Additive Manufacturing Integration in E-commerce Supply Chain Network to Improve Resilience and Competitiveness

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Abstract

In light of recently increased e-commerce, also a result of the COVID-19 pandemic, this study examines how additive manufacturing (AM) can contribute to e-commerce supply chain network resilience, profitability and competitiveness. With the recent competitive supply chain challenges, companies aim to decrease cost performance metrics and increase responsiveness. In this work, we aim to establish utilisation policies for AM in a supply chain network so that companies can simultaneously improve their total network cost and response time performance metrics. We propose three different utilisation policies, i.e. reactive, proactive – both with 3D printing support – and a policy excluding AM usage in the system. A simulation optimisation process for 136 experiments under various input design factors for an (s, S) inventory control policy is carried out.

We also completed a statistical analysis to identify significant factors (i.e. AM, holding cost, lead time, response time, demand amount, etc.) affecting the performance of the studied retailer supply chain. Results show that utilising AM in such a network can prove beneficial, and where the reactive policy contributes significantly to the network performance metrics. Practically, this work has important managerial implications in defining the most appropriate policies to achieve optimisation of supply network operations and resilience with the aid of AM, especially in times of turbulence and uncertainty.

Keywords: Additive manufacturing, 3D printing; inventory optimisation; supply chain; e-commerce; resilience

1. Introduction

According to the United Nations Conference on Trade and Development (UNCTAD), the e-commerce sector witnessed a substantial rise in its share of all retail sales, from 16 per cent to 19 per cent in 2020 (UNCTAD, 2021). Furthermore, propelled by the unprecedented circumstances of the recent COVID-19 lockdowns, businesses have turned to e-commerce to stay financially viable, increasing final consumers' purchasing via online platforms. In this vein, many companies, including retailers, have been enriching or even amending their entire business models via the contemporary technologies of the Industry 4.0 era (Grabowska et al., 2020; Jiang and Stylos, 2021).

AM, also referred as 3D printing technology can provide significant benefits to e-commerce retailers in several ways: it speeds up production, reduces costs and inventory waste, and allows for custom-made and highly spersonalised product design, etc. For instance, some well-known shoe manufacturers (Adidas, Nike, New Balance, and Under Armour) are already implementing AM into their strategies.

Recent studies (Afshari et al., 2020; Attaran, 2020) posits that AM can significantly alter the roles of suppliers and manufacturers. 3D printing technology can transform the prevailing context of conventional supply methods – which may involve a high cost of ordering small-sized parcels – as companies typically tend to order large sizes in one run for current and expected future demands. As previously highlighted, massive production and logistics networks create a physical inventory of spare parts that may or may not be used in the future, also causing costly storage and management of that inventory (Esmizadeh and Mellat Parast, 2021). Thus, due to its ability to save significantly on physical inventory and logistics, the use of 3D printing within supply chains is expected to continue to increase (Molcho, 2020). As a result, the global AM market size is estimated to reach USD 76.16 billion by 2030, growing at a CAGR of 20.8% (Businesswire, 2022). Figure 1 shows the AM market forecasted growth based on sectors. Accordingly, consumer products play a major role in AM market trends and are expected to grow.

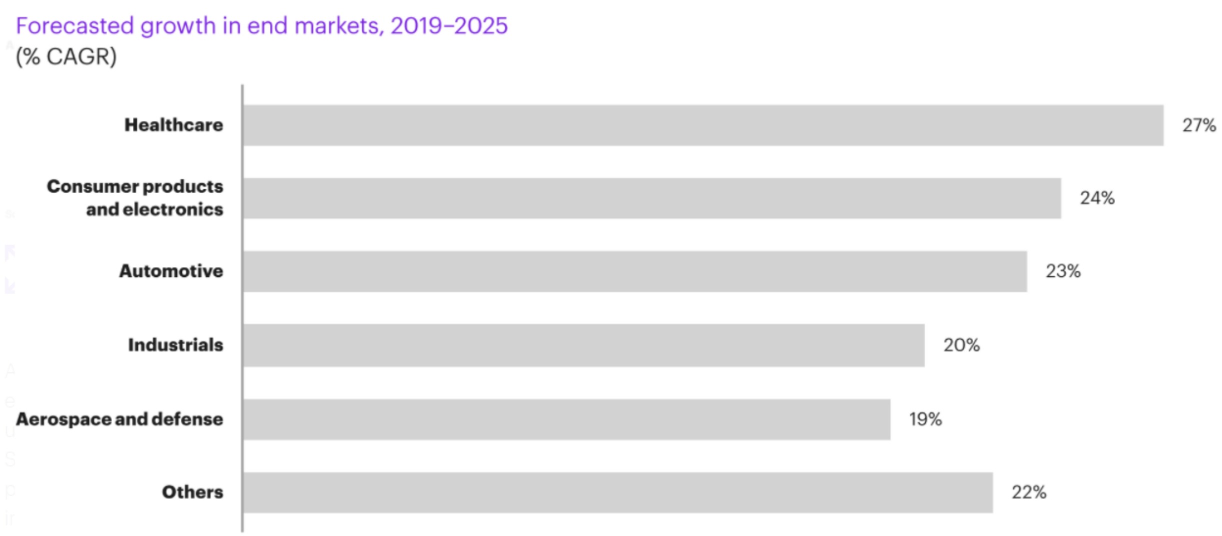

Figure 1. Global AM market share based on sectors (adopted from Kearney, 2019).

It has been reported that the benefits of AM are numerous including accelerated prototyping, customisation, energy and environmental savings, inventory stock reduction, and flexible production (Mehrpouya et al., 2019). However, it also comes with some disadvantages, such as slow processing as well as high production costs. In this study, we focus on the inventory stock reduction advantage of AM in the retail supply chain by considering that components are printed on-demand, which is cost-efficient compared to ordering from a higher echelon supplier; a reduction in inventory stock can be anticipated as well.

Interestingly, until recently, very little empirical research has existed in this particular field of enquiry. For instance, Kunz et al. (2014) examine the potential key contributions of 3D printing technology in times of crises and great uncertainty as a medium to address real shortages of vital products that cannot be fulfilled with traditional mass-production approaches. Taken together, this study examines the following research questions:

RQ1: Which integration policy would be the most beneficial to utilise AM technology in a two-echelon supply chain network?

RQ2: Which input parameters (e.g., unit cost and time-related parameters) would significantly influence the performance of that supply chain network?

Specifically, *RQ1* investigates which integration policy would be the most beneficial to utilise a 3D printer: a reactive or a proactive policy? Here, reactive policy refers to 3D printer response (i.e., production) to inventory deficiency after it happen, also known as make-to-order policy in the extant literature. Proactive policy refers production of inventory by the 3D printer before demand occurs. This policy is also known as the make-to-stock policy in the extant literature. *RQ2* investigates the input design factors (e.g., unit cost and time-related parameters) significantly influencing the performance of the proposed supply network.

From a theoretical perspective, this study builds upon the work of Rodríguez-Espíndola et al. (2020) and Tsai (2017) to extend current knowledge on measuring the influence of certain factors on the performance of a supply chain network, which incorporates 3D printing equipment. Furthermore, a sensitivity analysis was conducted for this research via three different scenarios which represent three different supply chain network policies. Practically, this work has important managerial implications for better understanding show AM can be best implemented to optimise supply network operations. Thus, the findings of this research could serve as a starting point for managers to evaluate the performance of their existing supply chain networks and how these could benefit by integrating 3D printing as a cornerstone for increasing system resilience, especially in times of turbulence and uncertainty.

2. Theoretical Background

2.1 Supply chains and system resilience

Modern organisations rely heavily on global supply chains and lean principles for achieving efficiency, though this approach may need to be reconsidered in turbulent times as they become more vulnerable, e.g. during the coronavirus outbreak (Ivanov, 2020). Over time, organisations have built up resilience by having risk mitigation inventories, subcontracting capacities, backup supply and transportation infrastructures, omnichannel distribution systems, flexible production technologies, and data-driven, real-time monitoring and visibility systems. However, the COVID-19 pandemic has shown that these measures were not good enough to deal with the sudden disruption on a global scale (Ivanov and Dolgui, 2020; Hosseini, Ivanov and Dolgui, 2019). This has compelled and accelerated organisations globally to explore alternative ways of meeting the demand surge and building resiliency in their supply chains. In addition, the ability of flexible and advanced manufacturing technologies to provide more adaptable production capabilities that are less susceptible to disruption has helped them to develop resilience in their supply chains (Zimmerling and Chen, 2021). Thus, the ability to respond rapidly turns out to be more important than long-term or planning for foundational changes in reducing the effect of a disruption (Shekarian et al., 2020). In this context, Chowdhury et al. (2021) respond to disruptions by quickly adapting product development cycle time, lead time, and customer services via an agile approach. Owing to the global supply chain disruptions and rising demand for essential goods and components, 3D printing has emerged as an alternative solution to address some of these challenges, where certain physical products can be manufactured locally or on-site (Abbink 2015, Durach at al., 2017).

2.2 Additive manufacturing and supply chains

AM is an important building block of the fourth industrial revolution and has been introducing infrastructural transformations in manufacturing, as well as in several service sectors, including the respective supply chains, to support these industries (Ivanov et al., 2019). 3D printing creates physical objects from a geometrical representation by successive additions of selected materials (Shahrubudin et al., 2019). The digital versatility, customisation, ability to deal with complex designs and quick prototyping of 3D printing have recently empowered a rapid smobilisation of this technology in response to emergencies.

