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Flowshop scheduling problem including learning and fatigue effects: theoretical contributions and case study

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Abstract

Despite the rise of automation, hand-intensive production systems are still in use due to the need for flexibility and accuracy in completing certain tasks. The impact of learning and fatigue on manual task productivity arouses growing interest. The focus of this study is on a flowshop scheduling problem (FSSP) that considers the effects of learning and fatigue. Firstly, a literature review was conducted on the scheduling problem with learning and deterioration effect. After that, a theoretical approach was used to address the problem of FSSP with learning effect. Mathematical models that minimize the makespan were presented. Exact methods and heuristics were proposed for solving the problem in small and large instances. As fatigue is a type of deterioration, a multi-agent model was proposed to integrate the muscular fatigue into the FSSP by minimizing the total fatigue dose. Finally, the framework was validated by a case study application that took place in a manual picking line. The modeling of learning and fatigue effects and the computation of model parameters from real data were discussed. A bi-objective approach was proposed to minimize both makespan and total fatigue dose simultaneously. Break policies are recommended depending on the company's needs and the objective to prioritize. The aim of this work is to inspire future work that is interested in addressing operations research problems with a responsible incorporation of human factors.

Keywords: Scheduling; Flowshop; Learning effect; Fatigue effect

Résumé

Malgré l'essor de l'automatisation, les systèmes de production à forte main d'œuvre sont toujours utilisés en raison de la nécessité de flexibilité et de précision dans l'exécution de certaines tâches. Dans de tels contextes, on s'intéresse à l'impact de l'apprentissage et de la fatigue sur la productivité des tâches manuelles sur un problème d'ordonnancement de flowshop (FSSP). Dans un premier temps, une revue de la littérature a été réalisée sur le problème d'ordonnancement en considérant les effets d'apprentissage et de détérioration. Une approche théorique a été utilisée pour aborder le problème du FSSP avec effets d'apprentissage. Des modèles mathématiques minimisant la durée totale des travaux (makespan) ont été présentés. Des méthodes exactes et des heuristiques ont été proposées pour résoudre le problème pour des instances de petite et grande tailles. La fatigue étant un type de détérioration, un modèle multi-agents a été proposé pour valider l'intégration de la fatigue musculaire dans la FSSP en minimisant la dose accumulée de fatigue. Enfin, le cadre a été validé sur une étude de cas réalisée sur une ligne de préparation de commandes manuelle. La modélisation des effets d'apprentissage et de fatigue ainsi que le calcul des paramètres du modèle générés à partir de données réelles ont été discutés. Une approche bi-objectif a été proposée pour minimiser simultanément la durée totale des travaux et la dose de fatigue accumulé. Des politiques de pause sont recommandées en fonction des besoins de l'entreprise et de l'objectif à prioriser. L'objectif de ce travail est d'inspirer les travaux futurs qui s'intéressent à la résolution des problèmes de recherche opérationnelle avec une intégration responsable des facteurs humains.

Mots-clés: Ordonnancement; Flowshop; Effet d'apprentissage; Effet de fatigue

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- Isabel Allende -

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List of Abbreviations

The following list describes the significance of various abbreviations used in the thesis.

ACO: Ant Colony Optimization
AJ: Agent Jobs
ANOVA: AnalysisofVariance
API: Adjacent Pairwise Interchange
AS: Agent Station
AW: Agent Worker
BR: Balancing Related
BP: Break Policy
C-DE : Cumulative Deterioration Effect
CMR: Costumer Related
CR: Cost Related
CSA: Cloud Theory-based Simulated Annealing Algorithm
DJ-LE : DeJong's Learning Effect
DS: Diversification Strategy
EDD: Earliest Due Date
EMG: Electromyography
EP-LE: Exponential Learning Effect Based on Position
EST-LE: Exponential Learning Effect Based on Sum-of-Processing-Time
FastPGA: Fast Pareto Genetic Algorithm
FD: Fatigue Dose per Worker
FD_s: Standardized Total Fatigue Dose
FSSP: Flowshop Scheduling Problem
GA: Genetic Algorithm
GAKA: Genetic-Kangaroo Hybrid Algorithm
GE: Global Environment
GSD: Global Scheduling
HR: Heart Rate
HFSA: Hybrid Metaheuristic based on an SA Algorithm and a Firefly Algorithm
KA: Kangaroo Algorithm
JR: Johnson's rule
JRO: Job-related Objectives
LR: Learning Rate
LS: Local Search Operator
MET: Maximum Endurance Time or Maximum Fatigue for Muscular Exertion
MILP: Mixed-integer Linear Programming
MINLP: Mixed-integer Non-Linear Programming
MIP: Mixed-integer Programming
MOGA: Multi-objective Genetic Algorithm
MOSA: Multi-objective Simulated Annealing
MVC: Maximum voluntary Contraction
NSGA-II: Non-dominated Sorting Genetic Algorithm
NEH: Nawaz-Enscore-Ham A65lgorithm
NAPI: Non-Adjacent Pairwise Interchange

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NB: Number of Breaks
P-DE: Position-based Deterioration effect
P-LE: Position-Based Learning Effect
PSO: Particle Swarm Optimization
PST-LE: Combining Position and Sum of Processing Time-Based Learning Effect
PTA: Picking Technical Actions
RMA : Rate-modifying Activities
SA: Simulated Annealing Algorithm
SKU: Stock-keeping Unit
SPT: Shortest Processing Time
ST-LE: Sum-of-Processing-Time-Based Learning Effect
TBD: Total Break Duration
TFD: Total Fatigue Dose
TP-LE: Truncated Position-Based Learning Effect
TPT : Total Processing Time
TRO: Time-related Objectives
TS: Tabu Search
TSPOP: Population-based Tabu Search Algorithm
TST-LE: Truncated Sum-of-Processing-Time-Based Learning Effect
UOR: Utilization of Resources
UP: Upper Bound
LB: Lowe Bound
VO2: Oxygen Consumption
WIP: Work in Process
WMSD: Work-Relatel Musculoskeletal Disorder
WSPT: Weighted Shortest Processing Time

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Chapter 1

Introduction

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1.1 General Overview and Motivation

Scheduling is a decision-making process that plays an important role in manufacturing and service environments. It allows allocating limited resources to activities while optimizing one or more criteria (Leung, 2004; Pinedo, 2008). Studies in scheduling theory date back to the 1950s. Over the years, one of the main assumptions about scheduling problems has considered fixed job processing times, implying that humans participating in the system do not induce variability. Furthermore, when humans are considered, simplifications are incorporated. For instance, authors considered people not as a major factor or resource but as deterministic, predictable, stationary, and even emotionless (Lodree *et al.*, 2009).

In developing countries, human workers are still an essential resource in manufacturing systems and assembly lines, where production systems are largely manual, and factories are frequently seen as a source of employment (Baudin, 2020). Even in developed countries, many manual tasks remain in sectors such as luxury. As industrial automation technologies have limited flexibility (Kadir *et al.*, 2019), complex tasks still require typical human skills (e.g. precision, intelligence, analysis, and logic) (Sánchez-Herrera *et al.*, 2019) and have been involved in production systems implicitly or explicitly since its appearance (Dessouky *et al.*, 1995). Therefore, scheduling problems lend themselves to analysis from this perspective, as the production systems under study within this field inherently feature human workers in actual industrial scenarios. This perspective allows for analysis of scheduling problems, as production systems inherently involve human workers.

Industrial managers have been urged to develop more human-centred production systems under the framework of the fifth industrial revolution (Industry 5.0) (Goujon *et al.*, 2023; Katiraee *et al.*, 2022). The paradigm change requires the proposal of strategies that guarantee a sustainable, human-centred, and resilient industry (European Commission, 2022). Hence, government policies are becoming rigorous to reconcile the productive system and worker relationship, facing the challenge of ensuring that technology and workers work together in an environment that enhances and supports human work full-time, resulting in better system performance and worker well-being (Rossi *et al.*, 2023).

For years, the separation between human factors and operations management has been clear, as presented by Neumann and Dul (2010), who indicated in their review that human well-being publications are rarely published in business or management journals, even though the execution of a task may affect both systems and humans (Figure 1.1). Therefore, there is a need to address operational problems in a multidisciplinary way to facilitate the design of systems and respond to the current needs of needs.

Humans are usually more complex with more unpredictable behaviors than the inanimate resources associated with traditional scheduling models (Lodree *et al.*, 2009) due to their nature, capabilities, limitations, and the socio-technical interaction involving humans with other resources in the system (Neumann and Dul, 2010). In this interaction, elements to be considered include the cause of physical and cognitive or psychological

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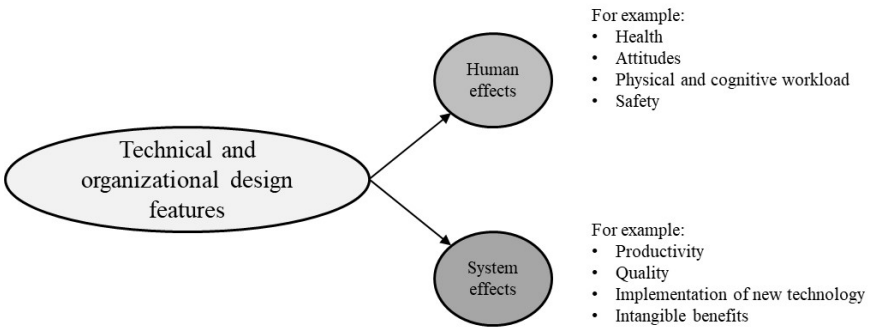

Figure 1.1: Effects of completing a task (Neumann and Dul, 2010)

loads generated by environmental factors (e.g. noise and temperature), ageing or forgetting phenomena, ergonomic factors (e.g. posture and repetitive work), and mental effort, which can trigger a resource deterioration, fatigue, poor motivation, and stress. All these can lead to adverse problems such as a lost of productivity, a low quality of products and-or services, poor personal satisfaction, and musculoskeletal disorders (Hsie *et al.*, 2009). Nonetheless, processes such as learning and recovery can enhance productivity levels.

Considering human characteristics, as called in the literature, results in scheduling problems with variable job processing times. Moray *et al.* (1991) presented one of the first contributions including humans in scheduling problems, incorporating behavior and workload when operators were confronted with several tasks. Dessouky *et al.* (1995) concluded that some characteristics and human behaviour attitudes may affect human performance at work, impacting the job processing time. Moreover, Lodree and Norman (2006) suggested that integrating human factors into scheduling approaches may include the following problem types: work-rest scheduling problems, job-rotation problems, personnel problems, and the job sequencing problems.

Pinedo (2008) puts forward that including humans in scheduling problems impacts the processing times of jobs and system performance in general, presenting learning and deterioration effects as the main phenomena that affects tasks involving manual operations. Indeed, certain characteristics are located within the learning effect category that decreases processing times (e.g. the learning process, motivation, and recovery). Others are human characteristics of the deterioration effect, including those that increase the processing time, such as forgetting, ageing, physical fatigue, cognitive fatigue, and stress (Ostermeier, 2020b).

Biskup (2008) classified the learning effect into induced and autonomous learning. Induced learning refers to the possibility of management investing in employee knowledge through additional training or changing the production environment. In contrast. autonomous learning (or learning by doing) cannot be influenced by the company, but it is achieved by repeating similar tasks, familiarization and routine. The last class is often associated with monotonous and repetitive activities.

During these activities, workers must perform awkward postures and repetitive movements with a high level of effort, triggering work-related fatigue (Finco *et al.*, 2020). Fatigue is a multidimensional condition (Grandjean, 1979) that can be mental (i.e. cogni-

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tive) and physical. Hand-intensive systems are interested in physical fatigue, particularly muscular fatigue linked to Work-related Musculoskeletal Disorders (WMSDs), one of the main causes of lost productivity in these industries (Finco *et al.*, 2020). For instance, in France, the annual cost of WMSDs for companies in the agrifood sector amounts to over 77 million euros (Ameli, 2023). Therefore, controlling risk, fatigue level, and WMSDs is necessary to guarantee workers' well-being, product quality, and efficiency (Finco *et al.*, 2020; Otto and Scholl, 2011).

These two phenomena are commonly observed in hand-intensive systems such as the textile and footwear industry, and also in assembly picking lines of every sectors. These systems involve sequential operations, resembling either a flowshop or a hybrid flowshop system, which in real circumstances, accurately represent numerous manufacturing settings (Botta, 1996; Ozsoydan and Sağir, 2021; Rudek, 2011). These industries are known for their high demand for repetitive and monotonous tasks.

The flowshop scheduling problem (FSSP) considers the problem of scheduling a set of n independent jobs, $j = 1, ..., n$, to be processed by a set of m resources (machines or workers), $i = 1, ..., m$. All jobs must follow the same production routing, resources are organized in series: job j is executed first by the resource 1, then by resource 2,..., and finally by resource m. Each resource is capable of process one job at a given time and preemption of a job is not allowed. All resources are available at the beginning of production horizon.

To deal with scheduling problems that incorporate human characteristics, Lodree and Norman (2006) propose a framework and identifies the main components that should be included

1. *job processing time models* allow for the representation of the effects of human learning, fatigue, stress, etc.,
2. *definition of breaks* also known as rate-modifying activities, necessary to recover during shifts,
3. *human performance metrics* related with human factors engineering such as reducing errors, improving productivity, enhancing safety, and improving comfort.

Performance metrics, such as minimizing cumulative physiological load, maximum heart rate, and maximum blood pressure, are also relevant. Figure 1.2, shows these components and the main contributions of this thesis in each of them.

This thesis was conducted based on such a framework, considering that addressing this problem requires decisions at different company levels. By using the contributions made to the assembly line problem of Finco *et al.* (2021) and Dolgui *et al.* (2022) and making a parallel for the scheduling problem, we can categorise the decisions (Table 1.1). Obtaining the schedule of jobs refers to operational decisions made in the short term (e.g. monthly, weekly, or daily). Moreover, the process and workplace design, workforce dimensioning (Dolgui *et al.*, 2018), and defining breaks and recovery policies are at the tactical level.

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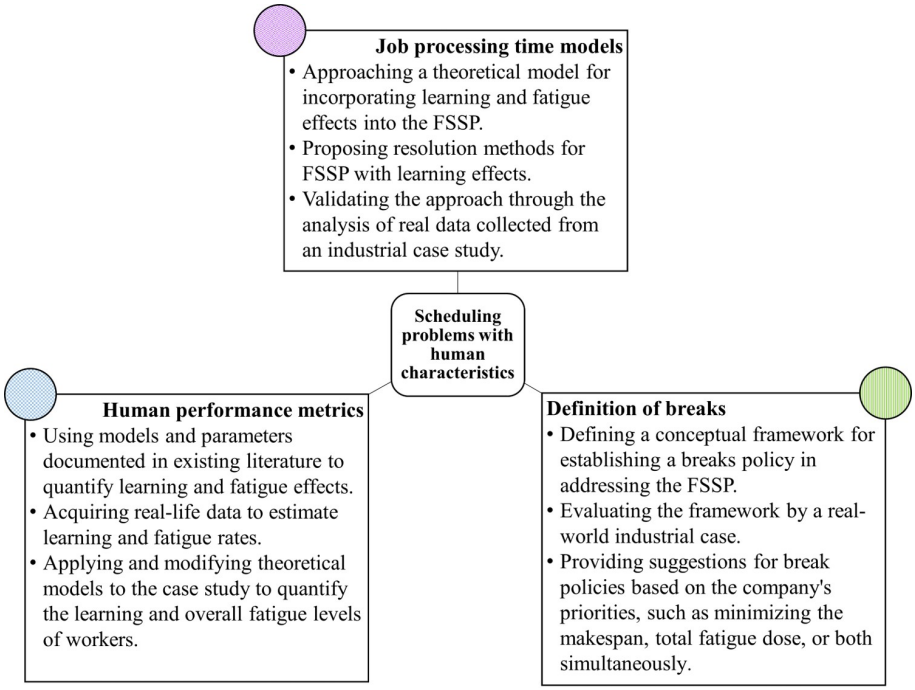

Figure 1.2: Scheduling Problems with Human Factors: Framework and Contributions (adapted from Lodree and Norman (2006))

Table 1.1: Decisional levels in scheduling problems with human characteristics (adapted from Finco *et al.* (2021) and Dolgui *et al.* (2022))

Decisional level	Type of decision
Strategic ♦	Configuration of the system Level of automation.
Tactical ★	Workplace design Process design Workforce dimensioning Breaks and recovery policies
Operational ▲	Job scheduling Planing period

The inclusion of human characteristics makes the problem more realistic, requires accurate modeling (Oujana *et al.*, 2022), but also presents at least two challenges. The first one is to model human characteristics, while the second to develop decision tools to address the problem and aligned with the needs of companies and their decision levels. As a result, the research questions and objectives of this thesis are defined in the following section.

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1.2 Research Questions and Objectives

Based on the previous overview, the general research questions for this doctoral thesis are as follows:

- ***RQ1***: What is the current state of the literature on scheduling problems with learning and deterioration effects regarding problem characteristics, optimization algorithms, and techniques used to solve them?
- ***RQ2***: How could the flowshop scheduling problem with a learning effect be modeled and which algorithms are suitable for its solution?
- ***RQ3***: How can physical fatigue and recovery be modeled and integrated into the FSSP with learning effects?
- ***RQ4***: How to find a balance between the objectives related to the system and human performance objectives (economic and social respectively) in the problem in question?

The objective of this thesis is to model the flowshop scheduling problem that considers the learning effect and incorporates fatigue while developing methods to solve such problems. Specific objectives are proposed for its development:

1. To characterize manual scheduling problems with human resources in order for identifying the key elements of learning and deterioration effects leading to mathematical modelling of such a problem.
2. To model the learning and fatigue effects, such as the type of deterioration in the flowshop scheduling problem.
3. To develop methods for solving the flow shop scheduling problem with learning effects and the incorporation of fatigue.
4. To validate the proposed approach through the application in a real case study.

1.3 Thesis Outline

Chapter 2 presents a systematic literature review of scheduling problems with learning and deterioration effects to identify characteristics of similar problems to be addressed in this thesis, methods to model the learning and deterioration effect, and solution approaches. In C**hapter 3**, four cases of learning effects identified in Chapter 2 are selected. Here, the flowshop scheduling problem with a learning effect minimizing the makespan is modelled. Small-size instances are solved optimally, while, for large instances, the Johnson's rule and an adapted Nawaz-Enscore-Ham algorithm are proposed for the two-resources flowshop. Finally, to solve large-size instances, a simulated

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annealing approach is developed by testing two local search operators. The proposed algorithms are experimented, comparing the four learning cases. **Chapter 4** incorporates a model for physical fatigue and recovery into the flowshop scheduling problem. Hence, a multi-agent system model is proposed. Computational experiments are conducted to evaluate two break policies and their impact on both the system and human performance. **Chapter 5** shows an application of the approach presented in the previous chapters in a real case study, and a bio-objective approach is proposed to minimize the makespan and the total fatigue dose. It shows how the learning and fatigue parameters are approximated using real data. Finally, **Chapter 6** provides the general conclusions of this thesis, with perspectives for future research. Most of the results from Chapters 2 and 3 were published in journal articles or conferences. A journal article compiling the contributions of Chapters 4 and 5 is currently in progress during the writing of this thesis. The scientific production is summarised in section 1.4.

Figure 1.3 presents the thesis structure, showing how research questions are connected with the chapters. Similarly, the coloured circles represent each chapter's characteristics from the framework purpose by Lodree and Norman (2006) (Figure 1.2). Finally, the design level of the problems addressed in each chapter is identified from the symbols stated in Table 1.1.

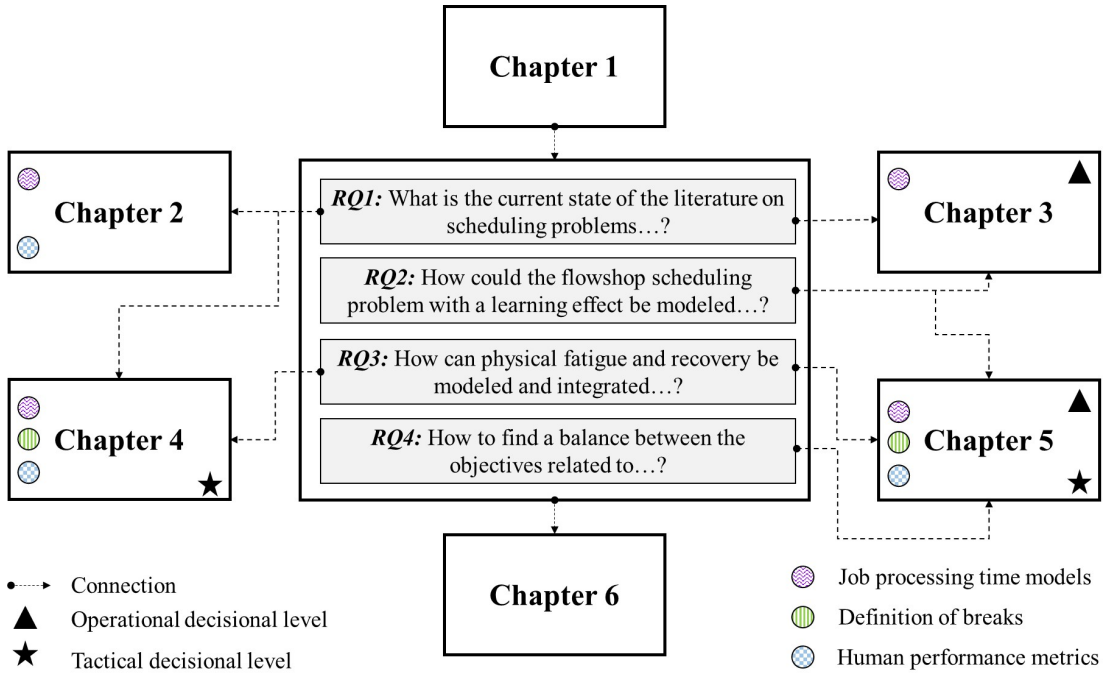

Figure 1.3: Thesis Structure

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1.4 Research Outcomes

Journal papers

- *Paredes-Astudillo, Y. A., Botta-Genoulaz, V., and Montoya-Torres, J. R. (2023). Impact of learning effect modelling in flowshop scheduling with makespan minimization based on the Nawaz-Enscore-Ham algorithm. International Journal of Production Research, 1-16, https://doi.org/10.1080/00207543.2023.2204967*

- *Paredes-Astudillo, Y. A., Montoya-Torres, J. R., and Botta-Genoulaz, V. (2022). Taxonomy of scheduling problems with learning and deterioration effects. Algorithms, 15(11), 439, https://doi.org/10.3390/a15110439*

- *Paredes-Astudillo, Y. A., Montoya-Torres, J. R., Botta-Genoulaz, V., Caro, M. P. and Jimenez, J.F. Flowshop scheduling problem with learning effect and incorporation of fatigue phenomena: a case study, to be submitted.*

Conference with proceedings

- *Paredes-Astudillo, Y. A., Botta-Genoulaz, V., and Montoya-Torres, J. R. (2022). Comparing linear and non-linear modelling approaches of learning effects in 2-stage flowshop scheduling problems. In IFAC-PapersOnLine: 10th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2022 (Vol. 55, pp. 842-847). Elsevier. https://doi.org/10.1016/j.ifacol.2022.09.517*

- *Paredes-Astudillo, Y. A., Montoya-Torres, J. R., and Botta-Genoulaz, V. (2023, October). Comparison of Nawaz-Enscore-Ham Algorithm and Local Search Operator in Flowshop Scheduling with Learning Effects. In Operations Research and Analytics in Latin America: Proceedings of ASOCIO/IISE Region 16 Joint Conference 2022 (pp. 77-86). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-28870-8_6*

- *Paredes-Astudillo, Y. A., Jimenez, J.F., Montoya-Torres, J. R., and Botta-Genoulaz, V. (2023). Fatigue integration to the flowshop scheduling problem. Service Oriented, Holonic and Multi-Agent Manufacturing Systems for Industry of the Future: Proceedings of SOHOMA 2023 (to appear). Annecy, France, September 28-29, 2023.*

Conference with abstracts

- *Paredes-Astudillo, Y. A., Botta-Genoulaz, V., Montoya-Torres, J. R., and Caro, M. P. (2023, June). Approach to Integrate the Learning and Fatigue Effect Into the Flowshop Scheduling Problem. The Fourth International Workshop on Dynamic Scheduling Problems, Winterthur, Switzerland, June 5-6, 2023.*

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- *Paredes-Astudillo, Y. A., Botta-Genoulaz, V., and Montoya-Torres, J. R. (2022). Comparison of two linear modeling of the learning effect in a two-resources flowshop. 23ème édition du congrès annuel de la Société Française de Recherche Opérationnelle et d'Aide à la Décision - ROADEF 2022, Lyon, France, February 23-25, 2023.*
- *Paredes-Astudillo, Y. A., Botta-Genoulaz, V., and Montoya-Torres, J. R. (2022). Comparison of nawaz-enscore-ham algorithm and Johnson's rule in a two-resources flowshop with learning effects. The Escuela Latinoamericana de Verano in Investigación Operativa - ELAVIO summer school 2022, Monterrey, Mexico, June 13-17, 2022.*

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Chapter 2

Literature Review

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2.2.2 Collection and Selection of Articles . . . 14
2.2.3 Analysis and Presentation of Results . . . 15
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2.3.3 Modeling of Learning and Deterioration Effects . . . 21
2.3.4 Resolution Methods . . . 28
2.4 Discussion . . . 32
2.5 Conclusions . . . 34

The content of this chapter is based on the following publication:

- *Paredes-Astudillo, Y. A., Montoya-Torres, J. R., and Botta-Genoulaz, V. (2022). Taxonomy of scheduling problems with learning and deterioration effects. Algorithms, 15(11), 439, https://doi.org/10.3390/a15110439*

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Abstract

This first chapter gives an overview of scheduling problem with learning and deterioration effect. These effects can decrease or increase the actual processing time when workers execute a job. In order to achieve a comprehensive understanding of this domain, we review relevant contributions addressing the scheduling problem with learning and deterioration effects. To begin with, the methodology is stated. Secondly, a bibliometric analysis is developed. Subsequently, an in-depth analysis based on problems characteristics, modeling approaches of learning and deterioration effects and resolution methods used in the literature is conducted. Finally, some opportunities for future research have been identified.

2.1 Introduction

Scheduling problems with learning and/or deteriorating effect is part of the family of scheduling problems with time-changing effects. Since the 1990s, authors have expressed their interest in such problems where the job processing times are affected by their location in the sequence. While it is true that the first idea that arises from learning processes relates to the tasks carried out only by humans, it is also relevant in mixed environments (interaction between machines and humans) because human expertise in activities, such as maintenance and monitoring are decisive in system performance. In the same way, machines and devices managed by artificial intelligence can take advantage of the learning process (Rudek, 2012). Similarly, when we talk about deterioration processes, the term can refer to two phenomena: the first one being job deterioration, where the job itself deteriorates while waiting for processing. The second one causes us to think of a phenomenon in which the resource degrades because of its use or its age, for example. We tend to see it as only affecting machines, but it can also occur with humans, such as fatigue or aging. Consequently, it is relevant to take into account these adaptations to the traditional scheduling problem.

In recent years, the number of publications addressing scheduling problems with learning or deterioration effects has increased. Some of the published literature reviews focus mainly on the learning effect. For instance, Anzanello and Fogliatto (2005) presented a state-of-the-art related to learning and forgetting curves, describing each model and showing their opportunities and limitations for applications in industrial settings. Biskup (2008) reviewed the progress of the learning effect on scheduling problems and formally distinguished position-based and time-based learning. Lodree *et al.* (2009) presented a framework for scheduling and integration of human factors (physical and/or cognitive human characteristics and behaviors). While they emphasized the importance of interdisciplinary cooperation, Azzouz *et al.* (2018) reviewed several learning models and proposed categories to classify the most common approaches. Recently, Xu and Hall (2021) presented a review of fatigue forecasting and measurement methods, as well as the integration of fatigue forecasting into work–rest scheduling, shift scheduling and personnel scheduling. In 2022, Pei *et al.* (2022) propose a classification scheme for learning and deterioration model used in scheduling problems. It categorizes the effects of learn-

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ing and deterioration into three broad categories: general processing, batch scheduling, and group scheduling.

The review proposed in this chapter builds upon those previous works by proposing an approach quantitative and descriptive instead of following a narrative structure. The objective is to conduct a review of relevant publications from 1999 to July 2023, followed by an analysis of the scope and contributions of the selected studies, with the aim of identifying research gaps. The review protocol presented in this chapter can be further replicated to update future research progress on this topic. Our contribution is twofold. First, with the arrival of the fifth industrial revolution (Industry 5.0), productive systems become human-centered systems. Therefore, understanding how the behavior of human beings can be modeled contributes to improving decision-making in labor-intensive manufacturing systems, especially where labor is costly (Glock *et al.*, 2019a). Second, reviewed models can help to incorporate changes in working conditions due to new challenges and needs for industrial systems, mainly when they require human workers.

This chapter is organized as follows. Section 2.2 presents the research methodology. Section 2.3 describes the results. This includes bibliometric analysis, categorization and analysis associated with the problem characteristics. In addition, different approaches to modeling learning and deteriorating effects are introduced. It is proposed a classification of the resolution methods found in the literature. Section 2.4 discusses the main findings of this review and highlights opportunities for future research. Conclusions are drawn in Section 2.5.

2.2 Materials and Methods

In this chapter, we follow the principles of literature reviews (Badger *et al.*, 2000; Snyder, 2019) to build upon published works and analyze the current state of knowledge. In contrast to narrative reviews, a systematic approach allows the application of a well-defined, unbiased, and reproducible protocol for the identification and analysis of documents. The literature review presented here was carried out according to the protocol presented by Badger *et al.* (2000): (i) identification of the research question; (ii) collection and selection of articles; and (iii) analysis of short-listed articles and presentation of results. This protocol is documented below.

2.2.1 Specific Research Questions

With the objective of identifying approaches related to scheduling problems with learning and deteriorating effects, a general research question was defined as follows: *To what extent have scheduling problems been modeled and solved to deal with learning and deteriorating effects in job processing times?* Five specific research questions (SRQ) have been created to address the above question as follows:

- *SRQ1*: What are the directions toward which researchers are focusing scheduling

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problems with learning and deterioration effects?

- *SRQ2*: What are the system configurations studied in the literature?
- *SRQ3*: Which have been the most common objective functions considered?
- *SRQ4*: What approximations have been used in the scientific literature to model both learning and deterioration effects?
- *SRQ5*: What resolution methods have been used to solve the problems?

2.2.2 Collection and Selection of Articles

SCOPUS and Web of Science databases were chosen to locate studies related to the research topic. The rationale for this choice is that these databases are world leaders in peer-reviewed journal ranking and evaluation (Zhu and Liu, 2020). They are two global and multidisciplinary databases that have the highest score in the visibility index. This means that the quality of the research results is already guaranteed because there is a demanding process to review articles published in journals within these databases.

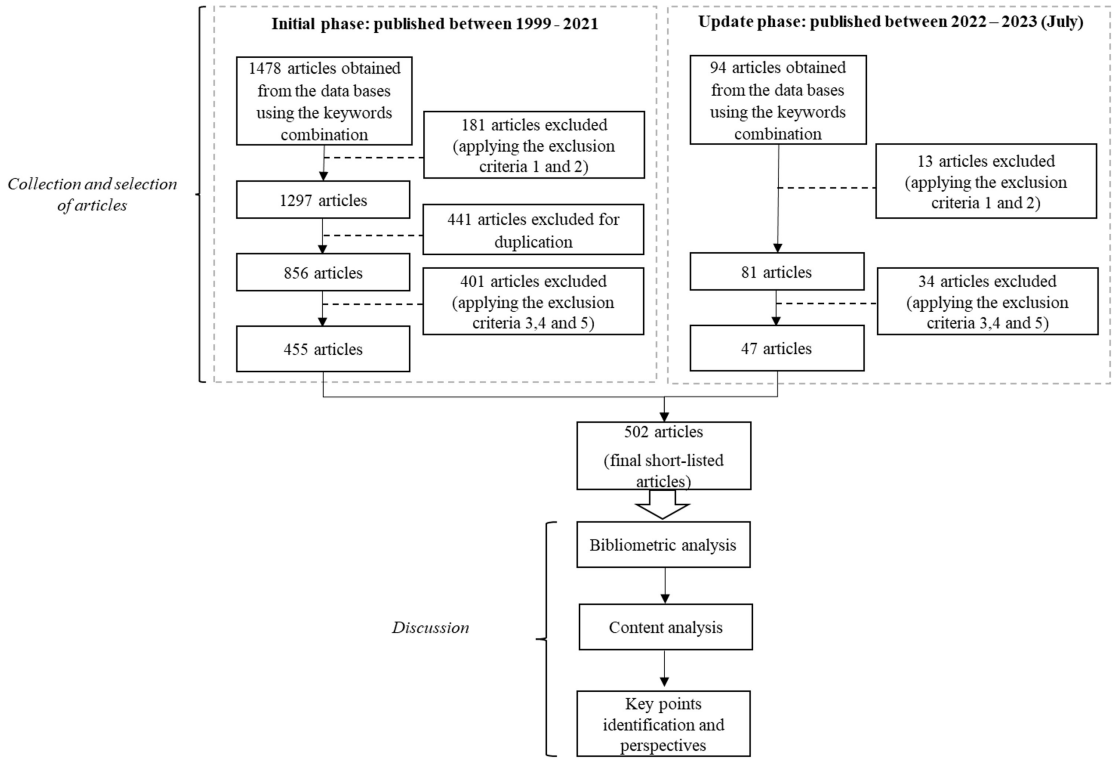

Figure 2.1: Flowchart of the sequence followed for the literature review

This review was conducted at two main phases: i) January to December 2021, starting with a pilot test to define the most appropriate keywords used in the literature to approach this topic. ii) In July 2023, an update was made to the articles that were published in 2022 and 2023. The searches were then limited, and the databases were asked to search

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for the following equation in Title–Abstract–Keywords: ((scheduling) AND ("learning effect" OR "deterioration effect")), this search equation was used together with SCOPUS and Web of Science. In addition, inclusion and exclusion criteria were defined as follows:

1. Only papers written in English were included.
2. Book chapters and conference papers were not considered.
3. Review papers, editorial notes, letters to the editor or similar documents were not included. Review papers were nevertheless useful in providing information on progress on this topic and were taken as a starting point for the development of this review.
4. Only papers explicitly defining a system configuration (e.g., single machine, flow-shop, etc.) were included.
5. Papers had to address a scheduling problem.

As shown in Figure 2.1, in the initial phase, the output of combining the keywords string produced a set of 1478 documents. After filtering by papers written in english and excluding conference papers and book chapters, a set of 1297 research articles was evaluated. In a third step, duplicated articles were removed. Finally, titles and abstracts were read in detail to remove papers that were not within the scope of this review, in addition to those not dealing with scheduling problems or not explicitly presenting a shop configuration as well as literature review articles. With regard to the update phase, the same steps previously outlined were followed for the papers published between 2022 and 2023. The search was conducted in SCOPUS, the database that yielded the highest quantity of contributions in the previous phase. There were 455 articles included in Paredes-Astudillo *et al.* (2022b), and 47 were added in the last update, bringing the total to 502 research papers short-listed for further analysis and classification.

2.2.3 Analysis and Presentation of Results

A preliminary bibliometric analysis was conducted for the short-listed articles. The software VOSviewer was used to find and develop a co-occurrence analysis of author countries and possible thematic trends. The final set of 502 research papers was analyzed in detail and key information was abstracted. The results are summarized and classified considering descriptive information such as (1) journal and year of publication, (2) type of system configuration under study, (3) objective function(s), (4) proposed resolution method, and (5) effects on the processing time (learning and/or deterioration). The proposed analysis is intended to answer the previous research question. The analysis steps followed and sections in this paper are listed in Table 2.1 (following a similar format used by Parente *et al.* (2020).

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Table 2.1: Approaches to Address the Review's Research Questions

SRQ	Section	Methodologies	Outputs
1	2.3.1	Bibliometric analysis of the final short-list articles (from Scopus and Web of Science).	Identify publications by year, country, distribution of main publishing journals, and thematic trends.
2, 3	2.3.2	Classification, descriptive analysis, and content analysis of short-listed articles.	Identification of system configuration approach, types of objective functions, and the criteria taken into consideration.
4	2.3.3		Identify relevant models proposed to address the learning and deterioration effect regarding scheduling problems.
5	2.3.4		Recognize resolution methods employed in these problems and the frequency of use.

2.3 Results

2.3.1 Bibliometric Analysis

Bibliometrics analysis consists of the use of quantitative research methods to analyze bibliographic material, with a view of mapping research works (Merigó and Yang, 2017; Montoya-Torres *et al.*, 2021; Noyons *et al.*, 1999). Bibliometric analysis also serves to evaluate research performance (per country, university, etc.) and allows us to understand relations between scientists. From an academic point of view, applying bibliometric analysis to map research works on scheduling with learning and deteriorating effects will help both researchers and practitioners better understand the advances and trends in the field, as well as enable them to make decisions and take action in a more informed way (Gaviria-Marin *et al.*, 2019). From a static perspective (i.e., printing year), this literature review includes articles published from 1999 (first official publication on the topic) to July 2023. Biskup (1999) published the first study. His paper can be considered the starting point of research activities related to this field. The number of articles has since grown, with a peak in 2013 (see Figure 2.2). There has been a rising trend in this area since 2009, with an average of 31 articles per year in the period 2009–2023 (July). This result may be explained by the fact that around 2011, the concept of the fourth industrial revolution appeared. Despite the high levels of automation, this has brought the challenge of integrating humans into production systems and redefining their roles.

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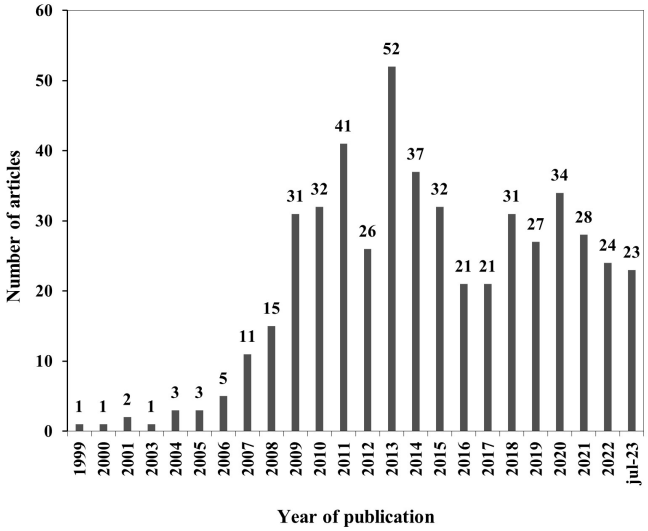

Figure 2.2: Frequency of publications per year

Figure 2.3 presents the most relevant journals in this area by the number of publications. Each of these journals published ten or more articles, meaning 56.5% of the total number of publications. Surprisingly, we can observe that the top three journals do not particularly focus on operations research.

