The impact of location of 3D printers and robots on the supply chain

Shunichi Ohmori*

*Waseda University, Japan

**ABSTRACT**

3D printers and robots (3DPR) are new technologies that may disrupt traditional supply chains. The location of the manufacturing place can be moved toward more customer side in the supply chain, which brings both agility and the ability of customization. The impact is yet to be examined quantitatively. In this paper we study the location of 3DPR in the supply chain. We present and compare three models of supply chains: Traditional supply chain; 3DPR at warehouse; 3DPR at shop. The semodels are compared by the equipment installation cost, the production cost, and inventory cost for safety-stock. The study presents a practical case study motivated from a real-world apparel company, discusses the three models under various parameter settings, comparing the obtained total cost and discovers the advantages and disadvantages.

**Keywords:** 3D printing, supply chain, Safety stock placement, Multi-echelon inventory optimization

1. Introduction

Recent advancement in emerging technologies like 3D printers and robots (3DPR) opens up new opportunities in manufacturing. 3D printers (3DP) are known as additive manufacturing, rapid manufacturing or direct digital manufacturing (Khajavi et al., 2014; Holmström et al., 2010; Sasson & Johnson, 2015; Rogers et al., 2016). It is a disruptive and innovative technology that may change supply chains (Halassi et al., 2018). This technology has been rapidly applied in many industries such as the apparel industry and service parts for the electronic industry. The advantages of using 3DP from a manufacturing and supply chain point of view, has been widely discussed in the past literatures. For example, Holmström et al.’s (2014) opinions on the advantages of using 3DP have been widely cited: (1) No tooling is needed significantly reducing production ramp-up time and expense; (2) Small production batches are feasible and economical; (3) Possibility to quickly change design; (4) Allows product to be optimized for function; (5) Allows economical custom products (batch of one); (6) Possibility to reduce waste; (7) Potential for simpler supply chains; shorter lead times, lower inventories; (8) Design for customization.

| Table 1 | portion of push and pull supply chain with 3DPR |
|---------|-----------------------------------------------|
| Portion | Push | Pull |
| Unit production cost | Low | High |
| Inventory across a supply chain | Low | High |
| Outbound Leadtime | Long | Short |
| Number of stock points | More | Less |
| Number of 3DPRs | Less | More |

As with always the case with new technologies, however, it brings not only new opportunities but also new challenges for manufacturers, who will need to strategically integrate a wholly new supply chain model into their operations (Sohdi & Tang,
Especially, the location of 3DPR forms a basis for supply chain characteristics and significantly impacts the efficiency of the supply chain. Traditionally, manufacturing is made only in factories. However, 3DPR can be installed in warehouses or shops as in Fig. 1. By doing so, the push-pull boundary is forward to the customer side. This entails push-pull supply chain trade-offs as summarized in Table 1.

Traditional supply chain; 3DPR at warehouse; 3DPR at shop. These models are compared by the equipment installation cost, the production cost, and inventory cost for safety-stock. The inventory cost for safety-stock is obtained by the guaranteed-service model proposed by Graves and Willems (2000). We present a practical case study motivated from a real-world apparel company. We discuss the three models under different parameter settings, comparing the obtained total cost. By doing so, we discover the advantages and disadvantages.

Remainder of research is as follows. In section 2, we review related research. In section 3, we present the proposed modeling framework. In section 4, we present numerical experiments and managerial implications. In section 5, we make concluding remarks and future work.

2. Literature review

2.1 3D printer and robotics

There are many publications to introduce 3DPR (Eyres & Dotchev, 2010; Berman, 2012; Lipson & Kurman, 2013; Fawcett & Waller, 2014; Gao et al., 2015; Rayna et al., 2015; Rayna & Striukova 2016). These papers discuss potential benefits of 3DPR from a manufacturing perspective, such as cost-effectiveness, tooling, quality and modularity. The barriers for application are also well discussed topics. One well discussed topic is energy consumption and CO2 emission. On one hand, it reduces the excess production (Gebler et al., 2014). On the other hand, energy consumption of additive processes is higher than that of conventional bulk-forming processes (Yoon et al., 2015). Legal issues, such as data management and intellectual property protection, are also discussed topics, as it is one of the barriers for industries to apply. Rideout (2011) studied the copyright implications of 3DP. Doherty 2012 claimed that patent law was a roadblock to the 3D printing revolution.

