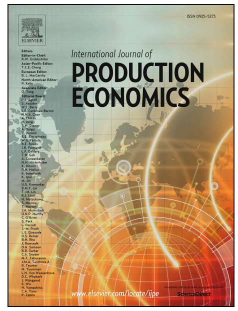

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A joint network design and multi-echelon inventory optimisation approach for supply chain segmentation

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Abstract

Segmenting large supply chains into lean and agile segments has become a powerful strategy allowing companies to manage different market demands effectively. A current stream of research into supply chain segmentation proposes demand volume and variability as the key segmentation criteria. This literature adequately justifies these criteria and analyses the benefits of segmentation. However, current work fails to provide approaches for allocating products to segments which go beyond simple rules of thumb, such as 80-20 Pareto rules. We propose a joint network and safety stock optimisation model which optimally allocates Stock Keeping Units (SKUs) to segments. We use this model, populated both with synthetic data and data from a real case study and demonstrate that this approach significantly improves cost when compared to using simple rules of thumb alone.

Keywords: Supply chain segmentation, network optimisation, inventory optimisation, guaranteed service approach

1. Introduction

Supply chain segmentation has emerged as a strategic tool by which a supply chain is categorised (segmented) to create multiple supply chains. The aim is to establish individual, operationally efficient, and profitable supply chains which are designed to meet specific service, cost or risk objectives (cf. to McKinsey and Company, 2008).

The traditional approach to segmentation is to use predefined rules to categorise products, markets, customers and so forth, and build tailored sub-supply chains for each category. For example, Fisher (1997) encourages companies to consider the nature of demand for their products noting two generic types - fashion products and commodities. The two product types respond to different market requirements and therefore require different supply chain approaches. A functional product, typically with stable demand should be served by an efficient supply chain, whereas an innovative product, subject to greater uncertainty requires a responsive supply chain. Lee (2002) goes further, incorporating the idea of demand and supply uncertainty into the segmentation; this becomes increasingly relevant as supply chains lengthen to encompass global operations (Peck and Jüttner, 2002). Lee (2002) identifies four supply chains each assigned to a combination of demand and supply uncertainty. Recent work finds demand volume and variability to be common segmentation criteria (see, for example, Godsell et al., 2011). The majority of these segmentation approaches are either explicitly or by implication grounded in the lean and agile paradigms.

A common issue with previous work is that it does not provide robust solutions for determining the parameters of segmentation rules. The supply chain segmentation literature focuses on proposing segmentation criteria (e.g. volume and variability) but does not elaborate on how to determine the parameters of these criteria. It follows then that we currently do not know the impact of setting the parameters of the segmentation criteria on supply chain performance. This study demonstrates, through a numerical study, that the use of suboptimal parameters for the volume and variability criteria of a particular segmentation has a significant impact on total supply chain cost.

We propose a combined network and inventory optimisation model to analyse the impact of segmentation on total cost. More specifically, as safety stocks are often used to hedge against demand uncertainty in make-to-stock (MTS) environments, we optimise the safety stock in the supply chain. Supply chain segmentation often considers the volume and the variability of demand (e.g. Godsell et al., 2011). The inclusion of safety stocks enables us to model the impact of variability explicitly. Our model assesses volume-based costs, such as manufacturing, transport and cross-docking, in addition to the cost of demand variability through holding cost. Based on our preliminary analysis, the combined network and inventory optimisation model achieves a cost reduction 10% greater than the network model alone.

The main contribution of this paper is a combined network and inventory model. This model is capable of finding the optimal supply chain network and inventory solution for an organisation operating a segmented supply chain strategy. Our approach provides insights into how segmented strategies can be realised and quantifies the cost benefits. Specifically, we evaluate the impact of segmentation on three distinct supply chain configurations: i) a traditional, unsegmented supply chain network optimised for lean or agile operation (Type I); ii) a segmented supply chain network optimised using predefined rules (Type II); iii) a segmented supply chain, where segmentation and configuration are optimised jointly (Type III). To aid granularity, we define a set of Type II scenarios, which test the impact of predefined volume and variability limits on total cost assuming a customer service level. The three configurations are compared to determine to what extent a segmented supply chain can be optimised. We also quantify the suboptimality of the predefined segmented supply chain configurations. Finally, we use sensitivity analysis to determine how system parameters (fixed and variable manufacturing cost and inventory holding cost) affect the optimal segmentation. In this way, we inform the discussion on how supply chains can be segmented using rules based on volume and variability.

We find that in addition to volume and variability, additional criteria are relevant when allocating products or markets to specific supply chain segments. For example, a supply chain comprises three segments, one of which is constrained by available capacity. This capacity constraint is preserved, by allocating some products whose volume and variability characteristics would naturally place them in the capacity constrained segment to an alternative segment.

Our research follows the tradition of empirical, analytical modelling as proposed by Bertrand and Fransoo (2002). We use empirical data for the numerical analysis supplied by a large, global FMCG (Fast Moving Consumer Goods) company. Thus allowing us to test our model using real-world demand and lead time data, along with manufacturing and transport costs. The paper proceeds as follows. Section 2 reviews relevant literature on supply chain segmentation and network modelling. Based on this we propose an inventory and network optimisation model for segmented supply chains in Section 3. Our analysis uses real data from a case company which has implemented and tested a volume/variability based segmentation approach in their global supply chain. Section 4 describes the data, the construction of the numerical analysis and presents the results. Section 5 concludes the paper.

