Computers & Industrial Engineering 197 (2024) 110602

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

An iterative price-based combinatorial double auction for additive manufacturing markets

Juan De Antón [a,*], Félix Villafáñez [a], David Poza [a], Adolfo López-Paredes [a,b]

[a] GIR INSISOC – Department of Business Organisation and Market Research, School of Industrial Engineering, University of Valladolid, Valladolid, Spain
[b] Department of Economics and Business Management, Universidad de Málaga, Málaga, Spain

ARTICLE INFO

Keywords:
Additive manufacturing
Combinatorial auctions
Electronic platforms
E-procurement
Iterative bidding

ABSTRACT

The increasing adoption of additive manufacturing (AM) in the industrial sector is leading to an imbalance between supply and demand of additively manufactured subcomponents: companies demanding AM services require very specific products and AM suppliers differ widely in their capabilities. Some existing proposals aim to help match supply and demand by merely making customer–supplier allocations. Only a few recent works go beyond allocation issues and propose market mechanisms to also address pricing aspects. However, we observe that these mechanisms do not fully exploit the potential of additive manufacturing techniques. The aim of this paper is to design a market mechanism that considers the particularity of AM techniques, wherein suppliers can benefit from manufacturing multiple heterogeneous parts from multiple customers in the same build area to increase production throughput. This market mechanism has been implemented as an iterative combinatorial double auction that adapts to this feature of the AM market: customers will bid to get their orders produced and suppliers will submit asking quotes to win the production of combinations of those orders. The mechanism solves the allocation and pricing of AM orders while seeking the maximization of social welfare. The procedure is simulated in a theoretical environment to evaluate its performance and to identify the most appropriate conditions for its implementation in a real environment. Unlike other existing proposals for client-supplier allocation mechanisms in additive manufacturing, the proposed mechanism allows a single supplier to produce a combination of orders from different clients, leading to a pricing system that maximizes social welfare without participants disclosing sensitive information.

1. Introduction

Additive manufacturing (AM) technology has transformative and disruptive potential in almost every industry (Byskov & Vedel-Smith, 2023; Spieske et al., 2023). However, due to the high cost of high-performance AM machines —especially metal AM machines— and the need for great technology expertise, it is becoming increasingly common for most industrial companies to outsource the production of additively manufactured subcomponents to specialized AM manufacturers (Khajavi et al., 2020; Kucukkoc, 2019; Li et al., 2019). These consequent changes in the supply chain are leading to a redesign of production networks in which new markets are emerging (Calignano & Mercurio, 2023; Meyer et al., 2021; Priyadarshini et al., 2023). These markets involve subcomponent-demanding companies (i.e., customer companies) and companies that use additive manufacturing techniques to provide the demanded subcomponents (i.e., supplier companies).

However, the lack of coordination between supply and demand in the current AM service transactions evidences that these markets are not yet fully developed (Wu et al., 2022; Zehetner & Gansterer, 2023; Zhou et al., 2017; 2018). On one side, demanders of AM services require very specific products with detailed requirements. On the other side, since AM is not yet a mature technology, AM manufacturers may differ widely in their capabilities: they need to evaluate if they are capable of manufacturing the specific parts demanded to them and analyze whether it is profitable to place the orders. Consequently, it may be difficult for demanders to find an appropriate supplier (Friedrich et al., 2022; Rayna et al., 2015). This process results in large transaction costs for both demanders and suppliers (Tsay et al., 2018), which are even worsened due to the high degree of customization and complexity of parts in AM. In view of the growth of these markets, one of the key

* Corresponding author at: Paseo Prado de la Magdalena s/n, 47011 Valladolid, Spain.
E-mail addresses: juan.anton@uva.es (J. De Antón), felixantonio.villafanez@uva.es (F. Villafáñez), david.poza@uva.es (D. Poza), loppar@uma.es (A. López-Paredes).

https://doi.org/10.1016/j.cie.2024.110602
Received 5 October 2023; Received in revised form 10 July 2024; Accepted 23 September 2024
Available online 24 September 2024

challenges is how to use the Internet and advanced IT techniques to eliminate the unbalanced demands and supplies of AM resources in a distributed environment (Cui et al., 2022).

The emergence of electronic (online) platforms in the AM procurement sector provided an environment that facilitated contact between a large number of customer companies demanding a wide variety of customized products and a distributed network of independent suppliers (Liu et al., 2021; Mendonça et al., 2022; Zhong et al., 2022), thus drastically reducing transaction costs (Morar et al., 2023; Yang et al., 2021). These first platforms helped match supply and demand by merely facilitating bilateral conversations between customers and suppliers, but they did not actually make any customer–supplier allocations (Holzmann et al., 2020). For this reason, in recent years there have been proposals of mechanisms that actively allocate orders from demanders to suppliers, eliminating negotiation and selection tasks from market participants, thereby further reducing transaction costs (Tolio et al., 2023). Although these mechanisms successfully address the allocation problem, pricing concerns are left unaddressed in most of these works (Framinan et al., 2023; Mashhadi & Salinas Monroy, 2020). As shown in the literature review (see section 2), only a few recent works go beyond allocation issues and propose market mechanisms to address pricing aspects as well. However, we observe that these mechanisms do not fully exploit the potential of additive manufacturing techniques.

The aim of this paper is to design a market mechanism for a two-sided electronic platform that solves allocation and pricing problems while seeking the maximization of social welfare in the emerging AM market for subcomponents. This proposed mechanism considers the particularity of AM techniques wherein suppliers can benefit from manufacturing multiple heterogeneous parts in the same build cycle to optimize resource utilization (Chergui et al., 2018; Ying et al., 2022; Zipfel et al., 2023). By occupying the maximum build area of the machines, AM manufacturers can increase production throughput. Consequently, suppliers would earn higher revenues from accepting a selected combination of orders from several customers than from accepting single production orders (De Antón et al., 2022; de Antón et al., 2023; Oh et al., 2020).

To leverage this property of AM, the market mechanism proposed in this paper is based on an iterative price-based combinatorial double auction that adapts to the AM environment. The platform gathers the two sides of the market: customer companies that request orders of 3D-printed parts and supplier companies with available AM resources. Customers will submit production orders of one or more parts to be 3D-printed[1] and suppliers will be given the opportunity to compete for combinations of the production orders submitted to the platform. A third actor called the platform (or *the auctioneer* at a later stage) is the agent who coordinates trade between customers and suppliers through an iterative auction procedure. Once the buying bids from customers and the selling bids from suppliers have been received, the platform will solve the allocation of orders through an iterative auction process. As a result, not only is an allocation obtained (i.e., determining which orders are manufactured by which supplier), but also the prices to be paid by the customers and the revenue for the suppliers are determined. This market mechanism, aimed at increasing social welfare, is simulated in a theoretical environment to evaluate its performance and identify the most appropriate conditions for its implementation in a real-world setting.

The rest of this paper is organized as follows. The related literature about e-platforms and mechanisms to match supply and demand in AM markets is reviewed in Section 2. Section 3 details the steps of the auction mechanism, while in Section 4 the algorithm for implementing the auction is described. A computational study of the auction is conducted in Section 5 and the results are discussed in Section 6. Lastly, Section 7 ends with the reached conclusions and proposals to further extend this work.

[1] In the submission, customer companies will send digital 3D files with the geometric information of the parts requested. Parts in the same production order are assumed to have the same production requirements (i.e., material, colour, surface quality, etc.).

2. Literature review

2.1. Electronic platforms in additive manufacturing

The initial platforms to emerge were those that simply connected demanders and suppliers to enable the exchange of AM services. An exhaustive list of this type of commercial platforms can be found in the works by Rayna et al. (2015) and Baumann & Roller (2017). However, these platforms merely acted as comparison sites and customers still needed to select suppliers individually. Consequently, transaction costs were little decreased, and market efficiency barely increased (Stein et al., 2020; Yang et al., 2021).

Platforms that actively coordinated supply with demand in AM markets started to emerge as a more efficient alternative. These platforms acted as intermediaries between demanders and suppliers and used matching mechanisms to determine the allocation of orders from demanders to suppliers, thus eliminating time-consuming negotiation tasks (Tolio et al., 2023). Besides addressing the allocation problem, platforms seeking a further market optimization also introduced pricing mechanisms to determine how to establish prices or to structure the market such that prices were set in a competitive manner (Einav et al., 2015; Mashhadi & Salinas Monroy, 2020). Table 1 summarizes the main proposals of platform mechanisms to optimize the market of AM services that have emerged since 2017. This table has been updated from the review conducted in De Antón et al., 2024. The platforms are classified based on whether they exclusively address the allocation problem or also consider pricing. It is noticeable that only five examples of platforms addressing both allocation and pricing have been found.

Numerous proposals of platforms that solve the allocation of orders from demanders to suppliers in the AM environment have emerged in recent years. Two main trends are identified in the mechanisms designed for these platforms: mechanisms centered in the matching between supply and demand, and mechanisms focused on providing overall production scheduling solutions.

Examples of mechanisms that exclusively address the matching between AM demanders and AM suppliers are found in the works by Luo et al. (2020), Yang et al. (2021) and Zhang et al. (2022). The first two works presented supply–demand matching methods based on graph theory, whereas the last proposal was based on complex networks.

Table 1
Main proposals of mechanisms for addressing the allocation of AM tasks to AM resources.

Reference	Allocation	Pricing	Auctions
(Zhou et al., 2017)	√		
(Zhou et al., 2018)	√		
(Pahwa et al., 2018)	√	√	√
(Liu et al., 2019)	√		
(Chen, 2019)	√		
(Mashhadi & Salinas Monroy, 2019)	√	√	√
(Luo et al., 2020)	√		
(Ma, 2020)	√		
(Mashhadi & Salinas Monroy, 2020)	√	√	√
(Stein et al., 2020)	√	√	
(Liu et al., 2021)	√		
(Yang et al., 2021)	√		
(Cui et al., 2022)	√		
(Wu et al., 2022)	√		
(Zhong et al., 2022)	√		
(Zhang et al., 2022)	√		
(Kang et al., 2023)	√		
(Zehetner & Gansterer, 2023)	√	√	√
(Gao, 2024)	√		

Although primarily focused on the matching method, several works also introduced scheduling concerns to provide an AM service matching and task scheduling solution. This research line includes the works of Zhou et al. (2017; 2018), where they proposed and extended a 3D printing service selection method to reduce delivery time of tasks from demanders to suppliers; the works of Liu et al. (2019; 2021), proposing non-cooperative selection methods based on game theory to schedule 3D printing tasks in a dynamic environment; and the works of Kang et al. (2023) and Gao (2024). While the last two works presented 3D printing service allocation solutions, Kang et al. (2023) seeks to maximize the net revenue of the platform, whereas Gao (2024) aims to minimize the makespan.