The impact of 3DPR on supply chain strategy has been widely discussed in recent years (Holmström et al., 2014). Of many advantages of 3DPR, the capability of customization is the most discussed topic (Eyres & Dotchev 2010, Fandel et al., 2012; Wieland et al., 2012, Rayna et al., 2015, Petrick & Simpson 2013). The location of manufacturing is moved towards more customer side (D’Aveni, 2013; Mellor et al., 2014; Gebler et al., 2014; Khajavi et al., 2014). As a result, the number of intermediate suppliers is expected to be decreased (Mellor et al., 2014; Christopher & Ryals 2014). The production can
be on a made-to-order basis. Postponement or delayed differentiation are made possible and more customization can be achieved at a lower cost. The outbound lead time becomes shorter. The inventory is reduced due to the better anticipating incoming orders. These advantages discussed above are advantages of pull-based supply chain (Simchi-Levi, 2010).

Most of the above cited research discusses the opportunity and challenge to use 3DPR qualitatively. The impact is yet to be examined quantitatively. Due to the large number of factors influencing the optimal setup, however, profound quantitative analysis is required to exploit its full potential. This research makes the contribution by validating the issues addressed in the paper quantitatively. We analyzed the implications of locating 3DPR at warehouses and shops, at the tactical level of decision-making. We present a mathematical model and compare the supply chain configurations with respect to the location of 3DP under different parameter settings and discuss when, how much and why one configuration is better than each other. Considering the quantitative implications jointly, the analysis provides a valuable tool to support rational decision-making and implementation in practice.

2.2 Strategic safety stock placement

The models presented in the paper are compared by the equipment installation cost, the production cost and inventory cost for safety-stock. Among such, the equipment installation cost and the production cost can be calculated by the simple multiplication. To calculate the inventory cost, however, one needs the tactical decision on where and how much inventory in the multi-echelon supply chain, out of a large combination of alternatives. This entails the multi-echelon inventory optimization, called the strategic safety stock placement problem. In this section, we review the strategic safety stock placement problem. The strategic safety stock placement problem is a tactical model to determine the amount and positioning of safety stocks in supply chains. There has been growing opportunities to optimize supply-chains in a global manner, due to the rapid progress of information technology. One of the most attractive areas among the supply chain optimization is to minimize inventory over the entire supply chain. Many real-world supply-chains are multi-echelon systems that consist of several stages, where each stage has millions of dollars of inventory to protect the system against stock-outs. Often in practice, it is difficult for managers to manage thousands of SKUs with different demand characteristics, and thus, needs to optimize with mathematical-programming techniques has been emerging. There are two research streams, namely, the Stochastic-service (SS) model and the Guaranteed-service (GS) model. Particularly, the GS model has taken a growing interest to both academia and practice in the past two decades, as it is a simple, easily accessible model, run on personal computers. There have been extensive model expansions for the strategic safety stock placement model (See Topan et al., 2020) for the review). The original model dates back to Clark and Scarf (1960) for a serial supply chain. Graves and Willmes (2000) proposed the model for the spanning tree. Graves and Willmes (2009) proposed the GS model for non-stationary demand, Schoenmeyr & Graves (2009) consider evolving demand forecasts, Inderfurth (1993) proposed a model to incorporate stochastic lead-times, Sitompulet al., (2008), Schoenmeyr (2008) proposed capacity constraints, Li and Chen (2012) proposed a model under the continuous-review batch ordering policy. Graves and Schoenmeyr (2016) proposed a strategic safety-stock placement in supply chains with capacity constraints with inner queue.

There are many industrial applications as automotive (Moncayo-Martinez et al., 2014; Rambau & Schade 2014), computer hardware (Billington et al., 2004; Graves & Willmes 2005; Li & Womer 2008; Graves & Willmes, 2005; Neale & Willmes 2009), consumer goods (Farasyn et al., 2011, Humair et al., 2013), digital imaging (Graves & Willmes, 2000), electronic test equipment (Schoenmeyr & Graves, 2009), industrial chemicals (Bossert & Willmes, 2007; You & Grossmann, 2008; You & Grossmann, 2011; Humair et al., 2013; Ni & Shu 2015), industrial electronics (Klosterhalfen et al., 2014), machinery (Graves and Willmes 2003, Neale and Willmes 2009, Funaki 2012), metal mechanics (Moncayo-Martinez & Zhang 2013), semiconductor (Tian et al., 2011; Wiel et al., 2012).

