Integrating waste minimization concerns in operations scheduling

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Réduire les déchets industriels : une approche par l'ordonnancement des opérations

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Réduire les déchets industriels : une approche par l'ordonnancement des opérations

Résumé:

Confronté à des enjeux économiques et environnementaux croissants, le monde industriel doit s'adapter afin de répondre aux problématiques actuelles. La production industrielle est responsable de 83% de la production mondiale de déchets solides et de 40% de la consommation d'énergie, et l'ordonnancement s'avère être un levier prometteur pour agir sur ces enjeux. L'état de l'art réalisé montre que les travaux de recherche traitent en majorité des enjeux énergétiques. Cette thèse propose de s'intéresser à la problématique suivante :

Comment intégrer la réduction des déchets dans l'ordonnancement des opérations ?

L'état de l'art sur le sujet faisant émerger une terminologie disparate, une classification est proposée pour unifier ce champ de recherche hétérogène. Pour répondre à la problématique, nous proposons une méthodologie combinant le suivi des flux de matière avec les paramètres d'ordonnancement pour permettre l'identification des opportunités de réduction de la génération de déchets par l'ordonnancement, et la caractérisation du problème d'ordonnancement correspondant. Une étude de cas valide la méthodologie et l'intérêt des résultats obtenus. En se basant sur ces résultats, un problème d'ordonnancement bi-objectif machine-unique avec réentrance dans un contexte de fabrication à la commande est modélisé en programmation linéaire. Deux méthodes de résolution – exacte et métaheuristique – sont comparées et démontrent le potentiel de l'ordonnancement pour la réduction de la génération de déchets industriels. Cette résolution fournit aux preneurs de décision des solutions alternatives adaptées, et permet une réduction des déchets significative en contrepartie d'une augmentation de stock limitée. Ces travaux se concentrant sur les déchets ouvrent la voie à d'autres enjeux environnementaux comme l'intégration des enjeux énergétiques et d'émissions atmosphériques, et à la considération du critère social afin d'englober les trois piliers du développement durable.

Mots-Clés: Ordonnancement, Prévention des déchets, Programmation Linéaire, Analyse environnementale, Optimisation biojectif, Suivi de flux, Algorithme Génétique

Integrating waste minimization concerns in operations scheduling

Abstract:

Faced with growing environmental and economic concerns, the industrial world needs to adapt in order to tackle these issues. Industrial production is responsible for 83% of the global solid waste production and 40% of worldwide energy consumption. Operations scheduling appears to be a promising tool to address both the environmental and economic aspects of this problem. A literature review shows that numerous studies have been focusing on reducing energy consumption. This dissertation focuses on a relatively nascent field, namely the topic of waste generation minimization through operations scheduling. The motivating research question can be formulated as:

How to integrate waste minimization into operations scheduling?

A state-of-the-art on the subject shows a heterogeneous field with a disparate terminology, and a classification scheme is proposed to help unify research on this topic. To answer the research question, a methodology combining flow assessment tools and scheduling parameters is proposed, which enables the identification of waste-minimizing scheduling opportunities in a production system and the characterization of the corresponding scheduling problem. A case study is carried out and validates the applicability of this methodology and the interest of the results it provides. Based on those results, a single-machine waste-minimizing scheduling problem with reentrance in a make-to-order context is modeled using linear programming. Two solving approaches – one exact and one metaheuristic – are compared, and highlight the potential of operations scheduling to reduce industrial waste. Alternative solutions provide relevant trade-offs to decision-makers, offering significant waste reduction in return for a limited increase in inventory. As this methodology focuses on waste, it paves the way for the integration of new environmental aspects such as energy consumption and atmospheric emissions, as well as the social criteria in order to fully encompass the triple bottom line of sustainable development.

Keywords: Scheduling, Waste prevention, Linear Programming, Environmental assessment, Biobjective optimization, Flow assessment, Genetic Algorithm

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"Il suivait son idée. C'était une idée fixe, et il était surpris de ne pas avancer."
Jacques Prévert

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Corentin Le Hesran

TABLE OF CONTENTS

TABLE OF CONTENTS – *Continued*

LIST OF FIGURES

LIST OF TABLES

ACRONYMS

1DCSP 1-Dimensional Cutting Stock Problem
ABC Activity Based Costing
ABEC Activity Based Environmental Costing
B&B Branch and Bound
BAT Best Available Technique
CSP Cutting Stock Problem
EAM Environmental Activity Management
EIPPCB European Integrated Pollution Prevention and Control Bureau
EMA Environmental Management Accounting
EMS Environmental Management System
FU Functional Unit
GA Genetic Algorithm
GHG GreenHouse Gases
HVAC Heating, Ventilation and Air Conditioning
ICSP Integrated Cutting Stock Problem
ILP Integer Linear Programming
INLP Integer Non Linear Programming
ITO Input-Throughput-Output
LCA Life Cycle Assessment
LP Linear Programming
LSP Lot Sizing Problem
MEW Material, Energy and Waste
MFA Material Flow Assessment
MFAM Material Flow Assessment in Manufacturing
MFCA Material Flow Cost Accounting
MFN Material Flow Network
MILFP Mixed Integer Linear Fractional Programming
MILP Mixed Integer Linear Programming
MINLP Mixed Integer Non Linear Programming
MIOT Monetary Input Output Table
MOEA Multi-Objective Evolutionary Algorithms
NSGA Nondominated Sorting Genetic Algorithm
PESA Pareto Envelope based Selection Algorithm

PIOT Physical Input Output Table
PSO Particle Swarm Optimization
RWGA Random Weighted Genetic Algorithms
SA Simulated Annealing
SPEA Strength Pareto-Archived Evolution Strategy
QHSE Quality, Health, Safety and Environment
VOC Volatile Organic Component
VSM Value Stream Mapping
WBGA Weight-Based Genetic Algorithms
WFM Waste Flow Mapping

CHAPTER 1

Context and research question

Contents

Résumé du chapitre 1

Ce chapitre d'introduction présente les principales notions qui seront approfondies dans ce manuscrit, ainsi que la problématique à laquelle ces travaux cherchent à répondre. Partant du constat que le monde de l'industrie est responsable de presque la moitié de la consommation d'énergie mondiale et de la génération d'une large majorité des déchets solides, des solutions doivent être trouvées afin de réduire leur impact environnemental. Les déchets tels que définis par le code de l'environnement français représentent « toute substance ou tout objet, ou plus généralement tout bien meuble, dont le détenteur se défait ou dont il a l'intention ou l'obligation de se défaire ». Cette définition, qui exclut les émissions gazeuses mais comprend les eaux usées, sera celle utilisée durant le reste de ce manuscrit. La prévention de ces déchets est un des objectifs de la production durable, qui a pour but la mise en place de systèmes de production et services à la fois non-polluants, économiquement viables et socialement responsables. Les techniques de production durable peuvent être mises en place à divers niveaux de décision, à savoir les niveaux stratégique (long terme), tactique (moyen terme) et opérationnel (court terme). Les industriels ont longtemps favorisé les niveaux stratégique et tactique, même si le niveau opérationnel peut apporter des solutions efficaces et nécessitant peu d'investissements. L'une de ces solutions concerne l'ordonnancement des opérations, qui consiste à séquencer les différentes tâches à réaliser et les assigner à des ressources disponibles afin d'optimiser un ou plusieurs objectifs. Une étude de la littérature sur le sujet de l'ordonnancement durable révèle que le thème de la consommation énergétique est largement majoritaire, le thème de la réduction des déchets restant sous-représenté. Enfin, il est important de noter que le coût de ces déchets est régulièrement sous-estimé par les entreprises. Ainsi, une meilleure quantification des économies qui pourraient être réalisées en réduisant les déchets permettrait d'inciter les entreprises à mettre en place des mesures de production durable, et notamment à travers l'ordonnancement. Ainsi, la problématique de ces travaux de thèse peut être résumée de la façon suivante:

Comment l'ordonnancement des opérations peut-il réduire la génération de déchets industriels?

Pour répondre à cette question, trois principales contributions sont proposées. La première concerne les caractéristiques des problèmes d'ordonnancement minimisant

les déchets, traitée au Chapitre 2 où une classification est proposée suite à un état de l'art de la littérature sur le sujet. La seconde, présentée au Chapitre 3, traite de l'identification des opportunités de réduction des déchets par l'ordonnancement, et notamment de la détermination des objectifs environnementaux et économiques à minimiser. Pour ce faire, une méthodologie pour l'identification et la modélisation de ces problèmes est proposée et validée grâce à une étude de cas. Enfin, la troisième concerne la résolution de ces problèmes, et notamment la gestion des objectifs à la fois environnementaux et économiques. Dans le Chapitre 4, un problème bi-objectif machine-unique avec tâches couplées dans un contexte de fabrication à la commande est résolu grâce à deux approches, exacte et métaheuristique, et des expérimentations numériques illustrent le potentiel de cet outil. Les résultats de ces trois contributions sont discutés dans le Chapitre 5 et des perspectives de recherches évoquées avant une conclusion.

Context and research question

This chapter introduces key notions and concepts that will be investigated in this manuscript. It firstly presents a broad depiction of the context surrounding this research, then defines the research question. Finally, the three main contributions that will constitute this manuscript are introduced.

1.1 Waste generation in the industrial context

Industrial production (including the building industry) was responsible for around 83% of the world's solid waste production (Song et al., 2015) and 40% of global energy consumption (Biel and Glock, 2016) in 2011. In a context of resource scarcity and global warming, mitigating the environmental impact of manufacturing operations has become crucial to achieve environmental goals set by states as part of international agreements such as the 2016 Paris agreement. All the while, emissions of pollutants and waste have been steadily increasing despite all efforts as increased life standards in developing countries bolster consumption and mass production. Two main concerns are affecting industrial production: energy consumption, responsible for releasing GreenHouse Gases (GHG), and waste generation which creates both GHG and pollutants that need to be dealt with. It creates a complex mix of interwoven relationships between industrial, regulatory and civil society actors tied-up by economic, environmental and social interests. This section explains several notions regarding industrial waste and how they are related to various stakeholders.

1.1.1 Waste and emissions characterization

As different legislations ascribe differing definitions to these terms, it is important to draw clear boundaries regarding what a waste is and how it differs from other types of industrial effluents. The 2008-98-CE directive of the European parliament (European Parliament and Council, 2008) on waste defines waste as "any substance or object which the holder discards or intends or is required to discard". Three specific types of waste are mentioned, namely hazardous waste, bio-waste and oils. These refers to waste presenting dangerous properties (see annex III of European Parliament and Council (2008)), food and vegetal waste, and mineral or synthetic lubrication or industrial oils respectively. Additionally the following items are, among others, excluded from this directive:

- gaseous effluents emitted into the atmosphere;
- radioactive waste.

Wastewaters and waste resulting from extraction activities (quarries, mining...) are also excluded as they are already covered by other European legislation.

The French legislation, through the Environmental Code, Book V, Title IV (Code de l'environnement, 2017), adheres to the very same definition of waste. However, while gaseous emissions are also excluded from its scope, wastewaters are not. It also adds the concept of final waste, which is a waste that cannot be further treated or used in valorization. Hazardous waste includes special industrial waste such as sludges, solvents, asbestos or acids..., special household waste such as batteries or phytosanitary products, and healthcare waste which can present infectious or chemical risks.

For the rest of this study, the categorization of waste and emissions defined in the French environmental code will be the one used. That is to say, the term "waste" encompasses solids and wastewater, while the term "emission" includes gaseous effluent as well as heat, vibrations or noise. This thesis focuses on preventing upstream industrial waste generation (i.e. reducing its quantity or impact) through operations scheduling. Therefore, topics such as sustainable manufacturing processes, end-of-pipe management or waste treatment technologies are not covered. Similarly, municipal waste management, which is the most investigated topic as far as waste and scheduling are concerned (interested readers can refer to Ghiani et al. (2014)), is not studied here.

1.1.2 Waste management strategies

The 2008-98-CE directive and French Environmental Code also describe a waste management hierarchy which lays down a priority order of what constitutes the best overall environmental option in waste legislation and policy. It is based on five tiers of waste management which are described below.

Prevention : Prevention negates all drawbacks of waste generation, saving resources, money and the need for treatment. It can be achieved through organisational means (such as Environmental Management Systems (EMSs)), the use of non-polluting materials or adequate production scheduling.

Preparing for re-use : Re-use refers to the usage for production of what was previously considered a waste. Re-use can be enabled by the design of products which allow for example to cut new shapes out of what was previously scrap. Industrial ecology is also a powerful enabler, as waste generated by some industrial plants can be used in other types of production.

Recycling : Recycling is the transformation of waste, usually scrap materials such as glass, paper or plastic, into its base material which can then be used anew. Product design is especially important for complex pieces which need to be dismantled to be recycled.

Other recovery : Recovery means that waste is used as substitutes to other materials for a specific purpose. This can be e.g. fuel in the case of energy recovery, or the use of construction waste to create banks.

Disposal : Disposal regroups all other waste management techniques that do not include recovery of any kind. Landfills and incineration are the most common techniques of waste disposal.

1.1.3 Waste management cost

While industrial companies are subject to environmental laws and consumer pressure, their base objective remains generating profit. As such, they tend to prioritize economic criteria over environmental ones when it comes to production planning or managerial choices. One aspect of waste generation that tends to be overlooked is that the actual cost of waste in manufacturing is oftentimes substantially higher than calculated by firms (ADEME, 2019). Thus, in addition to providing new technological and managerial improvements to industrialists, accurately calculating waste costs could be an economic incentive for decision-makers to reduce their waste generation. In most organizations, production and product pricing is done based on general accounting, which is destined to stakeholders and financial regulators. This leads to a dilution of information, with certain environmental costs (e.g. waste related costs) being included in broader categories, hence a loss of visibility regarding potential savings (Jasch, 2003). A cost division commonly used in environmental cost accounting methods such as Environmental Management Accounting (EMA) or Material Flow Cost Accounting (MFCA) consists in materials costs (i.e. the cost of the material loss incurred due to waste), systemic costs (i.e. the cost of using machinery, workforce or equipment resulting in waste) and waste management costs (i.e. the cost of waste storage, collection and treatment) (Jasch, 2008). Implementing environmental cost accounting methods provides decision-makers with accurate economic information regarding their generated waste, and potential savings which can offset or even negate the cost of waste prevention measures.

1.1.4 Stakeholders

Several actors are related to waste generation in the industrial sector, either through production, regulation or influence, namely the industrial, regulatory and civil society stakeholders. Their characteristics are detailed in the next paragraphs.

Civil society

The civil society suffers from the environmental impact of this generated waste. It is able to influence the activity of industries though various means. As the main consumer of manufactured products, it is incentivized to buy goods which have a lesser impact on the environment, thus influencing companies' environmental policy. Additionally, it is the actor with the closest proximity with production plants and the waste they generate. Through local representatives, it can have a say on the implantation, extension or operation of a factory. On a broader scale, it can choose to elect representatives (deputies, senators, mayors, president) with different leanings towards environmental issues, thus enabling or preventing the enactment of environmental laws.

Regulators

Regulators are the policy-makers and agencies mandated by the states to ensure that environmental policies are correctly implemented and carried out. They can act at the supranational (European parliament, 2019), national (Ministère de la transition écologique et solidaire, 2019) or regional level (Inspection des Installations Classées, 2019). They decide on emissions limits for the different industrial sectors and companies based on the type of waste and surrounding environment, as well as define the waste management options available. Their decisions are based on scientific studies, both quantitative and qualitative, and what is known as the Best Available Techniques (BATs) (EIPPCB, 2019) to produce less waste and promote better waste treatment processes. Their range of action lies from non-binding proposals to forced cessation of activities in case laws are not respected.

Industrial companies and decision-makers

Industrial companies are responsible for the generation of waste through manufacturing of products. Through their decision-makers, they aim at maximizing profits while also complying with environmental regulations and satisfying consumers expectations and ethical views. To achieve this, they can act at three different levels of decision, namely the strategic, tactical and operational levels, i.e. long-term, mid-term and short-term respectively.

The strategic level includes decisions regarding production capacity investments, marketing plans and new markets penetration as well as product design. Tactical decisions concern management methods (including waste management), yearly and monthly Master Production Schedules, machinery replacement or purchase. Finally, the operational level deals with weekly or daily production schedules, machine maintenance and process optimization. Each of those levels can affect waste generation and/or management in different ways, which will be covered in the next section.

1.2 Sustainable production

Sustainable production is defined as "the creation of goods and services using processes and systems that are non-polluting; conserving of energy and natural resources; economically viable; safe and healthful for workers, communities, and consumers; and socially and creatively rewarding for all working people" (Lowell Center for Sustainable Production, 1998). This research field combines environmental, economics and management sciences as well as operational research and engineering. Since the 2000s, it has been increasingly seen as an answer to many environmental issues affecting industry and defined by Giret et al. (2015) as:

- New regulations on polluting emissions (solid, liquid, gaseous, thermal and acoustic) ;
- Increased energy prices and volatility ;
- The rarefaction of raw materials and natural resources ;
- An increasing demand of customers for ecological products.

Sustainable production has been steadily developing within companies, albeit mostly at the strategic level of decision-making (supply chain, use of recycled materials, ...) (Chofreh and Goni, 2017). It provides the double advantage of improving resource efficiency and reducing the emissions resulting from production. While it requires additional involvement (and potentially investments) from companies, it is socially and environmentally beneficial. Additionally, through a reduction in resource consumption and waste management costs, it can also be economically sound for a company to implement sustainable production techniques. Examples of sustainable production strategies for each level of decision-making are presented in the next sections.

1.2.1 At the strategic level

The strategic level deals with long term decisions such as the implementation of new managerial systems, supply chain organization or investment in new plants. Several actions can be taken at that level to improve a company's environmental performance, such as:

Environmental Management System implementation: EMSs are described in the ISO 14001 (2015) standard as the "part of the management system used to manage environmental aspects, fulfill compliance obligations, and address risks and opportunities". Using the Plan-Do-Check-Act framework, companies are encouraged to better control and reduce their environmental impact in a socially and economically sound manner through continuous improvement. Obtaining EMS certifications such as the ISO 14001 can be an incentive for companies, as it provides better brand image as well as market differentiation.

Green supply chain: by choosing their suppliers or materials according to environmental criteria, companies can improve their environmental impact along the life cycle of their products. Several frameworks have been proposed for Sustainable Supply Chain Management, such as GREENSCOR (LMI Goverment Consulting, 2003). Best practices for sustainable supply chain management are also provided in Chardine-Baumann and Botta-Genoulaz (2014).

Ecodesign practices: these consist in designing products so that their environmental impact during manufacturing, usage or end-of-life is minimized. Such practices can be, e.g., the use of recycled or more sustainable materials, product shaping to avoid material losses during processing or product design to facilitate its dismantling and recycling when discarded (Rossi et al., 2016).

1.2.2 At the tactical level

The tactical level refers to mid-term decisions, typically on a horizon of one year to one month. These involve process optimization, industrial ecology or waste management measures. Some examples of sustainable production techniques at the tactical level are given in Garetti and Taisch (2012); Dursun and Sengul (2006); Haapala et al. (2013), and noticeably:

Using BATs: based on the European Industrial Emission Directive, these represent the best current production techniques affordable for companies and environmentally acceptable (Laforest, 2014). The European Integrated Pollution Prevention and Control Bureau (EIPPCB) released a list of technical documents called BREFs (EIPPCB, 2019) used as a reference guide at the European level and describing each of these techniques.

Industrial ecology: by collaborating with neighbouring companies and local actors and mutualizing their resources such as waste treatment facilities, industrialists can improve their environmental performance. Examples of synergistic interaction between producers include e.g. the transfer of waste from one company to another for a direct reuse or recycling, wasted heat or cooling water transfers, waste collection and treatment collaboration or the creation of networks for best practices exchange.

Better machinery maintenance: this includes e.g. heating systems and boilers (for a better efficiency), air filtration systems (better Heating, Ventilation and Air Conditioning (HVAC) efficiency and air quality) or purification systems (higher yield and effluent quality).

1.2.3 At the operational level

The operational level concerns short term decision-making and production planning, such as weekly production schedules and material and workforce management, including:

Inventory optimization: managing the storage of materials, semi-finished and finished products appropriately can improve the environmental performance of a company. Storage of dangerous materials can require additional energy use (HVAC or cooling), and products can expire if stored for too long resulting in both economic and environmental losses. Also, storage space enables more flexibility regarding the production of different products, which can allow for more efficient or environmentally friendly schedules.

Machining techniques: as described in Jawahir and Jayal (2011), new machining techniques can reduce energy and auxiliary products consumption as well as material wastage. These include the use of new machining tools but also different operating parameters such as temperature, rotation speed or lubricant composition.

Sustainable scheduling: according to Pinedo (2008), scheduling "deals with the allocation of resources to tasks over given time periods and its goal is to optimize one or more objectives", i.e. operations sequencing and machine assignment. Those objectives typically feature indicators such as the makespan and production rate, with the aim of maximizing production efficiency and profits. Sustainable scheduling refers to the design of production schedules that reduce environmental impact. By sequencing operations differently or assigning specific machines to certain operations, it is possible to generate less pollution and still comply with production objectives. While not a common approach, sustainable scheduling has the benefit of requiring no investment or drastic organizational changes. Several strategies are available depending on the production system, focusing either on reducing inputs (such as energy consumption) and outputs (waste or emissions), or both, and are listed below:

- Operations sequencing : by ordering operations in a certain way, it is possible to reduce the number of setups or cleaning operations which can oftentimes generate waste (Adonyi et al., 2008). One example is for painting operations where the painting nozzles need cleaning each time a new color is used.
- Machine assignment : by assigning the most efficient machines to the most impacting operations, it is possible to reduce the energy or auxiliary

material (such as lubricant or solvent) consumption. An example of such a method is given in Grau et al. (1994).

- Product grouping : by grouping different product adequately, scrap materials resulting from cutting or machining operations can be minimized, as shown in Wuttke and Heese (2018). This is especially relevant in industries such as cardboard, paper or textile where cutting operations are predominant.
- Machine idleness and peak power-consumption : While energy use can be reduced through maximizing machine efficiency, other techniques have been proposed (Fang et al., 2011a). Bruzzone et al. (2012) adapt the schedule in order to avoid consumption peaks which result in stress on the electrical grid as well as over-costs for the manufacturer. Alternatively, Chen et al. (2013) work on machine idleness. By regulating the turning on and off of different machines, it is possible to avoid unnecessary energy consumption from idle machines.

Due to the complexity of scheduling problems, most earlier studies have focused on optimizing only one objective, usually associated with economic indicators. Advances in computational power as well as algorithmics and programming have enabled the tackling of bi- and multi-objective optimization problems, paving the path for the inclusion of sustainable criteria into production scheduling research.

In their literature reviews on sustainability in manufacturing operations scheduling, Fang et al. (2011b), Giret et al. (2015) and Akbar and Irohara (2018) show that research thus far has mostly focused on the reduction of energy consumption; detailed reviews on energy efficient scheduling can be found in Gahm et al. (2016) and Biel and Glock (2016). Noting that 97% of the reviewed studies focus on reducing energy consumption and only 3% address the issue of waste, Giret et al. (2015) emphasize the need to address the outputs resulting from scheduling (waste, scrap, pollution) to design sustainable schedules, since there are few works on this topic. This can be explained by the fact that companies are incentivized to reduce their energy consumption over their waste generation as it represents a direct reduction on their electricity/fuel bills. Waste management costs, on the other hand, tend to be grouped in overheads with other costs, and thus oftentimes go unnoticed by decision-makers even when reducing those could represent significant financial savings.

1.3 Research question

Following on the various concepts described in the previous sections, the scope and aims of this research are explained below.

1.3.1 Problem description

Several conclusions can be drawn from the previous pages. Firstly, industrial manufacturers need to integrate sustainability in their decision-making process if they are to continue their activity. To do this, numerous approaches are available, and each of them should be considered depending on the context. While manufacturers have been focusing on the tactical and strategic levels of decision, working at the operational level can provide effective solutions requiring no large investment of either time or money. Secondly, while researchers are adding sustainable considerations in the scheduling research field thanks to the integration of environmental criteria, their work has been centered on reducing energy consumption and waste-minimizing scheduling problems remain largely unnoticed. Finally, besides its environmental and public image benefit for companies, the potential economic gain of waste reduction has yet to be recognized by decision-makers. Providing them with efficient trade-off solutions between waste reduction and implementation cost would be an incentive for companies to embrace sustainable production, and noticeably at the operational level. This work aims at providing answers to all three of these issues, and is driven by the following research question:

"How to integrate waste minimization into operations scheduling?"

1.3.2 Structure of the manuscript

To answer this research question three main research axis have been investigated, each shedding light on a particular aspect of this topic, which can be summed up with the following interrogations:

What are the characteristics of waste-minimizing scheduling problems? Although the literature on waste-minimizing scheduling problems is limited, several relevant studies have been carried out. To better grasp the nature of the problem at hand and how it can be solved, it is necessary to accurately define its characteristics and how they can vary depending on the context or industry type. This will be the main focus of Chapter 2 which provides a comprehensive review of the existing work on the subject and proposes a classification scheme.

How to identify opportunities for waste minimization through scheduling ? As a relatively recent field of research, waste-minimizing scheduling lacks the extensive literature available for other types of scheduling problems. It is then important to provide both researchers and industrialists with a way to identify opportunities of waste reduction through scheduling. Chapter 3 presents a review of several methodologies for material and waste flow assessment. Based on this review, a new methodology to facilitate the identification and modeling of waste-minimizing scheduling problems is then proposed, assessing the changes that would occur regarding both environmental and economic aspects in a production system. An application case is presented to prove the usefulness of this methodology.

How to solve waste-minimizing scheduling problems? Once identified and characterized, the solving of waste-minimizing scheduling problems remains a complex process. The inclusion of environmental criteria requires the use of multiobjective optimization. Additionally, waste generation mechanisms can differ from usual scheduling considerations, and add further complexity to the problem. Finally, the obtained results need to be relevant for practitioners. This means providing clear and useful information such as efficient trade-off points in a practical time-frame, which can be done through the use of metaheuristics. In Chapter 4, a waste-minimizing scheduling problem identified during the previous application case is presented and solved using both exact and metaheuristic methods. Numerical experiments highlight the potential for operational improvements, and managerial implications are discussed.

After investigating these three questions, the contributions of this thesis are first presented in Chapter 5. The implications of this work for both practitioners and researchers are discussed, and perspectives are finally presented on how to expand the work developed in this manuscript and apply it to real-life situations.

CHAPTER 2

Literature review and problems classification

Contents

Results from this review have been published in:
C. Le Hesran, A. L. Ladier, V. Botta-Genoulaz, and V. Laforest. Operations scheduling for waste minimization: A review. *Journal of Cleaner Production*, 206: 211–226, 2019b. ISSN 09596526. doi: 10.1016/j.jclepro.2018.09.136.

Résumé du chapitre 2

Ce chapitre cherche à répondre à la première des interrogations introduites dans le chapitre précédent, et qui peut être exprimée ainsi:

Quelles sont les caractéristiques d'un problème d'ordonnancement minimisant les déchets?

Pour ce faire, un état de l'art de la littérature sur le sujet est réalisé. L'utilisation du moteur de recherche Web Of Science avec des mots-clés liés à la fois à l'environnement et à l'ordonnancement fait émerger 71 articles correspondant à des problèmes d'ordonnancement minimisant les déchets. Ceux-ci sont groupés selon quatre catégories de problèmes d'ordonnancement auxquelles ils appartiennent, à savoir les problèmes d'ordonnancement de lots (batch) et treuils (hoist), les problèmes de découpe (Cutting Stock), de découpe intégrée (Integrated Cutting Stock), et finalement les problèmes d'atelier de fabrication (shop-floor). Au sein de ces catégories, les différents articles sont classés en fonction de la façon dont ils cherchent à réduire les déchets générés (e.g. en réduisant changements de série, en adaptant leur inventaire, ...). Une classification est ensuite proposée afin de structurer ce champ de recherche hétérogène. Des critères basés sur les caractéristiques environnementales et d'ordonnancement (objectifs environnementaux et économiques, approche de résolution, approche multiobjectif ...) sont utilisés. Chaque article est alors classifié au sein des quatre grandes catégories de problèmes identifiées précédemment, et leurs différentes caractéristiques détaillées. Une analyse de cette classification fait émerger un certain nombre de perspectives qui permettraient de développer ce champ de recherche, et notamment:

La définition de fonctions objectif environnementales adaptées. Une majorité d'études citées utilisent les quantités de déchets générés comme fonction objectif. Une analyse de leur impact environnemental réel, à l'aide d'outil comme l'Analyse de Cycle de Vie ou le suivi de flux, permettrait d'avoir une image plus précise de l'impact réel des déchets.

Le calcul précis du coût des déchets. Dans de nombreux cas, les déchets sont considérés du point de vue économique, en n'incluant que le coût des matières perdues ou les frais d'enlèvement. Le coût des déchets et leur impact environnemental n'étant pas corrélés, cela peut induire les preneurs

de décision en erreur. De plus, ces coûts sont généralement sous-estimés, ce qui réduit l'attention donnée à la réduction des déchets au profit d'objectifs de production.

Les stratégies d'optimisation multiobjectif. Moins de la moitié des articles étudiés proposent des solutions alternatives aux preneurs de décision, qui sont pourtant nécessaires pour faire le choix le plus adapté en fonction de la situation. Les approches par somme pondérée, bien que faciles à implémenter, restent limitées non seulement dans la définition des poids utilisés mais aussi dans l'information qu'elles fournissent. L'utilisation de fronts de Pareto est donc recommandée, notamment quand les deux objectifs économique et environnemental sont de nature difficile à aggréger.

Ainsi, l'état de l'art et classification proposés sont un premier pas pour l'unification de ce champ de recherche. Les perspectives qui s'en dégagent sont prises en considération dans la suite de ce manuscrit.

Literature review and problems classification

This chapter answers the first of the interrogations introduced in Chapter 1, which can be written as:

What are the characteristics of waste-minimizing scheduling problems?

To this end, a state-of-the-art of the current literature on waste-minimizing scheduling problems is first presented. Section 2.2 describes the methodology used for the review process, while all selected articles are grouped and described in section 2.3. A classification based on the observed problem characteristics is proposed in section 2.4. Section 2.5 discusses the issues that were identified through the review and classification process and how they will be addressed in the rest of this manuscript, while conclusions are presented in the last section.

2.1 Introduction

This chapter aims at reviewing the existing literature on waste-minimizing scheduling problems taking into account both the economic and environmental aspects, and provides insight into facilitating future research in this field. Although not very extensive, the literature dealing with waste concerns through operations scheduling is diverse, both in terms of industrial contexts (type of waste and process concerned) and scheduling problems involved. Research in this field does not yet possess a unified framework, and is not often labeled as pertaining to waste-minimizing scheduling. The interdisciplinarity and lack of standardized terminology do not allow for easy knowledge-sharing. This makes the realization of a state-of-the-art all the more important, along with the means to compare and analyze the scientific contributions. Thus, we propose a classification including the identification, listing and appropriate description of the different problem characteristics that can impact waste generation at the scheduling level. Through the classification process, we define categories of problems sharing similar characteristics and identify areas where further research is needed. Indeed, the typical description used for scheduling problems is the Graham notation (Graham et al., 1979), also called three-field notation, which comprises an α, β and γ field representing respectively (Pinedo, 2008):

Shop-floor configuration α: how the different machines and processes are related, and how this affects the possible scheduling process (e.g. number and types of machines, types of operations).

Constraints of the problem β: what is allowed and what is not when designing a schedule (e.g. due dates, precedence constraints…).

Objective function γ: what we seek to improve when using the scheduling model. It depends on the decision-maker and constraints of the system, and includes both an economic and environmental component.

No considerations are usually given to environmental aspects in this notation, although some new constraints and objective functions have been proposed regarding energy-efficient scheduling problems modeling.

The motivation for this work stems from the review on sustainable scheduling by Giret et al. (2015) and Akbar and Irohara (2018). Although our purposes are similar, the scope of our review is much more specific. Since their studies includes all kinds of works regarding sustainable operations scheduling, Giret et al. (2015) include only a portion of the existing literature judged "representative of the diversity of studies relevant to sustainable manufacturing operations scheduling", while Akbar and Irohara (2018) use a sample of only fifty studies. As a result, more than 90% of their referenced papers deal with the minimization of energy consumption, and only four articles address waste and are present in our review. Since waste represents a lesser portion of the literature, our aim is to be as complete as possible.

2.2 Methodology

Based on a sample of existing articles regarding scheduling-based waste minimization, a set of keywords was identified and listed in Table 2.1. The terms "waste" and "scheduling" were combined with a keyword from both the environmental and scheduling aspects, resulting in a total of 12 combinations. The Web Of Science search engine was then used to identify peer-reviewed articles featuring at least one of these combinations in their title, abstract and keywords.

Table 2.1: Keywords used in the literature search

Scheduling aspect related keywords	Sustainability aspect related keywords
Scheduling	Waste
Manufacturing	Environmental
Production	Sustainable

More than 2000 articles resulting from this literature search were screened to check whether they belong to our scope. Further research was made by looking at the references cited in the selected papers, as well as the articles citing our sampled papers. In case specific types of scheduling problems involving waste reduction were identified (e.g. the batch scheduling problem or cutting stock problem), additional research was made on this particular topic.

As a result, a total of 71 papers were selected. In Figure 2.1, they are grouped according to their publication year and research field, oriented towards operational research, chemistry and sustainable production respectively. The category "Other" includes conference proceedings and journals with no specific affiliation. Relatively few articles were published prior to year 2000, with the number rising sharply after 2007. This trend is not only present in the waste-minimizing scheduling literature, but more generally representative of the sustainable production literature as a whole. More than half (38) of the selected articles were published in operational research journals, followed by chemistry oriented journals (15), and sustainable production (10). A consequence of this fragmentation of disciplines is the difficulty to connect articles to one another. Those are usually addressing a specific problem of their field and do not automatically mention the waste-related scheduling aspect, thus highlighting the need for a state-of-the-art.

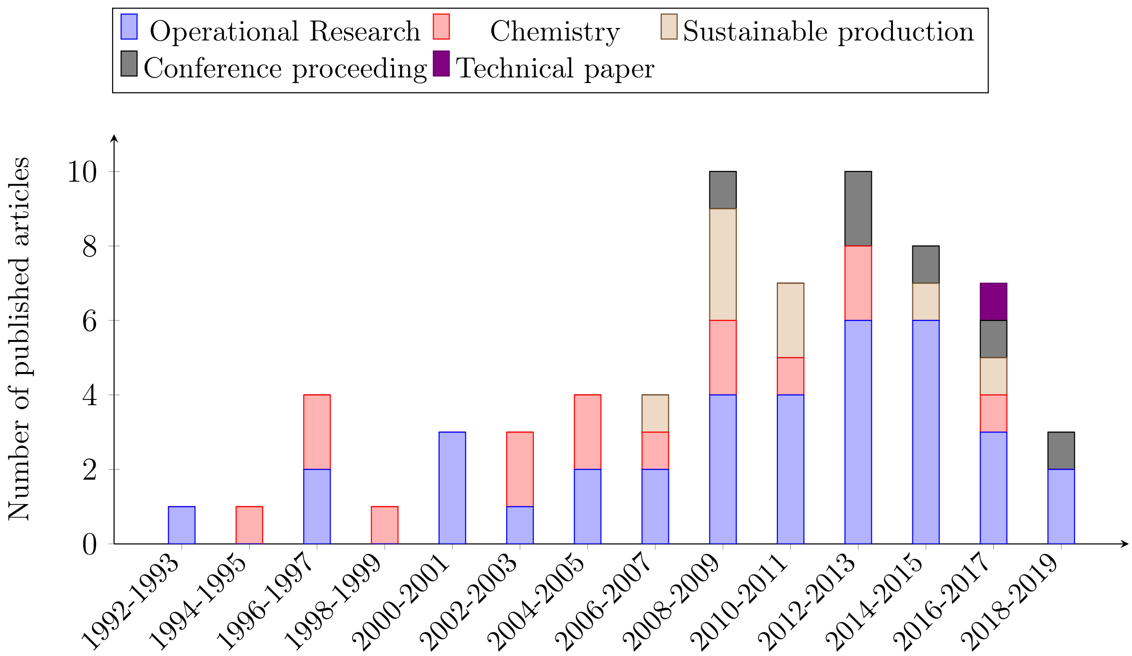

Figure 2.1: Number of publications on waste-minimizing scheduling with journal affiliation per year of publication

In Table 2.2, the detailed list of all cited journals and numbers of articles per journal is shown.

