João Branco Maranha Tiago

SCHEDULING OF POLYMER ADDITIVE MANUFACTURING PROCESSES – A SYSTEMATIC LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Dissertação no âmbito do Mestrado em Engenharia e Gestão Industrial orientada pelo Professor Doutor Samuel de Oliveira Moniz e apresentada ao Departamento de Engenharia Mecânica da Faculdade de Ciências e Tecnologia da Universidade de Coimbra

Outubro de 2021

• U C •

FCTUC FACULDADE DE CIÊNCIAS
E TECNOLOGIA
UNIVERSIDADE DE COIMBRA

DEPARTAMENTO DE ENGENHARIA
MECÂNICA

Scheduling of Polymer Additive Manufacturing Processes – a Systematic Literature Review and Theoretical Framework

Dissertação apresentada para a obtenção do grau de Mestre em Engenharia e Gestão Industrial

Autor

João Branco Maranha Tiago

Orientador

Professor Doutor Samuel de Oliveira Moniz

Júri

Presidente

Professor Doutor Cristovão Silva
Professor Associado com Agregação da Universidade de Coimbra

Vogal

Professor Doutor Miguel Jorge Vieira
Professor Auxiliar da Universidade Lusófona

Orientador

Professor Doutor Samuel de Oliveira Moniz
Professor Auxiliar da Universidade de Coimbra

Coimbra, Outubro, 2021

“Demonstra o teu valor!”

To the memory of Rui Prata Ribeiro, my godfather

Acknowledgements

To Professor Samuel Moniz for the guidance provided.

To all my lab colleagues for their availability.

To Pedro Coelho for his opinions.

To my sister, Ana, for her help.

To my family, especially my parents for their support.

To my friends, for their constant presence and interest.

To my beautiful wife, Madalena.

Abstract

Scheduling of Additive Manufacturing's (AM) processes can be considered a relatively recent topic, despite the last decade's progress and an increase in the body of work addressing AM. Since AM advantages are related to cost reduction, product redesign and environmental sustainability, and scheduling aims to optimise the distribution of jobs and allocate the necessary resources, studying scheduling problems with AM process through optimisation tools is very pertinent.

In this work, an extensive theoretical background on AM polymer technologies and scheduling problems is introduced. This background supported the elaboration of a classification and decision-support framework for characterising different AM technologies and a systematic literature review of 20 research articles regarding AM scheduling polymers problems that was organized according to: objectives, uncertainty, model formulation, solution method, shop configuration, problem classification, nesting, AM process and assessment method.

There is a considerable variety of features that must be accounted for while considering different AM technologies. The decision-support framework offers detailed and organised information on the main strengths and limitations of polymer AM technologies characteristics, costs, process features and physical properties of the produced parts. In addition, emergent AM technologies and applications are examined in detail.

It was also possible to understand the state of the art of AM scheduling problems. For example, centralised scheduling is the prefered type of problem classification used, and Powder Bed Fusion the most studied AM process category. Remarkably, half of the research works simplify the nesting problem by clustering parts into builds based on the maximum capacity of part volume and rarely validate their models through case studies.

In addition, a set of future projects aimed to enhance polymer AM scheduling research are proposed. The research opportunities identified included new statement problems of a never considered AM process category, the Material Jetting process. Furthermore, adding uncertainty to the mathematical models, problem classification other

than centralised scheduling, such as decentralised or cloud manufacturing scheduling, and considering 3D in the dimensionality of the part orientation.

Keywords: Additive Manufacturing, Production Scheduling, Process Otimisation

Abstract – Portuguese Translation

O sequenciamento de lotes de Fabrico Aditivo (FA) pode ser considerado um tópico relativamente recente, apesar do progresso da última década e do aumento do corpo de trabalho que aborda o FA. As vantagens do FA estão relacionadas com a redução de custos, redesenho do produto, sustentabilidade ambiental. Desta forma, uma vez que o sequenciamento visa otimizar a distribuição de trabalhos e alocar os recursos necessários, mostra-se pertinente estudar problemas de sequenciamento com o processo de FA por meio de ferramentas de otimização.

Nesta tese é apresentado um amplo enquadramento teórico sobre tecnologias de FA de polímeros e problemas de sequenciamento. Este enquadramento teórico apoiou a elaboração de uma estrutura de classificação e suporte à decisão para caracterizar diferentes tecnologias de FA e uma revisão sistemática da literatura composta por 20 artigos de pesquisa sobre problemas de sequenciamento de FA de polímeros, que foram organizados de acordo com: objetivos, incerteza, formulação de modelo, método de solução, configuração de chão de fábrica, classificação de problemas, *nesting*, processo FA e método de avaliação.

Há uma variedade considerável de recursos que devem ser considerados ao se ponderar as diferentes tecnologias de FA. A estrutura de suporte à decisão oferece informações detalhadas e organizadas sobre os principais pontos fortes e limitações das características, custos, recursos do processo e propriedades físicas das peças produzidas. Além disso, as tecnologias de FA emergentes são examinadas em detalhes.

Também foi possível entender o estado da arte dos problemas de sequenciamento de FA. Por exemplo, há preferências de estudo em relação ao tipo de classificação de problema usado, sequenciamento centralizado, e a categoria de processo de FA mais estudada, *Powder Bed Fusion*. É notável que metade dos trabalhos de pesquisa simplificam o problema de nesting agrupando peças em *builds* com base na capacidade máxima do volume da peça e raramente validam os seus modelos por meio de casos de estudo.

Além disto, é proposto um conjunto de projetos futuros com o objetivo de melhorar a pesquisa de sequenciamento FA de polímeros. As oportunidades de pesquisa identificadas incluem: novos enunciados de problemas de uma categoria de processo de FA nunca considerada, o *Material Jetting*, a incerteza nos modelos matemáticos, uma classificação de problemas diferente de sequenciamento centralizado – como sequenciamento descentralizado ou *Cloud Manufacturing* – e 3D na dimensionalidade da orientação da peça.

Keywords Fabrico Aditivo, Sequenciamento da Produção, Otimização do Processo

Index

Index of figures

Index of tables

Symbols and acronyms

Symbols

(1) – Single machine

(*Pm*) – Identical machines in parallel

(*Rm*) – Unrelated machines in parallel

(*Fm*) – Flow shop

(*Jm*) – Job shop

(*Lj*) – Lateness,

(*Tj*) – Tardiness

(*Cmax*) – Makespan

(*Lmax*) – Maximum lateness

(*dj*) – Due date

Acronyms

AM – Additive Manufacturing

CAL – Computed Axial Lithography

cDLP – Continuous Digital Light Processing

CMS – Cloud Manufacturing Scheduling

DLP – Digital Light Processing

FDM – Fused Deposition Modelling

GA – Genetic Algorithm

IM – Injection Moulding

IP – Integer Programming

LP – Linear Programming

ME – Material Extrusion

MILP – Mixed Integer Linear Programming

MIP – Mixed Integer Programming

MJ – Material Jetting

MJF – Multi Jet Fusion

OR – Operations Research

PBF – Powder Bed Fusion

SC – Supply Chain

SLA – Stereolithography

SLS – Selective Laser Sintering

TSP – Traveling Salesman Problem

VAM – Volumetric Additive Manufacturing

VP – Vat Photopolymerisation

1. INTRODUCTION

Additive Manufacturing (AM), commonly known as 3D printing, originated in the 1980s and emerged as a disruptive technology capable of creating three-dimensional structures through layer-by-layer material deposition according to computer-aided design (CAD) model data, whose purpose was application to rapid prototyping (Hull, 1984).

AM allows the production of customised parts from metals, polymers, and ceramic without a formative (e.g., injection moulding or casting) or a subtractive (e.g., milling and turning) manufacturing process (ISO/ASTM, 2015). Although, a wide range of polymers are used in different AM processes, the most commonly used are photosensitive resins, thermoplastic powders and filaments (Tan et al., 2020).

When the technology was being introduced, the materials used in AM did not exhibit good mechanical and surface properties, since the printed manufactured parts' purpose was only demonstrative. However, AM technologies' have greatly improved over time and AM covers a wide range of manufacturing processes and materials with better mechanical and surface properties. Thus, their application range is expanding beyond the domain of rapid prototyping, into rapid tooling and, into direct digital manufacturing (Srai et al., 2016).

A few of the main advantages of AM are: enabling rapid market response with production of on-demand spare parts, and thus reducing or eliminating inventory stocks (Calignano et al., 2017); allowing simpler product designs, i.e., more design freedom, with the redesign of multi-components parts by eliminating the need for assembly along with enhancing the performance of produced parts (Tan et al., 2020). In addition, it is viewed as an environmentally sustainable manufacturing process since it can potentially reduce up to 130.5 to 525.5 megaton of CO_2 emissions by 2025 regarding the entire product life cycle compared to traditional manufacturing processes (Gebler et al., 2014).

1.1. Scope of the dissertation

Currently, four different materials are associated with specific AM processes (also known in the literature as technologies): metal, polymer, composite, and ceramic (Bourell et al., 2017; ISO/ASTM, 2015). ISO/ASTM (2015) is the current ISO standard specific to AM. When consulting this standard, it is noticeable that, regarding single-set AM process, i.e., when the process is achieved in a single operation, the material polymer is associated with the most number of process categories (also known in the literature as techniques). Therefore, Table 1 and Figure 1 were formulated with information collected in this standard to better understand all the process categories present in the AM process.

Table 1 – Associations of processes categories to the materials

	Polymer	Ceramic	Metal	Multi-step*
Binder Jetting	√			√
Direct Energy Deposition			√	
Material Extrusion	√			
Material Jetting	√			
Powder Bed Fusion	√	√	√	√
Sheet Lamination	√		√	√
Vat Photopolymerisation	√			√

*Metal, Ceramic and Composite

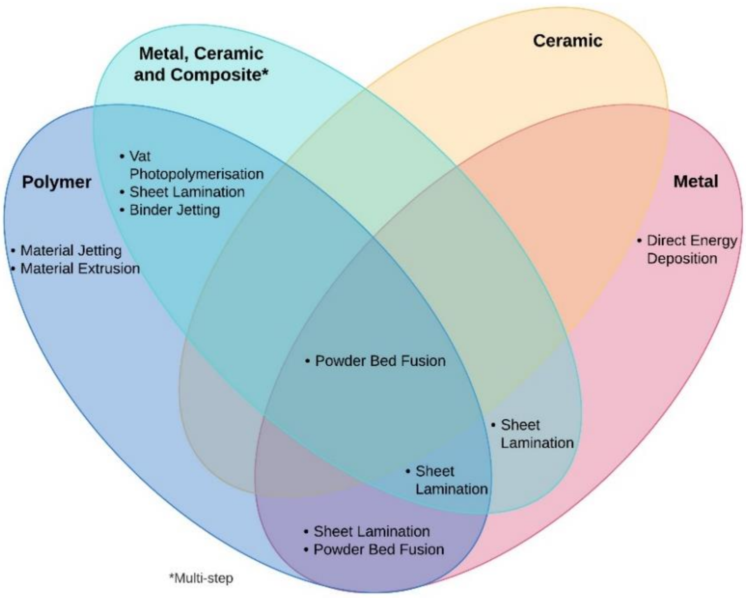

Figure 1 – Venn diagram representing the association of processes categories to the materials

By examining Table 1 and Figure 1, it is possible to conclude that Polymer has six associated process categories against three from metal. Since all of the process categories of polymer includes all process categories of other materials except one, Direct Energy Deposition, the focus of this study is the material polymer, thus, enabling a complete understanding of the current state of technologies associated with this specific material and covering process categories also common to other materials, while complying with the time limitation imposed on this thesis. However, as the results obtained in this work can later be extrapolated to other AM technologies and materials, by performing a similar analysis, to demonstrate the full potential application scope of the work, other AM materials will be referenced in specific examples throughout this work.

This dissertation main objective is to analyse the problems of scheduling focused on AM. AM scheduling problems are recognised in the literature as problems of regrouping parts and allocating them into jobs to optimise desired performance measures. After the first study published in 2016, this research field has been increasing while considering only a few variations of problems. This work aims to understand and analyse these variations and identify future research projects in AM scheduling.

1.2. Research gaps and research questions

Nowadays, organisations face a globally-oriented market, and in order to stay competitive, there is an undeniable necessity to understand how to connect the strategic, tactical and operational plan of an organisation with the markets, products and production (Olhager & Wikner, 2000). In terms of decision-making, production planning typically covers three time intervals: long term, medium-term and short term. Short-term planning involves daily scheduling operations such as job sequencing or control on a shop floor (B. Karimi et al., 2003). Scheduling decisions, applied to an individual, may seem of minor importance to an organisation when compared to strategic decisions with higher importance and impact. However, over time, scheduling can be crucial to the organisation in terms of cost and performance. Scheduling as a tool can lead to proper utilisation of production capacity, compliance with delivery dates, reduce work in progress and improve production responsiveness (Stevenson et al., 2005). Thus, scheduling propitiates the fulfilment of the organisation's plans at a higher strategic level. Therefore, the possibility of combining scheduling with AM – an improving manufacturing process with the potential to disrupt a production process – makes clear the relevance and need of studying the subject as an aggregate.

There has been an increase in studies featuring AM technologies, with a significant rise in the last two decades, from almost a thousand documents per year in 2000 to more than sixteen thousand last year (Jemghili et al., 2021). Regarding studies that discuss the impact of AM as a manufacturing technology, there are already almost a hundred studies and 24% of them are related to the impact on the industry (Caviggioli & Ughetto, 2019). By analysing Figure 2, it is noticeable that the topic of scheduling in AM has followed the growth trend, with over 140 research articles published.

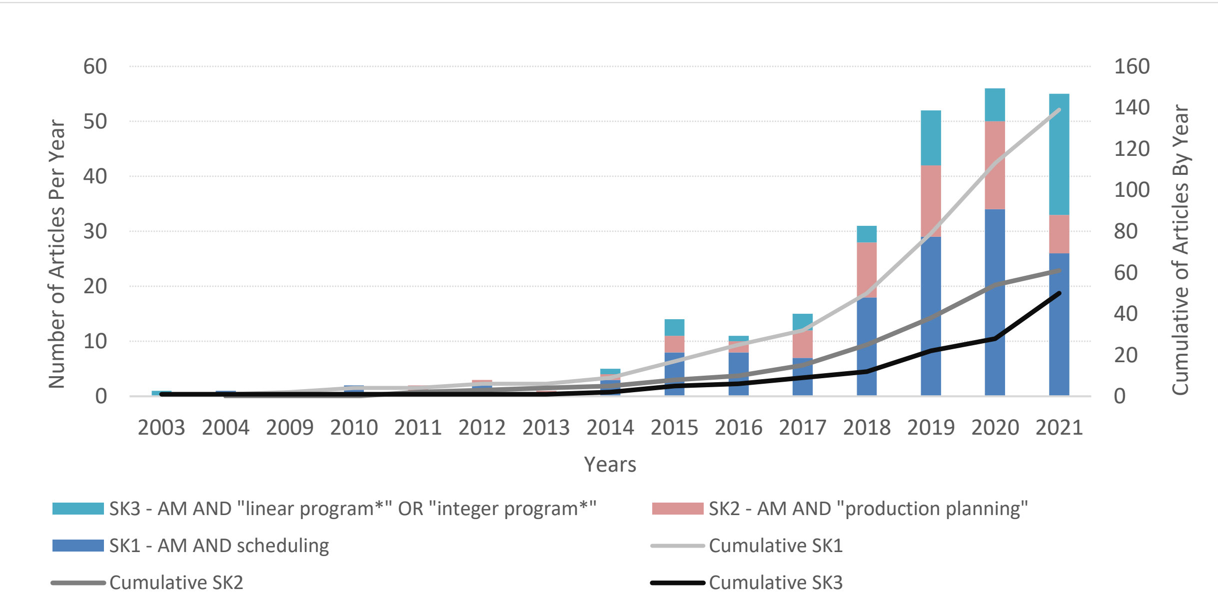

Figure 2 – Number of research articles published on specific AM topics

Nonetheless, there is a gap in the literature as there is no sufficient knowledge on the current advances of the subject scheduling in AM. Therefore, two fundamental questions guide this thesis:

- Research question number 1 (RQ1): What is the state of the art regarding AM polymer scheduling?

- Research question number 2 (RQ2): What are the future directions and possible research developments necessary to overcome present shortcomings in AM polymer scheduling?

By presenting a systematic literature review (SLR) on this subject, the author hopes to enhance the understanding of AM production scheduling and provide further advances in the area. However, to properly explore the theme of AM production scheduling another question requires prior attention: What are the characteristics of the processes used in polymer AM? By answering this underlying question, raised by our research questions, it was possible to elaborate a classification and decision-support framework to assess the suitability of different processes to specific manufacturing needs. This framework aided in answering the research questions by providing structured and organised information about a wide range of features of different AM technologies. Therefore, it can be a possible ally for managers who do not seek decision-making knowledge but easy-to-interpret information, allowing them to make a quick decision.

1.3. Research design and methods

There are two clear distinctions in research designs and methods carried out in this thesis – an exploratory literature search and an SLR.

In addition to the information collected to elaborate the theoretical background, it was necessary to conduct an exploratory literature search to recognise the applications of the AM process, compare polymer AM to the "rival" manufacturing process and differentiate the characteristics of the technologies. Finally, to systematise all the collected information, it was decided to elaborate a classification and decision-support framework.

The SLR aims to conduct a systematic, explicit, and reproducible literature review while minimising bias and ensuring rigour and relevance of the future challenges and current perspective of the AM scheduling problems. The design of the SLR follows the work of Thomé et al. (2016). Regarding the methodological choices, this SLR was mono method qualitative, following a archival research with a cross-sectional temporal horizon (Sauders et al., 2019).

1.4. Dissertation outline

This dissertation is organised into five chapters. Chapter 1 briefly framed the theme of the thesis, its motivation, and the lay research questions. Also, in this chapter, the methodology used to carry out the SLR is presented. In chapter 2, a theoretical background acquaints the reader with the theme by scrutinising different topics, such as mathematical models, scheduling and different polymer AM processes. In chapter 3, the information that enables the development of a classification and decision-support framework will be analysed. In chapter 4, the SLR of 20 research articles is accompanied by the most relevant research articles and suggestions for future work. Finally, chapter 5 presents the general conclusions of the work carried out and its limitations.

2. THEORETICAL BACKGROUND

This chapter presents an extensive theoretical basis on a miscellaneous set of subjects needed to understand the topic on which this thesis was built. The author argues that for elaborating an SLR on AM scheduling, it is imperative to have a well-founded theoretical basis for criticising, analysing, and understanding the literature. Therefore, it was necessary to address some complex concepts, such as mathematical models, deterministic models, AM processes and specific scheduling problems. Furthermore, if it were not for this theoretical background, it would be impossible to fully understand the mathematical models proposed in the AM scheduling problems and grasp the production technologies.

2.1. Mathematical models

Mathematical models are expressed by mathematical relationships, numbers, expressions and symbols. Operation Research (OR) uses mathematical models as a support to improve the decision-making process in industrial engineering and operations management of organisations. These models are the representations of real complex systems.

Using linear programming (LP) models, or simulation models, makes it possible to gather information and acquire insight that would be otherwise impossible without experimenting with the real system. Therefore, mathematical models can provide solutions to organisational problems and insight into the system. Even just by gathering data, treating it and defining the problem, modelling can be a powerful ally to understanding the system as a whole.

Nevertheless, a model cannot be the single source of decision-making mechanisms. The solution given by the model should be examined and, in case of feasibility, considered as an option. Williams (2013) defends that by consecutive questioning the solutions provided by the model and altering it, only then it is possible to comprehend the options available and obtain the desired understanding of the range of possibilities.

2.1.1. Linear Programming

As mentioned early, in mathematical models, there is a mathematical relationship between measurable quantities. The essence of that relationship are equations, inequalities, and logical dependencies (Williams, 2013). Although there are various mathematical models, a fundamental approach is the LP model. This tool for solving optimisation problems has all mathematical functions as linear, i.e., objective function and constraints. LP purpose is to find the decision variables' values that optimise the objective function that satisfies a given set of constraints (Winston, 2004). In this context of mathematical programming, the word programming does not have the same meaning as the word associated with computer programming. Programming in mathematics is adjacent to planning and model is not programmed in the most familiar sense of the word. For linear programming, the help of computational power can be necessary to arrive at a solution if the complexity of the models require it, but that is the only existing computer connection.

A common feature of the models used in mathematical programming is optimisation. i.e., the intention of maximisation or minimisation of a specific parameter, represented by an objective function (Clímaco et al., 2012). For instance, maximisation can be associated with profit and minimisation with costs. Let us use the example of LP to better explain this concept. According to Clímaco et al. (2012), an LP problem is defined through expressions 1 and 2.

$$\text{Max or Min z} = \sum_{j=1}^{n} c_j \, x_j \tag{1}$$

$$\text{Subject to: } \sum_{j=1}^{n} a_{ij} \, x_j \begin{Bmatrix} \leq \\ \geq \\ = \end{Bmatrix} b_i, \quad i = 1, \dots, m \qquad x_j \geq 0 \quad j = 1, \dots, n \tag{2}$$

Where:

- Expression 1 represents an objective function, where only one option of optimisation is possible, either maximise or minimise; The objective function is subject to a set of specific conditions – constraints and decision variables – portrayed in Equation 2;

- m represents the number of constraints, each of them being of the type '≥', '≤' or '=';
- n is the number of decision variables.

When all constraints are satisfied, we have a feasible solution, the collection of all feasible solutions is called the feasible region, and an optimal solution is feasible with the most favourable value of the objective function (Hillier & Lieberman, 2002).

