

Optimization of Human-Aware Manufacturing and Logistics Systems: A Comprehensive Review of Modeling Approaches and Applications

Thibault Prunet, Nabil Absi, Valeria Borodin, Diego Cattaruzza

▶ **To cite this version:**

Thibault Prunet, Nabil Absi, Valeria Borodin, Diego Cattaruzza. Optimization of Human-Aware Manufacturing and Logistics Systems: A Comprehensive Review of Modeling Approaches and Applications. 2022. hal-03788101

HAL Id: hal-03788101
https://hal.science/hal-03788101

Preprint submitted on 26 Sep 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

MINES Saint-Étienne

Une école de l'IMT

CENTRE MICROELECTRONIQUE DE PROVENCE

Optimization of Human-Aware Manufacturing and Logistics Systems: A Comprehensive Review of Modeling Approaches and Applications

Thibault Prunet[1], Nabil Absi[1], Valeria Borodin[1], and Diego Cattaruzza[2]

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

{thibault.prunet, absi, valeria.borodin}@emse.fr

[2]Univ. Lille, CNRS, Centrale Lille, Inria, UMR 9189 - CRIStAL - Centre de Recherche en Informatique Signal et Automatique de Lille, F-59000 Lille, France

{diego.cattaruzza}@centralelille.fr

September 26, 2022

Working Paper MSE CMP–SFL 2022/01

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 first 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 and solution approaches used to consider human characteristics, their practical relevance, and the complexity induced by their integration within optimization models. The material presented in this work has been retrieved through a semi-systematic search of the literature. Then, a comprehensive analysis of the retrieved corpus is carried out to map the related literature by class of problems encountered in manufacturing and logistics. These include: warehousing, vehicle routing, scheduling, production planning, and workforce scheduling and management. We investigate the mathematical programming techniques used to integrate human aspects into optimization models. Finally, a number of gaps in the literature are identified, and new suggestions on how to suitably integrate human aspects in OR-problems encountered in manufacturing and logistics systems are discussed.

Institut Mines-Télécom

INSPIRING INNOVATION SINCE 1816

Optimization of Human-Aware Manufacturing and Logistics Systems: A Comprehensive Review of Modeling Approaches and Applications

Thibault Prunet[a], Nabil Absi[a], Valeria Borodin[a], Diego Cattaruzza[b]

[a]*Mines Saint-Etienne, Univ. Clermont Auvergne, CNRS, UMR 6158 LIMOS, Center CMP, Departement SFL, F-13541 Gardanne France*
[b]*Univ. Lille, CNRS, Centrale Lille, Inria, UMR 9189 - CRIStAL - Centre de Recherche en Informatique Signal et Automatique de Lille, F-59000 Lille, France*

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 first 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 and solution approaches used to consider human characteristics, their practical relevance, and the complexity induced by their integration within optimization models. The material presented in this work has been retrieved through a semi-systematic search of the literature. Then, a comprehensive analysis of the retrieved corpus is carried out to map the related literature by class of problems encountered in manufacturing and logistics. These include: warehousing, vehicle routing, scheduling, production planning, and workforce scheduling and management. We investigate the mathematical programming techniques used to integrate human aspects into optimization models. Finally, a number of gaps in the literature are identified, and new suggestions on how to suitably integrate human aspects in OR-problems encountered in manufacturing and logistics systems are discussed.

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

Contents

1 Introduction **2**

2 Terminology, related background, scope, and motivations **4**
2.1 Definitions of human-related key concepts 5
2.2 Previous reviews 6
2.3 Scope 8
2.4 Motivations 8

3 Methodology **9**
3.1 Material collection methodology 9
3.2 Structure of the paper 10
3.3 Summary tables: Format and convention 11

4 Modeling frameworks of human aspects **11**

5 Logistics **12**
5.1 Warehousing 12
5.2 Vehicle routing 13

6 Production systems **15**
6.1 Machine scheduling 15
6.2 Assembly line balancing 17
6.3 Production planning and inventory management 18

6.4 Design of systems . . . 20

7 Workforce-related problems **21**
7.1 Workforce scheduling . . . 21
7.1.1 Job rotation . . . 21
7.1.2 Work-rest scheduling . . . 23
7.1.3 Shift scheduling . . . 24
7.2 Workforce management . . . 25
7.2.1 Workforce planning . . . 25
7.2.2 Workforce assignment . . . 26

8 Mathematical programming considerations **27**
8.1 Objective function . . . 27
8.1.1 Single objective optimization . . . 27
8.1.2 Multi-objective optimization . . . 28
8.2 Constraints . . . 30
8.3 Data . . . 33
8.3.1 Varying task time . . . 33
8.3.2 Varying quality . . . 34
8.3.3 Heterogeneous workforce . . . 34

9 Discussion and future research **35**

10 Conclusions **37**

Preamble

Given the large volume of material reviewed, which does not enable the authors 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 (the present paper) 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 collected material is then discussed thematically with respect to the subfields within the manufacturing and logistic communities. Particular attention is paid to the impact of human considerations on mathematical models. The second part of this work (Prunet et al., 2022) focuses on the modeling of human aspects in a broad sense. 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

Operations Research (OR) has been historically focusing on economic considerations, reflecting the concerns present in the industry. With the globalization of the economy, the increasing level of competition and demand customization have led to growing economic pressure on decision makers. This pressure has been particularly high in the manufacturing and logistics fields to reduce costs and improve the efficiency of operations, quality of services, and system agility. The concomitant development of data-driven optimization of operations, applied to a large variety of complex industrial problems, has shaped the current landscape of OR. The advance in the accessibility to computing power allows us to consider and successfully treat more complex problems that do not limit their scope to economic considerations. In this sense, additional topical considerations related to sustainable development have begun to appear in decision models after the early 2000s. This trend follows a more global societal shift, where ecological and social responsibility is more and more accounted for by decision makers, as growing pressure from the different stakeholders.

Sustainable development is increasingly becoming a major paradigm that reframes the global strategy of companies and organizations. The concept is defined as "*the development that meets the need of the present without compromising the ability of future generations to meet their own needs*" (Keeble, 1988). The main idea of this paradigm is to consider social and environmental indicators together with the economic

ones when considering business decisions and performance assessments. The three pillars of sustainable development, namely economic, environmental and social, are considered on the same level of importance, explaining the increasing concerns toward the social responsibility of companies. The consideration of Human Factors and Ergonomics (HF/E) in industry and the improvement of employees' working conditions fall within this context. *Decent working conditions* is actually one of the 17 sustainable development goals, that constitute the 2030 Agenda of sustainable development ratified by the United Nations in 2015[1]. Human factors are thus a critical and crucial aspect of an organizational system. According to the International Labour Organization (ILO)[2] and the World Health Organization (WHO)[3], over 2.3 million people die yearly from work-related causes (Takala et al., 2014). Studies show that, at any given time, 20% of employed adults suffer from Work-related Musculoskeletal Disorders (WMSD) (Vézina et al., 2011). Furthermore, from an economic perspective, the direct and indirect costs of work-related injuries are estimated at 4% of the world GDP (Takala et al., 2014). Therefore, the improvement of working conditions and the reduction of work-related health problems are still an important challenge in industrial countries. Moreover, a general ongoing trend in industrial countries is the aging of the population and a higher age of retirement (Calzavara et al., 2020). This evolution of the workforce is increasing the importance of HF/E considerations in industrial systems.

The present work focuses on HF/E in manufacturing and logistics systems. The consideration of human factors, at physical, cognitive, and organizational levels, is especially relevant in these fields. Furthermore, the need for human-aware optimization methods for manufacturing and logistics systems will continue to gain importance in the near future. Two arguments support this claim:

- **Regulatory aspect:** Companies in the manufacturing and logistics sectors still rely heavily on manual labor. This is, for example, the case for truck drivers in logistics, for labor-intensive and time-consuming order picking in warehousing (i.e., the operation of retrieving items from their storage locations to prepare customer commands) (Grosse et al., 2015b). Regarding manufacturing, assembly line operations often require a high degree of precision and flexibility, therefore manual labor is still very common (Battini et al., 2016a). Furthermore, the widespread use of human labor in manufacturing and logistics refers to jobs that can account for a high level of physical and cognitive stress, repetitive movements, lifting tasks, and awkward positions. This prevalence of risk factors is accounted for by firms and public policies, as the demand for social accountability of companies increases. In recent years, numerous regulations have been enforced on working conditions. In logistics, the European regulation EC 561/2006[4] and the American Hours of Service of Drivers regulation[5] both propose a framework to regulate the driving and working times of truck drivers. The manufacturing sector has also been subject to numerous regulations aimed at reducing the ergonomic risk in workplaces. Among others, one can cite the Directive No. 2006/42/EC of the European Parliament on machinery usage[6], the Directive No. 89/391/EEC on general measures to encourage improvements in safety and health of workers[7], or the Occupational Safety and Health Act of 1970[8]. Furthermore, several ergonomics standards have been developed by the International Organization for Standardization and the European Committee on Standardization to design production systems. Dul et al. (2004) listed up to 174 international ergonomic standards for production systems, going from general recommendations on the design of processes to specific requirements for manual handling, human-computer interactions, mental load, noise, heat, etc.

- **Integration aspect:** The second factor of the relevance of human considerations in manufacturing and logistics refers to the modeling of human characteristics and behaviors. Several empirical studies have identified a clear link between the ergonomic burden and individual performance in industry (see e.g., Shikdar and Sawaqed (2003); Erdinç and Yeow (2011); Ivarsson and Eek (2016)). In addition to poor ergonomic conditions, numerous other factors can impact the productivity of employees. These include fatigue (Yung et al., 2020), noise exposure (Szalma and Hancock, 2011), individual learning (Grosse et al., 2015a), stress and psychosocial factors (Halkos and Bousinakis, 2010), etc. Overall, the study of human factors is essential to understand and model the productivity of employees accurately. Manufacturing and logistics are heavily relying on the optimization of their operations, it is, therefore, crucial to model as accurately as possible the duration of the operations. This will gain even more importance with the spread of the Industry 4.0 paradigm. Oriented toward process automation, human-robot collaboration is becoming more common in production systems, where human operators and robots work on the same workstations. A thorough comprehension of the modeling of human characteristics is crucial for the success of such systems (Wang et al., 2017).

From an academic perspective, the issue of improving working conditions has been mainly tackled by Human Factors and Ergonomics (HF/E), as a human-centered scientific discipline aiming at a better understanding of the interactions between human operators and production or service systems (see Section 2). HF/E lies at the interface between psychology, anatomy, physiology, mechanics, design, and engineering (Bridger, 2018). This inter-disciplinarity results in a variety of methods used to evaluate work situations, from observational methods to statistics, passing by biomechanics, system theory, epidemiology, and occupational medicine. A number of these methods are presented in Part 2 (Prunet et al., 2022) of this review. However, OR and mathematical programming have not been part of the ergonomist toolbox until the beginning of the 21^{st} century. To our best knowledge, the pioneering work of Carnahan et al. (2000) was the first to use OR as a tool for ergonomic purposes to optimize a job rotation schedule (see Section 7.1.1).

In the OR literature, economic considerations have historically been largely dominant. However, other trends have emerged recently. Ecological considerations have made their way in the optimization literature, e.g., with green logistics (Sbihi and Eglese, 2010), sustainable manufacturing operations scheduling (Giret et al., 2015), circular economy in production planning (Suzanne et al., 2020). Human-aware considerations have also been considered for a couple of decades, from different perspectives, with different degrees of modeling accuracy. It is, however, still a maturing topic, addressed by different research communities within OR via various approaches. Human-aware modeling still misses the sound foundation of more established topics, it can be therefore difficult to get a grasp of it for a newcomer. Human aspects are hence quite challenging to integrate into existing optimization models, for several reasons:

- *At the problem statement level:* First, because of the large variety of human aspects and characteristics that may be relevant to consider given the industrial context, and the difficulty for an OR practitioner to identify them due to the lack of expertise.
- *At the modeling level:* Once the relevant aspects are identified, it is neither easy nor obvious to propose appropriate quantitative modeling without prior knowledge of HF/E.
- *At the instance level:* The data collection on this part often requires extensive field observations and measurements, that a OR practitioner does not have the time and knowledge to perform.
- *At the solution level:* The integration of human considerations often has a significant impact on problem complexity. Tools and frameworks commonly used in the HF/E community do not usually have nice mathematical properties such as linearity or convexity.

This review aims at bridging the understanding gap of OR academics and practitioners about HF/E methods, and at providing them with a broad understanding of the related problems, by presenting the models, methods, and tools used in the literature to design human-aware optimization methods for manufacturing and logistics systems.

Due to the length of the manuscript, the present work is divided into two separate papers. After the scope delineation, the first part of this review (the current paper) conducts a quantitative and thematic analysis of the retrieved corpus according to a semi-systematic methodology. Section 2 provides the related background of the present work with respect to the existing literature and defines clearly the scope of the review. Section 3 presents the search methodology used for the material collection. Sections 4 to 7 give an overview of the retrieved literature corpus structured by class of problems encountered in manufacturing and logistics systems, namely: logistics (warehousing and vehicle routing), production systems (machine scheduling, assembly line balancing, production planning, and system design), and workforce-related problems (workforce scheduling and management). Section 8 is specially dedicated to investigating the impact of human-aware considerations on mathematical models. Particular attention is put on the features added to an optimization model (e.g., new constraints, modification of the objective function) to account for the human aspects, and the impact on solution methods. Finally, Section 10 discusses the main finding of this first part. In the second part of this work (Prunet et al., 2022), the focus is set on the modeling of human characteristics. The approaches found in the related literature are presented and contextualized. This part has been written with the idea of being used as a "*human-aware modeling toolbox*" for interested academics and practitioners.

2. Terminology, related background, scope, and motivations

In this section, the present review is put in context and motivated with respect to the literature. First, we propose comprehensive definitions of the human-related key concepts used throughout this work. Then we

survey and synthesize our findings from the existing related reviews. From this analysis, we propose a clear delineation of the scope of this review.

2.1. Definitions of human-related key concepts

In the OR literature, the key terms related to human factors and ergonomics are found with various definitions and interpretations. A naive interpretation from an OR practitioner would be to think of the term *Human Factors* as any characteristic or behavior related to the human nature of employees, and all the involved consequences for mathematical modeling of industrial systems. However, such an interpretation is posing several semantic issues and is highly confusing.

We believe it is beneficial for the OR community to use a clear and accurate semantic when studying human-aware optimization problems. The topic being prone to cross-disciplinary work, any confusion should be avoided to facilitate the mutual comprehension between researchers and practitioners with different backgrounds.

The International Ergonomics Association[9] defines *Human Factors and Ergonomics* (HF/E) as follows:

> The word ergonomics, "the science of work", is derived from the Greek ergon (work) and nomos (laws). Ergonomics (or human factors) is the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimize human well-being and overall system performance (ratified by the IEA Council, 2000). The terms ergonomics and human factors are often used interchangeably or as a unit (e.g., human factors/ergonomics – HF/E or E/HF), a practice that is adopted by the IEA.

Interested readers can find a more thorough definition and explanations on HF/E in (Wogalter et al., 1998). Starting from this definition, let us adopt the following convention in the rest of this paper:

- **Human Factors and Ergonomics (HF/E)**: as a 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 HA based on 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.

In other terms, the concept of Human-Aware Modeling is the transposition of the aforementioned definition of HF/E to an OR context. The understanding of interactions between humans and other elements of a system relates to topics well studied in the recent developments of OR related to the modeling of human characteristics, how human workers interact with their job systems, and to the modeling of these interactions. It includes emerging topics such as learning, forgetting, error modeling, WMSD risks, and fatigue.

The application of the existing theory, principles, data, and methods to optimize human well-being and the overall system performance relates more clearly to optimization itself, especially when there is a human-related objective (equity, injury risks, pain, etc.) considered on top of (or instead of) classical economic objectives. It is also very relevant to situations where the objectives are solely human-related, e.g., job rotation and assembly line balancing problems, where all solutions are economically equivalent, and the objective is to discriminate between these equivalent solutions by balancing worker risks and discomfort, thus minimizing the overall ER.

Therefore, Human-Aware Modeling includes topics that are dealing with HAs, not necessarily connected to HF/E. For example, the problems including operator skills and/or learning are, in our opinion, relevant to be discussed in the current work, despite their connection rather with Human Resources Management than HF/E. Indeed, the aim of this paper is to survey the OR literature concerned with human considerations (i.e., "human-aware"). In this framework, we believe that the definition of Human-Aware Modeling as a novel concept (i.e., absent from the existing literature) is beneficial for the OR community. Two arguments are supporting this claim: It is more semantically rigorous, and it avoids confusion. Note that this definition focuses mostly on the interactions between a human and its work environment. In terms of scope restrictions, this means that we exclude papers modeling HA outside a work/firm environment. This refers, for example, to the modeling of human behavior as customer preferences or satisfaction, which would be an interesting topic, but out of the scope of this review.

2.2. Previous reviews

The integration of a HA in optimization problems is a broad subject, which is relevant in a large number of manufacturing and logistics contexts and can be addressed from different perspectives. As such, several reviews/surveys have been published on the topic. However, these works often focus on a single topic of manufacturing and logistics, yet with a scope broader than pure optimization problems, i.e., including material from other disciplines, such as industrial engineering or HF/E. In this section, a brief overview of the most relevant reviews is provided with respect to the context of the current work. Then we highlight the pertinence and the position of our work in this literature landscape.

- **Scheduling:** As reflected by the reviews on the topic, the scheduling community has been quite prolific in the consideration of HAs into their mathematical models. The reader is referred to (Lodree et al., 2009) for a general narrative review about Human-Aware Modeling in the scheduling domain. Lodree et al. (2009) deal with works on the topic published prior to 2007, including both OR-related and empirical HF/E studies, and provide an insightful analysis and a modeling framework on the sequencing of human tasks. More recently, Xu and Hall (2021) study fatigue in workforce scheduling in a broad sense. They focus on the work-rest scheduling and shift scheduling problems accounting for human fatigue, and derive insights from empirical studies and opportunities for OR applications. The introduction of learning aspects has also been extensively studied by the scheduling community, from the early works on learning in management science to the most recent development of this stream. Biskup (2008) provides a review on scheduling with learning effects jointly with a relevant analysis of the practical aspects of learning, as well as a discussion on the mathematical implications of the different ways to model such effects. Azzouz et al. (2018) present an update of the review of Biskup (2008), and propose a taxonomy and a classification framework to map the related areas of the prolific stream of scheduling with learning effects. From an OR perspective, Cheng et al. (2004) present a short survey on the mathematical implications of time-dependent processing times on scheduling models.

- **Warehousing:** Grosse et al. (2015b, 2017) study the integration of HAs in order picking (i.e., the action of retrieving, or "picking", items from the storage area to prepare orders) models. Grosse et al. (2017) perform a content analysis of the retrieved literature, and thus give a broad overview of the topics of interest and related trends. With a tighter scope, Grosse et al. (2015b) place the emphasis on planning models in order picking, by presenting a systematic methodology and introducing a new conceptual framework and taxonomy to classify and analyze this research stream. De Lombaert et al. (2022) study human aspects in order picking planning models, with a focus on the integration into mathematical models and insights from semi-structured interviews of practitioners.

- **Assembly lines:** Assembly lines are also a promising research topic for Human-Aware Modeling, due to the inherent balance of the workload between workers, which can be seen as a balance of the ER. Otto and Battaia (2017) propose a systematic review on line balancing and job rotation to reduce the physical ER in assembly. The authors provide an analysis of both the HAMFs available for assembly line practitioners, and the mathematical perspective of integrating such considerations in existing models.

- **Lot sizing:** Khan et al. (2011) review the integration of the economic order quantity models with errors from an OR point of view, without discussing the inherent human aspect in the source of such errors.

- **Vehicle routing problem:** Let us cite Vega-Mejía et al. (2019), that review the VRP with triple bottom line sustainable objectives, one of those being social. However, the paper focuses more on economic and ecological aspects, as they are more representative of their review corpus, the social aspect only being briefly discussed.

- **Workforce planning:** This class of problems has also been studied, especially with skill considerations. De Bruecker et al. (2015) present a state-of-the-art review on workforce planning with skills, focusing on both mathematical modeling and managerial implications. The authors also propose a new taxonomy for this research stream, based on what skills are exactly modeling (e.g., qualification, experience, technical capabilities), and how they are integrated into decision models. Their taxonomy constitutes the basis of our analysis of skills in (Prunet et al. (2022), *Skills*).

From a broader perspective, a number of works review the existing literature in the scope of a given HA, instead of an area of manufacturing and logistics.

- **Equity:** Karsu and Morton (2015) survey the issue of equity in OR models, and propose a taxonomy for these problems. Furthermore, they provide an analysis of the range of existing equity metrics and their modeling implications.

- **Learning:** The research on learning curves and learning effects being very prolific in management science, there are several reviews dedicated solely to this topic, with a more general perspective than OR. Anzanello and Fogliatto (2011) provide a narrative review on learning curves, with a focus on the mathematical models more than the areas of applications. Glock et al. (2019b) perform a rigorous systematic review on the application of learning curves in operations management. They cover a large spectrum of learning and forgetting models encountered in the manufacturing and logistics literature on this HA, and provide an analysis of the mathematical implications of such models. Another review is presented by Grosse et al. (2015a), that study learning curves in a production context. The authors have performed a meta-analysis of empirical studies on this topic. From the created database, they fitted the different functions of learning curves on the empirical datasets, providing a very insightful quantitative comparison of these models in various contexts.

- **HF/E-focused:** Several reviews have been conducted on a general integration of HAs in manufacturing and logistics systems with an HF/E point of view, without considering mathematical models. Padula et al. (2017) perform a systematic review about the job rotation to prevent WMSD in manufacturing industries. Loos et al. (2016) review the literature on HF/E within logistics via a quantitative and bibliometric approach. Kolus et al. (2018) review HF/E empirical studies dealing with human errors and their implications. Finally, Muhs et al. (2018) propose a systematic review on the temporal variability of tasks performed by a human operator, with a HF/E perspective.

To conclude, one can see that the topic on Human-Aware Modeling in the optimization of manufacturing and logistics systems had been extensively studied and reviewed. However, most of these reviews focus either on a single topic, or they conduct the study only through an OR or HF/E perspective, thus giving a restricted view on this interdisciplinary topic. In the present paper, we aim at broadening the scope to give a general picture and a more holistic analysis on the subject, that has not been done previously in the literature. Despite being tangent to different disciplines, this review is still seen through the lens of OR, as the main target of this paper, is OR academics and practitioners interested in the integration of Human-Aware Modeling in optimization problems.

2.3. Scope

The present work aims at surveying the research stream dedicated to the integration of Human-Aware Modeling in the optimization of manufacturing and logistics systems. The main focus of this review is put on mathematical models and optimization. However, considerations from Industrial Engineering and HF/E disciplines are heavily used to deepen the analysis of the studied corpus. The boundaries defining the scope of this corpus correspond to the intersection of the three key topics: **(i)** Optimization, **(ii)** Manufacturing or Logistics, and **(iii)** Human-Aware Modeling. As a consequence, to be relevant for this work, a paper must deal with:

I. Optimization. Despite being at the interface between several disciplines, we chose to review only the papers presenting an optimization model, either explicitly or implicitly, but clearly defined. The theoretical frameworks and modeling tools aimed at optimization models are also included.

II. Manufacturing or Logistics. According to the Cambridge Business English Dictionary (Press, 2011), manufacturing and logistics are defined as follows:

> **Manufacturing:** The business of producing goods in large numbers, especially in factories.
>
> **Logistics:** The process of planning and organizing to make sure that resources are in the places where they are needed so that an activity or process happens effectively.

These definitions clearly cover the classical topics of OR, which are planning and scheduling, when applied to a production process. However, other side activities enabling manufacturing to be processed, effectively and efficiently, are also covered by these definitions and are then meaningful for the present work. These activities are e.g.:

- Routing activities: to enable the delivery of goods where and when they are required.
- Inventory management: to provide storage and buffers at different steps of the manufacturing process.
- Warehousing activities: to efficiently operate this inventory management.
- Batching and lot sizing operations: to ensure efficient pacing of the production process.

III. Human-Aware Modeling. We consider that a paper fits in the scope of the present work if it considers the modeling of a HA or deals with the improvement of the employees' welfare.

2.4. Motivations

The research stream on Human-Aware Modeling is consistently growing due to the increasing concerns and the new regulations on working conditions. However, the study of the existing literature on the topic of Human-Aware Modeling in manufacturing and logistics systems shows a lack of a harmonized framework. The main goal of this paper is to fill this gap by providing a holistic picture of this broad topic, and a common framework for analysis. The second objective is to give to interested practitioners a comprehensive and insightful toolbox to model human characteristics, both from the HF/E and OR perspectives. These goals are expressed through the following research questions addressed throughout the current paper:

- Which HAs are studied in the related literature, and in which manufacturing and logistics areas are they present?

- How are HAs modeled in the related literature, and which HAMFs are available to take them into account?
- How are HAMFs integrated into optimization models, and how does their integration impact the models from a mathematical programming perspective?

From the investigation we perform on answering these questions, research gaps are derived, and research opportunities are highlighted.

3. Methodology

3.1. Material collection methodology

This section presents the methodology followed to collect the material for this review. The most common types of methodological approaches used to perform a literature review are: systematic, semi-systematic, narrative, integrative, and meta-analysis (Snyder, 2019). Motivated by the large number of papers fitting the scope defined in Section 2.3, we opt for a semi-systematic methodology. In short, the search methodology is systematic, to ensure that all relevant topics are covered by the review. However, the amount of material does not realistically allow a systematic analysis of every in-scope work, and thus the analysis and writing are narrative. This means that for some topics (specifically, papers dealing with skills and/or learning), the decision to include them in scope is made at the discretion of the authors. We are aware that this part is not reproducible, and therefore weakens our overall methodology, but better alternatives would not have been feasible, especially considering the already important length of this manuscript. The reader interested in systematic reviews on specific topics is referred to Section 2. Nevertheless, one should note that, even if a number of papers are excluded, the systematic search methodology ensures that all relevant topics and modeling approaches are covered in this paper. With the same philosophy, we highlight that the length of a given section does not necessarily reflect the bibliometric importance of the covered topic.

