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ORIGINAL RESEARCH

An overview on the use of operations research in additive manufacturing

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Abstract

Additive Manufacturing (AM) is a disruptive production technology that challenges many well-established, conventional practices in Operations and Supply Chain Management decisions. Consequently, new context-specific decision problems have appeared in this area, while existing decision problems must be adapted or extended to this context. In this overview, these decision problems in AM are highlighted and classified, describing the different decision in an unified manner and citing the underlying OR techniques that have been applied to solve them. The aim of the paper is that, by presenting an overview of the AM-related problems in a systematic, OR- or Decision-Making-centred (rather than technology-centred) manner, the OR community can become more aware of this stream of research and thus be more active and contribute with some high-quality work. Open research challenges, as well as avenues for future research are also discussed.

Keywords Additive manufacturing · Review · Operations research

1 Introduction

In the manufacturing industry, the term Additive Manufacturing (AM)—also denoted as 3D Printing (3DP) or Direct Digital Manufacturing (DDM)—is employed to denote the process of creating physical objects from a digital model by building them layer-by-layer. Regardless the specific underlying technology[1], AM is extremely disruptive when compared to traditional (i.e. subtractive or formative) manufacturing technologies as it does not require, in principle, component-dependent tools, which makes AM a universal production technology, not being tied to individual production steps (Baumung, 2020). In AM, different parts can be produced without retrofitting the tools, resulting in a unit production cost that is mostly

[1] Some of these technologies include Fused Deposition Modelling (FDM), Selective Laser Sintering (SLS), or Selective Laser Melting (SLM), among others. For a detailed review the reader is referred to e.g. Bogers et al. (2016).

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independent of the production volume (see e.g. Achillas et al., 2015 or Baumers et al., 2017). Furthermore, the fact that a single resource can—in theory—manufacture all range of parts in the company's portfolio is in stark contrast with the product-orientation concept that has led to the specialization of resources within the factory, of factories within the company, and of companies within the supply chain. Using AM, small manufacturing companies that may not have sufficient capacity on their own could now potentially compete against larger ones by pooling their resources and using emerging collaborative manufacturing paradigms.

Although currently AM is still limited due to its low throughput speed, it has been predicted that the AM market will increase steadily, even if the forecasts are highly variable (from \$12 billion by 2025 in Aloui and Hadj-Hamou (2021) to \$35.6 billion by 2024 in Wohlers (2015)). Since the aforementioned characteristics have a profound impact in the manner that operations in a AM context are managed, well-established best practices in Operations and Supply Chain Management (OSCM in the following) may no longer be the most efficient ones: There are traditional OSCM decision problems (such as e.g. scheduling) that have to be necessarily adapted to this new context, and there are *new* decisions problems (such as the optimal build orientation of the parts discussed later) that do not appear in traditional manufacturing. In this regard, the literature on decision problems in the AM context is steadily growing and there are several review papers describing the state of the art regarding specific decision problems (such as the reviews by Oh et al., 2020a exclusively for nesting and scheduling problems, or Di Angelo et al., 2020b solely for the build orientation problem). However, no review of the existing contributions in AM from the Operations Research (OR) perspective has been published, which may leave a good part of the OR researchers unaware of the potential research lines in the field. Our aim is that, by presenting an overview of the related decision problems in a systematic, OR- or Decision-Making-centred (rather than technology-centred) manner, the OR community can become more aware of this stream of research and thus be more actively involved by contributing with some high-quality work. Such holistic view may help to carry out research on integrated problems, an aspect discussed in Sect. 7.3.

Needless to say, even an overview of such an ample field must be necessarily succinct and confined to present the reader the gist of the different decision problems and provide the most relevant references where the knowledge on the specific research topics can be enhanced. In addition, some insights regarding the future developments in the field are provided. It is not, then, an exhaustive review of all existing contributions, as this would largely exceed the length and the purpose of the paper.

In order to establish the scope of our paper, it has to be taken into account that AM also bridges the gap between the traditionally separated business functions of design and manufacturing due to the aforementioned *universalisation* of the production technology. More specifically, since in principle any design is *manufacturable* using AM, this additional degree of freedom in the design greatly impacts the efficiency of manufacturing, thus becoming both design and manufacturing closely connected, hence possibly requiring some form of integrated—or coordinated—decision-making. As here the focus of the paper is primarily on research related to the manufacturing process, the decision problems related to the design of the products (parts) to be manufactured are left outside of the scope of this overview. In this regard, there is an array of contributions referring to designing or re-designing the product so it can be efficiently produced using AM. For reviews of the literature addressing these issues, the reader is referred to Oh et al. (2018b, 2021a) or Lopez Taborda et al. (2021).

A final word must be said regarding the methodology adopted when presenting the different decision problems: Since AM may radically change the framework for OSCM, there are several contributions (see e.g. Mellor et al., 2014; Newman et al., 2015; Baumung and Fomin, 2018; Baumung, 2020) proposing novel architectures and frameworks to carry out the

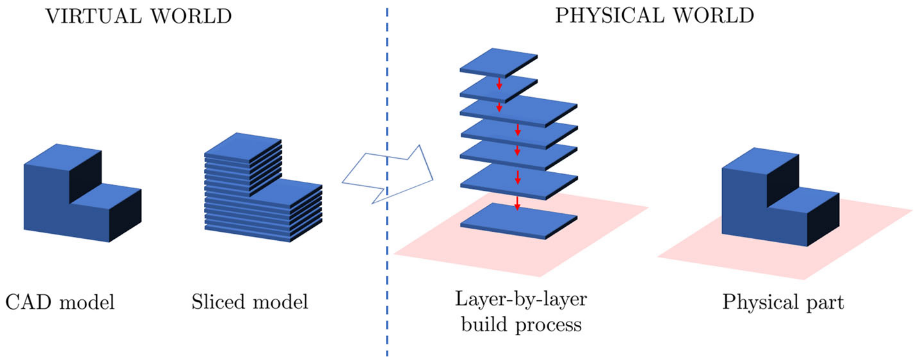

Fig. 1 Schematic representation of the AM building process

production planning and control functions in AM. From these architectures, different decision problems can be derived, and one of these architectures to present the decision problems could have been used. However, this may give the impression that these problems are linked to a specific decision framework, neglecting the fact that (1) AM may also foster different (albeit complementary) business models—such as the AM Cloud discussed below, and (2) it is foreseeable that conventional and AM manufacturing may co-exist in many scenarios. Therefore it seems to be more adequate not to link the review of the decision problems to any specific architecture for production planning and control. As a consequence, the decision problems have been presented separately one by one, although the relationship among some of these is also discussed.

The remainder of the paper is as follows: In Sect. 2 the foundations of AM technology are briefly outlined in order to better identify the decision problems related to OSCM in this context, and group them into the AM decision areas. The decision problems identified in these three areas are subsequently discussed in Sects. 3, 4, and 5 respectively, where these problems are described and the main references identified. Finally, in Sects. 6 and 7, several conclusions and future research avenues are discussed.

2 Operations and supply chain management in AM

2.1 Additive manufacturing: an outline

AM technologies produce physical objects from virtual, computer-stored models (typically a 3D CAD) as depicted in Fig. 1. First, the CAD model is virtually *sliced* so a number of layers are determined, and then the part is manufactured by physically generating the layers using a given technology (such as e.g. the deposition of fused material) and merging them on top of each other, i.e. the part is *built* layer-by-layer by a *AM machine* on a *building platform*, see Fig. 1. Since the generation of the layers is technology- and material- specific, most AM machines can only build a part from a rather narrow range of materials, which in turn influences the quality of so-obtained part.

