



Supply chain configuration for diffusion of new products: An integrated optimization approach

Mehdi Amini^{a,*}, Haitao Li^b

^a Department of Marketing and Supply Chain Management, Fogelman College of Business & Economics, University of Memphis, Memphis, TN 38152-3115, USA

^b Department of Logistics and Operations Management, College of Business Administration, University of Missouri—St. Louis, St. Louis, MO 63121-4400, USA

ARTICLE INFO

Article history:

Received 13 July 2009

Accepted 30 July 2010

Available online 7 August 2010

Keywords:

Operations management

Marketing

Product life cycle

Production planning and control

Mathematical programming

ABSTRACT

We develop an integrated/hybrid optimization model for configuring new products' supply chains while explicitly considering the impact of demand dynamics during new products' diffusion. The hybrid model simultaneously determines optimal production/sales plan and supply chain configuration. The production and sales plan provides decisions on the optimal timing to launch a new product, as well as the production and sales quantity in each planning period. The supply chain configuration provides optimal selection of options and safety stock level kept at each supply chain function. Extensive computational experiments on randomly generated testbed problems indicate that the hybrid modeling and solution approach significantly outperforms non-hybrid alternative modeling and solution approaches under various diffusion and supply chain topologies. We provide insights on optimal production/sales plan and supply chain configuration for new products during their diffusion process. Also, managerial implications relevant to effectiveness of the hybrid approach are discussed.

Published by Elsevier Ltd.

1. Introduction

In this paper, we consider the scenario where a firm needs to configure its supply chain before launching a new product. To respond to customer demand efficiently, the firm's supply chain configuration encompasses decisions including selection of suppliers; manufacturing and transportation modes; as well as locations in supply chain network to place appropriate levels of safety stocks.

Under a fixed production and supply capacity in the intermediate term, the firm might be overwhelmed by potentially rapid growth of demand for the new product due to marketing activities and positive word-of-mouth. Examples include Apple's iPhone [1] and Nintendo's Wii [2], where both manufacturers were hit by the rapid growth of demand for these innovative products. Often, such an impact affects not only the manufacturer itself, but also its vendors and suppliers through the supply chain. Example includes Apple's PowerMac G4 [3], where Motorola, as the supplier of G4 chips, was not able to catch up with the rapid growth of demand for the popular computer. Another potential scenario for the firm is to experience a slow growth in demand for the new product and hence resulting in major financial risks. For example, initial sales of Sony's Playstation 2 (PS2) were more than ten times that of the original PS's introduction five years earlier

[4]. However the launch of Playstation 3 (PS3) was not successful for Sony and hence resulted in \$1.8B annual loss in its game division and layoff of 3% of its workforce [5].

Manufacturers are often able to save inventory cost by not keeping any initial stock before launching the new product, but they (and related players in the supply chain) may suffer later when supplies of the new product are outpaced by the fast growth of demand. Often, the saving on inventory cost may not compensate the cost due to lost demand. On the other hand, when a firm experiences demand below expectation, the inventory cost of safety stocks located at different tiers of supply chain network has a negative effect on efficiency. Thus when launching a new product, efficiency in terms of cost and speed is not the only quality a successful supply chain can own. As noted by Lee [6], supply chains that fail to adapt to changes in market structure will not gain sustainable competitive advantage. These have motivated us to model marketing-supply chain interactions, and in particular, the interaction between new product's diffusion and the corresponding supply chain's configuration.

The dynamics of customer demand during diffusion of new products are well-captured by the classical Bass model [7]. Kumar and Swaminathan [8] and Ho et al. [9] have shown that the customer demand pattern during new product diffusion will affect the manufacturer's production planning decisions during the new product's lifetime. They extend the classical Bass model by considering production capacity of the firm, so that the demand of a new product may not be completely met due to the production capacity limit. Their model is used to find optimal

* Corresponding author. Tel.: +1 901 678 2479.

E-mail address: mamini@memphis.edu (M. Amini).

production and sales plans that maximize profit during the new product's lifetime, spanning from one to two years. They find that when supply constraint is present, the rapid growth of customer demand during diffusion may motivate manufacturer to buildup initial inventory and delay launching of the new product. We call their model the new product diffusion (NPD) model in the sequel. The NPD model focuses on the interactions between manufacturing and marketing/sales decisions *within* a firm by assuming a fixed per-unit product cost, but ignores other functions of the firm's supply chain like procurement, sourcing, assembly and distribution.

Graves and Willems [10] proposed a model optimizing the supply chain configuration for a new product, which we call the supply chain configuration (SCC) model. In this model, a firm selects options for each function (components, parts, or processes required) in the supply chain to minimize the system-wide total supply chain cost. Available options often differ in lead time and direct cost added. For instance, parts and raw materials can be purchased from different suppliers. Goods can be shipped via regular ground shipping or next day delivery. The SCC model also allows coordination among supply chain players by optimally determining their inbound and outbound service times, thus the inventory positioning through the supply chain. New product demand is assumed to be known in the form of mean and standard deviation for the entire planning horizon (usually 9 months–1 year). Because demand is exogenously given, the question of how the demand trajectory during new product diffusion will impact supply chain configuration is not addressed by the SCC model.

The problems addressed by the NPD and SCC models are closely related. Both problems are *tactical* in nature. During the new product's life cycle, the firm's production and sales plan is only part of the big picture. Given the expanded complexity and scope of modern supply chains, it is rare to have a single firm being involved through all stages of sourcing, manufacturing, assembly, transportation, warehousing and delivery. Thus the firm is facing more important and wider scope of decisions on how to configure its entire supply chain to allow products as well as the required parts and components (described by the new product's bill-of-materials or BOM) to be sourced, manufactured and delivered in an efficient and responsive manner.

Therefore, there is merit in developing an integrated optimization model to study the optimal supply chain configuration decision in concert with dynamic process of new product diffusion. On one hand, the demand pattern (in terms of mean and variation) during new product diffusion has an explicit impact on supply chain configuration. Specifically, the mean customer demand serves as the external demand to be satisfied by the supply chain network, and the variation of demand directly impacts the amount of safety stock to carry (or inventory positioning) through the supply chain. On the other hand, the configuration of supply chain may in turn affect the optimal diffusion pattern of the new product. This is due to the fact that in the general supply chain settings, the per-unit cost of product should be calculated as an accumulative cost due to selection of suppliers/vendors and manufacturing/transportation modes through different supply chain stages such as sourcing, assembly, transportation, etc. This implies that the per-unit cost assumed to be constant in manufacturing planning models during diffusion, as in [8], can be extended and generalized to the so-called unit manufacturing cost (UMC) determined through configuring the corresponding supply chain [10].

In this study, we present a hybrid model to configure a new product's supply chain by considering the dynamics of diffusion process through the product life cycle. Both the demand/supply pattern and unit-product cost are endogenously determined in

one model, as opposed to being exogenous as assumed in the separate models. Our model offers a decision support tool for simultaneously optimizing an innovator's production planning in a multi-period setting and supply chain configuration. It also provides a modeling framework to design a supply chain which is not only cost efficient, but also adaptive to the changing market demand during new products' lifetime.

