000471725400059.
- Polat, O., Kalayci, C., Mutlu, O., Gupta, S., 2016. A two-phase variable neighbourhood search algorithm for assembly line worker assignment and balancing problem type-II: An industrial case study. *Int. J. Prod. Res.* 54 (3), 722–741.
- Prescott-Gagnon, E., Desaulniers, G., Drexl, M., Rousseau, L.-M., 2010. European driver rules in vehicle routing with time windows. *Transp. Sci.* 44 (4), 455–473, Place: Catonsville Publisher: Informs WOS:000284307000003.
- Price, A.D., 1990. Calculating relaxation allowances for construction operatives - part 1: metabolic cost. *Appl. Ergon.* 21 (4), 311–317.
- Prot, D., Lapegue, T., Bellenguez-Morineau, O., 2015. A two-phase method for the shift design and personnel task scheduling problem with equity objective. *Int. J. Prod. Res.* 53 (24), 7286–7298, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000367048600009.
- Prunet, T., Absi, N., Borodin, V., Cattaruzza, D., 2024. Optimization of human-aware logistics and manufacturing systems: A comprehensive review of modeling approaches and applications. *EURO J. Transp. Logist.* 100136. <http://dx.doi.org/10.1016/j.ejtl.2024.100136>, <https://www.sciencedirect.com/science/article/pii/S2192437624000116>.
- Przybylski, B., 2018. A new model of parallel-machine scheduling with integral-based learning effect. *Comput. Ind. Eng.* 121, 189–194.
- Raghavendra, A., Krishnakumar, T., Muralidhar, R., Sarvanan, D., Raghavendra, B., 1992. A practical heuristic for a large scale vehicle routing problem. *European J. Oper. Res.* 57 (1), 32–38.
- Rancourt, M.-E., Cordeau, J.-F., Laporte, G., 2013. Long-haul vehicle routing and scheduling with working hour rules. *Transp. Sci.* 47 (1), 81–107, Place: Hanover Publisher: Informs WOS:000314620100007.
- Rancourt, M.-E., Paquette, J., 2014. Multicriteria optimization of a long-haul routing and scheduling problem. *J. Multi-Criteria Decis. Anal.* 21 (5), 239–255.
- Rattanamane, T., Nanthavanij, S., Dumrongkiri, A., 2015. Multi-workday vehicle routing problem with ergonomic consideration of physical workload. *Int. J. Adv. Manuf. Technol.* 76 (9), 2015–2026.
- Razavi, H., Ramezanifar, E., Bagherzadeh, J., 2014. An economic policy for noise control in industry using genetic algorithm. *Saf. Sci.* 65, 79–85, Place: Amsterdam Publisher: Elsevier WOS:000335127000010.
- Rekik, M., Cordeau, J.-F., Soumis, F., 2008. Solution approaches to large shift scheduling problems. *Rairo-Oper. Res.* 42 (2), 229–258, Place: Les Ulis Cedex A Publisher: Edp Sciences S A WOS:000255967900009.
- Rerkjirattikal, P., Olapiriyakul, S., 2021. Noise-safe job rotation in multi-workday scheduling considering skill and demand requirements. *J. Ind. Prod. Eng.* 38 (8), 618–627, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000670481000001. URL <https://www.webofscience.com/wos/woscc/full-record/WOS:000670481000001>.
- Rinaldi, M., Fera, M., Bottani, E., Grosse, E.H., 2022. Workforce scheduling incorporating worker skills and ergonomic constraints. *Comput. Ind. Eng.* 168, 108107, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000805828400002. URL <https://www.webofscience.com/wos/woscc/full-record/WOS:000805828400002>.
- Ruiz-Torres, A.J., Alomoto, N., Paletta, G., Perez, E., 2015. Scheduling to maximise worker satisfaction and on-time orders. *Int. J. Prod. Res.* 53 (9), 2836–2852, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000350451200017.