Given that one layer is built on top of another, in order to build a part where its upper layer is greater than the lower ones, *support structures* may be needed to prevent the deformation of the part when the bigger layer is built. Therefore, some layers may have areas (usually with lower density and/or cheaper/faster material) whose only function is to work as support for

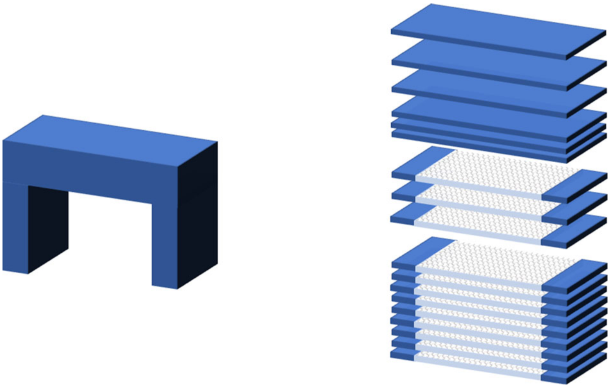

Fig. 2 Support structure in AM

the bigger layers (see Fig. 2). Obviously, this increases the time and costs (material, energy) required to build the part, and it is clear than using a different *build orientation* of the CAD model (i.e. in Fig. 2 simply to turn the model upside down) can result in faster and cheaper builds. Furthermore, as it is discussed later, the physical properties of the part are different depending on the orientation, therefore finding the optimal build orientation for a part is an important decision in AM.

Another key factor in AM is the size of the available building platform, which represents a physical restriction of the size of the parts that can be built, both respect to the area of the building platform as well as with respect to its maximum height (which is associated with the maximum number of layers that can handle the specific AM machine). Such area and height determine a volume—denoted in the following as *build volume*—where the part (or parts) to be built must fit into. A set of parts fitting into a build volume that are manufactured at the same time is denoted as a job, or more simply, a *build*.

For most AM technologies, the number of builds that has to be carried out to produce a set of parts is, by large, the most predominant cost/time factor, therefore naturally batching different parts in the same build plays a key role in the competitiveness of AM, as manufacturing one part per build is extremely ineffective (Piili et al., 2015). Thus, an important decision is that of *nesting* the parts, referring to how to group and place the parts into a build volume with the objective of maximising the number of parts that can be processed in a single build, or to minimise the time/cost of a single operation (build) in AM. As a result of the nesting problem, one or more jobs or sets of parts that can be processed in the same build are determined, together with the placement (position, orientation) of each part in the job.

If only one job is considered, then the nesting problem consists of how to arrange the parts (including their orientation) in the build volume in order to minimize a given objective, usually the time/cost of processing this job. Note that this is a decision problem itself in contrast to traditional manufacturing, where usually there is no decision problem once the parts have been allocated to a job (batch). If more than one job can be considered, the nesting problem also involves deciding which parts are assigned to the different jobs.

2.2 Distributed business models

Some of the technological features of AM discussed in the previous section—particularly the capability of the direct manufacture of entire parts and components out of their computer-stored models– make possible to embody manufacturing paradigms such as the Cloud Manufacturing or Factory as a Service (FaaS) (Kang et al., 2018). In this business model, there is a software system (sometimes denoted as a cloud manufacturing platform) that integrates different services for the manufacturing of goods in one web-based environment (Rudolph & Emmelmann, 2017). In other words, the AM resources of different manufacturers (each one in a different location) are centrally managed, so customer orders arrive to the system and are confirmed or rejected by the system. Such order processing takes into account different factors, including the technical feasibility of the AM resources to manufacture the parts contained in the order, pricing/costs aspects, and time-related issues (such as the availability of the different AM resources or the due dates requested by the customers). The output of the process is the set of accepted orders, together with the allocation of each part in the order to one of the AM resources in the AM cloud.

Note that, in this system, large orders that cannot be accepted by a single manufacturer due to its lack of capacity can be split across several manufacturers, so in this manner companies with limited capacity can compete against larger ones (for a recent synthesis of the expected advantages of AM in this regard the reader is referred to e.g. Demir et al., 2021). However, it is clear that the allocation of orders in this distributed AM network is a major challenge for the implementation of this system, as different constraints and objectives (ranging from physical or technical features of the parts to price or transportation considerations) must be handled. Although the concept of cloud manufacturing is not specific of AM, there are several unique factors within the AM context, as in conventional manufacturing models it is often assumed that there are always resources to satisfy the demand, which is not always the case in AM (Mashhadi & Salinas Monroy, 2020), or that the customer (buyer) makes no distinction between the resources provided by different sources (Mashhadi & Salinas Monroy, 2019).

2.3 Relevant decision areas

In order to present the decision problems outlined in the previous section in a coherent manner, they have been grouped using decision areas which roughly correspond to different business functions, although the allocation of some of the problems to a specific area is certainly debatable and done solely for classification purposes. The identified decision areas are the following:

- *Designing the AM process (DAM)* This area includes a number of decisions related to the conception of the manufacturing and distribution process, i.e. *Supply Chain (SC) design*. Roughly speaking, this decision problem involves determining the number, type and organisation of the different AM resources required to respond to an aggregated customer demand. Note that, at the time of these decisions, there is no clear visibility of the individual customers and that, in most cases, aggregated demand information is derived using some forecasts.
- *Planning in an AM process (PAM)* This entails the set of decisions regarding the commitment and configuration of the AM resources required to fulfil customer demand. The set of available AM resources are considered to be fixed, in contrast to DAM and, at the time of these decisions, there is usually a clear visibility of the set of the parts that have to be manufactured. In other words, there is a firm quotation from a specific set of customers. The decisions included in this area are the following:
  - *Selection of the AM technology* This problem refers to select the most suitable AM resource (among a set of heterogeneous AM resources) to manufacture a specific

part or set of parts. The selection of the AM technology may play an important role to maximise the output of a set of a AM resources. The contributions regarding this decision problem are discussed in Sect. 4.1.
  - *Nesting* The nesting problem refers to how to group and place the parts in the building platform with the objective of maximising the number of parts that can be processed simultaneously, or to minimise the time/cost of a single operation (build) in AM. As a result, one or more jobs (sets of parts that can be processed in the same build) are determined, together with the placement (position, orientation) of each part in the job. This decision problem is addressed in Sect. 4.2.
  - *Order acceptance and scheduling* The scheduling problem refers to sequencing and allocating the parts to the AM resources. Since the parts are not processed individually but grouped into a job, this problem is strongly connected to the nesting discussed above. Given the complexity of solving the integrated problem, nesting may be simplified by considering only the volume and area of each part and address the scheduling problem to group a set of parts in batches (jobs) that are allocated to the AM resources. Order acceptance can be seen as a special case of scheduling where all jobs do not necessarily have to be accepted, so obtaining the set of accepted (and scheduled) jobs is part of the decision problem. Scheduling and order acceptance is discussed in Sect. 4.3.
  - *Part allocation in a distributed AM network* As discussed previously, AM enables emerging business paradigms that may bring a number of advantages for AM manufacturers. However, the allocation of parts (possibly belonging to different customers) across the manufacturers in an AM network is far from being a trivial decision, which is discussed in detail in Sect. 4.4.

- *Operating of AM (OAM)* This area entails the set of decisions to be made once a specific part has to be processed in a specific AM resource. Note that, in this area, the AM resources are fixed (in contrast to DAM) and that the parts to be built have been already allocated to a specific AM resource (in contrast to PAM). These decisions include the following:
  - *Build orientation* Since the part is built layer by layer, it grows along a so-called *build direction*, which determines some of its physical and economic properties (such as cost, time or quality). Thus the build orientation problem refers to finding a build direction so the desired features of the part are optimal. This problem is reviewed in Sect. 5.1.
  - *Parametrization of the AM technology* This decision problem refers to the optimization of the technical parameters to be used in the AM technology. This problem is discussed in Sect. 5.2.

Table 1 provides a summary of the decision problems, together with a formal definition and their main features (typical input and output data). In the following sections each one of these decisions is reviewed in detail.