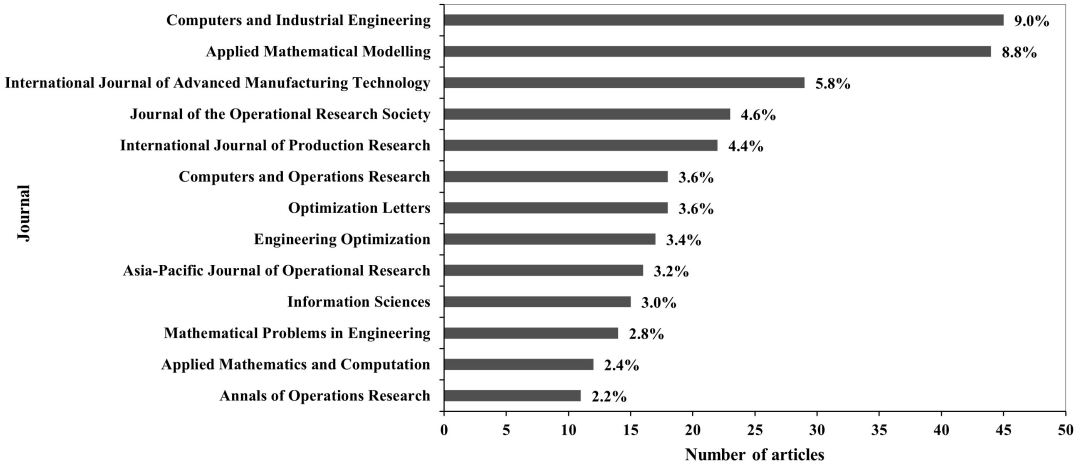

Figure 2.3: Frequency per journal (journal with ten contributions or more)

To deepen our comprehension of the short-listed papers, we used VOSviewer software (Van Eck and Waltman, 2010) to analyze the co-occurrences of a country's authors. Figure 2.4 shows the most productive countries in this field (with five or more articles) until 2023, of which China is in the lead. There are four clusters, the green cluster (China, USA, and Poland), the red cluster (Turkey, Iran, Canada, France, and Australia), the blue cluster (Taiwan and Tunisia), and finally, Hong Kong in yellow. In general, the Asian countries are interested in research in this field (even given the thick lines, high levels of cooperation between China-Taiwan and China-Hong Kong can be deduced). A possible cause for this might be that a large proportion of short-listed articles focus on the pro-

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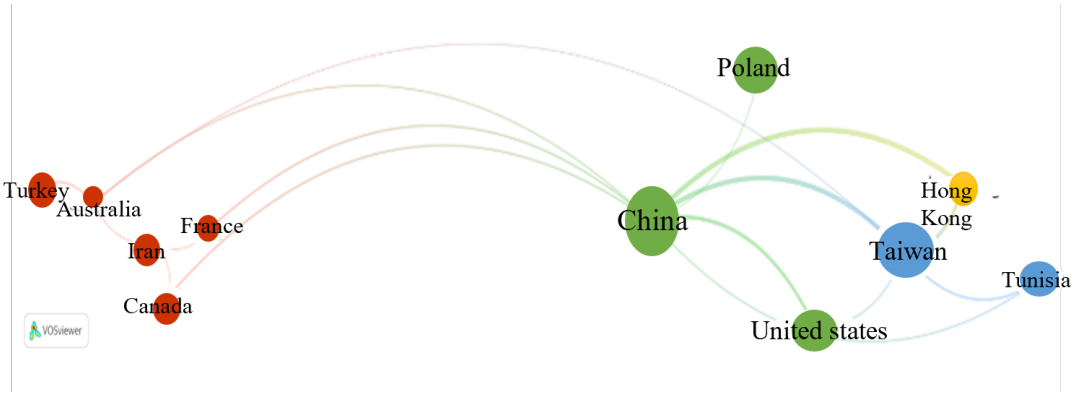

Figure 2.4: Co-authorship countries (source: VOSviewer)

posal of approximation algorithms, with the definition of dominant rules and bounds, a subject in which Asian countries have demonstrated considerable interest and progress. Moreover, the interest shown by Asian countries in such subjects may be explained by the fact that they have developed a strong manufacturing industry; it is of great benefit to understand and measure worker productivity in hand intensive tasks.

2.3.2 Classification Related to Problem Characteristics

After a preliminary paper scan to exclude papers that were not related to the scheduling problem (exclusion criteria 5), the final screening of the pre-selected articles was performed manually. Read first was the title, the abstract and then the methods for retrieving detailed information. We provide an analysis and categorization of all the selected articles based on the system configuration, type of job processing time and the type of objective functions.

System configuration

The output of the analysis allows six (6) categories to be identified, from the simplest single machine configuration to more complex configurations such as hybrid production systems. The single machine configuration with 317 articles (63.1%) has the highest frequency of works, followed by 111 articles that consider the flowshop system (22.1%) and 81 articles that study the parallel machine configuration (16.1%). Finally, the three least common configurations are the hybrid flowshop with 12 articles, 7 articles related to the job shop configuration and the flexible job shop with 7 articles. The importance of works related to the single machine scheduling problem may be because it makes it possible to understand and conceptualize the problem and to extrapolate solution alternatives to other shop configurations. In addition, this problem is particularly important because, as Pinedo (2008) explains, scheduling problems in complex configurations could be decomposed into single machine sub-problems. Figure 2.5 summarizes the distribution of articles per system configuration and per year.

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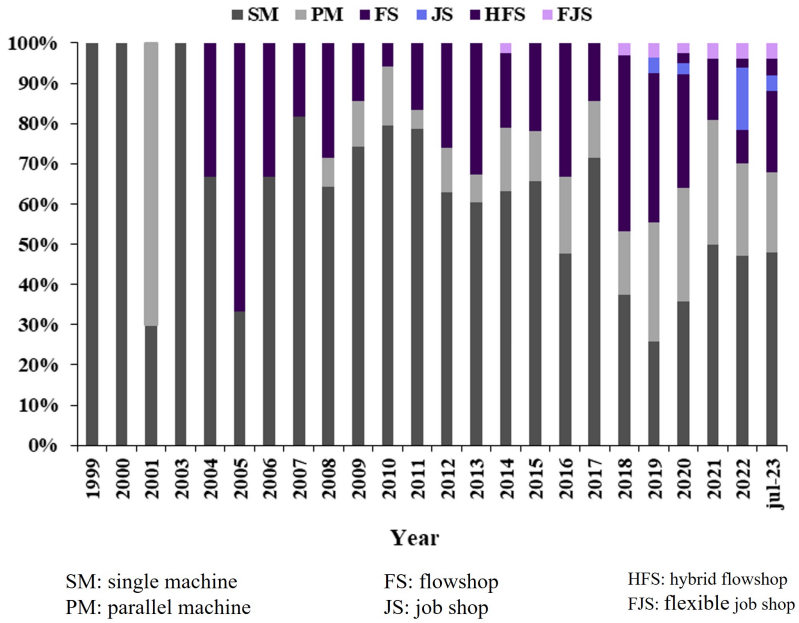

Figure 2.5: Distribution of short-listed articles according to the system configuration and year of publication

Job Processing Time

In general, scheduling problems are considered in a deterministic environment, but some authors have managed scheduling under uncertainty using stochastic parameters or fuzzy sets. The stochastic approach used to calculate processing times is found in 2.2% of short-listed articles, in single-machine configurations (Li, 2017; Luo, 2022; Roohnavazfar *et al.*, 2021; Shen, 2020; Soroush, 2014a; Soroush, 2014b; Wei, 2019; Zhang *et al.*, 2013), parallel machine shops (Shen, 2019; Wang and Qi, 2023), and flowshop (Fu *et al.*, 2018). The fuzzy approach is employed in 2.2% of the articles to model the job processing time. The single machine configuration appears in the majority of the contributions (Ahmadizar and Hosseini, 2011; Ahmadizar and Hosseini, 2013; Toksari and Arık, 2017), followed by the parallel machine configuration (Arık and Toksarı, 2021; Ebrahimi *et al.*, 2022; Geyik and Elibal, 2017; Li *et al.*, 2020; Pakzad-Moghaddam, 2016; Rostami *et al.*, 2015).

Objective Function

Our findings show that most short-listed research papers (71.5%) focus on a single optimization criterion, while 28.5% deal with the optimization of multi-criteria objective functions. In recent years, scheduling problems dealing with multi-criteria objective functions have become popular because of the more complex industrial environments (Jeong *et al.*, 2021).

Related to the classical criteria considered in scheduling problems, the most studied objective functions are the minimization of makespan (303 articles), the minimization of

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total completion time (178 articles), and the minimization of weighted completion time (86 articles). As the authors consider workers, machines, or both as resources, some objective function criteria such as machine hiring costs, maintenance costs and total energy consumption could be found.

Since more than 30 objective functions criteria were identified in the short-listed articles, a grouping is proposed, taking as a reference the taxonomies suggested by (Akbar and Irohara, 2018; Botta, 1996; Lee and Loong, 2019). The objective functions are classified as time-related objectives (TRO), job-related objectives (JRO), cost-related, and environmental objectives. The first category includes the utilization of resources and work-in-process. The second category covers objectives related to customer satisfaction and work balancing. The third and fourth categories, respectively, group together functions that evaluate costs and sustainability criteria (which include environmental and social criteria). Appendix A.1, shows the notation of the objective functions; however, variations concerning the original equations may occur depending on the configuration of the system studied.

The criteria that belong to the category TRO—utilization of resources criteria are more frequent. Then comes TRO—work in progress. In third, fourth and fifth place are JRO—customer-related, cost-related and JRO—balancing-related. Finally, sustainable objectives are rarely considered. As shown in Figure 2.6, most studies have been oriented towards traditional scheduling criteria, that means an economic benefit to the system.

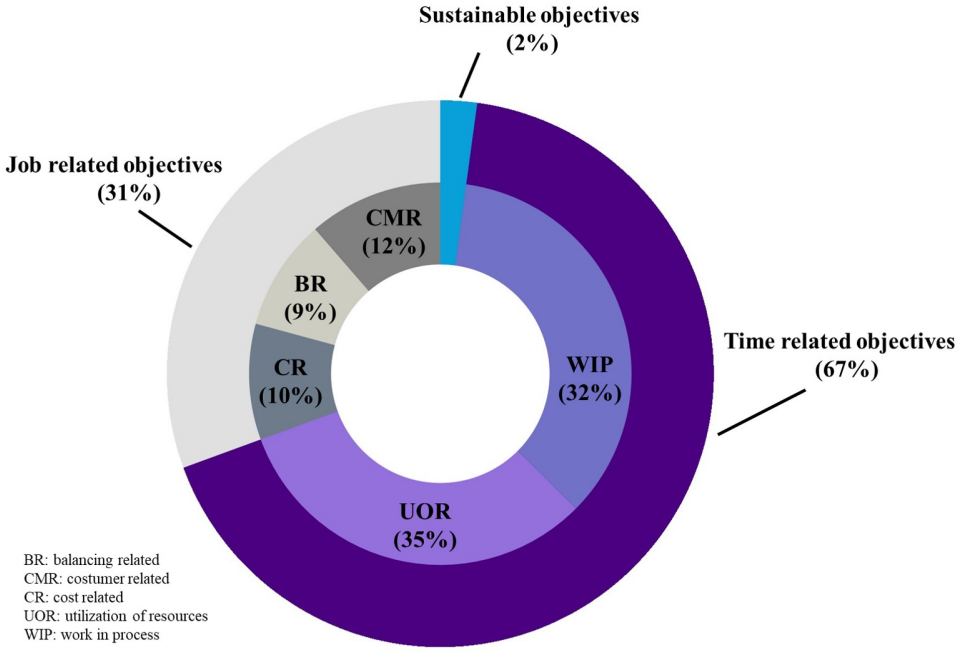

Figure 2.6: Distribution by objective function categories

In recent years however, there has been growing interest in working with sustainable systems, which has led to the integration of sustainability criteria into objective functions. In this last category, we include the criteria aimed at minimizing energy consumption or emissions (Abedi *et al.*, 2020; Li and Chen, 2023; Liu *et al.*, 2019; Peng *et*

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al., 2021; Sekkal and Belkaid, 2023; Soleimani *et al.*, 2020; Tigane *et al.*, 2019; Wang and Qi, 2023; Xin *et al.*, 2023), as well as criteria pertaining to socially-oriented objective functions such as minimization of Work-Related Musculoskeletal Disorder (WMSD) risks (Şenyiğit *et al.*, 2020), minimization of the average rate of workers' deterioration (Ostermeier, 2020a) and of the noise levels to which workers are exposed (Peng *et al.*, 2021). An increase has been observed in the incorporation of objective functions related to energy consumption minimization in the years 2022-2023. It can be attributed to the energy constraints resulting from the geopolitical conditions which arose in those years.

2.3.3 Modeling of Learning and Deterioration Effects

As pointed out previously, since production resources are not static and unchangeable over time, job processing times could increase when a resource deteriorates, or decrease when a resource improves in terms of productivity. When humans carry out tasks, many characteristics can have an effect and can be grouped into two categories known as learning effects and deterioration effects (Pinedo, 2008; Strusevich, Rustogi, *et al.*, 2017). The learning effect category includes characteristics that reduce processing times, such as the learning process, motivation, and recovery, among others. The deterioration effect category includes the aging and forgetting effect, for example. Figure 2.7 shows the classification of the approaches of learning and deterioration effects identified in this review. The categories are regrouped according to the key principle from which the model is developed. This section provides a summary and a description of the approaches to model the learning and/or deterioration effects of scheduling problems.

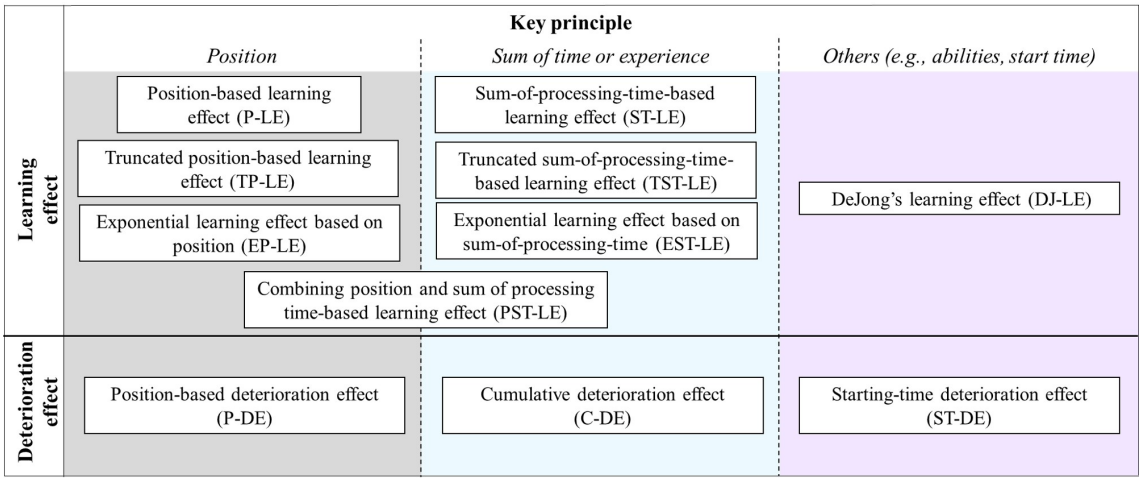

Figure 2.7: Taxonomy visualization

Learning Effect

The learning effect in manufacturing systems was introduced in the work of Wright (Wright, 1936), who stated the increase in productivity as a function of the number of units completed. Thus, monotonous activities have the potential to be improved to achieve a high level of productivity thanks to practical experience (Arditi *et al.*, 2001).

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As a result of the invention of the learning equation, certain models were proposed, enhanced, and brought closer to reality. The first study of scheduling with learning effects did not appear until 1999, with the seminal work of Biskup (Biskup, 1999) and then Cheng and Wang (Cheng and Wang, 2000), whose articles have become the baseline on the subject.

Several models have been proposed in the literature and have been grouped together for their analysis. Biskup (2008) classified them in two approaches: (i) position-based learning effects, and (ii) sum-of-the-processing-time learning. Azzouz *et al.* (2018) subsequently updated this classification and analyzed some works on the topic up to 2017. The sets that will be used from now on have their definitions listed below.

I:	Set of Workers
J:	Set of Jobs
R:	Set of Positions

It presents an analysis of articles that parts of the one proposed by Azzouz *et al.* (2018), with some modifications. The definition and certain reference models for each category are described below.

Position-Based Learning Effect (P-LE)

In this approach, the learning effect is affected by the number of jobs processed previously (Biskup, 2008). Job processing time therefore decreases with the number of repetitions rather than accumulated time (Azzouz *et al.*, 2018). In 1999, Biskup (1999) demonstrated that the single machine scheduling problem can be solved in polynomial time and introduced the equation to calculate the actual job processing time:

$$p_{jr} = \bar{p}_j r^{\alpha} \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.1}$$

where $\bar{p}_j$ is the baseline processing time, p_{jr} is the actual processing time of the job *j* located in position *r* of the schedule. The constant learning index is α ($\alpha < 0$). Even though some authors have modified Biskup's equation or proposed their own equations, they are all based on the principle of the number of repetitions. This approach is the one most commonly used in the short-listed articles.

Truncated Position-Based Learning Effect (TP-LE)

This phenomenon is intended to bring the learning effect closer to the reality. For a truncated based position learning effect, the processing time of the job depends on its position and a control parameter, which indicates the learning limitation. In the work of Cheng and Wang (2000) the existence of a learning threshold value is already mentioned. An approach in a single machine scheduling problem, where the actual processing time of a job (p_{jr}) is defined according to Equation 2.2. $\bar{p}_j$ is the baseline processing time, α is a parameter of learning effect ($\alpha < 0$) and β is a control parameter for learning truncation with ($0 < \beta < 1$). The last parameter introduces a lower bound on the processing time.

$$p_{jr} = \bar{p}_j \max\{r^{\alpha}, \beta\} \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.2}$$

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Some variations have been proposed, such as the one reported by Wang *et al.* (2021b), incorporating the consumption of convex resources. In their equation, $\alpha < 0$ is the job-dependent learning factor, η is a positive constant (Monma *et al.*, 1990; Shabtay and Steiner, 2007), and u_j is the amount of resource that can be allocated to job *j*.

$$p_j(r, u_j) = \left(\frac{\bar{p}_j \max\{r^{\alpha_j}, \beta\}}{u_j} \right)^{\eta} \quad j = 1, \ldots, J; \tag{2.3}$$

Exponential Learning Effect Based on Position (EP-LE)

Unlike position-based approaches, the exponential learning effect based on position explains a learning process where the job processing time decreases progressively, thus ensuring the quality of the products. Equation 2.4 shows the model proposed in a flow-shop scheduling problem by Cheng (2013), where $\bar{p}_{ij}$ is the baseline processing time, p_{ijr} denotes the actual processing time of job j on the $r-th$ position of the machine or worker i,

$$p_{ijr} = \bar{p}_{ij}\alpha^{r-1} \quad i = 1, \ldots, I; j = 1, \ldots, J; r = 1, \ldots, R \tag{2.4}$$

Sum-of-Processing-Time-Based Learning Effect (ST-LE)

The model presented by Kuo and Yang (2006a) in a single machine scheduling problem is based on the proposition that the more a worker performs a task, the higher his performance will be. From this point of view, the learning effect is expressed in terms of the total processing time of the previously completed jobs. The actual job processing time (p_{jr}) is defined by Equation 2.5, where $\alpha \leq 0$ is a constant learning rate and $\bar{p}_j$ is the baseline processing time.

$$p_{jr} = \left(1 + \sum_{k=1}^{r-1} p_k \right)^{\alpha} \bar{p}_j \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.5}$$

An alternative approach to this model was developed by Liang *et al.* (2019), who, keeping in mind that learning is a declining phenomenon, proposed a sum-of-logarithm-processing-times-based learning effect. These authors studied a flowshop scheduling problem. The equation is given as:

$$p_{ijr} = \left(1 + \sum_{k=1}^{r-1} \ln(p_{ik}) \right)^{\alpha} \bar{p}_{ij} \quad i = 1, \ldots, I; j = 1, \ldots, J; r = 1, \ldots, R \tag{2.6}$$

where $\bar{p}_{ij}$ is the baseline job processing time and $\alpha \leq 0$ is the learning rate.

Truncated Sum-of-Processing-Time-Based Learning Effect (TST-LE)

The use of the truncated function can indeed be justified since the learning is limited. For this model, the actual job processing time depends on the sum of processing times

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of jobs processed previously and a control parameter (Wu *et al.*, 2012b). Therefore, for the case of a single machine as studied by these authors, the actual processing time of a job (p_{jr}) is defined as follows:

$$p_{jr} = \max\left\{\left(1 + \sum_{k=1}^{r-1} p_k\right)^{\alpha}, \beta\right\} \bar{p}_j \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.7}$$

Another approach is proposed by Wu *et al.* (2011b) as below:

$$p_{jr} = \max\left\{\left(1 - \frac{\sum_{k=1}^{r-1} p_k}{\sum_{k=1}^{n} p_k}\right)^{\alpha}, \beta\right\}, \bar{p}_j \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.8}$$

where $\bar{p}_j$ is the baseline processing time, α the learning index, β the truncated parameter with $\alpha \leq 0$ and $0 < \beta < 1$.

Exponential Learning Effect Based on Sum-of-Processing-Time (EST-LE)

Some authors have included a learning effect based on an exponential sum of processing time. For instance, Wang *et al.* (2009) described this phenomenon using the following example: if human interactions have a significant impact during the processing of a job, workers will gain experience. The actual job processing time (p_{jr}) in a single machine scheduling problem is then as shown in Equation 2.10.

$$p_{jr} = (\delta\alpha^{\sum_{k=1}^{r-1} p_k} + \gamma)\bar{p}_j \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.9}$$

Wang *et al.* (2010) defined the actual processing time of a job (p_{jr}) as an exponential function of the sum of the logarithms of the processing times of the previously processed jobs.

$$p_{jr} = (\delta\alpha^{\sum_{k=1}^{r-1} ln(p_k)} + \gamma)\bar{p}_j \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.10}$$

where $\bar{p}_j$ is the baseline processing time, $\delta \geq 0$, $\gamma \geq 0$ and $0 < \alpha \leq 1$ are parameters obtained empirically, and $\delta + \gamma = 1$. They use Pegel's learning curve (Pegels, 1969) as a starting point.

Combining Position and Sum of Processing Time-Based Learning Effect (PST-LE)

This type of model mixes both phenomena, combining the position-based learning effect to model machine learning effects with the sum-of-processing time (Azzouz *et al.*, 2018). In the case of (Cheng *et al.*, 2008), the actual processing time of a job in the single machine problem is a function of the baseline total processing time of previously processed jobs, as well as the position. The model is presented below.

$$p_{jr} = \bar{p}_j \left(1 - \frac{\sum_{k=1}^{r-1} p_k}{\sum_{k=1}^{n} \bar{p}_k}\right)^{\alpha_1} r^{\alpha_2} \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.11}$$

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where α_1 and α_2 indicate the learning rate, with $\alpha_1 \geq 1$ and $\alpha_2 < 0$. On the other hand, Lu *et al.* (2015) propose a complex model for the job processing time in a single machine problem. This involves several approaches, and the authors define it as exponential sum-of-logarithm-processing-times-based and position-based learning effects, as in Equation 2.12.

$$p_{jr} = \max\left\{\left(\delta b^{\sum_{k=1}^{r-1}\ln(p_k)} + \gamma\right) r^{\alpha}, \beta\right\} \bar{p}_j \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.12}$$

where $\bar{p}_j$ and p_{jr} is the baseline and actual the baseline processing time respectively, β is a truncation parameter with $0 < \beta < 1$, α and *b* are learning rates, $\delta \geq 0$, $\gamma \geq 0$ are parameters obtained empirically (Pegels, 1969), and $\delta + \gamma = 1$.

DeJong's Learning Effect (DJ-LE)

The DeJong model was proposed by De Jong (1957) to explain the learning process in industrial contexts. This model considers residual skills resulting from prior experiences and implies that certain aspects of the process may not be further improved. The model has been viewed as having great relevance in real life (Azzouz *et al.*, 2018; Ji *et al.*, 2015). The DeJong learning curve follows the equation below:

$$p_{jr} = (M + (1 - M)r^{\alpha})\bar{p}_j \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.13}$$

where the parameter M represents the part of job processing time that is limited by some conditions and cannot be shortened (it represents the "factor of incompressibility"). Different values of M are recommended in the literature. For example, in a single machine problem, the DeJong model suggests $M = 0.25$ for labor-intensive jobs and $M = 0.5$ for machine-intensive jobs (Ji *et al.*, 2015).

Figure 2.8 shows the frequency by the system configuration (two or three more common ones) according to each learning effect approach until the year 2023.

Given the nature of the learning process, many aspects must be taken into consideration. Some authors, therefore, attempt to include them in their models without being limited to the principles of position and time. These aspects include, for example, previous experience (Janiak and Rudek, 2007), skills (Marichelvam *et al.*, 2020), the initial capability, learning ability and job difficulty (Peng *et al.*, 2021). In addition, we identified alternative approaches to model the learning effect, using a perceptron neural network learning algorithm (Fazlollahtabar *et al.*, 2012). We also found some articles corresponding to the inclusion of rate-modifying activities (RMA) (Arigliano *et al.*, 2017; Chung *et al.*, 2019; Rustogi and Strusevich, 2014; Rustogi and Strusevich, 2015; Sun *et al.*, 2021; Wang *et al.*, 2021a; Zhao and Tang, 2011; Zhu *et al.*, 2011), which changes the processing conditions in a system and adjusts the production rate of a resource. Two examples are maintenance activities or rest periods, which usually increase production rates.

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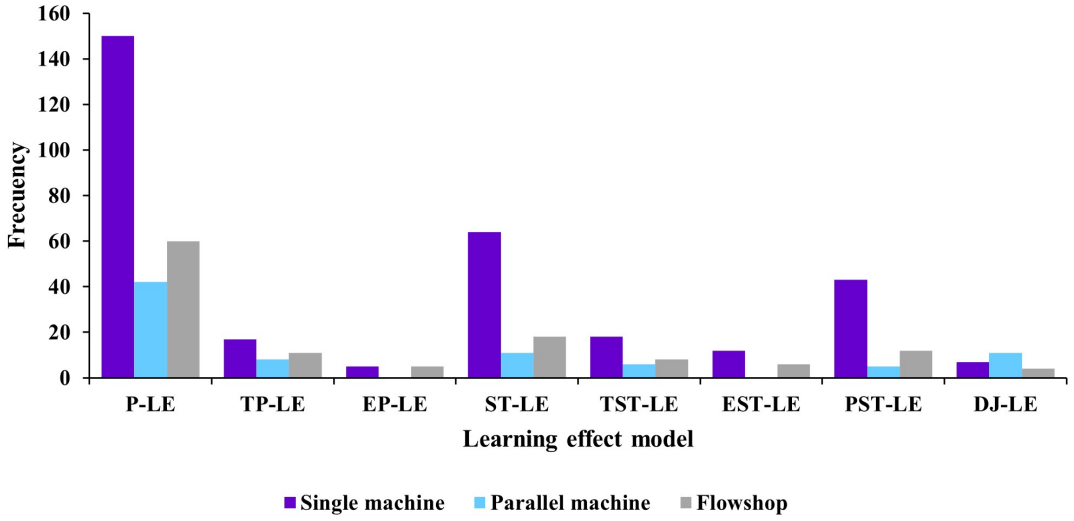

Figure 2.8: System configuration vs. learning effect approach

Deterioration Effect

In the real world, processing times could increase if producers and resources become less efficient over time. The literature refers to this phenomenon as the deterioration of the job or resources. The categories in which deterioration effects are grouped in the present review correspond to those mentioned by Li *et al.* (2019) and Strusevich, Rustogi, *et al.* (2017), such as (i) positional deterioration effect, (ii) cumulative deterioration effect and (iii) starting-time deterioration effect. The first two refer to resource deterioration, while the last one relates mainly to job deterioration.

Position-based deterioration effect (P-DE)

This model attempts to address the real context in which machines and equipment deteriorate with the number of jobs handled (Rostami *et al.*, 2020). For a flowshop scheduling problem, Lee *et al.* (2013) used a position-dependent deterioration model defined in (2.14) where $\alpha_{ij} \geq 0$ is the deterioration factor.

$$p_{ijr} = \bar{p}_{ij} r^{\alpha_{ij}} \quad i = 1, \ldots, I; j = 1, \ldots, J; r = 1, \ldots, R \tag{2.14}$$

The parallel machine scheduling problem is addressed by Montoya-Torres *et al.* (2022). Where a group of workers with idential skills process a set of jobs, their productivity deteriorates, increasing the job execution time based on the processing position (2.15), Where r is the position of the job in the job's permuation, and $\alpha > 0$ represents the deterioration rate.

$$p_{jr} = \bar{p}_j r^{\alpha} \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{2.15}$$

Lee and Yang (2012) consider two different models in a parallel machine scheduling problem. One of them is a declining convex model by which the actual processing time

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(p_{ijr}) is given by Parente *et al.* (2020), where $u_{ij} > 0$ is the amount of resource allocated to the job j, and η is a positive constant (see Monma *et al.* (1990)).

$$p_{ijr} = \left(\frac{\bar{p}_{ij} r^{\alpha}}{u_{ij}}\right)^{\eta} \quad i = 1, \ldots, I; j = 1, \ldots, J; r = 1, \ldots, R \tag{2.16}$$

This category also includes the aging effect, as this is a type of deterioration. Janiak and Rudek (2010) defined the actual job processing time in a single machine as:

$$p_j(r) = \bar{p}_j + b_j \left[\max\left(r - 1\right) - g_j, 0\right]^{\sigma_j} \quad j = 1, \ldots, J \tag{2.17}$$

where σ_j denotes various aging ratios provided by individual jobs, p_j and $\bar{p}_j$ are the actual and baseline processing time, r is the number of performed jobs (or position), and g_j and b_j are the aging threshold and aging ratio of job j.

Cumulative Deterioration Effect (C-DE)

The job processing time is an increasing function of the total processing time, load or difficulty related to the completion of previously scheduled works (Li *et al.*, 2019). For instance, Abedi *et al.* (2020) focus on a job-shop scheduling problem and define the work processing time, taking into account the cumulative deterioration effect of the speed-scaling machines.

$$p_{j_o(r)} = \frac{\bar{p}_{j_o}}{V_{il}} \left(a_i + b_i \sum_{k=1}^{r-1} p_{\xi_k}^{MA}\right) \quad j = 1, \ldots, J; o = 1, \ldots, O \tag{2.18}$$

O is a set of operations, $p_{j_o(r)}$ is the actual processing time, $\bar{p}_{jo}$ is the baseline processing time of the operation o of job j and V_{il} is the selected speed level l of the machine i for the operation. a_i and b_i are constants related to the deterioration of the machine, and $\sum_{k=1}^{r-1} p_{\xi_k}^{MA}$ refers to the volume of work that the machine has carried out just before the task and since the last maintenance activity. This approach incorporates speed as a key point, as one of their objectives is to minimize energy consumption (and it is true that the higher the speed, the more energy is needed).

Starting-time deterioration effect (ST-DE)

In this case, jobs deteriorate. Browne and Yechiali (1990) introduced the case where jobs deteriorate while waiting for a service, and their processing times increase while waiting. An example of job deterioration is when an ingot is waiting to be inserted into the rolling machine. The ingot cools down and has to be heated before rolling. Similarly, the time and effort required to control a fire increases when the wait to put out the fire is longer (Xingong and Guangle, 2010). Wu *et al.* (2019a) proposed the following equation for a linear deterioration. They applied the model to a flowshop problem.

$$p_{ijr} = \bar{p}_{ij} + b_j t \quad i = 1, \ldots, I; j = 1, \ldots, J; r = 1, \ldots, R \tag{2.19}$$

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where p_{ijr} is the actual job processing time, $\bar{p}_{ij}$ is the baseline job processing time, $b_j > 0$ is the deterioration ratio of job j, and t is the job starting time.

Figure 2.9 summarizes the frequency by the system configuration (two or three more common ones) according to each deterioration effect approach.

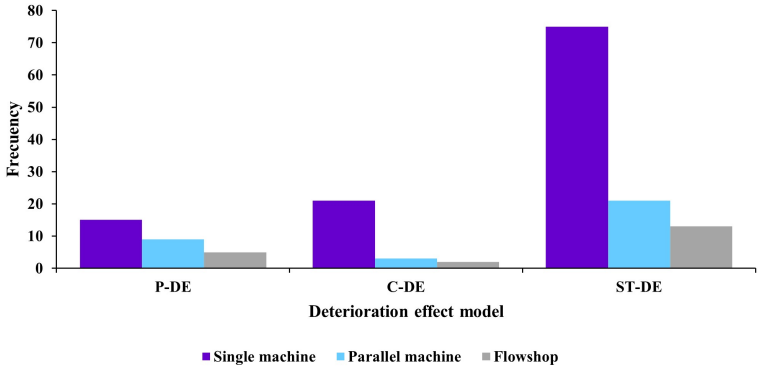

Figure 2.9: System configuration vs. deterioration effect approach

As with the learning effect, these summarized approaches are the ones most commonly employed in the literature. Although most short-listed articles use the term "deterioration effect" referring to job deterioration, few authors have employed the terms fatigue or forgetting (Heuser and Tauer, 2023; Marichelvam *et al.*, 2020; Ostermeier, 2020a; Ostermeier and Deuse, 2023; Pan *et al.*, 2014; Seidgar *et al.*, 2015; Wu *et al.*, 2015; Wu *et al.*, 2016; Yang and Chand, 2008). We can see that the learning and deterioration approaches are mainly based on the principle of position and sum-of-processing time. However, if models are mainly focused on the scheduling problem of hand-intensive tasks, they should be complemented by characteristics that address human behavior (e.g., experience, forgetting, fatigue).

2.3.4 Resolution Methods

A variety of resolution methods has been identified in the literature. For the purposes of our analysis, resolution approaches were grouped into the following categories: exact methods, heuristic, and metaheuristic. The last category includes only works proposing heuristic algorithms achieving the optimal solution for polynomial-solved special cases.

Exact Methods

In general, the NP-hardness of these scheduling problems makes it difficult to find exact methods to find solutions in polynomial time. Moreover, exact methods are usually proposed to mathematically formalize the problems and to solve small-sized instances. Similarly, they have been used to evaluate the performance of approximation algorithms. Modeling has mainly used mixed-integer linear programming (MILP), mixed-integer programming (MIP), mixed-integer non-linear programming (MINLP) or fuzzy mixed-integer non-linear programming (Mosheiov, 2001). In general, the solvers used to deal

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with these models are CPLEX (e.g., Bai *et al.* (2021) and Zheng *et al.* (2023)), GAMS (e.g., Eren (2009)) and LINGO (e.g., Ghodratnama *et al.* (2010)). Almost 11.3% of short-listed articles propose an exact method. However, in the 1970s, the research community found that some of the optimization problems, including scheduling problems, were difficult to solve. The first scheduling problem listed was minimizing the total weighted completion time on a single machine. Similarly, problems related to complex machine environments and time-changing effects have become computationally complex. Thus, the use of non-accurate methods to resolve them is more popular every day, as seen below.

Heuristics

Heuristic procedures are widely used due to the NP-hard nature of the scheduling problem, considering learning or deterioration effects. Dispatching rules are the most frequently employed (e.g., earliest due date, shortest processing time , weighted shortest processing time, as well as the Framinan and Leisten and Nawaz, Enscore, Ham based heuristics (Paredes-Astudillo *et al.*, 2022a; Rudek and Rudek, 2013; Wang *et al.*, 2020). Note that most of the authors tested the performance of the heuristics against each other. Likewise, heuristic algorithms have regularly been used to obtain the initial solution for the implementation of some metaheuristics. Constructive methods have great relevance to solve problems with variable job processing time. The case of the NEH algorithm is known, which showed good performance with problems with a high number of machines (Sauvey and Sauer, 2020) and minimized the makespan as an objective function (among the most common objective functions).

Even though the general case of the scheduling problem with learning and deterioration effect belongs to the family of NP-hard problems, research has also focused on finding special cases for which optimal solutions can be achieved in polynomial or pseudo-polynomial time. It is worth noting that with the beginning of the study of scheduling problems with learning and deterioration effects, some of the first approaches that address this issue suggested pseudo-polynomial and polynomial algorithms. For example, the paper of Mosheiov (2001) introduces polynomial solutions to the problem into single and parallel machine environments. This category is typically called approximation algorithms and is an intermediary point between exact methods and heuristics. In this case, the algorithms known as "heuristics with a guarantee" or "not-quite-exact" algorithms ensure the possibility of finding the optimal solution in certain cases (Sörensen, 2015). This category also includes work that deals with dominance rules and defines upper and lower bounds.

Some of the methods included in this category are based on the branch and bound (B&B) algorithm, based on dispatching rules or specific algorithms adapted to each problem. Another method, rarely used but also reported, is the bounds-based nested partition (BBNP) method applied by Liu *et al.* (2018b), He (2016), and studies related to worst-case and lower-bound definitions are also addressed. Despite the high frequency of use of heuristics leading to optimal solutions, these methods are not suitable for solving large-instance problems, or situations with specific characteristics of human behavior such as experience, fatigue, forgetting, etc., that constitute real problems (due to the uncertainty involved).

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Metaheuristics

Since metaheuristics have proved to be good methods to solve NP-hard combinatorial problems, this literature review identifies a wide variety of procedures to solve scheduling problems with learning and deteriorating effects. A set of 151 articles include metaheuristics. The genetic algorithm is the most widely used metaheuristic for resolving this type of problem, followed by simulated annealing and tabu search.

Research on metaheuristic algorithms started around the 1950s, and new methods continue to appear frequently. Sophisticated approaches have emerged in recent years, and some of these new metaheuristics, such as artificial bee colony, invasive weed optimizer, grey wolf optimizer, whale optimization algorithm, league champions algorithms, and artificial-based-molecule chemical reaction optimization, started to be applied in this field since 2019, and cat swarm optimization was the first used in 2020.

An overview of the evolution of metaheuristics can be found in the work of Sörensen (2015). Moreover, the use of hybrid metaheuristics has recently also become very popular. Hybrid procedures are a combination of algorithms to take advantage of their individual characteristics and performances simultaneously. These approaches are presented in more than 40% of the short-listed papers that use metaheuristics. In this review, we found several authors who hybridize genetic algorithms with other methods such as tabu search (Arık, 2021; Azadeh *et al.*, 2017; Rudek, 2021; Wu and Zheng, 2023), simulated annealing (Zou *et al.*, 2020), variable neighborhood search (Tayebi Araghi *et al.*, 2014; Wu *et al.*, 2018c), kangaroo algorithm (Muştu and Eren, 2018) and differential evolution (Kong *et al.*, 2020). Among other approaches, we found the particle swarm optimization hybridized with local search (Li *et al.*, 2020), a hybrid CS-JADE algorithm combining improved cuckoo search algorithms and self-adaptive differential evolution (Li *et al.*, 2020), a hybrid SC-VNS mixing society and civilization algorithm with variable neighborhood search (Pei *et al.*, 2021), and a hybrid VNS–ASHLO algorithm incorporating variable neighborhood search and adaptive simplified human learning optimization (Fan *et al.*, 2018).

Multi-criteria problems are usually solved using metaheuristics or hybrid metaheuristics, each with its special characteristics. The following are some of the approaches proposed by the authors: Deliktaş (2022) to minimize makespan and total tardiness, Abedi *et al.* (2020) to minimize total weighted tardiness and total energy consumption, and Wang *et al.* (2018) to minimize the weighted sum of makespan and total completion time, used a memetic multi-objective algorithm to obtain a set of solutions. First, the authors develop a non-dominated sorting method, and second, they appeal to the Pareto front.

Li and Chen (2023) use a multiobjective sparrow search algorithm to solve the job shop scheduling problem taking into account energy consumption and learning effect. With the objective of minimizing the makespan and total carbon emissions. Wu *et al.* (2019b) presented a multi-objective hybrid pigeon inspired optimization and simulated annealing algorithm to minimize the makespan and the total energy consumption in a flexible job-shop scheduling problem considering deterioration effects. In the same way, to minimize the makespan and total tardiness in a hybrid flowshop, Pargar *et al.* (2018) developed algorithms by hybridizing water flow like algorithms with non-dominated

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sorting and ranking concepts. Pakzad-Moghaddam (2016) developed a novel metaheuristic called lévy flight embedded particle swarm optimization to solve a multi-objective problem (minimizing the makespan and machine hiring cost). Yue *et al.* (2016) proposed a novel hybrid Pareto artificial bee colony algorithm, in which the advantage of using the Pareto front was to prioritize the obtained solutions, minimizing the makespan and the total weight tardiness simultaneously.

Some methods referred to in the literature are based on genetic algorithms, such as those by Bektur (2021), Shokoufi *et al.* (2019), and Tigane *et al.* (2019), who developed non-dominated sorting-based multi-objective algorithm based approaches. Marichelvam *et al.* (2020) hybridized a variable neighborhood search with the particle swarm optimization algorithm. Finally, Peng *et al.* (2021) proposed a hybrid discrete multi-objective imperial competition algorithm, where a simulated annealing is embedded in an imperialist competitive algorithm. Their article is particularly interested in three objective functions that are seldom mixed, such as the makespan, power consumption and noise level.