As we will show, solutions that optimize supply chain performance from either the NPD aspect or the SCC point of view alone would not obtain optimal solutions. Lower supply chain configuration cost is often achieved by a *myopic policy*, i.e. selling as much as possible in each time period. This leads to less variation of the realized demand, thus less safety stock. However, such myopic policy may perform poorly from the diffusion perspective due to loss of demand. On the other hand, a *buildup policy*, i.e. delaying the launch of the new product and building some initial inventory, may generate higher sales revenue from the diffusion perspective; but too many buildup periods may lead to increased amount of safety stocks and hence increase supply chain configuration cost. Determining the optimal number of buildup periods will not be an intuitive task without the aid of an integrative optimization model in which both supply chain configuration decisions and new product diffusion outcomes are simultaneously considered.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the integrated model. The computational experimental study and results are presented in Section 4. Section 5 draws conclusions and suggests future research directions.

2. Related literature

Our work is related to the research literature of supply chain configuration design in operations management and new product diffusion in marketing. In this section, we provide a review of the supply chain configuration and new product diffusion process literature. Also, we discuss the merit and objectives of the current study.

Supply chain configuration design is traditionally understood as determining the optimal manufacturing and distribution network of a firm at the strategic level (see, e.g., [11,12]). Such strategic decision problems focus on designing physical supply chain networks and often have a long-term impact for the firm from 5 to 10 years. In today's fast changing and competitive business environment, however, a new product's life cycle (often around or less than 1 year) is much shorter than the scale of strategic planning horizon. When designing supply chain for new products, it is critical that the supply chain adapts to the changing environment in terms of demand, lead time and cost in the intermediate run. Thus the supply chain configuration problem, addressed in this paper, focuses on tactical level decisions with a planning horizon that matches a new product's life cycle. Such tactical supply chain configuration problems are able to model all echelons in the supply chain and optimize the system-wide supply chain performance [10], as opposed to optimizing two or three echelons in strategic network design problems.

The tactical supply chain configuration problem on multi-echelon supply chains has its root in the so-called inventory positioning problem, which studies where in the supply chain to keep safety stock. Early models on inventory positioning, e.g., [13–16], optimize safety stock levels for an existing supply chain by assuming that the option chosen at each supply chain function is fixed.

Graves and Willems [10] developed a model that simultaneously determines the safety stock placement and option

selection decisions. Instead of taking the lead time and cost at each supply chain function as given, they treat the lead time and direct cost added of a function as decision variables dependent upon the option chosen for that function. Their model minimizes the system-wide total supply chain costs including not only the safety stock cost, but also the cost of goods sold (COGS) and the holding cost of pipeline inventory. A byproduct of their model is the optimal unit manufacturing cost (UMC) calculated as the cumulative cost through all stages of the supply chain.

One assumption made by the model in [10] is that the demand pattern of new products during the planning horizon is exogenously given. That is, the mean and standard deviation of demand is assumed to be known. Thus their model does not explicitly account for the impact of demand dynamics during new product diffusion, given that the length of planning horizon matches with the length of a new product's life cycle.

Adopted from diffusion models for the spread of technological innovations in the economics literature [17], the Bass model [7] has been widely used in marketing to forecast the demand trajectory of new products. We refer to [18–20] for a comprehensive survey on applications of Bass model and its variants.

There have been growing interests in applying Bass model to study the underlying demand in production planning in operations management. Kurawarwala and Mastuo [21] studied an inventory planning problem with demand dynamics characterized by the Bass model over the new product's entire life cycle. Their model does not incorporate capacity constraint from the supply side. Ho et al. [9] proposed an optimization model for jointly analyzing the dynamics of supply and demand. Their model addresses capacity sizing, time to market and demand fulfillment policy under an explicit supply constraint. They find that in a make-to-stock production environment, a myopic policy is always optimal. Kumar and Swaminathan [8] considered a more general problem setting, in which a variety of scenarios from complete backlogging to lost sales are captured. They showed that the buildup policy is robust and very close to optima on average, and under certain scenarios the myopic policy may deviate far from optima. Other work incorporating supply constraints in new product diffusion model includes that of Swami and Khairnar [22], where new products are available in limited quantity until a known expiration date.

The aforementioned studies focused on optimizing joint new product diffusion and production planning over the new product's lifetime. They implicitly assume that the per-unit cost has incorporated the costs of materials, sourcing of parts/components, and transportation involved through different stages of the corresponding supply chain. Thus the existing studies have focused on operations planning at one echelon of the supply chain, i.e. the production stage.

To our best knowledge, the impact of demand dynamics during new product diffusion on the configuration of the entire multi-echelon supply chain has not been addressed. Hence, the key objective of this study is to develop an integrated optimization model by which multi-echelon supply chain configuration decisions are made while explicitly considering demand dynamics resulting from the new product diffusion process throughout its life cycle. The integrated optimization model is capable of jointly determining the optimal production/sales plan and supply chain configuration in terms of inventory positioning and option selected at each supply chain function. On one hand, the model allows endogenously determining optimal demand/supply trajectory from the diffusion aspect for the supply chain configuration side. On the other hand, the model permits optimal configuration of supply chain and hence providing the optimal per-unit product cost. This in turn links the supply chain option selection decisions

to production planning during diffusion process. Our work is a first attempt to model the interaction between new product diffusion and supply chain configuration. Related research on designing *flexible* supply chains (cf. [23]) adapted to the dynamics and variability of demand can be found elsewhere, e.g. manufacturing network design [24] and sourcing [25].

3. Optimization model

Consider a firm which plans to launch a new product. With a short product life cycle and a long lead time for capacity expansion, the firm has a fixed production capacity throughout the life cycle of the product. The firm has to: (a) plan its production and sales over the product life cycle; and (b) configure the corresponding supply chain in terms of option selected and inventory level kept at each supply chain function. We formally describe the problem in Section 3.1. Section 3.2 presents the mathematical formulation. Model complexity, computational issues and solution approach are discussed in Section 3.3.

3.1. Problem description

We discretize the diffusion process into T time periods and assume that the firm is ready to start production at $t=0$. Once the diffusion process starts, the firm will decide how much to produce (r_t) and sell (y_t) at time period t . For the supply process, we consider the cumulative production R_t and the inventory of available products I_t at time period t . The total production up to time t equals the sum of inventory I_t and cumulative sales Y_t . The instantaneous and cumulative demand at time t is denoted by d_t and D_t , respectively. The demand process follows that described by a modified Bass model due to Kumar and Swaminathan [8]

$$d_t = p(m - D_t) + \frac{q}{m} Y_t (m - D_t) \quad (1)$$

where p stands for the coefficient of innovation and q represents the coefficient of imitation. The firm faces a fixed market potential m . The demand d_t at time t is expressed as a fraction of the remaining potential adopters $m - D_t$ consisting of two components: one due to the impact of mass-media or coefficient of innovation p , and the other proportional to the cumulative sales Y_t due to positive word-of-mouth or coefficient of imitation q . Notice the difference of (1) from the classical Bass model is that, the impact of word of mouth is influenced by the number of people who have successfully bought the product up to time t (Y_t), not necessarily by all the people who demanded the product up to time t (D_t), although this assumption may not always hold in practice. Eq. (1) is especially useful to capture the unmet demand under explicit supply capacity constraint. The unmet demand up to t can be represented as $D_t - Y_t$, which can be completely lost or backlogged at a percentage of ξ .

