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Optimum utilization of on-demand manufacturing and laser polishing in existence of supply disruption risk

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Abstract

3D printing has moved from being a rapid prototyping tool to an additive manufacturing method within the last decade. Additive manufacturing can satisfy the need in dire situations where spare parts distribution is an issue but access to a 3D printer is much more likely and rapid than access to original parts. Managing inventories of spare parts can be tackled with more ease thanks to the reduced part types with additive manufacturing. While quality (in terms of reliability) of additively manufactured spare parts in terms of mechanical properties seem to be lower than original parts (particularly due to the inherent staircase appearance and the corresponding stress concentration zones that can lead to premature fatigue failure), use of post-processing subtractive techniques to correct such surface irregularities are found to improve reliability. While each process adds another layer of complexity to the cost minimization problem, demand uncertainty and risk of supply disruption represent the modern global problems faced recently. The problem tackled in this study is the joint optimization of the supply reliability considering the effect of laser polishing parameters and the demand uncertainty. In this problem, a condition of random breakdowns of identical products is considered. Also, the original supplier of machine components is subject to exogenous disruptions, such as strikes, raw material scarcity, or the COVID-19 pandemic. As a result, the optimum control policy with the right cost parameters was shown via numerical experiments originated from mathematical analyses. This optimality can be critical in managing the system in the best possible way, particularly during times of unforeseen circumstances such as pandemics.

Keywords: Additive manufacturing; Laser polishing; Optimization; Supply disruption; Demand uncertainty

1. Introduction

Conventionally, subtractive manufacturing (which has become a retronym for manufacturing) has been used in producing goods in many industries [1]. On the contrary, additive manufacturing has traditionally been a method for prototyping due to its lack of process capabilities [2-4]. It is called “additive” because of the layer-by-layer nature of the process [4-6]. The major limitation of additive manufacturing that is the product mechanical quality has been overcome in many cases in the recent years [1-2, 4]. Therefore, it has become a process that can be a good alternative where subtractive methods fall short, such as when speed and cost are of concern. In terms of material costs as well as lead time and set-up time, additive manufacturing offers many advantages compared to its subtractive counterpart [7]. What has made additive manufacturing so popular before it became mainstream was its superior capabilities in terms of product complexity that allowed designers to iterate [8]. Since the complexity of the process is not affected much by the product geometry, it has been a good tool to reduce design costs by frequent iterations [7-8].

Currently, the main issue with additive manufacturing remains to be the observance of the layered manufacturing technique in a “staircase” appearance [9]. This inherent issue with the manufacturing method has not been much of an issue when it was used for prototyping since parts that are not for sale and only used for visualization purposes do not carry that much importance. However, once these parts become parts for use as it has been recently, the staircase appearance brings with itself some inherent issues. Aside from the visual suboptimalities, this appearance also means surface irregularity, which causes tolerancing issues [10]. Even worse, the surface irregularity may cause a stress concentration zone that will lead to premature fatigue failure of the part [11]. Therefore, if additive techniques are to replace subtractive manufacturing methods for production parts, the staircase appearance needs to be minimized or completely eliminated.

Researchers have been developing complicated methods to alleviate the staircase appearance by approaching the part from different directions. To accomplish this task, a 6-DoF robot or a 5-axis printing equipment can be employed so that the part that is printed is virtually "sideless" [12-13]. If there are no sides but all surfaces of the part are "top," then there cannot be a staircase appearance as it is a feature created due to the side surface. However, these machines can be quite costly making them not at all cost-efficient. Therefore, many researchers also work on developing methods that can be used to alter the surface quality after the printing is complete. These methods are called post-processing techniques and fall into the category of subtractive manufacturing [14]. If the equipment for these methods is already acquired or can be easily obtained without much cost, use of the post processing method can be justified. One method that is relatively easy to obtain and apply without much of an investment is laser beam polishing [15]. In this technique, the irregularities on the part surface are removed by a focused laser beam to make the surface smoother [15]. The smooth surface then makes the part more reliable via improved fatigue life due to eliminated stress concentrations [15]. Therefore, use of laser polishing assistance to the additive manufacturing process can be a reliability booster. However, appropriate selection of parameters in laser polishing is essential. If one is not careful, the effect of laser polishing may not be observed after the post-processing. Even if it is observed, the effect may be too small to provide any meaningful benefit. The worst-case scenario is if the laser parameters are adjusted too aggressively – in which case a burnt part surface with quality worse than before it was laser polished could be a possibility.

Considering the 3D-printing capabilities, as well as the possible effects of laser polishing on part quality, production planning can take different shapes than a single option [16]. In today's world, where relatively lightweight and easier to use 3D-printers are getting more common by the day, logistical problems need to be revisited with new constraints. Conventionally, shipping of goods for customer use requires careful thus expensive packaging. However, "shipping" of software and designs of products can be done quickly and without the attached cost of shipping. If raw materials that do not need such careful handling are shipped and used to create the part at the destination, transportation costs can be significantly reduced [17]. Moreover, holding inventory of finished goods would become unnecessary and inventory of raw materials that can make up any product as a spare part would be the norm. This "on-demand manufacturing" thought can only be materialized with a good understanding of how and how much benefit can be extracted from new technologies such as 3D-printing [14].

In addition to on-demand manufacturing, companies are forced to adapt themselves to abrupt changes in their supply chains [17]. Such changes most commonly manifest themselves as demand and supply uncertainty for a manufacturer. Specifically, customer demand of any finished products is subject to uncertainty. This randomness has been addressed by theoretical probability distributions and stochastic processes, such as Normal distribution or compound Poisson process in the literature. In addition to the demand risk, exogenous factors, such as labor strikes in suppliers' plants, inaccessible ports or raw material shortage due to outbreak of a pandemic disease, *e.g.* COVID-19, can lead to disruptions in raw material of semi-finished goods supply chains.

Supply chain disruption is a widely studied topic in the literature from the perspective of supply chain and inventory management perspectives. Hekimoğlu and colleagues state that the supply risk in supply chain can manifest itself in different forms [17]. The most common forms are lead time fluctuations (suppliers' postponed deliveries), partial fulfillment of replenishment orders, and temporary unavailability of suppliers. In 1990s suppliers' temporary (Markovian) unavailability was recognized by scholars considering stochasticity of demand and supply in a single echelon setting [18-19]. They considered hedging the supply risk by increasing the inventory level of a raw material or semi-product in order to satisfy the demand during supply unavailability. Similarly, hedging the effect of lead time fluctuations with inventory increase has been analyzed by researchers [20-22]. They recommend optimal control policies to increase the order quantities to supplier in advance when the lead time fluctuations increase due to some exogenous factors in the supply side. Muharremoğlu and Tsitsiklis are the first ones considering the effect of lead time fluctuations in a multi-echelon supply chain setting consisting of a depot and multiple production facilities [23]. Tomlin considered different strategies: inventory increase, finding an additional supply source, and capacity reservation for hedging supply risk from inventory management perspective, and characterized the conditions in which each strategy is the most favorable [24]. Li and colleagues as well as Hekimoğlu and colleagues are the first ones combining the effects of multiple supply risk forms in a single study [17, 25]. Li and colleagues developed a supply risk estimator utilizing lead time and other endogenous measures within a supply chain to quantify the supply risk within a spare parts supply chain [25]. Hekimoğlu and colleagues considered the combined effect of lead time and supply risk within a single echelon setting [17]. They found that the combined effect of the two types of supply risk creates more cost increase (need higher inventory hedging) compared to the individual effect of each supply risk form on a company. In none of these studies reviewed here, the effect of supply risk in existence of on-demand manufacturing capability, i.e. 3D printers, has been studied. It is recognized that increasing usage of additive manufacturing stimulates increased localization of the manufacturing process as producers have the capability of manufacturing as a whole instead of relying on dozens of suppliers for components. With the additional manufacturing capability of 3D printers, manufacturers will be able to respond to supply chain fluctuations using in-house solutions [26-27]. Therefore, it is important to address the optimal strategy of a manufacturer in existence of 3D-printing capability when supply risk becomes apparent. To move this research question further, we present a motivational case study depicting such a problem for a manufacturing facility.

1.1. Motivational case study of a manufacturing facility adapting additive manufacturing

In this section, we provide a case study, first introduced by Öberg and Sham who consider the additive manufacturing as a solution to supply problems of machine components [28]. In this section, we added some details, which are inspired by another case study [17] on supply problems in spare parts supply chains to their business case to emphasize this relation and motivate our problem setting and model provided in the next section.