Other Methods

Alternative approaches have been adopted in certain articles, such as the hypothetical analysis based on simulation. Li (2017), for instance, uses the monte carlo simulation, Ostermeier (Ostermeier, 2020a; Ostermeier, 2020b; Ostermeier and Deuse, 2023) employees discrete event simulation, and Exposito-Izquierdo *et al.* (2019) work with a multi-agent simulation approach. In addition, there is growing interest in incorporating the multi-agent scheduling problem (Agnetis, 2012; Perez-Gonzalez and Framinan, 2014) when there is more than one criterion to optimize. Each agent then aims for an objective, and they compete to improve their performance. The most frequent in the short-listed papers (with 18 papers) is the two-competing-agents approach (Cheng, 2012; Cheng *et al.*, 2011a; Cheng *et al.*, 2011b; Lee *et al.*, 2015; Li and Hsu, 2012; Li *et al.*, 2014; Liu *et al.*, 2010; Liu *et al.*, 2018c; Shiau *et al.*, 2015; Wu *et al.*, 2011a; Wu *et al.*, 2013; Wu, 2013; Wu *et al.*, 2014; Wu *et al.*, 2017).

In contrast, some contributions have focused on explaining and demonstrating the degree of complexity of such problems rather than solving them. Rudek has explored the subject in depth (Janiak and Rudek, 2007; Rudek, 2011; Rudek, 2012; Rudek, 2013; Rudek, 2014), showing that the single machine scheduling problem with learning effects becomes strongly NP-hard (Rudek, 2014). In the same way, there are also complexity studies in other types of configuration such as the flowshop (Chen *et al.*, 2017), in which they have shown that due to the complexity of the two-machine-flowshop scheduling problem, the Johnson's rule does not guarantee an optimal solution (Wang and Xia, 2005).

It appears that the articles that use exact methods and heuristics leading to optimal solutions lean towards these methods because they have focused on simplified versions of problems and used experimental data sets. This is in part because few articles support real data or include case studies.

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2.4 Discussion

This literature review provides an overview of studies related to scheduling problems with learning and deteriorating effects. The discussion is offered in two phases. The first one answers the questions put forward in Section 2.2.1, which enable us to understand the progress in this field. The second one, identifying opportunities and challenges.

Giving the answer to $SRQ1$, the findings suggest that research related to the scheduling problem with learning and deteriorating effects has generated much interest in recent years. It was noted that the number of articles has increased significantly since 1999. The majority of short-listed articles focused on managing the problem by studying the complexity and developing algorithms that can be comparable in their performance with others already proposed. This implied continuing to maintain classic objective functions, which are sometimes far from being the criteria of interest for stake-holders today. Thus, interaction with business partners would allow us to bring the problems closer to reality, thus ensuring sustainability, taking into account economic, social, and environmental dimensions.

In terms of $SRQ2$, various types of configuration have been studied, with the most studied one being the single resource system. However, more recently, authors have been exploring more complex configurations such as the flowshop and the hybrid flowshop (Bozorgirad and Logendran, 2016; Yin *et al.*, 2021). They involve multiple types of resources (machines, workers, etc.), which must be managed as well as possible (Schumacher and Buchholz, 2020), in addition to the fact that they correspond to the most common and realistic configurations in the industry (Botta, 1996; Yang, 2011).

Regarding $SRQ3$, in most cases, the approach considered a single objective, with only 28.8% combining two or more criteria in the objective function. The most recurrent categories of criteria are those involving TRO—work in progress and TRO—utilization of resources, as per the taxonomy of Botta (1996), Akbar and Irohara (2018), and Lee and Loong (2019). This shows the authors' preference to orient towards economic objectives. In this category, the makespan is the most well-studied criterion. In the sustainable category, starting from 2021, a significant increase is being observed in the inclusion of social orientation criteria, related with the environment (e.g., minimization of energy consumption, carbon emissions).

In the matter of $SRQ4$, findings show that the learning effect has been modeled primarily by the equation in terms of the number of jobs previously processed or the sum of the processing times. These basic models have been improved by adding truncation parameters, for example. Another important finding is the treatment of the deterioration effect in the literature. This term is typically used for job deterioration (117 articles) but has also been used by some authors for deteriorating resources. In the latter case, the effect may result from the number of jobs previously processed or the cumulative effect of the deterioration. Recently, the combination of learning and deterioration has become increasingly common in the literature.

Concerning $SRQ5$, this present study has shown that the resolution method employed to solve the problem is highly dependent on the type of configuration under

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study. The development of algorithms for the optimal solution in polynomial time is regularly applied in single machine systems. For other configurations such as job shops, flowshops, hybrid flowshops and flexible job shops, methods such as heuristic and metaheuristics become relevant. There is a trend towards proposing novel methods for optimization (Sörensen, 2015) or using hybrid metaheuristics, in response to the computational complexity that these problems involve, by taking advantage of the characteristics of different metaheuristics operating simultaneously (Talbi, 2002). In recent years, tools such as simulation and multi-agents have garnered increasing interest, particularly when parameter uncertainty is included. Extensive use has also been made of the competitive agent approaches, where two or more criteria need to be optimized. These approaches generally are accompanied by the use of any metaheuristic.

Despite significant progress in these areas, many research opportunities can still be identified. They are described in depth below. Table 2.2 provides an overview of the opportunities and challenges.

- The current results show that the literature is oriented toward the development of models, the analysis of complexity, and the design and implementation of a resolution method, instead of representing the real conditions more accurately. Most of the works evaluate modeling and resolution approaches using theoretical problems, while few papers provide case studies (Marichelvam *et al.*, 2020; Ostermeier, 2020a; Rostami *et al.*, 2020; Rudek, 2012). Verification of the proposed assumptions and models for addressing the learning and deterioration effect in real-life production environments is an interesting area of research (Glock *et al.*, 2019a). Thus, for example, collaboration with a business stakeholder makes it possible to study industrial problems with real constraints and to validate the proposed optimization methods.

- The industry's current landscape is characterized by stringent environmental policies and complex geopolitical dynamics. As a result, since 2022, there has been a notable integration of environmental considerations in objective functions, including the minimization of carbon emissions and energy consumption. Similarly, there is a change in the approach to learning and deterioration, based on a human-centred approach. This is reflected in objective functions aimed at minimizing noise exposure levels and mitigating the risks of WMSD. It is possible that this is a response to the industry's challenges and the formal definition of Industry 5.0 by the European Union in 2022.

- Every learning and deterioration model is based on one principle, such as job position or time. However, in the real world, there are other types or variables that could impact human behavior e.g., environment, cognition, worker abilities, difficulty of work (Lodree *et al.*, 2009; Peng *et al.*, 2021). There are opportunities for developing studies that address the estimation of parameters such as learning, deterioration or truncation. In general, the values of these parameters are based on the literature benchmark.

- As few articles include variables such as previous experience and task complexity in learning models (Peng *et al.*, 2021), there is the possibility to deepen the

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topic to integrate these variables in models based on the position and the sum-of-processing-time. With regard to the approaches pertaining to deterioration, there is evidence of the need to integrate fatigue by addressing it through the inclusion of physiological variables, as pointed out in the literature (Xu and Hall, 2021). There is likewise a need to study the effect that breaks periods (location and duration) or rate-modifying activities (RMA) may have on performance.

Table 2.2: Opportunities and challenges for the scheduling problem with learning and deterioration effects

Opportunities	Challenges
Approach the problem through complex considerations and a more realistic perspective	Manage and solve real instances of the problem in situations of high computational complexity. Capitalize on the few articles that consider complex configurations from the theoretical perspective and bring them closer to reality.
Incorporate novel criteria into objective functions.	Look at industrial partners and identify the objectives they aim to optimize. Go back to articles that integrate increasingly important social and environmental objectives. Create collaborative relationships with industrial stakeholders.
Develop models of learning and deterioration effects closer to real human behavior. Accurate estimation of the parameters included in these models.	Carry out multidisciplinary work that aims to incorporate human factor-related tools into scheduling problems.
Devise and develop methods to solve the problem within a reasonable time.	Modeling human phenomena such as learning, fatigue, and the incorporation of breaks increases the complexity of these problems, especially in real-world instances.

2.5 Conclusions

The main objective of this chapter has been to present a framework of published works on the inclusion of learning and deterioration effects in scheduling problems. The review included 502 research articles published between 1999 and 2023 (July). The purpose was to show and analyze the current state of research on To obtain a global analysis, short-listed papers were classified according to certain characteristics such as system configu-

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ration, objective function, resolution methods, and modeling approach for learning and deterioration effect. This review showed a growing body of research on this subject, as well as the different approaches to model the learning and deterioration effects.

Much effort has gone into analyzing the complexity of the problem and developing efficient techniques based on heuristics and metaheuristics. As far as objective functions are concerned, most studies are mainly related to a single economic optimization criterion. Finally, the evolution of production systems is a challenge for the active integration of the human factor in problems addressed from the perspective of operational research. This integration is essential to achieve a balance between economic and social objectives.

In the development of this thesis, we address a the remarkable gap in the existing literature. Specifically, there are no prior studies that provide both a theoretical framework and practical applications for scheduling problems in hand intensive systems, taking into account factors such as learning and deterioration effect, with emphasis on the effects of fatigue.

In Chapter 3, we will focus on the flowshop scheduling problem (FSSP) with learning effect to minimize the makespan. Chapter 4 introduces an approach to influence fatigue in the FSSP. Afterwards, Chapter 5 presents, a case study to illustrate how the models and approach can be applied to real industries, and how learning parameters can be calculated from real data.

As stated by Tropschuh *et al.* (2023), there are five challenges in integrating human characteristics into scheduling problems, summarized as: *i)* Rare interdisciplinary approaches, *ii)* Understanding the influence of workers' health and well-being on productivity, *iii)* Simplified workers' characteristics, *iv)* difficulties in assessing physiological and mental aspects and *v)* lack of a practical overview.

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Chapter 3

FSSP with Learning Effect

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3.6	Conclusions	67

The content of this chapter is based on the following publications:

- *Paredes-Astudillo, Y. A., Botta-Genoulaz, V., and Montoya-Torres, J. R. (2023). Impact of learning effect modelling in flowshop scheduling with makespan minimisation based on the Nawaz-Enscore-Ham algorithm. International Journal of Production Research, 1-16, https://doi.org/10.1080/00207543.2023.2204967.*

- *Paredes-Astudillo, Y. A., Botta-Genoulaz, V., and Montoya-Torres, J. R. (2022). Comparing linear and non-linear modelling approaches of learning effects in 2-stage flowshop scheduling problems. In IFAC-PapersOnLine: 10th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2022 (Vol. 55, pp. 842-847). Elsevier. https://doi.org/10.1016/j.ifacol.2022.09.517*

- *Paredes-Astudillo, Y. A., Montoya-Torres, J. R., and Botta-Genoulaz, V. (2023, October). Comparison of Nawaz-Enscore-Ham Algorithm and Local Search Operator*

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in Flowshop Scheduling with Learning Effects. In Operations Research and Analytics in Latin America: Proceedings of ASOCIO/IISE Region 16 Joint Conference 2022 (pp. 77-86). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-28870-8_6

Preliminary findings of this chapter were presented at:

- *Paredes-Astudillo, Y. A., Botta-Genoulaz, V., and Montoya-Torres, J. R. (2022). Comparison of nawaz-enscore-ham algorithm and Johnson's rule in a two-resources flowshop with learning effects. Presented at the Escuela Latinoamericana de Verano in Investigación Operativa - ELAVIO summer school 2022, Monterrey, Mexico.*
- *Paredes-Astudillo, Y. A., Botta-Genoulaz, V., and Montoya-Torres, J. R. (2022). Comparison of two linear modeling of the learning effect in a two-resources flowshop. Presented at 23ème édition du congrès annuel de la Société Française de Recherche Opérationnelle et d'Aide à la Décision - ROADEF 2022, Lyon, France.*

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Abstract

In this chapter, the flowshop scheduling problem with learning effect minimising the makespan is modeled using Mixed-Integer Linear Programming (MILP) and Mixed-Integer Non Linear Programming (MINLP). Four approaches to model the learning effect, well-known in the literature and identified in the Chapter 2, are outlined. Mathematical models for each of the case and the optimal solutions for small instance problems are provided. Due to the FSSP with learning even with two resources becomes NP-hard, we compare the performance of an adapted Nawaz-Enscore-Ham algorithm and the Johnson's rule for two-resources FSSP with learning. For large instances and considering more than two resources, a Simulated Annealing algorithm is proposed and its performance with two local search operators are compared. Computational experiments carried out in this chapter use benchmark datasets from the literature.

3.1 Introduction

As presented in Chapter 2, the learning effect is one of the most studied human characteristics. This effect was induced scientifically by Wright (1936), but it was until 1998 that Dondeti and Mohanty (1998) spoke about the role of learning and fatigue in single-machine problems, when the job processing time depends on the content of both the present and the previously processed jobs. Biskup (1999) formalized the effect of learning on one machine. Since then, a significant number of papers have proposed different ways of modeling the learning effect on scheduling problems (Paredes-Astudillo *et al.*, 2022b; Pei *et al.*, 2022).

As it was seen in the previous chapter, among the most commonly used approaches we identify the position-based learning effect (Biskup, 1999; Cheng and Wang, 2000; Dolgui *et al.*, 2012), and the sum-of-processing-time-based learning effects (Koulamas and Kyparisis, 2007; Kuo and Yang, 2006a; Kuo and Yang, 2006b; Kuo and Yang, 2006c), as well as its variations, including truncated parameters (Wang *et al.*, 2013; Wu *et al.*, 2011b). This integration into scheduling problems has been done mostly in the single machine environment, because it is possible to conceptualize the problem and extrapolate alternatives for other types of configurations. However, less studies consider flowshop configurations and their variations (e.g., hybrid flowshop), which are frequently encountered in complex manufacturing systems, due to the necessity to perform sequential operations, as in the case of textiles, footwear and in the automotive industry (Chen *et al.*, 2017; Fernandez-Viagas, 2022; Rudek, 2011).

This chapter focuses on the flowshop scheduling problem with a learning effect, minimizing the makespan. Four approaches for modeling the learning effect, which have been extensively discussed in Chapter 2, were selected for testing. The FSSP considering the learning effect has been solved using several methodologies, however there is a lack in the contributions that compare the efficiency of solution methods depending on the learning effect modeling. After an overview of the literature about the FSSP with learning effect, the contributions of this chapter are:

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- FFSP mathematical models that address the learning effect with the four approaches referred to in the literature to solve small-problem instances optimally.
- A comparison between an adapted Nawaz-Enscore-Ham (NEH) algorithm and the Johnson's rule (JR) for 2-resources FSSP with learning effect.
- A simulated annealing (SA) algorithm, using the adapted NEH algorithm to get the initial solution, and two local search operators, to solve large-sized instances.
- A discussion on the effectiveness of the SA algorithm and its performance regarding the way the learning effect is modeled through a sensitivity analysis.

The computational experiments in this chapter were run with benchmark datasets.

3.2 Related Literature

Wright (1936) introduced the concept of the learning effect in manufacturing systems, an effect stemming from practical experience, particularly in monotonous activities (Arditi *et al.*, 2001). In recent years, the inclusion of the learning effect when dealing with operations management problems has become more widespread and has produced several learning models published in the literature. The baseline of scheduling with learning effects was established by Biskup (1999), who modeled a position-based learning effect into a single-machine scheduling problem.

The flowshop scheduling problem without learning and with makespan minimization is known to be NP-hard for the case of more than two machines (Wang and Xia, 2005). When dealing with learning in processing times, the problem becomes NP-hard even for the case of two machines (Pinedo, 2008). This means that optimal solutions cannot be obtained for large-sized datasets in reasonable computational time. Because of this computational intractability, the literature has witnessed a variety of solution methods to solve flowshop scheduling problems with learning effects.

Wang and Xia (2005) used the classical Johnson's rule in the two-resources flowshop scheduling minimizing the makespan demonstrating that it does not get optimal solution. Moreover, polynomial algorithms, for special cases, mainly based on dispatching rules, provide optimal or near-optimal solutions. The shortest processing time (SPT) has been extensively utilized, as shown by the articles written by Wang and Wang (2012), Wang and Wang (2011), Rudek (2011), Xu *et al.* (2008). Regarding the weighted shortest processing time (WSPT), we have identified its utilization in Liang *et al.* (2019), Wang *et al.* (2019), Kuo *et al.* (2012) and Wang and Wang (2011) articles. For the earliest due date (EDD) we could mention Kuo *et al.* (2012) and Zhang (2020).

Regarding heuristics, we found several, for example, the Framinan and Leisten heuristic. Wang and Zhang (2015) use it to address the problem of minimizing the weighted sum of makespan and total completion time, where the processing times are supposed to vary according sum of the logarithms of the processing time. Considering the FSSP minimising the energy consumption with an exponential time-dependent learning effect,

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Liu *et al.* (2018b) proposed the Bounds-based Nested Partition and compare the results with Framinan and Leisten heuristic and NEH. The NEH is one of the most frequently cited heuristic in the literature for addressing this problem (Mosheiov and Pruwer, 2021; Rudek and Rudek, 2013; Tamer, 2013; Wang and Wang, 2014; Wu *et al.*, 2018a)

To deal with a two-machine flowshop scheduling problem with truncated learning effects, both Cheng *et al.* (2013) and Wu *et al.* (2012a) proposed a genetic algorithm (GA) and a branch and bound algorithm, while minimizing the makespan and the total completion time by applying some dominance rules. Zou *et al.* (2020) addressed a two-stage three-machine flowshop scheduling problem with a sum-of-processing-times-based learning effect to minimize the makespan. They proposed a branch-and-bound algorithm incorporating dominance properties, three heuristics based on Johnson's rule, and a GA. Wu *et al.* (2020b) studied a two-stage three-machine flowshop scheduling problem with a truncated sum-of-processing-time-based learning effect, minimizing the makespan. They present some dominance rules, and develop a branch-and-bound algorithm and a GA to obtain near-optimal solutions.

In addition to GA, other metaheuristics such as simulated annealing (SA) have been widely used. Wu *et al.* (2018a) dealed with the re-entrant permutation flowshop scheduling with a sum-of-processing-times-based learning effect to minimize the makespan. They proposeed four heuristics and a SA to approximate solutions. Sun *et al.* (2020) considered the flowshop problem of minimizing the total weighted completion time, where the job processing time is computed according to a general position-weighted learning effect. SA and branch and bound algorithms are proposed. Liu *et al.* (2010) also proposeed a SA to solve the two-stage three-machine flowshop, while approaching the learning effect as a truncated function of sum-of-processing time in order to minimize makespan. Azizi *et al.* (2016) studied the m-machine flowshop scheduling problem, considering sequence-dependent setup times and truncated learning function to minimize the makespan. To do so, they developed both GA and SA. Lai and Wu (2015) used GA, SA, ant colony optimization (ACO) and particle swarm optimization (PSO) to minimize the makespan. They incorporated three kinds of variations of learning effect models: job-dependent, machine-dependent, and job-and machine-dependent learning effects, depending on the position.

Rudek and Rudek (2013) and Wu *et al.* (2018b) dealed with two-and three-machine flowshop problems to minimize makespan and described the job processing time by learning based on the position. They constructed a NEH algorithm, a tabu search (TS) with neighborhood search, and SA algorithms that solve the problem.

Some authors have recently addressed this problem through hybrid-metaheuristics (algorithms that combine or hybridize multiple metaheuristic techniques). For example, Wu *et al.* (2018b) and Zou *et al.* (2020) alternatively included a cloud theory-based simulated annealing algorithm (CSA). Fu *et al.* (2019) considered a flowshop scheduling problem with learning and deterioration effects and proposeed an artificial-molecule-based chemical reaction optimization algorithm (ACRO). Vahedi Nouri *et al.* (2013) studied a flowshop scheduling problem with learning effects and maintenance activities. They develop a hybrid meta-heuristic algorithm based on an SA algorithm and a firefly algorithm (HFSA) to solve it. Muştu and Eren (2018) addresed a flowshop scheduling problem un-

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der a position-based learning effect and minimize the makespan. They proposed a kangaroo algorithm (KA) and a genetic-kangaroo hybrid algorithm (GAKA) to solve large instances of this problem. Arık (2021) dealt with flowshop scheduling problems with position-dependent learning effects and linear deterioration. He proposed a population-based tabu search algorithm (TSPOP) with evolutionary strategies.

In terms of multi-objective problems, Hosseini and Tavakkoli-Moghaddam (2013) dealt with a two-machine flowshop scheduling problem with learning effects that minimizes the total idle time and the mean deviation from a common due date. They solved the problems with a multi-objective genetic algorithm (MOGA) and a multi-objective simulated annealing (MOSA) algorithm. Eren and Güner (2008) studied a two-machine flowshop scheduling problem with learning effects based on the position, the objective function of which is the minimization of a weighted sum of total completion time and makespan. They presented heuristic algorithms and a TS algorithm to solve large-sized problems. Chen *et al.* (2006) addressed a bi-criteria two-machine flowshop scheduling problem with learning effects based on the position. They proposed a branch-and-bound algorithm, a heuristic and a SA algorithm to approximate solutions for large instances of the problem. Table 3.1 summarized the works that use metaheuristics in the solution of FSSP with learning effect.

3.3 Problem Modeling

We consider the permutation flowshop scheduling problem with a set I of workers, and a set J of independent jobs, which are processed in the same sequence to minimize the makespan C_{max}. Each worker can process one job at a given time, and preemption of a job is not allowed (that is, the execution of a job cannot be interrupted once its processing has started). All workers are available at the beginning of the scheduling horizon and have a 100% production rate. The inclusion of intermediate buffers between workers is not considered in this approach. The baseline processing time of the $i-th$ operation of the j-th job is noted as $\bar{p}_{ij}$. In this section, we model the standard FSSP and the FSSP with learning, considering four learning models (four cases) identified previously.

3.3.1 MILP and MINLP models

The standard flowshop scheduling problem with makespan minimization (which we will refer as *Case 0*) can be modeled as a mixed-integer linear programming (MILP) model. The definition and notations are shown below:

Set

I: Workers

J: Jobs

R: Positions

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Table 3.1: Metaheuristics for the FSSP with learning effect

Author and Year	Metaheuristics	Objective function (minimization)	Learning model
Arık (2021)	TSPOP	makespan	P-LE
Azizi *et al.* (2016)	GA, SA	makespan	Other
Chen *et al.* (2006)	SA	weighted sum of the total completion time and maximum tardiness	P-LE
Eren and Güner (2008)	TS	weighted sum of total completion time and makespan	P-LE
Fu *et al.* (2018)	ACRO	makespan	P-LE
Lai and Wu (2015)	GA, SA, ACO, PSO	makespan	P-LE
Liu *et al.* (2010)	SA	makespan	TSM-LE
Muştu and Eren (2018)	KA, GAKA	makespan	P-LE
Sun *et al.* (2020)	SA	total weighted completion time	P-LE
Hosseini and Tavakkoli-Moghaddam (2013)	MOGA, MOSA	total idle time and mean deviation from a common due date	P-LE
Vahedi Nouri *et al.* (2013)	HFSA	makespan	P-LE
Wu *et al.* (2018a)	SA	makespan	SM-LE
Wu *et al.* (2018b)	SA, CSA	makespan	P-LE
Wu *et al.* (2020b)	GA	makespan	TSM-LE
Wu *et al.* (2012a)	GA	maximum lateness and total weighted completion time	SM-LE
Zou *et al.* (2020)	GA, CSA	makespan	SM-LE

Position-based learning effect (P-LE); Truncated position-based learning effect (TP-LE); Sum-of-processing-time based learning (SM-LE); Truncated sum-of-processing-time based learning (TSM-LE)

Parameters

$\bar{p}_{ij}$: baseline processing time of job j executed by worker i

M: represents a very large number or Big M

Decision Variables

$$x_{jr} = \begin{cases} 1, & \text{if job } j \text{ is processed in position } r \text{ of the schedule,} \\ 0, & \text{otherwise.} \end{cases}$$

c_{ij}: completition time of job j on worker i

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C_{max}: makespan value

Objective function

$$Minimize \quad Z = C_{max} \tag{3.1}$$

Subject to

$$\sum_{r \in R} x_{jr} = 1 \quad j = 1, \ldots, J \tag{3.2}$$

$$\sum_{j \in J} x_{jr} = 1 \quad r = 1, \ldots, R \tag{3.3}$$

$$c_{1j} \geq \bar{p}_{1j} \quad j = 1, \ldots, J \tag{3.4}$$

$$c_{ij} - \bar{p}_{ij} \geq c_{(i-1)j} \quad i = 2, \ldots, I; j = 1, \ldots, J \tag{3.5}$$

$$\begin{gathered} c_{ij} - \bar{p}_{ij} + M(1 - x_{j(r+1)}) \geq c_{ih} - M(1 - x_{hr}) \\ i = 1, \ldots, I; j = 1, \ldots, J; h = 1, \ldots, J; r = 1, \ldots, R-1 \end{gathered} \tag{3.6}$$

$$C_{max} \geq c_{ij} \quad i = 1, \ldots, I; j = 1, \ldots, J \tag{3.7}$$

$$x_{jr} \in \{0, 1\} \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{3.8}$$

$$C_{max} \geq 0 \tag{3.9}$$

$$c_{ij} \geq 0 \quad i = 1, \ldots, I; j = 1, \ldots, J \tag{3.10}$$

The objective function (3.1) corresponds to the minimization of the completion time of the last job of the sequence, i.e. the makespan. Constraints (3.2) and (3.3) guarantee that every job is assigned to one position in the sequence, and each position has only one job. Constraints (3.4) are related to the completion time of jobs for the first worker (i.e. first operation). This ensures the non-negativity constraint, which is usually formalized with constraints (3.9) and (3.10). Constraints (3.5) and (3.6) calculate the completion time of jobs for the remaining workers. Constraints (3.7) define the makespan. Constraints (3.8) define the values of binary decision variables.

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The previous mathematical model can be modified to take into account the different approaches for modeling the learning effect, as proposed by several authors such as Biskup (2008), and Azzouz *et al.* (2018). These models have been selected because they are the basis for other approaches. The four cases studied are:

- *Case 1:* with position-based learning $p_{ijr} = \bar{p}_{ij} r^{\alpha}$
- *Case 2:* with truncated position-based learning $p_{ijr} = \bar{p}_{ij} max\{r^{\alpha}, \beta\}$
- *Case 3:* with sum-of-processing-time-based learning $p_{ijr} = \left(1 + \sum_{k=1}^{r-1} p_{ijk}\right)^{\alpha} \bar{p}_{ij}$
- *Case 4:*: with truncated sum-of-processing-time-based learning
  $p_{ijr} = \max\left\{\left(1 + \sum_{k=1}^{r-1} p_{ijk}\right)^{\alpha}, \beta\right\} \bar{p}_{ij}$

Where α is the learning index ($\alpha < 0$), β is a control parameter with $0 < \beta < 1$, and θ is a conversion factor (e.g., $\frac{1}{3600}$ to convert hours to seconds). In *Case 1*, the job processing time is based on the position, so taking the baseline flowshop model, a new decision variable is added:

p_{ij} : actual processing time of job j by worker i

To calculate the actual job processing time, constraints (3.11) and (3.12) are needed:

$$p_{ij} = \sum_{r \in R} \bar{p}_{ij} x_{jr} r^{\alpha} \quad i = 1, \ldots, I; j = 1, \ldots, J \tag{3.11}$$

$$p_{ij} \geq 0 \quad i = 1, \ldots, I; j = 1, \ldots, J \tag{3.12}$$

We replace Constraints (3.4), (3.5) and (3.6) by (3.13), (3.14) and (3.15) respectively.

$$c_{1j} \geq p_{1j} \quad j = 1, \ldots, J \tag{3.13}$$

$$c_{ij} - p_{ij} \geq c_{(i-1)j} \quad i = 2, \ldots, I; j = 1, \ldots, J \tag{3.14}$$

$$\begin{gathered} c_{ij} - p_{ij} + M(1 - x_{j(r+1)}) \geq c_{ih} - M(1 - x_{hr}) \\ i = 1, \ldots, I; j = 1, \ldots, J; h = 1, \ldots, J; r = 1, \ldots, R-1 \end{gathered} \tag{3.15}$$

From *Case 1* and changing constraints (3.11) for (3.16), we would get *Case 2*:

$$p_{ij} = \sum_{r \in R} \bar{p}_{ij} x_{jr} max\{r^{\alpha}, \beta\} \quad i = 1, \ldots, I; j = 1, \ldots, J \tag{3.16}$$

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In *Case 3*, the decision variables c_{ij} and p_{ij} are replaced by c_{ir} and p_{ir}, where c_{ir} is the competition time of the job scheduled in position $r \in R$ for worker $i \in I$, and p_{ir} is the actual processing time of the job scheduled in position $r \in R$ for worker $i \in I$.

Furthermore, equations (3.17) and (3.18) are included and both replace equation (3.11) from *Case 1* :

$$p_{ir} = \left(1 + \theta \sum_{q \in R}^{q<r} p_{iq}\right)^{\alpha} \left(\sum_{j \in J} \bar{p}_{ij} x_{jr}\right) \quad i = 1, \ldots, I; r = 1, \ldots, R-1 \tag{3.17}$$

$$p_{i1} = \sum_{j \in J} \bar{p}_{ij} x_{j1} \quad i = 1, \ldots, I \tag{3.18}$$

Constraints (3.19), (3.20) and (3.21) control the completion times of the jobs at the machines, and ensure the non-negativity constraint, which is usually formalized with Constraints (3.22).

$$c_{1r} \geq p_{1r} \quad r = 1, \ldots, R \tag{3.19}$$

$$c_{ij} - p_{ir} \geq c_{(i-1)r} \quad i = 2, \ldots, I; r = 1, \ldots, R \tag{3.20}$$

$$\begin{gathered} c_{ir} - p_{ir} + M(1 - x_{j(r+1)}) \geq c_{ir} - M(1 - x_{hr}) \\ i = 1, \ldots, I; j = 1, \ldots, J; h = 1, \ldots, J; r = 1, \ldots, R-1 \end{gathered} \tag{3.21}$$

$$c_{ir} \geq 0 \quad i = 1, \ldots, I; r = 1, \ldots, R \tag{3.22}$$

For *Case 4*, the set E, which states $\{1 : Learning \quad 2 : Truncate\}$ was taken into consideration, as were the two variables:

u_{ire}: actual processing time of the job scheduled in position $r \in R$ for worker $i \in I$ in state $e \in E$

ξ_{ir}: maximun actual processing time of the job scheduled in position $r \in R$ for worker $i \in I$

Equations (3.23), (3.24), (3.25), (3.26) and (3.27) are used to calculate the actual job processing time instead of equations (3.17) and (3.18). Constraint (3.28) and (3.29) are the non-negative constraint:

$$p_{i1} = \sum_{j \in J} x_{j1} \quad i = 1, \ldots, I \tag{3.23}$$

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$$u_{ir1} = \left(1 + \theta \sum_{q \in R}^{q<r} p_{iq}\right)^{\alpha} \left(\sum_{j \in J} \bar{p}_{ij} x_{jr}\right) \quad i = 1, \ldots, I; r = 2, \ldots, R \tag{3.24}$$

$$u_{ir2} = \sum_{j \in J} \bar{p}_{ij} x_{jr} \beta \quad i = 1, \ldots, I; r = 2, \ldots, R \tag{3.25}$$

$$\xi_{ir} \geq u_{ire} \quad i = 1, \ldots, I; r = 1, \ldots, R; e = 1, \ldots, E \tag{3.26}$$

$$p_{ir} = \xi_{ir} \quad i = 1, \ldots, I; r = 2, \ldots, R \tag{3.27}$$

$$u_{ire} \geq 0 \quad i = 1, \ldots, I; r = 1, \ldots, R; e = 2, \ldots, E \tag{3.28}$$

$$\xi_{ir} \geq 0 \quad i = 1, \ldots, I; r = 1, \ldots, R \tag{3.29}$$

We thus obtain two MILP models (*Case 1* and *Case 2*) and two mixed-integer non-linear programming (MINLP) models (*Case 3* and *Case 4*).

3.3.2 Computational Experiments and Results

Experimental Setting

The mathematical models were coded in Python and solved using Pyomo (Hart *et al.*, 2011). In order to evaluate and compare the suggested model for each case, several experiments were designed. These experiments included the number of machines, jobs, learning and control parameters. Integer values of processing times were generated using a uniform distribution between 1 and 100. The number of workers was 2, while the number of jobs was defined to be 5 and 7, although the size of these instance does not accurately reflect a real-world scenario. The rationale for the values of alpha (α) and beta (β) is based on the most common values used in the literature (Amirian and Sahraeian, 2015; Muştu and Eren, 2018; Rudek and Rudek, 2013; Wu *et al.*, 2020a). A total of 30 instances for each combination of jobs-machines were executed, giving a set of 1500 experiments. Table 3.2 provides a summary of set of problem instances tested in this section. Experiments were carried out on a PC with AMD Ryzen 2.0GHz and RAM 8 Gb. Glpk and Bonmin solvers (Hart *et al.*, 2011) were used for solving the linear (*Case 0, Case 1* and *Case 2*) and non-linear cases (*Case 3* and *Case 4*) respectively.

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Table 3.2: MILP and MINLP models - Summary of set of problem instances

Parameter	*Case 0*	*Cases 1 and 3*	*Cases 2 and 4*
Number of workers (I)	2		
Number of jobs (J)	5, 7		
Learning index (α)	–	-0.152, -0.322, -0.515	
Truncation parameter (β)	–	–	0.25, 0.5, 0.75

Analysis of Results

In order to illustrate the impact of the learning effect modeling on the schedule, Figure 3.1 presents the Gantt chart for an exemplary instance of five jobs and two workers, $\alpha = -0.515$ and $\beta = 0.5$ if required. The makespan presents variations of 43.8%, 34%, 42.2%, and 33.7% from *Case 0* to *Case 1*, *Case 2*, *Case 3*, and *Case 4*, respectively.

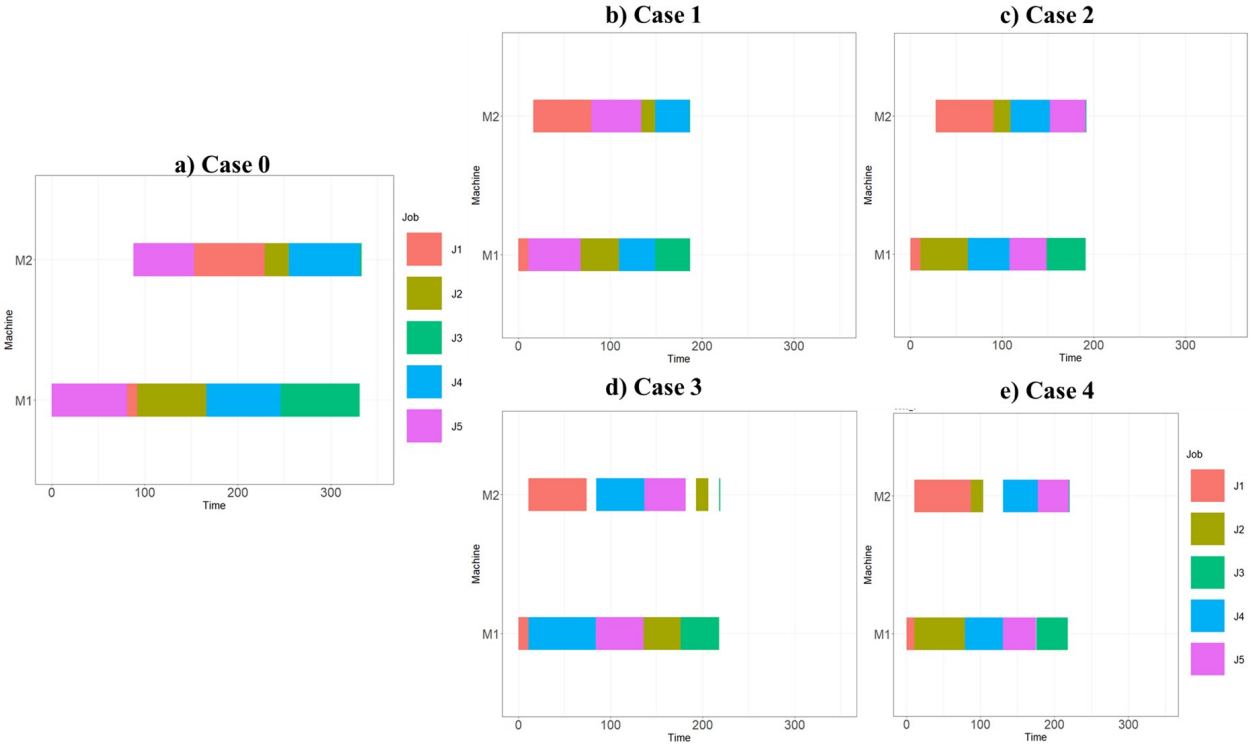

Figure 3.1: Gantt charts: a) Case 0, b) Case 1, c) Case 2, d) Case 3, e) Case 4

In regard the full experiment for 2 workers and 30 instances, Table 3.3 shows a summary of the outcomes. It is important to note that *Case 1* and *Case 2* model the actual processing time based on the position, reduce the job processing time faster than in *Case 3* and *Case 4*. Similarly, it was found that in the case with a truncation parameter, the objective function is higher than those without a truncation parameter. This is due to the control parameters that play an important role in the performance of the C_{max}. The minimum average deviation (for the 2 workers and 5 jobs problem and α = -0.152) from the *Case 0* of C_{max} (12.36%) is observed with the *Case 3* and *Case 4*. It happens with the *Cases 4* when truncation value is not reached due to low truncation value.

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It can also be seen that the CPU times values change significantly between experiments with 5 and 7 jobs, especially those that are not linear, such as *Cases 3* and *Cases 4*. Thus, when it was intended to test with 8 jobs for these cases, it was not possible to obtain the optimal solution before 8 hours. This fact supports the outcomes previously reported about the complexity of this type of problems.

