Towards Open Production: Designing a Marketplace for 3D-Printing Capacities

Completed Research Paper

Nikolai Stein
Julius-Maximilians-University
Josef-Stangl-Platz 2
97070 Würzburg, Germany
nikolai.stein@uni-wuerzburg.de

Christoph M. Flath
Julius-Maximilians-University
Josef-Stangl-Platz 2
97070 Würzburg, Germany
christoph.flath@uni-wuerzburg.de

Benedikt Walter
BMW Group
Petuelring 130
80809 Munich, Germany
benedikt.walter@bmw.de

Abstract

In recent years, IT systems have facilitated the creation of open systems and thereby served as an enabler for resource sharing across various industries. Often electronic marketplaces have been established as opening processes. In the manufacturing sector, marketplaces focus primarily on the direct purchase of standardized products as highly specialized machine tools impede capacity trading. However, the emergence of additive manufacturing changes this logic, giving firms the opportunity to trade 3D-printing capacities. In this paper, we pursue a design-oriented research approach to develop and evaluate a prototypical platform for market-based coordination of 3D-printing capacities. The platform allows firms to enhance profits by marketing surplus capacity or hedge risks by mitigating capacity mismatches. Such sharing of production capacities instantiates a form of an open production system. Our artifact leverages methods from information systems, operations research, and economics to cope with the complexity of the task.

Keywords: 3D printing, open production, smart markets, scheduling

Introduction

Manufacturing companies face constant economic pressure to optimize production capacity usage. Yet, uncertainty arising from future demand or machine availability pose significant challenges to this end as uncertainties can result both in overcapacity and capacity shortages. In both cases, firm profitability is hurt by either excess cost or lost sales. However, at any given point in time, other manufacturing companies are likely facing the converse problem–either suffering from insufficient demand or lacking the capacity to serve demand. Naturally, this offers an opportunity to tap into the benefits of IT-enabled openness and its ability to reduce the costs of coordination increasing to facilitate joint usage of production resources and benefit from economies of sharing (Gurbaxani and Whang 1991; Kranton and Minehart 2001).

By drastically reducing the transaction costs of matching supply and demand, the Internet has fostered solutions for resource sharing across many industries: Platforms as intermediaries efficiently allocate otherwise unused capacities and in turn increase social welfare. Examples of these platforms include Uber or Airbnb, which either enable car owners to offer otherwise unoccupied seats as car capacity or unused apartments (Kenney and Zysman 2016; Zervas et al. 2017).

These services trade capacities in a highly liquid manner as buyers accept compromises and can partly depart from their expectations, which increases the likelihood of matching demand and supply.

In the manufacturing context, matching of production capacities to production batches has traditionally been impossible as highly specialized machine tools rule out simple assignments of production jobs to decentral capacities. However, the emergence of additive manufacturing (also known as 3D printing) disrupts the manufacturing sector (Petrick and Simpson 2013) and changes this logic as 3D printers can produce highly differentiated products with minimal setup costs (Thiesse et al. 2015). Following Schlagwein et al. (2017), IT-enabled openness is a promising way to leverage these potentials. With 3D-printers serving as open resources and a platform for capacity trading as an open process, an open production system delivers flexibility as well as scalability and allows companies to acquire virtual operational flexibility as opposed to setting up a flexible production footprint (Jordan and Graves 1995).

The success of platforms as intermediaries between supply and demand in other parts of the economy indicates their potential for matching supply and demand of production capacities and motivates researching this topic. As an integral part of such a trading platform, manufacturing jobs have to be allocated to available production capacities. In this paper, we put forward an IT artifact for automatic matching of production capacities and manufacturing jobs. The effectiveness of this matching procedure is crucial for the success of the platform (Veit et al. 2001). To cope with the complexity of this task and to enable real-time decisions to customers, the platform relies on methods from operations management to automatically schedule jobs on distributed printers. The scheduling system must cope with a very large number of jobs given the relative smallness of 3D printing capacities vis-a-vis large manufacturing tools. To this end, we propose a heuristic scheduling approach. We are particularly interested in systems with aggregate surplus demand to ensure scarcity of production capacities. Thereby, the number of served jobs weighted by their willingness to pay becomes a central dimension of evaluating the system performance. Our IT artifact illustrates the potential of platforms which enable trading of production capacities by means of additive manufacturing for production companies. To structure our work and to emphasize its focus, we pose the following research questions:

RQ1 What are design elements of a platform for trading production capacities between companies efficiently?

RQ2 What is the relative performance of our online optimization approach compared to the benchmark case of complete information?

RQ3 To what extent can production jobs increase their likelihood of admittance through increased willingness to pay and temporal flexibility?

Addressing these questions, we seek to illustrate the potential of expanding the existing use cases of additive manufacturing to trading production capacities, establishing an economic basis for open production systems. In the following, we highlight additive manufacturing as a disruptive technology and provide an overview of the associated emergence of 3D printing platforms. After presenting the research methodology, we describe and evaluate the IT artifact.

Related Work and Background

We position our research at the intersection of two topics in information systems research: The emergence of additive manufacturing with side-lining platforms as well as market design and potentials of decentral coordination.

The Emergence of Additive Manufacturing Platforms

Although technologies associated with the term “3D printing” have primarily attracted the attention of the economy and media in recent years, their development dates back to the 1980s (Carver et al. 1990; Fudim 1989; Sachs et al. 1990). While the term “3D printing” is prevailing, it describes only one of the technologies belonging to the field of additive manufacturing (Gibson et al. 2010). All these technologies share the transformation of digital 3D models into products (Weller et al. 2015) and allow low volume production (Berman 2012). Well-known use cases include medical prosthetics, rapid prototyping, or the production of spare parts (Ben-Ner and Siemsen 2017; Khajavi et al. 2014). Although additive manufacturing does not substitute traditional production methods in all sectors, it constitutes a novel tool in the production toolbox and enables new use cases providing promising applications for business users (Holweg 2015).

Rayna et al. (2015) provide a comprehensive overview of platforms which try to leverage the potential benefits of additive manufacturing and emphasize the influence on co-creation and user innovation. Their survey illustrates that the diffusion of additive manufacturing and the emergence of platforms have enabled individuals to become "makers." Major drivers of this technology diffusion and the associated maker movement were reductions in software and hardware prices, which made the technologies accessible to individuals (Anderson 2012). Makers develop their own 3D models, exchange them with others and collaboratively work on them, or sell them on marketplaces. Furthermore, individuals offer their own printers to others for printing products (Weller et al. 2015). While this do-it-yourself-movement existed before, additive manufacturing has reinforced it as central part platforms instantiate primarily open processes for design. They can either facilitate interactions between individuals from different groups as two-sided markets or between individuals of a homogeneous group as peer-2-peer-platforms (Gassmann et al. 2014). In either case, they are characterized by network effects, which makes it essential to attract a critical mass (Buxmann and Hinz 2013).

