Competing through the last mile: Strategic 3D Printing in a city logistics context

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Abstract

Recently, 3D Printing (3DP) has started disrupting transportation worldwide by providing enormous simplifications to transportation requirements, especially in the context of city logistics. In the near future, the potential exists to replace multi echelon transportation hubs with integrated city logistics and 3D printing manufacturing hubs. This study investigates this integrated concept, particularly for healthcare product distribution (i.e., hearing aids) to customers located within a city environment. We propose an efficient mathematical model to investigate various scenarios of integrated 3DP production and transportation planning and provide insightful analysis. It might seem counter-intuitive that tighter delivery time slots can improve the utilization of capacity and 3DP machines, but this study finds that intelligent selection of production and delivery policies can simultaneously benefit both customer and supplier. By integrating both production and delivery, this study identifies opportunities for firms to survive and thrive in the era of challenging city logistics.

Keywords: 3D printing, last mile logistics, operations research, healthcare

1. Introduction

The technologies of 3D Printing (3DP) have been widely-touted as offering the potential to transform the future of manufacturing (see, e.g., Economist, 2011; Lipson and Kurman, 2013; D'Aveni, 2018). By enabling product manufacture directly from a 3D computer model, 3DP offers a range of potential benefits for products, processes, and supply chains as discussed in Table 1.

Due to the apparent advantages of 3DP, many authors suggest future manufacturing output will be underpinned by the application of the technologies (see e.g., Esmaeilian et al., 2016; Ghobakhloo, 2018). However, there are three fundamental and inter-related problems with this assertion. The first problem concerns *printability*, and the assumption that 3DP enables any given product to be produced by printing. This is an unfortunate fallacy, since whilst in theory 3D printing enables the production of an almost infinite range of product geometries (Hague et al., 2003), limitations in both materials and process capabilities significantly constrain what is commercially feasible in reality. The second problem concerns *production economics*, and the disconnect between 3DP machines

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Table 1: Synthesis of expected advantages for 3DP from key concept review papers

Dimension	Advantageous	Holmström et al. (2010)	Petrovic et al. (2011)	Holweg (2015)	D'Aveni (2015)	Ngo et al. (2018)
Product	- Potential for quick changes to design	⋆				⋆
	- Optimization of products for function	⋆				
	- Opportunities for design customization	⋆	⋆			⋆
	- Allows customer co-creation in the design process			⋆		
	- Ability to produce endless customization of shapes, sizes, and colors				⋆	⋆
	- Able to produce complex geometries				⋆	⋆
Process	- Elimination of tooling reduces production costs	⋆	⋆			
	- Elimination of tooling reduces ramp-up times	⋆				
	- Small batch production is economical	⋆				
	- Economical production of individual custom parts (i.e., mass customization)	⋆	⋆	⋆		⋆
	- Achieves direct translation from design to manufactured product					
	- Offers freeform capabilities not available in traditional techniques		⋆	⋆		
	- Can produce complex parts rather than assemblies of components			⋆	⋆	
	- Fully dense products can be made		⋆			
	- Allows for automation in production					⋆
Supply Chain	- Opportunities for waste reduction	⋆	⋆			⋆
	- Potential for simpler supply chains; shorter lead times, lower inventories.	⋆				
	- Enables on-demand production in response to customer demand			⋆		
	- Faster response to aftermarket demand than convention technology			⋆		
	- Allows for a time-to-market reduction due to high speed of the process			⋆		

being able to produce 'one-off' products as required with the need to ensure full 3DP machine utilization to minimize setup costs and amortize production overheads (see, e.g., Atzeni et al., 2010; Baumers and Holweg, 2019). The third problem concerns the *strategic advantage* arising from the adoption of 3DP, and more specifically, whether a strategic advantage even exists. If issues of printability are overcome for a given product, then 3DP is effectively a 'general purpose technology' (Hedenstierna et al., 2019), able to produce a wide range of products, just as computers are employed for a range of tasks in manufacturing planning and control systems (Brynjolfsson et al., 2010). With sufficient resource any firm can purchase a 3D printer and requisite materials to satisfy market demand, and so if all players have the same production capabilities and draw on the same material suppliers, how does any given firm achieve a competitive advantage over its rivals? Given machine production costs are likely to be extremely similar between firms, cost-based competition through manufacturing becomes an undesirable race to the bottom in the erosion of profit margins.

For sustained competitiveness in 3DP firms obviously need to be cost-competitive, but what if this competitiveness was not solely achieved within the factory environment? Tang and Veelenturf (2019) emphasize that logistics is a competitive weapon which allows firms to compete on speed and reliability, as well as cost. In 3DP research, the emphasis has not been to exploit logistics for strategic advantage, but to instead actively minimize the need for logistics. Studies have typically espoused the virtues of localized production models for 3DP (Holmström et al., 2010; Kleer and Piller, 2019), with on-demand production occurring in close geographical proximity to requirements. Such research expects lead-times to be reduced, and thus the local inventory stockpiles (that are usually essential to counteract transportation time from centralized production facilities) to become redundant. Crucially there has been scant quantitative evaluation of such propositions, and of the very limited research available, the overall commercial feasibility of switching from centralized to localized production remains questionable (Roca et al., 2019).

Against this backdrop of expected but largely unproven advantage for 3DP, the current study extends the notion of localized 3DP production to embrace the opportunities afforded by integrating production and logistics strategies. We focus specifically on the opportunities in the 'last mile', and provide an empirical examination of 3DP in a city logistics context. We note that there is a dearth of literature that unifies the 3DP and city logistics concepts. However, the 3DP industry is expected to be worth $35.6bn by 2024, continuing a trend of significant year-on-year growth since the beginning of the century (Wohlers, 2019), and there is much enthusiasm for the technologies in the even longer term. Originally employed in product prototyping applications, increasingly the technologies are being deployed to produce products for end user consumption. The current logistics challenge is to bring manufactured products to the customer's property, and this will continue in the future. Today, 54% of the world's population lives in urban areas; within thirty years this is expected to reach 66%, and by the end of the century this figure is projected to reach 85% Savelsbergh and Van Woensel (2016). To supply customers will require new last mile solutions to ensure seamless and alternative manufacturing capability (Deutsche Post, 2016). There is an increasing enthusiasm that 3DP can support local production (Weller et al., 2015; Ryan et al., 2017), and that the next years will see 3DP facilities within city environments to satisfy local demand (Ryan et al., 2017)

The production of healthcare devices represents one of the most successful use cases of 3DP (Ramola et al., 2019; Wohlers, 2019), and in this work we draw on a realistic example of a local production hub producing and delivering customized medical devices for the local community. We consider the well-established case of 3DP Hearing Aids which have already been demonstrated as technically and commercially viable in centralized 3DP manufacturing facilities, and explore whether localized production combined with city logistics can offer any advantages for customers, manufacturers, or transport operators. We propose a new mixed-integer linear programming (MILP) model to production planning that allows customers to request convenient delivery periods, from which we demonstrate how production and transportation can be optimized for competitive order fulfillment. In doing so, we examine the extent to which both manufacturing and transport flexibility can be leveraged, and show how resource utilization plays a key role in achieving competitiveness. As yet there has been very little consideration of production planning for 3DP, and to our knowledge, no investigation of a unified production and logistics strategy for the last mile, satisfying both customer and manufacturing requirements.

There are three principal contributions that arise from this study. Firstly, this is the first paper to explore 3DP from a city logistics perspective, highlighting the opportunities for integrated 3DP production and last mile logistics strategies. More specifically, we introduce the 3D printing and transportation problem (3DTP). Secondly, we provide a MILP based algorithm that enables both single-period and multi-period planning for the 3DTP. The proposed algorithm is capable of handling a reasonable number of customer orders for a small to medium-sized manufacturing company that wishes to utilize 3DP in the context of city logistics. Finally, we connect the algorithm to an empirical case study to provide a realistic evaluation of the proposed model, highlighting both the opportunities and constraints of the proposed approach.

The paper is structured as follows. In Section 2, we examine the existing literature, highlighting a general death of 3DP production planning literature, and establishing the research gap concerning the integration of logistics in planning activities. In Section 3, we introduce the investigated problem and develop our general MILP model. A generic algorithm which is built on a MILP formulation is presented in Section 4. A case study is presented in Section 5 while computational results are provided in Section 6. We conclude the paper in Section 7.

2. Literature review

We now provide a brief literature review on deployment options for 3DP, production planning for 3DP, and transportation planning in the context of city logistics.

2.1. 3DP deployment options

Choosing where to locate production facilities has long been one of the key strategic decisions for manufacturers (MacCarthy and Atthirawong, 2003), which affects both facility location and the logistics arrangements for raw materials and finished goods. There is much enthusiasm in the research literature for 3DP to challenge centralized production models, where a single production site fulfils demand for a wide geographic catchment (Öberg et al., 2018). 3DP literature typically terms such production as being 'distributed', and the nature of this distribution has been shown to include at-home, mobile, local, regional, and national production models (Ryan et al., 2017). Instead of production occurring within a small number of large centralized manufacturing facilities (with finished goods being transported to their destination), decentralized/distributed 3DP allows for a greater number of smaller facilities that are more local to the end demand. One of the earliest proponents of such approaches was Walter et al. (2004), who postulated the idea of replacing local aerospace inventory stockpiles with local production capabilities; later research has extended this notion to other industries (e.g., Attaran, 2017) with the aim of eliminating the wastes associated with warehousing (Jiang et al., 2017).

Whether decentralized production addresses the three fundamental 3DP problems is somewhat contested in the literature. From a printability perspective, given the same production equipment is deployed in different locations, the localization of production is unlikely to positively affect the ability to manufacture parts. Indeed, a dilution of production experience can be expected as aggregate production is split over a range of sites, though there has been little exploration of this in the literature. Instead, the emphasis has been on production economics, and whether decentralized implementations of 3DP can compete with centralized approaches employing conventionally technologies. For example, Khajavi et al. (2014) identify 3DP achieving favourable results in distributed spare part manufacture using 3DP, highlighting reductions in operation costs, downtime, inventory management, as well as greater potential for customer satisfaction, robust supply chains, and sustainability improvements. Authors such as Holmström et al. (2016) highlight the benefits of on-demand, local production in eliminating the costs associated with stocked inventories of conventional products. By comparison, when considering aerospace spare part production in a factory location context, Roca et al. (2019) identified few benefits of localizing 3DP. Key to their findings was the loss of critical scale economies - quite simply the localized production systems had insufficient demand to amortize the overhead operating costs. Taking a broader strategic perspective, several authors have highlighted key advantages of localization. For example, Bogers et al. (2016) suggest such localization reduces reliance on both inventory stocks and demand forecasting, whilst simultaneously increasing the responsiveness in supply increases the value of the offering to the customer. Moreover, such localization allows firms to offer products tailored specifically to local requirements.