2.3 Operations scheduling for waste minimization in the literature

In this section, a state-of-the-art of the current literature on waste minimization through operations scheduling is presented. The reviewed articles have been grouped into four main categories related to the scheduling problem they address, and subdivised according to the way the waste-minimization issue is handled. A classification of this review is presented in Section 2.4.

2.3.1 The batch and hoist scheduling problems

The process industry is a big waste producer, and one of the biggest contributor regarding hazardous waste (United States Environmental Protection Agency, 2006). Due to the nature of the processes and materials used, large quantities of wastewater are generated during the production and equipment cleaning steps. The two biggest types of problem encountered are the batch scheduling problem (e.g. for the production of chemicals or food products) and the hoist scheduling problem (e.g. for surface treatment).

Batch scheduling, which is related to process manufacturing, occurs when several jobs can be processed simultaneously on a single machine. Its fundamental characteristic is that the batch processing time is equal to the longest processing time of the jobs included on the batch. Thus, determining the composition of a batch becomes an important factor for the overall makespan and production costs. Batch scheduling optimization is extensively covered in the scientific literature (Méndez et al., 2006) regarding economic criteria (production costs, productivity...). However, new legislation regarding the management of hazardous waste (European Parliament and Council, 2008), as well as an increasing awareness regarding environmental issues have fostered the inclusion of environmental factors into the more recent studies.

The hoist scheduling problem deals with the scheduling of handling devices, also called hoists, mostly in electroplating lines. This includes the determination of the soaking times, the use of several tanks, and the coordination of multiple hoists on possibly conflicting routes with possible improvements regarding the wastewater generation. More information is available in Manier and Bloch (2003). In the specific

Table 2.2: List of articles' source

Journal or Proceeding name	Number of articles
Operational Research	
Annals of Operations Research	2
Applied Mathematical Modelling	2
Applied Soft Computing Journal	1
arXiv preprint	1
Computers and Operations Research	6
European Journal of Operational Research	6
International Journal of Production Economics	3
International Journal of Production Research	2
IIE Transactions (Institute of Industrial Engineers)	1
INFORMS Journal on Computing	1
International Journal of Advanced Manufacturing Technology	1
Journal of the Franklin Institute	1
Journal of the Operational Research Society	3
Mathematical and Computer Modelling	1
Omega	1
Optimization and Engineering	1
Optimization Methods and Software	1
OR Spectrum	1
Pesquisa Operacional	3
Pesquisa Operacional para o desenvolvimiento	1
Tendencias em Matematica Aplicada e Computacional	1
Chemistry	
American Institute of Chemical Engineers	1
Chemical Engineering Communications	1
Chemical Engineering Science	1
Computer Aided Chemical Engineering	1
Computers and Chemical Engineering	9
Industrial & Engineering Chemistry Research	3
Sustainable production	
Clean Technologies and Environmental Policy	1
International Journal of Environmental Research and Public Health	1
Journal of Cleaner Production	7
Proceedings	
International Conference on Control, Decision and Information Technologies, CoDIT	1
IEEE 15th International Symposium on Intelligent Systems and Informatics	1
IEEE International Conference on Emerging Technologies and Factory Automation, ETFA	1
IEEE International Conference on Industrial Engineering and Engineering Management	1
48th CIRP Conference on manufacturing systems	1
International Conference on Industrial Engineering and Operations Management	1

case of batch and hoist scheduling problems, the design and operation of the water reuse network and plant design problem is addressed in this review only if combined with a scheduling problem. Other works concerning plant or water reuse network design can be found in Stefanis et al. (1997) or Barbosa-Póvoa (2007).

In the following, the literature concerning waste reduction in the batch and hoist scheduling problems is reviewed and organized into five subcategories featuring different angles from which to address waste generation.

Equipment cleaning and setup considerations

Seminal works on sustainable operations scheduling are mostly focused on reducing the waste outputs, mainly wastewater originating from equipment cleaning.

Grau et al. (1994) propose to identify all generated waste and by-products and classify them according to a pollution index (based on a product's properties such as toxicity). Production apparatuses and material collectors are also listed. A first production plan being established, an environmental impact is calculated by multiplying each output quantity by its corresponding pollution index. The output with the biggest impact is identified, and a new schedule is made that minimizes its impact, e.g. by allocating it to the most efficient equipment available or reducing the quantity used. Once this is done, all the production steps where materials collecting and/or reuse are possible are identified, and the most beneficial are implemented. While waiting times might be introduced to enable such measures, all production constraints still have to be complied with. When all possible changes are done, the output with the second biggest impact is considered, and so on until the end of the list. A formal methodology combining these steps is proposed by the authors and applied to a batch production example. An additional work (Grau et al., 1996) includes energy consumption into the objective function as well. Adonyi et al. (2008) tackle the problem of reducing the outputs generated by equipment cleaning due to setups in a paint production factory. They propose an algorithm based on previous work by Sanmartí et al. (2002) on S-graphs, which takes into account the cleaning costs of the various equipments. Alternative solutions are obtained by allowing for different operating times resulting in different cleaning schedules. The efficiency of their algorithm is compared with the Mixed Integer Linear Programming (MILP) model from Endez and Cerda (2003), showing drastically reduced computation times while providing multiple solutions.

In Capon-Garcia et al. (2011), both MILP and Mixed Integer Non Linear

Programming (MINLP) are used in the case of setup-waste minimization for acrylic fibers fabrication. Using Messac et al. (2003)'s normal constraint method, a Pareto front is generated. A Pareto front represents the set of non-dominated solutions in the case of multiobjective optimization, i.e. solutions that cannot be improved without degrading at least one of the other objectives (more details about Pareto fronts are available in Blasco et al. (2008) and in Section 4.3.4). The tri-objective problem with the profit, operating time and environmental impact criteria is also considered and a tri-dimensional Pareto frontier generated. Yue and You (2013) tackle the issue of the multi-purpose batch scheduling problem in surface treatment. They propose a bi-objective optimization of productivity and environmental impact originating from changeovers in production, calculated from a Life Cycle Assessment (LCA) database. A Mixed Integer Linear Fractional Programming (MILFP) is used with the ε-constraint method (details on the ε-constraint method are available in Mavrotas (2009) and in Section 4.3.4) to obtain a Pareto frontier of possible solutions in a satisfactory time.

Zhang et al. (2017) propose to use particle swarm optimization and local search in order to minimize the pollutant emissions in a textile dyeing process with sequence-dependent family setup costs. A bi-objective function considering total tardiness and emission of water pollutants caused by the cleaning operations is defined and alternative Pareto efficient solutions are obtained. Adekola and Majozi (2017) also consider sequence-dependent setup costs along with a profit maximization objective. Based on a MILP formulation by Seid and Majozi (2012), their goal is to minimize an aggregated cost function accounting for profit and either setup or freshwater consumption cost.

In the food industry, Berlin et al. (2006) develop a heuristic which minimizes the number of setups in a dairy production plant. This heuristic is applied to two scenarios in Berlin and Sonesson (2008), which show a significant decrease in setup-related waste generation. The consequences of implementing such schedules onto the planning of downstream activities are also discussed, and are shown to be particularly relevant in industries with perishable products such as the dairy industry.

Process requirements

Process requirements refer to all the operational constraints regarding the processes themselves. Such constraints are e.g. the concentration of chemicals in a tank, the soaking duration for a bath or the recipe used for a product. Using alternative recipes, concentrations or soaking times, it is possible to adjust the schedule to reduce waste generation.

Song et al. (2002) use MILP with the ε-constraint method in the case of an oil refinery. They obtain a Pareto front of trade-off solutions balancing profit and environmental impact (based on an LCA tool assessment) by adapting the production schedule based on oil flow rates between storage, blending and product tanks. Chaturvedi and Bandyopadhyay (2014) propose a MILP formulation of the bi-objective optimization of freshwater consumption and productivity. Based on the required chemical concentrations for different processes, they use the ε-constraint method to obtain a Pareto front of alternative schedules. Xu and Huang (2004) consider freshwater consumption reduction for a single product hoist scheduling problem. They propose a search algorithm based on a free move matrix which first determines all the possible optimal schedules from a cycle time perspective, which may have different soaking times or soaking bath concentrations. Then, water consumption for all of these schedules is determined, and the most environmentally-friendly one is selected. Kuntay et al. (2006) choose the same approach and use a two-step algorithm, which first maximizes the production rate and then minimizes the quantity of chemicals and water used.

Subaï et al. (2006) address the subject of wastewater output regulation in a surface treatment plant. In addition to the criteria of chemical concentrations and bathing time, they consider the energy consumption and smoothing of wastewater discharge over time in order to avoid overloading the water treatment plant. They proceed in two steps, first solving a classical hoist scheduling problem and then selecting the best remaining solutions after adding additional constraints. They show that environmental criteria can be included into objective functions without negatively affecting productivity and with reasonable computation times.

El Amraoui and Mesghouni (2014) propose a bi-objective optimization of cycle time and waste generation using a genetic algorithm. Process requirements in terms of soaking time and chemicals concentration are included into the problem formulation in order to reduce the wastewater generated. Likewise, Liu et al. (2012) propose a triple-objective optimization aiming at reducing simultaneously the water and electricity consumption while maximizing productivity. Using a mixed integer dynamic optimization model, they generate a three-dimensional Pareto frontier from which a schedule can be selected. Arbiza et al. (2008) present an LCA-based optimization process, where financial and environmental modules that assess a schedule's economic and environmental impacts are proposed. By using different recipes and raw materials for a same product, the schedule can be adapted according to both modules. Using a genetic algorithm, they are able to generate Pareto-efficient solutions providing trade-off between environmental impact and economic efficiency. Finally, Vaklieva-Bancheva and Kirilova (2010) address the case of optimal production recipes choice in multipurpose batch scheduling. Using the example of curd production from the dairy industry, a genetic algorithm is developed to choose the most appropriate recipes in order to minimize the environmental impact of production while still complying with production goals.

Use of intermediate storage tanks

An intermediate storage in the batch production context is a vessel used to store either a byproduct, a co-product, or wastewater. This storage can be combined with a regeneration equipment, or used simply to wait for later reuse or discharge.

Majozi (2005), further developed in Majozi and Gouws (2009), tackles the case of wastewater output minimization in the presence of an intermediate storage tank. Using MINLP, they compare scenarios where a storage tank for wastewater is present or not, and adapt the production schedule in order to minimize the wastewater output. Experiments show that a reduction up to 20% of the wastewater generated is possible. In Gouws and Majozi (2008), the authors consider the same problem with multiple storage vessels and multiple contaminants. They also allow for reuse of stored wastewater for some processes, and use MINLP to obtain the schedule that minimizes the amount of wastewater in a set time horizon. Adekola and Majozi (2011) consider the problem of batch scheduling with intermediate storage and wastewater regeneration unit. By linearizing a MINLP formulation of the problem, they manage to obtain schedules that minimize the wastewater generation by allowing for an efficient use of the regeneration unit. Based on the previous work of Majozi and Gouws (2009), Nonyane and Majozi (2012) propose a state sequence network representation which also aims at minimizing the wastewater output in presence of a storage tank. The novelty of their work is the use of cyclic scheduling to tackle larger planning horizons, dividing it into eight 23-hours long periods.

Plant and process design

This section refers to scheduling problems that involve process or plant design, be it proactive or for a retrofitting.

Stefanis et al. (1997) study the relationship between environmental impact, scheduling and production plant design. They apply previous work from Barbosa-Póvoa and Macchietto (1994) to three food industry cases and obtain trade-off solutions between production cost, plant design cost and wastewater generation in a dairy plant using MILP. Similarly, Al-Mutairi and El-Halwagi (2010) propose to use MINLP to generate trade-off solutions between both design and scheduling issues with economic and waste reduction objectives. They apply their model to the case of a refinery, comparing scenarios with and without retrofitting of equipments.

2.3.2 The Cutting Stock Problem with scheduling aspects

Cutting Stock Problems (CSPs) are widely studied in operational research. Those problems appear when one or several pieces of materials need to be cut into products of smaller dimensions, and are present in many industries such as textile, paper, furniture or metal sheet production. For a more precise typology of cutting and packing problems, readers can refer to the works of Dyckhoff (1990) and Wäscher et al. (2007). The traditional objective of a CSP is the minimization of wasted material, also called trim loss. Trim loss occurs when residual material is left after all possible products have been cut from the primary material. Those typically have dimensions inferior to those of the smallest available product, which makes them unusable for posterior processing. Since minimizing trim loss equates to increasing productivity and reducing materials costs, it has been the usual objective of CSPs. One important aspect about the recent CSP literature is the need to treat the production scheduling problem as a whole, and not simply from a cutting patterns viewpoint. This has led to the appearance of new forms of CSPs such as the CSP with pattern reduction or CSP with usable leftovers. Those typically take into account both the trim loss minimization through efficient patterns, and the effect of using such patterns on production scheduling. As an example, using only the most efficient patterns typically requires switching patterns more often in order to fulfill demand. This in turn leads to larger setup times and costs, which can offset the gains made by reducing trim loss. Thus, new criteria for production efficiency have been introduced besides trim loss, such as the number of different patterns, sequencing or overproduction. This leads to merging traditional CSPs and Lot Sizing Problems (LSPs) that deal with determining efficient production schedules. Moreover, trade-off solutions have become necessary to balance the materials and operating costs and better reflect real-life situations. In this section, the literature regarding the CSP problem with scheduling and waste minimization concerns is reviewed and classified.

CSP with setup considerations

Minimizing trim loss might require using a large number of patterns, and thus a large number of setups (e.g. adjustment of the knives in paper cutting). This is not necessarily a problem as long as the impact of a setup is negligible when compared with material losses. When the setup time or cost is big enough however, it becomes sensible to limit the number of patterns used even if it generates more trim loss.

Harjunkoski et al. (1999) consider the 1-dimensional CSP (1DCSP) using MINLP in the paper converting industry. They define various objective functions that take into account respectively the number of patterns, number of pattern changes, total waste, makespan, energy consumption and overproduction. They compare the results of each objective over these different criteria, and also propose a hybrid objective function minimizing total waste and energy consumption. They emphasize the interest of such hybrid functions, and the fact that knowledge of the processes, while requiring additional research, is key in improving the quality of the results. Likewise, Schilling and Georgiadis (2002) study the 1DCSP with setup costs. The authors define an aggregated objective function that includes the profit, the setup cost and, interestingly, the waste disposal cost. They propose a MILP model, stressing that the addition of changeover and waste disposal costs are responsible for an increased problem difficulty. Similarly, Kolen and Spieksma (2000) study the case of the 1DCSP with trim loss and pattern number minimization. They also consider two types of jobs, one that allows for a certain degree of over or underproduction, and one with exact demand. They develop a Branch and Bound (B&B) algorithm that produces a set of Pareto-optimal solutions.

In Westerlund (1998), a two-dimensional CSP with setup times is modeled using MILP. Two aggregated objective functions are tested, one based on Westerlund et al. (1996) that minimizes losses due to trim waste, overproduction and setups, and one maximizing the profit represented by income from deliveries and overproduction minus all production costs. This method was successfully implemented in a Finnish paper-converting mill. Wuttke and Heese (2018) propose a more detailed version of this problem, with sequence-dependent setup times (based on the previous position of the cutting knives) and tolerances on product widths. A two-stage heuristic first identifies a set of efficient patterns, then determines a sequence to optimize the knife-mounting operations, thus reducing the setup times. This heuristic is able to treat instances of realistic size, and is effectively tested on data reflecting the annual demand of a textile firm, improving setup times up to 50% with low trim loss.

In Nonas and Thorstenson (2000), a CSP with setup and inventory considerations is studied. The authors use the case of steel plate cutting with an aggregated objective function combining the cost of waste during the cutting operation, the steel plates holding cost and the setup cost incurred for each new pattern or steel dimension. Both problems are solved simultaneously using various methods such as the one proposed by Murty (1968), three local search algorithms and a column generation procedure. The authors improve their column generation algorithm in Nonas and Thorstenson (2008) using their previous work and a heuristic proposed by Haessler (1971), obtaining better solutions in less time. Mobasher and Ekici (2013) look at the same problem and propose two local search algorithms and a column generation algorithm, then study the impact of the respective weights of the waste and setup costs in the objective function. Their column generation algorithm is more effective when dealing with low setup costs, while local search is better when setup costs are high.

Araujo et al. (2014) consider a bi-objective optimization of the number of patterns used and the trim loss incurred. Using a genetic algorithm, they generate a set of non-dominated solutions. Compared with other existing solving methods for similar problems using both real-life and randomly generated instances, they obtain good quality results with reasonable computing times. Golfeto et al. (2009) also use a genetic algorithm with a multi-objective optimization for the 1DCSP. They produce a Pareto front showing the trade-offs between trim loss and the number of setups, and suggest parallel processing as a perspective to improve their genetic algorithm computation time. Cui and Liu (2011) also address the issue of the number of patterns in the 1DCSP and propose a sequential heuristic procedure based on the successive generation of pattern sets (called C-sets) that fit the remaining products to be cut. Although their proposed method might require large computing time when applied to practical cases, the authors acknowledge the potential of C-sets for future research in this area. Cui et al. (2014, 2015) later propose a two-step procedure where a set of patterns is first generated using a sequential grouping procedure. MILP is then used to obtain a solution based on this pattern set, showing nearly optimal results in minimizing the pattern number without increasing trim loss.

CSP with inventory considerations

In some cases, inventory capacity and cost are the limiting factors in scheduling. Bolat (2000) looks at a scheduling problem with buffer stock capacity in the corrugated boxes industry. Several parameters are considered, the aim being to maximize the throughput of converting machines under a constraint of maximum acceptable trim loss and limited storage capacity for boards to be processed. Setup and loading times of the boards into the converting machines are also considered. A successive linear programming relaxations algorithm is proposed, which first optimizes throughput and then the trim losses, and analyses the trade-offs between those two objectives. A similar problem is considered in Gramani and França (2006), where inventory and setup costs are considered with the minimization of cut plates. MILP is used first, followed by a staged combined model heuristic to solve a shortest path problem. Experiments on real life data show that gains up to 13% can be made on profits when considering both problems at the same time instead of sequentially. Lucero et al. (2015) address the issue of a 2-scheme strip cutting problem with sequencing constraints in the corrugated cardboard industry. Their goal is to define a schedule minimizing trim loss when only two different products can be processed at a time (the number of products stacks being limited to two). Additionally, a maximum lateral waste per pattern is allowed, and a small over and underproduction is permitted for each order. After developing four different integer programming methods based on a graph approach, they propose a greedy heuristic which greatly improves the computation time without losing in solution quality. Na et al. (2013) propose a heuristic for solving a scheduling problem of float glass production. Their goal is to produce a schedule that meets demand while minimizing two types of scrap: layout scrap, which is linked to the glass snapping patterns used, and cycle time scrap, which originates from the inefficient offloading of cut glass panels into inventory. They use a two-phase heuristic in order to maximize a yield ratio based on the total quantity of scrap divided by the overall quantity of glass used, and manage to improve manufacturing yields from 95% up to 99%.

CSP with due dates

While most cases consider a time horizon for the processing of all orders, some articles consider due dates for each job to be processed. Reinertsen and Vossen (2010) address the CSP with due dates in a steel manufacturing process. Using Integer Linear Programming (ILP) and a sequential heuristic procedure, the operational performance is calculated based on the resulting waste and tardiness of the orders. The objective function consists of the aggregated costs of raw materials and tardiness. Arbib and Marinelli (2014) consider the same problem and propose a more efficient formulation using ILP and a dynamic period splitting procedure. An interesting point raised by the authors is that the weights given to each objective (tardiness and raw materials consumption respectively) are largely dependent on the industry and materials used.

2.3.3 The Integrated Cutting Stock Problem

In this section, articles addressing the Integrated Cutting Stock Problem (ICSP) are reviewed. A recent literature review of ICSP has been proposed by Melega et al. (2018), who describe the ICSP as a problem that "considers simultaneously the decisions related to both problems [LSP and CSP] so as to capture the interdependency between these decisions in order to obtain a better global solution". Along with their review, the authors propose a generalized 3-level integrated lot-sizing and cutting stock model based on formulations by Gilmore and Gomory (1961) for the CSP and Trigeiro et al. (1989) for the LSP. They consider two types of integration which are necessary for a problem to be considered as an ICSP. The first one is the integration across time periods, with inventory providing a link between those. The second one is the integration across production levels, i.e. purchase/fabrication of material (L1, related to LSP), cutting of pieces (L2, related to CSP) and finally assembly into the final product (L3, related to LSP). They consider that a problem must include at least two production levels (L1-L2, L2-L3 or L1-L2-L3) and have a multi-period dimension to be categorized as an ICSP. Their work is extensive, and is mostly focused on the modelization aspect with information regarding the type of pieces being cut and operational constraints such as setups and capacity. In order to obtain the additional information needed for our classification, especially regarding waste minimization, a review of the papers cited in Melega et al. (2018) was conducted. As a result, 21 out of the 30 papers present in their work are considered in this study, as the others did not include environmental aspects relating waste generation and scheduling.

ICSP with setup considerations

In Hendry et al. (1996), a two-stage procedure is used to solve an ICSP with setup times. The study takes place in a foundry where copper logs are melted, then cut to the appropriate size. The aim is to reduce both the number of furnace charges and the trim loss due to the logs cutting, with the possibility of storing both molten copper and surplus cut logs at a negligible cost. The problem is solved by first determining the number of logs necessary, and then determining a furnace schedule which meets the demand. The authors test several heuristic methods in order to solve the first step, and use integer programming for the second step. This procedure is tested using real data from a manufacturer, showing improved results on both makespan and trim loss compared to the method previously in place.

ICSP with inventory considerations

In Reinders (1992), the case of a wood-processing company is considered. Two cutting stages (one for tree trunks and one for boards) are integrated into a larger tactical level, where machine capacity constraints, inventory costs and lot-sizing are included. The authors use column generation with dynamic programming for the cutting stages and goal programming is used for scheduling at the tactical level, with different scenarios considered. While the results of numerical experimentations are not discussed, the use of an integral optimization over a search of multiple local optima is considered more efficient. In Correia et al. (2004), the case of paper reels and sheets production is addressed. All the operational constraints (such as dimension specification, capacity, paper types...) are included in a linear program, where the objective function consists simply of minimizing material consumption. Additionally, some of the produced paper reels may be cut into paper sheets, thus a need to manage the production and inventory over time in order to fulfill demand of both reels and sheets. Using a three-stage procedure, the authors first generate the cutting patterns, then use Linear Programming (LP) and a heuristic to obtain a schedule that minimizes raw material consumption. They offer two different linear programs where overproduction is either allowed or not. Their method was implemented in a paper mill, showing good results with paper pulp saving.

Gramani et al. (2011) use a model based on work by Gramani et al. (2009) for a case of metal plate-cutting, but remove the setup cost from the objective function. They propose an exact solution method based on column generation that minimizes storage and production costs, that is compared with the decomposition method commonly used in the industry. Gains up to 12% are made on global costs, and other scenarios with different production parameters are also investigated. Silva et al. (2014) consider a case of 2-dimensional ICSP with possible storage of leftovers. They minimize an objective function composed of waste, material, operational and storage costs and propose two ILP models based on work by Silva et al. (2010) and Dyckhoff (1981) respectively. Two heuristics are also proposed, and results show that the two ILP models manage to obtain exact solutions even for large instances. Poldi and de Araujo (2016) consider a multi-period 1-dimensional ICSP. The objectives are to minimize the trim loss and inventory costs (of both raw materials and finished products) over a set of production periods. An arc flow formulation based on Valério De Carvalho (1999) complemented by a heuristic procedure is proposed, and instances are solved with different weights assigned to the holding costs. The results show effective computation time even with large instances. The authors also point out that their approach requires less patterns than the classical approach.

The skiving option in ICSP is introduced by Arbib and Marinelli (2005) in a gear belt manufacturing plant: it is the possibility to combine components (including leftovers) to obtain larger parts. The authors introduce a two-stage method, with a cut-and-reuse and inventory focus at the operational level, and transportation and lot sizing focus for the mid-term planning level (one week horizon instead of day-by-day). Using ILP, they integrate those aspects into an aggregated objective function, and also consider the integration of last-minute orders into the schedule. While the quality of the solutions is high (up to 40% cost reduction compared to previous models), computational time for real-life instances remains prohibitive.

ICSP with setup and inventory considerations

Santos et al. (2011) use MILP for the 2-dimensional ICSP in the furniture industry. The authors consider a problem with rolling horizon where setup, inventory and production costs are minimized with the trim loss. Additionally, saw cycle times are considered and security stocks are defined with penalties incurred when these are not respected. Their model is tested on data from a furniture manufacturing firm, but no comparison is made with the actual results from the plant since several real-life techniques used are not included in the model. Campello et al. (2017) also address the integrated 1-dimensional ICSP with setup and inventory cost considerations. Using MILP and a heuristic, they construct a Pareto front of the LSP (inventory and setup cost) and CSP (trim loss and inventory cost) using the ε-constraint method. They observe the variations between the two and the possible trade-offs, concluding that increasing inventory is an effective way of reducing material waste. Suliman et al. (2014) address a similar problem in the aluminum industry. They first use Integer Non Linear Programming (INLP) for the cost and trim loss minimization problem over several planning periods. Given the complexity of the problem, they then propose an LS-CSP algorithm that proceeds from the last planning period to the first, assessing the needs for inventory pieces based on demand for this period and the available production capacity. Patterns are generated and selected according to different criteria using a pattern generation-selection algorithm. The algorithm produces efficient results when compared to the INLP and industry standards.

An integrated model is proposed by Vanzela et al. (2017), which solves the CSP and LSP simultaneously in order to minimize the production and inventory costs for furniture production. The results from the integrated model are compared with the sequential solving of the LSP then CSP, showing good results. An impact analysis of the different cost weights is then done by varying the inventory and material costs. Gramani et al. (2009) use the same approach in the case of a 2-dimensional ICSP involving plate cutting. Their objective function accounts for material, setup and inventory costs, and is minimized using a heuristic based on Lagrangian relaxation. They compare the performance of their heuristic with a decomposed approach which solves the LSP and CSP consecutively, and observe a slight increase in inventory but substantial reduction in setup costs and material use. In Melega et al. (2016), the authors propose three integrated models based on Trigeiro et al. (1989) and Eppen and Martin (1987) for the LSP. The CSP part is based on work by respectively Kantorovich (1960), Gilmore and Gomory (1961) and Valério De Carvalho (1999), and extended to accommodate the multiperiod and multi-object cases. Two heuristics are proposed to minimize an aggregated function of setup and inventory cost, and the results of numerical experimentations emphasize the difficulty of obtaining large numbers of feasible solutions.

Wu et al. (2017) consider the same model as Gramani et al. (2009) but transform the capacity constraint on the surface of processed material into a time capacity constraint. They propose a new approach based on Dantzig-Wolfe decomposition for obtaining lower bounds, which are then used in a progressive selection algorithm. This algorithm is compared with the Lagrangian-relaxation heuristic from Gramani et al. (2009). Leao et al. (2017) address an ICSP with multiple machines having different sizes and capacities. An aggregated objective function regroups the holding cost of items, setup and production costs as well as waste cost from the cutting stage. The authors propose three mathematical formulations, with item, pattern and machine decomposition orientations respectively. Those formulations are used for finding lower bounds, and a rounding heuristic and a neighborhood search heuristic are tested on literature and real-world instances. While the rounding heuristic performs poorly on real-life data, the neighborhood search heuristic produces good schedules in reasonable time. Poltroniere et al. (2008) address the issue of an ICSP with parallel machines and setup time and cost. Using the paper industry as an example, they aim at minimizing an aggregated function of production, setup, waste and inventory costs. They propose two methods using heuristics for the cutting-stock problem and the lot-sizing one. The first one solves the LSP and then the CSP using several iterations. The second one proceeds in the opposite order, solving the CSP first and then the LSP, showing better performances. In Poltroniere et al. (2016), the authors propose an extension to their heuristic and model, and develop a new model with an arc flow formulation based on the work by Valério De Carvalho (1999) which obtains better upper bounds.

A case of robust scheduling for the ICSP is addressed by Alem and Morabito (2012) in the furniture industry with the objective of minimizing production, setup, inventory and backlog costs in addition to trim loss. A first deterministic mathematical formulation based on Gramani et al. (2009) is proposed, and three robust models are then detailed. Those models account for uncertainties in either the objective function coefficients, the demand parameters, or both at the same time. After experimenting on real and simulated instances, the authors conclude that uncertainty in demand parameters has more impact on solution quality than uncertainty in objective function coefficients. In Alem and Morabito (2013), a similar problem with stochastic demand is also considered and uncertainty is added to the setup times, which are now counted as a capacity constraint and not as a cost. A deterministic model and four 2-stage stochastic models with different risk management strategies are tested. The performance of each model is compared using real life data and different scenarios. Risk mitigation comes at the expanse of higher production costs, and the authors consider extending their framework for risk-aversion to different types of industries.

ICSP with setup and due dates considerations

In Aktin and Özdemir (2009) a case of ICSP with due dates is handled with a two-stage method. First, a heuristic generates a set of cutting patterns that cover the demand with the objective of minimizing trim loss. Then, an ILP model is responsible for finding a cutting plan minimizing an aggregated cost function that includes material, setup and lateness costs. Their method is implemented in a coronary stent manufacturing company, providing efficient full cutting plans and patterns. Malik et al. (2009) propose a genetic algorithm for solving an ICSP with cycle service level, which represent the probability that the customer's demand will be met on time. In their model, that allows for a certain delay in meeting demand, an aggregated function of inventory, setup and trim loss costs is minimized. The authors compare their approach to a decomposed one where the CSP and LSP are solved sequentially. While their integrated approach delivers more cost-efficient solutions, it also tends to worsen the cycle service level. Thus, the authors propose to use multi-objective optimization to find trade-off solutions.

2.3.4 Shop floor scheduling

Apart from batch, hoist, CSP and ICSP scheduling problems, research dealing with waste minimization has been conducted for less specific production processes. Those are labeled as shop floor scheduling problems, and regroup various shop floor configurations such as jobshops, flowshops, single or parallel machines.

Setup considerations

Freeman et al. (2014) study the case of non-identical parallel machines subject to sequence-dependent setup costs and times, where the waste generated and processing time of a product depend on machine assignments. The authors minimize an aggregated function of the cost of waste (which originates from setups and operation processing) and overtime (when the hiring of additional workforce is needed). They solve the problem using greedy and decomposition heuristics, and conclude that considering the trade-off between waste and overtime cost is financially beneficial, especially in high value manufacturing environments. In Gould et al. (2016), a single-machine problem where waste is generated by sequence-dependant setups is studied. Depending on the sequence of products, short, medium or long cleaning operations need to be performed which generate increasing amounts of waste, the objective being to minimize the total amount of waste generated. The impact of each combination of products is first calculated using a source-destination matrix, and the problem is firstly solved using a comprehensive search algorithm. Optimal results are obtained but computation times become prohibitive when more than ten products are involved. A genetic algorithm is then proposed which is able to obtain optimal results for sequences of 50 products, and the authors comment that it is likely to be a useful tool for larger and more complex sequences. In Pulluru et al. (2017), the authors propose a water-integrated lot-sizing and scheduling approach for hybrid flowshops. Their study takes place in a cheese manufacturing plant that includes two production stages: a milk skimming step refers to process manufacturing while the cheese production step belongs to discrete manufacturing. The authors base their model on a previous MILP developed by Camargo et al. (2012) for parallel-machines in cases involving both continuous and discrete manufacturing. Their MILP aims either at minimizing the freshwater consumption by avoiding cleanings due to sequence-dependent setups and production campaign changes, or alternatively at minimizing the makespan with a restricted amount of available water. Zhang (2018) study the case of color changes in the automotive industry. Cars have to pass through a painting line, with a sequence-dependent amount of waste generated at each color change, before continuing to an assembly line. A buffer is available in-between that allows for a partial re-sequencing of the painted cars. The authors first propose a MILP, then use a multi-objective particle swarm optimization heuristic to obtain a Pareto front of solutions minimizing the painting line waste and tardiness. They compare the results of their heuristic with two existing genetic algorithms, obtaining near-optimal results and an overall better performance.

Idle time considerations

In Harbaoui et al. (2017), the problem of waste due to machine idle-time in a hybrid flowshop is tackled. The problem occurs in an industrial case of pasta production where the machines need to be cleaned if production is interrupted for more than 30 minutes, resulting in wasted material. The authors propose two MILP formulations, one aiming at minimizing production time and the other aiming at minimizing the material waste due to long production interruptions. Both models are tested on generated instances, showing that material waste can be avoided at the expense of an increase in makespan. They conclude by stating the need for metaheuristic methods in order to solve large instances and the possible inclusion of multi-objective optimization techniques.

Operations sequencing

Hanoun and Nahavandi (2012) address a bi-objective optimization problem in the joinery industry, with a flowshop where tardiness and material cost are to be minimized. Jobs using similar materials possess a saving factor which represents the achievable waste reduction when processing those jobs sequentially on the first machine. Moreover, different materials have different prices, meaning that reducing waste is more advantageous for some materials than for others. The problem is solved in lexicographic order using a greedy heuristic for waste minimization followed by simulated annealing for lateness minimization. Near optimal results are obtained with low computation times. The authors consider extending their model to handle hybrid flowshops and provide the decision-maker with a set of Pareto-optimal solutions for more flexibility. A similar problem is considered in Hanoun et al. (2012), this time solved using a cuckoo search heuristic. An approximate Pareto front is generated and compared with the true Pareto front obtained using a complete enumeration method. The authors report high accuracy with low computational cost, and aim at comparing their heuristic with other methods in further research. Coca et al. (2019) study the case of a flexible job-shop scheduling problem with economic, environmental and social considerations. Based on the case of metal pieces producing company, their objective function includes production costs, emissions of CO2, water consumption and steel and chrome waste. Social indicators are based on work arduousness due to vibrations, noise or temperature. Environmental and social indicators are then normalized and aggregated into a single value using weights. A Pareto front is then calculated to determine alternative schedules. They use two genetic algorithms based on the NSGA-II and NSGA-III methods respectively, finding schedules that improved the company's performance on all indicators. They acknowledge the interest of developing reactive scheduling methods for such production systems to avoid costly time and material losses in case of unforeseen event, as well as prioritize on which type of event would be the most disruptive.

2.4 Literature classification

In this section, all 71 previously reviewed articles are organized into classification tables, which are then discussed. Defining a classification enables a grouping of the issues addressed and provides a standardized terminology. Table 2.4, 2.5, 2.6 and 2.7 list the papers related to the batch and hoist, CSP, ICSP, and shop floor scheduling problems respectively, and their proportions are shown in Table 2.3.

