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# Optimization of Human-Aware Manufacturing and Logistics Systems: A Survey on the Modeling Frameworks of Human Aspects

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# Optimization of Human-Aware Manufacturing and Logistics Systems: A Survey on the Modeling Frameworks of Human Aspects

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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 manufacturing and logistics systems. A focus is put on the modeling frameworks proposed to represent 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 manufacturing and logistics systems are surveyed. The existing Human-Aware Modeling Frameworks (HAMF) are classified and reviewed by domain in the form of a toolbox. 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 HAMFs 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.

# Optimization of Human-Aware Manufacturing and Logistics Systems: A Survey on the Modeling Frameworks of Human Aspects

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## 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 manufacturing and logistics systems. A focus is put on the modeling frameworks proposed to represent 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 manufacturing and logistics systems are surveyed. The existing Human-Aware Modeling Frameworks (HAMF) are classified and reviewed by domain in the form of a toolbox. 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 HAMFs 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.

*Keywords:* Optimization, Human Factors, Ergonomics, Manufacturing, Logistics

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## Preamble

Given the large volume of reviewed material, which does not allow us to present a substantive analysis in a single paper, the present work of literature review has been split into two separate papers (parts), that are highly connected. The first part of this work (Prunet et al., 2022) starts with a clear definition of the scope of the literature review, and an explanation of the methodology applied to collect the relevant material. The current paper focuses on the modeling of human aspects in a broad sense, and surveys the modeling approaches found in the Operations Research (OR) literature to integrate human aspects into decision models. It is intended as a toolbox for the interested reader, presenting the existing range of *Human-Aware Modeling Frameworks* that can be applied to integrate human considerations into decision models.

## 1. Introduction

This paper is part of a review work that studies the integration of human-aware considerations in optimization models addressing applications in manufacturing and logistics. In this paper, we present the models and methods found in the collected material that integrate a *Human Aspect (HA)* (i.e., a characteristic or behavior that is typically human) into a decision-support model. A model that expresses and quantifies a HA is called a *Human-Aware Modeling Framework (HAMF)*. The present paper is intended as a *toolbox* for an interested OR practitioner and aims to provide an overview of available methods for the integration of a HA in their work. In the first part of this work (Prunet et al., 2022), 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., 2022) 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 the 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, the 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 the 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 HAs with their models. The present work gives an overview of the literature on the integration of HAs in decision models, and provides a holistic study of this topic.

*Structure of the paper.* In the current paper, we focus on the modeling frameworks found in the collected material, which represent the human aspects in decision problems. This paper is intended as a *toolbox* for an interested OR practitioner: We present the main HAMFs found in the literature, and derive some insights on their respective industrial and ergonomic relevance, the ease of use, and the related difficulties. We first present in Section 2 the key concepts, related to human-aware modeling, that structure the rest of our work. In the same section, we introduce the background related to *Human Factors and Ergonomics (HF/E)*, and give a general introduction on the HAMFs studied in the paper: methods, validity, ease of use, etc. After this brief introduction, Sections 3 to 8 review the different HAMFs 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 HAs 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 HA. Finally, we conclude this paper in Section 9.

As already mentioned, this paper is part of a larger work that includes (Prunet et al., 2022). The collection of the material for the discussion in both papers had been performed at the same time. Thus, we provide details of our semi-systematic collection methodology only in (Prunet et al., 2022) to which the interested reader is referred. Prunet et al. (2022) also provide a more substantial introduction and contextualization of the overall work, a review of the OR literature integrating HAs, and an analysis of the related mathematical programming considerations. Note that the discussion on the collected material, and the potential research gaps we identified, are presented in (Prunet et al., 2022).

## 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 all along of this paper. We will refer to:

- **Human Factors and Ergonomics (HF/E):** as the scientific discipline that studies the interactions between a human operator and his/her work system, with a concern on the improvement of the working conditions.
- A **Human Aspect (HA):** 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.
- **Human-Aware Modeling:** as the understanding and quantification of the interactions between humans and other elements of a system, and the application of theory, principles, data, and methods to optimize human well-being and overall system performances. Human-Aware Modeling deals with

the quantification and modeling of HAs based on the principles and methods from both HF/E and OR.

- A **Human-Aware Modeling Framework (HAMF)**: as a quantitative model representing a HA. It represents a quantitative metric for a HA, enabling its integration into an optimization model. It is based on principles and methods from both OR and HF/E.
- **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.
- **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 **Production or Service System**: as a set of elements (e.g., employees, machines, information) that interact with each other with the aim to create products or services for customers, either internal or external.

It is brought to the reader's attention that these definitions are consistent with those introduced in (Prunet et al., 2022), 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 HAMFs 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 HAs: 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 HAs. In this case, we refer to these works as using *implicit metrics* (see Section 8.1 for more details). In the vast majority of the research works included in the collected material, the authors use a defined framework to model a HA. This HAMF 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 HAMFs is HF/E, and unsurprisingly, a lot of HAMF 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). However, there are also concepts that originate from the fields of Human Resource Management (e.g., skills in Section 3.1), psychology (e.g., learning curves in Section 3.2), or system engineering (see e.g., health states and total cost functions in Sections 8.5 and 8.9). It is important to keep in mind the origin of a HAMF, to estimate its validity and ease of use.

*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<sup>1</sup>. 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 HAMFs. 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, that 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 HAMF.* In the rest of this paper, we present the HAMFs found in the collected material. For each of them, we try to briefly introduce the background they rely on, and present some thoughts on the use of this HAMF in decision models. When discussing the advantages of a given HAMF, 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 HAMF 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 HAMF. 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 HAMFs 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 an 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 HAMF, 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 HAMFs. 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:

- *Skills*, as the competences of employees in Section 3.1. In the literature, the concept of *skills* is used to model both the required qualifications to perform a job and the proficiency of an individual at a given task. The distinction between these two notions is explained, and both topics are discussed. Skill improvement through training is also introduced via *training*, i.e., a specific training activity, scheduled to increase the proficiency of an employee (or a group of employees). Although training implies learning at an individual level, the benefit is provided via a specific activity. It is therefore called *induced learning*.
- *Learning*, as the autonomous improvement of the skills of employees in Section 3.2. In opposition to skill improvement by training, learning takes place autonomously, with the repetition of similar tasks leading to an improvement in performance. It is modeled with either *learning curves* or *learning effects*. The opposite notion of learning is forgetting, which occurs after a prolonged idle period on a specific task. Forgetting is also addressed in this section.

#### 3.1. Skills

Skill is one of the most prolific research streams in Human-Aware Modeling, due to the ease of modeling and the applicability to a large variety of contexts. 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). This section ends with a discussion of innovative applications found in the literature.

*Qualifications.* The simplest way to deal with skills in the literature is to consider the compatibility between employees and tasks. This is a very common feature in workforce assignment or scheduling problems, and is included in a large number of papers jointly with other more complicated features (Van den Bergh et al., 2013). Basically, each worker has a set of tasks he/she is allowed to perform, and this is enforced by a hard compatibility constraint (see Prunet et al. (2022), *Compatibility constraints*). In this way, despite being qualified as *skills*, this would be more applied to a *qualification* in a real-life context. Koltai and Tatay (2013) provide an analytical introduction to this HAMF. Among all existing papers considering this HAMF, one can cite early works such as (Stewart et al., 1994) for workforce sizing, or (Cai and Li, 2000) for work scheduling. Manavizadeh et al. (2013) study an assembly line balancing problem with a relevant distinction between permanent and short-term workers. Anoshkina and Meisel (2020) apply the qualification model to vehicle routing and drivers' scheduling (inter- and intra-day). For the works focusing on industrial applications, 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. Shuib and Kamarudin (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 different jobs, rather than *skills* that are often modeled with more sophisticated approaches.



*Skill levels.* One other very common approach to model skills in optimization models is through varying task times (see [Prunet et al. \(2022\)](#), *Varying task times*), where the processing time of a given task varies depending on the assigned operator. This approach is usually used in more recent works compared to *qualifications*. This HAMF is also fairly easy from the modeling perspective. It reflects more accurately what a skill actually is, i.e., an indicator of proficiency at a given task, instead of qualification. However, the integration into mathematical models increases their complexity, since the processing time of a task is not anymore a fixed exogenous parameter. With this approach, the task duration depends on the skill level of the operator assigned to it. 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 (see, e.g., [Marichelvam et al. \(2020\)](#); [Lanzetta et al. \(2016\)](#)). Sometimes this approach is associated with the aforementioned task/worker compatibility constraints. The skill levels are used extensively in various areas of manufacturing and logistics. 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. The model proposed by [Egilmez et al. \(2014\)](#) is slightly more sophisticated with stochastic task duration, simulated using a Monte Carlo approach, where the expected processing time and variance are different for each worker. This approach has been encountered in ([Hong, 2018](#)) applied to a warehousing context, where the author models stochastic task times (skill-dependent) to study the impact of delays in a bucket brigade.

*Skill-dependent error rate.* Another class of HAMFs used to account for skills in an optimization model is related to the error rate or the quality level. 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 often modeled very similarly to the skill-dependent processing time, with an error rate or quality rate depending on the skill level of the operator assigned to the task (see [Prunet et al. \(2022\)](#), *Varying quality*). This is most often done with a parameter matrix with two entries: operator and task. [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 the 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. Fuzzy reasoning is indeed a reasonable choice to model such a process, where real-life inputs are uncertain.

*Skill-dependent cost.* Another common consideration about skills is of economic nature. It is a reasonable assumption that a better performing employee, or a very versatile one with a large skill set, is associated with a higher wage. This HAMF is 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. Wages and training costs are integrated into a total cost function. In ([Aryanezhad et al., 2009a](#); [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. [Moon et al. \(2009\)](#) apply a skill-dependent cost function within assembly line balancing. In ([Zhang and Gen, 2011](#)), the financial aspect is integrated as a parameter for each task, depending on the operator performing the task. [Yan et al. \(2019\)](#) integrate skill-dependent costs into vehicle routing.

*Skill improvement via training.* Another well-studied aspect of skills in the optimization of logistics and manufacturing systems is the variation of the competence levels. 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 effects and learning curves (see Section 3.2). 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., 2009a), 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. In (Stewart et al., 1994; Hopp et al., 2004; Olivella and Nembhard, 2017), the authors study different cross-training strategies, and establish a comparison between them, with respect to different objectives either regarding the workforce composition (more generalist/specialist), or the robustness of the solution to buffer the variability related to the workforce availability. McDonald et al. (2009) 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.

*Applications.* Finally, some research works focus their contributions on the explicit modeling of skills, instead of a generic *skill level*. There is indeed an additional effort to make to pass from a more academic-centered work to a real-life application, where different skills have to be identified and the employees' proficiency assessed on those skills. Kiassat and Safaei (2019) study the effect of imprecise skill level evaluation in workforce rotation frameworks. 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). 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. These skills and personality traits, as well as individual preferences, are used to classify employees into several homogeneous categories, enabling an easier computation (see Prunet et al. (2022), *Heterogeneous workforce*). Matusiak et al. (2017) also exert substantial modeling efforts on the skill representation. They study order batching and assignment in a warehouse with a focus on order picker skills, and 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). Koltai et al. (2014) study an assembly line balancing problem in a bike manufacturing company with a modeling effort put on skills based on real-life considerations.

### 3.2. Learning effect and individual learning

Learning curves and learning effects have been extensively studied in the collected material, and the amount of literature available on this topic is abundant. Furthermore, several reviews have been published recently on the topic, thus we chose not to go into extensive details on the models available in the literature. An interested reader can find a detailed analysis on the topic in (Anzanello and Fogliatto, 2011) or (Glock et al., 2019b). The latter provides a recent systematic literature review on the application of learning curves to production and operations management.