During severe disruptions in supply chains, as seen during the recent COVID-19 pandemic, critical parts can be manufactured on-demand by any sdecentralised 3D printing facility around the world by leveraging designs shared online (Choong et al., 2020). Many examples of 3D printing applications have been used, particularly addressing the essential healthcare supply woes during this pandemic. Since the emergence of the COVID-19 pandemic, there has been widespread media coverage of healthcare organisations globally reling on 3D printing communities and companies to ease the breakdown in the medical supply chain by 3D printing time-critical parts on demand, such as face shields, respirators, and spares for ventilators (Salmi et al., 2020). Recent studies have also shown that 3D printing can be used to support the spare parts market (Ballardini et al., 2018; Khajavi et al., 2020; Knofius et al., 2021; Heinen and Hoberg, 2019). Liu and Evans (2016) suggest that 3D printing presents significant potential to enable companies to think of new methods of creating objects and better deal with global manufacturing challenges. Overall, it is clear from these discussions that 3D printing may play a significant role during emergencies in addressing supply chain issues caused by sudden peaks in demand when supplies from traditional means are difficult.

2.3 Retail SMEs, supply chains and relevant networks optimisation

Small and Medium Enterprises (SMEs) play a major role in most economies and represent about 90% of businesses and more than 50% of employment worldwide (The World Bank, 2019).However, evidence suggests that SMEs are relatively less prepared than larger organisations to cope with disruptions due to the volatile and resource-constrained environment in which SMEs operate (Bak et al., 2020). Because of the critical role that SMEs play in the supply chains, including those of the retail sector, the preservation of their manufacturing capability and supply network capacity is paramount, especially under conditions of uncertainty such as the ongoing pandemic and environmental shocks (Devin and Richards, 2018). In line with this, managing the available resources effectively is a critical part of the supply chain networks. For example, useful insights on how collaboration in agri-food supply chains impacts firm performance have been provided by Zaridis et al. (2020), focusing on the moderating role of scale constraint and firm strategy on supply chains under uncertainty. They found that supply chain collaboration positively impacts SME performance, and scale constraints moderate the supply chain collaboration-SME performance relationship.

There is also evidence that the SME retail strategy moderates the supply chain collaboration-SME performance relationship (Gawankar et al., 2020). Besides, SMEs can sstrategise their supply chain collaborations by removing scale constraints, which would make offering customised solutions to end-user customers a financially viable solution to retailers while successfully meeting or exceeding their customers' expectations (Bijmolt et al., 2021). Overall, SMEs' performance improves when supply chain collaborations help SMEs overcome financial, efficiency or innovation constraints.

2.4 Resource Capabilities in SMEs

Resources have been scategorised as physical capital, human capital, and organisational capital (Barney, 1991) and are further enhanced by financial, technological, and reputational capital (Grant, 1991). They may be tangible, such as infrastructure, or intangible, such as information or knowledge sharing (Groebler & Grubner, 2006). For the scope of this study, we focus on *organisational*, *technological*, and *financial capital* only.

Resources are considered to be "something a firm possesses or has access to, not what a firm is able to do" (Groebler & Grubner, 2006, p. 460). They may not provide value themselves, but they are rather required to be processed or used in bundles to drive performance (Newbert, 2007).

Bundling refers to combining resources to allow capability development (Sirmon, Gove & Hitt, 2008), with SMEs in the retail sector particularly benefitting from this practice (Chinakidzwa & Phiri, 2020). A combination of resources is required "to exploit opportunities and/or mitigate threats" in particular contexts or industries for organisations to be able to produce or maintain a competitive advantage (Sirmon et al., 2008; p. 922).

Conceptually, the Resource-based view theory posits that firms utilise and sorganise their resources in ways to establish and augment their dynamic capabilities (Beltagui et al., 2021). Dynamic capabilities are defined as organisations' capacity to create, extend, or modify their resource base, i.e. processes such as product development and making strategic decisions such as determining the reallocation of their resources, to build and maintain connections effectively (Barney, 1991; Eisenhardt and Martin 2000). These aid firm's ability to reconfigure their resources and respond successfully to complex and uncertain business environments, such as the one in which SMEs currently operate (Devin and Richards, 2018; Zaridis et al., 2020). Furthermore, SMEs can extend their resource stocks (inventories) by utilising resources, assets and skills external to a firm and maximising their value (Popli et al. 2017). Supply chain collaboration, considered a higher-level dynamic capability, offers a double gain for SMEs: a) lower transaction costs and b) access to external resources and capabilities (Hitt, Xu, and Carnes 2016).

The reduction in transaction costs should benefit SMEs having *financial capital* strategies, while access to external resources enables benefits for SMEs investing in the differentiation of quality. However, collaboration with a strategic partner may prove unconstructive as a supply chain collaboration may show deficiencies for SMEs in relation to risks stemming from information asymmetries, hold-up costs, and resource misuse (Arend and Wisner, 2005). There are times when the relationship is helpful and fruitful, but when disruptions are evident in supply chains, then the issue of demand for resources and their allocation is not as harmonious since partners compete for the same resources (Bak et al., 2020; Devin and Richards, 2018).

Under these conditions, reactive policies are needed to smooth out the supplier constraints i.e., external collaborators unable to meet manufacturing demands lead to alternative forms of fulfilling supply demands in the production cycle. Under uncertainty and resource constraints, the emergence of 3D printing can provide useful alternatives to pick up slack in the production cycle and overcome shortfalls of access to external resources (Salmi et al., 2020). In this case, the financial capital transaction costs might be greater per unit produced. However, the effect of the agility for meeting the demand via fulfilling orders using 3D printers may compensate for the shorter term fluctuations of demand and relevant capacity issues, as those small/medium size retailers frequently deal with (Mkansi, 2021); though this approach wouldn't be suitable to be implemented under normal conditions such as for larger orders of stock/ resources (Arend and Wisner, 2005; Sirmon et al., 2008).

Dynamic capabilities are needed to develop responsiveness and resilience in the supply chain of SMEs, particularly under extreme conditions, with the most recent ones relating to the COVID-19 crisis (Rashid and Ratten, 2021). Furthermore, with stock control being an important component of SME business, there is a need to control demand under constraints (Devin & Richards, 2018). 3D printing provides useful dynamic abilities for SME businesses to use financial capital reactively to address higher resource demand (Newbert, 2007). That is, 3D printing can absorb external supply difficulties, and while the use of 3D printing might prove to be more costly, it still provides an efficient way of dealing with sudden peaks of demand within the shorter turnaround timeframes for products to create strategic value (Popli et al., 2017).

Technological capital is a resource capability that is useful for meeting demands in the supply process through the normal production cycle and extends to the existing supply capabilities (Hitt, Xu & Carnes, 2016). For example, 3D printing provides a technological capital resource, an extended resource capability providing a proactive use of resources to meet demand internally within a quicker response time for relatively small demand requirements (Grant, 1991, Salmi et al., 2020). The capability of the organisation to reduce stock-outs is by planning and controlling the flow of demand in order to protect organisational capital (Bak et al., 2020; Chowdhury et al., 2021).

The *organisational capital* includes the intra and inter-organisational resources and capabilities to deliver strategic value (Grant, 1991; Barney, 1991). By controlling the supply of stock/ inventory, uncertainty is reduced, and the organisation's capability to meet demand dynamically is increased through an additional capability, thus gaining an extension of its current resource offering (Eisenhardt and Martin 2000). By sutilising 3D printing, SMEs can reduce the holding costs of storing inventory and respond to short-term small supply resource requirements (Kunovjanek & Reiner, 2020), thus providing the ability to meet the demand for a proactive policy (Devin and Richards, 2018, Salmi et al., 2021). It can absorb smaller scale supplier issues, thus reacting more resiliently to uncertainty in the environment and preserving organisational capital.

Overall, *financial capital,* technological capital, and organisational capital resources are key factors in delivering value and meeting demand fluctuations in retail SMEs (Ding et al., 2020).

3. Methodological approach

3.1 Case study setting and context

This paper studies how 3D printer utilisation may positively affect a retailer supply network performance and under which network input parameter values the network performance may be optimised. By identifying those, an organisation can decide on whether or not to adopt a 3D printer for its network. The most relevant works are related to work by Song and Zhang (2020) and by McDermott et al. (2021). The former aims to provide a framework to sminimise long-run average system cost by determining which parts to stock and which to print. The latter assesses the preferred AM-enabled supply chain configuration for varying intermittent demand patterns and AM production capacity levels. As far as the current study is concerned, the effect of AM on supply chain cost has been analysed by taking into account several factors: holding cost, lead time, response time, demand amount, etc. by ANOVA, by also involving response time constraint in the model. As part of our motivation to contribute positively to the extraordinary epidemic situations such as COVID-19, which has caused sudden changes in demand for tangible products and services, we study a two-echelon supply network for a small-size retailer, utilising a 3D printer as in Figure 2. Note that any small-size two-echelon supply network can also utilise the findings proposed by this study. This figure show information and product flows by dashed and solid lines, respectively. Here, we assume that Supplier 1 represents an e-store (e.g., a small shoe company) applying an (s, S) inventory control policy for the replenishment of the supply network from an upper echelon (i.e., Supplier 2). The terms s and S represent the reorder and order up-to levels for inventory control, respectively. Namely, when the current inventory level (I) at Supplier 1 is smaller than or equal to the reorder level s, the Q amount of order is placed from Supplier 2, calculated by (1).

$$Q = \begin{cases} S - I, & \text{if } I \leq s \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

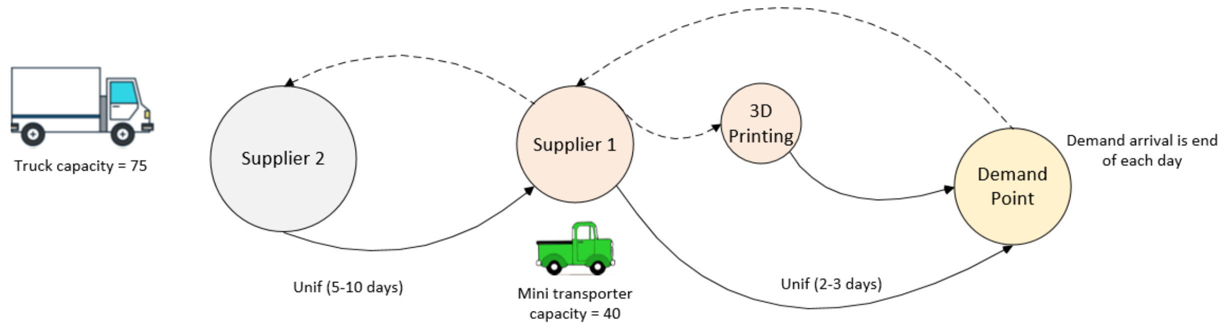

Figure 2. The shypothesised network system design for this study.