Table 2.3: Percentage of articles reviewed per type of scheduling problem

Batch and Hoist	ICSP	CSP	Shop floor
37%	30 %	23%	10%

In Giret et al. (2015), the reviewed articles are organized using, in addition to the modeling approach, three keys which reflect observed typologies:

- type of means addressed in the scheduling method, respectively the input (i.e. reducing resource consumption), output (i.e. reducing emissions) and mixed approaches considering input and output simultaneously;
- multi-objective approach considered (i.e. what objectives are to be minimized in priority or considered as constraints);
- scheduling approach used, respectively proactive (i.e. uncertainties are taken into account with off-line scheduling), reactive (i.e. the schedule can be adjusted on-line in response to unforeseen events) or hybrid (i.e. both off-line and on-line scheduling).

In Akbar and Irohara (2018), the classification is based on the three field notation commonly used in scheduling (Graham et al., 1979), but features objectives and constraints specific to sustainable scheduling. Each of their reviewed article is classified using the following items:

- workshop type (e.g. single-machine, parallel-machines, job-shop, flow-shop);
- multi-objective approach considered (i.e. whether the objective function considers one or more objectives);
- model type (e.g. linear programming, integer programming, MILP . . .);
- solving method (i.e. heuristic, exact or a commercial solver);
- economic objective;
- environmental objective;
- social objective;
- economic constraints;
- environmental constraints;
- social constraints.

Similarly, we present this review using key features reflecting the different typologies observed. Our classification features an assortment of these entries and aims at identifying more accurately the different factors that are influencing waste generation and can be addressed through scheduling.

2.4.1 Classification criteria

The reviewed articles are grouped by problem type and scheduling concerns (see tables 2.4 - 2.7), then classified according to six criteria described below:

- **Economic objective:** economic aspect of the objective function (if there is one) to optimize in the scheduling problem. This includes both cost functions (such as production or inventory costs) and traditional scheduling objectives such as the makespan. The possible entries are:
  - Productivity: amount of product(s) produced per unit of time;
  - Profit: financial gain after all production (materials and operating) costs have been deduced from the selling price of the products;
  - Makespan: date of the end of the last operation to be processed;

- Tardiness: difference between a job's last operation's due date and its execution date;
- Setup time: time loss incurred at each operation changeover;
- Number of patterns (in the case of a CSP);
- Setup, inventory, materials, backlogging, transportation and overtime costs.

- **Environmental objective:** environmental aspect of the objective function (if there is one) to optimize in the scheduling problem. Those objectives can be related to resource efficiency (such as the trim loss, wastewater generation or freshwater consumption), or LCA assessment. The entries present are:
  - Waste and wastewater: output of waste and wastewater resulting from the production process;
  - Environmental impact: impact of the waste generation according to one or several criteria commonly used in LCA;
  - Materials and freshwater consumption: materials and freshwater input into the production system;
  - Environmental management cost: economic cost resulting from either the equipment cleaning operations or the environmental management measures in place, such as operating a water treatment plant;
  - Discharged effluents: quantity of wastewater discharged per unit of time (i.e. volume that the wastewater treatment plant needs to handle at a given moment);
  - Trim loss (cost or quantity): loss of material resulting from inefficient patterns during a cutting operation.

- **Solution method:** type of method used to solve the scheduling problem, in accordance with the common denominations found in the scientific literature. In case multiple methods were used, several entries can be present. Two entries separated with a '/' mean that the two approaches were used separately. A '+' between two entries means that the approaches were used jointly to solve the problem. The various entries can be seen e.g. in Table 2.4.

- **Multiobjective approach:** refers to the way the multiplicity of objectives (if relevant) was handled:

  - Lexicographic : the objectives are arranged in order of importance during the solving process;
  - Pareto front : a Pareto front is obtained which represents the set of non-dominated solutions for the multiobjective optimization, i.e. solutions that cannot be improved without degrading at least one of the other objectives;
  - Alternative solutions : several solutions with various trade-offs are provided, which might or not be part of the Pareto-efficient solution set;
  - Aggregated cost function : all objectives are combined into a single-objective function through the use of weights.

- **Scheduling approach:** type of scheduling approach used, according to three different entries (see Chaari et al. (2014) for more details):
  - Deterministic: no uncertainty in the data;
  - Proactive: scheduling takes uncertainty into account when designing off-line schedules;
  - Reactive: the schedule can be updated on-line to react to unpredicted events such as machine breakdowns or new orders.

- **Industrial context**: Type of industry or plant in which the scheduling problem takes place.

Table 2.4: Classification of batch and hoist scheduling related literature

Concern	Reference	Economic obj	Environmental obj	Solution method	Multiobjective approach	Deterministic	Proactive	Reactive	Industrial context
Setup considerations	Grau et al. (1994)	Makespan	Environmental Impact	Heuristic	Lexicographic	✓			Chemical plant
	Adonyi et al. (2008)	Makespan	Environmental management cost	S-Graph	Alternative solutions	✓			Paint
	Capon-Garcia et al. (2011)	Profit	Environmental impact & heat consumption	MILP / MINLP	Bi and tridimensional Pareto front	✓			Acrylic fibers
	Malmborg (1996)	Makespan	Waste minimization	Random search heuristic	Alternative solutions	✓			Chemical plant
	Berlin et al. (2006)		Environmental impact	Heuristic		✓			Dairy
	Berlin and Sonesson (2008)		Environmental impact	Heuristic		✓			Dairy
	Zhang et al. (2017)	Tardiness	Waste minimization	Local Search algorithm + Particle Swarm Optimization	Alternative solutions	✓			Textile dyeing
	Adekola and Majozi (2017)	Profit	Freshwater consumption	MILP	Aggregated cost function	✓			
	Grau et al. (1996)	Makespan, Productivity	Energy and waste minimization	Heuristic	Lexicographic	✓			Chemical plant
	Yue and You (2013)	Productivity	Environmental impact	MILFP	Pareto front	✓			Multipurpose batch
Process requirements	Xu and Huang (2004)	Productivity	Freshwater consumption	Movement graph	Lexicographic	✓			Electroplating
	Kuntay et al. (2006)	Productivity	Freshwater and chemicals consumption	Two-step algorithm	Lexicographic	✓			Electroplating
	Song et al. (2002)	Profit	Environmental Impact	MILP	Pareto front	✓			Refinery
	Liu et al. (2012)	Productivity	Freshwater and energy consumption	Mixed Integer Dynamic Optimization	Tridimensional Pareto front	✓			Electroplating
	Arbiza et al. (2008)	Profit	Environmental Impact	Genetic Algorithm	Alternative solutions	✓			Chemical plant
	Subaï et al. (2006)	Productivity	Discharged effluents	two-step Algorithm	Lexicographic	✓			Electroplating
	Vaklieva-Bancheva and Kirilova (2010)	Makespan	Environmental impact	Genetic Algorithm	Alternative solutions	✓			Dairy
	Chaturvedi and Bandyopadhyay (2014)	Productivity	Freshwater consumption	MILP	Pareto front	✓			
	El Amraoui and Mesghouni (2014)	Productivity	Energy and waste minimization	Genetic Algorithm	Pareto front / lexicographic	✓			Electroplating
Intermediate storage	Nonyane and Majozi (2012)	Profit	Wastewater treatment cost	State Sequence Network		✓			Multipurpose batch
	Majozi (2005)		Wastewater minimization	MINLP		✓			Multipurpose batch
	Majozi and Gouws (2009)		Wastewater minimization	MINLP		✓			Multipurpose batch
	Gouws and Majozi (2008)		Wastewater minimization	MINLP		✓			Multipurpose batch
	Adekola and Majozi (2011)		Wastewater minimization	MINLP		✓			Multipurpose batch
Plant and process design	Stefanis et al. (1997)	Profit	Environmental impact	MILP	Pareto front	✓			Dairy
	Al-Mutairi and El-Halwagi (2010)	Profit	Environmental management costs	MINLP	Aggregated cost function	✓			Refinery

Table 2.5: Classification of CSP related literature

Concern	Reference	Economic obj	Environmental obj	Solution method	Multiobjective approach	Deterministic	Proactive	Reactive	Industrial context
Setup considerations	Nonas and Thorstenson (2000)	Cutting, setup, and holding costs	Trim loss cost	Ranking point / local search / column generation	Aggregated cost function	✓			Metal
	Mobasher and Ekici (2013)	Setup cost	Materials cost	local search algorithms + column generation	Aggregated cost function	✓			Chemical fiber
	Araujo et al. (2014)	Number of patterns	Trim loss	Genetic algorithm	Alternative solutions	✓			Chemical fiber
	Cui et al. (2015)	Setup cost	Materials cost	Sequential Grouping Procedure + MILP	Aggregated cost function	✓			
	Golfeto et al. (2009)	Setup cost	Trim loss	Genetic algorithm	Pareto front	✓			
	Harjunkoski et al. (1999)	Setup number / Makespan	Waste cost / Energy cost	MINLP	Aggregated cost function	✓			Paper
	Kolen and Spieksma (2000)	Number of patterns	Trim loss	B&B algorithm	Alternative solutions	✓			Abrasives
	Cui and Liu (2011)	Number of patterns	Trim loss	Sequential Heuristic Procedure	Lexicographic	✓			
	Schilling and Georgiadis (2002)	Profit	Trim loss	MILP	Aggregated cost function	✓			Paper
	Wuttke and Heese (2018)	Setup time	Trim loss	Heuristic		✓			Textile
Inventory considerations	Bolat (2000)	Productivity	Trim loss	Successive Linear Programming Relaxation	Lexicographic	✓			Cardboard
	Lucero et al. (2015)		Trim loss	MILP / Heuristic		✓			Cardboard
	Gramani and França (2006)	Inventory and setup costs	Trim loss	Staged Combined Model	Aggregated cost function	✓			
	Na et al. (2013)	Materials cost	Trim loss	Two-phase heuristic	Aggregated cost function	✓			Float glass
Due Dates considerations	Arbib and Marinelli (2014)	Tardiness	Materials cost	ILP	Aggregated cost function	✓			Metal
	Reinertsen and Vossen (2010)	Tardiness	Materials cost	ILP + Sequential Heuristic Procedure	Aggregated cost function	✓			Metal

Table 2.6: Classification of ICSP related literature

Concern	Reference	Economic obj	Environmental obj	Solution method	Multiobjective approach	Deterministic	Proactive	Reactive	Industrial context
Setup considerations	Hendry et al. (1996)	Makespan	Trim loss	Two stage IP procedure	Lexicographic	✓			Metal
Inventory considerations	Reinders (1992)	Capacity and inventory use, service rate	Trim loss	Column generation + dynamic programming and goal programming	Aggregated cost function	✓			Wood
	Correia et al. (2004)		Material cost	Three stage MILP + Heuristic procedure		✓			Paper
	Gramani et al. (2011)	Production, inventory and setup costs	Trim loss	Column generation	Aggregated cost function	✓			Furniture
	Silva et al. (2014)	Material, cutting and storage costs	Waste cost	IP models + heuristics	Aggregated cost function	✓			Furniture
	Poldi and de Araujo (2016)	Inventory cost	Trim loss	Arc flow + heuristic	Aggregated cost function	✓			
	Arbib and Marinelli (2005)	Inventory and transportation costs	Trim loss	ILP	Aggregated cost function	✓		✓	Gear Belt
Setup and inventory considerations	Santos et al. (2011)	Production, inventory and setup costs	Trim loss	MILP	Aggregated cost function	✓			Furniture
	Campello et al. (2017)	Production costs	Trim loss	Heuristic	Pareto front	✓			Paper
	Suliman et al. (2014)	Production, inventory and setup costs	Trim loss	INLP / Algorithm	Aggregated cost function	✓			Metal
	Vanzela et al. (2017)	Production and inventory costs	Trim loss cost	MILP	Aggregated cost function	✓			Furniture
	Gramani et al. (2009)	Production, inventory and setup costs	Trim loss	MILP with Lagrangian relaxation heuristic	Aggregated cost function	✓			Furniture
	Melega et al. (2016)	Setup and inventory costs	Trim loss	Heuristics	Aggregated cost function	✓			
	Wu et al. (2017)	Production, inventory and setup costs	Trim loss	Progressive selection method with Dantzig-Wolfe decomposition	Aggregated cost function	✓			
	Leao et al. (2017)	Production costs	Trim loss	MILP / Rounding Heuristic	Aggregated cost function	✓			Paper
	Poltroniere et al. (2016)	Cutting, setup and holding costs	Trim loss cost	Arc flow / Heuristic	Aggregated cost function	✓			Paper
	Alem and Morabito (2012)	Production, setup, inventory and backlogging costs	Trim loss	Stochastic models	Aggregated cost function		✓		Furniture
	Alem and Morabito (2013)	Production, overtime, inventory and backlogging costs	Trim loss	Two-stage stochastic models with risk-aversion strategies	Aggregated cost function		✓		Furniture
Setup and due date considerations	Aktin and Özdemir (2009)	Production costs	Trim loss	Heuristic + ILP / Neighborhood Search Heuristic	Aggregated cost function	✓			Coronary stent
	Malik et al. (2009)	Setup and inventory costs	Trim loss	Genetic algorithm	Aggregated cost function	✓			Paper
	Poltroniere et al. (2008)	Cutting, setup and holding costs	Trim loss cost	Heuristics	Aggregated cost function	✓			Paper

Table 2.7: Classification of shop floor scheduling related literature

Concern	Reference	Economic obj	Environmental obj	Solution method	Multiobjective approach	Deterministic	Proactive	Reactive	Industrial context
Setup considerations	Pulluru et al. (2017)	Makespan	Water consumption	MILP	Lexicographic	✓			Dairy
	Freeman et al. (2014)	Overtime cost	Waste minimization	MILP / Greedy and decomposition heuristics	Aggregated cost function	✓			
	Gould et al. (2016)		Waste minimization	Comprehensive search algorithm / GA		✓			Multiproduct
	Zhang (2018)	Tardiness	Waste minimization	MILP / Particle Swarm Optimization	Pareto front	✓			Automotive
Idle Time	Harbaoui et al. (2017)	Makespan	Waste minimization	MILP		✓			Food
Operations sequencing	Hanoun et al. (2012)	Tardiness	Materials cost	Cuckoo search	Pareto front	✓			Joinery
	Hanoun and Nahavandi (2012)	Tardiness	Materials cost	Greedy heuristic + Simulated annealing	Lexicographic	✓			Joinery
	Coca et al. (2019)	Production cost	Wastewater, CO2 and waste minimization	Genetic algorithm	Pareto front	✓			Metal

2.4.2 Classification analysis

Batch and hoist scheduling related classification

A total of twenty-six papers belong to this category (see Table 2.4). As can be seen from the concern column, the literature is relatively varied regarding the angles from which waste minimization is addressed. Setup and process requirement-related literature represents more than half of the reviewed articles (9 and 7 respectively), while intermediate storage, environmental impact and plant design make up the rest. Only six articles do not possess any economic objective (Majozi (2005); Majozi and Gouws (2009); Gouws and Majozi (2008); Adekola and Majozi (2011); Berlin et al. (2006); Berlin and Sonesson (2008)). For those which do, productivity and profit are the two main objectives, the others being time-related indicators such as lateness and cycle time. From the perspective of environmental objectives, it can be seen that environmental impact and water-related objectives (wastewater production and freshwater consumption) are predominant. This is consistent with the scheduling problem studied (batch and hoist), and the industries identified, since their processes require intensive use of water and chemical products. Some articles have interpretations of environmental objectives in terms of cost, such as Adonyi et al. (2008) (equipment-cleaning cost), Nonyane and Majozi (2012) (wastewater treatment cost) or Al-Mutairi and El-Halwagi (2010) (environmental management costs). Exact and heuristic solution methods are evenly used (11 and 15 times out of 26 respectively). Only seven articles do not include a multi-objective approach, five of which deal with intermediate storage concerns where only wastewater minimization is considered. For those which do, bi-objective optimization is the most common (17 out of 26), and only two use an aggregated cost function. Only deterministic scheduling is considered. In accordance with the type of scheduling problem studied, all papers deal with process manufacturing, in industries such as the production of chemical products, multipurpose batch plants, food processing or electroplating.

CSP related classification

Sixteen papers involving CSP with scheduling are classified in Table 2.5. Most of those address setups (10), the rest being focused on due date and inventory considerations (6). In the cutting stock problem, trim loss minimization is considered both as an economic and environmental objective, since reducing losses equates to reducing materials cost and waste generation. As a result, nine economic objectives are cost-oriented (this includes materials, production, inventory and setup costs), with respectively four being time-related and three concerning the number of patterns. Similarly, all sixteen environmental objectives refer to either materials cost or trim loss reduction. Regarding the solution method, heuristic and metaheuristic approaches are the most common (9 out of 16). Four use linear programming, two propose a combination of both a heuristic and linear program, and one consider both linear programming and heuristic approaches. In accordance with the frequency of cost functions used as objectives, aggregated cost functions (9 out of 16) are the most common way to deal with multiple objectives. The rest propose lexicographic (2), alternative solutions (2) or Pareto front (2) approaches, and one is single objective with the trim loss serving as both environmental and economic indicator. All the reviewed papers use deterministic scheduling, and are set in specific industries such as paper and cardboard, furniture and metal sheet production where cutting operations are prominent.

ICSP related classification Twenty-one papers addressing ICSP are present in Table 2.6. Since CSPs and ICSPs are very similar in nature, the same trends can be observed in both Table 2.5 and Table 2.6. As a result from solving both the CSP and LSP into one integrated problem, the number of concerns addressed tends to be larger than for the CSP. Seven articles address only one concern, i.e. inventory only (6) or setups only (1). The rest consider both setup and inventory (11) or setup and due date (3) at the same time. Regarding the economic objective, eighteen papers have cost-oriented objective functions and two possess time-related objectives. Same as for the CSP, all environmental objectives consider materials and trim loss cost or trim loss reduction. Eleven papers use a heuristic-only approach and four use only linear programming, while the rest use both either jointly (4) or separately (2). Regarding the multi-objective approach, all but three papers use aggregated cost functions. The Pareto front and lexicographic approaches are both used once, and the remaining study uses the trim loss cost as both an economic and environmental objective. While most of the reviewed papers use deterministic scheduling, Alem and Morabito (2012, 2013) account for uncertainty in demand and production parameters, thus providing robust schedules. Arbib and Marinelli (2005), after proposing a deterministic model, consider a reactive feature by allowing for the introduction of urgent orders into the schedule, which results in prohibitive computing time. Finally, the industrial sectors concerned are the same as for CSPs, ranging from the paper, metal or wood to the furniture industry.

Shop floor scheduling related classification

Eight shop floor scheduling problems are classified in Table 2.7. Setup minimization and operations sequencing are the most commonly encountered (four and three times out of eight), the idle time concern being the only exception. Time-related economic objectives are considered five times, while Freeman et al. (2014) use overtime costs, which is the monetary consequence of an excessive makespan, Coca et al. (2019) considers production costs and Gould et al. (2016) has no economic objective. The waste minimization objective is used five times out of eight; materials cost and water consumption appear twice and once, respectively. The solution approaches are distributed between heuristics (5) and linear programming (3), all with a deterministic scheduling. The multiple objectives are mainly handled with Pareto front (3) and lexicographic (2) approaches, while aggregated cost function and single objective appear once and twice respectively. The joinery, plasturgy, automotive and food industries are considered.

2.5 Discussion and research perspectives

In this section, the trends emerging from the classification are discussed and analyzed in the perspective of waste minimization through scheduling. As the objectives and research approaches may vary depending on the type of industry, scheduling problem and research focus at stake, a transversal analysis provides a good overview of the problems involved.

The first observation that can be made from this classification is the lack of environmental impact analysis in the objective functions. Most articles focus on waste minimization through better resource efficiency, and only nine (all in the process industry category) consider the environmental impact as an indicator. Only three articles (Yue and You (2013); Song et al. (2002); Arbiza et al. (2008)) propose an LCA analysis, highlighting the need for a better assessment of the actual impact of waste rather than considering only its cost or raw quantity, as was observed in Smith and Ball (2012). Expanding the scope of the environmental objective function might also be necessary in order to avoid deteriorating the overall environmental outcome by focusing solely on one aspect. In order to facilitate this assessment process, several new tools have emerged during the last decades regarding the management of waste streams in the manufacturing field. Among them is the Environmental Management Accounting (EMA), and more specifically the Material Flow Cost Accounting (MFCA). Its aims are the identification, gathering, analysis and use of information regarding the various materials and energy flows in a production system (ISO 14040, 2006). With a better understanding of the costs and environmental impacts of these flows, it becomes easier to design more relevant objective functions for the scheduling problems and for the decision-makers to decide on trade-off solutions.

It is also important to point out that many times, waste is treated as an economic objective (via waste cost), which is insufficient for several reasons. Firstly, as mentioned in Section 1.1.3, the actual cost of waste tends to be underestimated by companies as those only account for removal fees by external providers (ADEME, 2016). Other internal costs such as production or handling costs are rarely considered in the overall waste cost accounting, leading to a misconsideration of their actual impact. Secondly, environmental impact and economic cost are not necessarily correlated, which can result in skewed priorities in decision-making. Hence a need for a better knowledge of processes and waste impacts, which needs to be coupled with multi-objective scheduling to account for all aspects of the problem. It is especially important in the light of how the duality between economic and environmental objectives is handled. In total, 30 papers propose an aggregated cost function, a number largely due to the predominance of cost-oriented objectives in the CSP and ICSP categories (27 out of 37). While aggregated approaches have the benefit of being easier to solve and providing direct information regarding the economic aspect, several studies insist on the importance of considering trade-offs for decision making. The Pareto front, lexicographic and alternative solutions approaches are evenly represented with respectively 13, 10 and 7 cases. Finally, 12 papers consider a single-objective approach, and notably all five articles related to the intermediate storage concern (see Table 2.4). The use of multi-objective optimization and trade-off solutions enables the introduction of previously ignored criteria into the decision-making process, and serves in raising awareness regarding environmental issues in production scheduling. It is also an efficient way to provide practical solutions that can be implemented depending on the practitioners' priorities. This should help industrialists implement sustainable scheduling in their companies. Additionally, while shop-floor scheduling problems are less prominent than industry-specific problems such as the batch and hoist scheduling problem or the CSP, they have progressed in the last years. Since they are more diverse in their configuration and involved constraints, this classification should help increase their representation in waste-minimizing scheduling problems literature.

2.6 Conclusion

This chapter aims at shedding light on the characteristics of waste-minimizing scheduling problems by looking at the existing studies on this topic. After defining the literature review methodology, the articles identified as relevant are described and grouped according to the type of scheduling problem they address and their waste generation mechanism. Based on this review, all articles are classified according to several criteria pertaining to their scheduling and environmental characteristics as well as their solving approach. In the discussion section, two main concerns are raised, regarding the determination of relevant environmental objectives and the usefulness of the results provided to decision-makers.

Although they remain limited in number, articles on waste minimizing scheduling problems feature various types of production systems and waste generation mechanisms. However, the limited existing literature makes modeling new problems and application cases difficult, as scientists in operations research are rarely versed in environmental assessment, while environmental researchers are seldom trained in operations scheduling. The proposed classification is a first step in unifying a heterogeneous field of research with a disparate terminology, as it fills a gap in the current literature and provides a structure for characterizing and grouping these problems.

To further address this issue, the next chapter provides answers to the concerns highlighted in the discussion section. Chapter 3 proposes a new methodology combining environmental assessment and scheduling aspects, which provides guidelines on how to identify waste minimization opportunities through scheduling. Illustrated through an application example, this should help enrich the literature on waste-minimizing scheduling, as well as give researchers guidance on how to determine relevant environmental objectives for scheduling problems.

CHAPTER 3

A methodology for waste-minimizing scheduling problems identification

Contents

The results presented in this chapter have been published in:

- C. Le Hesran, A.-L. Ladier, V. Botta-Genoulaz, and V. Laforest. A methodology for the identification of waste-minimizing scheduling problems . *Journal of Cleaner Production*, 2019c

- C. Le Hesran, A.-L. Ladier, V. Laforest, and V. Botta-Genoulaz. Using flow assessment to identify a scheduling problem with waste reduction concerns : a case study. In *6th International EurOMA Sustainable Operations and Supply Chains Forum, Göteborg, Sweden.*, 2019d

Résumé du chapitre 3

L'objectif de ce troisième chapitre est de répondre à la deuxième interrogation exprimée dans l'introduction, à savoir:

Comment identifier les opportunités de réduction des déchets par l'ordonnancement?

Prenant en compte les considérations du chapitre précédent, une méthodologie est proposée pour identifier et caractériser précisément les opportunités de réduction des déchets par l'ordonnancement dans un système de production. Pour ce faire, une revue de littérature des méthodologies de suivi de flux existantes est réalisée. Celles-ci sont groupées en fonction de leur niveau de décision (stratégique et tactique ou opérationnel), et de leur prise en compte des critères environnementaux et économiques. Aucune méthodologie existante ne permettant de répondre à notre question, nous nous basons sur les connaissances tirées de la littérature pour proposer notre propre méthodologie en quatre étapes. Une première étape basée sur l'utilisation de l'analyse de cycle de vie, de comptabilité des flux de matière (Material Flow Cost Accounting, MFCA) et de la méthode intrants-débit-sortants (Input-Throughput-Output, ITO) permet de diviser le système de production en sous-systèmes indépendants vis à vis de la question, et d'estimer leur coût et impact environnemental. Le(s) sous-sytème(s) présentant le plus grand potentiel de réduction des déchets par l'ordonnancement sont sélectionnés pour la suite de la méthodologie. Grâce aux résultats de la méthode ITO, un inventaire permettant d'identifier les flux pouvant être affectés par l'ordonnancement est réalisé. Celui-ci est suivi d'une évaluation des coûts (grâce à la méthode Activity Based Environmental Costing, ABEC)) et de l'impact environnemental (grâce à l'Analyse de Cycle de Vie, ACV)) afin de déterminer les fonctions objectif à considérer. Finalement, la quatrième étape reprend l'ensemble des informations obtenues jusqu'ici afin de présenter selon la notation de Graham (α, β, γ) (type d'atelier, contraintes et fonctions objectif), les données du problème d'ordonnancement correspondant.

Cette méthodologie est testée et validée via l'étude de cas d'une usine de fabrication d'enjoliveurs. Un potentiel de réduction de 10% des déchets dangereux générés est identifié, et le problème d'ordonnancement machine unique avec tâches couplées dans un contexte de fabrication à la commande correspondant est caractérisé. Cette étude de cas démontre l'intérêt que peut avoir cette

méthodologie à la fois pour les chercheurs et les entreprises, en permettant l'introduction de critères environnementaux pertinents dans des problèmes d'ordonnancement réels.

A methodology for waste-minimizing scheduling problems identification

This chapter aims at addressing some of the issues raised in the previous chapter, namely the lack of literature on waste-minimizing scheduling problems, especially shop-floor scheduling problems, and the need to properly characterize and classify them, thus providing an answer to the following question:

How to identify opportunities for waste minimization through scheduling ?

In the next sections, an overview of the current literature on flow assessment methodologies is given, and the advantages and shortcomings of existing methodologies are identified. As it turns out that no current methodology is suited for our purpose, we define the specifications needed for our proposed methodology to answer our research question, and a framework for its implementation is proposed in Section 3.3. To validate its usefulness, a practical case is studied in Section 3.4 followed by discussion, and conclusions are drawn in the last section.

3.1 Introduction

As expressed in Chapter 2, current waste-minimizing scheduling literature suffers from a lack of precision regarding the environmental objective function as well as the waste cost assessment. While the classification provided previously can help in standardizing such objective functions, finding new problem types or characteristics and defining them appropriately will foster the apparition of new studies on this topic. In order to accurately identify waste minimization opportunities, it is important to determine where and how waste is generated. Part of this endeavor involves flow assessment, or the study of how resource flows (be they materials or energy) circulate within a production system and how they are consumed at the operational level. From a decision-maker's perspective, knowledge regarding the cost and environmental impacts of the various flows is important in order to consider trade-offs, especially since the real cost of waste flows tends to be severely underestimated (ADEME, 2016). Providing environmental information linked to operational parameters would facilitate the integration of environmental aspects into the objective functions or constraints when modeling scheduling problems, taking advantage of the growth of multi-objective optimization in recent years. As stated in the discussion of the previous chapter, several methodologies exist for flow assessment (Jasch, 2003), involving economic or environmental criteria. They can be used at different decision levels, i.e. the operational, tactical and strategic ones, although they tend to be ill-adapted to improving production scheduling (Gould et al., 2016). To address this lack, we first review the existing methodologies for flow assessment, then propose a new framework which includes economic and environmental criteria, while simultaneously focusing on the operational level of production. By incorporating parameters related to schedule efficiency into the quantitative and qualitative flow assessment, we mean for this methodology to facilitate the rapid identification and assessment of waste-related issues in scheduling manufacturing processes.

3.2 Material flow assessment methodologies overview

In this section, an overview of the current literature regarding flow assessment and activity characterization is presented, especially at the operational level. The combination of the following keywords was used during the literature search: material, flow, modeling and waste. As in Chapter 2, terms referring to urban waste collection and management were excluded, i.e. municipal; national; regional. The Web Of Science search engine was used to identify peer-reviewed articles featuring the aforementioned combination of keywords in their title, abstract and keywords. All articles resulting from this literature search were screened to check whether they belong to our scope, and the ones deemed most relevant selected. Further research was made by looking at the references and methodologies cited in the selected papers as well as the articles citing our sampled papers. This review focused specifically on studies published in the English language. One way to enrich it might be to consider articles written in German or Japanese, as these two countries have been at the forefront of research on material flow assessment. In addition to their consideration of environmental and economic criteria, the reviewed studies have been grouped according to the decision level they consider in their methodology, respectively the strategic or tactical and operational levels.

3.2.1 Strategico-tactical approaches

Most applications of material flow assessment methods take place at the strategic and tactical levels of decision-making. They can cover production sites, regions or even national economies in the case of some studies, and often provide information regarding possible investments or process improvements that can increase resource efficiency. While they are usually not suited for improving production scheduling, they can provide insight regarding data collection, environmental indicators or cost assessment. In the following paragraphs, the reviewed methodologies are grouped into three categories depending on whether they include environmental, economic or both environmental and economic criteria.

Environmental criteria

Environmental Management Accounting (EMA) is a framework first developed in Germany, and later formalized internationally (United Nations Division for Sustainable Development, 2001). Its aims are the identification, collection, analysis and use of information regarding material and energy flows within a system as well as their related costs and environmental impacts (ISO 14051, 2011). While production and product pricing is usually done based on general accounting, which is destined to stakeholders and financial regulators, this can lead to a dilution of information, environmental costs (e.g. waste related costs) being included in broader categories. This results in a loss of visibility regarding potential savings (Jasch, 2003). EMA aims at solving this issue by proposing a combined approach between flow assessment, general and analytical accounting. It uses metrics that are both physical (for flows) and monetary (for costs, revenues and savings), and can be used for the performance assessment of a system or the evaluation of environmental projects. Within the EMA framework, several tools are proposed to improve environmental performance. One of those is Material Flow Assessment (MFA), which aims at identifying the various material flows circulating within a system in order to detect possible inefficiencies. It is based on the principle of material balance, which states that material flows entering a quantity center eventually leave it under the form of either product or material loss. MFA is useful for figuring out where inefficiencies in resource consumption happen, providing the decision-maker with a map of flows in the system. By reducing resource consumption, it is possible to reduce the environmental impact. MFA is mostly used on large scales, such as the regional and national ones (Patrício et al., 2015) or across whole industries (Wang et al., 2016).

Life Cycle Assessment (LCA) is defined by the ISO 14040 (2006) as "a technique for assessing the environmental aspects and potential impacts associated with a product”, based on its whole life cycle from raw materials extraction to end-of-life. LCA provides a comprehensive environmental assessment of products and material flows, with existing databases describing the impact of materials and processes for multiple criteria such as resource depletion, effects on human health or on the ecosystem. As it is much more specific than other methods, LCA is often used in complement with other EMA methods in order to provide comprehensive environmental information. Its applications are mostly focused on strategic planning, scenario comparison and product development and improvement (ISO 14040, 2006).

Economic criteria

Activity Based Costing (ABC) aims at accurately reflecting the costs of each activity performed in an organization. The method focuses on tracing the resources consumption (cost drivers) and cost associated with each activity and product (cost object). It is based on traditional cost accounting techniques, with two main purposes. The first one is to prevent cost distortion, which occurs when multiple costs (such as waste costs) are grouped into overhead, losing the respective source of each cost. The second purpose is to prevent non value-added activities by avoiding inefficiencies in production (Mahal and Hossain, 2015). Activity Based Environmental Costing (ABEC) follows the same principles as ABC, but assigns the costs of all environmental activities to their corresponding products. This allows product costs to truly reflect their environmental costs instead of being allocated to overheads (Phan et al., 2018). In a study of Australian manufacturers, Phan et al. (2018) review the implementation of Environmental Activity Management (EAM) methods, including ABEC, among companies. While ABEC is shown to improve environmental performance when implemented, especially regarding resource usage, results show low adoption rates. Additionally, its primary focus is on the accurate cost assessment of activities, which include environmental activities, and environmental impact reduction comes as a consequence of considering environmental costs.

Viere et al. (2010) propose a Verbund-Model (or network model) based on Petri nets for scenario comparison. They use Petri net components, transitions (for transformation and transportation processes), places (for storage) and arrows (i.e. connections between places and transitions) to model the production system, and flows are represented as Sankey diagrams (Schmidt, 2008). From a mathematical point of view, transitions are computed independently, each calculation starting when an adjacent arrow demands or delivers material. Costs are assigned to flows based on the results provided by the material flow network. Implemented in a chemical company, the Verbund-Model is used to create scenarios of future demand, prices or production parameters. The authors report use in strategic planning such as forecasts regarding shortages or surpluses of materials on several years or identification of projects to avoid future issues.

Environmental and economic criteria

To improve their versatility and usefulness, some of the previously described methodologies have been extended in order to include additional information regarding environmental and economic aspects. As an extension of MFA, Material Flow Cost Accounting (MFCA) is one of the main tools within the EMA framework for flow assessment. It is defined as a “tool for quantifying the flows and stocks of materials in processes or production lines in both physical and monetary units" (ISO 14051, 2011). MFCA’s main goal is a better knowledge of the nature and costs of material flows and energy use in order to support decision-making in production and improve the environmental and financial performances. Similarly to MFA, it is based on the material balance principle within a system, but adds the cost of each flow to the information provided. Once a boundary for the system has been defined, all flows and costs within the system can be linked to quantity centers (i.e. selected part or parts of a process for which inputs and outputs are quantified in physical and monetary units), and a cartography of their circulation is possible. By observing which flows represent the biggest impact or cost, it becomes possible to identify inefficiencies in the system and propose improvements. These tend to focus on process improvement or product and plant design (Wang et al., 2017), although some cases of efficiency improvement through lot-size are proposed by Zhao et al. (2013). More detailed information on the MFCA process is available in ISO 14051 (2011). In a review on MFCA applications and prospective expansion, Schaltegger and Zvezdov (2015) observe that most applications of MFCA are done based on short and long term past information in order to identify inefficiencies and possible improvements in production. Their approach is however largely focused on the strategic and tactical levels, with considerations on investment or procurement strategies, and they do not mention MFCA use for operational efficiency. Christ and Burritt (2015) also review MFCA implementations, coming to the conclusion that while enjoying the interest of researchers, the adoption of MFCA by companies is quite low outside of action-based cases. The research perspectives concentrate on the relationship between researchers and companies regarding MFCA, and do not include potential prospects in the scope of the method or its implementation level (strategic, tactical or operational). While the introduction of the ISO 14051 standard might facilitate its adoption in industrial companies, research has so far concentrated on the implementation process of MFCA within a company rather than on extending potential its applications, especially to the operational level.

Propositions have been made to improve the applicability of MFCA, such as Schmidt (2013) who proposes an extension of MFCA (Ext-MFCA) that adds environmental information to each flow in addition to physical and economic data. Using mathematical equations, he links each flow to its corresponding greenhouse gases emission equivalent, which permits to easily switch between physical, economical and environmental representations. This additional information provides new insight for the decision-maker, since the physical and environmental dimensions are not necessarily correlated (i.e. a flow with a high impact on physical metrics might not have a high environmental impact, and conversely). Schmidt et al. (2015) improve energy flow modeling in MFCA to provide more accurate information on energy consumption. They also extend the costs information related to each flow, and propose economic estimations for investments based on an MFCA analysis.