All platforms and websites exemplify the decoupling of design and production as well as the opportunity of individualizing products through additive manufacturing. Hence, we distinguish between design and printer platforms. First, design platforms serve as an exchange for user-generated content such as 3D models. Users collaboratively work on designs by exploiting and modifying existing 3D models. Many of these design exchange platforms offer an additional printing service or inspections which ensure that all designs are printable. As the biggest community of 3D printing in the world, the peer-2-peer-platform Thingiverse is the most prominent example. Flath et al. (2017) examine the activities on the platform and observe how existing knowledge is reused by its members to create new ideas. These remixing activities can be interpreted as an organizational intervention in creative processes (Friesike et al. 2019). Second, printer platforms enable users to collaboratively use their 3D printers in the sense of the sharing economy. The community connects users seeking to print 3D models with a network of users offering capacity on their printers. Consequently, it helps to allocate additive manufacturing capacities efficiently among individuals.

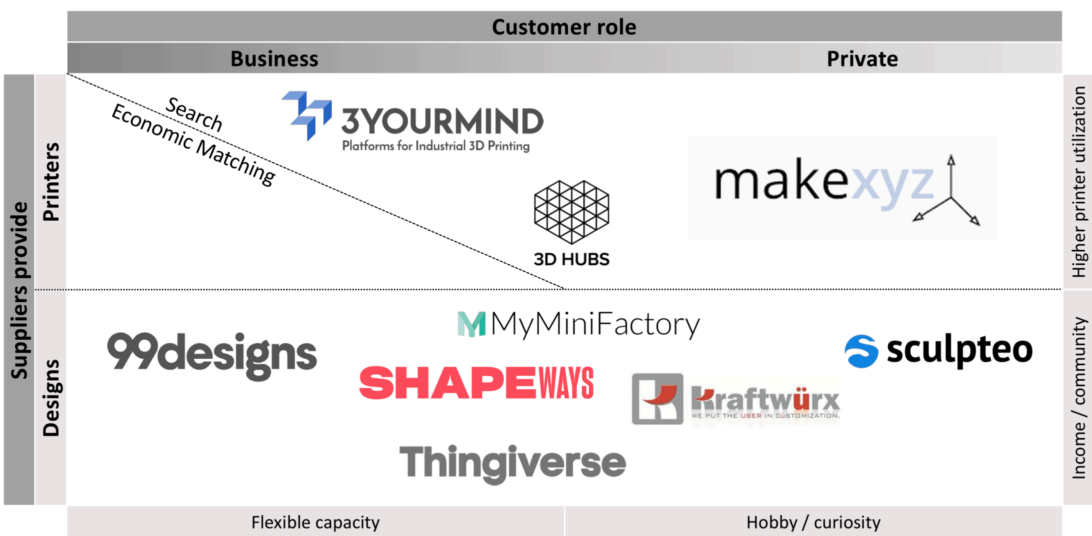


Figure 1. 3D Design and Printing Platforms

Figure 1 illustrates the limited number of additive manufacturing platforms in the commercial space compared to private use cases. Even though there exist companies individually providing design or print services, they do not act as intermediaries between suppliers and customers and, thus, do not constitute platforms for sharing of 3D-printing capacities. While the lack of communities of designers providing designs for companies seems little astonishing, the absence of platforms mediating between suppliers of printers and companies strikes.

Our research aims to design a platform allowing to trade additive manufacturing capacities between companies. Such a platform differs from the current offers regarding the efficient allocation of production capacities. Companies such as those mentioned in Rayna et al. (2015) act as print service providers helping other companies to address excess demand by printing their products, these companies themselves face the same challenges as manufacturing companies: At one point in time, they might face insufficient demand; at another time, demand might exceed their capacity. Other companies such as 3yourmind do not own printers themselves, but instead, provide an overview of printing services. However, as customers choose providers individually, these websites primarily act as comparison sites instead of actively assigning jobs to available capacity. In summary, although these companies provide valuable services to their business clients, they do not sufficiently address the mentioned inefficient allocation of production capacities.

Market-based Coordination

Marketplaces form the foundation for interaction and communication between suppliers and customers. In recent years, numerous electronic marketplaces have established themselves that specialize primarily in the direct purchase of standardized products and services (e.g., Alibaba.com, Mercateo.de). In the B2B sphere, procurement platforms for different suppliers are the dominant platform type. These services allow companies to speed up the search for suitable suppliers. We envision a solution which goes one step further: Firms are matched with production facilities to which they can temporarily outsource or expand their production. This concept increases long-term productivity and leads to improved utilization of production in networked process chains. The economic backbone of such a platform is a suitable market and matching mechanism.

To enable efficient trading of capacities in a dynamic environment, the players must execute the transactions in an algorithmically supported trading environment, a so-called smart market. In addition to the processing and communication of bids and inquiries, the system must solve two complex sub-problems: the allocation decision and pricing. The theoretical foundations for these problems are investigated within the framework of market-based scheduling (Beil and Wein 2003; Clearwater 1996; Wellman et al. 2001). The research area of market engineering has established process models for the design of such electronic marketplaces. These methods draw on concepts and solutions from information systems, operations research, and economics (Weinhardt et al. 2003). To exclude false incentives, pricing must be based on the results of the mechanism design theory (Nisan and Ronen 2001). On the other hand, research into the decision support systems required for practical implementation is still in its infancy (Bichler et al. 2010).

Here, the particular challenge is that systems must be individually designed for the respective application context in order to enable market participants to communicate their preferences and capacities in the given transaction context. Current research is divided into a large number of individual contributions on specific problems (Bichler et al. 2010; Chang 2009; Dauer et al. 2013; Leskelä et al. 2007; Salido et al. 2012). There is currently no integrated market platform for production capacities that links operational and cross-company value-added processes and permits complete individualization of supply.