The mathematical model presented in this paper is based on the guaranteed service model. Our paper is the application of the model in the new business context. In most of the models presented in the above cited papers the strategic safety stock placement problem is solved under a given supply network. On the other hand, we compare and discuss the advantages and disadvantages of the different supply networks under different parameter settings.

3. The proposed model

The following section describes the modeling framework based on the GS model. Section 3.1 presents a summary of the notation, section 3.2 presents the general strategic safety stock placement problem following that of Graves & Willmes (2000), section 3.3 presents the specific formulation for the traditional supply chain, the 3DPRW and the 3DPRS.

3.1 Notation

The summary of notation is presented as follows:

- \( N \): A set of stages
- \( N_a \): A set of leaf-nodes (external customers)
- \( N_m \): A set of source-nodes (external material suppliers)
A supply chain is modeled as a spanning-tree network of stages, where each stage represents a necessary function, such as procurement, assembly, or transportation. Let $N$ denote a set of stages and $N_d$ denote a set of leaf-nodes (external customers) and $N_s$ denote a set of source-nodes (external suppliers). Let $A$ denote a set of arcs. Each stage operates according to a periodic review policy with a common review period.
Demand Process

Let \( \phi_{ij} \) denote the number of units of the upstream component \( j \) required per downstream unit \( i \), \( \mu_i \) denote the average demand for stage \( i \), \( d_{it} \) denote demand for stage \( i \) at period \( t \). The demand at upstream stage \( j \) in period \( t \) and the average demand at stage \( j \) is:

\[
\begin{align*}
\phi_{ij} &= \sum_{j \in A} \phi_{ij} d_{it}, \\
\mu_j &= \sum_{i \in A} \Phi_{ij} \mu_i.
\end{align*}
\]

The key assumption of the GS model is that demand is bounded to make the service-time guarantee. The demand at stage \( i \) for \( \tau \) periods is bounded by \( D_i(\tau) \) as

\[
D_i(\tau) = d_i + \cdots + d_i(T_{t-\tau-1}).
\]

\( D_i(t) \) is assumed as increasing and concave function with \( D_i(0) \). If the demand follows the normal distribution, i.e. \( d_{it} \sim \mathcal{N}(\mu_i, \sigma_i^2) \), \( D_i(\tau) \) can be defined as

\[
D_i(\tau) = \tau \mu_i + \kappa \sigma_i \sqrt{\tau}.
\]

Guaranteed Service Time

In the GS model, each stage \( i \) can quote a guaranteed-service time \( s_i^{\text{out}} \) that it can always satisfy to its customer stages. Demand order \( d_i \) must be filled by time \( t \) + \( s_i^{\text{out}} \). Each stage \( i \) must hold sufficient inventory so that it can always satisfy the 100% service-time commitment. Such a commitment can be accomplished with a finite stock of inventory due to the bounded demand assumption.

Periodic-Review Base-Stock Replenishment Policy

Each stage operates according to a periodic review policy with a common review period. The order policy at each stage is base-stock policy. Each stage \( i \) has a base-stock level \( B_i \). Each stage \( i \) observes demand \( d_{it} \) at period \( t \) and places a replenishment order \( u_{it} = d_{it} \). This can be interpreted as a special case of \( (s, S) \) policy as \( (B_i, B_i) \).

Inventory dynamics of stage \( i \) under base-stock policy is written as in Eq. (1).

\[
I_{it} = l_{ik(t-1)} - d_i(t - s_i^{\text{out}}) + u_i(t - s_i^{\text{in}} - p_i) = I_{i0} - \sum_{k=s_i^{\text{in}}}^{s_i^{\text{out}}} d_i(t-k)
\]

where \( I_{it} \) denotes inventory level at stage \( i \) at period \( t \), \( u_{it} \) denotes order quantity at stage \( i \) at period \( t \) (\( u_{it} = d_{it} \)), \( s_i^{\text{in}} \) denotes in-bound service time at stage \( i \), \( p_i \) denotes processing time at stage \( i \).