The supply of the new product involves a set $V = \{1, 2, \dots, N\}$ of N functions. A function $i \in V$ refers to a component, part or a process required by the new product as described in bill-of-materials (BOM). Function N refers to the end product. We assume that the design of the product has completed, i.e. the BOM structure is given as a graph $G(V, E)$ with E being a set of arcs describing the demand dependencies in BOM. An arc $(i, j) \in E$ has a weight of ρ_{ij} specifying the units of i required by 1 unit of j . Without loss of generality, we assume that ρ_{ij} equal 1. We also assume that the external demand occurs only at the end product N . The mean and standard deviation of such external demand is determined endogenously through the new product diffusion process described earlier. Any other function has only internal demand μ_i from its immediate successors, which can be

calculated as follows:

$$\mu_i = \sum_{(i,j) \in E} \rho_{ij} \mu_j \quad (2)$$

Following Graves and Willems [16], each supply chain function i quotes a guaranteed *outbound service time* s_i^{out} by which i will satisfy its demand. The time for function i to receive all the required inputs from its predecessors is called the *inbound service time* s_i^{in} , which equals the maximum of outbound service times quoted to function i by its predecessors. The *net replenishment time* τ_i of function i , i.e. the time required to provide i , is given by the following:

$$\tau_i = s_i^{in} + p_i - s_i^{out} \quad (3)$$

The amount of safety stock SS_i held at function i can be calculated as

$$SS_i = \kappa \sigma_i \sqrt{\tau_i} \quad (4)$$

where σ_i refer to function i 's mean and standard deviation of demand, respectively. The constant κ is the z-value associated with a pre-specified service level.

As in Graves and Willems [10], a set of O_i options are available for each function $i \in V$. Each option differs in lead time and direct cost added, reflecting the time-cost tradeoff. Exactly one option needs to be selected for each function. The firm's supply chain configuration problem involves determining which supplier/vendor and manufacturing/distribution option to choose for its supply chain functions.

The new production diffusion process and supply chain configuration problem are related in the following two ways:

Link 1: Unlike in [8] where the per-unit product cost is assumed to be 1, the per-unit product cost in our model refers to the unit manufacturing cost (UMC, [10]), which will be determined by the configuration (options chosen) for the new product's supply chain.

Link 2: The product diffusion process will shape the demand/sales pattern for the entire planning horizon, by determining the mean, μ , and standard deviation, δ , of demand for the new product.

The integrated/hybrid supply chain configuration problem for diffusion of new products is defined as the problem of choosing a feasible production plan and configuration of the corresponding supply chain over the new product's entire life cycle, so that the total net profit is maximized. A mixed-integer nonlinear programming (MINLP) formulation of the problem is presented next.

3.2. Model formulation

In this section, we present three sets of decision variables relevant to supply chain configuration, new product diffusion process and decision variables linking supply chain configuration and diffusion process. Next, we discuss an integrated optimization model depicting supply chain configuration and product diffusion process.

Model parameters

m	initial size of potential adopter population of product
T	number of time periods of the planning horizon
V	set of functions in the supply chain
N	number of functions in the supply chain ($N = V $)
E	set of arcs in the supply chain
ξ	fraction of unmet demand that is backlogged
p, q	coefficients of innovation and imitation
K	production capacity per time period

π	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 function i
P_{ik}	lead time of the k th option for function i
C_{ik}	direct cost added of the k th option for function i
L	due date of the outbound service time of the end product
κ	z-value determined by user-specified service level

The coefficient of innovation p and imitation q can be determined using regression as described in Bass [7]. The issue of finding the best fit parameters for a new product is a non-trivial one and requires analyzing the sales history data of a similar product in the same product family or industry, which goes beyond the scope of this paper. Our current study considers a generic product having an average p and q being 0.03 and 0.4, respectively, based on the study of Sultan et al. [26] on 213 applications of diffusion models in 15 articles. The length of planning horizon is chosen to be 30 as in [8]. The selling price ratio π is a markup over the product's cost. The inventory holding cost rate h is the percentage of inventory cost over the value of the goods, which can be provided the accounting department of the firm. Lead time and direct cost added of each option are readily available from suppliers/vendors of the supply chain. The due date of outbound service time of the end product is specified by customers.

Decision variables related to the supply chain configuration

$x_{ik} = 1$, if function i 's k th option is selected, 0 otherwise
s_i^{in}	, inbound service time of function i , i.e. the time to receive all inputs from its suppliers
s_i^{out}	, outbound service time of function i , i.e. the time by which i will satisfy its demand
$c_i \geq 0$, direct cost added for function i
\bar{c}_i	, cumulative cost for function i
$p_i \in Z^+$, lead time of function i

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

μ_N	, mean supply of the end product (function N) over the diffusion horizon
σ_N	, standard deviation of supply of the end product over the diffusion horizon

Objective function

The objective function may be formulated as follows:

Maximize: Total Net Profit = Total Life-Cycle Revenue – Supply Chain Configuration Costs,

where,

$$\text{Total Life-Cycle Revenue} = \sum_{t=0}^T \bar{c}_N [\pi y_t - r_t - w L_t - h I_t] \quad (5)$$

$$\text{Supply Chain Configuration Costs} = \text{Pipeline Stock Cost} + \text{Safety Stock Cost} \quad (6) \quad \sum_{k=1}^{O_i} x_{ik} = 1 \quad \forall i = \{1, \dots, N\} \quad (24)$$

$$\text{Pipeline Stock Cost} = \sum_{i=1}^N h(\bar{c}_i - c_i/2)p_i\mu_i \quad (7) \quad \mu_i = \sum_{j:(j,i) \in E} \mu_j \quad \forall i = \{1, \dots, N\} \quad (25)$$

$$\text{Safety Stock Cost} = \sum_{i=1}^N h\bar{c}_i\kappa\sigma_i\sqrt{s_i^{in} + p_i - s_i^{out}} \quad (8) \quad s_i^{in}, s_i^{out} \geq 0 \text{ and integer } \forall i = \{1, \dots, N\} \quad (26)$$

$$x_{ik} \in \{0,1\} \quad \forall i = \{1, \dots, N\}, k \in \{1, \dots, O_i\} \quad (27)$$

The objective function is to maximize the total net profit over the new product’s lifetime as the difference between the total life-cycle revenue and supply chain configuration costs. In (5), the total life-cycle revenue is calculated as the total sales revenue minus three items: the cost of goods produced, waiting cost of backlogged demand and inventory holding cost of finished goods. Notice that the per-unit product cost is represented by the cumulative cost of the end product \bar{c}_N , which is determined through configuring the corresponding supply chain. This reflects Link 1 in the hybrid model. The supply chain configuration cost is defined as the sum of pipeline stock cost in (7) and safety stock cost in (8). The pipeline stock cost (7) follows the Little’s Law as in [10], where the term $\bar{c}_i - c_i/2$ denotes the average value of goods over its lead time p_i . The safety stock cost (8) is obtained combining (3) and (4).

Constraints

The set of constraints includes constraints for product diffusion, supply chain configuration and the linking constraints. We state and describe these constraints below.

