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# A hybrid optimisation approach to configure a supply chain for new product diffusion: a case study of multiple-sourcing strategy

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Configuring a supply chain for a new product is a challenging task due to the lack of historical demand data and the dynamic/uncertain nature of the new product diffusion process. An integrated supply chain configuration (SCC) and new product diffusion (NPD) model is developed to explicitly account for the impact of demand dynamics during a new product's diffusion on an optimal supply chain configuration. Our hybrid NPD-SCC model allows a manufacturer to source from multiple suppliers, vendors or modes for its supply chain entities. Such a multiple-sourcing approach not only helps the manufacturer to diversify its pool of suppliers and maintain bargaining power, but also builds redundancy into the supply chain to hedge against potential demand surge and supply disruption during the new product life cycle. Through a case study and a comprehensive computational study, we find that although the single-sourcing solution is able to achieve lower unit-manufacturing cost (UMC), the multiple-sourcing approach is superior to single-sourcing on the overall supply chain performance in the environment with random supply disruptions. By building-in redundancy as multiple suppliers and modes, the resultant supply chain has less chance of being disrupted and achieves higher overall profit on average. We also draw several other managerial insights closing the gap between some supply chain operations and marketing strategies.

**Keywords:** supply chain design; production planning; new product diffusion; sourcing; supplier selection; supply risks; mathematical programming



## 1. Introduction

Before launching a new product, a manufacturer must decide the timing of the product launch and the production/sales plan over time. By choosing to launch the product immediately after production begins, the manufacturer saves inventory cost without keeping any initial stock, but might later be overwhelmed by the rapid growth of demand for the new product due to marketing efforts and positive word-of-mouth. For instance, the initial demand of Apple's iPhone and Nintendo's Wii grew so rapidly that neither company was able to meet the demand after the initial launch due to their limited supply capacity (cf. Financial Times 2007, Business Week 2008).

The dynamics of customer demand during diffusion of new products are captured by the well-known Bass model (Bass 1969). Kumar and Swaminathan (2003) and Ho *et al.* (2002) extend the classical Bass model to consider production capacity of the firm. Their new production diffusion (NPD) models maximise the total net profit of a single manufacturer during the product's lifecycle. They show that with limited supply capacity, the rapid growth of customer demand during diffusion may motivate manufacturers to build-up initial inventory and delay launching the new product.

Given the expanded complexity and scope of modern supply chains, it is rare that a single firm gets involved in all stages of sourcing, manufacturing, assembly, transportation and delivery. Therefore, the impact of new product diffusion may affect not only the manufacturer alone, but also its suppliers, vendors, logistics providers, customers and other players involved in the supply chain. Examples include Apple's PowerMac G4 (New York Post 1999): without sufficient initial inventory, Motorola, as the sole supplier of G4 chips, was not able to catch up with the rapid growth of demand for the popular computer. Thus to gain sustainable competitive advantage, it is desirable to design a supply chain that adapts to the changes and dynamics in market structure (Lee 2004).

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Recent work by Amini and Li (2011) is such an attempt. They study the interactions between new product diffusion and the corresponding supply chain configuration (SCC). Due to the short lifecycle of many innovative products in today's market, the addressed SCC problem is one which considers the 'tactical' level sourcing and inventory positioning decisions as in Graves and Willems (2005). It differs from the traditional supply chain design which focuses on determining the optimal manufacturing and distribution network of a firm at the 'strategic' level (cf. Geoffrion and Graves 1974, Daskin 1995). In SCC, location and capacity of facilities are usually assumed to be fixed, whereas the focus is on choosing optimal options (modes) to realise each supply chain entity. For instance, parts and raw materials can be procured from different suppliers; goods can be shipped via different modes such as regular ground shipping or next day delivery. These available options may differ in direct cost added and lead time. SCC also considers the inbound and outbound service times of each supply chain activity to optimise the level and location of safety stock through the entire supply chain network to meet uncertain demand. Through their integrated NPD-SCC model, Amini and Li (2011) find that optimising supply chain performance from either the NPD or SCC perspective alone may not obtain optimal production/sales policy.

One assumption made by Graves and Willems (2005) and Amini and Li (2011) concerning SCC is single-sourcing, i.e. the firm selects exactly one option for each supply chain activity. While single-sourcing has certain merits of maintaining close supplier relationship, which may result in better information sharing and more focused investment in dedicated or relation-specific assets to lower cost and improve quality (Dyer *et al*. 1998), it also has several deficiencies. First, such a partnership is costly to setup and maintain, and may reduce a firm's bargaining power and ability to switch away from inefficient suppliers (Helper 1991). Second, from the supply chain risk management perspective, single-sourcing might be vulnerable to the uncertain market environment such as unexpected demand and/or supply disruption (Sheffi and Rice 2005).This is particularly relevant when we design supply chains for new products, as the demand for innovative new products can be highly uncertain due to unavailability/lack of historical data and the dynamics of the diffusion process. Even for products with more predictable demand, failure or disruption of a supplier can be destructive to the entire supply chain.

Recent examples of supply chain risks include: the 1999 earthquake in Taiwan which struck Chi-Chi Inc. and disrupted its supply of semiconductors to many PC manufacturers including Apple and Dell (Zsidisin 2001); the 2000 fire in a Royal Philips Electronics plant in Albuquerque, New Mexico, which disrupted the flow of chips to both cell-phone makers Nokia Corp. and Ericsson (Sheffi 2005); the bankruptcy of UPF-Thompson, the sole supplier of chassis frames for Land Rover in 2001, demanding an additional $60 million above the contractually agreed amount to continue delivering Land Rover's chassis requirements (Lester 2002); and the supply shortages in the United States of items such as coffee, oysters and fuel due to hurricane Katrina in 2005 (Stone 2005). The more recent catastrophic earthquake and tsunami of Japan has disrupted the global supply chains of companies in a variety of industries including automobiles, consumer electronics, agriculture, and luxury goods (New York Times 2011). We refer to Zsidisin *et al*. (2004) for a comprehensive survey on techniques to assess supply risks, and Blackhurst *et al*. (2005) and Thun and Hoenig (2010) for empirical studies on supply chain risks and disruptions.

It has been widely accepted that focusing on cost, time and quality are required but not sufficient for competitive advantages in an uncertain environment (Lee 2004). It is desirable to build a resilient supply chain by introducing redundancy and flexibility in the design of supply chains (cf. Chopra and Sodhi 2004, Sheffi and Rice 2005). This has motivated us to model the multiple-sourcing decisions when configuring supply chains for new product diffusion process.

Our current study attempts to offer a decision-support tool, enabling supply chain managers to build robust and resilient supply chains adaptable to the dynamics of demand during new products' lifetime. This is achieved by allowing multiple sourcing for each supply chain activity. In addition to the production/sales planning and inbound/outbound service time decisions as considered in Amini and Li (2011), the firm also makes sourcing decisions to optimally split demand among the available suppliers or modes. Our multiple-sourcing NPD-SCC modelling effort attempts to provide a vehicle for understanding the impact of diffusion characteristics on the optimal total net profit. The key objectives of this paper are to:

(a) introduce a hybrid optimisation model representing a supply chain configuration problem for diffusion of a new product where multi-sourcing strategy is considered;
(b) develop and implement alternative solution approaches for this problem;
(c) present and analyse a case study to validate our modelling efforts;
(d) conduct a comprehensive computational study to compare alternative solution approaches followed by parametric sensitivity analyses; and

(e) draw key managerial conclusions to assist supply chain managers in making effective supply chain configuration decisions for new product diffusion where multi-sourcing is considered.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents the multiple-sourcing NPD-SCC hybrid optimisation model. Alternative solution methods are introduced in Section 4 to evaluate the performance of our optimisation approach. A case study is provided in Section 5 to illustrate how the model can be applied for decision support in the real life setting. Section 6 presents a rigorous computational experimental study to further validate the model and gain managerial insights. Section 7 draws conclusions and discusses future research opportunities.

## 2. Related literature

Our work is related to the research literature in the areas of supply chain configuration, new product diffusion, supplier selection and supply risk management. In this section, we briefly review the existing research in these areas and discuss objectives and contributions of our current study.