3 Designing the AM process

3.1 Background and definition

The acquisition of AM resources by some/all nodes in the SC allows the node to build some/all parts required by its customers instead of ordering them to its supplier. This may allow the

Table 1 Summary of identified decision problems

Decision area	AM resources	Part allocation to AM resources	Decision problem	Basic definition	Typical output
Design of the AM process	Not fixed	–	AM supply chain design	To determine the number, type and organisation of the different AM resources required to respond to an aggregated customer demand.	Number and type of AM resources
Planning the AM process	Fixed	Not fixed	Selection of AM technology	To select the most suitable AM resource (machine) from a set to manufacture a specific part or set of parts.	Part allocation to AM resource type
			Part allocation in a AM network	To allocate a set of parts (possibly belonging to different customers) to AM resources distributed across a network.	Part allocation to AM resource
			AM order acceptance and scheduling	To sequence and allocate a set of parts (fully or a subset) to the AM resources.	Part allocation to AM resource and build*
			AM nesting	To group and place the parts in the building platform with the objective of maximising the number of parts that can be processed simultaneously, or to minimise the time/cost of a single operation (build) in AM.	Part allocation to AM and build incl. position in the build**
Operating the AM process	Fixed	Fixed	Build orientation	To detemine the orientation of a part / set of parts that minimises a criterion or set of criteria	Part allocation to AM and build incl. position in the build
			Parametrization of AM technology	To determine the optimal set of technical parameters used in the AM resource/technology	Set of parameters to be employed in the AM resource

**Estimated* feasibility of the build is obtained by relaxing the AM nesting problem
**Feasibility of the placement within the built is obtained by relaxing the build orientation problem

SC to be more responsive to customer demand, as it is usually assumed that the time to build the part in the AM resource is smaller than the supplier lead time. On the other hand, the cost of printing a part is usually much higher than that of purchasing the part from the supplier, particularly taking into account the cost of acquisition of the AM resource. Therefore, a decision problem arises in a SC in which some of the nodes may possess AM resources (in the following we denote this SC as AMSC). Such decision problem can be formalised as follows: given a SC *structure* defined by a number of nodes (suppliers, distribution centres, manufacturers,...) each one located at a distance (time) from each other, allocate AM resources to some of them in order to improve SC performance.

A key assumption for this problem is whether the status of the AM technology (particularly in terms of costs, times, quality, etc.) can be considered to be fixed, or not. In the former case (Static AM Technology or SAMT), the decision consists of finding the best AMSC structure with the AM technology at hand whereas in the latter case (Prospective AM Technology or PAMT) the potential evolution of the AM technology is considered and the decision is to determine *when* it is more convenient to change the current SC structure.

For each one of the assumptions, two approaches can be adopted for the decision problem:

1. Optimal AMSC Design, i.e. finding the SC structure providing the best performance for the SC. For the SAMT case, this problem is a special case of the well-known *facility location problem* with a different cost structure and constraints.
2. Scenario Modelling. In this approach, several *scenarios* or AMSC structures are modelled and their performance compared. This problem is referred also as *AM performance* in some literature (see e.g. Smith & Kerbache, 2017). The scenarios are usually chosen *a priori* in this approach. For the SAMT version of the problem, a number of scenarios have been considered in the literature:

   - TSC: Traditional Supply Chain, i.e. the supply chain without considering AM resources.
   - C-AMSC: Centralised - One centralised AM facility delivers parts to the rest of the retailers
   - D-AMSC: Decentralised - Each retailer possesses AM resources
   - H-ASMC: Hub ASMC - Some retailers (hubs) possess AM resources and deliver parts to the rest of the retailers.

   For the PAMT case—both for optimal AMSC design and scenario modelling, the prospective AMSC scenarios are defined in terms of different evolution of the AM technology.

3.2 Evolution and problem variants

The contributions for the different versions for the problem vary greatly, as there are more references for scenario modelling than for optimal design. To the best of our knowledge, the first reference dealing with the problem adopting the scenario modelling approach (both in its SAMT and DAMT version) is Khajavi et al. (2014), where the centralised and decentralised current and future scenarios are explored. In their setting, C-AMSC is the preferred one in terms of operating costs (including downtime). Further contributions only explore the SAMT case and while Li et al. (2019c) reaches similar conclusions in the context of heterogeneous demand, in the analysis by Rinaldi et al. (2021), D-AMSC yields better results in terms of several operation-based indicators (utilisation, lead times, AM resources employed), instead of costs as in the previous references. Xu et al. (2021) also stress the poor relative performance

Table 2 Summary of references dealing with scenario modelling under the assumption of Static AM Technology (SAMT case)

References	Scenarios	Area	Model	Performance indicators
Khajavi et al. (2014)	C-AMSC versus D-AMSC (current and future)	Spare parts	Simulation (DES)	Costs (total operation costs)
Mashhadi et al. (2015)	AMSC versus TSC	Generic	Simulation (DES/ABS)	Inventory/lead time
Li et al. (2017b)	AMSC versus TSC	Spare parts	Simulation (SD)	Costs (total operation costs)
Ghadge et al. (2018)	AMSC versus TSC	Spare parts	Simulation (SD)	Inventory costs/inventory levels
Zhang et al. (2019)	AMSC versus TSC	Spare parts	Simulation (DES)	Costs (total operation costs)
Cestana et al. (2019)	AMSC versus TSC	Spare parts	ANM (Markov chain)	Costs (total operation costs)
Knofius et al. (2019)	AMSC versus TSC	Spare parts	ANM (Markov Chain)	Costs (total operation costs)
Li et al. (2019c)	C-AMSC versus D-AMSC	Spare parts	Simulation (DES)	Costs/lead time
Haddad et al. (2019)	AMSC versus TSC	Spare parts	Simulation (ABS)	Costs (total operation costs)
Arbabian and Wagner (2020)	AMSC (retailer) versus AMSC (manufacturer)	Spare parts	ANM (Stackelberg game)	Revenue
Kunovjanek and Reiner (2020)	AMSC with different speeds of AM adoption	Generic	Simulation (SD)	Inventory
Chen et al. (2021)	On-line versus. In-store AMSC	Retail	ANM (inventory theory)	Costs (total operation costs)
Xu et al. (2021)	C-AMSC versus D-AMSC versus H-AMSC	Spare parts	Simulation (DES/ABS)	Costs/lead time/cannibalization
Westerweel et al. (2021)	AMSC for different parts based on quality requirements	Spare parts	ANM (Markov decision process)	Operational costs (inventory costs/asset availability)
Rinaldi et al. (2021)	C-AMSC versus D-AMSC versus TSC	Generic	Simulation (DES)	Utilisation/costs/lead time/fill rate/AM resources employed
Rodriguez et al. (2021)	AMSC versus TSC	Generic	Simulation (SD)	Order completion time
Arbabian (2022)	AMSC (retailer) versus AMSC (manufacturer)	Spare parts	ANM (inventory theory)	Revenue
Mindt et al. (2022)	Framework for comparison	Spare parts	Simulation (ABS)	Costs/environment

ABS Agent-based simulation, *ANM* Analytic model, *DES* Discrete-event simulation, *SD* System dynamics of D-AMSC, but in their study they also explore some intermediate scenario (H-AMSC) and found that it outperforms the centralised one in terms of responsiveness. Also within the SAMT approach, the first comparison between ASMC and TSC scenarios is Mashhadi et al. (2015), providing an illustration of the changes in SC indicators (mostly inventory) if AM resources are adopted. Similar analyses by Li et al. (2017b) or Cestana et al. (2019) (see the full list in Table 2) using different techniques have established that, under a range of conditions and performance indicators, AMSC presents a range of advantages over TSC.

With respect to Scenario Modelling under the PAMT assumption, apart from the already discussed reference by Khajavi et al. (2014), Achillas et al. (2015) is the only contribution in this area. In their work, the authors propose using MCDM (i.e. Electre III) to chosen among six different prospective scenarios.

Regarding the optimal AMSC design approach, the first reference is Scott and Harrison (2015) for the PAMT case, presenting a stochastic programming model to determine the factors that most impact AM performance in a SC. Kunovjanek and Reiner (2020) and Lacroix et al. (2021) also address this problem, using the Bass diffusion model to foresee the evolution of AM technology. In the SAMT case, the first reference is Barz et al. (2016), who formulate a MILP model based on the facility location problem to determine the location of AM resources with limited production capacity in a two-stage SC that minimizes fixed and transportation costs. After these authors, several references address the same problem considering different types of costs, assuming deterministic data or a stochastic arrivals/processing times. Table 3 summarises the contributions in this area.

With respect to problem variants, note that, at a node level, the problem of using or not an AM resource to produce a part instead of ordering it to a provider resembles to the *make-or-buy* (in this case, *print-or-buy*) decision problem. In this regard, Chekurov and Salmi (2017) and Togwe et al. (2019) use Monte Carlo simulation to quantify how the proportion of printed parts improves replenishment times. Song and Zhang (2020) present an analytical model to determine the utilization of an AM resource when facing stochastic demand that minimises the expected operation costs.