Consider a food packaging and processing firm, offering packaging, filling machines, and processing for dairy, beverages, ice cream, and cheese. The company supplies machines for production to its customers. For these machineries, they also provide components and spare parts for their customers. Currently, the company utilizes a network of suppliers to obtain necessary parts of a machine component and assemble those parts to provide a solution for its customers. Lately, they introduce additive manufacturing to their business. Doing so allowed them to manufacture consolidated parts as one component rather than multiple components supplied from different companies and assembled into one.

Recently, one of the component suppliers announces that they will not be able to deliver parts for 3 months due to facility shutdown during the COVID-19 pandemic. To circumvent this supply disruption, the manufacturing department of the company initiates a project for producing the necessary component using additive manufacturing combined with laser polishing. During their literature review, they realize that by manipulating the scanning speed and energy density of laser polishing, they can increase the reliability of parts to a certain extent in exchange of increased production cost of the part. The production engineer realizes that there is a trade-off between the selection of laser energy density, hence reliability level, of the printed part and the original part's reliability, production cost, and the duration of supply disruption.

In this study, a solution to the production process planning problem of spare parts with 3D printing is provided in existence of a laser polishing option (to increase part reliability), as well as demand uncertainty and supply disruption risk. To be able to have a full grasp of the problem, first the theory is explained in detail in terms of the effect of laser polishing (Section 2) and how it is applied to the supply chain problem (Section 3). To facilitate understanding of the discussion in the theory, a detailed nomenclature is provided in Table 1. This includes how the minimum total of discounted cost in the finite planning horizon can be mathematically modeled subject to perfectly healthy supply as well as two types of supply disruptions: short-and-frequent and long-and-infrequent. Therefore, changes in optimum manufacturing and supply policy of a manufacturer can be understood. After the results are presented alongside with discussions in Section 4, concluding remarks follow in Section 5.

Table 1. Nomenclature

ξ: laser energy density
P: the density of a laser's energy is directly proportional to its power
v: velocity
D: spot diameter
$\tilde{p}$: part reliability
p: the original spare part failure probability without any laser polishing
Δ: the discriminant of the quadratic polynomial in $\tilde{p}(\xi)$
c^o: the acquisition cost of the original part
c^p: the cost of manufacturing a part in a 3D printer
c^{lp}: the cost of laser polishing
R_a: surface roughness
υ: energy density
lt: lead time
q_t^r: the amount of parts ordered to the original part supplier (OPS)
$\bar{q}_t^p$: the amount of parts printed at different energy densities
$\bar{m}$: the number of working printed parts at different quality levels
h: holding rate
b: backlogged rate
y_t: inventory level at the beginning of period t
$\bar{d}^p$: the number of broken parts from other quality levels
d^o: the amount of original parts broken during a period
m_0: the number of working original parts
c^r: unit cost of original parts
s: the status of supply at the beginning of the period t, $s \in \{H, F\}$. H indicates healthy supply and F indicates failed supply
$q_t^{p_i}$: the amount of printed and polished parts using laser density level ξ_i
$\phi(H)$: the probability of the supplier's staying healthy in the next period
$\phi(F)$: the probability of supplier's revocery from disruption in the next period

2. Theory

The major theory of this work is the joint optimization of part reliability and the inventory level in presence of demand and supply uncertainty. Under such uncertain conditions as well as uncertain reliability of parts, increased type and amount of parts stored at inventory is expected, which increases inventory costs. Additive manufacturing can be deployed as a method that uses the same raw material as input (which decreases inventory costs by reducing the type of parts stored) and outputs a replacement for any part that fails (which decreases inventory costs by reducing the amount of parts stored). The level of commonality that can be obtained by using additive manufacturing is unmatched by any other current method, which is the main contribution that is studied in this work. On the one hand, increasing the use of additive manufacturing brings such an advantage. On the other hand, additive manufacturing has not yet reached the level of conventional manufacturing methods in terms of reliability of products produced. This is mostly due to the fact that reliability has been shown to be affected by the surface quality, which is the most apparent inherent issue with additive manufacturing. Decreased surface quality results in stress concentrations on the part, which leads to crack initiation and propagation. These cracks are irreversible after a certain point and they cause unexpected failure of the part, which is the depiction of the reliability issue. Although occurrence and measurement of these surface quality issues can be in many different forms, average surface roughness measured by a surface profilometer is the conventional way followed. Hence, in this study, amount of decrease in surface roughness is used as a metric showing the increase in part reliability.

2.1. Laser polishing effect and cost

Since the “staircase appearance” of parts is inherent to additive manufacturing, many researchers work on ways to overcome this issue. Robotic 3D-printing and 5-axis 3D-printing are some ways they have found to work since changing the angle of approach to the part enables the removal of the staircase structure that causes increased surface roughness. However, these processes make the whole system unnecessarily complex and additive manufacturing loses its main appeal of being a low-complexity process. Therefore, finding a different way of reducing surface roughness without increasing the process complexity significantly is key.

2.1.1. Previous work

In this sense, using a post-processing step, provided that the post-process is sufficiently simple, becomes a good compromise. Researchers showed that using a laser cutter to polish the surface of the additively manufactured part and removing the staircase appearance is not only possible, but also leads to favorable results. With only a marginal cost term added to the whole production system, the reliability of manufactured parts can be increased significantly [10, 29]. Conventionally, the effect of laser polishing can be measured with its energy density (ξ). It was shown that the density of a laser’s energy is directly proportional to its power (P), and inversely proportional to its velocity (v) and spot diameter (D). Therefore, it is possible to adjust the laser effect by speeding up or down the laser scanning, or increasing or decreasing the laser power level.

Researchers showed that without sufficient laser energy density (low laser power level and/or high laser scanning speed), surface was not polished at all. They also showed that at laser energy density that is too high (high laser power level and/or low laser scanning speed), surface can get burnt, causing structural problems while not solving the roughness issue. Thus, it is important to find the optimal level of laser energy density that gives the best results. Chang *et al.* developed an inverse quadratic empirical model to represent this behavior of surface roughness with changing laser energy density, which can be utilized in the joint optimization suggested in this work (Figure 1) [29]. Then, Perez Dewey and Ulutan showed that this model can be applied to other materials such as plastics as well (Figure 2) [10]. Finally, Hekimoğlu and Ulutan used this model to create a reliability model of additively manufactured parts with and without laser polishing [14]. According to this model, part reliability $\tilde{p}$ can be taken as a function of only the laser energy density as shown in (1). In this equation, a, r, s, and p are constants of the equation and $a, r \geq 0$, $s < 0$ constraints ensure the best representation of the physical phenomenon. The original spare part failure probability without any laser polishing is provided with p.

$$\tilde{p}(\xi) := p + \frac{1}{a + r\xi + s\xi^2} \tag{1}$$

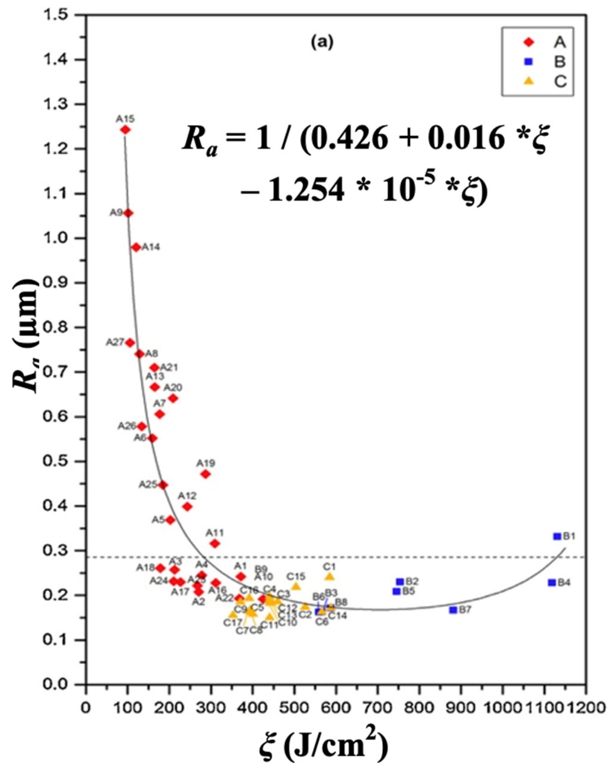

Fig. 1. (a) Inverse quadratic approximation of experimental surface roughness measurements (R_a) under changing laser energy density (ξ) for a metal part [29].