Alternatively, the literature also includes proposals that emphasize optimizing the allocation and scheduling of tasks for a network of 3D printers. Chen (2019) proposed a 3D printing cloud platform for the allocation and scheduling of tasks that considered uncertainty and early termination. Ma (2020) developed an optimization model that allocates printing tasks to a network of 3D printers while minimizing environmental impact. More recently, Cui et al. (2022) developed a platform prototype to interconnect distributed 3D printers in which a heuristic is applied to determine the proper assignment and schedule to the pool of available 3D printers. Similarly, Wu et al. (2022) proposed a cloud platform for centralized production scheduling through a network of 3D printers with real-time tracking. Shortly thereafter, Zhong et al. (2022) deployed a cloud AM platform that utilizes resource sharing to assign printing tasks to distributed 3D printers efficiently.

The reviewed works address the matching and allocation of tasks to resources in AM platforms and, in some cases, also integrate the scheduling of those tasks in their assigned resources. Notably, many of these works have flourished under the Cloud Manufacturing paradigm since it is suitable for the AM environment.[2] Although the works reviewed successfully deal with the allocation problem, pricing concerns are left unaddressed (Framinan et al., 2023; Mashhadi & Salinas Monroy, 2020). Indeed, they employ allocation mechanisms that are not market-oriented as they focus mainly on finding efficient scheduling solutions rather than improving the market's social welfare.

Only a few proposals for market-oriented electronic platforms that address both the allocation and pricing problems have emerged in the AM field. Stein et al. (2020) presented a market-based coordination mechanism aimed at raising social welfare in which pricing issues were considered. The mechanism was designed for a platform where AM suppliers with excess demand can temporarily outsource their production orders to other suppliers with idle resources. However, this mechanism regulates a unilateral market in which only providers participate, within a framework of collaborative manufacturing. Within this same collaborative framework, the proposal by Zehetner & Gansterer (2023) employs a combinatorial auction to resolve both manufacturing order allocation and pricing. Finally, we find cases such as Mashhadi & Salinas Monroy (2019; 2020) and Pahwa et al. (2018), where auctions are also employed as mechanisms to resolve both allocation and pricing, but in this case, they are implemented in a bilateral market involving both providers and demanders of AM.

After conducting this literature review, we found only five proposals that address both allocation and pricing mechanisms (Table 1). Of these five, four utilize auction mechanisms to solve both problems simultaneously. Given these findings, it is worthwhile to further explore these auction mechanisms to analyze their properties and their suitability for the additive manufacturing market.

[2] Cloud Manufacturing (CMfg) was introduced as a new service-oriented manufacturing model by (B. H. Li et al., 2010). It provided a centralized platform for sharing on-demand manufacturing resources and capabilities over the Internet. The combination of CMfg and AM has been recurrently highlighted as a promising means for improving the management of AM services (Baumann & Roller, 2017; Cui et al., 2022; Framinan et al., 2023; Shoeb et al., 2023; L. Zhang et al., 2020; Zhao et al., 2018; Zhou et al., 2018).

2.2. Auction mechanisms in AM markets

The literature review conducted has allowed us to identify only four proposals of e-platforms implementing auctions to coordinate AM markets (Table 1). Pahwa et al. (2018) presented a mechanism similar to a reverse auction in which buyers state their bid prices and the platform assigns a supplier that agrees with the price. In this mechanism, suppliers do not compete with each other as the platform internally solves the allocation. Later, Mashhadi & Salinas Monroy (2019) proposed a multi-item forward auction that allocates printing area to the winning buyers and determines prices. The mechanism, which is centrally managed by an AM cloud, pools manufacturers' resources to collaboratively satisfy demand. In Mashhadi & Salinas Monroy (2020), the previous auction was refined with a deep neural network that allowed an increase in the utility obtained from the allocation and pricing process. More recently, Monroy et al. (2023) have proposed a novel system architecture to ease the access of demanders and suppliers to the AM market based on their previous works on auction mechanisms.

Although the previous proposals offer solutions to the problem of allocation and pricing in additive manufacturing platforms, we observe that these mechanisms do not fully exploit the potential of the decentralized AM market: The reviewed mechanisms do not consider the particularity of AM techniques that enable manufacturers to enhance production throughput by producing many heterogeneous components in the same build area. Consequently, suppliers could benefit from a mechanism that allows them to combine orders from different customers. Also, we find two other improvement points as regards the auction features. First, the mechanisms reviewed are one-sided auctions where only buyers actively place bids, whereas suppliers play a passive role. Secondly, these mechanisms require auction participants to disclose private information for the auction to derive an efficient outcome.

The proposal of our paper is to design a market mechanism that adapts to the characteristics of the AM market while exploiting the advantages of using combinatorial auctions. Specifically, the market mechanism proposed is an iterative combinatorial double auction aimed at solving both the allocation and pricing problems while seeking the maximization of the social welfare in the AM market. Unlike existing mechanisms, this approach also incorporates a privacy-preserving strategy for the participants.

The only work proposing a combinatorial auction to coordinate an AM market is the recent article by Zehetner & Gansterer (2023). However, as we have seen in the previous section, it is used in a unilateral market context where only manufacturers participate under a collaborative production framework. In contrast, we aim to address the scenario of a bilateral market involving both AM providers and demanders of these services.

The market mechanism proposed in this paper gives AM suppliers the opportunity to combine orders placed by different customers and thereby benefit from a higher machine utilization. The combinatorial double auction used for its implementation leverages this feature of the AM market: customers will bid to get their orders produced and suppliers will submit asking quotes to win the production of combinations of those orders. The mechanism will then solve the allocation and pricing of AM orders while seeking the maximization of social welfare. To the best of the authors' knowledge, this is the first proposal of a market mechanism that allows matching supply and demand in AM markets while also enabling suppliers to manufacture combinations of customer orders, thus exploiting this peculiarity of additive manufacturing.

3. Auction mechanism

Auctions that allow bidding on item combinations are generally known as combinatorial auctions (Cramton et al., 2006). This auction variant is particularly interesting for the context of AM because, in contrast to the conventional single-part sequential production of traditional manufacturing systems, AM features complementarity in the production of parts (Bogers et al., 2016; De Antón et al., 2020; Kim & Kim, 2022). This occurs when producing a combination of items for different customers in the build surface of a single AM machine is more cost-effective than producing a very small number of parts for single customers (Canellidis et al., 2013; Y. Zhang et al., 2016). When items of an auction show complementarities, it is preferable for agents to place bids on combinations of items rather than just individual items. Combinatorial auction mechanisms have already been successfully applied in other allocation problems (radio spectrum, airport slots, truckload transportation, etc.). Recently, Palacios-Huerta et al. (2024) presented a survey of CAs that have been deployed in practice.

The auction designed in this work is a combinatorial auction with multiple customers and suppliers trading multiple heterogeneous goods. This particular type of combinatorial double auction is also called a combinatorial exchange in the literature (Abrache et al., 2004; Lubin et al., 2008; Mittelmann et al., 2021).

Fig. 1 shows an example of this market scheme with five orders and three suppliers. Each supplier bids for a combination of orders that is consistent with their available resources (recall that the actual resources are, however, private information to each supplier). Supplier 1 places two bids for the production of orders 1 and 4, and 2 and 3, respectively; Supplier 2 bids for orders 2, 3 and 5; and Supplier 3 bids for orders 1 and 2. The auction will consist of several rounds in each of which a temporary allocation (i.e. which combination of parts will be produced by which supplier) will be made. In each successive round, buyers and sellers are given the possibility to update their bids, and thus new temporary allocations will be formed. After several rounds, a final allocation will be made. In the example shown in Fig. 1, Supplier 1 will manufacture the combination of parts demanded by customers 1 and 4, and Supplier 2 will provide the parts demanded by customers 2, 3, and 5. Supplier 3 did not achieve the production of any of the orders.

The proposed auction introduces an iterative process in which provisional allocations are being made and agents are allowed to update their bids. This iterative setting helps agents express their preferences without the need to directly disclose their private valuations (Parkes, 2006).

3.1. Auction steps

To match the classic auction terminology, customers that request 3D-printed parts orders will be referred to as buyers and suppliers with available AM resources will be referred to as sellers as regards the market mechanism. When requesting a production order, a buyer will submit a buying offer showing the amount of money he or she is willing to pay for that order, traditionally called a buying bid or simply a *bid* (Friedman, 1993). After analyzing the set of orders in the market, a seller will submit a selling offer indicating the price he or she would be willing to accept for producing a subset of orders, which is called an asking bid or simply an *ask* (Friedman, 1993). Hence, buyers will place bids for single orders and sellers will submit asks for bundles of orders.

The development of the auction consists of several steps, which are shown in Fig. 2.

Step 0 (Requesting period, T). The platform collects parts orders from buyers.
Step 1 (Asking period, t_a). Sellers send asks on combinations of items.
Step 2 (Clearing period, t_c). The auctioneer makes a temporary allocation.
Step 3 (Updating period, t_u). Non-winning agents are requested to update their prices.
Step 4 (Ending period, t_e). The auctioneer makes the final allocation.

A detailed description of the actions performed at each step is shown below. Table 2 summarizes the notation used in the auction model.

Step 0: Requesting period

A requesting period T is considered before starting the auction. During this period, the platform (from now on *the auctioneer*) collects the buying bids sent by buyers. Two considerations must be noted at this point:

- Each order collected by the platform is considered one item i for the auction and orders cannot be decomposed (i.e., items are indivisible).
- Buyers are required to submit a purchase price (pp_i) for each order i requested to the platform, which is the price that buyers are initially willing to pay to have their orders produced. Thus, a bid $b_i = \{i, pp_i\}$ is placed for each auction item by the corresponding buyer.