In the shypothesised network, we seek the best way of utilising a 3D printer by Supplier 1 to decrease the network cost. It is well known that, with the recent competitive supply chain targets, companies are searching for ways to be more competitive, especially in terms of responsiveness, while operating their costs efficiently (Bak et al., 2020; Popli et al., 2017). Towards that concept, utilisation of 3D printing technology might be a proper implementation in supply chains in the case of lack of inventory, cost-efficient inventory holding, postponing ordering from the upper echelon, etc. Identifying when, and "in what capacity it would be suitable to utilise a 3D printer in a supply chain" is a key research topic to study. Also, "what type of supply chain structure can mostly benefit from 3D printing technology?" is another one. Taken together, we have assumed a two-echelon supply chain network of small size in terms of system capacity and respective demand to be served, testing for supply production policies that would prove most beneficial. Additionally, input factors that may significantly affect the system performance of the supply network have also been integrated into our analysis in order to quantify their influence on the total cost of running the proposed supply chain network.

To address the first research question (*RQ1*), *Reactive* and *Proactive* policies are studied to meet the demand imposed by the pandemic. Details of those policies are explained in Sections 3.1 and 3.2, respectively. To examine the second research question (*RQ2*), we have selected and implemented the Analysis of Variance (ANOVA) as a suitable statistical technique. ANOVA can properly support the identification of statistically significant design factors affecting the network performance (i.e., total cost). The details of this analysis are explained in the Results section.

According to the network appearing in Figure 2, it is assumed that demand arrives at a small-size e-store company, Supplier 1, and the e-store sends the products to the demand point by mini-transporters whose capacity is 40 products. Replenishment from Supplier 2 is completed by trucks whose capacity is 75 products per truck. A single 3D printer in the network could be utilised under two different production policies, reactive and proactive, whose implementation procedures are explained in the sub-sections below.

3.1.1 Retailers and Reactive Policy

Emerging from its definition, reactive means a response to a problem after it happens, such as a disruption to the supply chain. Then, from its immediate responsive attribute, this policy may also be referred as a make-to-order policy from the literature (Song and Zhang, 2020). For many companies, the reactive response is a viable way of operating (Angkiriwang et al., 2014; Topan and van der Heijden, 2020). This is because planning so many possible scenarios and carrying stocks to support them might be extremely expensive. In the reactive approach, a 3D printer is utilised when the back order is to meet demand unfulfilled within the normal product lifecycle. Namely, in this policy, Supplier 1 supplies the remaining amount of demand by the 3D printer that cannot be met from its current inventory (resource stocks are low). To detail, after demand arrives at Supplier 1, it first checks whether or not there is a required amount of product in its inventory (resource availability). If there is not, then Supplier 1 starts to produce the remaining amount of demand by the 3D printer that can be met within the desired response time. The mini-transporters immediately send the demand amount that can be met from the current inventory to the customer point (see Figure 2). However, products manufactured by the 3D printer are sent later, by a separate transporter once all are produced. Since we have a response time constraint in the system design, the 3D printing process is stopped if it is estimated that the newly produced product cannot reach the demand point in the desired response time target. After the 3D printing process ends, if there is still unmet demand, then that amount is assumed to be a lost sale.

3.1.2 Retailers and Proactive Policy

The proactive strategy involves the planning of inventory for anticipated sales or demand. Forecasting is one of the best ways to take charge of inventory proactively. With real-time data gathering and tracking tools, companies can understand the demand pattern and can utilise this data to plan the next purchasing round of inventory stock. Against this background, this policy may also be referred to as the make-to-stock policy from literature (Song and Zhang, 2020). In this work, the proactive policy is regarded as the utilisation of 3D printers proactively sutilised in the supply network system.

Specifically, in the proactive policy, the 3D printer production centre produces more outputs in anticipation of demand. For that policy, we treat the 3D printer station as another source of product for Supplier 1. In other words, in the proactive policy, some of the products are supplied from a 3D printer instead of Supplier 2. Hence, ordering and holding costs might decrease in the network.

By treating the 3D printer centre as a separate product supplier for Supplier 1, we assume that this centre has its own s_p, S_p inventory control policy. Namely, when the current inventory amount in Supplier 1 is less than that reorder point of s_p value, then the 3D printer centre prints Q_p amount of products calculated by (2):

$$Q_p = \begin{cases} S_p - I, & \text{if } I \le s_p \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where $s_p < S_p$. Here, S_p represents the order up-to level of the 3D printer. The output produced by the 3D printer is counted in the inventory of Supplier 1, immediately. Note that the main difference between reactive and proactive policies is the following: in reactive policy,, the output is produced in response to an unmet demand case; in proactive policy, the output is produced in advance to an unmet demand case. The products produced by the 3D printer in proactive policy incur holding costs, while the products produced by the 3D printer in reactive policy do not incur any holding costs.

In this study, the performances of reactive and proactive policy scenarios are compared, not only with each other but also with a scenario assuming the absence of a 3D printer in the system. It is reminded that in RQ1, we aim to explore which policy – i.e. reactive or proactive – works well/better in a network utilising a 3D printer. In RQ2, we explore which input factors (e.g., unit cost and time parameters related) significantly affect the network's performance. In the following section, we give the details of the statistical approach, ANOVA, that we implement for *RQ2*.

3.2 Parameterisation of proposed network policies

In this work, we also aim to find out which input factors significantly affect the performance of three separate network policies (i.e., reactive, proactive and no-3D printer case). By that, we aim to understand under what supply network structure (i.e., in terms of unit costs and times), it is more beneficial to utilise a 3D printer. The experimental design factors and their levels are given in Table 1.

Table 1: Experimental design factors and their levels.

Factors	Levels
3D printing unit cost ($/product)	5, 10
Unit holding cost ($/product-day)	1, 2
3D printing time (hour)	UNIF (0.5, 1.5), UNIF (1, 5)
Lead time for 3D printed products (day)	0, UNIF(2, 3)
Maximum response time, MRT, (day)	3.5, 4
Daily demand amount distribution	Lognormal (35, 20), Lognormal (70, 40)

According to Table 1, we consider six factors, each of which has two levels: low and high. We combine each factor level and simulate each of those combinations to observe their results. As a result, a total of $2^6 = 64$ experiments are completed separately for reactive and proactive policies. Besides, we also applied an experimental study for the network design where there is a no-3D printer in the system. In that system, we did not consider the 3D printing design factors in Table 1. We have completed a total of $2^3 = 8$ experiments. Consequently, 64 (for reactive policy) + 64 (for proactive policy) + 8 (for no-3D printing case) = 136 system designs are experimented and optimized. Note that, in this work, we aim to soptimise the total network costs under those 136 experiments for their (s, S) decision variables.

Each design factor considered in Table 1 is explained with their considered levels below:

***3D printing unit cost*:** This factor considers the cost of a single product produced by the 3D printer. By considering the ordering cost per item as $1 from Supplier 2, we set the levels for this input factor at 5 and 10 times the ordering cost value, which is $5/item and $10/item, respectively. Here, we aim to investigate how 3D printing unit cost affects reactive and proactive policies separately.

***Holding unit cost*:** Holding cost takes place due to carrying products on hand in a time interval. Supplier 1 carries inventory to respond to customer demand shortly. After replenishment takes place, the arriving products to Supplier 1 are counted as inventory incurring holding costs. The holding cost is also incurred in the proactive policy when a 3D printer produces the products in advance of the supply need. The daily holding cost of a product on hand is the same as the ordering cost per item, $1/item for the low-level design and $2 per item for the high-level scenario in the experimental design.

***3D printing time*:** 3D printing time is the time required to produce an item by a 3D printer. Since we have a response time constraint in the optimisation process, 3D printing time might significantly affect the system performance, so this factor has been included in the experimental analysis. Note that the average lead time distribution from Supplier 1 to the demand point takes 2.5 days (See Figure 2). Besides, we consider the maximum response time MRT between 3.5 and 4 days to set the two levels for the 3D printing times such that it would be feasible to utilise 3D printers under those MRT scenarios. Hence, we have set the 3D printing time values based on two distributions: UNIF (0.5, 1.5), and UNIF (1, 5) hours.

***Lead time for 3D printed products*:** Note that lead time distribution from Supplier 1 to the demand point follows a UNIFORM distribution with parameters: UNIF(2, 3) days (see Figure 2). Namely, on average, it takes 2.5 days to deliver a product to the demand point. Therefore, by assuming that the 3D printer is established at the Supplier 1 location, we consider the same lead time for 3D printed products as Supplier 1's for delivery of customers, in the high level of this factor. However, in the low level of this factor, we assume that the 3D printer is located at the periphery of the demand point so that the lead time for the 3D produced products is ignored (e.g. near zero). By those two levels, we also aim to decide where to locate the 3D printer centre: at the supplier's location or a separate location closer to the customer point.