2.1.2. Mathematical framework

The following proposition provides the properties of the inverse quadratic model important to the solution of the supply chain problem (taken from [14]).

Proposition 1*: The following statements hold:*

1. *If* $s\alpha < \frac{r^2}{4}$, *then* $\tilde{p}(\xi)$ *is a convex function of* ξ *and decreasing in* $\left[0, -\frac{r}{2s}\right]$.
2. $p - \min_{\xi} \tilde{p}(\xi)$, *which is named as the originality difference, is* $-\frac{4s}{\Delta}$, *where* Δ *is the discriminant of the quadratic polynomial in* $\tilde{p}(\xi)$.

Proof

The first statement will be shown using the second derivative test as $\tilde{p}(\xi)$ is a continuous function of ξ. For notational simplicity, define $A = a + r\xi + s\xi^2$. Then $\tilde{p}(\xi) = p + \frac{1}{A}$. $\frac{\partial \tilde{p}(\xi)}{\partial \xi} = -\frac{A'}{A^2}$, and $\frac{\partial^2 \tilde{p}(\xi)}{\partial \xi^2} = -\frac{A''A^2 - 2A(A')^2}{A^4}$, where $A' = \frac{\partial A}{\partial \xi} = r + 2s\xi$, and $A'' = \frac{\partial^2 A}{\partial \xi^2} = 2s$.

Using this, $\frac{\partial^2 \tilde{p}(\xi)}{\partial \xi^2} = -\frac{2}{A^3}\left[sA - A'^2\right] = -\frac{2}{A^3}\left[s\alpha - r^2 -\right.$

$3\xi sr - 3s^2\xi^2]$. If $s\alpha - r^2 - 3\xi sr - 3s^2\xi^2 < 0$, the equation is positive, since $s\alpha - r^2 - 3\xi sr - 3s^2\xi^2$ is a concave function. It has a single maximum point at $\xi = -\frac{r}{2s}$. Substituting this value into the polynomial in square brackets, we get $s\alpha - \frac{r^2}{4}$ which is the upper bound of the polynomial.

The condition in the statement ensures that $\frac{\partial^2\,\tilde{p}(\xi)}{\partial\,\xi^2} > 0$ as $A > 0$ for $\xi \in [0, -\frac{r}{2\xi}]$. This makes $\tilde{p}(\xi)$ a convex function if the condition holds. Convexity implies that there is a unique point ξ^* that minimizes the function, and it can be obtained with $\frac{\partial\,\tilde{p}(\xi)}{\partial\,\xi} = \frac{r+2s\xi}{A^2} = 0 \Rightarrow \xi^* = -\frac{r}{2s}$. Statement 1 is proven.

For statement 2, we calculate $\boldsymbol{\tilde{p}(\xi^*) - p}$ for $\boldsymbol{\xi^*} = -\frac{\boldsymbol{r}}{\boldsymbol{2s}}$. This leads us to $\frac{4s^2}{4s^2\,\alpha - r^2 s}$. Define $\boldsymbol{\Delta = r^2 - 4\alpha s}$. Then $\frac{4s^2}{4s^2\,\alpha - r^2 s} = -\frac{4s}{\Delta}$. Q.E.D.

The cost of manufacturing a part in a 3D printer, c^p, is considered to be lower than the acquisition cost of the original part, denoted by c^o. In addition, the cost of laser polishing (c^{lp}), which is assumed to be an additive cost component for the printing cost of spare parts, is assumed to be (convex) increasing function of the laser energy density as follows: $c^{lp}(\xi) := c_0\xi^\gamma$.

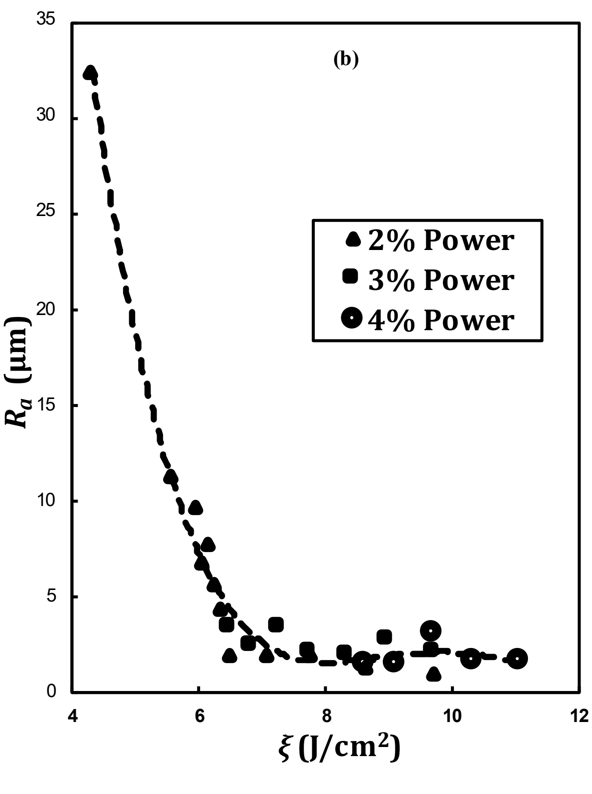

Fig. 2. Inverse quadratic approximation of experimental surface roughness measurements (R_a) under changing laser energy density (ξ) for a plastic part [10].

2.2. Spare Parts Inventory Control During a Finite Planning Horizon

In this study we consider a periodic review inventory control problem during a finite planning horizon. Finite horizon periodic review feature of the system refers to a single order placed to the supplier within a period during until a certain time point in future. Such a system can be exemplified with spare parts orders that are placed to original equipment manufacturer at the beginning of each week until all machines are retired from use. The inventory control of spare parts is an important problem for companies as too much inventory creates significant financial burden on the company whereas frequent shortages cripples the productivity and customer loss. From the technical point of view, spare parts inventory control is a challenging problem as demand is a stochastic process over time. In addition, in most practical cases, spare parts are delivered after a certain lead time, which means it is impossible to correct inventory levels quickly in case of shortages.

In periodic review systems inventory managers place an order at the beginning of each period by looking at the current level of inventory, the amount of previous undelivered orders and the demand distribution. Random demand makes the inventory level (and the associated cost factors) a random process. Therefore, the manage total inventory costs, one needs to control the inventory level process dynamically at each decision epoch.

2.3. Total cost

The study in this work is an exploratory one whereby developing a mathematical model that minimizes the total discounted cost that occurs in a finite planning horizon consisting of fixed time periods such as weeks, months, etc., is aimed. At each period, parts at different quality levels working in a finite amount of identical capital products, denoted by N, fail with different probabilities. For traceability of the optimal control model, we assume that there is a finite amount of different energy densities, denoted by v, that can be used in the laser polishing process. From a mathematical point of view, this is equivalent to having a finite amount of quality levels ($v + 1$ different failure probabilities) that can be selected for printing spare parts during the planning horizon. Two examples of such a discretization of reliability for $v = 3$ and $v = 10$ are given in Figure 3 against the continuous case ($v = \infty$).

In the problem setting, we assume that events occur in the following order. First, delivery of the order that is placed lead time (lt) periods ago is delivered and a new order, q_t^r, is placed to the Original Part Supplier (OPS). Then random breakdowns (spare parts demand) are realized during the period. Once all random breakdowns are realized, original parts in inventory are used for maintenance of machinery. When spare parts inventory is short, the printing process takes place. The event order of each period is depicted in Figure 4.

At each period of the planning horizon, a periodic cost function in (2), consisting of acquisition cost, printing cost (printing plus laser polishing), holding and downtime costs is incurred. The cost function depends on the amount of parts ordered to the original part supplier (OPS), denoted by q_t^r, parts printed at different energy densities, $\overline{\mathbf{q}}_{\mathbf{t}}^{\mathbf{p}} := (q_t^{p_1}, q_t^{p_2}, \ldots, q_t^{p_v})$, and the number of working printed parts at different quality levels denoted by $\bar{\mathbf{m}} := (m_1, m_2, \ldots m_v)$.

If an original spare part is held at inventory for one period, holding cost is incurred with rate h. When a machine stays down for a period due to the lack of available (original or printed) parts, then downtime cost with a rate of b is incurred. Assuming each machinery has a single spare part, then the conditional expectation of holding and downtime cost can be expressed with (2).

$$L(y, q^p, d) = h(y-d)^+ + b(d-y-q^p)^+, \tag{2}$$

where $\bar{\mathbf{d}}^p = (d_1, \ldots, d_v)$. The first term of (2) is the amount of excess inventory at the end of a period whereas the second term is the total downtime cost at the same period given that the amount of original parts broken during a period is d_0 and the number of broken parts from other quality levels are $d_i, i = 1,2, \ldots, v$. Mathematical models for the optimum cost of printing and acquisition are given in (3) and (4).