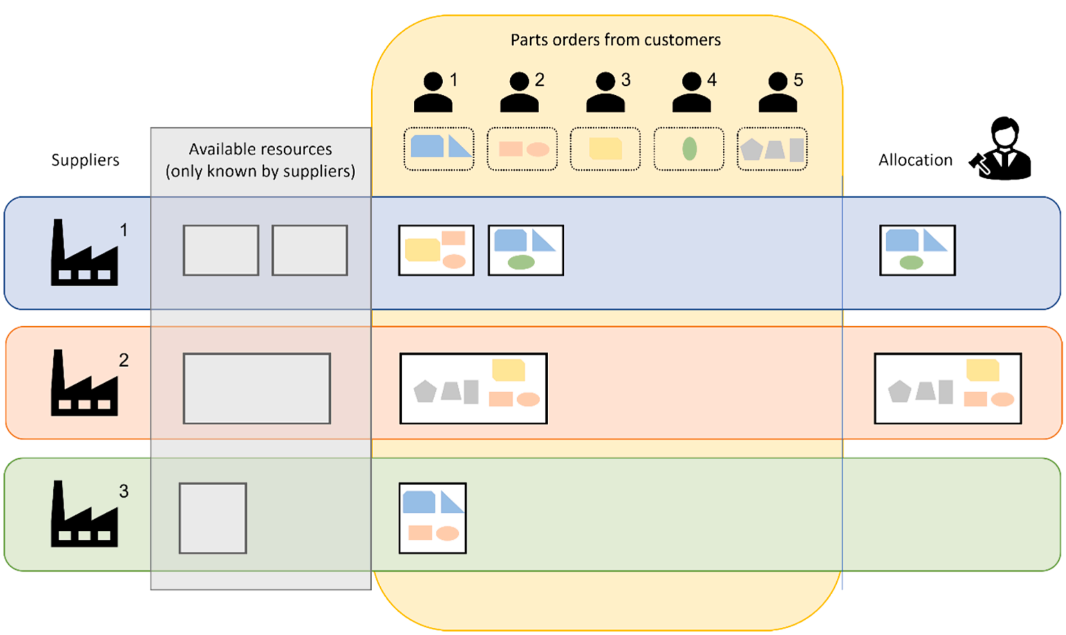

Fig. 1. Outline of the combinatorial auction mechanism for an AM market.

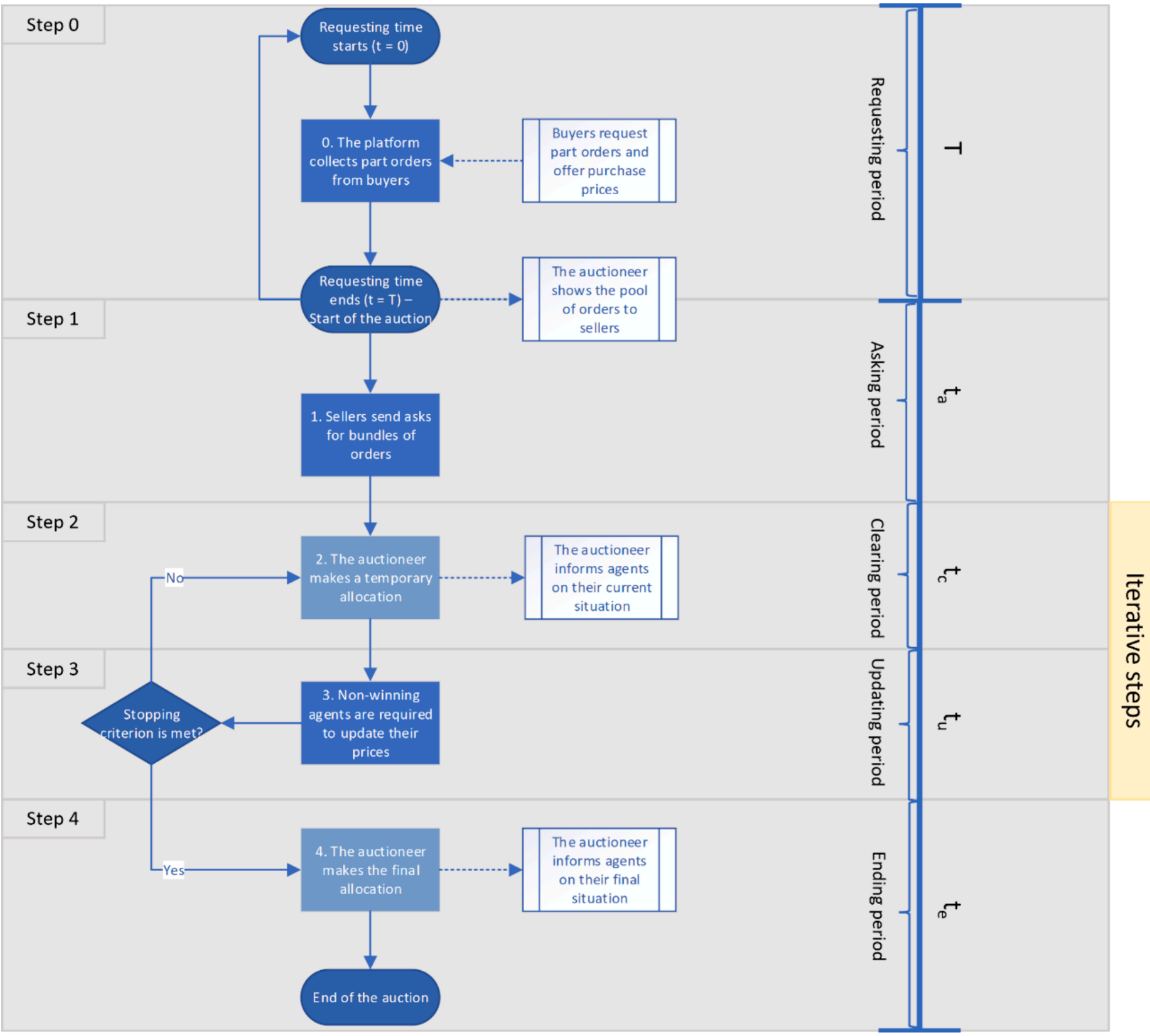

Fig. 2. Flowchart of the auction steps sequenced in their corresponding periods.

Table 2
Summary of notations used for the auction model.

N	→	Set of items
$i \in N$	→	Index for an item
M	→	Set of bundles
$j \in M$	→	Index for a bundle
b_i	→	Bid on item i
pp_i	→	Purchase price associated with bid b_i
rp_i	→	Reservation price for item i
a_j	→	Ask for bundle j
ap_j	→	Ask price associated with ask a_j
S_j	→	Subset S⊆N associated with ask a_j
c_j	→	Production cost of bundle j (or of subset S_j)

Hence, before starting the auction, the auctioneer knows the pool of items and the purchase price offered for each item. Once the time T is reached, the auctioneer will trigger the auction to match supply with demand through an iterative process consisting of several rounds.

Step 1: Sellers send asks on combinations of items.

The auctioneer informs participants of the start of the auction and reveals the set N of distinct items to be auctioned. During the asking period t_a, sellers will place asks for the combinations of items in which they are interested. Recall that sellers must make their own calculations to determine which combinations of items provide them with the highest utility (i.e., it is assumed that sellers place asks for the combinations of items that optimize the capacity of their AM machines). A seller wishing to win a subset of items $S \subseteq N$ will submit an ask $a_j = \{S_j, ap_j\}$. The ask is composed of the desired subset S_j and the ask price ap_j which shows the amount of money that the seller is willing to charge for producing this bundle of items. These combinations cannot be changed in following rounds and no asks on new combinations can be placed.

Step 2: The auctioneer makes a temporary allocation

After the asking period, the auctioneer has already received all the asks placed by sellers and knows the bids initially submitted by buyers. At this point, the auctioneer determines the temporary allocation of items to sellers by solving the Winner Determination Problem (WDP). The time devoted to performing this step is called the clearing period t_c. In the WDP, the allocation of items that optimizes the objective function considered is obtained. In this case, the maximization of the auctioneer's revenue is pursued. The WDP is formulated as a binary integer problem (BIP) in Section 3.3.

Once the WDP has been solved, the auctioneer reveals the following information to agents about the current allocation:

- Buyers are informed whether their order(s) will be manufactured at the current purchase price(s).
- Sellers are informed whether their ask(s) is/are winning at the current ask price(s).

Step 3: Non-winning agents are requested to update their prices. Current losing agents who want to participate in the next round are given an updating period t_u to revise their prices. Non-winning buyers are requested to raise their purchase prices, while non-winning sellers are requested to decrease their ask prices. The auctioneer sets a minimum amount to update prices. Once the time t_u has elapsed, either the process returns to step 2 if the stopping criterion is not met and a new bidding round is started, or the process moves on to step 4 otherwise.

Step 4: The auctioneer makes the final allocation

When the stopping criterion has been reached, the temporary allocation of items resulting from step 2 is now announced as the final allocation. The auctioneer informs winning agents of the final allocation of items and the corresponding prices. Lastly, the auctioneer announces the closing of the current auction round. This last step takes place during the ending period t_e.

This is a price-based iterative combinatorial double auction setting in which combinatorial bidding is only allowed on the selling side of the market. Therefore, buyers bid for single items —their own requested items— while sellers ask for combinations of items. These combinations are set in the first round and cannot be changed anymore. Instead, prices are updated after each round: non-winning buyers will offer higher purchase prices, while non-winning sellers will ask for lower payments.

3.2. Modeling of participants' utility

Buyers and sellers are modelled as rational and self-interested agents who try to maximize their utilities by participating in the market. In this AM market, the utility that a buyer can obtain from a production order requested through the platform is calculated as the difference between the value that the order holds for the buyer and the price that they need to pay to have it produced. In this regard, the value of a good for a buyer is expressed as the maximum price the buyer is willing to pay for the good (i.e., the buyer's reservation price for this good). Let rp_i be the reservation price of a buyer for item i, pp_i be the purchase price that the buyer must pay for the item and x_i be a binary variable to indicate that i is a winning item; the utility obtained by the buyer for this item (BU_i) is defined as:

$$BU_i = x_i \cdot (rp_i - pp_i) \tag{1}$$

$$x_i = \{0,1\} = \begin{cases} 1, ifbidb_i winsauction \\ 0, inothercase \end{cases}$$

After observing the set of orders in the AM market, a seller must determine the combination that brings a better utility to them. The utility for a seller is calculated as the difference between the price they can charge to produce a combination of orders and the cost incurred when producing these orders. Let c_j be the cost incurred by a winning seller in producing the combination S_j, ap_j be the price the seller charges for that combination and y_j be a binary variable to indicate that a_j is a winning ask; the utility obtained by the seller for that combination (SU_j) is defined as:

$$SU_j = y_j \cdot (ap_j - c_j) \tag{2}$$

$$y_j = \{0,1\} = \begin{cases} 1, ifaska_j winsauction \\ 0, inothercase \end{cases}$$

Both buyers and sellers will place bids and asks that bring them the highest utility.