2.2. Production planning for 3DP

There has been very limited emphasis on production planning for 3DP within the literature (Li et al., 2017; Chergui et al., 2018; Zhang et al., 2018). Given that fixed costs of 3DP (particularly machines) dominate the economics of production in 3DP (Ruffo et al., 2006; Atzeni et al., 2010; Baumers and Holweg, 2019), multi-part building to ensure full utilization of the machine build chamber is typically considered as an appealing solution to cost effectiveness in contrast to producing a single part at a time (Piili et al., 2015). As such, a prominent focus on planning has been build configuration - parts can be produced in a high-variety batch in order to reduce operational cost and total manufacturing time (Rickenbacher et al., 2013). This is typically done by nesting or bin packing analysis; various algorithmic approaches to part arrangement in 2D and 3D can be taken to optimize capacity utilization without compromising quality of output (Gogate and Pande, 2008; Zhang et al., 2016, 2018; Griffiths et al., 2019). In particular, Zhang et al. (2018) and Griffiths et al. (2019) have advanced the build configuration problem by incorporating build orientation which affects number of parts that can be fit in the build chamber. While nesting or bin packing analysis tackles the unique build configuration problem confronted in 3DP production, optimization is often cost-oriented and is focused on individual build at local machines. Makespan or lead time is another important performance measure for 3DP production which competes on quick response. However, absolute optimization as time measure involves quickly becomes impossible to achieve due to aggregation of NP-hardness in computation (Kucukkoc, 2019).

Li et al. (2017) was the first study that explicitly defined how production planning problems for 3DP differs from similar problems (e.g., batch scheduling) in traditional manufacturing; 3DP production time is subject to build configuration and machine scheduling which are also associated with capacity utilization and determine production costs (Chergui et al., 2018; Kucukkoc, 2019). A simplified build configuration was adopted in combination of job allocation and sequencing on different 3DP machines with varying specifications to illustrate cost optimization (Li et al., 2017). Chergui et al. (2018) then proposed a heuristic solution to planning and scheduling on identical 3DP machines in parallel, where maximum lateness is minimized by taking due dates into consideration in job configuration. A recent contribution by Kucukkoc (2019) addresses 3DP scheduling problems from the perspective of optimizing process makespan on single, multiple identical, and different machines while indicating there is a trade-off between capacity utilization and job process time. For example, a build job with a higher utilization rate would involve higher volume of parts in the build chamber, thus a longer build time, than those with lower utilization rates. An optimal solution to balancing capacity utilization with lead time performance can become a very complex problem to resolve. More recently, Thürer et al. (2020) extended 3DP production planning research by offering a unique production control solution - Workload Control - to 3DP shops where post-processing constrains lead time performance. The study provides a starting point to incorporate downstream processes/operations in 3DP production planning for an overall improvement on order fulfillment.

3DP high-variety batch production offers firms an innovative opportunity to achieve economies of scope which has been a challenge in conventional high-variety production. However, as can be seen from the above discussion, production economics focus on capacity utilization which is often at the expense of responsiveness as machines wait for enough work to be economically viable. The dilemma between production cost and lead time blurs the definition of 3DP strategic advantage. Due to the complexity of 3DP production planning, optimal solutions discussed in the literature tend to be confined to either cost or lead time instead of both. The proposal of integrating 3DP production with 'last mile' logistics planning opens up new opportunities to tackle the trade-off challenge between cost and responsiveness, consequently, enhance order fulfillment performance.

2.3. Transportation planning in the context of city logistics

Due to the increase in e-commerce last mile delivery volumes, the participation of customers has switched from a passive position to an active one. Satisfying customers' needs with respect to delivery times and delivery costs has become one of the most important key performance indicators in a highly competitive retail and transport industry (Savelsbergh and Van Woensel, 2016). More specifically, the ever-increasing number of online orders and the associated time pressure have put a strain on online companies. This is even more challenging for populated city environments due to congested traffic networks and a lack of parking spaces. As a new remedy, city logistics has gained a great deal of interest in the last decade. By definition, city logistics is used to describe distribution which takes place in urban areas and introduces new strategies, policies and best practices that can help improve transport efficiency while reducing negative externalities of transportation (see e.g., Deckert, 2020; Johansson, 2020; Eshtehadi et al., 2020). For more readings on city logistics, we refer the reader to the work of Anand et al. (2012) and Savelsbergh and Van Woensel (2016).

In operations research literature, 3DP and transportation are rarely investigated together as an integral problem; Transportation has typically been seen as an activity that falls out of the service range/expertise of manufacturers, hence is generally assigned to logistics service providers after the completion of production. To the best of our knowledge, there is no prior study looking at both operations from a mathematical perspective. Among a handful of studies investigating 3DP from a supply chain perspective, Santander et al. (2020) address economic as well as environmental feasibility of a distributed plastic recycling approach. The authors propose a MILP as an evaluation tool and report a case study of a distributed recycling to recover 3D printing wastes from schools in France. Arbabian and Wagner (2020) study the impact of 3D printing on a simple supply chain, including a manufacturer and a retailer, that serves stochastic customer demand. The authors analyze the equilibrium of Stackelberg games in which 3DP is either adapted by the manufacturer or by the retailer. Within the context of city logistics, manufacturers are increasingly embracing the challenge/opportunity of offering last mile service solutions. In particular, the inclusion of last mile delivery in manufacturing has appeared to be indispensably necessary for certain industry sectors, including medical. New last mile solutions such as next day, same day or instant deliveries could be offered to customers with the help of advanced additive manufacturing technologies.

2.4. Literature review summary

As revealed in the above discussion, 3DP shows a great potential for materializing competitiveness within the context of city logistics by offering distributed manufacturing solutions. However, there is little evidence reported in extant literature on how a 3DP last mile solution might look like due to a lack of integration between research topics. From an operations scheduling perspective, 3DP production planning research has been mainly focused on build chamber configuration, machine allocation, and job sequencing, all of which optimize production only. The impact of a production oriented solution on transportation performance and vice versa, consequently the overall design/configuration of a 3DP last mile solution, remain unknown. In response to this gap, we consider 3DP production and transportation as an integral problem in proposing 3DP last mile solutions.

3. Problem description

This section provides both formal and mathematical details of the problem at hand.

3.1. Problem definition

The 3D printing and Transportation Problem (3DTP) is an operational-level production and delivery problem specifically proposed to be used by small to medium enterprises (SMEs) in the context of city logistics. The problem is defined for a set of customers' orders with specific delivery time window (delivery slot) preferences in a customized production planning with multiple production slots. The problem considers the characteristics of 3DP machines ($m \in \mathcal{M}$, $m = 1, 2, ..., |M|$) and a number customers' orders ($o \in O, o = 1, 2, ..., |O|$) to be printed and delivered to the customers during a planning period (i.e., a day or week). In this research we consider Digital Light Projection (DLP) machines which are widely used in printing medical products. Each medical product may require more than one part in each order and each part is generally defined based on its geometric shape/volume, or required material and color, which structure the main features of the proposed MILP formulation.

In our problem setting, each 3DP machine has its own volume capacity and all activities of the printing are completed in a predefined production slot. Following Eyers and Potter (2017) we characterize these activities in terms of Design, Pre-processing, Manufacturing, and Post-processing. For example, a print from design to post-processing with the DLP type 3DP machine takes approximately three hours. This would give sufficient time for completing the order and making it ready to be shipped. The total required times of each machine are used to define production slots within the planning period as shown in Figure 1.

As seen from Figure 1, we consider fixed production slots to ease the complexity of the production planning and to enable scheduled delivery slots for customers. We argue that it is necessity to have scheduled production slots to offer appealing last mile services, such as same day. To enable a fixed (scheduled) production and delivery, we explain all concepts and their definitions in Table 2. We will detail each concept in the next section.

Next to production operation, the delivery of customers' orders is also planned as the on-time delivery is crucial for city logistics applications. Each order must be delivered within the time window (delivery slot) defined by a customer. Delivery slots can be characterized as 1-hour time slot or longer time periods (i.e., 1 hour, 5-hours, 10-hours, several days). For all orders printed with DLP machine, the delivery of orders can be organized on the same day or in any other day during the planning horizon. The notations used in the 3DTP are listed in Table 3 below.

3.2. Assumptions

In order to fully represent the operational characteristics of 3DP-based production and city logistics, we explain all assumptions. (i) customer orders, delivery preferences, total production and delivery times are deterministic (see e.g., Kim, 2018) (ii) each production slot consists of four stages of 3DP, including design, pre-processing, production, and post-processing (see, e.g., Eyers and Potter, 2017), and has a fixed duration (i.e., 3 hours for DLP machines). (iii) only parts which require to use of same material can be printed at the same time (see, e.g., Gibson et al., 2015), (iv)