2.1.2. Other methods

There are other methods of mathematical programming, for instance, integer programming (IP), which has an adjacent restriction of all variables being integer values, i.e., (0, 1, 2, ...) (Hillier & Lieberman, 2002). Keep in mind that a special kind of integer variable is a binary variable. There are specific situations in which IP appears to be more suitable to a problem statement, for example, when we approach quantities that, due to their intrinsic characteristics, can only be accounted for as integer values, e.g., people and goods. However, although this seems obvious, it is often more desirable to use conventional LP and round off the optimal solution values to the nearest integers (Williams, 2013).

In OR the relaxation is a method usually applied to IP problems. The resolution method tends to solve an IP problem as if it were an LP problem by dropping the integrality requirements (Williams, 2013).

If there is a need to use integer and non-integer variables simultaneously, the model is a mixed integer programming (MIP) model. Thus, there is a differentiation between the variable's value – discrete and continuous. Last, but not least, there are mixed integer linear models (MILP), which are mathematical programmes with continuous and discrete variables and linearities in the objective function and constraints. In this type of model, the computational resources are more demanding and require the inclusion of more complex algorithms such as branch-and-bound.

2.1.3. Nonlinear programming

The recurrent use of LP models is related to its ease of resolution due to having only global optimal. In contrast, in nonlinear programming (NLP), any solution that satisfies the optimal local conditions may not be an optimal (global) solution to the problem (Clímaco et al., 2012).

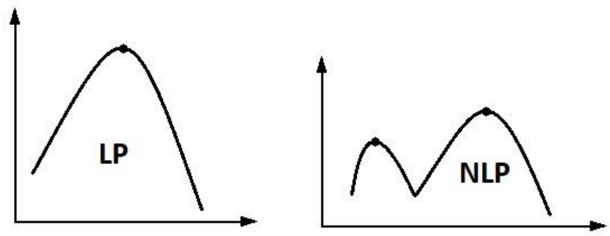

Figure 3 – Graphical comparison of global optimal solution (LP) vs local optimal solutions (NLP)

Nonlinear problems are fundamentally more difficult to solve. Therefore, the techniques used to solve nonlinear programming problems tends to be more complex. Thus, nonlinear programming can sometimes be converted into a suitable linear form to facilitate the resolution of the problem.

2.1.4. Resolution algorithms

Algorithms are step-by-step procedures for solving a problem. Williams (2013) defines algorithms as a set of mathematical rules for solving a particular class of problem or model. An algorithm is said to solve a problem if it applies to any instance of the problem with a guarantee of solution (Garey & Johnson, 1979). In a broad sense, an algorithm's performance is linked to its complexity and the computing resources available. An algorithm is called efficient if it operates in time upper bounded by a polynomial in the length of its input (Garey et al., 1976). Meaning it is paramount that an algorithm is optmised to use the least amount of resources possible and come up with a valid solution (as fast as possible). The length of an algorithm is a formal measure of size, defined as a number of characters obtained from the encoding scheme describing the problem (Garey & Johnson, 1979).

In OR, algorithms are fundamental tools for problem-solving. They can rely on exact methods as LP and other mathematical programming types. More complex problems make us use approximative approaches like heuristics and metaheuristics. A profound body of literature provides us with a set of efficient algorithms for scheduling problems developed over the years. Some benefit from an efficient implementation and may be available in a few commercial or open-source software. However, due to their specificity or novelty, some problems require scholars to develop new tailor-made approaches.

2.1.5. Approximate and exact methods

Scheduling algorithms are divided into exact optimisation methods and approximate methods (Jian Zhang et al., 2019). In this article, the authors differentiate all classes of exact and approximate methods.

When resorting to an approximation algorithm to solve an optimisation problem, the solution will have a slight variation in relation to the exact solution, close to the optimum result yet desirable, i.e., approximate algorithms can find a near-optimum solution. In contrast, exact algorithms can find the optimum solution with precision, but since an exact method may not find a solution, approximation algorithms are appealing methods with more certainty of finding solutions. Therefore, approximate methods can be used for "difficult" problem statements, i.e., can come up with a solution in a reasonable time period. Moreover, computer resources do not scale up exponentially with the growing complexity of the problem. These types of problems are classified as P problems (scheduling problems using polynomial-time algorithms). The complexity of scheduling problems is covered in the following section.

Let us use the Traveling Salesman Problem (TSP), a well-known problem in OR, as an example. TSP is a problem of finding a minimum travel distance between c cities, with the condition of starting and finishing in the same city, and only visiting another city exactly once. Although its problem statement seems straightforward, the TSP can be highly challenging and has a strong presence in the literature with hundreds of substantial contributing research articles. If we were to solve this problem with an approximate method, a heuristic, the Stem-and-Cycle (S&C) algorithm would be a good approach (Rego et al., 2011). In contrast, Branch and Cut aim to solve the problem with an exact algorithm, i.e., resort to mathematical optimisation (Padberg & Rinaldi, 1991). However, even though exact algorithms guarantee an optimal solution, the solution space follows the complexity problem and thus slower resolution response. In contrast, heuristics do not guarantee an optimal solution, but, in the end, it may be beneficial to get a near optimal solution on a shorter resolution time.

Another concept used in OR is metaheuristics, another approximate method. As verified before, when we have a specific statement problem, heuristics is a fair approach. In opposition, metaheuristics can be viewed as a technique for problem statement independence. One significant advantage is that they do not require constraints or objective functions to be conveyed as linear functions of the decision variables (Sörensen & Glover, 2013). A metaheuristic is intended to be in the dark regarding the problem statement it intends to solve. There is a distinction from the exact method since it does not prove that the optimal solution will be found in a finite amount of time, even if it is extensive (Sörensen & Glover, 2013). Instead, they aim to find a non-optimal solution with quality in a reasonable computing time. Therefore, have a broader range of application.

2.1.6. Problem complexity

Even though there has been a significant research effort in deterministic scheduling (covered in depth in section 2.2.1) to find solutions for P problems, sometimes this is impossible (Pinedo, 2016) and it is necessary to use non-deterministic polynomial time algorithms, or abbreviated NP-hard problems. A significant contribution to the topic of NP hard problems was the following work (Garey & Johnson, 1979). When comparing a non-NP-hard problem with an NP-hard, the difference lies on the level of complexity, which means that the computation time associated with solving an NP-hard problem increases with the complexity of the problem. Some examples of NP-hard problems in AM are nesting problems (a topic covered later in section 2.2.4) (Y. Zhang et al., 2017) and batch scheduling problems (Kucukkoc, 2019).

2.2. Scheduling

In an industrial environment, usually, there are a few workstations or machines, both with specific characteristics. Due to these limited resources, a set of jobs, i.e., a group of operations processed by workstations/machines exclusive to a product, need to occur in synchronicity. The purpose of scheduling is to optimise the distribution of jobs to a workstation/machine at a specific time by avoiding scheduling conflicts and allocating the necessary resources.

2.2.1. Deterministic models

In OR, the theory of sequencing and scheduling is characterised by deterministic models, stochastic models and an unlimited number of other problem types. Nonetheless, most research regarding scheduling has been on deterministic machine scheduling. Deterministic models have no randomness, instead, all quantities are known, meaning that the models will present identical results for a particular set of characteristics.

Sequencing and scheduling focus on the ideal of allocation scarce resources to activities at the right time. A machine is a resource meant to perform a specific activity, and the activity is called a job. Therefore, in this context, a machine can only perform a job at a time. Nevertheless, a machine is solicited for several jobs, and jobs need several resources. Consequently, this restriction is one of the study subjects of scheduling, studying the allocation of resources to jobs at an operational level. Because we know which machine is solicited for which jobs using which resources in advance, all the information needed to formulate the problem is available, providing the second restriction, the deterministic nature of the problems. Even though the information available – e.g., the data – could be subjected to randomness, stochastic machine scheduling will not be addressed in this section.

In the literature, machine scheduling problems have proper classification and representation as well as a specific notation regarding machines and jobs. Thus, making it possible to clearly identify the characteristics of the problem to solve. Graham et al. (1979) introduced a new three-field classification system for scheduling problems, $\alpha \mid \beta \mid \gamma$ concerning job, machine and scheduling characteristics. Since its introduction 40 decades ago, new problems in the scheduling field have appeared, so other authors have reformulated and extended the notation (Blazewicz et al., 1996; Brucker, 1995; Carsten, 1996; M. L. Pinedo, 1995). Varela (2007) compared nomenclatures proposed by nine different authors by reviewing the fields α and β and classifying each author's work with a qualitative characterisation of the nomenclatures. Regarding the qualitative characterisation, Varela's

(2007) criteria are clarity and objectivity; coverage; detail, nomenclature; ease of integration and use. Three authors stand out: Blazewick, Brucker and Pinedo. In addition, after consulting Varela's reviewing of the fields α and β, it is notorious that the nomenclatures chosen by Pinedo are in general better formulated. Pinedo (2016) successfully and objectively explains some important concepts and notions regarding scheduling that are the basis for important theoretical concepts presented in this section. Bear in mind that in problems regarding scheduling, the number of jobs and machines are recognised as finite.

For a better understanding of the subject, let us use the terms *i* and *j*, to refer to machines and operations of a job respectively, for the following concept:

- Due date (*dj*) – date agreed upon with the client for the competition of the job *j*. In case the due date needs to be referred to as a deadline, it is denoted by $\bar{d}_j$.

Whereas the following fields describe a scheduling problem:

- α – illustrates the machine environment. Contains one entry;
- β – provides details of processing characteristics and constraints. Contains no entry, a single entry, or multiple entries;
- γ – conveys an optimisation criterion i.e., the objective to be minimised. Often contains a single entry.

The possible sequencing machine environments specified in the α field are:

- Single machine (1) – the most straightforward environment possible, an individual machine;
- Machines in parallel – *m* machines in parallel are available for a job *j* of a single operation that can be executed in any one of the *m* machines or of a given subset. If the job requires a specific machine subset *Mj*, it appears in the β field. There are different environments for parallel machines:
- Identical (*Pm*) –all machines have the same speed;
- Unrelated (*Rm*)– each machine has unique speeds for all jobs.
- Flow shop (*Fm*) – has *m* machines in series. The conditions to complete

operations on this entry are that all jobs *j* must be processed on all available machines and must follow a specific route;

- Job shop (*Jm*) – the jobs follow predetermined routes with *m* machines available.

Regarding the *β* field, due dates are not specified in this field since the objective function gives a sufficient indication of whether or not there are due dates. Thus, the remaining possible entries in this field is:

- Batch processing (*batch(b)*) – a machine can have the capability of simultaneous processing of jobs, i.e., can process a batch of up to *b* jobs at the same time.
    - If *b* presents with the value of 1, then the scheduling problem reduces to a conventional scheduling environment;
    - If *b* is considered ∞, there is no limit to the number of jobs the machine can handle at any time.

As has been mentioned before, the *γ* field regards optimisation and is a translation of the system's performance. Pinedo (2016) gives particular relevance to the criteria expressed as a function of completion times of jobs, or alternative due dates, supported by concepts such as lateness and tardiness. These concepts are penalties regarding compliance, or not, of due dates/completion times of jobs.

When *Cij* denotes job completion time, it means there is a consideration of the machine used and the job. In contrast, if *Cj* represents the completion time of a job *j*, the only concern is when job *j* finishes all his processing. Lateness, *Lj*, is the difference between the completion time of a job and the respective due date (*Lj* = *Cj* – *dj*). If the value verified is positive, it implies delay; otherwise, it imposes anticipation. Although the concept of anticipation seems to be positive, it can be the opposite if it implies unexpected costs, such as storage and transportation. Tardiness (*Tj*) only measures delay in the processing of a job. Therefore, tardiness cannot present negative values.

There are a few objective functions to take into consideration:

- Makespan (*Cmax*) – is the completion time of the last job to leave the system, i.e., the length of time that elapses from the start of a set of jobs to the end. Makespan is focused on being minimised since it implies a good utilisation of machines;

- Maximum Lateness (*Lmax*) – measures the worst violation of the due dates;
- Weighted number of tardy jobs ($\sum wjUj$) – an appealing function for its data collection requirement.

Table 2 – Summary of entries for each field using the notation of Pinedo

Field	Description	Value
α	Different sequencing machine environments	1, *Pm, Rm, Fm, Jm*
β	Batch process	0, *batch*(*b*): 1, ∞
γ	Optimisation of system performance	C_{max}, L_{max}, $\sum w_j U_j$

The concepts presented here are only necessary for understanding this document, so what is presented here is a brief and specific version for understanding AM scheduling problems.

2.2.2. Classification of scheduling problems

Object-oriented systems, by default, are designed taking into account two basic entities: objects and method. Considering that this topic can be lengthy to dissect (Bennett et al., 2010; Booch et al., 2007), let us simplify it as much as possible. Objects are associated with different types of entities or concepts, e.g., jobs and machines. The method is implemented in the system through operators, i.e., their manipulative actions on objects' attributes. M. Pinedo & Yen (1997) defend a set of advantages in following object-oriented design in developing scheduling problems: the ease and speed increase of the design process.

After two decades of research and development on scheduling, the authors concluded that object-oriented design appears helpful to provide guidelines that simplify and standardise the design and development of scheduling systems. Thus, in our literature review, object-oriented design will be considered to classify different scheduling problems.

There are four classifications of scheduling problems regarding object-oriented systems – Centralised Scheduling, Distributed Scheduling, Cloud Manufacturing Scheduling (CMS) and Decentralised Scheduling, and (Jiang et al., 2021).

Centralised Scheduling is the most traditional scheduling problem where only one factory is considered. Pinedo's (2016) approach is part of this classification. It is characterised by two models, whether deterministic or stochastic, has different possible environments, as well as resource and constraints to be considered, and can be single objective or multi-objective.

Distributed Scheduling eliminates the concept of only one factory in an organisation processing jobs when there is the possibility of cooperation between the organisation's factories to carry out jobs. Also known as multi-factory production planning and scheduling, this type of scheduling problem has an additional task involved – sequencing operations on machines for jobs to available factories (Lohmer & Lasch, 2020). Furthermore, additional constraints need to be deliberated, such as technical and logistics.

CMS aims to achieve the optimal allocation of manufacturing resources in services by combining and selecting the most appropriate service-oriented for the task. It uses hierarchical task networks and semantic matching methods such as cloud computing, the Internet of Things (IoT), and service-oriented architecture to accomplish the intended (Jiang et al., 2021; Liu et al., 2019).

The last classification of scheduling problems, Decentralised Scheduling, is pointed by Jiang et al. (2021) to be more suitable for dynamic production systems with frequent disturbances and the need for rescheduling. In this type of problem, there are essential players denominated as agents. This intelligent decision-making entity acts as an autonomous individual to manage priorities and workloads and allocate resources. They represent resources or tasks on the production system. The agent intends to elaborate on the best scheduling plan to achieve the objective based on the internal state and the external environment.

2.2.3. Scheduling research

Alemão et al. (2021) analysed 65 papers published on manufacturing scheduling to grasp how many and which resource requirements were considered while developing real scheduling problems. The criteria for recording the results for the analysis were sequencing machine environments, resource requirements, and solutions' objectives. The author defends that the best possible requirements are not always chosen for real planning problems. Furthermore, since only 10% of the analysed research articles solved a real-world scenario, there is not enough literature on real scheduling problems.

Lohmer & Lasch (2020) provide a systematic and comprehensive review of distributed scheduling approaches. Compared to Alemão et al. (2021) and their article review, the number of research articles reviewed was almost double, 128, and the criteria for recording the results for the analysis was deepened. In addition, there was more effort to accumulate specific criteria of the problems such as factory type, types of models (or even simulation), network structure, type of programming and use of heuristics/meta-heuristics. Lohmer & Lasch (2020) conclude that there has been a shift of academic focus regarding sequencing machine environments to flow shops and job shops over the last decade. Also, there is a trend on Distributed Scheduling to adopt from iterated greedy algorithms, knowledge-based systems and learning algorithms in contrast to genetic algorithms.

As a reflection of global increased awareness for sustainability, manufacturing companies are starting to look at sustainable scheduling since energy usage substantially impacts manufacturing companies' sustainable development (Gahm et al., 2016). These authors review 35 research articles regarding scheduling approaches that aim to improve energy efficiency. The criteria for registering the results was extensive as the analysis of Lohmer & Lasch (2020). Regarding energy, they studied how the problems focus on energetic coverage and the supply and demand. Furthermore, the study's objective was whether there was a monetary focus and if the objective function was single or multi. The machine environment and model type were criteria explored as well.

Lohmer & Lasch (2020) and Alemão et al. (2021) reached a few similar points of view and conclusions. First, both defend that transportation should be considered when coming up with the models since it impacts costs and logistics, which are usually not taken into consideration by authors. Second, both conclude that the makespan dominates the literature as the focus of objective functions. Gahm et al. (2016) concluded that the predominance was the use of the model formulation MILP and one-objective problems. Lastly, the authors established that more specialised solution methods should be developed to improve the results of these types of problems meaning that there is not enough literature and effort on this topic to have a clear contribution and gain for the manufacturing companies.

2.2.4. Nesting

When approaching AM scheduling, it is necessary to explain some additional concepts to understand the topic better. One of them is nesting, when parts are made in one single process cycle and are located such that their bounding boxes, arbitrarily oriented or otherwise, will overlap (ISO/ASTM, 2015). The bounding box is a term used in Computer Aid Manufacturing (CAM) and implies an orthogonally oriented minimum perimeter cuboid that contains all points on the surface of a 3D object. Studies of nesting methods aim to optimise build jobs and machine utilisation, improve yield, increase production rate, and enhance the efficiency of process planning and production management (Oh et al., 2020). Figure 4 is an excellent visual example of nesting.

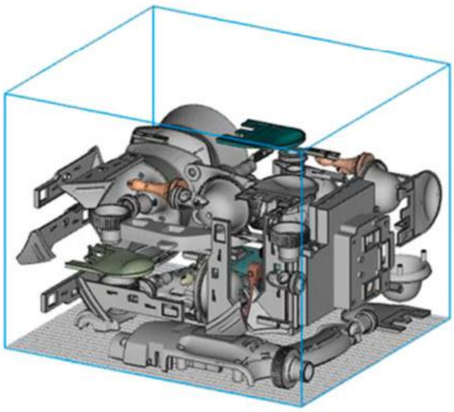

Figure 4 – Visual example of nesting result (Jianming Zhang et al., 2020)

In scheduling literature, the subject of placement problems is known. However, due to unique AM constraints, specific process characteristics and different part requirements, the placement problem is different from other classic nesting or packaging problems, e.g., box-pack and knapsack (Y. Zhang et al., 2016).

Nesting and scheduling in traditional manufacturing are not usually considered in the same planning stage (Oh et al., 2020; Jianming Zhang et al., 2020). In contrast, scheduling for AM focuses on improving productivity by sequencing and allocating workloads to AM machines, i.e., machine utilisation, same as nesting. Therefore, it is essential to think of nesting and scheduling in the same planning stage when approaching AM. Thus Oh et al. (2020) propose a taxonomy for nesting and scheduling problems in AM, described in Table 3, based on a hierarchy of three dimensions: i) Part – united material that forms a partial or total functional element of an intended product (ISO/ASTM, 2015); ii) Build – a group of components simultaneously produced by an AM machine in a single build cycle (Oh et al., 2020); and iii) AM Machine. The three dimensions lead to the origin of six classes as classification criteria to define and identify cluster problem characteristics and types.

Table 3 – Oh et al. (2020) proposed taxonomy for nesting and scheduling problems in AM

Part level	**Build level**	**AM Machine level**	**Machine identicalness**
Multi-part (M)	Single-build (S)	Single-machine (S)	x
	Multi-build (M)	Single-machine (S)	x
		Multi-machine (M)	Identical machines (iM)
			Non-identical machines (nM)
- (N/A)	Multi-build (M)	Multi-machine (M)	Identical machines (iM)
			Non-identical machines (nM)

A helpful note to comprehend the proposed taxonomy is that addressing a single part is meaningless in nesting and scheduling problems. Therefore, in the table, it is only visible in the part level the one option, multi-part. Another aspect to consider is that machine identicalness is not a dimension but a subcategory of AM Machine Level. Lastly, the authors account parts as builds in the dimension part level, i.e., when an AM machine produces only one part for a build cycle. The last two rows corroborate this situation. For a quick identification of one type of problem, the authors use the following nomenclature [Part level, Build Level, AM Machine level – Machine identicalness], e.g., [M/M/iM] is specific to a problem of multi-part in a multi-build in an environment of identical multi-machine.

In his study, Oh et al. (2020) surveyed and classified 53 technical papers to conclude that [M/M/S], [M/M/iM] and [M/M/nM] are the types of problems that have nesting and scheduling in consideration. However, the class problems [M/M/nM] simplify nesting issues and focus on scheduling issues. Another point demonstrated is that research trends regarding this topic have changed with a shifting focus to scheduling-oriented problems for AM. Thus, the research scope of scheduling AM is no longer a single build with a single machine but multiple builds covering multiple machines. The authors also suggest that in the future is necessary to study flow-shop (*Fm*) and job-shop (*Jm*) scheduling models for AM since there is not a sufficient number of studies in this area.

Furthermore, Oh et al. (2020) provide eight additional criteria to further define the nesting and scheduling problems. However, the content of three of them have already been addressed in greater detail in section 2.2.1, as such they will not be presented in the table detailing and summarising the additional criteria defining nesting and scheduling problems. (Table 4).