2. Literature

Skinner (1969) observes that the manufacturing capability of a firm is critical to its competitiveness and that diverse customer requirements require distinct manufacturing strategies. With the evolution of the supply chain, the requirement for differentiated strategies, not only for manufacturing but across the whole supply chain became apparent. Fuller et al. (1993) extend the concept to logistics, while Fisher (1997) notes explicitly that the source of differentiation should move backwards and embrace the supply chain perspective. The literature contains a variety of approaches to differentiate the supply chain. The majority take either a product or customer-based perspective.

Product based segmentation often follows the lean and agile paradigms. Lean thinking embraces the elimination of all wastes; activities that consume resources but generate no redeeming value in the eyes of the customer (Womack and Jones, 1996). While the agile paradigm emphasises flexible, timely action in response to rapidly changing demand environments. It is common to cite the lean and agile paradigms as opposing philosophies; however, they share a common objective, to meet customer demand at the least cost. It is in the nature of the demand and the basis for meeting that demand that the two processes differ (Goldsby et al., 2006). The idea that the two paradigms may be combined, resulting in a single supply chain having both lean and agile elements leads to the idea that the supply chain might be designed or be adapted based on segmentation principles (Christopher and Towill, 2002; Christopher, 2000). The theory of focused demand chains is based on the premise that in the complex real world context no one demand chain strategy can service all requirements. A focus is required, to ensure that demand chains are engineered to match customer requirements, enabled by segmentation via product characteristics (Childerhouse et al., 2002). A classification approach allows the segmentation of products into groups based on market demand, followed by the development of alternative strategies for each segment to maximise competitive objectives. Naylor et al. (1999) use product characteristics of demand variability and variety to determine when companies should aim at agility and when at leanness. They combine the proliferation of variants in production (variety) with changing customer requirements (variability), echoing the work of Slack (1998) who uses demand variability and variety to segment manufacturing processes. Later, Christopher and Towill (2000) propose a classification system to codify the selection of value streams according to lean and agile principles - DWV3 - Duration of the product lifecycle, time Window, Volume, Variety and Variability. Several studies have applied this system. For example, Childerhouse et al. (2002) find that the priority ranking of the five variables depends on the level of sophistication used to segment the demand chains within an organisation, i.e. the extent to which the chains are focused.

While product-centric approaches provide useful insights for fulfilling product demand, they lack a customer perspective. Customers are increasingly sophisticated with highly differentiated preferences leading to a proliferation of Stock Keeping Units (SKUs) and the continuous customisation of products and services (Godsell et al., 2011). A behavioural segmentation of customers by buying behaviour allows the segmentation of a supply chain by understanding the customer that it serves. A corresponding supply chain strategy is then developed, seeking to select a supply chain type (lean, agile, fully flexible and continuous improvement) which will respond most appropriately to the major demand patterns in each segment. Gattorna et al. (1991) propose this as the idea of alignments. Some studies investigate segmentation of the supply chain into customer groups, supplying different products or services to the identified groups. In most cases, these studies propose analytical or game theoretic analyses which identify whether it is more profitable for the company to operate a dual channel strategy as opposed to a single channel. Examples from this stream include Coskun et al. (2016), Seifbarghy et al. (2015), Chen and Bell (2012), and Khouja et al. (2010). In all cases, the results of the modelling reveal that there exist circumstances in which customer segmentation is a profit enhancing activity, but that in each case it depends on the costs of the particular context. Godsell et al. (2011) argue that supply chain solutions, which aim to achieve a differentiated supply chain strategy, are not only affected by the needs of the customer but also reflect the characteristics of the product. In particular, the volume and the variability of the demand. The challenge is then, to ensure that supply chain capability combines market segment and product characteristic considerations. Gunasekaran et al. (2007) also find that demand uncertainty and variability are inherent to most operations and can require different types of responsiveness and different internal capabilities. Simchi-Levi et al. (2013) reiterate the importance of demand variability. They determine supply chain segments by focusing on demand uncertainty and customer relationships where each segment requires a different supply chain strategy.

Supply chain segmentation implies the ability to manage the supply chain at a more granular level. However, although the lean and agile paradigms dominate the literature, there exists no standardised way to segment the supply chain, with most of the discussion remaining on a qualitative level. In practice, many supply chain management (SCM) issues faced by companies involve operational decisions rooted in quantitative analysis; how to design and operate a segmented supply chain is no exception. Supply chain network design, where the number, size, location and interrelation of facilities within a network are determined, is no doubt one of these decisions (Farahani et al., 2014). The area of network design has a long pedigree with many published reviews, evaluating a large number of models and frameworks. The interested reader is referred to Melo et al. (2009) (for the facility location problem and SCM), Mangiaracina et al. (2015) (for distribution network design), Farahani et al. (2014) (for techniques applied in supply chain network design), and Farahani et al. (2015) (for modelling of the location-inventory problem). The existing literature demonstrates that the factors that drive network configuration decisions are divergent, including the number of echelons, selection of segments, the number of facilities, proximity to customers or suppliers, inventory required, and degree of centralisation. Despite this diversity, the factors can be classified using three dimensions: facility location, inventory, and transportation (Perl and Sirisoponsilp, 1988). Mangiaracina et al. (2015) identify 42 different factors from 126 reviewed papers and propose a framework based on a classification of these factors into five major groups based on their common characteristics: product characteristics, service requirements, demand features, supply characteristics, and economic variables. They find that factors relating to demand, such as volatility and volume, receive the most attention, as they have the widest influence. This dimension has been incorporated into many mathematical models, mainly to incorporate the impact of demand uncertainty. Mangiaracina et al. (2015) find the second most prevalent factor group to be service requirements, often measured by item fill rate, delivery frequency, and lead time. The remaining three groups (product, supply and economic factors) have received less attention to date, but have the potential to have a significant impact on the design of a network. Aligned with the three dimensions of Perl and Sirisoponsilp (1988), recent studies have focused on tactical decisions such as detailed inventory planning and decisions related to transport, production and procurement. Consideration of tactical problems inevitably leads to much more complex models, due to the large size of the problems that may result (Melo et al., 2009).