Constraints on product diffusion

$$R_{t+1} = R_t + r_t \quad \forall t = \{0,1, \dots, T-1\} \quad (9)$$

$$D_{t+1} = D_t + d_t \quad \forall t = \{0,1, \dots, T-1\} \quad (10)$$

$$Y_{t+1} = Y_t + y_t \quad \forall t = \{0,1, \dots, T-1\} \quad (11)$$

$$d_t = p(m - D_t) + \frac{q}{m} Y_t(m - D_t) \quad \forall t = \{0,1, \dots, T\} \quad (12)$$

$$I_t = R_t - Y_t \quad \forall t = \{0,1, \dots, T\} \quad (13)$$

$$L_{t+1} = \xi(L_t + d_t - y_t) \quad \forall t = \{0,1, \dots, T\} \quad (14)$$

$$L_t \geq 0 \text{ and } L_0 = 0 \quad (15)$$

$$I_t \geq 0 \text{ and } I_0 = 0 \quad (16)$$

$$r_t \leq K \text{ and } R_0 = 0 \quad (17)$$

Constraints on supply chain configuration

$$p_i = \sum_{k=1}^{O_i} P_{ik}x_{ik} \quad \forall i = \{1, \dots, N\} \quad (18)$$

$$c_i = \sum_{k=1}^{O_i} C_{ik}x_{ik} \quad \forall i = \{1, \dots, N\} \quad (19)$$

$$\bar{c}_i - \sum_{j:(j,i) \in A} \bar{c}_j - c_i = 0 \quad \forall i = \{1, \dots, N\} \quad (20)$$

$$s_i^{in} \geq s_j^{out} \quad \forall i = \{1, \dots, N\}, j : (j,i) \in E \quad (21)$$

$$s_i^{in} + p_i - s_i^{out} \geq 0 \quad \forall i = \{1, \dots, N\} \quad (22)$$

$$s_N^{out} \leq L \quad (23)$$

Linking constraints

$$\mu_N = Y_T / (T + 1) \quad (28)$$

$$\sigma_N = \sqrt{\sum_{t=0}^T (y_t - \mu_N)^2 / T} \quad (29)$$

Constraints (9) through (17) are similar to those in Kumar and Swaminathan [8]. Constraints (9) through (11) calculate the cumulative production, demand and sales of the product in each time period, respectively. Constraint (12) follows (1) as explained earlier. Constraint (13) calculates the inventory of finished product in each time period as the difference between cumulative production and cumulative sales. Constraint (14) states that a fraction ξ of the unmet demand is instantaneously backlogged. By adjusting ξ , the model is able to capture various scenarios ranging from complete loss of sales ($\xi=0$) to complete backlog ($\xi=1$). Constraints (15) through (17) specify the bounds of the decision variables relevant to the product diffusion side.

Constraints (18) through (27) are similar to those in the supply chain configuration optimization model of Graves and Willems [10]. Constraints (18) and (19) calculate the lead time and direct cost added of each function, respectively. Constraint (20) calculates the cumulative cost added for each function. Constraint (21) states that the inbound service time of a function must be no less than the outbound service time of its immediate predecessors. Constraint (22) ensures that the net replenishment time of a function is non-negative. Constraint (23) guarantees that the deadline of the new product (end function N) be satisfied for delivery to customers. Constraint (24) assigns exactly one option to a function. Constraint (25) follows (2) and calculates the internal demand of each function assuming ρ_{ij} equal 1.

Constraints (28) and (29) calculate the mean and standard deviation of sales of the new product over its entire life cycle, respectively. Notice that the demand pattern now becomes endogenously determined by the production plan during the new product diffusion process. They establish Link 2 between the product diffusion and supply chain configuration.

3.3. Complexity and solution methods

The above MINLP is *NP-hard* as the objective function involves minimizing a concave function in (7), and it is well-known that the general problem of minimizing a concave function is *NP-hard* [27]. Further computational complexity arises due to the existence of integer variables and nonlinear equalities as in (12) and (29).

Various computational algorithms have been developed to tackle MINLPs. We refer to Floudas [28] for a comprehensive survey of MINLP algorithms. An MINLP with a large number of nonlinear equality constraints can be handled by the so-called outer approximation with equality relaxation (OA/ER, [29]) algorithm. The OA/ER algorithm relies on the assumption that the expressions in an MINLP are convex. Viswanathan and Grossmann [30] generalized the OA/ER algorithm to include an

augmented penalty (AP) function, called OA/ER/AP, to avoid the limitations imposed by the convexity assumption made in OA/ER. Given the presence of concave functions in our MILP model, OA/ER/AP fits better for our needs.

The OA/ER/AP algorithm has been implemented in the DICOPT solver by GAMS [31]. It starts by relaxing the integer requirement of decision variables and solving the relaxed NLP problem. If the solution to this relaxed problem is integer, the search stops. Otherwise, it continues with a sequence of NLP subproblems by fixing the integer variables, and mixed-integer linear program (MIP) master problems generated by augmented penalty function. Integer cuts are added to the MIP to exclude previous visited integer solutions. When objective function is convex, solving the MIP master problem provides an upper bound on the objective function (for a maximization problem); when objective function is concave as in our case, however, solving the master problem may not provide a valid upper bound. Thus the OA/ER/AP algorithm may not guarantee optimal solutions for our MINLP model and will serve as a heuristic approach for solving our hybrid model. For implementation and technical details about the DICOPT solver, we refer the readers to [32].

In order to evaluate solution quality, we adapt a linear approximation approach described in [33] and [34] to approximate the concave term (8) in the objective function. In our implementation, we use one linear piece to approximate (8). With such approximation, the objective function becomes convex (as two other terms (5) and (7) are convex), for which a local optima is also global optima when all integer variables are relaxed. The optimal solution (or upper bound) to this approximated/relaxed problem provides an upper bound to the original problem.

4. Computational experimental study

We conduct a computational experimental study to analyze the performance of our integrated optimization model under various topologies characterized by problem parameters from both the product diffusion and supply chain configuration perspectives. We compare solutions obtained from the integrated model with those found by different heuristic policies to draw observations and insights concerning the addressed problem.

4.1. Design of experiments

The computational experimental design for this study includes two sets of factors (parameters): set one characterizing the supply chain network, and set two defining the parameters impacting new product diffusion process. We consider serial supply chains with number of echelons being 2, 4 or 8. We also consider different cost and lead time accrual functions, which captures the speed at which lead time and cost cumulate along the supply chain. Following Graves and Willems [10], three profiles: $f(x)=x^{0.25}$, x and x^2 are included, where x denotes the cumulative position x in a serial supply chain, and $f(x)$ is a function which calculates the lead time or cumulative cost of all low-cost options for position x . We refer to [10] for details about the functional form of $f(\cdot)$, and discussions on how different profiles capture various supply chain structures ranging from the traditional consumer-electronics-manufacturing to original equipment manufacturing (OEM). To eliminate the undesired effect of different magnitudes of lead time and value of products, we scale the cost and lead time of low cost option configuration to \$100 and 100 days, respectively. We follow [8] for the choice of diffusion side parameters. We consider high, medium and low price ratios $\pi=1.1, 1.2$ and 1.3 . In a similar way, we choose inventory holding cost rate $h=0.001, 0.005$ and 0.01 , and waiting cost rate $w=0.005,$

0.008 and 0.01 . We consider full backlogging ($\xi=1$), lost sales ($\xi=0$) and partial-backlogging ($\xi=0.5$). This generates a total of 2187 random testbed problem instances.

Other parameters are chosen as follows. As in [8], we set the market potential $m=3000$ to be exhausted in $T=30$ periods, with each period representing two to four weeks. This results in an entire product life cycle of about 1 to 2 years. The production capacity per period is chosen to be $K=100$. The coefficient of innovation p , and coefficient of imitation q are set to be 0.03 and 0.4 , respectively, which represents a generic product based on the study of [26].