The material is collected using Scopus and Web of Science databases, by applying the following set of rules:

- Only papers published in English are considered.
- All publication dates are considered up to 2020.
- A category filter is applied on both databases to target the relevant papers. On Scopus, the search is limited to *Computer Science* and *Decision Science* categories. On Web of Science, the following categories are considered: *Computer Science (Theory methods, artificial intelligence & interdisciplinary applications)*, *Operations research and management science*, *Engineering Industrial*, *Management*, *Transportation*, *Transportation science technology* & *Mathematics interdisciplinary applications*.
- Only articles published in journals and book chapters are considered. Conference proceedings are excluded from this study.
- According to the scope of this review, two sets of keywords are created, one for manufacturing and logistics, and one for Human-Aware Modeling. Each combination of one keyword from both sets is searched. Both sets of keywords are presented in Table 1 as string notations used by the search engines.

Table 1: List of keywords in the search string

Manufacturing and Logistics		**Human-Aware Modeling**
warehous*, storage, pick*, batch*, assembly, production, "lot sizing", manufactur*, planning, routing, logistic*, schedul*, maritime	AND	musculoskeletal, welfare, postur*, lift*, "human factor*", ergonomic*, "human error*", "learning curve", "learning effect", "forgetting", "human learning", pain, noise, bored*, fatigue, break, rest, cognitive, equity, safe, discomfort, turnover, absenteeism, vibration, repetit*, injury, "social benefit*", skill*, psychosocial, "workload smoothing"

From the collected list of papers, we only retain the works that fall into the scope of the review, those that verify the following three conditions, in accordance with what is presented in Section 2.3:

1. The paper provides an optimization mathematical model, an optimization solution method, or a modeling tool that can be used in an optimization model.
2. The paper explicitly considers Human-Aware Modeling in its title, abstract, or keywords. The mention of HA or social welfare is explicit. Moreover, these aspects are explicitly modeled.
3. The paper deals with manufacturing or logistics.

Studies dealing with *skills* and *learning* include a lot of papers, and we decided to exclude some of them. Even if the exclusion process is not reproducible, the following guidelines are applied for the paper selection:

- Papers falling in the scope of the review, and focusing their contribution on Human-Aware Modeling are systematically included. This ensures that every relevant assessment or modeling approach found in the literature is addressed by the present review.
- Papers focusing their research contributions on the algorithmic side, and using a basic *ad hoc* HAMF are more likely to be excluded. For example, when tackling the topic related to *skills*, the majority of papers use a simple constraint to impose the compatibility between tasks to schedule and workers that are allowed to perform them. Despite its vast use, this simple HAMF presents a limited interest in the scope of this review, thus most of the papers proposing it are not included.

As a result of this search methodology, a total of 623 papers are retrieved. After a thorough reading, 321 papers are excluded because deemed out of scope. The final corpus thus includes 302 papers.

3.2. Structure of the paper

The first part of this literature review (i.e., the current paper) is organized as follows. First, the collected material is presented in Sections 4-7. To ease readability, this presentation is decomposed into a class of problems related to manufacturing and logistics. This decomposition aims at giving to the interested reader an overview of what is done about Human-Aware Modeling in a specific research area. The collected materials are presented in the following sections:

- First, we present the work focusing on HAMFs in Section 4. These papers do not provide an optimization model *per se*, but develop new frameworks to model HAs in the scope of mathematical programming.
- In Section 5, we present the literature related to logistics. The work is divided into two subsections by class of OR problems: warehousing in Section 5.1, and vehicle routing in Section 5.2.
- In Section 6, we present the work related to manufacturing, and more specifically to the production process. In Section 6.1, we focus on machine scheduling problems. In Section 6.2, we study the assembly line balancing problem, and in Section 6.3 the production planning and inventory management aspects.
- In Section 7, we present workforce-related problems in manufacturing and logistics. The first sections correspond to workforce scheduling problems. The problems studied in the different sections correspond to the taxonomy introduced by Lodree et al. (2009) for workforce scheduling problems, namely the job rotation problem in Section 7.1.1, the work-rest scheduling problem in Section 7.1.2, and the shift scheduling problem in Section 7.1.3. In Section 7.2, we study the literature related to the management of the workforce at a more tactical decision level. This section is divided into two topics: the workforce planning problem in Section 7.2.1, and the workforce assignment problem in Section 7.2.2.

Note that this decomposition in different research areas is performed to ease the reading, not to introduce a consistent classification of the field. Therefore an overlap is present among some sections, and some works could be classified into several categories. However, we decided to include each paper in a single section, where it seemed the most relevant.

Section 8, the last part of the current paper, is dedicated to the study of the collected material from a mathematical programming perspective. More specifically, we studied how the different HAs are integrated into optimization models, either in the objective function (see Section 8.1), the constraints (see Section 8.2) or the data (see Section 8.3). In the end, we discuss the collected material, and propose some promising research directions, related to both parts of this review work, and Section 10 concludes this paper.

3.3. Summary tables: Format and convention

The collected material is presented via tables in the next sections. These tables are intended as a reading guideline, and as such their entries point to the different topics studied in this literature review, both the current paper and the second part (Prunet et al., 2022). The tables contain the following columns:

- **Reference** The reference of the paper in the bibliography.
- **Case study** In this column, we register if the work is applied to a real-life case study. When this is the case, the industrial sector of the concerned company is given, otherwise, this field is empty.
- **Modeling** In this column we register how the HAMF used in the paper is integrated into the optimization model. The different options correspond to the subsections of Section 8, and include *MO* for true multi-objective, *MO-He* for an heterogeneous aggregation of several objective functions, *MO-Ho* for an homogeneous aggregation of several objectives, and *SO* for a single objective function. Concerning the constraints, *CC* is used for compatibility constraints, *TC* for threshold constraints, *TWC* for time window constraints, *FSC* for forbidden sequence constraints, and *FBC* for forward-backward constraints. Concerning the data, *VTT* designates a variable task time, and *VQ* a variable quality.
- **HW** In this column we look at the modeling of the workforce. More precisely we check if the workforce is modeled heterogeneously or not, i.e., if different employees are modeled with different characteristics, or if they are all interchangeable. If the modeling is heterogeneous, this column specifies which kind of parameter is a defining characteristic of an employee. The different options include the skills *S*, the learning rate *LR*, physical properties *PP*, cognitive and psychosocial properties *CPP*, and preferences *P*.
- **HAMF** In this column we look at which modeling framework is used in the paper to represent the considered human aspects. The different options correspond to the section of the second part of this review (Prunet et al., 2022).

4. Modeling frameworks of human aspects

In this section, we present the research works focusing on Human-Aware Modeling. The related papers do not provide an optimization model, however, they develop new frameworks to model HAs that can be integrated into a mathematical model.

Human performance. First, a number of papers focus on human performances. In traditional OR approaches, the productivity is assumed to be constant through a work shift, and identical among employees. These assumptions usually make the problem easier to solve. However, they are not realistic since the workforce is heterogeneous, and various factors may impact the productivity of manual labor. This lack of accuracy in the performance modeling can therefore lead to a loss of efficiency in the logistics and production systems. This has for example been studied by Buzacott (2002), who shows that worker differences (e.g., competencies) can lead to suboptimal decisions with respect to the system output when not accounted for, especially when more complicated tasks are involved. Lanzetta et al. (2016) propose a worker performance model depending on several HAs: skills, environment, motivation, etc. The topics related to motivation and its adverse effect, boredom, have been studied in several papers (see Prunet et al. (2022), *Motivation and boredom*). Azizi et al. (2013) propose a mathematical formulation to express boredom at work based on a probabilistic framework.

Table 2: Human-Aware Modeling

Reference	Case study	Modeling	HW	HAMS
Buzacott (2002)			S	skills
Jaber and Guiffrida (2004)				learning, human errors
Jaber and Sikstrom (2004)				learning
Jaber et al. (2013)		VTT		learning, LFFRM
Azizi et al. (2013)				motivation
Jaber and Glock (2013)				learning
Sobhani et al. (2015)		MO-Ho		health state
Givi et al. (2015a)				learning, LFFRM, human errors
Lanzetta et al. (2016)	Pisa hospital	VTT	S, PP, CPP	skills, motivation
Małachowski and Korytkowski (2016)			S, LR	skills, learning
Sobhani et al. (2017)		MO-Ho		health state
Sobhani and Wahab (2017)		MO-Ho		health state
Korytkowski (2017)				skills, learning
Caputo et al. (2017b)				human errors
Caputo et al. (2017a)				human errors
Kong (2019)				cognitive
El Mouayni et al. (2020)				RA
Peltokorpi and Jaber (2020)				learning

Skills and learning. Another important part of performance evaluation is the modeling of the competencies of employees and their variations (i.e., learning and forgetting). A lot of research has been done on the topic of learning curves since the seminal paper of Wright (1936). To cite some of them, Jaber and Glock (2013) develop a learning curve with both motor and cognitive elements, Peltokorpi and Jaber (2020) refine further the model, by considering collective learning for a work team. In (Jaber et al., 2013), the authors develop the Learning Forgetting Fatigue Recovery Model (LFFRM), which integrates learning, forgetting, fatigue and recovery. This model has been used in several optimization models (see Prunet et al. (2022), *Learning forgetting fatigue recovery model*). It has been further refined in (Givi et al., 2015a) with the integration of errors and quality aspects. More details on learning curves can be found in the dedicated part of the review, in (Prunet et al. (2022), *Learning*). Jaber and Sikstrom (2004) propose a numerical comparison of different learning curve models. Apart from pure learning, some works focus on more accurate modeling of employees' competencies, e.g., in (Małachowski and Korytkowski, 2016), further refined in (Korytkowski, 2017). Instead of a classical skill model (see Prunet et al. (2022), *Skills*), they develop a graph-based model, where the practice of one competence for an operator improves its proficiency in this competence, but also affects other related skills.

More than productivity, performance variations have been also studied from the errors and quality perspective. (Caputo et al., 2017a,b) propose a taxonomy and modeling frameworks for human errors, respectively in the kitting and part supply processes, applied to an assembly context. Jaber and Guiffrida (2004) adapt the learning curve model of Wright (1936), by integrating an error rate, and an additional processing time to account for the rework of defective products.

Working conditions. Finally, the modeling of the ergonomic conditions of the workplace has been addressed in the literature. Kong (2019) proposes a new framework for the ergonomic evaluation of a workstation, accounting for both physical and cognitive load, linked to the complexity evaluation of tasks. In (El Mouayni et al., 2020), the authors develop a simulation-based time allowance indicator. The time allowance designates the rest time needed for a full recovery after a work period (see Prunet et al. (2022), *Rest allowance*). Sobhani et al. (2017, 2015) develop a new model to account for the ergonomic conditions at work and work-related injuries. This model is based on the *health state* of an employee, modeled via a Markov chain, that can be healthy, in pain, or injured. They estimate the indirect costs of poor ergonomics by looking at the steady state of this chain, and inferring the total cost of work-related injuries (see Prunet et al. (2022), *Health states*).

5. Logistics

5.1. Warehousing

Warehousing is one of the key components of a logistics network. Its activities, and especially order picking, still heavily rely on manual labor (de Koster et al., 2007), and the work can be physically demand-

ing. The integration of HAs into mathematical models has therefore gained attention from OR researchers on this topic.

Storage. The most studied topic in the field of warehousing is storage, where the main decision is to assign items to storage locations. The solution methods to optimize storage decisions vary from class-based storage (Battini et al., 2016b), to rule-based storage assignment methods (Hwang et al., 2003), or applied U-shaped picking zone storage (Diefenbach and Glock, 2019). In (Otto et al., 2017), the storage decision is integrated with the zoning decision (each order picker is assigned to a zone in the warehouse he/she is responsible for) with the goal of balancing the ER. In (Al-Araidah et al., 2017), storage and routing are optimized altogether for a vehicle-aided order picker, where the aim is to group items, so that one cluster corresponds to the items reachable by the picker when the vehicle is stopped (i.e., within arm range while remaining properly sited in the vehicle). The goal is to minimize the number of stops of the vehicle. Kudelska and Pawłowski (2020) study the impact of storage decisions on the ER using simulation. Grosse et al. (2013) study the effects of worker learning and forgetting on storage assignment and reassignment decisions.

Table 3: Warehousing

Reference	Case study	Modeling	HW	HAMS
Marvel et al. (2001)	food warehouse	CC		handling
Hwang et al. (2003)		SO		biomechanical
Grosse et al. (2013)		VTT	LR	learning
Grosse and Glock (2015)		VTT	LR	learning
Battini et al. (2016b)		MO		EE, RA
Calzavara et al. (2017)		MO		EE
Otto et al. (2017)		SO		handling
Battini et al. (2017b)	food warehouse		S	posture, RA
Al-Araidah et al. (2017)				visual, anthropometric
Larco et al. (2017)	automotive part warehouse	MO		expert collaboration
Matusiak et al. (2017)	retailer	VTT	S	skills
Hong (2018)		VTT	S	skills
Diefenbach and Glock (2019)		MO		EE
Glock et al. (2019a)	paint manufacturer	MO		biomechanical
Calzavara et al. (2019a)	food and home care products warehouses	MO		EE, posture
Kudelska and Pawłowski (2020)		MO		implicit

Layout. Another common topic is the layout of the warehouse. The organizational layout of the picking zone, and especially the choice of storage containers, may have a large impact on the ER of order pickers. In (Calzavara et al., 2017, 2019a), the layout decisions include the choice of picking from a full pallet, or from half pallets on the floor and upper shelves. A full pallet might have a better space efficiency, but this comes at a cost in terms of ER. In (Glock et al., 2019a), there is the possibility of rotating the pallets to enable easier access to the stored items.

Other related topics of interest. They include the workforce scheduling applied to a warehousing context (Dewi and Septiana, 2015; Zhao et al., 2019), or operational factors in the bucket brigade efficiency (Hong, 2018). The picker batching with a job assignment is also considered by Matusiak et al. (2017).

HAMF. The most common one is energy expenditure (see Prunet et al. (2022), *Energy expenditure*), that has been adapted to warehousing operations by Battini et al. (2017b). Lifting and manual handling are also a major related concern, either with the NIOSH-equation, presented in Prunet et al. (2022), *Manual handling* (Otto et al., 2017; Marvel et al., 2001), or with special-purpose biomechanical models (Glock et al., 2019a). The postural load is also commonly used as a measure of the ER, for instance, Al-Araidah et al. (2017); Calzavara et al. (2019a) compute it with the OWAS method (see Prunet et al. (2022), *Postural ER*). Learning and forgetting have been studied through their impacts on the warehousing decisions in (Grosse and Glock, 2015; Grosse et al., 2013). Finally, Larco et al. (2017) use a regression from workers' opinions as an input to their model, and Matusiak et al. (2017) conduct a regression analysis from historical data to determine the different skills and skill levels of the employees.

5.2. Vehicle routing

The Vehicle Routing Problem (VRP) and its extensions represent an important class of problems studied in the OR literature. In the scope of this review, this class of problems is also discussed.

Breaks scheduling. The main HAMFs considered in the VRP literature deal with breaks scheduling. In this problem, the aim of the model is to design a routing plan, that is valid for classical VRP constraints (e.g., capacity, time windows), while respecting the regulations on drivers working and driving times. The starting time and duration of the rest breaks are introduced as new decisions to be scheduled in the model. It is indeed an important topic since recent regulations enforce the explicit scheduling of rest breaks in routing plans (see Prunet et al. (2022), *Regulatory breaks*). Furthermore, the integration of driver breaks scheduling into vehicle routing makes the problem more challenging (see Section 8.2 on forward-backward constraints). For these reasons, this problem has attracted the attention of the research community. It has first been rigorously introduced in (Goel, 2009), some previous work had however already dealt with the breaks scheduling aspect via less sophisticated methods. As an example, Brandao and Mercer (1997) study a rich multi-trip routing problem. More recent works on this problem include (Rancourt et al., 2013; Rancourt and Paquette, 2014; Goel and Vidal, 2014).

Rest breaks. They have also been considered in routing decision models without using actual regulation frameworks. A common consideration is the scheduling of a *meal break* in the routing plan, to enable drivers to get a full break during their shift (see Prunet et al. (2022), *Meal breaks*). This is most of the time modeled with time windows for the break to take place (see Section 8.2 on time windows constraints). This HAMF is found in vehicle routing (Coelho et al., 2016), waste collection routing (Kim et al., 2006; Benjamin and Beasley, 2010), or for more recent work in home dialysis visit scheduling and nurse routing (Kandakoglu et al., 2020), where the authors apply their proposed approach to an industrial case at Ottawa Hospital.

Fatigue and rest breaks have also been considered with other modeling techniques that are worth mentioning. In (Bowden and Ragsdale, 2018), fatigue is seen as a lack of alertness and increased sleepiness to be reduced for road security reasons. Service times at customer locations are modeled as dependent on the fatigue level of the employee in (Yan et al., 2019).

Table 4: Vehicle routing

Reference	Case study	Modeling	HW	HAMS
Brandao and Mercer (1997)		FBC		regulatory breaks
Kim et al. (2006)	waste collection	MO-He, TWC		meal breaks, equity
Erera et al. (2008)		FBC		regulatory breaks
Goel (2009)		FBC		regulatory breaks
Ceselli et al. (2009)		FBC		regulatory breaks
Benjamin and Beasley (2010)		TC, TWC		meal breaks
Kok et al. (2010b)		FBC		regulatory breaks
Kok et al. (2010a)		FBC		regulatory breaks
Prescott-Gagnon et al. (2010)		FBC		regulatory breaks
Wen et al. (2011)	meat supplier	FBC	S	regulatory breaks
Goel (2012)		FBC		regulatory breaks
Melton and Ingalls (2012)		MO-Ho		psychosocial
Hollis and Green (2012)	beverage distributor	MO-He, TWC		visual, meal breaks
Rancourt et al. (2013)		FBC		regulation breaks, psychosocial
Rancourt and Paquette (2014)	distribution company	MO, FBC		regulatory breaks
Goel and Vidal (2014)		FBC		regulatory breaks
Rattanamanee et al. (2015)		SO, TC	PP	EE
El Hachemi et al. (2015)	forestry	TWC		meal breaks
Battini et al. (2015)	hospital & restaurant logistics companies	VTT	LR	learning
Min and Melachrinoudis (2016)		FBC		regulatory breaks
Coelho et al. (2016)		TWC		meal breaks
Liu (2016)		MO-He		equity
Bowden and Ragsdale (2018)		TC		regulatory breaks
Mathlouthi et al. (2018)		CC, TWC	S	meal breaks
von Elmbach et al. (2019)		SO		handling
Yan et al. (2019)		VTT	S	skills, deterioration effect
Matl et al. (2019)		MO		equity
Lehuédé et al. (2020)		MO		equity
Kandakoglu et al. (2020)	Ottawa hospital	MO-He, CC, TWC	S	meal break, equity, skills
Rabbani et al. (2020)		MO		equity
Mayerle et al. (2020)		TWC, FBC		regulatory breaks
Anoshkina and Meisel (2020)		MO-He, CC	S	skills, psychosocial
Ulmer et al. (2020)		MO, VTT	S, CPP	learning

Equity. Another frequent HA studied in vehicle routing is the workload equity between drivers. Equity has been a growing trend in VRP in the last years, focusing on the drivers' workload as it is reviewed in the present work, as well as a general balance of the available resources (Matl et al., 2018). In the current scope, Kandakoglu et al. (2020) use an equity objective for nurse visit routing and scheduling. Rabbani et al. (2020) study the hazardous waste collection problem with workload balancing among drivers. This is also done by Kim et al. (2006) for a classical waste collection vehicle routing problem with meal breaks. Liu (2016) study the periodic delivery problem while trying to balance workload. From a more general perspective, Matl et al. (2019) compare different equity functions for the VRP. They assess the impact on the solution depending on which resource is balanced among drivers: number of visited customers, traveled distance, load handled, etc.

Other topics of interest. Among other topics that are studied about Human-Aware Modeling in vehicle routing, one refers to the familiarity of drivers with the routes they are assigned to. It is indeed a reasonable hypothesis to decrease driving/processing times if one driver is familiar with the itinerary and/or customer locations. This is done by Battini et al. (2015), who use a learning curve (see Prunet et al. (2022), *Learning*) for drivers. They compare a daily optimized routing plan and a fixed routing plan, where a route is always assigned to the same driver, thus gaining efficiency over time. This is also the case in (Ulmer et al., 2020), where the familiarity of the drivers with customer locations is accounted for when optimizing the routing plan. Another interesting HAMF is addressed by Anoshkina and Meisel (2020), who study the intraday and interday technician routing, accounting for skills (see Prunet et al. (2022), *Skills*) and team consistency. Hollis and Green (2012) aim at improving efficiency, by producing visually attractive routes that would be more natural to follow for a driver.

6. Production systems

6.1. Machine scheduling

The general definition of machine scheduling is very broad (Chen et al., 1998), and can fit a large class of problems. However, in this section, we consider scheduling problems where the main decisions are the assignment and sequencing of a set of jobs on a set of machines. This differs from the other sections dealing with scheduling problems, where the main decision is the scheduling of human operators' activities. In this case, the HAs are accounted for indirectly in optimization models, since they are not intrinsically represented by the decision variables. Existing studies mainly focus on modeling the *learning effects* and/or *fatigue*, or integrating HAs via the *objective function*.

Learning effects. The most common HAMF found in the machine scheduling literature is learning effect (see Prunet et al. (2022), *Learning*). The underlying idea is that the more similar tasks are repeated, the more *know-how* is acquired and the execution time decreases accordingly. More details on varying task time modeling can be found in Section 8.3.1. One could argue that learning might not be determinant in the context of machine scheduling, which is very operational, with a "short-term" planning horizon. However, this effect has been widely accepted (Biskup, 2008). This topic has been extensively studied in the context of single machine scheduling (Biskup, 1999), parallel machine scheduling (Eren, 2009), or flow-shop scheduling (Wang and Xia, 2005). In this context, processing times, or setup times, are not constant over the schedule, but depend on the position in the schedule (Amirian and Sahraeian, 2015), or the sum of processing times of similar tasks already processed (Cheng and Wang, 2000). It is also common to suppose that the processing times depend on both the position and the sum of processing times for similar tasks already processed (Wu and Lee, 2008; Wang et al., 2019).

Fatigue. With a modeling technique similar to that of the learning effect, the processing times of the tasks to be scheduled can be affected by the fatigue level of the operators. It is indeed a reasonable assumption that tiredness has a negative impact on productivity (see Prunet et al. (2022), *Fatigue and breaks*). In the scope of machine scheduling, fatigue is often not modeled at the individual level of the operator, but as a general factor. The modeling approach uses the deterioration effect and rate-modifying activities (see Prunet et al. (2022), *Deterioration effect and rate-modifying activities*). In short, the integration of the deterioration effect to a model means that productivity decreases as time passes. This is often modeled with a linear decay function (Lodree Jr. and Geiger, 2010). The so-called rate-modifying activities (RMA) are scheduled in order to reset the productivity to its maximum level. An RMA represents a break that,

when scheduled, enables recovery of human operators, and thus improves their performance afterward (see, e.g., Zhu et al. (2017)). Analytical results on the scheduling problem with deterioration are provided by Lodree Jr. and Geiger (2010). In some studies, the deteriorating effect is modeled by a more sophisticated function, possibly accounting for both fatigue and other factors. This is for example the case in (Wang et al., 2020) with fatigue and boredom, or (Bautista et al., 2015), where adaptation improves productivity at the beginning of the work shift, and fatigue reduces it at the end.

Table 5: Machine scheduling

Reference	Case study	Modeling	HW	HAMS
Biskup (1999)		VTT		learning
Cheng and Wang (2000)		VTT		learning
Mosheiov (2001)		VTT		learning
Mosheiov and Sidney (2003)		VTT		learning
Wang and Xia (2005)		VTT		learning
Tang et al. (2006)	computer disassembly	VTT, VQ	S	skills
Wang (2007)		VTT		learning
Wu and Lee (2008)		VTT		learning
Aravindkrishna et al. (2009)		FSC		implicit
Lee and Wu (2009)		VTT		learning
Eren (2009)		VTT		learning
Lodree Jr. and Geiger (2010)		VTT		deterioration effect
Anzanello and Fogliatto (2010)		VTT	LR	learning
Janiak and Rudek (2010)		VTT		skills, learning
Pargar and Zandieh (2012)		VTT		learning
Lee et al. (2012)		VTT		learning
Nembhard and Bentefouet (2012)		VTT	S	learning
Wang et al. (2013)		VTT		skills
Zhang et al. (2013)		VTT		learning
Costa et al. (2014)		VTT	S	skills
Anzanello et al. (2014)	footwear manufacturer	TC, VTT		learning, repetitive movements
Bautista et al. (2015)	automotive powertrain manufacturer	VTT		deterioration effect
Ji et al. (2015)		VTT		learning
Ruiz-Torres et al. (2015)		MO, TC	P	satisfaction
Amirian and Sahraeian (2015)		VTT		learning
He (2016)		VTT		learning
Zhu et al. (2017)		VTT		deterioration effect
Pei et al. (2017)		VTT		learning
Gong et al. (2018)		VTT	S	skills
Przybylski (2018)		VTT		learning
Li et al. (2018b)		VTT	LR	learning
Lu et al. (2019)		MO		noise
Petronijevic et al. (2019)				learning, fatigue
Sanchez-Herrera et al. (2019)		VTT	S	deterioration effect
Jamili (2019)		TWC		meal breaks
Sun et al. (2019)	steel structure machining	TWC		meal breaks
Wang et al. (2019)		VTT		learning
Sheikhalishahi et al. (2019)		MO		human error
Ruiz-Torres et al. (2019)		MO-He	P	satisfaction
Gong et al. (2020a)		CC	S	skills
Savino et al. (2020)		TC		posture
Kaya et al. (2020)	notebook manufacturer	MO		noise, vibration, posture
Şenyiğit et al. (2020)		VTT		learning, repetitive movements
Fu et al. (2020)		MO		noise
Gong et al. (2020b)		VTT	S	skills
Marichelvam et al. (2020)	automotive parts manufacturer	VTT	S, LR, PP	skills, learning
Wang et al. (2020)		VTT		deterioration effect, motivation

Ergonomic objective. Some existing studies on machine scheduling deal with the integration of HAs via an objective function. The human-centered objective completes a more classical economic objective, giving rise to a multi-objective approach (see Section 8.1.2). Note that this approach is not very common in machine scheduling. When it is the case, the risk factor can be noise pollution (see Prunet et al. (2022),

Noise), for instance, in (Lu et al., 2019), or in (Fu et al., 2020) associated with dust pollution. Kaya et al. (2020) consider noise pollution, alongside with vibration exposure (see Prunet et al. (2022), *Vibrations*) and posture. Finally, Sheikhalishahi et al. (2019) study a machine scheduling problem with human errors (see Prunet et al. (2022), *Human errors*), and incorporate them into an optimization model.