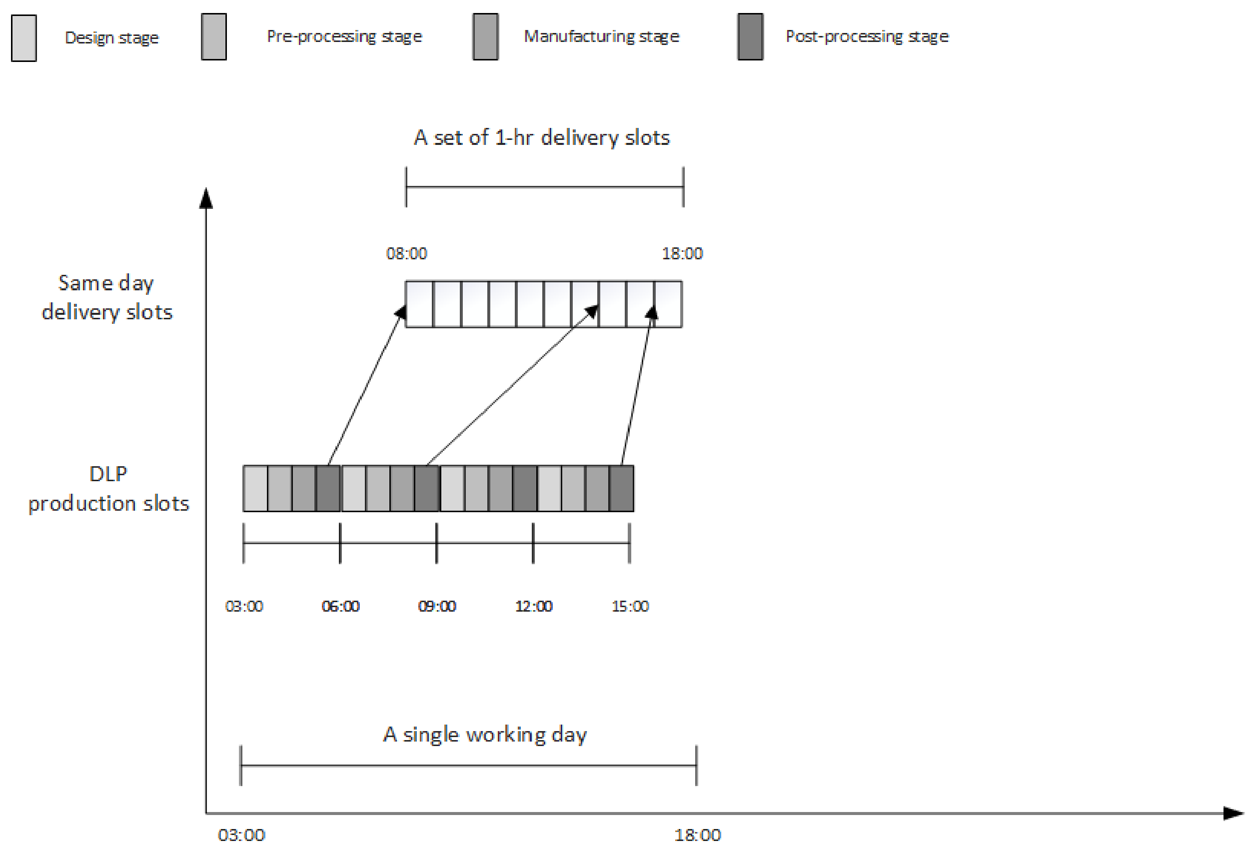

Figure 1: An illustration of integrated production and same day delivery slots for the DPL type 3DP machine

Table 2: Central concepts and their definitions

Concept	Description
3D printing	An umbrella term that encompasses a group of 3D printing processes
City logistics	A study of the dynamic management and operations of urban freight transport and distribution systems
Production policy	The production rule which is decided by a firm. It includes leveled, forward and backward rules, which will be explained in the next subsection.
Delivery policy	The delivery rule which is decided by a firm. Similarly, it includes leveled, forward and backward rules, which will be explained in the next subsection.
Production slot	The time period dedicated for the scheduled production by a firm
Delivery slot	The time period dedicated for the promised delivery by a firm
Machine utilization	The percentage of machine production slots that are planned for the production. It is calculated by dividing the number of used slots by the total number of available slots.
Capacity utilization	The percentage of average capacity use that are planned for the production. It is calculated by dividing the total dedicated capacities by the total number of slots.
Slot utilization	The percentage of delivery slots that are planned for the delivery. It is calculated by dividing the number of used slots by the total number of slots.

order cannot be delivered before its production completed, (v) order cannot be printed if there is no available time slot in the defined planning horizon, (vi) each type of 3DP machine has a fixed

Table 3: A list of sets and parameters used in the study

Notation	Definition
Sets	
$\mathcal{O} = \{1, 2, ..., \|O\|\}$	Set of orders
$\mathcal{C} = \{1, 2, ..., c\}$	Set of materials
$\mathcal{O}^c = \{1, 2, ..., \|C\|\}$	Subset of O that involves material c for each order o
$\mathcal{M} = \{1, 2, ..., \|M\|\}$	Set of DLP type 3DP machines
$\mathcal{T} = \{1, 2, ..., \|T\|\}$	Set of production slots
$\mathcal{D} = \{1, 2, .., \|D\|\}$	Number of days
$\mathcal{K} = \{1, 2, .., \|K\|\}$	Dedicated delivery slots
Parameters	
$[a^t, b^t]$	Production slot t, where a^t and b^t represent the lower and upper bounds, respectively.
$[c^k, d^k]$	Delivery slot k, where c^k and d^k represent the lower and upper bounds, respectively.
$[e^o, f^o]$	Customer's time window, where e^o and f^o represent the lower and upper bounds, respectively.
L^k	Available number of vehicles at period k
σ_1^{mt}	The score of using machine m at production slot t
σ_2^k	The score of using delivery slot k
σ_3^o	The penalty score of not fulfilling an order o
cap^o	The uni measure for capacity of part(s) in an order o
CAP^{mt}	An up-to-date capacity of machine m at time period t
U^{mt}	Available capacity of machine m at time period t
W	Very large number (i.e., 10,000)

Table 4: A list of decision variables used in the model

Notation	Definition
z_o^{mt}	A binary variable equal to 1 if and only if order o is printed by machine m ($m \in M$) in production period t ($t \in T$), 0 otherwise.
y^{mct}	A binary variable equal to 1 if and only if machine m ($m \in M$) in period t ($t \in T$) used material c, 0 otherwise.
x_o^k	A binary variable equal to 1 if and only if order o is going to delivered at time slot k, $o \in \mathcal{O}, k \in \mathcal{K}$
pen_o^1	A binary variable equal to 1 if an order o cannot be printed due to lack of production capacity, 0 otherwise. $o \in \mathcal{O}$
pen_o^2	A binary variable equal to 1 if an order o cannot be delivered due to lack of delivery capacity, 0 otherwise. $o \in \mathcal{O}$
s^k	An integer variable showing how many vehicles need to be dispatched at time slot k ($k \in \mathcal{K}$)
d^o	A continuous variable showing the departure time of order o ($o \in \mathcal{O}$)
u^{mt}	A continuous variable showing the current utilization of machine m at time period t

capacity in terms of its volume (see e.g., Eyers et al., 2018), and (vii) only a limited number of orders can be delivered within a specific 1-hour time window.

As discussed earlier, the consideration of operational costs for 3DP should not be used as an objective in integrated production and delivery. We, therefore, propose a new approach to offer higher planning flexibility to medical firms operating in cities. This approach is termed a 'scoring mechanism' defined for every production and delivery slots. In our setting, we assign values (weights) to each slot based on three different approaches. These include leveled, forward and backward approaches. A Leveled approach ensures that each slot has the same weight and can be considered equally during the planning horizon. This approach provides higher flexibility and can be used when there is no priority over slots. The second approach is called Forward in our research. This approach gives priority to earlier slots as a firm may want to complete its production/delivery relatively earlier than the end of the planning horizon. The last approach is called Backward which helps to prioritize later slots. This is the most popular approach as it helps firms to wait till last minute and consolidate orders to increase the utilization of board chamber of 3DP machines.

However, this might also lead to unfulfilled orders due to lack of capacity in later periods.

3.3. Mathematical formulation

In the following subsections the MILP model is presented in detail.

3.3.1. Objective function

The objective of the studied problem is to minimize the total score of production, delivery and the penalties for the unfulfilled orders over the planning horizon.

$$\text{minimize} \quad \sum_{m\in\mathcal{M}}\sum_{c\in C}\sum_{t\in T}\sigma_1^{mt}\, y^{mct} \tag{1}$$

$$+ \sum_{k\in\mathcal{K}}\sigma_2^{k}\, s^{k} \tag{2}$$

$$+ \sum_{o\in\mathcal{O}}\sigma_3^{o}\, pen_o^1 \tag{3}$$

$$subject\, to:$$

The objective function is the minimization of three components. These include the total score for chosen production slots, the total score for chosen delivery slots (aka the number of vehicles used in each delivery slot), and the total penalty score for unfulfilled orders. More specifically, we consider a more flexible objective function where both production and transportation are explicitly considered. The first component (1) helps to consolidate orders if they require the same type of 3DP technology and material. The second component helps to consolidate shipments for certain time slots. And finally, the last component (3) is used if the machine, capacity, and delivery slot do not allow to print a certain order, this penalty score helps for obtaining the feasible solution. The scoring mechanism is especially helpful when certain production slots or delivery slots are preferable. For example, a company can prefer to chose early production slots and later delivery slots. This would also help choose less preferred machines in the planning horizon.

3.3.2. Production constraints

The decision of the allocation of customers' orders to machines and production slots are considered with the following constraints.

$$\sum_{m\in\mathcal{M}}\sum_{t\in\mathcal{T}} z_o^{mt} = 1 \qquad \forall o \in \mathcal{O} \tag{4}$$

$$\sum_{o\in\mathcal{O}} z_o^{mt} cap^o \leq U^{mt} \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{5}$$

$$\sum_{o\in\mathcal{O}} z_o^{mt} \leq W y^{mct} \qquad \forall m \in \mathcal{M}, c \in \mathcal{C}, t \in \mathcal{T} \tag{6}$$

$$\sum_{c\in\mathcal{C}} y^{mct} \leq 1 \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{7}$$

$$d^o - \sum_{m\in\mathcal{M}}\sum_{t\in\mathcal{T}} z_o^{mt} b^t \geq 0 \qquad \forall o \in \mathcal{O} \tag{8}$$

It is worth noting that each order can only be assigned to a single machine within the planning horizon (see constraint 4). If an order has multiple parts to be printed, all parts of the same order is printed on the same machine, if possible. One of the operational constraints of 3DP machines is the production capacity for printing. Since each machine has a specific volume capacity, the total volume should not violate the available capacity of each machine (5). Constraint (6) ensures that binary variable y^{mct} gets the value of one if any order is assigned to machine m at period t. W is a very large number. Each 3DP machine can be used maximally one time in each period as shown in constraint (7). Constraint (8) shows the completion time (or earliest departure time) at the end production slot if any printing has occurred.