Table 3.3: MILP and MINLP models - Experimental results

				Makespan			**CPU time**		
Case	J	α	β	Mean	Std	Dev. Cmax	Mean	Std	Min - Max
0	5	-	-	306.37	52.81	-	0.13	0.01	0.12 - 0.15
1	5	-0.152	-	262.45	45.36	-14.33%	0.16	0.01	0.14 - 0.19
	5	-0.322	-	223.12	39.46	-27.17%	0.16	0.01	0.13 - 0.18
	5	-0.515	-	209.22	29.48	-31.71%	19.47	3.75	14.61 - 30.7
2	5	-0.152	0.25	262.45	45.36	-14.33%	0.15	0.02	0.13 - 0.23
	5	-0.152	0.5	262.45	45.36	-14.33%	0.15	0.01	0.13 - 0.17
	5	-0.152	0.75	262.45	45.36	-14.33%	0.14	0.01	0.13 - 0.17
	5	-0.322	0.25	223.12	39.46	-27.17%	0.15	0.01	0.13 - 0.16
	5	-0.322	0.5	223.12	39.46	-27.17%	0.14	0.01	0.13 - 0.17
	5	-0.322	0.75	243.65	42.28	-20.47%	0.15	0.01	0.13 - 0.17
	5	-0.515	0.25	187.84	33.6	-38.69%	0.14	0.01	0.13 - 0.17
	5	-0.515	0.5	192.29	34.34	-37.24%	0.14	0.01	0.13 - 0.17
	5	-0.515	0.75	240.82	41.83	-21.4%	0.14	0.01	0.13 - 0.17
3	5	-0.152	-	268.58	42.84	-12.36%	18.56	2.81	15.03 - 27.57
	5	-0.322	-	236.88	35.44	-22.68%	19.5	4.79	13.87 - 33.75
	5	-0.515	-	209.22	29.48	-31.71%	19.47	3.75	14.61 - 30.7
4	5	-0.152	0.25	268.5	42.84	-12.36%	21.48	3.58	17.15 - 30.3
	5	-0.152	0.5	268.5	42.84	-12.36%	20.84	3.04	16.48 - 28.79
	5	-0.152	0.75	268.5	42.84	-12.36%	22.16	3.87	17.37 - 31.99
	5	-0.322	0.25	236.58	35.37	-22.78%	22.94	3.78	17.97 - 35.72
	5	-0.322	0.5	236.58	35.37	-22.78%	24.15	6.79	16.92 - 38.53
	5	-0.322	0.75	249.39	40.9	-18.6%	24	4.51	16.81 - 39.53
	5	-0.515	0.25	208.69	29.3	-31.88%	23.66	4.49	17.55 - 32.93
	5	-0.515	0.5	209.2	29.85	-31.71%	22.42	2.84	16.33 - 29.8
	5	-0.515	0.75	245.67	41.43	-19.81%	25.62	7.82	17.14 - 50.77
0	7	-	-	412.13	60.91	-	1.87	0.46	1.36 - 3.55
1	7	-0.152	-	338.03	51.98	-17.98%	2.34	0.11	1.91 - 2.56
	7	-0.322	-	272.75	43.43	-33.82%	2.23	0.13	1.91 - 2.51
	7	-0.515	-	216.7	36.39	-47.42%	2.03	0.16	1.59 - 2.35
2	7	-0.152	0.25	338.03	51.98	-17.98%	2.4	0.34	1.91 - 4.09
	7	-0.152	0.5	338.03	51.98	-17.98%	2.33	0.1	1.91 - 2.46
	7	-0.152	0.75	338.48	52.05	-17.87%	2.38	0.27	2.22 - 3.78
	7	-0.322	0.25	272.75	43.43	-33.82%	2.28	0.3	1.92 - 3.73
	7	-0.322	0.5	272.75	43.43	-33.82%	2.23	0.11	1.9 - 2.36
	7	-0.322	0.75	322.73	49.1	-21.69%	2.29	0.1	1.91 - 2.4
	7	-0.515	0.25	216.7	36.39	-47.42%	2.03	0.16	1.59 - 2.26

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Table 3.3: MILP and MINLP models - Experimental results

				Makespan			**CPU time**		
Case	J	α	β	Mean	Std	Dev. Cmax	Mean	Std	Min - Max
	7	-0.515	0.5	239.66	39.3	-41.85%	2.11	0.14	1.8 - 2.34
	7	-0.515	0.75	320.48	48.44	-22.24%	2.36	0.32	1.89 - 3.99
3	7	-0.152	-	345.33	58.66	-16.21%	1545.6	82.59	1298.52 - 1698.71
	7	-0.322	-	295.08	45.83	-28.4%	1568.47	95.38	1217.26 - 1728.54
	7	-0.515	-	253.19	36.14	-38.57%	1527.75	126.08	1234.86 - 1770.29
4	7	-0.152	0.25	345.14	58.66	-16.26%	1780.96	83.64	1601.88 - 2001.2
	7	-0.152	0.5	345.14	58.66	-16.26%	1788.59	75.49	1664.55 - 1976.39
	7	-0.152	0.75	345.22	58.81	-16.24%	1766.17	102.48	1576.24 - 2045.67
	7	-0.322	0.25	294.5	45.9	-28.54%	1766.17	102.48	1576.24 - 2045.67
	7	-0.322	0.5	294.5	45.9	-28.54%	1766.6	99.53	1606.46 - 2045.38
	7	-0.322	0.75	323.7	57.9	-21.46%	1769.39	98.74	1568.32 - 1966.54
	7	-0.515	0.25	252.42	36.18	-38.75%	1708.86	121.19	1508.64 - 2032.83
	7	-0.515	0.5	256.75	39.6	-37.7%	1738.64	134.08	1465.45 - 2090.44
	7	-0.515	0.75	319.68	57.79	-22.43%	1714.05	138.6	1512.3 - 2295.98

Standard deviation (Std); Average deviation from Case 0's makespan (Dev. Cmax); CPU time in seconds

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3.4 Two-resources FSSP with Learning Effect

For the problem with two resources, we compare the performance of the adapted NEH algorithm (hereinafter referred to as NEH for practical purposes) and the Johnson's rule (JR), taking into account the four cases identified previously and the problem without learning effect (*Case 0*).

3.4.1 Algorithms

In this section we describe the proposed algorithms as follows:

Adapted NEH Algorithm

- *Step 1:* Calculate the total processing time (TPT) on all resources or workers for each job j. This initial TPT per job is calculated with the baseline processing time and does not account for the learning effect.
- *Step 2:* Sort all the jobs in decreasing order of TPT in a list.
- *Step 3:* Select the two jobs with the highest TPT and remove them from the list. Two possible sequences are obtained with these jobs.
- *Step 4:* Calculate the actual processing time of each job j according to the equation of the respective case (*Case 1, 2, 3* or *4*).
- *Step 5:* Compute the C_{max} for each sequence and select the sequence with the minimal C_{max}.
- *Step 6:* If the list is not empty, select the next job from the list and calculate all possible inserts within the sequence. Return to steps 4 and 5. Keep the sequence with the lowest makespan.

Johnson's Rule

- *Step 1:* Enlist the baseline job processing time for each job on both workers.
- *Step 2:* Select the job with the shortest baseline job processing time on either worker.
- *Step 3:* If the shortest baseline job processing time is on the first worker, the job is scheduled in the first permutation position. If not, the job is scheduled at the end.
- *Step 4:* Remove from the list, the jobs already scheduled.
- *Step 5:* Repeat steps 2,3, and 4 to the remaining jobs.
- *Step 6:* The final C_{max} is calculated based on the actual processing time.

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3.4.2 Computational Experiments and Results

Experimental Setting

Computational experiments were conducted to compare the performance of both heuristics. The algorithms were coded in Python and were carried out on a PC with AMD Ryzen 2.0GHz and RAM 8 Gb. Job processing times were generated from a uniform distribution between 1 and 100. The values of alpha (α) and beta (β) are the same tested in the previous section (Table 3.2). The number of workers was set to be $i = 2$, and the number of jobs $j = 10, 20, 50$ and 100. Each combination was encoded such as *Case* _i _j _α _β (for example, $C2$_ 2 _ 100_ -0.515 _ 0.25, corresponds to *Case 2* with 2 workers, 100 jobs, $\alpha = -0.515$ and $\beta = 0.25$). A total of 30 replications for each combination of factors were performed. Table 3.4 provides a summary of set of problem instances tested for the two-resource FSSP.

Table 3.4: Two-resource FSSP - Summary of set of problem instances

Parameter	***Case 0***	***Case 1* and *Case 3***	***Case 2* and *Case 4***
Number of workers (I)	2		
Number of jobs (J)	10, 20, 50, 100		
Learning index (α)	–	-0.152, -0.322, -0.515	
Truncation parameter (β)	–	–	0.25, 0.5, 0.75

Analysis of Results

We note that the performance of the NEH and JS can vary according to the case. Thus, for *Case 1* and *2* (linear models based on position), it is noted that the makespan obtained with NEH is smaller than that achieved with JS. As for *Case 3* and *4*, the makespan values obtained with the NEH and JS are quite closer. Figure 3.2 shows the average results obtained for 2 workers and 100 jobs.

Because the learning effect is limited, models with truncation parameters appear to be closer to the real human behavior. An upper bound (UB) to these problems could be achieved by solving with JS the FSSP without learning effect (*Case 0*). Also, a lower bound (LB) may be reached by solving through the JS the FSSP which has reached the learning asymptote with the lowest truncation parameter value. It was found that for *Case 4*, the performance of JS and NEH appears to be quite similar with respect to upper ($\frac{\bar{C}^{JS}_{max} - \bar{C}^{UB}_{max}}{\bar{C}^{UB}_{max}}$) and lower ($\frac{\bar{C}^{JS}_{max} - \bar{C}^{LB}_{max}}{\bar{C}^{LB}_{max}}$) bound. For instance, in the combination $C4$_2_100_-0.515_0.25, the variations of JS from the lower and upper bound are 20.4% and -69.9%, for NEH, they are 20.1% and -70.0% respectively. However, the heuristic performance in relation to bounds shows larger differences in *Case 2*. Thus, in the combination $C2$_2_100_-0.515_0.25, the variations of JS from the lower and upper bound are 8.3% and -72.9%. For NEH, they are 3.1% and -74.2% respectively. The Table 3.5 shows the results of the comparison between JS and NEH for the average variation in C_{max} and the CPU time (*CT*) for each of the cases.

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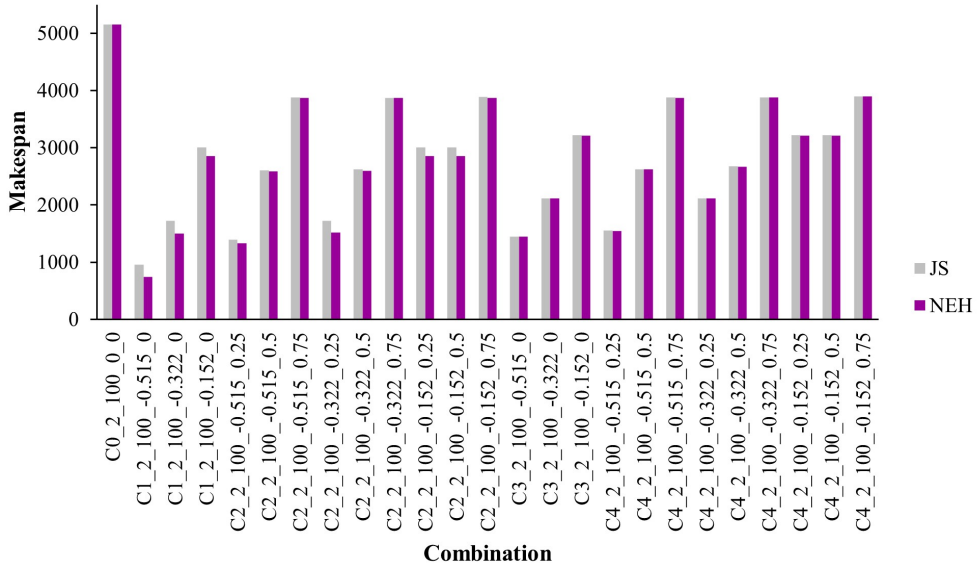

Figure 3.2: Experimental results for 2-worker 100-job instances NEH vs JS

Table 3.5: Experimental results - comparison JS vs NEH

Case	I	$\mathcal{J}$	α	β	$\frac{C_{max}^{JS}-C_{max}^{NEH}}{C_{max}^{JS}}$		$CT_{JS}-CT_{NEH}$	
					Mean	Std	Mean	Std
0	2	100	-	-	0.00%	0.00%	-2.41	1.22
1	2	100	-0.515	-	22.08%	3.13%	-3.82	2.02
	2	100	-0.322	-	12.54%	2.55%	-3.68	2.01
	2	100	-0.152	-	4.77%	1.95%	-3.86	2.00
2	2	100	-0.515	0.25	4.74%	2.67%	-3.90	2.08
	2	100	-0.515	0.5	0.63%	0.69%	-3.89	2.07
	2	100	-0.515	0.75	0.13%	0.17%	-3.90	2.07
	2	100	-0.322	0.25	11.62%	2.52%	-3.76	2.05
	2	100	-0.322	0.5	1.14%	0.98%	-3.80	2.08
	2	100	-0.322	0.75	0.15%	0.19%	-3.90	2.05
	2	100	-0.152	0.25	3.27%	2.64%	-3.87	2.05
	2	100	-0.152	0.5	4.77%	1.95%	-3.91	2.09
	2	100	-0.152	0.75	4.75%	1.94%	-3.91	2.08
3	2	100	-0.515	-	0.16%	0.08%	-7.30	3.86
	2	100	-0.322	-	0.11%	0.07%	-7.08	3.90
	2	100	-0.152	-	0.06%	0.03%	-7.41	3.89
4	2	100	-0.515	0.25	0.23%	0.11%	-15.44	8.22
	2	100	-0.515	0.5	0.17%	0.16%	-15.38	8.14
	2	100	-0.515	0.75	0.10%	0.13%	-15.71	8.02
	2	100	-0.322	0.25	0.11%	0.07%	-15.00	8.29
	2	100	-0.322	0.5	0.13%	0.10%	-15.06	8.30
	2	100	-0.322	0.75	0.06%	0.07%	-15.54	8.25
	2	100	-0.152	0.25	0.06%	0.03%	-15.51	8.32
	2	100	-0.152	0.5	0.06%	0.03%	-15.16	8.20
	2	100	-0.152	0.75	0.05%	0.04%	-14.95	8.18

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The computational complexity of NEH algorithm to solve the FSSP with constant processing time and makespan minimization is $O(MN^3)$ (Rudek, 2021). However this type of greedy heuristics has an outstanding performance to solve the FSSP, even considering the learning effect, either by the position or sum-of-processing-time based approaches. This may be because this type of algorithm makes the best choice at each step, especially with regard to the processing times of jobs that vary from step to step. Taking advantage of the properties of NEH, it could be utilized as an initial solution embedded in a metaheuristic thereby enhancing its performance.

3.5 Simulated Annealing Approach for more than Two-resources

In this section, we propose a SA algorithm to solve the FSSP with learning effect. The NEH algorithm was used as a start point because of its efficiency in minimizing the makespan in the FSSP (Ruiz and Maroto, 2005; Turner and Booth, 1987) furthermore, the outcomes from our previous experiments. Likewise, it corresponds to one of the heuristics commonly referred to in the FSSP approach with a learning effect (Mosheiov and Pruwer, 2021; Rudek and Rudek, 2013; Wang and Wang, 2014; Wu *et al.*, 2018a; Wu *et al.*, 2018b).

The SA, first proposed by Kirkpatrick *et al.* (1983), is a popular metaheuristic widely used to solve different variants of the flowshop scheduling problem (with or without learning effects), as discussed previously. SA is a local search metaheuristic capable of escaping from a local optimum due to the hill-climbing moves (Henderson *et al.*, 2003). The analysis sensitivity of SA parameters such as initial temperature (T_0), cooling velocity (λ), and final temperature (T_f) are presented in the section 3.5.3. The solution representation proposed is shown in Figure 3.3 (permutation of jobs).

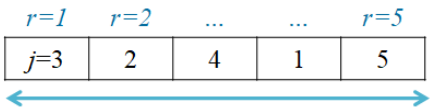

Figure 3.3: SA - Solution representation

3.5.1 Algorithm

Initial Solution: Adapted NEH

The initial solution is obtained by a greedy heuristic proposed by the (NEH) (Nawaz *et al.*, 1983), stated in section 3.4.1.

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Neighborhood Generation Phase

After obtaining the original solution S, the neighborhood generation phase is implemented, which is composed of a diversification strategy (DS) and a local search operator (LS). The diversification strategy is based on a randomized insertion, and follows these steps:

- *Step 1:* Randomly choose a job-j and position-r as part of the solution S.
- *Step 2:* Insert the j-th job on the r-th position (Figure 3.4), to obtain a new solution S_0. Compute the $C_{max}(S_0)$.
- *Step 3:* Replace S by S_0.

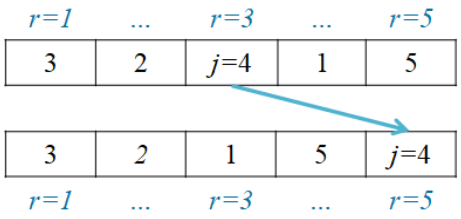

Figure 3.4: SA - Diversification strategy representation

Once solution S is obtained, a first improvement LS operator is implemented to improve the quality of this solution. In this case, the Adjacent Pairwise Interchange (API) and Non-Adjacent Pairwise Interchange (NAPI) operators were selected as they are commonly used to solve flowshop scheduling problems, and have yielded good results (Della Croce *et al.*, 1996; Lin, 2018). The SA algorithm with the API and NAPI operators will be named SA_{API} and SA_{NAPI} respectively. K_1 and K_2 are the selected positions within the permutation sequence to be switched.

The API operator swaps jobs from adjacent positions as follows:

- *Step 1:* If $K_1 = 1$ and $K_2 = K_1 + 2$, then the jobs between position K_1 and K_2 are swapped respectively (Figure 3.5).
- *Step 2:* The new solution is denoted S_0.
- *Step 3:* If $C_{max}(S_0)$ is less than $C_{max}(S)$, then S is replaced by S_0 and the local search algorithm stops.
- *Step 4:* Otherwise, $K_1 = K_1 + 1$ and $K_2 = K_2 + 2$ and the process is repeated until the $C_{max}(S)$ can be improved or up to $K_1 = R - 2$, or until all the position's permutations have been evaluated.

The NAPI operator swaps jobs from non-adjacent positions as follows:

- *Step 1:* If $K_1 = 1$ and $K_2 = K_1 + 1$, then the jobs between position K_1 and K_2 are swapped (Figure 3.6).

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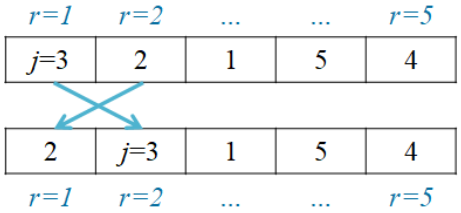

Figure 3.5: SA - API operator

- *Step 2:* The new solution is denoted S_0.
- *Step 3:* If $C_{max}(S_0)$ is less than $C_{max}(S)$, then S is replaced by S_0 and the local search algorithm stops.
- *Step 4:* Otherwise, $K_1 = K_1 + 1$ and $K_2 = K_2 + 1$ and the process is repeated until the $C_{max}(S)$ can be improved or up to $K_1 = R - 1$, or until all the position's permutations have been evaluated.

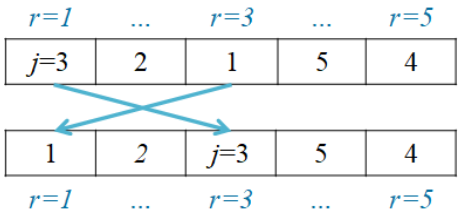

Figure 3.6: SA - NAPI operator

Acceptance Probability

A new given solution is accepted if its C_{max} value is lower than the C_{max} value of the stored solution ($\Delta f \leq 0$). However, when a worse solution is found ($\Delta f > 0$), a uniform random number is generated. If this random number is less than the probability of acceptance (Equation 3.30), then the solution is acceptable.

$$P_{\text{accept}} = \begin{cases} 1 & \Delta f \leq 0 \\ e^{-\frac{\Delta f}{T}}, & \Delta f > 0 \end{cases} \tag{3.30}$$

Where P_{accept} is the probability of acceptance, Δf is the change in objective function and T is the current temperature.

Stopping Condition

In this algorithm, T decreases inf function of the cooling velocity. Once T_f is reached (the stopping condition), the SA stops.

The flowchart in Figure 3.7 details the components and operation of SA algorithm.

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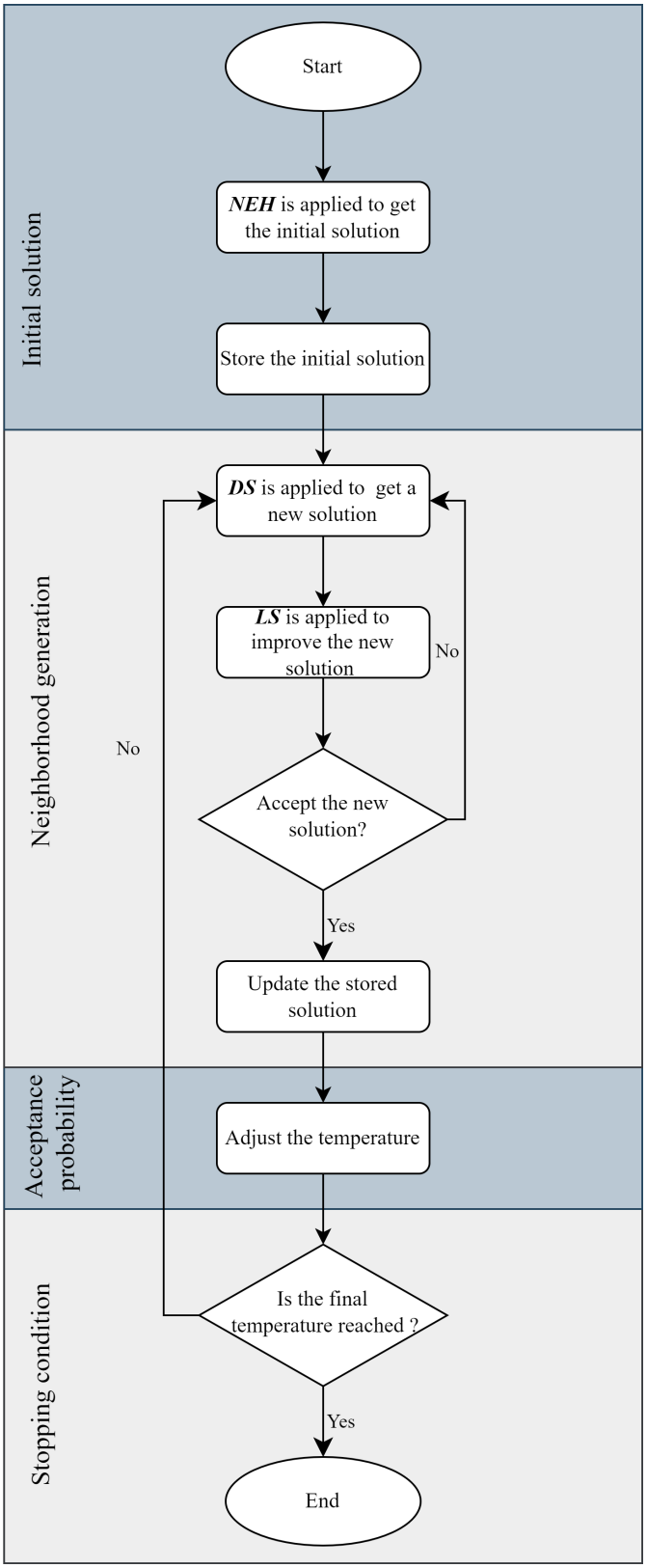

Figure 3.7: SA - Flowchart

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3.5.2 Computational Experiments and Results

Description of Data Sets

A set of problem instances containing 1440 independent data sets (480 small and 960 large-sized instances) was used to test the performance of the proposed algorithm. The characteristics of each instance are briefly outlined in Table 3.6. The rationale for the values of alpha (α) and beta (β) corresponds to the values chosen and tested previously. For the small-size instances, integer values of processing times were generated using an integer uniform distribution between 1 and 100. For the case of large-size datasets, the instances proposed by Taillard (1993) were used. In practice, combinations are referred to in the characteristics of instances as previously done. Each combination was encoded as *Case_*i *_*j *_*α *_*β (for example, *C2*_10 _100 _-0.515_0.5, corresponds to *Case 2* with 10 workers, 100 jobs, α = -0.515 and β = 0.5). A set of 10 instances for each combination was considered.

Table 3.6: SA - Summary of Problem Instances

Instances	Category	***Case 1* and *Case 3***	***Case 2* and *Case 4***
Small-size	Number of workers (I)	2	
	Number of jobs (J)	5, 7	
	Learning index (α)	-0.152, -0.322, -0.515	
	Truncation parameter (β)	–	0.25, 0.5, 0.75
Large-size	Number of workers (I)	5, 10	
	Number of jobs (J)	50, 100	
	Learning index (α)	-0.152, -0.322, -0.515	
	Truncation parameter (β)	–	0.25, 0.5, 0.75

Experimental Results Small-size Instances

The mathematical models were coded in Python and solved using Pyomo as was stated in section 3.3.2. The error percentage of the solution obtained by the simulated annealing algorithm (SA_{API} and SA_{NAPI}) from the optimal solution is calculated as (Equation 3.31):

$$OPT - SA_{API} = \frac{S_{OPT} - SA_{API}}{S_{OPT}} \tag{3.31}$$

Where S_{OPT} is the optimal solution for each instance and SA_{API} is the makespan value obtained from the metaheuristic (SA_{API} in this case). Table 3.7 provides a comparison of the mean percentage and the standard deviation of error and CPU time (of all instances by combination). For small-size instances, both SA_{API} and SA_{NAPI} achieved mean error percentages are below 1%. As there is no significant difference between the error percentage of SA_{API} and that of SA_{NAPI}, it is not possible to conclude at this point with which one the SA triggers a better performance.

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Table 3.7: SA - Comparison for small-size instances

Case	I	J	α	β	$OPT - SA_{API}$		$OPT - SA_{NAPI}$		CPU time SA_{API}		CPU time SA_{NAPI}		CPU time OPT	
					Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
1	2	5	-0.152	-	0.02%	0.06%	0.02%	0.07%	0.02	0.02	0.05	0.04	0.16	0.02
	2	5	-0.322	-	0.15%	0.37%	0.21%	0.41%	0.03	0.02	0.04	0.04	0.15	0.01
	2	5	-0.515	-	0.27%	0.62%	0.51%	1.00%	0.03	0.02	0.05	0.07	0.17	0.01
	2	7	-0.152	-	0.03%	0.12%	0.04%	0.09%	0.05	0.05	0.11	0.09	2.32	0.05
	2	7	-0.322	-	0.07%	0.28%	0.21%	0.49%	0.06	0.05	0.1	0.09	2.26	0.09
	2	7	-0.515	-	0.11%	0.28%	0.37%	0.90%	0.06	0.1	0.1	0.08	2.1	0.11
2	2	5	-0.152	0.25	0.02%	0.06%	0.03%	0.08%	0.03	0.02	0.05	0.04	0.15	0.01
	2	7	-0.515	-	0.11%	0.28%	0.37%	0.90%	0.06	0.1	0.1	0.08	2.1	0.11
	2	5	-0.152	0.5	0.02%	0.06%	0.02%	0.08%	0.03	0.02	0.05	0.04	0.15	0
	2	5	-0.152	0.75	0.02%	0.06%	0.02%	0.07%	0.03	0.02	0.05	0.04	0.15	0.01
	2	5	-0.322	0.25	0.13%	0.34%	0.22%	0.42%	0.02	0.02	0.05	0.04	0.15	0.01
	2	5	-0.322	0.5	0.12%	0.34%	0.21%	0.41%	0.02	0.02	0.04	0.04	0.14	0.01
	2	5	-0.322	0.75	0.00%	0.00%	0.01%	0.13%	0.02	0.02	0.03	0.03	0.15	0.01
	2	5	-0.515	0.25	0.31%	0.69%	0.46%	0.94%	0.03	0.02	0.04	0.04	0.14	0.01
	2	5	-0.515	0.5	0.72%	2.12%	0.47%	1.58%	0.02	0.02	0.04	0.03	0.15	0.01
	2	5	-0.515	0.75	0.01%	0.12%	0.01%	0.12%	0.03	0.02	0.03	0.02	0.15	0.01
	2	7	-0.152	0.25	0.03%	0.09%	0.04%	0.09%	0.05	0.04	0.13	0.16	2.32	0.06
	2	7	-0.152	0.5	0.02%	0.08%	0.04%	0.10%	0.05	0.04	0.13	0.22	2.37	0.07
	2	7	-0.152	0.75	0.02%	0.09%	0.04%	0.12%	0.05	0.04	0.11	0.09	2.31	0.06
	2	7	-0.322	0.25	0.07%	0.31%	0.22%	0.48%	0.05	0.04	0.1	0.09	2.25	0.09
	2	7	-0.322	0.5	0.07%	0.27%	0.19%	0.40%	0.05	0.04	0.1	0.09	2.25	0.06
	2	7	-0.322	0.75	0.02%	0.03%	0.02%	0.03%	0.03	0.03	0.04	0.03	2.29	0.06
	2	7	-0.515	0.25	0.08%	0.19%	0.28%	0.67%	0.05	0.04	0.1	0.09	2.1	0.1
	2	7	-0.515	0.5	0.11%	0.44%	0.31%	1.11%	0.04	0.03	0.06	0.05	2.17	0.07
	2	7	-0.515	0.75	0.00%	0.04%	0.01%	0.09%	0.03	0.04	0.03	0.02	2.33	0.07

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Table 3.7: SA - Comparison for small-size instances

Case	I	J	α	β	$OPT - SA_{API}$		$OPT - SA_{NAPI}$		CPU time SA_{API}		CPU time SA_{NAPI}		CPU time OPT	
					Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
3	2	5	-0.152	-	0.00%	0.00%	0.00%	0.01%	0.03	0.03	0.07	0.05	18.48	3.53
	2	5	-0.322	-	0.06%	0.22%	0.06%	0.20%	0.04	0.03	0.07	0.06	19.12	3.05
	2	5	-0.515	-	0.01%	0.03%	0.06%	0.41%	0.04	0.03	0.07	0.06	19.33	2.88
	2	7	-0.152	-	0.00%	0.00%	0.00%	0.01%	0.08	0.06	0.18	0.15	1580.88	22.66
	2	7	-0.322	-	0.00%	0.00%	0.00%	0.02%	0.08	0.06	0.17	0.14	1591.9	48.29
	2	7	-0.515	-	0.00%	0.01%	0.07%	0.21%	0.08	0.07	0.17	0.14	1586.26	98.26
4	2	5	-0.152	0.25	0.01%	0.01%	0.01%	0.01%	0.07	0.06	0.12	0.1	20.6	3.48
	2	5	-0.152	0.5	0.01%	0.01%	0.01%	0.01%	0.07	0.06	0.12	0.1	22.32	2.74
	2	5	-0.152	0.75	0.01%	0.01%	0.01%	0.01%	0.07	0.06	0.12	0.09	23.76	3.77
	2	5	-0.322	0.25	0.11%	0.22%	0.09%	0.19%	0.08	0.06	0.12	0.1	24.16	4.15
	2	5	-0.322	0.5	0.09%	0.21%	0.10%	0.21%	0.08	0.06	0.12	0.1	25.23	7.5
	2	5	-0.322	0.75	0.00%	0.00%	0.01%	0.05%	0.06	0.05	0.1	0.09	25.53	5.07
	2	5	-0.515	0.25	0.31%	0.70%	0.34%	0.73%	0.07	0.06	0.12	0.1	22.87	3.06
	2	5	-0.515	0.5	0.31%	0.70%	0.33%	0.71%	0.07	0.06	0.12	0.1	23.78	2.67
	2	5	-0.515	0.75	0.00%	0.00%	0.00%	0.05%	0.06	0.05	0.09	0.07	27.36	8.29
	2	7	-0.152	0.25	0.02%	0.04%	0.02%	0.04%	0.16	0.14	0.36	0.3	2570.01	919.55
	2	7	-0.152	0.5	0.02%	0.04%	0.02%	0.04%	0.16	0.15	0.36	0.3	2172.26	209.46
	2	7	-0.152	0.75	0.02%	0.04%	0.02%	0.04%	0.16	0.13	0.36	0.29	2457.82	724.04
	2	7	-0.322	0.25	0.04%	0.08%	0.04%	0.08%	0.16	0.13	0.35	0.29	2494.9	725.52
	2	7	-0.322	0.5	0.04%	0.08%	0.04%	0.08%	0.16	0.13	0.35	0.29	2207.21	241.34
	2	7	-0.322	0.75	0.00%	0.02%	0.00%	0.03%	0.11	0.1	0.19	0.18	2292.46	440.64
	2	7	-0.515	0.25	0.05%	0.09%	0.10%	0.24%	0.17	0.14	0.34	0.28	2385.95	436.48
	2	7	-0.515	0.5	0.01%	0.03%	0.03%	0.05%	0.14	0.12	0.33	0.27	2496.02	994.31
	2	7	-0.515	0.75	0.00%	0.02%	0.01%	0.04%	0.1	0.09	0.13	0.13	2069.05	222.7

**CPU time in seconds*

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Experimental Results - Large-size Instances

An experimental design was conducted to evaluate the performance of the SA algorithm. Three main parameters required for the SA (T_0,T_f and λ) were included in the experiment. The algorithms were codified in Python 3.8 and run on a 64-Core server with CPU AMD EPYC 7702 and 512 G RAM. Table 3.8 summarizes the data used. Three replications per instance were run for a total of 155.520 executions.

Table 3.8: SA - Large instances summary experiment

	Parameter	Level	Values
Factors	Initial temperature – (T_0)	3	0.5, 0.3, 0.1
	Final temperature – (T_f)	3	0.001, 0001, 0.00001
	Cooling velocity – (λ)	2	0.9, 0.5
Treatments			(2x3x3x2) = 36
Combination			144
Instances per combination.			(144x10) =1440
Instamce per combination x treatment			(1440x36) = 51840
Size of the experiment			(51840x3) = 155520

As we cannot compute the optimal solution, we use the makespan value obtained by the NEH algorithm as the reference. The percentage of improvement of the initial solution obtained by NEH with respect to the simulated annealing algorithm SA_{API} and SA_{NAPI} is calculated as follows (Equation 3.32):

$$\Delta SA_{API} - NEH = \frac{SA_{API} - S_{NEH}}{S_{NEH}} \tag{3.32}$$

where S_{NEH} is the solution obtained with the heuristic NEH and S_{SA} is the solution achieved with the simulated annealing algorithm (with SA_{API} for this case) for each instance. With a *p-value* of $2x10^{-16}$ and a confidence level of 95%, the percentage of improvement of SA_{API} with the NEH ($\Delta SA_{API} - NEH$) is better than the improvement obtained with SA_{NAPI} ($\Delta SA_{NAPI} - NEH$). Table 3.9 shows a comparison of the mean percentage and standard deviation of improvement and CPU time. Due to the quality of the initial solution, the API operators works as intensive operators, without making any drastic modification of the solution obtained constructively from NEH. Meanwhile, NAPI operators, by making a major change to the solution, seems to be moving away from a promising search zone, explaining the dominance of SA_{API} over SA_{NAPI}.

Figure 3.8 shows a representative example with 10 workers and 50 jobs, to show the improvement of the two simulated annealing algorithms (SA_{API} and SA_{NAPI}) in relation to the NEH, segmented by combination.

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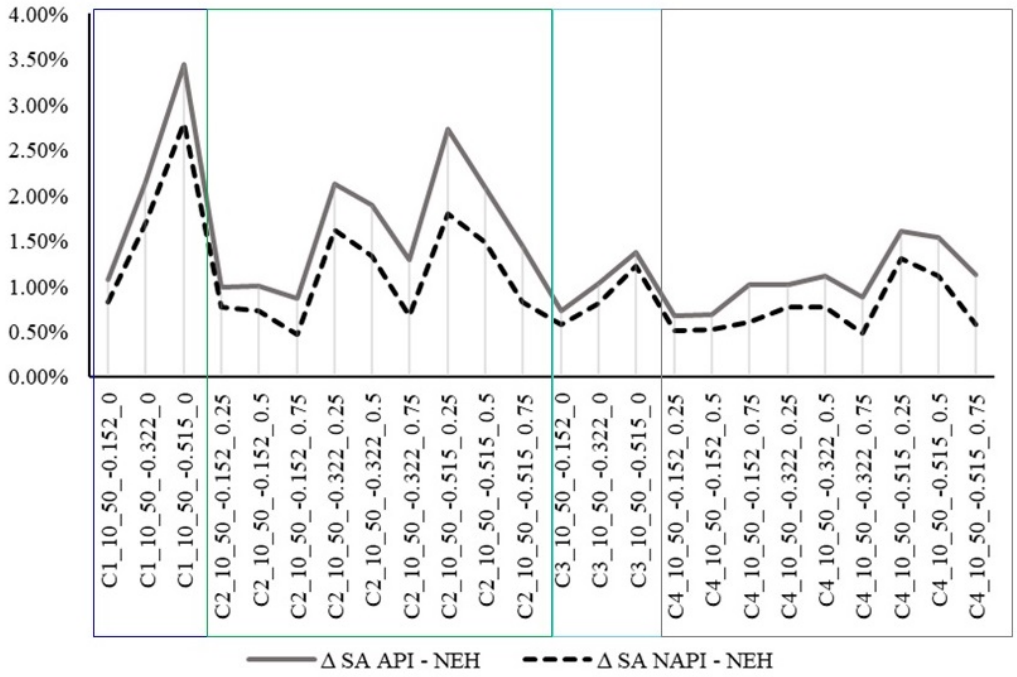

Figure 3.8: SA - Comparison of $\Delta SA_{API} - NEH$ vs. $\Delta SA_{NAPI} - NEH$

In most of the cases, SA_{API} outperforms SA_{NAPI}. An example in Figure 3.8 and the results in the Table 3.9 evidence that the simulated annealing algorithms proposed (both SA_{API} and SA_{NAPI}) improve the initial solutions. This applies to combinations with small λ values or strong learning rates (remembering that $\alpha = log_2 LR$), where LR is the learning rate, e.g., LR = 70% , α=-0.515), for *Cases 1* and *3* without truncation parameters. In the same way, we note that for fast learning effect, the convergence of the algorithm is fast with respect to CPU time (Table 3.9), as described in the findings of Muştu and Eren (2018). For example, going back for combinations *C3*_10 _100 _-0.515_0.0 and *C3*_10 _100 _-0.152_0.0 solved with SA_{API}, the mean CPU time is respectively 27.36 $\pm$ 9.88, 36.59 $\pm$ 18.97 seconds.

