Optimal Design of Additive Manufacturing Supply Chains

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Abstract

Additive Manufacturing (AM) is one of the most trending production technologies, with a growing number of companies looking forward to implementing it in their processes. Producing through AM not only means that there are no supplier lead times needed to account for, but also enables production closer to the end customer, reducing then the delivery time. This is especially true for companies with a wide range of low and variable demand products. This paper proposes a mixed integer linear programming (MILP) model for the optimal design of supply chains facing the introduction of AM processes. In the addressed problem, the 3D printers allocation to distribution centers (DC), that will make or customize parts, and the Suppliers- DC-Customers connections for each product need to be defined. The model aims at minimizing the supply chain costs, exploring the trade-offs between safety stock and stockout costs, and between buying and 3D printing a part. The main relevant characteristics of this model are the introduction of stock service levels as decision variables and the use of a linearization of the cumulative distribution function to account for demand uncertainty. A real-world problem from a maintenance provider is solved, showing the applicability of the model.

Keywords
Supply Chain Network Design, Mixed Integer Linear Programming, Additive Manufacturing, Inventory Management

1. Introduction

Flexible and customizable production can be achieved by means of different technologies such as Additive Manufacturing (AM) (Trancoso et al., 2018, Avventuroso et al., 2018). AM has progressively gained relevance as a viable manufacturing process for a series of industries (Trancoso et al., 2018). The advantages provided by this technology have shown the potential to greatly impact supply chains, manufacturing systems and products, allowing more complex parts to be made (Guo and Leu, 2013) with a reduced lead time and in a more cost-effective manner (Dickens and Waterman, 1994). Despite the existing limitations, AM systems have consistently grown in the number of applications, ranging from dental implants (Nazarian, 2017) to injection molding matrices (Nelson et al., 2017), and also in helicopter engine components (Engines, 2015).

In this paper, we address the problem of designing supply chains that incorporate the AM processes. In particular, we address a real-world case of a maintenance and spare parts supply chain of a world-leading company of elevators. The elevator maintenance business has a series of inherent challenges in its Supply Chain Network Design (SCND) and inventory management policies that could benefit from using AM technologies. On the one hand, companies providing elevator maintenance services must meet short response times and assure high service availability. On the other hand, there is a wide range of elevator models and of components for each model that can fail and must be replaced. These characteristics lead to complex implications for the supply chain, *i.e.*, the supply chain must be designed in a form that it is able to satisfy short response times, while at the same time controlling the quantity of stock kept (reducing inventory costs) in different distribution centers.

The introduction of AM technologies can help mitigate the difficulty of managing such a supply chain. It enables the possibility of internally producing spare parts (*i.e.*, perform manufacturing postponement using 3D printing directly in the Distribution Centers (DCs)), which means that there are no supplier lead times needed to account for, which decreases the response time of the maintenance service (Mashhadi et al., 2015). Although researchers and industrial practitioners agree that AM has potential to play an important role on enhancing the performance of supply chains in the future, how this technology should be implemented within the existing supply chains is still in its infant stage and it is difficult to find an assertive answer on how to define an adoption strategy for AM (Trancoso et al., 2018).

Albeit aiming to solve a specific real problem on AM integration on a supply chain, this paper also tries to provide more hints on creating an analytical answer for these questions, focusing on assuring that the adoption of AM can minimize the overall supply chain costs. It does so by creating and solving a MILP model of the problem, which main relevant characteristics are the usage of stock service levels as decision variables and of a linearization of the cumulative distribution function for the normal distribution to account for demand uncertainty. The model decides the 3D printer allocation to DCs, the supplier of each part to each DC (which can be an external supplier or another DC) and the inventory management policy parameters for each part kept in each DC (the safety stock and the order-up-to level).

This paper is organized as follows. Section 2 presents the relevant background literature of AM and SCND. Section 3 shows the problem description. Section 4 details the proposed solution to design a supply chain using a mathematical model. Section 5 shows an experimental use case and evaluates the proposed solution. Finally, Section 6 presents the concluding remarks and future work.