Each problem instance is randomly generated and solved by different solution methods. In addition to our hybrid model, a set of two-layer supply chain strategies are considered. Layer one strategy involves the product diffusion side and includes *myopic* and *buildup* strategies as considered in Kumar and Swaminathan [8]. In the myopic strategy, production and sales of the product starts in the first period, while the buildup strategy includes inventory buildup periods followed by launching the new product. In our experiment, we pick three possible number of buildup periods: 2, 6 and 12. Thus there are four layer one strategies. Then for each of these four strategies, we consider two sub-strategies concerning the supply chain configuration side as in Graves and Willems [10], i.e. the lowest cost (MinCost) and lowest lead time (MinLT) configuration. This leads to a total of eight alternative heuristics. For brevity, we name these solution methods as follows.

Hybrid Model: It simultaneously determines the optimal sales/demand plan and supply chain configuration. The hybrid model is solved using the DICOPT solver in GAMS.

Myopic+MinCost: This policy keeps no buildup period for the diffusion process and chooses the least cost option for each supply chain function.

Myopic+MinLT: This policy keeps no buildup period for the diffusion process and chooses the least lead time option for each supply chain function.

Buildup(n)+MinCost: This policy keeps n buildup periods for the diffusion process and chooses the least cost option for each supply chain function, where n refers to 2, 6 or 12.

Buildup(n)+MinLT: This policy keeps n buildup periods for the diffusion process and chooses the least lead time option for each supply chain function, where n refers to 2, 6 or 12.

Table 1 summarizes the parameters and their values used in the experimental study.

4.2. Computational experimental results

We first present results on the overall performance of different solution approaches, followed by results on the effect of problem parameters. Also, our discussions present key findings.

Table 1
Summary of experimental parameters and their levels.

Parameters	Levels
Number of echelons N	{2, 4, 8}
Lead time accrual function	$\{x^{0.25}, x, x^2\}$
Cumulative cost accrual function	$\{x^{0.25}, x, x^2\}$
Selling price ratio π	{1.1, 1.2, 1.3}
Inventory holding cost rate h	{0.001, 0.005, 0.01}
Waiting cost rate w	{0.005, 0.008, 0.01}
Percentage of backlogged ξ	{0, 0.5, 1}
Number of buildup period n	2, 6, 12
Initial size of adopter m	3000
Planning horizon T	30
Production capacity per period K	100
Coefficient of innovation p	0.03
Coefficient of imitation q	0.4

4.2.1. Overall performance

Table 2 summarizes the cost and revenue items found by each solution method. The Buildup6+MinLT heuristic generates the highest total revenue on average, but also incurs the highest average COGS; while the Myopic+MinCost heuristic incurs the lowest COGS on average, but only achieves the lowest average total sales revenue. Increasing the number of buildup periods may reduce the cost of lost sales (e.g., Buildup12+MinCost is the best in this category), but incurs more inventory cost for holding finished products in stock; the myopic policy, on the other hand, does not incur any cost for finished goods inventory, but suffers higher cost due to unsatisfied demand. For the pipeline stock, a minimum lead time configuration heuristic might be advantageous as it results in shorter supply chain cycle time (the time an entity takes to traverse the entire supply chain [35]), but higher cumulative costs of work-in-process inventory at the same time; a minimum cost configuration heuristic might be advantageous as it results in lower cumulative costs of work-in-process inventory, but longer cycle time. Such a tradeoff depends on the cost and lead time structure of specific problem settings. For the safety stock, a smoothed demand pattern is desirable as it leads to less variation of demand, thus less safety stock cost. In our experiment, Myopic+MinLT appears to have best performance on supply chain configuration in terms of pipeline stock (column 5) and safety stock costs (column 6). Strikingly, our hybrid model does not excel in any individual category of these revenue and cost measures.

Table 3 reports solution quality of different approaches at a more aggregate level. The Myopic+MinLT performs best in terms of supply chain configuration cost due to lower SPC and lower SSC

(columns 5 and 6 in Table 1). However, it has a medium performance in total life-cycle revenue (column (7) in Table 2). Our hybrid model generates the highest total life-cycle revenue on average (with modest variation compared with others). And despite its higher spending on the supply chain configuration cost, the hybrid model achieves highest average total net profit (with an average gap of 2.57% from upper bound).

An interesting finding is that best solutions for the integrated new product diffusion process and its supply chain configuration problem do not necessarily lead to lowest total supply chain costs. (The Myopic+MinLT policy results in least supply chain configuration cost, but has an average of 6.67% deviation from upper bound.) That is, purely minimizing the supply chain configuration cost without considering the diffusion process may lead to local optima. We may draw the following insight from Tables 2 and 3.

Observation 1: Different performance measures on new product diffusion and its supply chain configuration interact and have tradeoffs with each other. They must be considered in a unified framework to achieve optimal solutions; optimizing each individual measure may only lead to local optima.

Observation 1 provides useful insights for managing production/sales and supply chain in practice. An optimal production/sales plan or supply chain configuration for a new product does not necessarily lead to maximum amount of sales revenue from the marketing perspective, or minimum amount of costs from the supply chain configuration perspective. Production/sales planning and supply chain configuration for new products need to be considered simultaneously to obtain optimal solutions.

Fig. 1 through Fig. 3 depict the topologies of relative solution quality for different heuristic approaches. For the product

Table 2 Summary of solution cost and revenue items found by each approach.

Supply chain strategy	TSR (1)	COGS (2)	TWC (3)	TIC (4)	SPC (5)	SSC (6)
Hybrid model	374.61 (49.52)	287.89 (32.56)	4.06 (5.69)	1.31 (2.28)	3.68 (3.26)	1.70 (1.78)
Myopic+MinCost	347.66 (67.12)	267.21 (48.10)	4.57 (6.29)	0 (0)	4.89 (4.41)	1.81 (1.99)
Myopic+MinLT	358.46 (69.03)	275.53 (49.59)	4.76 (6.54)	0 (0)	3.55 (3.21)	1.57 (1.72)
Buildup2+MinCost	363.40 (48.21)	279.26 (31.62)	3.85 (5.39)	1.48 (2.03)	5.07 (4.48)	2.14 (2.22)
Buildup2+MinLT	374.86 (48.78)	288.10 (31.97)	3.98 (5.58)	1.60 (2.21)	3.71 (3.29)	1.88 (1.96)
Buildup6+MinCost	363.93 (47.68)	279.69 (31.28)	3.65 (5.11)	2.43 (2.05)	5.08 (4.49)	2.48 (2.61)
Buildup6+MinLT	375.23 (48.02)	288.41 (31.44)	3.77 (5.29)	2.58 (2.26)	3.72 (3.30)	2.21 (2.37)
Buildup12+MinCost	349.60 (64.35)	268.63 (45.46)	3.51 (4.78)	4.22 (3.37)	4.87 (4.36)	3.04 (3.29)
Buildup12+MinLT	360.85 (65.61)	277.34 (46.62)	3.63 (4.95)	4.35 (3.44)	3.57 (3.21)	2.80 (3.20)

1. TSR—total sales revenue, COGS—cost of goods sold, TWC—total cost due to waiting, TIC—total inventory cost for holding finished products, SPC—supply chain pipeline stock cost, SSC—supply chain safety stock cost.
2. Numbers are in thousands, numbers in parenthesis represent standard deviation.
3. Bold entry indicates the best performance for the corresponding item (column).