3.3. Winner determination problem

The main problem faced when designing a combinatorial auction (CA) is deciding how to allocate bundles of items amongst the bidders so as to optimize some criterion (De Vries & Vohra, 2003). This problem is generally dubbed the *Winner Determination Problem* or WDP. A binary integer problem (BIP) is developed to formulate the WDP of the auction proposed in this work. The objective function is the maximization of the auctioneer's surplus (AS) and is expressed in equation (4).

Let N ($i \in N$) be the set of production orders (items) requested by buyers. A bid $b_i = \{i, pp_i\}$ placed by a buyer is defined as a two-valued array in which the first value indicates the item index i, and the second value expresses the purchase price offered for that item pp_i. As an example, a bid of a buyer offering 20€ for item 4 would be expressed as $b_4 = \{4, 20€\}$.

Let M ($j \in M$) be the set of bundles of items requested by sellers. An ask $a_j = \{S_j, ap_j\}$ submitted by a seller is defined as a two-valued array in which the first value is a one-zero vector in the form of $S_j = (s_{j0}, \ldots, s_{ji}, \ldots, s_{jN})$ to define the subset of items requested, and the second is a number to express the ask price for that subset. Considering a set of $N=5$ items, a seller willing to charge 30€ for the supply of the bundle of items 1, 3 and 4 would submit an ask (say $j = 1$) expressed as $a_1 = \{(1,0,1,1,0), 30€\}$.

The revenue that the auctioneer obtains from a bundle allocation (AR_j) is calculated as the difference between the sum of the purchase prices offered for items of a winning combination S_j and the ask price submitted by a seller for that combination. The binary variable y_j is included to indicate that a_j is a winning ask, and the coefficient s_{ji} is used to indicate if the item i is in subset S_j according to the input data of the instance. Equation (3) shows the calculation of AR_j.

$$AR_j = \left(\sum_{i=1}^{N} s_{ji} \cdot pp_i - ap_j \right) \cdot y_j \tag{3}$$

The objective function of the WDP is thus to maximize the sum of AR_j (i.e., the auctioneer surplus, AS) by selecting the most profitable ask-bids pairs, as expressed in (4). Hence, the items are allocated seeking to maximize the difference between buyers' total payment and sellers' total revenue.

$$maximizeAS = \sum_{j=1}^{M} \left[\left(\sum_{i=1}^{N} s_{ji} \cdot pp_i - ap_j \right) \cdot y_j \right] = \sum_{j=1}^{M} AR_j \tag{4}$$

Lastly, two constraints must be included to ensure feasible solutions. Constraint (5) ensures that no winning exchange yields a negative profit: the sum of the purchase prices of the items in a winning combination is not lower than the ask price of that combination. Constraint (6) ensures that overlapping sets of items are never assigned.

$$AR_j = \left(\sum_{i=1}^{N} s_{ji} \cdot pp_i - ap_j \right) \cdot y_j \geq 0 \forall j \in M \tag{5}$$

$$\sum_{j=1}^{M} s_{ji} \cdot y_j \leq 1 \forall i \in N \tag{6}$$

$$y_j, s_{ji} \in \{0,1\}$$

$$pp_i, ap_j \geq 0$$

4. Auction algorithm

This section presents the algorithm designed for implementing and simulating the iterative auction procedure. In a real-world context, the auction will allow distributed buyers and sellers to participate by sending bids and asks and updating prices at their discretion. However, for simulation purposes, the algorithm will define a procedure to simulate agents' decisions, assuming rational and self-interested behavior. The iterative auction procedure and its implementation algorithm are detailed in Section 4.1. Section 4.2 presents a simple case example of a realistic auction implementation to enhance understanding of the mechanism.

4.1. Iterative auction procedure

The multi-round process is designed to guide the auction toward efficient market results while distributing computation across agents. In each round t, the auctioneer makes a provisional allocation W^t by solving equation (4) with the ask prices and purchase prices from the current round t. These data are stored in the array W^t, which collects the purchase prices of the winning items pp_i^t, the ask prices of the winning asks ap_j^t and the combinations of those winning asks S_j.

Agents failing to win their bids/asks in the provisional allocation will be requested to update their bid/ask prices. While agents winning the current round will have no incentives to update their prices, non-winning agents must update theirs to have a chance of winning the auction. At the start of the auction, the auctioneer will set the minimum quantities λ and μ by which prices are to be updated. Non-winning buyers will have to raise their purchase prices by at least μ units to participate in the next round; non-winning sellers will have to decrease their ask prices by at least λ units to hold their asks.

The auction procedure is started based on the information collected by the platform from the buyers' requests during the *requesting period* (step 0 defined in Section 3.1). In this phase, the auctioneer receives order requests together with their associated bids from buyers. Thus, the input data of the auction algorithm are the set N of items and the bids on round $t = 1$: $b_i^{t=1} = \{i, pp_i^{t=1}\}$. Likewise, the number of bundles M is set according to the number of sellers that is going to participate in the auction. In addition, the auctioneer determines the values of the parameters λ and μ for the current auction. According to the procedure explained in Section 3.1, the auction is a 4-step process: steps 1 and 4 are one-shot phases, whereas steps 2 and 3 are iterative phases.

In the first step (lines 1–4 of Algorithm 1), the auctioneer collects the asks from sellers; the combinations of items S_j $(S \subseteq N)$ desired by sellers are therefore set and will not be changed in future rounds. This step is only computed once.

Subsequently, the iterative procedure starts with the while loop in line 5 of Algorithm 1. Within each iteration of the auction, the WDP is solved in step 2 and a temporary allocation W^t is obtained (line 6 of Algorithm 1). After updating the round index t, the prices from non-winning agents are updated according to the price updating scheme in step 3 (lines 8–19 of Algorithm 1). Please note that, although in a real-world scenario both customers and manufacturing companies will update their bids and asks respectively as they see fit, in this simulation of the auction, we have established that the agents' bids and asks are updated by exactly the minimum quantity. Specifically, non-winning buying agents will increase their bids by λ monetary units, while manufacturing agents will decrease their asks by μ monetary units.

Lastly, once the termination condition is reached (line 20 of Algorithm 1), the iterative process ends and the temporary allocation from the ongoing round (W^t) is announced as the final allocation W in what constitutes step 4 (line 21 of Algorithm 1). The final winning ask and bid prices are saved in variables ap_j^f and pp_i^f respectively. Now the market is cleared.

Algorithm 1 Price-Based Iterative Combinatorial Double Auction

Input: N (Set of items), M (Set of bundles)
$b_i^{t=1} = \{i, pp_i^{t=1}\}$
λ, μ
Output: W(Set of winning asks)
1: Start of the auction. Initial round $t = 1$ {Step 1: Asking period}
2: **for** all j in M **do**
3: Collect ask $a_j^t = \{S_j, ap_j^t\}$
4: **end for**
5: **while** termination condition is not true **do**
6: The auction is cleared by (4) and W^t is obtained {Step 2: Winner determination}
7: $t \leftarrow t + 1$
8: **for** all j in M **do** {Step 3: Price update} #Ask price update
9: **if** ap_j^{t-1} not in W^{t-1}:
10: **if** $ap_j^{t-1} - \lambda \geq c_j$:
11: $ap_j^t = ap_j^{t-1} - \lambda$
12: **else** $ap_j^t = ap_j^{t-1}$
13: **end for**
14: **for** all i in N **do** #Purchase price update
15: **if** pp_i^{t-1} not in W^{t-1}:
16: **if** $pp_i^{t-1} + \mu \leq rp_i$:
17: $pp_i^t = pp_i^{t-1} + \mu$
18: **else** $pp_i^t = pp_i^{t-1}$
19: **end for**
20: Termination condition checking:
if stopping criterion == True: **break**
21: $W\ [pp_i^f, ap_j^f, S_j] \leftarrow W^t\ [pp_i^t, ap_j^t, S_j]$ {Step 4: Final allocation}

4.2. Case example

A simplified example of the auction in the market environment exposed is presented for a better understanding of the mechanism. Within the timespan set for requesting orders (the requesting period T), three customer companies (i.e., buyers) submit the orders they want to get produced. Then, the auctioneer starts the auction with two AM suppliers (i.e., sellers) that desire to obtain bundles of those orders. The final allocation resulting from the auction mechanism will clear the market.

The input parameters considered for this example case are N=4 items, b_i^1 as set below, M=2 bundles (i.e., one ask per seller), and $\lambda = \mu = 2$ currency units (€). Also, the stopping criterion selected for this example is that no prices are updated from one round to the next.

Requesting period

Buyers accessed the platform and requested four production orders (items) with their corresponding purchase prices (pp_i). As these are initial bids, they are collected as $b_i^{t=1} = \{i, pp_i^{t=1}\}$. Therefore, four bids are collected by the auctioneer. Buyer 1 requested *i1* and offered a purchase price of 8€ ($b_1^1 = \{1, 8€\}$); buyer 2 offered 10€ for *i2* ($b_2^1 = \{2, 10€\}$) and 6€ for *i3* ($b_3^1 = \{3, 6€\}$); buyer 3 requested *i4* and offered 5€ ($b_4^1 = \{4, 5€\}$). These initial bids can be seen in Fig. 3 above their corresponding items.

Round 1

After making their own calculations, each of the two sellers placed one ask in the current round $t = 1$ ($a_j^{t=1} = \{S_j, ap_j^{t=1}\}$) for a combination of production orders: seller 1 bid for the bundle $j = 1$ of items i2 and i4 with an ask price of 12€ ($a_1^1 = \{(0,1,0,1), 12€\}$); seller 2 asked for 30€ to manufacture the bundle $j = 2$ of items i1, i2 and i3 ($a_2^1 = \{(1,1,1,0), 30€\}$). The two asks are shown in Fig. 3 next to their corresponding bundles of items and identified by color.