- Ryan, B., Qu, R., Schock, A., Parry, T., 2011. Integrating human factors and operational research in a multidisciplinary investigation of road maintenance. *Ergonomics* 54 (5), 436–452, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000290298000003.
- Sadeghi, P., Rebelo, R., Ferreira, J., 2018. Balancing mixed-model assembly systems in the footwear industry with a variable neighbourhood descent method. *Comput. Ind. Eng.* 121, 161–176.
- Salehi, M., Maleki, H., Niroomand, S., 2018. A multi-objective assembly line balancing problem with worker's skill and qualification considerations in fuzzy environment. *Appl. Intell.* 48 (8), 2137–2156.
- Salvendy, G., St, C., 2022. Handbook of Human Factors and Ergonomics Fourth Edition.

- Samouei, P., Ashayeri, J., 2019. Developing optimization & robust models for a mixed-model assembly line balancing problem with semi-automated operations. *Appl. Math. Model.* 72, 259–275, Place: New York Publisher: Elsevier Science Inc WOS:000470051900015.
- Sana, S.S., Ospina-Mateus, H., Arrieta, F.G., Chedid, J.A., 2019. Application of genetic algorithm to job scheduling under ergonomic constraints in manufacturing industry. *J. Ambient Intell. Humaniz. Comput.* 10 (5), 2063–2090, Place: Heidelberg Publisher: Springer Heidelberg WOS:000463151400031.
- Sawik, T., 2010. An integer programming approach to scheduling in a contaminated area. *Omega* 38 (3), 179–191.
- Sayin, S., Karabati, S., 2007. Assigning cross-trained workers to departments: A two-stage optimization model to maximize utility and skill improvement. *European J. Oper. Res.* 176 (3), 1643–1658, Place: Amsterdam Publisher: Elsevier Science Bv WOS:000242102800021.
- Schaub, K., Caragnano, G., Britzke, B., Bruder, R., 2012. The European assembly worksheet. *Theor. Issues Ergonomics Sci.* 14, 1–23.
- Schultz, K., Schoenherr, T., Nembhard, D., 2010. An example and a proposal concerning the correlation of worker processing times in parallel tasks. *Manage. Sci.* 56 (1), 176–191.
- Şenyigit, E., Atici, U., Şenol, M., 2020. Effects of OCRA parameters and learning rate on machine scheduling. *CEJOR Cent. Eur. J. Oper. Res.*
- Shafer, S., Nembhard, D., Uzumeri, M., 2001. The effects of worker learning, forgetting, and heterogeneity on assembly line productivity. *Manage. Sci.* 47 (12), 1639–1653.
- Shahbazi, B., Akbarnezhad, A., Rey, D., Fini, A.A.F., Loosemore, M., 2019. Optimization of job allocation in construction organizations to maximize workers' career development opportunities. *J. Constr. Eng. Manag.* 145 (6), 04019036, Place: Reston Publisher: Asce-Amer Soc Civil Engineers WOS:000464567400001.
- Sheikhalishahi, M., Eskandari, N., Mashayekhi, A., Azadeh, A., 2019. Multi-objective open shop scheduling by considering human error and preventive maintenance. *Appl. Math. Model.* 67, 573–587, Place: New York Publisher: Elsevier Science Inc WOS:000456492500035.
- Shin, D., Mittal, M., Sarkar, B., 2018. Effects of human errors and trade-credit financing in two-echelon supply chain models. *Eur. J. Ind. Eng.* 12 (4), 465–503, Place: Geneva Publisher: Inderscience Enterprises Ltd WOS:000444011200001.
- Shuib, A., Kamarudin, F., 2019. Solving shift scheduling problem with days-off preference for power station workers using binary integer goal programming model. *Ann. Oper. Res.* 272 (1), 355–372.
- Smunt, T., 1987. The impact of worker forgetting on production scheduling. *Int. J. Prod. Res.* 25 (5), 689–701.