3.3.3. Delivery constraints

Another decision is to find the right delivery slot for the printed orders as formulated in the following constraints.

$$d^o - Wpen_o^2 - \sum_{k\in\mathcal{K}} x_o^k c^k \le 0 \qquad \forall o \in \mathcal{O} \tag{9}$$

$$e^o \le \sum_{k\in\mathcal{K}} x_o^k c^k \le f^o \qquad \forall o \in \mathcal{O} \tag{10}$$

$$pen_2^o + \sum_{k\in\mathcal{K}} x_o^k = 1 \qquad \forall o \in \mathcal{O} \tag{11}$$

$$pen_1^o - pen_2^o = 0 \qquad \forall o \in \mathcal{O} \tag{12}$$

$$\sum_{o\in\mathcal{O}} x_o^k \le s^k L^k \qquad \forall k \in \mathcal{K} \tag{13}$$

$$\sum_{o\in\mathcal{O}} cap^o z_o^{mt} + U^{mt} - u^{mt} = 0 \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{14}$$

$$U^{mt} = CAP^{mt} \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{15}$$

$$s^k \le L^k \qquad \forall k \in \mathcal{K} \tag{16}$$

$$z_o^{mt} \in \{0,1\} \qquad \forall o \in \mathcal{O}, m \in \mathcal{M}, t \in \mathcal{T} \tag{17}$$

$$y^{mct} \in \{0,1\} \qquad \forall m \in \mathcal{M}, c \in \mathcal{C}, t \in \mathcal{T} \tag{18}$$

$$x_o^k \in \{0,1\} \qquad \forall o \in \mathcal{O}, \forall k \in \mathcal{K} \tag{19}$$

$$pen_1^o \in \{0,1\} \qquad \forall o \in \mathcal{O} \tag{20}$$

$$pen_2^o \in \{0,1\} \qquad \forall o \in \mathcal{O} \tag{21}$$

$$s^k \ge 0 \, and \, integer \qquad \forall k \in \mathcal{K} \tag{22}$$

$$d^o \ge 0 \qquad \forall o \in \mathcal{O} \tag{23}$$

$$u^{mt} \ge 0 \qquad \forall m \in \mathcal{M}, t \in \mathcal{T}. \tag{24}$$

Constraint (9) ensures that a delivery can only be processed after the printing. We note that W is a very large number. Customers' delivery time preferences are satisfied in constraint (10). Constraint (11) ensures only one delivery slot per order. If there is no delivery slot available for an order o, the decision variable pen_2^o will get the value of one. If an order cannot be delivered (i.e., due to transport capacity), the order cannot be printed. This is ensured in constraint (12). Only a number of deliveries can be arranged in each delivery slot as shown in constraint (13). Constraint (14) is used to calculate the utilization rate of each machine at each period. Constraint (15) ensures the available capacity of machine m at period t. Constraint (16) is used to limit the number of vehicles available for delivery slot k. The domains of decision variables are shown in constraints (17)–(24). We note that z_o^{mt}, y^{mct}, x_o^k, pen_1^o, and pen_2^o are binary variables, s^k is an integer decision variable and finally d^o and u^{mt} are used as continuous decision variables.

The complexity of the provided MILP model grows based on its input. In order to capture the complexity, the big-O complexity analysis can be used. For the model, the big-O complexity is O($|O||M||T|$) if the number of materials is less than the number of orders (i.e., $c \leq o$). If not, the big-O complexity is calculated as $O(|M||C||T|)$. Considering the explosion in complexity along with the increase in order size, number of machines and number of periods, fixed production and delivery slots help to reduce the complexity of the model. A complexity analysis with five examples is provided in Table 5.

Table 5: A complexity analysis of five example instances

Instance	Continuous variables	Binary variables	Number of constraints
1A	2	5	20
1B	3	8	28
1C	20	141	272
1D	30	810	1,700
1E	150	6,400	7,910

1A: Single order, single part, single machine, one type of material, one production slot, one delivery slot
1B: Single order, single part, two machines, one type of material, one production slot, one delivery slot
1C: Ten orders, single part, one machine, one type of material, 10 production slots, one delivery slot
1D: Ten orders, two parts, two machines, four type of materials, 10 production slots, 10 delivery slots
1E: 100 orders, two parts, five machines, four type of materials, 10 production slots, 10 delivery slots

As can be seen from Table 5, the complexity of the model grows with the number of inputs. This basic analysis shows us that the MILP model is only capable for small to medium sized problem instances. More detailed analysis will be provided in section 6.1. In order to generate multi-day planning, we provide a sequential algorithm in the following section.

4. A sequential algorithm for multi-day planning

This section provides details of the proposed algorithm for the multi-day 3DTP. In order to consider a multi-day plan (i.e., five working days), we have adapted the MILP model to run for several days while considering the arrival of new orders at the end of each day. A flowchart explaining the algorithm is provided in Figure 2. A pseudo-code of the generic algorithm is presented in Algorithm 1.

As also illustrated in Figure 2, the algorithm is initialized with a planning period, set of orders, set of 3DP machines, set of production and delivery slots as inputs and returns a integrated production and delivery plan for each day. The algorithm is run for the number of days. For each day, the algorithm considers the updated list of available orders, production, and delivery slots. Then, a MILP model is run for each day as discussed in the previous subsection. After running the model, the production and delivery plans are obtained. The availability and utilization of slots are updated at the end of each day.

Since the machine capacity can be planned for the later days, in each day the algorithm should update the current machine, capacity and slot utilization. We consider the following constraints for

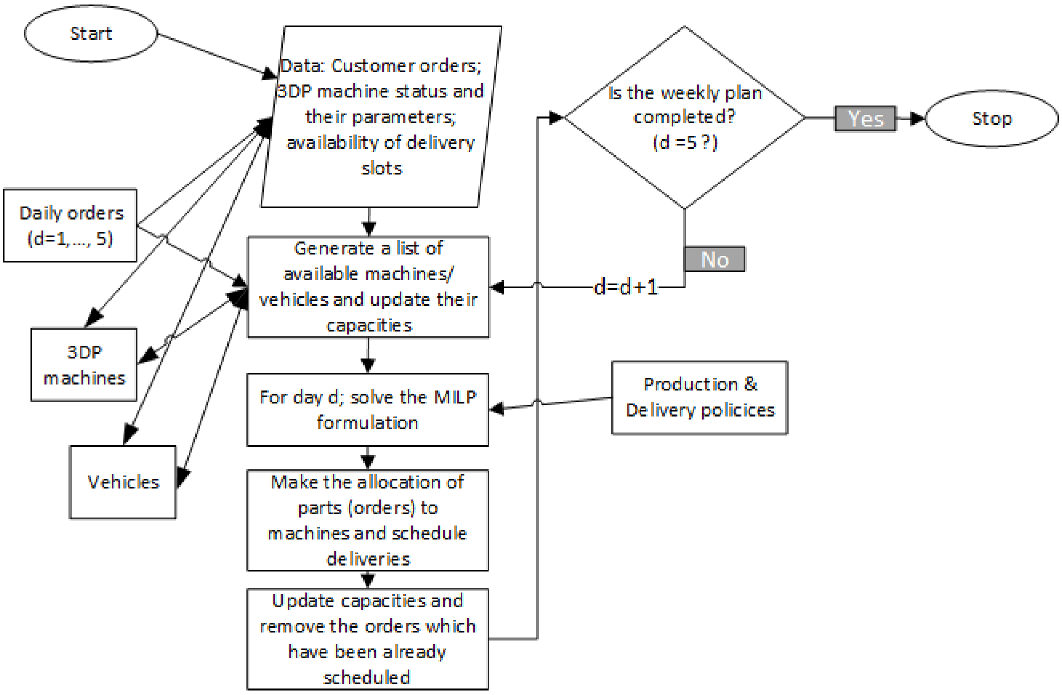

Figure 2: Flowchart of the proposed multi-day planning algorithm

Algorithm 1: Pseudocode of the proposed multi-day planning algorithm for the 3DTP

Input : Planning period, number of days ($\mathcal{D}$), set of current orders ($\mathcal{O}$), set of 3DP machines ($\mathcal{M}$), set of delivery slots ($\mathcal{K}^d$)
Output: Production ($\mathcal{P}$) and delivery ($\mathcal{D}$) schedule per each working day, a list of unfulfilled orders

repeat
- Receive the updated list of orders ($\mathcal{O}$) and their details
- Check availability of machines ($\mathcal{M}$)
- Prepare the list of machines with their available capacity
- Run the MILP model for the rest of the planning period as shown in section 3.3.3
- Obtain the optimal allocation of orders
- Plan for the production based on the optimal schedule
- Plan the deliveries based on the optimal delivery schedule
- Complete the scheduled production and delivery, if any
- Update machines and delivery slots
- Review machine utilization

until for each working day $d \in \mathcal{D}$

the following days in the planning algorithm.

$$y^{mct} - 1 = 0 \qquad \forall m \in \mathcal{M}, c \in \mathcal{C}, t \in \mathcal{T} \tag{25}$$

$$x_o^k - 1 = 0 \qquad \forall o \in \mathcal{O}, k \in \mathcal{K} \tag{26}$$

$$U^{mt} = CAP^m - \sum_{o \in \mathcal{O}} z_o^{mt} cap^o \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{27}$$

Constraint 25 ensures that the chosen production slot is input in the algorithm for the consecutive days. Accordingly, constraint 26 ensures that time slots are updated for the next days. The capacity utilization of each machine at period t is updated in constraint 27. These constraints replace constraint (15). Moreover, the available number of vehicles at delivery slot k (L^k) needs to be updated for the following days.

5. Case study

This section provides details of the case study that is used to illustrate the application of the 3DTP algorithm.

5.1. Case overview

We consider the application of 3DP in a city logistics context for the production of In-The-Ear Hearing Aids (hereafter 'hearing aids'), which are well-established in the market, and can be considered an exemplar commercially-successful example of 3DP. Indeed, the production of hearing aids using 3DP technologies has now completely replaced conventional manufacturing processes (D'Aveni, 2015; Sandström, 2016), therefore providing confidence in the general viability of the product for consideration in this work.

A significant part of the value derived for the customer comes from the achievement of geometric customization; poorly fitting products may be both uncomfortable and have inferior functionality. Every ear is different, and customers may need either one or two hearing aids. This means that every order must have individual 3D design files specifically for the given customer, and so all production is based on the receipt of actual orders, rather than produced to stock. Furthermore, the production system needs to be responsive, as delays to order fulfillment directly affect the quality of life for the waiting patient.