Network related approaches to implementing segmentation strategies include postponement (Goldsby et al., 2006), assemble-to-order, make-to-order, lead time reduction, transshipments (Herer et al., 2002) and consumer segmentation related to green issues (Coskun et al., 2016). These approaches link to a question: where is the stock held in the supply chain? The inventory decision is a key factor in determining the leanness and agility of a supply chain network and is widely studied. Extant work, however, remains predominantly conceptual. Quantitative literature in this area takes an aggregated approach to evaluating the objectives and constraints defined in supply chain segmentation. There is very little literature which formally presents network design models which explicitly incorporate strategic supply chain segmentation criteria in a disaggregated sense; particularly if we focus on models which incorporate inventory planning (location inventory problem). The paper of Purvis et al. (2014) is an exception, it illustrates the formation of the lean/agile/leagile network from the perspective of supply flexibility, but they do not develop any mathematical models. Ameknassi et al. (2016)'s closed-loop supply chain network model captures the customer segmentation concept but with a tactical focus on transport and warehousing rather than inventory planning. Goldsby et al. (2006) develop comparative models of lean, agile and leagile networks but do not consider inventory.

In summary, aligning supply chain strategy to the demands of the customer and the product group has the potential to improve performance across the supply chain. When designing or optimising a supply chain network the consideration of different factor groups or requirements leads to different optimal network configurations. The logical extension of this is that a company may not have a single supply chain but a set of focused supply chains each of which with a unique network. The physical supply chain, by which a product is made and delivered, depends both on product and customer characteristics. There is very little literature which formally addresses this problem quantitatively, particularly when considering the location inventory model. A key contribution of this paper is, therefore, the presentation of such a model.

3. Mathematical formulation

A previous supply chain segmentation study with a large global FMCG company inspired this study. The company's supply chain segmentation strategy is designed around the leagile paradigm, using volume-variability based demand profiling.

A specific characteristic of the underlying case is that every end-market has individual packaging requirements; hence, every SKU is specific to a market and cannot be transshipped or supplied to another market. Applying a postponement strategy is not practical due to the highly integrated manufacturing and packaging process. This case study motivates the setting and the model assumptions. However, our model is general enough to apply to many different make-to-stock FMCG supply chains with a large number of products, particularly those subject to regulation such as wine, spirits and pharmaceuticals.

Following segmentation into lean and agile segments, each factory is designed to operate in a specific segment s, which can be either lean ($s = 1$) or agile ($s = 2$). Fixed and variable manufacturing costs and lead times are factory specific and depend on the production segment. Lean factories operate at higher fixed costs, lower variable costs and higher lead times than the more reactive, agile factories. Before the implementation of the segmentation strategy, all factories operated in a mixed configuration; this did not take advantage of either the economies of scale of a lean design or the responsiveness of an agile design.

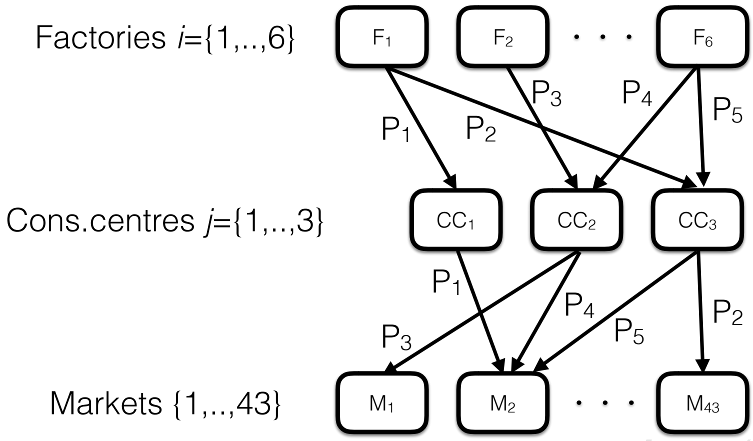


Figure 1: Three-stage serial supply chain

Our model considers a three-echelon supply chain, as depicted in Figure 1, which can accommodate any number of supply chain segments. However, we limit our analysis to two segments, one lean and one agile. Similar to the underlying case we assume that each SKU is sold in only one specific market. We further assume for simplicity that each SKU is produced in one factory and shipped through one consolidation centre. Hence, this implies a serial supply chain for every SKU, with each SKU allocated to a specific supply chain segment, operating in segment s. This allocation affects not only manufacturing cost and lead time but also distribution cost and transport time. The relevant costs and lead times differ according to the assigned segment. The notation is presented below.