Table 4 – Specific criteria for nesting and scheduling problems

	Description	Values	Explanation
Nesting	Dimensionality (Nα)	2D	placing parts on the build surface[1] (or often the build platform[2]) where all parts are in contact with it
		3D	placing parts within the build space, and parts are allowed to be stacked with other parts
	Rotation freedom of parts (Nβ)	ABC	representation of the freedom of rotation around the axes X, Y, and Z, respectively. Aspect to consider when dealing with multiple parts
		C	a single axis of freedom, the Z-axis. Studies often facilitate and only consider this parameter
	Build volume boundness (Nγ)	Bounded	restrictive build volume
		Unbounded	flexibility in some dimensions of the build volume
	Set of nested parts (Nδ)	Full	all parts are fully nested
		Subset	only one set of parts from the set are chose
Scheduling	Generation methods of build (Sα)	Nested	builds are clustered from parts by a nesting algorithm
		Grouped	simplification by clustering parts into builds based on the maximum capacity of part volume
		Created	builds are randomly generated
		Given	information regarding the build information, e.g., total volume and maximum height are provided in a problem

1) AM machine component – area where the material is deposited and gradually forms the desired geometry.
2) AM machine component – base provider of a surface for the printing process.

Table 4 was designed to summarise and explain the additional essential criteria, and consequently, facilitate the understanding of nesting in AM scheduling since nesting as an isolated topic is complex and needs extensive research for a complete understanding. The table also allows us to understand the authors' statements regarding some studies that facilitate nesting issues and focus on scheduling. For instance, in dimensionality, they only consider 2D, or in the rotation of free parts, only contemplate the C value and in the generation of build methods having the value given.

2.2.5. Additive Manufacturing

Considering the printing time associated with AM and the unit cost per part, nesting problems for AM aim to maximise the number of agglutinated parts processed simultaneously and minimise the build time and cost of a single operation for an AM machine. However, depending on the choice of the criteria parameters, the problem can become more complex, i.e., longer computational resolution time. Furthermore, scheduling for AM focuses on improving productivity by sequencing and allocating the agglutinated parts to several AM machines. It is also possible to increase the complexity of a scheduling problem by selecting a multi-objective or shop configuration that differs from a single machine.

Thus, it is noticeable that the combination of nesting and scheduling in AM scheduling problems can be beneficial for indicators such as throughput or lead time. Therefore, there are three fundamental questions in the AM scheduling process:

1) How to maximise the number of processed parts simultaneously?

2) How to minimise the build time?

3) How to allocate jobs (agglutinated parts) to each machine in compliance with restrictions?

For each problem, the researchers need to decide whether they will restrict the problem to one or several specific AM process categories, to make a balanced choice and focus on a problem that, though unsolved so far, has the possibility of resolution.

2.3. Establish Additive Manufacturing technologies

It is necessary to compare and contrast the main characteristics of all polymer AM processes to identify which type of technology is most suitable for a specific production process. In order to provide a comprehensive review of the state-of-the-art on AM technologies for polymers, it is necessary to introduce the existing polymer AM processes.

The polymer AM technologies have six process categories: Material Extrusion, Material Jetting, Powder Bed Fusion, Binder Jetting, Vat Photopolymerisation and Sheet Lamination (ISO/ASTM, 2015). The distinction between categories starts in the state of fusion, where there is a thermal or chemical reaction bonding, and ends in the principle used by each process. Figure 5 allows studying in detail the differentiation between the processing principles of all six process categories.

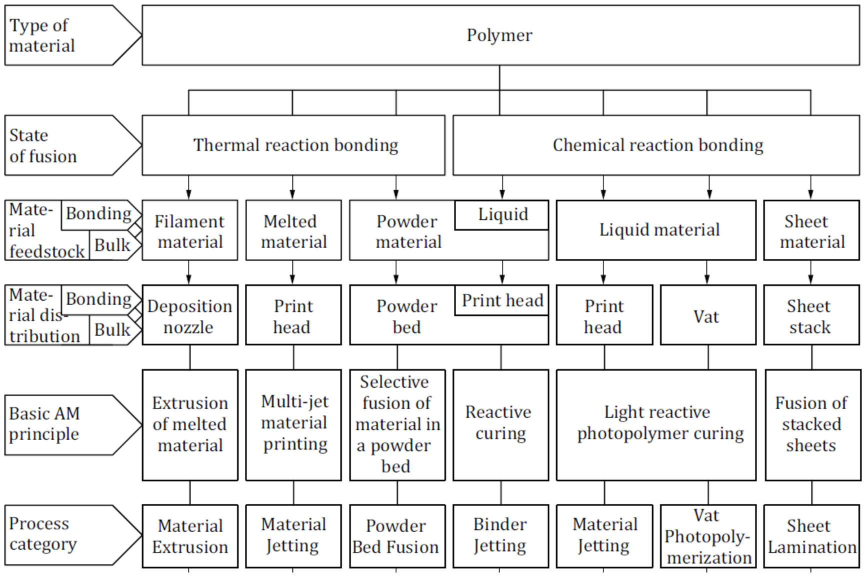

Figure 5 – Overview of single-step AM processing principles for polymer materials (ISO/ASTM, 2015)

Even though the International Standard for Additive Manufacturing notes six process categories for AM polymer, no technology for Binder Jetting and Sheet Lamination was found while searching the topic. The poster Additive Manufacturing Technologies by Hubs (2021) proves this finding.

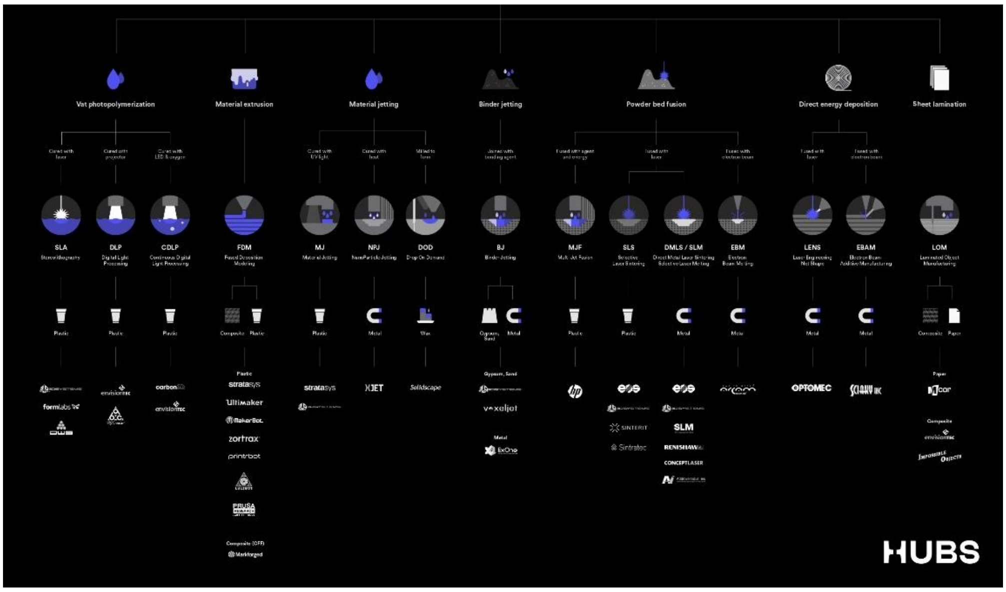

Figure 6 – Additive Manufacturing Technologies Poster (Hubs, 2021)

Hubs, also known as 3D Hubs, is a leading online manufacturing platform, after its start as one of the world's largest peer-to-peer networks of 3D printing services. The Dutch company ventures with manufacturing companies in other countries to offer strong manufacturing capacity and a broad range of manufacturing capabilities. Their poster contains all the different processes in AM, their associated technologies and the organisations that hold patents for this type of technology. The poster reinforces that the market has only technological solutions for four of the six processes. Therefore, all processes categories considered in this study are represented in Figure 7.

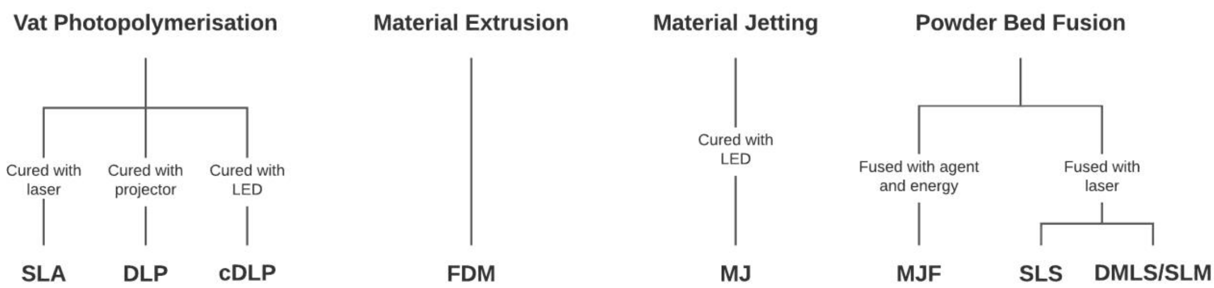

Figure 7 – Different AM processes categories and their corresponding technologies

The next sections consist of the description of the different processes and their respective techniques, where, in addition to a description, technical aspects are addressed.

2.3.1. Key characteristics

Despite the differences between processes, some printer characteristics fall in a standardised set of parameters that specify their operating range: printer dimensions, maximum printing volume, built-in accessories, or even the displacement of the build platform. Other generic characteristics are the type of power supply, the existence of an application that allows remote control or access, and if the printer has a screen to assist the production process. Concerning the printing process itself, some relevant parameters are the thickness of the printed layers, the calibration mechanism, the heat source, the need for support structures. In Figure 8, it is possible to consult some of the main and secondary features of a 3D printer. They are distributed according to their degree of importance.

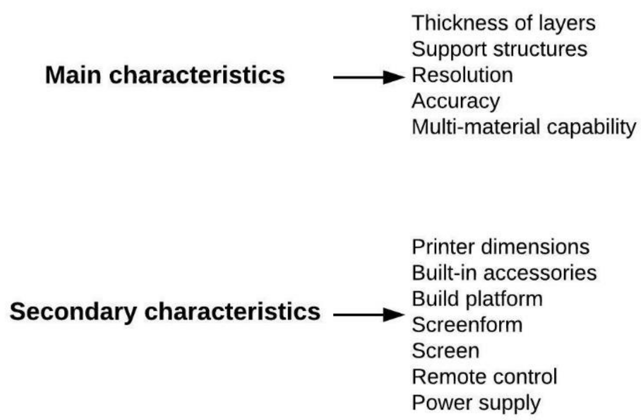

Figure 8 – Characteristics of a 3D printer

Although technology depended, it is generally agreed upon that The AM process has three distinct phases: pre-processing, processing, and post-processing. The processing step is usually where the most significant differences are felt since different technologies print parts using different methods. However, pre- and post-processing steps can also have significant differences among technologies. For instance, some of these printed parts require a thermal process, and others need to remove the support structures used during the printing process. In addition, all AM technologies have different labour intensive time consuming pre and post-processing operations. Thus, when choosing what AM technology is more suitable for a specific case, the pre- and post-processing steps must be considered in the decision-making process.

2.3.2. Material Extrusion (ME)

Material Extrusion is an AM process in which material is selectively dispensed through a nozzle[1] or orifice (ISO/ASTM, 2015). In this process, there is only one technology adjacent – Fused Deposition Modelling (FDM).

2.3.2.1. Fused Deposition Modelling (FDM)

In this technology, the part's production performs with a dispensing head that sequentially deposits material in layers, in a fluid state, onto the base. Since the material is in a fluid state, its temperature is controlled to solidify instantaneously upon extrusion. With the injected material colliding and fusing, multiple layers of a variable thickness form according to the object's shape (X. Wang et al., 2017).

The main advantages of FDM are the cost and simplicity of the process, making it one of the most popular technologies for end-users. However, high printing time, weak mechanical properties, layer-by-layer appearance, and low surface quality (Chohan et al., 2017) in addition to the produced parts not being watertight, make the use of FDM difficult at an industrial scale.

2.3.3. Vat Photopolymerisation (VP)

This process has a liquid photopolymer in a vat selectively cured by light-activated polymerisation (ISO/ASTM, 2015). A vat is a large container used for storing the liquid photopolymer. Three technologies belong to this process.

2.3.3.1. Stereolithography (SLA)

Three-dimensional objects with SLA are formed based on a liquid resin's spatially controlled solidification through a photopolymerisation reaction (Melchels et al.,

[1] Mechanical part of the 3D printer that extrudes the material.

2010). With a computer-controlled laser beam, a pattern illuminates the resin surface. As a result, the resin is solidified to the defined depth and pattern, causing it to adhere to the support platform. After photo polymerising the first layer, an elevator system moves the platform away from the surface to deploy the next liquid resin layer. The curing process and the platform's movement repeat until the part's final geometry is printed.

SLA is relatively slow, expensive, and the range of printing materials is limited compared to other technologies. These limitations make the technology unsuitable for industrial applications where the relationship between costs and output is the primary driver (X. Wang et al., 2017). Despite these limitations, SLA can be valuable for applications where high resolution is a crucial requirement. In addition, SLA can print hollow, watertight, and transparent parts.

2.3.3.2. Digital Light Processing (DLP)

This technology is very similar to SLA since it also uses photopolymerisation. The main difference lies in the light source (X. Wang et al., 2017). DLP printers use a digital screen to project an image onto the resin's surface and cure an entire layer during a single exposure. While the exposed resin hardens, the printer platform moves to set the stage for a new layer of fresh resin to be coated to the object and cured by light, just like SLA.

Although DLP is known for providing high-resolution products at a moderate price range (Mostafa et al., 2017), its resolution may vary depending on the projector resolution and its distance from the optical window. Meaning if the projector is closer to the optical window, the pixels are smaller, and consequently, the resolution is better. Thus, this technology is usually used for smaller parts that require high resolution or bigger parts whose resolution can be compromised. Like SLA, DLP also prints watertight parts.

2.3.3.3. Continuous Digital Light Processing (cDLP)

This technology's production process is essentially the same as DLP, except that the machine-building platform undergoes a continuous displacement on the Z-axis during printing instead of discrete displacements (Tumbleston et al., 2015). This modification considerably influences the printing time since the photopolymerisation process does not need to stop after each layer's production. By advancing continuously on the Z-axis, it also theoretically allows to print parts without visible layers and achieve isotropic properties in all directions, in contrast to other 3D printing methods that usually have stronger strength in X-Y axes and less in the Z-axis (EnvisionTEC, 2018). The production speed of this technology makes it attractive for mass production.

2.3.4. Powder Bed Fusion (PBF)

The PBF process has thermal energy selectively fusing regions of a powder bed (ISO/ASTM, 2015), where the type of material in the bed can be plastic or metal. Another difference in the technologies of this process is the fusion medium, as seen in Figure 7. The figure shows that there are four technologies of this process. The type of material used in Selective Laser Melting (SLM) and Direct Metal Laser Sintering (DMLS) is metal. These technologies are recurrently chosen together with Selective Laser Sintering (SLS) in the mathematical models that will be discussed in section 4.2. Despite the different materials, they use the same technological principle, fusion with a laser, so researchers do not distinguish between these technologies and SLS.

2.3.4.1. Selective Laser Sintering (SLS)

This technology uses a thin layer of powder heated with a high-intensity laser to bind powder materials via solid-state sintering or melting of binding agents of a selected area according to the desired geometry (C. Y. Yap et al., 2015). Process parameters, such as laser power, laser type, scanning rate, bed temperature and layer thickness, are thoroughly adjusted to form the desired layers. However, this technique has a few drawbacks – poor surface quality and dimensional inaccuracy – all pre-requisite for industrial applications. In this case this drawbacks must be minimised with post-processing operations, lengthening the process (Olakanmi et al., 2015; C. Y. Yap et al., 2015). However, since this technology uses powder, which acts as a support, support structures are reduced or even eliminated, reducing the number of post-processing operations.

SLS printing materials such as nylon are well understood and highly recyclable.

The unused materials of the printing process can be effectively recycled and reused in future productions. However, constant reuse of the same powder can affect its quality (Weinmann & Bonten, 2020).

2.3.4.2. Multi Jet Fusion (MJF)

MJF technology can almost be considered an emergent technology, as it was recently debuted by Hewlett-Packard (HP) in 2016. However, it is already being used in many industrial applications. HP Development Company LP, (2018) describes MJF machines as capable of building high-quality parts, up to 10 times faster and at a lower cost than FDM and SLS printer solutions[2].

This technology concept is similar to SLS, though it does not use a laser. Instead, it uses transforming agents and lamps with infrared light, which are the energy source. The transforming agents can be fusing or detailing agents. The homogeneity of the printed parts and the processing speed suggest that MJF has an enormous potential to facilitate the broader adoption of AM by the manufacturing systems (O'Connor et al., 2018).

2.3.5. Material Jetting (MJ)

Material Jetting is a process in which droplets of build material are selectively deposited (ISO/ASTM, 2015). There is only on technology that uses polymer and has the same name as the process category.

2.3.5.1. Material Jetting (MJ)

MJ uses piezo printing heads[3] to deposit droplets of photopolymers and UV lamps to perform the curing process. Multiple photo-curable resins are selectively deposited to produce multi-material parts using Drop on Demand (DOD) inkjet printers, where instead of a continuous jet, it is possible to inject droplets when an actuation pulse is provided (Y.

[2] This comparison was performed with FDM and SLS high-end printers from $100,000 USD to $300,000 USD, when producing a part with the size of 30cm^3 with a layer thickness of 0.08 mm.

[3] printheads with piezoelectric elements which contract in response to an applied voltage, ensuring a mechanical pressure to eject droplets of material.

L. Yap et al., 2017). Since these printers are equipped with more than one printing head, they can print different colours and soluble supports.

MJ is quite effective in producing smooth surface finishes with very high dimensional accuracy, even when compared to injection moulding. Furthermore, the produced parts have homogeneous mechanical and thermal properties, but although they are homogeneous, mechanical properties obtained from this technology might not be appropriate for functional prototypes because of a low elongation at break. However, if there is the need to build a non-functional large part (up to 1000x800x500mm) without compromising the dimensional accuracy (typically ± 0.1%), this might be the appropriate technology (Bournias Varotsis, 2019).

2.4. Emerging Additive Manufacturing technologies

In this section some emerging technologies, which can soon become available solutions for manufactures, are analysed to understand their differentiating characteristics as future technologies.

After approaching some 3D printing processes, it is noticeable that the desired parts are obtained through the sequential deposition of layers. The limitations regarding the physical properties of the materials used and the constrains to design the parts are also apparent such as restrictions of process aids, support structures and post-processing tasks. This section presents some emerging AM technologies capable of overcome some of these weaknesses and disadvantages of current AM processes.

2.4.1. Rapid and multi-material printing technologies

High-Area Rapid Printing (HARP), which is based in SLA, is an emergent technology that uses a dead layer-free approach (similar to cDLP) to continuously print over large areas at a rapid vertical printing speed (Walker et al., 2019). This technology is already known as the world’s fastest resin-based 3D printer, and it can create plastic structures as large as a person in a few hours (Zastrow, 2020).

Other exciting technologies are focused on printing multiple materials together.

For instance, a printer capable of depositing up to eight different polymers from one nozzle, switching between them or even mixing them as it prints (Skylar-Scott et al., 2019). Alternatively, a printer that combines four different nozzles makes it possible to extrude molten polymer, light-sensitive resin, and wires and circuitry from tiny metal dots (Roach et al., 2019).

2.4.2. Volumetric Additive Manufacturing (VAM)

All the existing AM technologies are, in fact, a type 2D printing process that runs along the Z-axis. However, VAM approaches the process with all three dimensions simultaneously by single-step irradiation to a transparent resin bath from multiple angles, which provides a local accumulation of light dose and the consequent simultaneous solidification of specific object voxels[4] (Loterie et al., 2020). Thus, it allows printing extremely complex structures without layers and the need for support structures. A few distinct development techniques are VAM processes: Computed Axial Lithography (CAL) (Kelly et al., 2019), Xolography (Regehly et al., 2020) and Tomographic (Loterie et al., 2020).

The CAL technique projects a set of 2D images at different angles, which allows the necessary energy to solidify the material with the desired geometry. The major drawback of this technology is that the printed object must be small enough (centimetre-scale) for the light to pass through it to cure it. However, the developers state that CAL is scalable to larger print volumes and is several orders of magnitude faster than layer-by-layer methods under a wide range of conditions (Kelly et al., 2019). CAL is inspired by computed tomography, a medical imaging technique. Therefore, Tomography is similar to CAL.

Both techniques share advantages and disadvantages, including the identical drawback of centime-scale parts and the impressive ultrafast production. In addition, Tomography can print with highly viscous resins instead of layer-by-layer methods, which results in stronger materials and more accurate prints (Loterie et al., 2020).

Xolography is a dual-colour technique that resorts to the projection of a sequence

[4] minimum unit of a three-dimensional digital image.

of images during a synchronise movement of the resin volume through the fixed optical setup, where it ends up continuously producing the desired geometry. Compared to CAL, the resolution is ten times higher due to feedback optimisation. However, it cannot produce parts as big as CAL (Regehly et al., 2020).

All the inventors of these techniques agree that one of the major challenges in VAM is scaling up from cubic centimetres to cubic meters.

3. PROPOSED DECISION SUPPORT FRAMEWORK

The main goal of this chapter is fourfold – first, an overview of AM usage in different sectors; second, a comparison between AM and a well-known alternative manufacturing technique – injection moulding (IM); third, a thorough review of the features of the established technologies; fourth, a classification and decision-support framework to aid the adoption of these technologies.

The purpose of the framework elaboration was the organisation of information related to a broad set of features of each AM technology already discussed. Furthermore, the framework turned out to support the author during the elaboration of the thesis to allow understanding different technological aspects addressed in different mathematical models present in the research articles under study.