In Cagno et al. (2012), the Extended Activity Based Environmental Costing (ExtABEC) method is described, which considers not only the products but also by-products and waste as cost objects, in a similar approach to MFCA. A 12-step methodology is proposed, with a set of four cost indexes to evaluate the production efficiency:

- efficiency waste versus product, which represents the inefficiency of resource usage;

- waste cost unseen, which is the cost represented by all waste without explicit knowledge of the management (and which ExtABEC aims at disclosing);

- two performance indexes regarding the costs of resources and activities spent on waste versus the total resource and activity costs respectively.

Their method is implemented in an Italian company where they estimate that waste contribute to 8% of the cost of a product.

Study of material flows is also present in the building industry, which is the main waste producer in volume (Llatas, 2011). In this specific case, material flows and their resulting waste flows are usually calculated predictively in order to organize the construction or destruction plan to minimize their impact, as well as estimate their costs. In Li et al. (2016), a Work Breakdown Structure is used to determine each individual component of the construction plan, and waste-conversion indices serve to calculate their respective waste flow based on their materials requirements. Materials are divided into four categories, and a subsequent analysis of the calculated waste flow reveals the most impacting materials or activities for a potential improvement.

On a larger scale, input-output tables are tools that enable monitoring of flows at the level of national economies or industrial sectors. Physical Input Output Table (PIOT) is a variant of the Monetary Input Output Table (MIOT). PIOTs share a lot of similarities with the MFA methodology (Nakamura et al., 2007), although waste tends to be overlooked, for which a first solution was proposed in Nakamura and Kondo (2002) and examplified in Nakamura and Nakajima (2005). They rely on a matrix representation of inputs (at varying degrees of processing) and processes in order to calculate the different flows, and conversions can be made from MIOT to PIOT for both economic and environmental assessments. A framework for constructing PIOTs with environmental criteria is proposed in Hoekstra and van den Bergh (2006). Additionally, Xue et al. (2007) propose a framework for aggregating individual processes into larger production systems when using input-output tables.

3.2.2 Operational approaches

While strategic and tactical approaches mostly focus on the flows themselves, operational approaches tend to consider the processing units and their characteristics in the system description. This is particularly relevant to our research question, since waste-minimizing scheduling concerns primarily originate from the processes.

Environmental criteria

Gould and Colwill (2015) propose a new framework for Material Flow Assessment in Manufacturing (MFAM). In their five-steps methodology, the authors first define the production system scope, carry out the material flow inventory and assessment, then propose an improvement scenario, an interpretation phase being applied during the whole process. They identify three manufacturing processes that can affect material flows, namely transformation, storage and transport processes. Transformation processes can have environmental and economic impacts on the various flows, while storage and transportation steps are mostly related to scheduling considerations. After the flow inventory and assessment step, the authors propose an improvement scenario modeling step, where factors such as process sequencing, process substitution or process optimization are investigated. This step is supposed to be iterative, as each measure taken might introduce additional problems. This framework is implemented in Gould et al. (2016) in the case of two production lines with five processes each and more than 1000 products using over 1000 raw materials. Based on the first three steps, the cleaning operations associated with product changeover are deemed the most impacting, and the improvement scenario aims at minimizing the resource consumption from these changeovers. To this end, a Genetic Algorithm (GA) is proposed and compared with a comprehensive search method, and results show that the GA is more suited for instances with more than nine products. In Gould et al. (2017), the same production system is considered but the system scope is reduced to a single process responsible for the resource intensive changeovers. Improvement scenarios with process design changes are modeled and tested using k-means clustering and ant colony optimization, providing the most efficient scenario regarding resource usage and process design changes. The authors conclude on future extensions for this study, such as improving the MFAM methodology to include order quantities and fulfillment requirement, or adding flexibility to their algorithm to accommodate rescheduling. The inclusion of cost considerations is also important, especially in the case of process design changes where retrofitting is needed. The addition of multi-parameter assessment (to balance water, energy and materials consumption) will also be a future focus. This methodology enables the decision-maker to focus on the most impacting issues and implement improvement measures accordingly. It is a generic method, and while it can lead to changes on scheduling, it does not provide information regarding costs and the economical aspect of the improvement scenarios.

Economic criteria

The Input-Throughput-Output (ITO) method (Schubert et al., 2011) aims at gathering information on processes at the operational level. At the core of the ITO method is the flexibility of the information it can process regarding input, throughput and output. While the EMA framework focuses on costs and material flows, the ITO method aims at characterizing activities based on their operating parameters. In addition to physical flows that enter and exit an activity, information related to its operation is also included. Machining parameters or geometrical characteristics are gathered, which allows for a parametric description of the process (or at least its aspects pertaining to improving efficiency). This is particularly relevant for the research question of this chapter, as the modeling of a production system requires obtaining the different parameters that affect it; in our case information regarding scheduling issues. Using parametrization, it also becomes possible to model the output flows of an activity based on its input characteristics and operating parameters. If this process is extended to the whole system, it allows for a characterization of all flows based on the characteristics of the raw materials used and the processes they go through.

Value Stream Mapping (VSM) is a lean management method that aims at identifying all non value-added activities along a production or supply, for the improvement of economic performance – e.g. reducing waiting times, inventory or overproduction. See Rother and Shook (2003) for a detailed explanation of VSM implementation. It is based on the description of all consecutive production processes, including storage and transportation. VSM provides a current-state mapping of all operations and the transitions between them, with operational information such as processing and setup times or inventory space. Based on the current-state map and identified non value-added activities, a future-state map is devised to assess the possible improvements resulting from implementing lean measures. While VSM does include material flows in its mapping, those flows mostly concern products and parts used rather than physical quantities of materials. Although the term “waste" is commonly used in VSM, it typically represents non value added activities rather than material waste.

Environmental and economic criteria

VSM was originally created for the improvement of economic performance, but several studies have attempted to integrate sustainable development indicators into its implementation (Faulkner and Badurdeen, 2014). In Vinodh et al. (2015), a framework is proposed for a Sustainable VSM (Sus-VSM), in which green metrics are included in order to improve economic, environmental and social performance. The authors study the case of an automotive parts production plant, and collect both physical data (material and power consumption) and operational information (lead time, cycle time). Information on each activity is also collected, such as processing times or in-process inventories. A state map of the production line is made, including the gathered data related to the environmental and social metrics, and lean improvement measures are proposed according to different scenarios. While less extensive than MFCA regarding flow assessment and less precise than ITO in terms of activity description and linking, this approach has the benefit of grouping in a same representation environmental, economic and social metrics as well as operational parameters. In Brown et al. (2014), the Sus-VSM method is applied to different manufacturing environment (low variety - high volumes, high variety - low volumes and low variety - medium volumes respectively), showing its flexibility in regards to the shop floor configuration.

Lambrecht and Schmidt (2010) use a Material Flow Network (MFN) based on Petri nets to improve the efficiency of a waste incineration plant. They provide a prototype add-on to the LCA software Umberto[1] in which production parameters are embedded in transitions and places (i.e. transformation and storage processes). This allows for simulations of the production process with variable input parameters. Using successive simulations, their aim is to optimize the material flows for better efficiency. Although their add-on does lead to improvements in efficiency through better product mix, the authors also comment on its black-box nature which results in no analytic information about the material flow model, hiding potential improvements. A methodology for the mathematical modeling of MFNs is proposed in Lambrecht and Thißen (2015), and implemented in the case of a tungsten recycling facility in Lambrecht et al. (2018).

3.2.3 Multi-level approaches

The previously described methods focus on specific decision levels. We now review the methodologies that integrate both operational and strategic/tactical aspects in their implementation, be it regarding the information used, the modeling level or the decision support provided.

[1]https://www.ifu.com/en/umberto/lca-software/

Despeisse et al. (2013) present an approach for the systematic identification of improvement opportunities in resource efficiency. They propose an Integrated Factory Modeling tool (Integrated FM), which spans different decision levels such as plant and process planning, supporting facilities or production scheduling. A production plant is modeled using the IES Virtual Environment modeling and simulation tool[2], and an analysis is made to identify improvement measures. Their simulation is extensive but requires a lot of data (physical, architectural, operational) in order to be carried out. The scale of the study (factory level, including supporting facilities and buildings) might not be suited to the modeling of a scheduling problem as it expands beyond the scope of the operational level.

Smith and Ball (2012) introduce a methodology for sustainable manufacturing through Material, Energy and Waste (MEW) flows. Based on the IDEF0 modeling methodology (Colquhoun et al., 1993), they propose a MEW Process Flows Modeling (MEW-PFM) representing the activities of a system as well as their input, control, output and mechanism. A hierarchical decomposition of activities can be done to provide more detailed representations. A quantitative analysis is made on process flows, and a Pareto analysis serves to rank them based not only on their quantity, but also on the ability to influence them. A sequence of sixteen guidelines is provided for the implementation of the methodology. The authors comment on the lack of dedicated metrics and tools for the modeling and evaluation of shop floor performance. This study brings insight on data collection and system modeling, but does not consider scheduling in its improvement methodology.

Finally, Kurdve et al. (2015) propose a Waste Flow Mapping (WFM) approach in a multi-site case study, examining wasted material flows, costs, material efficiency and operational efficiency in waste management systems of 16 automotive production sites. The identified waste flows are grouped into streams with similar characteristics, facilitating the implementation of improvement measures. Three steps are considered, namely a first mapping of value and non-value adding outputs, followed by horizontal and vertical efficiency analyses. Improvements in waste handling, management and treatment are then proposed based on the waste hierarchy advocated in Kurdve and Bellgran (2011).

[2]https://www.iesve.com/

3.2.4 Flow assessment methodologies review analysis

All previously described methodologies can be grouped according to their decision level and criteria considered. As shown in Figure 3.1, only five out of seventeen methodologies consider both economic and environmental criteria on the operational decision level. While those five studies do consider operational parameters in their approach, scheduling is not explicitly considered as an improvement lever. Only Despeisse et al. (2013) include production schedules in their model (Integrated FM), and only Gould et al. (2016) use production scheduling to improve the environmental performance (MFAM), although economic performance is not considered in the results. Finally, the decision-support tools provided take different forms: some enable the decision-maker to identify inefficiencies, and others directly provide improvement scenarios.

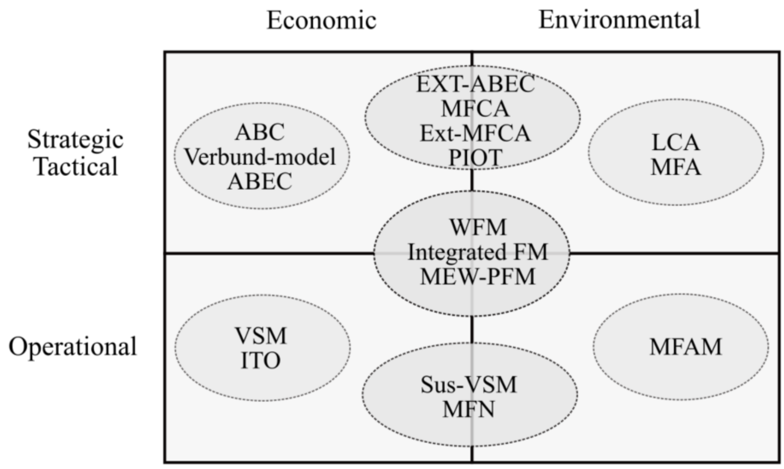

Figure 3.1: Methodologies grouping according to their included criteria and decision-level

Several conclusions can be drawn from this review of the flow assessment methodologies. First, it highlights the absence of dedicated tools relating flow assessment and waste minimization through scheduling. Second, although none of the reviewed methodologies are directly fit to answer our research question, they provide insights regarding the problem at hand which can be used to build our required framework. LCA already has established and well-tried guidelines for defining the perimeter of a study and in allocation methods for environmental impact assessment. MFCA comes with a lot of documentation and examples of material flow inventory applications, both on environmental and economic aspects. From the operational point of view, the ITO method is effective in describing process parameters, and the MFN method provides examples of mathematical modeling of the flows. Finally, MFAM shows that it is possible to identify inefficiencies in a system using flow assessment and propose solutions through scheduling, even if this approach does not expressly consider scheduling parameters or economic evaluation in the flow assessment model. Although flow assessment is a promising tool in order to promote waste-minimization through scheduling, no dedicated methodology for this specific purpose has been proposed yet. This would allow for the identification of accurate environmental objective functions as well as help highlight the actual cost of waste to decision-maker. Additionally, it is a great way to identify new problem types and waste-generating mechanisms linked to scheduling, which would enrich the classification proposed in Chapter 2. In the following section, a new methodology for the identification of waste minimization opportunities through scheduling is presented.

3.3 Proposed methodology

Section 3.2 shows that no existing flow assessment methodology can provide answers for our research question, i.e. to support the identification and characterization of waste-minimizing shop-floor scheduling problems. Using the insight provided by all these studies, we propose a methodology composed of four steps. The contribution of this section does not lie in the novelty of the methodological steps proposed, as they are inspired from other preexisting approaches. Rather, its added value consists in utilizing and combining knowledge from the aforementioned studies in order to tackle a problem not yet covered by researchers. It is necessary to keep the level of complexity low enough for an easy use in an industrial context while still being representative of real-life situations. To facilitate the implementation of this methodology, the data used is deterministic, with no uncertainty in parameters or unexpected machine failures.

Figure 3.2 summarizes the four steps that we propose for supporting the identification and characterization of waste-minimizing shop-floor scheduling problems. These steps consist in a first broad definition of the product system and its boundaries. It is then split into subsystems, the impacts of which are estimated (Step 1). A flow inventory (Step 2) and flow assessment (Step 3) are carried out on the subsystem(s) with the most potential for improvement. Finally, based on the information from the previous steps, a description of the waste minimizing scheduling problem is made (Step 4). These steps are explained in detail in the following sections.

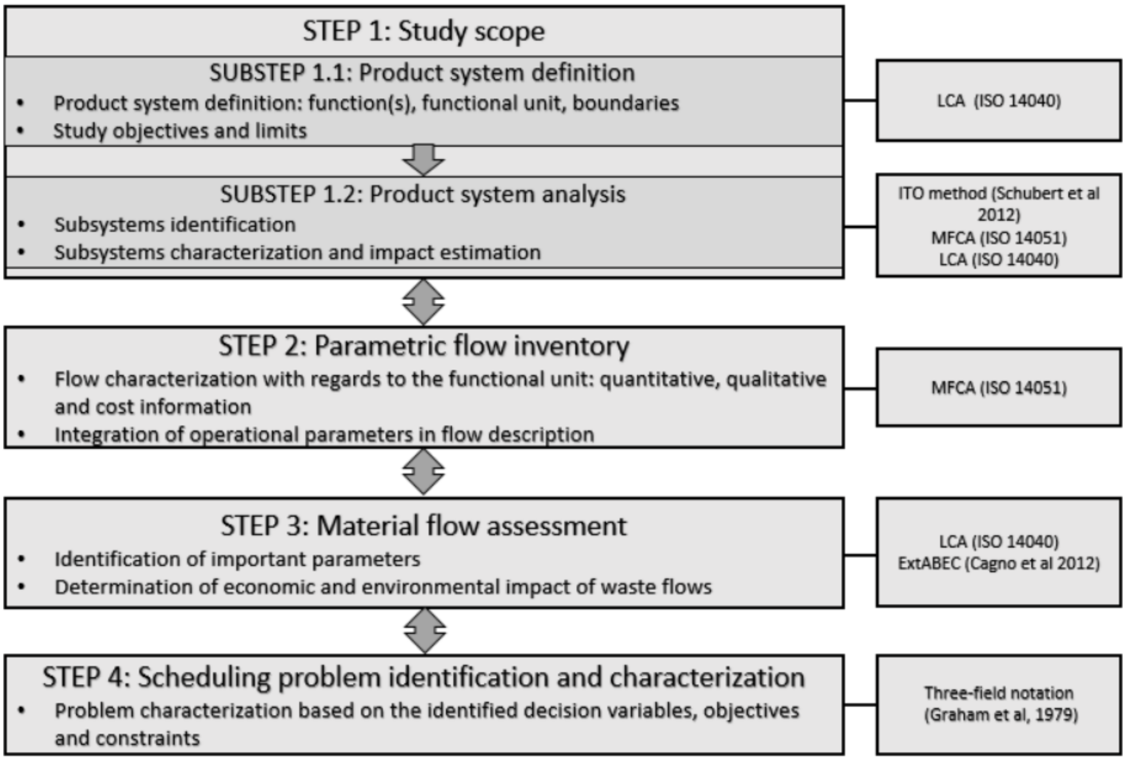

Figure 3.2: Proposed methodology implementation steps and associated tools

3.3.1 Step 1: Study scope

The use of this methodology can be motivated by a need to conform to environmental regulations, to obtain a certification, to comply with larger corporate policy or to improve brand image. The choice of the product system considered can depend on this motivation, e.g. a legal injunction to reduce a specific pollutant will make the product system responsible for generating this pollutant the focus of this methodology. The aim of this first step is to identify processes or activities within a product system where improvements could be made regarding waste generation.

Substep 1.1: Product system definition

This first substep defines the scope of the system considered. Following the guidelines of the ISO 14040 (2006) standard for LCA, several items should be clearly identified and defined, which are summarized in Figure 3.3.

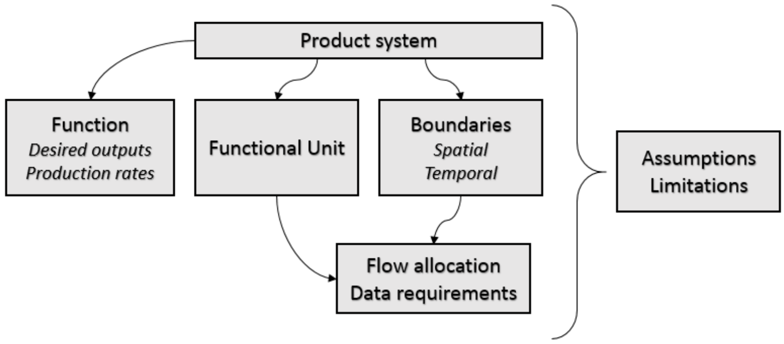

Figure 3.3: Scope and boundaries definition

The product system is "a collection of unit processes with elementary and product flows, performing one or more defined functions, and which models the life cycle of a product" (ISO 14040, 2006). It can be a whole factory or a subpart of a system, and is equivalent to the production system for which a schedule must be determined. Each of the unit processes perform one or several functions, which all contribute to the function of the product system as a whole. This function should be defined in terms of objectives, such as the manufacturing of certain products, and specify if any other characteristics are required for the production. Such characteristics can be e.g. a minimum production rate or a certain product quality range. Once the product system and its function have been defined, its boundaries can be determined.

The spatial boundary includes all unit processes that fulfill a part of the system function, i.e. the machines considered in the scheduling problem, as well as auxiliary processes, i.e. processes that contribute to the overall objectives without directly being involved in the product manufacturing such as wastewater treatment plants or byproduct regeneration units. The input and output flows that enter or exit the system boundary are called elementary flows, and will be the basis of the impact assessment. This assessment relies on determining the physical quantities of materials which circulate in the system. These physical quantities are later translated into environmental (based on a number of environmental indicators) and economic (i.e. the cost of generating and managing each waste output flow) impacts using LCA and a cost assessment method. It is necessary to determine a temporal boundary for the system, which defines the length of time over which the flow assessment is carried out.

The Functional Unit (FU) is also a concept from the LCA methodology, and represents the "quantified performance of a product system for use as a reference unit" (ISO 14040, 2006). The functional unit may be a certain quantity of product(s) to manufacture, a set amount of production time or a certain input flow for example. Flows within the system are defined to fulfill the function expressed by the functional unit.

The flow allocation corresponds to the repartition of input and output flows between all processes for the determination of their respective impacts. Procedures for flow allocation can be found in Pradel et al. (2016). Finally, it is necessary to define the requirements regarding data collection (timescale, accuracy...) and explain the assumptions made regarding the product system as well as the limitations of the study. An example of product system is shown in Figure 3.4.

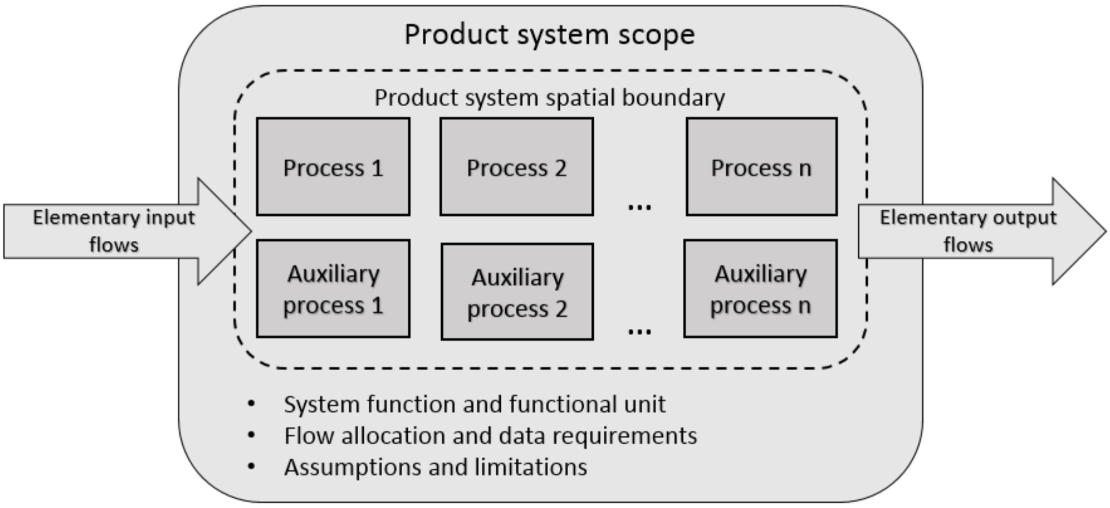

Figure 3.4: Example of product system

The product system definition is important as the impacts will be calculated based on the elementary output flows. The results and improvement measures proposed might change by including or not some unit processes and auxiliary processes. Product system definition is not a one time process, and should be modified or updated as the methodology implementation progresses and new information is available. It is also relevant to consult the decision-makers involved with the product system, as they can bring information on the operating process, waste management or production objectives. An example of survey is available in Appendix C.

Substep 1.2: Product system analysis

Quantity centers characterization: Once the product system and study scope are described, it is necessary to identify the most relevant parts to focus on. The first step is to accurately delimit all the independent subsystems (subsets of quantity centers) composing the global product system. Two subsystems are independent if no constraint or restrictions are carried from one to the other (either through material or information flows), meaning that their respective scheduling problems are decorrelated. Such decoupling can appear e.g. through the use of buffers between processes, and should be identified by looking at the products structure trees. Checking for buffers and bottlenecks can also provide information. Subsequently, the different quantity centers composing each subsystem need to be characterized. According to the ISO 14051 (2011) standard on MFCA, a quantity center is a selected part or parts of a process for which inputs and outputs are quantified in physical and monetary units. Quantity centers include the machines that compose the workshop, but also the auxiliary processes. They can represent transformation (i.e. processes where the nature of flows can be affected), transport or storage processes, such as presented in Gould and Colwill (2015). Information regarding quantity centers is gathered using the ITO method (Schubert et al., 2011), as it provides information regarding both the flows that cross a quantity center (input and output) and the parameters within that quantity center affecting these flows (throughput). Basic information to be collected (see Figure 3.5) includes:

- Input flows and their characteristics (type, concentrations, composition, cost...);
- Process parameters: description of how these processes affect the input flows and operational parameters (i.e. throughput, setups, capacity, operating costs, failure rate, resource consumption and efficiency...);
- Output flows characteristics based on the input flows and process parameters.

The ISO 14033 (2012) standard provides information regarding environmental

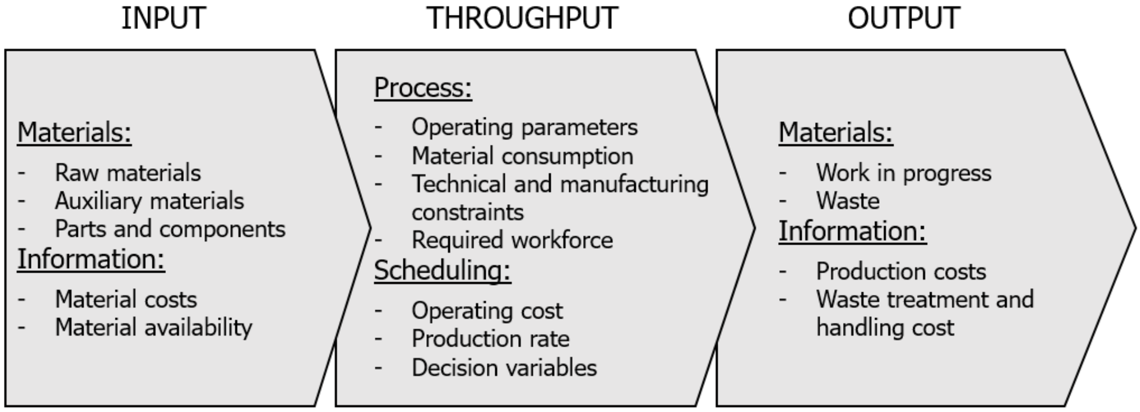

Figure 3.5: Example of quantity center characteristics

data collection and usage, especially regarding data aggregation for the subsystems and product system.

Regarding information on operational parameters, already available data should be collected using technical documents of machines and processes, and products bills of material and routing. Knowledge from experts and machine operators can also be used. If more data is necessary, the addition of adequate sensors or measurements might be required. Regarding the evaluation of costs, the ExtABEC method proposed in Cagno et al. (2012) calculates the costs of products, by-products and waste. The resources and activity costs are taken into account, and a set of cost indexes is given to evaluate the efficiency of production.

Information flows circulating in the subsystem should be detailed. As for the VSM representation (Vinodh et al., 2015), such flows include data regarding time-related information (due dates, schedule updates...), orders or stock levels. It is also important to consider the interactions between all quantity centers within a shop floor, how they are related to each other and which flows they exchange. Information such as the objectives or scheduling constraints can be linked to several quantity centers simultaneously, or even to the subsystem as a whole. Using the information system and the knowledge of people responsible for production planning, operators and foremen is a powerful way to gather the necessary information.

Subsystems impacts: At this point, all the different subsystems are identified and characterized. The inputs, outputs and throughput of each quantity center are known, and the relationships between them understood. This results in a triple representation for each subsystem, namely the physical, economic and environmental one, as shown in Figure 3.6. Operational and cost information appears in each quantity centers (rectangles), and the flows (arrows) circulating in the system carry physical and economic information as well as environmental information for waste flows, as is proposed in Schmidt and Nakajima (2013).

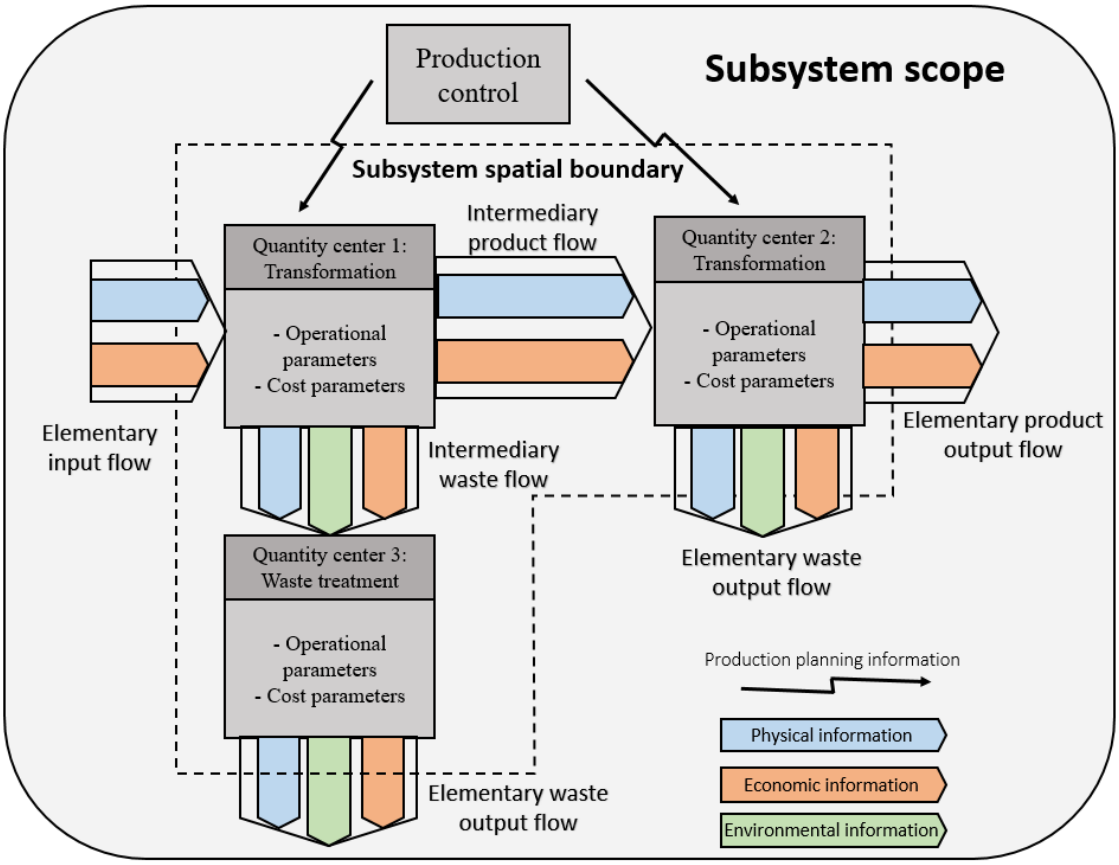

Figure 3.6: Example of subsystem with three quantity centers - physical, economic and environmental representation

Based on the gathered information regarding the different subsystems, it becomes possible to estimate their respective impacts (economic and environmental). This can be done by looking at the aggregated waste generation of each subsystem as well as the costs entailed by these generated waste. The ISO 14031 (2009) standard on environmental performance evaluation provides comprehensive guidelines on how to interpret the impact of waste flows. Information regarding waste quantities and cost is available through the accounting and Quality, Health, Safety and Environment (QHSE) departments. The nature of materials used and their respective monetary value and/or environmental impact need to be taken into account. As an example, a small amount of high value/high impact waste might have more importance than a bigger flow with more benign characteristics. Also, current and future legislation need to be considered, as well as normative aspects. If a company intends to apply for a certification (e.g. the ISO 14001 standard), more emphasis might be needed on certain types of waste which could be problematic for the certification. Decision-makers which are involved with the product system should also be consulted.

What these indicators represent also needs to be explained so that the decision-makers can make an informed choice based on their priorities. It is important to remind them of the regulations that can apply, as well as explain how each indicator impacts the current or future objectives of the system.

Table 3.1: Economic and environmental indicators

Environmental indicators	Economic indicators
Material intensity	Materials cost
LCA Environmental impact	Systemic cost
	Management cost

The environmental indicators chosen, shown in Table 3.1, are the quantity of waste generated per Functional Unit (FU) (material intensity) and the environmental impact represented by their resource usage and end-of-life treatment. The environmental impact is calculated using an LCA software, and can include as many impact categories as necessary. Since not all indicators might be relevant, a screening can be carried out for indicators with negligible impacts to reduce unnecessary information. The ReCiPe assessment method (NIPHEN, 2019) provides three aggregated endpoint indicators representing damage to human health, ecosystem and resource availability respectively, which can be an effective way to present environmental impacts in a concise and comprehensive manner. It is also important to indicate when assumptions are made regarding the LCA, since databases might not always contain the exact data regarding some materials, wastes or processes.

Regarding the economic assessment, a cost division commonly used in EMA and other environmental cost accounting methods consists in materials costs, systemic costs and waste management costs (Jasch, 2008). We use the same classification as it accurately depicts the costs involved with waste and can easily be aggregated to represent the full cost of a waste flow.

Subsystems ranking: The evaluation of subsystems depends on the priorities of the decision-maker (e.g. environmental policy or ecosphere). It is necessary to confer with them to decide on the rank assigned to each subsystem, following these steps:

1. Select a subsystem;
2. Using the information collected in steps 1.1 and 1.2, calculate the environmental and economic impact indicators listed in table 3.1;
3. Through discussion with the decision-makers, define importance of the environmental and economic criteria and rank subsystems;
4. Look at the regulations and environmental objectives set by the company and reassign ranks if necessary.

Once the subsystems have been ranked, they are then further studied to check if scheduling is a possible lever to reduce waste generation. If possible, the magnitude of the possible improvement should be estimated, as some subsystems with lesser impacts but higher flexibility regarding scheduling might be more relevant to improve than higher ranked but very constrained ones. If a subsystem does not have any scheduling lever available, it is removed from the ranking and the next one is checked. Since many mechanisms related to scheduling can be responsible for waste generation, looking at existing studies regarding waste-minimizing scheduling might provide insight regarding which parameters are important. As such, the review and classification of waste-minimizing scheduling problems done in Chapter 2 can provide a first basis for identifying important parameters. The application of the ITO method should also provide sufficient information to ensure that all sources of waste are known. Each waste output from a quantity center should be quantified as a function of its operating parameters (e.g. as a scrap percentage, proportional to a number of setups). Storage and transportation processes, while less likely to generate waste, should also be considered from such an angle. Such considerations include, but are not limited to, product expiration due to long storage times; product deterioration during transportation; or leaks from storage units. While subsystems with no identified scheduling lever are removed from the ranking, the obtained information remains useful to consider other waste prevention methods (e.g. process or materials change, reuse, ecodesign . . .).

Once all subsystems have been checked this process ends and the second methodology step can start. After this iterative process, only the most relevant subsystems selected are kept in the product system. This allows for a synthetic representation and description, and avoids time-consuming investigations on systems that cannot be improved through scheduling.

3.3.2 Step 2: Parametric flow inventory

After having described the different quantity centers composing the product system, the parametric flow inventory step aims at mapping and quantifying the circulation of flows within the system. According to the ISO 14051 (2011) on MFCA, three main types of flows are identified:

Elementary input flows: the flows that enter the boundaries of our system. Those can be raw materials for the production, subcomponents, or auxiliary materials (materials used in a process but not directly used for the product, such as cleaning water). The characteristics of these flows need to be precisely defined (quantity, composition, volume...) as they will be used to calculate all downhill flows.

Intermediate flows: the flows that circulate within the system boundaries, from one quantity center to another. Their properties can change depending on the quantity center they go through (i.e. wether it is a transformation process or not). They can be split or combined.

Elementary output flows: the flows that come out of the system boundaries. Those flows are the ones that serve to calculate the different impacts of the system in terms of cost or environmental impacts, and are the results of all the transformation processes present in the system.

Based on guidelines provided by the ISO 14051 (2011) standard, the different types of flows within the system should be categorized as they will have different effects on its evaluation. Raw materials, finished and semi finished products, by-products and waste might not need the same indicators. As an example, it is more important to gather environmental information on waste flows than on finished products, and by-products that are reused within the system might not need to be considered. Also, creating families of similar products or materials (depending on shape or color for example) can simplify the model, as long as those differences do not have an impact on the schedule or waste generated (all products in a family need to have the same final impacts). This allows for a reduced number of flows to account for.