A platform for trading additive manufacturing capacities requires market designers to handle the underlying complexity of the problem and to allocate capacities efficiently. In general, this problem belongs to the group of scheduling problems. They are characterized by the goal of assigning a number of jobs to a number of printers such that the resulting allocation optimizes a specific criterion. While numerous variants of these problems exist (Maccarthy and Liu 1993; Senthilkumar and Narayanan 2010), a general categorization divides them into offline and online problems. In offline scheduling problems, complete information regarding jobs and machines exists when deciding on the schedule. However, in many real-world problems, perfect information is not available. These problems are referred to as online scheduling problems. Scheduling as part of a platform for trading additive manufacturing capacities also belongs to this category: Available information is restricted to the jobs which have arrived so far and to the available capacity, whereas future jobs are unknown. In this regard, Hosseini et al. (2012) point to the complexity of resource allocation in situations with uncertainty, multiple agents, and a large number of resources. They argue that the problem grows exponentially with the number of participants and resources. Consequently, the problem at hand with the inherent uncertainty regarding supply and demand and the extensive network of printers is characterized by an enormous complexity. Due to this complexity and the need for instant decisions, which makes optimizing the problem infeasible, heuristics are required to solve this allocation problem. To this end, several heuristics exist for solving problems whose complexity impedes optimizing them (Pruhs et al. 2004).

Research Methodology

In summary, the elaborations above emphasize the complexity of the problem due to the numerous agents and the uncertainty associated with supply and demand. If market-based coordination addresses these challenges, additive manufacturing enables trading production capacities flexibly and tackles the inefficient allocation of excess and needed capacities. In order to design a smart market for the capacity trading problem at hand, we put forward a suitable allocation mechanism. Apart from handling the problem complexity, the allocation mechanism must ensure real-time decisions regarding the acceptance or rejection of jobs, allowing instant feedback to customers. Additionally, the allocation algorithm should incentivize customers to reveal private information in order to improve allocation results and reach a market outcome as close to the optimal solution as possible.

Based on these explanations, this paper introduces an IT artifact which addresses several of the challenges mentioned above and demonstrates a possible allocation mechanism for the demand and supply of additive manufacturing capacities. Before examining the IT artifact, we shortly cover our research methodology to structure our work and increase the transparency for readers. We apply a design-oriented research approach to conceptualize the mechanism for trading production capacities as part of a platform. To do this, we rely on the guidelines put forward by Hevner et al. (2004):

- **Problem Relevance:** Uncertain, fluctuating demand results in firms either having excess capacity or missing capacity to serve demand. A production matching platform allows companies to buy and sell production capacities and in turn, helps to allocate production capacities more efficiently.
- **Research Rigor:** To match supply and demand and to allow instant feedback to customers, we formulate the problem in the sense of a mixed integer program. Subsequently, we put forward an online optimization approach and benchmark it against the optimal offline solution determined under perfect information.
- **Design as a Search Process:** We base the proposed online optimization as well as the mixed integer program for the offline solution on relevant papers solving related problems in the context of smart energy markets (Ströhle et al. 2014).
- **Design as an Artifact:** We design an IT artifact with four modules. The IT artifact and each of its modules are described in detail and implemented using Python.
- **Design Evaluation:** We analyze possible market outcomes utilizing a simulation study. Based on the results, we derive economic implications for purchasers as well as suppliers of 3D-printing capacities and discuss the limitations of the proposed artifact.
- **Research Contribution:** The main contribution of this research is to demonstrate that additive manufacturing, in combination with existing methods of operations management, allows building a platform based open production system.
- **Research Communication:** Our research invites scholars to examine the opportunities enabled by additive manufacturing to trade production capacities. For practitioners, the research indicates the potential of additive manufacturing to address the challenge of excess and missing capacities.

The following section of the paper describes the IT artifact with its four modules in detail. This includes the presentation of inputs and outputs, the underlying parameter assumptions, and an elaboration on the matching algorithm.

Problem Formalization

Before we examine the artifact design in detail, we first describe the input parameters regarding the available printers and the incoming jobs. Here, the set I describes the printers offered on the platform. Each printer i is described by its compatibility regarding size and materials g_i, the minimum price expected for providing the capacity m_i (reservation price) and its availability. Similarly, the set of incoming jobs J are described by a variety of parameters. Here, the size and material requirements of job j are summarized under the parameter c_j. Additionally, the release date r_j, the production deadline d_j, the processing time p_j, and the bid offered by the customer v_j are provided. Table 1 summarizes the relevant parameters. As a simplification of the problem, the availability of printers is modeled as known. On the other hand, demand is modeled as unknown since information regarding jobs is restricted to those jobs which have already arrived, whereas future jobs are unknown.

Parameter	**Description**
g_i	Compatibility regarding size and materials of printer i
m_i	Reservation price for capacity on printer i
c_j	Requirements regarding size and materials of job j
r_j	Release of job j
d_j	Deadline of job j
p_j	Processing time of job j
v_j	Bid offered by the customer for job j

Table 1. Model Parameters

Based on these assumptions and parameters, we can define an offline mixed integer program describing the allocation problem at hand. As the allocation can be modeled in the sense of a scheduling problem, we use a similar problem formulation. To this end, the binary decision variable $a_{i,j}$ takes value 1 if job j is scheduled on printer i and 0 otherwise. The variable $t_{i,j}$ specifies the starting time of job j on printer i and the binary variable $x_{i,j,k}$ indicates if job j precedes job k on machine i.

In classic scheduling problems, all jobs have to be fulfilled, and the objective is to minimize the total makespan. In contrast, we have to find an alternative objective function as not all jobs have to be accepted in the problem at hand. To this end, we choose to maximize the total revenue. As shown in Equation 1, we model the revenue as the sum of the bids of all accepted jobs.

$$\max \sum_{i=1}^{I} \sum_{j=1}^{J} a_{i,j} v_j \tag{1}$$

In addition to the objective function, several constraints limit the available scheduling options. Equation 2 ensures that a job can be accepted by at most one printer.

$$\sum_{i=1}^{I} a_{i,j} \leq 1 \qquad \forall j \tag{2}$$

Even though we assume perfect foresight in the offline case, Equation 3 is required to ensure that a job cannot be scheduled prior to its arrival. Additionally, all accepted jobs have to be finished prior to their deadline (Equation 4).

$$t_{i,j} \geq r_j - (1 - a_{i,j})M \qquad \forall i,j \tag{3}$$

$$t_{i,j} + p_j \leq d_j + (1 - a_{i,j})M \qquad \forall i,j \tag{4}$$

$$t_{i,k} + p_k \leq t_{i,j} + M x_{i,j,k} \qquad \forall i,j,k \tag{5}$$

$$t_{i,j} + p_j \leq t_{i,k} + M(1 - x_{i,j,k}) \quad \forall i,j,k \tag{6}$$

The latter two constraints (Equations 5 and 6) ensure consistency between jobs and are adopted from Ku and Beck (2016). They prevent that more than one job is processed on one printer at any time. The following two constraints address the consistency between jobs and printer: Equation 7 makes sure that jobs are only scheduled on compatible printers, e.g., regarding their sizes or printable materials. Equation 8 guarantees that a job is only assigned to a printer if the bid offered for printing this job exceeds the minimum price expected by the provider of this printer.