A key aspect in AMSC design with capacity (i.e. production) constraints is the fact that lead times are not constant, but affected by the work-in-progress/throughput. A common way to describe and implement such relationship are the so-called *operating curves* (or CT-TH curves). Since these operating curves are technology-dependent, some references (Stittgen & Schleifenbaum, 2020 and Stittgen & Schleifenbaum, 2021) have developed simulation models of a AMSC to provide such curves.

Another problem variant arises as a non-negligible amount of waste may be generated by the AM technologies, a special case in supply chain design is related to the recycling of this waste. In this regard, Santander et al. (2020) develop a MILP model to evaluate the feasibility of a supply network devoted to plastic recycling of AM waste, while Sun et al. (2020) use game theory to study pricing and material selection decisions in a closed-loop supply chain recycling AM waste.

Table 3 Summary of references dealing with optimal AMSC design under the assumption of Static AM Technology (SAMT case)

References	Approach	OR technique	Constraints	Costs							
				F	T	M	B	O	P	I	L
Barz et al. (2016)	Deterministic	MILP/solver	Production	x	x						
Emelogu et al. (2016)	Stochastic*	SAA	Production	x	x			x		x	x
Smith and Kerbache (2017)	Stochastic**	Exhaustive search/queueing theory	Buffer								
Afshari et al. (2019)	Deterministic	MILP/solver	Production	x	x		x	x		x	
Chiu and Lin (2016)	Deterministic	MILP/solver	Production		x	x	x	x	x		
Strong et al. (2018)	Deterministic	MILP/solver	–	x	x	x		x			
de Brito et al. (2019)	Deterministic	MILP/solver	Production	x	x			x			
Do Chung et al. (2018)	Deterministic	MILP/solver	Production	x	x						
Emelogu et al. (2019)	Deterministic	Non-linear model/heuristic	Production	x	x			x		x	
de Brito et al. (2021)	Deterministic	MILP/solver	Production	x	x						

Costs sources: F: Fixed, T: Transportation, M: Material consumption/procurement, B: Backlog, O: Operation, P: Pollution, I: Inventory, L: Lead time costs
*Demand is stochastic
**Demand and arrival times are stochastic

4 Planning in an AM process

4.1 Selection of the AM technology

4.1.1 Background and definition

Although the AM technologies allow for a universalization of the manufacturing process, this by no means implies that all AM technologies or all AM resources are equally efficient in building a part, nor that the desired final features of a part can be obtained with any AM technology. In general, not all AM technologies can cope with any raw material and, even if this is the case, different AM technologies entail different building times and can achieve different degrees of the desired characteristics of the final part (quality, finishing, etc.). Even within a specific AM technology, there may be resources with different size of their building platform and, therefore, they cannot process parts of an arbitrary size. It is then usual that manufacturers have a range of AM technologies available, diverse material suppliers, as well as AM resources with different size of their building platform. Finally, given the coexistence in many companies of AM technologies with conventional manufacturing technologies, the manufacture of some parts can be allocated to conventional resources. As a consequence, a comprehensive and robust AM technology selection is paramount for the users and (given the aforementioned specifics of AM technology), unlike in conventional manufacturing processes, the selection of the AM technology is a non-trivial task (Wang et al., 2017).

Thus, the decision problem can be stated as follows: given a set of parts and a set of manufacturing resources (which may consists of both AM and conventional manufacturing resources), the goal is to find the best allocation of the parts to the resources. This problem is sometimes denoted as the *printer selection* problem (see e.g. Ransikarbum & Khamhong, 2021).

In this decision problem, different aspects can be considered simultaneously, including geometric aspects (such as the dimensional accuracy, resolution, or surface finish), functional aspects (such as the mechanical or thermal properties of the part), manufacturing/quality aspects (such as the reliability or the time to manufacture), economic aspects (such as costs), sustainability aspects (such as waste disposal or recycling potential), and subjective aspects (such as experts opinions). Furthermore, some/all of the values of these aspects can be considered as known (certain) or uncertain. In the latter case, the uncertainty can be captured using random variables, fuzzy numbers, or intervals. Different decision methods (i.e. stochastic methods, fuzzy methods, or interval analysis) can be applied accordingly.

4.1.2 Evolution and problem variants

Although the problem of selection of the AM technology has been long addressed, the initial initial contributions have sought to develop databases or rule repositories/expert systems to support the decision problem (see e.g. Campbell & Bernie, 1996), an approach that continues up to date. Other early references (Chuk & Thomson, 1998) rely on simple weighting functions, while Braglia and Petroni (1999) is the first work to use AHP for the decision process. The first references assuming the uncertainty of the data are Wilson and Rosen (2005), Lan et al. (2005) and Fernandez et al. (2005), who model this uncertainty using interval, fuzzy or stochastic approaches, respectively. Subsequent contributions have then focus on refining/hybridizing existing approaches to handle multicriteria decision making. Regarding the type of criteria handled, while most references address geometric, functional, manufacturing and costs aspects, Lokesh and Jain (2010) also considers environmental aspects. Liao et al. (2014) is the first reference including subjective experts' opinions as additional criteria. The contributions on this problem are summarised in Table 4.

The problem under consideration is related to the problem of assessing the suitability of a part to be manufactured using a specific AM technology. However, this latter problem cannot be considered a manufacturing technology selection problem since it does not explicitly consider different alternatives for manufacturing, but tries to identify if a part is eligible to be manufactured using AM taking into account a number of factors ranging from its design or geometric complexity, to the existence of adequately-trained human resources in the company. The vast majority of references on this problem use a qualitative approach, even if recently some contributions attempt to introduce some automated decision support system (see e.g. Yang et al., 2020 where a supervised Machine Learning model is employed to this end).

4.2 AM nesting

4.2.1 Background and definition

The nesting problem in the context of AM can be defined as follows: given a set of parts to be processed in a set of AM resources, determine how to best group and place the parts in the build volumes. This problem is also referred to in the literature as *optimal packing* (see e.g. Canellidis et al., 2016). Nesting problems can be considered a type of cutting and packing problem and have been intensively dealt with in the literature. Nevertheless, it is to mention that the AM nesting problem represents the most extreme case of 3D packing, as parts usually have arbitrary sizes and no limits on part orientation or the position in the volume (Dickinson & Knopf, 2002). A specific classification for AM nesting problems has been proposed by Araújo et al. (2020a, 2019), and a taxonomy for nesting problems in AM can be found in Oh et al. (2020a). The classification includes three criteria:

- *Dimensionality* The nesting problem refers, in general, to the 3D packing problem since the parts have to be placed in the building volume(s). Nevertheless, for some AM technologies, the most relevant constraint is the requirement of support structures, which makes inefficient placing one part on top of another. Instead, in these AM technologies (which include popular ones such as FDM or SLS discussed earlier), parts are placed aside each other after a proper building orientation for each one has been chosen. As a consequence, the interaction between the parts occurs in the plane and the nesting problem becomes a 2D packing problem. Therefore, the AM nesting problem can be addressed under its 3D or 2D versions.
- *Objective function* Several objective functions can be considered for nesting. The most employed are the output maximization (applied when the demand for parts is higher than the capacity of the AM resource), single input minimisation (minimizing the build volume required to build a number of parts in a single build), or criteria related to costs and/or times (usually expressed either as the makespan or time to build the whole set of parts, or as a due-date related criterion assuming that each part has a due date).
- *Build volume type* This refers to the nature of the volume(s) where the set of parts are to be simultaneously produced. First, it can be considered that the set of parts has to be fit either into a single build volume, or into multiple build volumes. Furthermore, a build volume can be considered to be of fixed dimensions, or with (one or more) variable