Normally the manufacture of medical devices is a specialized activity, meaning that individual companies typically focus on the production of specific products in centralized production facilities. However, the proven ability of 3DP to produce the focal products, together with identified opportunities for decentralized production offers the potential for a localization of production near final demand.

We therefore postulate a plausible scenario where a single manufacturer receives 3D design files from an audiologists in the city region. Using appropriate 3DP technologies, materials, and labor resources, this single manufacturer wholly produces and delivers from a single manufacturing location to serve a specific geographic community.

5.2. Characteristics of 3DP

We now provide the details for each stage of 3DP for the ITE Hearing Aid case study.

5.2.1. Design

ITE hearing aids are established products, for which designs have been carefully created by the IP rights holder, and for which details of required customization is needed for production to occur. For each customer there will be extensive geometric customization, and normally the elicitation of the required geometries is performed by the healthcare professional treating the patient. There will also be a range of configuration options to choose from, including the color of the device. These activities are normally done at a private consultation, and the 3DP manufacturer has no engagement in this process.

5.2.2. Pre-proceesing

Once the design configuration is known for a given product, the 3DP manufacturer will normally validate the final 3DP design to ensure optimal manufacturability. This is normally a fairly automated process, whereby software tools specific to the product type check for common issues and make recommendations to human operators for enhancement. Next, production planning is undertaken to identify which 3DP machine will be used, and when. In this case four different materials are available (producing different colored devices to match the wearers skin color), and so batches are color-specific and require a specific machine setup.

5.2.3. Manufacturing

In the production of hearing aids a DLP process is employed to produce these small plastic parts. DLP machines use UV light to cure photosensitive resins, turning the liquid into a robust solid shell within which to house electrical components. The advantage of DLP is that parts can be made quickly, with relatively inexpensive machines, and with a high degree of accuracy in bio-compatible materials. In practice a variety of machines may be used for hearing aid production, but for the focal case we consider a machine that can produce a batch of up to 40 individual hearing aid shells per build.

5.2.4. Post-processing

Once manufacturing is complete the 3DP machine is emptied, and post-processing performed to finish the parts. The 40-unit build is split into individual parts, which require minor finishing and visual quality inspection. Next, the electronics are added and configured by hand, the device tested, and packed for dispatch to the customer.

5.2.5. Delivery

Once the production phase is complete, hearing aids are transported by road to audiologists. Given the small size of the parts theoretically hundreds of orders could be fulfilled in a mid-sized van; in practice the constraint is therefore not volume, but time. In our city logistics model we consider that five drops are feasible per van, per hour, within the city region.

5.3. Data generation

In order to further investigate the 3DP production with transportation planning, we have generated different sets of instances. The number of customer orders in these instances ranges from 50 to 500. The instances includes randomly generated medical orders. All other machine-related parameters are obtained from the interviews with specialists.

The proposed algorithm was implemented in MS Visual Studio 2015 C++. All experiments were conducted on a Microsoft Windows 10 laptop with an Intel core i7 CPU and 8.00 GB RAM. We do not claim that our choice of parameter values is the best possible. However, we have used realistic data on our instances, where possible. Our MILP model contains 13 parameters which are shown in Table 6. The parameters used in proposed algorithm are grouped into four categories as described below.

6. Scenarios

This section first introduces the scenarios of analysis and provides computational results obtained with the proposed algorithm. To examine pertinent elements of 3DP production and delivery planning, we generate various scenarios derived from the Case Study. As we progress through each we introduce additional complexity to our work, mirroring challenges faced in real-life operations. We define four main scenarios of 3DP production and delivery planning, which are summarized as:

Table 6: A list of parameters used in the case study

Group	Parameter	Meaning	Chosen value
(i)	$\mathcal{T}$	Planning period	4 – 28 production slots
	$\mathcal{D}$	Number of days	1 day – 5 days
(ii)	$\mathcal{O}$	Set of orders	50–500 orders
	cap_o	Number of parts per order o	1–2 units
	$[e^o, f^o]$	Time window	Same day (10hr, 5hr and 1hr) or in other days
	σ_3^o	The score of unfulfilled order (i.e., penalty value)	1,000
(iii)	$\mathcal{M}$	Available number of machines	$\{1, .., 5\}$
	$\mathcal{T}^m$	Production slots for machine	3 hours
	CAP_m	Capacities of DLP machine	40 units
	σ_1^{mt}	The score of production slot	[500, 1000]
(iv)	$\mathcal{K}$	Delivery slots on each day	[8–18] hours
	σ_2^k	The score of delivery slot	[10, 100]

Scenario A: We investigate the limitations of the proposed model that is tailored to be used by SMEs. We look at three most important features of the problem, namely the number of machines, the preference of materials offered, and the number of daily orders.

Scenario B: We investigate the impact of customer's delivery time preferences (i.e., delivery flexibility) on production and delivery utilization. Through this scenario we examine whether giving customers increasing choice over when their products are delivered has a notable impact on the fulfilment operations.

Scenario C: We investigate the impact of production and delivery policies on production and delivery utilization, exploring forward, backward, and leveled policies that were previously introduced in Section 3.

Scenario D: We extend the previous single-day scenarios to explore how multi-day production and delivery planning may be performed using the proposed algorithm.

First, we provide the characteristics of defined scenarios in Tables 7 and 8. More specifically, Table 7 presents the studied planning period, the number of orders, the number of machines, the number of parts, production slots and the number of delivery slots of each scenario. In Table 8 production and delivery slots as well as policies are provided.

Table 7: The characteristics of Scenarios - I: Production

Scenario	Planning period	Number of orders	Number of machines	Number of materials	Number of parts per order	Production slots	Delivery slots
$A(1)$	Single day	50 – 500	1 to 5	4	1 or 2	4	10
$A(2)$	Single day	50 – 500	2	1 to 4	1 or 2	4	10
$A(3)$	Single day	300	1 to 5	1 to 4	1 or 2	4	10
B	Single day	250	2	4	1 or 2	4	10
C	Single day	250	2	4	1 or 2	4	10
D	Multi days (5 days)	150 per day	1	4	1 or 2	4 * 6 (M, T, W, Th) 1 * 4 (F)	50

M: Monday, T: Tuesday, W; Wednesday, Th: Thursday and F: Friday

6.1. Scenario A: Analyses of computational performance of the proposed algorithm

This initial scenario is intended to demonstrate the performance of the proposed algorithm in the basic planning of production for single-day demand, thereby confirming whether the algorithm can be useful for medical SMEs who wish to operate in the context of city logistics. In first analysis, we look at increasing order quantities in each instance. The order book is processed at midnight,

Table 8: The characteristics of Scenarios – II: Production and delivery times

Scenario	Production (scoring)	DLP – production slots 03–06	06–09	09–12	12–15	15–18	18–21	Delivery (scoring)	Delivery tolerance: Next days	Same day: 10–hr	5–hr	1–hr
$A(1)$	Lev	X	X	X	X			Lev		X		
$A(2)$	Lev	X	X	X	X			Lev		X		
$A(3)$	Lev	X	X	X	X			Lev		X		
B	Lev	X	X	X	X			Lev		X	X	X
C	Fwd, Bwd	X	X	X	X			Fwd, Bwd		X	X	X
D	Lev, Fwd, Bwd	M T W Th F	M T W Th F	M T W Th F	M T W Th F	M T W Th	M T W Th	Lev, Fwd, Bwd	X	X	X	X

Lev: Leveled; Fwd: Forward; Bwd: Backward; M: Monday; T: Tuesday; W:Wednesday; Th:Thursday; F: Friday

and production occurs in four time slots during the day. All orders must be delivered in same-day within the defined 10–hr delivery time slots. These time slots are defined from 8:00 am in the morning to 18:00 in the evening. Within this scenario we vary two of three key parameters, and observe the impact on production planning.

The first column in Table 9 gives the instance name reported as 3DPT_Cy, where C refers to complexity and y is the number of instance. The second column reports the number of orders, for which there may be one or two parts. The next three blocks show several performance indicators for a given number of DLP machines. In each group, the first column presents the Ful. (%) indicator. The fulfillment is calculated as (the total number of orders) - (the number of unfilled orders) / (the total number of orders). The second columns in each group, called "M/C (%)", report the percentage of total usage in which a machine is used. The columns under "CAP (%)" report the average percentage values of capacity utilization. Finally, the columns 'CPU (sec)' present the normalized CPU times required for each instance. We note that the solution time is set to 1,200 seconds for each instance.

Table 9: Scenario A: Varying number of machines and demand levels, whilst constraining number of parts

Instance	Orders	Number of M/Cs =1: Ful. (%)	M/C (%)	CAP (%)	CPU (sec)	Number of M/Cs =3: Ful. (%)	M/C (%)	CAP (%)	CPU (sec)	Number of M/Cs =5: Ful. (%)	M/C (%)	CAP (%)	CPU (sec)
3DPT_c1	50	100	100	49	0.3	100	33	49	0.5	100	20	49	0.1
3DPT_c2	100	99	100	94	1.2	100	42	76	0.9	100	25	76	4.8
3DPT_c3	150	77	100	99	1.9	100	67	71	130.1	100	40	71	533.0
3DPT_c4	200	65	100	99	2.1	100	75	83	213.0	100	45	83	674.2
3DPT_c5	250	58	100	99	2.5	100	100	77	163.4	100	60	77	1,200*
3DPT_c6	300	51	100	99	10.2	99	100	93	697.7	100	65	86	1,200*
3DPT_c7	350	45	100	99	10.4	93	100	99	1,200*	100	75	87	1,200*
3DPT_c8	400	40	100	100	56.0	85	100	100	1,200*	100	85	89	1,200*
3DPT_c9	450	36	100	100	7.3	77	100	99	1,200*	100	90	95	1,200*
3DPT_c10	500	32	100	100	831.0	72	100	100	1,200*	99	100	92	1,200*

* could not be solved to optimality within 1,200 seconds.