2. Literature Review

In the last few years, the theme of AM integration in a supply chain has received substantial research attention. With the current trend of decreasing costs, this technology may become widely adopted and change significantly the interaction among suppliers, manufacturers, and consumers (Thomas, 2016). AM can bring significant changes, by allowing manufacturers to move from a manufacturer-centric perspective to a consumer-centric value logic. A major shift is to move from centralized to decentralized supply chains (Bogers et al., 2016), where consumer goods manufacturers can implement a hybrid approach with a focus on localization and accessibility, increasing the availability of parts in challenging locations of the supply chain (Holmström and Partanen, 2014).

For example, research work in the healthcare area suggest that the changes on the supply chain can have a societal impact by permitting customized products to improve population health, quality of life, and reduce environmental impact for manufacturing sustainability (Huang et al., 2013). The environmental impact that AM can have on supply chains was also studied by Barz et al. (2016), who performed a computational study to compare two-stage supply networks on four indicators (total costs, ton-kilometers per customer on production to customer site transport, number of open production sites and proportion of transport costs) and concluded that all indicators improve by using AM and having the production sites closer to the customers.

Specific application cases were also studied by Khajavi et al. (2014), who explored the impact of AM on a spare parts supply chain for the aeronautics industry. Several scenarios, each with a different supply chain configuration, were modeled to obtain the cost trade-offs and find the preferable configuration. Also in the aeronautics industry, Huang et al. (2014) evaluated the impact of AM in the aircraft spare parts supply chain through an operation reference model. Three supply chain scenarios are investigated; namely, conventional (as-is) supply chain, centralized AM supply chain and distributed AM supply chain. A case study is conducted based on data obtained in the literature. The result shows that the use of AM can bring various opportunities for reducing the required safety inventory of aircraft spare parts.

To the best of our knowledge, modelling the design of additive manufacturing supply chains has been addressed only by Emelogu et al. (2016). In this study, a stochastic cost model was proposed to quantify the supply-chain level costs associated with the production of biomedical implants using AM techniques. The authors investigated the economic feasibility of using such technologies to fabricate biomedical implants at the sites of hospitals. The problem was formulated in the form of a stochastic programming model, which determines the number of AM facilities to be established and volume of product flow between manufacturing facilities and hospitals.

However, several works can be found addressing non-AM supply chains. You and Grossmann (2008) addressed the optimization of SCND and planning under responsive criterion and economic criterion with the presence of demand uncertainty. The supply chain consisted of multi-site processing facilities and corresponded to a multi-echelon production network with both dedicated and multiproduct plants. By using a probabilistic model for stock-out, the expected lead time was proposed as the quantitative measure of supply chain responsiveness. The probabilistic model could also predict the safety stock levels by integrating stock-out probability with demand uncertainty. These were all incorporated into a multi-period mixed-integer nonlinear programming (MINLP) model. The problem was formulated as a bi-criterion optimization model that maximizes the net present value and minimizes the expected lead time. More studies on designing a supply chain with safety stock level decisions can be found, such as the research done by Schuster Puga et al. (2018), who proposed a SCND model that integrates facility location with safety stock placement and delivery strategy decisions, to reflect their interdependence and ultimately improve the resulting SCND. The resulting nonlinear model is formulated as a conic quadratic mixed-integer program, which can be solved to optimality.

Real case study applications have also been explored, such as developing an optimization model to maximise the after-tax profit of a closed-loop global supply chain for medical devices under uncertainty (Zegordi and Nikbakhsh, 2015). The uncertainty of the decision-making environment was modelled using the uncertainty budget concept in interval robust optimization. To tackle this problem, a memetic algorithm was developed that incorporates adaptive variable neighborhood search as its local search heuristic.