Table 4 Main references on the selection of the AM technology

References	Type	G	F	M	C	E	S	Data type	Methodology to weight the aspects
Braglia and Petroni (1999)	AM	x	x	x	x			Deterministic	AHP
Wilson and Rosen (2005)	AM	x	x	x	x			Interval	Interval analysis
Lan et al. (2005)	AM	x	x	x	x			Fuzzy	Fuzzy synthetic evaluation, AHP
Fernandez et al. (2005)	AM	x	x					Stochastic	Utility theory
Mahesh et al. (2005)	AM	x	x	x				Fuzzy	Fuzzy sets
Byun and Lee (2005)	AM	x	x		x			Fuzzy	Modified TOPSIS
Rao and Padmanabhan (2007)	AM	x	x		x			Deterministic	Graph theory
Armillotta (2008)	AM	x	x	x	x			Deterministic	AHP
Lokesh and Jain (2010)	AM	x	x	x	x	x		Deterministic	AHP
Zhou and Chen (2010)	AM			x				Fuzzy	Fuzzy comprehensive evaluation
Rao and Patel (2010)	AM+CM	x	x		x			Fuzzy	Fuzzy AHP, PROMETHEE
Khrais et al. (2011)	AM	x		x				Fuzzy	Fuzzy sets
Chakraborty (2011)	AM+CM	x	x		x			Deterministic	MOORA
Munguia et al. (2011)	AM+CM	x	x		x			Fuzzy	Fuzzy logic, ANN
Vahdani et al. (2011)	AM	x	x		x			Fuzzy	Modified TOPSIS
Ic (2012)	AM	x	x		x			Deterministic	TOPSIS + design of experiments
Mahapatra and Panda (2013)	AM	x	x		x			Fuzzy	fuzzy TOPSIS, grey relational analysis
Roberson et al. (2013)	AM	x		x	x			Deterministic	Ranking system
Wang et al. (2013)	AM	x	x		x			Deterministic	Grey relational analysis + design of experiments
Junior et al. (2014)	AM		x	x	x			Deterministic	Weighted average

Table 4 continued

References	Type	G	F	M	C	E	S	Data type	Methodology to weight the aspects
Liao et al. (2014)	AM				x		x	Deterministic	DEMATEL, VIKOR
Vinodh et al. (2014)	AM+CM	x	x	x	x			Fuzzy	Fuzzy VIKOR
Zhang and Bernard (2014)	AM	x	x	x	x			Deterministic	Grey incidence analysis
Achillas et al. (2015)	AM+CM			x	x			Fuzzy	ELECTRE III, DEA
Çetinkaya et al. (2017)	AM			x	x	x		Fuzzy	Fuzzy AHP, PROMETHEE
Han and Jia (2017)	AM+CM				x			Deterministic	MILP, differential evolution algorithm
Peko et al. (2018)	AM		x	x	x			Fuzzy	Fuzzy AHP, PROMETHEE
Khamhong et al. (2019)	AM		x	x	x		x	Fuzzy	Fuzzy AHP
Prabhu and Ilangkumaran (2019a)	AM		x	x	x			Fuzzy	Fuzzy AHP, VIKOR, ELECTRE III
Prabhu and Ilangkumaran (2019b)	AM		x	x	x			Fuzzy	Fuzzy AHP, grey relational analysis-TOPSIS
Justino Netto et al. (2019)	AM	x	x	x	x			Deterministic	AHP
Chen and Wu (2021)	AM	x	x	x				Fuzzy	Fuzzy AHP
Ransikarbum and Khamhong (2021)	AM	x	x	x	x		x	Fuzzy	Fuzzy AHP, TOPSIS
Sharma and Dixit (2021)	AM+CM				x			Fuzzy	Fuzzy sets

G: Geometric, F: Functional, M: Manufacturing/quality, C: Costs, E: Environmental, S: Subjective information included dimensions. In turn, for the multiple build volumes case, the volumes can be considered identical, or heterogeneous.

The classification by Araújo et al. (2019) includes a fourth parameter not related to the type of decision problem, but to the characteristics of the instances where the solution procedures for the decision problem are to be tested (e.g. different number of parts and different number of complexity of the parts in the testbed problems). Therefore, this criterion will not be discussed here.

4.2.2 Evolution and problem variants

The first application of OR techniques for the AM nesting problem is Wodziak et al. (1994), who use Genetic Algorithms to solve the 2D version of the problem with the objective of minimizing the input, while Ikonen et al. (1997) address the 3D version for the first time. Subsequent improvements to their method in terms of computation times are provided by Dickinson and Knopf (1998), Hur et al. (2001), and Dickinson and Knopf (2002). While other objectives have been considered (see Table 5 for a summary), the first attempt to integrate different objectives (including build time, support structures, or part quality) is carried out by Gogate and Pande (2008).

Most of the referees addressing the 3D version of the problem use variations of the so-called Deepest Bottom-Left-Fill (DBLF) heuristic, which considers the deepest position in the build volume, packing the parts as close to the bottom and left (in that order) on the deepest level as possible. This approach has been usually combined with metaheuristics, being the main challenge to achieve a proper trade-off between the quality of the solution (i.e. the minimization of the gaps in the build volume) and the computational effort (which increases as the volume of the part is coded in a more accurate manner and with the strategy chosen to place the parts). A recent study regarding this trade-off is Araújo et al. (2020b). Regarding the metaheuristics employed, it is noteworthy that the overwhelming majority of contributions use Genetic Algorithms (see Table 5).

4.3 Scheduling

4.3.1 Background and definition

The scheduling problem in an AM context—also denoted in the literature as the AM *production planning* problem—can be described as follows: a set of parts have to be build on one or more AM resources (machines), each one with its own characteristics (i.e. different build volume, different production time/costs). The problem consists of assigning the parts to builds (jobs), allocating these jobs to the AM machines, and sequencing these jobs in the machines. Other usual constraints include eligibility constraints (not all parts can be built in any machine, due to e.g. build volume or type of material), due dates, etc.

Unless it is assumed that only is assigned one part per build (which may not be realistic in some scenarios), scheduling is, in principle, tightly connected to the nesting problem discussed in Sect. 4.2. However, the nesting problem may be simplified by considering the grouping of parts solely based on their volume and/or area (recall the simplification carried out in the nesting problem to transform the 3D bin packing into a 2D packing), which makes the scheduling problem to be similar to that of scheduling batch machines. Nevertheless, in the latter problem, the batch processing time is determined by the largest processing time,

Table 5 Main references on the AM nesting problem

References	Dim	Objective function	Build volume	OR technique
Wodziak et al. (1994)	2D	Input min	Single fixed	Genetic algorithms
Ikonen et al. (1997)	3D	Input min	Single fixed	Genetic algorithms
Dickinson and Knopf (1998)	3D	Output max	Single fixed	Genetic algorithms
Hur et al. (2001)	3D	Input min	Single, variable height	Genetic algorithms
Dickinson and Knopf (2002)	3D	Output max	Single fixed	Heuristic
Zhang et al. (2002)	3D	Min. build height	Single, variable height	Simulated annealing
Stoyan et al. (2005)	3D	Input min	Single, variable height	Mathematical modelling
Canellidis et al. (2006)	2D	Output max	Single fixed	Genetic algorithms
Egeblad et al. (2007)	3D	Input min	Single, variable height	Greedy local search
Gogate and Pande (2008)	3D	Input min	Single, variable height	Genetic algorithms
Egeblad et al. (2009)	3D	Input min	Single, variable height	Guided local search
Egeblad (2009)	3D	Input min	Single, variable height	Guided local search
Chernov et al. (2010)	3D	Input min	Single, variable height	Mathematical modelling
Lutters et al. (2012)	3D	Input min	Single, variable height	Local search
Baumers et al. (2013)	3D	Output max	Single fixed	Heuristics
Canellidis et al. (2013)	2D	Output max	Single fixed	Genetic algorithms
Wu et al. (2014)	3D	Multiobjective	Single, variable height	Multi-objective genetic algorithms
Liu et al. (2015)	3D	Input min	Single, variable height	Local search
Chen et al. (2015)	3D	Input min	Single, variable height	Heuristics
Canellidis et al. (2016)	2D	Output max	Single fixed	Genetic algorithms
Verkhoturov et al. (2016)	3D	Input min	Single, variable height	Greedy local search
Zhang et al. (2016)	2D	Multiobjective	Single fixed	Genetic algorithms
Zhang et al. (2018)	2D	Input min	Single fixed	Genetic algorithms
Jiang et al. (2019)	2D	Output max	Single, variable height	Heuristics
Araújo et al. (2020b)	3D	Min. build height	Single, variable height	Heuristic, genetic algorithms

which is not the case here, where the processing time of the build is usually estimated as a function of the physical characteristics of the parts included in the job.