One of the challenges for commercial 3D printing operators is the need to offer a range of materials for their customers. Although several 3DP machines support multi-material production (e.g., dual extrusion Fused Deposition Modelling), in practice most large scale processes remain single-material builds. For ITE production using DLP different colored resins are used to approximately match the device color to the customer's skin tone. In this scenario demand for colors is assigned randomly between each of the four colors. Table 9 shows that where an operator has a single-machine offering, the machine must run four times — once for each material color. This means full machine utilization occurs at modest demand levels (50 orders/79 parts), but capacity utilization is relatively low (avg 49%); in other words the machine is typically half-full. To promote machine efficiency firms usually aim for full capacity utilization before starting production (Ruffo and Hague, 2007), since running machines half-empty is sub-optimal from a production cost perspective, but it does enable total fulfilment of demand. As demand increases beyond 100 orders (151 parts) demand quickly swamps available capacity and fulfillment rates fall markedly.

As the number of machines increases, the available capacity for production increases. Where demand is low relative to supply capacity (e.g., 5 machines, 100 orders), firms have a choice. They can either run all their machines with low capacity utilization, or run only part of the machine set, but focus on filling build-chambers. The latter is the option favoured by the algorithm, and this is evidenced by high capacity utilization despite low machine utilization. We note that the number of orders and number of machines increases the complexity of the model and it is not possible to find optimal solutions for many instances.

Next, we vary the number of materials and demand levels and look at similar indicators in Table 10.

Table 10: Scenario A(2): Varying material offering and demand levels, whilst constraining machine supply

Instance		Number of material =1				Number of material =2				Number of material =4			
	Orders	Ful. (%)	M/C (%)	CAP (%)	CPU (sec)	Ful. (%)	M/C (%)	CAP (%)	CPU (sec)	Ful. (%)	M/C (%)	CAP (%)	CPU (sec)
3DPT_c11	50	100	34	99	0.6	100	40	99	0.3	100	50	49	0.5
3DPT_c12	100	100	63	94	3.0	100	80	76	2.9	100	63	76	1.1
3DPT_c13	150	100	84	94	5.9	100	100	94	6.7	100	100	71	8.4
3DPT_c14	200	99	100	93	8.8	100	100	93	6.0	99	100	92	17.7
3DPT_c15	250	90	100	100	198.7	90	100	100	1.4	90	100	99	741.3
3DPT_c16	300	78	100	100	9.6	78	100	100	15.4	78	100	99	1,200*
3DPT_c17	350	71	100	100	4.3	71	100	100	7.7	71	100	100	1,200*
3DPT_c18	400	64	100	100	22.2	65	100	100	36.5	65	100	100	1,200*
3DPT_c19	450	60	100	100	37.6	60	100	100	68.2	60	100	100	1,200*
3DPT_c20	500	57	100	100	23.3	57	100	100	27.3	56	100	100	1,200*

* could not be solved to optimality within 1,200 seconds.

This scenario explores how a 3DP manufacturer with fixed machine capacity can satisfy different levels of demand, and the effect of offering variety in materials affects overall production fulfilment. Recall that each machine can produce up to 40 same-colored parts; to produce a different color requires a specific machine setup.

As shown in Table 10, where there is a single material color capacity utilization is prioritized by the algorithm; effectively every build is filled to capacity before a new machine slot is opened. Fulfilment only drops once all of the available capacity has been fully used (beyond 200 orders). Moving to two materials makes a given build material-specific, though as the distribution of materials is approximately even, there is little performance difference relative to a single machine. Once the number of materials exceeds the number of machines, the problem becomes more difficult to solve and CPU times extend significantly. Now, whilst overall demand volumes are the same, the increase in material distribution leads to build chambers running at lower utilization levels, whilst the machines are fully employed.

The third scenario in this category looks at varying material offering and machine capacity for a fixed number of orders (i.e., 300 orders) as shown in Table 11.

Given a constant aggregate demand, firms would typically avoid introducing variety; to do so typically leads to dis-economies of scale, and hence there is often no commercial benefit. In Table 11, we eliminate the effect of material choice by offering only a single material color. In instances of one or two machines, full machine and capacity utilization are unable to fulfil demand in full. Only once three machines are employed can demand be met, for which capacity utilization remaining

Table 11: Scenario A(3): Varying material offering and machine capacity, but with unchanged demand

Instance	M/Cs	Number of material =1				Number of material =2				Number of material =4			
		Ful. (%)	M/C (%)	CAP (%)	CPU (sec)	Ful. (%)	M/C (%)	CAP (%)	CPU (sec)	Ful. (%)	M/C (%)	CAP (%)	CPU (sec)
3DPT_c21	1	52	100	99.4	2.8	52	100	99.4	1.0	51	100	99.4	7.6
3DPT_c22	2	78	100	99.7	6.3	78	100	100.0	17.4	78	100	99.1	1,200*
3DPT_c23	3	100	100	93.5	4.5	100	100	93.5	17.2	99	100	92.3	1,200*
3DPT_c24	4	100	75	93.5	27.1	100	75	93.5	70.4	100	81	86.3	1,200*
3DPT_c25	5	100	60	93.5	27.1	100	60	93.5	1,200*	100	65	86.3	1,200*

* could not be solved to optimality within 1,200 seconds.

high. Increasing machine availability beyond three serves no purpose; this excess capacity leads only to reductions in overall machine utilization. As more material options increase we find little effect on the production system at this level of demand. Relative to single color choices there is a very slight increase in unfulfilled orders. There is also a slight increase in machine utilization, which is to the detriment of capacity utilization.

In summary these three sub-scenarios therefore serve to test the performance and operation of the algorithm in the context of a real-world problem. We show how three fundamental principles of production operations (production capacity, demand volume, and order variety) can be considered using the algorithm, and highlight the management impact of these in different configurations of the 3DP facility in practice.

6.2. Scenario B: The impact of delivery preferences on utilization

Scenario A demonstrated the effectiveness of the algorithm to plan production, given a variety of constraints. Building on these foundations, in Scenario B we explore how customers' preferences for deliveries affect production. We provide our results in Table 12. The first column in Table 12 gives the instance name reported as 3DPT_Ty, where T emphasize the time dimension and y is the number of instance.

In this scenario we show a 2-machine facility, with a constant demand of 250 orders / 370 parts, offering the full range of four material colors. Setting demand to a high level (relative to machine capacity) is intentional to highlight the impact of different delivery preferences. We look at three different delivery time slot preferences, stated as (10hr, 5hr, 1hr). In the second column, we show the percentage of each time slot preference in each instance. We also look at only morning and only afternoon delivery preferences in the corresponding 5hr and 1 hr delivery preferences. Moreover, we present fulfillment, machine utilization, average, minimum and maximum capacity utilization for each instance. Furthermore, we present slot utilization (Slot (%)), total number of dispatches along with minimum and maximum number of dispatches for each instance.

Table 12: Scenario B: Analysis of delivery slots preferences on solutions

Instance	Time slot (10hr, 5hr, 1hr)	Ful. (%)	M/C (%)	CAP (%)	Min (%)	Max (%)	Slot (%)	Total number of dispatches	Min number of dispatches	Max number of dispatches
3DPT_T1	(100,0,0)	89.6	100	99	98	100	100	45	1	10
3DPT_T2	(0,100,0)	89.6	100	100	98	100	100	45	1	10
3DPT_T3	(0,0,100)	88	100	98	85	100	100	45	3	6
3DPT_T4	(50,50,0)	89.6	100	99	98	100	100	45	1	10
3DPT_T5	(50,0,50)	89.6	100	99	98	100	100	45	1	10
3DPT_T6	(0,50,50)	89.6	100	99	98	100	100	45	1	10
3DPT_T7	(0,M,0)	73.6	75	99	98	100	50	37	4	10
3DPT_T8	(0,A,0)	89.6	100	100	98	100	50	45	7	10
3DPT_T9	(0.0, M)	65.2	75	85	50	100	50	33	3	9
3DPT_T10	(0,0,A)	89.6	100	99	98	100	50	45	8	10

M: Morning hours: 08:00-13:00; Afternoon hours: 13:00-18:00

As shown in Table 12, the first instance (T1) shows that, given no constraints over delivery time, 89.6% of demand can be fulfilled by the 3D printers. Applying the first constraint of either morning or afternoon delivery in T2, there is no impact on production fulfillment, and in T3 we find that by offering 1-hour delivery slots there is an almost negligible drop in fulfillment levels.

With reference to Figure 3, we observe that to maintain fulfillment levels, the algorithm produces short term inventory buffers. Considering logistics for these three lines, we find that as delivery slots become shorter in duration, vehicle utilization increases, with minimum routes increasing to three, but maximum routes reducing to six.

To explore this effect further, in T4-T6 we split demand between the different time constraints by the percentages show in Table 12. This approach serves to moderate the extremes of i-iii, and we find no impact on fulfillment or logistics. In T7 we constrain all demand to morning deliveries, and in T8 constrain to single-hour slots in the morning. For both examples, short-term inventory cannot be built before delivery (Figure 3), and this negatively affects fulfillment. Machine utilization is reduced due to afternoon capacity being idle, but capacity utilization remains almost total. As production is reduced, the number of deliveries also falls, though by compressing all deliveries to half-day the vans are shown to be busier. By comparison, in T9 we constrain all demand to afternoon deliveries, and in T10 to single-hours within the afternoon, both of which allow for inventory building in the morning (Figure 3). As a result, fulfillment levels reach unconstrained values (89.6%), but since there is only an afternoon to deliver products, the vans are shown to be much busier.

These results provide some interesting contributions beyond current published research. First, whilst the literature often proclaims the advantage of 3DP is 'on-demand' printing, unless there is ample spare capacity, in practice there is the need to rely on short-term inventory to maintain fulfillment levels. As the emphasis in most 3DP cost models argues machine depreciation as a major cost to be amortized, keeping reserve machine capacity would be a costly endeavor and something managers would have to carefully evaluate. In the example of ITE hearing aids their physical size together with environmental requirements are minimal, and so in practice short-term storage on shelving is likely to be a more sensible option than extra machine capacity. Second, the data shows that offering customers increasing choice as to when their products will be delivered need not affect fulfillment levels, even at high levels of demand - providing scope to produce inventory is possible.

6.3. Scenario C: The impact of policies on utilization

This scenario extends the previous examples by introducing production and delivery policies: forward (make / deliver as soon as possible) and backward (make / deliver as late as possible). As before we show a 2-machine facility with a high demand of 250 orders / 370 parts, and four material options to ensure high utilization of resources. We explore how these policies when combined with customer-delivery preferences affect the operations in Table 13. Note that fulfillment levels are identical to scenario B as, although difference policies are being applied, overall capacity for production and delivery is unaffected.