Although in a general sense supply chain configuration (SCC) may cover a wide scope of supply chain network design topics (Chandra and Grabis 2007), the SCC problem addressed in this paper is rooted in the safety stock placement (inventory positioning) problem, which studies decisions regarding the placement of safety stock in supply chain networks to meet a certain service level. Earlier models on safety stock placement all assumed fixed sourcing decisions, i.e. each supply chain activity has a fixed lead time and direct cost added (cf. Simpson 1958, Inderfurth and Minner 1998, Graves and Willems 2000).

The SCC model of Graves and Willems (2005) simultaneously determines the safety stock placement and sourcing decisions. They treat the lead time and direct cost of a supply chain activity as decision variables dependent upon the supplier/mode chosen for that activity. Their model minimises not only the safety stock cost, but also the cost of goods sold (COGS) and holding cost of pipeline (work-in-process or WIP) inventory. One assumption made by the model is that the demand pattern of new products during the planning horizon is exogenously given in terms of mean and standard deviation. Thus the SCC model alone does not explicitly account for the impact of demand dynamics during new product diffusion (NPD). In addition, the study assumes single-source of supply for each supply chain activity and does not address the issue of resilience and robustness in supply chain configuration.

Kumar and Swaminathan (2003) and Ho *et al.* (2002) extend the classical Bass model to optimise joint new product diffusion and production/sales planning of a single manufacture subject to its limited supply capacity. Both models assume that the unit manufacturing cost (UMC) including the costs of materials, sourcing of parts/components and transportation is fixed. Thus they are limited in operations planning at one echelon, i.e. the production stage of the supply chain. Also, the issues relevant to multi-sourcing and multi-echelon supply chain resilience and robustness are not considered.

Amini and Li (2011) develop an integrated NPD-SCC model to make multi-echelon SCC decisions while explicitly considering demand dynamics of the NPD process through the product's lifecycle. They show the merit of merging the two, and find that neither myopic policy (i.e. selling as much as possible in each time period) nor build-up policy (i.e. delaying launch of the new product and building some initial inventory) with too many build-up periods may lead to global optima. Similar to Graves and Willems's (2005) study, a limitation of their model is the assumption of single-sourcing, which does not address the issue of robust and resilient design of supply chains.

Supplier selection has been one of the central research topics in supply chain management, as a typical industrial firm spends more than half of every sales dollar on purchased products (US Census Bureau 1985). A supplier selection methodology based on the analytical hierarchy process (AHP; Saaty 1980) was developed by Sarkis and Talluri (2002) to consider multiple strategic, operational, tangible and intangible measures in decision making. Recent studies in this area include a multi-period problem with assembly sequence using genetic algorithm (Che 2010), a hybrid data envelopment analysis (DEA) and AHP approach (Wang *et al.* 2009), and methodologies based on fuzzy methods (Sevkli 2010).

The question of whether single-sourcing or multiple-sourcing is preferable is debatable. Dyer *et al.* (1998) studied the state-of-the-art practices of arm's-length model (multiple-sourcing) and partner model (single-sourcing) in the US and Japanese auto industries. The generally perceived benefits of single-sourcing include quantity discounts due to order consolidation, reduced lead times, and logistics cost reduction as a result of small-size supplier pool (cf. Hahn *et al.* 1986 and Bozarth *et al.* 1998). However, other research shows that a goodwill trust must be achieved in order to maintain the partnership in the single-sourcing paradigm (McCutcheon and Stuart 2000); and sometimes a good level of trust is rarely attained (Elmaghraby 2000) or such effort can be too costly to justify the benefit of single-sourcing (Bhote 1987). From the risk management perspective, it is generally believed that multiple-sourcing strategies have the advantage of being robust and resilient to unexpected supply disruptions (cf. Chopra and Sodhi 2004, Sheffi and Rice 2005). Many analytical studies show that under various randomness factors, such as procurement prices (Horowitz 1986), delivery lead times (Ramasesh *et al*. 1991), and supply/demand (Agrawal and Nahmias 1997), multiple-sourcing is often preferable to single-sourcing.

There has been growing interest in studying sourcing strategies in an uncertain supply environment. Berger *et al*. (2004) proposed a decision analysis approach to find the optimal number of suppliers subject to probabilistic supply disruptions. Burke *et al*. (2007) compared single-sourcing versus multiple-sourcing strategies under potential supply disruptions in an approach that integrates product prices, supplier and inventory costs, supply capacities and historical supplier reliabilities. They found that single-sourcing is only dominant when supplier capacities are large enough relative to demand. Kull and Closs (2008) studied the optimal inventory level in a serial supply chain within the context of second-tier supply failure. Kumar *et al*. (2010) proposed a model for cost minimisation in a multi-echelon global supply chain. Ravindran *et al*. (2010) developed a multi-criteria supplier selection model while considering supply risks. Beyond cost measures, the financial impact of recovering from a disrupted single-supplier can be significant. According to *The Economist* (2006), typically a company's stock price dropped by around 8% in the first day or two after the announcement of supply disruption problems. Some more severe disruptions may result in ultimate withdrawal of business (Sheffi 2005) and disruption of supply chains in various industries at the global level (New York Times 2011). An updated survey on this line of research was provided by Jain *et al*. (2009).

To our best knowledge, sourcing strategies have never been studied in the context of supply chain configuration for new product diffusion. Thus the main objective of this paper is to develop an integrated optimisation model which allows multiple-sourcing and safety stock placement decisions in concert with the demand dynamics during the new product diffusion process throughout its life cycle. Such development is of particular interest and importance for the following reasons. First, manufactures and suppliers in the supply chain can be overwhelmed by the rapid growth of demand right after the launch of the new product, which justifies the choice of a multiple-sourcing strategy to build redundancy and resilience into the supply chain. Second, it will be interesting to understand the cost-and-benefit tradeoffs of multiple-sourcing configuration versus the single-sourcing option under potential supply disruptions. Furthermore, unlike many existing studies in this area which relies on certain assumptions about the structure of the supply chain (e.g. serial, two-tier, spanning tree, etc.), our model is built upon a very general supply chain network structure, so that the results and insights drawn in this study have fewer barriers to be generalised to the real world scenarios.

## 3. Optimisation model

We formally describe the integrated NPD and SCC problem with multiple-sourcing in Section 3.1. A framework based on project scheduling network is presented in Section 3.2 to model the multiple-sourcing decisions. Section 3.3 presents the mathematical formulation for the addressed problem.

### 3.1 *Problem description*

Let a new product's supply chain be described by a directed acyclic activity-on-node (AON) network $G(V, E)$, where $V$ denotes a set of supply chain *entities* such as a component, part or a function (e.g. manufacturing, assembly, transporting, etc.) in the product's bill-of-materials (BOM), and $E$ consists of a set of arcs representing both demand- and time-dependency. An arc $(i, j) \in E$ has a weight of $\rho_{ij}$ specifying the units of $i$ required by one unit of $j$, i.e. the demand-dependency.

Figure 1 shows three examples of supply chains for different products and combinations of entities. The beverage supply chain in (a) consists of several production and logistics processes (Wagner and Meyr 2005). Its network structure is divergent, which is typical in distribution networks (Minner 1997).The flat rack supply chain in (b) is a simplified version from Li and Womer (2010), and consists of parts/components for manufacturing a flat rack. It is convergent as in a typical assembly environment (Minner 1997). The laptop supply chain in (c) is adapted from Graves and Willems (2005), which consists of a mixture of parts/components and functions. Note that neither (b) nor (c) assumes a spanning tree structure as in Graves and Willems (2005): our model studies supply chains with more general structures.