Maximum response time**:** Maximum response time is the maximum time limit that the organisation targets to deliver the demanded products to customer points. Not only is the cost performance metric important for a supply network performance, but also responsiveness is another significant performance metric in the supply network performance. With the recent competitive supply chain targets, companies tend to increase their responsiveness. There is a trade-off between these two performance metrics: cost and responsiveness. When responsiveness (i.e. delivery time) decreases, network cost increases too. To deal with this multi-objective optimisation problem, we applied the responsiveness objective function as a constraint in the problem. Note that from Figure 2, we understand that the maximum lead time for product delivery from Supplier 1 is 3 days from the UNIF (2, 3) days distribution. Then, the minimum MRT could be 3 days according to that distribution assumption. To be able to implement the reactive policy effectively, which applies 3D printing of products in response to unmet demand cases, we consider higher, although nearby, values compared to MRT. Therefore, in the experimental design application, we have set the experimental values as 3.5 days and 4 days for this factor.

Daily demand amount distribution**:** In the supply network system, demand is assumed to arrive at the end of each day. By assuming a small to medium size company in this system, demand amounts are assumed to be random, and they follow a lognormal distribution with these parameters: Lognormal (35, 20), Lognormal (70, 40). It should be noted that the lognormal distribution that is skewed to the right might fit well for demand distributions due to not creating negative random variates and its ability to create highly variable data (Gholami and Mirzazadeh, 2018).

3.3 Data analysis

3.3.1 Simulation Network Model

We have run simulation optimisation for various experimented combinations. ARENA 16.0, a commercial software developed by Rockwell Automation, has been employed to simulate the shypothesised design structures appearing in Table 1 (Kelton, 2002).

A simulation optimisation process is applied to find out the optimal cost for the decision variables of (*s*, *S*) values with respect to the policies assumed. The appropriate (*s*, *S*) levels are determined by the OptQuest soptimiser provided in the ARENA 16.0 (OptTek Systems Inc., 2021). The simulation model assumptions are ssummarised below (see Figure 2):

- A continuous (*s, S*) inventory control policy is applied to the inventory review policy.
- The mean inter-arrival time for demand is constant and one day. The mean amount of demand follows a lognormal distribution with mean and standard deviation as (35, 20) and (70, 40), depending on the experimental scenario.
- The capacity of a truck carrying products from Supplier 2 to Supplier 1 and the capacity of mini transporter carrying products from Supplier 1 to the demand point is assumed to be 75 and 40 units, respectively.
- Lead time from Supplier 2 to Supplier 1 follows a UNIFORM distribution with parameters (5, 10) days.
- Lead time from Supplier 1 to the demand point follows a UNIFORM distribution with parameters (2, 3) days.
- The investment cost of a 3D printer is assumed to be $50/printer.
- Truck fixed cost is assumed to be $100/truck.
- The ordering cost is assumed to be $1/item.

- Holding cost is assumed to be \$1/item and \$2/item depending on the scenario.
- 3D printing cost is assumed to be \$5/item and \$10/item depending on the scenario.
- Total network cost is computed by considering holding, ordering, 3D printing, fixed truck and investment cost on 3D printer costs.
- It is aimed to achieve at least a 95% fill rate level in the optimisation process.

The simulation model is set to run for one year. The length of the warm-up period is determined by the eyeball approach, which in this case is one month. Ten independent replications are performed in the simulation experiments which are determined by the desired half-width values of the random outputs of the experiments. In an effort to decrease variance between replications, a common random variance reduction technique is utilised while running the simulations. In an effort to decrease variance between replications, a common random variance reduction technique is utilised while running the simulations. That variance reduction technique is used in the simulation model when we compare two or more alternative configurations. The same random number stream is used for all other configurations in that approach. Thus, the variance reduction is ensured. The simulation models are verified and validated by debugging the codes and animating the system.

The simulation pseudo-codes are shown in Figures 3-6. Firstly, in Figure 3, the pseudo-codes for the procedure of meeting demand in Supplier 1 are provided. Figure 4 shows the codes for how the 3D printing procedure works in a reactive policy. In Figure 5, the pseudo-codes for the (*s*, *S*) replenishment procedure of Supplier 1 from Supplier 2 are presented. Lastly, in Figure 6, we provide the pseudo-codes for the 3D printing working procedure in the proactive policy. Depending on the considered policy (i.e., reactive, proactive, or no-3D printing), some combinations of these algorithms work in parallel. Figure 7 shows which algorithm combinations work in parallel based on the policy under consideration. For instance, in the reactive policy, algorithms 1-3 work together in parallel. In proactive policy, algorithms 1, 3 and 4 run in parallel and, in no-3D printing policy algorithms 1 and 3 runs in parallel.

```
Start
i = 1                                   //day
While i <= 360
D_i = DA                                //incoming demand at the i^th day
If D_i > 0
TD = TD + D_i
If I_t >= D_i then
      I_t = I_t - D_i
  Delay with UNIF (2, 3) days          //lead time from Supplier 1
  D_i = 0
Else
  If I_t > 0 then
     D_i = D_i - I_t
     I_t = 0
     Delay with UNIF (2, 3) day        //lead time considered from Supplier 1
  End If
End If
LS = LS + D_i
End If
i = i+ 1
End While
FL= (TD - LS) / TD
End
```

Figure 3. Algorithm 1 - Meeting demand procedure by Supplier 1.

```
Start
j = 1                                   //j^th remaining product to meet the demand
While j <= D_i                          //utilize 3D printer for the unmet demand
3DLT_ij = 3DLT                          //create random variate from 3DLT distribution
3DPT_ij = 3DPT                          //create random variate from 3DPT distribution
TPT = TPT+ 3DPT                         //total printing time by the 3D printer
If TPT < (MRT - 3DLT_ij) × 24
   Delay with 3DPT_ij hour              //printing time by 3D printer
   TPC = TPC + PC
Else
   j = BigM
End If
TPT = TPT- 3DPT
j = j + 1
End While
End
```

Figure 4. Algorithm 2 - 3D printing procedure in the reactive policy.

```
Start
If I_t <= s
  Q_t = S - I_t
  NT_t = NT_t + round down ((Q_t / 75 //Truck Capacity) + 1)
  Delay with UNIF (5, 10) day        //lead time from Supplier 2 to Supplier 1
  I_t = I_t + Q_t
End If
TOC = TOC + OC
TTC = TTC + NT_t × TrC
End
```

Figure 5. Algorithm 3 - Continuous (*s*, *S*) replenishment policy from Supplier 2.

```
If I_t <= s_p
  Q_p = S_p - I_t
  j = 1
  While  j <= Q_p
         3DPT_j = 3DPT              //create random variate from 3DPT distribution
         Delay with 3DPTj hour      //printing time by 3D printer
         j = j + 1
  End While
  Delay with 3DLT day               //lead time from 3D Printing Center to demand point
  I_t = I_t + Q_p
End If
End
```

Figure 6. Algorithm 4. 3D Printing procedure in proactive policy

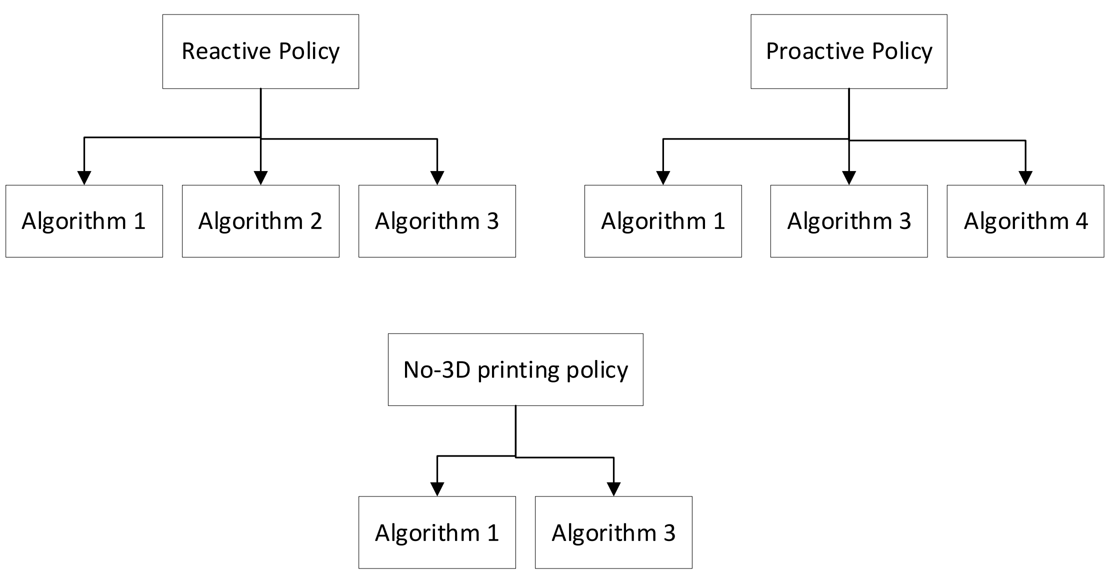

Figure 7. Algorithm combinations running in parallel based on the policies.

Time-based average inventory I_{AVG}, and yearly average inventory I_{AVGY} are calculated by (3) and (4), respectively. Here time period T is 365 days.

$$I_{AVG} = \int_0^T I_t \, dt \tag{3}$$

$$I_{AVGY} = I_{AVG} \times \mathrm{T} \tag{4}$$

(For other notations included in this subsection, please check Appendix B.)