$$c_j \leq g_i + (1 - a_{i,j})M \qquad \forall i, j \tag{7}$$

$$v_j \geq m_i - (1 - a_{i,j})M \qquad \forall i, j \tag{8}$$

The objective function and the constraints constitute the mixed integer program for matching the supply of additive manufacturing capacities with the demand for print jobs. Solving it results in an optimal schedule which maximizes the revenue on the platform. However, two conditions prevent us from doing so in the use case at hand: First, solving the stated problem requires complete information regarding the arriving jobs. However, the information in the online scheduling problem is restricted to the jobs which have already arrived. Second, even if complete information were available, the complexity of the problem would result in extremely long solution times since solving it is computationally hard, i.e. the worst case computational complexity is exponential in the number of jobs (Pinedo 2016).

Because of incomplete information and the necessity of quasi-instant customer feedback in an online matching platform, solving the offline mixed integer problem is not an option. Instead, we focus on solving the online problem using a simulation-based heuristic approach.

Artifact Design

Figure 2 illustrates the IT artifact. Incoming jobs and available printers are passed to the system as inputs. Based on these inputs, the allocation module and the simulation module execute several simulations for each job. Within each simulation, a job is either scheduled and, thus, accepted, or rejected. The results of these simulations are then passed to the decision module, which decides based on the acceptance rate of each job, whether it is accepted or not. Afterward, the accepted jobs are transferred to the scheduling module together with formerly accepted jobs. This module generates an optimized schedule. Based on these calculations, the system outputs accepted and rejected jobs. Accepted jobs are then re-entered into the system when new jobs arrive, provided that these accepted jobs have not been executed already. They are denoted as pre-committed jobs. On the other hand, formerly accepted jobs which have already been completed are denoted as completed jobs and do not re-enter the system again.

The design of the IT artifact enables real-time decisions, which allows instant feedback to customers. All four modules are implemented using Python. Based on the previous paragraph, the following sub-sections describe the functionality of the modules in detail.

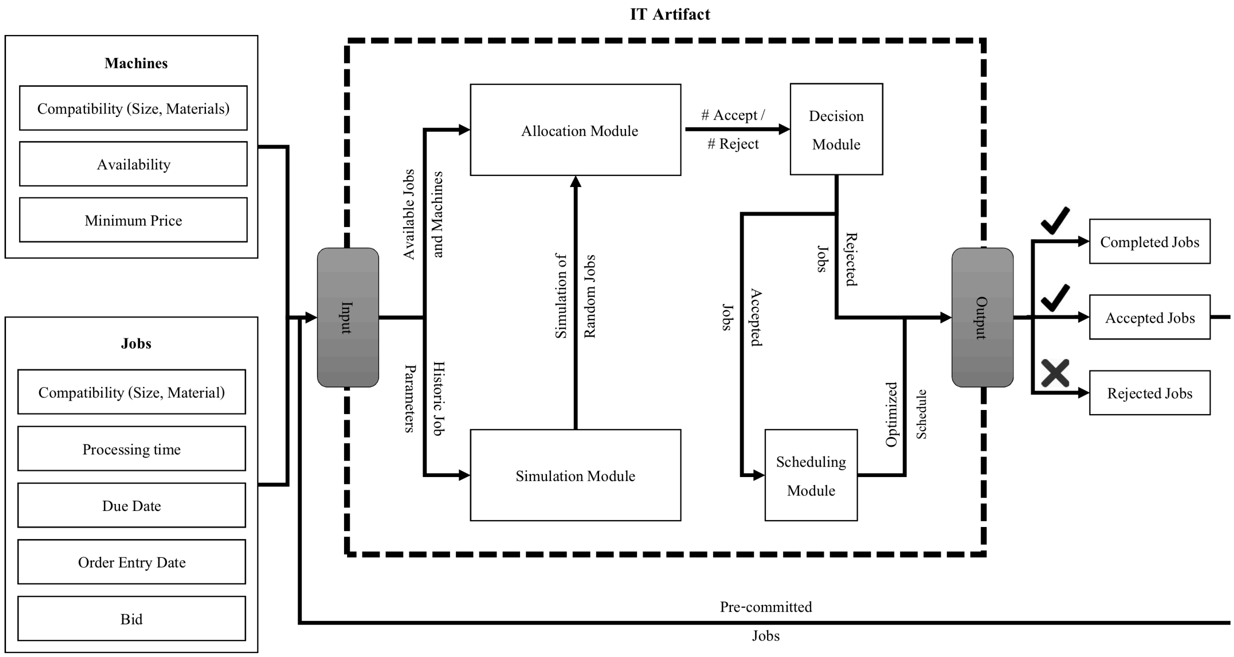


Figure 2. Artifact Overview

Allocation Module

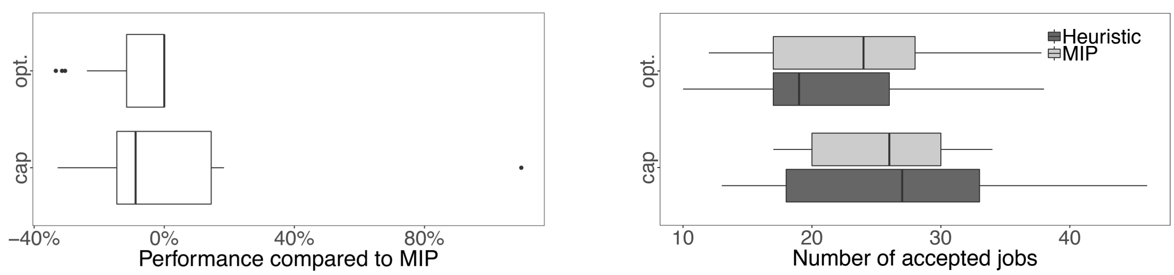
As noted before, an exact solution procedure for the online problem cannot be determined. Instead, we follow Ströhle et al. (2014) and apply a value density heuristic to tackle the problem at hand. This procedure first sorts available printers based on increasing flexibility. A printer's flexibility is described by its versatility in terms of build volume, printing speed, materials, and precision. Subsequently, pre-committed jobs are allocated to the least flexible printers as early as possible. This step ensures that all jobs the platform committed to print are made in the least capacity-impairing manner possible. Subsequently, the jobs are sorted by decreasing value density. In this paper, we define value density as the bid offered by a customer divided by the processing time of the job. Based on this ordered job list, the heuristic allocates the jobs by decreasing value density to the available printers. If a job can be assigned to several printers, the least flexible printer of this set is chosen. Once the heuristic cannot schedule any further job, the simulation terminates, and the final schedule is returned. The procedure is summarized in Algorithm 1.