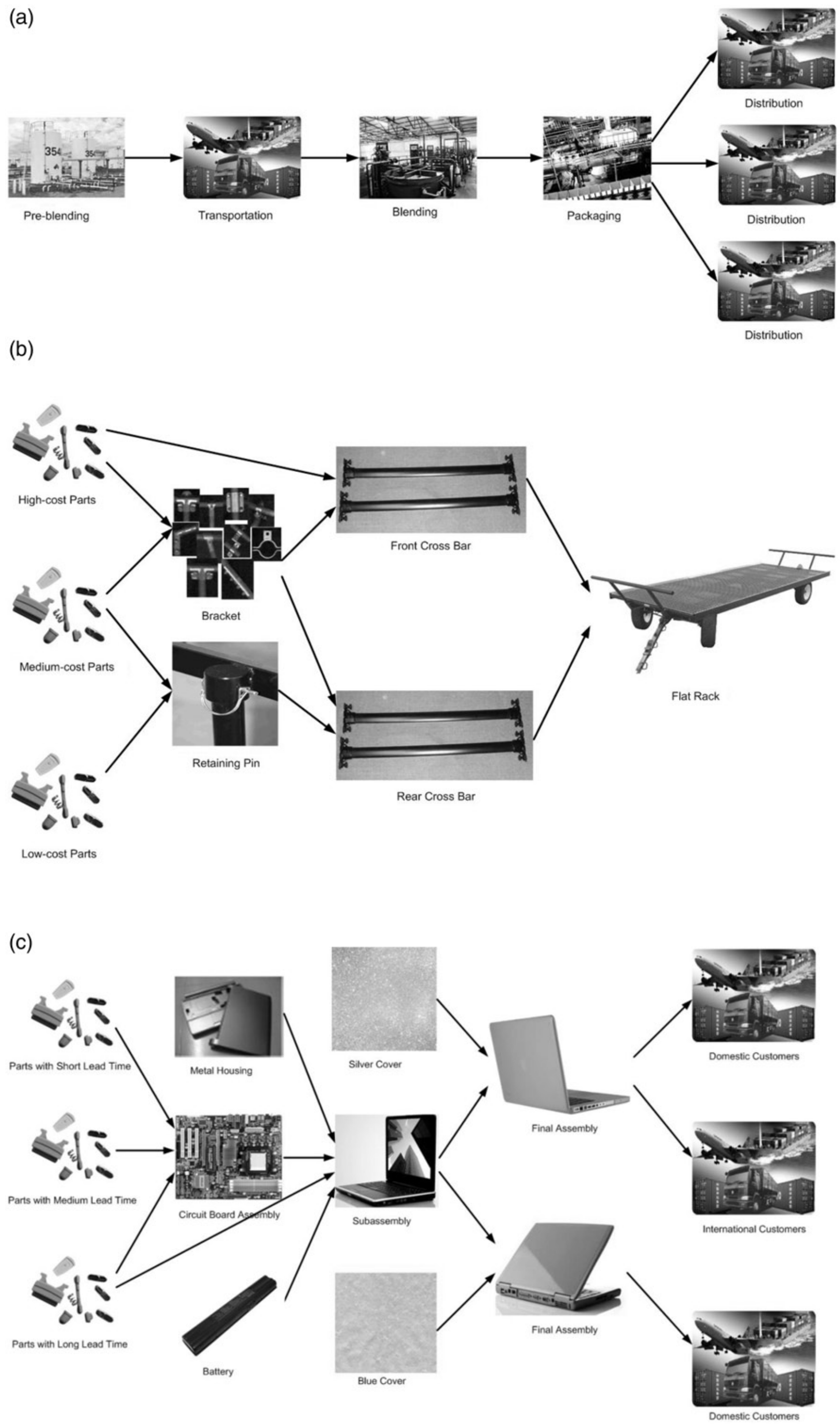


Figure 1. Three examples of supply chains with different combinations of entities. (a) A beverage supply chain. (b) A flat rack supply chain, and (c) a laptop supply chain.

Given the external demand $\mu_{|V|}$ of the finished product $|V|$ (the last node in the AON network), the dependent demand of other entities can be calculated using the following formula as in a standard BOM procedure:

$$\mu_i = \sum_{(i,j)\in E} \rho_{ij}\mu_j \tag{1}$$

The time-dependency follows the guaranteed service time assumption of Graves and Willems (2005), such that for $(i, j) \in E$ the inbound service time $s_j^{\text{in}}$ of $j$ must be no less than the outbound service time $s_j^{\text{out}}$ of $i$. For instance, the inbound service time of packaging in Figure 1 (a) must be greater than or equal to the outbound service time of blending.

Using fundamental inventory calculation, the safety stock held at entity $i$ to achieve a certain service level is $k\sigma_i\sqrt{\tau_i}$, where $\sigma_i$ is the entity $i$'s standard deviation, $\kappa$ is the $z$-value associated with the service level. $\tau_i$ is the net replenishment time of $i$, which can be calculated as in Graves and Willems (2005):

$$\tau_i = s_i^{\text{in}} + p_i - s_i^{\text{out}}, \tag{2}$$

where $p_i$ is the lead time of entity $i$, and dependent upon the option(s) selected for $i$.

Each entity $i \in V$ has a set $O_i$ of options available to choose from. Each option $k$ of $i$ differs in lead time $P_{ik}$ and the directed cost added $C_{ik}$ reflecting the time-cost tradeoff. When multiple options are selected, entity $i$'s demand $\mu_i$ must be allocated among selected options (suppliers, vendors, or modes). We make the following two assumptions regarding option selection:

(1) $P_{ik}$ is a constant and does not depend on the demand allocated for option $k$. In a global supply chain setting, quantity is often not the only factor affecting lead time. For instance, sourcing abroad may incur longer lead time anyway, no matter how much the quantity is.
(2) $C_{ik}$ is a constant and does not depend on the demand allocated for option $k$. That is, we do not consider quantity discount.

While Graves and Willems (2005) assume that the demand pattern is characterised by mean $\mu_{|V|}$ and standard deviation $\sigma_{|V|}$ as constants, we treat demand as being endogenously determined by the diffusion process. Following Amini and Li (2011), we let $d_t$ and $D_t$ denote the instantaneous and cumulative demand at time $t$, respectively. The firm's cumulative sales up to $t$ is $Y_t$. Then the demand process can be described by the following modified Bass model:

$$d_t = p(m - D_t) + \frac{q}{m} Y_t(m - D_t), \tag{3}$$

Where $p$ stands for the coefficient of innovation and $q$ represents the coefficient of imitation. The firm faces a fixed market potential $m$. We refer to Kumar and Swaminathan (2003) for detailed expositions on (3). The demand pattern $\mu_{|V|}$ and $\sigma_{|V|}$ can then be derived from the dynamics of $Y_t$.

### 3.2 *Modelling multiple-sourcing*

Supply chain entities can be realised from multiple sources, which will interact with each other in terms of demand, time and cost. Here we use a project scheduling based approach to model multiple-sourcing. The key idea is to treat each available source as a sub-activity associated with a supply chain entity, then the interactions among inbound and outbound service times can be modelled as the time-dependencies in project scheduling (Li and Womer 2008).

The Gantt chart in Figure 2 depicts such a project scheduling based modelling framework for two adjacent supply chain entities with Entity-1 being a predecessor of Entity-2. Each horizontal bar represents a source for

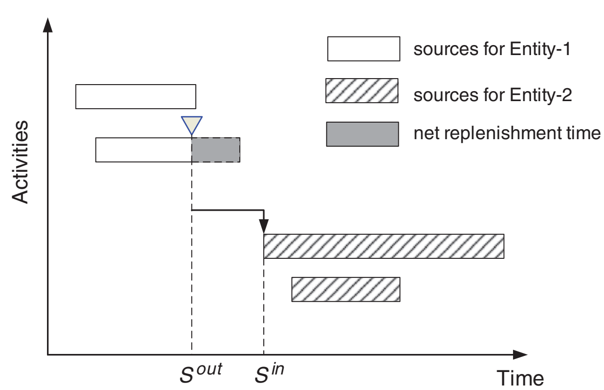


Figure 2. Framework for modelling multiple-sourcing decisions.

an entity, which has its own inbound service time $S^{\text{in}}$ (start of a horizontal bar), lead time (length of a bar) and outbound service time $S^{\text{out}}$ (the point as indicated by the little inverse triangle). Then the time dependencies between Entity-1 and Entity-2 must hold for all their sub-activities. For instance, $S^{\text{in}}$ of one source for Entity-2 must be greater than or equal to $S^{\text{out}}$ of one source for Entity-1. Such a precedence relationship is indicated by the solid arrow (only one such relationship is indicated to keep the graph easy to read). Modelling multiple-sourcing in this way enables us to simply define $S^{\text{in}}$ and $S^{\text{out}}$ for each available source, which are subject to the time dependency constraints.