The dynamics Eq. (1) can be rewritten in the following form as in Eq. (2),

\[
I_{it} = B_i - d_i(t - s_i^{\text{in}} - p_i, t - s_i^{\text{out}}),
\]

where \( B_i = I_{i0} \) denotes base-stock level of stage \( i \) and \( d_i(T_1, T_2) \) denotes demand at stage \( i \) over the time interval \( (T_1, T_2) \) as follows:

\[
d_i(T_1, T_2) = d_i(T_1 + 1) + \cdots + d_i(T_2)
\]

The Eq. (2) can be derived from backward substitution. From the Eq. (2), the base-stock level \( B_i \) to hold \( I_{it} \geq 0 \) to provide 100% service is as in Eq. (3):

\[
B_i \geq d_i(t - s_i^{\text{in}} - p_i, t - s_i^{\text{out}})
\]

The least base-stock to satisfy the inequality (3) is as in Eq. (4):

\[
B_i = D_i(\tau) \text{ where } \tau_i = s_i^{\text{in}} + p_i - s_i^{\text{out}}
\]

Expected Inventory Level

Expected inventory level \( I_{iE} \) is given as follows in Eq. (5)
\[ E_{\{i\}}[I_{i\epsilon}] = E_{\epsilon}[B_i - d_i(t - s_{i}^{\text{in}} - p_i t - s_{i}^{\text{out}})] = E_{\epsilon}[d_i(t - s_{i}^{\text{in}} - p_i t - s_{i}^{\text{out}})] = D_i(t_i) - \mu_i t_i \tag{5} \]

For the case where demand follows normal distribution \( d_{it} \sim \mathcal{N}(\mu_{ij}, \sigma_{ij}^2) \), the problem becomes as follows in Eq. (6)

\[ E_{\{i\}}[I_{i\epsilon}] = k h_i \sigma_i \sqrt{\tau_i} \tag{6} \]

**Formulation**

Expanding the discussion above to multi-stage problem, the GS model to safety stock placement problem:

\[
\text{minimize} \quad \sum_{i=1}^{N} k h_i \sigma_i \sqrt{\tau_i} \\
\text{subject to} \quad \tau_i = s_{i}^{\text{in}} + p_i - s_{i}^{\text{out}} \quad i = 1, \ldots, n \\
\tau_i \geq 0, \quad i = 1, \ldots, n \\
\sigma_{ij}^{\text{in}} - \sigma_{ij}^{\text{out}} \geq 0, \quad \forall (i, j) \in A \\
\sigma_{ij}^{\text{out}} \leq T_i, \quad \forall i \in N_d \\
\sigma_{ij}^{\text{in}}, \sigma_{ij}^{\text{out}} \in Z^+ \\ 
\]

where \( h_i \) denotes unit-inventory holding cost rate at stage \( i \), and \( T_i \) denotes service level target for external customer \( i \in N_d \).

The decision variables are service time \( \sigma_{ij}^{\text{out}} \) and \( \sigma_{ij}^{\text{in}} \). The objective function (7a) is the expected inventory holding cost as discussed in the equation (6). The constraint (7b) is the definition of \( \tau_i \). Constraints (7c)-(7f) assure that the service times are feasible. The constraints (7e) assure that the net replenishment time of each stage is nonnegative. The constraints (7d) assure that the inbound service time at every stage is at least as large as the largest outbound service time quoted to the stage. The constraints (7e) assure that the outbound service times to the customer must be no greater than the required lead-time. The constraints (7f) assure that the service times must be nonnegative and integer.

The problem (7) is the nonlinear concave minimization problem. To solve the problem (7), typically the dynamic programming or piecewise linearization technique is applied.

**3.3 Network settings**

In this section, we present three models of supply chains: traditional supply chain, 3DPR at warehouses supply chain (3DPRW), and 3DPR at shops supply chain (3DRPS).