Compared to the exponential runtime of the mixed integer program, the suggested value density heuristic has a worst-case complexity of $O\big(i \cdot \log(i) \ + j \cdot \log(j) \ + (d_j - r_j)\big)$, i.e., the complexity is linear in the length of the planning horizon $(d_j - r_j)$ and log-linear in the number of printers and the number of incoming jobs. In the latter two cases, the main driver of complexity is the sorting algorithm that is required at the beginning of the heuristic. Leveraging the suggested algorithm and its attractive complexity allows us to instantaneously solve much bigger problem instances in comparison to the mixed integer program.

Algorithm 1 Value Density Heuristic

procedure ValueDensityHeuristic($I, J, c, g, v, p, t, m, r, d$)
    var $int\ time$, **var** $list\ scheduledJobs$
    $sort(I)$ by increasing size g_i, $sort(J)$ by decreasing value density $\frac{v_j}{p_j}$
    for $j \in (J \cap$ *pre-committed*$)$ **do**
        schedule pre-committed job j on printer i at $t_{i,j}$
    for $j \in (J \cap$ *not pre-committed*$)$ **do**
        for $i \in I$ **do**
            if $c_j \leq g_i \wedge m_i \leq v_j$ **then**
                $time = r_j$
                while $time + p_j \leq d_j$ **do**
                    if $noJobScheduledinRange(time, time + p_j)$ **then**
                        $t_{i,j} = time$, $a_{i,j} = 1$, append i to $scheduledJobs$
                        break
                    $time = time + 1$
    return $scheduledJobs$

To assess the performance of the heuristic approach, we create schedules for 50 instances. We then determine the hypothetical optimal solutions by solving the offline mixed integer program under complete information. As the run time of the mixed integer program grows exponentially, the solving time is capped at 120 seconds. Overall, the average total revenue determined by the heuristic is 4.4% below the revenue of the mixed integer solution. However, in many complex instances, the value density approach is able to outperform the time-limited offline approach (Figure 3a). When compared to instances that can be solved optimally, the suggested approach performs only 6.9% worse. Figure 3b illustrates that the MIP outperforms the heuristic mainly by scheduling more jobs–the heuristic allocations turn out to be too conservative. In summary, we conclude that the heuristic approach achieves a very satisfactory solution quality for the problem at hand.



(a) Profitability **(b) Accepted Jobs**

Figure 3. Comparison of the Heuristic Schedule Quality with the Offline Optimum

Simulation and Decision Module

In order to decide on the acceptance or rejection of incoming jobs in real-time, a decision under uncertainty of future arriving jobs has to be made. To ensure robust results, we base these decisions on simulated future demand. To this end, the simulation module generates a random number of virtual jobs arriving according to a Poisson distribution. The distributions of the job parameters are derived from historic incoming jobs and are updated periodically. Subsequently, virtual jobs, as well as the real incoming job and previously pre-committed jobs, are passed to the allocation module, and the optimal schedule is determined. Based on this schedule, we are able to determine if a job has been accepted in a given simulation run. This process is repeated s times, and the number of times a job has been accepted is passed forward to the decision module. Based on a specified, modifiable threshold and the acceptance rate of a job, an arriving job is either accepted or rejected. If the acceptance rate exceeds the threshold, the job is accepted; otherwise, it is rejected.

Afterward, the accepted jobs are passed together with the pre-committed jobs to the scheduling module, which creates an optimized schedule by means of the value density heuristic. Together with the accepted and rejected jobs, the optimized schedule constitutes the output of the system. As soon as new jobs arrive, already accepted jobs are re-inserted into the system for consideration and the restrictions they pose in future acceptance and scheduling decisions. In particular, this design facilitates real-time decisions and instant feedback to customers regarding the acceptance or rejection of their job.

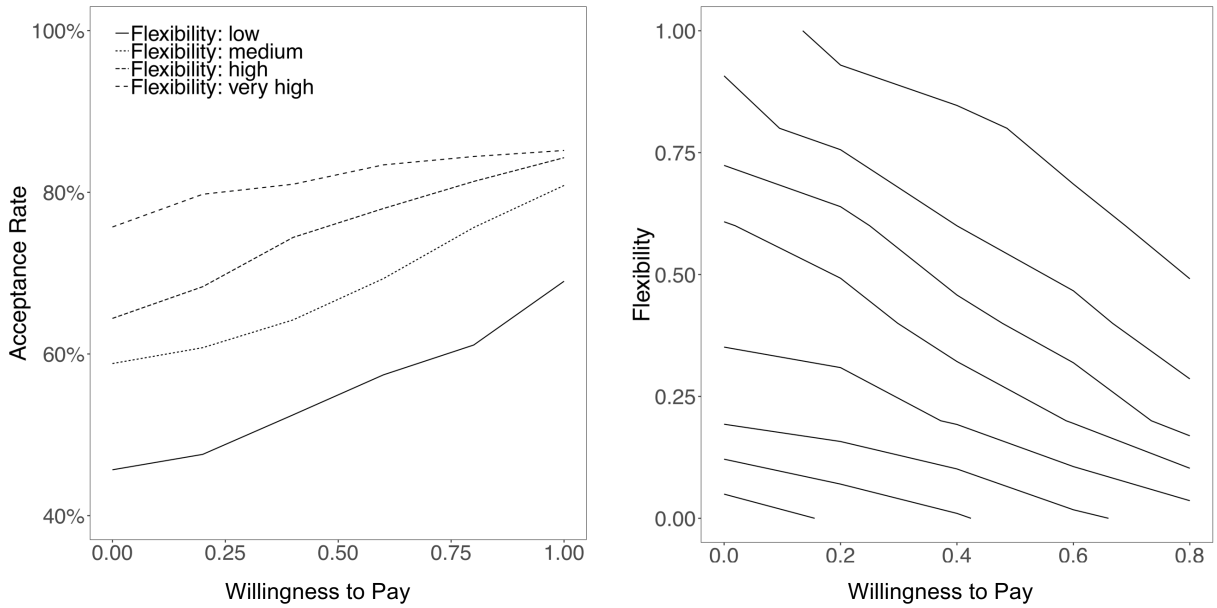
Evaluation

The importance of the artifact evaluation is emphasized by Hevner et al. (2004). We apply a numerical simulation scheme to evaluate the determinants of market-based coordination in an additive manufacturing capacity market. In particular, we examine how temporal flexibility and the willingness to pay influence a job's likelihood of being accepted. Based on these evaluations, we explore how the IT artifact can serve as a platform prototype for trading additive manufacturing capacities and to what extent it addresses the mentioned challenges of designing such a platform. To ensure stable and robust findings, we simulate 1,000 schedules with a total of over 32,000 jobs. Here, the number and properties of available printers as well as the parameters of the job distributions are randomly sampled from appropriately chosen distributions. In particular, job arrival, as well as the processing times, are modeled to follow a Poisson process. Temporal flexibility is modeled to follow a truncated normal distribution, while valuations are drawn from a gamma distribution taking the processing times of the jobs into account.