While the cumulative cost of a supply chain entity is straightforward to obtain in the single-sourcing case, one must consider the effect of demand split among sources in the multiple-sourcing case. For this purpose, we define the weighted cumulative cost of an entity as the weighted average of the cumulative costs from different sources, with weights being the percentage of demand allocated to the corresponding sources. That is, the weighted cumulative cost $\bar{c}_i$ of entity $i$ can be calculated as:

$$\bar{c}_i = \sum_{k=1}^{O_i} \bar{c}_{ik} x_{ik}, \tag{4}$$

where $\bar{c}_{ik}$ refers to the cumulative cost if $i$ is sourced from $k$, and $x_{ik}$ is the decision variable determining the percentage of demand for $i$ allocated to source $k$.

### 3.3 *Mathematical formulation*

We now present a mixed-integer nonlinear programming (MINLP) formulation for the addressed problem.

*Model parameters*

| | |
|---|---|
| $m$ | Initial size of potential adopter population of product. |
| $T$ | Number of time periods of the planning horizon. |
| $V$ | Set of entities in the supply chain. |
| $N$ | Number of entities in the supply chain ($N = \lvert V \rvert$). |
| $E$ | Set of arcs in the supply chain. |
| $\xi$ | Fraction of unmet demand that is backlogged. |
| $p, q$ | Coefficients of innovation and imitation. |
| $K$ | Production capacity per time period. |
| $\pi$ | Selling price ratio. |
| $w$ | Waiting cost rate per unit backlogged per unit time. |
| $h$ | Inventory holding cost rate per time period. |
| $O_i$ | Number of candidate options for entity $i$. |
| $P_{ik}$ | Lead time of the $k$th option for entity $i$. |
| $C_{ik}$ | Direct cost added of the $k$th option for entity $i$. |
| $\kappa$ | The $z$-value determined by user-specified service level. |
| $\tau$ | Customer-specified maximum outbound service time of end products. |
| $\delta$ | Maximum percentage of demand allocated to a supplier. |

Parameter $\delta$ is the one that enforces multiple-sourcing strategies. Although a supplier may be able to provide 100% demand of a part or component, the firm might want to impose an upper-bound on the percentage of demand allocated to one supplier for a variety of reasons, e.g. to maintain and enhance its bargaining power, to build in redundancy and resilience for the supply chain, etc. as discussed in Section 1. For discussions and justifications on other parameters we refer to Amini and Li (2011).

*Decision variables related to the supply chain configuration*

| | |
|---|---|
| $x_{ik} \geq 0$ | percentage of demand of entity $i$ allocated to source $k$. |
| $S_{ik}^{\text{in}} \geq 0$ | and integerinbound service time of entity $i$ sourced from $k$, i.e. the time to receive all inputs from its suppliers. |
| $S_{ik}^{\text{out}} \geq 0$ | and integeroutbound service time of entity $i$ sourced from $k$, i.e. the time by which $i$ will satisfy its demand. |

$\bar{c}_{ik}$ cumulative cost for entity $i$ sourced from $k$.
$\bar{c}_i$ (weighted) cumulative cost for entity $i$.

The continuous variable $x_{ik}$ enables demand allocation among multiple-sources. Both inbound and outbound service times are defined for each available source. $\bar{c}_i$ takes account for the effect of demand split when calculating the cumulative cost of an entity.

*Decision variables related to product diffusion*

$y_t \geq 0$ sales of product at time $t$.
$Y_t \geq 0$ cumulative sales of product at time $t$.
$d_t \geq 0$ demand at time $t$.
$D_t \geq 0$ cumulative demand of product at time $t$.
$L_t \geq 0$ cumulative number of backlogged orders at time $t$.
$I_t \geq 0$ inventory at time $t$.
$r_t \geq 0$ production at time $t$.
$R_t \geq 0$ cumulative production at time $t$.

*Decision variables connecting supply chain configuration and product diffusion*

$\mu_N$ mean supply of the end product (entity $N$) over the diffusion horizon.
$\sigma_N$ standard deviation of supply of the end product over the diffusion horizon.

*Objective function*

The objective is to maximise the life cycle net profit, which is the difference between the total life cycle revenue and total supply chain costs:

$$\text{Life cycle net profit} = \text{Total life cycle revenue} - \text{Total supply chain costs} \tag{5}$$

The total life cycle revenue is calculated in a similar way as in Kumar and Swaminathan (2003), but with the end product cumulative cost $\bar{c}_N$ being a decision variable to be determined by the corresponding supply chain configuration:

$$\text{Total life cycle revenue} = \sum_{t=0}^{T} \bar{c}_N[\pi y_t - r_t - wL_t - hI_t] \tag{6}$$

The total supply chain costs consist of both pipeline stock cost and safety stock cost:

$$\text{Total supply chain costs} = \text{Pipeline stock cost} + \text{Safety stock cost} \tag{7}$$

The pipeline stock cost and safety stock cost are calculated in a way similar to that of Graves and Willems (2005), except that our formulation adds up over all supply chain entities and available sourcing options to allow for multiple sourcing:

$$\text{Pipeline stock cost} = \sum_{i=1}^{N} \sum_{k=1}^{O_i} h\left(\bar{c}_{ik} - \frac{C_{ik}}{2}\right) P_{ik} x_{ik} \mu_i \tag{8}$$

$$\text{Safety stock cost} = \sum_{i=1}^{N} \sum_{k=1}^{O_i} h\bar{c}_{ik} \kappa \sigma_i \sqrt{s_{ik}^{\text{in}} + P_{ik} - s_{ik}^{\text{out}}} \tag{9}$$

Combining (5) to (9), the objective function can be written as:

$$\begin{aligned} \max \ & \sum_{t=0}^{T} \bar{c}_N[\pi y_t - r_t - wL_t - hI_t] - \sum_{i=1}^{N} \sum_{k=1}^{O_i} h\left(\bar{c}_{ik} - \frac{C_{ik}}{2}\right) P_{ik} x_{ik} \mu_i \\ & - \sum_{i=1}^{N} \sum_{k=1}^{O_i} h\bar{c}_{ik} \kappa \sigma_i \sqrt{s_{ik}^{\text{in}} + P_{ik} - s_{ik}^{\text{out}}} \end{aligned} \tag{10}$$

*Constraints on product diffusion*

Cumulative production calculation:

$$R_{t+1} = R_t + r_t \quad \forall t = 0, 1, \ldots, T-1 \tag{11}$$

Cumulative demand:

$$D_{t+1} = D_t + d_t \quad \forall t = 0, 1 \ldots, T-1 \tag{12}$$

Cumulative sales:

$$Y_{t+1} = Y_t + y_t \quad \forall t = 0, 1, \ldots, T-1 \tag{13}$$

Instantaneous demand calculation as in (3): the instant demand $d_t$ at time $t$ is a fraction of the remaining potential adopters $m - D_t$ consisting of two components: one due to impact of innovation coefficient $p$, and the other due to coefficient of imitation or positive word-of-mouth.

$$d_t = p(m - D_t) + \frac{q}{m} Y_t(m - D_t) \quad \forall t = 0, 1, \ldots, T \tag{14}$$

Inventory calculation: difference between cumulative production and sales.

$$I_t = R_t - Y_t \quad \forall t = 0, 1, \ldots, T \tag{15}$$

Backlogged demand: is a fraction $\xi$ of the unmet demand in the previous period.

$$L_{t+1} = \xi(L_t + d_t - y_t) \quad \forall t = 0, 1, \ldots, T \tag{16}$$

Boundary conditions: (17) to (19).

$$L_t \geq 0 \quad \text{and} \quad L_0 = 0 \tag{17}$$

$$I_t \geq 0 \quad \text{and} \quad I_0 = 0 \tag{18}$$

$$r_t \geq K \quad \text{and} \quad R_0 = 0 \tag{19}$$

*Constraints on supply chain configuration*

Demand allocation: for each supply chain entity, the total (100%) demand is allocated among all its available suppliers.

$$\sum_{k=1}^{O_i} x_{ik} = 1 \quad \forall i = 1, \ldots, N \tag{20}$$

Upper bound on allocation: the maximum percentage of demand of $i$ allocated to supplier $k$ cannot exceed $\delta$.

$$x_{ik} \leq \delta \quad \forall i = 1, \ldots, N; \quad k = 1, \ldots, O_i \tag{21}$$