The total holding cost during the simulation run, *THC*, is calculated by (5).

$$THC = I_{AVGY} \times HC \tag{5}$$

TOC is calculated by (6).

$$TOC = \sum_{t=1}^{T} Q_t \times OC \tag{6}$$

TPC is calculated by (7).

$$TPC = \sum_{p=1}^{T} Q_P \times PC \tag{7}$$

TTC is calculated by (8).

$$TTC = \sum_{t=1}^{T} NT_t \times TrC \tag{8}$$

Consequently, total network cost *TC* is calculated by (9).

$$TC = THC + TOC + TPC + TPIC + TTC \tag{9}$$

FL is calculated by (10).

$$FL = 1 - \frac{\sum_{t=1}^{T} LS_t}{TD} \tag{10}$$

Note that *fill rate FL* represents the ratio of products that the network can meet during the simulation run. Hence, 1 – *FL* would be the ratio of the unmet demand in the network. The details of the simulation optimisation are explained in the following section.

3.4.2 Simulation Optimisation

When dealing with the optimisation of complex systems within a stochastic environment, it is often difficult to develop a mathematical representation of the problem. In that case, heuristic solution procedures are common approaches for the solution to those problems. Genetic Algorithms (GAs), Tabu search (TA), Simulated Annealing (SA) and Scatter Search (SS) are some examples of metaheuristics in the OptQuest soptimiser tool also utilises some of them in its engine. SS is the main approach applied in OptQuest, which combines with the Tabu search strategies' powerful features and neural networks to obtain high-quality solutions (Laguna, 2011).

The usefulness of OptQuest tool in inventory optimisation has been established in several publications, including Kleijnen and Wan (2007) and Ekren et al. (2021). For the current study, three main policies, i.e. the reactive, proactive and no-3D printer utilisation ones, are modelled with ARENA 16.0 software package, and the OptQuest tool soptimiser soptimises the (s, S) decision variables for replenishment. The optimisation model is entered in the OptQuest tool according to (11)-(14).

With respect to this set of equations, the objective function is given by (11) considering the sminimisation of the total cost of the supply network. Moreover, the constraints are shown by (12)-(14). In (12), the desired *FL* is defined as at least 95% level, meaning that customer demand is guaranteed to be met at least 95% of the time. (13) shows that the reorder level should be smaller than the order up-to inventory level. Since a large customer response time would be undesirable, *MRT* is limited to 3.5 or 4 days, as defined in the experimental design table.

Minimise	TC		(11)
subject to	$FL \geq 0.95$	$FL \in R^{+}$	(12)
	$s \leq S - 1$	$(s, S) \in Z^{+}$	(13)
	$MRT \leq 3.5$ or 4	$MRT \in R^{+}$	(14)

In the OptQuest optimiser, the user is allowed to enter an initial value, lower and upper values for the range definition of the search procedure for the decision variables. The optimisation process would conclude when further improvement in the sminimisation of TC could not occur for a large period of time. Later, to obtain better results, that optimal result is utilised as the initial solution for the next run by decreasing the range of the decision variables. The details of simulation modelling are demonstrated in the Results section.

4. Results

4.1 Simulation Optimisation Outputs

The simulation optimisation results of the experiments conducted are demonstrated in Figures 8 and 9, covering low and high-demand profiles, respectively. The following subsections provide the findings according to the shypothesised policies.

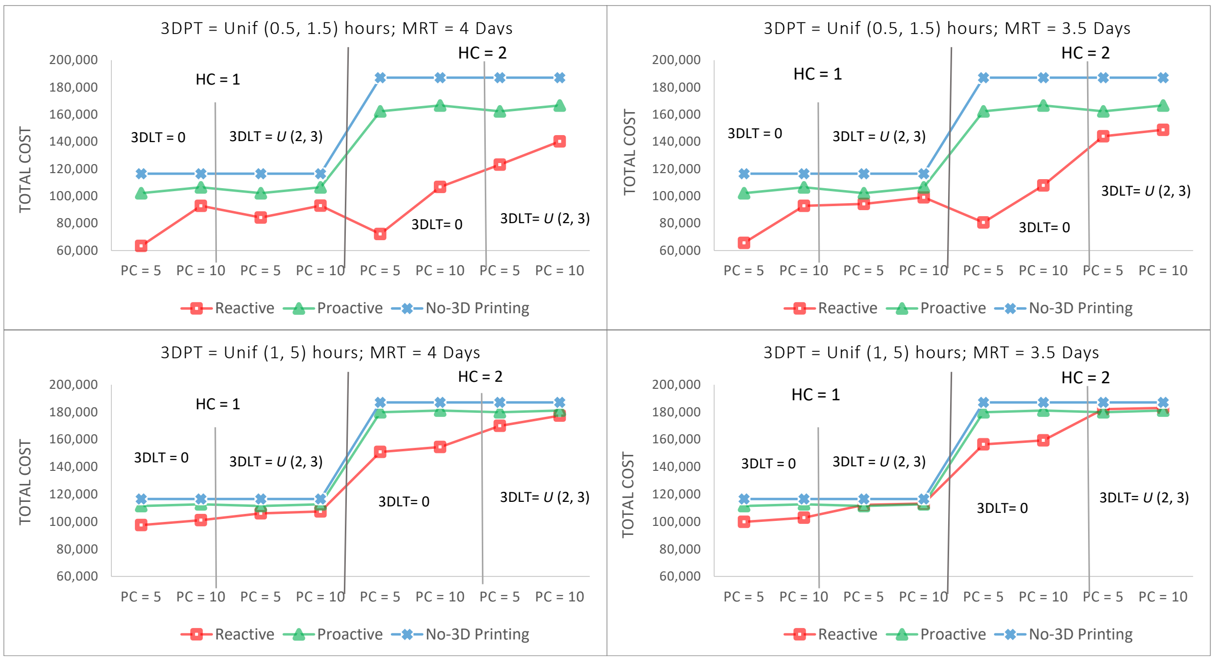

Figure 8. The experimental results when the demand distribution is Lognormal (35, 20)

4.1.1 *Discussion of the Reactive Policy scenario*

The reactive policy works better among all shypothesised scenarios, as demonstrated in Figures 7 and 8. This is probably because the reactive policy does not involve a holding cost in the network. It also contributes to a decrease in ordering costs from Supplier 2. When the demand profile increases (i.e., increased mean and variance), the reactive policy's performance (i.e., total network cost) approaches the other two policies. This means that, in a low-demand profile, utilisation of a 3D printer is better than a high-demand profile. This is probably due to the response time restriction. However, if there is a high demand, the supply chain designer may choose to increase the number of 3D printers in the network. In this case, if more than one 3D printer were assumed as part of shypothesised network system, then the system performance could improve via parallel production of multiple 3D printers. Overall, the application of 3D printing provides useful dynamic abilities for retailer businesses to act in a reactive fashion and address unexpected resource demand peaks (Newbert, 2007).

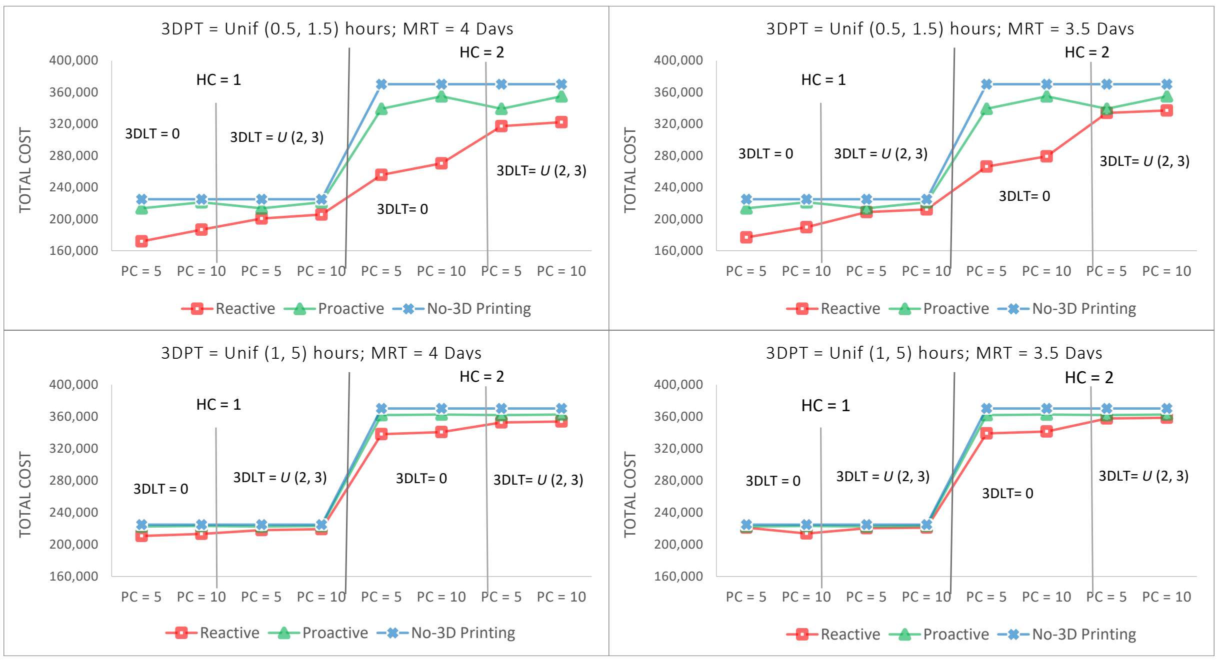

Figure 9. The experimental results when the demand distribution is Lognormal (70, 40)

Both Figures 8 and 9 suggest that when 3D printing time per product increases, the reactive policy's performance deteriorates. This is probably because of the response time constraint. Therefore, since the reactive policy cannot reach the required amount of products within the response time constraint in higher levels of 3D printing time (3DPT), the network tends to carry more inventory instead of 3D printing all units demanded. In this case, the network cost increases, and the result approaches parity with the other policies.