As a result, not only the processing time of the build results from solving the scheduling problem, but—since the underlying nesting problem is not addressed—also an estimate of the processing time of each build has to be provided to compute the fitness of the allocation/sequencing. Several models have been developed in the literature. The simplest model (Freens et al., 2016) assumes that the processing time of the build is essentially determined by the build height, which in turn depends on the total volume of the parts allocated to the build. In perhaps the most employed model, the processing time of the build is a linear combination of the sum of the volumes of the parts in the build plus the maximum height of the parts in the build, such as in Kucukkoc et al. (2016), or simply the sum of the volume plus the height of each job in the case of the SLS technology, see Altekin & Bukchin, 2022). Finally, other papers present sophisticated estimation models using machine learning (see Baumung & Fomin, 2019 or Yamashiro & Nonaka, 2021), or a regression model calibrated from empirical data (Aloui & Hadj-Hamou, 2021).

4.3.2 Evolution and problem variants

The first reference addressing the AM scheduling problem is Freens et al. (2016), who address the problem of allocating a set of parts to builds of different AM machines. The problem is modelled as an extension of the classical bin packing problem (being the parts the bins, and the build volume the size of the bin). The objective here is to minimize the number of builds required. After this seminal contribution, several authors have addressed different layouts and objectives. Oh et al. (2020a) perform a recent review on the contributions on the nesting and scheduling problem, although given the interest of the topic, many references have been added since.

Apart from the variants originated from the fact of considering different objectives and machine layouts, one interesting variant of the AM scheduling problem takes into account that it is possible to build a part as a whole, or split it into several components that are built and assembled later. In this manner, in general, different *processing alternatives* to complete a job can be considered, and some references (Kim et al., 2017 or Kim & Kim, 2020) introduce this degree of flexibility that cannot be found in traditional batch scheduling problems.

Another variant of the scheduling problem appears if not all the set of parts have to be printed, as it might be that it is not profitable for the company in order to better utilise the build volume, or in the case that the costs exceeds the benefits. This problem is referred as the *Order Acceptance and Scheduling (OAS) AM* problem. The first reference addressing this variant is Ransikarbum et al. (2017), and it has been also later addressed by other authors—see Table 6 for a summary, also considering its dynamic counterpart (i.e. not all parts/orders are known at the beginning of the decision period).

Along to the papers in Table 6, Ziegler et al. (2021) combine simulation and MILP for nesting (and possibly) scheduling, but no further details are provided regarding the characteristics of the model, as it is discussed in the context of a whole production control system for additive-subtractive manufacturing.

In a recent contribution, Kucukkoc (2021) shows the intimate connection between scheduling and nesting, proving that the minimization of the build area does not necessarily correspond to minimizing the makespan. In other words, the best solution in terms of nesting does not lead to the best solution in terms of scheduling. As a consequence, the author points to the need of simultaneously addressing both problems.

Table 6 Main references on the AM scheduling problem

References	Problem	Context	Objetive	OR technique
Freens et al. (2016)	S	SM	Min. cost function	Mathematical model
Kucukkoc et al. (2016)	S	RM	Min. production costs	Mathematical model Heuristics
Kim et al. (2017)	S	PM/PA	Min. makespan	Matematical model Genetic Algorithms
Ransikarbum et al. (2017)	OAS	RM	Multiobjective (costs, time)	Mathematical model
Li et al. (2017a)	S	RM	Min. average production costs	MILP model Constructive heuristics
Oh et al. (2018c)	NS	R	Min. cycle time	Heuristics
Dvorak et al. (2018)	NS	RM	Min. makespan, tardiness	Constraint programming constructive heuristics
Kucukkoc et al. (2018)	S	RM	Min. maximum lateness	Genetic algorithms
Fera et al. (2018)	S	SM	Min. lateness/earliness costs	Genetic algorithms
Chergui et al. (2018)	NS	PM	Min. tardiness	MILP model, heuristic
Li et al. (2018)	OAS	RM	Maximize profit	Metaheuristic (Optimal foraging)
Stein et al. (2019)	OAS	RM	Max. revenue	MILP model
Kucukkoc (2019)	S	R	Min. makespan	MILP model
Li et al. (2019b)	OAS	R	Max. profit	Mathematical model Heuristic

Table 6 continued

References	Problem	Context	Objetive	OR technique
Li et al. (2019a)	OAS (dynamic)	R	Max. profit	Heuristic
Wang et al. (2019)	NS	R	Max. nesting rate	Heuristic
Luzon and Khmelnitsky (2019)	S	SM, F	Min. exp. makespan, flowtime	Queueing theory
Fera et al. (2020)	S	SM	Min. lateness/earliness costs	Tabu search
Agostino et al. (2020)	S (dynamic)	R	Min. response time	ANN, ARIMA
Zhang et al. (2020)	NS	R	Min. makespan	Evolutionary algorithm
Kim and Kim (2020)	S	P/PA/SU	Min. makespan	Mathematical model Genetic Algorithms
Alicastro et al. (2021)	S	SM	Min. makespan	Iterated local search
Rohaninejad et al. (2021)	S	R	Min. weighted tardiness	Hybrid GA, Local Search
Aloui and Hadj-Hamou (2021)	NS	R	Min. total lateness	MILP model, heuristic
Kucukkoc et al. (2021)	NS	R	Min. total tardiness	Genetic algorithms
Altekin and Bukchin (2022)	NS	RM	Minimize costs, makespan	MILP model
He et al. (2022)	S (incl. delivery)	SM	Min. delivery times, transportation costs	MILP, Branch and price
Kim and Kim (2022)	S (sequence-dependent setup)	SM	Makespan	MILP model, heuristic, revised metaheuristics

Problem: S-Scheduling, NS-Nesting & scheduling, OAS-Order Acceptance and Scheduling. Context: SM-Single Machine, PM-(identical) Parallel Machines, RM-Unrelated (parallel) machines, PA-Processing Alternatives, SU-Set-Ups, F-Failures

4.4 Part allocation in a distributed AM network

4.4.1 Background and definition

As discussed before, one of the business model that can be implemented using AM is that of the cloud manufacturing. In this decision problem, there is a set of AM resources, each one with its own technical characteristics (material, max. physical dimensions of the parts that can build, accuracy, etc.) possibly belonging to distinct companies and thus located in different places. A centralised system in place receives job orders from a set of customers that must be allocated to the different resources in order to achieve certain common goal. Order rejection is sometimes possible (i.e. not all job orders have to be processed) and, in contrast to scheduling models, the capacity of each resource is considered at an aggregated level (i.e. there is no considerations regarding the grouping of parts in a build, but a constant build time of each part is considered). Apart from the aforementioned capacity constraints, usual constraints may include the following:

- Size (S). There is a maximum build volume, which is AM resource -specific.
- Maximum acceptable costs (C). In some references, the maximum cost that can be accepted by the customer is considered a constraint.
- Material type (M). Some references include the material type that can be used in the AM resources. A special case of material type is Luo et al. (2020), where the colour of the part is considered.
- Raw material (R). The availability of raw materials can be seen as a restriction to fulfill the customer orders.
- Quality (Q), usually in terms of precision or printing accuracy, but in some reference (e.g. Luo et al., 2020) it also refers to the failure rate of the AM machine.
- Transportation (T). In some references, constraints referring to the location of the AM resources and the time/cost/distance from the customers is considered to be a constraint.

4.4.2 Evolution and problem variants

The first works presenting this problem are Mai et al. (2016) and Rudolph and Emmelmann (2017), where the architecture of such centralised system is described. Although the problem of matching the demand with the existing resources in the cloud is identified as an NP-hard problem, the solution procedures are only hinted and details are not provided in these references. Note that this problem can be seen as a special case of the problem of task allocation in a cloud manufacturing context (i.e. without specific AM features such as the size of the parts), a problem for which different contributions exist. In this section, the focus is set on the specific AM case (in this regard, see Cui et al., 2022 for a recent overview—not OR-focused—of AM in cloud manufacturing). Table 7 summarises the main contributions on the topic.

An interesting problem variant arises taking into account that, in the context of cloud manufacturing, setting the price is far from trivial issue, and it largely determines the decisions of the subsequent allocation models. The paper by Pahwa and Starly (2020) precisely addresses AM pricing using Machine Learning techniques.