- Sobhani, A., Wahab, M.I.M., 2017. The effect of working environment-ill health aspects on the carbon emission level of a manufacturing system. *Comput. Ind. Eng.* 113, 75–90, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000418207900007.
- Sobhani, A., Wahab, M.I.M., Jaber, M.Y., 2019. The effect of working environment aspects on a vendor-buyer inventory model. *Int. J. Prod. Econ.* 208, 171–183, Place: Amsterdam Publisher: Elsevier Science Bv WOS:000457952300012.
- Sobhani, A., Wahab, M.I.M., Neumann, W.P., 2015. Investigating work-related ill health effects in optimizing the performance of manufacturing systems. *European J. Oper. Res.* 241 (3), 708–718, Place: Amsterdam Publisher: Elsevier WOS:000347605100012.
- Sobhani, A., Wahab, M., Neumann, W., 2017. Incorporating human factors-related performance variation in optimizing a serial system. *European J. Oper. Res.* 257 (1), 69–83.
- Soriano, J., Rex Jalao, E., Ann Martinez, I., 2020. Integrated employee scheduling with known employee demand, including breaks, overtime, and employee preferences. *Journal of Industrial Engineering and Management-Jiem* 13 (3), 451–463, Place: Barcelona Publisher: Omniascience WOS:000608139400002. URL <https://www.webofscience.com/wos/woscc/full-record/WOS:000608139400002>.
- Stanton, N.A., Hedge, A., Brookhuis, K., Salas, E., Hendrick, H.W., 2004. *Handbook of Human Factors and Ergonomics Methods*. CRC Press, Google-Books-ID: RApSggShPc8C.
- Stewart, B., Webster, D., Ahmad, S., Matson, J., 1994. Mathematical models for developing a flexible workforce. *Int. J. Prod. Econ.* 36 (3), 243–254.
- Stratman, J., Roth, A., Gilland, W., 2004. The deployment of temporary production workers in assembly operations: A case study of the hidden costs of learning and forgetting. *J. Oper. Manage.* 21 (6), 689–707.
- Sueer, G.A., Tummaluri, R.R., 2008. Multi-period operator assignment considering skills, learning and forgetting in labour-intensive cells. *Int. J. Prod. Res.* 46 (2), 469–493, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000252337300009.
- Szalma, J., Hancock, P., 2011. Noise effects on human performance: A meta-analytic synthesis. *Psychol. Bull.* 137, 682–707.
- Takala, E.-P., Pehkonen, I., Forsman, M., Hansson, G.-A., Mathiassen, S.E., Neumann, W.P., Sjogaard, G., Veiersted, K.B., Westgaard, R.H., Winkel, J., 2010. Systematic evaluation of observational methods assessing biomechanical exposures at work. *Scand. J. Work, Environ. Health* 36 (1), 3–24.
- Tang, Y., Zhou, M., Gao, M., 2006. Fuzzy-petri-net-based disassembly planning considering human factors. *IEEE Trans. Syst., Man, Cybern. Part A:Syst. Hum.* 36 (4), 718–725.
- Taris, T.W., Schreurs, P.J.G., 2009. Well-being and organizational performance: An organizational-level test of the happy-productive worker hypothesis. *Work Stress* 23 (2), 120–136. <http://dx.doi.org/10.1080/02678370903072555>, Publisher: Routledge.
- Teyarachakul, S., Chand, S., Ward, J., 2011. Effect of learning and forgetting on batch sizes. *Prod. Oper. Manage.* 20 (1), 116–128.
- Tharmmaphornphilas, W., Norman, B.A., 2004. A quantitative method for determining proper job rotation intervals. *Ann. Oper. Res.* 128 (1), 251–266, Place: Dordrecht Publisher: Springer WOS:000220092800013.
- Tharmmaphornphilas, W., Norman, B.A., 2007. A methodology to create robust job rotation schedules. *Ann. Oper. Res.* 155 (1), 339–360, Place: Dordrecht Publisher: Springer WOS:000248940200018.