**Traditional supply chain**

In traditional supply chain, we assume that there is only one factory, and the factory is connected to \( n_w \) warehouses. Each warehouse is connected to \( n_s \) shops. Each stage, i.e., factory, warehouse, and shop, has inventories of \( n_p \) different types of products, each of which is represented by a node. We let \( N_F \subseteq N = \{i | i = 1, \ldots, n_p\} \) be a factory node. We let \( N_W \subseteq N = \{i | i = n_p + 1, \ldots, n_p \times (1 + n_w)\} \) denote a set of warehouse nodes. We let \( N_S \subseteq N = \{i | i = n_p \times (1 + n_w) + 1, \ldots, n_p \times (1 + n_w) + n_p \times n_w \times n_s\} \) denote a set of shop nodes. Note that \( N_s \) is equivalent to \( N_d \) described in the section 2.2. There are directed arcs all pairs between factory nodes and warehouse nodes, i.e., from \( \forall i \in N_F \) to \( \forall j \in N_W \). There are directed arcs all pairs between warehouse nodes and shop nodes, i.e., from \( \forall i \in N_W \) to \( \forall j \in N_S \). We do not consider online channel, although it is an interesting topic, and do not consider the shipment from warehouse to customers. In traditional supply chain, we assume that the product is manufactured at the factory and the factory holds product inventory. We assume that the product service time from outside suppliers is identical and we let \( s \) denote the inbound service time from outside suppliers. We assume that the outbound lead-time to customer needs to be zero. Figure 2 illustrate supply chain configurations for the traditional supply chain with \( n_p = 3, n_w = 2, n_s = 2 \). We assume that stage \( i \) in warehouse is quoted the same inbound service time \( s_{i}^{\text{in}} \) from material suppliers \( s_{i}^{\text{in}} = s_{f}^{\text{in}} \), \( \forall i \in N_F \) and stage \( i \) quotes the same guaranteed service time \( s_{i}^{\text{out}} \) to all downstream stages \( s_{i}^{\text{out}} = s_{f}^{\text{out}} \), \( \forall i \in N_F \). Similarly, we assume the same inbound service time \( s_{w}^{\text{in}} \) and the same guaranteed service time \( s_{w}^{\text{out}} \) for all stages in warehouse node, and the same inbound service time \( s_{w}^{\text{in}} \) and guaranteed service time \( s_{w}^{\text{out}} \) for all stages in warehouse node.

The problem can be reduced the following problem.

\[
\text{minimize} \quad k(n_w n_s h_s \sigma_s \sqrt{\tau_s} + n_w h_w \sigma_w \sqrt{\tau_w} + h_f \sigma_f \sqrt{\tau_f}) \\\n\text{subject to} \quad \tau_f = \sigma_{f}^{\text{in}} + p_f - \sigma_{f}^{\text{out}} \\
\tau_w = \sigma_{w}^{\text{in}} + p_w - \sigma_{w}^{\text{out}} \tag{8a} \]

(8b)
\begin{align*}
\tau_z &= s^\text{in}_z + p_z - s^\text{out}_z \\
\tau_p, \tau_w, \tau_f &\geq 0 \\
s^\text{out}_w &\leq s^\text{in}_w \\
s^\text{out}_w &\leq s^\text{in}_z \\
s^\text{out}_w &= 0 \\
s^\text{in}_w &= s^\text{in}_i
\end{align*}

We let \( h_0, h_4, h_9 \) denote the inventory holding cost for the stage in \( N_0, N_4, N_9 \) respectively. Let \( \sigma_0, \sigma_4, \sigma_9 \) denote the standard deviation of demand for the stage in \( N_0, N_4, N_9 \) respectively. Let \( p_0, p_4, p_9 \) denote the processing time for the stage in \( N_0, N_4, N_9 \) respectively. Further, for the constraint (8f)-(8g) has a single component, and thus can be reduced to \( s^\text{out}_i = s^\text{in}_i \) and \( s^\text{out}_w = s^\text{in}_w \). Substituting the constraints (8b)-(8d) the problem becomes as follows.

\[
\text{minimize } k(n_w n_3 h_3 \sigma_3 s^\text{out}_w + n_3 h_2 \sigma_2 s^\text{out}_f + s^\text{in}_f + p_0 - s^\text{out}_f + h_f \sigma_f s^\text{in}_f + p_f - s^\text{out}_f)
\]

\[
\text{subject to } s^\text{out}_i, s^\text{out}_w \geq 0
\]

The problem has only two decision variables \( s^\text{out}_i, s^\text{out}_w \) and thus can be solved easily.