3.1. Applications of AM Technologies

Although we tend to associate AM to the automobile industry with rapid prototyping, the applications of AM technology are not restricted to a limit set of industries. The implementation of this technology will be increasingly adopted in different industries in future years. Competitive sectors, i.e., those that need innovative processes to distinguish and maintain their rank in the market, were not reluctant to test the implementation of this technology in their production processes. Thus, some industries have AM as an ally in their production process, e.g., the automotive and healthcare industry. Table 5 exemplifies a set of applications used in different industry areas and the corresponding technology already discussed.

Table 5 – Examples of application of technologies with industry distinction

AM technology	Reference	Industry	Application
FDM	(Artley, 2020; Pearson, 2020; Stratasys Ltd., 2020)	Automotive	Prototypes, parts with limited production runs
	(Boissonneault, 2019b), (3D Printing Media Network, 2017)	Aerospace	Flight-ready parts, robot prototypes
	(Chen et al., 2020)	Healthcare	Anatomical models
SLA	(Ali et al., 2020; Redwood, 2019a)	Jewellery	Investment casting, prototypes, moulds
	(Lai et al., 2020; Manapat et al., 2017)	Industrial	Nanocomposites
	(Redwood, 2019b)	Healthcare	Prosthetics, anatomical replicas, hearing aids
DLP	(Boissonneault, 2020a; Essop, 2020)	Jewellery	Investment casting, prototypes, moulds
	(Kim et al., 2018), (Xue et al., 2019), (Dikova, 2019; Sher, 2020c)	Healthcare	Tissue regeneration, cell-seeding, temporary crowns and bridges, dental moulds
cDLP	(Essop, 2019)	Footwear	Midsoles
	(Boissonneault, 2019a; Sher, 2019, 2020a)	Automotive	Parts with limited production runs
SLS	(Tampi, 2020) , (Sher, 2020b)	Footwear	Midsoles, flipflops
	(Kinstlinger et al., 2020; Sher, 2020d), (Strömbergsson, 2020)	Healthcare	Blood vessels, implants and medical devices
MJF	(Benedict, 2016; Farish, 2019; Sher, 2020a)	Automotive	Parts with limited production runs
	(Boissonneault, 2020b)	Healthcare	Dental moulds
MJ	(Valdivieso, 2020a, 2020b)	Automotive	Prototypes
	(Jabari et al., 2020)	Manufacturing	Nanocomposites

In this example, it is noticeable that the industries that stand out, with the most applications are the Automotive and Healthcare industries. For all technologies discussed it was possible to find a practical example of applications for at least one of these sectors. At the beginning of AM, prototyping or model production was one of the primary reasons to resort to this process. This fact seems unchanged since AM continues to be used by different industries for rapid prototyping and, therefore, quick introduced to the market. However, the application to parts with limited production runs begins to be recurrent in the AM technologies addressed in this work.

3.2. Comparison with Injection Moulding

The thermoplastic injection in moulds is embedded in the plastic production process. According to the annual report of CEFAMOL, Portugal's National Mould Industry Association, 71% of the moulds produced are for the automotive industry, and the second is packaging with 11% (CEFAMOL, 2021). With four European countries as our top importers: Spain, Germany, France and the Czech Republic, our exportation value was 566 million euros. In the 2018 document available by DGAE, Portugal's general direction of economic activities, entitled Mould Industry – Synopsis, one can find the total volume of business of the most 20 successful mould companies in the country, almost 333 million euros (DGAE, 2019). Considering that these moulds will produce thermoplastic parts, investigating the differences between IM and AM is necessary to identify the challenges and opportunities for AM.

The development and production of a thermoplastic injection mould is a very demanding process. Each mould is unique, may have hundreds of different components and various geometries. The production of each mould component requires high precision and very tight dimensional tolerances. Usually, the components to be machined are raw purchased from a steel supplier. Next, a large number of operations are required, which might include thermal treatments. After several working weeks, or even months (Achillas et al., 2017), the final assembly of the mould is executed, where all the internal machined components are assembled and fine-tuned to produce the mould in its final shape. Thus, it is easy to understand the long lead times and high costs of producing thermoplastic injection moulds. Figure 9 presents a brief comparison between the processes of AM and IM.

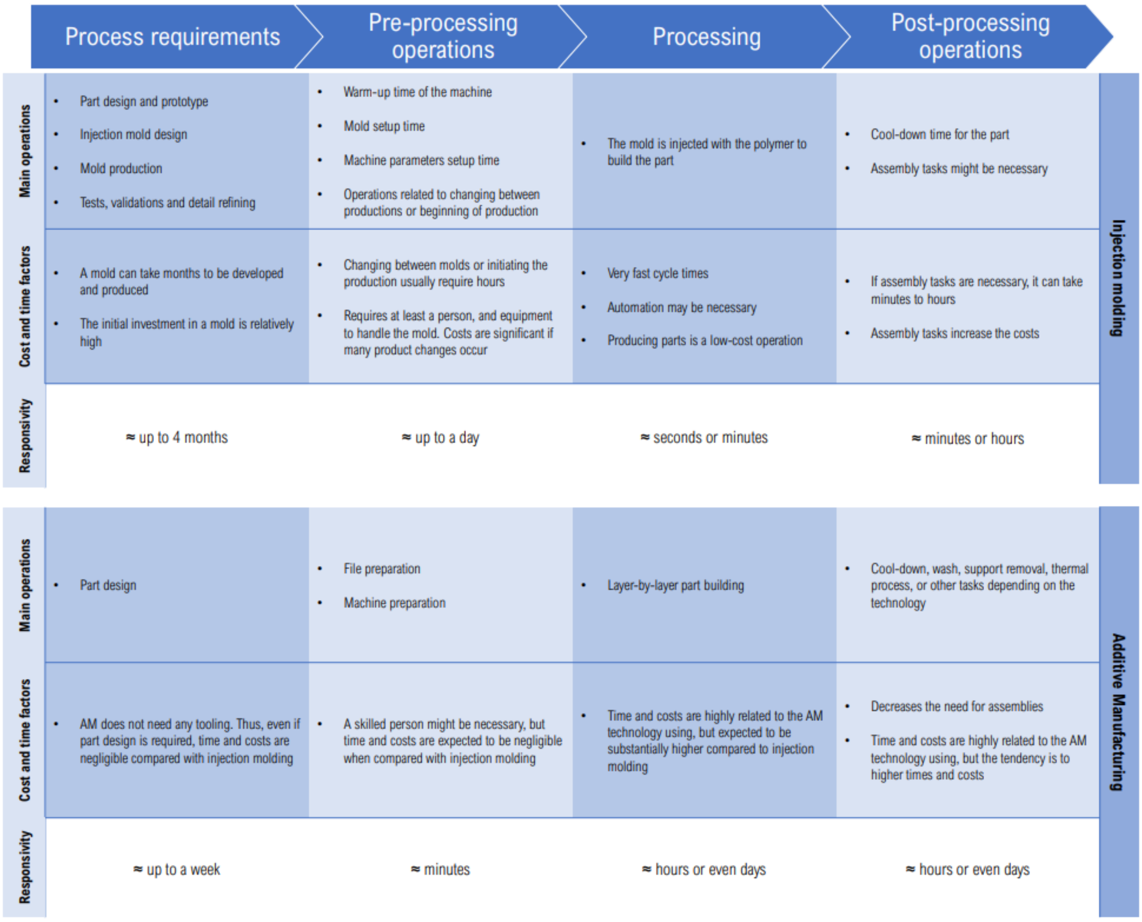

Figure 9 – Overview of AM versus IM manufacturing processes

By analysing the Figure 9, we can understand that IM has a high lead time associated. In contrast, AM, even if the part needs to be designed, has a small lead time, when compared with IM. The difference derives from the fact that AM needs nearly no tool to produce parts, and thus, production can start almost instantaneously. Regarding pre-processing operations, IM also tends to be less costly and time-effective. However, once the mould is ready for production, it can run with relatively short cycle times, while for AM the printer capacity severely limits the output of the process, making IM is a lot faster than AM, and thus, it seems logical to conclude that the tipping point in produced parts will be rapidly achieved. The threshold depends on many factors, e.g., the complexity and size of the part or the AM technology used. Table 6 presents several thresholds that can be used as a reference to select AM technologies over IM.

Table 6 - Cost and lead time thresholds between AM and IM

Reference	AM technology	Cost threshold in function of parts quantity	Lead time threshold in function of parts quantity	Observations
Franchetti & Kress (2017)	FDM	200	-	Material cost/kg is the variable with the most impact on the cost break-even point
Achillas et al. (2017)	FDM SLA SLS	150 – 250 100 – 150 500	500 – 600 1500 – 2000 5000 – 7000	Results presented up to 1000 parts. Ranges above that were obtained by polynomial regressions
Paulsen (2020)	SLS MJF	30 – 250 250 – 2000	-	Small and larger parts were analysed, hence the wide range of the break-even
Stratasys Ltd. (2017)	FDM	2000 – 8000	2000	Results valid for certain small parts

Since the values presented consider the cost and time needed to produce the mould, IM is still the best option for long production (whether is in time or number of parts). However, AM tends to be the best manufacturing technique for small to medium quantities, mainly if small parts are to be produced.

3.3. Features of AM technologies

Three main drawbacks still limit the adoption of AM at a large scale (Ngo et al., 2018): i) inferior mechanical properties and anisotropic behaviour of 3D printed parts; ii) high-cost production for high quantities of the same product; and iii) time-consumption for large quantity production. Nevertheless, as the continuing research efforts are undertaken, the limiting factors that inhibit the use of AM process will begin to fade, and the adoption of AM over traditional manufacturing techniques will tend to grow.

Since there is the possibility to produce parts in one single manufacturing process, the benefits of introducing AM include:

- the reduction of lead times and costs (Chekurov et al., 2018);
- deliver products in hard-to-reach locations (Meisel et al., 2016);
- improved environmental and social sustainability (Beltagui et al., 2020; Ford & Despeisse, 2016; Y. Li et al., 2017);

- inventory reduction (Ben-Ner & Siemsen, 2017; Kunovjanek & Reiner, 2020), a higher degree of flexibility (Verboeket et al., 2021).

Keep in mind, this might not always be true since the introduction of AM can lead to various outcomes and should be evaluated on a case-by-case basis (Khajavi et al., 2020). As noted by some authors, most of the successful implementations of AM are essentially limited to: i) low demand, small and geometrically complex products (Verboeket & Krikke, 2019); and ii) firms that offer customised products down to an order size of one (de Brito et al., 2021).

However, introducing AM into current or new production processes is challenging because AM processes have very different characteristics from the prevailing technology that it aims to substitute (e.g., injection moulding, CNC machining, vacuum casting). Therefore, a successful introduction of AM in a manufacturing environment must rely on an industrialisation strategy that combines the AM process characteristics with production and logistic features. There are a great variety of characteristics that differentiate AM technologies and need to be considered when designing new processes. Thus, a critical question arises: what are the main characteristics of AM technologies, and how do they differ among them?

Therefore, a thorough analysis of the characteristics of AM technologies is presented in this section. This analysis is of particular importance because the main features of current AM technologies enable designing efficient and optimised production and logistic processes.

In the literature there can be found tables with the differentiating characteristics of AM polymer technologies – Ligon et al. (2017) and L. J. Tan et al. (2020).

However, it is imperative to provide a more comprehensive analysis of the characteristics crucial to the manufacturing process, as showed in Table 7.

Table 7 - Comparison of AM technologies and their characteristics by printers' size

Technology	State of matter	Printer dimension	Printing Volume		Resolution[1]	Accuracy	Materials	Printing speed	[1] Resolution is measured differently depending on the AM technology (explained in the text)
FDM	Filament	**Small**	152x190x196 mm^3 - 254x254x254 mm^3	5.7 - 22.3 [dm^3]	400 µm (xy) 20 - 400 µm (z)	± 200 µm (xyz)	ABS, ASA, HIPS, Nylon, PC, PC-ABS, PETG, PLA, PVA, PVB, TPU	[1] 500 mm/s [2] 0.18 l/h	[1] printing head travel speed [2] building rate
		Large	330x270x200 mm^3 - 914x609x914 mm^3	23.8 - 508.8 [dm^3]	305 - 1020 µm (xy) 127 - 508 µm (z)	± 89 µm or 1.5 µm/mm (xyz) additional -0.000/+ slice height (z)	ABS, Antero, ASA, Nylon, Onyx, PC, PC-ABS, PC-ISO, PETG, PLA, PPSF, ST, ULTEM	N/A	
SLA	Liquid	**Small**	140x140x180 mm^3 - 335x200x300 mm^3	3.5 - 20.1 [dm^3]	25 µm (xy) 25 - 300 µm (z)	N/A	Invicta, Flexa, Fusia, Precisa, Therma, Vitra	N/A	
		Large	300x300x300 mm^3 - 1500x750x550 mm^3	27.0 - 618.8 [dm^3]	6.35 µm (xy) 50 - 150 µm (z)	± 1 - 2 µm/mm (xyz)	ABS[1], Invicta, Flexa, Fusia, PC[1], PP[1], Precisa, Therma, MicroFine, Vitra,	[2] 3.5 m/s (130 $µm^3$) - 25 m/s (760 $µm^3$)	[1] similar properties [2] drawing speed in the xy plan [3] laser beam size
SLS	Powder	**Small**	150x200x260 mm^3 - 165x165x300 mm^3	7.8 - 8.2 [dm^3]	200 µm (xy) 110 µm (z)	N/A	Flexa, Nylon 11/12, PA11/12, TPE, TPU, ABS	[1] (10 mm/h => [2] 0.27 l/h)	[1] building rate [2] considering value given by Formlabs (10 mm/h) which considers full capacity of the machine
		Large	Ø160x400 mm^3 - 550x550x460 mm^3	8.0 - 139.2 [dm^3]	60 - 180 µm (z)	[1] ± 300 µm (xyz)	Alumide, FR-106, HP 11-30, PA 640 GSL, EOS TPU, Nylon 11/12, PA 1101/1102/2200/2201/3200, PrimeCast 101, PP, PrimePart ST, PA 2105, PEKK	[2] 6 m/s [3] 3 l/h	[1] information obtained after direct contact with Sintratec [2] drawing speed in the xy plan [3] building rate
DLP	Liquid	**Small**	96x54x100 mm^3 - 96x54x127 mm^3	0.5 - 0.7 [dm^3]	[1] 25 µm (xy) 20 µm (z)	N/A	ABS[2], **Biocompatible**, **Casting**, **Dental**, E-Glass, E-Silicone, E-Tool, HTM140, PU[2], Q-View, R5	[3] (100 mm/h => [4] 0.66 l/h)	[1] information obtained after direct contact with B9Creations [2] similar properties [3] building rate [4] considering full capacity of the machine **Dental** - E-Gum, E-Partial, E-Denstone, E-Model **Biocompatible** - NextDent C&B MFH, NextDent Denture 3D+, E-Guide, E-Guard, E-Shell, E-Clear **Casting** - EC, EPIC, PIC, WIC100
		Large	233x141.5x180 mm^3 - 216x381x356 mm^3	5.9 - 29.3 [dm^3]	75 µm (xy) 50 - 100 µm (z)	N/A	ABS[2], **Biocompatible**, **Casting**, **Dental**, E-CE, E-EA90, E-Glass, E-Mould, E-Poxy, E-Silicone, E-Tool, E-UA, HTM140, Photosilver, Pro Gray, PU[2], Q-View, R5/11, RC, xCE, xGPP, xMED	N/A	**Dental** - E-Gum, E-SepFree, E-Partial, Press-E-Cast, E-Denstone, E-Model **Biocompatible** - BIORES, NextDent Denture 3D+, E-IBD, E-Guide, KeySplint Soft, E-Guard, E-Shell, E-Clear **Casting** - EC, EPIC, PIC, WIC100, B9R
cDLP	Liquid	**Small**	180x101x85 mm^3	1.5 [dm^3]	60 - 93 µm (xy) 50 - 150 µm (z)	N/A	ABS[1], **Biocompatible**, **Casting**, **Dental**, E-Aquasol, E-Mould, E-UA, E-3955 FST HH, NextDent Tray, PU[1], Q-View, R5	[2] (80 mm/h => [3] 1.45 l/h)	[1] similar properties [2] building rate [3] considering full capacity of the machine **Dental** - E-Gum, Press-E-Cast, E-Model **Biocompatible** - BIORES, NextDent Denture 3D+, E-IBD, E-Guide, KeySplint Soft, E-Guard **Casting** - Easy Cast, EPIC, PIC
		Large	189x118x326 mm^3 - 400x250x508 mm^3	7.3 - 50.8 [dm^3]	75 µm (xy) 100 µm (z)	± 200 µm (xyz)	CE, DPR, EPU, EPX, FPU, MPU, RPU, SIL, UMA, KeySplint Soft, Lucitone, Crown and Bridge, Fotodent	[1] (1000 mm/h* => [2] 22.3 l/h)	[1] building rate/information obtained after direct contact with Carbon [2] considering full capacity of the machine
MJF	Powder	**Small**	332x190x248 mm^3	15.6 [dm^3]	20 µm (xy) 80 µm (z)	± 200 µm - parts below 100mm ± 0.2% - parts over 100mm (xy)	PA11/12, PP, TPU	[1] 1.817 l/h	[1] building rate
		Large	380x284x380 mm^3	41 [dm^3]	20 µm (xy) 80 µm (z)	± 200 µm - parts below 100mm ± 0.2% - parts over 100mm (xy)	PA11/12, PP, TPU	[1] 5.058 l/h	
MJ	Liquid	**Small**	140x200x190 - 294x211x144 mm^3	5.3 - 8.9 [dm^3]	≈ 32 µm (x) ≈ 28 µm (y) ≈ 32 µm (z)	± 1 - 2 µm/mm (xyz)	ABS[1], PC[1], Elastomers, Vero	N/A	[1] similar properties
		Large	490x390x200 - 518x381x300 mm^3	38.2 - 59.2 [dm^3]	≈ 34 - 42 µm (xy) ≈ 13 - 16 µm (z)	± 1 - 2 µm/mm (xyz)	ABS[1], PC[1], Elastomers, Vero	N/A	[1] similar properties

The table considers a division in size of the printer, i.e., small printers (also known as desktop printers) and large printers (adapted to the industry). Thus, enabling an introductory level analysis of additive manufacturing for organisations needing to test the adaptation of an AM technology to their production process, without the need of a significant initial investment. The table is also a registry of all the materials available, a detail that many organisations cannot overlook.

The information was gathered by analysing catalogues and manufactures' websites for a large range of products of the following manufacturers: Stratasys, MakerBot, Prussa, LULZBOT, Ultimaker, Zortax, Markforged, Formlabs, DWS, 3D Systems, Envisiontec, Carbon, Natural Robotics, EOS, Sintatrec, and HP Jet Fusion. In addition, some information was obtained from direct contact with the manufactures. However, it was verified that the manufacturers do not follow any standard for cataloguing, which has complicated the process of correct information gathering. For example, it is not uncommon to mistake accuracy and resolution and not provide the build rate or production speed. This lack of clarity is due to possible considerable variation of parameters depending on the materials utilised and the part to be produced, hence manufacturers have difficulty realising more accurate figures.

As it can be seen, the analysis includes seven main characteristics: state of matter, machine dimension, printing volume, resolution, accuracy, materials, and printing speed. In the author's opinion, the term printing speed is more appropriate than build rate, given that build rate does not apply to all technologies addressed. Let us start a closer look the table by analysing the type of material, since it influences the overall quality of the part. For instance, printing with a filament has physical limitations that do not allow a high resolution comparing to a spot laser or even a high-resolution projector. The same thing applies with surface finishing since printing with liquid resins usually produces a better surface finishing. The type of material also influences how easy it is to print with multi-materials, e.g., it is still a challenge to print multi-materials using powder. These are just some of the properties affected by the type of material. Thus, any decision will immediately narrow the AM technologies available for producing a part.

With the increasing number of applications of AM, the printer dimensions must be considered. Large printers can be used in industrial environments because they have a higher capacity to satisfy the demand. On the other hand, small printers are usually used for prototyping, research, academia, or even home printing, as they are cheaper and have less of a learning curve and maintenance. Moreover, small printers have HUB platforms that reuse part designs, unlike large printers and other manufacturing technologies.

Printing volume is directly related to the printer dimensions. Therefore, even if two printers have a similar printing volume, the measures along the three axes can be significantly different. Printing volume influences the direction in which a part needs to be printed, affecting, ultimately, the quality of the part because AM printed parts tend to have better properties along the X and Y axes than the Z-axis.

The resolution influences the printing quality in all axes. However, some manufacturers only share this value for the Z-axis. The Z-axis resolution is related to the thickness of the layer, while the resolution in the XY plan depends on the technique that the respective AM technology uses. For SLA and SLS, XY resolution is related to the laser's spot size and the increments it can be controlled. For DLP and cDLP, XY resolution is related to the pixel size, i.e., the smallest feature that the projector can reproduce, and for MJF and MJ, it is dependent on the size of the droplets.

Regarding FDM, XY resolution can be related to the nozzle diameter as it produces layers by depositing lines of molten material. A higher resolution might not always be the best because a higher Z resolution leads to a thinner layer, and having more layers increases the chances of failed layers. Resolution is essential if there are sharp edges, smooth transitions, and complex designs, while simpler designs might even achieve higher-quality prints with lower resolutions. One limitation associated with the resolution is that the higher the resolution, the more time it will take to print the part since more layers are needed. Thus, the trade-off between resolution and printing speed should also be considered, as it will directly affect the production time.