Sets/Indices

$\mathcal{N}$	set of factories indexed by i
$\mathcal{R}$	set of consolidation centre (CCs) indexed by j
$\mathcal{S}$	set of s segments available; where $s = 1 \ldots$ lean, $s = 2 \ldots$ agile segment
$\mathcal{P}$	set of products indexed by p

Parameters

λ_p	service factor for product p
μ_p	mean of demand of product p per month
σ_p	standard deviation of demand of product p per month

f_{is}	fixed cost per lot at factory i in segment s
c_{is}^{fac}	variable cost of per unit at factory i in segment s
$\bar{c}_{isp}$	average cost of per unit at factory i in segment s
Q_p	production lot size of product p
c_{ijs}^{up}	transport cost per unit from factory i to CC j in segment s
c_{jsp}^{dn}	transport cost per unit from CC j to the market of product p in segment s
h	stock holding cost rate in %
r_j	throughput cost per unit at CC j
t_{is}^{fac}	production lead time at factory i in segment s
t_{ijs}^{up}	transport time from factory i to CC j in segment s
t_{jsp}^{dn}	transport time from CC j to the market of product p in segment s
S_{isp}^{fac}	guaranteed service time at factory i in production segment s for product p
S_{jsp}^{cc}	guaranteed service time at CC j in transport segment s for product p
SSC_{isp}^{fac}	safety stock cost at factory i in segment s, for product p
SSC_{ijsp}^{cc}	safety stock cost at CC j in segment s for product p, shipped from factory i
SSC_{ijsp}^{wh}	safety stock cost at the market for product p in segment s, shipped from factory i through CC j
SSC_{ijsp}^{*}	optimal safety stock cost in the system, i.e. at factory i, CC j, and the market for product p in segment s

Decision variables

X_{ijsp}	1 if product p is from factory i through CC j in segment s, and 0 otherwise

Auxiliary variables

Z_{is}	1 if segment s is chosen in factory i, and 0 otherwise

220 *3.1. Network model*

The objective is to minimise total cost TC by solving the optimization problem

$$TC = \min_{X_{ijsp}} \sum_{p\in P}\sum_{s\in S}\sum_{i\in N}\sum_{j\in R} X_{ijsp}\left(SSC_{ijsp}^{*} + \frac{\mu_p}{Q_p} f_{is} + \mu_p c_{is}^{\text{fac}} + \mu_p c_{ijs}^{\text{up}} + \mu_p c_{jsp}^{\text{dn}} + \mu_p r_j \right) \tag{1}$$

subject to the following constraints

$$\sum_{i\in N}\sum_{j\in R}\sum_{s\in S} X_{ijsp} = 1 \qquad \forall p \tag{2}$$

$$X_{ijsp} \leq Z_{is} \qquad \forall i, j, s, p \tag{3}$$

$$\sum_{s\in S} Z_{is} = 1 \qquad \forall i. \tag{4}$$

The model optimises the allocation of products to factories and consolidation centres and determines the segment to which the product belongs. The first cost term in the objective function corresponds to the inventory holding cost for all echelons; this is estimated using the guaranteed service model. These costs can be pre-calculated very efficiently before solving (1) because the optimal inventory control parameters in a serial supply chain for such a model have been shown to be border solutions. See Section 3.2 for a detailed discussion.

The second cost term refers to the fixed manufacturing cost per batch, where Q_p is the batch size. Note that we will assume in the following numerical analysis $Q_p = \mu_p$, i.e. every product is produced in exactly one batch per month. The third term refers to the variable manufacturing cost. Terms four and five capture the transport cost from the factory to the consolidation centre and from the consolidation centre to the end-market, respectively. Note that inventory holding cost for pipeline inventory is included in the parameters c^{up}_{ijs} and c^{dn}_{jsp}. The last term refers to the throughput cost at the consolidation centres.

Constraint (2) establishes the allocation of every product p, to exactly one supply chain segment, one factory and one consolidation centre. Constraint (3) ensures that a product can be allocated to a factory i, if and only if the factory belongs to the same supply chain segment. Finally, constraint (4) ensures that each factory operates in only one segment s.

3.2. The guaranteed service model

The complexity of location-inventory models lies in their nonlinear nature, inherited from inventory models. The degree of complexity increases with the number of stages, as these models seek to optimise inventory levels across all stages, by determining the optimal numbers of stocking locations and associated amount of stock (Shu et al., 2005; Daskin et al., 2002; Melo et al., 2009). The guaranteed service model (GSM) and the stochastic service model (SSM) are the two main approaches for modelling multi-echelon inventory systems. These approaches are distinct from characteristics such as demand propagation, material flow, and the resulting service time and are widely researched (Eruguz et al., 2012, 2016). Studies related to SSM focus on basic network topologies, as the approach requires exact system understanding. Whereas, the adaptability of GSM allowing it to handle a range of network structures permits its use in a wide variety of industrial applications. Examples include Hewlett-Packard in Billington et al. (2004), Procter and Gamble in Farasyn et al. (2011), and Cisco in Hua and Willems (2016a). Eruguz et al. (2016) provide a summary of the applications of GSM in real-life cases from 10 different industries. In addition, the demand-related assumptions of GSM are reasonably justifiable from managerial experience (Graves and Willems, 2000). Thus, we adopt GSM as the inventory control framework in our study.