Dependent demand: calculated using the demand ratio $\rho_{ij}$ in the BOM setting as in (1).

$$\mu_i = \sum_{j:(i,j)\in E} \rho_{ij}\mu_j \quad \forall i = 1, \ldots, N \tag{22}$$

Cumulative cost of an entity sourced from a supplier: calculated as the sum of direct cost added $C_{ik}$ and the cumulative cost of all the entity's predecessors.

$$\bar{c}_{ik} - \sum_{j:(j,i)\in A} \bar{c}_j - C_{ik} = 0 \quad \forall i = 1, \ldots, N; \quad k = 1, \ldots, O_i \tag{23}$$

Cumulative cost of an entity: calculated as the weighted average of cumulative cost sourced from all available suppliers as in (4).

$$\bar{c}_i = \sum_{k=1}^{O_i} \bar{c}_{ik} x_{ik} \quad \forall i = 1, \ldots, N \tag{24}$$

Guaranteed service time: the inbound service time of any source for an entity must be no less than the outbound service time of any sources for its immediate predecessors. The formulation is similar to that in Graves and Willems (2005), except that we specify such time dependency for each source of an entity to allow multiple sourcing.

$$s_{ik}^{\text{in}} \geq s_{jk'}^{\text{out}} \quad \forall i = 1, \ldots, N; \quad j : (j, i) \in E; \quad k = 1, \ldots, O_i; \;\; k' = 1, \ldots, O_j \tag{25}$$

Non-negative net replenishment time: the net replenishment time as in (2) must be non-negative. Here we again need such non-negativity constraint for each source of an entity.

$$s_{ik}^{\text{in}} + p_{ik} - s_{ik}^{\text{out}} \geq 0 \quad \forall i = 1, \ldots, N; \quad k = 1, \ldots, O_i \tag{26}$$

Upper bound on outbound service time of end product:

$$s_{Nk}^{\text{out}} \leq \tau \quad \forall k = 1, \ldots, O_N \tag{27}$$

Domain of decision variables:

$$s_{ik}^{\text{in}}, s_{ik}^{\text{out}} \geq 0 \text{ and integer } \forall i = 1, \ldots, N \tag{28}$$

$$x_{ik} \geq 0 \quad \forall i = 1, \ldots, N; \quad k = \{1, \ldots, O_i\} \tag{29}$$

*Linking constraints*

Mean of end product: calculated as the average of sales over the planning horizon $T + 1$ time periods.

$$\mu_N = \frac{Y_T}{(T+1)} \tag{30}$$

Standard deviation of end product:

$$\sigma_N = \sqrt{\frac{\sum_{t=0}^{T} (y_t - \mu_N)^2}{T}} \tag{31}$$

Constraints (30) and (31) are the key constraints connecting the SCC and NPD components of the model. Here, the demand pattern characterised by mean $\mu_N$ and standard deviation $\sigma_N$ is endogenously determined by the sales plan $y_t$ during the planning horizon, rather than being assumed to be constant in Graves and Willems (2005).

It is clear that the above MINLP is NP-hard as its objective function involves minimising a concave function (9). It is well-known that the general problem of minimising a concave function is NP-hard (Sahni 1974).

## 4. Solution approaches

Among many available MINLP algorithms (Floudas 1995), we choose the outer approximation with both equality relaxation and augmented penalty (OA/ER/AP) algorithm developed by Viswanathan and Grossmann (1990). We refer to Amini and Li (2011) for detailed justifications on choosing OA/ER/AP for this category of problems. OA/ER/AP is conveniently available in the DICOPT solver GAMS (2008). The following alternative solution approaches are developed to evaluate the performance of our multiple-sourcing hybrid model.

### 4.1 *Upper-bounding method*

An upper-bounding method is adapted from the piece-wise linear approximation approach as described in Magnanti *et al*. (2006) and Shu and Karimi (2009) to approximate the concave objective function in the safety stock placement problem. In our implementation, we use one linear piece to approximate the concave function (9). Thus the optimal solution (or upper bound) to this approximated problem provides an upper bound to the original problem.

### 4.2 *Heuristic methods*

We also consider heuristic methods to mimic the way decisions are made in practice without using our hybrid model developed in this paper. They essentially rely on a decomposition approach which considers production/sales planning for new product diffusion and supply chain configuration in a sequential fashion. This decomposition heuristic can be sketched as follows.

**Step 1:** Obtain production/sales plan for the diffusion horizon using heuristic policies;

**Step 2:** Based on the production/sales plan obtained in Step 1, use Equations (30) and (31) to calculate the demand pattern characterised by mean (30) and standard deviation (31);

**Step 3:** Solve the supply chain configuration problem minimising the total supply chain costs (10) subject to constraints (20) through (29).

The heuristic policies used in Step 1 are the myopic and build-up policies following Kumar and Swaminathan (2003). In the myopic policy, production and sales of the product begins in the first period. The build-up policy, however, incurs no sales during the initial inventory build-up periods followed by launching the new product.



## 5. A case study

In this section, a case study adapted from the work of Kilger and Schneeweiss (2005) is presented to provide better understanding of the addressed optimisation problem, and how our modelling approach can provide an effective decision-support for supply managers.

ABC Inc. has completed the design of its long-waiting new innovative PC, and is about to start producing and launching the new model in its European market. The company's Chief Operations Manager (COM) in the Logistics and Supply Division is in charge of configuring the new PC's supply chain so that it can operate efficiently to meet customer demand. Consider a multi-echelon supply chain network for the new PC as depicted in Figure 3. Although a simplified version, it captures most characteristics of a real life PC assembly supply chain. It is convergent which is typical in assembly manufacturing. Also note that the network considered here has a *general acyclic structure* (Magnanti *et al*. 2006), which includes the serial, two-tier and spanning-tree structures as special cases.

The company sources most of the parts and components from suppliers and vendors around the world. After using a supplier scoring method similar to the approach proposed by Sarkis and Talluri (2002) while taking account for a number of quantitative and qualitative factors, the managers have narrowed down three candidate options for each supply chain entity as shown in Table 1.

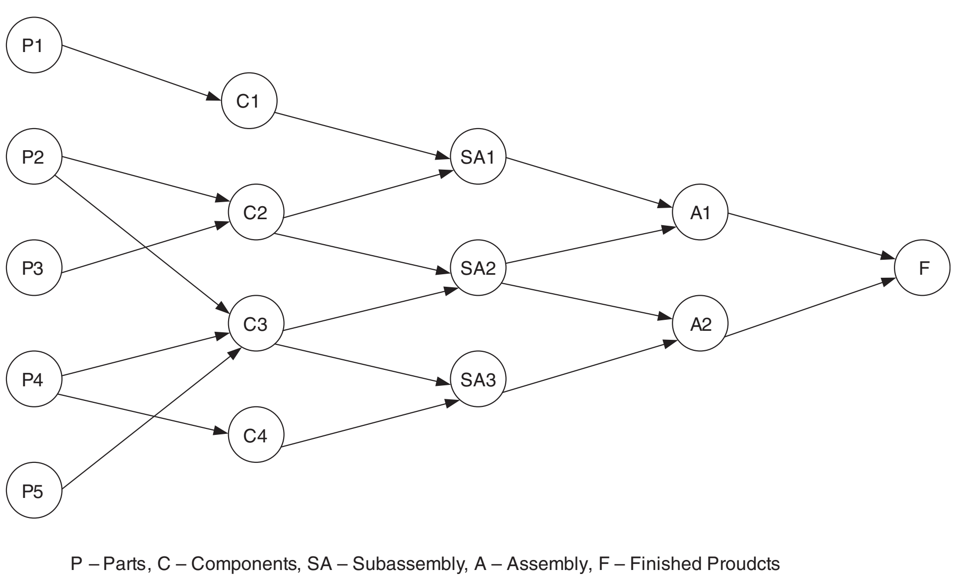


Figure 3. A multi-echelon supply chain for PC assembly.