Note that *skill improvement via training* is studied in the previous section, which is a form of learning, induced by an exogenous source. In this section, we focus on autonomous learning, where the repetition of a given action by an individual makes him/her more efficient over time.

*Learning effects.* The early work on learning focuses on learning effects, where a production system increases its productivity rate as time goes as a consequence of a general improvement of processes and increased knowledge of the system. This is commonly called the *learning effect*, partly due to the cognitive process of learning from employees, but also to the operational improvement from the firm, for example when launching a new production line. Learning effects have been first integrated into lot sizing models, to account for the improvement of the production processes over time. Some early papers include (Muth and Spremann, 1983; Smunt, 1987; Elmaghraby, 1990), that study analytically how learning and forgetting

effects affect lot sizes and production quantities. Learning effects are also extensively studied in machine 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. One can cite (Biskup, 1999), which was among the first paper to integrate learning effects into the scheduling theory. Other early works on the topic include (Cheng and Wang, 2000; Mosheiov, 2001; Mosheiov and Sidney, 2003), where learning parameters depend on the job category. Research on single machine scheduling with a learning effect is still ongoing, as many papers are still publishing studies with more and more sophisticated approaches, for example, (Li et al., 2018b) integrates the worker experience, or (Pei et al., 2017) with serial batching and deterioration effects. Flowshop scheduling problems have also been considered with learning effects (Wang and Xia, 2005; Amirian and Sahraeian, 2015; Pargar and Zandieh, 2012). There are attempts to integrate learning effects with other families of problems, although less frequently. For instance, Otto and Otto (2014) study learning effects on assembly line balancing with a different learning curve for each task, Zanoni et al. (2012) apply them to the vendor managed inventory problem. Zhang et al. (2013) study both induced and autonomous learning in machine scheduling, and Jaber and Peltokorpi (2020) study group learning, the effect of which depends on the group size.

*Individual learning.* Learning curves are used to model the autonomous learning of individual employees. It is indeed a natural hypothesis when studying learning in logistics and manufacturing systems that, the more an operator repeats a specific task, the more proficient he/she becomes with it. The modeling of individual learning instead of a general learning effect enables a finer granularity in modeling the heterogeneity of the workforce in terms of initial capacities, as well as learning capabilities. Some works study the impact of the workforce heterogeneity on the solutions provided by optimization models within a learning context, for example, (Shafer et al., 2001; Nembhard and Shafer, 2008) with simulation methods and industrial data. These works show that individual modeling might have a significant impact on solutions, and is therefore interesting to integrate into optimization models. A discussion on the impact of a heterogeneous workforce on optimization models is also provided in (Prunet et al. (2022), *Heterogeneous workforce*). 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 Bentoufouet, 2014), that use more sophisticated models with several competences considering learning effects. Individual learning parameters have also been used in machine scheduling (Anzanello and Fogliatto, 2010; Janiak and Rudek, 2010). In assembly line problems, Bukchin and Cohen (2013) study the shared work, where the workload of a new employee is partly carried out by seasoned workers. This shared part decreases over time according to a learning curve. This HAMF is also found in lot sizing, especially to compute the Economic Order Quantity (EOQ) (Kazemi et al., 2015, 2016a). Lohmann et al. (2019) study the grouping of workers with a similar learning profile to increase productivity. Finally, Korytkowski (2017) proposes a new model to assess the performances of multi-skilled workers depending on learning, forgetting, experience and competencies.

*Learning curves.* Considering the broad scope of this review, we are not presenting the different models of learning curves found in the literature. Interested readers are directed to the several insightful reviews published on this topic (see Prunet et al. (2022), *Previous reviews*), in particular (Glock et al., 2019b) or (Anzanello and Fogliatto, 2011).

Learning is most often considered through Learning Curves (LC), i.e., a mathematical expression of productivity/task duration depending on the time spent on similar tasks, or its position in a schedule. Learning curves have been first introduced in the seminal work of Wright (1936) through an equation of the form displayed in (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. This learning curve, although still broadly used by the community, presents several flaws that limit its suitability to model realistically the learning phenomenon. The first of these limitations is its asymptotic behavior, where the marginal production time  $y_x$  tends toward zero as  $x$  grows, which is unrealistic for most applications. Several other LC models have been developed in the literature. First, there are several other log-linear models that have a general behavior similar to the LC of Wright (1936), yet with more sophisticated mechanisms to better reflect real-life considerations. Jaber and Bonney (2003) propose a formulation with a *plateau effect*. De Jong (1957) addresses the problem with an irreducible minimum 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. [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 \(2020\)](#).

Log-linear learning curves are the most common ([Glock et al., 2019b](#)), but models based on other shapes of LCs exist in the literature. Exponential models are based on an exponential decay mechanism, for instance, the curve developed by [Levy \(1965\)](#). Another common family of LC is based on a hyperbolic dynamic, as introduced by [Mazur and Hastie \(1978\)](#). [Jaber and Sikstrom \(2004\)](#) and [Grosse et al. \(2015\)](#) study different classical LC models and draw a comparison between them.

Some recent OR works have also tried to develop new models. [Przybylski \(2018\)](#) study parallel machine scheduling, with learning based on a proper Riemann integral, and [Kleiza and Tilindis \(2016\)](#) develop an “almost learning curve” for manual assembly. [Jaber and Peltokorpi \(2020\)](#) focus on group learning and study the impact of the group size on the learning mechanism. 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.

*Forgetting.* Forgetting is commonly associated with learning in Human-Aware Modeling. Learning models are used to represent the proficiency an employee acquires by repeating the same task. In this context, forgetting designs the deterioration of performances due to the assignment of the employee to different tasks. 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., 2018b](#)). Additionally, [Huang et al. \(2012\)](#) integrate learning and forgetting into a newsvendor model, and [Ayough et al. \(2020\)](#) model LCs in a line balancing problem.

The most common learning and forgetting HAMF 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. The forgetting exponent in this model is a function of the learning rate, the cumulative experience of the employee, and the total time for complete 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](#)).

*Applications.* In this paragraph, we highlight some interesting applications of learning models in manufacturing and logistics systems, among the vast literature published on the topic. [Kazemi et al. \(2016b\)](#) 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. Another lot-sizing application is ([Teyarachakul et al., 2011](#)), where the authors study analytically the effect of learning and forgetting on batch sizes. In ([Anderson Jr. and Parker, 2002](#)), learning is accounted for in the in-house or outsourcing production decisions. Some interesting applications have been studied in the routing literature. [Battini et al. \(2015\)](#) compare daily routing optimization, where a new routing plan is assigned to drivers on each day, 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. Other interesting works include ([Şenyiğit et al., 2020](#)), which studies the effect of the OCRA parameters (see Section 5.4) on the learning rate in machine scheduling. In ([Corominas et al., 2010](#)), the learning curves affect the performances on related tasks: Performing one task also gives experience on other related tasks, and the higher the relation between tasks, the higher the impact of learning. Another innovative application area concerns the learning of new employees or short-term workers. [Stratman et al. \(2004\)](#) estimate the shadow cost of learning and forgetting in hiring workers for short-term activities. In ([Bukchin and Cohen, 2013](#)), a learning curve is used to model new performances of employees, and a part of their workload is assigned to seasoned workers during the learning period.

## 4. Fatigue and breaks

In this section, we discuss the HAMFs 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). The topics covered in this section are:

- *Energy expenditure* in Section 4.1 representing a measure of the metabolic energy consumption over a given work period. This HAMF is a field-validated measure of the accumulation of fatigue for an operator.
- *Rest allowance* in Section 4.2 is a concept relying on the energy expenditure. The broad idea is to associate a work activity (that generates fatigue) with a rest break allowance (that enables some recovery to keep fatigue at a reasonable level).
- *Deterioration effect and rate modifying activities* in Section 4.3, where the processing time of a task is increased as work time goes, to account for the increasing fatigue level of an employee, and breaks can be scheduled to reduce this fatigue.
- The *Learning forgetting fatigue recovery model* in Section 4.4, where fatigue, recovery, learning, and forgetting are all accounted for to model the processing time of a task.
- *Meal break* in Section 4.5, that is a rather basic HAMF of break placement, where a time window is used to constraint the placement of breaks.
- *Regulation breaks* in Section 4.6, that model regulatory frameworks ruling the placement of breaks in a work shift. This mainly applies to transportation problems that take into account the enacted laws to keep truck drivers fatigue at a reasonable level.
- *Work-stretch duration* in Section 4.7 is very similar to regulatory breaks, but with different applications. The scheduling of rest breaks is indeed not regulated in most activity sectors, the modeling is, therefore, less homogeneous.

This section provides an overview of each of the aforementioned topics. The reader interested in examining in depth the subject is referred to (Xu and Hall, 2021), which propose a detailed literature review conducted on the topic of fatigue in OR, and especially in work-rest and shift scheduling, and derive insights from empirical studies and opportunities for OR applications.

### 4.1. Energy expenditure

Metabolic energy expenditure 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. The most common method applied to compute it was developed by Garg et al. (1978), originally for material handling applications. Note that energy expenditure is used as a general concept (i.e., the metabolic energy consumption associated with a task), and as a specific HAMF that most of the time follows the definition of Garg et al. (1978). Energy expenditure 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 energy expenditure of this period.

In the collected material, the concept of energy expenditure is sometimes used as an implicit metric without being properly described. Dewi and Septiana (2015) study a workforce scheduling problem with a physical and mental workload, balanced between workers, and use energy expenditure as a HAMF for physical workload based on the Indonesian National Standard. It uses a simple traffic light classification with a score assigned to each task. Rattanamanee et al. (2015) study a multiple workday vehicle routing problem, where the goal is to balance the physical workload, defined with an implicit metric, among the driver pool. Zhao et al. (2019) use energy expenditure defined based on the work of Wu and Wang (2001): The HAMF is mainly based on the heart rate and other parameters of the concerned individual. It computes a maximum work duration for a given task, as well as the corresponding productivity and error rate incurred when performing the task. In (Zhao et al., 2019), this HAMF is applied to a work-rest scheduling problem in manual order picking. Kara et al. (2014) study an assembly line balancing problem with physical and psychological ER, posture and illumination level. A threshold level of energy expenditure for each employee

over a shift is enforced in the model constraints (see [Prunet et al. \(2022\)](#), *Threshold constraints*). Another example is provided by [Diefenbach et al. \(2020\)](#), who study the tow train design for material handling. Their model accounts for the ER of the different operations implicitly, but energy expenditure is used as the HAMF in their numerical applications.

*Manual order picking in warehousing.* In this context, the majority of papers are based on the definition of energy expenditure introduced by [Garg et al. \(1978\)](#). This HAMF is very common in manual order picking in warehouses. One can cite ([Calzavara et al., 2017, 2019a](#)), which aim at finding the optimal rack layout among several options (full pallets, half pallets with or without pullout systems). The picking action is decoupled in elementary tasks, and the energy expenditure, as well as picking time, is computed for each layout option. [Calzavara et al. \(2017\)](#) study different scenarios, and [Calzavara et al. \(2019a\)](#) extend the previous work to integrate the design choices with storage assignment decisions. [Battini et al. \(2016b\)](#) and [Diefenbach and Glock \(2019\)](#) also study storage assignment with energy expenditure while reducing overall walking time and ER. Finally, [Battini et al. \(2016b\)](#) use as well the energy expenditure and rest allowance, and [Diefenbach and Glock \(2019\)](#) integrate the layout design of the U-shape picking zone into their decision model.