Table 3 Descriptive statistics of solution quality of each solution approach.

	Total life-cycle revenue (7)=(1)–(2)–(3)–(4)				Supply chain configuration costs (8)=(5)+(6)				Total life-cycle net profit (9)=(7)–(8)			
	Min	Max	Avg.	Std.	Min	Max	Avg.	Std.	Min	Max	Avg.	Std.
Hybrid model	38.82	123.65	81.35	26.01	0.42	15.54	5.39	4.13	27.70 (0)	123.18 (19)	75.96 (2.57)	26.25
Myopic+MinCost	37.61	120.00	75.88	26.08	0.37	19.46	6.70	5.36	23.81 (3)	119.49 (31)	69.17 (12.04)	26.00
Myopic+MinLT	38.74	123.65	78.17	26.85	0.30	15.44	5.11	4.08	27.69 (0)	123.18 (19)	73.05 (6.67)	26.69
Buildup2+MinCost	36.83	119.94	78.81	25.21	0.51	20.41	7.22	5.52	23.11 (1)	119.38 (32)	71.59 (8.63)	25.67
Buildup2+MinLT	38.33	123.58	81.18	25.94	0.42	18.33	5.59	4.29	26.46 (0)	123.07 (34)	75.59 (3.08)	26.22
Buildup6+MinCost	32.72	119.72	78.16	25.05	0.51	22.13	7.56	5.83	17.59 (0)	119.05 (55)	70.61 (10.01)	25.68
Buildup6+MinLT	33.23	123.33	80.47	25.76	0.42	26.51	5.93	4.64	17.18 (0)	122.75 (53)	74.54 (4.54)	26.19
Buildup12+MinCost	33.28	122.61	73.23	25.43	0.43	26.56	7.90	6.26	17.36 (1)	121.52 (57)	65.33 (17.5)	26.03
Buildup12+MinLT	35.17	122.67	75.53	26.12	0.35	26.49	6.37	5.25	17.21 (0)	121.91 (56)	69.16 (12.2)	26.49

1. Numbers (except those in parenthesis) are in thousands.
2. Bold entry indicates the best performance for the corresponding item (column).
3. Numbers in parenthesis are the percentage of gap between upper bound calculated as gap=100*(upper bound – obj. value)/upper bound.

diffusion side (Fig. 1), the MinLT heuristic on average outperforms the MinCost heuristic (given the cost and lead time structures assumed in our experiment). For the same supply chain configuration heuristic, as the production diffusion policy evolves from myopic (number of buildup periods equals 0) to the buildup policy up to 12 periods, the solution quality first improves, then deteriorates. This is probably due to the policy's tradeoff between backlog waiting (or lost sale) cost and inventory holding cost. If there is no buildup period, the firm is too aggressive in stimulating the demand, incurring large cost due to backlog or lost sales although inventory holding is low; if there are too many buildup periods, the firm becomes too conservative while spending too much on inventory holding cost. In our experiment, the best number of buildup periods occurs at 2. We then have Observation 2. Paired *t*-test was conducted to test this hypothesis. The *p*-value is less than 0.01, which supports the hypothesis at a confidence level of 99%.

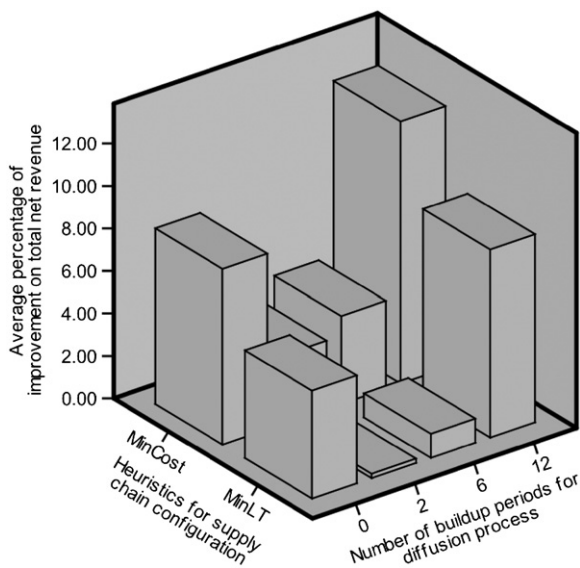


Fig. 1. Average percentage improvement of hybrid model over heuristic approaches on total revenue.

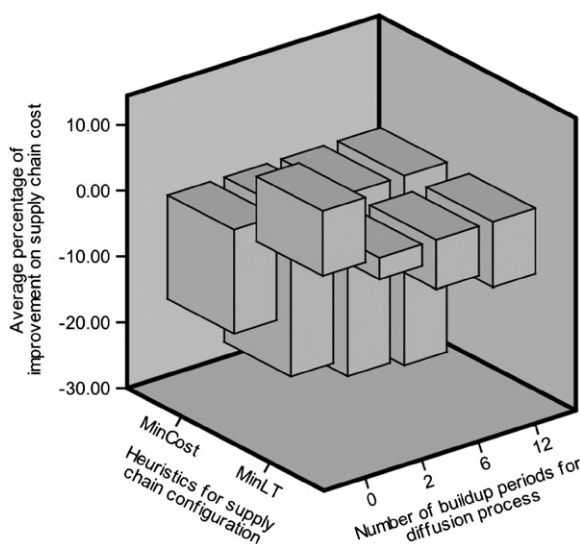


Fig. 2. Average percentage improvement of hybrid model over heuristic approaches on supply chain configuration cost.

Observation 2: For the product diffusion process alone, neither myopic nor buildup policy with many buildup periods may result in maximum net revenue.

For the supply chain configuration side alone (Fig. 2), as the product diffusion policy evolves from myopic to the buildup policy with up to 12 periods, its performance on supply chain configuration cost becomes worse. This is probably caused by the higher variation of demand and sales due to the buildup periods; while the myopic policy in general leads to smoother demand and sales pattern with smaller variation, which may not be desirable for the new production diffusion process alone, but is preferable for planning and configuring the associated supply chain. In particular, smaller variation of demand and sales lead to less safety stock cost through the supply chain (see column 6 in Table 1). This leads to Observation 3. Paired *t*-test was conducted to test this hypothesis, with the *p*-value being less than 0.01.

Observation 3: For the supply chain configuration side alone, myopic policy outperforms buildup policies in supply chain configuration cost: the more buildup periods, the higher the supply chain configuration cost.

Observation 3 reveals the relationship between the number of buildup periods from the production planning side and the supply chain configuration side. A smooth and even production/sales plan results in less inventory holding costs for the supply chain, but may suffer significant loss of sales by neglecting the dynamics of market demand. On the other hand, a production plan with certain number of buildup periods may increase sales revenue, but also incurs more supply chain configuration costs due to increased variation of sales.

Fig. 3 shows the relative performance on the overall solution quality of total life-cycle net profit. The cost savings from the myopic policy is not sufficient to compensate the shortage on net revenue of the myopic policy, thus the myopic policy fails to achieve the quality of the hybrid solution. On the other hand, the surplus of net revenue from the buildup policy (with many buildup periods) is not sufficient to cover the extra spending on supply chain configuration, thus the buildup policy (with many periods) may also fail to obtain optimal solutions. Observation 4 follows. Paired *t*-test was conducted to test this hypothesis, with the *p*-value being less than 0.01.