The first column in Table 12 gives the instance name reported as 3DPT_Py, where P emphasizes policies and y is the number of instance. In the second column, we show the percentage of each time slot preference in each instance. The third and fourth columns, for each instance, present the chosen production and delivery policies, respectively. We consider only forward and backward policies. Similarly, we present production related indicators along with delivery ones.

In P1-P4 we show the various combinations of policy on production and delivery where customer preference is 10 hours (i.e., anytime), for which there is no effect on production or delivery performance. In P5-P8 (5hr) we see very minor impacts on capacity utilization for the machines, but no effect on fulfilment or the overall performance of production or delivery. For P9-P12 (1hr)

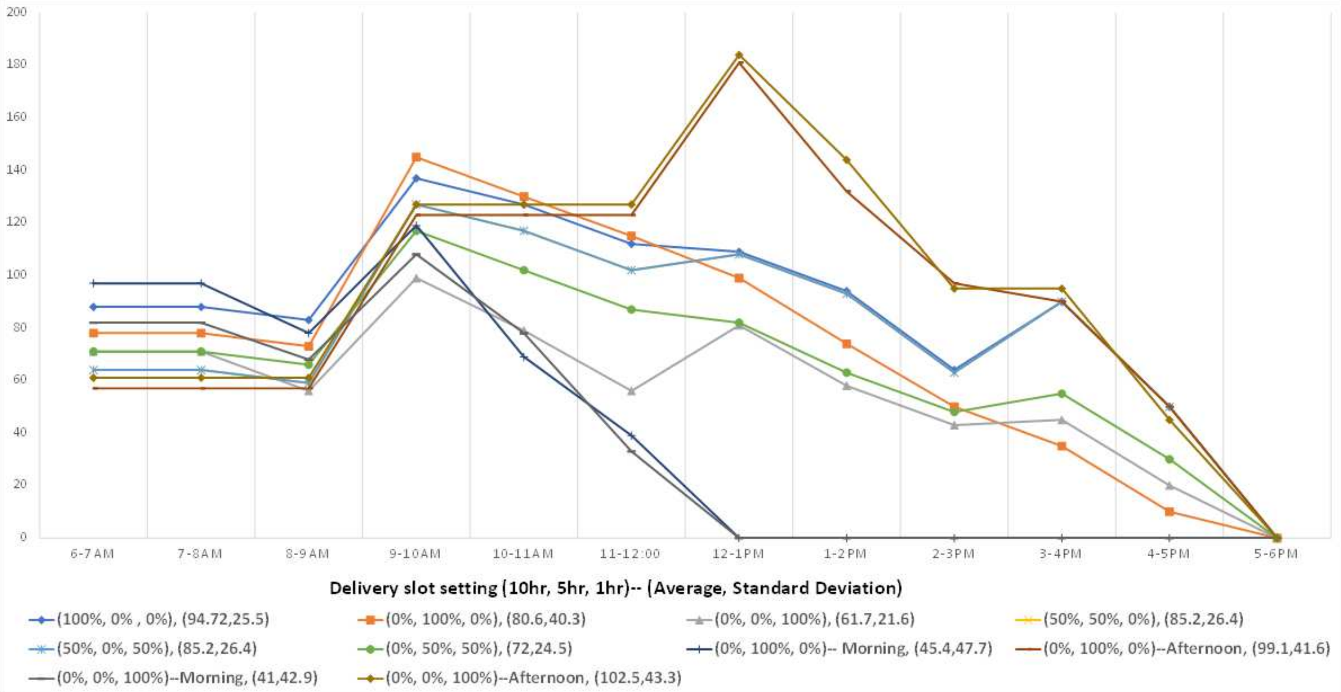

Figure 3: Scenario B: Inventory of finished goods by hour

Table 13: Scenario C: Analysis of policies on solutions

Instance	Time slot (10hr, 5hr, 1hr)	P.P.	D.P.	Ful. (%)	Unfil.	M/C (%)	Avg (%)	Min (%)	Max (%)	Slot (%)	Total number of dispatches	Min of dispatches	Max of dispatches
3DPT_P1	(100,0,0)	Fwd	Fwd	89.6	26	100	99.4	97.5	100	50	45	8	10
3DPT_P2	(100,0,0)	Fwd	Bwd	89.6	26	100	99.4	97.5	100	50	45	5	10
3DPT_P3	(100,0,0)	Bwd	Bwd	89.6	26	100	99.4	97.5	100	50	45	5	10
3DPT_P4	(100,0,0)	Bwd	Fwd	89.6	26	100	99.4	97.5	100	50	45	8	10
3DPT_P5	(0,100,0)	Fwd	Fwd	89.6	26	100	99.4	97.5	100	70	45	3	10
3DPT_P6	(0,100,0)	Fwd	Bwd	89.6	26	100	99.7	97.5	100	60	45	5	10
3DPT_P7	(0,100,0)	Bwd	Bwd	89.6	26	100	100	100	100	70	45	5	10
3DPT_P8	(0,100,0)	Bwd	Fwd	89.6	26	100	99.7	97.5	100	100	45	3	10
3DPT_P9	(0,0,100)	Fwd	Fwd	88.0	30	100	98.1	85	100	100	45	3	6
3DPT_P10	(0,0,100)	Fwd	Bwd	88.0	30	100	98.1	85	100	100	46	3	7
3DPT_P11	(0,0,100)	Bwd	Bwd	88.0	30	100	98.1	85	100	100	46	3	7
3DPT_P12	(0,0,100)	Bwd	Fwd	88.0	30	100	98.1	85	100	100	45	3	6

P.P.: Production Policy; D.P.: Delivery Policy; Fwd: Forward; Bwd: Backward

there is no impact on performance. Whilst the production policies have no impact on fulfilment, and seemingly little effect on the performance of machines and vans, it is notable that short-term inventory holding is markedly changed by the choice of policy (Figure 4).

The findings of this scenario are very significant for the planning of production and transportation. We show that managers can take intelligent policy-based decisions to influence short-term inventory holding, without affecting service levels. Indeed, providing there is appetite to hold some inventory during the planning period, 3DP providers have the opportunity to offer very tight time windows to their customers, without affecting service levels. In a city logistics context this may be particularly important where access to customer premises by vehicle is restricted at certain times of the day (e.g. inner city shopping centres), or where firms want to gain a competitive edge on rivals by using timeslots to differentiate their service offering.

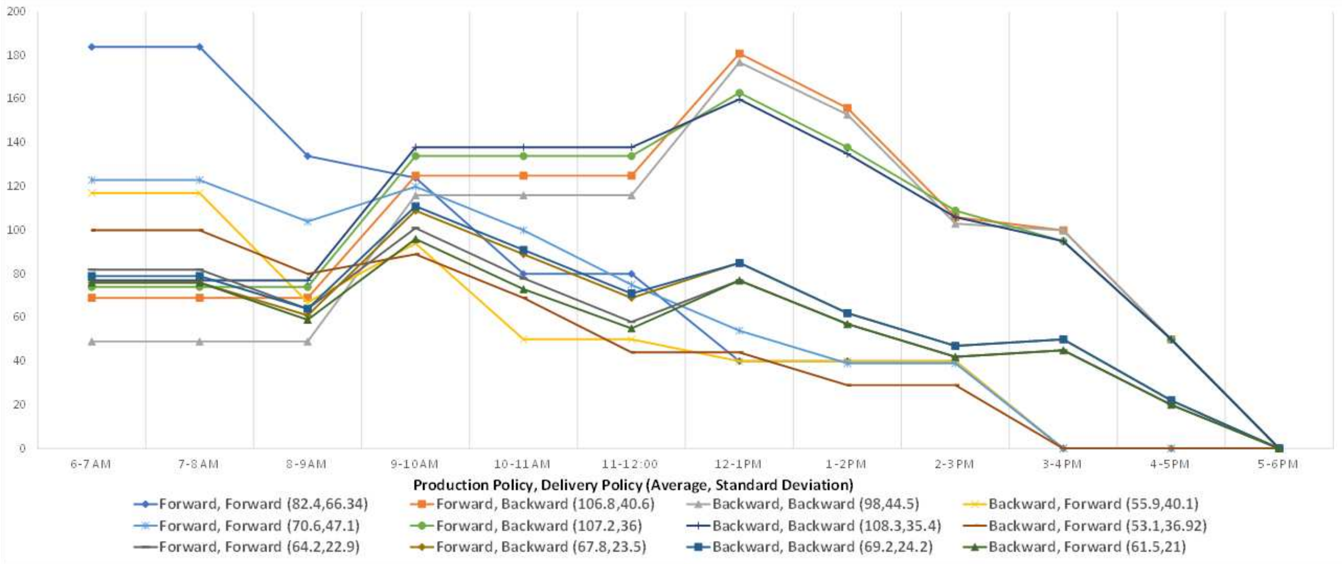

Figure 4: Scenario C: Inventory of finished goods by hour

6.4. Scenario D: Multi day planning

In this final scenario we bring together the earlier work on production planning, customer preference, and production/delivery policies and extend the planning horizon from a single day to five days. In doing so, we are able to more clearly show the combined effect of these constraints on the operations of the facility, and examine a realistic planning horizon as commonly found in many SME 3D print facilities.

The first column in Table 14 gives the instance name reported as 3DPT_My, where M emphasizes the multiple days setting and y is the number of instance. Similarly, we present indicators for the nine instances.

We consider a small 3DP facility that has a single machine, and new demand of 150 orders (226 parts) per day is introduced at midnight for each of the five days. This is quite representative of a small-scale operation setting up to serve a small city's population. To account for the range of population in the city the full compliment of four material colors is offered, with demand for each evenly distributed. In the previous scenarios 100% of demand must be produced same-day, however for scenario D we reduce this to 75%, equally divided between 10hr/5h/1h delivery requirements. The remaining 25% of daily demand is required same-week (i.e. at some point within the current planning horizon). As previous, we apply combinations of production and delivery policies forward, backward, levelled to identify the implications for the operations.