When the holding network costs are high, the advantage of reactive policy increases. This can be observed from both demand profile graphs, where the difference compared to the other policies increase in the reactive policy. Although 3D printing contributes to relatively costly solutions, it provides efficiency in dealing with higher levels of demand within the shorter turnaround timeframes for products to create strategic value (Popli et al., 2017). Hence, we conclude that a network structure exhibiting a high holding cost can utilise 3D printing more effectively than a network structure having a low holding cost.

In fact, both Figures 8 and 9 suggest that building a 3D printing facility at the periphery of the customer point where the lead time is near zero could be a really useful approach in supporting the reactive policy. However, this can work well when the network design has a low printing time in the 3D printing centre. This, in reactive policy, a 3D printer can produce more products within the response time constraint leading to a decreased holding cost in the network.

Consequently, the reactive policy works better compared to the other production policies under a high *FL* target (i.e., 95%), especially when demand surges under unexpected conditions such as sudden pandemic diseases (e.g. COVID-19), natural disasters, etc. Organisations may consider investing in 3D printers by implementing a reactive production policy to improve their operations' ability to provide dynamic capabilities, thus extending their current resource offerings (Eisenhardt and Martin 2000). However, to decide at what level 3DPs should be utilised in their inventory policies, then optimisation should be sought to reduce stock-outs and control resources; these could prove valuable for making an optimal decision on (s, S) levels, as well as for determining the number of 3D printers to employ as part of the supply network system.

4.1.2 Discussion of the Proactive Policy scenario

The proactive policy seems more costly than the reactive policy scenario, according to Figures 7 and 8. The main reason seems to be that proactive policy involves a holding cost in the network. Here are some additional discussion points on the optimisation outputs, as these appear in Figures 8 and 9:

- It is observed that proactive policy results do not change with the response time constraint. This is probably because the proactive policy produces products in advance and are available before demand arrives. Hence, this policy is not sensitive to the response time restriction. This result can also be observed in the ANOVA result that the MRT factor does not affect the proactive policy network cost significantly.
- Both figures 7 and 8 indicate that the proactive policy performance is not affected by the 3D printer lead time (3DLT), which can also be observed in the ANOVA results following next. This is also probably due to the same reason as mentioned above. Namely, it is due to the production in advance by the 3D printer.
- An increase in 3D printing time negatively affects the system's performance (i.e., total cost); this is not only a reactive policy characteristic but also a proactive policy one. This might be interpreted as when 3D printing time increases, the centre tends to start production earlier, resulting in increased holding costs compared to the low printing time scenario. However, note that there is also a 3D printing cost involved in implementing this option. Hence, instead of proactively producing, the system orders from the upper echelon, which is more beneficial than the holding cost and 3D printing cost involved in proactive production.
- When the demand profile increases, the proactive policy approaches no-3D printing case. Namely, proactive production tends to decrease. However, when the holding cost is high,

proactive policy still renders better results than the case where the unit holding cost is low. This is, again, probably because that proactive policy incurs holding costs when the production is completed.

According to the overall observations, the proactive policy may work better, especially under very high holding costs and tight fill rate, where response time to customer point is tight so that reactive policy cannot reach the products within the tight response time.

Note that our base comparison is the no-3D printing scenario. It is observed that when there is no 3D printer in the network, this results in the worst performance across all scenarios. However, as the results suggest, the 3D printing unit cost (PC), 3DPT, and holding cost (HC) affect the system performance significantly; hence, a decision on which policy to utilise in the network effectively depends on those parametric values. If those parametric values do not provide good network cost results, a no-3D printer scenario could also be followed instead of investing in a 3D printer. As a result, we suggest that industry practitioners would need to decide on whether or not to employ a 3D printer by conducting an optimisation analysis.

4.2 Analysis of Variance (ANOVA) for statistically significant network model factors

To better understand the role of inputs and cost performance in the network design of Figure 2, ANOVA analysis was performed via the Minitab 17.0 statistical software. We aim to identify the most statistically significant input factors affecting the system performance. Analyses have been undertaken for the reactive, proactive and no-3D printing network scenarios.

The ANOVA is a statistical technique relying on sanalysing differences among two or more means (Pallant, 2016). The ANOVA starts via developing a proper experimental design. Then, the

ANOVA is implemented to determine the influence of independent variables (i.e. input design factors) on the dependent variables (i.e. performance measure; in this case, the total cost). In this study, the ANOVA has been used separately for the reactive, proactive and no-3D printing network scenarios, investigating how the network model factors affect network cost. The ANOVA results are shown in Figures 10, 11 and 12 (and in Appendices A1, A2 and A3, in detail), for the reactive, proactive and no-3D printing policy scenarios, respectively.

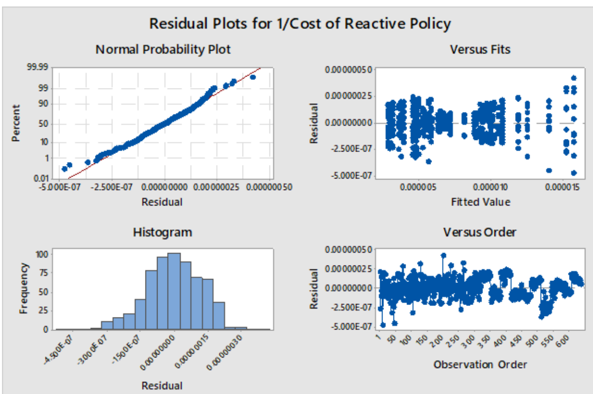

Figure 10a: Residual plots for reactive policy.

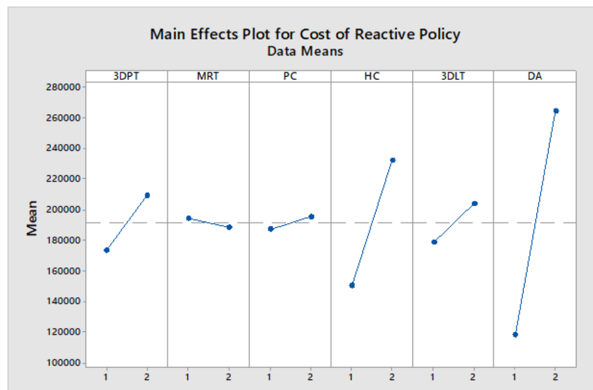

Figure 10b: Main effects plot for reactive policy.

The interpretation of the ANOVA results relies on the model adequacy, which requires that a) the ANOVA residuals should be normally distributed, b) they should have a mean of zero and c) they should have a constant variance. Suppose one of these assumptions is not met. In that case, a suitable transformation such as inverse, logarithm, natural logarithm, square root, inverse square root, etc. can be applied to the performance measures to achieve model adequacy. In the current model of reactive policy, since the ANOVA residuals requirement is not met, an inverse transformation on the total cost values has been applied. As a result, all ANOVA assumptions are met (see Figure 10a). According to the detailed ANOVA results in Appendix A1, all input factors are statistically significant for the total network cost ($p < 0.05$). Additionally, Figure 10b indicates that the most significant factors are: DA, HC, 3DPT, 3DLT, PC and MRT in descending order.

The ANOVA results for the proactive policy scenario are presented in Figure 11. Drawing on the detailed ANOVA results provided in Appendix A2, all factors are statistically significant on total network cost, except for MRT and 3DLT. Figure 11b indicates that the most significant factors affecting the proactive policy are: DA, HC, 3DPT and PC in descending order.

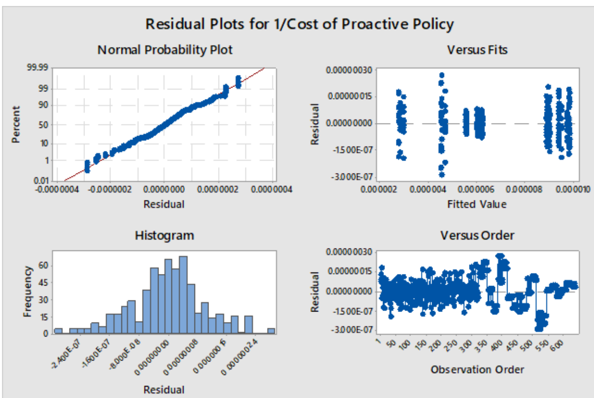

Figure 11a: Residual plots for proactive policy.

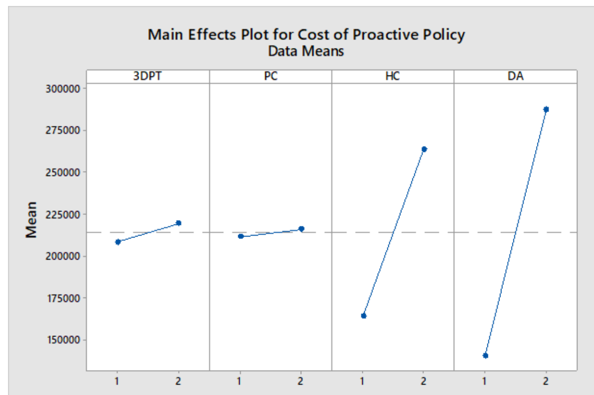

Figure 11b: Main effects plot for proactive policy.

Lastly, Figure 12 provides the ANOVA outputs for the no-3D printing policy scenario based on a 1/square root transformation. Also, from Appendix A3, it can be observed that factors HC and DA influence the network cost significantly. As expected, the MRT factor does not significantly affect the network system.