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Table 3.9: SA - Comparison for large-size instances

Case	I	J	α	β	$\Delta SA_{API} - NEH$		$\Delta SA_{NAPI} - NEH$		CPU time SA_{API}		CPU time SA_{NAPI}	
					Mean	Std	Mean	Std	Mean	Std	Mean	Std
1	10	100	-0.152	-	0.55%	0.39%	0.43%	0.38%	29.82	19.61	255.58	247.18
	10	100	-0.322	-	1.25%	0.74%	1.06%	0.68%	27.57	18.6	199.49	204.12
	10	100	-0.515	-	1.92%	1.01%	1.48%	0.92%	20.95	10.12	136.46	138.62
	10	50	-0.152	-	1.06%	0.68%	0.82%	0.57%	12.53	13.25	53.82	50.18
	10	50	-0.322	-	2.14%	1.4%	1.68%	1.15%	9.2	9.53	44.19	44.06
	10	50	-0.515	-	3.43%	2.1%	2.8%	1.84%	6.19	5.87	30.83	31.74
	5	100	-0.152	-	0.47%	0.3%	0.41%	0.28%	13.77	7.58	116.41	119.11
	5	100	-0.322	-	1.41%	0.78%	1.14%	0.7%	12.76	6.24	101.79	101.48
	5	100	-0.515	-	2.98%	1.35%	2.28%	1.19%	11.15	4.6	74.33	74.41
	5	50	-0.152	-	0.73%	0.41%	0.62%	0.36%	4.29	4.22	24.77	24.69
	5	50	-0.322	-	1.56%	0.99%	1.22%	0.83%	4.23	4.21	23.37	23.13
	5	50	-0.515	-	3.19%	1.43%	2.49%	1.26%	3.26	2.78	18.47	19.29
2	10	100	-0.152	0.25	0.5%	0.35%	0.35%	0.32%	29.71	12.54	142.74	87.91
	10	100	-0.152	0.5	0.51%	0.35%	0.36%	0.3%	29.34	12.21	140.76	89.08
	10	100	-0.152	0.75	0.37%	0.37%	0.15%	0.21%	54.32	36.32	72.82	54.85
	10	100	-0.322	0.25	1.06%	0.6%	0.79%	0.55%	27.02	12.36	107.23	81.5
	10	100	-0.322	0.5	0.68%	0.48%	0.38%	0.37%	46.69	33.39	59.46	44.12
	10	100	-0.322	0.75	0.54%	0.39%	0.23%	0.28%	61.12	40.76	86.4	68.92
	10	100	-0.515	0.25	1.12%	0.77%	0.47%	0.69%	38.1	30.91	39.4	23.06
	10	100	-0.515	0.5	0.63%	0.57%	0.22%	0.36%	58.46	42.07	61.5	45.99
	10	100	-0.515	0.75	0.47%	0.35%	0.19%	0.22%	65.5	44.62	83.53	64.26
	10	50	-0.152	0.25	0.99%	0.63%	0.76%	0.53%	8.45	5.36	36.34	24.32
	10	50	-0.152	0.5	1%	0.63%	0.72%	0.51%	8.41	5.27	36.34	24.05
	10	50	-0.152	0.75	0.86%	0.65%	0.46%	0.51%	12.5	7.51	26.69	21.39
	10	50	-0.322	0.25	2.12%	1.43%	1.61%	1.11%	8.05	5.66	33.53	25.48

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Table 3.9: SA - Comparison for large-size instances

Case	I	J	α	β	$\Delta SA_{API} - NEH$		$\Delta SA_{NAPI} - NEH$		CPU time SA_{API}		CPU time SA_{NAPI}	
					Mean	Std	Mean	Std	Mean	Std	Mean	Std
	10	50	-0.322	0.5	1.9%	0.9%	1.33%	0.83%	9.97	7.46	21.05	17.89
	10	50	-0.322	0.75	1.29%	0.66%	0.67%	0.54%	14.77	10.32	28.16	21.86
	10	50	-0.515	0.25	2.72%	1.81%	1.8%	1.81%	7.75	7.31	9.62	6.87
	10	50	-0.515	0.5	2.08%	1.04%	1.48%	1.01%	11.26	9.05	19.04	15.84
	10	50	-0.515	0.75	1.44%	1.07%	0.82%	0.88%	16.22	11.31	27.24	21.5
	5	100	-0.152	0.25	0.44%	0.27%	0.36%	0.25%	14.75	5.8	82.86	59.67
	5	100	-0.152	0.5	0.45%	0.28%	0.37%	0.25%	14.68	5.77	82.37	59.31
	5	100	-0.152	0.75	0.17%	0.26%	0.05%	0.12%	42.32	29.65	23.93	12.26
	5	100	-0.322	0.25	1.27%	0.71%	0.91%	0.62%	13.52	5.43	64.83	50.93
	5	100	-0.322	0.5	0.41%	0.28%	0.2%	0.23%	25.8	20.57	24.07	12.48
	5	100	-0.322	0.75	0.24%	0.29%	0.08%	0.14%	38.04	30	23.97	12.51
	5	100	-0.515	0.25	1.27%	0.78%	0.8%	0.83%	18.1	13.82	23.11	11.57
	5	100	-0.515	0.5	0.58%	0.51%	0.22%	0.34%	33.8	28.03	23.75	11.98
	5	100	-0.515	0.75	0.24%	0.25%	0.05%	0.09%	42.84	32.28	24.05	12.53
	5	50	-0.152	0.25	0.7%	0.39%	0.58%	0.34%	4.43	2.92	19.86	15.04
	5	50	-0.152	0.5	0.69%	0.38%	0.57%	0.32%	4.43	2.93	19.99	14.99
	5	50	-0.152	0.75	0.29%	0.29%	0.12%	0.19%	10.08	7.19	5.94	4.06
	5	50	-0.322	0.25	1.51%	0.99%	1.12%	0.76%	4.51	3.07	19.55	14.86
	5	50	-0.322	0.5	0.68%	0.45%	0.16%	0.21%	9.39	7.35	5.33	3.34
	5	50	-0.322	0.75	0.47%	0.41%	0.18%	0.28%	10.85	8.33	5.54	3.85
	5	50	-0.515	0.25	2.37%	1.22%	1.27%	1.05%	5.78	5.99	5.18	3.33
	5	50	-0.515	0.5	0.57%	0.47%	0.32%	0.41%	9.03	7.63	5.25	3.32
	5	50	-0.515	0.75	0.56%	0.44%	0.28%	0.36%	10.29	8.3	5.62	3.81
3	10	100	-0.152	-	0.29%	0.27%	0.23%	0.25%	36.59	18.97	224.76	149.59
	10	100	-0.322	-	0.56%	0.56%	0.35%	0.41%	32.89	16.5	214.97	153.84

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Table 3.9: SA - Comparison for large-size instances

Case	I	J	α	β	$\Delta SA_{API} - NEH$		$\Delta SA_{NAPI} - NEH$		CPU time SA_{API}		CPU time SA_{NAPI}	
					Mean	Std	Mean	Std	Mean	Std	Mean	Std
	10	100	-0.515	-	1.11%	1%	1.07%	0.96%	27.36	9.88	177.34	143.78
	10	50	-0.152	-	0.73%	0.58%	0.57%	0.51%	16.07	17.74	76.51	65.82
	10	50	-0.322	-	1.03%	0.83%	0.81%	0.67%	10.72	10.63	63.96	56.64
	10	50	-0.515	-	1.37%	0.85%	1.21%	0.88%	10.29	10.56	56.34	54.35
	5	100	-0.152	-	0.11%	0.18%	0.09%	0.14%	19.98	8.64	127	112.24
	5	100	-0.322	-	0.25%	0.4%	0.12%	0.21%	18.64	6.79	139.82	117.37
	5	100	-0.515	-	0.42%	0.61%	0.37%	0.6%	18.79	7.52	136.64	117.23
	5	50	-0.152	-	0.25%	0.28%	0.15%	0.19%	5.28	4.9	36.44	37.26
	5	50	-0.322	-	0.47%	0.57%	0.35%	0.5%	4.96	4.21	37.63	37.84
	5	50	-0.515	-	0.62%	0.79%	0.49%	0.63%	5.01	4.33	34.13	35.02
4	10	100	-0.152	0.25	0.27%	0.25%	0.23%	0.24%	48.44	17.42	270.22	162.62
	10	100	-0.152	0.5	0.29%	0.26%	0.22%	0.23%	48.33	17.21	271.38	164.23
	10	100	-0.152	0.75	0.34%	0.36%	0.14%	0.22%	82.48	43.82	155.47	115.06
	10	100	-0.322	0.25	0.55%	0.53%	0.35%	0.42%	47.1	18.13	256.4	170.64
	10	100	-0.322	0.5	0.43%	0.51%	0.25%	0.33%	71.07	45.4	134.68	105.81
	10	100	-0.322	0.75	0.39%	0.36%	0.17%	0.22%	98.19	58.1	154.63	116.75
	10	100	-0.515	0.25	0.77%	0.91%	0.47%	0.69%	42.8	18.59	119.17	82.63
	10	100	-0.515	0.5	0.52%	0.6%	0.31%	0.54%	81.85	53.2	119.77	86.46
	10	100	-0.515	0.75	0.49%	0.44%	0.21%	0.28%	99.01	62.21	160.01	122.57
	10	50	-0.152	0.25	0.66%	0.54%	0.5%	0.44%	13.43	7.61	66.44	39.02
	10	50	-0.152	0.5	0.68%	0.53%	0.51%	0.45%	13.12	7.49	66.32	39.17
	10	50	-0.152	0.75	1.01%	0.78%	0.59%	0.58%	17.19	10.74	46.96	36.02
	10	50	-0.322	0.25	1.01%	0.8%	0.77%	0.62%	12.15	7.82	60.74	41.52
	10	50	-0.322	0.5	1.1%	0.82%	0.77%	0.68%	15.29	11.2	37.65	29.96
	10	50	-0.322	0.75	0.88%	0.7%	0.47%	0.53%	23.87	14.81	48.79	36.04

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Table 3.9: SA - Comparison for large-size instances

Case	I	J	α	β	$\Delta SA_{API} - NEH$		$\Delta SA_{NAPI} - NEH$		CPU time SA_{API}		CPU time SA_{NAPI}	
					Mean	Std	Mean	Std	Mean	Std	Mean	Std
	10	50	-0.515	0.25	1.61%	0.98%	1.3%	0.94%	12.35	8.61	54.03	42.13
	10	50	-0.515	0.5	1.54%	0.83%	1.1%	0.79%	19.84	13.63	39.12	30.65
	10	50	-0.515	0.75	1.13%	0.97%	0.57%	0.67%	23.51	15.39	44.51	34.54
	5	100	-0.152	0.25	0.12%	0.18%	0.09%	0.15%	33.57	11.68	168.48	127.62
	5	100	-0.152	0.5	0.11%	0.17%	0.09%	0.13%	33.73	11.99	168.45	128.98
	5	100	-0.152	0.75	0.05%	0.06%	0.03%	0.04%	79.31	53	65.13	36.41
	5	100	-0.322	0.25	0.24%	0.38%	0.12%	0.21%	32.4	10.84	186.74	132.94
	5	100	-0.322	0.5	0.11%	0.2%	0.06%	0.13%	49.4	37.95	63.46	34.01
	5	100	-0.322	0.75	0.1%	0.1%	0.04%	0.07%	86.04	67.31	56.53	27.82
	5	100	-0.515	0.25	0.37%	0.5%	0.23%	0.4%	31.09	10.78	95.11	63.07
	5	100	-0.515	0.5	0.22%	0.32%	0.1%	0.17%	58.28	44.58	58.42	28.61
	5	100	-0.515	0.75	0.15%	0.17%	0.05%	0.11%	88.55	65.61	57.29	27.5
	5	50	-0.152	0.25	0.26%	0.31%	0.14%	0.18%	7.91	5.13	43.49	33.79
	5	50	-0.152	0.5	0.27%	0.3%	0.15%	0.19%	8.05	5.3	43.91	33.96
	5	50	-0.152	0.75	0.22%	0.27%	0.09%	0.17%	17.21	12.99	15.3	10.83
	5	50	-0.322	0.25	0.52%	0.64%	0.34%	0.5%	7.8	5.16	44.45	33.57
	5	50	-0.322	0.5	0.28%	0.36%	0.16%	0.27%	11.27	9.6	17.7	12.88
	5	50	-0.322	0.75	0.33%	0.26%	0.17%	0.23%	22.24	17.42	14.34	10.16
	5	50	-0.515	0.25	0.58%	0.8%	0.32%	0.42%	8.34	5.53	42.69	32.98
	5	50	-0.515	0.5	0.47%	0.49%	0.19%	0.3%	19.11	14.71	13.42	8.97
	5	50	-0.515	0.75	0.32%	0.34%	0.17%	0.29%	22.08	17.68	13.06	8.93

**CPU time in seconds*

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For learning models with truncation, the improvement by SA_{API} or SA_{NAPI} of the solution obtained from NEH turns out to be quite poor when β is larger. This could be explained by the fact that a bigger β means that the learning effect stops quickly reaching the asymptote in a short planning horizon (units or accumulated time as the case may be). Therefore, the NEH solution might be a good approach because the processing time cases to be varied quickly. When β is smaller, the learning effect remains during a longer horizon.

3.5.3 Sensitivity Analysis

For the evaluation of SA_{API} parameters, an (analysis of variance) ANOVA test was applied. Experimental factors refer to T_f, T_0 and λ with three, three, and two levels, respectively. The statistical test results showed that the double interaction T_0 T_f and T_f λ have an effect on the algorithm performance with a *p-value* of 0.0013 and 3.47x10^{-6}, respectively. Figure 3.9 shows plots of double interaction effects for each case. A more favorable mean of the $\Delta SA_{API} - NEH$ is found in the four cases where for the double interaction $T_f\lambda$, the levels are $T_f = 0.00001$ and $\lambda = 0.9$. In both linear and non-linear models, this combination of parameters improves the initial solution obtained through the NEH. It can be assumed that the small values of T_f reinforce the intensification, and that the large values λ, together with the acceptance probability, contribute to diversify the solution.

The maximum mean improvement is close to 3%, which would show that if the NEH produces a good quality initial solution, this may be because this heuristic makes the best choice at every step, particularly regarding to the processing times of jobs that vary from step to step.

3.6 Conclusions

This chapter addressed makespan minimization of FSSP with learning effects, modeling this phenomenon from 4 linear and non-linear models reported in the literature. We presented the mathematical models and used a mathematical programming solver to solve small-instances problem. For the problem with two resources, a comparison between an adapted NEH algorithm and the Johnson's rule was carried out. To solve large-instances problems a SA algorithm testing two local search operators was proposed, with the initial solution by means of the NEH algorithm; and it has shown remarkable results in addressing these problems.

The flowshop scheduling problem with learning effects is NP-hard even in the case of two resources, for problems with 2 workers and 8 jobs (*Cases 3* and *4*, non-linear models), it was not possible to reach the optimum through the mathematical model within a time limit of 8 hours. The Johnson's rule for two-resource FSSP with learning effects failed to achieve the optimal solution. On the other hand NEH achieved outstanding results by addressing scheduling problems with variable job processing times. This may be because this algorithm makes the best choice at every step, particularly with regard to the job

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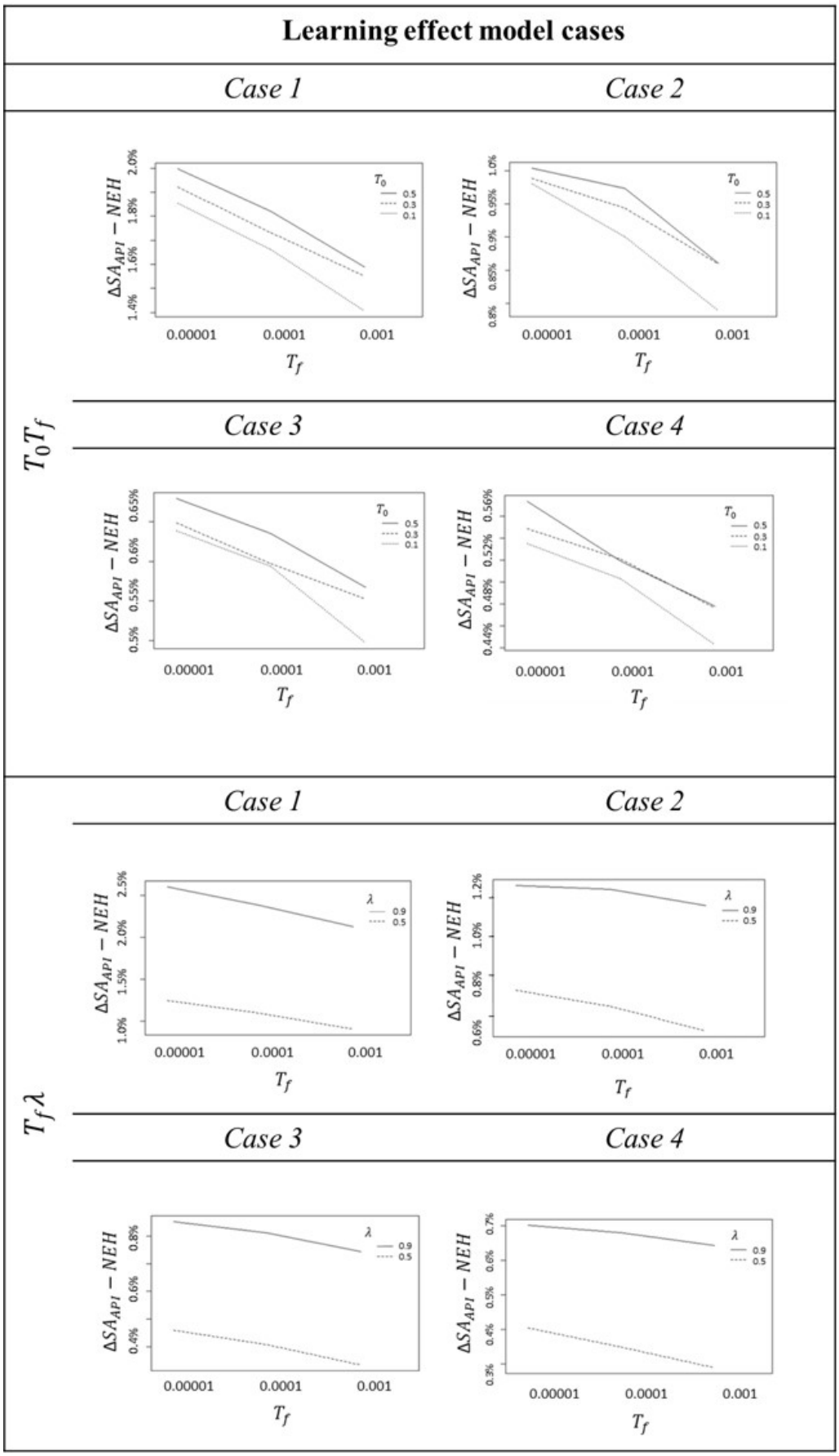

Figure 3.9: SA - Double interaction plot

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processing times that vary from step to step.

Two variants of the simulated annealing algorithm were developed (SA_{API}, SA_{NAPI}), which get the initial solution from NEH and apply the different local search operators. SA_{API} shows improved performance in relation to SA_{NAPI}. Concerning the SA_{API} parameters' sensitivity, the double interaction $T_f\lambda$ ($T_f = 0.00001$ and $\lambda = 0.9$) has a positive effect on metaheuristic performance for the four cases studied here.

Job scheduling is a crucial operational decision for companies, typically made at the start of each shift or working day. The findings of this chapter provide insights into potential tools for addressing and solve the FSSP in hand-intensive systems, where the learning effect has an impact on job processing times, and various modeling approaches can be utilized. The sequencing of jobs is an input for the next chapter which will discuss the integration of the effect of physical fatigue and the definition of break policies. Some of the algorithms proposed here will be used in Chapter 5 of the case study development.

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Chapter 4

Incorporating the Fatigue effect

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The content of this chapter is based on the following publication in progress:

- *Paredes-Astudillo, Y. A., Montoya-Torres, J. R., Botta-Genoulaz, V., Caro, M. P. and Jimenez, J.F. (in progress). Flowshop scheduling problem with learning effect and incorporation of fatigue phenomena: a case study. To be submitted.*

Preliminary findings of this chapter were presented at:

- *Paredes-Astudillo, Y. A., Jimenez, J.F., Montoya-Torres, J. R., and Botta-Genoulaz, V. (2023). Fatigue integration to the flowshop scheduling problem. Service Oriented, Holonic and Multi-Agent Manufacturing Systems for Industry of the Future: Proceedings of SOHOMA 2023 (to appear). Annecy, France, September 28-29, 2023.*

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Abstract

The focus of this chapter is on incorporating fatigue into the flowshop scheduling problem (FSSP). A model for physical fatigue and recovery is being proposed, based on what has already been reported in the literature. A multi-agent system is introduced to analyse the incorporation of physical fatigue's workers into the FSSP. In order to examine the Multi-agent system, we conducted exploratory computational experiments. Two break policies (location and duration of breaks) are evaluated to identify their impact on human and system performance. Benchmark datasets are used in the exploratory experiments.

4.1 Introduction

Including human factors into the operations and logistical system means both challenges and opportunities. The learning and deterioration effects are the two main categories that group the phenomenon experienced by humans that could affect the job processing time. As discussed in Chapter 2, there is a notable number of contributions that address scheduling problems taking into account the learning effect. However, in the context of deterioration, especially when considering human-beings and factors such as the fatigue, the research are still ongoing.

The FSSP with learning and deteriorating effect belongs to the family of scheduling problems with time changing effects, whose requires a hard computational effort (Mosheiov, 2001). The problem is included into the NP-hard class. Integrating fatigue into this context is also a challenging task due to: i) its dynamic nature (i.e., fatigue levels can fluctuate based on workload, and it can impact the overall system's performance), and ii) its modeling requires a multidisciplinary approach.

When executing manual tasks, muscular fatigue accumulates cycle by cycle, driving to a rise of discomfort and potentially leading to an occupational disease. Consequently, ensuring adequate recovery for workers engaged in physically activities becomes imperative (Neumann *et al.*, 2020). The high prevalence of muscular fatigue in manual-intensive systems has caught research interest. Particularly within the scope of scheduling, the concept of rest allowance (RA) has recently been introduced, incorporating breaks after physical tasks (Prunet *et al.*, 2022).

Our goal in this chapter is to show how to model the fatigue effect and integrate it into the FSSP without learning effect. To test the impact of break policies on system performance and validate the incorporation of physical fatigue, a multi-agent model is proposed. To evaluate the viability of the multi-agent system, some exploratory computational experiments were carried out using benchmark data sets. In Chapter 5, this approach is validated and applied by implementing it into a real industrial case study.

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4.2 Related Literature

Grandjean (1979) defines fatigue as a loss of efficiency caused by external effort, which can be physical or mental. Work-related fatigue, caused by work, has a multidimensional effect on operational performance across production systems and worker (i.e., workers' illness, loss of productivity, and increased rate error) (Xu and Hall, 2021). The focus of this study is on muscular fatigue, which is a type of physical fatigue. It is mainly caused by repetitive physical tasks and is linked to the occurrence of Work-Related Musculoskeletal Disorder (WMSD). Therefore, determining appropriate work-rest times and breaks policies in industrial environments are crucial to reduce this risk.

The inclusion of breaks is a crucial factor in addressing the phenomenon of fatigue. The definition of break done by Jett and George (2003) states that a break as either a planned or spontaneous interruption from work on a task that disrupts the flow of activity and continuity. Therefore, breaks are frequently used during the shift to allow the workers to recover from mental and/or physical fatigue (Di Pasquale *et al.*, 2015).

In the field of operations research, there are some approaches to defining the breaks policies in the literature. Jaber and Neumann (2010) deal with the dual resource constrained system and the fatigue's impact on production, presenting a MILP model that describes fatigue and recovery in the system. Perez *et al.* (2014) investigated workers' fatigue exposure. By using discrete-event simulation implemented on an assembly line, their approach allows for the prediction of mechanical exposure and fatigue accumulation of operators. Incorporating fatigue and recovery models, the simulation evaluated the performance of the systems based on the organization of work patterns and breaks. Likewise, Dode *et al.* (2016) combine a discrete-event simulation model and a predictive approach to determine how fatigue occurs as a result of changes in system design configuration, and work organization. Within an assembly line, they analyzed how they affected the quality level of the product.

Calzavara *et al.* (2019) used the McNaughton algorithm for job scheduling minimizing the makespan, and integrating a fatigue and rest model. A mathematical model was proposed to estimate the duration of breaks (rest time) for each worker. In the same way, Berti *et al.* (2019) used several constructive heuristics to minimize the makespan of a manufacturing cell. Each worker was assigned tasks based on their accumulated fatigue and rest requirements.

On the other hand, El Mouayni *et al.* (2020) presented an alternative approach by developing an agent-based simulation model to determine rest periods. They evaluated three system configurations such as production line, cell manufacturing, and an hybrid configuration. The study identified which configurations respond to rest requirements, keeping productivity.

Within the context of scheduling problems with variable job processing times, breaks and maintenance activities share similarities. These are referred as rate-modifying activities (RMA), the term used to describe an activity that changes the production rate of a resource. A RMA where the resource is restored to 'as new' or 'less deteriorated' is presented, such as preventive maintenance. This effect is similar to the one caused

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by breaks on workers. Therefore, referring to the literature on maintenance activities scheduling could be useful.

In the last review of Geurtsen *et al.* (2023), focused on production scheduling that involves maintenance activities, the flowshop and hybrid flowshop system are typically solved using mathematical programming and metaheuristics such as ant colony optimization and genetic algorithms (GA) (i.e., Figielska (2006) and Figielska (2009)).

Regarding multi-objective problems of this nature, Yazdani *et al.* (2019) deal with a flexible job shop scheduling problem minimizing the makespan, critical machine workload and total workload of machines. They propose two types of multi-objective evolutionary algorithms including fast elitist non-dominated sorting genetic algorithm (NSGA-II) and non-dominated ranking genetic algorithm. Abedi *et al.* (2020) focus on the job shop scheduling problem to minimize the total weighted tardiness and total energy consumption simultaneously. To do so, a multi-population, multi-objective memetic algorithm is proposed. Likewise, to minimize the makespan and total energy consumption within an hybrid flowshop problem, Xing *et al.* (2019) develop an hybrid multi-objective algorithm combining an improved algorithm based on the NSGA-II. Azadeh *et al.* (2015) deal with the open shop scheduling problem, minimizing the makespan, machine availability, and total tardiness. A NSGA-II and a multi-objective particle swarm optimization are proposed to solve it. Wang and Liu (2015) also used a NSGA-II to solve a multi-objective parallel machine scheduling problem. The objective functions are the makespan and unavailability of resources due to maintenance activities.

Wang and Liu (2014) deal with two-stage hybrid flowshop scheduling problem, to minimize the unavailability of the first stage machine and to minimize the makespan simultaneously. They construct a multi-objective tabu search. Lei (2013) focuses on the multi-objective flexible job shop scheduling problem whose objective functions are to minimize interval makespan and a newly defined objective called total interval tardiness. A multi-objective artificial bee colony is proposed.

The literature review on maintenance scheduling was great, as it helped us identify alternative solutions that were suitable and enrich the literature approach in Chapter 2. The following section outlines the methodological framework proposed for addressing this problem.

4.3 Methodological Framework

This chapter focuses on integrating the fatigue effect in the FSSP. Solving the FSSP enables us to determine the permutation of jobs, which corresponds to an operational decision. Therefore, addressing the fatigue phenomenon, the need to define break policies constitutes a tactical decision. Since two decisions were made at different times, the approach is divided into two phases.

- In the first phase, the FSSP and makespan minimization was solved using some of the algorithms proposed in Chapter 3.

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- In the second phase, the resulting permutation of jobs was transmitted as an input to the multi-agent simulation model that incorporates the fatigue's worker (section 4.5).

Some break policies were tested to determine the effect on both objective functions makespan (as economic objective) and total fatigue dose (as social objective).

4.4 Fatigue Model

The phenomenon of resource deterioration, particularly among workers within the context of task sequencing, is closely related to the concept of fatigue and its impact on job processing. In this scenario, the rate at which a worker performs a given job decreases as a function of the worker's fatigue level (He *et al.*, 2021). In practice, as outlined by Xu and Hall (2021), four types of methods can be used to measure fatigue.

(i) *Online operator monitoring*, which enables real-time performance measurement and provide some alerts (i.e., electroencephalogram, heart rate and electrocardiography).

(ii) *Quantification of accumulated fatigue*, it allows to collect and compute information and understand the ergonomic impacts of alternatives in the system design (i.e., maximum endurance time (MET) or maximum fatigue for muscular exertion, level of the muscle's maximum voluntary contraction (MVC).

(iii) *Performance-based monitoring*, measured based on the performance of the primary features of the operator's function (i.e., vehicle speed while driving and service time).

(iv) *Subjective measures of fatigue*, the measurement of fatigue is based on the worker's perception (i.e., occupational fatigue exhaustion recovery scale and the Samn-Perelli fatigue scale).

These methods have been used to build fatigue estimation models in operations research. For instance, Calzavara *et al.* (2019) and Finco *et al.* (2021) propose models for fatigue evaluation and rest allowance estimation, using oxygen consumption. Models suitable for tasks where the whole body is used rather than a specific part stressed. For a specific body segment, when worker perform one repetitive task with muscular force, Imbeau *et al.* (2009) and Xu and Hall (2021) agree that the MET models are the most frequently used such as the case of Jaber and Neumann (2010), Perez *et al.* (2014), Dode *et al.* (2016) and Jaber *et al.* (2013). These models estimate the point at which the required force level cannot be exerted. Glock *et al.* (2019b) present a model which estimates that total static fatigue cannot directly imitate the dynamic fatigue of the activities involved. They calculate the dynamic fatigue by multiplying the estimated total static fatigue level by a coefficient. Finally, Ma *et al.* (2015) state that characteristics like recovery are influence by external load, workload history, and individual characteristics (such as gender, age, muscle mass).

The approach of muscle biomechanics characteristics is not within the scope of this

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work. Therefore, the proposed model is a general model for hand-intensive tasks. The following notation is used to present the model:

MET	Maximum endurance time for performing the job
MVC	Maximum muscular voluntary contraction or maximum force a muscle can generate voluntarily
%MVC	Fraction of maximum voluntary contraction (MVC)
λ	Fatigue exponent or fatigue rate
μ	Recovery exponent
F_0	Initial fatigue level at the beginning of a shift
$F_(t)$	Total fatigue level at time t
δ	Parameter that represent effect of fatigue on the job processing time
$\bar{p}_{ij}$	Baseline processing time of job j executed by worker i

Assuming that a worker only executes one technical action during each job processing; and considering that the execution of a technical action during job processing can engage multiple muscle groups, it is relevant to calculate the recommended MET representative of muscular groups. It facilitates the recuperation of all involved muscles. The procedure for evaluating is based on the one proposed by Imbeau, Farbos, *et al.* (2006) and Imbeau *et al.* (2009): Calculate the 15th percentile of %MVC per each muscle and keep the highest value and use the general model as outlined by Equation (4.1), and compute the MET.

$$MET = 7.96e^{-4.16*\%MVC} \tag{4.1}$$

The fatigue rate of a technical action is expressed by Equation (4.2). Where F_{max} is the value reached at the MET or its maximum level ($F_{\max} \sim 100\%$) (Glock *et al.*, 2019a). The recovery rate is currently being attributed to the mechanical characteristics of workers in the existing literature (Liu *et al.*, 2018a; Ma *et al.*, 2015). Since this approach is not only suited to personal characteristics, the value of μ will be taken from the reference values of the population in the literature.

$$\lambda = \frac{1}{MET} \ln\left(\frac{1}{1 - F_{\max}}\right) \tag{4.2}$$

The proposed model is based on the exponential model state as in the work of Jaber *et al.* (2013). We consider that fatigue is caused by the processing of a job by a worker. Idle and break times significantly impact the level of fatigue, by reducing it. The assumptions are:

1. All workers are available at the beginning of work shift.
2. Each worker can process one job at a given time.
3. All workers are unavailable at the end of work shift.
4. At the beginning and end of the shift, there are no work in process at any worker's stations.

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5. The breaks start and end at the same time for all workers. However, if a worker is processing a job, she/he will not be able to go out on the break until the job is completed.
6. For all the workers, the initial level of accumulated fatigue is zero.
7. The fatigue rate for all workers is the same.

$F(t)$ represents the total fatigue level at time t, where t and t-1 are the current and previous discrete unit of time respectively. Equation (4.3) is the level of fatigue before processing the first job. Equation (4.4) computes the continuous fatigue level while a worker is processing a job. Equation (4.5) calculates the continuous recovery or reduction of fatigue when a worker is on a break or in idle time.

$$F(0) = F_0 \tag{4.3}$$

$$F(t) = F(t-1) + (1 - F(t-1))(1 - e^{-\lambda}) \tag{4.4}$$

$$F(t) = F(t-1)e^{-\mu} \tag{4.5}$$

The response variable has been defined as the fatigue dose (FD) per worker, obtained as the area under the fatigue curve (Dode *et al.*, 2016) (see Figure 4.1). This is due to the fact that in a flowshop system, machines or workers initiate their tasks at different times and to ensure the stability of the system. The FD was taken between the start of the processing of the first job by the last worker and the completion of the last job of the first worker, the time window is visually highlighted in red in the Figure 4.1.

As fatigue increases, the baseline job processing time grows up a δ margin (varying from 0 to 1), being δ the effect of fatigue on the baseline job processing time (Ferjani *et al.*, 2017; Ostermeier, 2020b). It is computed using Equation (4.6), where $\bar{p}_{ij}^{f}$ is the baseline job processing time affected by the fatigue and $F(t)$ is the fatigue level at the start of the job.

$$\bar{p}_{ij}^{f} = (1 + \delta F(t))\bar{p}_{ij} \tag{4.6}$$

We use the MET representative of the muscular group involved in a technical activity, which gives an idea of the maximum degree of fatigue that certain muscular group could experience. So, if the maximum FD is attenuated during breaks, it guarantees that all the muscles that belong to this muscular group could recover.

4.5 Incorporating the Fatigue Effect

We start from the standard FSSP (refered to as *Case 0* in the Chapter 3). Some of the algorithms previously detailed in Chapter 3 (i.e., SA_{API}, NEH) were used to solve it.

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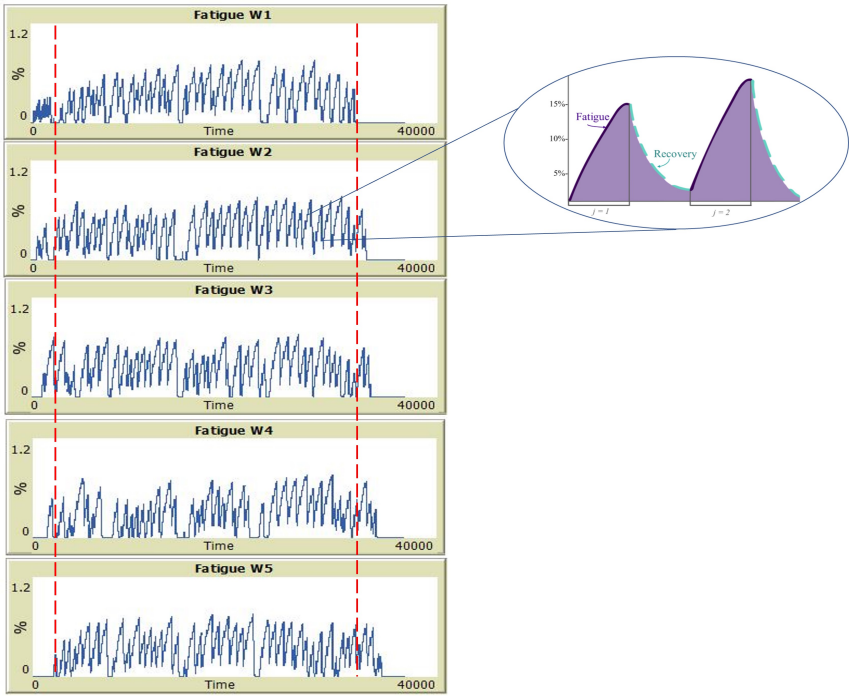

Figure 4.1: Fatigue Dose Representation

The output of the algorithm is the permutation of jobs and the makespan, for practical purposes, it will be denoted as C^L_{max}.

Agent-based simulation is recognized by its advantages to treat dynamic phenomena such as human fatigue (Liu *et al.*, 2023). This approach uses a multi-agent system approach to include the fatigue within the modeling of the manufacturing process. In fact, it is expected to evaluate the impact of fatigue inclusion and the break of workers with the production efficiency and the worker performance.

4.5.1 The Multi-agent System

The problem of incorporating fatigue is modeled as a multi-agent system to identify the behaviors and interactions within production operations. The model defines a global environment (i.e., manufacturing environment), a global scheduling agent and three types of agents that interact within the environment (i.e., production environment).

a) **Agent Jobs (AJ)** which represent a job within the production order.

b) **Agent Worker (AW)** which represent a production worker that execute a subset of the tasks to complete the agent job.

c) **Agent Station (AS)** which represents the position within the flowshop.

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Agent's Description

Agent's attributes are shown in the Figure 4.2 and are detailed below.

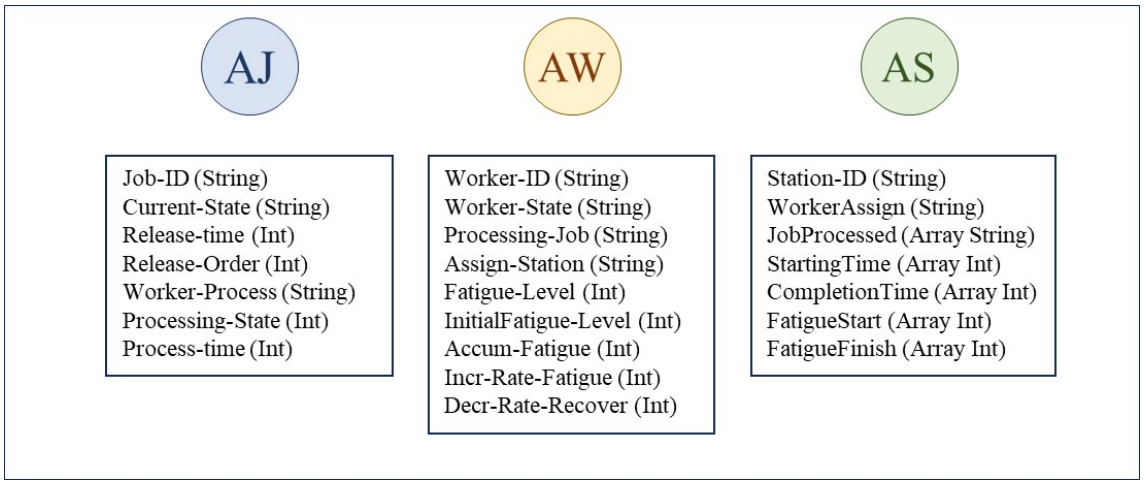

Figure 4.2: Agent's attributes within the production environment

1. **Global environment (GE)**: The GE represents a flowshop scheduling problem where a set of jobs $J = \{1, 2, 3, ..., N\}$, needs to be processed on a set of stations. For this environment, a set of workers $I = \{1, 2, 3, ..., I\}$ are assigned to each station in a one-to-one relationship for executing the corresponding operation.

2. **Global scheduling (GSD)**: The GSD hosts the information of the FSSP related to the set of jobs, set of workers and the baseline job processing time. It has embedded the algorithm in charge of obtaining the job sequencing, minimizing C^L_{max}. Its output is the permutation of jobs, that is transferred to the agent job (**AJ**). This agent generates the permutation of jobs, which can be a result of solving the FSSP, with or without learning. In this chapter, we only consider without learning, to focus on the impact of fatigue and break policies

3. **Agent Job (AJ)**: An AJ represents a job within the set of jobs to be processed within the production environment. These agents contain several attributes, the processing start time, the current state within the system, and the progression within the processing route.

4. **Agent worker (AW)**: An AW represents a worker within the production environment. These agents contain attributes, such as the state of worker, the current job being processed, the current fatigue, the initial fatigue level, the accumulated fatigue, and the associated station. In addition, these agents contain several attributes related to increasing rate of fatigue depending on the worker and job being processed, and the recovery rate depending on the worker and job previously processed. These two last attributes are parameters that compute the fatigue level during processing, idle states of workers or breaks. These agents focus in registering and monitoring the fatigue level of the worker within the job processing.

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5. **Agent station (AS)**: It contains the position of the stations in the flowshop. This allows recognizing whether an **AJ** has entered, is currently in process, or has left the station

Interactions Between Agents

The multi-agent system is used in this approach to take advantage of modeling interaction and behaviors of agents within the manufacturing environment. In general, the interactions between agents occur through communication. These interactions are as follows:

- The production order is generated and transmitted (**GSD** $\rightarrow$ **AJ**).
- Requesting an operation execution (**AJ** $\rightarrow$ **AW**).
- Confirming the starting and completion of an operation (**AW** $\rightarrow$ **AJ**).
- Requesting the registration to a station and requesting saving the operation statistics (**AW** $\rightarrow$ **AS**) and confirming registration to the station (**AS** $\rightarrow$ **AW**).

In this model, **AJ** and **AS** do not communicate.

Simulated System

The simulated system represents a FSPP in a hand-intensive environment. Each worker has an initial fatigue rate and it increases during the job processing. In addition, a recovery rate that is incrementally affected during idle time or during breaks. Each station has an associated worker whose job processing time depends on the worker and job. Finally, within the simulation, the worker (**AW**) updates the fatigue level during the processing, idles times of execution or breaks time, the job (**AJ**) registers the level of completions while it passes through the stations, and the station (**AS**) controls the starting and completing of operations while it registers them for statistical purposes. Figure 4.3 depicts the dynamic behavior sequentially between the agents of the system.

4.5.2 Exploratory Computational Expriments

This multi-agent system emulates the FSSP problem using NetLogo Version 6.2.2 (Figure 4.4). The advantage of NetLogo and in general of agent-based simulation softwares, is their capability to address complex systems, owing to the capacity to represent distinct entities that can interact with each other (Tisue and Wilensky, 2004). In this section some experiments to examine the impact of break location and break duration on productivity and fatigue level are presented. For these experiments, the **GSD** used the NEH code in Python 3.0 and the permutation of jobs is communicated to the **AJ** within the NetLogo model. The computational experiments were run on a PC with processor AMD Ryzen 7 4700U 2.0GHz and RAM 8 Gb.