The Cost-Flexibility Trade-Off

Based on the simulated data, we examine how temporal flexibility and willingness to pay influence the likelihood of a job being accepted. Figure 4a presents the average acceptance rates of jobs based on their flexibility and bid. The different lines represent the quartiles of temporal flexibility while the percentiles of the bids are visualized on the x-axis. As expected, both factors have a positive impact on the average acceptance rate. The marginal benefit of the willingness to pay is decreasing with higher levels of temporal flexibility. Vice versa, the marginal benefit of temporal flexibility is decreasing with the willingness to pay. Additionally, we see that jobs offering low bids but high temporal flexibility are more likely to be accepted than jobs with high bids and low temporal flexibility. This suggests that temporal flexibility is relatively more important than the willingness to pay if jobs are inflexible in one dimension. Analyzing the flexibility-valuation interaction in greater detail, we find that the variability of the acceptance rates decreases if both factors are high. This can be explained by the diminishing marginal benefit of each factor if the other factor is already high. Hence, jobs that already have a very high bid only need a limited amount of temporal flexibility to ensure high acceptance rates and vice versa.

Visualizing the acceptance rate iso-quants in Figure 4b, we see that both measures affect job acceptance and that neither measure alone can guarantee particularly high acceptance rates. Furthermore, we find that, on average, moderate levels of value density and flexibility lead to a higher acceptance rate than a very high value of one dimension combined with a limited value of the other. Furthermore, the results show that even very high flexibility and value density combined cannot guarantee job acceptance. This may necessitate additional transactions forms like forward agreements to render a marketplace attractive for actors with very high reliability requirements.



(a) Marginal Acceptance Rates **(b) Acceptance Rate Isoquants**

Figure 4. Trade-off between Temporal Flexibility and Willingness to Pay

Economic Implications

By automatically matching supply and demand for additive manufacturing capacities, the described IT artifact helps improve capacity utilization. From a business model perspective, the platform constitutes a peer-to-peer platform since it acts as an intermediary between companies (Gassmann et al. 2014). Concerning the value proposition, the platform connects firms disposing of excess capacity with those facing additional demand. From a firm's perspective, the platform helps to deal with fluctuating, uncertain demand and enables them to increase revenues–either by allowing firms to satisfy additional demand which could not be met with their own capacities or by offering excess capacity to other firms. From the economy's perspective, the IT artifact raises social welfare. Consequently, the prototype illustrates that additive manufacturing combined with methods from electronic market design and operations management is capable of transforming individual production capacities into tradable goods and in turn pave the way towards an open production system.

Naturally, firms cannot shift all of their production capacities into additive manufacturing capacities. Instead, additive manufacturing will primarily complement existing production technologies. Therefore, the question arises in which situations the proposed platform is of use for companies. From a capacity provision perspective, the platform enables companies to generate additional revenues whenever they can offer otherwise unused capacities of their printers. In the case of a capacity consumer, the platform allows companies to serve demand which cannot be covered with their own capacities. In this regard, companies can purchase outside capacities for printing products when demand exceeds their own base capacities.

Furthermore, the situation of a company being unable to serve demand may also arise when a supplier fails to deliver certain components for the company's products. In these situations, companies can rely on additive manufacturing capacities provided by other firms to print these components. This virtual capacity enables these companies to deal with supplier failures and deliver their products on time. Other circumstances in which firms are unable to keep their delivery promises and additive manufacturing might prove useful are machine breakdowns. Consequently, although additive manufacturing tends to be more expensive than traditional manufacturing techniques in most situations, buying additional capacities on a platform is worthwhile if the potential losses in revenue and goodwill exceed the costs of printing the products.

When setting up a trading platform for additive manufacturing capacities, attracting a sufficient number of users constitutes a major challenge. Otherwise, a too small user group would result in most companies not finding a transaction partner. On the other hand, these network effects are a central driver for companies to concentrate on a limited number of platforms instead of spreading across a wide range of platforms. Therefore, network effects should ensure a sufficient number of platform participants to enable an efficient matching mechanism of additive manufacturing capacities. As indicated by the evaluation results, the IT artifact enables real-time decisions regarding the acceptance or rejection of a job. By providing instant feedback to the demand side, the system increases the planning reliability of the companies on this side and enables them to re-evaluate their bids instantaneously: If a job is rejected initially, the buyer might decide to increase the offer and re-enter the job. If the job is still rejected after raising the bid, the buyer may once again decide to re-raise the bid. This procedure is repeated until the job is either accepted, or the buyer decides to forego higher bids as their height would exceed the benefit from having the job accepted. This demonstrates two effects: First, while our results indicate that the probability of a job being accepted depends both on its value density and flexibility, bidders can significantly increase this probability by offering a higher bid compared to other customers. Consequently, if customers offer an extremely high bid for a high priority job, in the majority of cases, the platform accepts this job. Second, the mechanism incentivizes both bidders and the suppliers to reveal private information on valuation and flexibility truthfully.

Conclusion and Outlook

The presented prototype allows companies to tap into the potentials of distributed 3D-printing. Consequently, an open production system can achieve output volume through many decentralized production facilities (3D-printers). The joint capacity of many units supersedes volume flexibility of an individual production unit. Thereby, the volume flexibility of the production system as a whole is instantiated by a large number of decentral printing units. Our prototype addresses some key challenges of designing such a platform for trading additive manufacturing capacities: First, it allows to handle uncertain demand and the complexity of the underlying problem resulting from the numerous actors and the extensive network of printers.