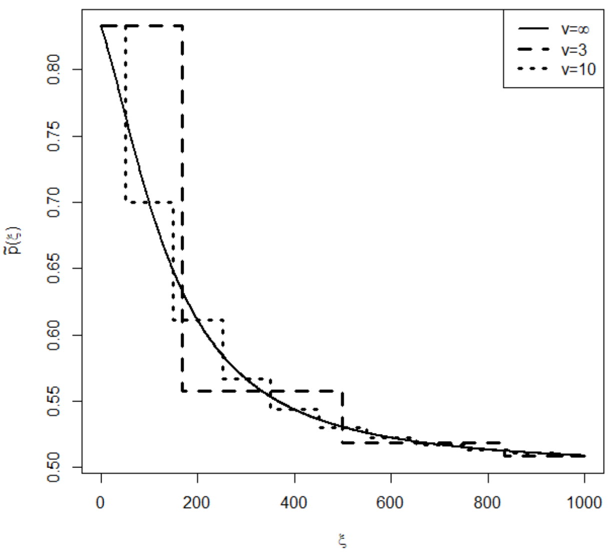

Fig. 3. Discretization of laser energy density

Fig. 4. Event order within a review period

$$V_t(\bar{\mathbf{q}}^r_t, y_t, m_0, \bar{\mathbf{m}}) = \min_{q_t^r \ge 0}\{c^r q_t^r + E[\bar{\bar{G}}(y, \bar{\mathbf{q}}^r_{t+1}, m_0, \bar{\mathbf{m}}, D^o, \bar{\mathbf{D}}^p, H)]\} \tag{3a}$$

$$\Gamma_t(\bar{\mathbf{q}}^r_t, y_t, m_0, \bar{\mathbf{m}}) = E[\bar{\bar{G}}(y, \bar{\bar{\mathbf{q}}}^r_{t+1}, m_0, \bar{\bar{\mathbf{m}}}, D^o, D^p, F)] \tag{3b}$$

In (3a) the optimum t period cost-to-go function for healthy supply case is given with. $V_t(\bar{\mathbf{q}}^r_t, y_t, m_0, \bar{\mathbf{m}})$, which has four parameters: The first parameter is the outstanding order vector $\bar{\mathbf{q}}^r_t := (q^r_{t-lt}, q^r_{t-lt+1}, \ldots, q^r_{t-1})$ including previous orders that have not been delivered. The second parameter y_t is the inventory level at the beginning of period t, whereas the third parameter is the amount of original parts installed in the machine part and fourth parameter is the vector $\bar{\mathbf{m}}$ including the amount of printed parts at quality levels $1,2, \ldots, v$. When the supply is healthy, the inventory manager can place an order to OPS at the beginning of the period t. After the delivery and order placement, the pipeline vector $\bar{\mathbf{q}}^r_t$ becomes $\bar{\mathbf{q}}^r_{t+1}$ and $V_t(.)$ is calculated as a result of a minimization over q^r_t. The minimization in (3) yields the optimum order to OPS. The first term in this minimization is the acquisition cost, $c^r q^r_t$, whereas the second term gives the expected cost of printing spare parts in case of inventory shortage at the end of period t.

When the supply is disrupted, it is impossible place an order to OPS. Therefore, after the pipeline vector becomes $\bar{\bar{\mathbf{q}}}^r_{t+1} := (0, q^r_{t-1}, \ldots, q^r_{t-LT+1})$ and the t-period cost to go function, denoted by $\Gamma_t(\bar{\mathbf{q}}^r_t, y_t, m_0, \bar{\mathbf{m}})$, is equal to the expected value of the cost at the end of the period. The status of supply at the beginning of the period t, also affects the system's evolution between healthy and disrupted supply. It is indicated with the parameter $s \in \{H, F\}$ of $\bar{\bar{G}}(.)$, which is the cost calculated after the replacement of broken parts from inventory and 3D printing at the end of period t.

$$\begin{aligned} &G_t(\bar{\bar{\mathbf{q}}}^r_{t+1}, y_t, m_0, \bar{\bar{\mathbf{m}}}, d^o, \bar{\mathbf{d}}^{\mathbf{p}}, s) \\ &= \min_{\substack{\mathbf{q}^{\mathbf{p}}_{\mathbf{t}} \ge 0, \\ (d^o + \sum_i d^{p_i} - y)^+ \ge \sum_{i=1}^{v} q_t^{p_i}}} \left\{ \sum_{i=1}^{v} c^{p_i} q_t^{p_i} + L\left(y, \sum_i q_t^{p_i}, d^o + \sum_i d^{p_i}\right) \right. \\ &+ \alpha\phi(s) V_{t+1}\left(\bar{\mathbf{q}}^r_{t+1}, \left(y_t - d^0 - \sum_i d^{p_i}\right)^+, m_0 - d^o + \left(y \wedge \left(d^o + \sum_i d^{p_i}\right)\right), \bar{\bar{\mathbf{m}}} - \bar{\mathbf{d}}^{\mathbf{p}} + \mathbf{q}^{\mathbf{p}}_{\mathbf{t}}\right) \\ &+ \alpha(1-\phi(s))\Gamma_{t+1}\left(\bar{\mathbf{q}}^r_{t+1}, \left(y - d^o + \sum_i d^{p_i}\right)^+ + q^r_{t-LT}, m_0 - d^0 + \left(y \wedge \left(d^o + \sum_i d^{p_i}\right)\right), \bar{\bar{\mathbf{m}}} \right. \\ &\left.\left. - \bar{\mathbf{d}}^{\mathbf{p}} + \bar{\mathbf{q}}^{\mathbf{p}}_{\mathbf{t}}\right)\right\} \end{aligned} \tag{4}$$

The boundary condition for recursive equations (3) and (4) is $V_T(\overline{\mathbf{q}}^{\mathbf{r}}_{\mathbf{T}}, y_T, m_0, \overline{\mathbf{m}}) = \Gamma_t(\overline{\mathbf{q}}^{\mathbf{r}}_{\mathbf{t}}, y_t, m_0, \overline{\mathbf{m}}) = 0$ for all state variables of the function. The minimization in (4) gives the optimum printing decisions when the supply is healthy when $s = H$, whereas it leads to the optimum choice of printing in case of disrupted supply if $s = F$. In both equations the amount of printed parts in v different quality levels is denoted by $\overline{\mathbf{q}}^{\mathbf{p}}_{\mathbf{t}} := (q_t^{p_i}, i = 1,2, \ldots v)$ where $q_t^{p_i}$ is the amount of printed and polished parts using laser density level ξ_i. Given the amount of broken original and printed parts, denoted by d^0 and $\bar{\mathbf{d}}^{\mathbf{p}} := (d^{p_i}, i = 1,2, \ldots, v)$, and the vector of printed parts at work, $\bar{\overline{\mathbf{m}}}$, the summation of printing cost and the expected cost from future periods in case of healthy supply is denoted by $G_t(\overline{\mathbf{q}}^{\mathbf{r}}_{\mathbf{t+1}}, y_t, \bar{\overline{\mathbf{m}}}, d^o, \bar{\mathbf{d}}^{\mathbf{p}}, s)$, $s = H$. The first parameter of this conditional expectation is the outstanding order vector $\overline{\mathbf{q}}^{\mathbf{r}}_{\mathbf{t+1}}$. Note that printing decision is made after the delivery of q^r_{t-lt} and the placement of q^r_t (Figure 3) so, the pipeline vector is already updated from $\overline{\mathbf{q}}^{\mathbf{r}}_{\mathbf{t}}$ to $\overline{\mathbf{q}}^{\mathbf{r}}_{\mathbf{t+1}}$. The second and the third parameters of the function are the inventory level at the beginning of period t and the amount of original parts at work at the beginning of period t. Similarly, the amount of printed parts (at different quality levels) are denoted by the vector $\overline{\mathbf{m}}$ at the beginning of period t.

Note that the reason behind optimizing the two ordering decisions, q^r_t and $\overline{\mathbf{q}}^{\mathbf{p}}_{\mathbf{t}}$, in separate minimizations in (3) is that part printing takes place after demand realization (*on-demand manufacturing*) whereas, orders to OPS are placed at the beginning of a period. Therefore, the number of printed parts is a deterministic outcome of the printing policy whereas orders to OPS are placed using the expected cost.