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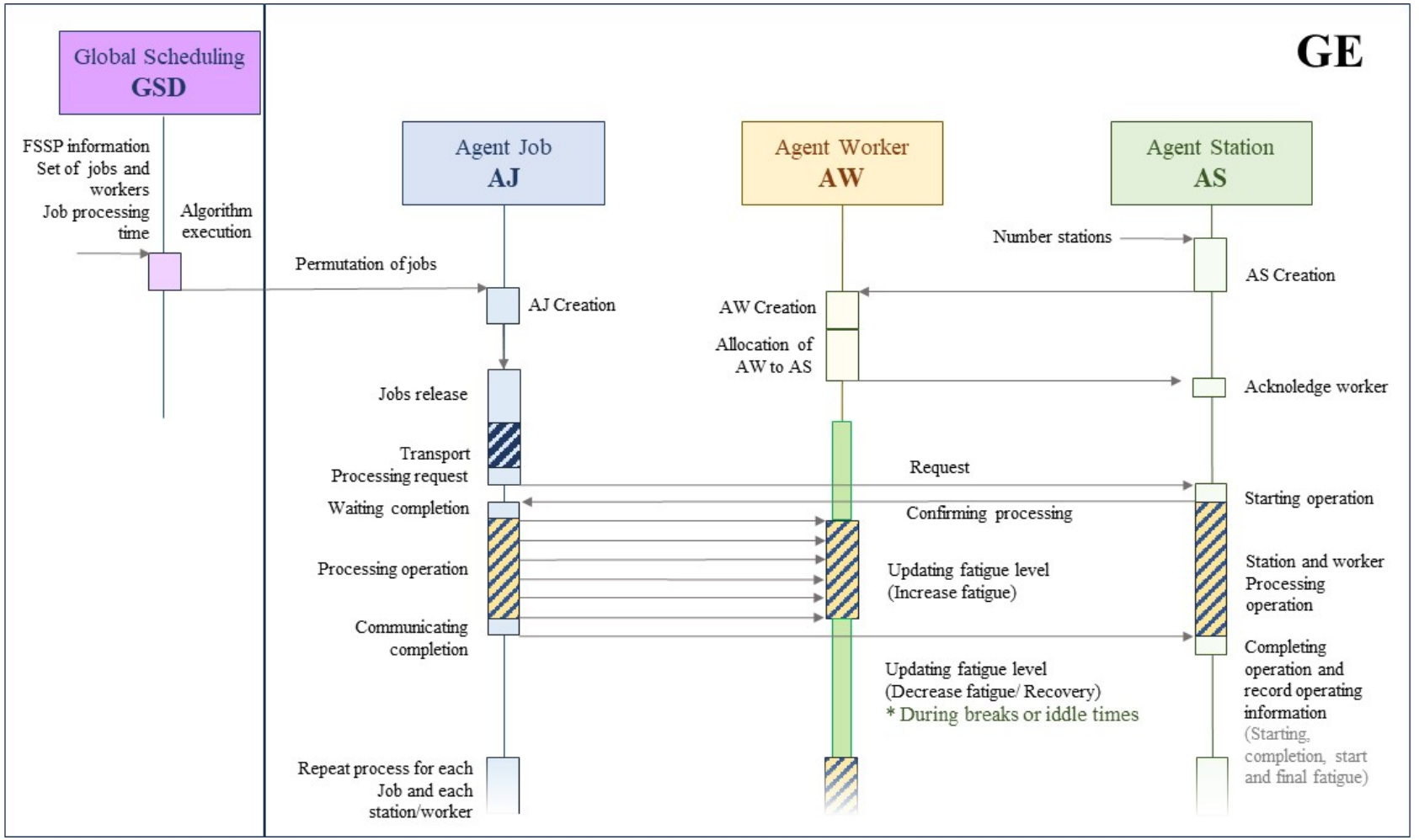

Figure 4.3: Agents dynamic behavior

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- The baseline job processing times ($\bar{p}_{ij}$) were taken from Taillard (1993).
- The Fatigue parameter (λ) for all workers were set at 0.00128, 0.00311 and 0.006841 (small, medium and large, respectively), values referred by Glock *et al.* (2019b).
- The Recovery parameter (μ) was defined as 0.03 referenced by Ostermeier (2020b).
- The value of parameter δ was established in consideration of the Ostermeier (2020b) (δ = 0.15).
- The total breaks duration (TBD) was 6% of the shift (for the purposes of this experiments the shift duration will be the C^L_{max} provided by **GSD**).
- Two break policies were tested, the first one (called from here on BP-1) consisting of two breaks at 33.3% and 66.6% of C^L_{max} and the second one (BP-2) consisting of three breaks located at 25%, 50%, and 75% of C^L_{max}. They were selected based on the hypothesis that more frequent, shorter breaks would result in lower levels of fatigue compared to less frequent, longer breaks (Kakarot *et al.*, 2012; Yi and Chan, 2013).

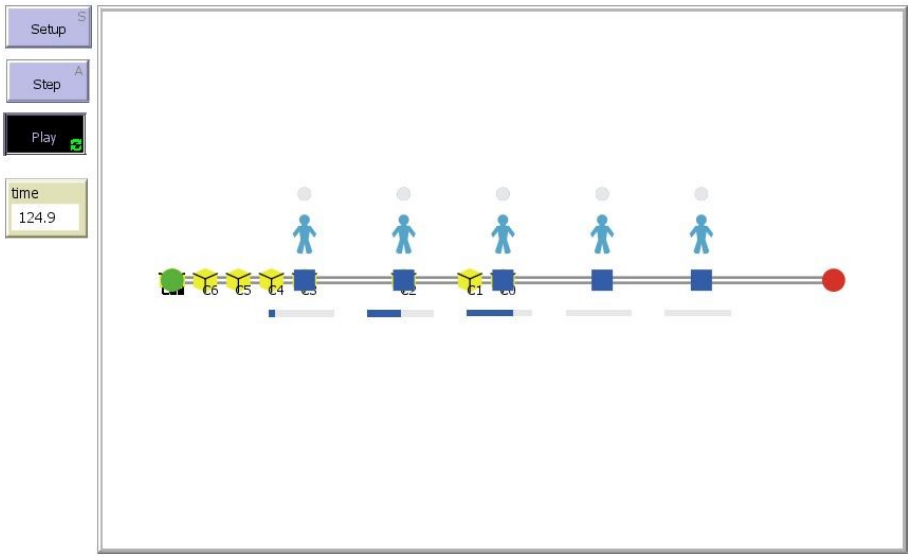

Figure 4.4: Multi-agent system using NetLogo software

A combination refers to the problem characteristics denoted by the number of workers, jobs, fatigue, and recovery rate. A code for each combination was defined such as *i_j_*λ*_k* (for example, 5_100_0.00128_0.03, corresponds to 5 workers, 100 jobs, λ = 0.00128 and k is the instance). For each combination, a set of 10 instances was tested. We performed a full factor-blocking experimental design where break policies is the factor with two levels, as described earlier. Every combination per worker was managed by us as a block of the experiment. A total of 120 executions were carried out. A summary of the experimental design is provided in Table 4.1.

The Table 4.2 shows the total fatigue dose (TFD) results, which represent the sum of the fatigue doses of all workers for each of the break policies. Additionally, it provides information on the mean fatigue dose (FD mean) and standard deviation (FD std).

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Table 4.1: Experimental Design Summary

Name	Values
Algorithm used by the GDS	NEH
Combinations	5 workers x 50 jobs and 5 workers x 100 jobs $\lambda = 0.00128$, $\lambda = 0.00311$ and $\lambda = 0.006841$ $\mu = 0.03$
Factor	2 breaks - 33.3% and 66.6% of C^P_{max} 3 breaks - 25% , 50% and 75% of C^P_{max}
Total of treatments	2
Total of combinations	6
Total instances per combination	(6x10) = 60
Size of experiments	(60x2) = 120

Notably, in 56.7% of cases, it was observed that the total fatigue dose was higher when employing the BP-1 policy. We compute the FD during the time window per worker, the Shapiro-Wilk normality test was applied to each block (*p-values> 0.05*) to confirm the normality of the data, and an Analysis of Variance (ANOVA) was performed. The results indicate that the blocks included in the experiment had a significant effect, as was expected (*p-value* < 0.05). With respect to the factor of our interest, the break policies effect over the FD received by each worker is significant with *p-value* $=$ *0.00258*.

Table 4.2: Total Fatigue Dose - Exploratory Results

I	$\mathcal{J}$	λ	k	*BP-1*			*BP-2*		
				TFD	FD Mean	FD Std	TFD	FD Mean	FD Std
5	100	0.006841	0	217333.67	43466.73	2110.03	92722.15	18544.43	1128.57
5	100	0.006841	1	198922.24	39784.45	1523.59	217723.35	43544.67	2176.13
5	100	0.006841	2	203163.39	40632.68	2172.25	198871.86	39774.37	1530.24
5	100	0.006841	3	198792.03	39758.41	1291.67	202824.59	40564.92	2203.70
5	100	0.006841	4	208195.00	41639.00	2102.84	198641.59	39728.32	1307.01
5	100	0.006841	5	205097.56	41019.51	1596.31	208000.56	41600.11	2175.09
5	100	0.006841	6	206146.59	41229.32	2951.40	205033.71	41006.74	1569.01
5	100	0.006841	7	198463.19	39692.64	2313.45	206325.31	41265.06	2917.61
5	100	0.006841	8	216672.82	43334.56	1516.02	199974.45	39994.89	2430.22
5	100	0.006841	9	215994.41	43198.88	1593.52	216536.77	43307.35	1443.63
5	50	0.006841	0	98058.74	19611.75	1916.77	216057.04	43211.41	1542.30
5	50	0.006841	1	105058.10	21011.62	1622.55	98595.28	19719.06	1888.79
5	50	0.006841	2	92982.56	18596.51	1073.86	105174.40	21034.88	1631.68
5	50	0.006841	3	100417.09	20083.42	1848.72	99037.04	19807.41	1917.89
5	50	0.006841	4	104073.02	20814.60	2150.72	104013.48	20802.70	2178.17
5	50	0.006841	5	102779.30	20555.86	1537.29	102513.05	20502.61	1519.12
5	50	0.006841	6	101069.82	20213.96	1628.33	100959.19	20191.84	1619.83
5	50	0.006841	7	97619.38	19523.88	1582.39	98011.19	19602.24	1528.76
5	50	0.006841	8	90541.12	18108.22	1461.29	90285.51	18057.10	1387.66

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Table 4.2: Total Fatigue Dose - Exploratory Results

I	$\mathcal{J}$	λ	k	*BP-1*			*BP-2*		
				TFD	FD Mean	FD Std	TFD	FD Mean	FD Std
5	50	0.006841	9	99057.03	19811.41	895.69	100422.78	20084.56	903.39
5	100	0.00311	0	170665.91	34133.18	1974.79	170799.05	34159.81	2039.96
5	100	0.00311	1	155164.27	31032.85	1352.19	155135.93	31027.19	1337.46
5	100	0.00311	2	158000.09	31600.02	2014.94	157543.29	31508.66	2044.17
5	100	0.00311	3	154234.77	30846.95	1224.91	154009.69	30801.94	1244.22
5	100	0.00311	4	162609.50	32521.90	1810.20	162319.71	32463.94	1918.67
5	100	0.00311	5	160034.58	32006.92	1520.79	160122.84	32024.57	1487.23
5	100	0.00311	6	160821.31	32164.26	2641.11	161086.13	32217.23	2603.70
5	100	0.00311	7	154745.79	30949.16	2118.57	155329.76	31065.95	2189.88
5	100	0.00311	8	170035.13	34007.03	1441.16	169977.49	33995.50	1431.53
5	100	0.00311	9	169995.15	33999.03	1413.32	170046.64	34009.33	1305.49
5	50	0.00311	0	76365.52	15273.10	1771.57	77110.73	15422.15	1676.96
5	50	0.00311	1	81969.67	16393.93	1505.07	82804.12	16560.82	1494.93
5	50	0.00311	2	72439.39	14487.88	1027.28	71590.67	14318.13	1148.81
5	50	0.00311	3	78869.78	15773.96	1641.80	77397.30	15479.46	1673.82
5	50	0.00311	4	81782.59	16356.52	1946.40	81683.13	16336.63	1978.77
5	50	0.00311	5	80474.61	16094.92	1398.52	80198.42	16039.68	1371.08
5	50	0.00311	6	78794.26	15758.85	1452.63	78546.40	15709.28	1475.46
5	50	0.00311	7	76394.99	15279.00	1410.43	76635.48	15327.10	1358.34
5	50	0.00311	8	69829.71	13965.94	1302.03	69441.26	13888.25	1193.89
5	50	0.00311	9	77816.75	15563.35	752.43	78866.73	15773.35	745.77
5	100	0.00128	0	106469.84	21293.97	1473.20	106278.58	21255.72	1510.61
5	100	0.00128	1	95640.56	19128.11	1022.98	95608.69	19121.74	1034.98
5	100	0.00128	2	98024.43	19604.89	1426.01	97114.98	19423.00	1468.23
5	100	0.00128	3	94387.89	18877.58	987.97	94806.35	18961.27	983.18
5	100	0.00128	4	100740.15	20148.03	1263.07	100682.73	20136.55	1344.05
5	100	0.00128	5	99179.59	19835.92	1148.89	99258.65	19851.73	1183.21
5	100	0.00128	6	99779.62	19955.92	1936.70	99792.14	19958.43	1842.53
5	100	0.00128	7	95713.14	19142.63	1468.26	96086.28	19217.26	1554.84
5	100	0.00128	8	106309.91	21261.98	1105.49	106354.54	21270.91	1073.08
5	100	0.00128	9	106263.19	21252.64	989.95	106190.77	21238.15	891.04
5	50	0.00128	0	47179.88	9435.98	1298.14	47944.89	9588.98	1170.15
5	50	0.00128	1	51654.87	10330.97	1081.15	51625.19	10325.04	1092.13
5	50	0.00128	2	44618.08	8923.62	764.43	44129.48	8825.90	864.35
5	50	0.00128	3	49069.13	9813.83	1184.26	48059.54	9611.91	1273.82
5	50	0.00128	4	104073.02	20814.60	2150.72	50918.04	10183.61	1428.38
5	50	0.00128	5	49939.46	9987.89	1002.45	49732.56	9946.51	957.57
5	50	0.00128	6	48694.62	9738.92	1039.68	48468.15	9693.63	1065.29
5	50	0.00128	7	47405.93	9481.19	995.85	47468.85	9493.77	954.50
5	50	0.00128	8	42631.79	8526.36	908.65	42254.75	8450.95	796.78
5	50	0.00128	9	48460.58	9692.12	517.74	49169.46	9833.89	450.93

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Between them, BP-2 stands out for the fact that the adoption of this policy results in an average FD lower than BP-1. BP-2 proposes to place the breaks at 25%, 50% and 75% of the shift, with a total duration of 6% of the shift time (this aligns with the International Labour Organization - ILO, which suggests a minimum of 30 minutes for a shift that exceeds 5.5 hours. This represents approximately the 6% of an 8-hour shift). This alternative allows a redistribution of effective break times to minimize the FD perceived per worker, conform to the conclusions of Jaber and Neumann (2010): short and frequent breaks improve system performance because they do not allow fatigue to accumulate.

The multi-agent model enables us to recognize the potential positive effects of an issue that has traditionally been with negative connotation to productivity, such as idles times. However, these effects can only be realized if the idle times are controlled and managed effectively. Meanwhile, it is necessary to guarantee and appropriate job scheduling which maintains productivity standards.

Adding the TBD to the C^L_{max} obtained by the **GDS**, this will result in a provided makespan (C^P_{max}) such as, $C^P_{max} = C^L_{max} + TBD$. The result of C^P_{max} differs from the observed makespan (C^O_{max}) obtained by the multi-agent simulation model. It is due to the effect of fatigue on the jobs processing time and system-specific actions such as displacements between stations. The makespan percent difference ($\%\Delta makespan$) is calculated using Equation (4.7). Figure 4.5 compared $\%\Delta makespan$ per break policy, being for BP-2 the lowest average. This finding is consistent as a lower FD represents a lower effect on the job processing time.

$$\%\Delta makespan = \frac{C^O_{max} - C^P_{max}}{C^P_{max}} \tag{4.7}$$

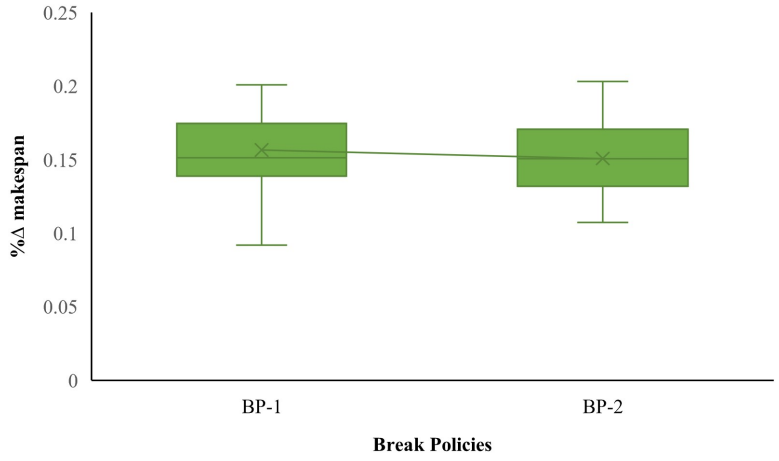

Figure 4.5: Comparison of $\%\Delta makespan$

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4.6 Conclusions

Our contribution in this chapter was to develop a model that incorporates fatigue into a flowshop system, and to evaluate the impact of break policies on the total fatigue dose and makespan. Building upon the literature, we proposed a method to model physical fatigue and particularly muscular fatigue. A Multi-agent simulation model was proposed to analyze the incorporation of physical fatigue's workers into the FSSP. Our approach represents a decision-making tool that supports the design or the redesign of an intensive manual system, assisting in the tactical decision of how to establish the breaks during the shifts.

The exploratory computational experiments demonstrated how the location and duration of breaks are tactical decisions made by organizations that directly impact fatigue level and productivity. Likewise, the results were in accordance with the literature, which recommends short and frequent breaks during shifts to mitigate the total fatigue dose. Thus, the policy with 3 breaks distributed at 25, 50, and 75% of the shift turned out to be more favorable for reducing this indicator.

We provided a conceptual overview of the proposed approach, which we believe that this work will contribute to the community that has begun to become interested in this topic, which involves integrating human factors into operational research problems. The next chapter presents a case study that illustrates how the tools introduced in Chapters 3 and 4 can lead to practical solutions to real industrial problems.

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Chapter 5

Case Study Application

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The content of this chapter is based on the following publication in progress:

- *Paredes-Astudillo, Y. A., Montoya-Torres, J. R., Botta-Genoulaz, V., Caro, M. P. and Jimenez, J.F. (in progress). Flowshop scheduling problem with learning effect and incorporation of fatigue phenomena: a case study. To be submitted.*

Preliminary findings of this chapter were presented at:

- *Paredes-Astudillo, Y. A., Botta-Genoulaz, V., Montoya-Torres, J. R., and Caro, M. P. (2023, June). Approach to Integrate the Learning and Fatigue Effect Into the Flowshop Scheduling Problem. In The Fourth International Workshop on Dynamic Scheduling Problems, Winterthur, Switzerland.*

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Abstract

An application in a manual picking line of a dry food distributor company validates the proposed framework. This chapter presents a methodological approach to the flowshop scheduling problem with learning effect that included physical fatigue in a manual picking line, where the case study is conducted. A bi-objective approach is proposed to minimize the makespan and the total fatigue dose simultaneously, and the company is used to validate the framework. Break policies recommendations are defined. Finally, the chapter discusses the results with highlights.

5.1 Introduction

As discussed in Chapter 2, most approaches incorporating human characteristics, reach the point of proposing models and computational experiments, but they lack validation in real environments. The challenge in this phase is selecting the appropriate model to address human characteristics and to estimate their parameters. It requires interdisciplinary work explaining the lack of applications and holistic principles to rigorously integrate human factors in order-picking operations (De Lombaert *et al.*, 2023).

Therefore, this chapter shows interdisciplinary work integrating learning and fatigue effects into the flowshop scheduling problem. The case study was conducted in collaboration with a Colombian dry food distributor company and the Center for Ergonomics Studies at Pontificia Universidad Javeriana Bogotá. They provided us with training and support on human factor topics and allowed us to utilize their equipment during the data collection phase.

The case study focuses on a manual picking line as one hand-intensive system recently received much attention. Due to product variants (Bortolini *et al.*, 2016) and order preparation systems, the global demand for highly customized products requires processing many orders in short time windows (Vanheusden *et al.*, 2023). Based on the findings of Lavender *et al.* (2012), picking activities, especially order picking, have a significant risk of developing Work-Related Musculoskeletal Disorders (WMSDs) and lumbar injuries. Consequently, an increasing number of companies have invested in developing ergonomic tools to mitigate the risk of repetitive actions in picking activities, known to be potential contributors to WMSDs (Grosse *et al.*, 2015).

5.2 Related Literature

Different variables can influence the system, such as the order to be fulfilled during picking activities (Calzavara *et al.*, 2018). Consequently, the learning process (Zhang *et al.*, 2023) and fatigue accumulation (Calzavara *et al.*, 2018) can impact the system's overall performance. Grosse *et al.* (2015) summarized the influence of human factors on the efficiency of operations and picking, indeed, as shown in Figure 5.1. Resolving the job scheduling problem and defining breaks policies can impact two design characteristics

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of picking operations (i.e., sequencing and work conditions), directly affecting outcome time and worker well-being.

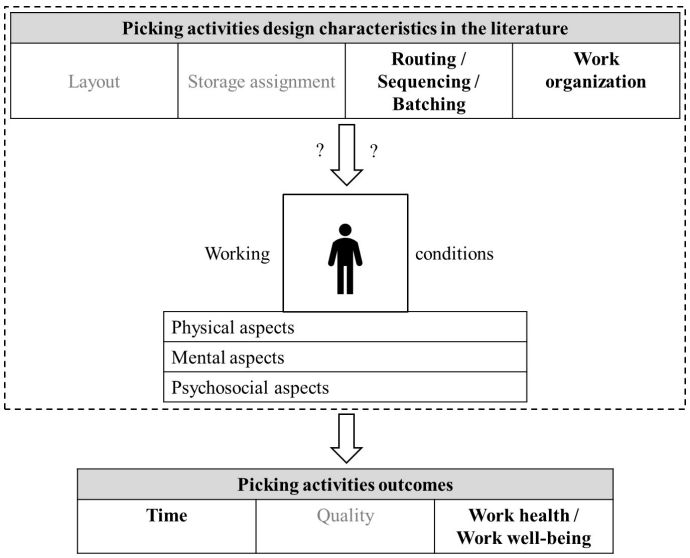

Figure 5.1: Picking task efficiency determined by human factors (adapted from: Grosse *et al.* (2015))

Zhang *et al.* (2023) mentioned that the learning effect in picking activities is attributed to familiarizing oneself with the location of items. This type of learning is called autonomous learning, where knowledge acquisition occurs through repetition and familiarization with similar tasks, inherent to the dynamics of the production environment with repetitive and monotonous tasks (Biskup, 2008).

The log-linear model proposed by Wright (1936) is considered the simplest and most commonly used model in scheduling problems. It is shown in Equation (5.1). where $y(\chi)$ is the average time to produce all jobs up to the $\chi - th$, χ is the amount of jobs, $\alpha \geq 0$ is the learning speed parameter, and p_1 the time required to produce the first job.

$$y(\chi) = p_1 \chi^{-\alpha} \tag{5.1}$$

Most learning models in the scheduling problems area have been based on the log-linear model. Its flexibility has resulted in widespread use in various industries, particularly in the manufacturing sector (Azzouz *et al.*, 2018). Numerous studies incorporating case studies have employed this model due to its capacity to describe manual tasks and its comprehensible estimation of parameters (Anzanello and Fogliatto, 2011), as happens with picking operations, for example. Grosse and Glock (2013) demonstrated the effect of learning on selecting workers by analyzing data from industrial applications, remarking that basic learning models, such as those proposed by De Jong (1957), are suitable.

Meanwhile, Grosse *et al.* (2015) highlighted that picking activities involve excessive manual handling, which can result in muscle fatigue and discomfort. Calzavara *et al.* (2018) summarized existing methods for monitoring physical fatigue during picking operations. Table 5.1 shows their applications, advantages, and disadvantages.

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Table 5.1: Methods for monitoring physical fatigue in picking operations (adapted from: Calzavara *et al.* (2018))

Method	**Application**	**Advantages**	**Disadvantages**
Self-report questionnaires	Applicable to different situations	Inexpensive, standard, easy to understand and apply	Subjective
Self-report interview	Applicable to different situations	Inexpensive, flexible, easy to understand and apply	Subjective, time consuming
Measure of EMG	Recording of myoelectric activity of the muscle	Objective and does not consider personal characteristics	High investment, necessary preparation
Energy expenditure based on VO2 monitoring	Continuous monitoring of aerobic activity	Objective, continuous monitoring.	High investment, necessary preparation, considers personal characteristics
Energy expenditure based on HR monitoring	Continuous monitoring of aerobic activity	No so expensive, real-time feedback	Considers personal characteristics, stress can influence the results

Electromyography (EMG); Oxygen consumption (VO2); Heart rate (HR)

Grosse *et al.* (2017) indicated promising opportunities to integrate human factor aspects into the picking operation process. Their literature review focused on order picking and revealed that human learning analysis was the most popular aspect. Nevertheless, ergonomic aspects such as fatigue are still relevant and require more attention.

5.3 Case Study Description

The case study is situated on the picking line of a Colombian dry food distributor company. The line comprised 14 picking zones linked by a conveyor where all orders were prepared in containers with the same routing. This type of picking system involved two main elements: 1) the worker in each zone for picking products and 2) the container following the routing (Ho and Lin, 2017), visiting all picking zones, and filling all the items of each stock-keeping unit (SKU) belonging to its order. Caro *et al.* (2018) explained in detail the components of the picking operation (Figure 5.2). For the purposes of this

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work, they are referred to as picking technical actions. Assume that picking technical actions (PTA) remain unaffected by the quantity of SKU items. Thus, even when filling a container with one, two, or more items of a specific SKU, only a single PTA is needed.



Figure 5.2: Components of picking operation (adapted from: Caro *et al.* (2018))

After gathering data from a typical month of operation, key points are highlighted:

- The company's work pattern consisted of three eight-hour shifts with an average of 35 minutes of breaks.
- An average of 1400 containers are processed per shift.
- During the week, workers rotated through different picking stations assigned at the start of the shift.
- A single break was situated in the middle of the shift.
- The company aims to minimize the time to complete the final work and the level of fatigue.
- The picking line configuration can be considered as a flowshop system, with operations located consecutively.

5.4 Methodology

Figure 5.3 presents a schema of the methodology proposed and shows how this chapter's sections are connected. Due to the company's twofold needs, a bi-objective approach is followed. Some algorithms proposed previously are used to minimize the makespan in an FSSP with a learning effect (Section 5.5.3). The result is the permutation of jobs sent to the Fast Pareto genetic algorithm (FastPGA) (Section 5.7.1) and to the multi-agent simulation model incorporating worker fatigue (Section 5.6.3). FastPGA's chromosomes represent a possible solution for break policies to directly impact the level of fatigue. The multi-agent simulation is launched to calculate the objective function values of each chromosome in FastPGA to explore better solutions for the two objectives of makespan and total fatigue dose. The results are job processing sequences and a break policy.

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This methodology enables the addressing of FSSP with learning effect, incorporating the fatigue, and defining break policies. Furthermore, it concurrently minimizes both the makespan and the total fatigue dose simultaneously.

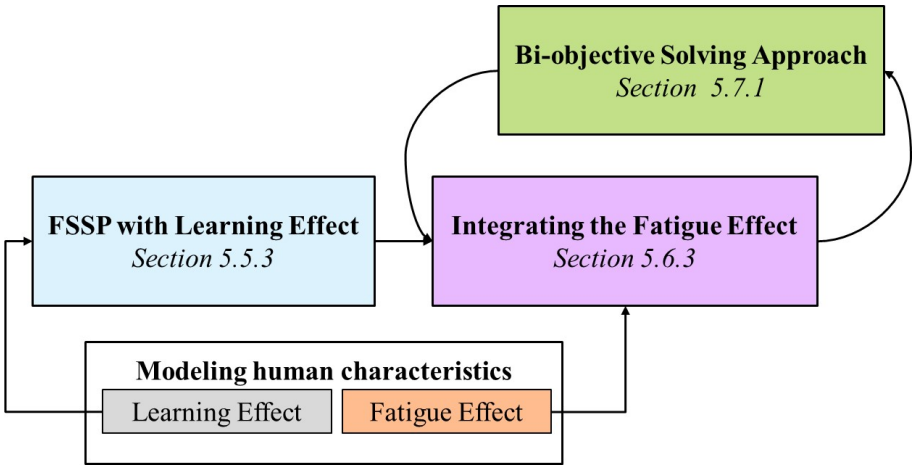

Figure 5.3: FSSP with learning and fatigue methodology

5.5 Learning Effect

As Tilindis and Kleiza (2017) indicated, the power and simplicity of the log-linear model make it a fundamental tool for modeling learning, suitable for picking operators, as referred to in Section 5.2. To estimate α, we employed the two intervals method Tilindis and Kleiza (2017) referred to, using Equation 5.2. Here, T_{12} was the total time required to process jobs from χ_1 up χ_2 and the total time to produce the units from χ_3 up χ_4 is T_{34}, when $\frac{\chi_2-\chi_1}{\chi_4-\chi_3} < \frac{T_{12}}{T_{34}}$.

$$\frac{\chi_2^{1-\alpha} - \chi_1^{1-\alpha}}{\chi_4^{1-\alpha} - \chi_3^{1-\alpha}} = \frac{T_{12}}{T_{34}} \tag{5.2}$$

This method corresponded to a deterministic and mathematical approach, different from statistical methods that may be in appropriated in certain cases. The situation resulted from collecting a large amount of data, which is limited in this type of domain within the enterprises.

Hence, we fit experimental data to the models based on Wright's model, commonly used in the scheduling problem due to the review carried out in Chapter 2, such as,

- Position-Based Learning Effect Model (P-LE)

$$p_{jr} = \bar{p}_j r^{\alpha} \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{5.3}$$

- Sum-of-Processing-Time-Based Learning Effect Model (ST-LE)

$$p_{jr} = \left(1 + \theta \sum_{k=1}^{r-1} p_k\right)^{\alpha} \bar{p}_j \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{5.4}$$

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- DeJong's Learning Effect Model (DJ-LE)

$$p_{jr} = (M + (1 - M)r^{\alpha})\bar{p}_j \quad j = 1, \ldots, J; r = 1, \ldots, R \tag{5.5}$$

where $\bar{p}_j$ the baseline processing time without learning, p_{jr} is the actual processing time of the job *j* located in position *r*, α was the learning speed parameter ($\alpha < 0$), θ is a conversion factor (e.g., 1/3600 to convert hours to seconds), and M represented the "factor of incompressibility" ($M = 0.5$ in our case). To compare the fitness to the experimental data of each model, we use the mean absolute percentage error (MAPE) per the literature to measure the fit of similar phenomena (Bailey and McIntyre, 1997; Digiesi *et al.*, 2009). The data collection phase is described below.

5.5.1 Data Collection

Participants

The data collection phase took place in October 2022, involving a total of twelve participants, comprising four women and eight men. Half had internal work experience of less than six months, while the rest had more than six months. All participants signed an informed consent after being informed about the test (Appendix B).

Materials and Protocol

This test was designed to determine if the picking worker was impacted by a remarkable learning effect (mainly related to the SKU position) at the beginning of a shift. It was performed in the training laboratory for the preparation operations of the company (with characteristics similar to the actual operation). The test consisted of processing a typical order (with 21 SKUs). Thus, each worker had to fill and repeat the order six times, one at a time (see Figure 5.4). While selecting the order SKUs, it was assumed that they were distributed within the laboratory. For the test execution, the workers were provided with a RFD scanner with the same characteristics as the real operation to read the order information, scan SKUs, and confirm order completion. The execution of experiments was recorded by video.

5.5.2 Data Analysis and Modeling

Employing the previously described two intervals method (Tilindis and Kleiza, 2017), we computed the learning rate (LR) based on experimentally collected data. Remembering that $\alpha = \frac{Log_{10}LR}{Log_{10}2}$, and due to this approach is based on Wright's model, as expressed in Equation (5.1), where $\alpha \geq 0$. In our case, α was multiplied by (-1) to achieve better compression, indicative of a time decrease.

Table 5.2 presents the LR values per worker, classified into inexperienced (less than 6 months) and experienced workers (with more than 6 months of work). Remarkably,

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Figure 5.4: Collection data - Learning effect

our results for LR values ($79.77\% \pm 4.47\%$) were similar to those reported in the existing literature, suggesting that the rate for manual labor was approximately 80% (Anzanello and Fogliatto, 2011; Wright, 1936). The analysis of variance (ANOVA) test indicated that the experience level was not significant over the LR (*p-value = 0.483*).

Table 5.2: Learning rate per worker

Inexperienced		**Experienced**	
Worker	*LR*	*Worker*	*LR*
1	79.20%	7	75.40%
2	80.10%	8	80.40%
3	81.40%	9	78.20%
4	77.00%	10	80.30%
5	92.00%	11	78.70%
6	74.20%	12	78.40%

In this study, the data collected experimentally by each worker was adjusted to the learning models referred to in the beginning of Section 5.5, using the α parameter from the LR computed above. Table 5.3 shows the MAPE comparing the fit of the learning models. The results show that DJ-LE has the highest fit (75%), followed by ST-LE (25%). This would allow us to conclude that for the case study, these two models are the ones that represent the learning process of the workers.

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Table 5.3: Model fit comparison

Worker	P-LE	ST-LE	DJ-LE
1	15.6%	10.1%	4.3%
2	13.7%	20.9%	11.4%
3	13.1%	16.3%	9.4%
4	20.7%	7.6%	4.4%
5	6.2%	7.0%	4.3%
6	14.6%	27.0%	13.6%
7	26.1%	4.0%	6.3%
8	18.3%	6.9%	4.3%
9	19.6%	8.8%	6.2%
10	21.9%	3.1%	7.2%
11	23.1%	5.0%	7.9%
12	21.0%	8.3%	5.8%

5.5.3 Solving the FSSP with Learning Effect

This section presents an application of the approaches proposed in Chapter 3 in the case studied, minimizing the makespan. In this scenario, the planning horizon spanned a single shift, where the set of containers corresponded to the set of jobs. The workers are at the picking stations. The baseline processing time of jobs executed by a worker corresponded to the time required for a worker to process a container in a picking station hence, the total sum of the time of the baseline processing time of all picking technical actions required for processing the container.

From the real data, 30 instances were generated. The characteristics of these instances are briefly described in Table 5.4. For building the instances, 26.80% of 1082 SKUs were taken. The SKUs referenced in the preparation of the instances correspond to those that were presented during the fatigue data collection process (more details in section 5.6.1). The number of workers was fixed (J=14). The number of jobs was generated using a uniform distribution between 1200 and 1700. The α values were set based on the results of Section 5.5.2. The experimental results indicated no significant difference in the α value among workers, so all workers had the same value per instance. As result, during the experimental phase, 75% of the participants reported a more favorable MAPE index for the DJ-LE model, while the remaining 25% favored ST-LE. For the problem instances, 75% of the workers were randomly assigned to the DJ-LE model, while the rest were assigned to the ST-LE model. The SA parameters were set as the API local search operator, T_0 = 0.5, T_f = 0.00001 and λ = 0.9.

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Table 5.4: FSSP with learning - Summary of problem instances

Characteristics	Values
Number of workers (I)	14
Number of jobs (J)	U[1200 - 1700]
Learning index (α)	79.77% $\pm$ 4.47%
Learning models	*ST-LE, DJ-LE*
Total instances	30

Once the instances were defined, the application of the SA_{API} algorithm was processed, which in Chapter 3 demonstrated outstanding performance. Due to the problem size, the construction of initial solutions with NEH took more than 8 hours in a pilot test. Therefore, trying to keep the main characteristics of the algorithm but reducing computational time two alternatives were considered. The first one generates the initial solution randomly while the second one generally utilizes the NEH partition. The idea of partitioning involves a complete set of jobs divided into subsets, and each subscheduling problem is solved by the NEH algorithm (Luo *et al.*, 2014).

Table 5.5 shows the results per each instance (k) compares the makespan and CPU time achieved by SA_{API} with two different initial solutions: one from the NEH-partition ($SA_{API}NEHp$) and the other from a random solution ($SA_{API}Rand$). For $SA_{API}Rand$, three executions were performed for each instance, and the table displays the average, standard deviation, and the percentage of difference defined by Equation (5.6).

$$\%\Delta RN = \frac{\overline{SA}_{API}Rand - SA_{API}NEHp}{SA_{API}NEHp} \tag{5.6}$$

Where, $\%\Delta RN$ is the percentage difference, $\overline{SA}_{API}Rand$ is the average makespan of solutions obtained using random initial solutions. $SA_{API}NEHp$ represented the makespan of solutions obtained using the initial solution from the NEH-partition.

The solutions generated by $SA_{API}NEHp$ consistently outperformed the others, giving lower makespan values in 90% of instances. Random initial solutions took less time to generate at CPU time, but as we observed, the metaheuristic could take even longer to reach the stopping criterion. A quick initial solution did not imply a lower computational time. We selected the results obtained by $SA_{API}NEHp$ to solve the FSSP with learning problem in this case study and the instances proposed in Table 5.4. The permutation of jobs for each instance will be the input for the next phases in the approach mentioned in Section 5.4.

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Table 5.5: Comparison of $SA_{API}NEHp$ Vs. $SA_{API}Rand$

k	**Makespan**			$\%\Delta RN$	**CPU time (sec)**		
	$SA_{API}NEHp$	$SA_{API}Rand$			$SA_{API}NEHp$	$SA_{API}Rand$	
		Average	Std			Average	Std
1	20307.74	21489.51	515.64	5.8%	1423.41	1313.80	633.13
2	21701.15	22371.72	134.31	3.1%	1054.15	2485.44	1591.84
3	23454.18	24080.24	335.32	2.7%	1163.92	1487.42	421.52
4	16808.04	17315.17	279.34	3.0%	612.88	3789.28	5609.71
5	16869.99	17072.79	44.97	1.2%	1216.59	1632.73	1061.08
6	19324.54	19493.77	67.35	0.9%	2776.85	1429.11	527.81
7	15511.44	15891.67	74.25	2.5%	495.15	1088.18	295.89
8	21500.32	21904.90	268.30	1.9%	959.88	1343.37	612.16
9	17824.77	18105.51	94.96	1.6%	3861.03	2118.52	856.08
10	19027.91	18825.19	266.09	-1.1%	1361.18	2363.08	1459.68
11	18973.96	19482.39	102.30	2.7%	833.43	4161.16	4585.77
12	18447.77	18542.00	246.58	0.5%	1976.81	5300.52	6549.61
13	18348.69	18685.26	140.61	1.8%	1173.33	3456.40	3760.29
14	22165.37	22382.47	268.17	1.0%	714.21	2280.80	977.90
15	21946.65	22155.01	237.94	0.9%	885.67	4504.44	3461.59
16	23755.46	23974.46	249.36	0.9%	1589.70	4939.24	3664.75
17	21330.66	20824.95	104.92	-2.4%	1031.52	1680.06	753.79
18	19104.56	19677.44	181.00	3.0%	672.57	3119.18	2932.74
19	18165.38	18721.25	58.41	3.1%	789.85	3608.83	2274.05
20	18760.37	19098.37	108.18	1.8%	1743.09	4233.10	2717.58
21	18858.84	18934.75	155.19	0.4%	808.08	2906.43	1170.97
22	23043.80	23358.92	116.14	1.4%	6358.95	8056.83	6084.92
23	19714.65	19831.52	50.92	0.6%	846.31	2300.02	1530.65
24	19658.94	20232.71	361.80	2.9%	1186.04	2215.77	290.27
25	17953.60	18153.81	195.83	1.1%	495.74	628.65	387.94
26	20156.78	20961.35	68.94	4.0%	1657.32	1621.51	730.84
27	19942.47	20398.21	213.92	2.3%	631.70	981.06	467.49
28	18882.00	18884.58	255.70	0.0%	609.37	3320.06	1518.77
29	17137.88	17330.45	173.90	1.1%	786.29	2386.68	1525.54
30	22052.94	22942.99	129.81	4.0%	1073.42	1331.74	502.56

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5.6 Fatigue Effect

5.6.1 Data Collection

Participants

The data collection phase occurred during the period of July to August 2022, involving a total of fourteen picking workers (one per picking zone). Participants included seven women and seven men aged 18 to 34 ($26.21 y.o. \pm 5.23$). Participants agreed to participate in this study through informed consent (Appendix C).

Materials and Protocol

Muscle activity was registered with eight surface electromyography (EMG) sensors (SX230, BioMetrics Ltd., UK) following the guideline of Perotto (2011), with a sample rate of 1000 /second. Sensors were placed in the muscular bellies of the group muscles involved in the picking operation during 40 minutes of real work (see Figure 5.5). We selected the *extensor radial, extensor ulnaris, flexor radial, flexor ulnaris, deltoid, biceps* of the dominant arm, and the right and left erector spinae muscle. Per each participant, maximum voluntary contractions (MVC) were recorded for each muscle as the signal's peak value. The MVC measurement enabled us to normalize the EMG signals. We recorded the EMG signal for 26.80% of the 1082 SKUs registered in the warehouse. Due to the SKU rotation and based on the Pareto principle (80/20 rule), we achieved a representation of 67.6% of the current picking operation.