6.2. Assembly line balancing

Assembly line balancing (ALB) represents a particular class of scheduling problems, which are of great importance in manufacturing systems. The basic model, the Simple Assembly Line Balancing Problem, is the most studied in the literature (Boysen et al., 2007), and constitutes the core decision problem of its class. The goal of this problem is to assign a set of tasks to a set of workstations, and to schedule them over a finite time horizon. Each task is defined by a (constant) processing time. It is asked to minimize a given function related to the balance of the workload among all stations or to minimize the number of stations for a given cycle time. However, the scheduling of these tasks is subjected to *precedence constraints*, which must be respected.

Table 6: Assembly line balancing

Reference	Case study	Modeling	HW	HAMS
Doerr et al. (2000)		TC, VTT	S	skills
Carnahan et al. (2001)		MO-He		biomechanical
Chiang and Urban (2006)		VTT		skills
Choi (2009)		MO-He		implicit
Moon et al. (2009)		MO-Ho, CC	S	skills
Corominas et al. (2010)		VTT	S	skills
Otto and Scholl (2011)		MO-He, TC		whole body
Zhang and Gen (2011)		VTT	S	skills
Mutlu and Özgörmüş (2012)	textile manufacturer	TC		implicit
Cheshmehgaz et al. (2012)		MO		posture
Xu et al. (2012)	blender manufacturer	TC		biomechanical
Koltai and Tatay (2013)		CC	S	skills
Manavizadeh et al. (2013)		CC		skills
Kara et al. (2014)		MO-Ho, TC, CC	S, PP	EE, cognitive, skills
Koltai et al. (2014)	bike manufacturer	CC	S	skills
Otto and Otto (2014)		VTT		learning
Sotskov et al. (2015)		VTT		
Battini et al. (2016a)	high pressure cleaner manufacturer	MO		EE
Bautista et al. (2016b)	automotive manufacturer	MO-He, TC		handling, posture, repetitive movements
Polat et al. (2016)	TV manufacturer	CC, VTT	S	skills
Bautista et al. (2016a)	automotive manufacturer	SO		handling, posture, repetitive movements
Ritt et al. (2016)		VTT	S	skills
Battini et al. (2017a)	pump manufacturer	TC		EE
Bortolini et al. (2017)	kitchen appliance assembly	MO, VTT		deterioration effect, posture
Aroui et al. (2017)	truck manufacturer	SO	S	implicit
Sadeghi et al. (2018)	footwear manufacturer	MO-He, CC	S	skills
Alghazi and Kurz (2018)	automotive parts manufacturer	TC		implicit
Efe et al. (2018)	textile manufacturer	VTT	S, PP	skills
Tiacci and Mimmi (2018)		MO-He		repetitive movements
Salehi et al. (2018)	garment industry	CC, VTT, VQ	S	skills, human errors
Akyol and Baykasoglu (2019)		MO-He	S	repetitive movements
Samouei and Ashayeri (2019)		VTT	S	skills
Akyol and Baykasoğlu (2019)		VTT	S	skills
Zhang et al. (2020)		MO, VTT	S	repetitive movements
Finco et al. (2020b)		VTT		EE, RA
Ostermeier (2020)	automotive engine manufacturer	VTT		learning, LFFRM

Human-Aware Modeling has been extensively addressed while studying ALB. This is not surprising considering its nature. In fact, the usual objective function of these problems is already to balance the *workload* among workstations. In the classical literature, the workload is often expressed as a function of operation processing times, but it is not far-fetched to think of workload as a physical workload for human

operators. Furthermore, assembly line balancing problems are highly combinatorial, and their instances often admit a large number of optimal solutions. In this case, it is natural to discriminate between these solutions using a second objective function, for instance, with an ergonomic objective applied lexicographically, to get the solution with the lowest ER among economically-equivalent solutions.

Balancing the ER in the objective. It is not surprising that one of the main modeling approaches to integrate the ER into ALB problems is to enrich or add an objective function, especially within multi-objective optimization (see Section 8.1.2). In this case, one (or several) objective(s) deals with balancing the ER among workers. This risk is often determined using observational WMSD risk assessment methods from HF/E. For instance, Cheshmehgaz et al. (2012) and Bautista et al. (2016b) aim at balancing the WMSD risk associated with awkward postures, which are common in the assembly literature. The HAMFs used to model the ER are respectively the OWAS and RULA methods. This is also the case of Bortolini et al. (2017), who study the ALB problem while considering parts feeding, proposing an original modeling technique of parts picking time, with the associated risk measured via the REBA method. Section *Postural ER* of (Prunet et al., 2022) gives more details about the different postural load assessment methods. Material handling is also a risk factor in ALB (see Prunet et al. (2022), *Manual handling*), for example, in (Bautista et al., 2016b). Another risk factor, that is very important in the assembly systems, is the repetitive nature of the work. The high number of repetitions is indeed linked to the apparition of WMSD (Occhipinti, 1998). The OCRA index is the most common HAMF for this kind of risk (see Prunet et al. (2022), *Repetitive movements*), and several papers use it as their ER to balance, either alone (Zhang et al., 2020; Akyol and Baykasoglu, 2019; Tiacci and Mimmi, 2018), or jointly with other methods (Bautista et al., 2016b). The ER can also be modeled using the energy expenditure (see Prunet et al. (2022), *Energy expenditure*), linked to an overall fatigue (Battini et al., 2016a). Bautista et al. (2016a) consider a single ergonomic objective.

Threshold on the ER. The risk exposure can also be accounted for without being stated as an objective function. In assembly line balancing (and other scheduling problems), this is done by setting a threshold value on the maximum exposure an employee can sustain during his/her shift. This is modeled with a threshold constraint (see Section 8.2) for each workstation. WMSD risk assessment methods can be used as ER, the same way it is modeled with objective functions (Battini et al., 2017a), that use energy expenditure. However, in the retrieved corpus dealing with assembly line balancing, this modeling approach is mostly used with ad hoc ER metrics without being explicitly specified (e.g. Mutlu and Özgörmüş (2012); Alghazi and Kurz (2018)).

Varying task time. Another typical direction of work in ALB is to look at the modeling of varying task times (see Section 8.3.1). In this case, the duration of a task depends on the properties of the assigned worker, either his/her intrinsic characteristics or his/her level of productivity at the time he/she processes the task. When it is linked to the operator characteristics, the most common HA is the skill level (see Prunet et al. (2022), *Skills*), for instance, in (Samouei and Ashayeri, 2019; Polat et al., 2016; Zhang and Gen, 2011). Salehi et al. (2018) consider a varying processing time, that depends on the skill level of the operator, but with a fuzzy modeling approach. However, other operator-dependent processing time modeling techniques can be found in the literature. For instance, the completion time of a task depends on the age and gender of the performing operator in (Efe et al., 2018). The numerical values are computed with a statistical regression from an empirical dataset. When the processing time depends on the time the task is scheduled, it can be because learning is considered in the model: the more similar tasks have been scheduled before, the less time it takes (see Prunet et al. (2022), *Learning*). Otto and Otto (2014) and Ostermeier (2020) study this HAMF in assembly line balancing problems. Another possibility is when the task duration depends on the fatigue level of the operator processing it at the time the task is scheduled (see Prunet et al. (2022), *Fatigue and breaks*), as done by Finco et al. (2020b) and Ostermeier (2020).

Compatibility constraints. The skill level of an operator is also modeled through compatibility constraints (see Section 8.2), where some assignments task/workstation are infeasible, because the task at hand requires a specific skill set, that the employee operating this workstation does not possess (Koltai and Tatay, 2013; Manavizadeh et al., 2013).

6.3. Production planning and inventory management

Production planning. Production planning is a very crucial leverage of performance in any manufacturing system. Therefore, it is not surprising that the topic is well established in the OR community, and is a

prolific research area (Jans and Degraeve, 2008). Considering the integration of HAs in lot sizing models, the topic of learning and forgetting (see Prunet et al. (2022), *Learning*) is by far the most studied. In the context of batch manufacturing, it is quite natural to consider learning and forgetting effects. There can be a long time between the production of two similar batches, and a significant forgetting effect can occur during this period. It is seen as an increased setup cost, and in that case, it is natural to study the impact of learning and forgetting effects on the optimal batch size. The topic has received some attention in the early literature (Muth and Spremann, 1983; Smunt, 1987). Different forgetting functions have been studied to model this HA (Teyarachakul et al., 2011). In more recent studies, it is common to use more sophisticated learning models. For example, the learning and forgetting processes affect both the productivity and the quality of the production in (Jeang and Rahim, 2019; Jaber and Bonney, 2003). Kazemi et al. (2016a) account for both motor and cognitive learning. In (Jaber and Peltokorpi, 2020), the number of employees working in a team affects the learning process. Battini et al. (2017c) study an ergonomic lot sizing problem. They integrate the ER into the problem definition: It is measured using the energy expenditure as a HAMF (see Prunet et al. (2022), *Energy expenditure*), which models the overall physical load of a job, and is then converted into a rest allowance for break duration (see Prunet et al. (2022), *Rest allowance*) to enable recovery. This recovery time is then integrated into the objective function as an additional cost (see Section 8.1.2). Apart from the lot sizing problem, other aspects of production planning have been studied within Human-Aware Modeling. For example, Givi et al. (2015b) propose a model for worker performances accounting for the learning and forgetting effects as well as fatigue and recovery, and their impact on productivity and quality. Cui et al. (2020) study a coal production planning problem, by taking into account green and social objectives.

Table 7: Production planning

Reference	Case study	Modeling	HW	HAMS
Muth and Spremann (1983)				learning
Smunt (1987)		VTT		learning
Elmaghraby (1990)		VTT		learning
Anderson Jr. and Parker (2002)		VTT		learning
Jaber and Bonney (2003)		VTT, VQ		learning, human errors
Ryan et al. (2011)	road maintenance			expert collaboration
Teyarachakul et al. (2011)		VTT		learning
Khan et al. (2012)				learning, human errors
Huang et al. (2012)		VTT	S	learning
Zanoni et al. (2012)		VTT		learning
Khan et al. (2014)				learning, human errors
Givi et al. (2015b)		MO-Ho, VTT, VQ		learning, LFFRM, human errors
Kazemi et al. (2015)		VTT		learning
Andriolo et al. (2016)	assembly line	MO		handling
Kazemi et al. (2016a)				learning
Kazemi et al. (2016b)		VTT		learning, expert collaboration
Khanna et al. (2017)		VQ		human error
Battini et al. (2017c)		MO-Ho		EE, RA
Mokhtari and Hasani (2017)	home appliance manufacturer	MO		noise
Shin et al. (2018)		MO-Ho		human error
Sobhani et al. (2019)	automotive manufacturer			health state
Jeang and Rahim (2019)		VTT, VQ		learning
Condeixa et al. (2020)		MO-Ho		RA
Cui et al. (2020)		MO		total cost function
Gilotra et al. (2020)				human errors
Jaber and Peltokorpi (2020)		VTT		learning

Inventory control. From the perspective of inventory management, similar issues appear with the Economic Order Quantity (EOQ) model. The learning and forgetting effects have been studied in this context by Kazemi et al. (2015, 2016b) on an empirical study. They realized semi-structured interviews with industry experts to gain practical insights to design a more accurate learning curve for the EOQ model they develop. However, the most studied HAs in the inventory literature are the WMSD risk for employees (see Prunet et al. (2022), *WMSD risk assessment methods*). Andriolo et al. (2016) compute the social impact of a stock keeping unit in terms of material handling (see Prunet et al. (2022), *Manual handling*), and integrate it into a multi-objective EOQ model. Sobhani et al. (2019) study the effect of the working environment, modeled as health-states (see Prunet et al. (2022), *Health states*), on the vendor buyer inventory model. Condeixa et al. (2020) integrate the employees fatigue with the energy expenditure (see Prunet et al. (2022), *Energy*

expenditure) in a reverse logistics EOQ model with environmental and social considerations. Another interesting work on the EOQ has been done by Ryan et al. (2011) in the framework of a collaboration between operation researchers and ergonomists. An ergonomic field study is conducted on a road maintenance site to identify the most relevant HAs, which are then integrated into an EOQ model.

Supply chain management. Human-Aware Modeling has also been studied in supply chain management. Learning and forgetting are also usual considerations in this class of problems. Zanoni et al. (2012) study the vendor-managed inventory problem with learning and forgetting curves. Khan et al. (2012, 2014) study a vendor-buyer supply chain model with learning occurring on the production side, and human errors in the quality inspection for the customer side. The topic of human errors (see Prunet et al. (2022), *Human errors*) has actually been studied quite extensively in supply chain management, considering that it is not a prevalent topic in other decision problems. Gilotra et al. (2020) study a 2-echelon supply chain with considerations on carbon emissions and human errors. In (Shin et al., 2018), the human errors are integrated as an additional cost in the objective function for a 2-echelon supply chain model in the form of a total cost function (see Section 8.1.2). More classical HAs like workers' injuries are also considered (e.g., Mokhtari and Hasani (2017)).

6.4. Design of systems

In this section, we present research works dealing with system design in a broad sense. Several classes of problems are represented, sharing the common point of using an optimization method to design the inherent aspects (e.g., layout, processes) of a manufacturing system.

Layout design. In this research topic, the majority of studies on layout design aim at integrating the ER. For example, Finco et al. (2020a) study the design of an assembly line system, accounting for the vibration exposure of workers (see Prunet et al. (2022), *Vibrations*). In their model, a set of tools is available to reduce the exposure on the machines, and the objectives are to minimize both the workers ER and the equipment cost. An analog approach is used by Razavi et al. (2014), who consider the noise exposure of operators (see Prunet et al. (2022), *Noise*), which can be mitigated using personal equipment, by reducing the emission level of the source, or via equipment that limits the diffusion. Braun et al. (1996) and Antonio Diego-Mas et al. (2017) study the design of a workstation layout with ergonomic considerations. Another important aspect in layout design is the facility by itself, and especially the optimization of material handling operations, addressed, for instance, by Li et al. (2018a), where the placements of the different areas of the facility are optimized to facilitate the material handling among areas. Several risk factors are considered to quantify the ER of the handling activities: posture, force strength, job difficulty, space comfort, psychological load, etc. Zhang et al. (2018) use energy expenditure (see Prunet et al. (2022), *Energy expenditure*) as a HAMF for the ER assessment in material handling. They aim at balancing this ER and the handling distance, by optimizing the batch size and the sequencing of operations. In (Diefenbach et al., 2020), the material handling is performed using an electrical vehicle, and the focus is put on how to store the set of bins on the vehicle to minimize the ER during loading and unloading operations. Mateo et al. (2020) study a newspaper printing industry and optimize the machine feeding process (stack size, etc.) to reduce the risk of work-related injuries. An analog idea is developed by Glock et al. (2019c) on the packaging process, where the box size is optimized to reduce ER.

Process design. This stream of research concentrates on designing and organizing the industrial processes. For example, the problem studied by Botti et al. (2017) and Hu and Chen (2017) is to determine if each process should be manual or automated, depending on its characteristics. Al-Zuheri et al. (2013, 2016) study an assembly process with workers walking from one station to another. Pistolesi and Lazzerini (2019) study a disassembly line, where several operators work simultaneously on the product to disassemble. The main issue is to organize the operations so that workers are able to work simultaneously on different faces of the product. In several cases, it is the overall organization of the workforce that is designed. For example, the cross-training strategy is designed to improve the workforce flexibility in the works of (Hopp et al., 2004; Olivella and Nembhard, 2017). A work-sharing strategy is designed by Bukchin and Cohen (2013), where new employees share a part of their workload during their training time.

Table 8: System design

Reference	Case study	Modeling	HW	HAMS
Braun et al. (1996)	electromechanical switch manufacturer	MO		biomechanical
Celano et al. (2004)				organizational
Hopp et al. (2004)			S	skills
Al-Zuheri et al. (2013)		MO	S, PP	EE, skills
Bukchin and Cohen (2013)		VTT	S	skills, learning
Razavi et al. (2014)	press shop	MO-Ho, TC		noise
Al-Zuheri et al. (2016)	electrical boxes manufacturer	MO, TC		EE
Botti et al. (2017)	hard shell tool cases manufacturer	TC		repetitive movements
Antonio Diego-Mas et al. (2017)	toy factory	MO-He		biomechanical
Hu and Chen (2017)		VTT		deterioration effect
Olivella and Nembhard (2017)		SO	S	skills
Li et al. (2018a)	industrial machining	MO		cognitive, biomechanical
Zhang et al. (2018)	brake pad manufacturer	MO		EE
Pistolesi and Lazzerini (2019)	smartphone & washing machine refurbishing	MO		equity, organizational
Glock et al. (2019c)		MO-Ho, TC		LFFRM, biomechanical
Diefenbach et al. (2020)		SO		EE
Finco et al. (2020a)	minibus assembly	MO		vibrations
Mateo et al. (2020)	newspaper printing	TC		handling, anthropometric

7. Workforce-related problems

7.1. Workforce scheduling

7.1.1. Job rotation

Before being studied through the lens of OR researchers, job rotation first designates a managerial method that organizes worker shifts, such that an employee is assigned to different tasks/workstations throughout his/her shift. The purpose of this paradigm originates in HF/E with the objective of reducing occupational injuries. The frequent change of workstation indeed causes the physical exertion of the operator to be spread across different body regions, according to the proverb "a change is as good as a rest". Assembly line balancing problems already aim at spreading the physical workload among workstations, yet it may not be able to eliminate completely workstations with high ER. In this case, job rotation ensures that several operators will share the burden of this workstation. Several field studies have highlighted the benefice of the implementation of job rotation: It reduces the exposure to awkward posture (Hinnen et al., 1992), cardiovascular load (Kuijer et al., 1999), or muscle fatigue (Hinnen et al., 1992). Furthermore, job rotation, as an organizational method, is also used by Human Resources to maintain a multi-skilled workforce, ensuring more flexibility to deal with variability (Otto and Battaia, 2017).

Job rotation has been first formulated as a scheduling optimization problem by the pioneering work of Carnahan et al. (2000) that is, to the best of our knowledge, the first work that integrates methodologies from HF/E into OR and mathematical optimization. Compared with the other classes of problems introduced in this section, it is notable that job rotation scheduling is the only one that is, by definition, dealing with HAs.

Minimizing the ER. In job rotation scheduling, the aim is to assign a set of workers to a set of workstations for each time period of the planning horizon. The temporal aspect is therefore crucial in the problem statement. In the basic problem, the objective is to minimize the maximum ER accumulated by an operator over the planning horizon. In these problems, it is often the case that economic-related quantities (e.g., size of the workforce, number of workstations) and operational ones (e.g., cycle time) have already been optimized and are used as input data. A common modeling method in job rotation is therefore to use a single objective function (see Section 8.1.1) related to the maximum ER. This risk is measured using WMSD risk assessment methods from the ergonomist toolbox. It can be focused on the postural load (see Prunet et al. (2022), *Postural ER*), for example with the REBA index (Yoon et al., 2016), manual handling tasks with the JSI index (Tharmmaphornphilas and Norman, 2007), or whole body assessment methods (see Prunet et al. (2022), *Whole body*) like the EAWS (Otto and Scholl, 2013). It is also very frequent that several risk assessment methods are considered altogether in a single model with different objective functions (see Section 8.1.2). For example, Sana et al. (2019) use the NIOSH-equation for lifting tasks, the OCRA index for repetitive tasks, and the RULA index for awkward postures. Tharmmaphornphilas and Norman (2004)

Table 9: Job rotation

Reference	Case study	Modeling	HW	HAMS
Villeda and Dean (1990)		TC		hazard exposure
Carnahan et al. (2000)		SO	PP	handling
Tharmmaphornphilas and Norman (2004)	sawmill	SO	PP	handling, noise
Bhadury and Radovilsky (2006)		MO		motivation
Tharmmaphornphilas and Norman (2007)		SO	PP	handling
Asawarungsaengkul and Nanthavanij (2008)		TC		noise
Diego-Mas et al. (2009)		MO-He	PP, CPP	biomechanical
Aryanezhad et al. (2009b)		MO-He, TC, CC	S, PP	skills, noise
Nanthavanij et al. (2010)		SO, TC, VTT	S	skills, hazard exposure
Azizi et al. (2010)		SO, VTT	S, CPP	skills, motivation
Asensio-Cuesta et al. (2012b)	automotive part manufacturer	MO-He		repetitive movements
Asensio-Cuesta et al. (2012a)		MO-He, CC	S, PP, CPP	skills, whole body
Otto and Scholl (2013)	automotive manufacturer	SO		whole body
Huang and Pan (2014)	quartz blank manufacturer	SO		anthropometric
Mossa et al. (2016)	car seat manufacturer	VTT, TC	S	skills, repetitive movements
Yoon et al. (2016)	automotive manufacturer	SO, FSC		posture
Wongwien and Nanthavanij (2017)		CC, TC, VTT	S	skills, hazard exposure
Pata and Moura (2018)		SO, CC	PP, CPP	implicit
Gebennini et al. (2018)	plastic industry	MO, TC	PP	handling, EE
Hochdörffer et al. (2018)	automotive manufacturer	MO-He, CC	S	skills, whole body
Moussavi et al. (2019)	automotive assembly line	SO, FSC		biomechanical, equity
Sana et al. (2019)	plastic industry	MO		handling, repetitive movements, posture
Kovalev et al. (2019)		SO		implicit
Botti et al. (2020)	agricultural machine manufacturer	MO	PP, CPP	repetitive movements
Mehdizadeh et al. (2020)		SO		handling
Ayough et al. (2020)		VTT	S, LR, CPP	learning, motivation

and Aryanezhad et al. (2009b) consider the noise exposure of the operators, using the DND method (see Prunet et al. (2022), *Noise*), in addition to physical criteria. A number of works are also applied to industrial cases and rely on the ad hoc assessment methods developed for the company. For example, Moussavi et al. (2019) use a risk assessment method based on 20 biomechanical criteria.

Constraints on the ER. One of the main ideas behind job rotation is to ensure that one worker does not get assigned to a high ER task for a long period, thus avoiding increasing excessively the risk, especially on the same body region. To account for this consideration in mathematical programs, the common modeling technique is to use forbidden sequence constraints (see Section 8.2). In this case, the successive assignment of two high workload tasks to the same operator is not allowed (e.g. Moussavi et al. (2019); Yoon et al. (2016)). This aspect is taken into account with soft constraints, where one objective is to minimize the maximum number of consecutive periods with the same task assigned to a given worker (Bhadury and Radovilsky, 2006). However, in this paper, the modeling approach is used to prevent boredom (see Prunet et al. (2022), *Motivation and boredom*), not ER. Azizi et al. (2010) and Ayough et al. (2020) also study the job rotation scheduling problem with the idea of rotating the workforce to prevent boredom, which affects productivity.

Skills. As other classes of scheduling problems dealing with human operators, skill considerations (see Prunet et al. (2022), *Skills*) are often present in the work on job rotation scheduling. This can be modeled with compatibility constraints (see Section 8.2), where certain workstations require specific skills that not all workers possess. Hence, an employee can only be assigned to a workstation if he/she is able to perform

the task (see, e.g., Pata and Moura (2018); Hochdörffer et al. (2018)). Skills can also be modeled with different levels of proficiency, where the task duration will depend on the skill level of the employee it is assigned to. Nanthavanij et al. (2010) and Azizi et al. (2010) study a job rotation problem, where the task time is considered dependent on both the skill and boredom level.

7.1.2. Work-rest scheduling

In work-rest scheduling, the main decision is to determine when and how to place rest breaks in an employee's schedule. According to Lodree et al. (2009), the problem consists in "determining the number, placement, and duration of rest times during a work period". This problem is very relevant to industrial applications. Many empirical studies have shown the link between the fatigue level and: individual performances (Yung et al., 2020), diminished quality of work (Caruso, 2015) and increased safety problems (Lombardi et al., 2010). An interested reader is referred to (Xu and Hall, 2021) for a more detailed review of empirical work in work-rest scheduling.

Meal breaks. One of the most basic approaches to integrate rest breaks into workforce scheduling is to consider meal breaks (see Prunet et al. (2022), *Meal breaks*). This HAMF is quite common, as it emerges from a very clear and straightforward operational constraint when establishing employees' schedules. In most jobs, a break is planned for the employees to get lunch. Hence, either the break is fixed in time, or a degree of flexibility is allowed for its scheduling. The easiest way to integrate flexibility to a given extent into scheduling models is to have a time window, in which the meal break should be scheduled. For these reasons, this approach has been used in the early literature on workforce scheduling (Thompson, 1990; Brusco and Jacobs, 2000), but also in more recent works on the topic (Chen et al., 2013; Brusco, 2008). The use of time windows is not restricted to meal breaks and can be used to add some flexibility when scheduling several breaks in a work shift (Mehrotra et al., 2000; Topaloglu and Ozkarahan, 2003; Bonutti et al., 2017).

Work-stretch duration. Another common HAMF for rest break scheduling is to use work-stretch duration (see Prunet et al. (2022), *Work-stretch durations*) modeled via forward-backward constraints (see Section 8.2). This approach is more sophisticated than using time windows, in the sense that it provides more possibilities. The schedules should abide by a set of "rules" about break placement. For example, a maximum work duration without a break, a minimum break time to be scheduled during a shift, a minimum duration for a break, a minimum duration between the shift beginning and the first break. (Gärtner et al., 2001) is the first work, to our best knowledge, to propose this modeling framework, and other papers followed in this direction (Quimper and Rousseau, 2010; Restrepo et al., 2012; Rekik et al., 2010). An interested reader is referred to (Widl and Musliu, 2014) for a more theoretical analysis of the impact of work-stretch duration on scheduling models. In some cases, the rules determining the placement of breaks are modeled with sequence constraints (see Section 8.2). For example, Janiak and Kovalyov (2006, 2008) and Sawik (2010) study the workforce scheduling problem in contaminated areas. In their modeling, inspired by the related work regulations, each work period must be followed by a rest period, whose length depends (exponentially) on the duration of the work period.

Fatigue. To reduce the fatigue level, the benefits of a rest break has also been studied. In the related works, the productivity of a given employee reduces over time, as his/her fatigue increases, modeled with a varying task time (see Section 8.3.1). Breaks are not necessarily included in a solution, but they enable full or partial recovery of the operator, resetting his/her productivity to its initial level. This modeling framework is discussed in more detail in (Prunet et al. (2022), *Deterioration effect and rate-modifying activities*). This approach is especially suited for applications focusing on the fatigue modeling aspect since the break placement and duration are linked to HF/E observational methods, instead of being an exogenous input data of the problem. This approach has been used in early works with the basic HAMF developed by Bechtold (1979), then applied in early works on the topic (Bechtold et al., 1984; Bechtold, 1991), as well as more recent studies (Jamshidi and Seyyed Esfahani, 2014; Li et al., 2020).