Due to the extensive research found on the literature on this topic, several review articles are suggested for further reading, besides the examples presented above. Govindan et al. (2017) provided a comprehensive review of studies in the fields of SCND and reverse logistics network design under uncertainty. Their paper is organized in two main parts to investigate the basic features of these studies. In the first part, planning decisions, network structure, paradigms and aspects related to supply chain management are discussed. In the second part, existing optimization techniques for dealing with uncertainty are explored in terms of mathematical modeling and solution approaches. Garcia and You (2015) reviewed some principal research opportunities and challenges in the field of SCND. They stated that there are three major technical challenge areas where knowledge gaps can be addressed in SCND, namely multi-scale challenges, multi-objective and sustainability challenges, and multi-player challenges, and presented a perspective on how these challenges might be addressed. Farahani et al. (2014) reviewed, classified and introduced the major features of proposed models in the literature for SCND with competitor supply chains. They also developed a general framework for modeling the competitive SCND problems considering managerial insight and proposed potential areas for future research.

The problem of sustainable development integration with SCND was also tackled by Eskandarpour et al. (2015). They reviewed 87 papers in the field of sustainable SCND, and organized the review along four research questions, namely which environmental and social objectives are included, how are they integrated into the models, which methods and tools are used, and which industrial applications and contexts are covered in these models. The paper concludes with promising new avenues of research to more effectively include sustainability into SCND models.

Despite the significant advances in this area, it is clear that the topic of development of analytical methods for SCND on AM supply chains, to which this paper belongs, has not been researched widely and, facing the growth of AM, more contributions should be made in the future. Even so, there are relevant contributions on the topic of SCND on non-AM supply chains, which can serve as a solid ground for future research work on AM supply chains.

3. Problem Description

This paper refers to a real-world case of an elevator maintenance provider operating in Brazil. For each city where the company operates, it has a distribution center (designated as remote station). The remote station is where the maintenance teams are based and the spare parts stocks are kept. When a maintenance request is received, the maintenance team takes the necessary parts and travels to the end customer to perform the maintenance operation, whether it is corrective or preventive maintenance.

With the appearance of AM, the company wants to start deploying 3D printing units on its remote stations. The introduction of AM machines is seen as an opportunity for decreasing costs with external part supplying, speed up the response to stockouts and decreasing the costs with safety inventory. Although the adoption of this technology may be beneficial for the company, there are many decisions that must be made to define the adoption strategy for AM technology, both in terms of SCND and inventory management.

The design of AM supply chains, as considered in this work, encompasses: i) determining the number of 3D printers that should be allocated to each remote station, ii) deciding if a remote station will produce a part and, if not, who will be the supplier for that part (which can be another remote station or an external supplier); iii) determining the safety stock and order-up-to-level. Besides the difficulty of having to make a high number of decisions, the defined adoption strategy will impact a series of different costs of the supply chain, namely equipment and spare parts acquisition, production, transportation and delivery, inventory and stockout costs. The sum of these costs is the total supply chain cost, which the company aims to minimize.

4. Proposed Solution

The devised solution to design the supply chain is a MILP model. On the one hand, it can reach an optimal solution for smaller instances of the problem. On the other hand, it presents the problem on an organized and detailed form, so that it can be validated by the managers of the elevator maintenance provider company. In line with the problem statement, the model minimizes the total supply chain and its decision variables define both the SCND and inventory management parameters. The parameters, decision variables, constraints and objective function of the model are presented below.

4.1 Sets, indices and parameters

The sets and parameters of the model are the following:

R: set of the remote stations in the supply chain

P: set of the parts produced in the supply chain

S: set of suppliers in the supply chain

r: index of a remote station in the supply chain

p: index of a part produced in the supply chain

s: index of a supplier in the supply chain

D_{rp} : annual demand of part *p* in region *r*

FC^R : annual fixed cost of a remote station

FC^P : annual fixed cost of holding a 3D printer

C^P : annual capacity of a 3D printer (in hours)

$price_{sp}$: price of a unit of part *p* from supplier *s*

uc_p : unitary cost of production of part *p* on a remote station

pt_p : processing time for a 3D printer to produce part *p*

oc_{sr} : order cost for remote station *r* to supplier *s*

$\overline{SL}_{sr}$: average lead time of delivery of supplier *s* to region *r*

dc_r : delivery cost for remote station *r* to final client

cc : percentage of the average stock applied to calculate capital costs

$ioc_{r'r}$: internal order cost for remote station *r* to remote station *r'*

$\overline{ISL}_{r'r}$: average lead time of delivery for remote station *r'* to remote station *r*

RT: review time of the remote stations (in years)

$config = (a_{r'r}, \forall r', r \in R)$, where $a_{r'r} = 1$ represents that remote station *r'* supplies remote station *r*, and $a_{r'r} = 0$, otherwise. Represents an internal supply configuration.