*Assembly lines.* Another important area of application for energy expenditure is related to assembly line balancing. [Battini et al. \(2016a\)](#) propose a method to compute energy expenditure with tables using the predetermined motion capture system: This is a common tool in HF/E, where the range of feasible movements in a given work situation is decomposed into elementary movements (e.g., reach, grasp), and a value is associated with each of them. These values can be different depending on work situations (e.g., awkward posture, difficult hand grasp). 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. In ([Battini et al., 2016a](#)), the most common elementary movements found in assembly work are identified. The energy expenditure corresponding to these elementary movements is then computed with the model of ([Garg et al., 1978](#)), the results are presented in tables to form what is called a predetermined motion capture system. Their model is tested on an industrial case of a high-pressure cleaner manufacturer. [Battini et al. \(2017a\)](#) make use of this predetermined motion capture system to compute energy expenditure in an integrated assembly line balancing and part feeding model. [Al-Zuheri et al. \(2013, 2016\)](#) study manual assembly problems, with energy expenditure used as an objective function, associated with another biomechanical exposure variability metric, and a threshold constraint (see [Prunet et al. \(2022\)](#), *Threshold constraints*), respectively. [Finco et al. \(2020b\)](#) use the energy expenditure and rest allowance to modify the task time before solving an assembly line balancing problem.

[Battini et al. \(2017c\)](#) study a lot sizing problem with a total cost function accounting for the paid rest allowance of operators computed on energy expenditure. [Zhang et al. \(2018\)](#) use a 3D simulation software (IGRIP/ERGO) to compute the energy expenditure according to ([Garg et al., 1978](#)). [Gebennini et al. \(2018\)](#) study a job assignment problem with a threshold value on the energy expenditure (see [Prunet et al. \(2022\)](#), *Threshold constraints*), taking into account the physiological differences between operators.

*Advantages.* The model developed by [Garg et al. \(1978\)](#) assumes that a job can be divided into elementary tasks and that the energy expenditure of the job is the sum of the energy expenditure of its elementary components. The elementary tasks include maintaining a standing posture, walking, lifting, etc. Tables are used to compute the energy expenditure of the different tasks depending on their characteristics (speed of walking, carried load, etc). The HAMFs based on energy expenditure present several advantages for an OR practitioner, explaining their popularity in the collected material:

- It originates from HF/E, and is therefore soundly validated by empirical data and studies.
- It is linear, which is not always the case for other HAMFs based on works from HF/E. Indeed, an elementary movement is associated with an energy value, and the total energy consumption of an individual corresponds to the sum of the energy expenditure for all elementary movements in the work shift. It is actually quite uncommon for ER assessment methods to be designed without any coupling factors or non-linearities. The drawback of this linearity is that the method lacks some refinement in assessing the ER based on fatigue. It is indeed a convenient hypothesis to assume that the fatigue level (and the associated risk) grows linearly with time, yet it is not very realistic, as most other risk assessment methods originating from HF/E are non-linear (see Section 5).

#### 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 the full recovery and depends on the length and intensity of the work period it follows.

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 energy expenditure. The value of the rest allowance is computed according to Equation (2), where parameter  $E$  represents the energy expenditure of a task.

$$RA = \begin{cases} 0.41 \cdot E - 1.76, & \text{if } E > 4.2927 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

The higher the energy expenditure, the higher the ergonomic risk for the operator. If the average value of energy expenditure for a work period exceeds the threshold of 4.2927, then the risk is excessive, and a break should be scheduled to enable recovery (Price, 1990). Accordingly, the processing time of a task can be adapted to take into account this additional rest, as it is shown in Equation (3) where  $T$  is the nominal task time, and  $\hat{T}$  is the corrected one.

$$\hat{T} = T \cdot (1 + RA) \quad (3)$$

*Corrected task times with the rest allowance.* 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. In the collected material, this method had been, for example, used by Battini et al. (2016b) to model picking time in storage assignment. Battini et al. (2017a) and Finco et al. (2020b) study the assembly line balancing problem, and use rest allowance, based on energy expenditure, to compute new task times integrating rest breaks. Battini et al. (2017c) and Condeixa et al. (2020) use the rest allowance as a cost in a total cost function (see Section 8.9): 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.

*Other computation methods for the rest allowance.* Although Price (1990) provides the main computation method found in the collected material to assess rest allowance, other methods are present in the literature. Battini et al. (2017b) study the order picking and use the rest allowance in a total cost function. They compute it using the OWAS index of a task (see Section 5.3), instead of the energy expenditure. 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). Calzavara et al. (2019b) propose another analytical computation method for the rest allowance based on energy expenditure. Their model takes into account an exponential fatigue and recovery rate. The estimation of these parameters is performed using a heart monitoring system.

*Advantages.* Since the RA is based on energy expenditure, 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. (2022), *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 (see Prunet et al. (2022), *Varying task times*)

#### 4.3. Deterioration effect and rate modifying activities

*Deterioration effect* is another common family of HAMFs used to integrate fatigue into decision models. This effect is based on a simple hypothesis: The performance of an individual in a work situation (e.g., his/her productivity) decreases over the time spent without a break. Different functions can be used to model this productivity drop. To restore the productivity level, a rest break needs to be scheduled. During this break, the productivity level is restored, increasing according to another function up to its initial value. Since

breaks modify the productivity rate, they are called *Rate Modifying Activities (RMA)* in the related literature. The function modeling the deterioration effect is called the *decay function*, and the one modeling the breaks is called the *recovery function*. A model for deterioration effects and RMA is characterized by these two functions, several examples are found in the collected materials. The principle is quite simple: With working time going, fatigue increases, and thus the employee productivity (or error rate) decreases (resp. increases). Then recovery happens during breaks (i.e., RMAs), where the productivity is restored. This approach fits nicely in the existing scheduling literature. Furthermore, these HAMFs provide appropriate models of human fatigue with a limited number of required parameters, which explains their popularity in OR models.

*Linear decay and recovery.* An early HAMF on this topic is introduced by [Bechtold \(1979\)](#). The author develops a simple model for deterioration effect and RMA, based on linear functions for both decay and recovery, that is the basis of a more refined model introduced in more recent works. The model provided by [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, both the work-rate decay and the recovery are considered linear, with a maximum production rate at full rest. These functions are characterized by a set of parameters for each employee, as the workforce is considered heterogeneous (see Section 8.4 and [Prunet et al. \(2022\)](#), *Heterogeneous workforce*), and the goal is to find the best work-break schedule, where all employees take their break simultaneously. Figure 1 gives an illustration of this work-rate model.

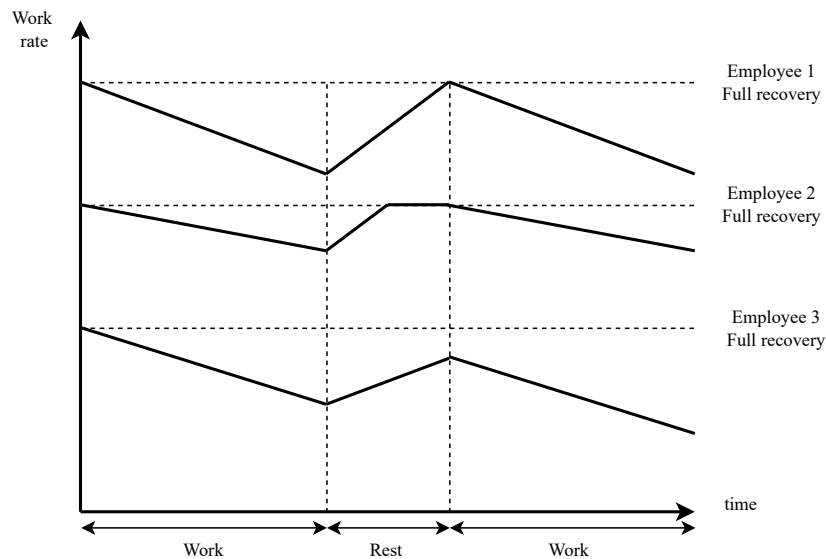


Figure 1: Three possible work-rate decay and recovery patterns based on ([Bechtold and Thompson, 1993](#))

*Position-dependent and time-dependent deterioration effect.* Another very common model for deterioration effect is a position-dependent or time-dependent effect. The literature on this topic is abundant, however, most of it is applied to machine scheduling, where the productivity of machines decreases over time, and RMAs corresponding to maintenance activities can be scheduled to restore this productivity. [Mosheiov \(2005\)](#) introduces the position-dependent deterioration effect, and provides a seminal work for this research stream. Despite being less common, the applications to human fatigue and recovery are still present in the literature. For example, [Lodree Jr. and Geiger \(2010\)](#) introduce the integration of time-dependent processing times and RMAs with human fatigue, and propose an analytical study of this HAMF in the scheduling theory. The proposed model is characterized by a simple linear decay function, and the recovery RMA is of fixed duration and fully restores the productivity to its initial level. The main difference with the model of [Bechtold \(1979\)](#) is the point of view: In the time-based deterioration effect, the decay function is applied directly to jobs instead of to the productivity of an individual. Note that 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. With a time-based deterioration effect, the processing time of a task depends linearly on its starting time in the sequence of tasks. In the



position-dependent deterioration effect, for example in (Mosheiov, 2005), the processing time of a task depends on its position on a sequence of tasks. The idea is that, for one job, the processing time increases as time passes over a shift with potentially a reset when an RMA break is scheduled if the model allows it. This is used, for instance, by Zhu et al. (2017), who study scheduling with interruption, fatigue effects, and rest breaks. Sanchez-Herrera et al. (2019) study a position-dependent deterioration effect based on fatigue, applied to a flowshop scheduling problem. Wang et al. (2020) study a position-based deterioration 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.

*Other frameworks.* Other models that refine the previous approaches are found in the collected material. Bautista et al. (2015) model both adaptation and fatigue affecting productivity: At the beginning of a shift the productivity increases slightly over time due to the adaptation of the individual to its work situation, then there is a plateau where the productivity remains constant, then the productivity decreases over time until the end of the shift, due to the fatigue of the employee. Jamshidi and Seyyed Esfahani (2014) integrate the impact of fatigue on error rate, instead of task time/productivity. Each machine has an exhaustion rate, that affects the work-rate decay of the individual assigned to it. When an employee reaches his/her exhaustion limit, then his/her production quality (e.g., error rate) decreases exponentially, until a rest break is scheduled to restore the fatigue level. Akbari et al. (2013) study a more tactical problem, where the production rate for one employee decreases for the second (or more) consecutive shift assigned to him/her. 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. Note that the fatigue/recovery component of the LFFRM presented in Section 4.4 is based on a deterioration effect introduced by Konz (1998) that extends the work of Bechtold (1979) by using exponential based decay and recovery functions, instead of exponential ones.

*Advantages.* One of the main advantages when working with deterioration effects is the existing body of literature on the topic: These models work analogously when applied to machines, whose productivity decreases over time until a maintenance operation is scheduled, 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 is not too time or competence intensive. Finally, the modeling with varying task times is studied extensively in the literature (see Prunet et al. (2022), *Varying task time*), providing a sound theoretical basis for the integration into decision models.

#### 4.4. Learning forgetting fatigue recovery model

The *Learning Forgetting Fatigue Recovery Model* (LFFRM) is a HAMF 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, the 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.

- 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), where the accumulated fatigue is computed as follows:

$$F(t) = 1 - e^{-\lambda t}, R(\tau_i) = F(t)e^{-\mu\tau_i}$$

Function  $F(t)$  is the accumulated fatigue level at time  $t$ , if the maximum endurance time is not reached. Function  $R(\tau_i)$  is the residual fatigue after a break of length  $\tau_i$ .  $\lambda$  and  $\mu$  are parameters that may vary among individuals. The behavior of these functions is illustrated in Figure 2.