Table 7 Main references dealing with allocation in AM cloud manufacturing

References	Constraints	Order rej	Objective	Techniques
Zhou et al. (2017)	S, M, Q, C, T	No	Min. average completion time	Heuristics
Zhou et al. (2018)	S, M, Q, C, T	No	Min. average service time	Genetic algorithms
Mashhadi and Salinas Monroy (2019)	S, Q, R, T	No	Min. overall costs	Heuristic (auction)
Liu et al. (2019)	S, M, Q	No	Min. makespan	Game theory
Chen and Wang (2019)	T	No	Max. workload balance	Mathematical programming
Chen (2019)	T	No	Min. Fuzzy makespan	Fuzzy logic
Mashhadi and Salinas Monroy (2020)	R	Yes	Max. revenue	Machine learning
Luo et al. (2020)	S, M, Q	No	–	Bipartite graph-based matching heuristic
Ma (2020)	–	No	Min. environmental impact	Mathematical programming
Liu et al. (2021)	S, M, F	No	Min. weighted makespan, cost, quality	Game theory genetic algorithms

5 Operating AM

5.1 Optimal build orientation

5.1.1 Background and definition

Since in AM the part is build layer by layer, the object grows along a so-called *build direction*, and this affects a number of properties (including cost, time and quality) of the manufactured part. Generally speaking, the layers are parallel to the build platform, so the part is built along the Z-axis of the AM machine, see Fig. 3. Therefore, given a part to be built (usually represented by a 3D model of the part), the model can be *placed* on the building platform (and then the build direction and the Z-axis of the model coincide), or it can be rotated along the X- and Y-axis as in the right pictures of Fig. 3. Thus, the tuple (α, β) represents a build orientation and determines how the part is to be built layer by layer. In turn, this determines a number of properties of the part, including mechanical characteristics (i.e. the tensile and yield strength along the layer are generally greater than among layers), quality features (i.e. dimensional errors and surface roughness appear more commonly among layers), building time (e.g. the building height is clearly affected by the part orientation), and building costs (such as e.g. energy costs or post-processing costs, clearly affected by the aforementioned building time and quality), among others.

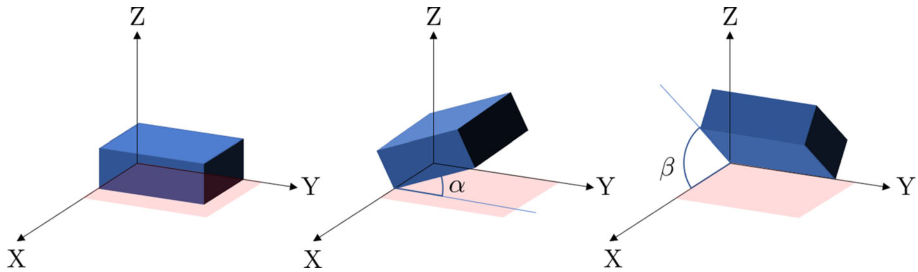

Fig. 3 Schematic representation of the build orientation problem

The optimal build orientation problem (also denoted as *optimal part orientation*) can be thus defined as follows: given a part to be processed in an AM resource, determine the best build orientation according to a number of production objectives. This problem has been intensively dealt with in the relevant literature, and the methods to address it can be classified either as one-step methods, or two-step methods. One-step methods develop an exhaustive search algorithm or use an optimisation technique to obtain a solution from the solution space. Basically, given a 3D model of the part and a set of production objectives, these methods iteratively improve the best-so-far solution by first generating a new build orientation (usually by rotating the part step by step along one of the axis), and then obtaining estimates of the values of the production objectives if the part is produced according to this build orientation.

In two-step methods, the first step consists on moving from an infinite search space (all possible build orientations) to a finite search space composed of a set of Alternative Build Orientations (ABOs). This set is obtained by several techniques (including feature recognition, convex hull generation, or facet clustering). The second step consists of using some optimisation method—usually multicriteria—to select one build orientation from the set (the so-called OBO or Optimal Build Orientation). In these methods, the computational effort required to evaluate many build orientations that do not essentially differ from others already explored is saved. Instead, rules based on users' preferences or desired patterns for the orientation of the part are derived so a finite set of build orientations is obtained. The main problem of these methods is that, no matter what technique is used to select the set of alternative build orientations, there is no guarantee that the optimal one is included in the set. Furthermore, some of the selection techniques have limitations and cannot deal with free form parts.

5.1.2 Evolution and problem variants

The first work dealing with the problem is Frank and Fadel (1995), who present an expert system based on users' interviews to help selecting the best build orientation. Lan et al. (1997) find that there is a relationship between build time and build height (as it is related to the number of layers), and use this fact to propose a specific geometric algorithm for the problem. The model describing the relationship between build time and height is later refined by several contributions, such as Xu et al. (1997), Thrimurthulu et al. (2004), Khodaygan and Golmohammadi (2018), Griffiths et al. (2019), or Di Angelo et al. (2020a), to account for other aspects influencing the build time such as the layer thickness, the generation of support structures, or the volume.

Since then, the optimal build orientation problem has been intensively dealt with in the relevant literature, and different papers reviewing the techniques employed for optimal build orientation—apart from an early overview by Kulkarni et al. (2000)—are Pandey et al. (2004), Taufik and Jain (2013), Canellidis et al. (2016), Di Angelo et al. (2020b) and recently Qin et al. (2021). More than 70 contributions can be identified, therefore it is not feasible to provide a summary of references as in other sections, and instead the interested readers are referred to the aforementioned reviews.

Given the inherent multi-objective nature of the problem, many approaches either weight the production objectives, or address the multi-objective optimisation problem, either using Pareto-fronts, or Multi Criteria Decision Making techniques such as DEA (Ransikarbum & Kim, 2017), AHP (Ransikarbum et al., 2021), TOPSIS (Di Angelo et al., 2020a), or fuzzy multi-attribute decision making (Qin et al., 2019).

In systems where the parts arrive one by one and the size and shape of the next coming parts cannot be predicted, it is (in some cases prohibitively) time-consuming to optimise the build orientation for each part. In these cases, a build orientation decision method or *build orientation policy* can be applied. Similarly to e.g. dispatching rules, these policies are based on a characteristic of the job that can be easily identified. Some worth-noting policies are the *Laying Policy* (LP) where the part is placed so it has its lowest height, or the *Standing Policy* (SP) where the part is placed so it has its highest height. A set of these policies are investigated in Oh et al. (2020b).

Finally, it is worth mentioning that most of the papers focus on finding the optimal build orientation for a single part. However, since a build usually consists of group of parts, an optimal (common) build orientation should be found. This problem is addressed by Zhang et al. (2017) using a two-step procedure.

5.2 Parametrization

The parametrization of the AM technology refers to determining the most suitable combination of operational parameters for a given AM technology. Clearly, this decision problem is completely technology-dependent.

There are not so many references using OR to tackle this problem. Among them, Jiang et al. (2020) or Sing et al. (2021), who use Machine Learning techniques to determine the best combination of parameters, can be cited, or Toklu et al. (2020), who use harmony search to optimize the nozzle movement for the additive manufacturing of concrete elements. In a more recent paper, a multi-objective differential evolution algorithm to optimize the parameters is used by Cruz et al. (2021).

6 Conclusions

In the previous sections, the different contributions on using OR techniques to solve AM-related decision problems have been classified and presented. Several conclusions can be obtained after this overview:

1. *New decision problems* The adoption of AM brings up *new* decision problems in the context of OSCM, either because these are technology-specific problems that do not appear in other types of manufacture (e.g. optimal build direction problem), or due to the emerging business models that AM enables (e.g. order allocation in a AM setting). The number of contributions to these decisions problems is highly variable, and there are some areas where it is clear that there is need of additional research. For instance, from the viewpoint of a research agenda, a high-priority topic would be to establish the

conditions for the efficient design of an AM SC, as the design outcome clearly would influence subsequent decisions, such as AM allocation or scheduling.