The accuracy measures how close the final printed part is to the digital model. In general, AM technologies provide reasonable accuracies, meaning that if parts can have a slight deviation from their digital model, accuracy should not be the main deciding factor. However, accuracy is paramount when a part needs to be produced with tight tolerances, e.g., junctions and unions that need to fit perfectly. Thus, one should decide how much deviation a part can have compared to its digital model, as a more accurate printer usually means more investment and maintenance. In contrast, a less accurate printer can result in more rejected parts, influencing the overall costs.

A technology that uses distinct materials should produce a higher range of different products with good quality and mechanical properties. However, while this might add some flexibility, it also introduces complexity to the production planning, given that most of the technologies can only use one material at a time. Either way, for polymer AM, all technologies have a reasonable range of different products that can be used. Even for MJF, which is mainly restricted to PA12 material, the printing agents allow different physical properties within the same material.

Speed is usually the most straightforward characteristic when comparing AM with other manufacturing technologies and is influenced by pre- and post-processing steps. The printing speed is one of the most relevant indicators to choose the AM technology. For example, high printing speed technology like MJF is adequate for a mass customisation strategy since the output needs to be enough to fulfil the demand while maintaining costs reasonably low. On the other hand, a slower technology like SLA is more suitable for delicate jobs where the quality of the part is more important than time or cost. Thus, depending on the competitive dimensions, different AM technologies should be chosen.

3.4. Classification and decision-support framework

Based on the features and operational characteristics discussed in section 3.3 and the quantitative data from Table 7, it is introduced a classification scheme in Figure 10 to assess and select AM technologies based on four main criteria: technological characteristics, cost, process features, and physical properties of the part. The AM technologies listed in each criterion are presented in alphabetical order. It should be noted that the technologies listed were considered the upper and lower bounds of the classification criteria utilised and if a technology is not listed in a specific criteria, it does not fit in any of the extremes but rather between them.

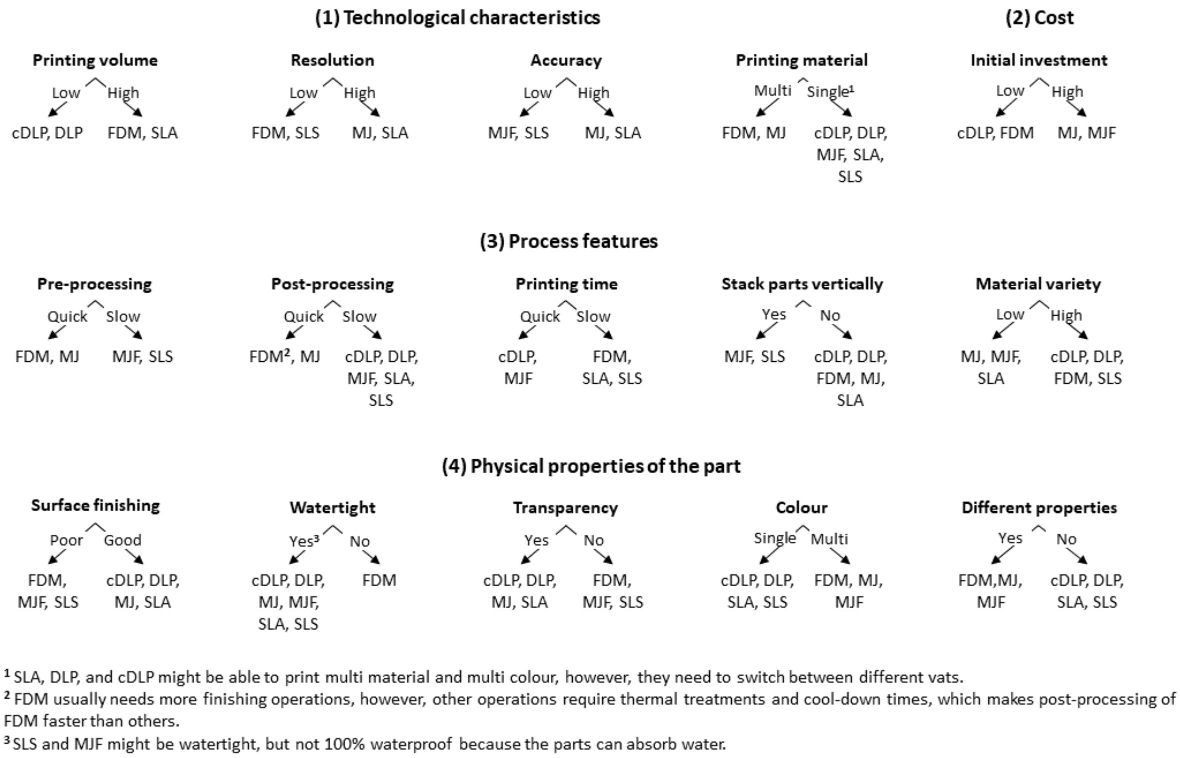

Figure 10 – Classification and decision-support framework

By analysing the decision-support framework, it is noticeable that DLP and cDLP printers have the lowest printing volumes. In order to achieve a good resolution in these technologies, the projector must be close to the printing surface, hence the associated difficulty of printing large parts. On the other hand, FDM printers provide one of the largest printing volumes available.

Another important feature is resolution. Here SLA and MJ provide the best results. SLA is the best technology regarding resolution in the XY plane, followed by MJF. Note that MJ printers have a significant advantage over MJF since they can deliver superior Z resolution compared with MJF printers while providing similar values for XY resolution. Overall, DLP printers provide high values of resolution. However, a clear disadvantage of this technology is that it cannot maintain such resolution for larger volumes. On the other hand, FDM and SLS have the lowest resolution values. This is because FDM printers use a nozzle to deposit lines of material, and SLS presents difficulty controlling the powder's sintering process. Nonetheless, the resolution provided by both printers, especially by SLS, is still very reasonable for many types of parts.

In terms of accuracy, SLA and MJ printers are the best ones opposite to SLS printers. The fact that FDM does not have one of the worst accuracies demonstrates that a lower resolution does not mean that the produced part is not accurate.

The usefulness of combining several materials in a single print is one of the most relevant features of AM processes, and the unique technologies that have this capability are FDM and MJ printers. The MJF printer is still limited to a single material, despite having transforming agents to convey different properties on different locations of the part. By switching between different vats, SLA, DLP, and cDLP can print different layers with different materials. However, since this process is not feasible within the same layer, these technologies cannot be considered multi-materials printers.

Regarding the initial investment, FDM is the most accessible technology, followed by cDLP. Some smaller SLA printers also provide a low initial investment; however, prices rise quickly for industrial printers. MJ and MJF are the most expensive technologies from an initial investment perspective.

The process features show that powder technologies have a lengthy pre/post-processing, mainly because the powder needs to heat up/cool down before the parts are produced/removed. In order to overcome these limitations and increase the output of the printer, dedicated stations can be used to do the post-processing operations and therefore release the printer to produce the next part. Thus, determining the number of these dedicated stations is a crucial decision to reduce the downtime of the printers.

Printing time is another relevant feature of AM technologies. Technologies like DLP, cDLP and MJF can print an entire layer at once, which significantly speeds up the process. cDLP is the fastest method regarding photo-polymerisation, given the continuous displacement on the Z-axis during printing. The use of multiple lasers for SLS and SLA and multiple nozzles for FDM might speed up the process; however, they are usually much slower compared with MJF and cDLP. Moreover, it is important to note that printing speed should be considered alongside the speed of the pre- and post-processing operations.

Another attractive characteristic is the ability to stack parts vertically. All AM technologies can stack parts vertically if support structures are used. Nevertheless, SLS and MJF are the only technologies able to do it without support structures because they use powder. From an industrial point of view, this might be one of the most critical features, alongside the printing speed, which is why SLS, MJF, and cDLP are currently the most appropriate AM technologies for mass production. Material variety can also change significantly, with technologies such as DLP having a high range of materials available compared with MJ, SLA, and MJF.

Different properties are presented regarding the physical properties of the part, though perhaps the most important is the ability to print parts that have different properties in different locations. MJF, MJ and FDM are the only technologies with that capability, as long as SLA, DLP, and cDLP do not use multiple vats.

4. CURRENT PERSPECTIVES AND CHALLENGES AHEAD

As said before, scheduling is an activity that involves allocating limited resources to operations within a certain period, thus affecting decisions and restrictions at various levels. Moreover, this activity is essential to an organisation due to its interdependence from other functions, such as sales, purchasing, production, and control. Thus, integrating optimisation models to support decision making has been of great interest and activity in development.

The number of researchers and authors focused on researching scheduling AM is restricted. Furthermore, the number of authors investigating and developing models that represent an evolution in the topic is even scarcer. Thus, this chapter intends to present the results of the conducted SLR to suggest further improvements and emphasise current perspectives on the problem and the challenges ahead.

4.1. Systematic Literature Review Methodology

The systematic method of literature reviews has grown in popularity in Operations Management research, allowing scholars to advance the current state-of-the-art in their field of study (Thomé et al., 2016). This section covers all the necessary steps taken to prepare the SLR based on the specific methodology proposed by Thomé et al. (2016), which is presented in detail.

According to Thomé et al. (2016), there are eight steps vital for an SLR: (i) planning and formulating the problem; (ii) searching the literature; (iii) data gathering; (iv) quality evaluation; (v) data analysis and synthesis; (vi) interpretation; (vii) presenting results, and (viii) updating the review (Thomé et al., 2016). In Table 8, all the information regarding the first step of Thomé et al. (2016) methodology is exposed.

Table 8 – First step information

Step	Task	Characteristic
i	Needs identification	Ascertain the current status of the topic in the literature
	Research team constitution	Thesis´s author
	Definition scope (Brocke et al., 2009; Cooper, 1988)	Focus – assessing research outcomes, research methods, investigate applications in the field of optimisation scheduling in AM
		Goal – integrative synthesis of existing literature, identifying critical issues and criticise
		Perspective – neutral
		Coverage – exhaustive
		Organisation - methodologically
		Audience – specialised scholars
	Conceptualisation of a topic	Scheduling problems in AM
	Research Questions	RQ1 and RQ2

The focus of the SLR is to assess research outcomes, research methods and investigated applications in the field of optimisation scheduling in AM. The goal of the SLR is an integrative synthesis of existing literature while also identifying critical issues and criticism. An attempt to maintain a neutral perspective was made, to obtain this is somehow difficult (Cooper, 1988). Regarding coverage, the aim is to be as exhaustive as possible and provide the details concerning our search process and inclusion/exclusion criteria. The organisation is treated methodologically, meaning after reviewing the literature set, we analyse objectives, uncertainty, model formulation, solution method, shop configuration, problem classification, nesting, AM process and assessment methods. However, the table that contains the literature analysis results is organised historically to enable the reader to benefit from diachronic analysis. Therefore, enabling an interpretation of the development of studies in the area in a timeline. Finally, this master's thesis audience are scholars and interested practitioners, as the reader of this topic needs specific knowledge. However, a theoretical background is provided for less experienced scholars to understand and follow the work.

The literature search was performed in August and repeated in October 2021. Although this update did not show any new results, this step is done to include the most recent contributions. Web of Science and Scopus were the two databases used. The research method in Web of Science is different from Scopus. The Web of Science advance search does not necessarily require a query string for search. It is possible to combine smaller searches with boolean logic and obtain a result. In Table 9, the specific results for which search are available for analysing.

Table 9 – Keywords and their specific results for the search in Web of Science

#	Keywords	Parameter	Results
1	"Additive Manufacturing" NOT path NOT topology NOT design NOT slicing NOT parameters NOT mechanical	Topic (TS), Title (TI), Abstract (AB) and Keywords (AK)	19,542
2	Scheduling		370,949
3	"Linear Program*"		155,536
4	"Integer Program*"		1,168
5	Metaheuristic* OR Meta-heuristic* OR Heuristic*		167,103
6	Model OR Modelling		10,441,848

Combinations	Results
#1 AND #2	90
(#1 AND #2) AND (#3 OR #4 OR#5 OR#6)	53

In column #1, the keywords used to restrict the search result of the term AM were used based on the knowledge gathered in elaborating the theoretical background. The terms in question are related to studies of materials used in AM or printing process research.

In Scopus, there is indeed the need to formulate a query string. It is vital to perform small validations as the query string is built. This way, it is guaranteed that the intended result is found. The following query string was used:

TITLE-ABS-KEY("Additive Manufacturing" AND Scheduling AND Optimi?ation) AND TITLE-ABS-KEY(Model OR Modelling OR Metaheuristics OR Heuristics OR "Linear Program*") AND NOT TITLE-ABS-KEY (path OR topology OR design OR slicing OR parameters OR mechanical)

The search started with 62 relevant publications after removing duplicates and ended up with 20 research articles for conventional content analysis. The flowchart of the literature search to obtain the content analysis is demonstrated in Figure 11 to clarify all the steps taken. The search was extended beyond the keywords for inclusiveness with the execution of 'snowball' backwards search, i.e., reviewing the literature cited in the research articles encountered from the keyword search and forward search, i.e., examining the research articles that cite the research articles examined. The result was the addition of two more research articles. The specified inclusion and exclusion criteria are registered in Table 10.

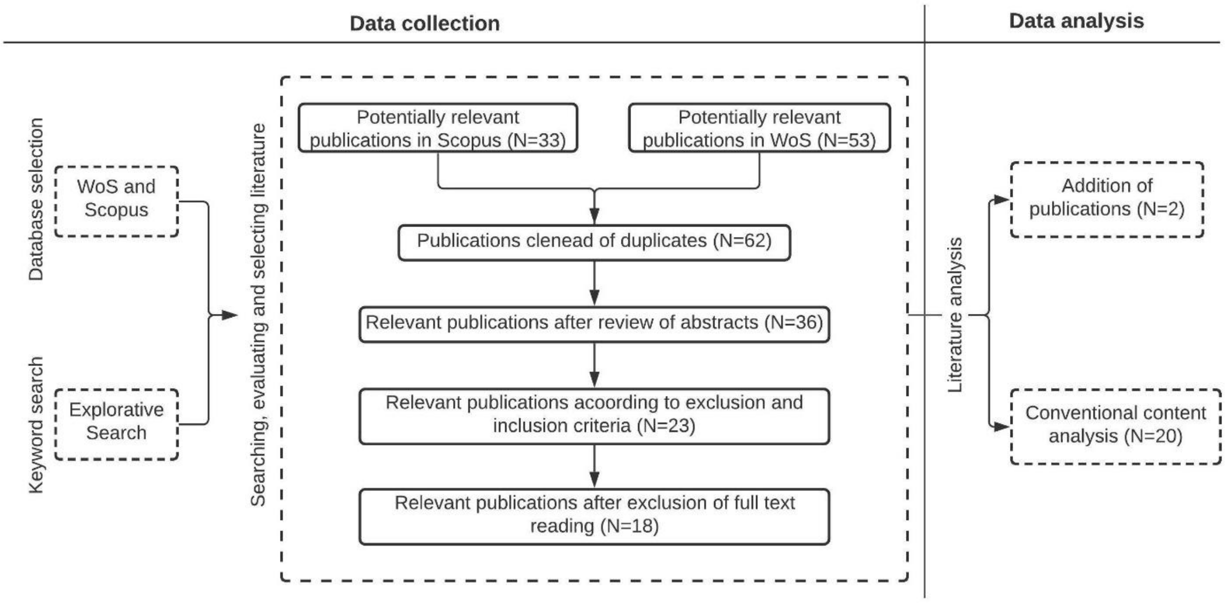

Figure 11 – Searching the literature (based on Micán et al., 2020)

Table 10 – Inclusion and exclusion criteria and their rationale for the literature review (based on Lohmer & Lasch 2020)

	Rationale
Inclusion criteria	
Publications in peer-reviewed journals and conference proceedings	Without peer review is not possible to guarantee high-quality research articles (Thomé et al., 2016)
Research articles that present a formulation of a mathematical model/algorithms to solve scheduling problems in AM	The focus is optimisation in AM scheduling. Research articles that address only one of the areas were disregarded
Quantitative papers instead of qualitative empirical papers	Research articles must contribute with a formulation model with a solution to a batch scheduling problem model
Exclusion criteria	
Research articles that focus on process categories that do not include single-step polymer's AM	Only process categories in common with the polymer material were considered
Research articles with the possibility of full access	Sometimes proceeding documents have access restrictions, e.g., monetary cost

The frequency of publications in scheduling AM is portrayed in Figure 12, with a distinction between publications per year and cumulative. Thus, there is an annual growth from 2016 to 2018. The only growth exception was in the year 2019. Considering that 2021 is still running, there may be an addition of research articles by the end of the year. Therefore, another year in which there was growth.

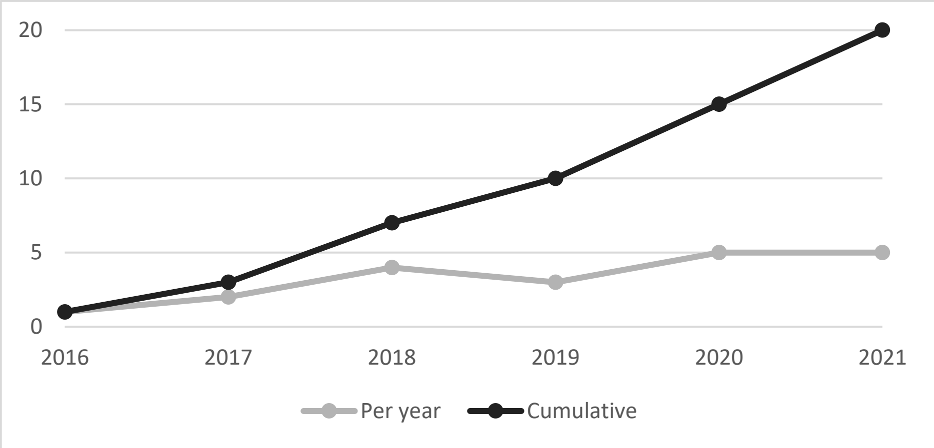

Figure 12 – Number of documents per year and cumulative

The most relevant sources concerning the number of research articles are exhibited in Figure 13. The majority of the research is published in Computer & Operations Research, Computers & Industrial Engineering and International Journal of Production Research. Also, proceedings documents account for 3 of the 20 publications. Regarding the topic in question, 14 different journals and conferences have published one or more research articles, which reveals some diversity of sources and stakeholders in the area

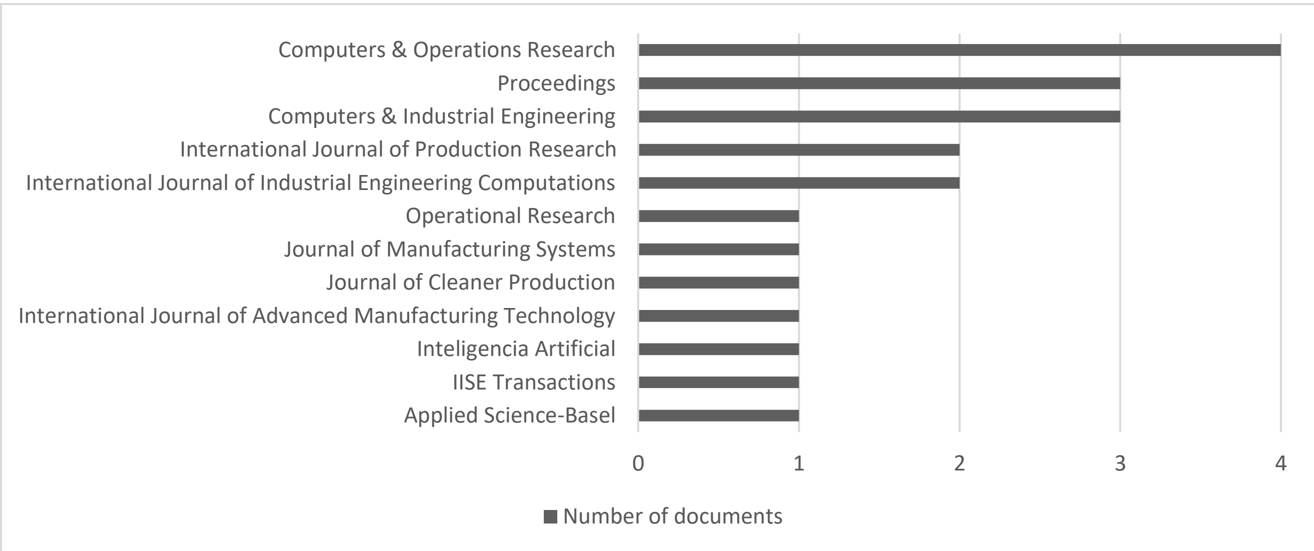

Figure 13 – Most relevant sources

Another aspect to debate is the result update. Since the search results stayed the same between the start and the update (four months apart), no update was necessary.

4.2. Results and critical analysis

Unlike classic scheduling problems, the processing time of a batch on an AM machine is not calculated or predicted just because the maximum processing time and all the individual parts processing times are known. Instead, other factors will influence the batch processing time: the pieces' height, orientation, total volume, and the different AM techniques since each technique have differentiating features. Therefore, after an analysis, what is recognised in the literature is the problem of regrouping parts and allocating them into jobs to optimise desired performance measures. By understanding the different problem statements of regrouping and allocating parts, it is now possible to answer the first research question:

- RQ1: What is the state of the art regarding AM polymer scheduling?

All publications focusing on process categories coincident with polymer AM analysed in this review are summarised in Table 11, categorising the literature according to the presented criteria covered throughout the theoretical background. The only exception is the prior explanation of case study, which intends to understand if the model proposed by its authors is tested and validated using real cases and thus increases its credibility.