Table 1. Candidate sourcing options for the PC supply chain.

| Entity | Mode | Lead time | Direct cost ($) | Entity | Mode | Lead time | Direct cost ($) |
|---|---|---|---|---|---|---|---|
| P1 | 1 | 40 | 120 | SA1 | 1 | 80 | 80 |
| | 2 | 20 | 125 | | 2 | 40 | 84 |
| | 3 | 10 | 128 | | 3 | 20 | 90 |
| P2 | 1 | 30 | 200 | SA2 | 1 | 60 | 40 |
| | 2 | 15 | 208 | | 2 | 30 | 45 |
| | 3 | 10 | 212 | | 3 | 15 | 52 |
| P3 | 1 | 20 | 150 | SA3 | 1 | 50 | 100 |
| | 2 | 10 | 155 | | 2 | 30 | 120 |
| | 3 | 5 | 158 | | 3 | 15 | 135 |
| P4 | 1 | 30 | 180 | A1 | 1 | 20 | 20 |
| | 2 | 20 | 185 | | 2 | 10 | 24 |
| | 3 | 10 | 190 | | 3 | 5 | 32 |
| P5 | 1 | 30 | 253 | A2 | 1 | 20 | 20 |
| | 2 | 15 | 258 | | 2 | 10 | 24 |
| | 3 | 3 | 264 | | 3 | 5 | 32 |
| C1 | 1 | 50 | 153 | F | 1 | 15 | 12 |
| | 2 | 25 | 157 | | 2 | 7 | 22 |
| | 3 | 0 | 160 | | 3 | 3 | 26 |
| C2 | 1 | 40 | 122 | | | | |
| | 2 | 20 | 125 | | | | |
| | 3 | 0 | 129 | | | | |
| C3 | 1 | 60 | 200 | | | | |
| | 2 | 30 | 220 | | | | |
| | 3 | 10 | 240 | | | | |
| C4 | 1 | 70 | 300 | | | | |
| | 2 | 50 | 320 | | | | |
| | 3 | 30 | 330 | | | | |

These options differ in direct cost added (including material, processing, handling and transportation costs) and lead time. For instance, Component C1 can be sourced from three suppliers: Supplier 1 is located in East Asia with a direct cost of $153/unit and long lead time of 50 days; Supplier 2 is located in South America with $157/unit and 25 days; Supplier 3 is located locally in the United States with the highest direct cost of $160/unit and a short delivery lead time of 0 (immediately available). The company also has three modes to ship the finished PC to its European market: container shipment by ocean with a lead time of 15 days and a direct cost (including handling and transportation costs) of $12/unit; regular air shipment with 7 days and $22/unit; and expedited air shipment with 3 days and $26/unit.

The company has two state-of-the-art assembly facilities in the United States, which are capable of doing all the sub-assembly and assembly work. For assembly operations, the company can choose from different production lines, which may differ in their efficiency (lead time) and unit operating cost (direct cost added). For instance, production lines with more advanced technologies and/or over-time labour may reduce lead time, but incur higher operating cost. COM's task is to choose option(s) for each supply chain entity. If multiple options are selected for one entity, demand needs to be properly split among them.

Another important decision COM would like to make is the location and level of safety stock in the supply chain to satisfy a certain (e.g. 95%) service level, assuming an inventory holding cost of 3% of the value of an item over the entire planning horizon. Making decisions regarding safety stock locations and levels would require an answer to the challenging question about the demand for the new PC. Such a challenge arises due to the following facts:

(i) The new PC is a highly innovative model from the design, material, and craftsmanship to configuration and performance. Historical sales data are available for similar models, but the marketing people are not sure how accurately they can predict demand for the new model.
(ii) ABC Inc.'s strategic plan is to use this flagship model to penetrate into its European market, where the company did not perform well in the past.

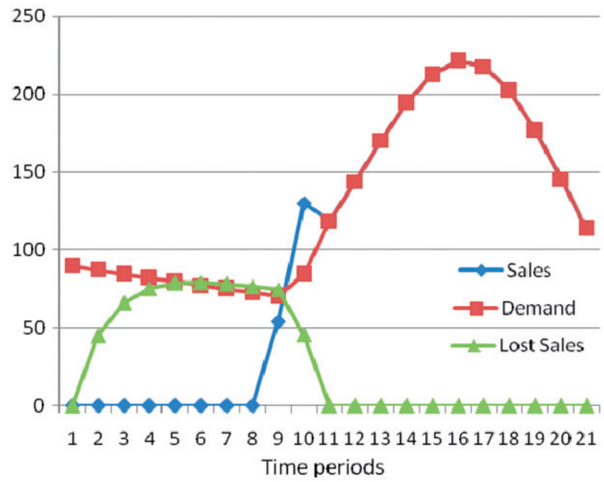


Figure 4. Sales, demand and lost sales trajectory over the planning horizon.

Table 2. Solution performance comparison with myopic and build-up policies.

| | Myopic policy ($1000) | Build-up (12) policy ($1000) | Optimisation approach ($1000) |
|---|---|---|---|
| COGS | 10,110.57 | 10,468.16 | 12,404.28 |
| Backlog cost | 27.77 | 23.96 | 16.20 |
| Finished goods inv. holding cost | 0 | 73.43 | 146.81 |
| Total net revenue | 5027.52 | 5136.69 | 6039.13 |
| Pipeline stock cost | 169.39 | 175.38 | 207.81 |
| Safety stock cost | 40.12 | 50.23 | 60.08 |
| Total net profit | 4818.01 | 4911.08 | 5771.24 |



Most of the past and existing sales data are from the company's North American and East Asian markets, which further reduces the credibility of the available data. On the other hand, without having an idea about the demand pattern such as its mean and standard deviation, there is no way for COM to estimate the safety and pipeline stock in the supply chain.

Realising the seriousness of the problem, COM communicates with the CEO of the company, who orders a corporate level meeting. The dilemma of predicting demand for the new model is presented to the Chief Marketing Analyst (CMA) associated with the company's Marketing Division. The key outcome of the corporate level meeting is to create a cross-functional team consisting of analysts from both Operations and Marketing divisions to tackle the supply chain configuration problem.

After weeks of data collection, data cleaning and statistical analysis, marketing analysts obtain estimates of two critical new product diffusion parameters, estimates for the coefficient of innovation ($p$) of 0.03, and coefficient of imitation ($q$) of 0.39. The two critical parameters reflect the dynamics of new product diffusion throughout its life cycle. They also estimate an average waiting cost rate of 0.5% and backlog rate of 50%. A conservative estimate of the unit selling price mark-up rate is 1.5. For the diffusion process, they assume a planning horizon of 30 two-week time periods, which roughly matches the length of the new model's lifecycle (about a year). The firm's production capacity per time period is 100 units.

Using the multiple-sourcing NPD-SCC model developed in this study, the research team obtains the following new product launching/sales plan and supply chain configuration solutions. As shown in Figure 4, the company delays the launch until the 9th period and builds up sufficient inventory to avoid excessive loss of customers: starting from the 11th period production and inventory will be able to satisfy the fast growing demand of the PC.

Table 2 compares the solution performance of our hybrid optimisation model with two heuristic policies as described in Section 4, i.e. the myopic policy and build-up policy with many (12) inventory build-up periods. One observes that neither heuristic policy may obtain optima. The myopic heuristic incurs the least cost of inventory in the form of pipeline stock, safety stock and finished goods, but achieves least sales perhaps due to excessive loss of demand. The build-up heuristic, on the other hand, is able to generate more total net revenue, but seems to be too conservative with many build up periods. The optimal diffusion process is obtained by the optimisation approach. Although spending highest overall total supply chain cost, it achieves almost 18% higher total net profit.

## 6. Computational experiments

The purpose of the computational study is to further show the value proposition of our modelling and solution approaches under various supply chain and new product diffusion topologies characterised by some critical problem parameters. Specifically we would like to:

(1) examine performance of the integrated model under various scenarios;

(2) understand the impact of problem parameters (such as $p$ and $q$) and sourcing strategies (single sourcing vs. multi-sourcing) on supply chain performance measured by profit and cost;
(3) compare multiple- and single-sourcing solutions under the risk of supply disruption.

To answer the aforementioned questions, we developed a computational experiment to study profitability of a firm under a large number of scenarios. We use the test bed of Amini and Li (2011) as base instances while incorporating additional parameters particularly interesting to this study, i.e. coefficient of innovation $p$, coefficient of imitation $q$, waiting cost rate $w$, percentage of backlogged demand $\xi$, and probability of supply disruption.