The WDP can already be solved with the data of bids and asks. By solving the BIP problem with the current prices, the temporary allocation $W^{t=1}$ is obtained. In this simple example at most one ask will win the auction since bundles S_1 and S_2 share item *i2* and overlapping sets of items cannot be assigned. Thus, the winning ask in the current round is $ap_1^1 = \{(0,1,0,1), 12€\}$ because the objective function (equation (4) takes a greater value from $AR_1 = \left(\sum_{i=1}^{N=4} s_{1i} \cdot pp_i^1\right) - ap_1 = (0\cdot8 + 1\cdot10 + 0\cdot6 + 1\cdot5) - 12 = 3$ than from $AR_2 = \left(\sum_{i=1}^{N=4} s_{2i} \cdot pp_i^1\right) - ap_2 = (1\cdot8 + 1\cdot10 + 1\cdot6 + 0\cdot5) - 30 = -6$. In fact, the ask a_2^1 could never be

Fig. 3. Summary of the auction rounds and the final allocation.

allocated because it yields a negative utility for the auctioneer. Objective function values for each ask –AR_1 and AR_2– are displayed under their corresponding bundles of items and identified by colors in Fig. 3.

Round 2

Now for round 2, non-winning bids/asks must update their prices. In this case example, it is assumed that all losing agents (both buyers and sellers) will update their prices exactly $\lambda = \mu = 2€$ to simulate the auction. Non-winning asks will update their ask prices according to $ap_j^t = ap_j^{t-1} - \lambda$; hence, the ask price from ask a_2 in round 2 will be $ap_2^2 = ap_2^1 - 2 = 28€$. Losing bids will update their purchase prices according to $pp_i^t = pp_i^{t-1} + \mu$; the purchase prices updated in round 2 are $pp_1^2 = 10€$ and $pp_3^2 = 8€$. From round 2 onwards, updated prices are shown in bold in Fig. 3, while non-updated prices are placed between parentheses. The WDP is newly solved with the current prices. The value of the objective function for the ask a_1 will be the same since their prices remain unchanged ($AR_1 = 3€$), whereas that value for ask a_2 is now $AR_2 = 0€$. As the value of AR_1 is still higher, the winning ask in round 2 is again a_1.

Round 3

Purchase prices pp_1^2 and pp_3^2 must be updated again. In this case, $pp_1^3 = pp_1^2 + 2 = 12€$ while pp_3^3 raises to 10€. The ask price of the losing ask is also updated to $ap_2^3 = ap_2^2 - 2 = 26€$. The temporary allocation of round 3, W^3, returns as winner the ask a_2 because $AR_2 = 6€ > AR_1 = 3€$.

Round 4

The only losing bid is now b_4, so the purchase price for round 4 is updated to $pp_4^4 = pp_4^3 + 2 = 7$. Losing ask a_1 decreases its ask price to $ap_1^4 = 10€$. The winner of round 4 is ask a_1 because $AR_1 = 7€ > AR_2 = 6€$.

Round 5

Losing prices to be updated are pp_1^4, pp_3^4 and ap_2^4. However, neither buyers can increase their bids since they are reaching their reservation prices, nor Seller 2 can decrease its ask price since that price is approaching the production cost. Thus, $pp_1^4 = 12$*, $pp_3^4 = 10$* and $ap_2^4 = 26$* are the final prices and they are displayed in red and signaled with an asterisk (*) in Fig. 3. As no prices have been updated from the previous round, the stopping criterion is satisfied and the auction is finished. The final allocation is $S_1 = (0,1,0,1)$ and the final prices are $pp_2^f = 10€$, $pp_4^f = 7€$, and $ap_1^f = 10€$. The revenue obtained by the auctioneer is $AS = AR_1 = 7€$.

A summary of the rounds can be found in Table 3; updated prices are written in bold, non-updated prices are written between parentheses and final prices are written in red and added an asterisk (*).

5. Computational study

A computational study is developed to simulate the operation of the auction mechanism by computing the algorithm proposed in this paper (Algorithm 1). The objective is twofold: (i) to evaluate the performance of the algorithmic procedure designed for simulating the auction and (ii) to identify the best conditions for the auction to be implemented in a real environment.

The main goodness of the auction mechanism proposed in this paper is that it allows obtaining an efficient allocation without information about reservation prices of buyers and production costs from sellers. This study is aimed at comparing the outcome of this iterative auction mechanism, in which private information from agents remains confidential (which we will call the iterative-auction outcome), with the allocation obtained by providing the solver with complete information about reservation prices and production costs (which we will call the complete-information outcome). The iterative-auction outcome is obtained by computing Algorithm 1 as explained in Section 4.1. On the other hand, the complete-information outcome is derived by providing the BIP model from Section 3.3 with the actual values of reservation prices and production costs. In the latter case, it is only necessary to run the solver once, and the returned solution will be considered optimal. This complete-information outcome will serve as an upper bound to assess the quality of the solution returned by the iterative auction mechanism (i.e., the iterative-auction outcome). This comparison will allow to evaluate the portion of the social welfare attained by the auction.

The rest of this section is structured as follows: first, the evaluation metrics are defined; next, the generation of simulation instances is

Table 3
Summary of the auction execution for the case example.

Round	Purchase and ask prices						Temporary allocation (current winning ask)	AR_j [€]
	Buyer 1	Buyer 2		Buyer 3	Seller 1	Seller 2		
	i1	i2	i3	i4	[i2, i4]	[i1, i2, i3]		
	pp_1 [€]	pp_2 [€]	pp_3 [€]	pp_4 [€]	ap_1 [€]	ap_2 [€]		
1	8	10	6	5	12	30	a_1 = {[2, 4], 12€}	3
2	**10**	10	**8**	5	12	**28**	a_1 = {[2, 4], 12€}	3
3	**12**	10	**10**	5	12	**26**	a_2 = {[1, 2, 3], 26€}	6
4	12	10	10	**7**	**10**	26	a_1 = {[2, 4], 10€}	7
5	**12***	10	**10***	7	10	**26***	a_1 = {[2, 4], 10€}	7

described; lastly, the simulation experiments are detailed.

5.1. Metrics

To obtain the complete-information outcome (i.e., the allocation that we will consider optimal, as it maximizes social welfare by taking into account the private information of the auction participants), the BIP model is directly provided with the actual information about reservation prices of buyers for items (rp_i) and the actual production costs of sellers for the combinations they want to procure (c_j), as shown in equation (7). Now, the objective function is to maximize the market's social welfare (SW) as the difference between buyers' reservation prices and sellers' production costs. This model with complete information will then return the optimal allocation W^* that results in the largest difference between the sum of reservation prices of winning items and the sum of production costs of winning combinations (see Eq. (7)). The solution obtained with this complete-information model (i.e., the social welfare of the optimal allocation *SW(W*)*, as calculated in equation (8)) will be used as the reference against which the auction solution will be compared (i.e., the upper bound).

$$maximizeSW = \sum_{j=1}^{M}\left[\left(\sum_{i=1}^{N} s_{ji}\cdot rp_i - c_j\right)\cdot y_j\right] \tag{7}$$

$$SW(W^*) = \sum_{i\in W^*} x_i\cdot rp_i - \sum_{j\in W^*} y_j\cdot c_j \tag{8}$$

To calculate the social welfare of the iterative-auction outcome, we first simulate the auction, in which agents update their purchase prices (pp_i) and ask prices (ap_j) round after round until a final buyer–seller allocation is obtained (W). Recall that the iterative auction aims to maximize the auctioneer's surplus (i.e., the objective function of the WDP model presented in Section 3.3, equation (4)). Also, recall that the participants' private information (i.e., the buyers' reservation prices rp_i and sellers' production costs c_j) are not revealed during the auction process. Then, we calculate the social welfare attained by the auction's allocation W (i.e., *SW(W)*) as the difference between winning items' reservation prices and winning bundles' production costs, as shown in equation (9).

$$SW(W) = \sum_{i\in W} x_i\cdot rp_i - \sum_{j\in W} y_j\cdot c_j \tag{9}$$

An efficiency metric *Eff(W)* is defined in (10) to compare the social welfare obtained in the final allocation W by Algorithm 1 (i.e., the iterative-auction outcome), in which the agents' reservation prices and production costs are not revealed, with the social welfare obtained in the optimal solution W^* (i.e., the complete-information outcome). This *Eff (W)* metric will show how effective the auction is in determining item allocations while maintaining confidentiality about the participants. The closer the value of *%Eff(W) is to 100 %*, the higher the quality of the iterative-auction outcome.

$$Eff(W) = \frac{SW(W)}{SW(W^*)} = \frac{\sum_{i\in W} x_i\cdot rp_i - \sum_{j\in W} y_j\cdot c_j}{\sum_{i\in W^*} x_i\cdot rp_i - \sum_{j\in W^*} y_j\cdot c_j} \tag{10}$$

$$\%Eff(W) = Eff(W)\cdot 100\% \tag{11}$$

Another key aspect of assessing the goodness of the auction mechanism is the amount of time it takes to reach the final solution. In a real context, reaching an efficient solution in as few rounds as possible will be crucial. In this case, the metric defined is precisely the number of rounds the auction needs to make the final allocation in the process defined in Algorithm 1. This metric will allow us to evaluate the time required to obtain the final solution in different market scenarios.

5.2. Design of testing data

The generation of instances follows a process aimed at designing feasible input values for each of the scenarios presented in Section 5.3. The data generated for each instance are the N items to be auctioned and the M bundles requested, the reservation price rp_i and the initial purchase price for each item pp_i^1, and the production cost c_j and the initial ask price for each bundle ap_j^1.

In the first place, a binary matrix *MxN* that represents the bundles of items requested by each supplier is generated using a saturation parameter δ. According to the value of δ, cells in the matrix will take 1 or 0 following a random procedure in which it is ensured that at least one cell of each row and one cell of each column is set to 1 (i.e., all the items are requested in at least one bundle and all the bundles have at least one item). For an instance with 10 buyers and 10 sellers (matrix of $10\cdot 10 = 100$) and a saturation of $\delta = 0.1$, a total of 10 cells ($0.1\cdot 100 = 10$) will take 1. Thus, the matrix for each scenario is generated from the number of rows M (bundles of items asked), the number of columns N (total items) and the saturation parameter δ.

Subsequently, initial purchase prices pp_i^1 are drawn uniformly at random from the interval [30, 80]. Reservation prices rp_i are then generated by adding to the purchase price a uniform random number from the interval [16, 120]. Then, the sum-product number (sp_j) of each row of the binary matrix and the array of initial purchase prices is calculated. Initial ask prices ap_j^1 are obtained by $ap_j^1 = sp_j + sp_j\cdot U(1, 1.6)$, being U a uniform distribution. Last, production costs for each ask submitted c_j are generated by $c_j = ap_j^1 - sp_j\cdot U(0.2, 1)$. All the values employed for the generation of initial prices have been derived from a preliminary tuning process.