Table 11 – An analysis AM scheduling literature

	Kucukkoc (2016)	Li (2017)	Ransikarbum (2017)	Kucukkoc (2018)	Fera (2018)	Luzon (2018)	Chergui (2018)	Oh (2018)	Dvorak (2018)	Kucukkoc (2019)	Li (2019)	Fera (2020)	Yilmaz (2020)	Ransikarbum (2020)	Karami (2020)	Zhang (2020)	Aloui (2021)	Che (2021)	Alicastro (2021)	Arik (2021)
Objective																				
Cmax									√	√			√					√	√	√
Lmax				√																
Tj			√		√		√					√					√			
Ej					√							√								
Cost		√	√		√						√	√		√						
Others	√		√			√		√	√					√	√	√				
Uncertainty																				
Deterministic	√	√	√	√	√		√	√	√	√	√	√	√	√	√	√	√	√	√	√
Stochastic						√														
Model formulation																				
MILP/MIP	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
Solution method																				
Heuristic		√				√	√	√	√	√	√		√			√	√	√		√
Metaheuristic	√			√	√				√			√				√		√	√	
Exact			√											√	√					
Shop configuration																				
1					√	√				√		√								√
Pm							√			√	√				√	√				
Rm	√	√	√	√				√	√	√			√	√	√		√	√	√	
Problem classification																				
Centralised Sche.	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
CMS																				
Decentralised Sche.																				
Distributed Sche.																				
Nesting																				
Nα - 2D		√					√	√	√		√					√	√	√		√
Nα - 3D																				
Nβ - C		√					√		√		√					√				√
Nβ - ABC								√										√		
Sα - Grouped	√		√	√	√	√				√		√	√	√					√	
AM process																				
Vat Photo.								√						√		√				
Material Extrusion			√											√	√					
Material Jetting																				
Powder Bed Fusion	√	√		√	√	√	√		√	√	√	√	√	√			√	√	√	√
Assessment method																				
Case study			√											√	√					

It is possible to draw some immediate conclusions after analysing the table:

- The most studied objective is minimising the makespan. A quarter of the problem statements are multi-objective and, within these, only one problem statement does not have cost as an objective;
- Only one problem statement has uncertainty considered;
- All models are formulated using MIP/MILP models, i.e., none of the models considers nonlinearity;
- When it comes to method solutions, few authors opt for exact methods. This choice is because all authors defend their problem statements as NP-Hard problems; therefore, challenging to arrive at an optimal solution.
- As a rule, the authors' choice regarding shop configuration is unrelated machines in parallel. There are some studies of a single machine;
- All verified problems are centralised regarding the problem classification, meaning the statement problem only considers one production process in a factory;
- Some authors facilitate their problem statement regarding the specific nesting problem;
- The most popular process category is the PBF, with a percentage of choice of 80%. No study considered the process category Material Jetting;
- Finally, only three research articles consider case studies in order to validate their models.

It is also necessary to carry out a more exhaustive analysis of the authors' works with some criticism, so let us start with the first article presented in the table. Kucukkoc et al. (2016) were the first authors in the literature to research the PBF scheduling AM problem of unrelated parallel machines (*Rm*) with the objective of increasing resource utilisation to respect delivery times of parts. The mathematically modelled problem was solved using a heuristic solution method.

Q. Li et al. (2017) presented a model with job allocation and sequencing on unrelated parallel machines to minimise the average production cost per volume material. The parts were considered with different properties, e.g., volume, area, heigh. The model has already been validated and the heuristics assessed by other researchers. However, this model has some weaknesses since due dates (dj), and parts' shapes were not contemplated (Q. Li et al., 2019).

Ransikarbum et al. (2017) propose a decision aiding model based on multi-objective optimisation for a batch of parts and multiple FDM printers considering total cost, load balance among printers, total tardiness, and the number of unprinted parts. The authors resorted to a case study with automotive parts to verify the functionalities of the model. They also conducted a designed experiment by varying the number of parts and printers to test the model's complexity and its computation time. Due dates were contemplated. The authors proposed solving a multi-objective model with four objective functions, and regarding nesting, the parts were fixed with an unrotated orientation, which resulted in an expected simplification. Without this simplification, with the added difficulty of the nesting problem complicating the problem statement, a resolution would probably not have been found in the imposed time frame.

Kucukkoc et al. (2018) introduced another problem in the literature by studying unrelated parallel machines with job allocation and sequencing with the objective of minimising maximum lateness ($Lmax$) with consideration to due dates. The solution method was by the Genetic Algorithm (GA) metaheuristic. The authors still maintained the focus on the PBF process category.

Fera et al. (2018) propose a mathematical model with a multi-objective function to minimise the earliness (Ej), tardiness (Tj) and production costs. The solution method was similar to Kucukkoc et al. (2018). However, Fera et al. (2018) modified the metaheuristic. Some constraints were relative to geometry, like the printing chamber's volume and others to scheduling rules, such as due dates. The single-machine (1) scheduling problem applied to AM, with a multi-objective function of cost and time, is addressed only by these authors.

However, yet another model simplifies nesting by only considering the parts' areas and volumes. The main difference of the problem statement of Ransikarbum et al. (2017) compared to Fera et al. (2018) is the shop configuration from a single machine to a parallel machine. Even with the possibility of considering a more developed nesting problem and guaranteeing a more elaborate problem statement than Ransikarbum et al. (2017), Fera et al. (2020) ended up only to modified the traditional tabu-search algorithm to solve theirs already formulated statement problem and compared results to the meta-heuristic used before. The results were positive in 3 of 4 evaluation parameters (the value of the objective function, production costs, and the service level) only to negatively affect running time.

Chergui et al. (2018) divided an AM problem into two subproblems: a nesting problem and a problem of parallel identical machines (*Pm)* and proposed a heuristic resolution. The authors proposed a heuristic approach while considering due dates to solve the problem. The first subproblem formulation is not addressed in this dissertation – a Binary Integer Quadratic Programming (BIQP) problem with an objective function built to minimise the total due date difference between parts of the same build. The BIQP is a combinatorial optimisation problem, i.e., it has a vast number of candidate solutions with discrete decision variables and a finite set of search space, which require exponential computational time to be solved optimally (Karimi-Mamaghan et al., 2022). Regarding the second subproblem, a MILP model was adapted to minimise the total tardiness.

Oh et al. (2018) focused on an AM production planning problem that included building orientation determination, 2D packing, and scheduling to minimise the total cycle time. Regarding the criteria for nesting, the authors consider that all axes had freedom of rotation. Only Oh et al. (2018) and Che et al. (2021) decided to increase the difficulty of the nesting problem by considering the three axes of rotation. In addition to the initiative of freedom of rotation of the axes, Oh's et al. (2018) considered the process of Vat Photopolymerisation (VP).

Dvorak et al. (2018) studied an AM machine scheduling problem with unrelated parallel machines by splitting the problem in two subproblems. The first one, the nesting problem, proposed a heuristic solution, and to the scheduling problem, a set of metaheuristics were proposed to minimise the makespan (*Cmax*). The authors were not the first to approach a problem with subproblems, although they were the first to resort to different solution methods. The nesting problem was eased despite all these improvements, and the model focused the study on a single machine.

Luzon & Khmelnitsky (2019) were the only ones to investigate their problem of scheduling in AM with an adoption of a stochastic scheduling model. Their objective was to sequence batches optimally while optimising the completion time and the total weighted completion time considering random maintenance requirements, i.e., random downtimes. Furthermore, for the resolution of their model, the authors develop heuristic methods. The article's highlight is that the authors are still the only ones to take uncertainty into account.

Q. Li et al. (2019) introduced the problem of dynamic order acceptance and scheduling in on-demand production, i.e., a series of parts orders arrive dynamically at a production facility. The objective of the problem is to maximise the average profit per unit during the whole makespan by aiding decision-making to manufacturers and providing the possibility of simultaneous decisions regarding acceptance and scheduling. However, the authors simplify the nesting problem by converting parts into simple geometry, rectangles.

While authors usually only focus on one shop configuration, Kucukkoc (2019) contributes by formulating three different MILP models – single machine, identical parallel machine and unrelated parallel machines – to allocate parts into jobs while minimising the makespan. The author was the first to propose the term *batch{AM}* to be consistent with the scheduling literature. The author applied CPLEX algorithms to solve these models. The models intend to arrive at an optimal solution while balancing capacity utilisation with lead time. This work is one of the most relevant to the literature because other authors such as Alicastro et al. (2021); Arık (2021) based their work on certain aspects, such as parts list, calculation methods, machine parameters and mathematical model.

Ransikarbum et al. (2020) changed their problem statement and elaborated a multi-objective MILP model focusing on the total number of unprinted parts, load balance, undelivered parts, total cost and lateness (*Lj*). In addition, in the objective function of minimising the total cost, the authors include the production and transportation costs, a detail usually ignored by researchers (Alemão et al., 2021; Lohmer & Lasch, 2020). Compared to the past model, the new one considers two additional categories of AM process: VP and PBF. As before, a case study was done, this time related to automotive and healthcare, to validate the formulated model. Furthermore, Ransikarbum et al. (2020) developed a decision-support tool to reduce the gap between researchers and practitioners in AM with an analytic hierarchy process based on criteria weights.

S. Karimi et al. (2021) approach their production scheduling problem for AM parallel machines by focusing on energy-awareness, i.e., addressing both process and scheduling level controls to save electricity costs. The authors formulate two MILP models to minimise energy costs in response to time-varying electricity price as well as demand while considering FDM. The models differ regarding shop configuration, one with identical parallel machines and one with unrelated parallel machines. The authors simplify the problem by opting for the most practicable model, the one with identical parallel machines. The authors are one of the few to choose an exact method. The assessment method is a case study since there is a collection of historical data for electricity prices. This study looks promising in a context where energy-awareness is an issue. Nevertheless, the statement problem can be improved by considering nesting (this study does not) and adding more AM process categories. Another possible improvement is to choose a more promising AM technology rather than FDM.

Aloui & Hadj-Hamou (2021) proposed two models, based on actual data, whose function is to estimate the job production time for PBF processes, where one of them is MJF. In addition, the authors resort to a new heuristic approach in order to improve the solution. Their model aims to minimise the total tardiness of all parts to be produced while maximising the AM machine occupation and respecting the sequencing rule Earliest Due Date. An aspect of great importance addressed by the authors is the consideration for AM's pre-and post-production times as technological constraints. Regarding results, the authors proved that the proposed heuristics had an excellent performance through comparative tests with an exact solution method, especially for small/medium instances (maximum of 20 parts). There was a 1/4760 reduction of average CPU time, and the feasible solutions proved to be within 18%

(on average) of optimal solution. It can be argued that this study is one of the most interesting due to three points:

1) It is the only study to address one of the most promising AM technology – MJF;
2) The consideration for AM's pre-and post-production times;
3) Considering the computational results and that AM tends to be the best manufacturing technique for producing small/medium quantities (section 3.2), this solution can be adequate for an organisation with the same problem statement and the intent to produce batches with a small/medium number of parts.

However, the authors' lack of specification of the method used for the rotation freedom of parts is a drawback for future implementation.

In SCs, there is a direct correlation between responsiveness and lead times, i.e., a high responsive SC implies low lead times and vice-versa. Yılmaz (2020) problem statement aims to reduce lead times to improve SC's responsiveness. Therefore, the author investigated the two-stage SC scheduling problem (supplier and manufacturer) with AM technology to minimise the makespan. The MILP model is solved with a best-fit heuristic-based approach, and five selection rules are developed to solve the problem. According to the shared computational results, one of the used algorithms substantially improves the makespan while considering the time spent on production and transportation.

Since SCs responsiveness is characterised as the ability of the chain to quickly reply to changes imposed by the demand regarding volume and mix of products (Holweg, 2005), it makes sense to study AM in the context of SC. For example, AM can significantly improve the resilience and responsiveness of the SCs, as it was seen in the fight against COVID-19 by quickly producing personal protective equipment and therapeutical devices, even though the costs incurred can be higher when compared to a centralised SC configuration (Verboeket et al., 2021). Thus, there is a potential improvement in the responsiveness of an SC if AM is an ally. Hence, the relevance of this work by considering two-stage SC. Furthermore, if the author proceeds with the study of multiple manufacturers and customers, the model developed may be quite relevant to the literature.

Jianming Zhang et al. (2020) are the last authors presented here to study the VP process. Their study involves the development of an improved evolutionary algorithm by combining a GA with a heuristic placement strategy considering the allocation and placement of parts. Their model objective is to minimise the maximum completion time of the job of identical parallel machines. In order to validate their proposed solution, the authors compare their improved evolutionary algorithm to state-of-the-art algorithms: GA and particle swarm optimisation. Even though their problem did not facilitate nesting, their research still resorts to commercial software to make assumptions such as building time estimation.

Che et al. (2021) studied an unrelated parallel machine scheduling problem considering the orientation of parts, with three axes of rotation of freedom and batch processing. To solve their problem, a MILP model was formulated and solved with a simulated annealing algorithm. Furthermore, four post-optimisation methods were proposed to refine solutions. Finally, the heuristic algorithms' efficiency was tested, and the best packing strategy for this problem was acknowledged. However, due date constraints were not considered. Che et al. (2021) defend that their work is an original contribution to the literature:

"It is the first work to consider the orientation selection for parts in machine scheduling with the objective to minimise the makespan." Although Che et al. (2021) give credit for their work as the first to study part orientation selection in machine programming to minimise makespan, they were not the first since Oh et al. (2018) have already done so.

Alicastro et al. (2021) tackled an identical parallel machine problem while considering the AM process PBF and minimising the makespan. To solve their MILP model, the authors propose a meta-heuristic, the Iterated Local Search. The authors resort to two authors already mentioned as literature instances. Contrary to the results of the authors Aloui & Hadj-Hamou (2021), the algorithm presented is capable of reaching reasonable time solutions when applied to medium/large instances. However, the statement problem simplifies the nesting problem.

Finally, Arık (2021) studies a single AM machine problem simultaneously with nesting. The author is the only one to propose a mixed-integer programming model. The solution method provided is a heuristic method with a simple local search mechanism. Considering the number of studies that have already focused on minimising the makespan with the same shop configuration that the author used, it may be arbitrary to continue to study this type of problem statement.

4.3. Future research

Based on the analysis of the previous section, it was possible to understand the current perspectives of the AM scheduling problem and the future challenges. In this way, established by the analysis of the current state, it is possible to draw up a list of challenges and opportunities for the future of this topic. Furthermore, answer to the second research question:

- RQ2: What are the future directions and possible research developments necessary to overcome present shortcomings in AM polymer scheduling?

Aloui & Hadj-Hamou (2021) were the first to introduce technological constraints in the production planning problem in AM. Since no studies have similar considerations, it would be an excellent contribution to the literature to produce a study that compares results. Thus, it would be possible to assess the effectiveness of the proposed approach of the authors.

In AM, there is an assumption that parts within the same build volume have identical process parameters. Hence, some parts are clustered into a single build cycle. However, there are AM machines that can produce in a build cycle parts with different process parameters. Oh et al. (2020) suggestion is to think of nesting and scheduling problems for specialised AM machines, e.g., multi-material or multi-extruder, to reduce the complexity of operational management. Furthermore, there is still a gap in the literature, as no one has yet considered technological characteristics, e.g., accuracy or resolution, as a restriction. That is, allocate jobs on non-identical parallel machines considering each job's technological requirements while considering different processes categories.

Regarding nesting, the detected opportunity in the literature is to perform studies that consider a three-dimensional placement or even actual shapes of parts. Usually, the focus is on regular shapes and with movement limitations of the part inside the bounding box. Nevertheless, since AM scheduling problems already have NP-hard complexity, this addition would make the problem more difficult to solve (Kucukkoc, 2019).

Given its advantages, it is understandable why the AM process category PBF is chosen as the target of several studies. Their technologies allow vertical stacking of parts, the MJF technology is one of the fastest in processing, and the process category includes both metal and polymer materials. However, it is not comprehensible why the MJ process category is not considered in a single study, after consulting the elaborated classification and decision-support framework (section 3.4) and conclude some advantages of the technology associated with this process category: high accuracy and resolution, quick pre-and post-processing, good surface finishing, and parts watertight, multicolour and transparent. Thus, the opportunity to be the first study in the category is still available.

Luzon & Khmelnitsky (2019) were the only authors to adopt a stochastic scheduling model considering random maintenance requirements, i.e., random downtimes. (Lohmer & Lasch, 2020). Furthermore, in Lohmer & Lasch (2020) study, only 8.6% of the authors considered the same criterion of random machine downtimes. Therefore, there is a gap in the literature regarding the consideration of uncertainty in models regarding maintenance, which may have relevance if there is a production process with AM implemented and a considerable number of machines.

Finally, to end the topic of the challenges and opportunities that AM scheduling may face in the future, it is necessary to address the lack of studies with a problem classification other than centralised. Even though with the development of AM technologies, decentralised manufacturing promises to revolutionise the SCs' design, many of the existing SCs are based on centralised production processes to benefit from economies of scale. However, organisations are expected to introduce AM technologies to potentiate the move from centralised to decentralised SCs, focusing on the customer (Srai et al., 2016). Relative to CMS scheduling problems, a few research articles did not make the final cut due to the inclusive and exclusive criteria that grasp the theme – Jiang et al. (2021); Y. Wang et al. (2019). Thus, it appears that there is already some interest in the literature. Therefore, it seems relevant to elaborate a problem statement in which the problem classification is decentralised.

5. CONCLUSIONS

Scheduling propitiates the fulfilment of an organisation's plans at a higher strategic level since it can lead to better utilisation of production capacity, fulfilment of delivery dates, decrease the work in progress and enhance production responsiveness. Since nowadays organisations face a globally-oriented market, and in order to stay competitive one of the main strategies is to develop responsiveness of the production process, scheduling can be crucial to an organisation in terms of cost and performance.

Scheduling influences the efficiency, sustainability, and costs of a manufacturing process production and AM enables cost reduction, redesign of product and sustainability, hence it becomes clear the possible gains to a productive system by aggregating both subjects as a topic of study.

AM scheduling problems combine nesting and scheduling problems and focus on maximising the number of processed parts simultaneously, minimising the build time and the best way to allocate jobs (agglutinated parts) to each machine in compliance with a set of restrictions. The problem statement includes choices regarding objectives, shop configurations, the AM process and the respective technologies.

One of the main contributions of this thesis is the elaboration of a classification and decision-support framework designed to help understand and differentiate the distinct characteristics of AM technologies. Its objective is to offer detailed and straightforward information on AM technologies characteristics, costs, process features and physical properties of the produced parts. In addition, the framework aims to aid managers who intend to implement a production system with polymer AM technology.

The other contribution of this thesis is a comprehensive and systematic review of the literature on AM polymer scheduling problems. The author analysed and systematised 20 research articles from the literature according to the following classification: objectives, uncertainty, model formulation, solution method, shop configuration, problem classification, nesting, AM process and assessment method. By clustering the most common features found in the literature of an AM scheduling problem, it is possible to characterise an AM scheduling problem as a centralised problem with a formulated MIP/MILP model, including the objective of minimising the makespan and an approximate solution method. Regarding shop configuration, it is an unrelated PBF machines in parallel, with the nesting problem statement facilitated. Lastly, no case study is performed to validate the model (RQ1).

There are gaps in the literature, as no one has yet considered technological characteristics, like accuracy or resolution as a restriction, and only Luzon & Khmelnitsky (2019) adopt a stochastic scheduling model considering random downtimes. Furthermore, there is still the opportunity to assess the effectiveness of the authors' Aloui & Hadj-Hamou (2021) proposed approach. They were the only authors to consider AM's pre-and post-production times as technological constraint in their problem statement. Also, there is still lacking in the literature a problem statement with a classification other than centralised, for example, a decentralised or cloud manufacturing scheduling problem. Regarding nesting, it has never been a nesting problem considering a 3D dimensionally. In addition, an AM MJ process has never been studied despite having good technological characteristics (RQ2).

The elaboration of an SLR is a long process and requires in-depth knowledge of research and methodologies. When we scratch the surface of our subject of study, it seems minor, but its diversity of topics requires a lot of study time and dedication, more than it is expected to carry out within a master's thesis. Even making solid efforts to expand the literature, some limitations can be pointed. Thomé et al. (2016) SLR methodology imples complex actions to comply with specific steps, e.g., coding. Since the development of codes and a codebook is paramount (Neuendorf, 2002), extensive training should be required before data gathering. Meantime, the adopted selection criterion may have limitations and have a small bias. However, it is expected that the main findings would be similar to broader research.

5.1. Future works

Only the process category Direct Energy Deposition was not taken into account during the literature review. Thus, adding the process category and redoing the work would be suitable since the perspective and challenges may undergo some additions. Moreover, in the future, by adding the remaining materials of AM to the study, the decision support framework could contemplate different materials and not restrict options to a single material.