GSM derives from the algorithm proposed by Simpson (1958) based on a serial production system. Graves and Willems (2000) develop and generalise the model to accommodate placement of safety stock in different network structures and Graves and Willems (2003) show how it can be used to formulate a supply chain configuration problem. Later work by You and Grossmann (2008) proposes a more complete location-inventory model using GSM along with a number of approaches for linearising the integrated model. Hua and Willems (2016b) analyse a two-stage serial supply chain for a single product considering alternative sourcing options with different cost and lead time parameters. Part of the problem is to select the optimal solution from these alternatives. They show that it is preferable to employ the same type of alternatives, low-cost long lead time or high-cost short lead time, in both stages.

In GSM, the supply chain follows a network structure where nodes are facilities and arcs denote flows of goods. The nodes operate under a periodic review base-stock policy. Note that in our setting the network for each product can be modelled as an independent three-echelon serial supply chain. Demand is assumed normally distributed with mean μ and standard deviation σ, bounded over a consecutive period. The demand bound can be formulated as $D(t) = t \cdot \mu + \lambda \cdot \sigma \cdot \sqrt{t}$, where λ is the service factor. Note that this model does not imply that demand never exceeds the bound. Instead, it represents the limit up to which demand nodes aim to satisfy demand directly from their safety stock. We assume that demand beyond the upper bound must be handled by extraordinary methods, e.g. expedited shipment.

Each node n in the network commits to a service time S_n within which it guarantees to fulfil the demand from the downstream nodes. In other words, for orders observed at review period, time t, node n must be ready to fulfil them by time $t + S_n$. These guaranteed service times are decision variables to be optimised, except for those at nodes facing external end-customer demand (in our model called end-markets). The outbound service time to end-customers in MTS environments is assumed to be zero to permit an immediate service to external customers. The lead time T_n which consists of transport time from the upstream node $n + 1$ and processing time at node n is an exogenous input variable. Under this setting, the time span required to cover demand variation using safety stock at node n is $S_{n+1} + T_n - S_n$. We can then easily find that safety stock at node n equals $SS_n = \lambda \cdot \sigma \cdot \sqrt{S_{n+1} + T_n - S_n}$. Using this model we derive the safety stock levels and corresponding holding costs for a given supply chain configuration.

In our setting with multiple products, the per unit holding cost for product p in factory i is $h \cdot \bar{c}_{isp}$, where we define $\bar{c}_{isp} = \dfrac{f_{is}}{Q_p} + c^{\text{fac}}_{is}$ and h as the annual stock holding cost rate for each echelon, added to the accumulated cost for the lower echelons. Let the guaranteed service time for product p from factory i to any consolidation centre be S^{fac}_{isp}, then the total inventory holding cost for the factory can be written as

$$SSC^{\text{fac}}_{isp}\left(S^{\text{fac}}_{isp}\right) = h \cdot \bar{c}_{isp} \lambda \sigma_p \sqrt{t^{\text{fac}}_{is} - S^{\text{fac}}_{isp}}. \tag{5}$$

Similarly, let the guaranteed service time from consolidation centre j be S^{cc}_{jsp}, then the total inventory holding cost for the consolidation centre is

$$SSC^{\text{cc}}_{ijsp}\left(S^{\text{fac}}_{isp}, S^{\text{cc}}_{jsp}\right) = h \cdot \left(\bar{c}_{isp} + c^{\text{up}}_{ijs} + r_j\right) \lambda \sigma_p \sqrt{S^{\text{fac}}_{isp} + t^{\text{up}}_{ijs} - S^{\text{cc}}_{jsp}}. \tag{6}$$

Finally, for the market warehouse, we can write

$$SSC^{\mathrm{wh}}_{ijsp}\left(S^{\mathrm{cc}}_{jsp}\right) = h \cdot \left(\bar{c}_{isp} + c^{\mathrm{up}}_{ijs} + c^{\mathrm{dn}}_{jsp} + r_j\right) \lambda \sigma_p \sqrt{S^{\mathrm{cc}}_{jsp} + t^{\mathrm{dn}}_{jsp}}. \tag{7}$$

This formulation results in the following optimal total safety stock cost for product p for a given configuration (i, j, s)

$$SSC^{*}_{ijsp} = \min_{S^{\mathrm{fac}}_{isp}, S^{\mathrm{cc}}_{jsp}} \left[SSC^{\mathrm{fac}}_{isp}\left(S^{\mathrm{fac}}_{isp}\right) + SSC^{\mathrm{cc}}_{ijsp}\left(S^{\mathrm{fac}}_{isp}, S^{\mathrm{cc}}_{jsp}\right) + SSC^{\mathrm{wh}}_{ijsp}\left(S^{\mathrm{cc}}_{jsp}\right)\right], \tag{8}$$

subject to the following constraints

$$0 \le S^{\mathrm{fac}}_{isp} \le t^{\mathrm{fac}}_{is} \qquad \forall i, s, p \tag{9}$$

$$0 \le S^{\mathrm{cc}}_{jsp} \le S^{\mathrm{fac}}_{isp} + t^{\mathrm{up}}_{ijs} \qquad \forall i, j, s, p. \tag{10}$$