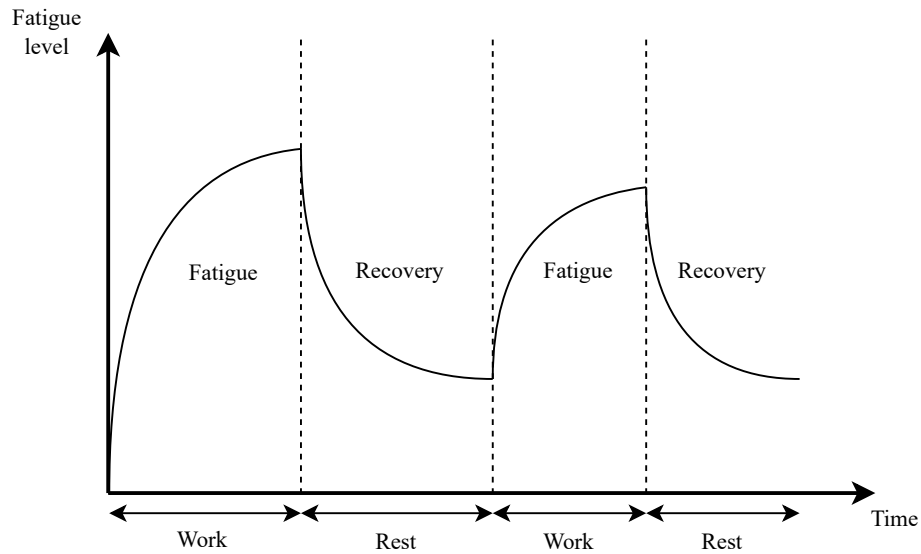


Figure 2: The dynamics of fatigue and recovery over time based on (Jaber et al., 2013)

*Usage of the LFFRM.* 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 of worker learning/forgetting and fatigue level. In the model presented by Givi et al. (2015b), one of the objectives is to reduce the error rate integrated with a total cost function. 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 use it in addition to biomechanical models (see Section 8.3), in order to find the optimal box size for an industrial packaging process. The objectives are the optimization of material handling, both from economic and ergonomic perspectives.

*Advantages.* The LFFRM is a HAMF composed of two different HAMFs, its advantages are therefore a mix of the advantages of the two 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 (see Prunet et al. (2022), *Varying task time*), which has the advantage of integrating two complementary HAs 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. 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 (see Prunet et al. (2022), *Time window constraints*). 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). Sometimes routing and scheduling are integrated. For instance, Kandakoglu et al. (2020) study an integrated visit scheduling and routing problem with considerations of meal breaks, skills, and equity. 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.

*Rest breaks seen as meal breaks.* Another common HAMF 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. In the collected material, this HAMF is often used in early works on work-rest scheduling (Mehrotra et al., 2000; Topaloglu and Ozkarahan, 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 HAMF 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 manufacturing and logistics 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 (see, e.g., work-stretch duration in Section 4.7).

#### 4.6. Regulatory breaks

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 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 a legislation, we call this HAMF *regulatory breaks* otherwise, we call it *work-stretch duration*. In this section, we discuss regulatory breaks, which are usually modeled with forward-backward constraints (see Prunet et al. (2022), *Forward-backward constraints*). In the collected material, they appear only in vehicle routing problems (VRP), mostly due to recent regulations that enforce companies to schedule the rest breaks in the routing plans of truck drivers (Kok et al., 2010b). Due to this obligation, the topic has seen substantial interest from the community.

*Different regulations depending on the country.* 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. Table 7 presents an overview of the main regulations found in the scope of this survey. For the European and Australian regulations, two alternate sets of rules are possible. Note that Table 7 presents a simplified and incomplete version of the concerned regulations to illustrate this section. An interested reader is referred to the end notes of this paper for the references to the actual regulations.

In the EU, the working time of truck drivers is regulated by the European Community (EC) Regulation No 561/2006<sup>2</sup>, which entered into force in April 2007. This law completes the Directive 2002/15/EC<sup>3</sup> that also regulates road transportation working hours. Since these regulations impose the logistics companies to schedule the breaks in their routing plans, they are the most studied in the context of this survey (Kok et al., 2010b; Prescott-Gagnon et al., 2010; Wen et al., 2011). Other regulations, apart from the European ones, are studied in the collected material, in particular in vehicle routing and drivers scheduling. Indeed, other countries have followed the example of the EU and produced their own set of rules for truck driver work times. The different 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<sup>45</sup>, Mayerle et al. (2020) the Brazilian ones<sup>6</sup>, in association with lunch break. Rancourt et al. (2013) and Rancourt and Paquette (2014) study a VRP with the US driving hours regulations<sup>7</sup>. (Rancourt and Paquette, 2014) also takes into account driver inconvenience in the design of routing schedules. 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.

Table 1: Examples of regulatory break rules

|  | US | EU<br>(basic) | EU<br>(alternate) | AUS<br>(basic) | AUS<br>(alternate) | BRA |
|--|----|---------------|-------------------|----------------|--------------------|-----|
| Max consecutive driving time                   | 8  | 4.5           | 4.5               | 5.25           | 6                  | 5.5 |
| Max driving time between two long rest periods | 11 | 11            | 9                 | 7              | 7                  | 12  |
| Min duration of a long rest period             | 11 | 9             | 10                | 12             | 14                 | 8   |
| Max on-duty time between two long rest periods | 14 | 12.25         | 14.25             | 12             | 14                 | 13  |
| Max duration between two long rest periods     | 14 | 13            | 15                | 17             | 17                 | 16  |
| Max driving time within six days               | 60 | 56            | 56                | 72             | 72                 | 72  |
| Max on-duty time within six days               | 60 | 60            | 60                | 72             | 72                 | 72  |

Some of these regulations enforce the dispatcher and logistics companies to integrate the corresponding requirements on work/break periods into their routing plans ([Kok et al., 2010b](#)). It is therefore not surprising that the topic has seen some attention from the literature. [Goel \(2009\)](#) is the first work, to our best knowledge, that integrate these regulatory frameworks into the VRP over a one-week planning horizon. Other works study these regulations, by integrating both vehicle routing and driver scheduling ([Kok et al., 2010a,b](#); [Prescott-Gagnon et al., 2010](#); [Wen et al., 2011](#)).

*Advantages.* There is no real advantage *per se* for this HAMF: 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 to use optimization methods, or to use simpler HAMFs 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

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. The mechanism is very similar to driving hours regulation, but the application differs since there is no transportation decision. The break rules are applied to shift scheduling or work-rest scheduling problems, often with additional side constraints. In other words, this HAMF is similar to regulatory breaks, 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 (see [Prunet et al. \(2022\)](#), *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. ([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. [Restrepo et al. \(2012\)](#) study a work-rest scheduling problem with breaks and overtime, applied in an industrial case of a parking lot. [Quimper and Rousseau \(2010\)](#) study a similar problem with formal language and automata to handle the complex break rules. [Rekik et al. \(2010\)](#) combine fractionable breaks and work-stretch duration in a work-rest scheduling problem. [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 HAMF 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, deterioration effect and RMA (see Section 4.3).

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

The HAMFs presented in this section consist in assessing the risk of the apparition of Work-related MusculoSkeletal Disorders (WMSD) for the operators. They are mostly derived from HF/E. Therefore one can claim that they are rather accurate in their assessment of work situations since they are 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. These HAMFs have been classified in different categories, introduced in the following subsections, depending on which risk they assess:

- *Whole body* assessment methods in Section 5.1 account for several body segments and risk factors. They aim at assessing a general risk.
- *Manual handling* risk assessment methods in Section 5.2 focus mostly on back pain for material handling tasks.
- *Postural* risk assessment methods in Section 5.3 study the work postures. These methods consider different parts of the body.
- *Repetitive movements* risk assessment methods in Section 5.4 focus mostly on the upper limb when performing repetitive tasks.

### 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 HAMF in this category, but some works using other frameworks are presented as well.

*European Assembly Worksheet.* The EAWS, introduced by [Schaub et al. \(2012\)](#), is a risk assessment framework designed to assess the ER as a whole that integrates different risk factors: postures, action forces, manual handling, whole body risk factors, and repetitive loads for the upper limb. It was created as an extension of the Automotive Assembly Worksheet (AAW), which is another whole body risk assessment method. To encourage improvements in the safety and health of workers, the EAWS generalizes the AAW to other activities, in the form of a method that fits the EU regulatory frameworks dealing with machining in manufacturing, namely the EU machinery directive No. 2006/42/EC<sup>8</sup> and the EU general framework No. 89/391/EEC<sup>9</sup>. The holistic vision of the EAWS is intended to capture a large variety of risk factors and to create a self-sufficient method for the ergonomic evaluation of assembly work.

The EAWS is based 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. An interested reader could find a detailed presentation of the computation method for each of the sections of the EAWS in ([Schaub et al., 2012](#)), which we only briefly introduce below:

- The general section is an additional one, included in the whole body score. This section gives additional points to the whole body score, depending on aspects that are not represented in the other sections, e.g., working on moving objects, or vibration exposure.
- The section related to working postures assesses the static working postures and the high-frequency movements. The computation methodology for the static postures is made using a worksheet, where 16 possible generic postures are described, and points are given depending on the time spent in each posture. Some asymmetric considerations (e.g., trunk rotation or lateral bending) are also considered for additional points.

- The section related to action forces uses a worksheet that gives a score depending on the force required, and the concerned body section. Then additional points are given depending on the working postures observed when these action forces occur.
- The manual handling section gives a score depending on the load weight and the sex of the worker carrying the load. Then additional points are given for the handling posture, pushing or pulling actions, the holding time, the traveled distance, and the frequency of load manipulation.
- The section related to the repetitive movements of the upper limbs gives the upper limb score using another worksheet. The force and grip quality, as well as the frequency of movements, are considered to compute the finger score. Then additional points are given depending on the hands and arms postures, and additional factors are accounted for (e.g., use of gloves, vibration exposure).

The overall score is then computed as the maximum between the whole body and upper limb scores. Depending on the value of this score the recommended action is determined by a traffic light evaluation system.

In the collected material the EAWS is used, for instance, in (Otto and Scholl, 2013; Hochdörffer et al., 2018), that study a job rotation problem in an automotive assembly line, where the goal is to balance the ER between the operators through industrial case studies. Hochdörffer et al. (2018) also consider skills, by taking into account the aging workforce in the manufacturing industry. The aged workforce 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.

*Other methods.* Some works in the collected material use an implicit metric for the ER, but provide details on the risk assessment methods that can be used within their model. Otto and Scholl (2011) study an assembly line balancing problem aiming at balancing the ER among workstations. The model is developed with a general risk assessment metric, and several HAMFs are presented to be used in this model, including the EAWS as well as the NIOSH-equation (see Section 5.2) and the Occupational Repetitive Actions index (see Section 5.4). Asensio-Cuesta et al. (2012a) study the job rotation problem with an aim of reducing the total ER. The authors 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.

*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 HAMF that can adapt to a large variety of work situations. The EAWS is designed to provide a self-sufficient checklist for the ergonomic assessment in manufacturing work. This completeness is an advantage, but also means that in specific situations, or 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, where it enables the use of a single worksheet instead of several different methods. 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

It is not surprising that manual handling, and especially lifting tasks, is 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 HAMFs 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).