The only difference between healthy and disrupted supply cases is the probability of the next period's supply state. Specifically, when $s = H$, $\phi(H)$ represents the probability of the supplier's staying healthy in the next period. When $s = F$, $\phi(F)$ represents the probability of supplier's recovery from disruption in the next period.

2.4. Optimization of Printing Quality

Total cost of printing is minimized through the vector $\overline{\mathbf{q}}^{\mathbf{p}}_{\mathbf{t}}$. The minimization in (4) is subject to two constraints: The first constraint is the positivity of $q_t^{p_i}, i = 1,2, \ldots, v$. The second constraint assumes that the total number of printed parts cannot be larger than the shortage of spare parts after the demand realization. This constraint is due to our assumption of preclusion of printing to stock. This rule is shown to be the optimal in Proposition 2. Under the assumption of on-demand production of spare parts with a 3D-printer, which can work infinitely fast, inventory holding cost of printed parts becomes redundant.

The first term of the minimization gives the total cost of printing spare parts whereas the function $L(y, \sum_i q_t^{p_i}, d^o + \sum_i d^{p_i})$ yields the cost of inventory holding and downtime costs. The last term, $V_{t+1}(\overline{\boldsymbol{q}}^{r}_{t+1}, (y_t - d^0 - \sum_i d^{p_i})^+, m_0 - d^o + (y \wedge (d^o + \sum_i d^{p_i})), \bar{\overline{\mathbf{m}}} - \bar{\mathbf{d}}^{\mathbf{p}} + \overline{\mathbf{q}}^{\mathbf{p}}_{\mathbf{t}})$, in the minimization yields the optimum discounted cost starting from period $t + 1$. In this term, the first parameter represents the pipeline vector. The second parameter gives the total amount of inventory at the beginning of the period $t + 1$. The third parameter of $V_{t+1}(.)$ is the amount of original parts after demand realization. This variable is denoted by $m_0 - d^o + (y \wedge (d^o + \sum_i d^{p_i}))$. The last parameter of $V_{t+1}(.)$ is the number of printed parts at the beginning of the next period, denoted by $\bar{\overline{\mathbf{m}}} - \bar{\mathbf{d}}^{\mathbf{p}} + \overline{\mathbf{q}}^{\mathbf{p}}_{\mathbf{t}}$.

When the supply is disrupted the optimum cost is represented with the function $\Gamma_t(\overline{\mathbf{q}}^{\mathbf{r}}_{\mathbf{t+1}}, y_t, \bar{\overline{\mathbf{m}}}, d^o, \bar{d}^p)$. The disruption probability of supply is represented with $\phi(H) \in [0,1]$. After the disruption, the supply system returns to healthy state with probability $\phi(F) \in [0,1]$, whereas it stays disrupted with probability $(1 - \phi(F))$. For the disruption function, order to the original supplier is not allowed and 3D printing is the only supply option to satisfy part need. The overall structure of the $\Gamma_t(.)$ is very similar to $V_t(.)$ in (3).

3. Methods

In this study, we conduct numerical experiments using recursive equations (2-4) to understand the characteristics of the optimal policy that controls the production of spare parts using additive manufacturing. To this end, the mathematical models (2-4) are analyzed using meticulously designed numerical experiments in order to explore the optimum inventory control policy. The optimum policy is benchmarked by the base stock policy. Also, we would like to investigate the effect of using a larger number of quality levels (higher v), which will allow finer control over the system in terms of total cost.

This investigation indicates the potential cost benefit of laser polishing combined with additive manufacturing of spare parts for a constant number of capital products at work. In our analyses, we first explore the optimum policies for perfectly healthy supply ($\phi(H) = 1$). Afterwards we evaluate two different disruption scenarios: Long and infrequent disruptions (low $\phi(H)$ and $\phi(F)$), and short and frequent disruptions (high ϕ(H) and $\phi(F)$).

To this end, the recursive equations (2-4) are coded in C++ with the parameter setting in Table 2. Our test bed consists of 96 different parameter combinations.

Table 2. Parameter setting for numerical experiments

horizon (T)	p	c^r	c_0	h	γ	b	v	$(\phi(H), \phi(F))$
50	0.5	100	10	0.25	0.5	3	1	(0.1, 0.1)
100				0.5	0.4	2	3	(0.5,0.5)
					0.3			

In this parameter setting, c^r represents the acquisition cost of the regular supplier whereas c_0 is the cost of printing without any laser polishing. In our numerical experiments, we consider three different laser energy densities which are 100, 200, and 300 J/cm^2. For these energy densities, calculated total printing cost and reliability levels are given in Table 3 where $\tilde{p}(\xi_i)$ are calculated using parameters values $\alpha = 3$, $r = 0.01$ and $s = -10^{-5}$ similar to the model suggested by Chang *et al.* [29]. For disruption characterization, long and infrequent disruptions are evaluated with $1 - \phi(H) = \phi(F) = 0.1$, and short and frequent disruptions are calculated with $\phi(H) = \phi(F) = 0.5$. These parameters can be interpreted as follows: Long and infrequent disruptions assume a disruption in every 10 periods (months, weeks etc.) and each disruption will last in 10 periods in expectation. This scenario represents serious (possibly global) events that halt suppliers' production processes such as strikes, global epidemic or hurricanes. Parameters for short and frequent disruptions assume supply problems in every 2 periods (in expectation) and each disruption is expected to stay for 2 periods. The parameters of the supply disruption and cost are derived from the literature as well as empirical case studies [17, 25] on supply problems.

The parameter settings for laser polishing were determined by studying Figure 1. On this figure, it can be observed that for a metal part, there could be a big difference between the surface roughness values polished under these settings.

Table 3. Calculated parameter levels for different laser energy densities (ξ_i)

		c^{p_i}		
ξ_i	$\tilde{p}(\xi_i)$	$\gamma = 0.5$	$\gamma = 0.4$	$\gamma = 0.3$
100	0.75	100.00	63.10	39.81
200	0.70	141.42	83.26	49.01
300	0.66	173.21	97.91	55.35

For each parameter combination, the recursive equations (3) and (4) are numerically solved by the value iteration algorithm and backward induction [30] on a finite state space of $\overline{\mathbf{Q}} \times \overline{\mathbf{N}}$, where $\overline{\mathbf{Q}} = \{(q_{t-1}^r, y): 0 \leq q_{t-1}^r \leq N, 0 \leq y \leq D_{max}\}$ and $D_{max} = N(LT + 1)$. The value iteration algorithm is a common solution method for stochastic dynamic programming models. It can be applied to recursive dynamic programming models with backward and forward induction approach. With the backward induction, the algorithm starts from the final period of the planning horizon and calculates the optimum cost and action for each state variable, a vector including the information set consisting of amount of inventory, the number of original and printed parts in use. Once the final period is complete, the algorithm proceeds to the previous periods one by one by calculating the optimum cost and actions in each period. Our calculations benefit from the existence of a finite number of machines in the system. This provides an upper bound on the range of demand distribution in our problem. Such an upper bound allows us to avoid the common problem of *curse of dimensionality* in dynamic programming solutions.

In these runs, we primarily observe the optimum control policy's ordering decisions to the regular supplier, q_t^r, and printing decisions at quality level i, denoted by $q_t^{p_i}$, for all i. Optimum actions are benchmarked to the base stock policy, which orders to the supplier by raising the inventory position, the summation of inventory level and the pipeline inventory, to a constant level. Base stock policy is one of the most common inventory control policy in the literature due it is simplicity and good performances in various circumstances. Also, we are interested in the optimum selection of quality level (optimum usage of laser energy density for polishing) for on-demand production of spare parts. In the following section, the structure of commonly observed control policy in our numerical experiments are presented.

4. Results

In our numerical investigation, we observe the effect of different model parameters on total cost as well as the structure of the optimal control policy for original parts inventory. In this section, we first present our overall results and intuition into the problem derived from these analyses. Next, we discuss the structure of the optimal policy.

4.1. Overall results

In our analysis, we find that cost of 3D-printing is the most important factor that determines the primary source of supply. Specifically, in our numerical experiments we find that when $\gamma = 0.3$ or $\gamma = 0.4$, the optimum action is to choose to satisfy spare parts demand using *only* additive manufacturing. Interestingly, all of these parts are printed at the lowest quality level where laser energy density is set to 100. This can be explained with the fact that γ is set to 0.3 or 0.4, additive manufacturing becomes cheaper than the cost of original part as $c^r = 100$ (Table 3). When $\gamma = 0.5$, the combined use of printing and original parts takes place in the optimum policy. This can be seen in Table 4.