- Thompson, G., 1990. Shift scheduling in services when employees have limited availability: An L.P. approach. *J. Oper. Manage.* 9 (3), 352–370.
- Thompson, G., Pullman, M., 2007. Scheduling workforce relief breaks in advance versus in real-time. *European J. Oper. Res.* 181 (1), 139–155.
- Tiacci, L., Mimmi, M., 2018. Integrating ergonomic risks evaluation through OCRA index and balancing/sequencing decisions for mixed model stochastic asynchronous assembly lines. *Omega-Int. J. Manag. Sci.* 78, 112–138, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000433606700009.
- Topaloglu, S., Ozkarahan, I., 2003. Implicit optimal tour scheduling with flexible break assignments. *Comput. Ind. Eng.* 44 (1), 75–89.
- Topaloglu, S., Ozkarahan, I., 2004. An implicit goal programming model for the tour scheduling problem considering the employee work preferences. *Ann. Oper. Res.* 128 (1), 135–158.
- Ulmer, M., Nowak, M., Mattfeld, D., Kaminski, B., 2020. Binary driver-customer familiarity in service routing. *European J. Oper. Res.* 286 (2), 477–493, Place: Amsterdam Publisher: Elsevier WOS:000536062000007.
- Valeva, S., Hewitt, M., Thomas, B., Brown, K., 2017. Balancing flexibility and inventory in workforce planning with learning. *Int. J. Prod. Econ.* 183, 194–207.
- Villeda, R., Dean, B., 1990. On the optimal safe allocation and scheduling of a work force in a toxic-substance environment. *Ieee Trans. Eng. Manag.* 37 (2), 95–101, Place: New York Publisher: Ieee-Inst Electrical Electronics Engineers Inc WOS:A1990DF98300003.
- Wang, Y., Wang, J.-Q., Yin, Y., 2020. Multitasking scheduling and due date assignment with deterioration effect and efficiency promotion. *Comput. Ind. Eng.* 146, 106569, Place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000548931200020.
- Wang, J.-B., Xia, Z.-Q., 2005. Flow-shop scheduling with a learning effect. *J. Oper. Res. Soc.* 56 (11), 1325–1330.
- Waters, T.R., Lu, M.-L., Occhipinti, E., 2007. New procedure for assessing sequential manual lifting jobs using the revised NIOSH lifting equation. *Ergonomics* 50 (11), 1761–1770.
- Waters, T., Occhipinti, E., Colombini, D., Alvarez-Casado, E., Fox, R., 2016. Variable lifting index (VLI): A new method for evaluating variable lifting tasks. *Hum. Factors* 58 (5), 695–711.
- Waters, T.R., Putz-Anderson, V., Garg, A., Fine, L.J., 1993. Revised NIOSH equation for the design and evaluation of manual lifting tasks. *Ergonomics* 36 (7), 749–776.
- Wen, M., Krappner, E., Larsen, J., Stidsen, T.K., 2011. A multilevel variable neighborhood search heuristic for a practical vehicle routing and driver scheduling problem. *Networks* 58 (4), 311–322, Place: Hoboken Publisher: Wiley WOS:000297413900007.
- Widl, M., Musliu, N., 2014. The break scheduling problem: Complexity results and practical algorithms. *Memetic Comput.* 6 (2), 97–112, Place: Heidelberg Publisher: Springer Heidelberg WOS:000343289900004.
- Wirojanagud, P., Gel, E.S., Fowler, J.W., Cardy, R., 2007. Modelling inherent worker differences for workforce planning. *Int. J. Prod. Res.* 45 (3), 525–553, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000244182400004.
- Wright, T.P., 1936. Factors affecting the cost of airplanes. *J. Aeronaut. Sci.* 3 (4), 122–128, Publisher: American Institute of Aeronautics and Astronautics. URL <https://arc.aiaa.org/doi/10.2514/8.155>.