C: set of all possible values for *config*

sc : stockout cost, the cost of having a stockout of a part on a remote station during a review time

$\sigma_{config\ rp}$: standard deviation of the demand on one review time of part *p* on remote station *r*, when the internal supply configuration is *config*

M: "very large" number

4.2 Decision variables

The decision variables of the model are the following:

n_r : number of 3D printers allocated to remote station *r*

$y_{r'rp}$: binary variable: 1 if remote station *r'* supplies part *p* to remote station *r*, 0 otherwise

z_{srp} : binary variable: 1 if supplier *s* supplies part *p* to remote station *r*, 0 otherwise

x_{rp} : binary variable: 1 if remote station *r* produces part *p*, 0 otherwise

is_{sr} : binary variable: 1 if supplier *s* is a supplier of remote station *r*, 0 otherwise

$\delta_{config\ p}, \forall config \in C, \forall p \in P$: binary variable: 1 if internal supply configuration *config* is used for part *p*, 0 otherwise

$score_{rp}$: z-score of the safety stock defined for part *p* on remote station *r*

$score1_{rp}$: component 1 of z-score of the safety stock defined for part *p* on remote station *r*

$score2_{rp}$: component 2 of z-score of the safety stock defined for part *p* on remote station *r*

$score3_{rp}$: component 3 of z-score of the safety stock defined for part *p* on remote station *r*

$\omega 1_{rp}$: auxiliary binary variable for component 1 of z-score of the safety stock defined for part *p* on remote station *r*

$\omega 2_{rp}$: auxiliary binary variable for component 2 of z-score of the safety stock defined for part *p* on remote station *r*

$\omega 3_{rp}$: auxiliary binary variable for component 3 of z-score of the safety stock defined for part *p* on remote station *r*

α_{rp} : service-level for part *p* on remote station *r*

ssc_{rp} : safety stock cost for part *p* on remote station *r*

4.3 Constraints

The proposed mathematical model considers the following problem constraints:

- The number of 3D printers allocated to a remote station must be greater than or equal to 0.

$$n_r \geq 0 \quad , \forall r \in R$$

- A station can only supply another station a certain part if it produces this part.

$$y_{r'rp} \leq x_{r'p} \quad , \forall r' \in R, r \in R, p \in P$$

- A station can only produce a part if it supplies itself or another station with this part.

$$\sum_{r \in R} y_{r'rp} \geq x_{r'p} \quad , \forall r' \in R, r \in R, p \in P$$

- A remote station cannot produce above its capacity.

$$\sum_{r \in R, p \in P} y_{r'rp} * D_{rp} * pt_p \leq C^P * n_{r'} \quad , \forall r' \in R$$

- A remote station must be supplied on a certain part by one, and only one, supplier or remote station.

$$\sum_{r' \in R} y_{r'rp} + \sum_{s \in S} z_{srp} = 1 \quad , \forall r \in R, p \in P$$

- Auxiliary constraints to define the value of is_{sr}.

$$is_{sr} \geq z_{srp} \quad , \forall s \in S, r \in R, p \in P$$

$$is_{sr} \leq \sum_{p \in P} z_{srp} \quad , \forall s \in S, r \in R$$

- Auxiliary constraints to define the value of $\delta_{config\ p}$.