Given the above procedure for generating instances, seven scenarios are simulated to evaluate the performance of the auction mechanism and the sensitivity of the parameters. The input data for those scenarios

Table 4
Simulation scenario settings.

Scenario	I	II	III	IV	V	VI	VII
Items (N)	10	10	20	20	20	40	40
Bundles (F)	10	20	10	20	40	20	40

is summarized in Table 4.

5.3. Simulation experiments

This section presents the two experiments conducted to evaluate the performance of the auction mechanism and to find the most convenient values of parameters for each scenario. The analysis focuses on the effect of the input size (number of agents) and the values of parameters on the efficiency of the solution reached and the time needed to find that solution. Consequently, the metrics that will be measured in the experiments are those defined in Section 5.1, i.e., the quality of the solution in terms of market efficiency *Eff(W)* and the number of rounds needed to reach the final solution.

The stopping criterion considered for all the experiments is that either no improvements of the objective function are obtained in 10 consecutive rounds or a maximum of 40 auction rounds are reached. As one of the objectives of the simulation is to analyze the conditions for the auction to be run in a real context, it seems reasonable to think that running an auction for more than 40 rounds is unpractical.

All the experiments are run using the COIN-OR CBC[3] solver to compute both the iterative-auction BIP model for the auction's WDP and the complete-information BIP model. All the simulations are implemented on a general-purpose computer with a Core i7 2.6 GHz processor with 16 GB of RAM, 512 GB of memory, and Windows 10 as the operating system.

The first experiment analyses the joint effect of the number of agents and the minimum price step on the auction results. The minimum price steps set by the auctioneer to both sellers (λ) and buyers (μ) are sensitive parameters for the simulation in terms of efficiency. Since this is an initial attempt to tune the parameters for implementing the auction in a real context, the value of both parameters is considered the same (i.e., $\lambda = \mu$). In this experiment, the seven scenarios are simulated for four different values of the price step: 1, 5, 10 and 15. The saturation parameter for all the scenarios is set to $\delta = 0.2$. Each type of instance is run 20 times. The results are averaged and shown in Table 5 and Table 6, respectively, and they will be discussed in Section 6.1.

The auctioneer will also be interested in knowing the best auction configuration to ensure a proper result. The saturation parameter δ will be analyzed to evaluate the auction response as the complexity of the item matrix increases. In this second experiment, the seven scenarios are simulated for three values of the δ parameter: 0.1, 0.2 and 0.3. The price step is fixed to $\lambda = \mu = 5$ for all the instances. Each scenario is run 20 times and the means of Eff(W) and of the number of rounds are obtained. The results of this experiment are summarized in Table 7 and Table 8, and they will be discussed in Section 6.1.

6. Discussion

This section is devoted to analyzing the simulation results and discussing the properties shown by the auction mechanism designed in this work. In Section 6.1, the conclusions reached from the simulation are discussed, and in Section 6.2, the auction features are examined.

6.1. Simulation results

This section reviews the results of the two experiments to discuss the best conditions for implementing the auction in a real environment. The objective of the auctioneer is to find an auction configuration with a good balance between efficiency and duration (measured as the number of rounds). Consequently, the auctioneer would be interested in knowing the most appropriate values of price step $\lambda(\mu)$ and saturation δ to be set for each scenario.

The results of the first experiment confirmed the importance of setting a proper minimum price step $\lambda(\mu)$ to ensure a good balance between efficiency and duration. It is observed in Table 5 that the efficiency of the auction increases as the size of the price step increases, which might seem counterintuitive. This occurs in all seven scenarios. Notwithstanding, this phenomenon is conditioned by the stopping criterion of 40 rounds maximum set for all the simulations (since we are interested in the conditions for practical implementation in a real context, as previously indicated). As shown in Table 6 the number of rounds on average is greater when the price step is small, and it is even around 40 for scenarios with a larger number of agents. These results suggest that in many of the instances with more agents and a smaller price step, it takes more than 40 rounds to find the best solution possible. However, the efficiency for instances with a greater price step does not significantly differ among the different scenarios, whereas the number of rounds clearly decreases as the price step increases. Thus, it can be concluded that the size of the price step greatly influences the duration of the auction but does not significantly affect the quality of the solution.

Similarly, the second experiment reports that the saturation of the matrix δ is a sensitive parameter for the auction duration but not for the efficiency of the resulting allocation. Results from Table 7 show only a slight decrease in the efficiency as the saturation increases, especially in large scenarios like VI and VII, while Table 8 reports a clear decrease in the number of rounds as the saturation decreases. There is also a significant reduction in the number of rounds for small scenarios (i.e., I and II) for all three different saturation values. Therefore, an instance with fewer agents and a lower saturation value should reduce the duration of the auction.

In light of the above results, the auctioneer must adapt the size of the price step and the saturation of the matrix to the number of agents in the auction. As the goal is to achieve an efficient result in the least number of rounds possible, the auctioneer will be interested in setting a greater price step as the number of agents increases. Also, the auctioneer should try to keep the matrix saturation at low levels when arranging the sellers and buyers that will participate in an auction.

According to the results, our proposed auction can be directly implemented in scenarios with fewer agents (i.e., I-IV) —with sellers and buyers updating their prices after each round— by selecting the appropriate parameter values. However, if the scenarios are more complex (i.e., VI-VII), it is advisable to explore the possibility of implementing an autonomous multi-agent system in which sellers and buyers have their software proxy agents that update their prices on their behalf. This proxy bidding system would allow the auction to run for more rounds with minimum effort from participants.

6.2. Model advantages and auction features

The primary advantage of the auction model developed in this work is that it allows for addressing both the allocation and pricing problems in a way that pursues market optimization while preserving desirable auction properties. Specifically, this auction shows budget balance, prevents collusion from participants, and achieves an efficient market result without revealing agents' private information. Subsequently, the auction features that allow obtaining these properties are discussed.

The auction mechanism presented in this work is designed to adapt to a highly competitive market environment such as the market of AM services. In this market scenario, agents are assumed to adopt a myopic best-response bidding strategy (Parkes, 2001): they bid focusing only on the current round of the auction and are influenced neither by the other agents' strategies nor by the evolution of the auction in future rounds. As buyers only bid on their own items, they know their valuations on those items, and these do not depend on the valuations of other buyers. Sellers place asks based on their own production costs, which are only known by themselves and are not affected by other sellers' cost functions. This behavior of the agents follows the *private value model* as defined in Vickrey (1961); agents only know their own values but not the values of others. These myopically rational agents participate in a market with private information to maximize their utilities.

[3] https://www.coin-or.org/.

Table 5
Efficiency results %Eff(W) for different values of the price step (λ, μ).

% Eff(W)							
Scenario	I	II	III	IV	V	VI	VII
Items (N)	10	10	20	20	20	40	40
Bundles (F)	10	20	10	20	40	20	40
Instances	20	20	20	20	20	20	20
$\lambda = \mu = 1$	66.949	68.907	64.374	64.390	75.430	51.669	64.650
$\lambda = \mu = 5$	98.838	98.939	91.833	96.412	95.683	83.518	90.180
$\lambda = \mu = 10$	99.872	99.504	99.994	99.734	98.675	93.341	97.950
$\lambda = \mu = 15$	99.420	98.929	99.861	99.765	99.506	98.481	98.757

Table 6
Number of rounds for different values of the price step (λ, μ).

Number of rounds							
Scenario	I	II	III	IV	V	VI	VII
Items (N)	10	10	20	20	20	40	40
Bundles (F)	10	20	10	20	40	20	40
Instances	20	20	20	20	20	20	20
$\lambda = \mu = 1$	31.601	35.568	33.719	37.308	39.949	33.741	40.000
$\lambda = \mu = 5$	26.854	31.830	38.355	39.439	39.899	39.848	39.748
$\lambda = \mu = 10$	13.246	16.254	27.715	30.307	33.352	38.695	39.638
$\lambda = \mu = 15$	9.038	10.741	19.096	19.803	20.362	35.832	36.986

Table 7
Efficiency results %Eff(W) for different saturations of the item matrix (δ).

% Eff(W)							
Scenario	I	II	III	IV	V	VI	VII
Items (N)	10	10	20	20	20	40	40
Bundles (F)	10	20	10	20	40	20	40
Instances	20	20	20	20	20	20	20
$\delta = 0.1$	98.692	99.162	99.743	99.321	99.403	99.116	99.633
$\delta = 0.2$	99.872	99.504	99.994	99.734	98.675	93.341	97.950
$\delta = 0.3$	99.658	99.859	94.697	98.133	97.484	88.760	89.990

Table 8
Number of rounds for different saturations of the item matrix (δ).

Number of rounds							
Scenario	I	II	III	IV	V	VI	VII
Items (N)	10	10	20	20	20	40	40
Bundles (F)	10	20	10	20	40	20	40
Instances	20	20	20	20	20	20	20
$\delta = 0.1$	4.416	5.570	18.227	15.610	20.716	33.142	35.760
$\delta = 0.2$	13.246	16.254	27.715	30.307	33.352	38.695	39.638
$\delta = 0.3$	17.678	20.566	34.125	36.901	36.284	39.848	39.797

To properly manage this competitive market, the auction shows three determinant features: an iterative procedure, a sealed-bid asking strategy, and a partial and anonymized information feedback scheme. This iterative sealed-bid-like configuration of the auction allows an efficient result without the agents revealing their true valuations, an undesirable feature of other types of auctions such as Vickrey auctions (Rothkopf et al., 1990). Also, collusion by a set of agents is prevented thanks to the partial information feedback strategy.

The asking procedure in each round of the auction is designed in a sealed-bid fashion since sellers submit their asks during the asking period without knowing the asks from other sellers (COPPINGER & SMITH, 1980). Indeed, sellers need not reveal their production costs to the auctioneer either. Classic combinatorial auctions that are centrally managed, such as the Generalized Vickrey Auction (GVA), require agents to disclose their values on items to obtain an efficient outcome (Parkes, 2001; Vickrey, 1961). However, the only information that the auctioneer receives in this auction setting is the purchase prices from buyers and the ask prices from sellers, whereas their values need not be informed. The auction proposed in this paper keeps agents' sensitive information confidential while obtaining efficient results.