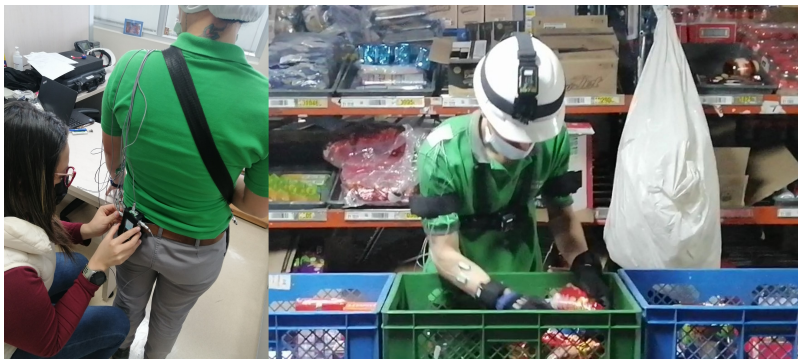

Figure 5.5: Collection Data - Fatigue Effect

5.6.2 Data Analysis and Modeling

Based on the approach proposed in Section 4.5, we presented an adaptation to this case study described below:

1. Once the Data Link software processed the surface EMG signals, the root mean signal was estimated using a 200 ms moving window. By linking the sign to every

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SKU item handled, we obtained the root mean signals of each muscle group per worker for each SKU item.

2. Subsequently, the signals were normalized with the recorded MVC for each muscle per worker, achieving the %MVC per each muscle per SKU item. Normalizing made it possible to compare EMG signals across muscles and subjects (Lehman and McGill, 1999). The 15th percentile of %MVC per muscle was calculated, and the highest values were saved, such as the reference value per SKU item.
3. As mentioned, a container could require more than one PTA (*A = set of PTA*). The Equation 4.1 is used to determine the MET_a or maximum endurance time for completing the PTA $a \in A$.
4. Due to the absence of empirical data on the technical action fatigue growth parameter, it was calculated with Equation 5.7 proposed by Glock *et al.* (2019b). θ_a corresponds to the fatigue rate parameter for a given action, $a \in A$. Equation 5.7 was a generalization of Equation 4.2 when more than one technical action was executed during job processing.

$$\theta_a = \frac{1}{MET_a} \ln\left(\frac{1}{1 - F_{\max}}\right) \tag{5.7}$$

Per Dotan (2022), the muscular occlusion-producing high of tensions should appear between 51.5% and 75.5% of F_{max}. Furthermore, Glock *et al.* (2019a) demonstrated that a lower F_{max} value resulted in longer recovery periods, which can become unfeasible for the production system, setting a F_{max} of 75% as an acceptable level.

5. The static fatigue of a worker from each technical picking action was calculated using Equation 5.8 adapted from the approach of Glock *et al.* (2019a), where $F_s(t_a)$ is the fatigue accumulated for executing the PTA $a \in A$. Moreover t_a was related to the time needed to execute the PTA. In this case, we use the baseline time without considering the effect of learning or fatigue:

$$F_s(t_a) = 1 - e^{\theta_a t_a} \tag{5.8}$$

Total static fatigue (F_s) of container processing (job processing) of the worker was the result of the execution of PTA, the accumulation of the static fatigue level, using Equation 5.9:

$$F_s = \sum_{a \in A} F_s(t_a) \tag{5.9}$$

6. Continuing with Glock *et al.* (2019a) approach, the dynamic fatigue of a PTA (Equation 5.10) was calculated by multiplying the estimated total static fatigue level $F_s(t_w)$ by the coefficient β. This coefficient was approached empirically. Studies have shown that static fatigue accumulates six times more quickly than dynamic fatigue for a task (Bakke *et al.*, 1996; Perez, 2011). We approximated beta $\beta = 0.17$ (Glock *et al.*, 2019a):

$$F_T(t_w) = \beta F_S(t_w) \tag{5.10}$$

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7. For the dynamic fatigue of the container processing, we calculated the exponential fatigue using Equation 5.11 per Glock *et al.* (2019b):

$$\lambda = -\frac{ln(1 - F_T(t_w))}{t_w} \tag{5.11}$$

This parameter was used in the accumulated fatigue model in the Equation 4.4.

8. Regarding the μ parameter, for Ma *et al.* (2015) it depended on the individual characteristics. However, to address this problem with engineering, we referred to Xia and Law (2008), indicating that the recovery rates depended on how the muscle fibers were ordered, as follows:

   - Type I muscle fibers are smallest fiber type, and crucial for prolonged periods of exertion ($\mu = 0.002s^{-}1$).
   - Type IIa muscle fibers are commonly referred to as intermediate muscle fibers, allowing us to work at high intensity for a slightly longer duration ($\mu = 0.01s^{-}1$).
   - Type IIb muscle fibers' peak strength was achieved faster, and they produced the most force but were easily fatigued ($\mu = 0.02s^{-}1$).

5.6.3 Incorporating the Fatigue Effect

For the integration of fatigue, we included critical considerations, such as a single eight-hour picking shift where the accumulated fatigue level was equal to 0 at the beginning. All workers were unavailable in the picking line at the end of the work shift. There were no containers in process at the start of the shift, and workers could not take breaks until they finished processing the container at that station. Table 5.6 contains information on the integration of fatigue, completing Table 5.4. The picking line was emulated using NetLogo Version 6.2.2 (Figure 5.6), considering the characteristics of the real system, such as the container's dimension and velocity.

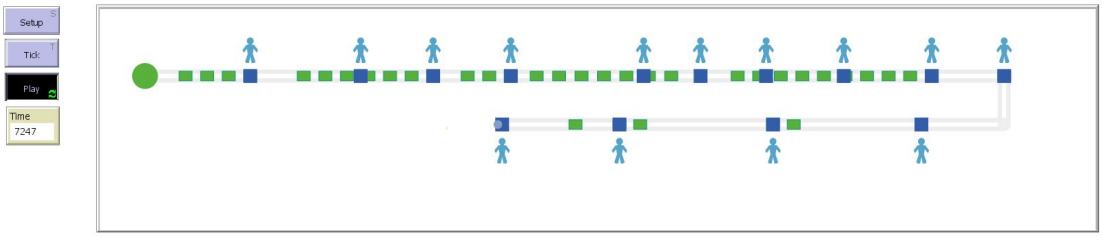

Figure 5.6: Case Study Multi-agent System Using NetLogo Software

Although there was not much literature for reference, we used the Ostermeier (2020b) method to calculate the delta value with the standard deviation of the baseline job processing time, which, in this case, was $\delta = 0.16$ (used in Equation 4.6). As for μ, it was found that the highest value of reference of the 15th percentile of $\%MVC$ was represented by the right erector spinae (24.05%) and the flexor ulnaris muscle (19.05%). The

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first muscle had type I fibers, while the second had type IIa and IIb fibers. Hence, μ values of 0.01 were selected, corresponding to intermediate fibers, and 0.03, a value commonly reported in the literature (Jaber *et al.*, 2013; Ostermeier, 2020a; Ostermeier, 2020b).

Table 5.6: Incorporating the Learning Effect Into FSSP - Summary of Problem Instances

Characteristics	Values
Fatigue rate	λ = Using Equation 5.11
Recovery rate	μ = 0.01, 0.03
Effect of fatigue on the job processing time	δ = 0.16
Initial fatigue level	F_0 = 0

5.7 Bi-Objective Solution Approach

In the context of metaheuristics, GA are probably one of the most recognized techniques to solve complex optimization problems, successfully used to solve routing, location, scheduling, and sequencing issues. Holland (1975) induced the term GA based on the principle of "survival of the fittest," like the natural selection process. If an object function evaluation requires too much resources, it can become impractical. In this case, we found an adaptation known as FastPGA in the literature. For multi-objective optimization, each solution evaluation was computationally and/or financially expensive (Eskandari and Geiger, 2008). Kaur (2016) proposed this technique motivated by simulation-based optimization research.

Since our approach involved highly costly and time-consuming objective function computation, adapting FastPGA was convenient for efficiently searching for the Pareto optimal frontier. This metaheuristic and its chromosome representation could be easily modified to other scenarios, such as scheduling other rate-modifying activities like maintenance and setups.

5.7.1 FastPGA Description

We proposed and developed FastPGA in this framework based on the one proposed by Eskandari and Geiger (2008). The flowchart in Figure 5.7 details the FastPGA. The steps and components are outlined as follows:

- *Step 1:* Create the initial population.
- *Step 2:* If this is the first generation, go to step 4. Otherwise, increase the number of generations and select the parents.
- *Step 3:* Applied the crossover and mutation operators to get an offspring.
- *Step 4:* Evaluate the objective functions (i.e., the makespan and total fatigue dose), launching the multi-agent system simulation. Calculate the fitness.

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- *Step 5:* Combine the offspring and the previous population to achieve a composite population.
- *Step 6:* Rank the solution of the composite population according to the ranking strategy.
- *Step 7:* Create a new population, by removing the inferior (dominated) solutions from the composite population. Calculate the fitness values.
- *Step 8:* FastPGA stops when the stopping condition is reached. Otherwise, return to step 2.

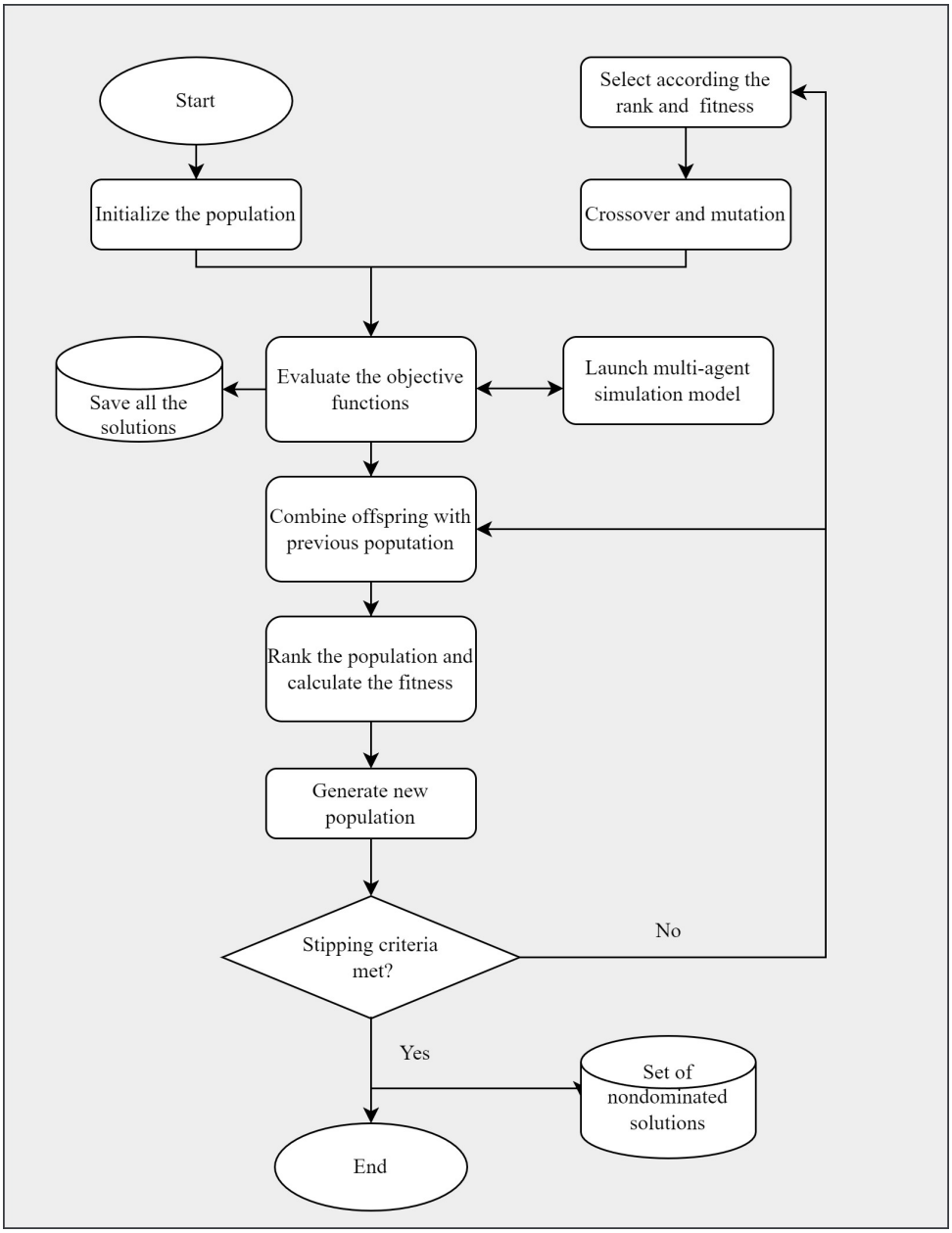

Figure 5.7: FastPGA - Flowchart (adapted from: Eskandari and Geiger (2008))

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Chromosome Representation

NB was the number of breaks of the policy while TBD was the total break duration, the chromosome's length (l) was 2NB, and the genes were between 0−1 . The first half of the chromosome corresponded to the location or beginning of each break (in green in 5.8), while the second half represented their respective duration (in blue in Figure 5.8). For example, the chromosome in Figure 5.8 represents a solution with three breaks starting at 35%, 62% and 87% of C^P_{max}. The duration of the first break is 0.22TBD, the second break is 0.78TBD, and the third is 0.10TBD (the sum of the genes in the second half equals 1).

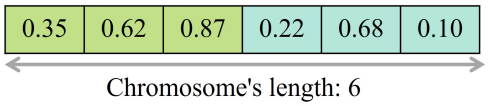

Figure 5.8: FastPGA - Chromosome representation

Initial Population

The initial population comprised chromosomes whose genes were randomly generated, guaranteeing feasibility. The population size was set at 50 in our experiments.

Ranking Strategy and Fitness Evaluation

This ranking strategy (outlined by Eskandari *et al.* (2007)) classified the composite population (CP) solutions into two categories (ranks) based on the dominance of the solutions. All non-dominated solutions were located in the first rank. Hence, there was no better solution than these in terms of the two objectives simultaneously. All dominated solutions were placed in the second rank. The fitness value was calculated for reproduction purposes for the solutions in this rank. The fitness of each dominated solution (χ_i) was equal to the sum of the strength values of all solutions it dominated minus the sum of the strength values of all solutions by which it was dominated (Equation 5.12).

$$F(\chi_i) = \sum_{\chi_i \succ \chi_j} S(\chi_j) - \sum_{\chi_k \succ \chi_i} S(\chi_k) \quad \forall \chi_j, \chi_k \in CP \wedge j \neq i \neq k \tag{5.12}$$

where each solution (χ_i) had an assigned strength value of $S(\chi_i)$, indicating the number of solutions it dominated (Equation 5.13).

$$S(\chi_i) = |\{\chi_j \mid \forall \chi_j \in CP \wedge \chi_i \succ \chi_j \wedge j \neq i\}| \tag{5.13}$$

Selection of Parents

We used the roulette-wheel method to select the parents. In this method, the probability of selecting chromosomes was proportional to the fitness.

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Crossover

The crossover operation required two parents to produce a new generation. In this study, we used the traditional one-point crossover, locating the cut point in the middle, as observed in Figure 5.9. Son 1 contained information regarding the location and duration of breaks from Parent 1 and Parent 2, respectively. Son 2 contained the location and duration information from Parent 2 and Parent 1, respectively.

It is possible that in this crossover, the offspring could become infeasible. In such cases, the offspring need to be repaired. For example, in Figure 5.9, the third break of Son 2 had a duration of 0.1 TBD. However, since the first part of the chromosome was from a parent that only considered two breaks, a gene was generated to indicate the beginning of this break.

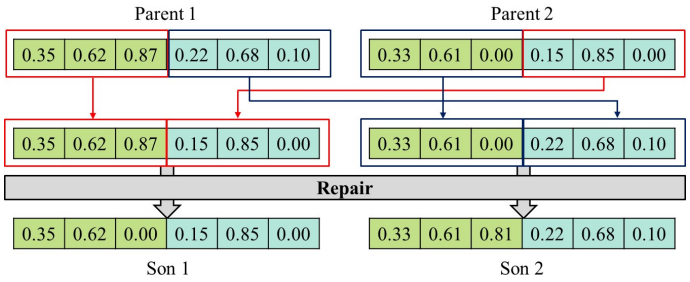

Figure 5.9: FastPGA - Crossover and repair operator

Mutation

If a mutation occurred, this operator randomly selected a chromosome's gene and changed its value. The mutation probability was set at 0.05, as Haupt (2000) recommended for cases involving a small population size. Mutation occurred while maintaining feasibility.

Stopping Condition

The stopping criterion was time, and a maximum time of 15 days was defined.

5.7.2 Analysis of Results

Table 5.7 shows the non-dominated solutions for any of the selected instances. For instance, we can observe that for the instance 1, with $\mu = 0.01$, the algorithm identified two non-dominated solutions. However, with the same $\mu = 0.01$, value, in instance 5, it found three dominated solutions. It is observed that regarding the values of the objective functions, $\%\Delta makespan$ is defined in Equation 4.7 because the instances tested are different from the TFD results and are presented as standardized total fatigue dose (FDs) between 0 and 1, calculated by Equation 5.14. The solution returned by FastPGA is represented by the chromosomes. Of the total results, 2.0% propose a break, 23.10%

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propose two breaks, and 74.90% propose three breaks during the shift. This means that a minimum of two breaks is recommended to balance the two studied objective functions.

$$FDs_i = \frac{TFD_i - min(TFD)}{max(TFD) - min(TFD)} \tag{5.14}$$

As an example, Figure 5.10, shows the Pareto front solution obtained for instance 3 with $\mu = 0.03$. The solution indicated in the circle presents a lower value for the fatigue criterion, while the solution indicated in orange reaches the lowest value with respect to the criterion of standardized total fatigue doses. The lowest values of both criteria simultaneously can be found in solutions whose distance to point (0,0) is shortest. The Euclidean distance (Equation 5.15) to (0,0) was calculated for each of these solutions.

$$d_i = \sqrt{(\%\Delta makespan_i - 0)^2 + (FDs_i - 0)^2} \tag{5.15}$$

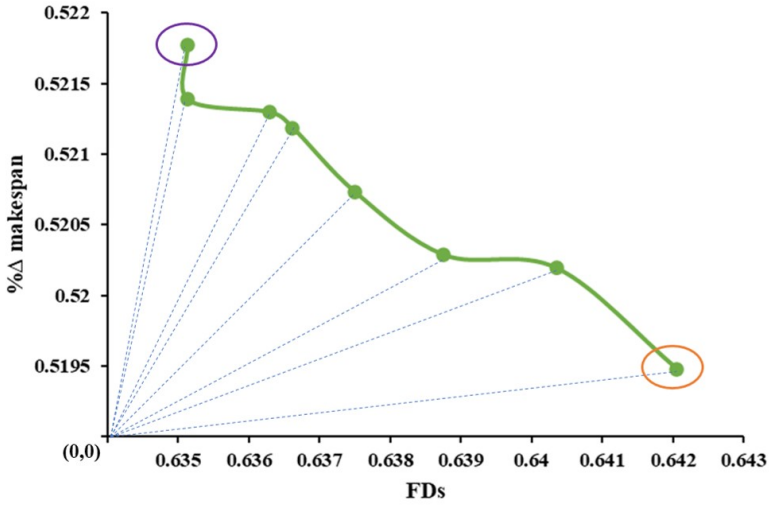

Figure 5.10: Example of Pareto Front for Instance 3 with μ = 0.03

Table 5.7: Non-dominated Solutions

Instance	μ	**# Breaks**	$\%\Delta makespan$	FDs	**Chromosome**
1	0.01	2	0.664	0.642	[0.27,0.54,0,0.21,0.79,0]
1	0.01	3	0.661	0.643	[0.46,0.55,0.95,0.16,0.43,0.41]
1	0.03	2	0.661	0.641	[0.25,0.37,0,0.38,0.62,0]
1	0.03	3	0.661	0.641	[0.25,0.47,0.55,0.15,0.09,0.76]
2	0.01	2	0.557	0.791	[0.22,0.79,0,0.49,0.51,0]
2	0.01	3	0.557	0.791	[0.15,0.35,0.75,0.52,0.13,0.35]
2	0.03	2	0.535	0.39	[0.26,0.91,0,0.58,0.42,0]
2	0.03	3	0.532	0.39	[0.11,0.45,0.8,0.8,0.13,0.07]
3	0.01	3	0.663	1	[0.27,0.41,0.84,0.49,0.12,0.39]
3	0.03	2	0.642	0.519	[0.15,0.24,0,0.42,0.58,0]
3	0.03	3	0.635	0.522	[0.18,0.56,0.85,0.28,0.67,0.05]

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Table 5.7: Non-dominated Solutions

Instance	μ	**# Breaks**	$\%\Delta makespan$	FDs	**Chromosome**
4	0.01	2	0.666	0.649	[0.3,0.95,0,0.31,0.69,0]
4	0.01	3	0.667	0.649	[0.11,0.5,0.84,0.55,0.13,0.32]
4	0.03	2	0.645	0.294	[0.29,0.59,0,0.72,0.28,0]
4	0.03	3	0.641	0.295	[0.17,0.41,0.91,0.1,0.28,0.62]
5	0.01	1	0.652	0.553	[0.4,0,0,1,0,0]
5	0.01	2	0.654	0.55	[0.12,0.38,0,0.88,0.12,0]
5	0.01	3	0.652	0.551	[0.51,0.73,0.82,0.55,0.04,0.41]
5	0.03	2	0.627	0.236	[0.04,0.31,0,0.09,0.91,0]
5	0.03	3	0.618	0.236	[0.22,0.49,0.78,0.32,0.16,0.52]
6	0.01	3	0.529	0.604	[0.45,0.55,0.87,0.37,0.12,0.51]
6	0.03	1	0.509	0.271	[0.13,0,0,1,0,0]
6	0.03	2	0.506	0.273	[0.44,0.65,0,0.67,0.33,0]
6	0.03	3	0.506	0.272	[0.42,0.94,1,0.6,0.16,0.24]
7	0.01	2	0.552	0.537	[0.1,0.2,0,0.27,0.73,0]
7	0.01	3	0.551	0.538	[0.1,0.24,0.84,0.57,0.38,0.05]
7	0.03	2	0.528	0.224	[0.24,0.43,0,0.89,0.11,0]
7	0.03	3	0.524	0.225	[0.16,0.33,0.6,0.73,0.16,0.11]
8	0.01	2	0.608	0.769	[0.32,0.48,0,0.1,0.9,0]
8	0.01	3	0.604	0.771	[0.32,0.48,0.93,0.16,0.67,0.17]
8	0.03	3	0.582	0.394	[0.31,0.7,0.99,0.67,0.08,0.25]
9	0.01	2	0.574	0.767	[0.19,1,0,0.43,0.57,0]
9	0.03	2	0.572	0.224	[0.24,0.43,0,0.89,0.11,0]
10	0.01	3	0.597	0.643	[0.2,0.41,0.95,0.07,0.1,0.83]
10	0.03	1	0.922	0.289	[0.03,0,0,1,0,0]
10	0.03	2	0.558	0.29	[0.12,0.84,0,0.03,0.97,0]
10	0.03	3	0.548	0.29	[0.64,0.81,0.97,0.86,0.12,0.02]
11	0.01	3	0.528	0.224	[0.24,0.43,0,0.89,0.11,0]
11	0.03	2	0.609	0.768	[0.25,0.35,0,0.49,0.51,0]
11	0.03	3	0.536	0.389	[0.26,0.65,0,0.91,0.09,0]
12	0.01	3	0.658	0.52	[0.28,0.67,0.91,0.41,0.46,0.13]
12	0.03	3	0.655	0.229	[0.14,0.24,0.66,0.54,0.24,0.22]
13	0.01	2	0.724	0.174	[0.04,0.16,0,0.55,0.45,0]
13	0.01	3	0.725	0.18	[0.35,0.85,0.93,0.42,0.06,0.52]
13	0.03	3	0.525	0.002	[0.42,0.89,1,0.17,0.33,0.5]
14	0.01	2	0.515	0.814	[0.09,0.54,0,0.19,0.81,0]
14	0.01	3	0.512	0.81	[0.3,0.6,0.93,0.31,0.45,0.24]
14	0.03	2	0.582	0.434	[0.15,0.41,0,0.66,0.34,0]
14	0.03	3	0.582	0.433	[0.16,0.3,0.87,0.5,0.37,0.13]
15	0.01	3	0.555	0.813	[0.19,0.45,0.55,0.44,0.46,0.1]
15	0.03	2	0.555	0.423	[0.25,0.82,0,0.84,0.16,0]
15	0.03	3	0.552	0.422	[0.22,0.64,0.82,0.47,0.34,0.19]
16	0.01	3	0.554	0.712	[0.17,0.27,0.79,0.35,0.55,0.1]
16	0.03	3	0.553	0.355	[0.08,0.28,0.56,0.53,0.43,0.04]
17	0.01	3	0.538	0.221	[0.11,0.35,0.65,0.8,0.07,0.13]

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Table 5.7: Non-dominated Solutions

Instance	μ	**# Breaks**	$\%\Delta makespan$	FDs	**Chromosome**
17	0.03	2	0.5	0.028	[0.08,0.25,0,0.33,0.67,0]
17	0.03	3	0.495	0.028	[0.01,0.17,0.69,0.5,0.22,0.28]
18	0.01	2	0.484	0.263	[0.14,0.35,0,0.26,0.74,0]
18	0.01	3	0.487	0.261	[0.14,0.25,0.41,0.14,0.66,0.2]
18	0.03	2	0.485	0.066	[0.32,0.4,0,0.66,0.34,0]
18	0.03	3	0.613	0.066	[0.18,0.47,0.6,0.16,0.52,0.32]
19	0.01	2	0.593	0.579	[0.02,0.16,0,0.91,0.09,0]
19	0.01	3	0.592	0.58	[0.27,0.68,0.78,0.8,0.16,0.04]
19	0.03	2	0.672	0.253	[0.27,0.49,0,0.79,0.21,0]
19	0.03	3	0.675	0.253	[0.15,0.84,0.95,0.15,0.57,0.28]
20	0.01	3	0.649	0.589	[0.07,0.32,0.95,0.09,0.18,0.73]
20	0.03	2	0.647	0.276	[0.11,0.39,0,0.66,0.34,0]
20	0.03	3	0.65	0.587	[0.32,0.4,0.59,0.17,0.26,0.57]
21	0.01	2	0.638	0.572	[0.16,0.35,0,0.49,0.51,0]
21	0.01	3	0.641	0.566	[0.04,0.24,0.36,0.17,0.7,0.13]
21	0.03	2	0.608	0.253	[0.19,0.35,0,0.93,0.07,0]
21	0.03	3	0.607	0.254	[0.52,0.79,0.97,0.04,0.12,0.84]
22	0.01	2	0.538	0.787	[0.22,0.38,0,0.56,0.44,0]
22	0.01	3	0.538	0.783	[0.25,0.85,0.95,0.39,0.16,0.45]
22	0.03	2	0.538	0.391	[0.09,0.17,0,0.35,0.65,0]
22	0.03	3	0.536	0.393	[0.28,0.95,1,0.34,0.36,0.3]
23	0.01	3	0.51	0.749	[0.29,0.95,1,0.17,0.54,0.29]
23	0.03	2	0.513	0.356	[0.23,0.35,0,0.73,0.27,0]
23	0.03	3	0.58	0.356	[0.07,0.24,0.98,0.54,0.22,0.24]
24	0.01	3	0.557	0.646	[0.04,0.14,0.35,0.62,0.23,0.15]
24	0.03	3	0.647	0.29	[0.44,0.81,0.97,0.84,0.1,0.06]
25	0.01	3	0.585	0.535	[0.05,0.2,0.47,0.52,0.18,0.3]
25	0.03	3	0.581	0.225	[0.23,0.56,0.77,0.69,0.12,0.19]
26	0.01	3	0.56	0.607	[0.11,0.19,0.29,0.64,0.15,0.21]
26	0.03	2	0.56	0.278	[0.07,0.17,0,0.05,0.95,0]
27	0.01	3	0.39	0.76	[0.05,0.34,0.57,0.13,0.82,0.05]
27	0.03	2	0.614	0.376	[0.02,0.18,0,0.61,0.39,0]
27	0.03	3	0.585	0.375	[0.02,0.37,0.59,0.2,0.24,0.56]
28	0.01	3	0.577	0.619	[0.2,0.4,0.96,0.25,0.57,0.18]
28	0.03	2	0.578	0.279	[0.2,0.65,0,0.17,0.83,0]
28	0.03	3	0.582	0.279	[0.21,0.4,0.57,0.16,0.8,0.04]
29	0.01	2	0.578	0.557	[0.14,0.3,0,0.66,0.34,0]
29	0.01	3	0.581	0.56	[0.14,0.89,0.99,0.22,0.12,0.66]
29	0.03	2	0.648	0.261	[0.16,0.39,0,0.04,0.96,0]
29	0.03	3	0.646	0.259	[0.18,0.29,0.39,0.75,0.17,0.08]
30	0.01	3	0.622	0.346	[0.19,0.3,0.38,0.44,0.07,0.49]
30	0.03	3	0.586	0.11	[0.02,0.19,0.77,0.05,0.67,0.28]

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As the policy of breaks can be modified based on the company's interests, the three scenarios, which prioritized either makespan, total fatigue dose, or both simultaneously, were analyzed. Table 5.8 displays the mean and the standard deviation that were calculated for the location and duration of breaks in the three scenarios and how they are affected by the recovery factor.

Table 5.8: Break Policy Recommended

μ	**NB**	**Policy**	$\%\Delta makespan$		FD_e		*Both*	
			mean	**std**	**mean**	**std**	**mean**	**std**
0.01	3	L-B1	0.202	0.131	0.139	0.085	0.192	0.130
		L-B2	0.463	0.230	0.389	0.209	0.430	0.220
		L-B3	0.738	0.236	0.682	0.206	0.701	0.232
		D-B1	0.380	0.205	0.499	0.256	0.379	0.207
		D-B2	0.309	0.232	0.263	0.210	0.336	0.230
		D-B3	0.311	0.211	0.239	0.200	0.285	0.199
	2	L-B1	0.166	0.092	0.184	0.510	0.176	0.098
		L-B2	0.470	0.272	0.381	0.490	0.433	0.229
		D-B1	0.451	0.248	0.510	0.294	0.480	0.282
		D-B2	0.549	0.248	0.490	0.294	0.520	0.282
0.03	3	L-B1	0.218	0.152	0.144	0.082	0.219	0.153
		L-B2	0.509	0.244	0.414	0.206	0.521	0.252
		L-B3	0.786	0.183	0.700	0.196	0.792	0.183
		D-B1	0.423	0.256	0.437	0.267	0.468	0.271
		D-B2	0.297	0.196	0.279	0.185	0.274	0.188
		D-B3	0.281	0.219	0.284	0.218	0.259	0.199
	2	L-B1	0.182	0.106	0.154	0.094	0.182	0.106
		L-B2	0.469	0.239	0.382	0.196	0.457	0.223
		D-B1	0.541	0.307	0.498	0.301	0.556	0.316
		D-B2	0.459	0.307	0.502	0.301	0.444	0.316

Localization Break 1 (L-B1); Location Break 2 (L-B2); Location Break 3 (L-B3); Duration Break 1 (D-B1); Duration Break 2 (D-B2); Duration Break 3 (D-B3)

Table 5.8 displays the duration and location of break policies suggested based on the objective prioritized. In the case of a $\mu = 0.01$ policy with a 3-break policy, the breaks' location changes like this.

- If $\%\Delta makespan$ is given priority, the results indicate that the breaks should be approximately 20.2%, 46.3%, and 73.8% of the C^P_{max}, with duration of 38%, 30.9%, and 31.1% of TBD.
- If FDs is priorized, these should be close to 13.9%, 38.9%, and 68.2% with duration of 49.9%, 26.3%, and 23.9% of the TBD.

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- To optimize both objectives simultaneously, the suggested location is at 19.2%, 43%, and 70.1%, with duration of 37.9%, 33.6% and 28.5% of the TBD.

According to these results, it is possible for the organization to adopt a policy that allows at least three breaks during the work shift. Given that logistical limitations may make this difficult, it may be appropriate to allow two breaks to balance the indicators related to makespan and fatigue. Generally, the first break should occur at 20% of the C^P_{max}, while the second one should occur at roughly 50% of the shift duration, with equal duration. This is explained by the fact that the scheduling problem with the learning effect schedules jobs with the longest duration (load) at the beginning of the shift. An early recovery break (after approximately 20% of theC^P_{max}) enables the resetting of fatigue levels, which has a direct impact on job-processing time.

If the two-break strategy is implemented, it might not be advantageous to schedule more breaks during the second half of the shift. This is because the permutation of jobs involves jobs that are either the shortest or least demanding, resulting in a lower learning effect and, consequently, lower fatigue levels currently. The company only has one break during their shift, which is located in the middle of the shift. These results allow her to recognize that at least one strategy with two breaks could be a superior benefit for fatigue mitigation.

5.8 Conclusions

This chapter presented the application of the whole framework to solve FSSP with the learning effect, including the fatigue effect, in a case study with realistic data. It was approached from the bi-objective approach, minimizing the makespan and the total fatigue dose, using a FastPGA to solve the FSSP with learning using the SA_{API} while involving fatigue through a multi-agent system model. We use an inter-disciplinary approach to model learning and fatigue effects. As a result, we acquired the permutation of jobs and the break policy suitable for this case. The recommended approach for preventing fatigue from short and frequent breaks was the break policy with the best performance for the system in general, as shown by numerical results.

In general, there are suggested policies for two to three breaks, and their duration and location depend on the objectives that were prioritized by the organization. However, in this case study, solutions with just one break are less attractive than those that propose two or three breaks. This is in line with the idea that short but more frequent breaks are more effective in mitigating muscular fatigue (Lyubykh *et al.*, 2022; Rohmert, 1973).

The definition of break policies is impacted by the recovery rate (μ), as the location of these can occur earlier for slow speeds. In our case study, we examined two reference values found in the literature, taking into account the muscle segments involved in the operations. Nevertheless, there was an opportunity for interdisciplinary research to accurately estimate these parameters.

We considered learning by doing associated with familiarizing and localizing SKUs, which happened to workers at the start of each shift. However, incorporating other

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variables, such as the training time of workers, particular capabilities, and the impact of learning on the error in the execution of tasks, was outside the scope of this study. Thus, the opportunity remains open to propose research allowing a suitable estimation of the δ parameter, which can be decisive in establishing a solution to real problems.

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Chapter 6

Conclusions and Future Research Opportunities

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6.1 Conclusions

In this thesis, we study the flowshop scheduling problem with the effects of leaning and fatigue, using both theoretical and practical approaches. In 2022, the European Commission formally defined the arrival of the fifth industry and, with it, a change of paradigm from the industrial context, which has had a direct impact on the approach to certain problems within academia. Recently, there has been growing interest from the academic community in having another optician of classical problems, such as scheduling problems, which results in the consideration and modeling of humans as a flexible and complex resource, among other things.

An approach to the phenomenon of autonomous learning in scheduling problems has been developed, based mostly on the log-linear model proposed by Wright in 1936. Based on this, numerous approaches have been developed, categorized mainly into position-based learning effects and sum of processing time-based learning effects. The deterioration effect has been studied less frequently, but in most cases, the deterioration of jobs has been addressed, where the job deteriorates over time. Some authors have begun to address the effect of resource deterioration by proposing approaches classified mainly into the position-based deterioration effect and the cumulative deterioration effect. Little work has applied the concept of deterioration, particularly to humans, in whom deterioration could be seen as fatigue and forgetting, for example. The NP-hard nature of these models leads to the use of methodologies such as heuristics and metaheuristics, mostly to solve the problems in a reasonable computational time.

Flowshop-type configurations are common in manual intensive production systems, and the inclusion of the learning effect for even two resources makes it a complex problem. In this thesis, four learning models (referred to as cases) were identified to evaluate the FSSP by minimizing the makespan. These problems were modeled mathematically, and for small instances, the optimal solution was obtained using the GLPK and Bonmin solvers from Pyomo in Python. For large instances, benchmark data sets were taken from the literature, and various algorithms were used, for example, Johnson's rule and adapted NEH for the case with two resources. To solve the general problem, a simulated annealing approaches with two alternatives were proposed, employing an API and an NAPI local search operator and obtaining the initial solution from the NEH. The SA_{API} showed outstanding performance through statistical tests. The sensitivity analysis allowed us to identify parameter values that improve the performance of the algorithm.

Physical fatigue in humans is strongly related to the occurrence of WMSD, which represents a significant budget for companies. Muscle fatigue caused by repetitive and monotonous jobs typically leads to WMSD in the long term. This thesis focuses on the study of muscle fatigue among workers in a flowshop–type system. A simulation based on agents was created to analyse the incorporation of fatigue into FSSP, taking the models referenced in the literature as a starting point. To mitigate fatigue, the definition of break policies (location and duration) is crucial. Therefore, exploratory experiments were conducted using benchmark data sets on a small instance of the problem to test the effect of two policies on fatigue levels. The mitigation of fatigue was found to be enhanced by policies that involve short but more frequent breaks.

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The theoretical approach to the problem was validated using a real case application. To validate an approach to real conditions, on-site data collection of workers' learning rates was carried out. By conducting experimental tests in the industrial partner's training laboratory, we were able to adjust the learning models. Using EMG, data on workers' actual muscle activity was collected in real conditions, which enabled the computation of fatigue rate parameters. A bi-objective approach was proposed to simultaneously minimize the makespan and the total fatigue dose. The FSSP with learning effect was solved by determining the permutations of jobs; then, this information was sent to a Fast Pareto genetic algorithm that proposes different break policies as a solution. The objective functions were calculated using the multi-agent simulation model. By examining the non-domained solutions, we were able to confirm that short and frequent breaks are indeed advisable, as previously demonstrated in the exploratory experiments. Alternatives for the location and duration of breaks are possible, based on the company's priorities (such as minimizing makespan, total fatigue dose, or both).

This work provides an independent, theoretical, and practical approach to the FSSP with learning effect that incorporates the phenomenon of fatigue. The design of this approach was based on the company's decision-making process for dealing with this type of problem. On the one hand, at the operational level, there is the problem of the FSSP with a learning effect, providing, as a result, the permutation of jobs for each of the planning horizons (such as a shift, day, etc). At the tactical level, there is a problem with fatigue integration that leads to the definition of break policies. Finally, as a decision-making tool, a bi-objective approach is proposed that allows for the simultaneous evaluation of these two decisions (economic and social objectives).

6.2 Future Research Opportunities

Many interesting perspectives have been identified through this work, which could expand both the scope and depth of this study. In addition, some of these perspectives could be transformed into future research opportunities. These are described below:

- The four most commonly reported learning models in the literature were chosen. Models that include individual characteristics that could be decisive in the learning process, such as experience and level of training, were not considered. The literature suggests that job processing time could be stochastic, a situation that would allow this problem to be addressed even with uncertainty. It could even be thought that the learning process remains dynamic and that a learning model adapted for a worker could change over time.
- Learning models with truncation seem to be well-adapted to reality, but their use in case study studies has not been extensive. Calculating the truncation parameter requires a large sample of data and adjusted estimates of baseline processing times. There is not enough literature available on methods for estimating parameters such as β and M in DeJong's model.
- Parallel machines, hybrid flowshop and flexible job shops configurations are in-

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creasingly common in the industry, particularly in manually intensive luxury industries. Therefore, it is pertinent to address this type of problem while considering these configurations. Furthermore, new objective functions could take into account the level of human error caused by fatigue and learning, for instance.

- Identifying the time it took for the NEH to find an initial solution in real instances (with more than 1200 jobs and 14 workers) led us to propose a solution for the SA_{API} based on an NEH partition. The algorithm's efficiency can be improved, or strategies can be used to achieve high-quality initial solutions with reduced computational consumption.

- The exponential model of fatigue accumulation is the basis of our contribution. However, a lack of depth in the study of this phenomenon was found. As the literature states that few studies have attempted to examine the phenomenon from an interdisciplinary perspective, the development of design tools that can calculate parameters such as μ and δ is crucial. Although it is true that it is conditioned by individual characteristics, it is important that work be done in this area to advance the design and engineering of productive systems that are more adjusted to the capacities and limitations of workers.