$$a_{r'r} - y_{r'rp} \geq 0 - \left(1 - \delta_{config\ p}\right) * M \quad , \forall config \in C, r \in R, r' \in R, p \in P$$

$$a_{r'r} - y_{r'rp} \leq 0 + \left(1 - \delta_{config\ p}\right) * M \quad , \forall config \in C, r \in R, r' \in R, p \in P$$

$$\sum_{config \in C} \delta_{config\ p} = 1 \quad , \forall p \in P$$

- The cumulative distribution function for the normal distribution was approximated to a piecewise function, with three different subfunctions: 0, for a z-score less than -1.5; $f(x) = \frac{1}{3}x + 0.5$, for a z-score between -1.5 and 1.5; 1, for a z-score greater than 1.5. The z-score is the sum of its three components.

$$score_{rp} = score1_{rp} + score2_{rp} + score3_{rp} \quad , \forall r \in R, p \in P$$

- Only one of three pieces that define the piecewise function for the z-score can be active.

$$\omega 1_{rp} + \omega 2_{rp} + \omega 3_{rp} = 1 \quad , \forall r \in R, p \in P$$

- A component of the z-score can be different from zero if, and only if, its corresponding piece of the piecewise function is active. These constraints also define the subdomains for each sub-function of the piecewise function.

$$-M * \omega 1_{rp} \leq score1_{rp} \leq -1.5 * \omega 1_{rp} \quad , \forall r \in R, p \in P$$

$$-1.5 * \omega 2_{rp} \leq score2_{rp} \leq 1.5 * \omega 2_{rp} \quad , \forall r \in R, p \in P$$

$$1.5 * \omega 3_{rp} \leq score3_{rp} \leq M * \omega 3_{rp} \quad , \forall r \in R, p \in P$$

- Definition of the service level for each remote station-part combination.

$$\alpha_{rp} = 0.5 * \omega 2_{rp} + \omega 3_{rp} + (1/3) * score2_{rp} \quad , \forall r \in R, p \in P$$

- Definition of the safety stock cost for each remote station-part combination, when it is internally supplied.

$$ssc_{rp} \geq (-1 + \delta_{config\ p}) * M - \left(\sum_{s \in S} z_{srp}\right) * M + cc * \sigma_{config\ rp} * score_{rp} * uc_p \quad , \forall config \in C, r \in R, p \in P$$

- Definition of the safety stock cost for each remote station-part combination, when it is externally supplied.

$$ssc_{rp} \geq (-1 + \delta_{config\ p}) * M - (1 - z_{srp}) * M + cc * \sigma_{config\ rp} * score_{rp} * price_{sp} \quad ,$$
$$\forall config \in C, s \in S, r \in R, p \in P$$

4.4 Objective function

The objective function of this model minimizes the total cost of the supply chain, which breakdown to capital, production, purchase, transport and delivery, inventory and stockout costs, and is given by:

$$\begin{aligned} min \quad & \sum_{r \in R} (FC^R + n_r * FC^P) + \sum_{r', r \in R, p \in P} y_{r'rp} * D_{rp} * uc_p + \sum_{s \in S, r \in R, p \in P} (z_{srp} * D_{rp} * price_{sp}) + \sum_{s \in S, r \in R} is_{sr} * \\ & * 1/(RT) * oc_{sr} + \sum_{r' \in R, p \in P} \left(dc_{r'} * no_{r'p} + \sum_{r \in R \setminus r'} y_{r'rp} * (1/RT) * ioc_{r'r} \right) + cc * (RT/2) * \\ & * \sum_{r' \in R, p \in P} \left(D_{r'p} * \sum_{s \in S} z_{sr'p} * price_{sp} + D_{r'p} * \left(1 - \sum_{s \in S} z_{sr'p}\right) * uc_p + uc_p * \right. \\ & \left. * \sum_{r \in R \setminus r'} y_{r'rp} * D_{rp} \right) + \sum_{r \in R, p \in P} ssc_{rp} + sc * (1/RT) * \sum_{r \in R, p \in P} (1 - \alpha_{rp}) \end{aligned}$$