The information received by agents at the end of each round is partial and anonymized. The auctioneer only informs agents about their current situation: whether they are winning their items (bundles) at the current purchase prices (ask prices). Hence, agents will keep updating their prices from one round to another according to their private valuations and utilities. A rational buyer will increase their purchase price over an item until its reservation price is reached. In contrast, a rational seller will decrease their ask price over a bundle of items until their estimated production costs for that bundle are reached.

This iterative procedure guides the auction towards an efficient result while keeping the computational complexity at a reasonable level by distributing the computation across all agents of the auction (Parkes, 2006). At the same time, the partial and anonymized information feedback scheme prevents agent collusion and untruthful bidding strategies. Since sellers do not know which buyer is requesting each item and vice versa, agents cannot pursue collusion strategies. Also, participants have no incentives to seek untruthful strategies as they only know their current market situation and nothing about the whole item allocation.

The auction model presented in this work provides the basis for further analysis of this market environment. The results obtained from the simulation experiments allowed the successful verification of the theoretical auction design and will serve as the first stage towards the validation of the model in a real context.

7. Conclusions and future lines

The growing adoption of AM by manufacturers in a variety of industries is leading to an imbalance between the supply and demand of additively manufactured subcomponents. The mechanisms proposed in the literature to match demand and supply do not fully exploit the potential of AM techniques. In this paper, we propose a market mechanism that considers the unique characteristics of AM techniques, wherein suppliers can benefit from manufacturing multiple heterogeneous parts from multiple customers in the same build area to increase production throughput. This market mechanism has been implemented as an iterative combinatorial double auction that adapts to this feature of the AM market: customers bid to have their orders produced, and suppliers submit asking quotes to win the production of combinations of those orders. The mechanism solves the allocation and pricing of AM orders while seeking to maximize social welfare.

The mechanism designed in this work entails advantages for both sides of an AM market. On one side, AM customers may easily access a wide range of manufacturers and acquire competitive prices without having to negotiate contracts individually. On the other side, AM suppliers can combine orders from different customers in a way that allows them to optimize their productive capacity.

Implementing the allocation mechanism through a combinatorial double auction ensures that the mechanism exhibits desirable properties of auctions, such as maximization of market welfare, budget balance and collusion prevention. An iterative sealed-bid configuration and a partial, anonymized feedback scheme are used to attain these properties. This auction design allows obtaining a final allocation that improves the overall utility of all the agents involved while it follows a privacy-preserving strategy that does not require agents to disclose sensitive information.

An algorithmic procedure to implement the auction is proposed. This procedure has been simulated in a theoretical environment to evaluate its performance and to identify the most appropriate conditions for its implementation in a real environment. The simulation results showed that for a scenario with no more than 20 buyers and 20 sellers and adjusting the size of the price step, the auction could be directly implemented and solved in a reasonable time. For larger scenarios, it would be advisable to implement a proxy bidding system so that buyers and sellers could automate their decisions.

Although the conducted simulations demonstrate that the proposed mechanism leads to an allocation that maximizes social surplus, it is important to consider that it relies on the assumption that manufacturers are capable of evaluating the combinations of batches they would be able to produce with their available resources. If suppliers encounter difficulties in formulating their combinatorial bids, the mechanism may result in suboptimal outcomes.

In this work, the study of the auction has been conducted by modeling the participants as rational agents in a theoretical environment. However, it may happen that in a real environment the agents do not behave rationally. As a future direction, it would be compelling to develop a multi-agent model for a more realistic simulation of the auction, considering sub-optimal behavior of the agents. This tuning of the mechanism's design will be the first step toward its implementation on electronic platforms, allowing customer companies and AM suppliers to benefit from the advantages of the allocation mechanism proposed in this paper.

CRediT authorship contribution statement

Juan De Antón: Writing – review & editing, Writing – original draft, Software, Investigation, Formal analysis. **Félix Villafáñez:** Software, Investigation, Formal analysis. **David Poza:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition. **Adolfo López-Paredes:** Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

The authors wish to acknowledge MCIN/AEI, Spanish Government, and /10.13039/501100011033/FEDER UE, European Union, for the partial support through the PID2022-137948OA-I00 Research Project and the grant FPU19/01304 received by the corresponding author. Also, this research has been partially financed by the Regional Government of Castile and Leon (Spain) and the European Regional Development Fund (ERDF, FEDER) with grant VA180P20.

References

Abrache, J., Crainic, T. G., & Gendreau, M. (2004). Design issues for combinatorial auctions. *4or, 2*(1), 1–33. https://doi.org/10.1007/s10288-004-0033-y

Baumann, F. W., & Roller, D. (2017). Additive manufacturing, cloud-based 3D printing and associated services—overview. *Journal of Manufacturing and Materials Processing, 1*(2), 15. https://doi.org/10.3390/JMMP1020015

Bogers, M., Hadar, R., & Bilberg, A. (2016). Additive manufacturing for consumer-centric business models: Implications for supply chains in consumer goods manufacturing. *Technological Forecasting and Social Change, 102*, 225–239. https://doi.org/10.1016/J.TECHFORE.2015.07.024

Byskov, J., & Vedel-Smith, N. (2023). Additive Manufacturing. *The Future of Smart Production for SMEs*, 357–362. https://doi.org/10.1007/978-3-031-15428-7_32

Calignano, F., & Mercurio, V. (2023). An overview of the impact of additive manufacturing on supply chain, reshoring, and sustainability. *Cleaner Logistics and Supply Chain, 7*, Article 100103. https://doi.org/10.1016/J.CLSCN.2023.100103

Canellidis, V., Giannatsis, J., & Dedoussis, V. (2013). Efficient parts nesting schemes for improving stereolithography utilization. *CAD Computer Aided Design, 45*(5), 875–886. https://doi.org/10.1016/j.cad.2012.12.002

Chen, T. C. T. (2019). Fuzzy approach for production planning by using a three-dimensional printing-based ubiquitous manufacturing system. *AI EDAM, 33*(4), 458–468. https://doi.org/10.1017/S0890060419000222

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

Coppinger, V. M., & Smith, V. L. (1980). INCENTIVES AND BEHAVIOR IN ENGLISH. *DUTCH AND SEALED-BID AUCTIONS. Economic Inquiry, 18*(1), 1–22. https://doi.org/10.1111/J.1465-7295.1980.TB00556.X

Cramton, P., Shoham, Y., & Steinberg, R. (2006). Combinatorial Auctions. *Combinatorial Auctions.* https://doi.org/10.7551/mitpress/9780262033428.003.0001

Cui, J., Ren, L., Mai, J., Zheng, P., & Zhang, L. (2022). 3D printing in the context of cloud manufacturing. *Robotics and Computer-Integrated Manufacturing, 74*(October), Article 102256. https://doi.org/10.1016/j.rcim.2021.102256

De Antón, J., David, P., Villafáñez, F., & López-Paredes, A. (2024). Limitations and Opportunities in e-Platforms for the Additive Manufacturing Market. Proceedings of the 17th International Conference on Industrial Engineering and Industrial Management (ICIEIM) – XXVII Congreso de Ingeniería de Organización (CIO2023). CIO 2023. Lecture Notes on Data Engineering and Communications Technologies, vol 206, 99–104. Springer, Cham. https://doi.org/10.1007/978-3-031-57996-7_18.

de Antón, J., Poza, D., López-Paredes, A., & Villafáñez, F. (2023). Defining Production Planning Problems in Additive Manufacturing. In Industry 4.0: The Power of Data: Selected Papers from the 15th International Conference on Industrial Engineering and Industrial Management (pp. 193–201). Springer, Cham. https://doi.org/10.1007/978-3-031-29382-5_20.