*NIOSH lifting equation.* 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<sup>10</sup>. The NIOSH updated its guidelines in 1991 and provided a *revised* lifting equation to account for the advances in the field (Waters et al., 1993). For this reason, the NIOSH lifting equation is sometimes called the *revised NIOSH lifting equation* in the literature. The NIOSH equation is now part of the ISO 11228 standard<sup>11</sup>, as well as the European standard UNI EN 1005-2:2009<sup>12</sup>, and the US Occupational Safety and Health Administration (OSHA) final rules for ergonomics standards No. 29 CFR Part 1910<sup>13</sup> (Caballini and Paolucci, 2020; Otto et al., 2017). The NIOSH equation assesses the risk of WMSD and low back pain related to manual handling tasks.

In the collected material, one of the main families of problems integrating the NIOSH equation concerns warehousing applications. It is indeed not surprising since warehousing-related tasks involve a notable amount of manual handling activities. Otto et al. (2017) study the picking area in warehouses (i.e., the area where the employees walk to pick the items associated with the different orders), and use standard and linearized versions of the NIOSH equation in the objective function to optimize. The aim is to balance the ER among the different picking zones. Marvel et al. (2001) focus on the storage assignment decision, and a recommended weight limit is computed for each storage slot. This depends on its characteristics (e.g., the height of the slot). Moreover, it is considered that an item can only be stored in a slot if its weight does not exceed the limit. This consideration can also be found in assembly line balancing problems (Bautista et al., 2016a,b; Sana et al., 2019), where the NIOSH equation is used in addition to other HAMFs (the OCRA and the RULA) to compute an accurate estimate of the ER of a task, which is balanced via an objective function. Note that the use of several WMSD assessment methods altogether is quite a common modeling practice to account for several body regions or different activities. The same logic is used by Caballini and Paolucci (2020) to schedule workers in the port of Genoa. 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. A general workforce assignment problem is studied by Gebennini et al. (2018), where the NIOSH equation is associated with energy expenditure (see Section 4.1) to compute limit values over a work shift. Finally, this HAMF is found in works on lot sizing (Andriolo et al., 2016), where the decisions are decoupled between (i) the in-house problem that determines the packaging size handled inside the plant, accounting for the recommended weight limit computed using the NIOSH equation, and (ii) the in-bound problem that determines the optimal lot size.

*Computation of the Recommended Weight Limit (RWL).* The NIOSH equation is based on three criteria to identify hazardous lifting tasks: biomechanical, physiological, and psychophysical (Waters et al., 2007). The NIOSH equation includes the computation of the *Lifting Index (LI)* associated with a task, that is the ratio between the actual weight (*AW*) to handle, and the *Recommended Weight Limit (RWL)*:

$$LI = \frac{AW}{RWL}$$

The RWL is computed starting from a Load Constant (*LC*) that equals 23kg adjusted by some multipliers, as shown in Equation (4). This load constant corresponds to the maximal weight that is safe to handle in a perfect situation. The different multipliers are associated with additional risk factors and reflect the gap between the ideal and actual situations.

$$RWL = LC \cdot HM \cdot VM \cdot DM \cdot AM \cdot FM \cdot CM \quad (4)$$

First, *HM* is the Horizontal Multiplier, *VM* is the Vertical Multiplier, and *DM* is the Distance Multiplier. They depend on the relative position of the gravity center of the item to handle with respect to the operator. The Asymmetric Multiplier (*AM*) depends on the handling posture of the operator. The Frequency Multiplier (*FM*) depends on the frequency of the handling. Note that this multiplier is non-linear with respect to the lifting frequency. The Coupling Multiplier (*CM*) depends on the quality of the worker grip on the lifted item. The values of these multipliers are computed using reference tables. An interested reader can find these tables and more details on the computation of the RWL in (Waters et al., 1993).

The value of the lifting index corresponds to a recommended course of action in a traffic light system:

- $0 \leq LI \leq 0.75$ : The risk level is acceptable and no corrective action is required.
- $0.75 \leq LI \leq 1$ : This corresponds to the uncertainty zone, and damages are possible for some categories of workers. The employees should be educated and the situation monitored.
- $LI \geq 1$ : The situation presents a clear level of risk, and corrective actions are required.

Note that the lifting index is computed for a single lifting task, and we usually cannot extrapolate this result over a whole shift, where other effects take place, especially considering the frequency of the lifting tasks that has a significant impact on the ER (Otto et al., 2017). Waters et al. (2016) extend the NIOSH equation to take into account the variety of lifting tasks that can be present in one shift, and provide a risk estimation over a whole shift. In this case, the frequency multipliers become dynamic and account for the succession of tasks, where the succession of high-risk tasks is particularly penalized, improving the accuracy of the method, but adding additional non-linearities in the computation. The alternative is to compute the LI for each task of the shift, and compute the time-average sum of the lifting indexes of the different tasks. This method is the one that is used in the vast majority of the works related to the NIOSH equation in the collected material. It is definitely not as accurate as the method of Waters et al. (2016), but is much easier to handle mathematically since it can be linearized.

*Advantages.* The NIOSH equation is a comprehensive and field-validated risk assessment method for manual handling tasks, designed based on biomechanical, physiological and psychophysical criteria. The main advantage of this HAMF is its widespread use in regulations and guidelines for handling work. The NIOSH equation is therefore commonly used by HF/E practitioners, which reflects on its use in OR. 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) that should be addressed in modeling or solution methods. The usual way to handle them is by making some assumptions and linear approximations (see e.g., Otto et al. (2017) for more details), which reduce the modeling accuracy of the method.

*Job Strain Index (JSI).* The JSI is a risk assessment method first developed by Ayoub et al. (1978) for lifting injury. As with the NIOSH equation, the index for a given task is the ratio between the lifted weight and the maximum safe lifting weight for a given individual. The JSI has been validated through field studies (Ayoub et al., 1983; Liles et al., 1984). The main difference between the JSI and the NIOSH equation is that the JSI focuses more on the individual performing the lifting task, and accounts for his/her characteristics (e.g., gender, age) to compute the maximum weight for safe handling. On the other hand, the NIOSH equation computes a score corresponding to the safety of a work situation, no matter the operator performing the task.

In the collected material, the JSI 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. The group constitution is then taken into account to assign tasks. 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. This method assigns a monetary cost to poor ergonomic conditions in a workplace, enabling the integration of this HAMF in a total cost function (see Section 8.9). Aryanezhad et al. (2009b) study a job rotation problem, where the ER of the operators is considered with two risk factors: the potential of low back injuries with the JSI, and the sound level with the daily noise dosage (more details in Section 7.1). 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.

*Computation of the JSI.* First, the different tasks performed by an individual are classified into groups of similar tasks. Let us suppose that there are  $n$  groups, and  $m_i$  tasks in group  $i = \forall i \in \{1, 2, \dots, n\}$ . Each task  $j \in \{1, \dots, m_i\}$  is executed with frequency  $F_j$  and is associated with a maximum weight  $WT_j^i$  lifted when performing the task. Additionally, the lifting capacity of the individual performing the task is denote by  $CAP_j^i$ . Let us indicate by  $h_i$  (resp.  $d_i$ ) the hours (resp. days) per day (resp. week) during which the individual performs tasks of group  $i$ . Moreover, let us indicate by  $h$  and  $d$  the working hours in a day and the working days in a week, respectively. The JSI is calculated according to the following formula:

$$JSI = \sum_{i=1}^n \frac{hours_i}{hours_t} \cdot \frac{days_i}{days_t} \sum_{j=1}^{m_i} \frac{F_j}{F_i} \cdot \frac{WT_j^i}{CAP_j^i} \quad (5)$$

The term  $\frac{hours_i}{hours_t}$  corresponds to the ratio between the number of hours per day during which the individual performs tasks of group  $i$  ( $hours_i$ ) and the total number of hours of work for a day ( $hours_t$ ). The term  $\frac{days_i}{days_t}$  is similarly the ratio between the number of days per week the individual performs tasks of group  $i$  and the



total number of work days in a week. In other words, these terms correspond to the time proportion spent on working on task  $i$ .

The JSI depends on the worker capacity to lift a weight. It is therefore needed to know the person that is performing the task to compute this score. This capacity corresponds to the maximum weight that a given person can lift repeatedly without overtiring. The work of [Ayoub et al. \(1978\)](#) proposes a field-validated model to compute this capacity based on the anthropometric data of the person (e.g., gender, age, weight, arm and back strength, shoulder height). A value of 1.5 and above for the index should be avoided.

*Advantages.* The JSI presents the advantage of being individualized, compared to the NIOSH equation. Its reliability is also validated by field studies. The individual capacity factor is computed using statistical regressions from 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 depending on the context.

### 5.3. Working posture

In this section, we present the WMSD risk assessment methods that focus on posture-related risks. It is clear that 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 aspect they focus on. 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.

*Ovako Working posture Assessment System (OWAS).* The 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 non-ergonomists with non-ambiguous results even if it leads to some simplifications ([Karhu et al., 1977](#)). It assesses postures on the whole body and accounts for the carried load if relevant in the work situation.

In the collected material, the OWAS is used in an assembly line balancing problem by [Cheshmehgaz et al. \(2012\)](#) with a simplified version of the index, where they give a five-points risk score to each body part. Then these risk scores are used as inputs to compute an index of “accumulated risk of postures”, 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. The OWAS is also found in manual order picking for warehousing problems since it assesses postural ER while accounting for manual handling. In ([Battini et al., 2017b](#)), the OWAS is used in addition to energy expenditure (see Section 4.1) to compute a rest allowance and ER for the operators. Ultimately, the aim is to compute a profitability index accounting for the operator unavailability due to injuries, absenteeism, or rest periods. [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. They also combine the OWAS with the energy expenditure for the ER assessment, applied to a real industrial case, where ergonomic inputs are measured using a motion capture system.

*Computation of the OWAS score.* The OWAS assessment method divides the body into three segments (back, arms and legs) with an additional factor corresponding to the weight of the handled load. For a studied posture, each body segment gets a 1-digit code, according to Table 2. Note that the criteria of Table 2 are very comprehensive, and come with an illustrative sheet in ([Karhu et al., 1977](#)) to be easy to use for an untrained professional. Then a fourth code is computed depending on the handled load ( $\leq 10kg$ ,  $10 - 20kg$  or  $\geq 20kg$ ). From this four-digit code, the OWAS index of the posture is retrieved using tables (see [Louhevaara et al. \(1992\)](#)), and a course of action is recommended depending on the index value, based on expert opinions.

*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. This fits order picking activities. However, the method lacks precision for complex activities, as several important body segments are not considered (neck, wrist), and both right

Table 2: OWAS posture codes for the different body segments based on (Cheshmehgaz et al., 2012)

| Body area | OWAS code | Description of position                        |
|-----------|-----------|--|
| Back      | 0         | Back straight                                  |
|           | 1         | Back bent                                      |
|           | 2         | Back twisted                                   |
|           | 3         | Back bent and twisted                          |
| Arms      | 0         | Both arms below shoulder level                 |
|           | 1         | One arm at or above shoulder level             |
|           | 2         | Both arms at or above shoulder level           |
| Legs      | 0         | Sitting  |
|           | 1         | Standing on both straight legs                 |
|           | 2         | Standing on one straight leg                   |
|           | 3         | Standing or squatting on both feet, knees bent |
|           | 4         | Standing or squatting on one foot, knee bent   |
|           | 5         | Kneeling on one or both knees                  |
|           | 6         | Walking or moving                              |

and left sides are not considered separately. Furthermore, the postures considered are only static. Thus, the OWAS appears to provide a simplified postural evaluation for most assembly activities. However, it has been designed to be easy to use and apply for non-ergonomists and to provide non-ambiguous results, even if it leads to some simplifications.