- Wu, H.C., Wang, M.J., 2001. Determining the maximum acceptable work duration for high-intensity work. *Eur. J. Appl. Physiol.* 85 (3), 339–344.
- Xu, S., Hall, N.G., 2021. Fatigue, personnel scheduling and operations: Review and research opportunities. *European J. Oper. Res.* 295 (3), 807–822, URL <https://www.sciencedirect.com/science/article/pii/S0377221721002629>.
- Yan, X., Xiao, B., Xiao, Y., Zhao, Z., Ma, L., Wang, N., 2019. Skill vehicle routing problem with time windows considering dynamic service times and time-skill-dependent costs. *IEEE Access* 7, 77208–77221.
- Yi, W., Chan, A.P.C., 2015. Optimal work pattern for construction workers in hot weather: A case study in Hong Kong. *J. Comput. Civ. Eng.* 29 (5), 05014009, Publisher: American Society of Civil Engineers. URL <https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29CP.1943-5487.0000419>.
- Yi, W., Wang, S., 2017. Mixed-integer linear programming on work-rest schedule design for construction sites in hot weather. *Comput.-Aided Civ. Infrastruct. Eng.* 32 (5), 429–439.
- Yilmaz, O.F., 2020. Operational strategies for seru production system: A bi-objective optimisation model and solution methods. *Int. J. Prod. Res.* 58 (11), 3195–3219, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000559798100001.

- Yoon, S.-Y., Ko, J., Jung, M.-C., 2016. A model for developing job rotation schedules that eliminate sequential high workloads and minimize between-worker variability in cumulative daily workloads: Application to automotive assembly lines. *Appl. Ergon.* 55, 8–15, Place: Oxford Publisher: Elsevier Sci Ltd WOS:000374074600002.
- Yung, M., Kolus, A., Wells, R., Neumann, W.P., 2020. Examining the fatigue-quality relationship in manufacturing. *Appl. Ergon.* 82, 102919, Place: Oxford Publisher: Elsevier Sci Ltd WOS:000501647900009.
- Zanoni, S., Jaber, M., Zavanella, L., 2012. Vendor managed inventory (VMI) with consignment considering learning and forgetting effects. *Int. J. Prod. Econ.* 140 (2), 721–730.
- Zhang, W., Fan, S., Xiong, J., Chen, S., 2018. A biobjective model for manual materials handling with energy consumption being accounted for. *Math. Probl. Eng.* 2018, 3474352, Place: London Publisher: Hindawi Ltd WOS:000437897700001.
- Zhang, W., Gen, M., 2011. An efficient multiobjective genetic algorithm for mixed-model assembly line balancing problem considering demand ratio-based cycle time. *J. Intell. Manuf.* 22 (3), 367–378, Place: Dordrecht Publisher: Springer WOS:000290574400004.
- Zhang, L., Li, Z., Wu, K.-J., Yang, W., 2019. Exploring the optimal safety person-job matching method of major equipment based on human reliability. *Appl. Sci. (Switzerland)* 9 (6).
- Zhang, Z., Tang, Q., Ruiz, R., Zhang, L., 2020. Ergonomic risk and cycle time minimization for the U-shaped worker assignment assembly line balancing problem: A multi-objective approach. *Comput. Oper. Res.* 118.
- Zhao, X., Liu, N., Zhao, S., Wu, J., Zhang, K., Zhang, R., 2019. Research on the work-rest scheduling in the manual order picking systems to consider human factors. *J. Syst. Sci. Syst. Eng.* 28 (3), 344–355.
- Zhu, Z., Zheng, F., Chu, C., 2017. Multitasking scheduling problems with a rate-modifying activity. *Int. J. Prod. Res.* 55 (1), 296–312, Place: Abingdon Publisher: Taylor & Francis Ltd WOS:000390416600019.