Comparison between HAMFs. Finally, there are works that study different break placement methods, and analyze the impacts on the produced schedules. For example, Bechtold (1979) proposes several models of fatigue and rest periods in the context of workforce scheduling. Rekik et al. (2008) study the modeling of both time windows and work-stretch duration. Thompson and Pullman (2007) study the comparison between scheduling breaks in advance and doing so in real time.

Table 10: Work-rest scheduling

Reference	Case study	Modeling	HW	HAMS
Bechtold (1979)				deterioration effect
Bechtold et al. (1984)		VTT		deterioration effect
Thompson (1990)		TWC		meal breaks
Bechtold (1991)		VTT	PP	deterioration effect
Bechtold and Thompson (1993)		VTT	PP	deterioration effect
Brusco and Jacobs (1993)		TWC		meal breaks
Aykin (1996)		TWC		meal breaks
Aykin (1998)		TWC		meal breaks
Mehrotra et al. (2000)		TWC		meal breaks
Brusco and Jacobs (2000)	call center	TWC		meal breaks
Gärtner et al. (2001)		FBC		work-stretch durations
Topaloglu and Ozkarahan (2003)		TWC		meal breaks
Topaloglu and Ozkarahan (2004)		MO-He, TWC	P	meal breaks, satisfaction
Janiak and Kovalyov (2006)		FSC		work-stretch durations, hazard exposure
Bard and Wan (2006)	postal service	TWC, FBC		meal breaks
Thompson and Pullman (2007)				work-stretch durations
Janiak and Kovalyov (2008)		FSC		hazard exposure, work-stretch durations
Bard and Wan (2008)	postal service	TWC		meal breaks
Rekik et al. (2008)		TWC, FBC		meal breaks, work-stretch durations
Sawik (2010)		FSC	S	hazard exposure, work-stretch durations
Rekik et al. (2010)	air traffic agency	FBC		work-stretch durations
Quimper and Rousseau (2010)		FBC		work-stretch durations
Restrepo et al. (2012)	parking lot operator	FBC		work-stretch durations
Chen et al. (2013)		TWC		meal breaks
Widl and Musliu (2014)		FBC		work-stretch durations
Jamshidi and Seyyed Esfahani (2014)		MO-Ho, VQ		human errors, deterioration effects
Yi and Chan (2015)	construction work		PP, CPP	heat tolerance
Gérard et al. (2016)		TWC		meal breaks
Restrepo et al. (2016)		TWC		meal breaks
Yi and Wang (2017)		TC	PP	heat tolerance
Bonutti et al. (2017)		TWC		meal breaks
Sungur et al. (2017)		MO, TWC		meal breaks
Zhao et al. (2019)		MO, TC, VTT		EE
Calzavara et al. (2019b)				EE, RA
Akkermans et al. (2019)		FBC		work-stretch durations
Li et al. (2020)		VTT		deterioration effect
Álvarez et al. (2020)	retailer			meal breaks

7.1.3. Shift scheduling

In the Shift Scheduling Problem (SSP), the main decision is to allocate the employees of a given workforce to different work shifts over a certain time horizon, usually weeks or months (Lodree et al., 2009). Each shift is characterized by a staff requirement, given by a number of employees to be scheduled in the shift, often with the associated skill set required to perform the operations that are planned. A shift scheduling problem often integrates a set of operational constraints on working hours regulations. The objective is often to minimize the cost of the plan with penalties, that can be applied to favor aspects desired in the solution: equity between employees, workers' preferences, overtime (Lodree et al., 2009).

Skills. Considering the nature of the SSP and the scope of the present review, it is not surprising that skills (see Prunet et al. (2022), *Skills*) are one of the main HAs considered in SSP (Akbari et al., 2013; Cai and Li, 2000; Eitzen et al., 2004). Skills are seen as different qualifications for the employees, and the manufacturing system cannot run during a shift, if certain jobs are absent from the production site, or are not in a sufficient number. This is well illustrated in industrial case studies. For example, Shuib and Kamarudin (2019) study a SSP in a power station, and the skills correspond to the different positions: chief charge engineer, senior/junior block operators, first/second patrolmen, control operators, etc.

Working hours regulations. The manufacturing systems modeled with an SSP are often running on a 24h schedule, thus include the shift scheduling aspect. And as such, working hours regulations are of foremost importance in the industrial context. In optimization models, this can be modeled with forward/backward

Table 11: Shift scheduling

Reference	Case study	Modeling	HW	HAMS
Cai and Li (2000)		TC		skills
Gans and Zhou (2002)		MO-Ho	S, LR	skills, learning
Eitzen et al. (2004)	power plant	TC	S	skills, equity
Pan et al. (2010)		MO, CC, FSC	S, P	skills, satisfaction
Knust and Schumacher (2011)		FBC		satisfaction
Akbari et al. (2013)		SO, CC, VTT	S, P	skills, deterioration effect, satisfaction
Lapegue et al. (2013)		MO, FBC		equity
Nishi et al. (2014)		MO-He, FBC		equity
Prot et al. (2015)	pharmacology	MO, FBC		equity
Dewi and Septiana (2015)	domestic freight	MO-He		EE, cognitive
Cheng and Kuo (2016)		MO-He, FSC	S, P	skills, satisfaction, equity
Shuib and Kamarudin (2019)	power plant	SO, CC	S, P	skills, satisfaction
Steenweg et al. (2020)		MO-He, CC	S	skills, equity
Caballini and Paolucci (2020)	port of Genoa	MO-He, CC, TC, FSC	S	skills, equity, handling, repetitive movements

constraints (Nishi et al., 2014; Knust and Schumacher, 2011; Prot et al., 2015) or forbidden sequence constraints (Cheng and Kuo, 2016; Pan et al., 2010). These modeling approaches are described in more details in Section 8.2.

Psychosocial considerations. Another important class of HAs considered in SSP relates to the psychosocial risk factors, the most popular being employee preferences and equity. In the 24h shift work, some shifts are more draining than others (i.e., night shifts). If applicable, some work periods are less preferred than others (i.e., weekends, public holidays). For a manager, it is crucial to account for these aspects to ensure fairness between employees and keep the workforce satisfied. In mathematical models, several works integrate the shift preferences of the employees (see Prunet et al. (2022), *Satisfaction and preferences*). In this case, each employee gives its preferred shifts and the resulting new equity objective is added to the model in a multi-objective approach (see Section 8.1.2) to ensure fairness between employees (Cheng and Kuo, 2016; Knust and Schumacher, 2011; Pan et al., 2010). In some models, the maximization of preferences is the sole objective (Akbari et al., 2013; Shuib and Kamarudin, 2019). The equity concerns in the SSP literature are not limited to preferences, other measures are used to balance the workload between employees, like the total working time, or the assigned shifts on public holidays (Prot et al., 2015; Lapegue et al., 2013; Cheng and Kuo, 2016).

7.2. Workforce management

7.2.1. Workforce planning

Apart from the SSP, there are other classes of tactical workforce scheduling problems. In this section, we focus on workforce planning problems. In this class of problems, the main decision is, for each period, to assign the employees to a set of tasks to be performed. The difference with the workforce scheduling problem lies in the planning horizon. The workforce planning process is located at the tactical level, therefore the planning horizon is rather long (e.g., weeks or months). This larger horizon means that tactical decisions (e.g., the size of the workforce) become available for the planner (De Bruecker et al., 2015). The hiring and firing processes are usually considered in these models, both coming at a monetary cost. However, most of the time, skills are considered, therefore the skill pool of the workforce should remain sufficient to fulfill the requirement of each work period. The interested reader is directed to (De Bruecker et al., 2015) for a detailed literature review on workforce planning with skill considerations.

Skills. The most common HA in this class of problems is skills (see Prunet et al. (2022), *Skills*). They can be modeled with compatibility constraints, where only qualified employees can be assigned to certain tasks when individual assignments are modeled, e.g., in (McDonald et al., 2009). Another modeling approach is with resource constraints: In this case, employees are not modeled individually, the number of employees at a given skill level is considered as a resource, that needs to be above a certain requirement in each planning period (Fowler et al., 2008). Skills can also be modeled with varying task times (see Section 8.3.1), where the productivity of an employee improves with his/her skill level (Wang et al., 2018). More than the productivity, the output quality level can vary with the skill of an employee (see Section 8.3.2), for instance, in (McDonald et al., 2009).

Skill development. With the tactical planning horizon, hiring and firing are not the only ways to adapt the skill set of the workforce. Some works explicitly consider human resource planning, where training can be scheduled to improve the skill level of an employee. In this case, the training comes at a monetary cost, either directly, or indirectly when an employee is unavailable due to training (see Section 8.1.2 and Othman et al. (2012); Mehdizadeh et al. (2016)). Fowler et al. (2008) and Wirojanagud et al. (2007) are interested in the *General cognitive ability* of employees, affecting the required training time to pass from one skill level to another. The skill development does not necessarily come with training, but also via individual (i.e., autonomous) learning. More details on the difference between induced and autonomous learning are provided in Prunet et al. (2022), *Learning*. This is also considered in several works on workforce planning, where the repetition of tasks requiring a given skill increases the proficiency of an employee at this skill. Learning curves are used to model this autonomous learning (Nembhard and Bentefouet, 2014; Cavagnini et al., 2020).

Table 12: Workforce planning

Reference	Case study	Modeling	HW	HAMS
Stewart et al. (1994)		SO, CC	S	skills
Bordoloi and Matsuo (2001)	semiconductor	MO-Ho	S	skills
Wirojanagud et al. (2007)		TC	S, LR	skills
Fowler et al. (2008)	semiconductor manufacturer	TC	S, LR	skills
Aryanezhad et al. (2009a)		MO-Ho, CC	S	skills
McDonald et al. (2009)	electronic assembly	MO-Ho, CC, VQ	S	skills
Othman et al. (2012)		MO-He	S, PP, CPP	skills, motivation
Kim et al. (2013)		MO-Ho		total cost function
Attia et al. (2014)		MO-He, CC, VTT	S, LR	skills, learning
Nembhard and Bentefouet (2014)		VTT	S, LR	skills, learning
Hewitt et al. (2015)		VTT		learning
Mehdizadeh et al. (2016)		MO-Ho, CC	S	skills
Valeva et al. (2017)		VTT	LR	learning
Wang et al. (2018)		VTT	S	skills
Shahbazi et al. (2019)		MO-He, VTT	S	skills, psychosocial
Cavagnini et al. (2020)		VTT		learning

7.2.2. *Workforce assignment*

In this section, we study workforce assignment. This is not a unified class of problems, but we chose to regroup problems that assign a set of operators to a set of jobs or workstations. Generally speaking, this assignment decision is not the focus of these works *per se*, but one aspect of the decision-making process.

Person/job assignment. First, there are some papers that study a general person/job assignment with a security concern (Zhang et al., 2019), while accounting workers' sensitivity to risk (Lazzerini and Pistolesi, 2018), or accounting for cognitive aspects of the job (see Prunet et al. (2022), *Cognitive strain*) and various human resources strategies (Fini et al., 2017). Brusco (2015) focuses on employees' preferences (see Prunet et al. (2022), *Satisfaction and preferences*) as a second objective function to determine the optimal person/job assignment. Sayin and Karabati (2007) use a 2-stage model to assign workers between several departments. The model is multi-period with the first stage consisting of assigning employees to departments by minimizing labor shortage, and the second stage aiming at maximizing skill development in the workforce (see Prunet et al. (2022), *Skills*). Nembhard (2001) studies a basic model of two jobs and workers with different learning rates. The author performs simulations under different experimental conditions to design a heuristic policy that maximizes total productivity.

Cellular manufacturing. Another important class of problems refers to the cellular manufacturing organization, where machines and processes are grouped into cells that produce a specific output, such as a part of a set of instructions. In this context, one step of the process is the assignment of workers to the set of cells. This class of problem is the most common in the literature related to workforce assignment. As usual, when dealing with problems related to the workforce optimization, skills are a very common HA (Wu et al., 2018; Lian et al., 2018). Norman et al. (2002) focus their modeling of the skill aspects, with both technical and human skills. Skill improvement can be considered through training (Norman et al., 2002), which is unusual with problems without a time horizon. In this example, a maximum training time is allowed to get the desired skill set in the workforce. The assignment can be multi-period (Sueer and Tummaluri, 2008),

Table 13: Workforce assignment

Reference	Case study	Modeling	HW	HAMS
Nembhard (2001)		VTT	LR	learning
Norman et al. (2002)		MO-Ho, CC, VQ	S, CPP	skills
Sayin and Karabati (2007)		MO	S	skills, learning
Sueer and Tummaluri (2008)		VTT	S	skills, learning
Egilmez et al. (2014)		VTT	S	skills
Brusco (2015)		MO-He	S, P	skills, satisfaction
Niakan et al. (2016)		CC, TC	S	skills, noise
Ferjani et al. (2017)		MO-He, CC	S	skills, deterioration effect
Azadeh et al. (2017)		MO	CPP	psychosocial
Fini et al. (2017)	construction	SO	S, PP, CPP	cognitive, organizational
Lazzerini and Pistolesi (2018)	shoes manufacturer	MO	CPP, P	satisfaction, expert collaboration
Wu et al. (2018)		MO-He, VTT	S	skills
Lian et al. (2018)		MO, VTT	S	skills, equity
Zhang et al. (2019)	iron	steel industry	MO-Ho, TC	expert collaboration
Yilmaz (2020)		MO, VTT	S	equity

dynamic (Niakan et al., 2016), or even online (Ferjani et al., 2017). In this case, the skill development can be considered through autonomous learning (Sueer and Tummaluri, 2008). More details on the difference between induced and autonomous learning can be found in (Prunet et al. (2022), *Learning*). Finally, equity is a common concern in this class of problems, where the aim is to balance the workload among employees (Lian et al., 2018; Wu et al., 2018).

8. Mathematical programming considerations

This section presents an analysis of the reviewed material from a mathematical programming perspective. The aim is to show how Human-Aware Modeling is taken into account in mathematical models. The integration of HAs is mainly performed through the objective function (see Section 8.1), or through constraints (see Section 8.2). This section highlights the impact of HAMFs on the structure and complexity of mathematical models and solution methods. Modeling approaches are linked to the most classical HAMFs they are applied with. Examples are provided for illustration purposes, but mostly links are made toward Prunet et al. (2022).

8.1. Objective function

We start by dealing with models, where HAs are considered in the objective function. Section 8.1.1 presents the models with a single objective. In that case, the ergonomic objective can be either the minimization of a single quantity (e.g., the ER) or a balancing objective (e.g., min-max balancing functions). Section 8.1.2 presents the models with several objectives. The distinction is made between true multi-objective models, aggregated multi-objective of heterogeneous quantities (e.g., via a weighted sum), and aggregated multi-objective models, where the different quantities are homogeneous (e.g., total cost functions).

8.1.1. Single objective optimization

A single ergonomic objective is very straightforward to handle from a mathematical point of view. However, considering only a HA-related objective is rarely sufficient while neglecting existing (economic) objectives. Since costs are not included in the objective, this modeling approach refers mainly to problems where the cost is fixed or bounded, and other quantities are balanced between employees/zones. This class of problems is mainly related to job rotation (Otto and Scholl, 2013), assembly line balancing (Bautista et al., 2016a), or storage assignment in warehousing (Otto et al., 2017). It can also be encountered in driver scheduling models (Otto et al., 2017). Mathematical models involving a single HA-related objective are used mainly in two cases: **(i)** for special-purpose models, or **(ii)** when dealing with equity concerns.

Special-purpose models. Special-purpose models heavily depend on the problem under study. One can cite Stewart et al. (1994), where different training strategies lead to different objective functions related to the workforce (e.g., minimizing the training cost, maximizing the workforce flexibility). Sometimes the objective is to minimize the total ER of a plan without accounting for individual employees (Diefenbach et al., 2020).

Single equity objective. The main application found in the literature is to deal with equity between employees or a number of lines in an assembly context. A single objective is relevant for decision problems where the number of resources is already decided, and the goal is to balance these resources in an efficient way. It is a very common application in assembly line balancing or job rotation to find an assignment of operations that balances the ER *evenly* between the park of workstations. In the case of HAMFs, this workload is, however, defined in terms of physical workload for the employees, or work-related injury risk. The HAMFs used to estimate the ER to balance in a single optimization objective, include most observational methods (see Prunet et al. (2022), *WMSD risk assessment methods*, (Bautista et al., 2016a)), especially with lifting activities (see Prunet et al. (2022), *Manual handling*), the NIOSH-equation (Otto et al., 2017) or the JSI (Carnahan et al., 2000), but also with noise exposure (Tharmmaphornphilas and Norman, 2004) (see Prunet et al. (2022), *Noise*).

Karsu and Morton (2015) provide a review on the different equity metrics found in the OR literature, i.e., the different functions that can be used to assess if a quantity is well balanced between a set of entities. In the works surveyed in the current review, where a single equity objective is used, the basic min-max balancing criterion is the most common. Here, a set of tasks $\mathcal{N}$, each with an associated ER p_i, $i \in \mathcal{N}$ has to be balanced between a set of employees $\mathcal{W}$ over a planning horizon $\mathcal{T}$. The assignment decision variable x_{iwt} is equal to 1, if task $i \in \mathcal{N}$ is assigned to employee $w \in \mathcal{W}$ during period $t \in \mathcal{T}$. Then the objective is to minimize the maximum accumulated risk over the planning horizon for the employees, as shown in the following equation:

$$\min \max_{w \in \mathcal{W}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} p_i x_{iwt}$$

For a further analysis, the interested reader is directed to (Karsu and Morton, 2015).

8.1.2. Multi-objective optimization

Multi-objective optimization is commonly used to include human well-being and safety in mathematical optimization. This is mainly due to the fact that multi-objective optimization allows taking into account both economic and ergonomic objectives at the same time. Despite the ease of modeling, the challenge of multi-criteria optimization resides in the handling of multiple (and often conflicting) objectives. We first focus on multi-objective models, where all objectives are handled altogether without any aggregation. Then, we study models where several objectives representing heterogeneous quantities are aggregated in a single objective function. Finally, we address the case where several objectives are expressed in a homogeneous quantity, and are therefore aggregated in a total cost function.

Multiple objectives. Multi-objective optimization is a rather common way to account for HAs. It is used in various areas of logistics: assembly (Battini et al., 2016a), job rotation (Botti et al., 2020), warehousing (Larco et al., 2017), routing (Liu, 2016), scheduling (Lu et al., 2019), lot sizing (Andriolo et al., 2016), or in more specific problems like hazardous waste collection (Rabbani et al., 2020), and disassembly (Pistolesi and Lazzerini, 2019). In terms of human aspects accounted for, the list is also diverse, but mostly focused on ER assessment methods that are reduced or balanced. It includes energy expenditure (see Prunet et al. (2022), *Energy expenditure*), manual handling risk assessment methods (see Prunet et al. (2022), *Manual handling*), posture assessment (see Prunet et al. (2022), *Postural ER*), or general workload equity concerns.

Dealing with multiple criteria decision-making has an impact both in terms of complexity and choice of solution approaches (Branke et al., 2008). This topic has been studied extensively, and in this section, we will shortly cover the main approaches found in the retrieved literature corpus to cope with several objectives. The multi-criteria aspect leads to several non-dominated optimal solutions with respect to the considered criteria, the so-called Pareto front. To compute an estimate of this front or some of its particular points, two methods are mainly found in the retrieved corpus: population-based metaheuristics, and non-interactive mathematical programming approaches.

Population-based metaheuristics are well-studied, and have proven their efficiency in dealing with large-scale multi-criteria optimization problems (Branke et al., 2008). Several solutions are kept in memory at all times, with consideration for the population diversity, thus enabling the generation of a set of non-dominated solutions at the end. The most common metaheuristics found are variants of genetic algorithms (Sana et al., 2019; Al-Zuheri et al., 2016), as the NSGA-II algorithm (Rabbani et al., 2020; Azadeh et al., 2017). More seldom, other metaheuristics frameworks have been used, like the artificial bee colony (Li et al., 2018a), the particle swarm optimization (Cui et al., 2020), or the Grey Wolf optimization (Lu et al., 2019).

As far as mathematical programming is concerned, several common multi-criteria methods have been used in the context of this literature review. The most common one is the ϵ-constraint method, which enables the computation of several points of the Pareto front by optimizing over one objective, while the others are constrained by a given value (Bortolini et al., 2017; Finco et al., 2020a). A more basic version of this method is the optimization using lexicographic objectives, where one objective is first optimized and then constrained to its optimal value, then another objective is optimized, and so on. Compared to ϵ-constraint, this approach is more straightforward in its design and implementation, but provides less information on the Pareto front (Lehuédé et al., 2020; Liu, 2016).

The most basic way to deal with several conflicting objectives is to aggregate them into a single one. The problem is then much easier to tackle from an OR practitioner perspective since only a single (aggregated) objective is considered. Therefore finding one good quality solution is sufficient, and thus a much larger set of solution methods is available to solve the resulting mono-objective problem. There are two possibilities to aggregate a multi-objective function:

- *Homogeneous quantities:* The first one is to express the objectives as homogeneous quantities (like money) that are comparable. In this case, they can be added to the objective without requiring additional information.

- *Heterogeneous quantities:* Another possibility is to work with objective functions expressed by heterogeneous quantities (like money and work-related ER), and to aggregate them nonetheless. The decision maker then has to position the objective function of interest with respect to its relative importance. In this case, the considered objectives are aggregated with weights (from basic to more complex methods), that need to be tuned to look at the desired area of the Pareto front. This is, however, non-trivial and often requires a fair amount of work (Branke et al., 2008).

Aggregation of multi-heterogeneous objectives. This modeling approach is fairly common since it is the most basic way to deal with economic and ergonomic objectives. In the retrieved corpus, it has been used in different areas of manufacturing and logistics. These include assembly line balancing (Otto and Scholl, 2011; Bautista et al., 2016b), job rotation (Diego-Mas et al., 2009), workforce scheduling (Yoon et al., 2016; Othman et al., 2012), and vehicle routing (Kim et al., 2006).

A naive method to construct an aggregate objective is, for a feasible solution $x \in X$, to associate with each objective function $g_i(x)$ a weight $0 < w_i < 1, i = \{1, 2, \ldots, n\}$. These weights are usually normalized so that their sum is equal to one. The aggregate objective function is then the weighted sum of n objectives:

$$g(x) = \sum_{i=1}^{n} w_i g_i(x)$$

This is analytically and computationally rather easy to do. However, the fine-tuning of these weights is far from trivial to translate well the preferences of the decision maker into quantified trade-offs. Its ease of use has made the weighted sum method fairly popular in the present corpus. One can cite (Bhadury and Radovilsky, 2006; Bautista et al., 2016b), or (Diego-Mas et al., 2009) with up to 45 criteria aggregated in a weighted sum. Goal programming is another widely used method to aggregate heterogeneous objectives. The idea is, for each objective function g_i to set a target value g_i^*, which corresponds to the desired value for the decision maker. Then the aggregate objective function is to minimize the weighted sum of the deviations from the target values. The advantage of goal programming over the weighted sum approach is that the target values have a concrete interpretation for the decision maker, and are therefore easier to compute. Furthermore, these targets provide natural values for the weights in the sum, by normalizing the deviation to the target value as a percentage. The objective function would then be:

$$g(x) = \sum_{i=1}^{n} w_i \frac{|\, g_i^* - g_i(x) \,|}{g_i^*}$$

An alternative exists, where the Chebychev distance metric is used instead, i.e., the objective is to minimize the maximum (weighted) deviation from the target values. Goal programming has been used, for instance, in (Choi, 2009; Sungur et al., 2017; Mokhtari and Hasani, 2017).

Overall, a heterogeneous aggregation of several objectives is much easier to handle than the true multi-objective optimization, both analytically and computationally. However, information is lost since a single solution is found instead of a set of non-dominated ones. This can make an actual implementation trickier to fine-tune to the decision maker preferences.

Aggregation of homogeneous quantities. Another way to deal with multiple objectives is to convert them into homogeneous quantities. This way they are comparable, and the trade-off is easier to find. The big advantage of this kind of modeling is that the model has only one objective, thus being analytically and computationally easier, without requiring the decision maker to quantitatively his/her needs to fine-tune an implementation of the model. However, to be feasible, the considered objectives should be expressed in homogeneous quantities, which, depending on the context, can be rather difficult. Usually, the aggregated objective is expressed as a total cost since it is a rather common concern for companies to quantify the direct and indirect economic impacts of their decisions.

This modeling approach is interesting to use since it combines both accuracy in the decision-making process and ease of computation. However, the problem at hand should be compatible with such modeling, which is not always the case. It is used in different areas of manufacturing and logistics, such as lot sizing (Battini et al., 2017c), assembly line balancing (Kara et al., 2014), workforce scheduling (Jamshidi and Seyyed Esfahani, 2014) or warehousing (Battini et al., 2017b). It is, however, more limited in terms of HAMFs compatible with this modeling.

One of the most common uses of this approach in the retrieved corpus is based on fatigue with energy expenditure and rest allowance (see Sections Prunet et al. (2022), *Energy expenditure and Rest allowance*). The general idea is that when the fatigue level of an employee increases, the ER increases accordingly. Therefore, for each work period, one can compute a rest allowance corresponding to a break period enabling the recovery, in order to maintain the fatigue level of each employee below the acceptable level. Then this rest allowance can easily be translated into a cost using the hourly wage of the employee since it corresponds to paid unproductive time (Battini et al., 2017c; Condeixa et al., 2020; Glock et al., 2019c). A high level of fatigue also leads to a rise in the error rate, which can easily be quantified as a cost and integrated into the objective function. For example, the error rate of an employee begins to drop after his/her fatigue level reaches a given threshold in (Kuo et al., 2014).

Another common modeling refers to the WMSD risk. A high level of work-related injuries might impact indirectly several cost items of a company. Sobhani et al. (2017), Sobhani and Wahab (2017) and Sobhani et al. (2019) try to quantify this monetary impact. The objective function they use is expressed in terms of a monetary cost and includes several terms that correspond to different cost items, potentially impacted by poor working conditions: performance loss, injury leave costs, increased insurance costs, hiring and firing costs for replacement short-term employees or to compensate a high turnover rate, etc. Another interesting approach is to account for the cost of risk-mitigation measures when faced with a hazardous work environment. For example, Razavi et al. (2014) account for noise control in a manufacturing environment, and their objective function includes personal and machine equipment to keep the noise-related risks (see Prunet et al. (2022), *Noise*) at an acceptable level.