BIBLIOGRAPHIC REFERENCES

3D Printing Media Network. (2017). *German Aerospace Center Uses Stratasys FDM to Produce TransRoPorter Mars Exploration Robot*. 3D Printing Media Network. https://www.3dprintingmedia.network/german-aerospace-center-uses-stratasys-fdm-produce-transroporter-mars-exploration-robot/

Achillas, C., Tzetzis, D., & Raimondo, M. O. (2017). Alternative production strategies based on the comparison of additive and traditional manufacturing technologies. *International Journal of Production Research*, *55*(12), 3497–3509. https://doi.org/10.1080/00207543.2017.1282645

Alemão, D., Rocha, A. D., & Barata, J. (2021). Smart manufacturing scheduling approaches—systematic review and future directions. *Applied Sciences (Switzerland)*, *11*(5), 1–20. https://doi.org/10.3390/app11052186

Ali, A., Soni, M., Javaid, M., & Haleem, A. (2020). A comparative analysis of different rapid prototyping techniques for making intricately shaped structure. *Journal of Industrial Integration and Management*, *5*(3), 393–407. https://doi.org/10.1142/S2424862219500179

Alicastro, M., Ferone, D., Festa, P., Fugaro, S., & Pastore, T. (2021). A reinforcement learning iterated local search for makespan minimization in additive manufacturing machine scheduling problems. *Computers & Operations Research*, *131*, 105272. https://doi.org/https://doi.org/10.1016/j.cor.2021.105272

Aloui, A., & Hadj-Hamou, K. (2021). A heuristic approach for a scheduling problem in additive manufacturing under technological constraints. *Computers & Industrial Engineering*, *154*, 107115. https://doi.org/https://doi.org/10.1016/j.cie.2021.107115

Arık, O. A. (2021). Additive manufacturing scheduling problem considering assembly operations of parts. *Operational Research*. https://doi.org/10.1007/s12351-021-00649-y

Artley, B. (2020). *Automotive 3D printing applications*. 3D Hubs. https://www.hubs.com/knowledge-base/automotive-3d-printing-applications/

Beltagui, A., Kunz, N., & Gold, S. (2020). The role of 3D printing and open design on adoption of socially sustainable supply chain innovation. *International Journal of Production Economics*, *221*(April 2018), 107462. https://doi.org/10.1016/j.ijpe.2019.07.035

Ben-Ner, A., & Siemsen, E. (2017). Decentralization and Localization of Production: The Organizational and Economic Consequences of Additive Manufacturing (3D Printing). *California Management Review*, *59*(2), 5–23. https://doi.org/10.1177/0008125617695284

Benedict. (2016). *BMW to use new HP Jet Fusion 3D printer for "serial part production & personal customization."* 3ders. https://www.3dprintersonlinestore.com/bmw-to-produce-customized-jet-fusion-3d-printer

Bennett, S., McRobb, S., & Farmer, R. (2010). *Object-Oriented Systems Analysis and Design* (4th ed.). McGraw-Hill Education Europe.

Blazewicz, J., Ecker, K. H., Pesch, E., Schmidt, G., & Weglarz, J. (1996). *Scheduling Computer and Manufacturing Processes* (1th ed.). Springer-Verlag Berlin Heidelberg.

Boissonneault, T. (2019a). *Lamborghini adopts Carbon 3D printing for automotive production at scale*. 3D Printing Media Network. https://www.3dprintingmedia.network/lamborghini-carbon-3d-printing/

Boissonneault, T. (2019b). *Marshall Aerospace and Defence using FDM 3D printing for flight-ready parts*. 3D Printing Media Network. https://www.3dprintingmedia.network/marshall-aerospace-defence-fdm-3d-printing/

Boissonneault, T. (2020a). *3D Systems presents new Figure 4 Jewelry system*. 3D Printing Media Network. https://www.3dprintingmedia.network/3d-systems-launches-new-figure-4-jewelry-system/

Boissonneault, T. (2020b). *SmileDirectClub to 3D print 20M unique aligner molds a year with HP MJF*. 3D Printing Media Network. https://www.3dprintingmedia.network/smiledirectclub-3d-print-20-million-aligner-hp/

Booch, G., Maksimchuk, R. A., Engle, M. W., Young, B. J., Conallen, J., & Houston, K. A. (2007). *Object-Oriented Analysis and Design with Applications* (3th ed.). Addison-Wesley.

Bourell, D., Kruth, J. P., Leu, M., Levy, G., Rosen, D., Beese, A. M., & Clare, A. (2017). Materials for additive manufacturing. *CIRP Annals*, *66*(2), 659–681. https://doi.org/https://doi.org/10.1016/j.cirp.2017.05.009

Bournias Varotsis, A. (2019). *Introduction to Material Jetting 3D Printing*. 3DHubs. https://www.3dhubs.com/knowledge-base/introduction-material-jetting-3d-printing/

Brocke, J. vom, Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., & Cleven, A. (2009). Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process. *17th European Conference on Information Systems (ECIS)*.

Brucker, P. (1995). *Scheduling Algorithms* (1th ed.). Springer-Verlag Berlin Heidelberg.

Calignano, F., Manfredi, D., Ambrosio, E. P., Biamino, S., Lombardi, M., Atzeni, E., Salmi, A., Minetola, P., Iuliano, L., & Fino, P. (2017). Overview on Additive Manufacturing Technologies. *Proceedings of the IEEE*, *105*(4), 593–612. https://doi.org/10.1109/JPROC.2016.2625098

Carsten, J. (1996). *Batching and Scheduling - Models and Methods for Several Problem Classes* (1th ed.). Springer-Verlag Berlin Heidelberg.

Caviggioli, F., & Ughetto, E. (2019). A bibliometric analysis of the research dealing with the impact of additive manufacturing on industry, business and society. *International Journal of Production Economics*, *208*, 254–268. https://doi.org/https://doi.org/10.1016/j.ijpe.2018.11.022

CEFAMOL. (2021). *Indústria Portuguesa de Moldes*.

Che, Y., Hu, K., Zhang, Z., & Lim, A. (2021). Machine scheduling with orientation selection and two-dimensional packing for additive manufacturing. *Computers & Operations Research*, *130*, 105245. https://doi.org/https://doi.org/10.1016/j.cor.2021.105245

Chekurov, S., Metsä-Kortelainen, S., Salmi, M., Roda, I., & Jussila, A. (2018). The perceived value of additively manufactured digital spare parts in industry: An empirical investigation. *International Journal of Production Economics*, *205*(July 2017), 87–97. https://doi.org/10.1016/j.ijpe.2018.09.008

Chen, M. Y., Skewes, J., Woodruff, M. A., Dasgupta, P., & Rukin, N. J. (2020). Multi-colour extrusion fused deposition modelling: a low-cost 3D printing method for anatomical prostate cancer models. *Scientific Reports*, *10*(1), 1–5. https://doi.org/10.1038/s41598-020-67082-7

Chergui, A., Hadj-Hamou, K., & Vignat, F. (2018). Production scheduling and nesting in additive manufacturing. *Computers & Industrial Engineering*, *126*, 292–301. https://doi.org/https://doi.org/10.1016/j.cie.2018.09.048

Chohan, J. S., Singh, R., Boparai, K. S., Penna, R., & Fraternali, F. (2017). Dimensional accuracy analysis of coupled fused deposition modeling and vapour smoothing operations for biomedical applications. *Composites Part B: Engineering*, *117*, 138–149. https://doi.org/10.1016/j.compositesb.2017.02.045

Clímaco, J. N., Antunes, C. H., & Alves, M. J. (2012). *Programação linear multiobjectivo: do modelo de programação linear clássico à consideração explícita de várias funções objectivo* (1th ed.). Imprensa da Universidade de Coimbra.

Cooper, H. M. (1988). Organizing knowledge syntheses: A taxonomy of literature reviews. *Knowledge in Society*, *1*(1), 104. https://doi.org/10.1007/BF03177550

de Brito, F. M., Junior, G. D. C., Frazzon, E. M., Basto, J. P. T. V., & Alcala, S. G. S. (2021). Design Approach for Additive Manufacturing in Spare Part Supply Chains. *IEEE Transactions on Industrial Informatics*, *17*(2), 757–765. https://doi.org/10.1109/TII.2020.3029541

DGAE. (2019). *Sinopse Indústria Moldes*.

Dikova, T. (2019). Production of high-quality temporary crowns and bridges by stereolithography. *Scripta Scientifica Medicinae Dentalis*, *5*(1), 33. https://doi.org/10.14748/ssmd.v5i1.5863

Dvorak, F., Micali, M., & Mathieug, M. (2018). Planning and Scheduling in Additive Manufacturing. *Inteligencia Artificial*, *21*, 40–52. https://doi.org/10.4114/intartif.vol21iss62pp40-52

EnvisionTEC. (2018). *The Ultimate Guide to 3D Printing with High Speed Continuous Technology*.

Essop, A. (2019). *Adidas unveils Carbon 3D printed shoe in collaboration with Stella McCartney*. 3D Printing Industry. https://3dprintingindustry.com/news/adidas-unveils-carbon-3d-printed-shoe-in-collaboration-with-stella-mccartney-152262/

Essop, A. (2020). *3D Systems expands material selection for Figure 4 platform and SLA 3D printing*. 3D Printing Industry. https://3dprintingindustry.com/news/3d-systems-expands-material-selection-for-figure-4-platform-and-sla-3d-printing-172296/

Farish, M. (2019). *BMW takes additive manufacturing from prototype to serial lines*. AMS Magazines. https://www.automotivemanufacturingsolutions.com/additive/3d-printing/bmw-takes-additive-manufacturing-from-prototype-to-serial-lines/39753.article

Fera, M., Fruggiero, F., Lambiase, A., Macchiaroli, R., & Todisco, V. (2018). A modified genetic algorithm for time and cost optimization of an additive manufacturing single-machine scheduling. *International Journal of Industrial Engineering Computations*, *9*, 423–438. https://doi.org/10.5267/j.ijiec.2018.1.001

Fera, M., Macchiaroli, R., Fruggiero, F., & Lambiase, A. (2020). A modified tabu search algorithm for the single-machine scheduling problem using additive manufacturing technology. *International Journal of Industrial Engineering Computations*, *11*, 401–414. https://doi.org/10.5267/j.ijiec.2020.1.001

Ford, S., & Despeisse, M. (2016). Additive manufacturing and sustainability: an exploratory study of the advantages and challenges. *Journal of Cleaner Production*, *137*, 1573–1587. https://doi.org/10.1016/j.jclepro.2016.04.150

Franchetti, M., & Kress, C. (2017). An economic analysis comparing the cost feasibility of replacing injection molding processes with emerging additive manufacturing techniques. *International Journal of Advanced Manufacturing Technology*, *88*(9–12), 2573–2579. https://doi.org/10.1007/s00170-016-8968-7

Gahm, C., Denz, F., Dirr, M., & Tuma, A. (2016). Energy-efficient scheduling in manufacturing companies: A review and research framework. *European Journal of Operational Research*, *248*(3), 744–757. https://doi.org/https://doi.org/10.1016/j.ejor.2015.07.017

Garey, M. R., & Johnson, D. S. (1979). *Computers and Intractability: A Guide to the Theory of NP-Completeness* (1th ed.). W.H. Freeman & Company.

Garey, M. R., Johnson, D. S., & Sethi, R. (1976). The Complexity of Flowshop and Jobshop Scheduling. *Mathematics of Operations Research*, *1*(2), 117–129. https://doi.org/10.1287/moor.1.2.117

Gebler, M., Schoot Uiterkamp, A. J. M., & Visser, C. (2014). A global sustainability perspective on 3D printing technologies. *Energy Policy*, *74*, 158–167.

https://doi.org/https://doi.org/10.1016/j.enpol.2014.08.033

Graham, R. L., Lawler, E. L., Lenstra, J. K., & Kan, A. H. G. R. (1979). Optimization and Approximation in Deterministic Sequencing and Scheduling: a Survey. In P. L. Hammer, E. L. Johnson, & B. H. Korte (Eds.), *Discrete Optimization II* (Vol. 5, pp. 287–326). Elsevier. https://doi.org/https://doi.org/10.1016/S0167-5060(08)70356-X

Hillier, F. S., & Lieberman, G. J. (2002). *Introduction to Operations Research* (7th ed.). McGraw-Hill.

Holweg, M. (2005). The three dimensions of responsiveness. *International Journal of Operations & Production Management*, *25*(7), 603–622. https://doi.org/10.1108/01443570510605063

HP Development Company L.P. (2018). *Technical White Paper - HP Multi Jet Fusion technology*.

Hubs. (2021). *Additive Manufacturing Technologies*. Hubs.Com. https://www.hubs.com/get/am-technologies/

Hull, C. W. (1984). *Apparatus for Production of Three-Dimensional Objects by Stereolithography* (Patent No. US4575330A).

ISO/ASTM. (2015). ASTM52900-15 standard terminology for additive manufacturing—general principles—terminology. In *ASTM International, West Conshohocken, PA* (Vol. 3, Issue 4).

Jabari, E., Liravi, F., Davoodi, E., Lin, L., & Toyserkani, E. (2020). High speed 3D material-jetting additive manufacturing of viscous graphene-based ink with high electrical conductivity. *Additive Manufacturing*, *35*(February), 101330. https://doi.org/10.1016/j.addma.2020.101330

Jemghili, R., Taleb, A., & Khalifa, M. (2021). A bibliometric indicators analysis of additive manufacturing research trends from 2010 to 2020. In *Rapid Prototyping Journal* (Vol. 27, Issue 7, pp. 1432–1454). https://doi.org/10.1108/rpj-11-2020-0274

Jiang, Z., Yuan, S., Ma, J., & Wang, Q. (2021). The evolution of production scheduling from Industry 3.0 through Industry 4.0. *International Journal of Production Research*, *0*(0), 1–21. https://doi.org/10.1080/00207543.2021.1925772

Karimi-Mamaghan, M., Mohammadi, M., Meyer, P., Karimi-Mamaghan, A. M., & Talbi, E.-G. (2022). Machine learning at the service of meta-heuristics for solving combinatorial optimization problems: A state-of-the-art. *European Journal of Operational Research*, *296*(2), 393–422.

https://doi.org/https://doi.org/10.1016/j.ejor.2021.04.032

Karimi, B., Fatemi Ghomi, S. M. T., & Wilson, J. M. (2003). The capacitated lot sizing problem: a review of models and algorithms. *Omega*, *31*(5), 365–378. https://doi.org/https://doi.org/10.1016/S0305-0483(03)00059-8

Karimi, S., Kwon, S., & Ning, F. (2021). Energy-aware production scheduling for additive manufacturing. *Journal of Cleaner Production*, *278*, 123183. https://doi.org/https://doi.org/10.1016/j.jclepro.2020.123183

Kelly, B. E., Bhattacharya, I., Heidari, H., Shusteff, M., Spadaccini, C. M., & Taylor, H. K. (2019). Volumetric additive manufacturing via tomographic reconstruction. *Science*, *363*(6431), 1075–1079. https://doi.org/10.1126/science.aau7114

Khajavi, S. H., Ituarte, I. F., Jaribion, A., An, J., Chua, C. K., & Holmström, J. (2020). Impact of Additive Manufacturing on Supply Chain Complexity. *Proceedings of the 53rd Hawaii International Conference on System Sciences*, *3,* 4505–4514. https://doi.org/10.24251/hicss.2020.551

Kim, S. H., Yeon, Y. K., Lee, J. M., Chao, J. R., Lee, Y. J., Seo, Y. B., Sultan, M. T., Lee, O. J., Lee, J. S., Yoon, S. Il, Hong, I. S., Khang, G., Lee, S. J., Yoo, J. J., & Park, C. H. (2018). Precisely printable and biocompatible silk fibroin bioink for digital light processing 3D printing. *Nature Communications*, *9*(1), 1–14. https://doi.org/10.1038/s41467-018-03759-y

Kinstlinger, I. S., Saxton, S. H., Calderon, G. A., Ruiz, K. V., Yalacki, D. R., Deme, P. R., Rosenkrantz, J. E., Louis-Rosenberg, J. D., Johansson, F., Janson, K. D., Sazer, D. W., Panchavati, S. S., Bissig, K. D., Stevens, K. R., & Miller, J. S. (2020). Generation of model tissues with dendritic vascular networks via sacrificial laser-sintered carbohydrate templates. *Nature Biomedical Engineering*, *4*(9), 916–932. https://doi.org/10.1038/s41551-020-0566-1

Kucukkoc, I. (2019). MILP models to minimise makespan in additive manufacturing machine scheduling problems. *Computers & Operations Research*, *105*, 58–67. https://doi.org/https://doi.org/10.1016/j.cor.2019.01.006

Kucukkoc, I., Li, Q., He, N., & Zhang, D. (2018). Scheduling of Multiple Additive Manufacturing and 3D Printing Machines to Minimise Maximum Lateness. *20th International Working Seminar on*

Production Economics.

Kucukkoc, I., Li, Q., & Zhang, D. (2016). Increasing the utilisation of additive manufacturing and 3D printing machines considering order delivery times. *19th International Working Seminar on Production Economics*.

Kunovjanek, M., & Reiner, G. (2020). How will the diffusion of additive manufacturing impact the raw material supply chain process? *International Journal of Production Research*, *58*(5), 1540–1554. https://doi.org/10.1080/00207543.2019.1661537

Lai, C. Q., Markandan, K., Luo, B., Lam, Y. C., Chung, W. C., & Chidambaram, A. (2020). Viscoelastic and High Strain Rate Response of Anisotropic Graphene-Polymer Nanocomposites Fabricated with 3D Stereolithography Printing. *Additive Manufacturing*, *37*(November 2020), 101721. https://doi.org/10.1016/j.addma.2020.101721

Li, Q., Kucukkoc, I., & Zhang, D. Z. (2017). Production planning in additive manufacturing and 3D printing. *Computers & Operations Research*, *83*, 157–172. https://doi.org/https://doi.org/10.1016/j.cor.2017.01.013

Li, Q., Zhang, D., Wang, S., & Kucukkoc, I. (2019). A dynamic order acceptance and scheduling approach for additive manufacturing on-demand production. *The International Journal of Advanced Manufacturing Technology*, *105*(9), 3711–3729. https://doi.org/10.1007/s00170-019-03796-x

Li, Y., Jia, G., Cheng, Y., & Hu, Y. (2017). Additive manufacturing technology in spare parts supply chain: a comparative study. *International Journal of Production Research*, *55*(5), 1498–1515. https://doi.org/10.1080/00207543.2016.1231433

Ligon, S. C., Liska, R., Stampfl, J., Gurr, M., & Mülhaupt, R. (2017). Polymers for 3D Printing and Customized Additive Manufacturing. *Chemical Reviews*, *117*(15), 10212–10290. https://doi.org/10.1021/acs.chemrev.7b00074

Liu, Y., Wang, L., Wang, X. V., Xu, X., & Zhang, L. (2019). Scheduling in cloud manufacturing: state-of-the-art and research challenges. *International Journal of Production Research*, *57*(15–16), 4854–4879. https://doi.org/10.1080/00207543.2018.1449978

Lohmer, J., & Lasch, R. (2020). Production planning and scheduling in multi- factory production networks : a systematic literature review systematic literature review. *International Journal of Production Research*, *0*(0), 1–27. https://doi.org/10.1080/00207543.2020.1797207

Loterie, D., Delrot, P., & Moser, C. (2020). High-resolution tomographic volumetric additive manufacturing. *Nature Communications*, *11*(1), 852. https://doi.org/10.1038/s41467-020-14630-4

Luzon, Y., & Khmelnitsky, E. (2019). Job sizing and sequencing in additive manufacturing to control process deterioration. *IISE Transactions*, *51*(2), 181–191. https://doi.org/10.1080/24725854.2018.1460518

Manapat, J. Z., Chen, Q., Ye, P., & Advincula, R. C. (2017). 3D Printing of Polymer Nanocomposites via Stereolithography. *Macromolecular Materials and Engineering*, *302*(9), 1–13. https://doi.org/10.1002/mame.201600553

Meisel, N. A., Williams, C. B., Ellis, K. P., & Taylor, D. (2016). Decision support for additive manufacturing deployment in remote or austere environments. *Journal of Manufacturing Technology Management*, *27*(7), 898–914. https://doi.org/https://doi.org/10.1108/JMTM-06-2015-0040

Melchels, F. P. W., Feijen, J., & Grijpma, D. W. (2010). A review on stereolithography and its applications in biomedical engineering. *Biomaterials*, *31*(24), 6121–6130. https://doi.org/https://doi.org/10.1016/j.biomaterials.2010.04.050

Micán, C., Fernandes, G., & Araújo, M. (2020). Project portfolio risk management: a structured literature review with future directions for research. *International Journal of Information Systems and Project Managment*, *8*(3), 18. https://doi.org/10.12821/ijispm080304

Mostafa, K., Qureshi, A. J., & Montemagno, C. (2017). *Tolerance control using subvoxel gray-scale DLP 3D printing*. *1*, 1–7. https://doi.org/10.1115/imece2017-72232

Neuendorf, K. (2002). *The Content Analysis Guidebook* (2th ed.). https://doi.org/10.4135/9781071802878

Ngo, T. D., Kashani, A., Imbalzano, G., Nguyen, K. T. Q., & Hui, D. (2018). Additive manufacturing (3D printing): A review of materials, methods, applications and challenges. *Composites Part B:*

Engineering, *143*(December 2017), 172–196. https://doi.org/10.1016/j.compositesb.2018.02.012

O'Connor, H. J., Dickson, A. N., & Dowling, D. P. (2018). Evaluation of the mechanical performance of polymer parts fabricated using a production scale multi jet fusion printing process. *Additive Manufacturing*, *22*, 381–387. https://doi.org/10.1016/j.addma.2018.05.035

Oh, Y., Witherell, P., Lu, Y., & Sprock, T. (2020). Nesting and scheduling problems for additive manufacturing: A taxonomy and review. *Additive Manufacturing*, *36*, 101492. https://doi.org/https://doi.org/10.1016/j.addma.2020.101492

Oh, Y., Zhou, C., & Behdad, S. (2018). Production Planning for Mass Customization in Additive Manufacturing: Build Orientation Determination, 2D Packing and Scheduling. *The ASME International Design Engineering Technical Conference and the Computer and Information in Engineering Conference (IDETC/CIE)*. https://doi.org/10.1115/DETC2018-85639

Olakanmi, E. O., Cochrane, R. F., & Dalgarno, K. W. (2015). A review on selective laser sintering/melting (SLS/SLM) of aluminium alloy powders: Processing, microstructure, and properties. *Progress in Materials Science*, *74*, 401–477. https://doi.org/https://doi.org/10.1016/j.pmatsci.2015.03.002

Olhager, J., & Wikner, J. (2000). Production planning and control tools. *Production Planning \& Control*, *11*(3), 210–222. https://doi.org/10.1080/095372800232180

Padberg, M., & Rinaldi, G. (1991). A Branch-and-Cut Algorithm for the Resolution of Large-Scale Symmetric Traveling Salesman Problems. *SIAM Review*, *33*(1), 60–100.