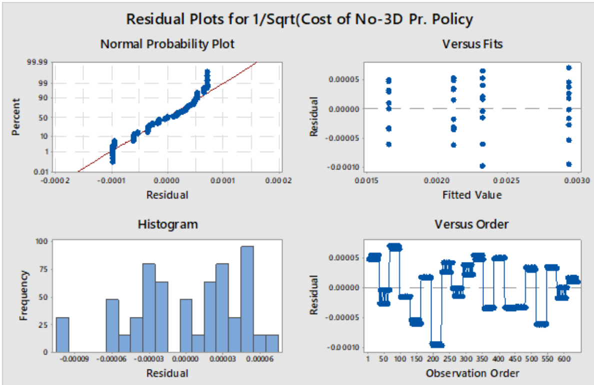

Figure 12a: Residual plots for no-3D printing policy.

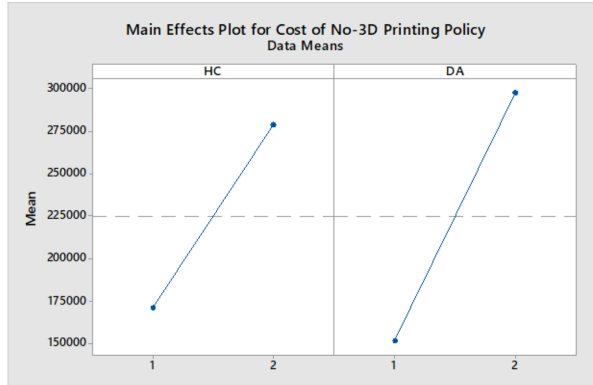

Figure 12b: Main effects plot for no-3D printing policy.

5. Conclusion

This paper studies a two-echelon supply network system within an e-commerce retailer context, and with a low demand to be served, by incorporating a 3D printer into this network system. We have investigated when, and at what amount the supply network should 3D-print products to meet customer satisfaction and decrease total network cost by implementing a simulation technique. This study examined two research questions. The first one sought to find under which production policy would it be most beneficial to utilise a 3D printer: a reactive or a proactive policy? The second research question sought to investigate the input factors (e.g., unit cost and time-related parameters) that significantly influences the proposed supply network's performance.

In regard to the first research question, we have run a simulation optimisation process for a total of 136 conducted experiments under a variety of input design factors, such as 3D printing unit cost, holding cost, 3D printing time, lead time for 3D printed products, maximum response time, and daily demand distribution. The results show that the reactive policy is more efficient in terms of the total cost spent to serve the demand, compared to proactive /no-3D printing ones. The proactive policy can be considered to perform better under very high holding costs and tight fill rate cases, and also where response time to customer constraint is tight, so the reactive policy cannot meet the products within that tight response time.

In response to the second research question, a statistical analysis applying the ANOVA was performed to identify which input factors significantly affect the system's performance. The ANOVA was implemented for the three policies (i.e. reactive, proactive and no-3D printing), and the results have shown that demand amount distribution affects all system performance significantly. Apart from the reactive policy, the factors that exert significant effects are 3DPT, 3DLT, PC and, MRT. Otherwise, for the proactive policy, these are HC, 3DPT and PC, as ordered according to the size of the effects, exerted. Accordingly, in the proactive one, MRT and 3DLT do not affect the system performance significantly.

Theoretically, the simulation of the shypothesised supply chain network contributes greatly to determinsing the influencing factors for optimizsing inventory control policy for replenishment of the supply network from an upper-echelon. The simulation experiments have indicated that depending on the 3D printing time, the maximum response time to meet the demand and the restrictions of the supply chain network, either a reactive or a proactive policy would soptimise the whole supply network. The outcomes of the simulations' can help retailers identify the best approach in dealing with complex problems and identify the best approach in dealing with complex problems and uncertainties such as COVID-19 and meet unexpected demand. Theoretically, having a 3DP implementation strategy shows how retailer industries can improve their *resource capabilities* (Grant, 1991, Salmi et al., 2020) under a reactive strategy and thus, depending on the supply issues, a viable option is to have another resource option. We have shown in the simulations different policies where this is useful, and as a result, an extension of the theory of resource-based view is shown where there is a higher cost of using 3DP under conditions of high demand with limited supply options (Hitt et al., 2016) and, there are benefits in extending this capability (Barney, 1991; Eisenhardt and Martin 2000). By sutilising 3DP, a reduction in the cost of holding or storing inventory can be anticipated because less items would need to be held, and there would be increased flexibility provided with agile responses to short-term small supply resource requirements in a proactive policy (Devin and Richards, 2018, Salmi et al., 2021). We have shown that 3DP provides a more resilient option to respond to environmental uncertainty, such as the current COVID-19 environment, and preserve organisational capital (Grant, 1991, Salmi et al., 2020). Thus, extending our understanding of when to use the capability and what financial and technological capital decisions are needed based on resource dependency to address the business performance when there are supply shocks in the supply chain, such as the COVID-19 pandemic (Bak et al., 2020; Chowdhury et al., 2021).

Implementing these policies to fit the given circumstances and parameters can significantly help retailers develop dynamic capabilities to improve their response to increase their capacity and meet timely sudden peaks of demand. Additionally, managers should consider conducting simulation experiments to respond to this dynamic type of problem – as time is a key parameter – rather than static solutions, as the latter ones may not reach realistic solutions under sudden demand fluctuations.

As with all studies, this one has certain limitations too. Since 3D printing-related (e.g., time and cost) parameters depend on what the company produces, in the experimental work, more parameter values would provide better insights into the problem. However, the ANOVA have provided robust findings on the significance tests. Besides, the number of 3D printers considered in the network (i.e., a single one) is another constraint that might be limiting the problem. Therefore, a model also involving a number of 3DPs as a decision variable in the system would be desirable work to extend the current study in the future.

In future research studies, more input factor design scenarios may be considered at various levels to build on our work. Additionally, factors such as fill rate, ordering cost, etc., could potentially be included in the sensitivity analysis. Finally, multiple 3D printers (farms) would be another option to examine how the 3D printers' capacity would influence the inventory optimisation of a given supply chain network. The development of analytical models producing important performance metrics from the system immediately depending on numerous input factor levels could be another significant work to consider in the future.

Acknowledgement

In accordance with Taylor & Francis policy and our ethical obligation as researchers, we are reporting that we do not have financial and/or business interests in, are not a consultant to and are not receiving funding from a company that may be affected by the research reported in the enclosed paper.

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Appendix A1: ANOVA results for reactive policy.

Factor Information

Factor	Type	Levels	Values
3DPT	Fixed	2	1, 2
MRT	Fixed	2	1, 2
PC	Fixed	2	1, 2
HC	Fixed	2	1, 2
3DLT	Fixed	2	1, 2
DA	Fixed	2	1, 2

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
3DPT	1	0.000000	0.000000	26519.12	0.000
MRT	1	0.000000	0.000000	835.47	0.000
PC	1	0.000000	0.000000	4977.07	0.000
HC	1	0.000000	0.000000	55922.36	0.000
3DLT	1	0.000000	0.000000	13867.06	0.000
DA	1	0.000000	0.000000	250976.46	0.000
3DPT*MRT	1	0.000000	0.000000	184.29	0.000
3DPT*PC	1	0.000000	0.000000	3680.78	0.000
3DPT*HC	1	0.000000	0.000000	343.52	0.000
3DPT*3DLT	1	0.000000	0.000000	4974.72	0.000
3DPT*DA	1	0.000000	0.000000	12386.64	0.000
MRT*PC	1	0.000000	0.000000	137.93	0.000
MRT*HC	1	0.000000	0.000000	0.30	0.583
MRT*3DLT	1	0.000000	0.000000	50.69	0.000
MRT*DA	1	0.000000	0.000000	434.33	0.000
PC*HC	1	0.000000	0.000000	68.26	0.000
PC*3DLT	1	0.000000	0.000000	2383.07	0.000
PC*DA	1	0.000000	0.000000	3608.49	0.000
HC*3DLT	1	0.000000	0.000000	409.41	0.000
HC*DA	1	0.000000	0.000000	4258.11	0.000
3DLT*DA	1	0.000000	0.000000	6021.92	0.000
3DPT*MRT*PC	1	0.000000	0.000000	97.92	0.000
3DPT*MRT*HC	1	0.000000	0.000000	11.16	0.001
3DPT*MRT*3DLT	1	0.000000	0.000000	4.94	0.027
3DPT*MRT*DA	1	0.000000	0.000000	60.67	0.000
3DPT*PC*HC	1	0.000000	0.000000	44.77	0.000
3DPT*PC*3DLT	1	0.000000	0.000000	2073.50	0.000
3DPT*PC*DA	1	0.000000	0.000000	2792.49	0.000
3DPT*HC*3DLT	1	0.000000	0.000000	459.73	0.000
3DPT*HC*DA	1	0.000000	0.000000	396.13	0.000
3DPT*3DLT*DA	1	0.000000	0.000000	1971.40	0.000
MRT*PC*HC	1	0.000000	0.000000	9.76	0.002
MRT*PC*3DLT	1	0.000000	0.000000	1.45	0.229
MRT*PC*DA	1	0.000000	0.000000	110.60	0.000
MRT*HC*3DLT	1	0.000000	0.000000	32.77	0.000
MRT*HC*DA	1	0.000000	0.000000	0.66	0.416
MRT*3DLT*DA	1	0.000000	0.000000	32.33	0.000
PC*HC*3DLT	1	0.000000	0.000000	33.74	0.000
PC*HC*DA	1	0.000000	0.000000	17.87	0.000
PC*3DLT*DA	1	0.000000	0.000000	1792.58	0.000
HC*3DLT*DA	1	0.000000	0.000000	440.40	0.000
3DPT*MRT*PC*HC	1	0.000000	0.000000	1.99	0.159
3DPT*MRT*PC*3DLT	1	0.000000	0.000000	1.69	0.195
3DPT*MRT*PC*DA	1	0.000000	0.000000	81.15	0.000
3DPT*MRT*HC*3DLT	1	0.000000	0.000000	13.73	0.000
3DPT*MRT*HC*DA	1	0.000000	0.000000	12.11	0.001
3DPT*MRT*3DLT*DA	1	0.000000	0.000000	5.22	0.023
3DPT*PC*HC*3DLT	1	0.000000	0.000000	8.89	0.003
3DPT*PC*HC*DA	1	0.000000	0.000000	14.29	0.000
3DPT*PC*3DLT*DA	1	0.000000	0.000000	1625.18	0.000
3DPT*HC*3DLT*DA	1	0.000000	0.000000	438.69	0.000
MRT*PC*HC*3DLT	1	0.000000	0.000000	2.69	0.102
MRT*PC*HC*DA	1	0.000000	0.000000	12.84	0.000
MRT*PC*3DLT*DA	1	0.000000	0.000000	0.93	0.335
MRT*HC*3DLT*DA	1	0.000000	0.000000	28.86	0.000
PC*HC*3DLT*DA	1	0.000000	0.000000	11.91	0.001
3DPT*MRT*PC*HC*3DLT	1	0.000000	0.000000	10.60	0.001
3DPT*MRT*PC*HC*DA	1	0.000000	0.000000	2.82	0.094
3DPT*MRT*PC*3DLT*DA	1	0.000000	0.000000	0.83	0.364
3DPT*MRT*HC*3DLT*DA	1	0.000000	0.000000	11.32	0.001
3DPT*PC*HC*3DLT*DA	1	0.000000	0.000000	1.46	0.228
MRT*PC*HC*3DLT*DA	1	0.000000	0.000000	2.72	0.100
3DPT*MRT*PC*HC*3DLT*DA	1	0.000000	0.000000	11.37	0.001
Error	576	0.000000	0.000000		
Total	639	0.000000			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0000001	99.86%	99.84%	99.82%