Finally, when considering employees' skills, it is possible to link the skill level to productivity rate (Norman et al., 2002), error rate (McDonald et al., 2009) and, of course, wages (Moon et al., 2009). All these aspects impact the cost structure.

8.2. Constraints

Another widespread way to consider human-related factors in optimization models is across constraints. Several types of human-aware constraints can be identified within the retrieved literature corpus: compatibility constraints, threshold constraints, forbidden sequence constraints, and work-stretch duration constraints.

Compatibility constraints. Compatibility constraints are one of the most basic ways to integrate human considerations into mathematical models. They are mostly used when dealing with assignment decisions, which aim to assign a set $\mathcal{W}$ of human resources (often employees) to a set $\mathcal{N}$ of tasks, in accordance with the skills of employees. Compatibility constraints are mostly used to model the skills and qualifications (see Prunet et al. (2022), *Skills*) for workforce scheduling (Pan et al., 2010) or assembly line balancing (Manavizadeh et al., 2013), more seldom, for vehicle routing when drivers scheduling is integrated (Anoshkina and Meisel, 2020).

To better reflect practical considerations, additional modeling layers can be added to the problem. The idea behind is always that a subset of assignments is forbidden. For example, each worker $w \in \mathcal{W}$ is associated with a set $\mathcal{N}(w)$ of tasks he/she is able to perform, or with the opposite view each task $i \in \mathcal{N}$ is associated with a set $\mathcal{W}(i)$ of workers that can perform it. When skills are explicitly accounted for, the problem definition contains a set $\mathcal{S}$ of skills that can represent either different competencies or

qualifications, or a single competence with different proficiency levels, or both at the same time. In this case, each employee w is associated with a set $\mathcal{S}(w)$ of skills he/she is able to perform, and each task i requires a set $\mathcal{S}(i)$ of competences to be operated (e.g., Pan et al. (2010)). Then an assignment is possible when the employee possesses the skills required for the task. Sometimes several employees can be assigned to a task, and the skill requirement applies to the group as a whole, and not to each individual. This is found in problems dealing with cell formation in manufacturing (Aryanezhad et al., 2009a), or technician routing problems (Mathlouthi et al., 2018), where the teams should have a broad skill set. Seldom, compatibility constraints are implemented as soft constraints (Shuib and Kamarudin, 2019). In that case, a constraint can be violated in a valid solution, but adds a penalty to the objective function.

From a complexity perspective, these constraints do not significantly change the problem. With fewer feasible assignments, the problem becomes more constrained. It could therefore be more complicated to find feasible solutions, depending on the number of constraints applied to a specific instance. However, in the reviewed papers, skill resources are often not scarce enough to make feasibility challenging. This modeling requires considering a heterogeneous workforce, increasing slightly the problem size depending on the granularity of the skill set. This HAMF is, apart from early work, used mostly in addition to other human aspects that are computationally more challenging to be considered in mathematical models.

Threshold constraints. Threshold constraints are mostly used when assigning or scheduling a set $\mathcal{N}$ of tasks to a set $\mathcal{W}$ of employees. The idea is that each task is associated with an ER. Then there is a threshold value for accumulated ER for an employee over a shift. This modeling is mostly used when dealing with risk estimation methods, like WMSD risk assessment methods (see Prunet et al. (2022), *WMSD risk assessment methods*) or energy expenditure (see Prunet et al. (2022), *Energy expenditure*). Sometimes it is also applied with environmental factors that are also linked to occupational risks, like noise (see Prunet et al. (2022), *Noise*) or heat (See Prunet et al. (2022), *Heat tolerance*). Cognitive strain can also be considered (see Prunet et al. (2022), *Cognitive strain*). It is applied to various kinds of manufacturing and logistics problems. The most common are assembly line balancing (Otto and Scholl, 2011) and job rotation (Mossa et al., 2016) since the primary goal of these problems when they integrate HAs is to balance or reduce the risk of occupational disease among the employees. It is also used in warehousing (Zhao et al., 2019), scheduling (Yi and Wang, 2017) or vehicle routing (Rattanamanee et al., 2015).

Threshold constraints are very classical in the OR literature, often called "capacity constraints". A set $\mathcal{N}$ of tasks has to be assigned to a set $\mathcal{W}$ of workers. Each task $i \in \mathcal{N}$ has a risk score $p_i > 0$. An assignment variable $x_{iw} \in \{0, 1\}$ is equal to 1, if task $i \in \mathcal{N}$ is assigned to worker $w \in \mathcal{W}$ during the shift. A threshold value p_{max} is given and should not be violated by the accumulated ER of tasks assigned to each employee, ensuring the risk remains at an acceptable level. Then, the threshold constraint is of the form:

$$\sum_{i \in \mathcal{N}} p_i x_{iw} \leq p_{max} \qquad \forall w \in \mathcal{W}. \tag{1}$$

The modeling of the assignment task/employee can be more sophisticated, especially when considering the scheduling of the tasks, where time is accounted for. Usually, in this family of constraints, the sequencing of tasks does not matter. Often the risk level of a task is weighted by the time spent performing this task, according to a given ER assessment method. Nevertheless, this family of constraints is ultimately equivalent to the basic form of Inequalities (1). The value of the threshold p_{max} is often derived from the risk assessment method and is set to an acceptable risk level for the shift. The risk assessment method can be: the OCRA index (Mossa et al., 2016), the NIOSH-equation (Mateo et al., 2020), the energy expenditure (Zhao et al., 2019), or the DND (Razavi et al., 2014). Sometimes the threshold value is set with respect to legal constraints about employees' exposure, e.g., related to toxic substance exposure (Villeda and Dean, 1990). In (Ruiz-Torres et al., 2015), the opposite constraint is used, where each employee satisfaction level should be above a given threshold.

Forbidden sequence constraints. Forbidden sequence constraints are used to avoid some successions of tasks/shifts when designing a schedule. Indeed, when performing a physical task of high intensity, the ER increases with the duration of the task. In observational risk estimation methods (see Prunet et al. (2022), *WMSD risk assessment methods*), the exertion duration is often a key parameter. It is therefore reasonable for a risk mitigation strategy to aim at a good distribution of high-intensity tasks throughout the work shift. A forbidden sequence constraint ensures a maximum (often one) number of successive strenuous tasks scheduled for a given operator. The aforementioned threshold constraints are thus a suitable method to limit the risk exposure of an employee on its shift, however, it misses a key component of the risk estimation,

which is the duration of the uninterrupted exertion. Forbidden sequence constraints are a way to bring more refinement and accuracy to models that already have mechanisms to limit/balance the ER over a shift (see e.g., Moussavi et al. (2019)).

Naturally, forbidden sequence constraints are mostly found in job rotation models (Moussavi et al., 2019; Yoon et al., 2016). The goal of such models is to propose a rotation of assigned tasks among the employees to reduce the overall ER, which can be defined in different ways. Therefore, it fits well the aim of reducing consecutive strenuous activities targeted by forbidden sequence constraints. Forbidden sequence constraints also appear in scheduling problems, since they also account for the sequence of assigned tasks to a workstation or an employee, for instance in the scheduling of a flow line cell manufacturing (Aravindkrishna et al., 2009). Finally, this modeling approach can be found in work-rest shift design (Gärtner et al., 2001). In that case, constraints related to work-stretch duration are, however, more common, because they allow more flexibility in the rules they are modeling, especially those enforced in the legislation.

In terms of complexity, these constraints are rather straightforward to handle from a modeling point of view. However, the problem becomes significantly more constrained. Moreover, the insertion of these constraints in an existing model might lead to infeasibility, and overall feasibility becomes more complicated to ensure. One should note that the reduction of successive high workloads is also commonly found as an objective function instead of a constraint (Asensio-Cuesta et al., 2012b; Botti et al., 2020). Modeling this aspect as an objective addresses the aforementioned drawbacks of the forbidden sequence constraints, however other difficulties might arise with the handling of several objectives (see Section 8.1).

Time window constraints. The time window constraint is a widely used modeling technique in OR. It applies mostly when scheduling a set of activities, that need to be performed in a given time frame. In these problems, decisions have to be made related to the start time of a given set $\mathcal{N}$ of operations. For a given activity $i \in \mathcal{N}$, a time window constraint ensures that the activity i starts during a given time window $[a_i, b_i]$. With t_i the decision variable defining the start time of the activity, the mathematical constraint is then $a_i \leq t_i \leq b_i$.

In the scope of this review, the activities concerned with time window constraints are work breaks. There are indeed several ways to model the integration of breaks in a workforce schedule, the most basic one being through time windows. It corresponds to mostly early work on the topic, where a meal break has to be scheduled in the work shift with a flexible start time (Thompson, 1990). However, the meal break should happen roughly at meal time, thus the time window. In the retrieved corpus, this modeling is mostly found in workforce scheduling problems (Brusco, 2008; Brusco and Jacobs, 2000), but also within the routing literature when driver meal breaks need to be scheduled (Kim et al., 2006; Coelho et al., 2016). Further details are provided in Prunet et al. (2022), *Meal breaks*.

Forward-backward constraints. Forward-backward constraints are commonly used when dealing with break scheduling. The general idea is to offer a degree of flexibility to the mathematical models in the way they integrate breaks into a schedule. Indeed, with this approach, a set of rules is defined to ensure that the quantity, duration, and/or placement comply with either work regulations or company policies. The objective is to give the mathematical models more freedom than using time windows while prohibiting schedules that are of poor interest in practice. For example, scheduling a break just after the shift starts, or scheduling all the breaks one after another. In practice, rest breaks should be spread over the work shift to enable recovery. The rules defining the forward-backward constraints vary from one paper to another, more details can be found in Prunet et al. (2022), *Regulatory breaks and Work-stretch durations*, but some examples would be:

- "The first break should be scheduled at least 2h after the shift starts".
- "A shift should contain one lunch break of a minimum duration of 1h".
- "The work duration between two consecutive breaks must be at least 2h, and at most 4h".

A more theoretical and general description of forward-backward constraints can be found in (Widl and Musliu, 2014; Rekik et al., 2008). There are two main areas of application to forward-backward constraints: shift scheduling and vehicle routing. In vehicle routing, these rules are usually aligned with official regulations. Several countries have legislated on truck drivers' working times. The rules depend on the country (see Prunet et al. (2022), *Regulatory breaks*), but follow the same framework. One can cite (Goel, 2009; Prescott-Gagnon et al., 2010) for EU regulations, and (Rancourt et al., 2013; Rancourt and Paquette, 2014)

for American ones. Work-rest scheduling is the other main application area of forward-backward constraints. There is no regulation to comply with in this case, however the flexibility allowed by this modeling is still worth considering (Gärtner et al., 2001; Restrepo et al., 2012; Quimper and Rousseau, 2010).

The flexibility gained from this modeling approach often leads to better quality solutions compared to time window constraints (Rekik et al., 2008, 2010). However, this flexibility comes at a cost in terms of complexity. One common technique to deal with this complexity is to consider break placement implicitly. This can be done directly in the formulation (Rekik et al., 2010), or these aspects can be convexified in the subproblem within a decomposition framework (Prescott-Gagnon et al., 2010; Ceselli et al., 2009).

8.3. Data

8.3.1. Varying task time

Varying task time is one of the main ways to model HAs in optimization models. It is indeed a very flexible tool, which can be adapted to a wide range of HAs, and fits well in the OR frameworks. The idea is rather simple: Instead of being a fixed parameter, the processing time of a task performed by a human operator is varying. This variation can be purely stochastic to model the intrinsic variability of the performance of a human operator, where the objective is to find a robust plan (Chiang and Urban, 2006; Egilmez et al., 2014; Sotskov et al., 2015). It can also be modeled based on the fuzzy set theory (Wang et al., 2013). However, most of the time, processing times are deterministic and depend on the characteristics of the operator (e.g., skill, fatigue level).

Concerning the areas of application, this modeling is mostly used in operational problems, where the granularity of the modeling allows us to consider individual execution times. A natural application of such an approach is thus the scheduling field. One can cite examples from flowshop scheduling (Gong et al., 2020b), single machine scheduling (Lee and Wu, 2009), parallel machine scheduling (Lee et al., 2012), workforce scheduling (Yilmaz, 2020), or assembly lines (Ostermeier, 2020). However, some applications have been found in other areas of logistics, such as warehousing (Matusiak et al., 2017), or vehicle routing (Yan et al., 2019). There are also applications in tactical problems, such as lot sizing (Jaber and Bonney, 2003), or vendor managed inventory (Zanoni et al., 2012). Furthermore, this topic has also been studied from a more theoretical perspective with complexity studies (Janiak and Rudek, 2010; Lee and Wu, 2009; Wu and Lee, 2008).

When the processing time of a task is deterministic, it can vary depending on several aspects considered in the model. This modeling can be used when dealing with workforce skills. In this case, the processing time of a task is a function of the skill level of the assigned employee (see Prunet et al. (2022), *Skills*). It is indeed natural to suppose that a more skilled operator is more efficient. This is for example found in assembly line balancing (Akyol and Baykasoğlu, 2019), job rotation (Azizi et al., 2010) or scheduling (Costa et al., 2014). The processing time of a task can also be based on its scheduled position in the work shift. This is especially the case when dealing with employee learning, where the repetition of a similar task improves the efficiency of the operator. In this case, the shape of the learning curve can correspond to various mathematical models. A more thorough description is given in Prunet et al. (2022), *Learning*. This learning effect on processing time is for example found in scheduling (Biskup, 1999), and assembly line balancing (Otto and Otto, 2014). This is also used to model the fatigue effect, where the productivity of an operator decreases as fatigue increases toward the end of a work shift (Sanchez-Herrera et al., 2019; Wang et al., 2020).

Another very similar modeling technique is to adjust the processing time of a task depending on the sum of the processing times of tasks scheduled before. This is also a very common modeling approach of the learning process (Zhang and Gen, 2011; Wang et al., 2019). It is also used when dealing with fatigue, where the productivity of an employee decreases according to a given function that depends on the time passed since the last rest break (see Prunet et al. (2022), *Deterioration effect and rate-modifying activities*). For example, this is used in (Bechtold, 1979; Bechtold and Thompson, 1993) with linear decay of the productivity, or more complicated decay functions by (Li et al., 2020). In some papers, learning and fatigue effects on processing times are considered altogether with their opposite effects. This is the case when the *Learning Forgetting Fatigue Recovery Model* is used (see Prunet et al. (2022), *Learning forgetting fatigue recovery model*). This HAMF is found in production planning (Givi et al., 2015b), or assembly lines (Ostermeier, 2020).

The impact on optimization models varies depending on which aspect is considered, and how it is integrated. It is therefore complicated to draw a general conclusion. Nevertheless, one can assume that considering varying task times will often increase the computational burden of the models. It is however

interesting that for scheduling models the problems seem to stay polynomial in several cases (see Wu and Lee (2008); Lee and Wu (2009)). There is a certain research interest on the complexity analysis for scheduling problems with varying task times (Janiak and Rudek, 2010; Wu and Lee, 2008; Lee and Wu, 2009).

8.3.2. Varying quality

Some researchers consider that the quality level of the production is not a fixed exogenous parameter, but depends on the characteristics of the employee operating the given task.

Several factors can be used to measure the quality level of production. The most common is the skill level of the employee performing the task. Equivalently to the processing time, it is quite natural to assume that a more skilled employee will make fewer errors on his/her job. A varying quality level is mainly used when dealing with workforce planning with it depends on the skill level (Norman et al., 2002; McDonald et al., 2009). This aspect has also been tackled using the fuzzy set theory (Salehi et al., 2018; Tang et al., 2006). Learning, as the determining factor of the quality level, has also been used in the literature. One can especially cite Givi et al. (2015b,a), who extend the learning forgetting fatigue recovery model (see Prunet et al. (2022), *Learning forgetting fatigue recovery model*) to account for a quality improvement in the learning process. Other examples include Jeang and Rahim (2019), who study lot sizing with the quality level of the production improving over a learning process. The error rate has also been modeled through a probabilistic framework. Khan et al. (2012, 2014) study the human error taxonomy and classification with associated probabilities. In some other applications errors are modeled using random variables with known density functions (Shin et al., 2018; Gilotra et al., 2020).

8.3.3. Heterogeneous workforce

Other models worth mentioning are those considering a heterogeneous workforce. This modeling approach is more transverse than the other modeling approaches described in this section. Historically, the homogeneity of the workforce is a common assumption in OR models. It is indeed generally very convenient from a mathematical point of view, and the hypothesis is valid for a number of applications. However, in some cases, a finer granularity in the modeling of the workforce is necessary to consider certain effects. Modeling the workforce as heterogeneous actually makes sense from an HF/E perspective (see Prunet et al. (2022), *Heterogeneous workforce*). This modeling is not attached to a particular HAMF and is most of the time used within another modeling approach (e.g., objective function, or constraints).

The most common class of problems dealing with a heterogeneous workforce concerns the ones dealing with skill considerations (see Prunet et al. (2022), *Skills*). Indeed, modeling skills with a homogeneous workforce would be pointless, since all employees would have the same skill set. This case is denoted *S* in the result tables. The underlying idea of integrating skills in an optimization model can be twofold:

- Employees as a heterogeneous set of resources. In this case, the skills represent different jobs or qualifications, and the qualifications of an employee should match the qualifications of the tasks assigned to him/her. This is enforced via *compatibility constraints* (see Section 8.2).
- Employees as a single set of resources, yet with different throughput/cost. In this case, the skills represent the proficiency of the employee on a set of tasks. This is enforced with *varying task times* (see Section 8.3.1), or *varying quality* (see Section 8.3.2).

Note that neither case is exclusive to each other. These two HAMFs are very common in the literature, we can cite, for instance, (Calzavara et al., 2019a; Hochdörffer et al., 2018; Joo and Kim, 2013) for skills with compatibility constraints, and (Hong, 2018; Khan et al., 2012; Matusiak et al., 2017) for skills with varying task times, among many other.

Related to skills, learning rates can also vary between employees. This case is denoted *LR* in the result tables. When working with learning curves (see Prunet et al. (2022), *Learning*) to model the processing times, or quality levels, it is reasonable to suppose that there is some discrepancy between employees in terms of learning rates. This modeling is mostly used in studies that focus on modeling with more accuracy the performances and their variations in a workforce. It has mainly seen use in workforce-focused problems, like workforce planning (Fowler et al., 2008; Attia et al., 2014), but also warehousing (Grosse and Glock, 2015; Grosse et al., 2013), machine scheduling (Marichelvam et al., 2020), shift scheduling (Gans and Zhou, 2002), and job rotation (Ayough et al., 2020).

The heterogeneity of the workforce can also be based on other intrinsic properties of its components. In the result tables, this is referred to as *PP* for Physical Properties, and *CPP* for Cognitive and Psychosocial Properties. These parameters are mostly risk factors for developing WMSD and are accounted for when computing the estimation of the ER of a work situation (see Prunet et al. (2022), *WMSD risk assessment methods*). It is indeed known that individuals have different chances of developing occupational diseases when facing a given work situation(Bridger, 2018). This can depends, for example, on the age of the person (Yi and Wang, 2017), his/her lifting capabilities (Tharmmaphornphilas and Norman, 2007; Carnahan et al., 2000), the physical fatigue he/she can safely sustain (Rattanamanee et al., 2015) or even its smoking and drinking habits (Yi and Chan, 2015). However, most of the time the individual physical parameters can be seen as *skills* in the sense that they affect the processing times of tasks or learning characteristics, like the age (Marichelvam et al., 2020), the gender (Efe et al., 2018), or the cognitive abilities (Fowler et al., 2008). Concerning psychosocial characteristics, they can be used to create teams with compatible decision-making styles (Azadeh et al., 2017), to account for the carefulness of the employees in a context of hazardous work environment (Lazzerini and Pistolesi, 2018), or to consider the motivation and personality of individuals when assigning tasks (Othman et al., 2012).

The last parameter that can differ between employees is their individual work preferences, noted *P* in the result tables. This parameter is straightforward, it is used when accounting for the satisfaction of the workforce (see Prunet et al. (2022), *Satisfaction and preferences*), either as an objective function, or threshold constraints that enforce a minimal satisfaction level for each employee, in a search for equity (Ruiz-Torres et al., 2015, 2019; Akbari et al., 2013).

Modeling the workforce as heterogeneous might have a substantial impact on decision models. The most obvious one is that a parameter that was constant over the workforce now depends on the concerned individual. This means that the decision variables should be able to model the individual assignment/schedule of the employees. Note that this is most of the time already the case in the problems studied in this review, especially the workforce-related ones (see Section 7). This person-dependent parameter can add some complexity to an existing model. However, it also breaks symmetries, which is often beneficial for the performance of solution approaches, especially when using mathematical programming-based methods (Margot, 2010).

9. Discussion and future research

The analysis of the collected material in the context of this review brings out a large variety of works on the topic of integrating HAs into decision models for manufacturing and logistics systems. This variety is present both in terms of studied problems, modeling approaches, and considered HAs. However, in the light of the insights gained from the cross-analysis performed in both parts of the review, some gaps still remain to be filled. In this section, we discuss the collected material and propose some research directions that appear promising for future works.

Considering well studied HAMFs in new problems. This is the most straightforward research direction. When studying the collected material, it appears that, for a given family of OR problems, the community often focuses on a few HAMFs to integrate into their models, and some classical models that could be relevant are understudied. This is for example the case for learning, which has been extensively studied within machine scheduling, yet few works integrate this aspect with job rotation or shift scheduling problems. This situation is easily understandable since some human aspects are not equivalently relevant to integrate into all the manufacturing and logistics problems: For a given problem, there are HAs that are more relevant than others. This is related to the risk factors present at a given work situation: For example the HAMFs related to repetitive movements are more adapted to assembly work, and the HAMFs related to material handling are well suited for warehousing problems. Nevertheless, a large number of combinations between decision problems and HAMFs are still unexplored. Overall, a lot of space is still available for interesting new research, by trying to integrate some HAs into new problems.

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

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

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

Available real-life data sets. As a consequence of the previous point, the amount of work using real-life data with risk assessment methods is scarce. It would be beneficial for the community to have access to some data sets issued from fieldwork and collaborations with ergonomists. This way OR researchers could confront their work and solution methods to real data.

Field work for models validation. From the previous points, it appears that it is sometimes difficult for an OR practitioner to work on real-life case studies. This will eventually raise the question of the validity of the work. It would indeed be beneficial to see more case studies, where human-aware optimization models are implemented in industrial contexts, and the results of such interventions. This kind of work could bring insightful feedback to the community, and lead to new research directions guided by industrial needs. Furthermore, it would highlight the role OR can play in the improvement of working conditions.

Collaborations with HF/E practitioners. As the topic of this review is heavily influenced by HF/E, it is only natural to highlight that an increased number of collaborations between both disciplines would be beneficial. First, as explained above, to validate the work of the OR community. But also to guide the field toward modeling problems that are relevant in practice, and the use of HAMFs that make sense in a given situation.

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

Heterogeneous modeling of employees. Human characteristics are intrinsically subjected to personal variability. This is the case when considering human performance estimation, where each individual will have different levels of productivity, depending on the task at hand, his/her age, experience, etc. Moreover, a task might present a high level of risk for an individual, and an acceptable risk for someone else. This could be affected by several characteristics of the individual, e.g., age, height, and health conditions. However, in the literature, the norm is mostly to consider the workforce as a homogeneous pool of employees. This assumption of homogeneity makes sense when not considering HAs, yet it leads to a net loss of accuracy in the modeling when human characteristics are involved. In HF/E, anthropometry (i.e., the study and measurement of the human body) is an important field of study (Pheasant and Haslegrave, 2018), as it provides help to design work situations that would be safe and adapted for a large part of the working population (e.g., suited for 95% of the concerned population).

Integration of human-related variability . There is an intrinsic variability in human performances. In this review, several works focused on the modeling of human aspects for performance evaluation, sometimes with sophisticated models. However, few works integrate stochasticity into their modeling, despite it being an appropriate tool for the modeling of the variability. Furthermore, stochastic optimization is a well-studied area of OR, which could lead to interesting developments, by using methods historically originating from OR to deal with HAs in models.

Economic quantification of the indirect cost of poor ergonomics. Some research studies presented in this review integrate HAs with their models by computing the cost of poor working conditions, due to e.g., injuries or turnover, and account for this cost in the objective function (see Prunet et al. (2022), *Total cost function*). However, further research in this direction could be beneficial for the community. This would indeed help to present more comprehensive models for decision makers and be the basis of cost/benefit analysis for the consideration of HAs in the optimization of manufacturing and logistics systems.

10. Conclusions

In the first part of this literature review, we have introduced the corpus of the reviewed material. It covers a large spectrum of classical logistics and manufacturing optimization problems, which shows the interest and continued need for designing human-aware models and solution methods. Pushed in particular by the sustainable development movement, human considerations are more and more involved in manufacturing and logistics systems, including: warehousing, vehicle routing, scheduling, production planning, and workforce scheduling and management. In the current part, we have studied the modeling systems of human aspects through the lens of mathematical programming, i.e.: Which HAs and how they are integrated into decision models from manufacturing and logistics fields? And, what is the impact induced by the integration of HAs into the available modeling approaches? Based on a cross-analysis of the current review, multiple opportunities for future research have also been discussed.

In the second part of this review (Prunet et al., 2022), we give a comprehensive presentation of the range of modeling frameworks found in the collected material dedicated to the representation and the quantification of both ergonomic risks and human characteristics. Each HAMF is explained in detail, and links are made to its relevance in the industrial context.

Acknowledgements

This work has been partially supported by the French National Research Agency through the AGIRE project under the grant ANR-19-CE10-0014[10]. This support is gratefully acknowledged.

Notes

1. The resolution A/RES/70/1 of the seventieth general assembly of the United Nations of 21 October 2015 on the 2030 Agenda of sustainable development. https://sdgs.un.org/2030agenda Access: September 26, 2022
2. Databse on labour statistics of The International Labour Organization. https://ilostat.ilo.org/ Access: September 26, 2022
3. World Health Organization Mortality Database. https://www.who.int/data/data-collection-tools/who-mortality-database Access: September 26, 2022
4. The European Community (EC) regulation No 561/2006 of 15 March 2006 on machine work. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A32006R0561 Access: September 26, 2022
5. The Federal Motor Carrier Safety Administration regulation No. 49 CFR Parts 385, 386, 390 and 395 about Hours of Service of Drivers. https://www.govinfo.gov/content/pkg/FR-2011-12-27/pdf/2011-32696.pdf Access: September 26, 2022
6. The Directive No. 2006/42/EC of the European Parliament and of the Council of 17 May 2006 on machinery usage. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A32006L0042 Access: September 26, 2022
7. The European Council Directive No. 89/391/EEC of 12 June 1989 on the introduction of measures to encourage improvements in the safety and health of workers at work. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A31989L0391 Access: September 26, 2022
8. The Occupational Safety and Health Act of 1970 https://www.osha.gov/laws-regs/oshact/completeoshact Access: September 26, 2022

9. The International Ergonomics Association (IEA). https://iea.cc/what-is-ergonomics/ Access: September 26, 2022.

10. https://anr.fr/Projet-ANR-19-CE10-0014

References

Akbari, M., Zandieh, M., Dorri, B., 2013. Scheduling part-time and mixed-skilled workers to maximize employee satisfaction. International Journal of Advanced Manufacturing Technology 64 (5), 1017–1027.