*Rapid Upper Limb Assessment (RULA).* The 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 and guidelines on postural assessment. It has, moreover, been designed to fulfill the requirements of both the European directive No. 90/270/EEC on the minimum safety and health requirements for work with display screen equipment<sup>14</sup> and the UK guidelines on the prevention of work-related upper limb disorders<sup>15</sup>.

In the collected material, the RULA is used jointly with other HAMFs to evaluate the ER of a given task by covering different risk factors: posture, repetition (OCRA), and sometimes material handling (NIOSH equation). It is applied in assembly by Bautista et al. (2016a,b), who study the impact of an ergonomic objective on an assembly line balancing problem in a multi-objective context. The authors apply their model to an industrial case study of an automotive engine assembly plant. Sana et al. (2019) study a job rotation scheduling problem, where the multiple objectives all relate to the minimization of the ER based on different risk factors (posture, repetitive movements, and manual handling).

*Computation of the RULA index.* The RULA is a survey method, i.e., it is based on a survey of the literature on postural risk assessment at the time of development (1993). A score is computed 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). These scores are computed with the aid of a worksheet, rather similar to the REBA worksheet presented in Figure 3. The scores are aggregated in two global scores:

- Score A: Upper arms, lower arms, wrists, and wrist twists.
- Score B: Neck, trunk, and legs.

Then an additional load is added to both scores for the muscle use and force score, giving respectively score C and score D. Then the final score is computed with a double entry table, depending on score C and score D. This score provides a guideline to assess the ER associated with the working postures.

*Advantages.* The RULA provides a comprehensive risk assessment method and is usable with only a minimal formation, without requiring former experience in HF/E. 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.

*Rapid Entire Body Assessment (REBA).* The REBA is a concise, worksheet-based, postural assessment method. It has been designed by a team of UK ergonomists in [Hignett and McAtamney \(2000\)](#), in order 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](#)).

In the collected material, the REBA index is found in assembly line balancing. For instance, [Bortolini et al. \(2017\)](#) consider component picking before assembly, where awkward postures concern the whole body. In this case, the REBA method is used to assess the ER both on assembly tasks and item picking. This risk is balanced between employees as a second objective and the method proposed by [Bortolini et al. \(2017\)](#) is applied to an industrial case of a kitchen appliance assembly. [Yoon et al. \(2016\)](#) study a job rotation scheduling problem, which aims at balancing the daily workload among employees and reducing sequential high workloads. The REBA is the method used to quantify these workloads. The proposed method is then applied to an industrial case in the automotive industry.

*Computation of the REBA index.* The REBA method 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, and handling. The computation of the REBA and RULA indexes is very similar since the REBA is an extension of the RULA to account for the whole body, instead of the upper limbs ([Madani and Dababneh, 2016](#)). Score A is computed as the sum of different body segment scores (trunk, legs, and neck) with a coupling factor to account for a high load. Score B is the sum of the posture scores for the wrists, upper and lower arms, with a coupling score for each hand. Figure 3 presents the worksheet used to compute the REBA score jointly with the details of the computation. Scores A and B are then aggregated into score C, according to a double-entry table. Score C is summed with an activity score, corresponding to an additional risk factor (e.g., a posture held for more than one minute, unstable base, high repetition). The REBA score is then computed considering all these factors, and a corresponding risk level is given with a traffic light system.

*Advantages.* The REBA is very similar to the RULA assessment method. The REBA index is actually a more recent method and has been designed to address some of the flaws of the RULA index, especially the consideration of the whole body, and an improved definition of neutral postures ([Madani and Dababneh, 2016](#)). 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](#)). Furthermore, the REBA presents similar advantages to the RULA: ease of use, and stress studied on different body sections.

#### 5.4. Repetitive movements

*Occupational Repetitive Actions (OCRA).* The OCRA index ([Occhipinti, 1998](#)) is a concise evaluation index based on epidemiological data designed to assess the risk of WMSD for repetitive handling movements with a low load and a high frequency, based on epidemiological data. It is computed 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 (e.g., applied forces, postures, and vibrations). The OCRA index is the recommended evaluation method for repetitive actions by the ISO 11228-3 standard<sup>16</sup>, as well as the European NF-EN 1005-5:2007 standard<sup>17</sup>.

The OCRA index is designed for highly repetitive tasks. It is therefore not surprising that, in the collected material, the OCRA index is used in works related to assembly lines ([Akyol and Baykasoglu, 2019](#); [Zhang et al., 2020](#); [Bautista et al., 2016b,a](#)), and in job rotation scheduling problems ([Mossa et al., 2016](#); [Asensio-Cuesta et al., 2012b](#); [Botti et al., 2020](#)). [Botti et al. \(2017\)](#) 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. Another interesting application of the OCRA method is found in the work of [Caballini and Paolucci \(2020\)](#), which creates a roster with the aim of balancing the ER in the container terminal of the Italian port of Genoa. [Şenyiğit et al. \(2020\)](#) study the effects of the different OCRA parameters in a machine 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.

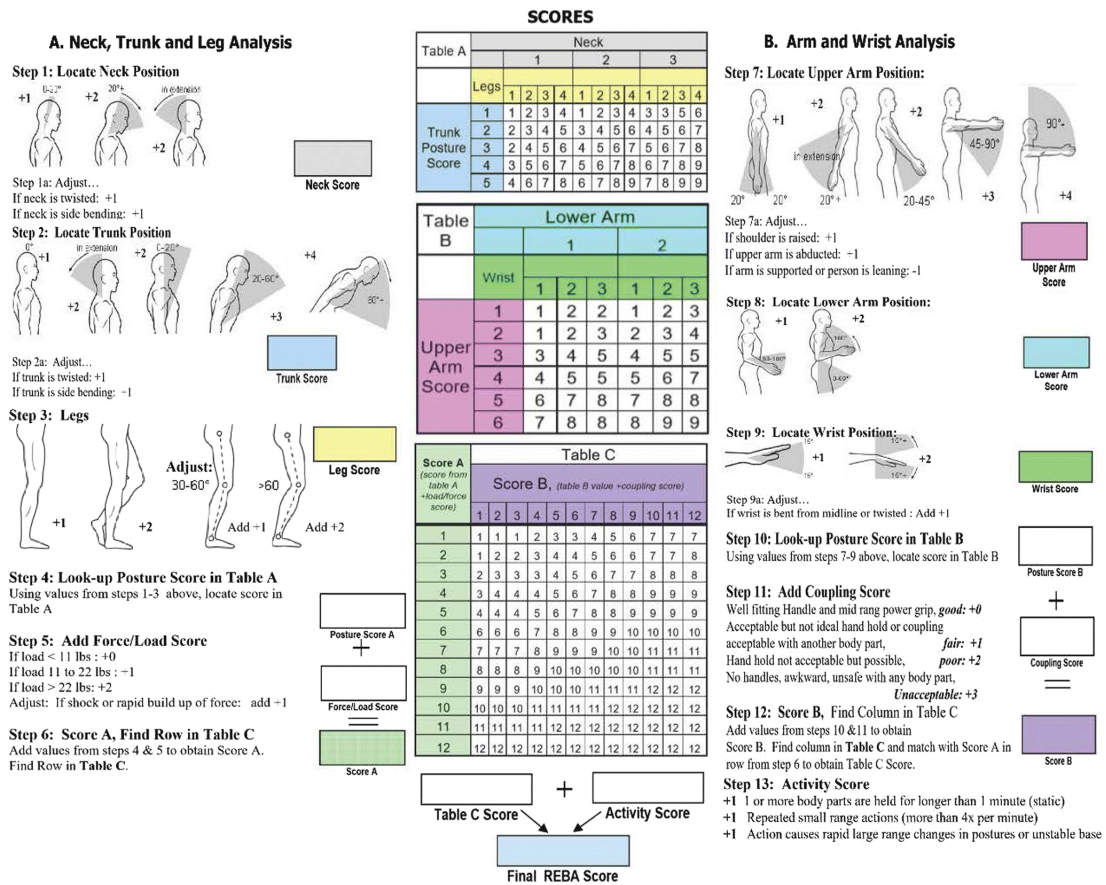


Figure 3: REBA scores worksheet based on (Hignett and McAtamney, 2000)

*Computation of the OCRA index.* For a single repetitive task, the OCRA score is computed according to Equation (6), as the ratio between the actual number of repetitions during the shift (Actual Technical Actions, ATA) and the recommended one (Reference Technical Actions, RTA).

$$OCRA = \frac{ATA}{RTA} \quad (6)$$

The higher the OCRA index, the higher the ER. The ISO norm defines a traffic light approach to classify the risk, depending on the value of the OCRA index:

- $OCRA \leq 2.2$ : Green zone, the risk level of the shift is acceptable and no corrective action is recommended.
- $2.2 \leq OCRA \leq 3.5$ : Yellow zone, the risk level of the shift is considered uncertain and conditionally acceptable. It is recommended to install health surveillance for this task.
- $OCRA \geq 3.5$ : Red zone, the task is classified as risky, and corrective actions are recommended (e.g., workstation/task redesign).

To compute the Reference Technical Actions (RTA), the index starts from a constant frequency, denoted by  $CF$  (30 actions per minute), which corresponds to the maximum safe frequency in perfect conditions, and is then multiplied by different multipliers reflecting the additional risk factors. However, with most applications in job rotation, a shift is often composed of several elementary tasks. For the general multitask model, the RTA is computed for each task and then weighted by the duration of the task in the shift, according to Equation (7). Most multipliers take their values between 0 and 1, the smaller they are, the higher the risk factor.

$$RTA = CF \left( \sum_{i=1}^n t_i \cdot F_i \cdot P_i \cdot R_i \cdot ARF_i \right) \cdot D_{shift} \cdot R_{shift} \quad (7)$$

For a given task  $i \in \{1, \dots, n\}$ ,  $t_i$  corresponds to the duration of the task,  $F_i$  the force multiplier, usually computed using worker perception with Borg scale (Tiacci and Mimmi, 2018) or tables (Akyol and Baykasoglu, 2019). The repetitiveness multiplier  $R_i$  is equal to 0.7 if the task represents more than 50% of the shift duration and the cycle time is greater than 15s, 1 otherwise.  $ARF_i$  is the additional risk multiplier, that considers various risk factors absent from other multipliers, such as the use of vibration tools, or exposure to an uncomfortable environment (noise level, light level, extreme temperatures), etc. Finally,  $P_i$  is the posture multiplier, computed with a simple posture worksheet based on biomechanical observations on the stress load on different body articulations.

Two general multipliers are considered on top of that, concerning the work organization on the whole shift: the repetitive task duration multiplier  $D_{shift}$  and the recovery period multiplier  $R_{shift}$ . They account respectively for the total duration of repetitive actions during the shift, and the frequency of recovery periods (i.e., breaks), and their values are computed with tables. The OCRA index is computed for both the right and left parts of the body. Then the value of the OCRA index of the workstation is set to the higher value between the right and left OCRA indexes (i.e., representing the worst ergonomic conditions).

*Advantages.* The OCRA assessment method is a major risk assessment method used in assembly line optimization. This is due to its suitability for this family of problems. 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 compared to other risk assessment methods 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 HAMF 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 a good accuracy considering the number of inputs required.

## 6. Cognitive and psychosocial human aspects

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 following topics:

- *Motivation and boredom* in Section 6.1, which are key factors of employee performances.
- *Satisfaction and work preferences* in Section 6.2, on the HAMFs found in the collected material dealing with the preferences of employees.
- *Psychosocial and organizational considerations* in Section 6.3, and their impacts on the workforce.
- *Cognitive ER* in Section 6.4, which arises in some jobs and has a negative impact on working conditions.