The operational information gathered during step 1.2 is integrated into the flow description, as their characteristics are affected by these parameters. Once all the data regarding the different flows and quantity centers has been gathered, the overall system can be modeled. The elementary input flows enter the system boundary, and go through a first set of quantity centers, where they can be transformed, stored or transported. After calculating the internal flows resulting from these centers, those go into the next set of quantity centers, and so on until they exit the system boundaries as elementary output flows. At each step, these flow properties are defined based on the operational parameters of each center. The elementary output flows are ultimately expressed according to the parameters of all the quantity centers they went through, or "parametric assessment". This process is represented in Figure 3.7 for a product system with three quantity centers and two elementary input flows.

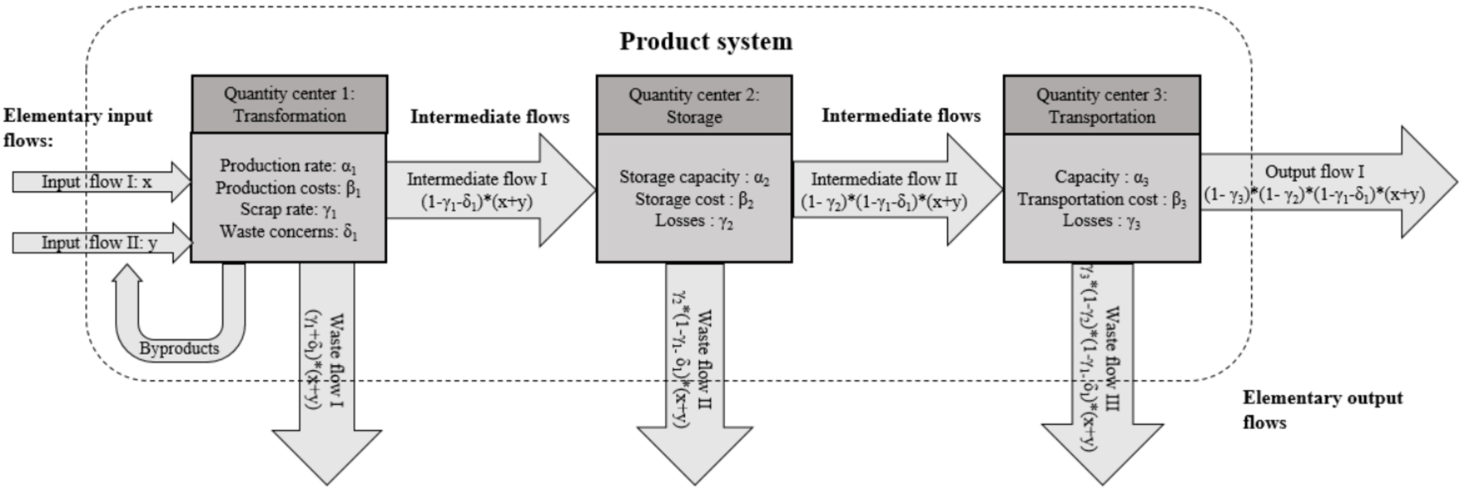

Figure 3.7: Example of parametric flow inventory with three quantity centers and two input flows

3.3.3 Step 3: Material flow assessment

Step 3 is the material flow assessment, where the waste output flows are characterized. Their environmental and economic impact evaluation is carried out, and their parametric representation is studied to identify how each parameter affects the output waste flows. This serves the dual purpose of finding which flow or process is responsible for waste generation/cost and in which proportion, as well as identifying all parameters (e.g. number of setups, operating speed. . .) that can influence both the schedule and the quantity of generated waste. An LCA evaluation can be carried out for precise environmental impact determination, and additional assessments can be made using different values for the waste related parameters, which can allow for an estimation of the new potential impacts if improvements were made. For the economic assessment, the ExtABEC method provides waste-related costs. As explained in Section 3.3.1, three types of costs are to be considered regarding waste, namely material, systemic and management costs. It is also important to consider scheduling-related costs such as work-in-progress and include them in the economic evaluation. These environmental and economic assessments provide the objective functions that will be used later for problem modeling by giving a mathematical equation relating flows and scheduling parameters.

As an example, the impact assessment of the product system presented in Figure 3.7 is done below (all parameters are given in the figure). Three waste flows are identified, one for each quantity center, due to scrapped products and process waste, storage losses and transportation losses respectively. The LCA should be carried out on these three flows which can be summed as :

$$\text{Waste}_{total} = (x + y) \times ((\gamma_1 + \delta_1) + \gamma_2 \times (1 - \gamma_1 - \delta_1) + \gamma_3 \times (1 - \gamma_2) \times (1 - \gamma_1 - \delta_1)) \quad (1)$$

This provides an accurate assessment of the contribution of each flow to the total impact. Similarly to what is proposed in Section 3.3.1, using the ReCiPe assessment method and its three aggregated endpoint indicators is recommended. More precise midpoints indicators can be used if relevant.

Material costs consist in the price of materials composing all three waste flows, whose quantities are given by the three waste output equations. Systemic costs consist in the production costs β_1 for quantity center 1, handling and storage space costs β_2 in quantity center 2 and transportation costs β_3 in quantity center 3. Management costs correspond to the storage, disposal and treatment costs of all three waste output flows. Finally, holding costs resulting from inventory keeping in quantity center 2 need to be added. Similarly to the environmental impact assessment, some parameters can be modified to look for potential savings.

3.3.4 Step 4: Scheduling problem identification

The aim of this step is to summarize all the information (operational, environmental and economic) gathered during the previous steps in order to identify the scheduling problem and help modeling it. In addition to the α, β and γ fields described in Chapter 2, we also gather information regarding:

Problem data: what is known about the system (e.g. processing times, lot sizes, due dates…);

Decision variables: variables that can be adjusted in order to improve the objective function (e.g. operations starting times, operations order…).

Table 3.2 sums up all the information related to the scheduling problem and at which step this information can be obtained.

Table 3.2: Problem identification process

Information	Identification step	Resulting notation
Problem data	Step 1 and 2	
Decision variables	Step 1.2, 2 and 3	Decision variables
Workshop configuration	Step 1 and 2	α
Constraints	Step 1 and 2	β
Objective functions	Step 3	γ

The data sets are determined using the information from step 1 and 2. Decision variables are the production variables that influence both scheduling and waste generation. They are first identified during substep 1.2, and their impact quantified during steps 2 and 3. The α and β fields (workshop configuration and scheduling constraints) can be determined based on the information gathered during steps 1 and 2. Finally, the γ field (objective function) is identified during step 3 by considering all waste outputs and costs that can be influenced by the decision variables. After this step, it later becomes possible to represent the problem mathematically by translating the objective functions and constraints into mathematical equations using the defined data. This can be done e.g. using Mixed Integer Linear Programming (MILP).

3.4 Application example

In this section, a practical application of the proposed methodology is carried out. This case involves a hubcap production plant which includes raw plastic reception and oven drying, injection moulding, painting, quality control and expedition. The different steps of the methodology are successively applied in order to identify the links between scheduling and inefficiencies in resource usage and waste generation, as well as define the scheduling problem. Through this example, the applicability and results of this methodology are demonstrated.

3.4.1 Study scope (Step 1)

Product system definition

The production of the hubcap manufacturing plant ranges from raw materials reception and preparation to the expedition of finished products. In Substep 1.1, the product system consists in the whole production site, including all storage facilities for materials, products and waste. The production is composed of three main families of products: plastic pieces, unicolor hubcaps and bicolor hubcaps. Hubcaps are composed of PVC onto which one or two paint coatings can be applied. After moulding, a metallic ring is inserted while a brand logo is clipped during the final quality control. Stringent requirements placed on automotive parts suppliers place each lot of hubcaps under a hard due date constraint. The functional unit chosen is the production of one day's worth of hubcaps, as the production schedule is determined on a daily basis. Such a functional unit combines scheduling (through the daily planning of production) and waste generation (represented by the daily waste output in normal operating conditions). The daily production capacity is 25 000 hubcaps, with job sizes ranging from 800 to 2000 pieces, hence between 30 and 100 jobs per day. An average of 250 workdays per year is assumed in this study. The spatial boundary considered for this product system is represented in Figure 3.8. Since due dates are involved, the temporal boundary for production is set as the last due date of the lots to be produced.

Product system analysis

Quantity centers characterization : Substep 1.2 focuses on each independent subsystem to estimate their cost and environmental impact, as well as the potential to mitigate these impacts using scheduling. As can be seen from the product system description in Figure 3.8, the plant is divided into three main workshops, namely the preparation, moulding, and painting/finishing ones. Buffer storage is present between each workshop, meaning that they can be considered as independent subsystems, as long as the buffer size and production capacity of each

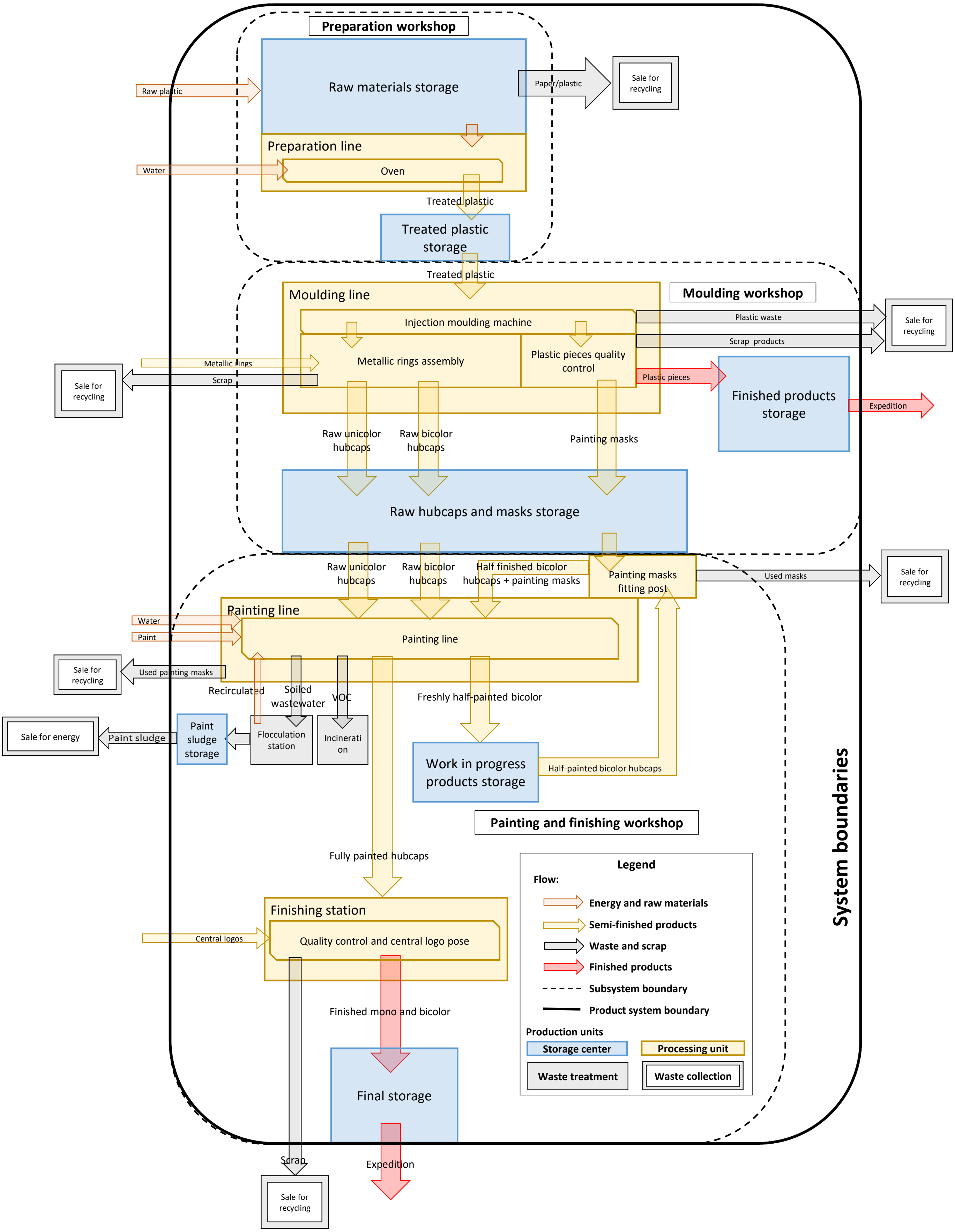

Figure 3.8: Hubcap product system description

workshop are assumed to be sufficient. The ITO method is applied to each quantity center to characterize it. The indices corresponding to each parameter are shown in Table 3.3.

Table 3.3: Parameters and flow indices

Cost parameters		Operational parameters		Waste parameters		Flows	
m_c	Material cost	p_r	Production rate	s_r	Scrap rate	x	Elementary input flow
o_c	Operating cost	cap	Capacity	c_r	Conversion ratio	y	Intermediary flow
s_c	Storage cost	s_t	Setup time	r_r	Recirculation ratio	z	Elementary output flow
wt_c	Waste treatment cost	nbs	Number of setups	set_w	Setup waste	QC	Quantity center
set_c	Setup cost			o_w	Operating waste		

The preparation workshop is responsible for producing the plastic used by the moulding machines. It generates few waste, namely packaging and wastewater. It has no constraints related to scheduling.

The moulding workshop manufactures plastic pieces, painting masks and raw hubcaps, and includes injection moulding machines, an assembly post as well as a quality control post. Its generated wastes are residual plastic coming from the moulding process and scrapped products from the quality control. From a scheduling perspective, waste production is impacted by changes in plastic compositions for the different pieces as well as mold changes, as the machines need to be purged each time a setup is required.

Once produced, the raw hubcaps and painting masks are sent to the painting and finishing workshop where they go through a painting line. Unicolor hubcaps only need a single coating, and go through the painting line only once before being sent to the finishing station. Bicolor hubcaps need to receive two coatings, with a mandatory 48 hours drying period between each coating in an intermediary storage. Painting masks are used during the second passage in the painting line and can be reused up to five times. All painted hubcaps are sent to the finishing line where a central logo is inserted and quality is controled. This workshop generates different types of wastes, namely paint sludge, scrapped products and used painting masks. Paint sludge is the result of soiled wastewater from the painting line going through an on-site flocculation process. It is considered a dangerous waste by the French environmental code (waste type 080113*, Assemblée des Chambres Françaises de Commerce et d'Industrie (2018)) and needs to be stored in a separate building before collection for energy recovery. Paint sludge comes from two separate mechanisms: the normal functioning of the painting line, and the setup operations required when changing the paint color. Like in the moulding workshop, scheduling impacts the waste generation through the number of required setups, i.e. the number of color changes.

Subsystems impacts and ranking : The moulding and the painting/finishing subsystems have been identified as opportunities for reducing waste through scheduling. To gather information on these subsystems and waste management, an interview was conducted with a QHSE manager. Missing information was extrapolated using studies from similar fields or from public sources. The yearly quantity of non-hazardous waste collected (not including scrapped products) is estimated to 54 tons. Non-hazardous waste is stored in outdoors metallic containers which were purchased by the company and have already been amortized. The price for plastic waste collection and recycling was estimated at 180€ per ton, based on price estimations by the French environmental agency (ADEME, 2019). The price for one ton of PVC is estimated at 912€, based on recent French market prices (UCAPLAST, 2019), while the price for one ton of ready-to-use paint is estimated to 3000€. Operating prices were calculated based on the workforce of each workshop (The Boyd Company Inc, 2016).

In the painting and finishing workshop, the company reported an average of 120 tons of paint sludge per year, with an annual cost of 38 000€ for collection. This price includes neither the operation and maintenance cost of the flocculation plant nor the handling cost for packaging and transport into storage. Salihoglu and Salihoglu (2016) report that costs for the flocculation station management represent around 46% of paint sludge management, which is the figure used for this study. A specific hangar is used for the paint sludge storage, further adding to the overall cost. Water is recirculated after treatment. Regarding environmental regulations, emission levels of paint sludge are currently compliant. There is however a concern regarding the ISO 14001 certificate renewal.

Table 3.4 gives the environmental and economic indicators assessment regarding the plastic and paint sludge waste flows. Treatment costs of paint sludge include management cost (152€ per FU), the flocculation station operating cost (70€ per FU) and waste storage cost (20€ per FU). Environmental impacts were calculated using the OpenLCA 1.7.4 software and the Ecoinvent 3.1 database, and consider both resource consumption for plastic and paint production as well as end-of-life treatment for wastes. LCA method used is the ReCiPe with three

Table 3.4: Moulding and painting workshop wasteflows assessment

	Impact	**Moulding workshop** Scrap Plastic	**Painting Workshop** Paint Sludge
Environmental	Material intensity	216 kg per FU	480 kg per FU
	Ecosystems (PDF $\times$ m^2 $\times$ year)	1.05×10^{-5} per FU	7.05×10^{-5} per FU
	Human health (DALY)	4.9×10^{-3} per FU	29.2×10^{-3} per FU
	Resources (MJ surplus)	57.5 per FU	104.5 per FU
Economic	Materials cost	197 euros per FU	1440 euros per FU
	Systemic cost	4901 euros per FU	3770 euros per FU
	Treatment cost	39 euros per FU	242 euros per FU

aggregated indicators (damage to ecosystems, damage to human health and damage to resources availability) for better clarity.

In the real-life situation for this case-study, paint-sludge is sent to a cement-kiln for co-incineration. This type of end-of-life treatment being unavailable in the Ecoinvent database, the end-of-life treatment method used for calculating the paint sludge impact was the hazardous waste incineration process. It is still representative of a typical paint-sludge treatment process, which is classified as a hazardous waste by the European waste code (European Commission, 2000). Scrap plastic is sold on the global market before being grounded into pellets for reuse. As shown in Table 3.4, paint sludge has a larger environmental impact as well as a higher economic cost. It is subject to governmental regulations, and a cause of concern regarding the ISO 14001 certification. For all these reasons, it was decided to limit this study to the painting and finishing workshop only.

3.4.2 Parametric flow inventory (Step 2)

The quantity centers contained in the painting and finishing workshops are:

- Painting line
- Painting masks fitting post
- Semi-finished products storage
- Flocculation station
- Paint sludge storage
- Finishing station
- Final storage

The detailed painting and finishing subsystem flow inventory is shown in Figure

3.9, using the various indices identified in Table 3.3.

Paint sludge	$z_1 = c_{r_3} \times ((x_1 + x_2) \times o_{w_1} + nbs_1 \times s_{w_1})$	(2)
Wastewater	$z_2 = (1 - r_{r_3}) \times (1 - c_{r_3}) \times ((x_1 + x_2) \times o_{w_1} + nbs_1 \times s_{w_1})$	(3)
Used masks	$z_3 = x_2 \times (1 - s_{r_1}) \times o_{w_6}$	(4)
Scrapped products	$z_4 = x_1 \times s_{r_1} + x_2 \times s_{r_1}^2$	(5)
	$z_5 = x_1 \times (1 - s_{r_1}) \times s_{r_4} + x_2 \times (1 - s_{r_1})^2 \times s_{r_4}$	(6)

Using the waste and operational parameters, each waste flow can be calculated based on the input flows as shown in equations (2)-(6). As an example, the paint sludge waste flow z_1 originates from the painting line operating waste multiplied by the product flows x_1 and x_2 plus the waste generated by setups, weighted by the conversion ratio c_{r_3} of the flocculation station. The parametric representation allows for quantifying each flow circulating in the subsystem as an equation. Cost information is also represented, and will be used in the next flow assessment step.

3.4.3 Material flow assessment (Step 3)

As the flows have all been quantified, their respective impacts and costs can be determined. Focus is given to the elementary output flows of waste and products, as those are the main factors to determine the economic and environmental impacts of the subsystem.

It can be seen that only output flows z_1 and z_2, respectively paint sludge and wastewater, are affected by the number of setups of the painting line nbs_1. Since no other parameter can be affected by scheduling, output flows z_3, z_4 and z_5 are not considered in the rest of this analysis.

Let us recall equation (2):

$$z_1 = c_{r_3} \times ((x_1 + x_2) \times o_{w_1} + nbs_1 \times s_{w_1})$$

We know from Section 3.3.1 that z_1 is equal to 120 tons per year, or 480 kg per day with 250 working days a year. Parameter c_{r_3} is the ratio of soiled wastewater converted into solid paint sludge during the flocculation process. The value used here is taken from Talbert (2007) with c_{r_3}=0.6 kg of paint sludge per liter of soiled wastewater. The transfer efficiency, i.e. the percentage of painting mix (paint plus solvent) that actually ends up on the product, is chosen as 60 percent which is an average value for liquid paint spray techniques. Paint mix consumption is 80 liters per hour of operation for the painting line, meaning that $ow_1 = 0.4 \times 80 = 32$ liter per hour. With an average of 20 operating hours per day ($x_1 + x_2 = 20$), we can

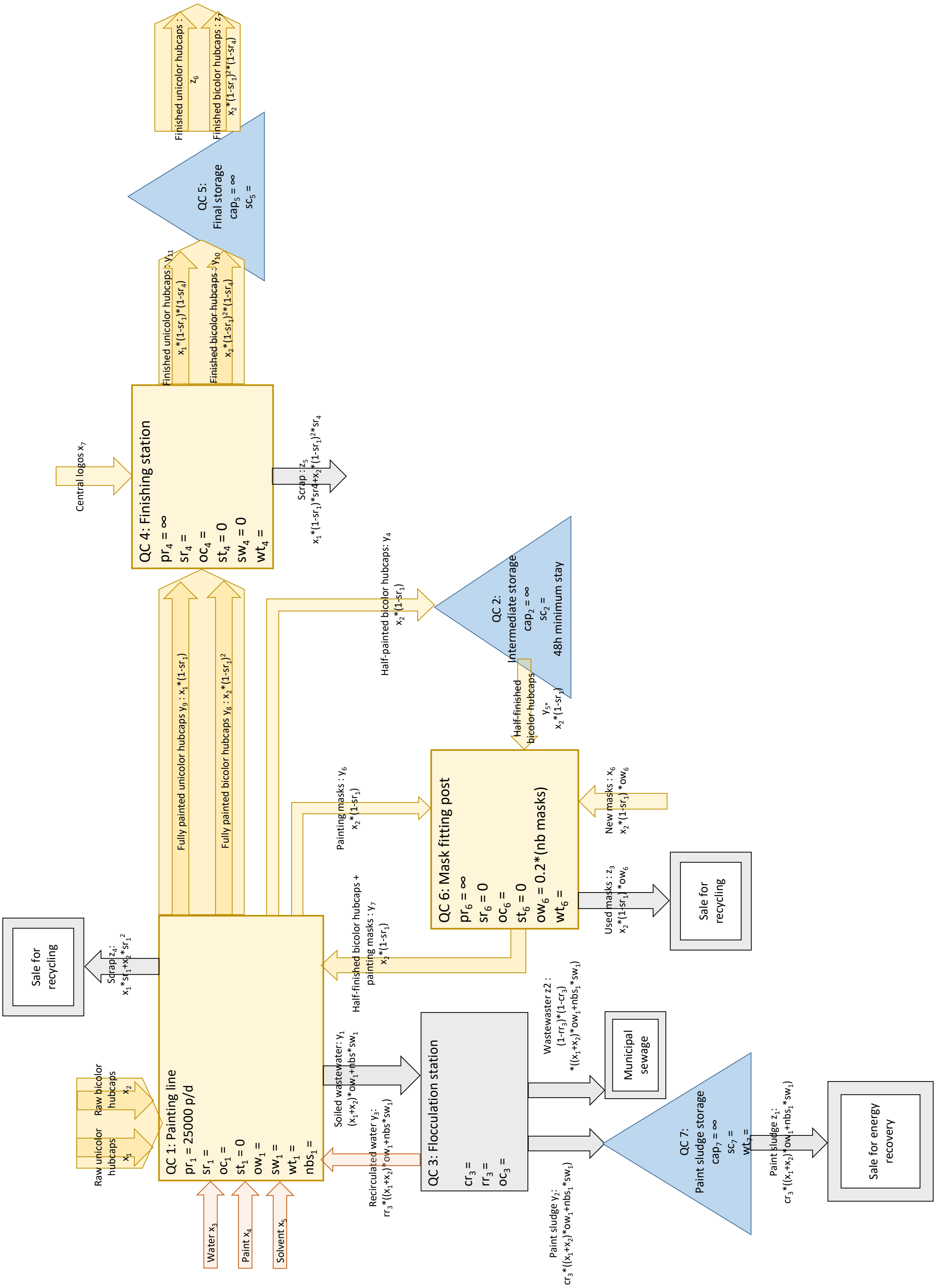

Figure 3.9: Painting and finishing subsystem flow inventory

calculate the total daily solid waste generated by operating the painting line (not including setup waste):

$$z_1^{\text{operating}} = c_{r3} \times ((x_1 + x_2) \times o_{w_1} = 0.6 \times 20 \times 32 = 384 \text{ kg per day}$$

A daily average of 384 kg of paint sludge is thus generated through the operation of the painting line, which is 96 tons a year. The remaining 24 yearly tons, or 96 kg per day, come from cleaning operations after each setup as defined below:

$$z_1^{\text{setup}} = c_{r3} \times (nbs_1 \times s_{w_1}) = 96 \text{ kg per day}$$

From this last equation, we can see that reducing the number of setups nbs_1 by half through better scheduling would reduce z_1^{setup} by half. This would avoid 12 tons of paint sludge a year, thus a 10% decrease on the total paint sludge generation of the company.

For equation (3), all of the water is recirculated on-site after going through the flocculation station, with $r_{r_3} = 1$, meaning that no reduction is necessary.

While the number of setups does not appear in any other flow from the subsystem, it still affects the rest of production at the operational level in terms of lot-sizing. Indeed, when considering unicolor and bicolor hubcaps as two products (differences in hubcaps shape are not relevant in the painting line among a same family), the lot-size for a production order is determined by the number of hubcaps processed between each color change. Increasing the number of setups tends to reduce lot-size, and conversely. This in turns affects the inventory (both for the intermediate and final storage) cost, as it depends on the number of products stored at any moment. In this perspective, the lot-size becomes the determining factor for balancing the number of setups (and by extension environmental costs) and the time spent in inventory (holding cost). The economic objective for this problem should include both the waste represented by flows z_1 and z_2, as well as the inventory costs. Also, because of the due dates constraint, a minimum number of setups might be unavoidable in order to comply with the orders requirements.

Based on the different activities and cost drivers described in the ExtABEC method, the detailed cost equations of flows z_1 and z_2 are given below:

$$c_{z_1} = m_{c_1} \times z_1 + c_{r_3} \times o_{c_3} \times y_1 + c_{r_3} \times nbs_1 \times set_{c_1} + s_{c_7} \times y_2 + wt_{c_7} \times y_2 \quad (7)$$

$$c_{z_2} = m_{c_2} \times z_2 + (1 - c_{r_3}) \times o_{c_3} \times y_1 + (1 - c_{r_3}) \times nbs_1 \times set_{c_1} \quad (8)$$

These costs are composed of different parts. In the case of z_1, the meaning of each term composing the equation is detailed below:

- $mc_1 \times z_1$: material cost of flow z_1, which is dependant on the price of flows x_3, x_4 and x_5;
- $c_{r_3} \times o_{c_3} \times y_1$: cost of operating the flocculation station. This operating cost is divided between flows z_1 (paint sludge) and z_2 (wastewater) according to the conversion ratio (part of the input flow transformed into paint sludge vs part transformed into water);
- $c_{r_3} \times nbs_1 \times set_{c_1}$: setup cost for the painting line. In this case, the assumption is made that the setup cost is wholly transferred to flow y_1 (soiled wastewater originating from the painting line) and not to the product flows y_7 and y_8. Similarly to the previous entry, this cost is divided between the paint sludge and wastewater using c_{r_3};
- $s_{c_7} \times y_2$: storage cost for the paint sludge. In this specific case, the storage cost is not dependant on time, as paint sludge does not incur any holding cost. It represents the cost of using and maintaining the building and containers used for storage;
- $wt_{c_7} \times y_2$: waste treatment cost, which is the price paid by the company to have the paint sludge collected and treated.

3.4.4 Scheduling problem identification (Step 4)

Table 3.5 presents the process and outputs of the problem identification step.

The main decision variable is the starting time of each operation s_{ij}, which is the primary way of improving the objective functions. Secondary decision variables such as the number of setups or the drying time also affect the objective functions, but are dependant on the main decision variable. The α, β and γ fields are obtained sequentially using all the previous information. It is to be noted that the objective functions z_{envir} and z_{eco} only comprise terms of equations (2)-(3) and (7)-(8) that are affected by the decision variables. From this problem definition step, the work can be carried on to fully model the scheduling problem.

3.5 Discussion

This case study provides some feedback as to how this methodology should be implemented and how it can promote waste reduction through scheduling. In the

Table 3.5: *Waste-minimizing scheduling problem identification step*

Information	Identification process	Resulting notation
Data sets	$\mathcal{I}$: set of jobs to be scheduled; $\mathcal{J}$: set of operations composing a job	$\mathcal{I}$, $\mathcal{J}$
Decision variables	The number of setups nbs depends on the respective starting times of operations with different colors $\rightarrow s_{ij}$: starting time of operation j of job i	Decision variables: s_{ij}
Workshop configuration	The painting line is the only relevant process to consider, the mask pose and finishing station have sufficient capacities and can be ignored in the scheduling problem $\rightarrow$ single machine problem	$\alpha = 1$
Constraints	Due dates d_i Coupled tasks constraint (a_i, L, b_i) (Blazewicz et al., 2012) Sequence-dependent setup cost	$\beta = d_i, (a_i, L, b_i)$, *dependent setup-cost*
Objective functions	z_{envir}: minimize waste from eq. (2) and (3) $\rightarrow z_{\text{envir}} = s_{w_1} \times nbs_1 \times ((c_{r_3} + (1 - r_{r_3}) \times (1 - c_{r_3}));$ z_{eco}: minimize waste and inventory costs $\rightarrow z_{\text{eco}} = nbs_1 \times set_{c_1} +$ inventory cost (intermediary, final)	$\gamma = \min(z_{\text{envir}}, z_{\text{eco}})$

following paragraphs, we discuss the issue of data collection and propose possible extensions for the scope of this methodology, before highlighting its potential for product system improvement.

3.5.1 Data collection

The most salient difficulty resulting from this application case is the issue of data collection and interpretation. This includes information on operational parameters, costs or waste management which are often not directly available and need to be either collected on-site or extrapolated from existing data. This is especially relevant for environmental costs (treatment and collection costs) which are often considered as overheads, or the waste generated by single quantity centers which is aggregated into larger groups. This issue can be addressed by using appropriate data collection techniques such as described in the ISO 14033 (2012). As a hybrid method between flow assessment, LCA and scheduling, this methodology requires input from different actors, which can be complex to combine. It is important to carefully prepare interviews with personel (QHSE and production managers, operators) as they are directly involved in the production process. To facilitate its implementation, the first step is especially useful in narrowing the study scope and reducing the necessary calculations for costs and environmental impacts. One should also remember that some of the data used represents averaged values (daily production, daily waste output, ...). Unforeseen events such as machine breakdowns are not explicitly considered although they can have large impacts on both environmental and economic performance. Including these events in the scheduling problem modeling could enable the use of environmentally robust schedules. To facilitate the methodology implementation process, developing a toolbox with appropriate guidelines, software userguides and a user interface would be an interesting development.

3.5.2 Energy and gaseous emissions

As stated in Section 1.1.1, neither energy consumption nor gaseous emissions are considered in this methodology. As a result, only physical flows are included when assessing both costs and environmental impacts (e.g. the LCA is carried out on the used resources and end-of-life treatment of waste, and not on the energy used during processes). This could certainly be an extension to this methodology, especially when considering the work already devoted to energy flow assessment (Liu et al., 2018) and energy efficient scheduling (Giret et al., 2015). Some processes can also emit gaseous pollutants such as Volatile Organic Components (VOCs) or nitrous and sulphur oxides which can have great environmental impacts. In the application case example, reducing paint sludge generation also reduces VOC generation, which is a further incentive to implement waste prevention techniques. However, this would lead to an increased complexity at all steps of the methodology, requiring more data collection and impact assessment, with an increased number of decision variables and objective functions. In some cases, the same decision variables are involved in reducing both waste generation and energy consumption (in the case of turning on some machines for example). It then seems appropriate to consider both energy and waste at the same time, as it does not greatly increase the problem complexity. Otherwise,addressing the energy consumption and waste reduction scheduling problems separately might be necessary.

3.5.3 Product system improvement

As this methodology's purpose is to identify waste reduction opportunities through scheduling, each of its step provides relevant information to the decision-maker.

Step 1 characterizes the product system and subsystems, and gives estimated impacts for each. This information can be used to identify the most impacting ones, and improvement measures can be devised even though no scheduling considerations are involved (e.g. process improvement, product design, materials replacement, ...). Step 2 provides the standard information on flows circulating within the system, but the parametric representation allows for more precision in identifying which quantity center/parameter is actually responsible for waste generation. This can serve as a basis for operational adjustments beyond the use of scheduling. Step 3 enables the identification of cost drivers in waste flows, which is especially relevant when these costs tend to be underestimated or misattributed. Using this information, decision-makers can make more informed choices and can be incentivized to reduce their waste generation after realizing their actual cost. Finally, step 4 provides a complete description of the waste-minimization scheduling problem at hand. This information can later be used to accurately model the problem using mathematical representation, and facilitate subsequent solving through the use of exact or approached methods. Simulating alternative production scenarios or drawing future-state maps such as the ones used in VSM are also effective ways to facilitate decision-making. It is important to note that each step of this methodology can be viewed not only as part of a process but also as an end by itself, providing useful information even if the methodology is not fully carried out due to lack of data or resources for example.

3.6 Conclusion

This chapter presents a new methodology for the identification of waste-minimizing scheduling problems using flow assessment. A literature review highlights the lack of dedicated tool regarding this issue, and four methodological steps are proposed. An application case of hubcap manufacturing serves to demonstrate its applicability and results. After defining the study scope, the product system is decomposed into independent subsystems. Environmental and economic impacts are estimated and the best subsystem to study chosen. Using the operational information gathered in the first step, a parametric flow inventory is conducted, providing a full description of material flows using the production parameters. An assessment of the waste flows is then made to identify possible improvements using scheduling, showing that a 10% decrease in hazardous waste generation is possible if the number of setups is halved. In the final step, a three-field notation of the associated scheduling problem is provided and relevant data and parameters identified. This results in a complete characterization of one or more subsystem which includes monetary, environmental and scheduling-related information. While more case studies need to be carried out to further validate and improve this methodology, it has proven to be effective in identifying a scheduling problem with waste minimization concerns and given a basis for a full problem modeling. For researchers, it is a new application of flow assessment oriented towards scheduling and waste minimization. For practitioners, it provides a new methodology to detect waste reduction opportunities within production systems.

Following on the results obtained in this case study, a mathematical modeling of the scheduling problem identified earlier is done in the next chapter.

CHAPTER 4

Bi-objective scheduling on a single-machine with coupled-tasks

Contents

Some results from this chapter were published in:

- C. Le Hesran, A. Agarwal, A.-L. Ladier, V. Botta-Genoulaz, and V. Laforest. Reducing waste in manufacturing operations: bi-objective scheduling on a single-machine with coupled-tasks. *International Journal of Production Research*, 2019a.

- C. Le Hesran, A.-L. Ladier, V. Botta-Genoulaz, and V. Laforest. Reducing waste in manufacturing operations: a mixed integer linear program for bi-objective scheduling on a single-machine with coupled-tasks. *IFAC-PapersOnLine*, 51(11):1695–1700, 2018. ISSN 24058963. doi: 10.1016/j.ifacol.2018.08.212

Résumé du chapitre 4

Dans ce quatrième chapitre, des élements de réponse sont apportés à la troisième des interrogations introduites au chapitre 1, à savoir:

Comment résoudre les problèmes d'ordonnancement minimisant les déchets?