The value of $p$ and $q$ characterises features of the new product. According to Bass (1969), the term $q/p$ represents the propensity to buy. We hypothesise that a higher value of $q/p$, i.e. the higher propensity to buy, the higher total net profit the firm will be able to achieve. The value of $w$ and $\xi$ characterises the diffusion process. It is expected that when $w$ increases, the total net profit will drop; when $\xi$ increases, the likelihood of losing customers will decrease, which will perhaps increase the net profit. We assume that the disruption rate follows a discrete distribution with probabilities 0.01, 0.04, 0.1, 0.15, 0.70 for total disruption (100% cap down), major disruption (75% down), moderate disruption (50% down), minor disruption (25% down), and no disruption, respectively. The random parameters and their probability distributions are provided in Table 3. $U[a, b]$ represents a uniform distribution over the closed range of a and b; D{} represents a discrete probability distribution.

For each randomly generated scenario, four solution approaches are executed:

- the NPD-SCC model with multiple-sourcing,
- the NPD-SCC model with single-sourcing,
- the best-performed build-up heuristic with two build-up periods, and
- the upper-bounding method.

Due to the consideration of supply disruption in this study, some scenarios will not be feasible for any of these approaches. These infeasible scenarios are eliminated in our analysis, which leaves us with a sample of 2000 problem scenario instances.

The overall solution quality statistics for the test bed instances are shown in Table 4. Our optimal multiple-sourcing NPD-SCC solutions have an average gap of 1.27% from the upper bound, and improve about 15% over the heuristic solutions on average. Insight 1 follows.

**Insight 1:** The multiple-sourcing NPD-SCC hybrid optimisation model is able to obtain high quality solutions and significantly improve over the heuristic solutions.

Among the 2000 scenario instance problems with potential capacity disruption, 780 (38.34%) are found infeasible for the single-sourcing approach. For the instances solved by both approaches, we compare their results in Table 5. The multiple-sourcing solutions generate 3.5% higher total net profit on average. Although the single-sourcing

Table 3. Parameters controlled in the experiment.

| Problem parameters | Probability distributions |
|---|---|
| Coefficient of innovation $p$ | U [0.02, 0.1] |
| Coefficient of imitation $q$ | U [0.25, 0.8] |
| Waiting cost rate $w$ | U [0.005, 0.1] |
| Percentage of backlogged demand $\xi$ | U [0, 1] |
| Disruption rate | D {0.01, 0.04, 0.10, 0.15, 0.70} |

Table 4. Multiple-sourcing solutions compared with UB and build-up heuristic.

| | Min | Max | Mean | Standard |
|---|---|---|---|---|
| Percentage gap with UB | 0.00 | 29.97 | 1.27 | 2.54 |
| Percentage improvement over heuristic | 0.61 | 68.05 | 14.56 | 14.45 |

Table 5. Comparison between single-sourcing and multiple-sourcing solutions.

| | Average total profit ($1000) | Average pipeline stock cost ($1000) | Average safety stock cost ($1000) | Average UMC ($1000) |
|---|---|---|---|---|
| Single-sourcing | 2000 | 57.50 | 61.24 | 5.34 |
| Multiple-sourcing | 2070 | 44.69 | 24.50 | 5.41 |

solutions achieve lower average unit manufacturing cost (UMC), their pipeline and safety stock costs are both higher; the multiple-sourcing solutions, on the other hand, are able to better trade-off between direct cost added and lead time, thus resulting in lower supply chain configuration costs and achieving higher total net profit. Paired $t$-test was conducted to test the hypothesis that multiple-sourcing achieves higher total net profit than single-sourcing. This hypothesis is supported at a significance level $\alpha$ of 0.01. Insight 2 summarises these findings.

**Insight 2:** The single-sourcing approach may lead to an infeasible solution in situations where potential for supply disruption is present. The multiple-sourcing approach can provide a configuration which is resilient to supply disruption and achieve higher total net profit on average.

Note that in our experiments, the relative improvement in profit does not account for the significant costs associated with managing crisis resulted from supply disruption. When considerable crisis management costs are accounted for, the relative improvement in the firm's profit would be significantly higher for multiple-sourcing than being reported here. For instance, supply chain disruption recovery cost for identifying, selecting, and acquiring supplies from alternative sources, as well as purchasing and transportation costs, will be significantly higher in case of crisis management than a normal sourcing approach, not to mention the potentially significant financial impacts (cf. The Economist 2006).

To further understand how total net profit is impacted by various problem parameters, we examine the effects of the new product's attractiveness (measured by its propensity to buy $q/p$) and nature of the diffusion process (characterised by waiting cost rate $w$ and percentage $\xi$ of backlogged demand). Figure 5 illustrates the relationship between total net profit and propensity to buy, both of which are with log-transformation. It can be observed clearly that as the product becomes more attractive to customers, i.e. as $q/p$ increases, the firm is able to achieve higher total net profit. Such effect, however, appears to be diminishing as $q/p$ becomes large.

A (constrained) nonlinear regression with log-transformation is used to quantify the relationship between the total net profit and three explanatory variables: $q/p$, $w$ and $\xi$. An exponential term is used to fit for the decreasing return-of-scale of $q/p$. The nonlinear regression function can be written as:

$$\ln(Y) = \beta_0 + \beta_1 e^{\beta_2 \ln}\left(\frac{q}{p}\right) + \beta_3 \ln(w) + \beta_4 \ln(\xi) + \varepsilon,$$

where $Y$ represents the total net profit obtained by multiple- or single-source approach, and $\beta_1$ and $\beta_2$ are subject to the constraint of being non-negative to fit for the shape of curve in Figure 5.

It is well-known that exact inference procedures about the regression parameters are generally not available for nonlinear regressions, unless the sample size is reasonably large. Fortunately, in our case we have a large sample of 2000 observations, and the Gauss-Newton method used to estimate the regression parameters converges fast (in 29 iterations), which is a good indication that the asymptotic properties of the regression estimates are applicable (Neter *et al.* 1996). Thus we were able to conduct linear regression type inferences to the model. The regression

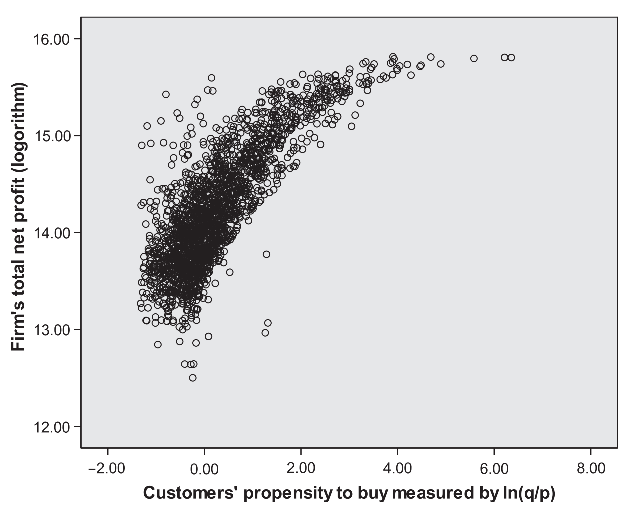


Figure 5. Relationship between firm's total net profit and customers' propensity to buy.

results are reported in Table 6. All regression coefficient estimates are significant at $a < 0.01$. We also provide the 95% confidence interval for the estimated regression coefficients. The model is able to explain about 73% (adjusted $R$-square) of the variation of total net profit for the multiple-sourcing approach and 62% for the single-sourcing approach.

The signs of $b_1$ and $b_2$ support the observation drawn from Figure 5. We are also interested in how the marginal effect of propensity to buy ($\ln(q/p)$) on total net profit differ in single- and multiple-sourcing approach. The first derivative of the exponential term with respect to $\ln(q/p)$ is

$$0.568 \cdot e^{-0.123 \ln\left(\frac{q}{p}\right)}$$

for multiple-sourcing, and

$$0.567 \cdot e^{-0.169 \ln\left(\frac{q}{p}\right)}$$

for single-sourcing. Thus the ratio of marginal effect of $\ln(q/p)$ between multiple- and single-sourcing is approximately $e^{-0.046 \ln\left(\frac{q}{p}\right)}$, which can be numerically depicted as a function of $q/p$ in Figure 6.