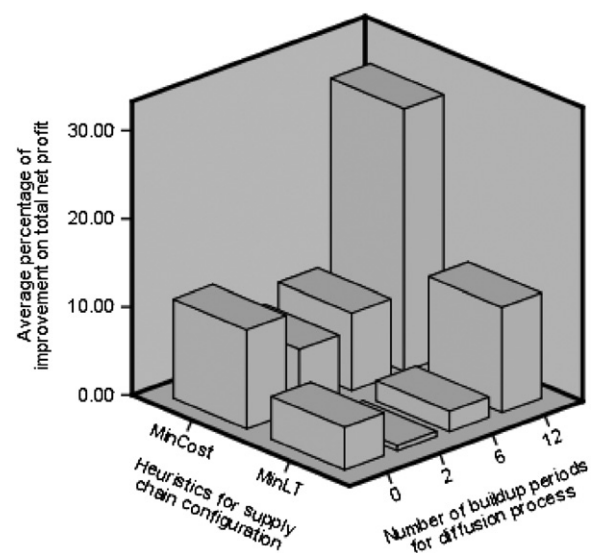


Fig. 3. Average percentage improvement of hybrid model over heuristic approaches on total net profit.

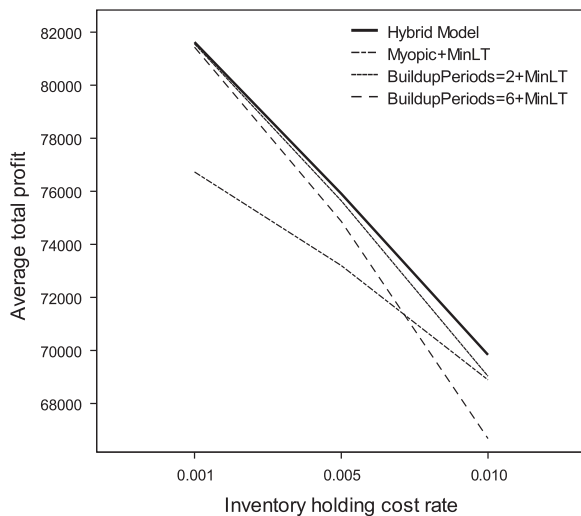


Fig. 4. Four best solution methods when inventory holding cost rate varies.

Observation 4: For the integrated product diffusion process and supply chain configuration problem, neither myopic nor buildup policy with many buildup periods may perform well.

4.2.2. Effect of parameters

The effect of inventory holding cost rate is illustrated by Fig. 4. None of the heuristics performs better than the hybrid model in all ranges of inventory cost rate. The second best solution is Buildup2+MinLT, which consistently outperforms Myopic+MinLT, although Myopic+MinLT leads to lower supply chain configuration cost. This again verifies the importance of integrating product diffusion and supply chain configuration. We also observe that as inventory holding cost rate increases, the difference of solution quality between myopic heuristics and hybrid model decreases; whereas the difference of solution quality between buildup heuristics and hybrid model increases. Observation 5 follows.

Observation 5: As inventory holding cost rate increases, the benefit of hybrid model over buildup policy increases; as inventory holding cost rate decreases, the benefit of hybrid model over myopic policy increases.

One-way ANOVA was conducted to test this hypothesis, with the p -value being less than 0.01. Inventory holding cost rate has impacts on both product diffusion and supply chain configuration sides. As inventory holding cost rate increases, buildup policy leads to not only increased amount of finished goods inventory on the product diffusion side, but also the pipeline and safety stock on the supply chain configuration side (due to increased demand/production variation). Thus a high inventory holding cost rate will make buildup policy less attractive. For the myopic policy, its main advantage is savings on inventory costs of finished goods, pipeline and safety stock: as myopic policy attempts to sell as much as possible, it incurs no finished goods inventory, and results in lower safety stock cost due to smaller demand/production variation. Such advantage of myopic policy will be amplified when the inventory holding cost rate is high.

The effect of percentage of backlogged demand is illustrated by Fig. 5. When percentage of backlogged demand (ξ) is either high or low, i.e. no loss of demand or complete loss of demand, there is less flexibility to shape the demand/production pattern, thus the advantage of hybrid model over heuristic policies is small; when ξ is around the middle (0.5), the hybrid model's advantage increases. Observation 6 follows.

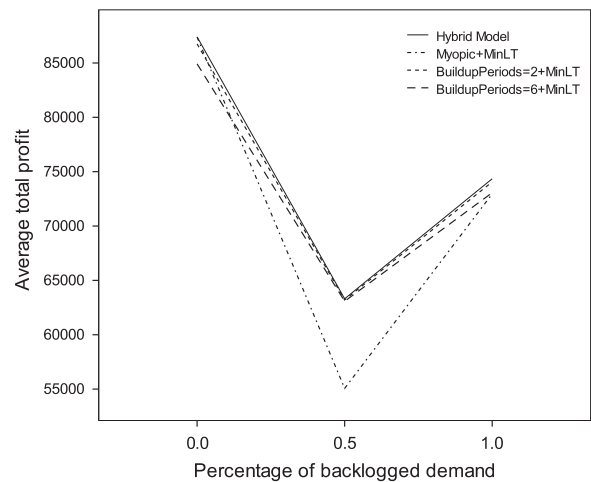


Fig. 5. Four best solution methods when percentage of backlogged demand varies.

Observation 6: The benefits of hybrid model are more pronounced when the percentage of backlogged demand is neither too high nor too low.

Two-sample t -test was conducted to test Observation 6, with the p -value being less than 0.01. The choice of ξ depends on the specific product and industry the model is addressing. A value of 0 represents an extreme where the unmet demand is completely lost. Examples of such case include highly seasonable goods. A value of 1 presents the other extreme that the unmet demand is completely backlogged. Examples of such case include various consumer goods for which the demand is not seasonable. The practical implication of Observation 8 is that for average value of ξ , the hybrid model is expected to significantly outperform heuristic decision rules.

We also examine effects of the parameters from the supply chain configuration side on total net profit. It is found that for various size supply chain networks and products ranging from the traditional consumer-electronics-manufacturing to an OEM, the hybrid model consistently outperforms heuristic decision rules.

5. Conclusions and future research

In this paper, we develop an integrated optimization model for configuring new products' supply chains while explicitly considering the impact of demand dynamics during new products' diffusion. It simultaneously determines optimal production/sales plan and supply chain configuration. The production and sales plan provides decisions on the optimal timing to launch a new product, as well as the production and sales quantity in each planning period. The supply chain configuration provides optimal selection of options and safety stock level kept at each supply chain function. The integrated model minimizes the total life-cycle profit during a new product's entire life cycle.

An in-depth computational experiment, including 2187 randomly generated testbed problem instances, was conducted to examine the performance characteristics of our integrated optimization model versus seven alternative heuristic policies under various diffusion and supply chain topologies. We obtain a number of managerial insights regarding production/sales planning and supply chain configuration for new products. (1) An optimal production/sales plan or supply chain configuration for a new product does not necessarily lead to maximum amount of sales revenue from the marketing perspective, or minimum amount of costs from the supply chain configuration perspective.