Furthermore, in all of our numerical experiments we find that the optimal cost is invariant to b since on-demand production of spare parts prevents having an unsatisfied demand during the entire planning horizon (Table 4). This feature of the optimal policy is explained in detail in the following section.

Recall that the number of broken parts in a given review period is a random variable and the original spare parts inventory and 3D printing decisions are made according to a control policy. In the mathematical model given in (3-4), we consider a finite horizon cost minimization problem where decision for q_t^r is followed by $q_t^{p_i}$ for all i. The mathematical structure of the optimum control policy is presented in the following subsections.

Table 4. Average optimum costs for different values of $b, \phi(H), \phi(F)$ and γ.

	b	γ	Cost
Long and Frequent Supply ($\phi(H) = \phi(F) = 0.1$)	3	0.5	125979.7
	3	0.4	89056.75
	3	0.3	28106.91
	2	0.5	125979.7
	2	0.4	89056.75
	2	0.3	28106.91
Short and Infrequent Supply ($\phi(H) = \phi(F) = 0.5$)	3	0.5	131867.6
	3	0.4	89056.75
	3	0.3	28106.91
	2	0.5	131867.6
	2	0.4	89056.75
	2	0.3	28106.91

4.2. Structure of the optimum on-demand spare parts production

To understand the mathematical structure of the optimum printing policy, we conduct a mathematical analysis of the model in (3-4). The following result, obtained from these analyses, shows the optimum decision for $t = T$ (the end of planning horizon).

Proposition 2*: At the end of the planning horizon, given that the total number of broken parts (from all quality* *levels) is* $d := d_0 + \sum_i^v d_i$ *, the optimal policy of laser polishing is* $q_T^{p_1} = (d-y)^+$.

Proof: Assume $V_T(.) = 0$ for all parameters. For $t = T$

$$G_T(\bar{\boldsymbol{q}}^r_{T+1}, y_T, m_0, \bar{\bar{\boldsymbol{m}}}, d^o, \bar{\boldsymbol{d}}^p) = \min_{\substack{\bar{q}_T^p \geq 0, \\ (d^o + \sum_i d^{p_i} - y)^+ \geq \sum_{i=1}^v q_T^{p_i}}} \{\sum_{i=1}^v c^{p_i} q_T^{p_i} + L(y, \sum_i q_T^{p_i}, d^o + \sum_i d^{p_i})\} \quad (5)$$

This implies for a given that the total number of breakdowns is d the function in the minimization is:

$$\sum_{i=1}^v c^{p_i} q_T^{p_i} + h(y-d)^+ + \left(d - y - \sum_i q_T^{p_i}\right)^+ \quad (6)$$

If $y \geq d$, then the constraint of the minimization leads to $\sum_i q_T^{p_i} = 0 \Rightarrow q_T^{p_i} = 0, \forall i$. If $y < d$, then minimization leads to $\sum_i q_T^{p_i} = d - y$. Hence, $\sum_i q_T^{p_i} = (d-y)^+$. Since the cost is increasing in i, $q_T^{p_i} > 0$ is subotimal for i>1. Q.E.D.

Proposition 2 implies that the optimum policy prints parts from the worst quality level (no laser polishing) as it is the cheapest option. This result is quite intuitive in the sense that the end of the planning horizon, there is no point of increasing quality levels of parts in exchange of extra cost.

Importantly, we realized that the result in Theorem 1 also holds for periods before the end of the planning horizon, i.e. $t < T$ in our numerical experiments. Our detailed investigation into the numerical results reveals that this result primarily stems from our assumption of the uncapacitated (capacity equal to infinity [31]) OPS. In our system, spare part production with 3D-printing is used in case of the shortage of original parts during maintenance of capital products. Since we assume that OPS is uncapacitated and production time of 3D printer is sufficiently smaller than a period, e.g. printing is completed in hours and the time period of the model is one week, the manufacturer does not print to stock and 3D printing is used as a contingency solution to avoid costly downtimes of capital products and using laser polishing does not create any additional cost reduction.

4.3. Structure of the optimum order to OPS in case of healthy supply

Given that in case of shortage spare parts are printed after the demand realization, control of original part inventory resembles to classical lost sales problem in the inventory control literature [32] depending on the magnitude of printing cost. In lost sales problems, customers refuse to wait for delivery of products and leave without buying anything when they cannot find their desired product in stock. The inventory control decisions are made based on the trade-off between costs of lost sales and inventory holding. In our problem setting, printed parts stand for lost sales from the perspective of the inventory manager of original spare parts. The cost of lost sales is equal to c^{p_i} for some i. The main difference of our problem stems from the fact that printed parts increases the future spare parts need of the system. Therefore, using printed parts stimulates more frequent failures and higher cost in the system. In the following subsections, we first explained the optimal orders to OPS when $y_t = 0$ and $\bar{\bar{\mathbf{m}}} \neq 0$. Next, we present the structure of the optimal policy when $y_t > 0$ and $m_0 = N$.

4.3.1. The optimum policy when $\gamma = 0.5$ $(c^r \leq c^{p_i}, i = 1,2,\ldots,v)$

When the cost of printing is more expensive than the original part, due to material and energy costs, the optimal control policy has a state-dependent structure in the sense that the total amount of existing inventory level and ordered quantity, $y_t + q_{t-lt}^r + q_t^r$, also known as inventory position after ordering, is small for low values of $y_t + q_{t-lt}^r$ and they are equal to base stock policy for moderate and large values of the summation. Note that the base stock policy is the optimum control policy for inventory control problems where unsatisfied demand is backlogged [31]. The optimal ordering policy to OPS places smaller orders than the base stock policy for low levels of inventory due to the fact that low inventory level leads to shortage which will be satisfied with 3D printing within the same period before the delivery of orders placed in the current period. On the other hand, in case of backlogged demand and a single supply source, where the base stock policy is optimal, unsatisfied demand is carried to the next period and keeps creating backlog cost until it is satisfied with new deliveries. This difference between the optimal orders to OPS for $y_t = 0$, $\bar{\bar{\mathbf{m}}} \neq 0$ and the base stock policy is depicted in Figure 5 for $v = 3$, $T = 50$, b =3, $h = 0.25$, $\gamma = 0.5$ and $N = 10$.

In Figure 5, optimal q_t^r for different y_t levels are given for two different $\bar{\bar{\mathbf{m}}}$ vectors which are (1,9,0,0) and (9,1,0,0). The first vector represents a case where only one of $N = 10$ of machines works with an original part while the rest works with parts printed without laser polishing. The second vector represents the case with nine original and one printed parts. Obviously, the optimum policy generates the same orders with the base stock policy with the order-up-to level being equal to 15, which is denoted by $BS(15)$, when the existing inventory level is larger than equal to 10 for the first vector. For the second vector, the optimum policy is much closer to the base stock policy as the optimum policy generates the same order sizes when the inventory level is larger than equal to 3. The difference between the two part vector is due to the fact that some of existing inventory level will be used to replace printed parts at work and remaining ones will be available for the satisfaction of broken spare parts within the review period when the number of printed parts at work are higher (as in $\bar{\bar{\mathbf{m}}}$=(1,9,0,0)).

When there is a positive amount of original spare parts in stock (and all capital products are working with original parts $N = 0$), the structure of the optimal policy is much closer to the base stock policy as depicted in Figure 6. In fact, when there are some parts in the pipeline, the optimal policy orders exactly the same with $BS(9)$. When there are no parts in the pipeline, the optimal policy is also the same with $BS(9)$ except $y_t = 0$.

4.3.2. The optimum policy when $\gamma < 0.5$ $(c^r > c^{p_i}, i = 1,2,\ldots,v)$

When acquisition cost is smaller than the cost of additive manufacturing, the optimal policy is never order from OPS and complete reliance on 3D printing for all states of the system. Interestingly, this is true for perfectly healthy supply as well as different types of disruption risks discussed below. The optimal pure-additive manufacturing strategy can be explained by the fact when on-demand manufacturing is cheaper than the regular manufacturer, the additional cost due to lower reliability of printed parts is lower than savings from holding cost. Recall that on-demand manufacturing does not need to incur holding cost as we assume that it is possible to manufacture a part when it is needed.