GSM is distinct from SSM in the treatment of excessive demand. Leading to differences in three characteristics: demand propagation, material flow and service time. Unlike GSM, SSM does not fulfil demand from safety stock. If it is not possible to fulfil demand, it waits until the next period. Therefore, the availability of items in the system affects the service time and back-ordering, yielding a stochastic replenishment time. In contrast, GSM assumes excessive demand will be fulfilled using external methods, with no backorders allowed. This assumption gives a deterministic replenishment time and allows identification of the properties of the optimal solutions for GSM, significantly reducing the complexity of the nonlinear nature embedded in the inventory model. One important example for our study, Simpson (1958) proves that applying GSM in serial supply chains leads to corner solutions. Therefore, in our model, the possible solutions are limited to one of the four combinations defined by (9) and (10). The optimisation of (8) can be executed very efficiently by evaluating the four corners. The runtime for the full case setting described in the following section, written in Python code, on our laptop, a standard Intel i5 dual-core processor with 4GB RAM, is less than 10 minutes.

4. Data

The numerical analyses presented in this paper are based in part on real data. The analysis of these data reveals the main effects, discussed in the following subsections. However, to isolate certain effects from noise, the cost and lead time parameters of the real data set were replaced by synthetic data. In particular, costs and lead times between nodes in the network vary significantly due to different market regions and the geographic distribution of sites. The synthetic data set consists of equal parameter values at arcs and nodes of the same type in the network. See Table 2 for full details of the parameters used in the numerical analysis. Please note that a dash "–" in the synthetic data column means that we use the real data for that item. The only two parameters not included in the case data are h and λ_p. Therefore, we assume commonly used values, which are the same both for the real and the synthetic settings.

The original company sourced data set consists of 4-years' worth of monthly sales data from end-markets. The data set includes relevant costs, lead time information for facilities and transport flows in each echelon (i.e. between factories, consolidation centres, and end-markets). New product introductions and end-of-life products are filtered out in the first stage. Product demand data includes monthly sales which are used to compute averages and coefficient of variations (cv) of monthly sales, see Figure 2. The production batch size is defined as average monthly sales, as the company's current policy is to manufacture every SKU once per month.

Due to the confidential nature of the data, we cannot disclose all of the data as part of this paper. Table 2, however, shows ranges of cost and lead time parameters. A normalised data set can be made available upon request by email from the corresponding author.

5. Numerical analysis

Figure 3 presents the optimal segmentation policy suggested by model (1), i.e. Type III, based on the real data. The red coloured points correspond to the products assigned to the agile supply chain segment, and the blue points represent those assigned to the lean

Table 2: Values used in the numerical analysis

Notation	Real case values	Synthetic values
Set		
$\mathcal{N}$	6 locations	–
$\mathcal{R}$	3 locations	–
$\mathcal{S}$	2 segments	–
$\mathcal{P}$	6,013 products	–
Demand parameters		
μ_p	[100, 200M] units	–
σ_p	[260, 107M] units	–
cv	[0.005, 5]	–
Cost		
f_{i1}	[60, 750]€/lot	400€/lot
f_{i2}	[12, 148]€/lot	40€/lot
c_{i1}^{fac}	[4.8, 12.3]€/10k units	10€/10k units
c_{i2}^{fac}	[4.3, 12.1]€/10k units	25€/10k units
c_{ij1}^{up}	[0.01, 1.04]€/10k units	0.015€/10k units
c_{ij2}^{up}	[0.07, 2.48]€/10k units	0.05€/10k units
c_{j1p}^{dn}	[0.001, 3.94]€/10k units	–
c_{j2p}^{dn}	[0.007, 12.2]€/10k units	–
Lead time		
t_{i1}^{fac}	1 month	–
t_{i2}^{fac}	0.2 month	–
t_{ij1}^{up}	[0.015, 0.08] months	0.25 month
t_{ij2}^{up}	[0.02, 0.5] months	0.1 month
t_{j1p}^{dn}	[0.0036, 0.04] months	0.22 month
t_{j2p}^{dn}	[0.0018, 0.04] months	0.08 month
Other parameters		
h	–	0.25
λ_p	–	3

segment.

Figure 3a shows, using real data that the separation of SKUs into lean and agile supply chain segments is not explained completely by a volume-variability function. However, the figure shows two clouds, one of which is dominated by each strategy, and there is a discernible pattern which allows the division of the SKUs into two groups based on volume and variability. Nevertheless, we observe a significant region of overlap which implies that the optimal allocation of SKUs to segments is affected by factors other than the volume