Akkermans, A., Post, G., Uetz, M., 2019. Solving the shift and break design problem using integer linear programming. Annals of Operations Research.

Akyol, S., Baykasoğlu, A., 2019. A multiple-rule based constructive randomized search algorithm for solving assembly line worker assignment and balancing problem. Journal of Intelligent Manufacturing 30 (2), 557–573.

Akyol, S. D., Baykasoglu, A., 2019. ErgoALWABP: a multiple-rule based constructive randomized search algorithm for solving assembly line worker assignment and balancing problem under ergonomic risk factors. Journal of Intelligent Manufacturing 30 (1), 291–302, place: Dordrecht Publisher: Springer WOS:000456588800022.

Al-Araidah, O., Dalalah, D., Azeez, M. A.-A., Khasawneh, M. T., 2017. A heuristic for clustering and picking small items considering safe reach of the order picker. European Journal of Industrial Engineering 11 (2), 256–269, place: Geneva Publisher: Inderscience Enterprises Ltd WOS:000397842000006.

Al-Zuheri, A., Luong, L., Xing, K., 2013. Prediction and analysis impact of operational design of a manual assembly system with walking workers on performance. International Journal of Computer Integrated Manufacturing 26 (6), 540–560, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000319325400005.

Al-Zuheri, A., Luong, L., Xing, K., 2016. Developing a multi-objective genetic optimisation approach for an operational design of a manual mixed-model assembly line with walking workers. Journal of Intelligent Manufacturing 27 (5), 1049–1065, place: Dordrecht Publisher: Springer WOS:000382682400010.

Alghazi, A., Kurz, M., 2018. Mixed model line balancing with parallel stations, zoning constraints, and ergonomics. Constraints 23 (1), 123–153.

Amirian, H., Sahraeian, R., 2015. Augmented epsilon-constraint method in multi-objective flowshop problem with past sequence set-up times and a modified learning effect. International Journal of Production Research 53 (19), 5962–5976.

Anderson Jr., E., Parker, G., 2002. The effect of learning on the make/buy decision. Production and Operations Management 11 (3), 313–339.

Andriolo, A., Battini, D., Persona, A., Sgarbossa, F., 2016. A new bi-objective approach for including ergonomic principles into EOQ model. International Journal of Production Research 54 (9), 2610–2627.

Anoshkina, Y., Meisel, F., 2020. Interday routing and scheduling of multi-skilled teams with consistency consideration and intraday rescheduling. EURO Journal on Transportation and Logistics 9 (3).

Antonio Diego-Mas, J., Poveda-Bautista, R., Garzon-Leal, D., 2017. Using RGB-d sensors and evolutionary algorithms for the optimization of workstation layouts. Applied Ergonomics 65, 530–540, place: Oxford Publisher: Elsevier Sci Ltd WOS:000408597400053.

Anzanello, M., Fogliatto, F., 2010. Scheduling learning dependent jobs in customised assembly lines. International Journal of Production Research 48 (22), 6683–6699.

Anzanello, M., Fogliatto, F., Santos, L., 2014. Learning dependent job scheduling in mass customized scenarios considering ergonomic factors. International Journal of Production Economics 154, 136–145.

Anzanello, M. J., Fogliatto, F. S., 2011. Learning curve models and applications: Literature review and research directions. International Journal of Industrial Ergonomics 41 (5), 573–583, place: Amsterdam Publisher: Elsevier WOS:000295242700019.

Aravindkrishna, T., Balasubramanian, V., Narendran, T., 2009. Ergonomic risk incorporated schedules (ERIS)-scheduling using genetic algorithm to reduce operator fatigue in flow-shop based cells. International Journal of Enterprise Network Management 3 (3), 184–200.

Aroui, K., Alpan, G., Frein, Y., 2017. Minimising work overload in mixed-model assembly lines with different types of operators: a case study from the truck industry. International Journal of Production Research 55 (21), 6305–6326, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000412561900006.

Aryanezhad, M., Deljoo, V., Mirzapour Al-E-Hashem, S., 2009a. Dynamic cell formation and the worker assignment problem: A new model. International Journal of Advanced Manufacturing Technology 41 (3), 329–342.

Aryanezhad, M., Kheirkhah, A., Deljoo, V., Mirzapour Al-E-Hashem, S., 2009b. Designing safe job rotation schedules based upon workers' skills. International Journal of Advanced Manufacturing Technology 41 (1), 193–199.

Asawarungsaengkul, K., Nanthavanij, S., 2008. Heuristic genetic algorithm for workforce scheduling with minimum total worker-location changeover. International Journal of Industrial Engineering-Theory Applications and Practice 15 (4), 373–385, place: Cincinnati Publisher: Univ Cincinnati Industrial Engineering WOS:000207714000005.

Asensio-Cuesta, S., Diego-Mas, J., Canós-Darós, L., Andrés-Romano, C., 2012a. A genetic algorithm for the design of job rotation schedules considering ergonomic and competence criteria. International Journal of Advanced Manufacturing Technology 60 (9), 1161–1174.

Asensio-Cuesta, S., Diego-Mas, J., Cremades-Oliver, L., González-Cruz, M., 2012b. A method to design job rotation schedules to prevent work-related musculoskeletal disorders in repetitive work. International Journal of Production Research 50 (24), 7467–7478.

Attia, E.-A., Duquenne, P., Le-Lann, J.-M., 2014. Considering skills evolutions in multi-skilled workforce allocation with flexible working hours. International Journal of Production Research 52 (15), 4548–4573.

Aykin, T., 1996. Optimal shift scheduling with multiple break windows. Management Science 42 (4), 591–602.

Aykin, T., 1998. A composite branch and cut algorithm for optimal shift scheduling with multiple breaks and break windows. Journal of the Operational Research Society 49 (6), 603–615.

Ayough, A., Zandieh, M., Farhadi, F., 2020. Balancing, sequencing, and job rotation scheduling of a u-shaped lean cell with dynamic operator performance. Computers & Industrial Engineering 143, 106363, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000525872600003.

Azadeh, A., Ravanbakhsh, M., Rezaei-Malek, M., Sheikhalishahi, M., Taheri-Moghaddam, A., 2017. Unique NSGA-II and MOPSO algorithms for improved dynamic cellular manufacturing systems considering human factors. Applied Mathematical Modelling 48, 655–672, place: New York Publisher: Elsevier Science Inc WOS:000403994400037.

Azizi, N., Liang, M., Zolfaghari, S., 2013. Modelling human boredom at work: Mathematical formulations and a probabilistic framework. Journal of Manufacturing Technology Management 24 (5), 711–746.

Azizi, N., Zolfaghari, S., Liang, M., 2010. Modeling job rotation in manufacturing systems: The study of employee's boredom and skill variations. International Journal of Production Economics 123 (1), 69–85.

Azzouz, A., Ennigrou, M., Ben Said, L., 2018. Scheduling problems under learning effects: classification and cartography. International Journal of Production Research 56 (4), 1642–1661.

Bard, J., Wan, L., 2006. The task assignment problem for unrestricted movement between workstation groups. Journal of Scheduling 9 (4), 315–341.

Bard, J., Wan, L., 2008. Workforce design with movement restrictions between workstation groups. Manufacturing and Service Operations Management 10 (1), 24–42.

Battini, D., Calzavara, M., Otto, A., Sgarbossa, F., 2017a. Preventing ergonomic risks with integrated planning on assembly line balancing and parts feeding. International Journal of Production Research 55 (24), 7452–7472, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000423135100012.

Battini, D., Calzavara, M., Persona, A., Sgarbossa, F., 2017b. Additional effort estimation due to ergonomic conditions in order picking systems. International Journal of Production Research 55 (10), 2764–2774.

Battini, D., Delorme, X., Dolgui, A., Persona, A., Sgarbossa, F., 2016a. Ergonomics in assembly line balancing based on energy expenditure: a multi-objective model. International Journal of Production Research 54 (3), 824–845, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000370669400012.

Battini, D., Faccio, M., Persona, A., Røpke, S., Zanin, G., 2015. Routing strategy in a distribution network when the driver learning effect is considered. International Journal of Logistics Systems and Management 21 (3), 385–411.

Battini, D., Glock, C., Grosse, E., Persona, A., Sgarbossa, F., 2016b. Human energy expenditure in order picking storage assignment: A bi-objective method. Computers and Industrial Engineering 94, 147–157.

Battini, D., Glock, C. H., Grosse, E. H., Persona, A., Sgarbossa, F., 2017c. Ergo-lot-sizing: An approach to integrate ergonomic and economic objectives in manual materials handling. International Journal of Production Economics 185, 230–239, place: Amsterdam Publisher: Elsevier Science Bv WOS:000395222400020.

Bautista, J., Alfaro, R., Batalla, C., 2015. Modeling and solving the mixed-model sequencing problem to improve productivity. International Journal of Production Economics 161, 83–95, place: Amsterdam Publisher: Elsevier Science Bv WOS:000349879200008.

Bautista, J., Alfaro-Pozo, R., Batalla-Garcia, C., 2016a. Maximizing comfort in assembly lines with temporal, spatial and ergonomic attributes. International Journal of Computational Intelligence Systems 9 (4), 788–799, place: Paris Publisher: Atlantis Press WOS:000379938400016.

Bautista, J., Batalla-García, C., Alfaro-Pozo, R., 2016b. Models for assembly line balancing by temporal, spatial and ergonomic risk attributes. European Journal of Operational Research 251 (3), 814–829.

Bechtold, S., 1979. Quantitative models for optimal rest period scheduling: a note. Omega 7 (6), 565–566.

Bechtold, S., 1991. Optimal work-rest schedules with a set of fixed-duration rest periods. Decision Sciences 22 (1), 157–170.

Bechtold, S., Janaro, R., Sumners, D., 1984. Maximization of labor productivity through optimal rest-break schedules. Management Science 30 (12), 1442–1458, place: Linthicum Hts Publisher: Inst Operations Research Management Sciences WOS:A1984AAP4000004.

Bechtold, S., Thompson, G., 1993. Optimal scheduling of a flexible-duration rest period for a work group. Operations Research 41 (6), 1046–1054, place: Linthicum Hts Publisher: Operations Research Soc Amer WOS:A1993MR00300004.

Benjamin, A., Beasley, J., 2010. Metaheuristics for the waste collection vehicle routing problem with time windows, driver rest period and multiple disposal facilities. Computers and Operations Research 37 (12), 2270–2280.

Bhadury, J., Radovilsky, Z., 2006. Job rotation using the multi-period assignment model. International Journal of Production Research 44 (20), 4431–4444.

Biskup, D., 1999. Single-machine scheduling with learning considerations. European Journal of Operational Research 115 (1), 173–178.

Biskup, D., 2008. A state-of-the-art review on scheduling with learning effects. European Journal of Operational Research 188 (2), 315–329.
URL http://www.sciencedirect.com/science/article/pii/S0377221707005280

Bonutti, A., Ceschia, S., De Cesco, F., Musliu, N., Schaerf, A., 2017. Modeling and solving a real-life multi-skill shift design problem. Annals of Operations Research 252 (2), 365–382.

Bordoloi, S. K., Matsuo, H., 2001. Human resource planning in knowledge-intensive operations: A model for learning with stochastic turnover. European Journal of Operational Research 130 (1), 169–189, place: Amsterdam Publisher: Elsevier Science Bv WOS:000167031900014.

Bortolini, M., Faccio, M., Gamberi, M., Pilati, F., 2017. Multi-objective assembly line balancing considering component picking and ergonomic risk. Computers and Industrial Engineering 112, 348–367.

Botti, L., Calzavara, M., Mora, C., 2020. Modelling job rotation in manufacturing systems with aged workers. International Journal of Production Research.

Botti, L., Mora, C., Regattieri, A., 2017. Integrating ergonomics and lean manufacturing principles in a hybrid assembly line. Computers & Industrial Engineering 111, 481–491, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000410468600040.

Bowden, Z. E., Ragsdale, C. T., 2018. The truck driver scheduling problem with fatigue monitoring. Decision Support Systems 110, 20–31, place: Amsterdam Publisher: Elsevier Science Bv WOS:000433273000003.

Boysen, N., Fliedner, M., Scholl, A., Dec. 2007. A classification of assembly line balancing problems. European Journal of Operational Research 183 (2), 674–693.
URL https://www.sciencedirect.com/science/article/pii/S0377221706010435

Brandao, J., Mercer, A., 1997. A tabu search algorithm for the multi-trip vehicle routing and scheduling problem. European Journal of Operational Research 100 (1), 180–191, place: Amsterdam Publisher: Elsevier Science Bv WOS:A1997XG48100013.

Branke, J., Deb, K., Miettinen, K., Slowiński, R. (Eds.), 2008. Multiobjective Optimization: Interactive and Evolutionary Approaches. Theoretical Computer Science and General Issues. Springer-Verlag.
URL https://www.springer.com/gp/book/9783540889076

Braun, W., Rebollars, R., Schiller, E., 1996. Computer aided planning and design of manual assembly systems. International Journal of Production Research 34 (8), 2317–2333.

Bridger, R. S., 2018. Introduction to human factors and ergonomics. CRC Press, OCLC: 987376231.

Brusco, M., 2015. A bicriterion algorithm for the allocation of cross-trained workers based on operational and human resource objectives. European Journal of Operational Research 247 (1), 46–59.

Brusco, M., Jacobs, L., 1993. A simulated annealing approach to the solution of flexible labour scheduling problems. Journal of the Operational Research Society 44 (12), 1191–1200.

Brusco, M. J., 2008. An exact algorithm for a workforce allocation problem with application to an analysis of cross-training policies. Iie Transactions 40 (5), 495–508, place: Philadelphia Publisher: Taylor & Francis Inc WOS:000254486200001.

Brusco, M. J., Jacobs, L. W., 2000. Optimal models for meal-break and start-time flexibility in continuous tour scheduling. Management Science 46 (12), 1630–1641, place: Linthicum Hts Publisher: Inst Operations Research Management Sciences WOS:000166263400009.

Bukchin, Y., Cohen, Y., 2013. Minimising throughput loss in assembly lines due to absenteeism and turnover via work-sharing. International Journal of Production Research 51 (20), 6140–6151, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000327867500010.

Buzacott, J., 2002. The impact of worker differences on production system output. International Journal of Production Economics 78 (1), 37–44.

Caballini, C., Paolucci, M., 2020. A rostering approach to minimize health risks for workers: An application to a container terminal in the italian port of genoa. Omega-International Journal of Management Science 95, 102094, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000534416300011.

Cai, X., Li, K., 2000. Genetic algorithm for scheduling staff of mixed skills under multi-criteria. European Journal of Operational Research 125 (2), 359–369.

Calzavara, M., Battini, D., Bogataj, D., Sgarbossa, F., Zennaro, I., 2020. Ageing workforce management in manufacturing systems: state of the art and future research agenda. International Journal of Production Research 58 (3), 729–747.

Calzavara, M., Glock, C., Grosse, E., Persona, A., Sgarbossa, F., 2017. Analysis of economic and ergonomic performance measures of different rack layouts in an order picking warehouse. Computers and Industrial Engineering 111, 527–536.

Calzavara, M., Glock, C., Grosse, E., Sgarbossa, F., 2019a. An integrated storage assignment method for manual order picking warehouses considering cost, workload and posture. International Journal of Production Research 57 (8), 2392–2408.

Calzavara, M., Persona, A., Sgarbossa, F., Visentin, V., 2019b. A model for rest allowance estimation to improve tasks assignment to operators. International Journal of Production Research 57 (3), 948–962, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000460630300018.

Caputo, A. C., Pelagagge, P. M., Salini, P., 2017a. Modeling errors in parts supply processes for assembly lines feeding. Industrial Management & Data Systems 117 (6), 1263–1294, place: Bingley Publisher: Emerald Group Publishing Ltd WOS:000407077300014.

Caputo, A. C., Pelagagge, P. M., Salini, P., 2017b. Modelling human errors and quality issues in kitting processes for assembly lines feeding. Computers & Industrial Engineering 111, 492–506, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000410468600041.

Carnahan, B. J., Norman, B. A., Redfern, M. S., 2001. Incorporating physical demand criteria into assembly line balancing. Iie Transactions 33 (10), 875–887, place: Dordrecht Publisher: Kluwer Academic Publ WOS:000168971700005.

Carnahan, B. J., Redfern, M. S., Norman, B., 2000. Designing safe job rotation schedules using optimization and heuristic search. Ergonomics 43 (4), 543–560, place: London Publisher: Taylor & Francis Ltd WOS:000086519100008.

Caruso, C. C., Oct. 2015. Reducing Risks to Women Linked to Shift Work, Long Work Hours, and Related Workplace Sleep and Fatigue Issues. Journal of Women's Health 24 (10), 789–794, publisher: Mary Ann Liebert, Inc., publishers.
URL https://www.liebertpub.com/doi/10.1089/jwh.2015.5481

Cavagnini, R., Hewitt, M., Maggioni, F., 2020. Workforce production planning under uncertain learning rates. International Journal of Production Economics 225, 107590, place: Amsterdam Publisher: Elsevier WOS:000532795300024.

Celano, G., Costa, A., Fichera, S., Perrone, G., 2004. Human factor policy testing in the sequencing of manual mixed model assembly lines. Computers & Operations Research 31 (1), 39–59, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000185555500003.

Ceselli, A., Righini, G., Salani, M., 2009. A column generation algorithm for a rich vehicle-routing problem. Transportation Science 43 (1), 56–69, place: Catonsville Publisher: Informs WOS:000263720200006.

Chen, B., Potts, C. N., Woeginger, G. J., 1998. A Review of Machine Scheduling: Complexity, Algorithms and Approximability. In: Du, D.-Z., Pardalos, P. M. (Eds.), Handbook of Combinatorial Optimization: Volume1–3. Springer US, Boston, MA, pp. 1493–1641.
URL https://doi.org/10.1007/978-1-4613-0303-9_25

Chen, S., Shen, Y., Su, X., Chen, H., 2013. A crew scheduling with chinese meal break rules. Journal of Transportation Systems Engineering and Information Technology 13 (2), 90–95.

Cheng, C.-H., Kuo, Y.-H., 2016. A dissimilarities balance model for a multi-skilledmulti-location food safety inspector scheduling problem. Iie Transactions 48 (3), 235–251, place: Philadelphia Publisher: Taylor & Francis Inc WOS:000375232400004.

Cheng, T., Wang, G., 2000. Single machine scheduling with learning effect considerations. Annals of Operations Research 98 (1), 273–290.

Cheng, T. C. E., Ding, Q., Lin, B. M. T., 2004. A concise survey of scheduling with time-dependent processing times. European Journal of Operational Research 152 (1), 1–13.
URL http://www.sciencedirect.com/science/article/pii/S0377221702009098

Cheshmehgaz, H., Haron, H., Kazemipour, F., Desa, M., 2012. Accumulated risk of body postures in assembly line balancing problem and modeling through a multi-criteria fuzzy-genetic algorithm. Computers and Industrial Engineering 63 (2), 503–512.

Chiang, W.-C., Urban, T. L., 2006. The stochastic u-line balancing problem: A heuristic procedure. European Journal of Operational Research 175 (3), 1767–1781, place: Amsterdam Publisher: Elsevier WOS:000241411500032.

Choi, G., 2009. A goal programming mixed-model line balancing for processing time and physical workload. Computers and Industrial Engineering 57 (1), 395–400.

Coelho, L. C., Gagliardi, J.-P., Renaud, J., Ruiz, A., 2016. Solving the vehicle routing problem with lunch break arising in the furniture delivery industry. Journal of the Operational Research Society 67 (5), 743–751.
URL https://doi.org/10.1057/jors.2015.90

Condeixa, L., Silva, P., Moah, D., Farias, B., Leiras, A., 2020. Evaluating cost impacts on reverse logistics using an economic order quantity (EOQ) model with environmental and social considerations. Central European Journal of Operations Research.

Corominas, A., Olivella, J., Pastor, R., 2010. A model for the assignment of a set of tasks when work performance depends on experience of all tasks involved. International Journal of Production Economics 126 (2), 335–340.

Costa, A., Cappadonna, F. A., Fichera, S., 2014. Joint optimization of a flow-shop group scheduling with sequence dependent set-up times and skilled workforce assignment. International Journal of Production Research 52 (9), 2696–2728, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000334051300013.

Cui, Z., Zhang, J., Wu, D., Cai, X., Wang, H., Zhang, W., Chen, J., 2020. Hybrid many-objective particle swarm optimization algorithm for green coal production problem. Information Sciences 518, 256–271.

De Bruecker, P., Van den Bergh, J., Belien, J., Demeulemeester, E., 2015. Workforce planning incorporating skills: State of the art. European Journal of Operational Research 243 (1), 1–16, place: Amsterdam Publisher: Elsevier WOS:000349592500001.

de Koster, R., Le-Duc, T., Roodbergen, K. J., Oct. 2007. Design and control of warehouse order picking: A literature review. European Journal of Operational Research 182 (2), 481–501.
URL https://www.sciencedirect.com/science/article/pii/S0377221706006473

De Lombaert, T., Braekers, K., De Koster, R., Ramaekers, K., Jun. 2022. In pursuit of humanised order picking planning: methodological review, literature classification and input from practice. International Journal of Production Research, 1–31.
URL https://www.tandfonline.com/doi/full/10.1080/00207543.2022.2079437

Dewi, D., Septiana, T., 2015. Workforce scheduling considering physical and mental workload: A case study of domestic freight forwarding. Procedia Manufacturing 4, 445–453.

Diefenbach, H., Emde, S., Glock, C. H., 2020. Loading tow trains ergonomically for just-in-time part supply. European Journal of Operational Research 284 (1), 325–344, place: Amsterdam Publisher: Elsevier WOS:000521510300025.

Diefenbach, H., Glock, C. H., 2019. Ergonomic and economic optimization of layout and item assignment of a u-shaped order picking zone. Computers & Industrial Engineering 138, UNSP 106094, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000500375600004.

Diego-Mas, J. A., Asensio-Cuesta, S., Sanchez-Romero, M. A., Artacho-Ramirez, M. A., 2009. A multi-criteria genetic algorithm for the generation of job rotation schedules. International Journal of Industrial Ergonomics 39 (1), 23–33, place: Amsterdam Publisher: Elsevier WOS:000263007600004.

Doerr, K., Klastorin, T., Magazine, M., 2000. Synchronous unpaced flow lines with worker differences and overtime cost. Management Science 46 (3), 421–435.

Dul, J., De Vries, H., Verschoof, S., Eveleens, W., Feilzer, A., 2004. Combining economic and social goals in the design of production systems by using ergonomics standards. Computers and Industrial Engineering 47 (2-3), 207–222.

Efe, B., Kremer, G. E. O., Kurt, M., 2018. Age and gender based workload constraint for assembly line worker assignment and balancing problem in a textile firm. International Journal of Industrial Engineering-Theory Applications and Practice 25 (1), 1–17, place: Cincinnati Publisher: Univ Cincinnati Industrial Engineering WOS:000431221200001.

Egilmez, G., Erenay, B., Süer, G., 2014. Stochastic skill-based manpower allocation in a cellular manufacturing system. Journal of Manufacturing Systems 33 (4), 578–588.

Eitzen, G., Panton, D., Mills, G., 2004. Multi-skilled workforce optimisation. Annals of Operations Research 127 (1), 359–372, place: Dordrecht Publisher: Kluwer Academic Publ WOS:000220092600011.

El Hachemi, N., El Hallaoui, I., Gendreau, M., Rousseau, L.-M., 2015. Flow-based integer linear programs to solve the weekly log-truck scheduling problem. Annals of Operations Research 232 (1), 87–97, place: Dordrecht Publisher: Springer WOS:000359747200005.

El Mouayni, I., Etienne, A., Lux, A., Siadat, A., Dantan, J.-Y., 2020. A simulation-based approach for time allowances assessment during production system design with consideration of worker's fatigue, learning and reliability. Computers & Industrial Engineering 139, 105650, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000509784000098.

Elmaghraby, S., 1990. Economic manufacturing quantities under conditions of learning and forgetting (EMQ/LaF). Production Planning and Control 1 (4), 196–208.

Erdinç, O., Yeow, P. H., Feb. 2011. Proving external validity of ergonomics and quality relationship through review of real-world case studies. International Journal of Production Research 49 (4), 949–962, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/00207540903555502.
URL https://doi.org/10.1080/00207540903555502

Eren, T., 2009. A bicriteria parallel machine scheduling with a learning effect of setup and removal times. Applied Mathematical Modelling 33 (2), 1141–1150, place: New York Publisher: Elsevier Science Inc WOS:000261301400038.

Erera, A., Karacik, B., Savelsbergh, M., 2008. A dynamic driver management scheme for less-than-truckload carriers. Computers & Operations Research 35 (11), 3397–3411, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000255671800002.

Ferjani, A., Ammar, A., Pierreval, H., Elkosantini, S., 2017. A simulation-optimization based heuristic for the online assignment of multi-skilled workers subjected to fatigue in manufacturing systems. Computers & Industrial Engineering 112, 663–674, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000413126700056.

Finco, S., Abdous, M.-A., Calzavara, M., Battini, D., Delorme, X., 2020a. A bi-objective model to include workers' vibration exposure in assembly line design. International Journal of Production Research.

Finco, S., Battini, D., Delorme, X., Persona, A., Sgarbossa, F., 2020b. Workers' rest allowance and smoothing of the workload in assembly lines. International Journal of Production Research 58 (4), 1255–1270, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000469115800001.

Fini, A. A. F., Akbarnezhad, A., Rashidi, T. H., Waller, S. T., 2017. Job assignment based on brain demands and human resource strategies. Journal of Construction Engineering and Management 143 (5), 04016123, place: Reston Publisher: Asce-Amer Soc Civil Engineers WOS:000398563900015.

Fowler, J. W., Wirojanagud, P., Gel, E. S., 2008. Heuristics for workforce planning with worker differences. European Journal of Operational Research 190 (3), 724–740, place: Amsterdam Publisher: Elsevier Science Bv WOS:000256902800010.