Note that these findings might be slightly different when we include a constraint on the number of printed parts that can be used per period due to limited number of replacements that can be performed per period. Although, details of the optimal policy might be somewhat different, our findings shed light on the main structure of the policy for such case: use printing as much as possible and order to OPS for the rest.

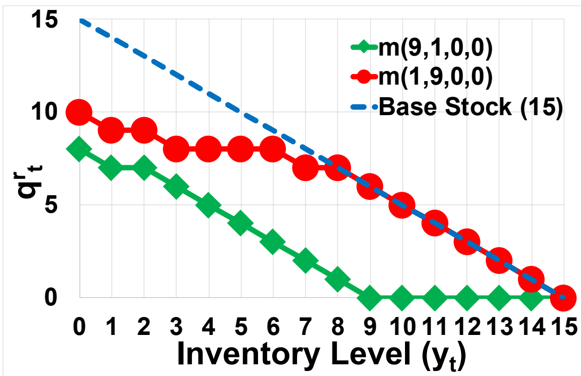

Fig. 5. For (perfectly) healthy supply difference between optimal ordering policy to OPS and the base stock policy for $v = 3$, $T = 50$, b =3, $h = 0.25$, $\gamma = 0.5$, $N = 10$, $lt = 1$, $y_t \geq 0$ and $\bar{\boldsymbol{m}} \neq 0$.

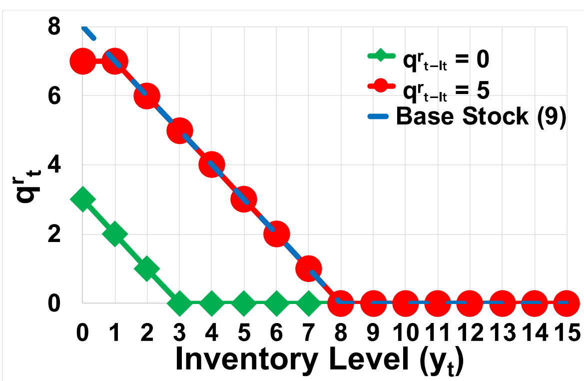

Fig. 6. Difference Between Optimal Ordering Policy to OPS for $v = 3$, $T = 50$, b =3, $h = 0.25$, $\gamma = 0.5$, $m_0 = N = 10$ and $lt = 1$, $y_t > 0$ and $\bar{\boldsymbol{m}} = 0$.

4.4. Structure of the optimum order to OPS in existence of supply risk

In our exploratory analysis of the optimal policy under supply risk, we elaborate four possible scenarios by considering holding and backlogging cost in terms of critical ratio and two different disruption scenarios. The first disruption scenario is reflecting the manner that disruptions occur infrequently $(\phi(H) = \phi(F) = 0.1)$ but the disruption time is long which means if the state jumps an unhealthy state, it jumps back healthy state with a low probability. In the second disruption scenario, there are frequent but short disruptions with probability $(\phi(H) = \phi(F) = 0.5)$. In these analyses we mainly consider the case of $c^r < c^{p_i}, i = 1,2,3$ in which $q^r_t \geq 0$ for some states. As we explained above, when $c^r \geq c^{p_i}$ it is never optimal to order to OPS and additive manufacturing is the main source of supply for the system.

In Figure 7, we examined the optimal policy of ordering to OPS under different disruption scenarios. In case of long and infrequent disruptions (L&I) the optimal policy orders to OPS more when $\bar{\mathbf{m}} = (1,9,0,0)$ compared to the case of $\bar{\mathbf{m}} = (9,1,0,0)$. This is due to the fact that lower reliability of printed parts forces the system to order more to OPS to avoid excessive costs. Furthermore, we find that the optimal policy orders less in case of short and frequent disruptions (S&F) compared to L&I. Importantly, we find that the quality levels of parts in use might be more effective than the type of disruption on the optimal policy. This can be observed by comparing the optimal policy curves for L&I with $\bar{\mathbf{m}} = (9,1,0,0)$ and S&F with $\bar{\mathbf{m}} = (1,9,0,0)$. The detrimental effect of L&I disruptions on the optimal policy, compared to S&F type supply problems, is also consistent with the findings in the supply chain literature. The difference of the optimal policy from the well-known base stock policy is also presented in Figure 7. Base stock policy orders linearly decreasing amounts of inventory as existing inventory increases. The main difference appears when the inventory level is low in which case demand shortage is satisfied with additive manufacturing. Therefore, on-demand manufacturing option decreases the optimum order levels compared to the base stock policy, which is the optimum policy of the case where there is only one supply option.

The effect of supply risk on cost can be observed from the percent difference of $\Gamma_t() - J_t(.)$ for the same states. This percent difference over different inventory levels is given in Figure 8. When inventory level is 0, cost of starting from failed state, $\Gamma_t(.)$, is higher than the cost of starting with healthy supply $J_t(.)$. Naturally this cost decreases in inventory level as the existing inventory is used to compensate the demand during the disruption period. Importantly, this difference is higher for long and infrequent disruptions compared to short and frequent ones as long disruptions has more serious effects on the supply system compared to the short ones.

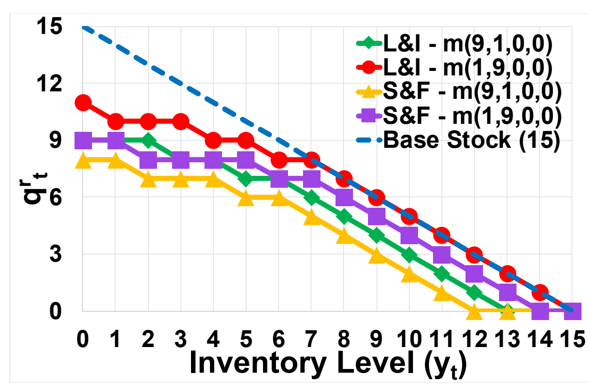

Fig. 7. Optimal Policy Under Long and Infrequent Disruptions $v = 3$, $T = 50$, b =3, $h = 0.25$, $\gamma = 0.5$, $N = 10$, $lt = 1$, $y_t \geq 0$ and $\bar{\boldsymbol{m}} \neq 0$.

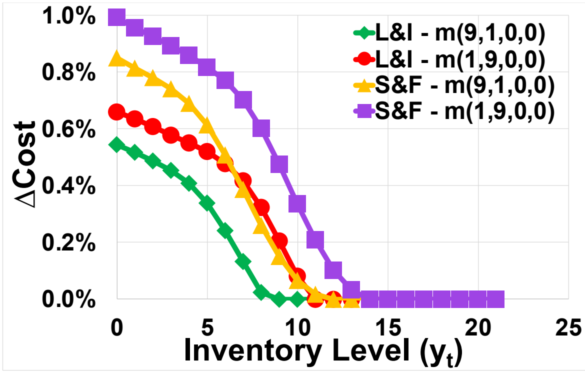

Fig. 8. The Percent Cost Difference Between $J_t(.) - \Gamma_t(.)$ for $v = 3, T = 50$, $b = 3$, $h = 0.25$, $\gamma = 0.5$, $N = 10$, $lt = 1$, $y_t \geq 0$ and $\bar{\boldsymbol{m}} \neq 0$.

5. Discussion and Conclusion

In this study, solution to a multi-disciplinary problem covering logistics, supply chain, and manufacturing systems is attempted. The process plan needs to include considerations of producing spare parts through conventional means, which includes handling, packaging, and shipment of finished goods. On the other side of the spectrum, raw materials can be transported without such care and expense, and with rapid and inexpensive transfer of digital information, spare parts can be additively manufactured on-site. To overcome the surface quality issue inherent to the additive manufacturing process that causes low reliability, post-processing methods such as laser polishing can be applied, which brings a new dimension to the problem. Demand is almost always uncertain, but with particular issues such as strikes and pandemic, disruption risk to the supply can be an important factor in transferring from finished part transportation to information transfer. Therefore, the relationship between optimum control policy and cost parameters was provided as a mathematical analysis in this study.

It is known that almost all companies face with exogenous supply risk in their operations. It is their ability to adapt to these new situations and develop mitigation measures that determines the survival of companies in the long run. As alternative supply sources, 3D printers provide an alternative supply option for spare parts of capital products and it is important to evaluate their economic usages in existence of supply risk.