L'étude de cas réalisée au chapitre précédent nous a permis d'identifier un problème d'ordonnancement minimisant les déchets, à savoir un problème machine unique avec des propriétés de tâches couplées et dans un contexte de fabrication à la commande. Ce problème correspond au passage d'enjoliveurs mono et bicolores dans une ligne de peinture où chaque changement de couleur génère des déchets additionnels. Les informations obtenues précédemment grâce à l'application de la méthodologie nous permettent de définir la notation de Graham de ce problème comme suit : $\{1 \mid d_i, (a_i, L, b_i), \text{dependent setup-cost} \mid z_{\text{setup}}, z_{\text{inventory}}\}$, où les fonctions objectif z_{setup} et $z_{\text{inventory}}$ correspondent respectivement au nombre de changements de série effectués et au niveau de stock (final et intermédiaire). Le problème est tout d'abord modélisé grâce à la Programmation Linéaire en Nombres Entiers (PLNE), puis résolu de façon exacte sur différents jeux d'instances grâce au solveur CPLEX. L'aspect biobjectif du problème (objectif économique du stock et environnemental des changements de série) est pris en compte en générant un front de Pareto des différentes solutions. Deux points d'intérêt sont proposés afin de fournir aux preneurs de décision une synthèse des résultats. Ils sont respectivement basés sur un critère de distance au point idéal et sur des pourcentages d'augmentation/réduction par rapport aux points extrêmes. Les résultats démontrent qu'il est possible de réduire jusqu'à 36% le nombre de setups, et donc les déchets qui leurs sont liés, en échange d'une augmentation de l'inventaire de seulement 12%. Cependant, les temps de calcul nécessaires deviennent prohibitifs pour des instances de taille industrielle. Pour résoudre ce problème, une métaheuristique est proposée. Basée sur l'algorithme génétique NSGA-II, elle obtient des résultats proches de l'optimal avec une réduction des setups jusqu'à 35% contre une augmentation d'inventaire de 11,5%, et ce en un temps largement inférieur à la PLNE. La résolution d'instances de taille industrielle par l'algorithme génétique permet de confirmer l'intérêt de cette méthode pour des situations réalistes, la proposition de solutions alternatives permettant d'adapter l'ordonnancement en fonction des priorités des preneurs de décision.

Bi-objective scheduling on a single-machine with coupled-tasks

In this chapter, the scheduling problem of hubcap manufacturing presented in the previous chapter is first modeled using linear programming. We then provide an exact and an approached solving method, answering the following question:

How to solve waste-minimizing scheduling problems?

A brief literature review on coupled-tasks scheduling problems is first presented in Section 4.2. The mathematical model is then developed and explained in Section 4.3. To solve this problem, exact and meta-heuristic approaches are used. The exact approach is presented in Section 4.4 along with numerical experiments. A GA is described in Section 4.5, and numerical experiments are carried out to compare its performance against the exact approach, followed by discussion on the results. Finally, conclusions are drawn in the last section.

4.1 Introduction

Our goal in this chapter is to show that scheduling can significantly reduce waste generation without affecting economic objectives too negatively, using an example where waste is avoided by reducing cleaning and setup operations. Following on the case study of hubcap manufacturing from Chapter 4, the waste-minimizing scheduling problem has been identified. The α, β and γ fields as well as decision variables and instance data, previously detailed in Table 3.5, are reminded below in Table 4.1 and used to model the problem mathematically and propose solving methods.

As can be seen, the objective function consists of an economic and environmental part. Increased complexity results from these additional objectives – scheduling problems being usually hard to solve optimally even when they are single-objective. The multiobjective nature of the waste minimizing problem might require the use of less precise but faster methods such as metaheuristics. Increasing the number of objectives also means that more solutions are available, and choosing the most appropriate trade-off solution can be a difficult task. Thus, it is important to provide only the most relevant solutions to the decision-maker, i.e. solutions that are suited to the operating conditions of a plant and do not prohibitively affect one of the objective functions.

Table 4.1: Scheduling problem three-field notation, data and decision variables

Information	**Notation**
Data sets	$\mathcal{I}$: set of jobs to be scheduled; $\mathcal{J}$: set of operations composing a job
Main decision variables	s_{ij}: starting time of operation j of job i
Workshop configuration	$\alpha = 1$
Constraints	$\beta = d_i, (a_i, L_i, b_i)$, *dependent setup-cost*
Objective functions	$z_{\text{envir}} = s_{w_1} \times nbs_1 \times ((c_{r_3} + (1 - r_{r_3}) \times (1 - c_{r_3}));$ $z_{\text{eco}} = nbs_1 \times set_{c_1} +$ inventory cost (intermediary, final)

4.2 The coupled-tasks scheduling problem

In a coupled-tasks scheduling problem, a set of n jobs comprising two operations has to be processed on the same single-machine (Shapiro, 1980), a job i being a set of similar products with a defined size. It is noted as $\{1 \ |(a_i, L_i, b_i)| \ -\}$. An exact amount of time, or time-lag L_i, needs to elapse between the end of the first operation of job i (processing time a_i) and the beginning of its second operation (processing time b_i). Operations from other jobs can be processed during this time-lag. Particular cases of interest can emerge when specifying the values of a_i, b_i or L_i. Blazewicz et al. (2012) provide a survey of research on coupled-tasks scheduling problems, as well as a list of important results for the most common variants and subproblems.

The complexity of the coupled-task scheduling problem was studied by Orman and Potts (1997). They prove the general problem to be NP-Hard, as well as several particular cases. Due to the complexity of the problem, heuristic-based methods are more frequent than exact methods. They usually focus on the makespan minimization, such as Shapiro (1980) who develops three sub-optimal algorithms for a specific case of radar scheduling, while Gupta (1996) develops several heuristic algorithms. Lin and Haley (1993) solve the makespan minimisation problem with arbitrary lower-bound time delays using greedy and iterative heuristics as well as a branch and bound algorithm. Lin et al. (1995) consider the same problem, using threshold acceptance and simulated annealing. Ahr et al. (2004) study the identical coupled-tasks problem where all processing times and time-lags are equal for all jobs (i.e. $a_i = a, b_i = b, L_i = L$), and define an exact algorithm to solve it. Their work is adapted by Brauner et al. (2009) to fit a one-machine robotic cell problem, both with an exact and bounded delay L. Potts and Whitehead (2007) study the makespan minimisation problem with upper and lower bounds for the time-lags and compare seven different heuristics. Condotta and Shakhlevich (2012) propose a tabu-search algorithm for the exact time-lag problem, and compare it with the join-and-decompose heuristic defined by Potts and Whitehead (2007) for the flexible time-lag problem. A tabu-search metaheuristic for solving the general case is also developed by Li and Zhao (2007), showing good results when compared with a theoretical lower bound, as well as some algorithms for NP-Hard special cases of the problem. Finally, Amrouche and Boudhar (2016) and Amrouche et al. (2017) consider the problem of the two-machine chain re-entrant with identical time lags. This problem, noted $\{F2|ChR, l_j = L|C_{\max}\}$ considers a two machine flowshop with exact time-lags where each task needs to be processed twice on the first machine. They develop nine heuristics, with numerical experiments marking two of those, $IH_{L_{RP}}$ and IH_{L6}, as more efficient. Courtad et al. (2017) study the single machine flowtime minimisation problem with paired-tasks, in which a minimum delay must occur between two tasks of a same job. They first use a MILP approach, then propose an insertion heuristic providing near-optimal results. Finally, Meziani et al. (2018) propose to minimise the makespan in a two-machine flowshop with coupled-tasks problem ($F2|a_j, b_j, L_j, c_j|C_{\max}$). They first propose a lower bound as well as four heuristics. A hybrid PSO and Simulated Annealing (SA) metaheuristic is developed and compared with the PSO and SA-only approaches, outperforming them both.

The coupled-task problem is a particular case of re-entrant problems, in which jobs are allowed to be processed by the same machine more than once. Re-entrant problems are mainly solved using heuristic approaches. Exact models are proposed by Chen and Chao-Hsien Pan (2006), who develop eight integer programming models for the re-entrant job-shop and flow-shop scheduling problem based on formulations by Wagner (1959), Manne (1960), Wilson (1989) and You and Chii-Tsuen (1992). Those initial models are not re-entrant, therefore Chen and Chao-Hsien Pan (2006) relax their assumption that every machine may only be visited once, in order to obtain new formulations for the re-entrant shop problem. Since re-entrant problems state that no two consecutive operations of a job can be processed on the same machine (Chen and Chao-Hsien Pan, 2006), this assumption must be relaxed for the coupled-task case.

Other works concern different objective functions or extensions of the problem. Focusing on radar control, Winter and Baptiste (2007) develop two heuristics and a local-search algorithm for a problem with lower and upper bounded time-lags, the objective function being the total cost minimization of the delay between an operation's ideal starting time versus its real starting time. Simonin et al. (2011) study the acquisition and treatment of data by torpedoes, and propose an algorithm for minimizing the makespan in a coupled-tasks problem with precedence constraints on treatment tasks $(1|\text{prec}, (a_i, L_i, b_i) \cup (T_i, pmtn), G_c|C_{\max})$. Sequence dependence in the coupled-tasks scheduling problem is introduced by Blazewicz (2010) who studies the cases of general and in-out precedence constraints tree.

To the best of our knowledge, none of the papers on coupled-tasks scheduling address the issue of setup minimization with hard due dates, as most consider the issue of makespan minimization. Additionally, no multi-objective problems involving coupled-tasks have been addressed. Although the issue of reentrance was tackled using for example genetic algorithms (Dugardin et al., 2010; Cho et al., 2011; Zhang et al., 2012) or large neighborhood search (Rifai et al., 2016), none of them consider an environmental criterion in their objectives.

4.3 Problem modeling

In this section, the problem is defined and the particularities of our approach compared to the previous works reviewed in Section 4.2 are highlighted. The mathematical model is then detailed and the different constraints explained.

4.3.1 Problem definition

Figure 4.1 shows a simple representation of the production system under consideration, from the arrival of raw hubcaps into the painting line to the expedition of finished products.

In the shop-floor, only one painting line is available for the processing of all products, making this a single-machine scheduling problem. A passage into the painting line is referred to as an operation, while the set of operations required for completion of an order is called a job. As represented in Figure 4.1 and explained already in Chapter 3, three options are possible when a hubcap goes through the painting line. If it is unicolor, it is painted once and can go directly to the finished

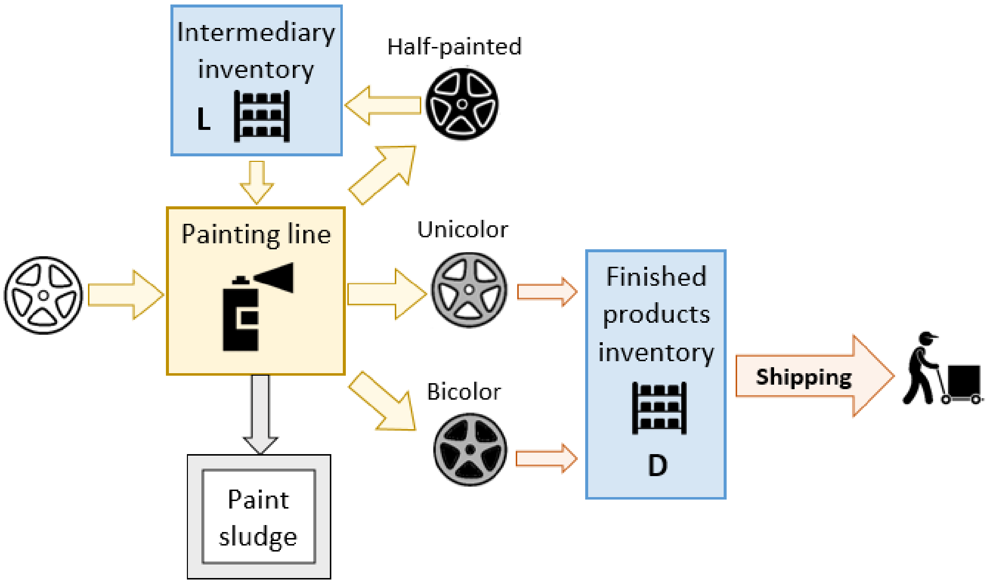

Figure 4.1: Simplified flow circulation in the hubcap production system

product inventory to await shipping, which must occur before a certain due date d_i. Indeed, we operate in a Make-To-Order setting and no lateness is allowed. If it is bicolor, it will receive its first coating and be sent to the intermediary inventory for a minimum period L, and receive its second coating and be sent to the finished product inventory to await shipping at its due date. As mentioned earlier, the aim is to minimize both the economic cost stemming from inventory keeping and waste management, as well as the environmental impact of the paint sludge generated in the painting line.

The environmental objective function identified in Table 4.1 is as follows:

$$z_{\text{envir}} = s_{w_1} \times nbs_1 \times ((c_{r_3} + (1 - r_{r_3}) \times (1 - c_{r_3}))$$

As can be seen, it is directly proportional to the number of setups nbs_1. Thus, for the rest of this chapter, the environmental objective function used will be

$$z_{\text{setup}} = \min(nbs_1).$$

The economic objective function from table 4.1 is:

$$z_{\text{eco}} = nbs_1 \times set_{c_1} + \text{inventory cost (intermediary, final)}$$

It includes two terms, one for minimizing the management cost of setup-induced waste, and one for the intermediary and final inventory costs. Since the setup-induced cost is already being accounted for through the minimization of z_{setup}, the economic objective function used for the rest of this study is the minimization of the time spend in inventory (both intermediary and final) of all products, noted $z_{\text{inventory}}$.

Based on this description, this problem can be written as $\{1 \mid d_i, (a_i, L, b_i), \text{dependent setup-cost} \mid z_{\text{setup}}, z_{\text{inventory}}\}$. The proposed mathematical model is based on the extension of Manne's model (Manne, 1960) by Chen and Chao-Hsien Pan (2006) which assumes that the jobs to be scheduled are composed of different numbers of operations. Their assumption that no machine can process two tasks of a same job consecutively was relaxed to allow for a single machine setting.

4.3.2 Problem data

The next paragraphs detail the different sets, data and decision variables necessary for the modeling of the problem as a MILP, reusing some notations provided in Table 3.5. While the studied case of hubcap manufacturing only considers two operations per job, this model also works for problems with more than two operations per job.

Data sets

- $\mathcal{I}$: set of the different jobs to be scheduled;
- $\mathcal{J}$: set of the different operations composing a job;
- $\mathcal{C}$: set of the different types of operations, in this case the colour of the paint used.

Data

- P_{ij}: processing time for operation j of job i;
- L: minimum drying time between two consecutive operations of a job;
- Q_i: number of products in job i;
- d_i: due date for job i;
- C_{ij}: type of operation j of job i;
- $Y_{ijkl} = 1$ if switching from operation j of job i to operation l of job k implies a setup, 0 otherwise (i.e. if C_{ij} and C_{kl} are different or not);

- N_i: number of operations for job i;
- M: maximum length of the planning horizon, i.e. $M = \max_{i \in \mathcal{I}} d_i$.

Decision variables

- y_{ijkl}: 1 if operation j of job i takes place just before operation l of job k, 0 otherwise;
- s_{ij}: starting time of operation j of job i;
- t_{ij}: drying time duration after operation j of job i, i.e. time spent in the intermediary inventory;
- e_i: earliness of job i (time between the end of the last operation and the due date of job i);
- g_{ij}: machine idle-time between the end of operation j of job i and the start of the next scheduled operation.

The objective function is composed of two elements:

- $z_{\text{inventory}}$: the total inventory, which represents all products finished early, that therefore must be stored until their due date. This includes semi-finished products that stay in the drying inventory longer than the minimum required amount of time;
- z_{setup}: the number of setups needed.

4.3.3 Mathematical model

The complete MILP is detailed in Figure 4.2.

Constraint set (9) ensures that all operations (but the first one) start only after the previous one on the same job is done and the drying time has ended. Constraints (10) ensure that no operation l of a job can be placed before operation j of a same job in the y_{ijkl} variables. Constraint set (11) defines job earliness as the difference between the due date and the completion date of the last operation on this job. The positivity constraint on e_i (18) ensures that no job can end after its due date.

$$
\begin{array}{lllr}
\min & z_{\text{inventory}} = \sum\limits_{i\in\mathcal{I}} Q_i \times e_i + \sum\limits_{i\in\mathcal{I}|N_i>1} \sum\limits_{j=1}^{N_i} Q_i(t_{ij} - L) & & \\
\min & z_{\text{setup}} = \sum\limits_{i\in\mathcal{I}} \sum\limits_{j=1}^{N_i} \sum\limits_{k\in\mathcal{I}} \sum\limits_{l=1}^{N_k} Y_{ijkl}\ y_{ijkl} & & \\
\text{s.t.} & s_{ij} + P_{ij} + t_{ij} \le s_{i,j+1} & \forall i \in \mathcal{I}, j \in \{1,\dots,N_i - 1\} & (9) \\
 & y_{ijil} = 0 & \forall i \in \mathcal{I}, j \in \{1,\dots,N_i\}, \forall l \in \{1,\dots,N_i \mid l \le j\} & (10) \\
 & e_i = D_i - s_{iN_i} - P_{iN_i} & \forall i \in \mathcal{I} & (11) \\
 & s_{ij} + P_{ij} + g_{ij} + M(1 - y_{ijkl}) \ge s_{kl} & \forall (i,k) \in \{\mathcal{I}^2 | k \ne i\}, j \in \{1,\dots,N_i\}, l \in \{1,\dots,N_k\} & (12) \\
 & s_{ij} + P_{ij} + g_{ij} \le M(1 - y_{ijkl}) + s_{kl} & \forall (i,k) \in \{\mathcal{I}^2 | k \ne i\}, j \in \{1,\dots,N_i\}, l \in \{1,\dots,N_k\} & (13) \\
 & \sum\limits_{i\in\mathcal{I}} \sum\limits_{j=1}^{N_i} \sum\limits_{k\in\mathcal{I}} \sum\limits_{l=1}^{N_k} y_{ijkl} = \sum\limits_{i\in\mathcal{I}} N_i - 1 & & (14) \\
 & \sum\limits_{k\in\mathcal{I}} \sum\limits_{l=1}^{N_k} y_{ijkl} \le 1 & \forall i \in \mathcal{I}, j \in \{1,\dots,N_i\} & (15) \\
 & \sum\limits_{k\in\mathcal{I}} \sum\limits_{l=1}^{N_k} y_{klij} \le 1 & \forall i \in \mathcal{I}, j \in \{1,\dots,N_i\} & (16) \\
 & t_{ij} \ge L & \forall i \in \{\mathcal{I} \mid N_i > 1\}, \forall j \in \mathcal{J} & (17) \\
 & s_{ij}, t_{ij}, e_i, g_{ij} \ge 0 & \forall i \in \mathcal{I}, j \in \mathcal{J} & (18) \\
 & y_{ijkl} \in \{0,1\} & \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{I}, l \in \mathcal{J} & (19)
\end{array}
$$

Figure 4.2: Mixed Integer Linear Program modeling the scheduling problem

Constraint sets (12) and (13) guarantee that only the operation l of job k, noted (k,l), consecutive to (i,j) can be started after (i,j) (including some possible time lag). They result from the linearisation of the following expression:

$$y_{ijkl} = 1 \Rightarrow s_{ij} + P_{ij} + g_{ij} = s_{kl}$$

Since y_{ijkl} is equal to one if and only if operation j of job i is directly followed by operation l of job k, each operation but the first one can have exactly one predecessor. Constraint (14) therefore makes sure that the number of possible successors is equal to the total number of operations minus one.

Constraint set (15) and (16) are used to make sure that a given operation (i,j) has no more than one successor or predecessor respectively. Constraint set (17) defines the minimum drying time between two operations of a same job. Finally, the non-negativity constraints and the binarity of y are given by constraint sets (18) and (19).

4.3.4 ε-constraint method

On a multi-objective scheduling problem, it is advisable to provide the decision-maker with alternative solutions that represent the variety of possible results. In the case of bi-objective optimization, this can be achieved using a Pareto front (Blasco et al., 2008). We generate this Pareto front using the ε-constraint method, that turns the multi-objective problem into a single-objective one by transforming other objective functions into constraints (Mavrotas, 2009). The fact that we only need to minimise two objectives, and that one (namely the number of setups z_{setup}) takes integer values makes this method especially convenient. The steps required for the obtention of the Pareto front are detailed in Algorithm 1. The initialization phase computes a mono-objective MILP, using α and β as parameters in the weighted sum objective function. The chosen weights α=1 and β=0.005 ensure that the inventory criterion takes precedence over the number of setups, therefore giving the leftmost point of the Pareto front.

Algorithm 1 Pareto front generation

1: **Input:** Instance data
2: **Output:** Pareto front
3: Compute the $(z^{\min}_{\text{inventory}}, z^{0}_{\text{setup}})$ point by solving the model with the following objective function: $z_{\text{weighted}} = \alpha z_{\text{inventory}} + \beta z_{\text{setup}}$
4: Set $\varepsilon = z^{0}_{\text{setup}} - 1$
5: **while** problem is feasible **do**
6: Solve the ε-constraint problem with $z_{\text{setup}} \leq \varepsilon$ as a constraint and $z_{\text{inventory}}$ as the objective function. Add the objective function value $(z^{\text{it}}_{\text{inventory}}, z^{\text{it}}_{\text{setup}})$ to the set of Pareto front points
7: Set $\varepsilon = z^{\text{it}}_{\text{setup}} - 1$
8: it = it + 1
9: **end while**

Once obtained, the Pareto front needs to be interpreted so that the decision-maker can make the most of it. Its size is limited by the maximum number of possible colour changes, which is equal to the total number of operations minus one. Although every point from it is an optimal solution, all of them might not be suited to a practical use. Thus, four key points are extracted for each instance.

Two extreme points $(z^{\min}_{\text{inventory}}, z^{0}_{\text{setup}})$ and $(z^{0}_{\text{inventory}}, z^{\min}_{\text{setup}})$, represent the cases where the decision-maker wishes to minimize one objective in priority, either the inventory or the number of setups respectively. The ideal point $(z^{\min}_{\text{inventory}}, z^{\min}_{\text{setup}})$ is defined using the two optimum values of these points, i.e. the minimum inventory and minimum number of setups achievable.

The coordinates of each point z^{it} are normalized using the formula $z^{\text{normal}} = \frac{z^{\text{it}} - z^{\min}}{z^{0} - z^{\min}}$ for both $z_{\text{inventory}}$ and z_{setup}. This norm provides new values between 0 and 1 ; scaling both objective functions enables us to compare values of different nature and order of magnitude. This is especially useful in our case where a holding cost and a number of setups cannot be compared directly. In case the Pareto front consists of only one point, i.e. $z^{0} = z^{\min}$ for inventory and setups, no normalization occurs and this single point is returned. Using these normalized values, the euclidean distance of each point to the ideal point is calculated. The solution located at the minimal distance from the ideal point $(z^{\text{min}}_{\text{inventory}}, z^{\text{min}}_{\text{setup}})$ is chosen as the trade-off point $z^{\text{trade-off}}$, which represents the best compromise in terms of number of setups reduction versus increase in inventory. The euclidean distance provides an accurate evaluation of the geometrical distance to the ideal point, and corresponds more closely to the shape of the Pareto front. Additionally, another trade-off point called z_{percent} is chosen as the point with the highest difference between waste percentage reduction and inventory percentage increase. This point aims at providing an attractive option for decision-makers that wish to improve their environmental impact without affecting their costs negatively. An example of Pareto front with its important points is shown in Figure 4.3.

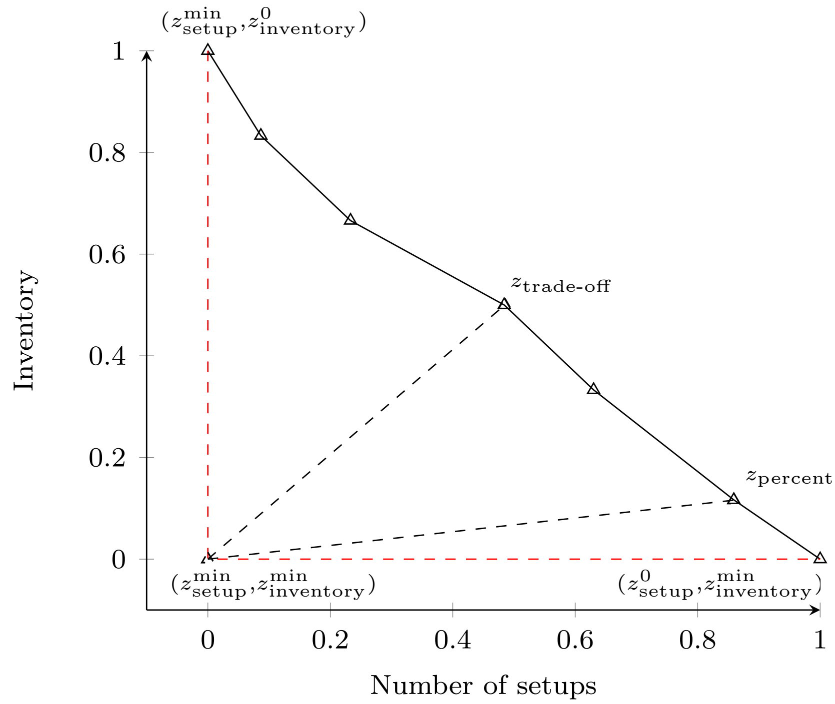

Figure 4.3: Example of Pareto front

4.4 MILP numerical experiments and results

4.4.1 Instances generation

An instance generator has been coded in C++. The data required to generate an instance consists of:

- the number of jobs n;
- the maximum number of operations per job m;
- the number of different types of operations $|\mathcal{C}|$.
- the distribution from which the number of operations N_i of each job i are drawn.
- the minimum drying time L;

The rest of the instance data is generated as follow:

- Using the chosen distribution, each job between 1 and n is assigned a number of operations N_i between 1 and m. Each operation is then assigned an operation type represented by an integer between 1 and $|\mathcal{J}|$ using a second discrete distribution. The result is a matrix of size $n \times m$ containing the details of each job.
- Q_i is drawn following a normal distribution $\mathcal{N}(20, 5)$.
- Processing time P_{ij} of operation j of job i is assumed to be a linear function of lot size Q_i, and all the operations of one job are assumed to have the same duration : $P_{ij} = \gamma_i Q_i$ for all $j \in \{1, ..., N_i\}$. We set $\gamma_i = 1$ for all jobs i without a loss of generality.
- A lower and upper bound are then calculated for the determination of the due dates. The lower bound lb_i of job i is defined as $lb_i = 2 \times \sum\limits_{j \in \mathcal{J}} P_{ij} + (N_i - 1) \times L$ for all i in $\mathcal{I}$, which is twice the sum of the processing and drying times necessary for job i. A time horizon for the problem is then set as: $M = 1.5 \left(\sum\limits_{i \in \mathcal{I}} \sum\limits_{j=1}^{N_i} P_{ij} + L \times \sum\limits_{i \in \mathcal{I}} N_i \right)$. This value was chosen big enough to ensure that a sufficient number of instances would be solvable, but would remain sufficiently constrained. The due dates D_i are then generated using a uniform distribution $\mathcal{U}(lb_i, M)$.

While this ensures that the first operation of a schedule is always feasible, note that it does not guarantee that every generated instance can be solved. A screening is done to remove unsuitable instances until the targeted number of solvable ones has been reached. Table 4.2 shows an example of a generated instance with ten jobs,

Table 4.2: Example of instance data

i	1		2		3		4		5		6		7		8		9		10	
j	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
C_{ij}	2	1	1	1	1	2	1	2	2	1	1	2	1	1	2	0	1	1	2	1
P_{ij}	21	21	15	15	25	25	24	24	18	18	17	17	32	32	27	0	13	13	24	24
d_i	148	148	494	494	290	290	419	419	207	207	156	156	522	522	305	305	80	80	584	584

with processing times P_{ij}, operation type C_{ij} and due date d_i associated with each operation j of job i.

Sets of instances were generated with a maximum of two operations per job. Parameters were set at $n \in \{10, 30\}$ and m=2 with an even repartition between both types (meaning that each operation has a fifty percent chance of being of type 1 or type 2). Different combinations for the distribution of variables N_i led to different configurations detailed in Table 4.3. For example, an 80%-20% distribution for N_i means that 80% of the jobs will consist of only one operation, while 20% will have two.

Table 4.3: Instance configurations

$\lvert\mathcal{I}\rvert$	$\lvert\mathcal{C}\rvert$	n	m	L	Distribution of N_i
2	2	10 30	2	4	80%-20% 50%-50% 20%-80%

4.4.2 Results

First experiments are carried out on the MILP model using the IBM ILOG CPLEX solver 12.6.2.0 version and a computer with an Intel i5 6200 2.3 GHz processor and 8 GB of RAM, in order to verify and validate it. A total of 110 instances are solved, namely thirty instances with ten jobs for each configuration and twenty instances of 30 jobs with the 80-20 configuration. Maximum solving time for a point is set to thirty minutes; in case the optimum is not reached after this time, a lower bound is returned by CPLEX. By using the ε-constraint-method, the model returns a Pareto front. Experiments results are shown in Table 4.4 and 4.5 for the case of the $z_{\text{trade-off}}$ and z_{percent} point.

Table 4.4 contains the mean values and standard deviation for the trade-off points that were obtained from each instance using the MILP and ε-constraint method. The

Table 4.4: Characteristics of the $z_{trade\text{-}off}$ point using MILP (standard deviation in parenthesis)

n	Distrib of N_i	$z^{\text{trade-off}}_{\text{setup}}$	$z^{\text{trade-off}}_{\text{inventory}}$	Setup % reduc.	Inventory % inc.	CPU time in seconds	Pareto size
10	80-20	3.13	3056	27.1 (22.7)	69.9 (95.5)	0.45 (1.2)	3.34
	50-50	3.93	5202	39.9 (17.9)	47.9 (53.7)	158 (449)	4.45
	20-80	4.38	7150	46.1 (19.2)	106.8 (286)	638 (737)	5.6
30	80-20	8.9	16764	38.5 (16.1)	54.8 (73.2)	1714 (384)	9.05

Table 4.5: Characteristics of the $z_{percent}$ point using MILP (standard deviation in parenthesis)

n	Distrib of N_i	$z^{\text{percent}}_{\text{setup}}$	$z^{\text{percent}}_{\text{inventory}}$	Setup % reduc.	Inventory % inc.	CPU time in seconds	Pareto size
10	80-20	3.86	2215	14.4 (20.7)	6.6 (11.4)	0.10 (0.67)	3.34
	50-50	4.34	4129	34.8 (17.7)	10.3 (9.2)	59 (191))	4.45
	20-80	5.4	5852	36.2 (22.9)	12.1 (11.4)	595 (762)	5.6
30	80-20	11	13179	25.9 (13.7)	12.3 (8.9)	1680 (392)	9.05

first four columns correspond to the number of jobs, configurations described above, and the average number of setup and inventory respectively. Columns five and six are the percentage of decrease in setups and percentage of increase in inventory in comparison with the $z^{\text{min}}_{\text{inventory}}$ point. Finally, the last two columns show the average CPU time in seconds consumed for obtaining this particular point in the case of the MILP, and the average number of points found on the Pareto front. Both the number of setups and inventory increase when the number of jobs with two operations increases (i.e. when the distribution switches from 80% - 20% towards 20% - 80%), which is a result of an increased number of operations. Similarly, Table 4.5 shows the same results for the z_{percent} point, and shows that it is possible to significantly reduce the number of setups with up to 36% less setups against a 12% increase in inventory, and thus the waste generation, with a relatively low increase in inventory. While the $z_{\text{trade-off}}$ point provides a better waste reduction, the increase in inventory is substantially higher than for the z_{percent} point. Computation times increase exponentially with the number of operations, resulting in impractical computation times for instances of 30 or more jobs, where it can take more than a half hour to get a single point of the Pareto front. In order to be able to solve industrial-size instances of more than a hundred jobs, it it thus necessary to consider a heuristic or metaheuristic approach.

4.5 Metaheuristic approach : genetic algorithm

Results from the MILP experiments show that an exact solving method is not appropriate for real-life situations, since the computation time required for such instances would be too large. Providing a heuristic or metaheuristic for solving industrial-size instances is thus necessary. Some metaheuristics such as PSO and SA (Meziani et al., 2018), tabu-search (Condotta and Shakhlevich, 2012; Li and Zhao, 2007), as well as various heuristics (Courtad et al., 2017; Amrouche et al., 2017) have been used to solve coupled-tasks scheduling problems. GAs have also been extensively used to solve scheduling problems, including problems involving reentrance characteristics which are similar to the coupled-tasks problems. For these reasons, and due to their applicability to both scheduling and multiobjective optimization as well as effectiveness for solving large instances, a GA was developed. The next sections provide an overview of GAs and their use in multiobjective optimization, after which the proposed GA structure is detailed.

4.5.1 Principle of GAs

The principle of GAs was first introduced by J. Holland in the 1960s, and later formalized in Holland (1992). They are based on the theory of evolution, and the improvement of solutions through repeated natural selection and modification. Their basic idea is to maintain a population of candidate solutions that evolves under a selective pressure that favours better solutions. In the application of production scheduling, a GA is an iterative procedure that operates on a finite population of solutions called chromosomes. Each chromosome represents a fixed schedule of jobs and machine assignation, and can be evaluated according to a fitness function, similar to an objective function. The members of the population are then interbred using various genetic operators like crossover (to select useful traits) and mutations (to introduce variety) to produce offspring. These offspring are evaluated based on the fitness function, and can replace the weaker chromosomes currently present in the population according to a defined population replacement strategy. This creates a new population of which new offspring can be created, and so on until a stopping mechanism is activated and the best solution is returned. GAs can be applied in many fields, including scheduling problems such as flowshops (Reeves, 1995), job-shops (Croce, 1995), flexible job-shops (Pezzella et al., 2008) and hybrid flowshops (Ruiz and Maroto, 2006). A good introduction to the use of GAs in scheduling can be found in Reeves (1996). Multiobjective optimization is also an important feature of GAs, with studies including environmental concerns (Arbiza et al., 2008; Vaklieva-Bancheva and Kirilova, 2010; El Amraoui and Mesghouni, 2014; Araujo et al., 2014; Golfeto et al., 2009; Malik et al., 2009), although mostly energy-related (Giret et al., 2015; Dugardin et al., 2010; Liu et al., 2016; Zhang and Chiong, 2016). While GAs are metaheuristics, and offer no guarantee of optimality, they have the advantage of requiring less computation time than exact methods, which is particularly relevant when dealing with large instances.

4.5.2 Multi-Objective GA design

Konak et al. (2006) identify various ways in which multiobjective GAs, also called Multi-Objective Evolutionary Algorithms (MOEA) can be designed. These include the fitness function design, the diversity mechanism, and the population replacement mechanism.

Fitness function

The fitness function represents the way each solution is evaluated with regards to the objective functions, and how it compares with other solutions. The first approach for MOEA is the weighted-sum, which assigns random or fixed weights to each objective. This includes Weight-Based Genetic Algorithms (WBGA) (Hajela and Lin, 1992) or Random Weighted Genetic Algorithms (RWGA) (Murata and Ishibuchi, 1995), which allow to easily transform a single objective GA into a multiobjective one. Other methods use specific objective functions such as the vector evaluated genetic algorithm which evaluates different populations with different objective functions, which may or may not alternate. Examples of multiobjective GAs using a weighted sum approach include e.g. WBGA-MO, where a different weight vector is given to each solution or RWGA using random weight combinations for each solution during the selection phase.

The second approach called Pareto ranking relies on a dominance relationship to rank the various solutions. The less a solution is dominated, the better its rank, and non-dominated solutions are assigned rank 1. Additional ranking mechanisms can also be based on the number of solutions a solution dominates, which favors solutions located in less densely populated areas. Examples of GAs using Pareto-ranking approaches include NSGA, NSGA-II (Deb et al., 2002) and NSGA-III (Jain and Deb, 2014a) or the Strength Pareto-Archived Evolution Strategy (SPEA) and

SPEA2 (Zitzler et al., 2001). All these numbered versions of NSGA and SPEA indicate how they have been reworked, improving some algorithms or employing different strategies to improve performance.