An optimal production/sales plan and supply chain configuration during new products' life cycle balances the tradeoffs among various cost and revenue components, and can only be achieved through an integrated optimization approach. (2) A smooth and even production/sales plan results in less inventory holding costs for the supply chain, but may suffer significant loss of sales by neglecting the dynamics of market demand. On the other hand, a production plan with certain number of buildup periods may increase sales revenue, but also incurs more supply chain configuration costs due to increased variation of sales/demand. Due to (1) and (2), our hybrid approach is more advantageous than models that consider production diffusion or supply chain configuration independently.

The hybrid optimization approach is also robust for supply chain networks with different topologies characterized by the number of functions in the network and the lead time/direct cost profile of the new product. We find that as the inventory holding cost rate increases, it becomes more costly for the buildup policy to avoid sales loss, thus the benefit of hybrid model over buildup policy increases. When the percentage of backlogged demand (ζ) deviates from two extreme cases, i.e. when ζ is neither high nor low as often the case in the real world, the benefit of hybrid model also increases.

This research opens a number of extension opportunities for analyzing the integrated new product diffusion and supply chain configuration problem. Here, we mention a few of these potential research extensions. First, our current study assumes a generic product with an average coefficient of innovation (p) and coefficient of imitation (q). It will be interesting to study the impact of different product diffusion characteristics captured by paired p and q for specific products/industries. Some industry-specific decisions and/or constraints may also be modeled. For instance, designing supply chains in the fashion industry may emphasize responsiveness in terms of the supply chain cycle time, thus a deadline on the cycle time may be necessary to be included as a constraint. Products in the high-tech industry may have a different cost and lead time accrual profile than that of consumer durable goods. Second, some assumptions in the supply chain configuration can be relaxed. For example, one could relax the single-sourcing assumption and allow multiple options to be assigned to a function. Third, the current model considers only single product, it will be interesting to extend the model to consider a family of new products sharing the same BOM. This would require that we consider the diffusion process of multiple correlated products simultaneously. Fourth, in real-world settings competitors might offer simultaneously similar products in the marketplace with the intention of capturing as much market share as possible. Obviously, the competitive environment impacts the supply chain configuration decisions and the dynamic demand pattern emerges from the new product diffusion process.

Then from the computational perspective, our current work relies on a commercial optimization solver to solve the integrated model. When problem size becomes large, solution times by solvers are not tractable. Thus a promising future research will be developing more advanced solution methods, e.g. various metaheuristics [36], to solve large size problems both effectively and efficiently.

Acknowledgements

The authors thank the associate editor and three anonymous referees for their helpful comments and suggestions that improve the contents and presentation of the paper. Mehdi Amini is

supported in part by the FedEx Institute of Technology and the Enterprise Simulation and Optimization Lab (eSOL) at the University of Memphis. Haitao Li is supported in part by the Center for Transportation Studies (CTS) at the University of Missouri—St. Louis.

References

- [1] Business Week, About that iPhone shortage, 2008, April 4.
- [2] Financial Times, Untimely Wii shortage hits Nintendo, 2007, December 24.
- [3] New York Post, Shortage chips apple net—suppliers delays will hold results down, 1999, September 21.
- [4] New York Times, Playstation sales zoom, 2000, March 7.
- [5] Los Angeles Times, Sony to cut game workers in US, 2007, June 7.
- [6] Lee HL. The triple-a supply chain. *Harvard Business Review* 2004;1–12. October.
- [7] Bass FM. A new product growth for model consumer durables. *Management Science* 1969;15(5):215–27.
- [8] Kumar S, Swaminathan JM. Diffusion of innovations under supply constraints. *Operations Research* 2003;51(6):866–79.
- [9] Ho T-H, Savin S, Terwiesch C. Managing demand and sales dynamics in new product diffusion under supply constraint. *Management Science* 2002;48(2):187–206.
- [10] Graves SC, Willems SP. Optimizing the supply chain configuration for new products. *Management Science* 2005;51(8):1165–80.
- [11] Geoffrion AM, Graves GW. Multicommodity distribution system design by benders decomposition. *Management Science* 1974;20(5):822–44.
- [12] Daskin MS. Network and discrete location: models, algorithms, and applications. New York: John Wiley & Sons, Inc.; 1995.
- [13] Simpson KF. In-process inventories. *Operations Research* 1958;6(6):863–73.
- [14] Minner S. Dynamic programming algorithms for multi-stage safety stock optimization. *OR Spectrum* 1997;19:261–71.
- [15] Inderfurth K, Minner S. Safety stocks in multi-stage inventory systems under different service measures. *European Journal of Operational Research* 1998;106:57–73.
- [16] Graves SC, Willems SP. Optimizing strategic safety stock placement in supply chains. *Manufacturing & Service Operations Management* 2000;2(1):68–83.
- [17] Mansfield E. Technical change and the rate of imitation. *Econometrica* 1961;29(4):741–66.
- [18] Mahajan V, Muller E, Bass FM. New product diffusion models in marketing: A review and directions for research. *Journal of Marketing* 1990;54:1–26.
- [19] Mahajan V, Muller E, Bass FM, Wind J. New product diffusion models. Thousand Oaks, CA: Sage; 2000.
- [20] Bass FM. Comments on "a new product growth for model consumer durables the bass model". *Management Science* 2004;50:1833–40.
- [21] Kurawarwala AA, Mastuo H. Forecasting and inventory management of short life-cycle products. *Operations Research* 1996;44(1):131–50.
- [22] Swami S, Khairnar PJ. Diffusion of products with limited supply and known expiration date. *Marketing Letters* 2003;14(1):33–46.
- [23] Chandra C, Grabis J. Role of flexibility in supply chain design and modeling—introduction to the special issue. *Omega* 2009;37:743–5.
- [24] Francas D, Minner S. Manufacturing network configuration in supply chains with product recovery. *Omega* 2009;37:757–69.
- [25] Yu H, Zeng AZ, Zhao L. Single or dual sourcing: decision-making in the presence of supply chain disruption risks. *Omega* 2009;37:788–800.
- [26] Sultan F, Farley JU, Lehmann DR. A meta-analysis of applications of diffusion models. *Journal of Marketing Research* 1990;27(1):70–7.
- [27] Sahni S. Computationally related problems. *SIAM Journal on Computing* 1974;3:262–79.
- [28] Floudas CA. Nonlinear and mixed-integer optimization: fundamentals and applications. New York: Oxford University Press; 1995.
- [29] Kocis GR, Grossmann IE. Relaxation strategy for the structural optimization of process flowsheets. *Industrial and Engineering Chemistry Research* 1987;26:1869–80.
- [30] Viswanathan J, Grossmann IE. A combined penalty function and outer approximation method for minlp optimization. *Computers & Chemical Engineering* 1990;14:769–82.
- [31] GAMS. Gams user's guide, GAMS Development Corporation, Washington DC, 2008.
- [32] Grossmann IE, Viswanathan J, Vecchieta A. DICOPT User's Manual. GAMS Development Corporation; 2008.
- [33] Magnanti TL, Shen Z-J, Shu J, Simchi-Levi D, Teo C-P. Inventory placement in acyclic supply chain networks. *Operations Research Letters* 2006;34:228–38.
- [34] Shu J, Karimi IA. Efficient heuristics for inventory placement in acyclic networks. *Computers & Operations Research* 2009;36:2899–904.
- [35] Hopp WJ. Supply chain science. New York: McGraw Hill; 2008.
- [36] Glover F, Kochenberger G. Handbook of metaheuristics. Springer; 2005.