It is straightforward to show that the ratio equals 1 when $q/p = 1$; is less than 1 when $0 < q/p < 1$; and is greater than 1 when $q/p > 1$. In the real-world settings, we are likely to be in the $q/p > 1$ region. Taking the empirical study of Sultan *et al.* (1990) for instance, the $q/p$ value of grand mean, refrigerator and European market are 7.55, 4 and 1.78, respectively (as shown in Figure 6), all of which are greater than 1. Insight 3 follows.

**Insight 3:** The propensity to buy has a positive effect (with a diminishing rate) on the total net profit. Such effect is likely to be more significant in multiple-sourcing than in single-sourcing.

Table 6. Nonlinear regression results.

| | Single-sourcing | | | Multiple-sourcing | | |
|---|---|---|---|---|---|---|
| | Estimates | Standard error | Confidence interval | Estimates | Standard error | Confidence interval |
| $b_0$ | 16.758 | 0.618 | [15.55, 17.97] | 18.028 | 0.635 | [16.78, 19.27] |
| $b_1$ | −3.354 | 0.618 | [−4.57, −2.14] | −4.616 | 0.636 | [−5.86, −3.37] |
| $b_2$ | −0.169 | 0.035 | [−0.24, −1.00] | −0.123 | 0.019 | [−0.16, −0.086] |
| $b_3$ | −0.235 | 0.019 | [−0.27, −0.20] | −0.234 | 0.010 | [−0.25, −0.21] |
| $b_4$ | 0.059 | 0.013 | [0.034, 0.085] | 0.037 | 0.007 | [0.023, 0.051] |

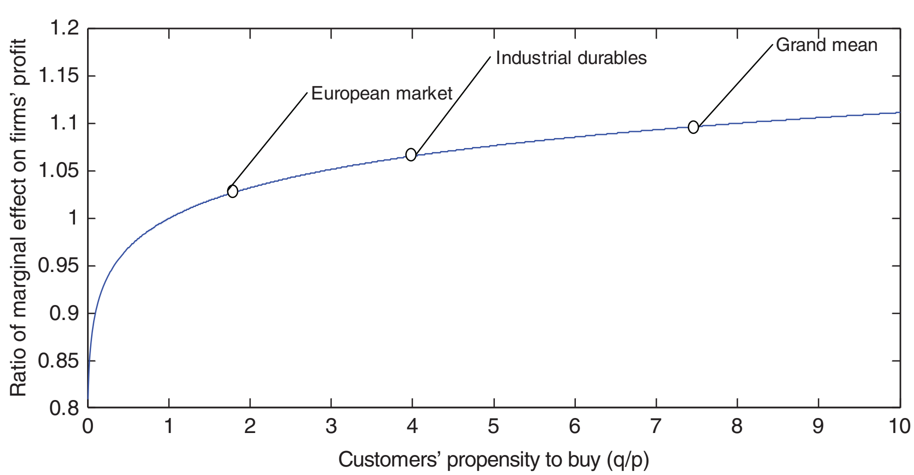


Figure 6. Ratio of $\ln(q/p)$'s marginal effect between multiple- and single-sourcing approach.

Insight 3 suggests that a firm is motivated to invest in R&D, marketing efforts, and/or customer relationship management (CRM) to improve the new product's attractiveness and customers' propensity to buy. The benefit of such improvement will likely be more significant in multiple-sourcing than in single-sourcing. It is also important for the firm to have an idea where it is on the curve of Figure 6, since such benefit diminishes as the propensity to buy is already large.

In addition, from the nonlinear regression model we may extract Insight 4 and Insight 5, regarding the waiting cost ($w$) and percentage backlogged demand ($\xi$) parameters, respectively, as follows.

**Insight 4:** The cost of waiting has a negative effect on the total net profit. Such effect is likely to be similar in multiple-sourcing and in single-sourcing.

**Insight 5:** The percentage of backlogged demand has a positive effect on the total net profit. Such effect is likely to be more significant in single-sourcing than in multiple-sourcing.

Insight 4 suggests that cost of waiting can be reduced to increase the product's life cycle net profit. This can often be achieved by offering discounts or compensations to unsatisfied waiting customers. The implication from Insight 5 is that a firm has the motivation to increase percentage of backlogged demand, possibly through creating the 'brand name effect' and maintaining customer loyalty. Such benefit will likely be more significant in single-sourcing than in multiple-sourcing.

One needs to be cautious about limits of the benefit from Insights 4 and 5 though. Either to reduce waiting cost or to increase percentage of backlogged demand (to reduce lost sales) may require significant marketing efforts which can be costly to a firm. The limits about how far the firm should go depend on the cost-benefit trade off between the cost of marketing effort and the benefit gained for net profit.

## 7. Conclusions and future research

Configuring a supply chain for a new product is a challenging task due to the lack of historical demand data and dynamic/uncertain nature of the new product diffusion process. An integrated supply chain configuration (SCC) and new product diffusion (NPD) model is developed to explicitly account for the impact of demand dynamics during new product diffusion process on optimal supply chain configuration. Our hybrid NPD-SCC model allows a firm to source from multiple suppliers, vendors or modes for its supply chain entities. Such a multiple-sourcing approach not only helps the firm to diversify its pool of suppliers and maintain bargaining power, but also builds redundancy into the supply chain to hedge against potential demand surge and supply disruption during the new product life cycle. Our model can be used by cross-functional teams consisting of marketing, logistics, and operations managers as a decision-support tool to configure a resilient supply chain before initiation of production and product launch.

Utilising a case study and a comprehensive computational experiment, the performance of our integrated optimisation model are evaluated. Managerial insights are obtained, closing the gaps between some operations and marketing issues for new products. We may conclude the following.

(1) As suggested by Insight 1, our hybrid multiple-sourcing model is able to obtain near optimal sales/demand patterns to support better configuration of the corresponding supply chain. Neither launching the product immediately (the myopic policy) nor heuristically specify a number of built-up periods will generate optimal sales/production plan. Our integrated optimisation model will provide optimal build-up periods in conjunction with the corresponding supply chain configuration.
(2) Insight 2 indicates that the multiple-sourcing solutions are advantageous over single-sourcing solutions in a real life environment with potential supply disruptions. Sourcing from a sole supplier may lead to disruption of the entire supply chain once the supplier is disrupted due to natural disaster, accident, or business/marketing conditions, whereas multiple-sourcing is more resilient to supply disruption and may lead to higher profitability.
(3) Insight 3 suggests that a new product's propensity to buy will result in higher life cycle net profit, although at a diminishing rate of effect. This justifies the firm's efforts on R&D and customer relationship management to enhance the new product's attractiveness and customers' experience. Multiple-sourcing approach is expected to benefit more from the improvement in the propensity to buy.

(4) Insight 4 indicates that it might be beneficial to reduce customers' cost of waiting, which motivates some promotion efforts to compensate the unsatisfied customers.
(5) Insight 5 shows that increasing the percentage of backlogged demand will have a positive effect on the total net profit. This justifies a firm's promotion efforts to create and maintain brand name and customer loyalty. Single-souring approach is expected to benefit more from the increase of backlogged demand.

In all, our study suggests that multiple-sourcing is generally advantageous over single-sourcing approach due to the built-in resilience (Insight 2), and the benefit from the improvement in customers' propensity to buy (Insight 3). However, the benefit of increasing the percentage of backlogged customers might be more significant for single-sourcing than multiple-sourcing.

Our multiple-sourcing hybrid NPD-SCC model offers the first approach to design supply chains which are adaptive to the dynamics of new product's diffusion process, while being robust/resilient to potential supply disruptions ubiquitous during the new product life cycle. It can be extended in several ways as future research. For instance, our current model does not account for more complicated and realistic sourcing scenarios such as quantity discounts, quantity-dependent lead time, etc. It will also be interesting to configure a supply chain for multiple new products (or a family of products) which shares the same BOM. There, we will have to consider the diffusion process of multiple correlated products. Finally, it might be fruitful to consider diffusion in a competitive market environment, where competitors may offer simultaneously similar new products which are supplementary to each other. The format war between Blu-ray of Sony and HD DVD of Toshiba was such an example (The Times 2008). There, one must consider the issue of winning market share and its impact on production, sales and supply chain configuration plans. In addition, considering the impact of significant cost of supply disruption recovery in supply chain configuration with single- or multi-sourcing strategies offers an interesting research extension.

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