- In picking activities, physical fatigue can also be conditioned by movement. Therefore, the integration of the methods used here regarding muscular fatigue with others, such as energy consumption or heart rate, would be valid to achieve an indicator of global physical fatigue. Mental fatigue plays a significant role in this type of work, which demands high levels of concentration and memory.

- The data collection in this thesis was done during the daytime, and we assumed that workers' performance did not change based on their work hours. Although it is known that physiological processes such as fatigue can increase at night, therefore, the comparison between day and night shifts remains an open research question. It is also important to address the forgetting effect, which can occur during breaks and decrease productivity. Likewise, in the long term, it will become relevant to evaluate aging phenomena given the real conditions of the current working population.

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Appendix A

Objective Function Classification

Time related objectives (TRO)	*Utilization of resources*	Makespan	$\max C_j$
		Total resource consumption	$\sum_{i\in I}\sum_{j\in J}\mu_{ij}$
		Total load	$\sum_{i\in I} C^i_{max}$
		Total idle time	$\sum_{i\in I}\sum_{j\in J} id_{ij}$
	Work in process	Total completion time	$\sum_{j\in J} C_j$
		Total weighted completion time	$\sum_{j\in J}\omega_j C_j$
		Discounted total weighted completion time	$\sum_{j\in J}\omega_j(1-e^{-\gamma C_j})$
		Total absolute differences in completion times	$\sum_{k\in J}\sum_{j\in J}\lvert C_k - C_j\rvert$
		The sum of the kth powers of completion times	$\sum_{j\in J} {C_j}^k$
		The sum of the quadratic job completion times	$\sum_{j\in J} {C_j}^2$

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		Total flow time	$\sum_{j\in J} F_j$
		Total absolute differences in waiting time	$\sum_{k\in J}\sum_{j\in J} \lvert C_k - C_j \rvert$
		Total waiting times	$\sum_{j\in J} W_j$
		Cycle time	CT
Job related Objectives (JRO)	*Costumer related*	Maximum tardiness	$\max \mathrm{T}_j$
		Maximum lateness	$\max \mathrm{L}_j$
		Maximum earliness	$\max \mathrm{E}_j$
		The number of tardy jobs	$\sum_{j\in J} U_j$
		Number of just-in time jobs	$\sum_{j\in J} V_j$
	Balancing related	Total tardiness	$\sum_{j\in J} T_j$
		Total weighted tardiness	$\sum_{j} \omega_j T_j$
		Total earliness	$\sum_{j\in J} E_j$
		Total lateness	$\sum_{j\in J} L_j$
	Cost related	Cost (penalties)	$\sum_{j\in J} bT_j$
		Earliness cost (penalties)	$\sum_{j\in J} aE_j$
		Maintenance cost or machine deterioration	$\sum_{l\in L}\sum_{j\in J} \pi_l Z_{lj}$ $\sum_{i\in I}\sum_{j\in J} \lambda y_{ij}$
		Machine hiring cost	$\sum_{i\in I} \rho_i \eta_i$
		Total resources consumption cost	$\sum_{i\in I}\sum_{j\in J} \mu_{ij} g_{ij}$
Sustainable objectives		Total energy consumption	$\sum_{i\in I}\sum_{j\in J} \epsilon_{ij} p_{ij}$

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Noise level	$10 * \log\left(\frac{\sum_{i\in I}\sum_{j\in J} 10^{0.1\nu_{ij}} p_{ij} y_{ij}}{\sum_{i\in I}\sum_{j\in J} p_{ij} y_{ij}}\right)$

Table A.1: Categories for objective functions criteria

I : *machines or workers*

J : *jobs*

c_{ij} : *the completion time of job j on machine or worker i*

d_j : *due date of j*

ω_j : *the weight of job j*

p_{ij} : *the processing time of the job j in the machine or worker i*

a *penalty factor for the unit time of the job earliness*

b *penalty factor for the unit time of the job tardiness*

π_l : *cost of maintenance activity l*

ρ_i : *cost of hiring the machine or worker i*

ϵ_{ij} : *the energy consumption of machine i per unit of job j*

rd_j : *the release date of job j*

sut_j : *setup time required for job j*

ν_{ij} : *the instantaneous a-weighted sound level of machine i processing job j*

μ_{ij} *the amount of resource allocated to complete job j on the machine or worker i*

g_{ij} : *cost of resource for job j on the machine or worker i*

id_{ij} : *idle time on machine or worker i between jobs in position j and j+1*

$$U_j : \begin{cases} 1, & \text{if job } j \text{ is is tardy, so it is when } C_j - d_j > 0, \\ 0, & \text{otherwise.} \end{cases}$$

$$V_j : \begin{cases} 1, & \text{if job } j \text{ is early or on time, so it is when } d_j - C_j > 0, \\ 0, & \text{otherwise.} \end{cases}$$

$$Z_{lj} : \begin{cases} 1, & \text{1: if the maintenance activity } l \text{ is carried out after the processing of job } j, \\ 0, & \text{otherwise.} \end{cases}$$

$$x_{ijm} : \begin{cases} 1, & \text{1: if job } j \text{ is assigned to the } m\text{-th sequence position at the machine or worker } i, \\ 0, & \text{otherwise.} \end{cases}$$

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$$\eta_i : \begin{cases} 1, & \text{1: if the machine or resource } i \text{ is available for processing,} \\ 0, & \text{otherwise.} \end{cases}$$

$$y_{ij} : \begin{cases} 1, & \text{1: if job } j \text{ is assigned to the machine or worker } i \text{ ,} \\ 0, & \text{otherwise.} \end{cases}$$

$$CT : \textit{cycle time} , \quad \sum_{i \in I} p_{ij} + \sum_{i \in I} \sum_{m \in M} x_{ijm} \leq CT \quad \textit{for } j = 1, \ldots, J$$

C_j : *the completion time of job j on the last machine or worker*

L_j : *the lateness of job j,* $L_j = C_j - d_j$

F_j : *the flow time of job j,* $F_j = C_j - rd_j$

T_j : *the tardiness of job j,* $T_j = \max(C_j - d_j, 0)$

E_j : *the earliness of job j,* $E_j = \max(d_j - C_j, 0)$

W_j : *the waiting time of job j,* $W_j = \max(C_j - p_j, 0)$

C^i_{max} :*the makespan of on the machine or worker i*

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Appendix B

Informed Consent No. 1

Consentimiento Informado N°1

Como participante en este estudio, usted tiene algunos derechos. El propósito de este formulario es informarle sobre sus derechos y de aceptarlo, obtener su consentimiento para participar. Los derechos del participante se listan a continuación:

1. No debo participar en esta prueba si no deseo.
2. Me han informado cual es el propósito del estudio y cómo participaré en él.
3. Me han indicado que los resultados del estudio beneficiarán a los trabajadores del proceso de picking de la compañía.
4. Un miembro del equipo investigador responderá a cualquier pregunta con respecto al procedimiento a seguir.
5. Soy libre de retirarme del estudio en cualquier momento al no sentirme cómodo
6. Tengo el derecho a ver mis datos y retirarlos del estudio si siento que debo hacerlo.
7. Los datos recolectados son de carácter confidencial. A estos datos únicamente tendrán acceso los investigadores.
8. Si así lo quisiera, tengo el derecho a ser informado de los resultados.
9. Si llegase a necesitar atención médica durante la realización de las pruebas de este estudio, el mecanismo por el cual recurriré a la atención médica necesaria será por medio de la EPS a la cual me encuentro afiliado.

Al firmar, indicó que he leído mis derechos en el marco de este estudio, he visto el video con la explicación de la prueba y he dado mi consentimiento para participar. La inclusión de su firma a continuación permitirá la inclusión de sus datos en este estudio.

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Fecha:

Nombre y apellidos del participante:

Edad (años):

Documento de identidad:

Firma del participante:

Informe del Investigador: Declaro que he proporcionado una explicación del propósito del estudio al participante.

Firma del Investigador principal:

Firma del Investigador auxiliar:

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Appendix C

Informed Consent No. 2

Consentimiento Informado N°2

Como participante en este estudio, usted tiene algunos derechos. El propósito de este formulario es informarle sobre sus derechos y de aceptarlo, obtener su consentimiento para participar. Los derechos del participante se listan a continuación:

1. No debo participar en esta prueba si no deseo.
2. Me han informado cual es el propósito del estudio y cómo participaré en él.
3. Me han indicado que los resultados del estudio beneficiarán a los trabajadores del proceso de picking de la compañía.
4. Un miembro del equipo investigador responderá a cualquier pregunta con respecto al procedimiento a seguir.
5. Soy libre de retirarme del estudio en cualquier momento al no sentirme cómodo
6. Tengo el derecho a ver mis datos y retirarlos del estudio si siento que debo hacerlo.
7. Los datos recolectados son de carácter confidencial. A estos datos únicamente tendrán acceso los investigadores.
8. Si así lo quisiera, tengo el derecho a ser informado de los resultados.
9. Si llegase a necesitar atención médica durante la realización de las pruebas de este estudio, el mecanismo por el cual recurriré a la atención médica necesaria será por medio de la EPS a la cual me encuentro afiliado.

El participante deberá tener en cuenta las siguientes consideraciones con el uso de los equipos electrónicos que serán usados para medir la actividad muscular y posturas:

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- Se le colocarán electrodos superficiales en los brazos, espalda y hombros, un dispositivo electrónico que permite adquirir señal en un computador personal. De igual manera se colocarán sensores de movimiento ajustados con correas a las piernas, brazos y pecho.
- En casos específicos es necesario realizar la depilación de las áreas de la piel en las que se ubicarán los electrodos.
- Los equipos que se utilizan para adquirir las señales son seguros eléctricamente.
- No se hará uso de elementos que sean peligrosos o atenten contra la salud de los participantes.
- Los datos adquiridos en las pruebas se almacenarán de forma digital, individual y confidencialmente.
- Para evitar el ruido en la señal, se debe dejar guardado el teléfono celular durante el tiempo que tome la prueba.

Esperamos que su participación en la presente investigación sea una experiencia agradable e interesante. Estamos muy agradecidos participación. En caso de tener alguna inquietud sobre el estudio, datos recolectados y/o sus derechos, no dude en realizarla al equipo investigador.

Fecha:

Nombre y apellidos del participante:

Documento de identidad:

Firma del participante:

Informe del Investigador: Declaro que he proporcionado una explicación del propósito del estudio al participante.

Firma del Investigador:

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Appendix D

Résumé Étendu en Français

La planification est un processus décisionnel qui joue un rôle important dans les environnements de fabrication et de services. Il permet d'allouer des ressources limitées à des activités tout en optimisant un ou plusieurs critères (Leung, 2004; Pinedo, 2008). Les études sur la théorie de l'ordonnancement remontent aux années 1950. Progressivement, l'une des principales hypothèses concernant les problèmes de planification a intégré les délais de traitement des tâches fixes, ce qui impliquait que les ressources humaines participant au système n'induisent pas de variabilité. De plus, lorsque l'on considère les ressources humaines, des simplifications sont incorporées. Par exemple, les opérateurs ne sont pas considérés comme des ressources majeures, mais comme des ressources (Lodree *et al.*, 2009) déterministes, prévisibles et même sans émotion.

Dans les pays en développement, les travailleurs constituent une ressource essentielle dans les systèmes de fabrication et les chaînes d'assemblage, où les systèmes de production sont en grande partie manuels et où les usines sont fréquemment considérées comme une source d'emploi (Baudin, 2020). Même dans les pays développés, de nombreuses tâches manuelles subsistent dans des secteurs comme le luxe. Étant donné que les technologies d'automatisation industrielle ont une flexibilité limitée (Kadir *et al.*, 2019), les tâches complexes nécessitent toujours des compétences humaines typiques (par exemple la précision, l'intelligence, l'analyse et la logique) (Sánchez-Herrera *et al.*, 2019) et sont impliquées implicitement ou explicitement dans les systèmes de production depuis leur apparition (Dessouky *et al.*, 1995). Par conséquent, les problèmes de planification se prêtent à une analyse dans cette perspective, dans la mesure où les systèmes de production étudiés dans ce domaine mettent intrinsèquement en vedette des travailleurs dans les scénarios industriels actuels.

Les dirigeants industriels ont été invités à développer des systèmes de production davantage centrés sur l'humain dans le cadre de la cinquième révolution industrielle (Industrie 5.0) (Katiraee *et al.*, 2022). Ce changement de paradigme nécessite la proposition de stratégies garantissant une industrie durable, centrée sur l'humain et résiliente (European Commission, 2022). Par conséquent, les politiques gouvernementales deviennent rigoureuses pour concilier le système productif et les relations entre travailleurs, face au défi de garantir que la technologie et les travailleurs œuvrent de concert dans un

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environnement qui améliore et soutient le travail à plein temps, ce qui se traduit par de meilleures performances du système et un bien-être accru des travailleurs.

Depuis des années, la séparation entre les facteurs humains et la gestion des opérations est claire, comme le présente Neumann and Dul (2010), qui, dans sa revue, indique que les publications sur le bien-être humain paraissent rarement dans des revues d'affaires ou de gestion, même si l'exécution d'une tâche peut affecter à la fois les systèmes et les ressources humains. Il est donc nécessaire d'aborder les problèmes opérationnels de manière multidisciplinaire pour faciliter la conception des systèmes et répondre aux besoins actuels.

Les ressources humaines sont généralement plus complexes, avec des comportements moins prévisibles, que les ressources inanimées associées aux modèles de planification traditionnels (Lodree *et al.*, 2009) en raison de leur nature, de leurs capacités, de leurs limites et de l'interaction sociotechnique impliquant les humains avec d'autres ressources du système (Neumann and Dul, 2010). Dans cette interaction, les éléments à considérer incluent la cause des charges physiques, cognitives ou psychologiques générées par des facteurs environnementaux (par exemple le bruit et la température), les phénomènes de vieillissement ou d'oubli, les facteurs ergonomiques (par exemple la posture et le travail répétitif) et l'effort mental ; ils peuvent déclencher de la fatigue, une démotivation et du stress. Tout cela peut entraîner des problèmes tels qu'une perte de productivité, une mauvaise qualité des produits ou des services, une mauvaise satisfaction personnelle et des troubles musculosquelettiques (Hsie *et al.*, 2009). Néanmoins, des processus tels que l'apprentissage et la récupération peuvent améliorer les niveaux de productivité.

La prise en compte des caractéristiques humaines telle qu'elle est évoquée dans la littérature entraîne des problèmes d'ordonnancement avec des délais de traitement des travaux variables. Moray *et al.* (1991) a présenté l'une des premières contributions incluant les ressources humaines dans les problèmes d'ordonnancement, intégrant le comportement et la charge de travail lorsque les opérateurs étaient confrontés à plusieurs tâches. Dessouky *et al.* (1995) a conclu que certaines caractéristiques et attitudes comportementales humaines peuvent affecter la performance au travail, affectant ainsi le temps de traitement du travail. De plus, Lodree and Norman (2006) a suggéré que l'intégration des facteurs humains dans les approches de planification pourrait donner lieu à des problèmes de planification travail-repos, de problèmes de rotation des tâches, des problèmes de personnel ou des problèmes de séquencement des tâches.

Pinedo (2008) avance que la prise en compte des ressources humaines dans les problèmes de planification influence les temps de traitement des tâches et les performances du système en général, car des effets d'apprentissage et/ou de détérioration sont les principaux phénomènes qui affectent les tâches impliquant des opérations manuelles. En effet, certaines caractéristiques se situent dans la catégorie des effets d'apprentissage qui diminuent les temps de traitement (par exemple le processus d'apprentissage en lui-même, la motivation et la récupération). D'autres sont des caractéristiques humaines de l'effet de détérioration, et augmentent le temps de traitement, comme l'oubli, le vieillissement, la fatigue physique, la fatigue cognitive et le stress (Ostermeier, 2020b).

Biskup (2008) distingue les apprentissages induit et autonome. L'apprentissage in-

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duit fait référence à la possibilité pour la direction d'investir dans les connaissances des employés grâce à une formation supplémentaire ou à une modification de l'environnement de production. L'apprentissage autonome (ou apprentissage par la pratique) ne peut pas être influencé par l'entreprise, il s'obtient par la répétition de tâches similaires, la familiarisation et la routine. Il est souvent associé à des activités monotones et répétitives.

Au cours de ces activités, les travailleurs doivent adopter des postures inconfortables et des mouvements répétitifs avec un niveau d'effort élevé, déclenchant une fatigue liée au travail (Finco *et al.*, 2020). La fatigue est une condition multidimensionnelle (Grandjean, 1979) qui peut être mentale (c'est-à-dire cognitive) et physique. Les systèmes intensifs en main d'œuvre s'intéressent à la fatigue physique – notamment musculaire – liée aux troubles musculosquelettiques induits par le travail (TMS), l'une des principales causes de perte de productivité dans ces industries (Finco *et al.*, 2020). Pour ce qui concerne la France, le coût annuel des troubles musculosquelettiques pour les entreprises du secteur de l'agroalimentaire s'élève à plus de 77 millions d'euros (Ameli, 2023). Par conséquent, contrôler les risques, le niveau de fatigue et les TMS est nécessaire pour garantir le bien-être des travailleurs, la qualité des produits et l'efficacité (Finco *et al.*, 2020; Otto and Scholl, 2011).

Ces deux phénomènes sont couramment observés dans les systèmes à forte intensité manuelle tels que l'industrie du textile et de la chaussure, ainsi que dans les chaînes de préparation ou d'assemblage de tous les secteurs. Ces systèmes impliquent des opérations séquentielles, ressemblant à des systèmes de fabrication comme flowshop, au flowshop hybride, (Botta, 1996; Ozsoydan and Sağir, 2021; Rudek, 2011). Ces industries sont connues pour leur forte demande de tâches répétitives et monotones.

Pour traiter les problèmes de planification qui intègrent des caractéristiques humaines, Lodree and Norman (2006) propose un cadre et identifie les principaux composants qui devraient être inclus *i) les modèles de temps de traitement des tâches* permettent de représenter les effets de l'apprentissage humain, de la fatigue, du stress, etc., *ii) définition des pauses* également appelées activités modificatrices de rythme, nécessaires à la récupération pendant les quarts de travail, *iii) mesures de performance humaine* liées à l'ingénierie des facteurs humains telles que la réduction des erreurs ou l'amélioration de la productivité, de la sécurité et du confort. Les mesures de performance, telles que la minimisation de la charge physiologique cumulée, la fréquence cardiaque maximale et la pression artérielle maximale, sont également pertinentes.

Cette thèse a été menée sur la base d'un tel cadre, considérant que la résolution de ce problème nécessite des décisions à différents niveaux de l'entreprise. En utilisant les contributions apportées au problème de chaîne d'assemblage de Finco *et al.* (2021) et de Dolgui *et al.* (2022) et en faisant un parallèle pour le problème d'ordonnancement, nous pouvons catégoriser les décisions. L'obtention du planning des travaux fait référence aux décisions opérationnelles prises à court terme (par exemple mensuellement, hebdomadairement ou quotidiennement). Alors que la conception des processus et du lieu de travail, le dimensionnement de la main-d'œuvre (Dolgui *et al.*, 2018) et la définition des politiques de pause et de reprise se situent au niveau tactique.

Les questions de recherche proposées pour cette thèse sont les suivantes:

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- ***RQ1***: Quel est l'état actuel de la littérature sur les problèmes d'ordonnancement avec des effets d'apprentissage et de détérioration en ce qui concerne les caractéristiques du problème, les algorithmes d'optimisation et les techniques utilisées pour les résoudre ?
- ***RQ2***: Comment le problème d'ordonnancement flowshop avec effet d'apprentissage peut-il être modélisé et quels algorithmes sont adaptés pour le résoudre ?
- ***RQ3***: Comment la fatigue physique et la récupération peuvent-elles être modélisées et intégrées dans le problème d'ordonnancement flowshop avec des effets d'apprentissage ?
- ***RQ4***: Comment trouver un équilibre entre les objectifs économiques et sociaux respectivement dans le problème en question ?

La Figure D.1 présente la structure de la thèse, montrant comment les questions de recherche sont liées aux chapitres.

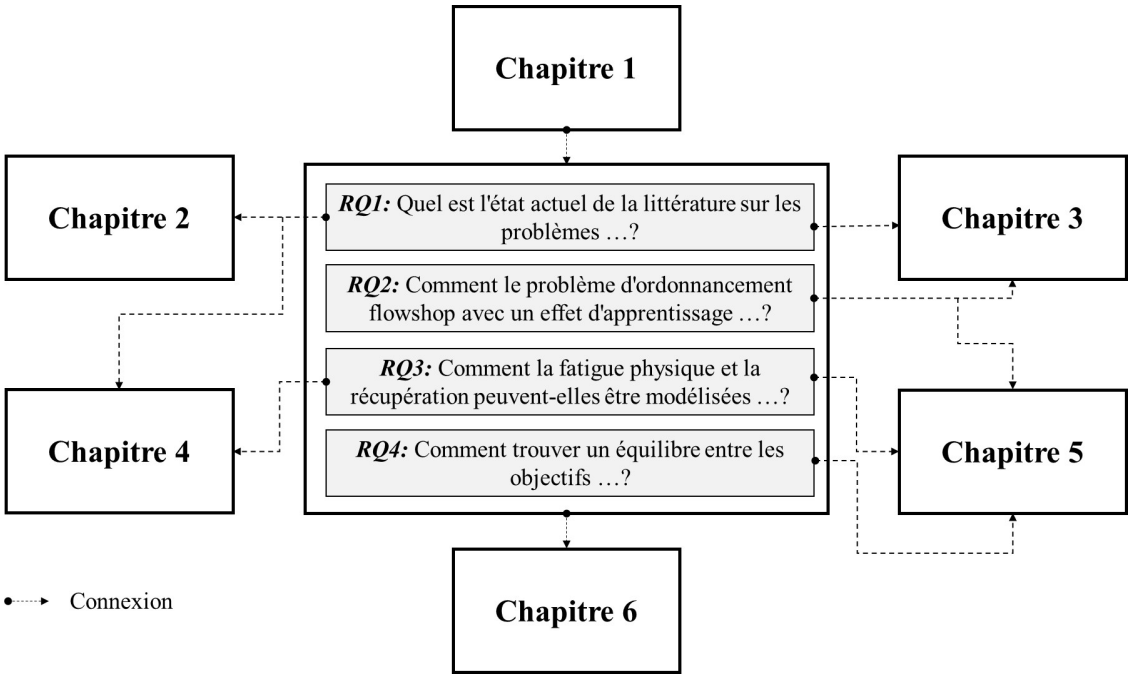

Figure D.1: Structure de la thèse

Vous trouverez ci-dessous une description des chapitres contributifs de cette thèse et de ses principaux résultats.

Le **deuxième chapitre** dresse un panorama des problèmes d'ordonnancement avec effets d'apprentissage et de détérioration. Ces effets peuvent diminuer ou augmenter le temps de traitement réel lorsque les travailleurs exécutent une tâche. Afin de parvenir à une compréhension globale de ce domaine, nous passons en revue les contributions pertinentes abordant le problème de planification avec les effets d'apprentissage et de détérioration. Pour commencer, nous présentons la méthodologie d'analyse de la

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littérature suivie. Ensuite, nous développons une analyse bibliométrique. Puis, nous menons un mode d'analyse approfondie fondé sur des approches de modélisation des effets d'apprentissage et de détérioration, des fonctions objectives et des méthodes de résolution utilisées dans la littérature. Enfin, nous identifions certaines opportunités de recherches futures.

Parmi les résultats importants, nous avons identifié que de nombreux efforts ont été consacrés à l'analyse de la complexité du problème et au développement de techniques efficaces fondées sur les heuristiques et les métaheuristiques. En ce qui concerne les fonctions objectives, la plupart des études sont liées à un seul critère d'optimisation économique. Par ailleurs, l'évolution des systèmes de production constitue un enjeu pour l'intégration active du facteur humain dans les problématiques abordées sous l'angle de la recherche opérationnelle. Cette intégration est essentielle pour atteindre un équilibre entre les objectifs économiques et sociaux. Comme l'indique Tropschuh *et al.* (2023), l'intégration des caractéristiques humaines dans les problèmes de planification présente cinq défis, résumés comme suit : *i)* approches interdisciplinaires rares, *ii)* compréhension de l'influence de la santé et du bien-être des travailleurs sur la productivité, *iii)* simplification des caractéristiques des travailleurs, *iv)* difficultés à évaluer les aspects physiologiques et mentaux, et *v)* manque de vision pratique. Avec cette thèse, nous comblons une lacune remarquable dans la littérature existante. Plus précisément, il n'existe aucune étude antérieure fournissant à la fois un cadre théorique et des applications pratiques pour les problèmes de planification dans les systèmes à forte intensité manuelle, prenant en compte des facteurs tels que l'apprentissage et l'effet de détérioration, en mettant l'accent sur les effets de la fatigue.

Dans le **troisième chapitre**, le problème de planification du flowshop (FSSP) avec un effet d'apprentissage minimisant le makespan est modélisé à l'aide de programmation linéaire à nombres entiers mixtes (MILP) et de programmation non linéaire à nombres entiers mixtes (MINLP). Nous présentons quatre approches permettant de modéliser l'effet d'apprentissage, bien connues dans la littérature et identifiées lors du deuxième chapitre. Nous fournissons des modèles mathématiques pour chacun des cas et la solution optimale au problème des petites instances. Étant donné que le FSSP avec apprentissage devient NP-difficile même avec deux ressources, nous comparons les performances de l'algorithme Nawaz-Enscore-Ham et la règle de Johnson pour le FSSP à deux ressources avec apprentissage. Pour les grandes instances et en considérant plus de deux ressources, nous proposons un algorithme de recuit simulé et comparons ses performances avec deux opérateurs de recherche locaux. Les expérimentations réalisées dans ce chapitre utilisent des jeux de données de référence issus de la littérature.

L'ordonnancement des travaux est une décision opérationnelle cruciale pour les entreprises, généralement prise au début de la création de chaque équipe ou d'une journée de travail. Les résultats de ce chapitre donnent un aperçu des outils potentiels pour aborder et résoudre le FSSP dans des systèmes à forte intensité manuelle, où l'effet d'apprentissage exerce un impact sur les temps de traitement des tâches, et où diverses approches de modélisation peuvent être utilisées. L'ordonnancement obtenu des tâches sera utilisé au prochain chapitre qui discutera de l'intégration de l'effet de la fatigue physique et de la définition des politiques de pause. Certains des algorithmes proposés

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ici seront utilisés dans le cinquième chapitre du développement de l'étude de cas.

L'objectif du **quatrième chapitre** est d'intégrer la fatigue dans le problème de planification des flowshop. Nous proposons un modèle de fatigue physique et de récupération fondé sur ce qui a déjà été rapporté dans la littérature. Nous introduisons un système multi-agents afin d'analyser l'intégration de la fatigue physique des travailleurs dans le FSSP. Nous évaluons deux politiques de pauses (caractérisées par leur nombre , leur positionnement sur l'équipe et leur durée) et analysons leur impact sur les performances humaines et les performances du système. Des jeux de données de référence sont utilisés dans les expérimentations exploratoires.

Notre contribution dans ce chapitre est double : développer un modèle qui intègre la fatigue dans un système de flowshop et évaluer l'impact des politiques de pauses sur la « dose totale de fatigue » et la durée de fabrication totale (makespan). En nous appuyant sur la littérature, nous proposons une méthode pour modéliser la fatigue physique. Nous présentons un modèle de simulation multi-agents permettant d'analyser l'intégration de la fatigue physique des travailleurs dans le FSSP. Notre approche représente un outil d'aide à la décision qui soutient la conception ou la refonte d'un système manuel intensif, aidant à la décision tactique sur la manière d'établir les pauses pendant les quarts de travail.

Une étude de cas dans une ligne de préparation manuelle d'une entreprise de distribution d'aliments secs valide le cadre proposé. Le **cinquième chapitre** présente une approche méthodologique du problème de planification des flowshops avec effet d'apprentissage qui inclut la fatigue physique, sur une ligne de prélèvement manuelle, où l'étude de cas est menée. Nous proposons une approche bi-objectif pour minimiser simultanément la durée totale de traitement et la dose totale de fatigue, les données du cas réel sont utilisées pour valider le cadre.

Les résultats de l'étude de cas sont en faveur des politiques à deux à trois pauses, et leur durée et leur positionnement dépendent des objectifs mis en avant par l'organisation. Dans le cas étudié, les solutions comportant une seule pause (ce qui est actuellement pratiqué par l'entreprise) sont moins attractives que celles proposant deux ou trois pauses. Cela est conforme à l'idée selon laquelle des pauses courtes mais plus fréquentes sont plus efficaces pour atténuer la fatigue musculaire (Lyubykh *et al.*, 2022; Rohmert, 1973).

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Dans cette thèse, nous étudions le problème de planification des flowshops avec les effets d'apprentissge et de fatigue, en proposant à la fois des approches théoriques et pratiques (étude d'un cas réel). En 2022, la Commission Européenne a formellement défini l'arrivée de la cinquième révolution industrielle et, avec elle, un changement de paradigme du contexte industriel qui a eu un impact direct sur l'approche de certaines problématiques au sein du monde universitaire. La communauté académique s'intéresse de plus en plus à l'idée d'obtenir un autre point de vue pour les problèmes classiques, tels que les problèmes d'ordonnancement, ce qui se traduit, entre autres, par la considération et la modélisation de l'humain comme une ressource flexible et complexe.

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Une approche du phénomène d'ordonnancement avec d'apprentissage autonome a été développée, établie principalement sur le modèle log-linéaire proposé par Wright en 1936. Sur cette base, de nombreuses approches ont été développées, classées principalement en effets d'apprentissage fondés sur la position ou sur la somme des temps opératoires L'effet de la détérioration a été étudié moins fréquemment, mais dans la plupart des cas, la détérioration des tâches a été abordée lorsqu'elle est liée au temps. Certains auteurs ont commencé à aborder l'effet de la détérioration des ressources en proposant des approches classées principalement selon que l'effet de détérioration est fondé sur la position, ou qu'il résulte d'une détérioration cumulative. Peu de travaux ont appliqué le concept de détérioration, notamment à l'humain, chez qui la détérioration pourrait être perçue comme de la fatigue et de l'oubli, par exemple. La nature NP-dure de ces modèles conduit à l'utilisation de méthodologies telles que les heuristiques et les métaheuristiques, principalement pour résoudre les problèmes de taille industrielle avec un temps de calcul raisonnable.

Les configurations de type flowshop sont courantes dans les systèmes de production manuelle intensifs, et l'inclusion de l'effet d'apprentissage même pour deux ressources en fait un problème complexe. Dans cette thèse, quatre modèles d'apprentissage (appelés cas) ont été identifiés pour évaluer le FSSP en minimisant le makespan. Ces problèmes ont été modélisés mathématiquement et, pour les petites instances, la solution optimale a été obtenue à l'aide des solveurs GLPK et Bonmin de Pyomo en Python. Pour les instances de grande taille, des ensembles de données de référence ont été tirés de la littérature et divers algorithmes ont été utilisés, par exemple la règle de Johnson pour le cas de deux ressources ou NEH (Nawaz-Enscore-Ham algorithm). Pour résoudre le problème général, deux alternatives de recuit simulé (SA, pour Simulated Annealing) ont été proposées, employant deux opérateurs de recherche local, API (Adjacent Pairwise Interchange) et NAPI (Non-Adjacent Pairwise Interchange), à partir de la solution initiale de l'algorithme de NEH. Le SA_{API} a montré des performances exceptionnelles grâce à des tests statistiques. L'analyse de sensibilité nous a permis d'identifier des valeurs de paramètres qui améliorent les performances de l'algorithme.

La fatigue physique chez l'homme est fortement liée à la survenue de TMS, ce qui représente un budget important pour les entreprises. La fatigue musculaire causée par des tâches répétitives et monotones conduit généralement à un TMS à long terme. Cette thèse porte sur l'étude de la fatigue musculaire chez les travailleurs dans un système de type flowshop. Une simulation fondée sur les agents a été créée pour valider l'intégration de la fatigue dans un FSSP, en prenant comme point de départ les modèles référencés dans la littérature. Pour atténuer la fatigue la définition des politiques de pause (positionnement et durée) est cruciale. Par conséquent, des expériences exploratoires ont été menées à l'aide de jeux de données de référence sur une petite instance du problème afin de tester l'effet de deux politiques sur les niveaux de fatigue. Il a été constaté que l'atténuation de la fatigue était renforcée par des politiques impliquant des pauses courtes mais plus fréquentes.

L'approche théorique du problème a été appliquée à un cas réel.. Pour valider une approche des conditions réelles, une collecte de données sur site des taux d'apprentissage des travailleurs a été réalisée. En effectuant des tests expérimentaux dans le laboratoire

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de formation du partenaire industriel, nous avons ajusté les modèles d'apprentissage. Grâce à l'EMG (Electromyography), des données sur l'activité musculaire actuelle des travailleurs ont été collectées en conditions réelles, ce qui a permis de calculer paramètres du taux de fatigue. Une approche bi-objectif a été proposée pour minimiser simultanément le temps de fabrication et la dose totale de fatigue. Le FSSP avec effet d'apprentissage a été résolu en déterminant les permutations de tâches ; ensuite, ces informations ont été envoyées à un algorithme génétique Fast Pareto qui propose différentes politiques de pause comme solution. Les fonctions objectives ont été calculées à l'aide du modèle de simulation multi-agents. En examinant les solutions non-dominées, nous avons pu confirmer que des pauses courtes et fréquentes sont bien conseillées, comme démontré précédemment dans les expériences exploratoires. Des alternatives pour le positionnement et la durée des pauses sont possibles, en fonction des priorités de l'entreprise (telles que minimiser la durée de fabrication, la dose de fatigue totale, ou les deux).

Ce travail propose des contributions, théoriques et pratiques au FSSP avec des effets d'apprentissage et de fatigue. Ces contributions adressent deux niveaux du processus décisionnel de l'entreprise face à ce type de problématique. Tout d'abord, au niveau opérationnel, se pose le problème d'ordonnancement du flowshop avec effet d'apprentissage, assurant ainsi la permutation des tâches pour chacun des horizons de planification (comme une équipe, une journée, etc.). Ensuite, au niveau tactique, il existe un problème d'intégration de la fatigue qui conduit à définir des politiques de pause. Enfin, comme outil d'aide à la décision, une approche multi-objectifs est proposée qui permet d'évaluer simultanément deux dimensions économique et social.

De nombreuses perspectives intéressantes ont été identifiées grâce à ces travaux, qui pourraient élargir à la fois la portée et la profondeur de cette étude. Celles-ci sont décrites ci-dessous:

- Les quatre modèles d'apprentissage les plus fréquemment rapportés dans la littérature ont été choisis. Les modèles incluant des caractéristiques individuelles susceptibles d'être décisives dans le processus d'apprentissage, telles que l'expérience et le niveau de formation, n'ont pas été pris en compte. La littérature suggère que le temps de traitement des tâches pourrait être stochastique, une situation qui permettrait de résoudre ce problème même en cas d'incertitude. On pourrait même penser que le processus d'apprentissage demeure dynamique et qu'un modèle d'apprentissage adapté à un travailleur pourrait évoluer au fil du temps.

- Les modèles d'apprentissage avec troncature semblent bien adaptés à la réalité, mais leur utilisation dans les études de cas n'a pas été étendue. Le calcul du paramètre de troncature nécessite un large échantillon de données et des estimations ajustées des temps de traitement de base. Il n'y a pas suffisamment de littérature disponible sur les méthodes d'estimation de paramètres tels que β et M dans le modèle de DeJong.

- Les machines parallèles, les ateliers de travail hybrides et les configurations de flowshops hybrides sont de plus en plus courants dans l'industrie, en particulier dans les industries de luxe à forte intensité manuelle. Il est donc pertinent d'aborder

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ce type de problème sur ces configurations. De plus, de nouvelles fonctions objectives pourraient prendre en compte le niveau des erreurs humaines provoquées par la fatigue et l'apprentissage, par exemple.

- Identifier le temps nécessaire à l'algorithme de NEH pour trouver une première solution dans des instances réelles (avec plus de 1200 taches et quatorze travailleurs) nous a conduit à proposer une solution pour le SA_{API} fondée sur une partition de NEH. L'efficacité de l'algorithme peut être améliorée, et des stratégies peuvent être utilisées pour obtenir des solutions initiales de haute qualité avec un temps de calcul réduit.

- Le modèle exponentiel d'accumulation de fatigue constitue la base de notre contribution. Cependant, un manque de profondeur dans l'étude de ce phénomène a été constaté. Comme la littérature indique que peu d'études ont tenté d'examiner le phénomène dans une perspective interdisciplinaire, le développement d'outils de conception capables de calculer des paramètres tels que u et delta est crucial. Même s'il est vrai que cela est conditionné par des caractéristiques individuelles, il est important de travailler dans ce domaine pour faire progresser la conception et l'ingénierie de systèmes productifs plus adaptés aux capacités et aux limites des travailleurs.

- Dans les activités de picking, la fatigue physique peut aussi être conditionnée par le mouvement. Par conséquent, l'intégration des méthodes utilisées ici concernant la fatigue musculaire avec d'autres, comme la consommation d'énergie ou la fréquence cardiaque, serait valable pour obtenir un indicateur de fatigue physique globale. La fatigue mentale joue également un rôle important dans ce type de travail qui demande des niveaux élevés de concentration et de mémoire.

- La collecte de données dans cette thèse a été effectuée pendant la journée et nous avons supposé que la performance des travailleurs ne changeait pas en fonction de leurs heures de travail. Bien que l'on sache que des processus physiologiques tels que la fatigue peuvent s'intensifier la nuit, la comparaison entre les quarts de jour et de nuit reste une question de recherche ouverte. Il est également important de s'attaquer à l'effet d'oubli, qui peut survenir lors des pauses et de la baisse de productivité. De même, à terme, il deviendra pertinent d'évaluer les phénomènes de vieillissement compte tenu des conditions réelles de la population active actuelle.

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INVITATION – SOUTENANCE PUBLIC

THESE DE L'INSA LYON, MEMBRE DE L'UNIVERSITE DE LYON

NOM : PAREDES ASTUDILLO Prénoms : Yenny Alexandra DATE de SOUTENANCE : 11/01/2024

LIEU : Bâtiment Jules VERNE – Amphi 132, INSA Lyon, NNT : 2024ISAL0003
HEURE : 14h00 – 17h00

TITRE : Flowshop scheduling problem including learning and fatigue effects: theoretical contributions and case study

NATURE : Doctorat

Ecole doctorale : Infomaths ED 512

Spécialité : Génie industriel

RESUME :

Malgré l'essor de l'automatisation, les systèmes de production à forte main d'œuvre sont toujours utilisés en raison de la nécessité de flexibilité et de précision dans l'accomplissement de certaines tâches. Dans de tels contextes, on s'intéresse à l'impact de l'apprentissage et de la fatigue sur la productivité des tâches manuelles sur un problème d'ordonnancement de flowshop (FSSP). Dans un premier temps, une revue de la littérature a été réalisée sur le problème d'ordonnancement en considérant les effets d'apprentissage et de détérioration. Une approche théorique a été utilisée pour aborder le problème du FSSP avec effets d'apprentissage. Des modèles mathématiques minimisant la durée totale des travaux (makespan) ont été présentés. Des méthodes exactes et des heuristiques ont été proposées pour résoudre le problème pour des instances de petite et grande tailles. La fatigue étant un type de détérioration, un modèle multi-agents a été proposé pour valider l'intégration de la fatigue musculaire dans la FSSP en minimisant la dose accumulée de fatigue. Enfin, le cadre a été validé sur une étude de cas réalisée sur une ligne de préparation de commandes manuelle. La modélisation des effets d'apprentissage et de fatigue ainsi que le calcul des paramètres du modèle générés à partir de données réelles ont été discutés. Une approche bi-objectif a été proposée pour minimiser simultanément la durée totale des travaux et la dose de fatigue accumulé. Des politiques de pause sont recommandées en fonction des besoins de l'entreprise et de l'objectif à prioriser. L'objectif de ce travail est d'inspirer les travaux futurs qui s'intéressent à la résolution des problèmes de recherche opérationnelle avec une intégration responsable des facteurs humains.

MOTS-CLÉS : Ordonnancement; Flowshop; Effet d'apprentissage; Effet de fatigue

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