The total cost is composed of three terms:

\[
C_f = C^E_f + C^P_f + C^I_f,
\]

where \( C^E_f \) is equipment installation cost, \( C^P_f \) is production cost, and \( C^I_f \) is inventory holding cost. The inventory holding cost is the objective function value of the solution of the problem (8). The production cost is calculated by \( C^P_f = c^P_f \sum_{i \in N_3} \mu_i \), where \( c^P_f \) is the unit production cost of the factory and \( \sum_{i \in N_3} \mu_i \) is the total demand.

**3DPR at warehouses supply chain**

In the 3DPRW supply chain, there is no factory node and materials are directly supplied to warehouse nodes. We assume that the product is manufactured at the warehouse after the request from shops, and each warehouse holds material inventory. We assume that inbound lead-time from outside suppliers is identical and we let \( s \) denote the inbound lead-time from outside suppliers. Fig. 3 illustrate supply chain configurations for the traditional supply chain with \( n_p = 3, n_w = 2, n_s = 2 \).

The similar discussion with the traditional supply chain case, the problem can be reduced to the following.

\[
\text{minimize } k(n_w n_3 h_3 \sigma_3 s^\text{out}_w + s^\text{in}_w + p_0)
\]

\[
\text{subject to } s^\text{out}_w \geq 0
\]

The problem has only one decision variable \( s^\text{out}_w \) and thus can be solved easily. The cost total cost is composed of the three terms

\[
C_w = C^E_w + C^P_w + C^I_w,
\]

where \( C^E_w \) is equipment installation cost, \( C^P_w \) is production cost, and \( C^I_w \) is inventory holding cost. Equipment installation cost is calculated by \( C^E_w = c^E_w \times n_w \), where \( c^E_w \) is the installation cost at warehouse. Production cost is calculated as \( C^P_w = c^P_w \sum_{i \in N_3} \mu_i \).

**3DPR at shops supply chain**

In the 3DPRS supply chain, there is no warehouse node and materials are directly supplied to shop nodes. We assume that the product is manufactured at the shops after request from customers, and each shop holds material inventory. Figure 4 illustrate supply chain configurations for the traditional supply chain with \( n_p = 3, n_w = 2, n_s = 2 \).

The similar discussion with the traditional supply chain case, the inventory cost is calculated deterministically as follows:

\[
k n_w n_3 h_3 \sigma_3 s + p_0
\]

The cost total cost is composed of the three terms
$C_s = C_s^E + C_s^P + C_s^I,$

where $C_s^E$ is equipment installation cost, $C_s^P$ is production cost, and $C_s^I$ is inventory holding cost. Equipment installation cost is calculated by $C_s^E = c_s^E \times n_w \times n_s$, where $c_s^E$ is the installation cost at each shop. Production cost is calculated as $C_s^P = c_s^P \sum_{i \in N_s} \mu_i$.

Fig. 2. An example illustrating the traditional supply chain with $n_p = 3, n_w = 2, n_s = 2$

Fig. 3. An example illustrating 3DPRW with $n_p = 3, n_w = 2, n_s = 2$

Fig. 4. An example illustrating 3DPRS with $n_p = 3, n_w = 2, n_s = 2$
4. Numerical examples

4.1 Experimental setting and datasets

Demand follows normal distribution $d_i \sim N(\mu, \sigma^2)$ with $\mu = 100$, $\sigma = 15$. We set $n_p = 30$, $n_w = 2$, $n_s = 20$. Equipment cost is $C_j^e = 100,000,000$, $C_p^e = (5,000,000 \times n_w \times \alpha) \times n_p$, $C_s^e = 5,000,000 \times n_w \times n_s$, where $\alpha \in [0,1]$ is the parameter to consider the economy of scale. In many supply chains, there will be some relative reduction in variability as demand streams are combined, which might incur lower equipment cost of 3DPRW than 3DPRS. We explicitly choose to let the parameter $\alpha$ to account for the economy of scale. In this experiment, we calculate the ratio of maximal demand as

$$
\alpha = \frac{n_p n_d \mu + k \sigma \sqrt{n_p n_s}}{n_s n_w (n_p \mu + k \sigma \sqrt{n_p})}
$$

where the numerator is the maximal total demand for 3DPRW and the denominator is the maximal total demand for 3DPRS. Unit production cost is $c_i^p = 30$, $c_p^p = 65$, $c_s^p = 70$. We consider that the price of product is $v = 100$. We assume that in the traditional supply chain, the inventory holding cost is 0.9$ at the factory, 0.95$ at warehouse, and $v$ at shops. We assume that in 3DPR at the warehouses, products are manufactured in the warehouses and the inventory holding cost is 0.5$ at warehouses and $v$ at shops. We assume that in 3DPR at the shops, products are manufactured in the shops after the purchase request, and the inventory holding cost is 0.55$ at shops.