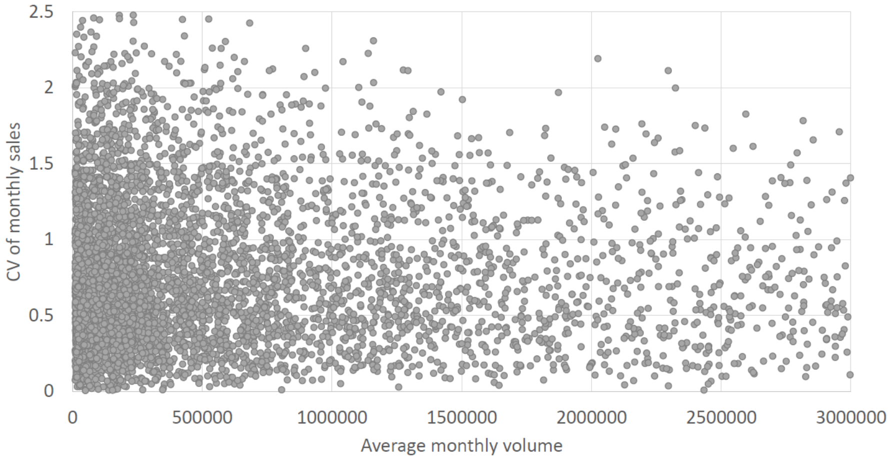
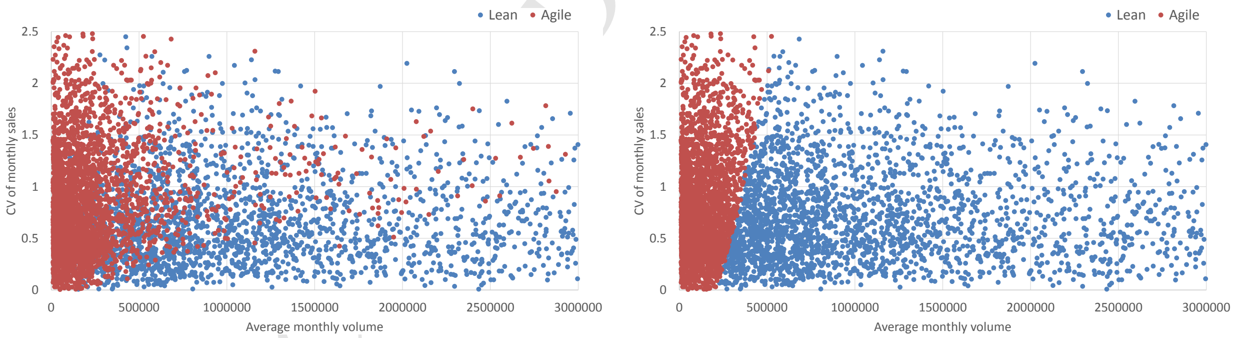


Figure 2: Volume vs. variability for sales data for approximately 6,000 SKUs

and variability of demand. Geographic dispersion means that transport legs have different cost and lead time parameters. This means that certain SKUs are allocated to non-optimal supply chain segments due to the geographic location of factories and end-markets. In these cases, actual transport cost outweighs the benefits of the optimal supply chain segment. The area of overlap captures the extent to which these factors influence the allocation.



(a) Real data (b) Synthetic data

Figure 3: Segmentation of SKUs into lean and agile segments for the base parameter set.

Figure 3b shows that, when using synthetic data, the optimal allocation of SKUs to supply chain segments can be described exactly by a function of the volume and variability (cv) of demand. To allow us to carry out sensitivity analysis, in the following subsections, we continue to use the synthetic data set. This allows us to understand exactly the changes which occur on the lean-agile border of the volume-variability plane.

5.1. Comparison of Type I, II and III segmented supply chains

As briefly discussed in the introduction, we classify segmented supply chains into three types: Type I, II and III segmented supply chains as shown in Table 3. In this section, we compare the performance improvement achieved by using, a) a Type III supply chain compared to a Type I, and b) a Type III supply chain compared to a Type II.

Table 3: Classification scheme for segmented supply chains

TYPE I	This supply chain is not segmented. It follows a "one size fits all" approach and handles all SKUs using the same strategy.
TYPE II	This supply chain is segmented. The allocation of SKUs (and facilities) is made using rules-of-thumb. For example, a supply chain may be segmented into lean and agile segments using the Pareto 80-20 rule.
TYPE III	This supply chain is segmented. The allocation of SKUs and facilities to a given set of segments is achieved using quantitative optimisation techniques. For example, in this paper, a mixed-integer optimisation model on total cost is used.

In our analysis, we assume two sub-types of unsegmented configurations: a lean supply chain and an agile supply chain. A lean supply chain operates entirely in a lean mode while an agile supply chain operates in a fully agile mode. As shown in Table 4, based on our simulation study, the performance gain of adopting a Type III segmentation strategy lies somewhere between 1 and 22%. We note that the two configurations shown in Table 4 are ideal configurations whereas in practice supply chains are often configured somewhere between these two extremes. These results suggest that a significant cost improvement is realistic, depending on the strategy applied. A comparison based on the synthetic data

Table 4: Increase in total cost for Type I supply chains compared to the Type III supply chain

		Type I		Type III
		Lean	Agile	
Synthetic data	Cost	23,647,011	40,615,093	22,565,905
	% increase	4.8%	80.0%	
Real data	Cost	15,532,849	12,859,485	12,747,245
	% increase	21.85%	0.88%	

yields even higher improvement potentials. However, it is likely that noise in imperfect real world settings reduces the actual performance gains achieved through optimisation.

When adopting a Type II segmented supply chain, i.e. segments are classified using predefined volume and variability criteria, it is critical to define the volume and variability parameters for separating the two segments. For example, Christopher and Towill (2002) suggest a Pareto based segmentation, e.g. an 80-20 rule, which states that the lean segment should contain approximately 20% of all SKUs which typically generate 80% of the volume. To understand the impact of such a decision, we apply this 80-20 rule to segment the SKUs in our model and given this product segmentation we determine the optimal network design. The model will still make optimal decisions in the allocation of factories to segments, the allocation of SKUs to factories, and the optimal routes to the end-markets, but the allocation of SKUs to segments is done using the Pareto rule.