### 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 (Fisher, 1993). Furthermore, it can have a substantial impact on employee performance in the short term, as well as long-term impacts as low job satisfaction might lead to absenteeism or turnover (Fisher, 1993).

Despite its importance, boredom is not easy to model, as it strongly depends on the considered individual and situation. The issue is still been tackled by some papers in the collected material with different levels of modeling granularity. Bhadury and Radovilsky (2006) study a multi-period job rotation problem, where one of the objectives is the reduction of boredom. It is modeled by encouraging frequent changes in the tasks assigned to an employee, one of the objective functions is then to minimize the maximal number of consecutive periods with the same task assignment among the employees. Othman et al. (2012) study a workforce planning problem, where employee boredom is modeled by a reduction of the productivity of the concerned individuals. The employees are clustered in different 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. In their model, the processing time of a waiting task decreases if its type is different than the current task. Azizi et al. (2010) develop a new modeling framework to take into account boredom, as well as learning/forgetting. Indeed, the two effects present a high similarity in the way they affect the processing time: When processing a new task, the productivity increases with learning until its maximum level, then decreases due to boredom after some time. A change of task induces a forgetting effect, but also a recovery of the boredom level. This model is also used by Ayough et al. (2020) to design and sequence a cell manufacturing unit, where the operator performances vary with learning, forgetting, and boredom. Finally, the model developed in (Azizi et al., 2010) is extended in (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 taking into account a large variety of effects and interactions, centered around boredom and performance variations.

### 6.2. Satisfaction and work preferences

While most classical efficiency-based criteria, or customer service-based ones, are obviously critical aspects of business performances, employee satisfaction is also 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. In the collected material, the 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. This HAMF is, for instance, used in (Brusco, 2015; Lazzarini and Pistolesi, 2018; Cheng and Kuo, 2016). Ruiz-Torres et al. (2015) study a scheduling problem where equity is considered on top of the maximization of the overall satisfaction, with a constraint ensuring a minimum threshold value of satisfaction for each employee. This equity concern is also present in the work of Ruiz-Torres et al. (2019) where the objective functions include the maximization of the total satisfaction and the maximization of the minimum satisfaction level among employees. Task variety is also considered to improve satisfaction. For instance, Akbari et al. (2013) address a shift scheduling problem with part-time employees, where one objective is to maximize the overall preference satisfaction. In this model, the individual preferences are multiplied by a factor representing the seniority in the company for the concerned employee, in order to favor more senior employees.

Another way to model employee satisfaction is by considering their preferences in shift types and work duration. Some persons are indeed more inclined to do overtime work than others, or more inclined to work on weekends. In (Topaloglu and Ozkarahan, 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 maximum number of consecutive workdays. All these aspects are integrated with soft constraints and goal programming. Pan et al. (2010) focus on overtime preferences, where employees agree or not with overtime, have preferred shift types, and preferred overtime patterns. Shuib and Kamarudin (2019) study a shift scheduling problem in a power plant with days off preferences, and one objective is to minimize the underachievement of these preferences. Finally, 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.

### 6.3. Psychosocial and organizational considerations

Organizational and managerial policies have a major impact on the performances of a production or service system, both economically and ergonomically. 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 within the scope of Human-Aware Modeling. In the collected material, few works focus on this topic.

The main topic of study relates to work team composition. This may indeed be an important factor of performance in assembly lines or cell manufacturing. Schultz et al. (2010) study the correlation between the productivity of employees working at nearby stations, and show that, to some extent, different 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), corresponding to the work methods of the different employees, and try to assign workers with similar decision-making style to the same cell. In ([Cheng and Kuo, 2016](#); [Anoshkina and Meisel, 2020](#)), the authors deal with multi-objective models, where one of the objectives is to maximize the team consistency between days, trying not to change the work team composition too often.

Some other studies deal with management policies in a broad sense. [Fini et al. \(2017\)](#) study a workforce assignment problem with cognitive and perceptual ER, skills, learning, and different strategies for the management of human resources. They propose a general model, which is then adapted to fit different strategies depending on the context, including safety improvement, skill enhancement, multiskilling, or dealing with an aging workforce. [Shahbazi et al. \(2019\)](#) aim at maximizing the employees career development, in a workforce planning problem. A promotion from one position to another is possible when the given employee possesses a required skill set, and the proposed model aims at favoring the development of this skill set for the employee. [Celano et al. \(2004\)](#) study a U-shaped assembly line, and the different organizational strategies available to deal with line interruptions or bottlenecks. For other applications, [Melton and Ingalls \(2012\)](#) study a vehicle routing and driver scheduling problem with relay points that enable the transfer of the trailer from one truck to another. The goal is to increase the home time of the truck drivers, and thus to reduce the turnover due to discontentment.

#### 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](#)). [Dewi and Septiana \(2015\)](#) study a shift scheduling problem in domestic freight with the objective of balancing the workload, both physical and mental, between the employees. To assess the cognitive ER of a task, they use the NASA-TLX model, which is a widely used questionnaire-based assessment method of perceived cognitive workload. [Li et al. \(2018a\)](#) study a facility layout problem, which integrates the physical and mental ER of employees. The mental strain is computed with the SWAT scale, which evaluates job difficulty by giving a 1-3 score to the three different criteria: time load, psychological effort load, and psychological stress load. [Kara et al. \(2014\)](#) study an assembly line balancing problem with different HAs considered. These include the cognitive strain of the work, which is measured with the weighted rigidity measure: Each task is labeled with a rigidity value from 1 to 10 corresponding to its cognitive strain. The cognitive ER then corresponds to the sum of the rigidity scores of the tasks performed during the work shift, weighted by the time spent on each task. In their model of ([Kara et al., 2014](#)), a threshold constraint enforces the ER to remain below a given limit for each employee (see [Prunet et al. \(2022\)](#), *Threshold constraints*). [Kong \(2019\)](#) develops a framework for the task complexity assessment in manufacturing processes, both physically and mentally. Finally, [Fini et al. \(2017\)](#) study a workforce assignment problem applied to construction work, and develop a model accounting for the brain resource requirements of tasks, which affect the productivity level. These resources consist of visual, auditory, cognitive, and psychomotor demands. The last two elements depend on the employee long-term experience to reflect the adaptation strategies of the seasoned workers, as well as, the usual learning process described in [Section 3.2](#). The results of their model are adapted according to different HR strategies: safety improvement, skill enhancement, addressing the aging workforce problem, or multiskilling.

## 7. Perceptual and environmental factors

In this section, we present the collected material related to perceptual and environmental HAs, and the corresponding HAMFs. Perceptual ergonomics is a major field of study within HF/E ([Bridger, 2018](#)). However, this human aspect has not seen much attention from the OR community comparatively 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 manufacturing and logistics systems. Some perceptual and environmental HAs have, however, been studied within the collected material. This section studies the following topics:

- *Noise exposure* in [Section 7.1](#), where we discuss the impact of a high sound level on operators.

- *Visual considerations* in Section 7.2, where we introduce the works that integrate visual HAs into their models.
- *Heat exposure* in Section 7.3, as a source of discomfort and potential injuries.
- *Vibration exposure* in Section 7.4, where we discuss the topic of vibration exposure when performing manual work and its consequences.

### 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<sup>18</sup>. 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). Furthermore, several empirical studies have shown the negative impact of noise exposure on individual performances (Szalma and Hancock, 2011). In the collected material, two HAMFs are found to model and quantify the noise exposure hazard either the *Daily Noise Dosage* (DND) or implicit metrics.

*Implicit metric.* Kaya et al. (2020) study a machine scheduling problem, embedded in a decision support system approach. Multiple criteria are considered including a noise-related criterion, measuring the noise exposition via an implicit metric. Mokhtari and Hasani (2017) study a production and transportation planning problem. Different objectives are considered both economic-related and non-economic (e.g., greenhouse gas emissions, risk of injury) including noise disturbance. Fu et al. (2020) present a hybrid flowshop model considering dust and noise exposures. The noise exposure level is a parameter that depends on both the concerned job and the machine it is scheduled on. It is indeed a reasonable hypothesis that an older machine would be noisier than a more recent one. Another interesting HAMF is found in (Lu et al., 2019), where the authors study a hybrid flowshop with energy reduction and noise exposure. The sources of noise are the machines, with a distinction between *working* machines and *idle* machines. The total perceived noise exposure is computed considering the state of each machine during the workday.

*Daily Noise Dosage (DND).* The most common HAMF in the collected material to account for noise exposure is the DND framework used to compute an acceptable noise exposure level over a work shift. Noise exposure is found integrated into job rotation scheduling problems, Asawarungsaengkul and Nanthavanij (2008) propose a model including a maximum daily noise exposure per worker, which is enforced in a feasible planning solution. In (Aryanezhad et al., 2009b), the DND is associated with the JSI (see Section 5.2) with the objective of balancing both sources of ER among workers. Tharmmaphornphilas 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. Niakan et al. (2016) present a cell formation and worker assignment problem with noise exposure considerations: A threshold value for the maximum daily exposure per operator, computed using the DND, is enforced by a hard constraint. Finally, Razavi et al. (2014) study a design and worker assignment problem in a press shop, where for each operator, a maximum exposure time is allowed at different noise pressure levels. The originality of the approach is that the objective cost function integrates the potential purchase of noise isolation material, personal equipment, or noise source reduction. In this way, the decision model can mitigate the risk with two levers: decreasing the source emission level, or the exposition of the operators.

*Description of the DND.* The DND standard is derived from NIOSH recommendations<sup>18</sup> and OSHA guidelines<sup>19</sup> on worker safety concerning noise exposure. Therefore, the usage of this HAMF is in accordance with existing regulations on noise hazards.

The DND is computed over one shift composed of the different tasks  $i \in \{1, 2, \dots, n\}$ . Each of these tasks is associated with its exposure duration  $C_i$  and the measured noise level, denoted by  $L_i$ , in A-weighted decibels (dBA) at the corresponding workstation. From the measured noise level  $L_i$  at the workstation, one can compute the associated maximum recommended exposure duration, denoted by  $T_i(L_i)$ . The formula used to compute  $T_i(L_i)$  varies between the different safety guidelines. We will present the one defined by the NIOSH guideline<sup>18</sup>, but other regulations use a similar formula, albeit with some changes in the constant



terms of the equation. The maximum recommended exposure duration  $T_i(L_i)$  is computed via Equation (8) for an 8-hour shift and a maximum exposure dose of 85 dBA.

$$T_i(L_i) = \frac{8}{2^{(L_i-85)/3}} \quad (8)$$

Based on  $T_i(L_i)$ , the exposure dosage  $D_i$  of task  $i$  is computed according to Equation (9). It corresponds to the ratio between the actual exposure duration  $C_i$  and the recommended maximum exposure duration  $T_i(L_i)$ .

$$D_i = \frac{C_i}{T_i(L_i)} \quad (9)$$

Then the total exposure dose  $DND$  over one shift is computed by summing all partial doses according to Equation (10).

$$DND = \sum_{i=1}^n D_i \quad (10)$$

A recommended upper value of 1 for the DND corresponds to an acceptable risk level, and higher values should be avoided. This limit can also be expressed in decibels with some transformations, decibels being a logarithmic scale. Equation (11) gives the formula to compute the Time Weighted Average (TWA) noise level over a shift. This value should be below 85 dBA. One should note that this value corresponds to an averaged exposure over a workday, and a short exposure above this level might not be hazardous.

$$TWA = 10 \log(DND) + 85 \quad (11)$$

## 7.2. Visual considerations

Visual considerations have not met great attention from the OR literature. Some works still try to integrate this HA with various modeling approaches. [Al-Araidah et al. \(2017\)](#) study a warehousing storage assignment problem. In this work, the order picking (i.e., the operation of retrieving items corresponding to orders) is performed by an operator on a mechanical platform. The aim of the presented model is to cluster the items so that one stop of the platform corresponds to one cluster, where the picking action is safe and easy for the picker. The picking time is a function of the distance between the picker hand and the item position, and the time to get visual contact with the stored item. The latter depends on its position compared to the picker visual field. [Hollis and Green \(2012\)](#) study a vehicle routing problem with consideration for the visual attractiveness of routes: In a multi-objective context, one of the objectives is to construct routes that are visually appealing for drivers, not to confuse them with intricate routes. This means that intra-route and inter-route crossings are avoided with convex hulls of the different routes not overlapping, if possible. Moreover, routes, where the driving time between customers is evenly distributed, are favored. The visual attractiveness of routes is also implicitly studied by [Raghavendra et al. \(1992\)](#) for bus transportation, where routes should go mostly forward.