The model described above is implemented coded in MATLAB run on the personal computer with Intel (R) Core (TM) i7-8700 CPU, 3.20GHz, 3.19GHz with 32.0GB memory.

4.2 Results

The obtained cost is summarized as in Table 2. The obtained net replenishment time is summarized as in table 3. The cost of the traditional supply chain is the lowest among three supply chains. While the inventory cost of the traditional supply chain is the highest, the equipment installation cost and the production cost are the lowest. The result indicates that the 3DPRW and 3DPRS could be expensive as the number of robots to be installed is high. Therefore, although automation is attractive in many industries, the 3DPR cannot fully bereplaced with the traditional manufacturing equipment.

The inventory cost of 3DPRS is the lowest, as the number of stock points is the smallest (one) and the inventory holding cost is also cheap. This result indicates that the 3DPRS could be an attractive option if the inventory related cost, such as the product value $v$, the standard deviation $\sigma$ and the number of products $n_p$. This will lead to the sensitivity analysis described in the section 4.3.

| Item                  | Traditional | 3DPRW       | 3DPRS       |
|-----------------------|-------------|-------------|-------------|
| Equipment installation cost | 100,000,000 | 198,909,710 | 200,000,000 |
| Production cost        | 24,000,000  | 52,000,000  | 56,000,000  |
| Inventory cost         | 55,869,407  | 14,937,206  | 39,200,000  |
| Total Cost             | 179,869,407 | 254,829,710 | 270,937,206 |

| Item                  | Traditional | 3DPRW       | 3DPRS       |
|-----------------------|-------------|-------------|-------------|
| Inventory at factory  | 11          | -           | -           |
| Inventory at warehouses| 0           | 0           | -           |
| Inventory at shops    | 3           | 5           | 3           |

4.3 Sensitivity analysis

In this section, we have conducted a sensitivity analysis, and understand which supply chain model is better under different parameter settings. We change the parameters of the product value $v$, the standard deviation $\sigma$, and the number of products $n_p$. All these parameters are relevant to the innovative-functional product segmentation. For the innovative product, $v$ and $\sigma$ are relatively high. Also, for the innovative product, we assume that the customer is willing to customize the product as they want. The result of sensitivity analysis with respect to the product value $v$ is presented in the Table 4. For $v \geq 300$, the 3DPRW is lower than the traditional supply chain, and for $v \geq 400$ the 3DPRS is lower than the traditional supply chain. The result indicates that as the value of product is the cost of 3DPRW and 3DPRS are relatively lower than the cost of the traditional supply chain. The result of sensitivity analysis with respect to the standard deviation $\sigma$ is presented in the table 5. For $v \geq 300$, the 3DPRW is lower than the traditional supply chain, and for $v \geq 400$ the 3DPRS is lower than the
traditional supply chain. The result indicates that as the value of product is the cost of 3DPRW and 3DPRS are relatively lower than the cost of the traditional supply chain. The result of sensitivity analysis with respect to the product value \( v \) is presented in the table 6. For \( v \geq 300 \), the 3DPRW is lower than the traditional supply chain, and for \( v \geq 400 \) the 3DPRS is lower than the traditional supply chain. The result indicates that as the value of product is the cost of 3DPRW and 3DPRS are relatively lower than the cost of the traditional supply chain. Finally, the values \( v, \sigma, n_p \) are changed simultaneously from smaller values to larger values. The result of sensitivity analysis is summarized as in Table 7. The results indicate that the increase of cost is smaller for the 3DPRW and 3DPRS models, whereas the cost of traditional supply chains increase sharply.