Appendix A2: ANOVA results for proactive policy.

Factor Information

Factor	Type	Levels	Values
3DPT	Fixed	2	1, 2
MRT	Fixed	2	1, 2
PC	Fixed	2	1, 2
HC	Fixed	2	1, 2
3DLT	Fixed	2	1, 2
DA	Fixed	2	1, 2

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
3DPT	1	0.000000	0.000000	1862.24	0.000
MRT	1	0.000000	0.000000	0.55	0.460
PC	1	0.000000	0.000000	217.23	0.000
HC	1	0.000000	0.000000	95914.45	0.000
3DLT	1	0.000000	0.000000	0.02	0.889
DA	1	0.000000	0.000000	212818.54	0.000
3DPT*MRT	1	0.000000	0.000000	0.32	0.569
3DPT*PC	1	0.000000	0.000000	117.11	0.000
3DPT*HC	1	0.000000	0.000000	10.70	0.001
3DPT*3DLT	1	0.000000	0.000000	0.08	0.772
3DPT*DA	1	0.000000	0.000000	854.27	0.000
MRT*PC	1	0.000000	0.000000	0.36	0.548
MRT*HC	1	0.000000	0.000000	0.49	0.483
MRT*3DLT	1	0.000000	0.000000	0.76	0.383
MRT*DA	1	0.000000	0.000000	0.55	0.460
PC*HC	1	0.000000	0.000000	12.28	0.000
PC*3DLT	1	0.000000	0.000000	0.95	0.329
PC*DA	1	0.000000	0.000000	29.55	0.000
HC*3DLT	1	0.000000	0.000000	0.00	0.955
HC*DA	1	0.000000	0.000000	10569.92	0.000
3DLT*DA	1	0.000000	0.000000	0.02	0.889
3DPT*MRT*PC	1	0.000000	0.000000	0.10	0.749
3DPT*MRT*HC	1	0.000000	0.000000	0.24	0.622
3DPT*MRT*3DLT	1	0.000000	0.000000	0.13	0.722
3DPT*MRT*DA	1	0.000000	0.000000	0.32	0.569
3DPT*PC*HC	1	0.000000	0.000000	7.67	0.006
3DPT*PC*3DLT	1	0.000000	0.000000	0.38	0.539
3DPT*PC*DA	1	0.000000	0.000000	7.43	0.007
3DPT*HC*3DLT	1	0.000000	0.000000	0.03	0.867
3DPT*HC*DA	1	0.000000	0.000000	14.85	0.000
3DPT*3DLT*DA	1	0.000000	0.000000	0.08	0.772
MRT*PC*HC	1	0.000000	0.000000	0.02	0.895
MRT*PC*3DLT	1	0.000000	0.000000	0.17	0.678
MRT*PC*DA	1	0.000000	0.000000	0.36	0.548
MRT*HC*3DLT	1	0.000000	0.000000	0.02	0.893
MRT*HC*DA	1	0.000000	0.000000	0.49	0.483
MRT*3DLT*DA	1	0.000000	0.000000	0.76	0.383
PC*HC*3DLT	1	0.000000	0.000000	0.82	0.365
PC*HC*DA	1	0.000000	0.000000	6.22	0.013
PC*3DLT*DA	1	0.000000	0.000000	0.95	0.329
HC*3DLT*DA	1	0.000000	0.000000	0.00	0.955
3DPT*MRT*PC*HC	1	0.000000	0.000000	0.53	0.466
3DPT*MRT*PC*3DLT	1	0.000000	0.000000	0.02	0.890
3DPT*MRT*PC*DA	1	0.000000	0.000000	0.10	0.749
3DPT*MRT*HC*3DLT	1	0.000000	0.000000	0.01	0.928
3DPT*MRT*HC*DA	1	0.000000	0.000000	0.24	0.622
3DPT*MRT*3DLT*DA	1	0.000000	0.000000	0.13	0.722
3DPT*PC*HC*3DLT	1	0.000000	0.000000	0.10	0.755
3DPT*PC*HC*DA	1	0.000000	0.000000	5.30	0.022
3DPT*PC*3DLT*DA	1	0.000000	0.000000	0.38	0.539
3DPT*HC*3DLT*DA	1	0.000000	0.000000	0.03	0.867
MRT*PC*HC*3DLT	1	0.000000	0.000000	0.29	0.594
MRT*PC*HC*DA	1	0.000000	0.000000	0.02	0.895
MRT*PC*3DLT*DA	1	0.000000	0.000000	0.17	0.678
MRT*HC*3DLT*DA	1	0.000000	0.000000	0.02	0.893
PC*HC*3DLT*DA	1	0.000000	0.000000	0.82	0.365
3DPT*MRT*PC*HC*3DLT	1	0.000000	0.000000	0.19	0.664
3DPT*MRT*PC*HC*DA	1	0.000000	0.000000	0.53	0.466
3DPT*MRT*PC*3DLT*DA	1	0.000000	0.000000	0.02	0.890
3DPT*MRT*HC*3DLT*DA	1	0.000000	0.000000	0.01	0.928
3DPT*PC*HC*3DLT*DA	1	0.000000	0.000000	0.10	0.755
MRT*PC*HC*3DLT*DA	1	0.000000	0.000000	0.29	0.594
3DPT*MRT*PC*HC*3DLT*DA	1	0.000000	0.000000	0.19	0.664
Error	576	0.000000	0.000000		
Total	639	0.000000			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0000001	99.82%	99.80%	99.78%

Appendix A3: ANOVA results for no-3D printing policy.

Factor Information

Factor	Type	Levels	Values
MRT	Fixed	2	1, 2
HC	Fixed	2	1, 2
DA	Fixed	2	1, 2

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
MRT	1	0.000000	0.000000	0.00	1.000
HC	1	0.000047	0.000047	24647.19	0.000
DA	1	0.000089	0.000089	46760.45	0.000
MRT*HC	1	0.000000	0.000000	0.00	1.000
MRT*DA	1	0.000000	0.000000	0.00	1.000
HC*DA	1	0.000001	0.000001	489.94	0.000
MRT*HC*DA	1	0.000000	0.000000	0.00	1.000
Error	632	0.000001	0.000000		
Total	639	0.000138			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0000436	99.13%	99.12%	99.11%

Appendix B: Memorandum of the acronyms used in the model and formulas.

3DLT	3D printed item's lead time to customer point (day).
3DPT	3D printing time (hour/product).
DA	daily demand amount distribution (Lognormal).
FL	fill rate.
HC	daily holding cost per product ($/product-day).
I_{AVG}	time-based average inventory (i.e., daily).
I_{AVGY}	yearly average inventory.
I_t	the total amount of inventory in the network at time *t*.
LS_{t}	the total amount of unmet demand (i.e., lost sales) by Supplier 1 at time *t*.
MRT	maximum response time to meet the demand of a customer (days).
NT_t	the total number of truck sent from Supplier 1 to Supplier 2 at time *t*.
OC	unit ordering cost.
PC	3D printing unit cost ($/product).
Q_P	the total amount of item produced by the 3D printer at time *p*.
Q_t	replenishment amount sent from Supplier 1 to Supplier 2 at time *t*.
s	reorder point for replenishment
S	order up to level for replenishment
s_{p}	re-production point for 3D printer
S_{p}	up to level for 3D printing
T	time period of the simulation run.
TC	total cost of the network during the simulation run.
TD	the total amount of demand arrived at Supplier 1 at the end of the simulation.
THC	total holding cost during the simulation run.

TOC	total ordering cost during the simulation run.
TPC	total cost of producing items by the 3D printer during the simulation run.
TPIC	3D printer purchasing cost.
TrC	truck fixed cost.
TTC	total truck cost during the simulation run.
U	utilisation of 3D printer.