Diversity preservation strategies

When determining a Pareto front, it is important to obtain solutions that are uniformly distributed along the whole front. Diversity preservation strategies serve this precise purpose in order to avoid the clustering of solutions on confined areas of the front.

The first of these strategies is called fitness sharing, and its idea is to calculate the density of solutions along the Pareto front (using euclidean distance, density functions or others...) and decrease the fitness of solutions in densely populated areas in order to promote diversity. One issue with this method is that it require the definition of a parameter σ_{share} called niche size which determines the size of the neighborhoods in which density is calculated, which is not trivial to obtain. Density can be checked either in the objective function space (value of the objective function) or the decision variable space (features of the solution regarding decision variables), although fitness sharing based on objective functions tend to perform better. Examples of GAs using fitness sharing include the multi-objective genetic algorithm or SPEA2.

The second strategy called crowding distance relies on calculating the perimeter of the cuboid created by the nearest neighbors of a solution. As it does not require any additional parameter to be determined, the crowding distance is easier to calculate. It can be used to discriminate between two solutions with the same rank. The assumption is that a solution with a high crowding distance is located far from other solutions, and should thus be favored for diversity purpose. This method is used e.g. in NSGA-II.

The third strategy is cell-based density. It relies on mapping the solution space into a grid composed of K-dimensional cells, K being the number of objectives. The number of solutions located into a cell define its density, and the density of each solution in this cell is equal to the cell density. The density of each solution can be then used to favor diversity during the selection process, such as in the Pareto Envelope based Selection Algorithm (PESA) or PESA-II.

Population replacement strategies

Population replacement refers to how new solutions are added to the population, potentially replacing older and less fit solutions. Two main approaches can be considered, namely the elitist and non-elitist ones. When using an elitist strategy, all the best solutions survive to the next generation, while non-elitist strategies allow for random solutions to be kept in the population to favor diversity. While they can be difficult to implement in MOEA since every non-dominated solution is an elite one, most recent GAs use elitist strategies as they tend to outperform their non-elitist counterparts. There are two main ways of implementing those, based on using an external archive or not. If no external archive is used, solutions need to be kept in the population which may not have a large enough size for the whole Pareto front. When the population is full of non-dominated solutions, tournament strategies are used where solutions of similar ranks are compared using the diversity strategy (fitness sharing, crowded distance or cell-density) and the most diverse ones are kept, such as in NSGA-II.

If an external archive is used, non-dominated solutions can be stored outside of the population. This archive needs to be updated each time new solutions are added, and older solutions removed if necessary. This process can become time-consuming if the number of solutions in the archive is high enough, and several propositions have been made to make this process more efficient. Since Pareto front can comprise very large amounts of solutions, limiting the size of the archive and pruning might also be necessary. Solutions from the archive can then be reintroduced into new generation, such as in SPEA2.

4.5.3 Development of a bi-objective GA based on NSGA-II

Table 4.6 shows the advantages and drawbacks of the GA design approaches described in the previous section.

Based on the problem modeling, we recall that some of the main characteristics of our problem so far are:

- A bi-objective optimization, which is well suited to Pareto-ranking approaches;
- Objective function weights that are not evident to determine, as was observed in Chapter 3;
- A discrete objective function for the number of setups, meaning that the size

of the Pareto-set is limited to the total number of operations minus 1;

- The information provided to the decision-maker should be synthetic and useful, meaning that it is not necessary to store every solution to the problem.

Table 4.6: Multiobjective GA design approaches advantages and drawbacks

Strategy	**Advantages**	**Drawbacks**
Fitness function		
Weighted-sum	Easy to implement Can be used with a single-objective GA	Hard to define weights Can converge Difficulty with non-convex Pareto fronts
Pareto-ranking	No need for weights Can handle multiple objectives	Harder to implement Computation time required for the ranking process
Diversity preservation		
Fitness sharing	Possibility to diversify in the objective function or the decision variable space	Need to calculate the σ_{share} parameter
Crowding distance	No need for a user-defined parameter	No possibility to diversify in the decision variable space
Cell-based density	Can be used to direct the search towards certain regions of the solution space Computational efficiency	Need to map the solution space
Population replacement		
Without external archive	Easy to implement	Importance of population size
With external archive	Possibility to conserve and reintroduce more solutions	Computation time required for the archive updating process

In Coello et al. (2006) and Konak et al. (2006), an analysis and description of the main MOEA is done and a comparison carried out. The results of this comparison show that the algorithm that fits our problem characteristics the best is the NSGA-II algorithm (Deb et al., 2000). Indeed, it uses a Pareto-ranking approach which removes the need to define weights for the objective functions. Its diversity strategy is the crowding distance which is easier to implement, and the decision variable space is not used in our case. Finally, the limited size of our Pareto-front means that no external archive is required. NSGA-II was thus chosen, also based on its proven efficiency regarding scheduling problems as well as its common use in the literature. While a NSGA-III algorithm has been proposed (see Jain and Deb (2014b,a) for more information), it was not used in this study as it would have brought unnecessary complexity for no benefit considering the low number of objectives in our problem. Thus, the NSGA-II structure was adopted, although some adaptations have been made to better suit our problem. Important parts of this structure are detailed in the following sections.

Chromosome representation

A sequence coding was adopted for chromosome representation. A chromosome represents a sequence of operations, its size being equal to the number of jobs times the maximum number of operations per job. Since not all jobs have the same number of operations, dummy operations with processing time zero are added to keep the chromosome size constant. This chromosome is constituted of genes, where a gene's position corresponds to the job it belongs to and its order within this job. The value of a gene represents its rank in the global operations sequence. Table 4.2 which shows an example of instance data is reminded below, and Table 4.7 is the corresponding chromosome, Seq giving the operations sequence, and the starting times s_{ij} in increasing order. Figure 4.4 presents the Gantt chart for this same instance. As an example, operation 1 of job 9 is processed first, while operation 2 of job 1 is processed sixth, and operation 2 of job 8 is a dummy operation.

Table 4.2: Example of instance data

i	1		2		3		4		5		6		7		8		9		10	
j	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
C_{ij}	2	1	1	1	1	2	1	2	2	1	1	2	1	1	2	0	1	1	2	1
P_{ij}	21	21	15	15	25	25	24	24	18	18	17	17	32	32	27	0	13	13	24	24
d_i	148	148	494	494	290	290	419	419	207	207	156	156	522	522	305	305	80	80	584	584

Table 4.7: Associated chromosome sequence

i	1		2		3		4		5		6		7		8		9		10	
j	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Seq	4	6	13	17	8	11	12	14	2	9	5	7	15	18	10	20	1	3	16	19
s_{ij}	36	49	67	80	104	118	139	164	189	238	265	344	380	395	419	451	475	490	560	584

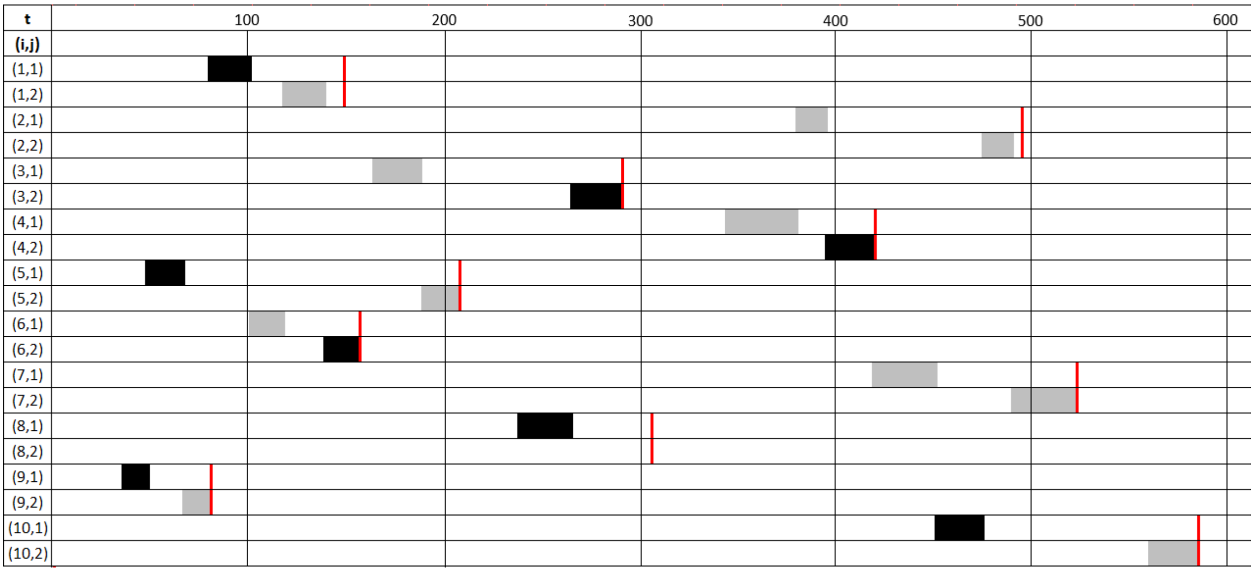

Figure 4.4: Gantt chart of a schedule with ten jobs

Once a sequence is known, the corresponding starting times are obtained using Algorithm 2. Here, L is the minimum drying time, s_k is the starting time of the k^{th} operation in the sequence, D_k its due date, and P_k its processing time. s_{last} refers to the starting time of the last operation to be scheduled, while $s_{\text{next}(k)}$ is the starting time of the operation scheduled right after operation k.

Algorithm 2 *Chromosome to starting times conversion*

Input: chromosome giving a sequence of operations
Output: starting time s_k for each operation k
$s_{\text{last}} = D_{\text{last}} - P_{\text{last}}$ (schedule the last operation in a "just-in-time" policy)
for each operation k to be scheduled, in decreasing sequence order, **do**
    if k is the only operation or the last operation of its job **then**
        $s_k = \min(D_k - P_k; s_{\text{next}(k)} - P_k)$
    else k is an operation followed by k' in its job, with drying time L in between:
        $s_k = \min(s_{k'} - P_k - L; s_{\text{next}(k)} - P_k)$
    end if
end for

It can be shown (see Appendix B for proof) that this algorithm returns minimal inventory for a given operations order.

Ranking method

Ranks are obtained using the fast non-dominated sorting algorithm (Deb et al., 2002) for all candidate solutions. In this strategy, the Pareto dominance relationship is used to assign each solution a rank based on a domination counter.

All solutions are compared, and all the non-dominated ones are assigned the rank 1. They are then removed from the current population, and the process is repeated with an incremented rank number, until all solutions have been assigned a rank. This provides a set of Pareto fronts $\mathcal{F}_i$, where all solutions of front $\mathcal{F}_k$ dominate the solutions of front $\mathcal{F}_{k+1}$.

Diversity preservation

In order to avoid the clustering of solutions, a crowding-distance comparison method is used. This crowding distance $\mathcal{I}[i]$ of a solution i is based on the neighboring points surrounding it, according to the different objectives. It is calculated as: $\mathcal{I}[i] = \sum\limits_{o \in \mathcal{O}} = \frac{z^{o}_{i+1} - z^{o}_{i-1}}{z^{o}_{\max} - z^{o}_{\min}}$ where $\mathcal{O}$ is the set of objectives, z^{o}_{i+1} and z^{o}_{i-1} the objective value of both neighboring solutions for the o^{th} objective, and $z^{o}_{\max}$ and $z^{o}_{\min}$ the maximum and minimum values for objective $o \in \mathcal{O}$. A crowded comparison operator is then used to discriminate between different solutions with the following logic: if a solution is ranked lower than another, it is preferred to its counterpart. If two solutions have the same rank, the one with the biggest crowding distance is preferred.

Initialization

The initialization step refers to the creation of the initial population. While randomization is a common method for generating initial solutions, it is usually used for binary encoding and when constraints are not so severe as to generate many unfeasible solutions. In our particular case, the due date and operations order constraints as well as the encoding used would make the use of a randomization method inefficient. For this reason, we use the following method. Based on the instance data, a single initial solution is created. An algorithm sorts the jobs by increasing due date. The operations of jobs with the lowest due dates are scheduled first, and operations of other jobs can be introduced whenever the job with the lowest due date is in the drying inventory. Once the initial solution is created, two mutation operators are applied in order to generate a sufficient number of new offspring. These constitute the initial population introduced into the GA.

Mutation operators

Two different mutation operators are considered, namely the swap (Sevaux and Dauzère-Pérès, 2003) and insertion operators. The swap picks two random genes within the chromosome and exchanges them. The insertion picks a random gene and inserts it somewhere else in the chromosome. Since the chromosome size may vary depending on the number of jobs, the mutation scales accordingly by applying a number of swaps or large swaps equal to the number of jobs $|I|$ divided by ten. Figure 4.5 shows an example of how both operators work on a ten-jobs chromosome.

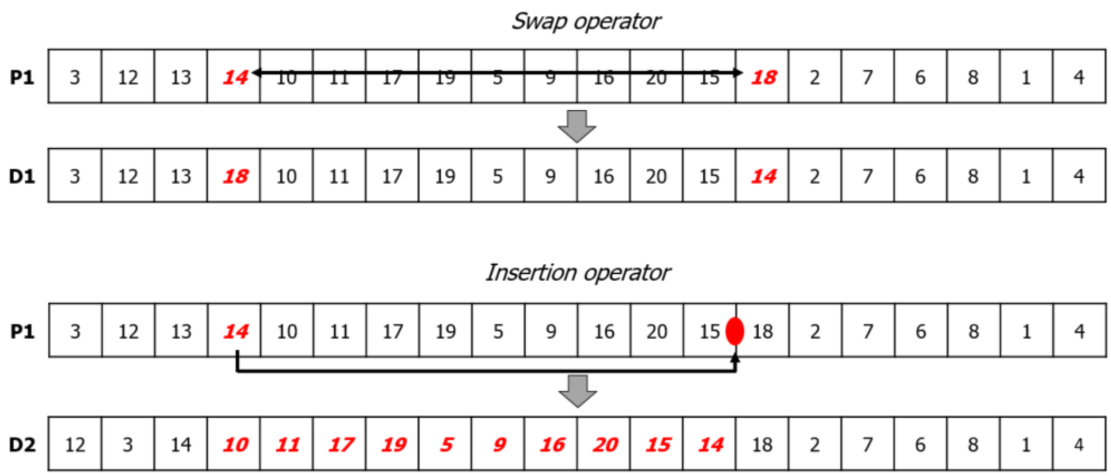

Figure 4.5: Swap (creates offspring D1) and insertion (creates offspring D2) operators and generated offspring

Crossover operators

Two types of crossovers are tested, namely the standard two-point crossover (Sevaux and Dauzère-Pérès, 2003) and the Linear Order Crossover (LOX) (Portmann, 1996).

The standard two-point crossover chooses two random genes in the first parent and swaps them with the corresponding genes of the second parent, as represented in Figure 4.6 where offspring D1 and D2 are created from parents P1 and P2. Similarly to the way mutation operators scale, this operator is designed to execute this swapping manoeuvre a number of time equal to the number of jobs divided by ten.

The other crossover operator used is the LOX operator, which also chooses two random genes as crossover points. The partial sequence contained between those

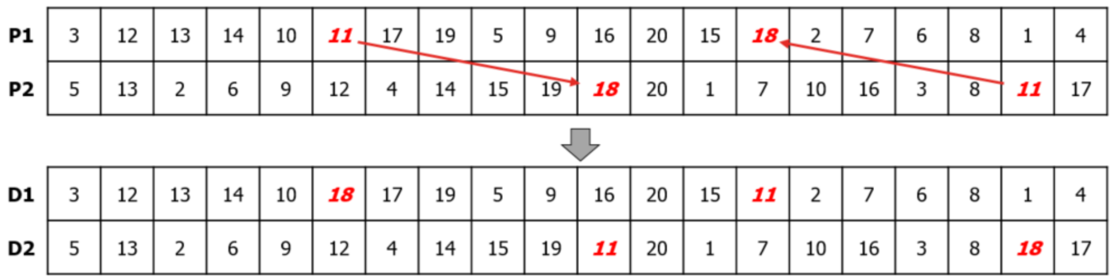

Figure 4.6: Two point standard crossover and generated offspring

two points is transmitted to the offspring. The rest of the offspring is then filled with the missing genes from the other parent starting from the beginning of the chromosome, as shown in Figure 4.7.

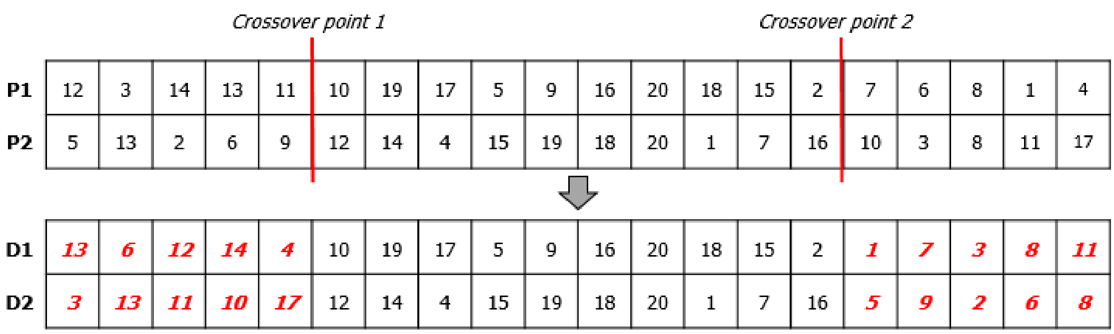

Figure 4.7: LOX operator and generated offspring

This operator has the merit of keeping a part of the first parent intact, as well as the relative order from the second one, which is important in a problem where due dates severely constrain the ordering possibilities.

Parents are chosen using a binary-tournament selection. This method chooses two random solutions from the population, and selects the fittest one using the crowded comparison operator described previously to define the first parent. The second parent is determined using the same process, and the crossover operators are then applied.

Unfeasible solutions

It is often useful in a GA to allow for unfeasible solutions to be part of the chromosome pool. Since optimal solutions are oftentimes found near the border of the search space, allowing for solutions located outside (but not too far from) these borders is a reasonable strategy. In the case of a Pareto ranking approach however, allowing unfeasible solutions in the population can be a problem, as these can be non-dominated solutions that might remain in the final solution pool, potentially replacing feasible solutions. It is possible to apply penalties to unfeasible solutions to reduce their fitness, but this is unpractical in the case of Pareto ranking. "Repairing" unfeasible solutions into feasible ones is also difficult due to the constrained nature of our problem. Thus, any unfeasible solution generated is immediately discarded and another one created to replace it.

Population replacement

The population replacement mechanism used is a purely elitist one, and based on the ranks assigned to each solution. Solutions of rank 1 are selected first, then rank 2 and so on until the new population has been filled. If the number of solutions in the current front $\mathcal{F}_i$ is higher than the number `Popsize` required to complete the new population, the crowded comparison operator is used. Solutions with the largest crowding distance (i.e. the ones located in the least densely populated part of the front) are favoured over the others.

Stopping mechanism

The stopping mechanism is twofold. The algorithm stops once a number `threshold` of generations, monitored with a counter called `Generationnumber` has been reached. While the value of `threshold` needs to be determined through experiments, it provides a consistency regarding computation time for instances of a same size. Additionally, the algorithm stops when `Iteration number` – monitored with a counter called `Iterations` – pairs of parents have been selected, without creating any new population. This avoids spending too much time generating new solutions when it is too computationally demanding. It is especially relevant for large population sizes where producing enough feasible solutions can be difficult.

GA structure

As all components of this GA have been defined in the previous paragraphs, its overall structure, represented in Figure 4.8, is now explained.

After the initialization phase in which the initial population is created, the GA iterations start. A pair of chromosomes is selected, and has a probability p_1 of being

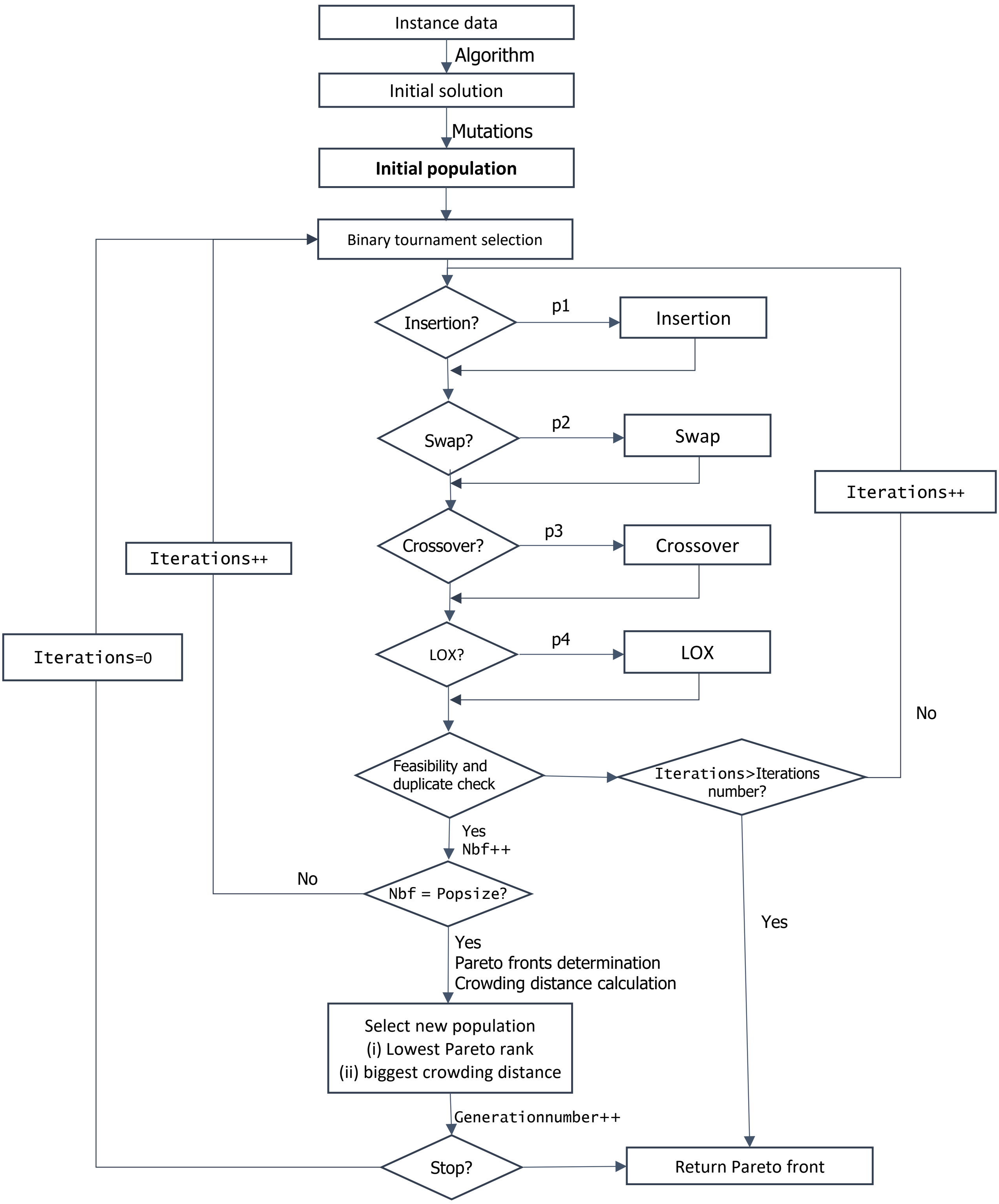

Figure 4.8: NSGA-II structure representation

subjected to the swap operator (each chromosome is mutated independently). The insertion operator is then applied with a probability p_2 (meaning that any given pair of chromosome can be subjected to either zero, one or two mutations). The resulting chromosomes then have a probability p_3 of being subjected to a standard two-point crossover (as parents), followed by a probability p_4 of being subjected to the LOX operator.

If those new chromosomes are feasible, they are kept in the offspring generation, and a counter called `Nbf` is incremented. If more offspring need to be generated to complete the population, the iteration counter `NbIterations` is incremented and a new pair of parents is selected and submitted to the operators. If the iteration counter reaches `Iteration number` before a new population has been created, the algorithm stops and the best current solutions are returned.

Once a number of offspring equal to the population size have been accepted, both the parent and offspring populations are combined and the Pareto-rankings determined. The population replacement strategy is applied, the new population is created, and the iteration counter is reset. This process goes on until the number of generations reaches `threshold` and the algorithm stops.

4.6 GA numerical experiments and results

Similarly to Section 4.4, all experiments are carried out using an Intel i5 6200 2.3 GHz processor with 8 GB of RAM, and using the same instances generated for the MILP experiments.

4.6.1 GA parameters definition

These first experiments aim at finding the parameter values that ensure that the algorithm is efficient in terms of computation time and solution quality. From the seven main parameters affecting the algorithm performance, a Taguchi table (Roy, 2001) is constructed. These parameters were considered in 8 experiments sets, switching between two extreme values and applied to instances of each configuration of 10 jobs and 80-20 instances with 30 jobs. Table 4.8 detail these experiments values and the obtained results.

Experimental values for each parameter were chosen after initial experiments and in order to consider a large possible range. The effect of each parameters on algorithm results is supposed to be linear, and only interactions of the first order between parameters are considered. In order to account for the biobjective aspect of the problem, optimum parameters are determined twice: one time to with regards to the inventory objective function, and a second time with regards to the number of setups. A compromise is then found, and resulting parameters values are the one kept for the following experiments.

Table 4.8: Taguchi table parameter values and results

	State 1	State 2	Results
Population size	10	30	30
Swap rate	0.5	0.8	0.8
Insertion rate	0.5	0.8	0.5
Crossover rate	0.1	0.5	0.3
LOX rate	0.1	0.5	0.1
Threshold	100	2000	1000
Iteration number	1000	3000	1000

4.6.2 Results

The same sets of instances solved using the MILP in section 4.4 are solved again, this time using the GA and the parameters defined in the previous section.

A first comparison of MILP and GA was carried out on the $z^{\text{min}}_{\text{inventory}}$ and z_{percent} points. The gap for any given instance is:

$$\text{gap} = \frac{z^{\text{GA}}_{\text{inventory}} - z^{\text{MILP}}_{\text{inventory}}}{z^{\text{MILP}}_{\text{inventory}}}$$

. Tables 4.9 and 4.10 give the average results over 30 instances of each configuration; the last column indicates for how many instances (over the 30 considered) the GA found the optimal solution.

Table 4.9: $z^{min}_{inventory}$ point comparison

n	Distrib of N_i	Average gap (%)	Nb opt/nb total
10	80-20	3%	27/30
10	50-50	1%	25/30
10	20-80	2%	21/30

As can be seen, the GA reaches the optimal solution a majority of the time, with average gaps not exceeding 3%. Results show that the $z^{\text{min}}_{\text{setup}}$ point is only reached half of the time, meaning that the GA can have trouble obtaining the entirety of

Table 4.10: $z_{percent}$ point comparison

n	Distrib of N_i	Average gap (%)	Nb opt/nb total
10	80-20	3,3%	28/30
10	50-50	1%	25/30
10	20-80	1,2%	21/30

the Pareto front. This is however not a problem when considering the implications for decision-makers, since the $z_{\text{setup}}^{\text{min}}$ point always results in a substantial increase in inventory, making these solutions unsuitable for practical applications.

The complete results for the $z_{\text{trade-off}}$ and z_{percent} are shown in Table 4.11 and 4.12 respectively.

Table 4.11: Characteristics of the trade-off point using the GA (standard deviation in parenthesis)

n	Distrib of N_i	$z_{\text{setup}}^{\text{trade-off}}$	$z_{\text{inventory}}^{\text{trade-off}}$	Setup % reduc.	Inventory % inc.	CPU time (s)	Pareto size
10	80-20	3.14	3084	23.9(22.4)	61.3 (89.1)	42.3 (42.2)	2.97
	50-50	4.1	5490	36,7 (18.2)	33.2 (38.5)	48.9 (37.6)	3.75
	20-80	5	6645	39 (17.7)	32.6 (41.4)	58.3 (42.7)	4.57
30	80-20	10,85	29848	34.3 (14.3)	85.7 (76.7)	103.6 (61,6)	6,55

Table 4.12: Characteristics of the $z_{percent}$ point using the GA (standard deviation in parenthesis)

n	Distrib of N_i	$z_{\text{setup}}^{\text{percent}}$	$z_{\text{inventory}}^{\text{percent}}$	Setup % reduc.	Inventory % inc.	CPU time (s)	Pareto size
10	80-20	3.76	2350	13.2 (20.7)	6.96 (12)	42.3 (42.2)	2.97
	50-50	4.34	4801	35 (17.9)	11 (9.5)	48.8 (37.6)	3.75
	20-80	5.46	6128	35.5 (24.6)	11.5 (10.8)	58.3 (42.7)	4.57
30	80-20	14.45	21118	14,66 (17,8)	6,33 (7,62)	103.6 (61.5)	6.55

The GA provides accurate results and manages to cover the majority of the pareto front. As an example, for the 20-80 configuration an average pareto front size of 4.6 is observed versus 5.6 for the MILP results. On average, a 4% gap is observed between the inventory values of the GA and the MILP, and 5% for the number of setups. Computing time is significantly lower than the MILP, as the GA is able to map most of the Pareto front in significantly less time than it takes for the MILP to find a single point, except for the 80%-20% - 10 jobs instances.

Figure 4.9 shows the average values of the four points $(z_{\text{inventory}}^{\text{min}}, z_{\text{setup}}^{0})$, $(z_{\text{inventory}}^{0}, z_{\text{setup}}^{\text{min}})$, $(z_{\text{inventory}}^{\text{trade-off}}, z_{\text{setup}}^{\text{trade-off}})$ and $(z_{\text{inventory}}^{\text{percent}}, z_{\text{setup}}^{\text{percent}})$ for the MILP (full line)

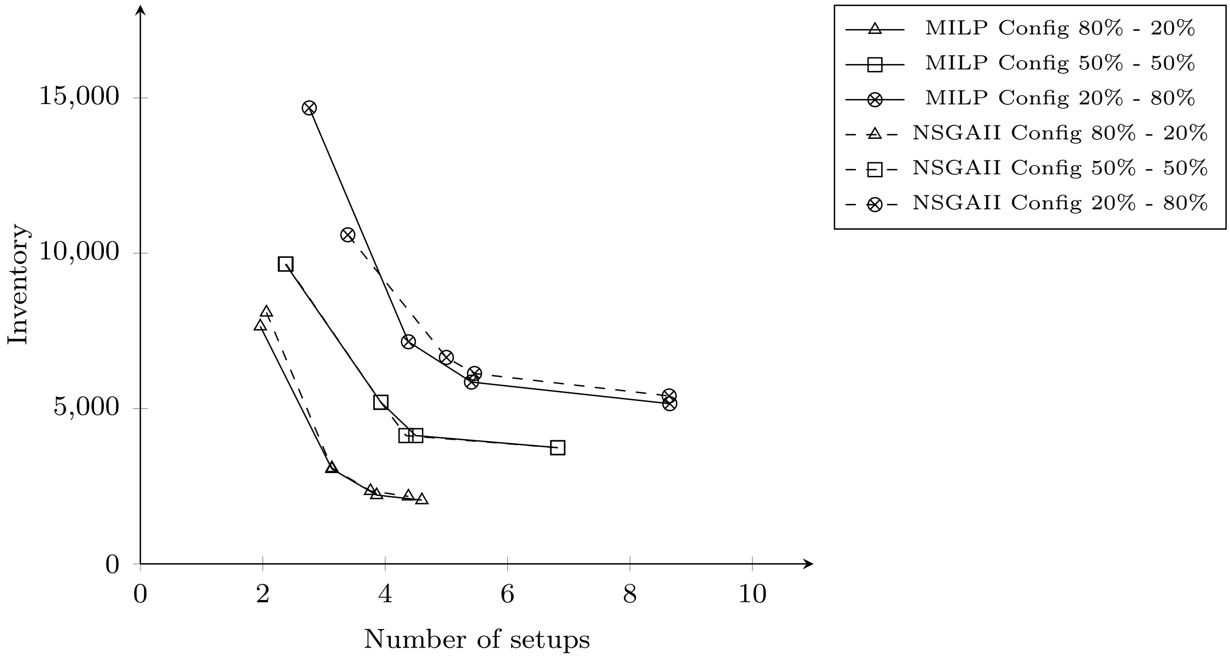

Figure 4.9: Average trade-off and extreme points for 30 instances of ten jobs

and GA (dashed line) and for each configuration. As can be seen, the number of setups can be reduced by 28% on average with a relatively low increase in inventory. When reaching the trade-off point, any additional reduction of setups results in a greater increase. This is visible in the rising steepness of the curve when reaching the trade-off point. Tracing the same curves for larger instances or different drying times yields similar results. The additional z_{percent} point also provides an efficient schedule for decision-makers since it is based on direct waste reduction and inventory increase percentages.

In order to simulate a real life situation, 10 instances of a 100 jobs (the size of a daily schedule in this plant) with the 80-20 configuration have been solved with the GA. Results for the z^{tradeoff} and z^{percent} point are available in Table 4.14. To account for the larger size of the Pareto front, the GA parameters have been adapted after some experiments, and new parameters values are shown in Table 4.13.

As can be seen, alternative daily schedules can be obtained in one hour and a half on average, which is an acceptable time-frame for a practical use. While percentages seem lower in both waste reduction and inventory increase, they still remain significant when large quantities are at play, and for some particular instances can provide very efficient schedules. It is also to be noted that the possible improvements are largely dependant on the instance, and can vary greatly

Table 4.13: Taguchi table parameter values and results

Parameter	Value
Population size	100
Swap rate	0.8
Insertion rate	0.8
Crossover rate	0.3
LOX rate	0.05
Threshold	2500
Iteration number	2500

Table 4.14: Points of interest for 100 jobs instances

	n	Distrib of N_i	z_{setup}	$z_{\text{inventory}}$	Setup % reduc.	Inventory % inc.	CPU time (s)
$z^{\text{trade-off}}$	100	80-20	34.2	253920	41.1 (8.5)	149.2 (98.2)	5718
z^{percent}	100	80-20	51.6	135431	11.1 (9.6)	4.3 (3.87)	5718

as shown by the high standard deviations. Furthermore, possible improvements on the results can be obtained at the cost of a longer solving time (through an increase in the number of iterations). This means that if the schedules are determined sufficiently in advance and solving times of several hours are allowed, even greater reductions of waste generation are possible. It is also possible that for companies where schedules are determined through old methods, the new schedules provided here will improve both the economic and environmental objective functions when compared with the previous method. Thus, it might be beneficial for the decision-maker to consider this trade-off schedule or other solutions located between this one and the $(z^{\text{min}}_{\text{inventory}}, z^0_{\text{setup}})$ point on the Pareto front, such as the z_{percent} point, when planning the production, in accordance with the respective prices of inventory-keeping and waste treatment.

4.7 Conclusion

This chapter investigates a single-machine scheduling problem with coupled-tasks aiming at reducing waste generation due to setups and costs induced by inventory, under the constraint of due dates. This problem has been shown to be NP-Hard, and the MILP model presents excessive computation times for industrial-sized instances. Therefore, a multiobjective GA based on the NSGA-II model is proposed, and performances of both GA and MILP are compared. The multiobjective aspect of the problem is accounted for through the ε-constraint method for the MILP, and the proposition of trade-off solutions to the decision-maker. Results show that the GA performs well on small instances, and strongly outperforms the MILP on large ones.