With the benefit of spare parts inventory control due to on-demand manufacturing of spare parts, additive manufacturing can be preferred as the best method [33]. Long downtimes can be avoided by utilizing this benefit rather than ordering from the Original Part Supplier (OPS) and waiting for the part to arrive. This wait can be costly in terms of business by losing customers to competitors or failure in customer satisfaction due to tardiness.

In this study, the joint optimization of a hybrid manufacturing scheme (with additive manufacturing and laser polishing) and an inventory management system was tackled in order to decrease the total operating costs. A recursive mathematical model was deployed to minimize the total discounted cost over a finite planning horizon and optimum control policies were searched for in existence of demand and supply uncertainty. The mathematical model also incorporated laser polishing density as it increases part reliability. However, failure of these parts is assumed to occur at a significantly later time than the original replacements are received from the OPS, which leads to the effect of laser energy density being insignificant in the problem. However, in supply disruption modes where a long amount of time might be required to receive original spare parts, the existence of laser polishing to increase part reliability would play a more important role. Furthermore, we observe that the type of supply disruption changes the optimal policy of ordering significantly. Ordering in case of long and infrequent disruptions resembles to base stock policy which is the optimal policy in case of a single supplier and in case of lost sales with 0 lead time. In case of short and frequent disruptions, on the other hand, optimum ordering resembles to the policy of the case with healthy supply and 3D printers.

Interpretation of our results for the real production facilities can be given as follows: In our analyses, we find that the main driver for the optimal utilization of additive manufacturing is its production cost (average cost per part, including material, energy, labor and setup costs) compared to the cost of original product. When printing a part is cheaper than the cost of original part, the additive manufacturing becomes the main source of supply for spare parts of machines. Even if the reliability of printed parts is lower, savings from holding cost (thanks to on-demand manufacturing) dominates the additional costs due to the lower reliability of printing. Also, laser polishing is occasionally utilized to increase the reliability of parts depending on the difference between printed and original parts. This result might be slightly different for large machine parts with limited maintenance capability, as in those cases the number of replacements per period must be limited. However, we estimate that even under this additional constraint, the benefit of additive manufacturing prevails and regular suppliers would only be used to complement the additive manufacturing. When additive manufacturing is more expensive, 3D printers are effective for contingency plans against supply disruptions. In such a case, printed parts are used as temporary solutions until disruption is over, so laser polishing becomes unimportant for the system.

This study builds on the previous work of the authors [14] by adding the supply disruption risk. However, there is still a huge amount of work to be done in this direction with rigorous mathematical analyses and changing part quality, original part receiving time, and uncertainty modes. Specifically, we consider only discounted cost finite horizon models in this study whereas our results need to be extended to infinite horizon cases. In addition, Markovian characteristic of the demand and disruption system should be generalized into a more general mechanism that allows endogenous demand and supply disruption evolution. Analytically characterizing the numerical results presented here is essential.

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References

[1] Srivastava M, Mishra M. 3D printing: additive manufacturing. International Journal of Engineering Science Advanced Research 2016; 2(2): 1-4.

[2] Bak D. Rapid prototyping or rapid production? 3D printing processes move industry towards the latter. Assembly Automation 2003; 23(4): 340-5. https://doi.org/10.1108/01445150310501190.

[3] Lewis GK, Schlienger E. Practical considerations and capabilities for laser assisted direct metal deposition. Materials & Design 2000; 21(4): 417-23. https://doi.org/10.1016/S0261-3069(99)00078-3.

[4] Gibson I, Rosen D, Stucker B. Additive Manufacturing technologies – 3D printing, rapid prototyping, and direct digital manufacturing. 2nd ed. New York: Springer; 2015.

[5] Bellini A, Güçeri S. Material characterization of parts fabricated using fused deposition modeling. Rapid Prototyping Journal 2004; 9(4): 252-64.

[6] Berman B. 3-D printing: the new industrial revolution. Business Horizons 2012, 55(2): 155-62.

[7] Paris H, Mokhtarian H, Coatanéa E, Museau M, Ituarte IF. Comparative environmental impacts of additive and subtractive manufacturing technologies. CIRP Annals 2016; 65(1): 29-32.

[8] Pereira T, Kennedy JV, Potgieter J. A comparison of traditional manufacturing vs additive manufacturing, the best method for the job. Procedia Manufacturing 2019; 30:11-8.

[9] Pandey PM, Reddy NV, Dhande SG. Improvement of surface finish by staircase machining in fused deposition modeling. Journal of Materials Processing Technology 2003; 132(1-3): 323-31.

[10] Perez Dewey M, Ulutan D. Development of laser polishing as an auxiliary post-process to improve surface quality in fused deposition modeling parts. 2017; ASME 2017 Proceedings. https://doi.org/10.1115/MSEC2017-3024.

[11] Maiya PS, Busch DE. Effect of surface roughness on low-cycle fatigue behavior of type 304 stainless steel. Metallurgical Transactions A 1975; 6(9), 1761.

[12] Lee K, Jee H. Slicing algorithms for multi-axis 3-D metal printing of overhangs. Journal of Mechanical Science and Technology 2015; 29(12): 5139-44.

[13] Ding D, Pan Z, Cuiuri D, Li H. A multi-bead overlapping model for robotic wire and arc additive manufacturing (WAAM). Robotics and Computer-Integrated Manufacturing 2015; 31: 101-10.

[14] Hekimoğlu M, Ulutan D. Optimum laser polishing decision-making for on-demand additive manufacturing of spare parts: an exploratory study. Süleyman Demirel University Journal of Natural and Applied Sciences 2020; 24(2): 516-25.

[15] Ma CP, Guan YC, Zhou W. Laser polishing of additive manufactured Ti alloys. Optics and Lasers in Engineering 2017; 93: 171-7.

[16] Sheopuri A, Janakiraman G, Seshadri S. New policies for the stochastic inventory control problem with two supply sources. Operations Research 2010; 58(3): 734-45.

[17] Hekimoğlu M, Van der Laan E, Dekker R. Markov-modulated analysis of a spare parts system with random lead times and disruption risks, European Journal of Operation Research 2018; 269(3): 909-22.

[18] Parlar, M., Wang, Y., & Gerchak, Y. A periodic review inventory model with Markovian supply availability. International Journal of Production Economics 1995; 42(2), 131-6.

[19] Özekici, S. & Parlar, M. Inventory models with unreliable suppliers in a random environment. Annals of Operations Research 1999; 91, 123-36.

[20] Kaplan, R. A dynamic inventory model with stochastic lead times. Management Science 1970; 16 (7), 491–507.

[21] Ehrhardt, R. (s,S) policies for a dynamic inventory model with stochastic lead times. Operations Research 1984; 32(1), 121-32.

[22] Song, J., & Zipkin, P. Inventory control with information about supply conditions. Management Science 1996; 42(10), 1409-19.

[23] Muharremoğlu, A., & Tsitsiklis, J. A single-unit decomposition approach to multi-echelon inventory systems. Operations Research 2008; 56(5), 1089-103.

[24] Tomlin, B. On the value of mitigation and contingency strategies for managing supply chain disruption risks. Management Science 2006; 52(5), 639-57.

[25] Li, X., Dekker, R., Heij, C., & Hekimoğlu, M. Assessing end-of-supply risk of spare parts using the proportional hazard model. Decision Sciences 2016; 47(2), 373-94.

[26] Shih, W. C. Global supply chains in a post-pandemic world. Harvard Business Review 2020; 98(5): 82-9.

[27] Öberg, C., Shams, T., & Asnafi, N. Additive manufacturing and business models: current knowledge and missing perspectives. Technology Innovation Management Review 2018; 8(6).

[28] Öberg, C., & Shams, T. On the verge of disruption: rethinking position and role–the case of additive manufacturing. Journal of Business & Industrial Marketing 2019.

[29] Chang CS, Chen TH, Li TC, Lin SL, Liu SH, Lin JF. Influence of laser beam fluence on surface quality, microstructure, mechanical properties, and tribological results for laser polishing of SKD61 tool steel. Journal of Materials Processing Technology 2016; 229: 22-35.

[30] Bertsekas DP. Dynamic programming and optimal control, Vol 1. Athena scientific. 1995. Belmont, MA.

[31] Porteus EL. Foundations of stochastic inventory theory. 2002. Stanford University Press.

[32] Zipkin P. On the structure of lost-sales inventory models. Operations Research 2008 56(4), 937-44.

[33] Westerweel B, Basten R, den Boer J, van Houtum G-J. Printing spare parts at remote locations: fulfilling the promise of additive manufacturing. Working paper. 2018. Eindhoven: Eindhoven University of Technology.