## 7.3. Heat exposure

*Working in a hot environment.* 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](#)). If the protection against climatic conditions is not possible, or not efficient, the use of a work-rest schedule is recommended<sup>20</sup>. It is therefore not surprising that in the collected material, heat tolerance is integrated within work-rest scheduling problems (see [Prunet et al. \(2022\)](#), *Work-rest scheduling*). [Yi and Chan \(2015\)](#) and [Yi and Wang \(2017\)](#) study such problems, with an application to construction workers in Honk-Kong, under heat stress conditions. In ([Yi and Chan, 2015](#)), the weather conditions are simulated by a multi-scenario framework with a Monte-Carlo approach, and the best work-rest schedule over the given scenarios is chosen. [Yi and Wang \(2017\)](#) directly compute the safety optimal work-rest schedule.

*Heat stress exposure.* The choice of a HAMF to compute the heat stress level of an individual is not straightforward without actually measuring the body temperature of the individual ([Lee, 1980](#)). The aforementioned works on work-rest scheduling use the *Heat Stress Model* to quantify the heat exposure. This HAMF has been introduced by [Chan et al. \(2012a\)](#) 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. The result of this regression is the *Rating of Perceived Exertion* (RPE) computed according to formula (12).

$$RPE = -5.43 + 0.11 \cdot WBGT + 1.40 \cdot T + 0.10 \cdot API + 0.06 \cdot A - 0.07 \cdot PBF + 2.28 \cdot DH + 0.50 \cdot SH + 0.14 \cdot EC + 0.16 \cdot RER - 0.01 \cdot RHR, \quad (12)$$

where *WBGT* stands for the wet bulb globe temperature, a measure designed to assess outdoor climatic conditions in the scope of heat stress. It accounts for different weather parameters: temperature, humidity, radiation, etc. *T* is the work duration, *API* the air pollution index, *A* the age of the concerned individual, *PBF* his/her percentage of body fat, *RHR* his/her resting heart rate, *DH* his/her drinking habit (absent = 0, occasional = 1, usual = 2), *SH* his/her smoking habit (same nomenclature), *EC* the energy consumption, and *RER* the respiratory exchange rate. The Heat Tolerance Time (HTT) index is computed from the RPE. It corresponds to the maximum duration a given individual can sustain his/her work without injuring him/herself (Chan et al., 2012b). This value can then be used to determine work-rest schedules.

#### 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.

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. To assess the vibration exposure level, they use the ISO 5349-1 standard<sup>21</sup>, which defines a threshold for vibration exposure over a work shift. Then they study the interactions of the two objective functions and derive some managerial insights from an industrial case from a minibus assembly plant.

According to the ISO 5349-1 standard<sup>21</sup>, the daily vibration exposure  $A(T_0)$  of a worker performing  $n$  different tasks is computed according to Equation (13):

$$A(T_0) = \sqrt{\frac{1}{T_0} \sum_{i=1}^n a_{hvi}^2 T_i}, \quad (13)$$

where  $T_0$  is the shift duration, and  $T_i$  is the duration of task  $i \in \{1, \dots, n\}$ . Parameter  $a_{hvi}$  is the vibration value of the tool used to perform task  $i$ . This daily vibration exposure index is limited by the standard to a value of  $5\text{m/s}^2$ , however, a value below  $2.5\text{m/s}^2$  is advised (Finco et al., 2020a).

## 8. Additional considerations

In this section, we present a number of additional considerations. They include both HAMFs that have not been addressed elsewhere, and transverse considerations related to several topics presented in this review. This section includes the following topics:

- *Implicit integration of HAs* in Section 8.1.
- *Anthropometric considerations* in Section 8.2, where we discuss the HAMFs related to the measurements of the human body.
- *Biomechanical considerations* in Section 8.3, where we introduce the set of HAMFs based on biomechanical methods.
- *Heterogeneity of the workforce* in Section 8.4, to provide more granularity on the modeling of the employee characteristics.
- *Health states* in Section 8.5, as a family of HAMFs that account for the health states of the employees.
- *Human errors* in Section 8.6, as an important factor of the individual performances.

- *Hazard exposure* in Section 8.7, on more specific hazards that are found in some work environments.
- *Equity* in Section 8.8, where we introduce the topic of an equitable repartition of the resources or the ER among the workforce.
- *Total cost function* in Section 8.9, where we discuss the works that integrate the HAs as an additional cost into their models.
- *Expert opinions and collaborations* in Section 8.10, on the collaborations between OR practitioners, and ergonomists.

### 8.1. *Implicit integration of human aspects*

There are works in the collected material that use implicit metrics to model HAs. In these works, the effort is focused on the solution methods, and the actual modeling of the human characteristics is disregarded. Most of the time, the concerned works aim at minimizing (or balancing) the *physical workload*, without more precision on what exactly is measured (see e.g., [Aravindkrishna et al. \(2009\)](#); [Mutlu and Özgörmüş \(2012\)](#); [Kudelska and Pawłowski \(2020\)](#)). Another common implicit metric is a general ER, provided without a clear definition, and no available detail about the computation method (see e.g., [Kovalev et al. \(2019\)](#); [Alghazi and Kurz \(2018\)](#)). These models are not discussed extensively in this review, since they focus their contributions on the conceptualization of new problems, or the solution methods, and are thus of little interest in the context of the present work that focuses on the modeling of HAs.

### 8.2. *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 work spaces 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, anthropometric considerations can be, for instance, found in the work of [Al-Araidah et al. \(2017\)](#), who study order picking with vehicles. The 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. To do that, they compute the safe reach envelope of a picker, i.e., the space area where a picker can pick an item while avoiding an awkward posture that can favor the apparition of WMSDs. This reach envelope depends naturally on the concerned individual, thus the authors use the anthropometric data for the 5<sup>th</sup> percentile of the picker population, thus fitting 95% of it. [Mateo et al. \(2020\)](#) address a problem arising in the printing industry dealing with the setup and machine feeding operations. 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. For the height, the anthropometric data on hand sizes are used (i.e., the length between the first articulation of the thumb and the second of the index finger in grip position). Finally, anthropometry is accounted for by [Huang and Pan \(2014\)](#), who study a job rotation problem, where an RGB-D camera is used to measure the anthropometric characteristics of the different employees. Moreover, a biomechanical model transforms the data into 3D measurements using an existing database. These data are then used to better assign tasks to employees: Each job is characterized by boundaries on some anthropometric measures to be comfortable for the person to whom it is assigned. The objective function is then to maximize the number of worker/task assignments falling into these boundaries. Additionally, anthropometric considerations are often used as input for biomechanical models, as presented in the next section.

### 8.3. *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 is used directly in the modeling. Some papers use an assessment method including a large number of criteria

(all of them being part of the objective functions), 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. It is used as a risk measure for low back injuries. [Glock et al. \(2019c\)](#) investigate the industrial packaging process (box size optimization and scheduling) 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. This is also used by [Xu et al. \(2012\)](#), who develop a new model based on the American Conference of Governmental Industrial Hygienists (ACGIH) to design a linear risk assessment method for hand activity level.

#### 8.4. Heterogeneity of the workforce

Considering the workforce heterogeneously is pertinent when modeling HAs 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. \(2022\)](#), *Heterogenous 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 (see Section 3.1), due to the differences between employees when skills are considered in an optimization model. Since skills often correspond to different qualifications (or jobs) when applying the models in an industry, they are not concerned by the regulations on personal data collection. The modeling of a heterogeneous workforce is also found, more seldom, in studies related to learning curves when employees are modeled individually (see Section 3.2), the works related to risk assessment methods when some parameters are individual-dependent (see Section 5), and in some cognitive modeling that accounts for the differences in terms of preferences, personalities or motivation levels (see Section 6). 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 work ([Prunet et al., 2022](#)), where information on this aspect is provided within the limits of the papers collected for this survey.

#### 8.5. Health states

An interesting way to work with the risk of WMSDs is through health states. In this HAMF, an employee can be in three different health states:

- 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. 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 its 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.

#### 8.6. Human errors

The error rate of a manual task is affected by HAs. 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 8.5). 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 modeling framework 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](#)).

#### 8.7. 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.

#### 8.8. Equity

The equity among the employees is a legitimate concern when trying to optimize human well-being in a production or service system. From an OR perspective, this thematic is rather common in the form of sharing the workload among different assembly lines/machines/work-teams in order to get a better utilization of the resources (for example, to minimize the cycle time or the makespan). Therefore considering worker equity as a HAMF 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 Lazzarini, 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).

### 8.9. Total cost function

A total cost function is a useful way to integrate HAs into optimization models. The general idea is to convert a HA 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. \(2022\)](#), *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](#)). In ([Shin et al., 2018](#)), the authors model a 2-echelon supply chain, where both the supplier and the customer are prone to errors when performing quality controls. Human errors can be considered as HAs since they are not exogenous to the system organization, as machine errors are, and depend on human considerations. For example, the error rate can depend on the skill level of the operators ([Norman et al., 2002](#)), or on the fatigue level of the employees ([Jamshidi and Seyyed Esfahani, 2014](#)), where the error-related cost increases when the exhaustion limit of an individual is reached.

An interesting approach to consider HAs 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. [Battini et al. \(2017c\)](#) study a lot sizing problem, where the objective includes the cost of material handling. This is computed as the total number of the workforce wages, accounting for the rest allowance. This is also used by [Condeixa et al. \(2020\)](#) in a reverse logistics lot sizing problem, and in ([Razavi et al., 2014](#)) where a rest time is required after high exposure to a noisy environment. 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 8.5) also provide an interesting modeling framework 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.

### 8.10. 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 Pistoiesi, \(2018\)](#), 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. Conclusions

In this second part of our literature review work, the conducted study focuses on modeling frameworks for human aspects. From the large corpus of literature related to manufacturing and logistics optimization, we extracted the existing methods used to represent and quantify HAs. 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 HAMFs, which enable the quantification of the inherently fuzzy human characteristics.

With the whole review work (Parts 1 & 2), we presented a broad picture of the integration of optimization models with Human-Aware Modeling in the scope of manufacturing and logistics. 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 the 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 comprehensive toolbox of the suitable HAs to integrate into their work, and the corresponding HAMFs.

Some HAMFs have been more thoroughly studied than others. Historically, the performance assessment models (e.g., learning effects) 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 (see [Prunet et al. \(2022\)](#), where we present some research

directions). The development of Human-Aware Modeling in OR 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<sup>22</sup>. 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.*

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## Notes

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