Fu, Y., Li, Z., Chen, N., Qu, C., 2020. A discrete multi-objective rider optimization algorithm for hybrid flowshop scheduling problem considering makespan, noise and dust pollution. IEEE Access 8, 88527–88546.

Gans, N., Zhou, Y. P., 2002. Managing learning and turnover in employee staffing. Operations Research 50 (6), 991–1006, place: Catonsville Publisher: Informs WOS:000179794700007.

Gebennini, E., Zeppetella, L., Grassi, A., Rimini, B., 2018. Optimal job assignment considering operators' walking costs and ergonomic aspects. International Journal of Production Research 56 (3), 1249–1268, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000429228100014.

Gilotra, M., Pareek, S., Mittal, M., Dhaka, V., 2020. Effect of carbon emission and human errors on a two-echelon supply chain under permissible delay in payments. International Journal of Mathematical, Engineering and Management Sciences 5 (2), 225–236.

Giret, A., Trentesaux, D., Prabhu, V., Oct. 2015. Sustainability in manufacturing operations scheduling: A state of the art review. Journal of Manufacturing Systems 37, 126–140.
URL https://www.sciencedirect.com/science/article/pii/S0278612515000606

Givi, Z. S., Jaber, M. Y., Neumann, W. P., 2015a. Modelling worker reliability with learning and fatigue. Applied Mathematical Modelling 39 (17), 5186–5199, place: New York Publisher: Elsevier Science Inc WOS:000357228100015.

Givi, Z. S., Jaber, M. Y., Neumann, W. P., 2015b. Production planning in DRC systems considering worker performance. Computers & Industrial Engineering 87, 317–327, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000360772100030.

Glock, C. H., Grosse, E. H., Abedinnia, H., Emde, S., 2019a. An integrated model to improve ergonomic and economic performance in order picking by rotating pallets. European Journal of Operational Research 273 (2), 516–534, place: Amsterdam Publisher: Elsevier Science Bv WOS:000452345600009.

Glock, C. H., Grosse, E. H., Jaber, M. Y., Smunt, T. L., 2019b. Applications of learning curves in production and operations management: A systematic literature review. Computers & Industrial Engineering 131, 422–441, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000468710600034.

Glock, C. H., Grosse, E. H., Kim, T., Neumann, W. P., Sobhani, A., 2019c. An integrated cost and worker fatigue evaluation model of a packaging process. International Journal of Production Economics 207, 107–124, place: Amsterdam Publisher: Elsevier Science Bv WOS:000454973200008.

Goel, A., 2009. Vehicle scheduling and routing with drivers' working hours. Transportation Science 43 (1), 17–26, place: Catonsville Publisher: Informs WOS:000263720200003.

Goel, A., 2012. A mixed integer programming formulation and effective cuts for minimising schedule durations of australian truck drivers. Journal of Scheduling 15 (6), 733–741, place: New York Publisher: Springer WOS:000314524100005.

Goel, A., Vidal, T., Aug. 2014. Hours of Service Regulations in Road Freight Transport: An Optimization-Based International Assessment. Transportation Science 48 (3), 391–412.
URL http://pubsonline.informs.org/doi/abs/10.1287/trsc.2013.0477

Gong, G., Chiong, R., Deng, Q., Gong, X., 2020a. A hybrid artificial bee colony algorithm for flexible job shop scheduling with worker flexibility. International Journal of Production Research 58 (14), 4406–4420, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000481660300001.

Gong, G., Chiong, R., Deng, Q., Han, W., Zhang, L., Lin, W., Li, K., 2020b. Energy-efficient flexible flow shop scheduling with worker flexibility. Expert Systems with Applications 141, UNSP 112902, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000496334800026.

Gong, X., Deng, Q., Gong, G., Liu, W., Ren, Q., 2018. A memetic algorithm for multi-objective flexible job-shop problem with worker flexibility. International Journal of Production Research 56 (7), 2506–2522, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000433968100006.

Grosse, E., Glock, C., Müller, S., 2015a. Production economics and the learning curve: A meta-analysis. International Journal of Production Economics 170, 401–412.

Grosse, E. H., Glock, C. H., 2015. The effect of worker learning on manual order picking processes. International Journal of Production Economics 170, 882–890, patent Number: C Place: Amsterdam Publisher: Elsevier WOS:000367486300016.

Grosse, E. H., Glock, C. H., Jaber, M. Y., 2013. The effect of worker learning and forgetting on storage reassignment decisions in order picking systems. Computers & Industrial Engineering 66 (4), 653–662, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000328234000004.

Grosse, E. H., Glock, C. H., Jaber, M. Y., Neumann, W. P., 2015b. Incorporating human factors in order picking planning models: framework and research opportunities. International Journal of Production Research 53 (3), 695–717, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/00207543.2014.919424.
URL https://doi.org/10.1080/00207543.2014.919424

Grosse, E. H., Glock, C. H., Neumann, W. P., 2017. Human factors in order picking: a content analysis of the literature. International Journal of Production Research 55 (5), 1260–1276, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/00207543.2016.1186296.
URL https://doi.org/10.1080/00207543.2016.1186296

Gärtner, J., Musliu, N., Slany, W., 2001. Rota: A research project on algorithms for workforce scheduling and shift design optimization. AI Communications 14 (2), 83–92.

Gérard, M., Clautiaux, F., Sadykov, R., 2016. Column generation based approaches for a tour scheduling problem with a multi-skill heterogeneous workforce. European Journal of Operational Research 252 (3), 1019–1030.

Halkos, G., Bousinakis, D., Jan. 2010. The effect of stress and satisfaction on productivity. International Journal of Productivity and Performance Management 59 (5), 415–431, publisher: Emerald Group Publishing Limited.
URL https://doi.org/10.1108/17410401011052869

He, H., 2016. Minimization of maximum lateness in an m-machine permutation flow shop with a general exponential learning effect. Computers and Industrial Engineering 97, 73–83.

Hewitt, M., Chacosky, A., Grasman, S., Thomas, B., 2015. Integer programming techniques for solving non-linear workforce planning models with learning. European Journal of Operational Research 242 (3), 942–950.

Hinnen, U., Läubli, T., Guggenbühl, U., Krueger, H., 1992. Design of check-out systems including laser scanners for sitting work posture. Scandinavian Journal of Work, Environment & Health 18 (3), 186–194, publisher: Scandinavian Journal of Work, Environment & Health.
URL https://www.jstor.org/stable/40965990

Hochdörffer, J., Hedler, M., Lanza, G., 2018. Staff scheduling in job rotation environments considering ergonomic aspects and preservation of qualifications. Journal of Manufacturing Systems 46, 103–114.

Hollis, B., Green, P., 2012. Real-life vehicle routing with time windows for visual attractiveness and operational robustness. Asia-Pacific Journal of Operational Research 29 (4).

Hong, S., 2018. The effects of picker-oriented operational factors on hand-off delay in a bucket brigade order picking system. OR Spectrum 40 (3), 781–808.

Hopp, W., Tekin, E., Van Oyen, M., 2004. Benefits of skill chaining in serial production lines with cross-trained workers. Management Science 50 (1), 83–98.

Hu, B., Chen, J., 2017. Optimal task allocation for human-machine collaborative manufacturing systems. IEEE Robotics and Automation Letters 2 (4), 1933–1940.

Huang, S.-H., Pan, Y.-C., 2014. Ergonomic job rotation strategy based on an automated RGB-d anthropometric measuring system. Journal of Manufacturing Systems 33 (4), 699–710, place: Oxford Publisher: Elsevier Sci Ltd WOS:000348883200023.

Huang, Y., Chu, F., Chu, C., Wang, Y., 2012. Determining the number of new employees with learning, forgetting and variable wage with a newsvendor model in pull systems. Journal of Intelligent Manufacturing 23 (1), 73–89.

Hwang, H., Oh, Y., Cha, C., 2003. A stock location rule for a low level picker-to-part system. Engineering Optimization 35 (3), 285–295.

Ivarsson, A., Eek, F., Jul. 2016. The relationship between physical workload and quality within line-based assembly. Ergonomics 59 (7), 913–923.

Jaber, M., Bonney, M., 2003. Lot sizing with learning and forgetting in set-ups and in product quality. International Journal of Production Economics 83 (1), 95–111.

Jaber, M., Guiffrida, A., 2004. Learning curves for processes generating defects requiring reworks. European Journal of Operational Research 159 (3), 663–672.

Jaber, M. Y., Givi, Z. S., Neumann, W. P., 2013. Incorporating human fatigue and recovery into the learning-forgetting process. Applied Mathematical Modelling 37 (12), 7287–7299, place: New York Publisher: Elsevier Science Inc WOS:000321535500012.

Jaber, M. Y., Glock, C. H., 2013. A learning curve for tasks with cognitive and motor elements. Computers & Industrial Engineering 64 (3), 866–871, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000315832300013.

Jaber, M. Y., Peltokorpi, J., 2020. The effects of learning in production and group size on the lot-sizing problem. Applied Mathematical Modelling 81, 419–427, place: New York Publisher: Elsevier Science Inc WOS:000521509900025.

Jaber, M. Y., Sikstrom, S., 2004. A numerical comparison of three potential learning and forgetting models. International Journal of Production Economics 92 (3), 281–294, place: Amsterdam Publisher: Elsevier Science Bv WOS:000225395300007.

Jamili, A., 2019. Job shop scheduling with consideration of floating breaking times under uncertainty. Engineering Applications of Artificial Intelligence 78, 28–36.

Jamshidi, R., Seyyed Esfahani, M. M., 2014. Human resources scheduling to improve the product quality according to exhaustion limit. TOP 22 (3), 1028–1041.
URL https://doi.org/10.1007/s11750-013-0310-z

Janiak, A., Kovalyov, M., 2006. Scheduling in a contaminated area: A model and polynomial algorithms. European Journal of Operational Research 173 (1), 125–132.

Janiak, A., Kovalyov, M., 2008. Scheduling jobs in a contaminated area: A model and heuristic algorithms. Journal of the Operational Research Society 59 (7), 977–987.

Janiak, A., Rudek, R., 2010. A note on a makespan minimization problem with a multi-ability learning effect. Omega 38 (3), 213–217.

Jans, R., Degraeve, Z., Mar. 2008. Modeling industrial lot sizing problems: a review. International Journal of Production Research 46 (6), 1619–1643, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/00207540600902262.
URL https://doi.org/10.1080/00207540600902262

Jeang, A., Rahim, A., 2019. Lot size determination for finite horizon under the effect of productivity and quality learning process. International Journal of Systems Science: Operations and Logistics 6 (3), 193–236.

Ji, M., Yao, D., Yang, Q., Cheng, T., 2015. Machine scheduling with DeJong's learning effect. Computers and Industrial Engineering 80 (1), 195–200.

Joo, C. M., Kim, B. S., 2013. Genetic algorithms for single machine scheduling with time-dependent deterioration and rate-modifying activities. Expert Systems with Applications 40 (8), 3036–3043, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000316522900024.

Kandakoglu, A., Sauré, A., Michalowski, W., Aquino, M., Graham, J., McCormick, B., 2020. A decision support system for home dialysis visit scheduling and nurse routing. Decision Support Systems 130.

Kara, Y., Atasagun, Y., Gokcen, H., Hezer, S., Demirel, N., 2014. An integrated model to incorporate ergonomics and resource restrictions into assembly line balancing. International Journal of Computer Integrated Manufacturing 27 (11), 997–1007, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000341924400004.

Karsu, O., Morton, A., 2015. Inequity averse optimization in operational research. European Journal of Operational Research 245 (2), 343–359, place: Amsterdam Publisher: Elsevier Science Bv WOS:000355360900001.

Kaya, B., Adem, A., Dağdeviren, M., 2020. A DSS-based novel approach proposition employing decision techniques for system design. International Journal of Information Technology and Decision Making 19 (2), 413–445.

Kazemi, N., Abdul-Rashid, S. H., Shekarian, E., Bottani, E., Montanari, R., 2016a. A fuzzy lot-sizing problem with two-stage composite human learning. International Journal of Production Research 54 (16), 5010–5025, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000380165700017.

Kazemi, N., Olugu, E., Abdul-Rashid, S., Ghazilla, R., 2016b. A fuzzy EOQ model with backorders and forgetting effect on fuzzy parameters: An empirical study. Computers and Industrial Engineering 96, 140–148.

Kazemi, N., Shekarian, E., Cárdenas-Barrón, L., Olugu, E., 2015. Incorporating human learning into a fuzzy EOQ inventory model with backorders. Computers and Industrial Engineering 87, 540–542.

Keeble, B. R., 1988. The brundtland report: 'our common future'. Medicine and War 4 (1), 17–25, publisher: Routledge _eprint: https://doi.org/10.1080/07488008808408783.
URL https://doi.org/10.1080/07488008808408783

Khan, M., Jaber, M. Y., Ahmad, A.-R., 2014. An integrated supply chain model with errors in quality inspection and learning in production. Omega-International Journal of Management Science 42 (1), 16–24, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000325953500003.

Khan, M., Jaber, M. Y., Guiffrida, A. L., 2012. The effect of human factors on the performance of a two level supply chain. International Journal of Production Research 50 (2), 517–533, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000303582300014.

Khan, M., Jaber, M. Y., Guiffrida, A. L., Zolfaghari, S., 2011. A review of the extensions of a modified EOQ model for imperfect quality items. International Journal of Production Economics 132 (1), 1–12, place: Amsterdam Publisher: Elsevier WOS:000291191500001.

Khanna, A., Kishore, A., Jaggi, C., 2017. Inventory modeling for imperfect production process with inspection errors, sales return, and imperfect rework process. International Journal of Mathematical, Engineering and Management Sciences 2 (4), 242–258.

Kim, B.-I., Kim, S., Sahoo, S., 2006. Waste collection vehicle routing problem with time windows. Computers and Operations Research 33 (12), 3624–3642.

Kim, K., Kim, T.-S., Lim, D.-E., Park, H. M., 2013. Managing the supply and demand uncertainty in workforce recruitment: planned or just-in-time acquisition. Journal of the Operational Research Society 64 (11), 1654–1663, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000325757800009.

Knust, S., Schumacher, E., 2011. Shift scheduling for tank trucks. Omega 39 (5), 513–521.

Kok, A., Hans, E., Schutten, J., Zijm, W., 2010a. A dynamic programming heuristic for vehicle routing with time-dependent travel times and required breaks. Flexible Services and Manufacturing Journal 22 (1), 83–108.

Kok, A. L., Meyer, C. M., Kopfer, H., Schutten, J. M. J., 2010b. A dynamic programming heuristic for the vehicle routing problem with time windows and european community social legislation. Transportation Science 44 (4), 442–454, place: Hanover Publisher: Informs WOS:000284307000002.

Koltai, T., Tatay, V., 2013. Formulation of workforce skill constraints in assembly line balancing models. Optimization and Engineering 14 (4), 529–545.

Koltai, T., Tatay, V., Kallo, N., 2014. Application of the results of simple assembly line balancing models in practice: the case of a bicycle manufacturer. International Journal of Computer Integrated Manufacturing 27 (9), 887–898, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000337245200006.

Kolus, A., Wells, R., Neumann, P., 2018. Production quality and human factors engineering: A systematic review and theoretical framework. Applied Ergonomics 73, 55–89, place: Oxford Publisher: Elsevier Sci Ltd WOS:000442711000008.

Kong, F., 2019. Development of metric method and framework model of integrated complexity evaluations of production process for ergonomics workstations. International Journal of Production Research 57 (8), 2429–2445.

Korytkowski, P., 2017. Competences-based performance model of multi-skilled workers with learning and forgetting. Expert Systems with Applications 77, 226–235.

Kovalev, S., Chalamon, I., Collignon, S., 2019. Minimizing maximum job dependent ergonomic risk. International Journal of Production Research.

Kudelska, I., Pawłowski, G., 2020. Influence of assortment allocation management in the warehouse on the human workload. Central European Journal of Operations Research 28 (2), 779–795.

Kuijer, P., Visser, B., Kemper, H., Sep. 1999. Job rotation as a factor in reducing physical workload at a refuse collecting department. Ergonomics 42 (9), 1167–1178, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/001401399185054.
URL https://doi.org/10.1080/001401399185054

Kuo, Y.-H., Leung, J., Yano, C., 2014. Scheduling of multi-skilled staff across multiple locations. Production and Operations Management 23 (4), 626–644.

Lanzetta, M., Rossi, A., Puppato, A., 2016. Modelling activity times by hybrid synthetic method. Production Planning and Control 27 (11), 909–924.

Lapegue, T., Bellenguez-Morineau, O., Prot, D., 2013. A constraint-based approach for the shift design personnel task scheduling problem with equity. Computers & Operations Research 40 (10), 2450–2465, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000321416800017.

Larco, J. A., de Koster, R., Roodbergen, K. J., Dul, J., 2017. Managing warehouse efficiency and worker discomfort through enhanced storage assignment decisions. International Journal of Production Research 55 (21), 6407–6422, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000412561900013.

Lazzerini, B., Pistolesi, F., 2018. Multiobjective personnel assignment exploiting workers' sensitivity to risk. IEEE Transactions on Systems, Man, and Cybernetics: Systems 48 (8), 1267–1282.

Lee, W.-C., Chuang, M.-C., Yeh, W.-C., 2012. Uniform parallel-machine scheduling to minimize makespan with position-based learning curves. Computers and Industrial Engineering 63 (4), 813–818.

Lee, W.-C., Wu, C.-C., 2009. A note on single-machine group scheduling problems with position-based learning effect. Applied Mathematical Modelling 33 (4), 2159–2163, place: New York Publisher: Elsevier Science Inc WOS:000262729300032.

Lehuédé, F., Péton, O., Tricoire, F., 2020. A lexicographic minimax approach to the vehicle routing problem with route balancing. European Journal of Operational Research 282 (1), 129–147.

Li, J., Tan, X., Li, J., 2018a. Research on dynamic facility layout problem of manufacturing unit considering human factors. Mathematical Problems in Engineering 2018, 6040561, place: London Publisher: Hindawi Ltd WOS:000423573600001.

Li, K., Xu, S., Fu, H., 2020. Work-break scheduling with real-time fatigue effect and recovery. International Journal of Production Research 58 (3), 689–702, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000465715900001.

Li, X., Jiang, Y., Ruiz, R., 2018b. Methods for scheduling problems considering experience, learning, and forgetting effects. IEEE Transactions on Systems, Man, and Cybernetics: Systems 48 (5), 743–754, conference Name: IEEE Transactions on Systems, Man, and Cybernetics: Systems.

Lian, J., Liu, C., Li, W., Yin, Y., 2018. A multi-skilled worker assignment problem in seru production systems considering the worker heterogeneity. Computers and Industrial Engineering 118, 366–382.

Liu, C.-H., 2016. Solving the bi-objective optimisation problem with periodic delivery operations using a lexicographic method. International Journal of Production Research 54 (8), 2275–2283, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000373740300006.

Lodree, E. J., Geiger, C. D., Jiang, X. C., 2009. Taxonomy for integrating scheduling theory and human factors: review and research opportunities. International Journal of Industrial Ergonomics 39 (1), 39–51, publisher: Elsevier.
URL https://www.cabdirect.org/cabdirect/abstract/20093022460

Lodree Jr., E., Geiger, C., 2010. A note on the optimal sequence position for a rate-modifying activity under simple linear deterioration. European Journal of Operational Research 201 (2), 644–648.

Lombardi, D. A., Folkard, S., Willetts, J. L., Smith, G. S., Jun. 2010. Daily Sleep, Weekly Working Hours, and Risk of Work-Related Injury: Us National Health Interview Survey (2004–2008). Chronobiology International 27 (5), 1013–1030, publisher: Taylor & Francis _eprint: https://doi.org/10.3109/07420528.2010.489466.
URL https://doi.org/10.3109/07420528.2010.489466

Loos, M., Merino, E., Rodriguez, C., 2016. Mapping the state of the art of ergonomics within logistics. Scientometrics 109 (1), 85–101.

Lu, C., Gao, L., Pan, Q., Li, X., Zheng, J., 2019. A multi-objective cellular grey wolf optimizer for hybrid flowshop scheduling problem considering noise pollution. Applied Soft Computing Journal 75, 728–749.

Manavizadeh, N., Hosseini, N.-S., Rabbani, M., Jolai, F., 2013. A simulated annealing algorithm for a mixed model assembly u-line balancing type-i problem considering human efficiency and just-in-time approach. Computers and Industrial Engineering 64 (2), 669–685.

Margot, F., 2010. Symmetry in Integer Linear Programming. In: Jünger, M., Liebling, T. M., Naddef, D., Nemhauser, G. L., Pulleyblank, W. R., Reinelt, G., Rinaldi, G., Wolsey, L. A. (Eds.), 50 Years of Integer Programming 1958-2008: From the Early Years to the State-of-the-Art. Springer, Berlin, Heidelberg, pp. 647–686.
URL https://doi.org/10.1007/978-3-540-68279-0_17

Marichelvam, M. K., Geetha, M., Tosun, O., 2020. An improved particle swarm optimization algorithm to solve hybrid flowshop scheduling problems with the effect of human factors - a case study. Computers & Operations Research 114, UNSP 104812, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000499768500017.

Marvel, J. H., Shell, R. L., Weckman, G. R., 2001. An application of heuristic algorithms for determining inventory location in a distribution warehouse. International Journal of Industrial Engineering-Theory Applications and Practice 8 (1), 5–15, place: Cincinnati Publisher: Univ Cincinnati Industrial Engineering WOS:000168224400001.

Mateo, M., Tarral, M., Rodríguez, P., Galera, A., 2020. Ergonomics as basis for a decision support system in the printing industry. Central European Journal of Operations Research 28 (2), 685–706.

Mathlouthi, I., Gendreau, M., Potvin, J.-Y., 2018. Mixed integer linear programming for a multi-attribute technician routing and scheduling problem. INFOR 56 (1), 33–49.

Matl, P., Hartl, R. F., Vidal, T., 2018. Workload equity in vehicle routing problems: A survey and analysis. Transportation Science 52 (2), 239–260, publisher: INFORMS.
URL https://pubsonline.informs.org/doi/abs/10.1287/trsc.2017.0744

Matl, P., Hartl, R. F., Vidal, T., 2019. Workload equity in vehicle routing: The impact of alternative workload resources. Computers & Operations Research 110, 116–129, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000474309800009.

Matusiak, M., de Koster, R., Saarinen, J., 2017. Utilizing individual picker skills to improve order batching in a warehouse. European Journal of Operational Research 263 (3), 888–899.

Mayerle, S., De Genaro Chiroli, D., Neiva de Figueiredo, J., Rodrigues, H., 2020. The long-haul full-load vehicle routing and truck driver scheduling problem with intermediate stops: An economic impact evaluation of brazilian policy. Transportation Research Part A: Policy and Practice 140, 36–51.

Małachowski, B., Korytkowski, P., 2016. Competence-based performance model of multi-skilled workers. Computers and Industrial Engineering 91, 165–177.

McDonald, T., Ellis, K., Van Aken, E., Patrick Koelling, C., 2009. Development and application of a worker assignment model to evaluate a lean manufacturing cell. International Journal of Production Research 47 (9), 2427–2447.

Mehdizadeh, A., Vinel, A., Hu, Q., Schall, M. C., Gallagher, S., Sesek, R. F., 2020. Job rotation and work-related musculoskeletal disorders: a fatigue-failure perspective. Ergonomics 63 (4), 461–476, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000512519000001.

Mehdizadeh, E., Daei Niaki, S., Rahimi, V., 2016. A vibration damping optimization algorithm for solving a new multi-objective dynamic cell formation problem with workers training. Computers and Industrial Engineering 101, 35–52.

Mehrotra, A., Murphy, K., Trick, M., 2000. Optimal shift scheduling: A branch-and-price approach. Naval Research Logistics 47 (3), 185–200.

Melton, K., Ingalls, R., 2012. Utilizing relay points to improve the truckload driving job. International Journal of Supply Chain Management 1 (3), 1–10.

Min, H., Melachrinoudis, E., 2016. A model-based decision support system for solving vehicle routing and driver scheduling problems under hours of service regulations. International Journal of Logistics Research and Applications 19 (4), 256–277, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/13675567.2015.1075475.
URL https://doi.org/10.1080/13675567.2015.1075475

Mokhtari, H., Hasani, A., 2017. A multi-objective model for cleaner production-transportation planning in manufacturing plants via fuzzy goal programming. Journal of Manufacturing Systems 44, 230–242.

Moon, I., Logendran, R., Lee, J., 2009. Integrated assembly line balancing with resource restrictions. International Journal of Production Research 47 (19), 5525–5541.

Mosheiov, G., 2001. Scheduling problems with a learning effect. European Journal of Operational Research 132 (3), 687–693.

Mosheiov, G., Sidney, J., 2003. Scheduling with general job-dependent learning curves. European Journal of Operational Research 147 (3), 665–670.

Mossa, G., Boenzi, F., Digiesi, S., Mummolo, G., Romano, V., 2016. Productivity and ergonomic risk in human based production systems: A job-rotation scheduling model. International Journal of Production Economics 171, 471–477.

Moussavi, S. E., Zare, M., Mahdjoub, M., Grunder, O., 2019. Balancing high operator's workload through a new job rotation approach: Application to an automotive assembly line. International Journal of Industrial Ergonomics 71, 136–144, place: Amsterdam Publisher: Elsevier Science Bv WOS:000466999800018.

Muhs, K. S., Karwowski, W., Kern, D., 2018. Temporal variability in human performance: A systematic literature review. International Journal of Industrial Ergonomics 64, 31–50, place: Amsterdam Publisher: Elsevier Science Bv WOS:000429512700005.

Muth, E. J., Spremann, K., 1983. Learning effects in economic lot sizing. Management Science 29 (2), 264–269.

Mutlu, O., Özgörmüş, E., 2012. A fuzzy assembly line balancing problem with physical workload constraints. International Journal of Production Research 50 (18), 5281–5291.

Nanthavanij, S., Yaoyuenyong, S., Jeenanunta, C., 2010. Heuristic approach to workforce scheduling with combined safety and productivity objective. International Journal of Industrial Engineering-Theory Applications and Practice 17 (4), 319–333, place: Cincinnati Publisher: Univ Cincinnati Industrial Engineering WOS:000286014300006.

Nembhard, D., 2001. Heuristic approach for assigning workers to tasks based on individual learning rates. International Journal of Production Research 39 (9), 1955–1968.

Nembhard, D., Bentefouet, F., 2014. Selection policies for a multifunctional workforce. International Journal of Production Research 52 (16), 4785–4802.