Table 4
A sensitivity analysis with respect to the product value \( v \).

| \( v \) | Traditional 3DPRW 3DPRS |
|-------|------------------------|
| 100   | 179,869,407 254,829,710 270,937,206 |
| 200   | 235,738,814 258,749,710 285,874,412 |
| 300   | 291,608,221 262,669,710 300,811,618 |
| 400   | 347,477,628 266,589,710 315,748,824 |
| 500   | 403,347,035 270,509,710 330,686,030 |

Table 5
A sensitivity analysis with respect to the standard deviation \( \sigma \).

| \( \sigma \) | Traditional 3DPRW 3DPRS |
|-----|------------------------|
| 10  | 179,869,407 254,829,710 270,937,206 |
| 20  | 235,738,814 258,749,710 285,874,412 |
| 30  | 291,608,221 262,669,710 300,811,618 |
| 40  | 347,477,628 266,589,710 315,748,824 |
| 50  | 403,347,035 270,509,710 330,686,030 |

Table 6
A sensitivity analysis with respect to the number of products \( n_p \).

| \( n_p \) | Traditional 3DPRW 3DPRS |
|-------|------------------------|
| 20    | 107,986,940 202,195,455 207,093,720 |
| 200   | 179,869,407 254,829,710 270,937,206 |
| 300   | 219,804,110 282,988,646 306,405,809 |
| 400   | 259,738,814 311,067,425 341,874,412 |
| 500   | 299,673,517 339,108,741 377,343,015 |
| 1000  | 499,347,035 479,110,522 554,686,030 |
| 3600  | 1,537,649,327 1,206,301,638 1,476,869,710 |

Table 7
A sensitivity analysis with respect to the product value \( (v, \sigma, n_p) \).

| \( (v, \sigma, n_p) \) | Traditional 3DPRW 3DPRS |
|------------------------|------------------------|
| (100, 10, 20)          | 110,386,940 209,074,943 212,693,720 |
| (200, 20, 40)          | 154,295,525 221,519,823 234,349,764 |
| (300, 30, 60)          | 265,247,999 238,834,248 273,930,456 |
| (400, 40, 80)          | 476,764,205 263,291,905 340,398,119 |
| (500, 50, 100)         | 822,367,588 297,212,685 442,715,077 |

All these results indicate that the functional product with lower product value, smaller demand uncertainty and smaller need for the customization, the traditional supply chain is still an attractive option. However, for innovative products, 3DPR could be an attractive option. Typically, as the 80%/20% rule goes, the most popular 20% of SKUs account for 80% of the volume. These items should be manufactured by the traditional supply chain as a push option. On the other hand, the remaining 80% of SKUs in the so-called “long-tail” of the curve, the 3DPR may be replaced with the traditional supply chain. Finally, for the future, as the cost of robots and the manufacturing is expected to be cheaper, the opportunity of using 3DPR becomes much higher.

5. Conclusion

Many companies are facing the challenge that customers are demanding highly customized products and services at an acceptable cost. Diverse needs and dramatic shortening of product life cycles lead to a need for an effective product variety management. The efficient design of multiple supply chains is a major challenge for many companies, given a number of factors and interactions involved. An important issue is installing 3D printers and robotics at warehouses or at shops.

In this paper, we study the location of 3DPR in the supply chain. We present and compare three models of supply chains: Traditional supply chain; 3DPR at warehouse; 3DPR at shop. These models are compared by the production cost, equipment installation cost, and inventory cost for safety-stock. The inventory cost for safety-stock is obtained by the guaranteed-service model proposed by Graves and Willems (2000). We present a practical case study motivated from a real-world
apparel company. We discuss the three models under the different parameter settings, comparing the obtained total cost. The experimental considers multiple factors which influence optimal supply chain design/configurations to use. Furthermore, the results indicate that the higher product value, higher demand variability, larger the number of products should be supplied by the 3DPR. For future works, the decision of the number of robots can be incorporated. This can be considered by the guaranteed service model with capacity constraints proposed by Graves and Schoenmeyr (2016). This model considers the inner queue at each stage, and the length of processing time can be controlled by the number of robots installed at each stage. Another related topic is the configuration of multiple supply chains, as the results indicated that the ideal supply chain is different by product types. Therefore, one-size-fits-all supply chain is no longer effective for the most of the supply chain. The postponement or the delayed differentiation can be also considered explicitly. The shipment from warehouse to customers should also be considered, as the increase of e-commerce and omnichannel retailing.

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