Table 14: Scenario D: Multi day planning

Instance	P.P.	D.P.	Ful. (%)	M/C (%)	CAP (%)	Min (%)	Max (%)	Slot (%)	Total number of dispatches	Min of dispatches	Max of dispatches
3DPT_M1	Lev	Lev	87.7	89	84.8	30	100	90	120	1	10
3DPT_M2	Fwd	Fwd	88.0	100	82.5	22.5	100	90	110	1	10
3DPT_M3	Bwd	Bwd	88.1	71	97.8	85	100	88	94	1	10
3DPT_M4	Lev	Fwd	88.1	100	80.3	22.5	100	88	109	1	6
3DPT_M5	Lev	Bwd	88.1	93	84.8	25	100	94	99	1	10
3DPT_M6	Fwd	Lev	88.0	100	82	27.5	100	98	100	1	7
3DPT_M7	Fwd	Bwd	88.0	100	83.1	32.5	100	92	98	1	10
3DPT_M8	Bwd	Lev	88.1	71	97.25	85	100	98	101	1	9
3DPT_M9	Bwd	Fwd	88.1	71	98.7	85	100	92	113	1	6

Lev: Leveled; Fwd: Forward; Bwd: Backward

Overall the data shows very slight variations in fulfillment performance, ranging 0.4%. On this basis, arguably, it does not matter which policy is chosen, as fulfillment is virtually the same. However, this fails to acknowledge how different policies affect production and delivery resource usage - which is a quandary faced by all 3DP operations. Should a firm produce as-early-as-possible to meet demand, or is there a benefit in waiting a while? The existing 3DP literature promotes capacity utilization (e.g. Baumers and Holweg (2019)), and in principal deferred production policies seek to ensure machine build chambers are full, improving the economics of machine operation. However, whilst seldom reported in 3DP literature, such approaches mean that overall production capacity is lost, as machines sit idle until a threshold demand is reached. Likewise production deferral would suggest additional challenges for transportation, since deliveries can only be undertaken once production has occurred. The later the production happens, the less time there is to deliver the product.

Based on the findings of Table 14 we show that a backward production policy (which defers production to the latest time) does indeed improve the economics of machine operation. In these instances we find almost full build chambers (97%+) are achieved, though with the lowest machine utilization (71%). Importantly, this is not at the degradation of service, for in M3, M8, and M9 we identity the highest fulfillment values, and so this can be considered the most efficient use of 3DP production resources.

Of course, what is good for production is not necessarily the case for delivery. Overall, we find that backward-based delivery policies result in the lowest number of dispatches being made. Combining backward production and delivery (M3) results in the best machine utilization / capacity utilization values, with the minimum number of dispatches, and would seem to be the most sensible approach for the 3DP facility. However, this approach places considerable strain on the delivery fleet. In quiet periods a single van is needed; but at peak ten vehicles are required to satisfy the orders. As a result for much of the week van resources are relatively idle, and so if the operation wished to minimize the number of vehicles owned (and thus associated costs), forward delivery polices would be a sensible option.

In this scenario arguably M9 provides the best compromise, with backward production policies promoting machine capacity utilization, but with forward delivery policies minimizing the number of vans required. This ensures the highest service levels are achieved, but with the compromise being a rise in the number of dispatches being needed over some of the other instances.

This is a complex scenario, and so to explore these policies in more detail we provide full production and delivery plans for both the 3DPT_M3 and 3DPT_M9 instances in Appendix A. For each of the five days we show the incremental addition of demand as the week progresses, along with the corresponding reduction in available planning periods for production and delivery.

6.5. Discussion

The four preceding scenarios have incrementally increased the complexity of our work, and overall offer some interesting insights for the strategic implementation of 3DP and transportation in the fulfillment of localized production.

From the production perspective, we have provided a detailed examination of different options, and the implications of these for the manufacturing operation. We started with explorations of variety (material color), demand volume (orders/parts), and capacity (machines), and highlighted the impact of these on key performance measures using numerical experiments with a wide range of values. These provide a managerial insight for firms into fundamental questions such as "how many colors of materials should we offer?" And "how many machines do we need?" Clearly the answers to these types of questions are interrelated, and so this initial scenario helps to understand how customer satisfaction can be maintained, without excessive capital investment in machines - in other words, it helps managers to identify whether it is possible to avoid trade-offs in their operation.

Next, after establishing what can be made within the given constraints, we showcased how the application of different production policies helps determine how planning activities can be intelligently undertaken to maintain service levels. We extend the conventional logic found in most 3DP publications that simply seeks to maximise machine capacity utilization, and instead introduce forward, backward, and levelled policies to explore other feasible approaches to both production and delivery. Interestingly, and somewhat counter-intuitive to expectations, sometimes offering better service to customers also helps suppliers. In the light of conducted computational experiments, we observe that dedicated delivery slots, a key requirement for the success of city logistics, can benefit production planning – within certain parameters, and sometimes relying on short-term inventory. Again, this utilization of short-term inventory is seldom associated with 3DP, where the emphasis in literature tends towards on-demand, just-in-time production. Within this study we show how short-term inventory holding can be a very sensible approach for firms, highlighting the benefits of strategic management of 3DP technologies as part of the overall fulfilment system.

Our integrated approach to production and transport planning does have significant effects on the efficient and effective provision of delivery services. Clearly the volume of items will affect how busy vans are, but crucially decisions over production policies, inventory holding, and promised delivery times are shown to influence the number of vehicles required, the number of routes they run, and the degree to which the van capacity is used. Scenario D is particularly helpful in this regard, showing that changing production and delivery policies has negligible effect on overall order satisfaction, but relatively large impact on how well production and delivery resources are utilized. The application of the principles in this study therefore provides the opportunity to compete through both production *and* logistics, enabling firms to best use their resources to meet the overall customer demand. In this study we show that offering 1-hour delivery time slots to customers is perfectly feasible, providing the supplier an opportunity to provide convenient service to customers, without negatively affecting the performance of the production or transportation operations. In turn, this may offer suppliers a competitive advantage over their rivals.

7. Conclusions

3DP offers some interesting opportunities regarding the geographic location of manufacturing, and provides a potential response for changes in the worldwide distribution of manufacturing. The trend towards offshoring of manufacturing, particularly to low-labor cost counties has led to a few countries dominating the world's manufacturing output, which relies heavily on effective transport operations to distribute outputs to their demand. However, as 3DP largely eliminates the need for labor in the manufacturing phase, the cost advantage enjoyed by countries with low-labor costs is somewhat eroded, and the sensibility of geographic separation of supply and demand becomes questionable. Instead of centralized production in a single location, 3DP offers opportunities for a variety of production models including decentralized manufacturing that is conducted 'on demand' and local to customer requirements (Ryan et al., 2017).

This paper has focused on production and delivery planning for a decentralized manufacturing system that produces customized medical products. Within the study we have developed an effective mathematical model for designing production and delivery schedules so that machine, capacity, and delivery utilization are optimized. In doing so, we provide an easily-reconfigurable scoreboard-based tool that is suitable for SME operations, and is capable of using non-financial drivers. Through the application of this tool, we are able to demonstrate the impact of different strategic choices on the manufacturing operation, highlighting opportunities where firms may achieve an advantage through intelligent planning and 3DP. To-date the very limited 3DP planning research has focused on production optimization, usually emphasizing the importance of capacity utilization for single machines. Our work therefore represents a significant extension, exploring multi-machine operations, short-term inventory management, together with production and delivery policies.

Whislt this study presents interesting and novel findings, we recognize that it also serves as a good step for further research. We note that the proposed algorithm is capable only for solving small and medium sized 3DTP instances with deterministic setting. In terms of solution methodologies, a potential research direction could be developing a hybrid simulation and optimization algorithm that generate good-quality solutions for reasonable-sized instances.

Moreover, as the considered production environment is subject to the used 3DP technology, algorithms with other type of technologies could be studied as well. Whilst the model presented is detailed, there are opportunities to extend it to include other additional components. For example, constraints could be introduced to force time-dependent production, and/or consider uncertainty in the demand profile of order data. Whilst this study aims to provide a realistic appraisal for real-life situations, fully deterministic parameters do not fully reflect the realities of life, and so future studies (both quantitative and qualitative) could seek to future explore and extend this study. One possible research method is to use distribution free approach to represent stochastic nature of the problem.

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Appendix A. Full production and delivery plans

Slots	Friday																									1	2	3	4
	Thursday																			1	2	3	4	5	6	7	8	9	10
	Wednesday														1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
	Tuesday							1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
	Monday	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
		Monday						Tuesday						Wednesday						Thursdsay						Friday			
Production	Monday	100	100	97.5	97.5																					27.5	5	25	42.5
	Tuesday							100	100	100	95																27.5	57.5	45
	Wednesday													100	97.5	97.5	95											62.5	45
	Thursday																			97.5	97.5	97.5	85				45	62.5	
	Friday																									100	100	100	100

Unfullfilled order

1	2	3	4	5	**Total**
17	11	11	13	37	89

SLOTS/ NUMBER of DISPACTHES

Delivery

Monday										Tuesday										Wednesday									
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1	1	1	1	1	1	1	1	6	1	1	1	1	1	1	2	2	2	7	1	1	1		1	1	2	2	3	7

Thursday										Friday									
31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
1	1	1	1	1	2	1	2	2	6			1		1	1	1	2	7	10

Figure A.5: An integrated production and delivery plan (3DPT_M3)

Slots

Friday																									1	2	3	4
Thursday																			1	2	3	4	5	6	7	8	9	10
Wednesday													1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Tuesday							1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Monday	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
	Monday						Tuesday						Wednesday						Thursdsay						Friday			

Production

Monday	100	100	100	100																					42.5	27.5	22.5	2.5
Tuesday							100	100	100	95																57.5	27.5	45
Wednesday													100	100	100	95										60	42.5	
Thursday																			100	100	100	85			100	100	100	100
Friday																												

Unfulfilled order

1	2	3	4	5	**Total**
17	11	11	13	37	89

SLOTS/ NUMBER of DISPACTHES

Delivery

Monday										Tuesday										Wednesday									
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
2	3	1	1	6	1	1	4	1	1	3	3	1	1	4	1	1	6	1	1	3	4	1		6	3	1	3	2	2

Thursday										Friday									
31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
4	3	1	1	6	1		4	1	1	4	6	1		5		1	4	1	1

Figure A.6: An integrated production and delivery plan (3DPT_M9)