Nembhard, D. A., Bentefouet, F., 2012. Parallel system scheduling with general worker learning and forgetting. International Journal of Production Economics 139 (2), 533–542.
URL http://www.sciencedirect.com/science/article/pii/S0925527312002162

Niakan, F., Baboli, A., Moyaux, T., Botta-Genoulaz, V., 2016. A bi-objective model in sustainable dynamic cell formation problem with skill-based worker assignment. Journal of Manufacturing Systems 38, 46–62.

Nishi, T., Sugiyama, T., Inuiguchi, M., 2014. Two-level decomposition algorithm for crew rostering problems with fair working condition. European Journal of Operational Research 237 (2), 465–473.

Norman, B. A., Tharmmaphornphilas, W., Needy, K. L., Bidanda, B., Warner, R. C., 2002. Worker assignment in cellular manufacturing considering technical and human skills. International Journal of Production Research 40 (6), 1479–1492, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000175277300010.

Occhipinti, E., 1998. OCRA: a concise index for the assessment of exposure to repetitive movements of the upper limbs. Ergonomics 41 (9), 1290–1311.

Olivella, J., Nembhard, D., 2017. Cross-training policies for team cost and robustness. Computers & Industrial Engineering 111, 79–88, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000410468600008.

Ostermeier, F. F., 2020. The impact of human consideration, schedule types and product mix on scheduling objectives for unpaced mixed-model assembly lines. International Journal of Production Research 58 (14), 4386–4405, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000480779200001.

Othman, M., Bhuiyan, N., Gouw, G., 2012. Integrating workers' differences into workforce planning. Computers and Industrial Engineering 63 (4), 1096–1106.

Otto, A., Battaia, O., 2017. Reducing physical ergonomic risks at assembly lines by line balancing and job rotation: A survey. Computers & Industrial Engineering 111, 467–480, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000410468600039.

Otto, A., Boysen, N., Scholl, A., Walter, R., 2017. Ergonomic workplace design in the fast pick area. OR Spectrum 39 (4), 945–975.

Otto, A., Scholl, A., 2011. Incorporating ergonomic risks into assembly line balancing. European Journal of Operational Research 212 (2), 277–286, place: Amsterdam Publisher: Elsevier WOS:000290084300006.

Otto, A., Scholl, A., 2013. Reducing ergonomic risks by job rotation scheduling. OR Spectrum 35 (3), 711–733.

Otto, C., Otto, A., 2014. Extending assembly line balancing problem by incorporating learning effects. International Journal of Production Research 52 (24), 7193–7208.

Padula, R. S., Caires Comper, M. L., Sparer, E. H., Dennerlein, J. T., 2017. Job rotation designed to prevent musculoskeletal disorders and control risk in manufacturing industries: A systematic review. Applied Ergonomics 58, 386–397, place: Oxford Publisher: Elsevier Sci Ltd WOS:000384776100044.

Pan, Q.-K., Suganthan, P., Chua, T., Cai, T., 2010. Solving manpower scheduling problem in manufacturing using mixed-integer programming with a two-stage heuristic algorithm. International Journal of Advanced Manufacturing Technology 46 (9), 1229–1237.

Pargar, F., Zandieh, M., 2012. Bi-criteria SDST hybrid flow shop scheduling with learning effect of setup times: water flow-like algorithm approach. International Journal of Production Research 50 (10), 2609–2623, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000304824400004.

Pata, A., Moura, A., 2018. Applying metaheuristics to minimize work-related musculoskeletal disorders. International Journal of Technology and Human Interaction 14 (2), 17–34.

Pei, J., Liu, X., Pardalos, P., Migdalas, A., Yang, S., 2017. Serial-batching scheduling with time-dependent setup time and effects of deterioration and learning on a single-machine. Journal of Global Optimization 67 (1), 251–262.

Peltokorpi, J., Jaber, M. Y., 2020. A group learning curve model with motor, cognitive and waste elements. Computers & Industrial Engineering 146, 106621, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000548931200046.

Petronijevic, J., Etienne, A., Dantan, J.-Y., 2019. Human factors under uncertainty: A manufacturing systems design using simulation-optimisation approach. Computers & Industrial Engineering 127, 665–676, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000460708800050.

Pheasant, S., Haslegrave, C. M., Dec. 2018. Bodyspace: Anthropometry, Ergonomics and the Design of Work, 3rd Edition. CRC Press, Boca Raton.

Pistolesi, F., Lazzerini, B., 2019. TeMA: A tensorial memetic algorithm for many-objective parallel disassembly sequence planning in product refurbishment. Ieee Transactions on Industrial Informatics 15 (6), 3743–3753, place: Piscataway Publisher: Ieee-Inst Electrical Electronics Engineers Inc WOS:000471725400059.

Polat, O., Kalayci, C., Mutlu, O., Gupta, S., 2016. A two-phase variable neighbourhood search algorithm for assembly line worker assignment and balancing problem type-II: An industrial case study. International Journal of Production Research 54 (3), 722–741.

Prescott-Gagnon, E., Desaulniers, G., Drexl, M., Rousseau, L.-M., 2010. European driver rules in vehicle routing with time windows. Transportation Science 44 (4), 455–473, place: Catonsville Publisher: Informs WOS:000284307000003.

Press, C. U., 2011. Cambridge Business English Dictionary. Cambridge University Press, google-Books-ID: XnAEiEaSPikC.

Prot, D., Lapegue, T., Bellenguez-Morineau, O., 2015. A two-phase method for the shift design and personnel task scheduling problem with equity objective. International Journal of Production Research 53 (24), 7286–7298, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000367048600009.

Prunet, T., Absi, N., Borodin, V., Cattaruzza, D., 2022. Optimization of human-aware manufacturing and logistics systems: A survey on the modeling of human aspects. Working Paper.

Przybylski, B., 2018. A new model of parallel-machine scheduling with integral-based learning effect. Computers and Industrial Engineering 121, 189–194.

Quimper, C.-G., Rousseau, L.-M., 2010. A large neighbourhood search approach to the multi-activity shift scheduling problem. Journal of Heuristics 16 (3), 373–392, place: Dordrecht Publisher: Springer WOS:000276908400008.

Rabbani, M., Nikoubin, A., Farrokhi-Asl, H., 2020. Using modified metaheuristic algorithms to solve a hazardous waste collection problem considering workload balancing and service time windows. Soft Computing.

Rancourt, M.-E., Cordeau, J.-F., Laporte, G., 2013. Long-haul vehicle routing and scheduling with working hour rules. Transportation Science 47 (1), 81–107, place: Hanover Publisher: Informs WOS:000314620100007.

Rancourt, M.-E., Paquette, J., 2014. Multicriteria optimization of a long-haul routing and scheduling problem. Journal of Multi-Criteria Decision Analysis 21 (5), 239–255.

Rattanamanee, T., Nanthavanij, S., Dumrongsiri, A., 2015. Multi-workday vehicle routing problem with ergonomic consideration of physical workload. International Journal of Advanced Manufacturing Technology 76 (9), 2015–2026.

Razavi, H., Ramezanifar, E., Bagherzadeh, J., 2014. An economic policy for noise control in industry using genetic algorithm. Safety Science 65, 79–85, place: Amsterdam Publisher: Elsevier WOS:000333512700010.

Rekik, M., Cordeau, J.-F., Soumis, F., 2008. Solution approaches to large shift scheduling problems. Rairo-Operations Research 42 (2), 229–258, place: Les Ulis Cedex A Publisher: Edp Sciences S A WOS:000255967900009.

Rekik, M., Cordeau, J.-F., Soumis, F., 2010. Implicit shift scheduling with multiple breaks and work stretch duration restrictions. Journal of Scheduling 13 (1), 49–75.

Restrepo, M., Gendron, B., Rousseau, L.-M., 2016. Branch-and-price for personalized multiactivity tour scheduling. INFORMS Journal on Computing 28 (2), 334–350.

Restrepo, M. I., Lozano, L., Medaglia, A. L., 2012. Constrained network-based column generation for the multi-activity shift scheduling problem. International Journal of Production Economics 140 (1), 466–472, place: Amsterdam Publisher: Elsevier WOS:000309375100045.

Ritt, M., Costa, A., Miralles, C., 2016. The assembly line worker assignment and balancing problem with stochastic worker availability. International Journal of Production Research 54 (3), 907–922.

Ruiz-Torres, A. J., Ablanedo-Rosas, J. H., Mukhopadhyay, S., Paletta, G., 2019. Scheduling workers: A multi-criteria model considering their satisfaction. Computers & Industrial Engineering 128, 747–754, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000458221900056.

Ruiz-Torres, A. J., Alomoto, N., Paletta, G., Perez, E., 2015. Scheduling to maximise worker satisfaction and on-time orders. International Journal of Production Research 53 (9), 2836–2852, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000350451200017.

Ryan, B., Qu, R., Schock, A., Parry, T., 2011. Integrating human factors and operational research in a multidisciplinary investigation of road maintenance. Ergonomics 54 (5), 436–452, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000290298000003.

Sadeghi, P., Rebelo, R., Ferreira, J., 2018. Balancing mixed-model assembly systems in the footwear industry with a variable neighbourhood descent method. Computers and Industrial Engineering 121, 161–176.

Salehi, M., Maleki, H., Niroomand, S., 2018. A multi-objective assembly line balancing problem with worker's skill and qualification considerations in fuzzy environment. Applied Intelligence 48 (8), 2137–2156.

Samouei, P., Ashayeri, J., 2019. Developing optimization & robust models for a mixed-model assembly line balancing problem with semi-automated operations. Applied Mathematical Modelling 72, 259–275, place: New York Publisher: Elsevier Science Inc WOS:000470051900015.

Sana, S. S., Ospina-Mateus, H., Arrieta, F. G., Chedid, J. A., 2019. Application of genetic algorithm to job scheduling under ergonomic constraints in manufacturing industry. Journal of Ambient Intelligence and Humanized Computing 10 (5), 2063–2090, place: Heidelberg Publisher: Springer Heidelberg WOS:000463151400031.

Sanchez-Herrera, S., Montoya-Torres, J. R., Solano-Charris, E. L., 2019. Flow shop scheduling problem with position-dependent processing times. Computers & Operations Research 111, 325–345, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000483411600023.

Savino, M. M., Riccio, C., Menanno, M., 2020. Empirical study to explore the impact of ergonomics on workforce scheduling. International Journal of Production Research 58 (2), 415–433, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000465710300001.

Sawik, T., 2010. An integer programming approach to scheduling in a contaminated area. Omega 38 (3), 179–191.

Sayin, S., Karabati, S., 2007. Assigning cross-trained workers to departments: A two-stage optimization model to maximize utility and skill improvement. European Journal of Operational Research 176 (3), 1643–1658, place: Amsterdam Publisher: Elsevier Science Bv WOS:000242102800021.

Sbihi, A., Eglese, R. W., Mar. 2010. Combinatorial optimization and Green Logistics. Annals of Operations Research 175 (1), 159–175.
URL https://doi.org/10.1007/s10479-009-0651-z

Shahbazi, B., Akbarnezhad, A., Rey, D., Fini, A. A. F., Loosemore, M., 2019. Optimization of job allocation in construction organizations to maximize workers' career development opportunities. Journal of Construction Engineering and Management 145 (6), 04019036, place: Reston Publisher: Asce-Amer Soc Civil Engineers WOS:000464567400001.

Sheikhalishahi, M., Eskandari, N., Mashayekhi, A., Azadeh, A., 2019. Multi-objective open shop scheduling by considering human error and preventive maintenance. Applied Mathematical Modelling 67, 573–587, place: New York Publisher: Elsevier Science Inc WOS:000456492500035.

Shikdar, A., Sawaqed, N., 2003. Worker productivity, and occupational health and safety issues in selected industries. Computers and Industrial Engineering 45 (4), 563–572.

Shin, D., Mittal, M., Sarkar, B., 2018. Effects of human errors and trade-credit financing in two-echelon supply chain models. European Journal of Industrial Engineering 12 (4), 465–503, place: Geneva Publisher: Inderscience Enterprises Ltd WOS:000444011200001.

Shuib, A., Kamarudin, F., 2019. Solving shift scheduling problem with days-off preference for power station workers using binary integer goal programming model. Annals of Operations Research 272 (1), 355–372.

Smunt, T., 1987. The impact of worker forgetting on production scheduling. International Journal of Production Research 25 (5), 689–701.

Snyder, H., 2019. Literature review as a research methodology: An overview and guidelines. Journal of Business Research 104, 333–339.
URL http://www.sciencedirect.com/science/article/pii/S0148296319304564

Sobhani, A., Wahab, M., Neumann, W., 2017. Incorporating human factors-related performance variation in optimizing a serial system. European Journal of Operational Research 257 (1), 69–83.

Sobhani, A., Wahab, M. I. M., 2017. The effect of working environment-ill health aspects on the carbon emission level of a manufacturing system. Computers & Industrial Engineering 113, 75–90, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000418207900007.

Sobhani, A., Wahab, M. I. M., Jaber, M. Y., 2019. The effect of working environment aspects on a vendor-buyer inventory model. International Journal of Production Economics 208, 171–183, place: Amsterdam Publisher: Elsevier Science Bv WOS:000457952300012.

Sobhani, A., Wahab, M. I. M., Neumann, W. P., 2015. Investigating work-related ill health effects in optimizing the performance of manufacturing systems. European Journal of Operational Research 241 (3), 708–718, place: Amsterdam Publisher: Elsevier WOS:000347605100012.

Sotskov, Y., Dolgui, A., Lai, T.-C., Zatsiupa, A., 2015. Enumerations and stability analysis of feasible and optimal line balances for simple assembly lines. Computers and Industrial Engineering 90, 241–258.

Stanton, N. A., Hedge, A., Brookhuis, K., Salas, E., Hendrick, H. W., Aug. 2004. Handbook of Human Factors and Ergonomics Methods. CRC Press, google-Books-ID: RApSggShPc8C.

Steenweg, P., Schacht, M., Werners, B., 2020. Evaluating shift patterns considering heterogeneous skills and uncertain workforce availability. Journal of Decision Systems.

Stewart, B., Webster, D., Ahmad, S., Matson, J., 1994. Mathematical models for developing a flexible workforce. International Journal of Production Economics 36 (3), 243–254.

Sueer, G. A., Tummaluri, R. R., 2008. Multi-period operator assignment considering skills, learning and forgetting in labour-intensive cells. International Journal of Production Research 46 (2), 469–493, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000252337300009.

Sun, X., Guo, S., Guo, J., Du, B., 2019. A hybrid multi-objective evolutionary algorithm with heuristic adjustment strategies and variable neighbor-hood search for flexible job-shop scheduling problem considering flexible rest time. IEEE Access 7, 157003–157018.

Sungur, B., Özgüven, C., Kariper, Y., 2017. Shift scheduling with break windows, ideal break periods, and ideal waiting times. Flexible Services and Manufacturing Journal 29 (2), 203–222.

Suzanne, E., Absi, N., Borodin, V., 2020. Towards circular economy in production planning: Challenges and opportunities. European Journal of Operational Research 287 (1), 168–190.

Szalma, J., Hancock, P., 2011. Noise effects on human performance: A meta-analytic synthesis. Psychological bulletin 137, 682–707.

Takala, J., Hämäläinen, P., Saarela, K. L., Yun, L. Y., Manickam, K., Jin, T. W., Heng, P., Tjong, C., Kheng, L. G., Lim, S., Lin, G. S., May 2014. Global Estimates of the Burden of Injury and Illness at Work in 2012. Journal of Occupational and Environmental Hygiene 11 (5), 326–337, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/15459624.2013.863131.
URL https://doi.org/10.1080/15459624.2013.863131

Tang, Y., Zhou, M., Gao, M., 2006. Fuzzy-petri-net-based disassembly planning considering human factors. IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans 36 (4), 718–725.

Teyarachakul, S., Chand, S., Ward, J., 2011. Effect of learning and forgetting on batch sizes. Production and Operations Management 20 (1), 116–128.

Tharmmaphornphilas, W., Norman, B. A., 2004. A quantitative method for determining proper job rotation intervals. Annals of Operations Research 128 (1), 251–266, place: Dordrecht Publisher: Springer WOS:000220092800013.

Tharmmaphornphilas, W., Norman, B. A., 2007. A methodology to create robust job rotation schedules. Annals of Operations Research 155 (1), 339–360, place: Dordrecht Publisher: Springer WOS:000248940200018.

Thompson, G., 1990. Shift scheduling in services when employees have limited availability: An l.p. approach. Journal of Operations Management 9 (3), 352–370.

Thompson, G., Pullman, M., 2007. Scheduling workforce relief breaks in advance versus in real-time. European Journal of Operational Research 181 (1), 139–155.

Tiacci, L., Mimmi, M., 2018. Integrating ergonomic risks evaluation through OCRA index and balancing/sequencing decisions for mixed model stochastic asynchronous assembly lines. Omega-International Journal of Management Science 78, 112–138, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000433266700009.

Topaloglu, S., Ozkarahan, I., 2003. Implicit optimal tour scheduling with flexible break assignments. Computers and Industrial Engineering 44 (1), 75–89.

Topaloglu, S., Ozkarahan, I., 2004. An implicit goal programming model for the tour scheduling problem considering the employee work preferences. Annals of Operations Research 128 (1), 135–158.

Ulmer, M., Nowak, M., Mattfeld, D., Kaminski, B., 2020. Binary driver-customer familiarity in service routing. European Journal of Operational Research 286 (2), 477–493, place: Amsterdam Publisher: Elsevier WOS:000536062000007.

Valeva, S., Hewitt, M., Thomas, B., Brown, K., 2017. Balancing flexibility and inventory in workforce planning with learning. International Journal of Production Economics 183, 194–207.

Vega-Mejía, C. A., Montoya-Torres, J. R., Islam, S. M. N., 2019. Consideration of triple bottom line objectives for sustainability in the optimization of vehicle routing and loading operations: a systematic literature review. Annals of Operations Research 273 (1), 311–375.
URL https://doi.org/10.1007/s10479-017-2723-9

Villeda, R., Dean, B., 1990. On the optimal safe allocation and scheduling of a work force in a toxic-substance environment. Ieee Transactions on Engineering Management 37 (2), 95–101, place: New York Publisher: Ieee-Inst Electrical Electronics Engineers Inc WOS:A1990DF98300003.

von Elmbach, A. F., Scholl, A., Walter, R., 2019. Minimizing the maximal ergonomic burden in intra-hospital patient transportation. European Journal of Operational Research 276 (3), 840–854, place: Amsterdam Publisher: Elsevier Science Bv WOS:000463121000004.

Vézina, M., Cloutier, E., Stock, S., Lippel, K., Fortin, E., 2011. Summary report. québec survey on working and employment conditions and occupational health and safety (eqcotest).
URL https://www.inspq.qc.ca/pdf/publications/1356_EnqQuebCondTravailEmpSanteSecTravail_VA.pdf

Wang, J.-B., 2007. Single-machine scheduling problems with the effects of learning and deterioration. Omega 35 (4), 397–402.

Wang, J.-B., Liu, F., Wang, J.-J., 2019. Research on m-machine flow shop scheduling with truncated learning effects. International Transactions in Operational Research 26 (3), 1135–1151.

Wang, J.-B., Xia, Z.-Q., 2005. Flow-shop scheduling with a learning effect. Journal of the Operational Research Society 56 (11), 1325–1330.

Wang, X., Li, W., Zhang, Y., 2013. An improved multi-objective genetic algorithm for fuzzy flexible job-shop scheduling problem. International Journal of Computer Applications in Technology 47 (2), 280–288.

Wang, X. V., Kemeny, Z., Vancza, J., Wang, L., 2017. Human-robot collaborative assembly in cyber-physical production: Classification framework and implementation. Cirp Annals-Manufacturing Technology 66 (1), 5–8, place: Amsterdam Publisher: Elsevier Science Bv WOS:000407985900002.

Wang, Y., Wang, J.-Q., Yin, Y., 2020. Multitasking scheduling and due date assignment with deterioration effect and efficiency promotion. Computers & Industrial Engineering 146, 106569, place: Oxford Publisher: Pergamon-Elsevier Science Ltd WOS:000548931200020.

Wang, Z., Hu, H., Gong, J., 2018. Modeling worker competence to advance precast production scheduling optimization. Journal of Construction Engineering and Management 144 (11), 04018098, place: Reston Publisher: Asce-Amer Soc Civil Engineers WOS:000444530400002.

Wen, M., Krapper, E., Larsen, J., Stidsen, T. K., 2011. A multilevel variable neighborhood search heuristic for a practical vehicle routing and driver scheduling problem. Networks 58 (4), 311–322, place: Hoboken Publisher: Wiley WOS:000297413900007.

Widl, M., Musliu, N., 2014. The break scheduling problem: complexity results and practical algorithms. Memetic Computing 6 (2), 97–112, place: Heidelberg Publisher: Springer Heidelberg WOS:000343289900004.

Wirojanagud, P., Gel, E. S., Fowler, J. W., Cardy, R., 2007. Modelling inherent worker differences for workforce planning. International Journal of Production Research 45 (3), 525–553, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000244182400004.

Wogalter, M. S., Hancock, P. A., Dempsey, P. G., Oct. 1998. On the Description and Definition of Human Factors/Ergonomics. Proceedings of the Human Factors and Ergonomics Society Annual Meeting 42 (10), 671–674, publisher: SAGE Publications Inc.
URL https://doi.org/10.1177/154193129804201001

Wongwien, T., Nanthavanij, S., 2017. Multi-objective ergonomic workforce scheduling under complex worker and task constraints. International Journal of Industrial Engineering-Theory Applications and Practice 24 (3), 284–294, place: Cincinnati Publisher: Univ Cincinnati Industrial Engineering WOS:000422758000003.

Wright, T. P., 1936. Factors affecting the cost of airplanes. Journal of the Aeronautical Sciences 3 (4), 122–128, publisher: American Institute of Aeronautics and Astronautics.
URL https://arc.aiaa.org/doi/10.2514/8.155

Wu, C.-C., Lee, W.-C., 2008. Single-machine scheduling problems with a learning effect. Applied Mathematical Modelling 32 (7), 1191–1197, place: New York Publisher: Elsevier Science Inc WOS:000255694600003.

Wu, L., Cai, F., Li, L., Chu, X., 2018. Cross-trained worker assignment problem in cellular manufacturing system using swarm intelligence metaheuristics. Mathematical Problems in Engineering 2018, 4302062, place: London Publisher: Hindawi Ltd WOS:000450749800001.

Xu, S., Hall, N. G., Dec. 2021. Fatigue, personnel scheduling and operations: Review and research opportunities. European Journal of Operational Research 295 (3), 807–822.
URL https://www.sciencedirect.com/science/article/pii/S0377221721002629

Xu, Z., Ko, J., Cochran, D., Jung, M.-C., 2012. Design of assembly lines with the concurrent consideration of productivity and upper extremity musculoskeletal disorders using linear models. Computers and Industrial Engineering 62 (2), 431–441.

Yan, X., Xiao, B., Xiao, Y., Zhao, Z., Ma, L., Wang, N., 2019. Skill vehicle routing problem with time windows considering dynamic service times and time-skill-dependent costs. IEEE Access 7, 77208–77221.

Yi, W., Chan, A. P. C., 2015. Optimal work pattern for construction workers in hot weather: A case study in hong kong. Journal of Computing in Civil Engineering 29 (5), 05014009, publisher: American Society of Civil Engineers.
URL https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29CP.1943-5487.0000419

Yi, W., Wang, S., 2017. Mixed-integer linear programming on work-rest schedule design for construction sites in hot weather. Computer-Aided Civil and Infrastructure Engineering 32 (5), 429–439.

Yilmaz, O. F., 2020. Operational strategies for seru production system: a bi-objective optimisation model and solution methods. International Journal of Production Research 58 (11), 3195–3219, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000559798100001.

Yoon, S.-Y., Ko, J., Jung, M.-C., 2016. A model for developing job rotation schedules that eliminate sequential high workloads and minimize between-worker variability in cumulative daily workloads: Application to automotive assembly lines. Applied Ergonomics 55, 8–15, place: Oxford Publisher: Elsevier Sci Ltd WOS:000374074600002.

Yung, M., Kolus, A., Wells, R., Neumann, W. P., Jan. 2020. Examining the fatigue-quality relationship in manufacturing. Applied Ergonomics 82, 102919, place: Oxford Publisher: Elsevier Sci Ltd WOS:000501647900009.

Zanoni, S., Jaber, M., Zavanella, L., 2012. Vendor managed inventory (VMI) with consignment considering learning and forgetting effects. International Journal of Production Economics 140 (2), 721–730.

Zhang, L., Li, Z., Wu, K.-J., Yang, W., 2019. Exploring the optimal safety person-job matching method of major equipment based on human reliability. Applied Sciences (Switzerland) 9 (6).

Zhang, W., Fan, S., Xiong, J., Chen, S., 2018. A biobjective model for manual materials handling with energy consumption being accounted for. Mathematical Problems in Engineering 2018, 3474352, place: London Publisher: Hindawi Ltd WOS:000437897700001.

Zhang, W., Gen, M., 2011. An efficient multiobjective genetic algorithm for mixed-model assembly line balancing problem considering demand ratio-based cycle time. Journal of Intelligent Manufacturing 22 (3), 367–378, place: Dordrecht Publisher: Springer WOS:000290574400004.

Zhang, X., Sun, L., Wang, J., 2013. Single machine scheduling with autonomous learning and induced learning. Computers and Industrial Engineering 66 (4), 918–924.

Zhang, Z., Tang, Q., Ruiz, R., Zhang, L., 2020. Ergonomic risk and cycle time minimization for the u-shaped worker assignment assembly line balancing problem: A multi-objective approach. Computers and Operations Research 118.

Zhao, X., Liu, N., Zhao, S., Wu, J., Zhang, K., Zhang, R., 2019. Research on the work-rest scheduling in the manual order picking systems to consider human factors. Journal of Systems Science and Systems Engineering 28 (3), 344–355.

Zhu, Z., Zheng, F., Chu, C., 2017. Multitasking scheduling problems with a rate-modifying activity. International Journal of Production Research 55 (1), 296–312, place: Abingdon Publisher: Taylor & Francis Ltd WOS:000390416600019.

Álvarez, E., Ferrer, J.-C., Muñoz, J. C., Henao, C. A., 2020. Efficient shift scheduling with multiple breaks for full-time employees: A retail industry case. Computers & Industrial Engineering 150, 106884.
URL http://www.sciencedirect.com/science/article/pii/S0360835220305751

Şenyiğit, E., Atici, U., Şenol, M., 2020. Effects of OCRA parameters and learning rate on machine scheduling. Central European Journal of Operations Research.