Furthermore, it provides instant feedback to the demand side regarding the acceptance or rejection of jobs. Therefore, it permits buyers to re-evaluate their offers and incentivizes them to reveal private information to improve scheduling results. By addressing these challenges, the platform enables companies disposing of excess capacities to generate additional revenues by offering them on the platform to other firms. On the other hand, companies facing excess demand can satisfy it by outsourcing print jobs to other companies. In summary, by acting as an intermediary between the demand and supply side, the platform leads to a more efficient allocation of production capacities, allows firms to increase revenues, and raises social welfare.

To tap into these benefits, some limitations of the described approach need to be considered. At the moment, the artifact assumes constant processing times of jobs across printers. However, in reality, processing times will differ depending on the printer. Furthermore, the heuristic does not explicitly consider printing costs in the scheduling decision. Instead, it restricts its monetary inputs to the minimum price demanded by the capacity provider and the bid offered by the person seeking capacities to print a job. Another simplification of the problem is modeling the supply of additive manufacturing capacities as known, whereas in a real-world setting, it is uncertain. If both sides are modeled as unknown, this complicates solving the problem. The allocation module also offers potential improvements. When assigning jobs to printers, the heuristic only considers their compatibility in terms of size and materials, and the bid offered for the job and the price expected for the printer. It then allocates the job to the smallest, available machine.

Consequently, this might lead to some jobs with high flexibility being scheduled quite early because of their high value density, although they could be assigned to later time intervals. On the other hand, other jobs with lower flexibility and earlier deadline might then be rejected since other jobs already occupy early time intervals. To prevent these situations and to improve scheduling decisions, it would make sense also to consider burden-sharing between printers and the flexibility of jobs when deciding on the acceptance of jobs. The omission of possible build failures is another limitation of our suggested approach. While the reliability of additive manufacturing technologies has significantly improved over the last years, there remains a probability for build failures, especially during the calibration phase (Baumers and Holweg 2019). An extension of our approach could account for this risk by incorporating a robust formulation of the problem where accepted jobs fail with a given probability. This would ensure that the overall performance of the system does not rely too heavily on a single job. We assume that incorporating these considerations would further improve the results of the IT artifact and increase the overall value of the accepted jobs. In summary, including these proposals would increase the transferability of the prototype to a real-world setting.

So far, the IT artifact only aims at maximizing the weighted number of accepted jobs by executing several simulations for each incoming job. One possible refinement which might improve the long-term performance of the platform is the reservation of a fraction of the available capacity to high-priority orders (Pibernik and Yadav 2008). These orders could either correspond to jobs with an extremely high value density or to jobs of a group of important customers. Consequently, the platform would reject lower-priority orders in some cases, even if capacity was available based on the executed simulations. To cope with privacy and trust issues, future research can also analyze the potential use of distributed ledger technologies such as block chain for the platform (Glaser 2017). For example, the matching mechanism could be implemented as a smart contract, facilitating the establishment, discovery, and acceptance of new value exchange formats.

Similarly, companies might fear the theft of specifications of their products' designs when other companies print their products. Again, blockchain technology may offer solutions to ensure the integrity of exchanged 3D-blueprint information (Engelmann et al. 2018; Yampolskiy et al. 2018). In order to transfer the prototype to a real-life setting, some of the stylized assumptions of the model have to be relaxed, which may increase the complexity of the problem. Apart from these design issues, we want to emphasize that such a platform does not convert all production capacities into tradable goods. Instead, it is restricted to additive manufacturing capacities which complement traditional production technologies.

Our research has highlighted another instance where additive manufacturing benefits from side-lining electronic platforms which complement existing usage scenarios. This finding is in-line with the reasoning by Holmström et al. (2016) who highlight the emergence of the 3D-printing ecosystem. Going forward, our prototype can serve as a basis for future research addressing the limitations mentioned above or tackling concrete implementation in a real-world supply network.

Acknowledgements

This study is based upon work supported by the German Federal Ministry of Education and Research BMBF under Grant No. 02K16C100 ("Dienstleistung für den integrierten Handel mit Produktionskapazitäten").

References

Anderson, C. 2012. "Makers: The New Industrial Revolution," New York: Crown Business).

Baumers, M., and Holweg, M. 2019. "On the Economics of Additive Manufacturing: Experimental Findings," Journal of Operations Management.

Beil, D. R., and Wein, L. M. 2003. "An Inverse-Optimization-Based Auction Mechanism to Support a Multiattribute Rfq Process," Management Science (49:11), pp. 1529-1545.

Ben-Ner, A., and Siemsen, E. 2017. "Decentralization and Localization of Production: The Organizational and Economic Consequences of Additive Manufacturing (3d Printing)," California Management Review (59:2), pp. 5-23.

Berman, B. 2012. "3-D Printing: The New Industrial Revolution," Business horizons (55:2), pp. 155-162.

Bichler, M., Gupta, A., and Ketter, W. 2010. "Research Commentary—Designing Smart Markets," Information Systems Research (21:4), pp. 688-699.

Buxmann, P., and Hinz, O. 2013. "Makers," Wirtschaftsinformatik (55:5), pp. 361-364.

Carver, L. L., Zamzow, C. E., Mladenoff, D. D., and Lovrien, G. A. 1990. "Integrated Aircraft Manufacturing System,").

Chang, T.-S. 2009. "Decision Support for Truckload Carriers in One-Shot Combinatorial Auctions," Transportation Research Part B: Methodological (43:5), pp. 522-541.

Clearwater, S. H. 1996. Market-Based Control: A Paradigm for Distributed Resource Allocation. World Scientific.

Dauer, D., Flath, C. M., Strohle, P., and Weinhardt, C. 2013. "Market-Based Ev Charging Coordination," Proceedings of the Web Intelligence (WI) and Intelligent Agent Technologies (IAT), 2013 IEEE/WIC/ACM International Joint Conferences on: IEEE, pp. 102-107.

Engelmann, F., Holland, M., Nigischer, C., and StjepandiĆ, J. 2018. "Intellectual Property Protection and Licensing of 3d Print with Blockchain Technology," Transdisciplinary Engineering Methods for Social Innovation of Industry 4.0: Proceedings of the 25th ISPE Inc. International Conference on Transdisciplinary Engineering, July 3–6, 2018: IOS Press, p. 103.

Flath, C. M., Friesike, S., Wirth, M., and Thiesse, F. 2017. "Copy, Transform, Combine: Exploring the Remix as a Form of Innovation," Journal of Information Technology (32:4), pp. 306-325.

Friesike, S., Flath, C. M., Wirth, M., and Thiesse, F. 2019. "Creativity and Productivity in Product Design for Additive Manufacturing: Mechanisms and Platform Outcomes of Remixing," Journal of Opeartions Management).