De Antón, J., Senovilla, J., González, J. M., & Acebes, F. (2020). Production planning in 3D printing factories. *International Journal of Production Management and Engineering, 8*(2), 75. https://doi.org/10.4995/ijpme.2020.12944
De Antón, J., Villafáñez, F., Poza, D., & Lopez Paredes, A. (2022). A Framework for Production Planning in Additive Manufacturing. *International Journal of Production Research, 61*(24), 8674–8691. https://doi.org/10.1080/00207543.2022.2160026
De Vries, S., & Vohra, R. V. (2003). Combinatorial auctions: A survey. *INFORMS Journal on Computing, 15*(3), 284–309. https://doi.org/10.1287/ijoc.15.3.284.16077
Einav, L., Farronato, C., & Levin, J. (2015). Peer-to-Peer Markets.
Framinan, J. M., Perez-Gonzalez, P., & Fernandez-Viagas, V. (2023). An overview on the use of operations research in additive manufacturing. *Annals of Operations Research, 322*, 5–40. https://doi.org/10.1007/S10479-022-05040-4
Friedman, D. (1993). The Double Auction Market Institution: A Survey. In D. Friedman & J. Rust (Eds.), The Double Auction Market: Institutions, Theories, and Evidence (pp. 3–26). Routledge. https://doi.org/10.4324/9780429492532-2.
Friedrich, A., Lange, A., & Elbert, R. (2022). Make-or-buy decisions for industrial additive manufacturing. *Journal of Business Logistics, 43*(4), 623–653. https://doi.org/10.1111/JBL.12302
Gao, P. (2024). Scheduling Modeling and Optimization of 3D Print Task in Cloud Manufacturing Environment Based on Quantum Wolf Pack Algorithm. https://doi.org/10.4108/EAI.17-11-2023.2342663.
Holzmann, P., Breitenecker, R. J., Schwarz, E. J., & Gregori, P. (2020). Business model design for novel technologies in nascent industries: An investigation of 3D printing service providers. *Technological Forecasting and Social Change, 159*. https://doi.org/10.1016/j.techfore.2020.120193
Kang, K., Tan, B. Q., & Zhong, R. Y. (2023). Cloud-based 3D printing service allocation models for mass customization. *International Journal of Advanced Manufacturing Technology, 126* (5–6), 2129–2145. https://doi.org/10.1007/S00170-023-11221-7/FIGURES/12
Khajavi, S. H., Ituarte, I. F., Jaribion, A., An, J., Kai, C. C., & Holmstrom, J. (2020). Impact of Additive Manufacturing on Supply Chain Complexity. Hawaii International Conference on System Sciences 2020 (HICSS-53). https://aisel.aisnet.org/hicss-53/in/digital_supply_chain/2.
Kim, Y. J., & Kim, B. S. (2022). Part-grouping and build-scheduling with sequence-dependent setup time to minimize the makespan for non-identical parallel additive manufacturing machines. *International Journal of Advanced Manufacturing Technology, 119*(3–4), 2247–2258. https://doi.org/10.1007/S00170-021-08361-Z
Kucukkoc, I. (2019). MILP models to minimise makespan in additive manufacturing machine scheduling problems. *Computers and Operations Research, 105*, 58–67. https://doi.org/10.1016/j.cor.2019.01.006
Li, B. H., Zhang, L., Wang, S. L., Tao, F., Cao, J. W., Jiang, X. D., Song, X., & Chai, X. D. (2010). Cloud manufacturing: A new service-oriented networked manufacturing model. *Jisuanji Jicheng Zhizao Xitong/Computer Integrated Manufacturing Systems, CIMS, 16*(1).
Li, Q., Zhang, D., & Kucukkoc, I. (2019). Order acceptance and scheduling in direct digital manufacturing with additive manufacturing. *IFAC-PapersOnLine, 52*(13), 1016–1021. https://doi.org/10.1016/j.ifacol.2019.11.328
Liu, S., Liu, Y., & Zhang, L. (2019). Distributed 3D printing services in cloud manufacturing: A non-cooperative game-theory-based selection method. *Communications in Computer and Information Science, 1094*, 137–145. https://doi.org/10.1007/978-981-15-1078-6_12/FIGURES/4
Liu, S., Zhang, L., Zhang, W., & Shen, W. (2021). Game theory based multi-task scheduling of decentralized 3D printing services in cloud manufacturing. *Neurocomputing, 446*, 74–85. https://doi.org/10.1016/j.neucom.2021.03.029
Lubin, B., Juda, A. I., Cavallo, R., Lahaie, S., Shneidman, J., & Parkes, D. C. (2008). ICE: An expressive iterative combinatorial exchange. *Journal of Artificial Intelligence Research, 33*, 33–77. https://doi.org/10.1613/JAIR.2440
Luo, X., Zhang, L., Ren, L., & Lali, Y. (2020). A dynamic and static data based matching method for cloud 3D printing. *Robotics and Computer-Integrated Manufacturing, 61*, Article 101858. https://doi.org/10.1016/J.RCIM.2019.101858
Ma, J. (2020). Environmentally sustainable management of 3D printing network: Decision support for 3D printing work allocation. *International Journal of Precision Engineering and Manufacturing, 21*(3), 537–544. https://doi.org/10.1007/S12541-019-00280-0/TABLES/1
Mashhadi, F., & Salinas Monroy, S. A. (2019). Economically-robust dynamic control of the additive manufacturing cloud. *IEEE Transactions on Services Computing, 15*(1), 527–538. https://doi.org/10.1109/TSC.2019.2954137
Mashhadi, F., & Salinas Monroy, S. A. (2020). Deep Learning for Optimal Resource Allocation in IoT-enabled Additive Manufacturing. IEEE World Forum on Internet of Things, WF-IoT 2020 - Symposium Proceedings. https://doi.org/10.1109/WF-IOT48130.2020.9221038.
Mendonça, P. A., da Piedade Francisco, R., & de Souza Rabelo, D. (2022). OEE approach applied to additive manufacturing systems in distributed manufacturing networks. *Computers & Industrial Engineering, 171*, Article 108359. https://doi.org/10.1016/J.CIE.2022.108359
Meyer, M. M., Glas, A. H., Eßig, Michael, & De, M. M. (2021). Systematic review of sourcing and 3D printing: make-or-buy decisions in industrial buyer-supplier relationships. 71, 723–752. https://doi.org/10.1007/s11301-020-00198-2.
Mittelmann, M., Bouveret, S., & Perrussel, L. (2021). A General Framework for the Logical Representation of Combinatorial Exchange Protocols. https://doi.org/10.48550/arxiv.2102.02061.
Monroy, S. S., Li, P., Fang, Y., & Loparo, K. A. (2023). Blockchain-empowered distributed additive manufacturing-as-a-Service: An architectural perspective. *IEEE Network, 1–7*. https://doi.org/10.1109/MNET.129.2200459
Morar, D., Hiller, S., & Petrik, D. (2023). How Additive Manufacturing Platforms are Digitizing the Manufacturing Value Proposition. ECIS 2023 Research Papers. https://aisel.aisnet.org/ecis2023_rp/226.
Oh, Y., Witherell, P., Lu, Y., & Sprock, T. (2020). Nesting and scheduling problems for additive manufacturing: A taxonomy and review. *Additive Manufacturing, 36* (August), Article 101492. https://doi.org/10.1016/j.addma.2020.101492
Pahwa, D., Starly, B., & Cohen, P. (2018). Reverse auction mechanism design for the acquisition of prototyping services in a manufacturing-as-a-service marketplace. *Journal of Manufacturing Systems, 48*, 134–143. https://doi.org/10.1016/J.JMSY.2018.05.005
Palacios-Huerta, I., Parkes, D. C., & Steinberg, R. (2024). Combinatorial auctions in practice. *Journal of Economic Literature, 62*(2), 517–553. https://doi.org/10.1257/jel.20221679
Parkes, D. C. (2001). *Iterative combinatorial auctions: achieving economic and computational efficiency*. University of Pennsylvania.
Parkes, D. C. (2006). Iterative combinatorial auctions. In *Combinatorial Auctions* (pp. 41–78). MIT Press.
Priyadarshini, J., Singh, R. K., Mishra, R., Chaudhuri, A., & Kamble, S. (2023). Supply chain resilience and improving sustainability through additive manufacturing implementation: A systematic literature review and framework. *Production Planning & Control*. https://doi.org/10.1080/09537287.2023.2267507
Rayna, T., Striukova, L., & Darlington, J. (2015). Co-creation and user innovation: The role of online 3D printing platforms. *Journal of Engineering and Technology Management - JET-M, 37*, 90–102. https://doi.org/10.1016/j.jengtecman.2015.07.002
Rothkopf, M. H., Teisberg, T. J., & Kahn, E. P. (1990). Why are vickrey auctions rare? *Journal of Political Economy, 98*(1), 94–109. https://doi.org/10.1086/261670
Shoeb, M., Kumar, L., Haleem, A., & Javaid, M. (2023). Trends in additive manufacturing: An exploratory study. *Advances in Additive Manufacturing Artificial Intelligence, Nature-Inspired, and Biomanufacturing, 15–25*. https://doi.org/10.1016/B978-0-323-91834-3.00027-2
Spieske, A., Gebhardt, M., Kopyto, M., Birkel, H., & Hartmann, E. (2023). The future of industry 4.0 and supply chain resilience after the COVID-19 pandemic: Empirical evidence from a Delphi study. *Computers & Industrial Engineering, 181*, Article 109344. https://doi.org/10.1016/J.CIE.2023.109344
Stein, N., Flath, C. M., & Walter, B. (2020). Towards open production: Designing a marketplace for 3D-printing capacities. 40th International Conference on Information Systems, ICIS 2019, 1–15.
Tolio, T. A. M., Monostori, L., Váncza, J., & Sauer, O. (2023). Platform-based manufacturing. *CIRP Annals, 72*(2), 697–723. https://doi.org/10.1016/J.CIRP.2023.04.091
Tsay, A. A., Gray, J. V., Noh, I. J., & Mahoney, J. T. (2018). A review of production and operations management research on outsourcing in supply chains: Implications for the theory of the firm. *Production and Operations Management, 27*(7), 1177–1220. https://doi.org/10.1111/POMS.12855
Vickrey, W. (1961). Counterspeculation, auctions, and competitive sealed tenders. *The Journal of Finance, 16*(1), 8–37.
Wu, Q., Xie, N., Zheng, S., & Bernard, A. (2022). Online order scheduling of multi 3D printing tasks based on the additive manufacturing cloud platform. *Journal of Manufacturing Systems, 63*, 23–34. https://doi.org/10.1016/J.JMSY.2022.02.007
Yang, H., Chen, R., & Kumara, S. (2021). Stable matching of customers and manufacturers for sharing economy of additive manufacturing. *Journal of Manufacturing Systems, 61*, 288–299. https://doi.org/10.1016/J.JMSY.2021.09.013
Ying, K. C., Fruggiero, F., Pourhejazy, P., & Lee, B. Y. (2022). Adjusted Iterated Greedy for the optimization of additive manufacturing scheduling problems. *Expert Systems with Applications, 198*, Article 116908. https://doi.org/10.1016/J.ESWA.2022.116908
Zehetner, D., & Gansterer, M. (2023). Decentralised collaborative job reassignments in additive manufacturing. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2023.2285403
Zhang, C., Li, Q., Han, H., Liu, J., Xu, B., & Yuan, B. (2022). Research on a supply–demand matching method for cloud 3D printing services based on complex networks. *Soft Computing, 26*(24), 13583–13604. https://doi.org/10.1007/S00500-022-07315-1/FIGURES/19
Zhang, L., Luo, X., Ren, L., Mai, J., Pan, F., Zhao, Z., & Li, B. (2020). Cloud based 3D printing service platform for personalized manufacturing. *Science China Information Sciences, 63*(2), 2019–2021. https://doi.org/10.1007/s11432-018-9942-y
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/10.1016/j.rcim.2015.11.003
Zhao, Z., Zhang, L., & Cui, J. (2018). A 3D printing task packing algorithm based on rectangle packing in cloud manufacturing. *Lecture Notes in Electrical Engineering, 460*, 21–31. https://doi.org/10.1007/978-981-10-6499-9_3
Zhong, R. Y., Kang, K., Yu, C., Zhang, Y., Tao, F., & Bernard, A. (2022). A resource sharing approach for PSS-enabled additive manufacturing platform. *CIRP Journal of Manufacturing Science and Technology, 39*, 414–426. https://doi.org/10.1016/J.CIRPJ.2022.10.004
Zhou, L., Zhang, L., Laili, Y., Zhao, C., & Xiao, Y. (2018). Multi-task scheduling of distributed 3D printing services in cloud manufacturing. *International Journal of Advanced Manufacturing Technology, 96*(9–12), 3003–3017. https://doi.org/10.1007/s00170-017-1543-z
Zhou, L., Zhang, L., Ren, L., & Laili, Y. (2017). Matching and selection of distributed 3D printing services in cloud manufacturing. In *Proceedings IECON 2017–43rd Annual Conference of the IEEE Industrial Electronics Society*. https://doi.org/10.1109/IECON.2017.8216815
Zipfel, B., Neufeld, J., & Buscher, U. (2023). An iterated local search for customer order scheduling in additive manufacturing. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2023.2167015