As this chapter deals with industrial manufacturing and is based on a realistic production plant, it is important to discuss the implication of the results for the decision-maker. Besides the two extreme points minimizing inventory or setup waste, two points of interest are proposed. When using a distance to the ideal point criteria, the $z_{\text{trade-off}}$ point is the most efficient. However, when looking at the actual percentage increase and decrease regarding inventory and waste, the z_{percent} point is more suited to managerial needs. While the $z_{\text{trade-off}}$ point tends to produce less waste (12% more setups reduction than the z_{percent} point on average), it also substantially increases inventory (a 94% inventory increase on average using MILP data), which might be unacceptable for decision-makers. On the other hand, the z_{percent} point increases inventory by only 9% on average for a 25% waste reduction, making it more suited to real-life decisions. Using the results from Chapter 3, it means that it is possible to reduce the total amount of paint sludge generated by 5% in the plant for a 9% of inventory on average, which cost might be offset by the savings on waste management. While numerical experiments have shown that using MILP is not an option for industrial-size instances, the results provided by the GA show that the $z_{\text{trade-off}}$ point can remain useful for decision-makers even for instances of a hundred jobs. Alternative solutions can be obtained rapidly, providing the decision-makers with different options depending on their priorities and current situation. If one was to assess the actual cost of waste management, alternatives schedules reducing waste generation could prove to be overall economically beneficial to companies.

Several perspectives can be considered for this study. Implementing new multiobjective GAs or metaheuristics could be an effective way to compare and possibly improve the results obtained using NSGA-II. Calculating accurate lower bounds for large instances, using e.g. a lagrangian relaxation, would also allow for a better knowledge about the performance of the metaheuristic when the number of jobs increases. Additionally, the proposed model and GAs can easily be adapted to tackle other cases of coupled-tasks scheduling problems. While the experiments considered in this chapter are limited to a maximum of two operations per job and two operation types, the developed model and GA can be used for higher values of m and $|\mathcal{J}|$. Similarly, new distributions regarding the operation type could be experimented on, as well specific minimum drying times L_i to better represent the variety of industrial production plants. Considering sequence-dependent setup times would be an interesting development, and an extension to a multi-machine environment could also be useful for cases with multiple painting lines sharing common operation types.

CHAPTER 5

Contributions, discussion and perspectives

Contents

Résumé du chapitre 5

Afin de répondre à la problématique introduite dans le premier chapitre de ce manuscrit, trois principaux axes de recherche ont été développés et sont rappelés ci-dessous:

- **Quelles sont les caractéristiques des problèmes d'ordonnancement minimisant les déchets?**
- **Comment identifier les opportunités de réduction des déchets par l'ordonnancement?**
- **Comment résoudre les problèmes d'ordonnancement minimisant les déchets?**

Trois principales contributions ont été apportées, pour répondre à chacune de ces interrogations. Dans le deuxième chapitre, un état de l'art sur les problèmes d'ordonnancement minimisant les déchets a été réalisé, faisant apparaître un domaine de recherche encore naissant et fragmenté. Une classification est proposée pour grouper ces travaux selon des critères liés à la fois à leur aspect environnemental et d'ordonnancement, offrant un premier cadre structuré à ce domaine hétérogène. De cette classification émergent plusieurs observations dont la prise en compte peut permettre de favoriser et approfondir la recherche sur ce sujet. La première concerne la définition des objectifs de réduction des déchets dans ce type de problèmes, qui souffre d'un manque de précision non seulement sur l'impact environnemental de ces déchets, mais aussi sur leur coût réel pour les entreprises. La deuxième a trait à l'aspect multiobjectif de ces problèmes, et à la façon d'extraire de leur résolution des informations utiles aux preneurs de décision.

Suite à cette analyse, le chapitre 3 présente une méthodologie qui a pour but l'identification des opportunités de réduction des déchets par l'ordonnancement, et qui permet de répondre, au moins partiellement, à notre deuxième interrogation ainsi qu'aux observations précedentes. Cette méthodologie se base sur des outils existants de suivi de flux, et intègre dans sa représentation des flux de matière des paramètres utiles à l'ordonnancement. Cette représentation permet d'identifier au sein d'un système de production les opportunités de réduction des déchets grâce à l'ordonnancement, qui peuvent alors être étudiées plus en profondeur. Un inventaires de flux suivi d'une analyse des impacts environnementaux et économiques de ces derniers permet de déterminer de façon précise les flux à minimiser et qui composeront nos fonctions objectif. Enfin, en se basant sur l'ensemble des informations obtenues lors des premières étapes, la notation de Graham (α, β, γ) du problème ainsi que les données et paramètres sont obtenus. Cette méthodologie est validée grâce à une étude de cas, et les résultats obtenus montrent son intérêt à la fois pour déterminer le potentiel de réduction des déchets dans un système de production et pour caractériser le(s) problème(s) d'ordonnancement correspondant(s). De nombreuses extensions sont possibles pour élargir le champ d'action de cette méthodologie, même si de nouvelles études de cas sont nécessaires pour tester son fonctionnement de façon plus robuste.

En se basant sur les résultats issus de l'étude de cas, le quatrième chapitre présente un exemple de résolution de problème d'ordonnancement machine-unique avec tâches couplées dans un contexte de fabrication à la commande minimisant les déchets et le stock. Ce problème biobjectif a pour but la minimisation du nombre de changements de série, qui génèrent du déchet, et la minimisation du nombre de pièces en stock, qui représentent un coût. Une première résolution exacte est réalisée grâce à la Programmation Linéaire en Nombres Entiers (PLNE), qui permet de valider le potentiel de l'ordonnancement pour réduire les déchets de changements de série de façon importante contre une augmentation de stock faible. Cependant, des temps de calcul trop longs rendent cette méthode inappropriée pour un usage pratique, et une méthode de résolution approchée est donc proposée. Un algorithme génétique de type NSGA-II est détaillé puis implémenté. Des expérimentations numériques montrent des résultats quasiment optimaux et des temps de calculs largement réduit par rapport à la PLNE qui permettraient une potentielle application industrielle. Des points d'intérêt sont également proposés afin de fournir aux preneurs de décision des informations synthétiques et adaptées à leurs besoins. Après une discussion sur les différentes implications de ces travaux, à la fois industrielles et académiques, de nombreuses perspectives de recherche sont évoquées, et notamment:

- L'utilisation plus large d'outils d'analyse environnementale comme l'Analyse de Cycle de Vie dans les fonctions objectifs, ainsi que l'utilisation d'outils d'aide à la décision multicritère pour concilier les natures différentes des objectifs économiques et environnementaux ;

- La considération de stratégies de réutilisation et regénération des déchets, à la fois dans la méthodologie proposée au chapitre 3 et dans la résolution des problèmes d'ordonnancement correspondants ;

- Une étude plus approfondie des mécanismes générateurs de déchets et pouvant être affectés par l'ordonnancement tels que les changements de série, les opérations de nettoyage ou de découpe ;
- La généralisation de la résolution des problèmes d'ordonnancement de façon robuste (i.e. prenant en considération les incertitudes de production), à la fois en termes de planning de production mais aussi de risques environnementaux ;
- La prise en compte du critère social dans les problèmes d'ordonnancement minimisant les déchets afin de considérer simultanément les trois piliers du développement durable.

Contributions, discussion and perspectives

In order to answer the research question identified in Chapter 1, three main axes have been investigated, and are reminded below:

- **What are the characteristics of waste-minimizing scheduling problems?**
- **How to identify opportunities for waste minimization through scheduling ?**
- **How to solve waste-minimizing scheduling problems?**

These questions have been addressed through a comprehensive review and classification of the literature, the proposal and use of a new methodology for problem identification, and a problem mathematical modeling and solving to demonstrate the interest of waste-minimizing through scheduling. In the following section, the contributions brought by this work are first reminded. The implications of this work for both researchers and practitioners are then discussed, followed by various perspectives.

5.1 Contributions

This worked was spurred by the following triple observation:

- While industrial companies need to reduce their environmental impact, their actions have mostly been focused on the tactical and strategical levels;
- Research on green scheduling has mostly been centered on reducing energy consumption thus far, and waste-minimizing scheduling is hardly represented;
- Companies can benefit from reducing their waste generation both environmentally and economically, as the current accounting methods underestimate the actual cost of waste management.

To address these issues, this manuscript provides three main contributions to answer the research question of how operations scheduling can reduce waste generation in industrial production.

The first one lies in accurately classifying waste-minimizing scheduling problems. Since research on this topic has been limited, few articles have been published, and many of them are not defined as such or are scattered in different journals and problem or industry types. In the second chapter, **we provide a state-of-the-art of the current literature on this subject, and classify the articles according to several criteria related to scheduling aspects as well as their waste generation concern**. This allows us to identify four main scheduling problem categories which can include waste minimization, namely the batch and hoist scheduling problems, the cutting stock and the integrated cutting stock problems, as well as less represented shop floor scheduling problems. An analysis of this classification highlights several issues that, if fixed, could facilitate the development of research on waste-minimizing scheduling. The first one concerns the environmental impact assessment of the generated waste, which is often only represented by a physical quantity although more accurate methods such as life cycle assessment should be used. The issue of waste management cost calculation is also raised, as better knowledge of the actual cost of waste could be an incentive for companies to improve their environmental performance. Finally, the handling of the multi-objective nature of such problems is discussed, especially regarding its consequences on the decision-making process.

Following on this analysis, we propose in Chapter 3 a new methodology to help address the issues of waste impact and cost assessment and the development of multi-objective scheduling, **and provide a new approach for identifying and characterizing waste minimization of opportunities through scheduling in a production system**. This four-steps methodology combines flow assessment, environmental analysis and scheduling concepts to determine the three-field notation, data and parameters required to model a waste-minimizing scheduling problem, including an environmental and economic assessment of the generated waste flows. To test and validate this methodology, a case study is carried out on a realistic example of hubcap production plant, with results showing that hazardous waste generation could be reduced by ten percent through adequate scheduling. While this methodology needs to be tested on further case studies and could be extended both in its scope and level of detail, it fulfills its goals and greatly facilitates the integration of relevant environmental objective functions into scheduling problems. By shedding light on the actual costs of the different waste flows generated by a production system, it also allows to take into account the savings from reduced waste generation into the objective function.

Finally, using the results from the previous case study, **a waste-minimizing**

scheduling problem is modeled and solved, in this case a bi-objective single-machine problem with coupled-tasks and hard due dates. Its objectives include minimizing both the products held in inventory, which is the economic objective, and the number of setups required, which entail cleaning operations that generate hazardous waste. The problem is first modeled and solved using mixed integer linear programming, using sets of instances with different characteristics. The results obtained with this exact method show that it is possible to reduce the number of setups, and thus the generated waste, up to 36% without increasing the inventory by more than 12%. However, the computation time required for solving instances of industrial size makes the use of an exact method inappropriate for real-life situations, where decision-makers need to obtain alternative solutions rapidly. Thus, an approached solving method using the multiobjective genetic algorithm NSGA-II is proposed. After detailing the algorithm structure, its parameters are determined using a Taguchi table, and numerical experiments are carried out. Results show that the algorithm performs well regarding the objective functions in comparison with the exact method, and requires considerably lower computation times for large instances. A decrease up to 35% of the number of setup is obtained against an 11.5% increase in inventory. Using two points of interest called $z_{\text{trade-off}}$ and z_{percent}, we can provide the decision-maker with efficient solutions in terms of waste reduction and inventory increase even for industrial-sized instances. While this metaheuristic method can still be improved and comparisons with other approached methods should be carried out, it highlights the potential of waste-minimizing scheduling for actual industrial problems.

5.2 Discussion

5.2.1 Academic implications

As was observed in the state-of-the-art of Chapter 2, the field of waste minimization through scheduling is a nascent one, with more than half of the papers on this subject published during the last ten years. While this topic has been identified in several literature reviews on sustainable scheduling (Giret et al., 2015; Akbar and Irohara, 2018), it has largely been eclipsed by energy considerations. Thus, this thesis represents a first milestone for the development of waste-minimizing scheduling. Through the proposition of a classification based on criteria pertaining to both environmental and economic factors, scheduling aspects and waste generation concerns we establish a first grouping of the existing studies. While it appears that waste-minimizing scheduling problems are often related to specific industries, such as the chemical or cardboard ones, different shop-floor scheduling problems have been studied and a large number of environmental and economic objectives are considered. Additionally, while the number of studies remains low with a total of 71 articles identified, the methodology provided in Chapter 3 enables the identification and characterization of new problems, waste generation concerns and industrial settings. As such, both the classification and methodology benefit from each other: the literature review and classification can serve as a basis when looking for cases where scheduling could reduce waste generation in the methodology used, looking either at the waste generation concern or industry type. Conversely, using the methodology to identify waste-minimizing scheduling problems will enrich the current classification, adding new objectives or waste generation concerns, which could bolster the research in this field. This is shown through the application case in Section 3.4. Starting from a waste generation concern due to setups in the painting workshop, a new single-machine with coupled-tasks problem is identified and characterized. The problem is solved in Chapter 4, showing that it is possible to apply the results from the methodology to obtain trade-off solutions that can be used in industrial settings. There is however a need to test the methodology on a larger panel of production systems, and action research and new case-studies should be a priority to validate it, especially regarding data collection protocols. This should also be an opportunity to further the collaboration between operations research and environmental sciences.

5.2.2 Industrial implications

While this thesis hopes to promote the development of research on waste-minimizing scheduling, it also offers new insight and decision-making tools for practitioners wishing to reduce their waste generation. While the literature classification can be informative, the methodology proposed in Chapter 3 offers a real potential of waste assessment and reduction, not only through scheduling, but during the entire process of subsystem ranking and flow assessment described in the different steps of Section 3.3. Additionally, using scheduling as a lever for waste reduction does not require any large investment as would process optimization or investing in new equipment, and can be implemented in a short time frame. Several issues remain however, especially regarding the cost-assessment of waste management in companies. As this cost is oftentimes underestimated, it is harder for companies to envision the economic gains resulting from producing less waste. Even though several methodologies have been proposed for the assessment of waste management costs, a shift in company accounting policy is likely to be necessary if they are to be convinced that implementing waste-minimizing schedules can be economically sound. This is especially important in order to provide relevant trade-off points for the decision-makers. As the results of the numerical experiments in Chapter 4 have shown, it is often more effective to go for compromises that can reduce waste by a reasonable amount while not increasing costs prohibitively. Where these best compromise solutions are located on the Pareto front depends on the respective importance of each objective, and the cost of waste not being accurately measured can skew this process. Additionally, while a full mathematical model and an exact and metaheuristic resolution methods are provided in Chapter 4, such a complete study of the scheduling problem might not be compulsory in order for companies to improve their environmental performance. As the methodology allows to identify the main sources of waste in the production system, technical know-how from operators and production managers could also be used to reduce waste generation through scheduling without a need for complex modeling and solving.

5.3 Perspectives

As this work is one of the first to consider waste-minimizing scheduling as its sole focus, many interesting perspectives have been identified which can expand both the scope and depth of this study. Aside from the ones already mentioned in the discussion sections of the previous chapters, several possible developments for this work are described below.

5.3.1 Waste environmental impact and cost assessment

As highlighted in Chapter 2, few waste-minimizing scheduling problems use accurate objective functions for environmental impact or waste cost calculation. The methodology provided in Chapter 3 is a first step in accurately identifying both environmental impacts and economics costs, but improvements can still be made regarding the problem characterization. In this regard, an interesting development would be to combine the classification scheme we propose with the one provided in Akbar and Irohara (2018). As their approach is centered on the description of the scheduling problem, they define a range of new constraints and objective functions centered around environmental and social aspects. While their notations can conflict with the commonly used three-field (α, β, γ) notation at times, it would be a worthwhile endeavour, especially since it might help structure the scheduling problem identification step described in Section 3.4.4. In the second chapter, our categorization of the papers reviewed is mostly focused on scheduling issues and how they relate to waste minimization. Linear programming and heuristic approaches rely on numerical inputs such as production data for problem solving, and their objective functions provide numerical values regarding costs or impacts. Similarly, decision-makers in industries rely mostly on quantitative information (measuring aspects in terms of magnitude) regarding production planning. This is understandable, as physical units (e.g. flow rates and materials weight) or economic indicators (e.g. costs, productivity and makespan) are the direct and observable causes and consequences of production. However, environmental sciences frequently consider qualitative criteria (examining distinguishing attributes) when determining the suitability of different alternatives (Linkov et al., 2009). Introducing a qualitative approach for impact assessment, e.g. through the use of methods such as AHP, ELECTRE or TOPSIS (Özcan et al., 2011), would allow for new objectives to be considered. For all these reasons, and given the importance of integrating sustainable aspects into scheduling, the use of multi-objective optimization is bound to become systematic in future research.

5.3.2 From waste to reused product

One way to reduce waste generation is through better resource efficiency, which can be summed up as producing more while using less materials and energy. In this context, by-products, co-products and waste reuse is an effective way to maximize resource usage. In the process industry, the use of intermediate storage tanks and regeneration units enables the reuse of wastewater, while skiving is an option to reuse the trim loss in certain industries with cutting operations. Other concepts such as the CSP with usable leftovers, as reviewed in Cherri et al. (2014), directly account for trim losses in the production schedule in order to optimize their size for reuse. By achieving better resource efficiency, companies can improve the outcome of their production on both the environmental and economical ends, by reducing their material bills and burden on waste management system at the same time. It is also important to consider the reuse of waste and byproducts in an integrated manner, rather than as a consequence of the production process. While it has been shown that environmental criteria can be added without degrading the economic aspect (Subaï et al. (2006); Xu and Huang (2004)), the example of the ICSP shows that sequential problem solving results in less efficient solutions. A global understanding of the production process is needed in order to identify where such improvements can take place and which output flows are susceptible to regeneration or reuse. Opportunities for reuse might also be highly dependent on the type of product considered: reuse of bath-water in an electroplating line avoids discharging potentially harmful wastewater; conversely, in the paper industry, trim loss can be easily recycled and reused for making paper pulp, making reuse less important. Thus, integrating the reuse of waste and by-product in scheduling, e.g. in the case of intermediate storage tanks, requires solid knowledge about the production process and substances involved. This aspect of waste management is one that could be added to the methodology proposed in Chapter 3, which currently only considers waste prevention opportunities. It is to be noted that, same as introducing energy considerations, adding waste reuse opportunities can result in increased complexity in both the problem characterization and solving process. However, the potential gains resulting from the implementation of such schemes cannot be overlooked.

5.3.3 Scheduling concerns for waste minimization

We identified different angles from which scheduling can address the waste minimization issue. Some of those are industry-related, such as the intermediate storage in multipurpose batch plants, or the ICSP in industries with cutting operations. Others are present in all four main problem categories, as they are related to a more generic scheduling problem and not to a specific type of production. However, some concerns, while similar in nature, can have different behaviors depending on the type of industry. In the case of setup minimization, which is considered in all four problem categories 23 times out of 71 articles reviewed in the state-of-the-art, setups are associated with different properties. They entail an economic cost, be it money, time or both, with additional considerations such as sequence dependence. In the case of process manufacturing, they also come with an environmental impact since the equipment needs to be cleaned after each change of operation. In the case of CSPs however, setups can be environmentally beneficial since they allow for more cutting patterns to be used, and thus a more efficient use of resources. Hence a need to relate each concern to its industrial context in order to grasp its true nature during the scheduling problem modeling. Setups have already been studied in the literature, Allahverdi (2015) providing a review of scheduling problems with setup time or cost. Their environmental impact however remains largely undocumented, barring work by Gungor and Evans (2016) who comment on the need to better study the underlying causes of setups impact. Better knowledge about setup-induced waste generation might lead to the appearance of new scheduling concerns, thus enriching the current classification and providing clearer information for future research. Therefore, further studying the interactions between scheduling and waste, as exemplified by setup-induced waste, should be a priority. Information about those concerns will help bridge the gap between operational research and environmental science, and foster the implementation of waste-minimizing schedules.

5.3.4 Need for reactive scheduling

An overwhelming majority of the articles reviewed in Chapter 2 (68 out of 71) chose a deterministic scheduling approach. Alem and Morabito (2012) and Alem and Morabito (2013) do consider uncertainty on demand and operational parameters, providing a robust schedule based on different risk-scenarios. Arbib and Marinelli (2005) is the only study in which reactive scheduling is present, with the possibility to introduce so-called “hot-orders“ into a preexisting schedule. This lack of proactive and reactive scheduling approaches has already been highlighted by Giret et al. (2015) in the case of energy-efficient scheduling problems. Since those problems are already NP-Hard, adding reactivity to their formulation has a big impact on computing time. Nevertheless, working on proactive and reactive scheduling will become increasingly necessary in the coming years, as the shift from Make-To-Stock to Make-To-Order and Just-In-Time policies results in an increased demand for flexibility and reactivity from the production. Providing schedules that account for uncertainty in production will serve as a way to mitigate the risks, which can be viewed from different angles. As shown by Alem and Morabito (2012), uncertainty in different parameters requires different schedules to ensure robustness. Similarly to ensuring a minimum service level even in case of machine breakdown, producing environmentally-robust schedules (i.e. schedules that ensure an acceptable level of waste even in case of unforeseen events) is necessary. Likewise, while the need for reactive scheduling in energy-efficient scheduling has already been discussed to address sudden changes in energy prices and reduce peak loads, its counterpart in waste minimization is equally important. Being able to generate on-line waste efficient schedules to accommodate shifts in demand or control effluent discharge over time in order to avoid overflows in treatment plants will become more and more relevant as research in sustainable manufacturing progresses. One of the assumptions regarding the methodology proposed in Chapter 3 is that the data is supposed to be deterministic. This assumption aimed at simplifying the data collection and problem characterization process, but shall be lifted as reactive scheduling becomes more and more ubiquitous. Introducing uncertainty at this level of problem identification could also prove to be an excellent opportunity to integrate environmental risks directly into problem modeling, thus facilitating the emergence of environmentally robust schedules.

5.3.5 Sustainable scheduling and the social aspect

While it is an important part of the triple bottom line of sustainable development, the social aspect is rarely considered in sustainable manufacturing studies regardless of the decision level. This is especially pronounced when working on sustainable scheduling, as a review on sustainable scheduling by Akbar and Irohara (2018) found only one paper out of fifty that included a social consideration in its modeling. This is due to several reasons. The first was evoked previously in this manuscript, namely the fact that industrialists and decision-makers originally focused on productivity-related objectives, at the expense of the environmental and social dimensions. The other reason is the difficulty to quantify social indicators when studying scheduling problems. While the economic and environmental dimensions can be translated into numerical quantities, social concerns are by nature human dependent, and thus less likely to be directly quantifiable. It is also harder to include social constraints or objectives into a scheduling problem modeling, and their inclusion would mean adding a third objective into problems that are difficult to solve already. Thus, companies tend to focus on other methods, mostly managerial, rather than scheduling to monitor and improve their social performance. It remains however an important consideration, especially since scheduling directly affects the production and thus the operators' working conditions (hourly production rate, type of tasks carried out, ...). It is however to be noted that social criteria have been included in other domains such a supply chain management (Gruat-La-Forme et al., 2007). As for the inclusion of environmental objectives, using multicriteria decision making techniques which allow for objectives of different nature to be compared should help increase the inclusion of the social aspect into scheduling, making it sustainable rather than only green.

APPENDIX A

List of notations

- $\mathcal{C}$: Set of the different types of operations
- C_{ij}: Type of operation j of job i
- c_r: Conversion ratio
- cap: Capacity
- d_i: Due date for job i
- e_i: Earliness of job i (time between the end of the last operation and the due date of job i)
- g_{ij}: Machine idle-time between the end of operation j of job i and the start of the next scheduled operation
- $\mathcal{I}$: Set of the different jobs to be scheduled
- $\mathcal{J}$: Set of the different operations composing a job
- L: Minimum drying time between two consecutive operations of a job
- M: Maximum length of the planning horizon, i.e. $M = \max\limits_{i \in \mathcal{I}} d_i$
- m_c: Material cost
- N_i: Number of operations for job i
- nbs: Number of setups
- o_c: Operating cost
- o_w: Operating waste
- p_r: Production rate
- Q_i: Number of products in job i
- QC: Quantity center
- r_r: Recirculation ratio
- s_{ij}: Starting time of operation j of job i
- s_c: Storage cost
- s_r: Scrap rate
- s_t: Setup time
- set_w: Setup waste
- set_c: Setup cost

- t_{ij}: Drying time duration after operation j of job i, i.e. time spent in the intermediary inventory
- wt_c: Waste treatment cost
- x: Elementary input flow
- y: Intermediary flow
- y_{ijkl}: 1 if operation j of job i takes place just before operation l of job k, 0 otherwise
- Y_{ijkl}: 1 if switching from operation j of job i to operation l of job k implies a setup, 0 otherwise (i.e. if C_{ij} and C_{kl} are different or not)
- z: Elementary output flow

APPENDIX B

Starting time definition algorithm optimality proof

Our aim is to prove that algorithm 2 returns starting times s_i that minimise the inventory objective function $z_{inventory}$ for a given sequence of operations input.

Let us define two subsets $\mathcal{K}^1$ and $\mathcal{K}^2$ from the set $\mathcal{K}$ of all operations, such that:

- $\mathcal{K}^1$ is the set of operations that are the only ones in their job and operations that are the last of their job;
- $\mathcal{K}^2$ is the set of operations after which a drying time is needed.

We have $\mathcal{K}^1 \cup \mathcal{K}^2 = \mathcal{K}$ and $\mathcal{K}^1 \cap \mathcal{K}^2 = \emptyset$

The inventory objective function

$$z_{inventory} = \sum_{i \in \mathcal{I}} Q_i * e_i + \sum_{i \in \mathcal{I} | N_i > 1} \sum_{j=1}^{N_i} Q_i (t_{ij} - L)$$

can be rewritten as:

$$z_{inventory} = \sum_{k \in \mathcal{K}^1} Q_k * e_k + \sum_{k \in \mathcal{K}^2} Q_k (t_k - L)$$

with $e_k = D_k - s_k - D_k$ and $t_k = s_{k'} - s_k - P_k - L$.

Similarly, constraints (9), (11) and constraint set (12) and (13) can be rewritten as:

$$\begin{array}{rlll} (9) \Rightarrow & s_{k'} - s_k - P_k \geq L & \forall k \in \mathcal{K}^2 & (20) \\ (11) \Rightarrow & s_k + P_k \leq D_k & \forall k \in \mathcal{K}^1 & (21) \\ (12) + (13) \Rightarrow & s_k \leq s_{next} - P_k & \forall k \in \mathcal{K} & (22) \end{array}$$

where k' is the next operation of the same job.

We wish to prove that for a given operations sequence, assigning the starting times s_k so that:

$$s_k = \begin{cases} D_{last} - P_{last} \text{ if k is the last operation} \\ \min\left(D_k - P_k; s_{next(k)} - P_k\right) \text{ if } k \in \mathcal{K}^1 \\ \min\left(s_{k'} - P_k - L; s_{next(k)} - P_k\right) \text{ if } k \in \mathcal{K}^2 \end{cases}$$

minimizes $z_{inventory}$. Since Q_k is always positive, minimising $z_{inventory}$ means minimising e_k and $(t_k - L)$

For each option, we have:

- If it is the last operation, we have $e_{last} = D_{last} - s_{last} - P_{last}$. If $s_{last} = D_{last} - P_{last}$, $e_k = 0$, which is the minimum possible value (since e_k is always positive).
- If $k \in \mathcal{K}^1$, constraints (21) and (22) apply. The value assigned to s_k is $\min(D_k - P_k; s_{next(k)} - P_k)$:
  - If $D_k - P_k \leq s_{next(k)} - P_k$, then $s_k = D_k - P_k$ and $e_k = 0$, which is the minimum value.
  - If $D_k - P_k \geq s_{next(k)} - P_k$, then $s_k = s_{next(k)} - P_k$. Since $e_k = D_k - s_k - P_k$ and D_k and P_k are fixed, minimising e_k is equivalent to maximising s_k. Since $s_k \leq s_{next(k)} - P_k$ due to constraint (22), e_k is at its minimum possible value.
- If $k \in \mathcal{K}^2$, constraints (20) and (22) apply. The value assigned to s_k is $\min(s_{next(k)} - P_k; s_{k'} - P_k - L)$:
  - If $s_{next(k)} - P_k \leq s_{k'} - P_k - L$, then $s_k = s_{next(k)} - P_k$ and $t_k = L$, which is the minimum value.
  - If $s_{next(k)} - P_k \geq s_{k'} - P_k - L$, then $s_k = s_{k'} - P_k - L$. Since $t_k = s_{k'} - s_k - P_k - L$, and P_k, $s_{k'}$ and L are fixed, minimising t_k is equivalent to maximising s_k. Since $s_k \leq s_{k'} - P_k - L$ due to constraint (20), t_k is at its minimum possible value.

Additionally, since by definition any previously scheduled operation $next(k)$ is scheduled with the maximum possible $s_{next(k)}$, the starting time s_k can also be set as high as possible (since $s_k \leq s_{next} - P_k$)

APPENDIX C

Product system definition survey example

A methodology for waste-minimizing scheduling problems identification

Step 1 questions example:

I) Introduction :

1) What do you expect from your participation to this study?

2) Have you ever carried out a Value Stream Mapping of your production system ? If not, you do have a graph describing your production system. Can you explain it?

Items to consider include :
- *Make-to-order / Make-to-stock production*
- *Production in small/medium/large batches*
- *Workshop configuration : specialized, production line, cells*

- Production launching organization : what are the respective proportions of unit/small/medium/large batches produced, and can you give an estimate of their average size ?

Batch	Percentage of affected references	Batch size (average or range)
Unit		
Small batch		
Medium batch		
Large batch		

II) Environmental policy :

2.1) Does your site possess the ISO14001 (or other) certification ?

If so, which part of it ? What are the main environmental aspects identified ? Which measures were taken ?

2.2) If the company has carried out an environmental audit:

When did dit take place ? What were the key elements identified ? Have measures been taken following this audit ?

If not, how does the company follow-up on environmental issues ?

2.3) Does the site possess one or more employees dedicated to environmental issues ?

If so, what are his/their role ?

With whom are these employees directly interacting with ?

If not, how is handled the company environmental policy ?

3) Has the company set objectives regarding environmental policy ?

What are the environmental indicators taken into account ?

- *Waste or resource consumption reduction*
- *Reverse-logistics*
- *Better waste treatment channels*
- *Energy consumption reduction*
- *Waste dangerosity reduction*

Residues handling :

Waste : any substance or object, whose owner gets rid of, has the intent or obligation to get rid of.

Byproduct : A production residue not considered a waste.

Non-compliant product : a product which does meet the production requirements, a need or expectation.

Non-hazardous industrial waste : Any waste not presenting one or more property that make a waste hazardous

Hazardous industrial waste: any waste presenting one or more of the properties listed in appendix III of the European parliament 2008/98/ CE directive.

Ask for residues treatment cost and valorization percentage

Byproducts				
Type	**Quantity**	**Production step**	**Treatment channel**	**Cost(s)**
Non-hazardous waste				
Type	**Quantity**	**Production step**	**Treatment channel**	**Cost(s)**
Hazardous waste				
Type	**Quantity**	**Production step**	**Treatment channel**	**Cost(s)**
Non-compliant products				
Type	**Quantity**	**Production step**	**Treatment channel**	**Cost(s)**

4) What are the critical steps of your waste management process ?
- *From a production perspective, e.g. :*
  - *Process producing dangerous waste*
  - *Resource inefficient process*
  - *Process using obsolete machinery*
- *From a management perspective, e.g. :*
  - *Storage of a large quantity of waste*
  - *Dangerous waste handling*
  - *Costly waste collection or treatment*

5) Is waste management a part of the production planning process ?

6) Have you taken measures for valorising byproducts ?

7) Have any reuse, recycling or valorization measure been implemented for returned products (non-compliant products, repairs, end-of-life) ?

8) How do you calculate the cost of your waste ?

9) Have you considered new waste management measures ? What aspects of your waste management could be improved ?

III) Production site characteristics

10) How is your production planning made ?
- *Which tools are used ? (e.g. : ERP, Excel sheet…)*
- *Batch sizes*
- *Who is involved in production planning ?*

11) What is, according to you, the main criterion that defines a good schedule ?
What makes a schedule better than another ?

e.g. :
- *Lead time*
- *Production cost*
- *Energy consumption*
- *Work-in-Progress*
- *Waste quantity generated*
- *Human resources*

Scheduling : the allocation of resources to tasks over given time periods, its goal is to optimize one or more objectives

12) Do you think you could improve some environmental aspects by changing your scheduling method ? Which ones ?

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FOLIO ADMINISTRATIF

THESE DE L'UNIVERSITE DE LYON OPEREE AU SEIN DE L'INSA LYON

NOM : LE HESRAN DATE de SOUTENANCE : 28/11/2019

Prénoms : Corentin Youenn Maël

TITRE : Réduire les déchets industriels : une approche par l'ordonnancement des opérations

NATURE : Doctorat Numéro d'ordre : 2019LYSEI111

Ecole doctorale : Infomaths ED 512

Spécialité : Génie industriel

RESUME :

Confronté à des enjeux économiques et environnementaux croissants, le monde industriel doit s'adapter afin de répondre aux problématiques actuelles. La production industrielle est responsable de 83% de la production mondiale de déchets solides et de 40% de la consommation d'énergie, et l'ordonnancement s'avère être un levier prometteur pour agir sur ces enjeux. L'état de l'art réalisé montre que les travaux de recherche traitent en majorité des enjeux énergétiques. Cette thèse propose de s'intéresser à la problématique suivante : Comment intégrer la réduction des déchets dans l'ordonnancement des opérations ? L'état de l'art sur le sujet faisant émerger une terminologie disparate, une classification est proposée pour unifier ce champ de recherche hétérogène. Pour répondre à la problématique, nous proposons une méthodologie combinant le suivi des flux de matière avec les paramètres d'ordonnancement pour permettre l'identification des opportunités de réduction de la génération de déchets par l'ordonnancement, et la caractérisation du problème d'ordonnancement correspondant. Une étude de cas valide la méthodologie et l'intérêt des résultats obtenus. En se basant sur ces résultats, un problème d'ordonnancement bi-objectif machine-unique avec réentrance dans un contexte de fabrication à la commande est modélisé en programmation linéaire. Deux méthodes de résolution – exacte et métaheuristique – sont comparées et démontrent le potentiel de l'ordonnancement pour la réduction de la génération de déchets industriels. Cette résolution fournit aux preneurs de décision des solutions alternatives adaptées, et permet une réduction des déchets significative en contrepartie d'une augmentation de stock limitée. Ces travaux se concentrant sur les déchets ouvrent la voie à d'autres enjeux environnementaux comme l'intégration des enjeux énergétiques et d'émissions atmosphériques, et à la considération du critère social afin d'englober les trois piliers du développement durable.

MOTS-CLÉS : Ordonnancement, Prévention des déchets, Programmation Linéaire, Analyse environnementale, Optimisation biojectif, Suivi de flux, Algorithme Génétique

Laboratoire (s) de recherche : DISP, EA 4570

Directrice de thèse: BOTTA-GENOULAZ Valérie

Président de jury :

Composition du jury :

Bernard Grabot, Professeur des Universités, Ecole Nationale d'Ingénieurs de Tarbes	Rapporteur
Pierre Baptiste, Professeur des Universités, Polytechnique Montréal	Rapporteur
Nicolas Perry, Professeur des Universités, Arts et Métiers ParisTech, Université de Bordeaux	Examinateur
Damien Trentesaux, Professeur des Universités, Université Polytechnique des Hauts de France	Examinateur
Valérie Botta-Genoulaz, Professeur des Universités, INSA Lyon, Laboratoire DISP	Directrice de thèse
Valérie Laforest, Directrice de recherche, Ecole des Mines de Saint-Etienne, Institut Fayol	Co-Directrice de thèse
Anne-Laure Ladier, Maître de conférences, INSA Lyon, Laboratoire DISP	Encadrante de thèse