Fudim, E. V. 1989. "Method and Apparatus for Production of Three-Dimensional Objects by Photosolidification,").

Gassmann, O., Frankenberger, K., and Csik, M. 2014. The Business Model Navigator: 55 Models That Will Revolutionise Your Business. Pearson UK.

Gibson, I., Rosen, D., and Stucker, B. 2010. "Additive Manufacturing Technologies, 3d Printing, Rapid Prototyping, and Direct Digital Manufacturing, Springer," New York Heidelberg Dordrecht London).

Glaser, F. 2017. "Pervasive Decentralisation of Digital Infrastructures: A Framework for Blockchain Enabled System and Use Case Analysis," Proceedings of the 50th Hawaii International Conference on System Sciences.

Gurbaxani, V., and Whang, S. 1991. "The Impact of Information Systems on Organizations and Markets," Communications of the ACM (34:1), pp. 59-73.

Hevner, A. R., March, S. T., Park, J., and Ram, S. 2004. "Design Science in Information Systems Research," MIS Quarterly (28:1).

Holmström, J., Holweg, M., Khajavi, S. H., and Partanen, J. 2016. "The Direct Digital Manufacturing (R) Evolution: Definition of a Research Agenda," Operations Management Research (9:1-2), pp. 1-10.

Holweg, M. 2015. "The Limits of 3-D Printing," Harvard Business Review).

Hosseini, H., Hoey, J., and Cohen, R. 2012. "A Market-Based Coordination Mechanism for Resource Planning under Uncertainty," Proceedings of the Twenty-Sixth AAAI Conference on Artificial Intelligence.

Jordan, W. C., and Graves, S. C. 1995. "Principles on the Benefits of Manufacturing Process Flexibility," Management Science (41:4), pp. 577-594.

Kenney, M., and Zysman, J. 2016. "The Rise of the Platform Economy," Issues in Science and Technology (32:3), p. 61.

Khajavi, S. H., Partanen, J., and Holmström, J. 2014. "Additive Manufacturing in the Spare Parts Supply Chain," Computers in industry (65:1), pp. 50-63.

Kranton, R. E., and Minehart, D. F. 2001. "A Theory of Buyer-Seller Networks," American economic review (91:3), pp. 485-508.

Ku, W.-Y., and Beck, C. 2016. "Mixed Integer Programming Models for Job Shop Scheduling: A Computational Analysis," Computers & Operations Research (73), pp. 165-173.

Leskelä, R.-L., Teich, J., Wallenius, H., and Wallenius, J. 2007. "Decision Support for Multi-Unit Combinatorial Bundle Auctions," Decision Support Systems (43:2), pp. 420-434.

Maccarthy, B. L., and Liu, J. 1993. "Addressing the Gap in Scheduling Research: A Review of Optimization and Heuristic Methods in Production Scheduling," The International Journal of Production Research (31:1), pp. 59-79.

Nisan, N., and Ronen, A. 2001. "Algorithmic Mechanism Design," Games and Economic Behavior (35:1-2), pp. 166-196.

Petrick, I. J., and Simpson, T. W. 2013. "3d Printing Disrupts Manufacturing: How Economies of One Create New Rules of Competition," Research-Technology Management (56:6), pp. 12-16.

Pibernik, R., and Yadav, P. 2008. "Dynamic Capacity Reservation and Due Date Quoting in a Make-to-Order System," Naval Research Logistics (NRL) (55:7), pp. 593-611.

Pinedo, M. L. 2016. Scheduling: Theory, Algorithms, and Systems. Cham: Springer.

Pruhs, K., Sgall, J., and Torng, E. 2004. "Online Scheduling,").

Rayna, T., Striukova, L., and Darlington, J. 2015. "Co-Creation and User Innovation: The Role of Online 3d Printing Platforms," Journal of Engineering and Technology Management (37), pp. 90-102.
Sachs, E., Cima, M., and Cornie, J. 1990. "Three Dimensional Printing: Rapid Tooling and Prototypes Directly from Cad Representation," 1990 International Solid Freeform Fabrication Symposium.
Salido, M. A., Rodriguez-Molins, M., and Barber, F. 2012. "A Decision Support System for Managing Combinatorial Problems in Container Terminals," Knowledge-Based Systems (29), pp. 63-74.
Schlagwein, D., Conboy, K., Feller, J., Leimeister, J. M., and Morgan, L. 2017. "“Openness”with and without Information Technology: A Framework and a Brief History," Journal of Information Technology (32), pp. 297-305.
Senthilkumar, P., and Narayanan, S. 2010. "Literature Review of Single Machine Scheduling Problem with Uniform Parallel Machines," Intelligent Information Management (2:08), p. 457.
Ströhle, P., Gerding, E. H., de Weerdt, M. M., Stein, S., and Robu, V. 2014. "Online Mechanism Design for Scheduling Non-Preemptive Jobs under Uncertain Supply and Demand," Proceedings of the 2014 International conference on Autonomous Agents and Multi-agent Systems.
Thiesse, F., Wirth, M., Kemper, H.-G., Moisa, M., Morar, D., Lasi, H., Piller, F., Buxmann, P., Mortara, L., Ford, S., and others. 2015. "Economic Implications of Additive Manufacturing and the Contribution of Mis," Business & Information Systems Engineering (57:2), pp. 139-148.
Veit, D., Müller, J. P., Schneider, M., and Fiehn, B. 2001. "Matchmaking for Autonomous Agents in Electronic Marketplaces," Proceedings of the fifth international conference on Autonomous agents: ACM, pp. 65-66.
Weinhardt, C., Holtmann, C., and Neumann, D. 2003. "Market-Engineering," Wirtschaftsinformatik (45:6), pp. 635-640.
Weller, C., Kleer, R., and Piller, F. T. 2015. "Economic Implications of 3d Printing: Market Structure Models in Light of Additive Manufacturing Revisited," International Journal of Production Economics (164), pp. 43-56.
Wellman, M. P., Walsh, W. E., Wurman, P. R., and MacKie-Mason, J. K. 2001. "Auction Protocols for Decentralized Scheduling," Games and economic behavior (35:1-2), pp. 271-303.
Yampolskiy, M., King, W. E., Gatlin, J., Belikovetsky, S., Brown, A., Skjellum, A., and Elovici, Y. 2018. "Security of Additive Manufacturing: Attack Taxonomy and Survey," Additive Manufacturing).
Zervas, G., Proserpio, D., and Byers, J. W. 2017. "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry," Journal of Marketing Research (54:5), pp. 687-705.