Paulsen, G. (2020). *What is the 3D Printing vs Injection Molding Cost-per-Unit Breakeven?* Xometry. https://www.xometry.com/blog/3d-printing-vs-injection-molding-breakeven/

Pearson, A. (2020). *INDYCAR keeps its cool in race against time with 3D printing*. Stratasys. https://www.stratasys.com/explore/blog/2020/indycar-with-stratasys

Pinedo, M. L. (1995). *Scheduling: Theory, Algorithms, and Systems* (1st ed.). Prentice Hall.

Pinedo, M. L. (2016). *Scheduling: Theory, Algorithms, and Systems* (5th ed.). Springer-Verlag New York. https://doi.org/10.1007/978-3-319-26580-3

Pinedo, M., & Yen, B. P.-C. (1997). On the design and development of object-oriented scheduling systems. *Annals of Operations Research*, *70*(0), 359–378. https://doi.org/10.1023/A:1018986524234

Ransikarbum, K., Ha, S., Ma, J., & Kim, N. (2017). Multi-objective optimization analysis for part-to-Printer assignment in a network of 3D fused deposition modeling. *Journal of Manufacturing Systems*, *43*, 35–46. https://doi.org/https://doi.org/10.1016/j.jmsy.2017.02.012

Ransikarbum, K., Pitakaso, R., & Kim, N. (2020). A Decision-Support Model for Additive Manufacturing Scheduling Using an Integrative Analytic Hierarchy Process and Multi-Objective Optimization. *Applied Sciences*, *10*(15). https://doi.org/10.3390/app10155159

Redwood, B. (2019a). *Jewelry 3D printing applications*. 3D Hubs. https://www.hubs.com/knowledge-base/jewelry-3d-printing-applications/

Redwood, B. (2019b). *Medical 3D printing applications*. 3DHubs. https://www.3dhubs.com/knowledge-base/medical-3d-printing-applications/

Regehly, M., Garmshausen, Y., Reuter, M., König, N. F., Israel, E., Kelly, D. P., Chou, C. Y., Koch, K., Asfari, B., & Hecht, S. (2020). Xolography for linear volumetric 3D printing. *Nature*, *588*(7839), 620–624. https://doi.org/10.1038/s41586-020-3029-7

Rego, C., Gamboa, D., Glover, F., & Osterman, C. (2011). Traveling salesman problem heuristics: Leading methods, implementations and latest advances. *European Journal of Operational Research*, *211*(3), 427–441. https://doi.org/https://doi.org/10.1016/j.ejor.2010.09.010

Roach, D. J., Hamel, C. M., Dunn, C. K., Johnson, M. V., Kuang, X., & Qi, H. J. (2019). The m4 3D printer: A multi-material multi-method additive manufacturing platform for future 3D printed structures. *Additive Manufacturing*, *29*(February), 100819. https://doi.org/10.1016/j.addma.2019.100819

Sauders, M., Lewis, P., & Thornhill, A. (2019). *Research Methods for Business Students* (8th ed.). Pearson Education Limited.

Sher, D. (2019). *Carbon and Lamborghini take part production into high(er) gear*. 3D Printing Media Network. https://www.3dprintingmedia.network/carbon-and-lamborghini-take-part-production-partnership-into-higher-gear/

Sher, D. (2020a). *How major automakers use AM for production today, part 1: Volkswagen additive manufacturing*. 3D Printing Media Network. https://www.3dprintingmedia.network/volkswagen-additive-manufacturing/

Sher, D. (2020b). *Impact F1, what next-gen, parametric, 3D printed flip flops look like*. 3D Printing Media Network. https://www.3dprintingmedia.network/impact-f1-what-next-gen-parametric-3d-printed-flip-flops-look-like/

Sher, D. (2020c). *Shapemode distributes Sisma 3D printers into dental segment*. 3D Printing Media Network. https://www.3dprintingmedia.network/shapemode-to-distribute-sisma/

Sher, D. (2020d). *Sweet! Rice researchers 3D print blood vessels using sugar and laser*. 3D Printing Media Network. https://www.3dprintingmedia.network/sweet-rice-researchers-3d-print-blood-vessels-using-sugar-and-laser/

Skylar-Scott, M. A., Mueller, J., Visser, C. W., & Lewis, J. A. (2019). Voxelated soft matter via multimaterial multinozzle 3D printing. *Nature*. https://doi.org/10.1038/s41586-019-1736-8

Sörensen, K., & Glover, F. W. (2013). Metaheuristics. In S. I. Gass & M. C. Fu (Eds.), *Encyclopedia of Operations Research and Management Science* (pp. 960–970). Springer US. https://doi.org/10.1007/978-1-4419-1153-7_1167

Srai, J. S., Kumar, M., Graham, G., Phillips, W., Tooze, J., Ford, S., Beecher, P., Raj, B., Gregory, M., Tiwari, M. K., Ravi, B., Neely, A., Shankar, R., Charnley, F., & Tiwari, A. (2016). Distributed manufacturing: scope, challenges and opportunities. *International Journal of Production Research*, *54*(23), 6917–6935. https://doi.org/10.1080/00207543.2016.1192302

Stevenson, M., Hendry, L. C., & Kingsman, B. G. (2005). A review of production planning and control: the applicability of key concepts to the make-to-order industry. *International Journal of Production Research*, *43*(5), 869–898. https://doi.org/10.1080/0020754042000298520

Stratasys Ltd. (2017). *Will 3D Printing Eliminate Injection Molding?*

Stratasys Ltd. (2020). *GM accelerates 3D printing capability with Stratasys for business agility and efficiency*. Stratasys. https://investors.stratasys.com/news-events/press-releases/detail/700/gm-accelerates-3d-printing-capability-with-stratasys-for

Strömbergsson, A. (2020). *Solvay and PrinterPrezz collaborate on SLS for medical devices*. 3D Printing Media Network. https://www.3dprintingmedia.network/solvay-and-printerprezz-collaborate-on-sls-for-medical-devices/

Tampi, T. (2020). *Siemens to Present Virtual Reference Factory at Formnext Connect with EOS and DyeMansion*. 3DPrint.Com. https://3dprint.com/275273/siemens-to-present-virtual-reference-factory-at-formnext-connect-with-eos-and-dyemansion/

Tan, L. J., Zhu, W., & Zhou, K. (2020). Recent Progress on Polymer Materials for Additive Manufacturing. *Advanced Functional Materials*, *30*(43), 2003062. https://doi.org/https://doi.org/10.1002/adfm.202003062

Thomé, A. M. T., Scavarda, L. F., & Scavarda, A. J. (2016). Conducting systematic literature review in operations management. *Production Planning \& Control*, *27*(5), 408–420. https://doi.org/10.1080/09537287.2015.1129464

Tumbleston, J. R., Shirvanyants, D., Ermoshkin, N., Janusziewicz, R., Johnson, A. R., Kelly, D., Chen, K., Pinschmidt, R., Rolland, J. P., Ermoshkin, A., Samulski, E. T., & DeSimone, J. M. (2015). Continuous liquid interface production of 3D objects. *Science*, *347*(6228), 1349–1352. https://doi.org/10.1126/science.aaa2397

Valdivieso, C. (2020a). *A review of the most innovative 3D printing applications in automotive!* 3D Natives. https://www.3dnatives.com/en/3d-printing-applications-in-automotive-ranking-081020204/#!

Valdivieso, C. (2020b). *Volkswagen enhances automotive design with 3D printing*. 3D Natives. https://www.3dnatives.com/en/volkswagen-enhances-automotive-design-with-3d-printing-021220205/

Varela, M. L. R. (2007). *Uma contribuição para o escalonamento da produção baseado em métodos globalmente distribuídos*. Universidade do Minho.

Verboeket, V., Khajavi, S. H., Krikke, H., Salmi, M., & Holmström, J. (2021). Additive Manufacturing for Localized Medical Parts Production: A Case Study. *IEEE Access*, *9*, 1–1. https://doi.org/10.1109/access.2021.3056058

Verboeket, V., & Krikke, H. (2019). The disruptive impact of additive manufacturing on supply chains: A literature study, conceptual framework and research agenda. *Computers in Industry*, *111*, 91–107. https://doi.org/10.1016/j.compind.2019.07.003

Walker, D. A., Hedrick, J. L., & Mirkin, C. A. (2019). Rapid, large-volume, thermally controlled 3D printing using a mobile liquid interface. *Science*, *366*(October), 360–364. https://doi.org/10.1126/science.aax1562

Wang, X., Jiang, M., Zhou, Z., Gou, J., & Hui, D. (2017). 3D printing of polymer matrix composites: A review and prospective. *Composites Part B: Engineering*, *110*, 442–458. https://doi.org/10.1016/j.compositesb.2016.11.034

Wang, Y., Zheng, P., Xu, X., Yang, H., & Zou, J. (2019). Production planning for cloud-based additive manufacturing—A computer vision-based approach. *Robotics and Computer-Integrated Manufacturing*, *58*, 145–157. https://doi.org/https://doi.org/10.1016/j.rcim.2019.03.003

Weinmann, S., & Bonten, C. (2020). Recycling of PA12 powder for selective laser sintering. *AIP Conference Proceedings*, *2289*(November), 020056. https://doi.org/10.1063/5.0029945

Williams, H. P. (2013). *Model Building in Mathematical Programming* (5th ed.). John Wiley & Sons.

Winston, W. L. (2004). *Operations Research - Applications and Algorithms* (4th ed.). Curt Hinrichs.

Xue, D., Zhang, J., Wang, Y., & Mei, D. (2019). Digital Light Processing-Based 3D Printing of Cell-Seeding Hydrogel Scaffolds with Regionally Varied Stiffness [Research-article]. *ACS Biomaterials Science and Engineering*, *5*(9), 4825–4833. https://doi.org/10.1021/acsbiomaterials.9b00696

Yap, C. Y., Chua, C. K., Dong, Z. L., Liu, Z. H., Zhang, D. Q., Loh, L. E., & Sing, S. L. (2015). Review of selective laser melting: Materials and applications. *Applied Physics Reviews*, *2*(4), 41101. https://doi.org/10.1063/1.4935926

Yap, Y. L., Wang, C., Sing, S. L., Dikshit, V., Yeong, W. Y., & Wei, J. (2017). Material jetting additive manufacturing: An experimental study using designed metrological benchmarks. *Precision Engineering*, *50*, 275–285. https://doi.org/10.1016/j.precisioneng.2017.05.015

Yılmaz, Ö. F. (2020). Examining additive manufacturing in supply chain context through an optimization model. *Computers & Industrial Engineering*, *142,* 106335. https://doi.org/https://doi.org/10.1016/j.cie.2020.106335

Zastrow, M. (2020). The new 3D printing. *Nature*, *578*(February), 20–24. https://doi.org/10.1038/d41586-020-00271-6

Zhang, Jian, Ding, G., Zou, Y., Qin, S., & Fu, J. (2019). Review of job shop scheduling research and its new perspectives under Industry 4.0. *Journal of Intelligent Manufacturing*, *30*(4), 1809–1830. https://doi.org/10.1007/s10845-017-1350-2

Zhang, Jianming, Yao, X., & Li, Y. (2020). Improved evolutionary algorithm for parallel batch processing machine scheduling in additive manufacturing. *International Journal of Production Research*, *58*(8), 2263–2282. https://doi.org/10.1080/00207543.2019.1617447

Zhang, Y., Bernard, A., Harik, R., & Karunakaran, K. P. (2017). Build orientation optimization for multi-part production in additive manufacturing. *Journal of Intelligent Manufacturing*, *28*(6), 1393–1407. https://doi.org/10.1007/s10845-015-1057-1

Zhang, Y., Gupta, R. K., & Bernard, A. (2016). Two-dimensional placement optimization for multi-parts production in additive manufacturing. *Robotics and Computer-Integrated Manufacturing*, *38*, 102–117. https://doi.org/https://doi.org/10.1016/j.rcim.2015.11.003

APPENDIX A – SUPPORTING INFORMATION

Brands and models studied for the process FDM:

- Small: Stratasys-F123; MakerBot-Method; Zortrax–M200 Plus, M300 Dual; Prusa-I3 MK3S; LULZBOT-TAZ Pro.
- Large: Stratasys-F900, F450mc; Ultimaker-S5 Pro; Zortrax– Endureal; Markforged-X7 (Gen2).

Brands and models studied for the process SLA:

- Small: Formlabs-Form3L; DWS-XFAB 3500HD.
- Large: DWS-XProQ; 3D Systems-ProX 950 e Stratasys-V650 Flex.

Brands and models studied for the process DLP:

- Small: Envisiontec-P4K series, Vida HD
- Large: Nexa3D-NXE 400; Envisiontec-Xtreme HD 3SP, ULTRA 3SP Hi-Res; B9Creations-B9 Core 550.

Brands and models studied for the process cDLP:

- Small: Envisiontec-Envision One Dental.
- Large: Carbon-M2 Printer, L1 Printer.

Brands and models studied for the process SLS:

- Small: Formlabs-Fuse 1; Sinterit-Lisa Pro.
- Large: EOS-EOS P 500, EOS P 396; FORMIGA P 110 Velocis; 3D Systems-ProX SLS 6100, sPro 140; Sintratec-S2.

Brands and models studied for the process MJF:

- Small: HP Jet Fusion 580 Color.
- Large: HP Jet Fusion 5200 Series 3D Printers.

Brands and models studied for the process MJ:

- Small: 3D Systems-ProJet MJP 2500; Stratasys-J55.
- Large: 3D Systems-ProJet MJP 5600; Stratasys-J8 Series.

Figure 14 – Table with a detailed record of AM technologies and their characteristics – FDM and SLA

Technology	State of matter	Printer dimension	Printing Volume		Resolution	Accuracy	Printing speed
FDM	Filament	**Stratasys F120**	254x254x254 mm	16,4	0.356 mm (xy) 0.127 - 0.330 mm (z)	± 0.2 mm or 0.002 mm/mm (xyz) additional - 0.000/+ slice height (z)	-
		Makerbot Method	152x190x196 mm	5,7	0.40 mm (xy) 0.02 - 0.40 mm (z)	± 0.2 mm (xyz)	500mm/sec - 50 mm^3/sec - 0.18 l/hr
		Zortrax M200 Plus	200x200x180 mm	7,2	0.30 - 0.60 mm (xy) 0.09 - 0.39 mm (z)	-	-
		Zortrax M300 Dual	265x265x300 mm	21,1	0.40 mm (xy) 0.15 - 0.20 mm (z)	-	-
		Prusa I3 MK3S	250x210x210 mm	11,0	0.40 mm (xy) 0.05 - 0.35 mm (z)	-	200 mm/sec
		Lulzbot Taz Pro	280x280x285 mm	22,3	0.50 mm (xy) 0.05 - 0.40 mm (z)	-	200mm/sec - 13.82 mm^3/sec - 0.05 l/hr
		Stratasys F900	914x609x914 mm	508,8	0.305 - 1.020 mm (xy) 0.127 - 0.508 mm (z)	± 0.089 mm or 0.0015 mm/mm (xyz) additional - 0.000/+ slice height (z)	-
		Stratasys F450mc	406x355x406 mm	58,5	0.254 - 508 mm (xy) 0.127 - 0.330 mm (z)	± 0.127 mm or 0.0015 mm/mm (xyz) additional - 0.000/+ slice height (z)	-
		Ultimaker S5 Pro	330x240x300 mm	23,8	0.25 - 0.8 mm (xy) 0.02 - 0.60 mm (z)	-	-
		Zortrax Endureal	400x300x300 mm	36,0	0.4 mm (xy) 0.2 mm (z)	-	-
SLA	Liquid	**Formlabs-Form 3L**	335x200x300 mm	20,1	0.025 mm (xy) 0.025 - 0.300 mm (z)	-	-
		DWS-XFAB 3500HD	140x140x180mm	3,5	0.01-0.10 mm (z)	-	-
		DWS X PRO Q	300x300x300 mm	27,0	0.01 - 0.10 mm (z)	-	-
		3DSystems ProX 950	1500x750x550 mm	618,8	0.00635 mm (xy) 0.05 - 0.15 mm (z)	± 0.001 - 0.002 mm/mm (xyz)	3.5 m/sec @ border spot (0.13 mm) 25 m/sec @ large hatch spot (0.76 mm)
		Stratasys V650 Flex	508x508x584 mm	150,7	0.0127 mm (xy) 0.1 mm (z)	-	3.8 m/sec @ 0.127 mm 17.8 m/sec @ 0.762 mm

Figure 15 – Table with a detailed record of AM technologies and their characteristics – SLS and DLP

Technology	State of matter	Printer dimension	Printing Volume		Resolution	Accuracy	Printing speed
SLS	Powder	**Formlabs Fuse 1**	165x165x300 mm	8,2	0.200 mm (xy) 0.11 mm (z)	-	10 mm/hr => 0.27 l/hr
		Sinterit-Lisa Pro	150x200x260 mm	7,8	0.075 - 0.175 mm (z)	± 0.05 mm (xy)	-
		EOS P 500	500x330x400 mm	66,0	0.06 - 0.18 mm (z)	-	up to 2 x 10 m/sec (scan/drawing speed during build process) up to 40 mm/hr - 6.6 l/hr (building rate)
		EOS P 396	340x340x600 mm	69,4	0.06 - 0.18 mm (z)	-	up to 6 m/sec (scan/drawing speed during build process) up to 3 l/hr (building rate)
		EOS Formiga P 110 Velocis	200x250x330 mm	16,5	0.06 - 0.12 mm (z)	-	up to 5 m/sec (scan/drawing speed during build process) up to 1.2 l/hr (building rate)
		3DSystems ProX SLS 6100	381x330x460 mm	57,8	0.08 - 0.15 mm (z)	-	up to 12.7 m/sec (scan/drawing speed during build process) up to 2.7 l/hr (building rate)
		3DSystems sPro 140	550x550x460 mm	139,2	0.08 - 0.15 mm (z)	-	up to 10 m/sec (scan/drawing speed during build process) up to 3 l/hr (building rate)
		Sintratec S2	Ø160x400 mm	8,0	0.1 mm (z)	± 0.3 mm (xyz)	8 - 51 mm/hr
DLP	Liquid	**B9Creations Core 550**	96x54x127 mm	0,7	0.025 mm (xy) 0.020 mm (z)	-	100 mm/hr => 0.66 l/h
		Envisiontec Vida HD	96x54x100 mm	0,5	0.05 mm (xy) 0.025 - 0.15 mm (z)	-	-
		Nexa 3D NXE 400	275x155x400 mm	17,1	0.075 mm (xy) 0.05 - 0.2 mm (z)	-	-
		Envisiontec Xtreme HD 3SP	216x381x356 mm	29,3	0.075 mm (xy) 0.05 - 0.1 mm (z)	-	-
		Ultra 3SP Hi-Res	266x175x193 mm	9,0	0.1 mm (xy) 0.05 - 0.1 mm (z)	-	-
		Envisiontec P4K 90	233x141.5x180 mm	5,9	0.090 (xy) 0.025 - 0.15 mm (z)	-	-

Figure 16 – Table with a detailed record of AM technologies and their characteristics – cDLP, MJF and MJ

Technology	State of matter	Printer dimension	Printing Volume		Resolution	Accuracy	Printing speed
cDLP	Liquid	**Envisiontec Envision One Dental**	180x101x85 mm	1,5	0.060 - 0.093 mm (xy) 0.05 - 0.15 mm (z)	-	up to 80 mm/hr => 1.45 l/h
		Carbon M2	189x118x326 mm	7,3	0.075 mm (xy) 0.1 mm (z)	± 0.2 mm (xyz)	1000 mm/h => 22.3 l/h
		Carbon L1	400x250x508 mm	50,8	0.16 mm (xy) 0.1 mm (z)	± 0.3 mm (xyz)	-
MJF	Powder	**HP Jet Fusion 580 Color**	332x190x248 mm	15,6	0.02 mm (xy) 0.08 mm (z)	± 0.2 mm for hollow parts below 100mm (xy) ± 0.2% for hollow parts over 100mm (xy)	up to 1.817 l/hr
		HP Jet Fusion 5200 Series	380x284x380 mm	41,0	0.02 mm (xy) 0.08 mm (z)	± 0.2 mm for hollow parts below 100mm (xy) ± 0.2% for hollow parts over 100mm (xy)	up to 5.058 l/hr
MJ	Liquid	**3DSystems ProJet MJP 2500**	294x211x144 mm	8,9	≈ 0.032 mm (x) ≈ 0.028 mm (y) ≈ 0.032 mm (z)	± 0.001 - 0.002 mm/mm (xyz)	-
		Stratasys J55	140x200x190 mm	5,3	0.018 mm (z)	± 0.18 mm for parts below 100mm (xyz) ± 0.2% for parts over 100mm (xyz)	-
		3DSystems ProJet MJP 5600	518x381x300 mm	59,2	≈ 0.034 - 0.042 mm (xy) ≈ 0.013 - 0.016 mm (z)	± 0.001 - 0.002 mm/mm (xyz)	-
		Stratasys J8 Series	490x390x200 mm	38,2	0.014 - 0.055 mm (z)	± 0.1 mm for parts below 100mm (xyz) ± 0.2 mm or 0.06% for parts over 100mm (xyz)	-