4.5 Post-processing calculations

After running the optimization model, the obtained values for the decision variables are used to calculate $ss_{rp}, \forall r \in R, \forall p \in P$ and $outl_{rp}, \forall r \in R, \forall p \in P$, which are, respectively, the safety stock and the order-up-to-level for each remote station-part combination. The following equations define these values:

$$ss_{rp} = \sum_{config \in C} \delta_{config\ p} * \sigma_{config\ rp} * score_{rp} \quad , \forall r \in R, p \in P$$

$$outl_{rp} = \left(D_{rp} + \sum_{r' \in R \setminus r} \left(y_{rr'p} * D_{r'p} \right) \right) * \left(RT + \sum_{s \in S} \left(\overline{SL}_{sr} * z_{srp} \right) + \sum_{r' \in R} \left(\overline{ISL}_{r'r} * y_{r'rp} \right) \right) + ss_{rp} \quad , \forall r \in R, p \in P$$

5. Numerical Results

The proposed mathematical model was programmed in IBM ILOG CPLEX Optimization Studio, version 12.6.
Three problem instances were tested. The first one for an early phase of AM technology adoption, which only embraces three remote stations, three types of spare parts to be produced and one external supplier. Then, the real case was tested, in which there are three remote stations, five types of spare parts and five external suppliers. Finally, a long-term case was studied, where the possibly of expanding the supply chain was explored by adding two fictional remote stations to the real instance.

The results of the execution of the model for the different problem instances are presented in Table 1. It is important to mention that the results were obtained by executing the optimization models in a Dell Latitude 7490 computer, equipped with 16 GB of RAM memory and an Intel Core i7-8650U processor (quad-core with 1.9 GHz clock frequency).

Table 1. Results of the model execution

Problem instance	Number of (suppliers, remote stations, parts)	Number of possible supply chain configurations (*C*)	Number of decision variables (binaries, integers, continuous)	Number of constraints	Integrality gap (%)	Execution time (seconds)
Pilot case	(1,3,3)	64	(267, 12, 45)	4752	0	7
Real case	(5,3,5)	64	(515, 18, 75)	11828	0	8
Long-term case	(5,5,5)	7776	(39255, 30, 125)	3110960	0	3596

The model was able to find the optimal solution for the problem in a short interval of time for both the pilot and real problem instances.

For the long-term scenario, the model took significant more time to be solved optimally. As can be seen, the increase of the number of remote stations by approximately 67% caused an increase of the number of decision variables by 6382% and of the model's constraints by 26202%. The main reason for this increase is that the number of some of the model's constraints depend on the number of possible internal supply chain configurations (*C*).

This exponential growth of the dimension of the problem with the number of remote stations led the execution time for the model to also increase to approximately one hour, showing that, for complex supply chains, with a high number of remote stations, the solution of the model (by this procedure) may not be suitable. To deal with the computational complexity of the larger instances, decomposition and non-exact methods can be applied.

6. Conclusions and Future Work

This paper presented a novel mathematical model for the optimization of SCND integrated with inventory management, in an AM context. The model was used to address specific problems on the elevator maintenance business, but it can be adapted to supply chains on other areas that use AM.

The proposed model was able to find optimal solutions for the problems addressed in an acceptable time interval. Nevertheless, the problem size grows exponentially with the increase of the number of distribution centers (remote stations), which makes the optimization problem difficult to solve to optimality. The usage of the set of possible supply chain configurations is one the main causes for the high number of constraints. This set is needed in order to make the model able to consider the correct values for the standard deviation of the demand in each remote station, which are used to determine the safety stock level.

Although in a first phase, the supply chain dimension is the one presented in the experimental results, and the proposed model delivers an effective solution, with the growth of AM supply chain an effort has to be made in future work to assure a solution method capable of handling larger problems, with more parts and more remote stations.

In this sense, two main research branches will be explored following this work. On the one hand, creating a version of the model for a supply chain in a “make-to-order” logic. In this kind of supply chain, safety stocks are not kept, which will eliminate the need for usage of the set of possible supply chain configurations in the model’s constraints and able it to be used on larger supply chains. On the other hand, solution methods able to tackle the original problem described in the paper on larger instances must be researched, may they be simpler mathematical models or approximate solution methods, such as heuristics and/or metaheuristics.

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Biographies

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