2. *Integrated decision-making* The possibility of concentrating all production steps into a single operation enabled by AM is at the heart of its disruptive nature and it makes the decision-making process extremely complex, since OSCM decisions that traditionally were separated or loosely integrated (e.g. planning vs. detailed scheduling vs. technical configuration of the machines) are now tightly connected (e.g. AM allocation vs. scheduling vs. nesting vs. optimal build orientation). As a result, the attempts to tackle single decision problems in an isolated manner should be seen as a first attempt to provide solution procedures for these extremely difficult problems, but it is clear that there is need of additional research to (a) integrating the different decision problems and (b) provide coordination schemes among the different decisions.
3. *Theory building* Most of the contributions use OR in an ad-hoc manner to solve specific problems. In this regard, little or no theory at all has been built around the different decision problems, unless these are closely connected to classical OR problems (e.g. the case of the nesting problem, or optimal build direction). There are hardly theorems or proofs that show properties of the space of solutions of the problems that might help in reducing the complexity of the problem, or in guiding the solution procedures. This is clearly another area where new contributions are needed.
4. *Solution procedures* Perhaps motivated by the scarcity of analysis and theory discussed in the previous item, it seems that in some cases, the selection of the solution procedure has not been subject of a deep reflection on the merits of the different options. In some contributions, the NP-nature of the problem has discouraged researchers to even try the formalization of the problem using some standard OR techniques (such as e.g. MILP models) that could, at worst, be useful to test the quality of the approximate solution procedures that have been proposed and that, at best, could have been used to understand some properties of the problem and hand and/or to combine them with approximate procedures in order to develop efficient matheuristics.

7 Future research lines

7.1 Problem extensions

Even if the number of contributions in the area is substantial, many of them address rather simplified versions of the corresponding decision problems. In this regard, there is ample room for research by tackling extensions of the problems presented in this overview. Among the many topics that can be researched, perhaps one of the most recurrent is that of AM scheduling taking into account the distribution of the parts to the final customer. In this regard, the paper by Yilmaz (2020) is the first to explore this avenue with the objective of makespan minimization, while Demir et al. (2021) address the so-called 3D printing and transportation problem (3DTP), where a set of customer orders have to be manufactured (printed) and delivered by a set of distributed machines. They formulate a MILP model with the objective to minimize a weighted function of the different costs integrating the process. The above problem is essentially the same to that by Chen and Lin (2019), where it has to be decided if an incoming customer order is to be manufactured in one of the (distantly located) facilities so he/she arrives just-in-time to the facility.

Along with the integration of transportation, another aspect representing a problem extension is the joint scheduling of the Material Handling Systems to load and unload the AM resources. The papers by Kim and Lee (2017) and Kim and Lee (2021) address this problem in order to minimize the cycle time using Petri nets.

7.2 Studying the overall impact of the decisions in AM

Given the high number (see item #1 in the conclusions) and their close interconnection (see item #2 in the conclusions) of the different decisions potentially involved in AM, it seems interesting to analyse their impact in the overall performance of the company and its SC. For instance, most of the contributions in operating in AM emphasize the importance of capacity utilization (e.g. build orientation, nesting, scheduling, etc), but up to now there are few evidences about whether using sophisticated procedures to (nearly) optimally solve these NP complex problems actually reaps greater benefits in terms of customer service or revenue than naive ones. For instance, it is unclear if, in a AM cloud, quickly responding to the customer request with a rough estimation of the time to process the order is better than producing an accurate evaluation of this time according to the many capacity constraints, a process for which much higher detailed information and computational effort is required. If the answer is yes, then simple and fast rules (or policies) could be employed instead of the sophisticated solution procedures that are the norm in the contributions up to now. In this regard, Machine Learning techniques could provide estimates of the time required to build a part or a set of parts, an area where the only contribution identified is Oh et al. (2021b).

Finally, since it is more than likely that the answer to the aforementioned question depends on the specific AM scenario, it would be interesting to determine the main factors that make one approach to be more suitable than the other. Although some work is being carried out in this direction (in Oh et al., 2018c it is investigated the effect of standing policies in front of laying policy, concluding that the former is better in terms of reducing the cycle time of the parts), clearly much more work is needed in this regard.

7.3 The trend towards the integration

Given the interrelated nature of some of the decisions that have been traditionally addressed in a separate way, there is a clear trend towards the integration of these related problems. Clearly, given the differences in the granularity and accuracy of the information required, it possibly does not make sense to integrate decisions in the DAM domain with the rest of the decisions, but this is not the case among decisions within PAM or OAM, or among decisions belonging to either of these areas. In Table 8 some recent work indicating the integrated decisions is presented. As it can be seen from the table, there are only a handful of references, and some of the decisions (e.g. AM parametrization or the selection of AM technologies) have not been integrated so far. Clearly, these areas (along with the improvement in the existing integrated solution procedures) may constitute a fruitful research area.

Another avenue on the integration of decisions lies in the inclusion of design aspects in the OSCM decisions. Although AM technology can, in principle, build a product as a single part, in the case of many bulky products, developing large-scale machines may not be practical in economic (such as large fixed investment) or performance (such as small scalability) terms. Therefore, a solution is to decompose the products into parts that can be better fitted in the AM machines and later assembled. This *part decomposition* problem has been addressed by different authors, usually as an isolated design problem (see the review

Table 8 References integrating different decisions

References	PAM				OAM	
	Selection AM	Nesting	Scheduling	Alloc. AM cloud	Optimal build orientation	AM Param.
Canellidis et al. (2016)		x			x	
Oh et al. (2018c)		x	x		x	
Griffiths et al. (2019)		x			x	
Zhang et al. (2020)			x		x	
Ransikarbum et al. (2020)			x	x		
Simeone et al. (2020)		x		x		
Kapadia et al. (2021)		x	x			
Che et al. (2021)		x	x		x	
Darwish et al. (2021)			x	x		
Calabrese et al. (2022)	x	x				

by Oh et al., 2018b). However, the interdependency between this design problem and the subsequent manufacturing problems (build orientation, nesting and possibly scheduling) are clear. In this regard, the work by Oh et al. (2018a), who propose a two-step method to first decompose the parts and later solve the (2D) nesting problem using Genetic Algorithms, is the only contribution identified.

7.4 OSCM decisions in hybrid systems

Despite the success of AM technologies, it is quite unlikely that, at least in the short term, it would entirely replace conventional ones in many scenarios as in some cases the low throughput and relatively high costs of AM would make them to coexist with traditional ones. Furthermore, even if all the parts are manufactured using AM, there are evidences (see e.g. Thürer et al., 2021) suggesting that the post-processing step is a key factor for AM performance. Therefore, special attention to post-processing steps (unpacking, cleaning etc.) has to be paid in some cases (Ziegler et al., 2021) as AM-built parts often have insufficient surface quality and dimensional accuracy for subsequent applications. All these aspects open the field for studying OSCM decisions in hybrid (i.e. a blend of AM and conventional manufacturing) scenarios. Although there are some works in this area, it has been noted that there is a lack of papers integrating pre- and post-treatment operations (Aloui & Hadj-Hamou, 2021). Regarding the inclusion of post-treatment operations, the works by Kapadia et al. (2019), Rossi and Lanzetta (2020), Thürer et al. (2021) and Arik (2021) have been identified. Kapadia et al. (2019) use a combination of simulation and Genetic Algorithms to study the impact of different scheduling policies on the cycle time and throughput of an AM facility, including post-processing operations. In Rossi and Lanzetta (2020), metaheuristics are employed for the scheduling problem in a hybrid additive/subtractive setting. Thürer et al. (2021) use simulation to investigate the performance of different sequencing rules in an AM jobshop where the post-processing step is a constraint on the system. Finally, Arik (2021) considers the problem of scheduling a single AM machine that later assemble the parts. To solve this problem, a MILP model and an ad-hoc heuristic are proposed. Despite these recent works, OSCM decisions in hybrid system represent an opportunity for research, particularly in the field of AM scheduling where flowshop and jobshop models could be built upon the existing (single- and parallel-machine) models (Oh et al., 2020a).

7.5 Emerging AM technologies: yet new decision problems

Given the close interlink between the technology and the decision support in AM, particularly in the PAM and OAM areas, it is considered that there are still many open issues (Manco et al., 2019) due to the technological advances. An example happens with multiple-material AM technologies (such as the multiple material stereo lithography), which allows the build of a single part using different materials. This technique may ease some decisions—such as the scheduling as parts from different materials could be grouped together, but at the same time requires to establish a schedule for the own build. A paper exploring this technology is Kim et al. (2010). The need of such schedule also happens in the fused filament technology if multiple extruders work in parallel to build a paper, as it is addressed in Jin et al. (2019) by means of a MILP model and *ad-hoc* heuristics. These are only two examples that show that the need for operations research in this area is continuously expanding and evolving.

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