Table 5 shows the cost differences between the optimal segmentation policy and three predefined segmentation policies based on the 80-20 rule. A product is defined as agile if it's average monthly volume is lower than the limit, or if the cv is higher than the corresponding limit. Although in all cases, the rule allocates 20% of the SKUs to the lean segment and 80% to the agile segment, we demonstrate that the parameters used to define the segmentation have a considerable impact on the total cost. Table 5 also shows that the least favourable cut-off limits increase the cost by nearly twice as much as the most favourable cut-off limits when compared to the cost achieved by the Type III segmented supply chain. In all cases,

Table 5: Increase in total cost for Type II supply chains with predefined segmentation based on the 80-20 rule, compared to the Type III supply chain

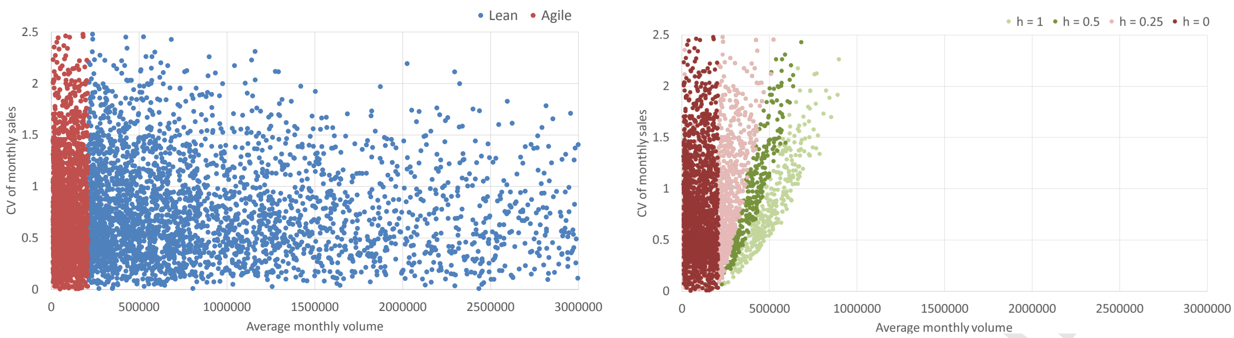
		Type II			Type III
	Volume	100k	500k	1,000k	
	cv	0.40	0.58	0.80	
Synthetic data	Cost	35,453,735	30,988,408	28,771,910	22,565,905
	% increase	36.4%	23.8%	17.5%	
Real data	Cost	13,337,438	13,794,287	14,043,770	12,747,245
	% increase	4.63%	8.21%	10.17%	

using a Type II segmented supply chain results in a cost which is 5 to 10% higher than the Type III segmented supply chain. When we use the synthetic data set, we find the difference to be between 17 and 36% which, again, can be explained by the idealised network setting.

Profitability is another segmentation criteria, often cited in the literature. In our setting, we do not consider the impact of the selling price of individual SKUs; though the cost per unit is a potential proxy for profitability. Note, however, that cost per unit is a consequence of the operational decisions made and is not known a priori. The opportunity to define a third dimension which would allow a perfect segmentation remains open (see Li and O'Brien (2001) for a similar discussion). Nevertheless, Figure 3a and Table 5 show that a segmentation based on volume and variability has the potential to provide a sound basis for designing the supply chain.

5.2. Impact of cost parameters

In this section, we analyse the impact of holding and manufacturing costs on the optimal segmentation and network design. Although we conduct our analysis using both synthetic and real data, our presentation here focuses mainly on the outcomes of the analysis using synthetic data. By doing so, we present the change in the optimal segmentation of SKUs by exclusively examining the volume and variability of demand characteristics under different cost parameters.



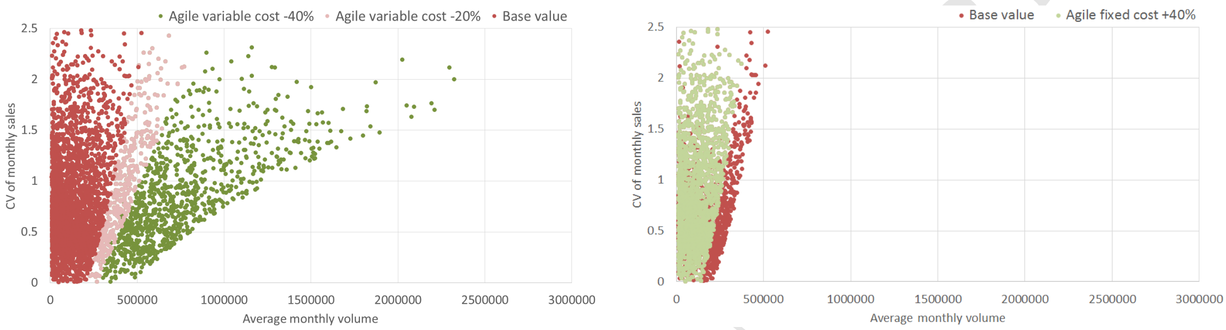
(a) Optimal segmentation, $h = 0$ (b) Change in the agile segment

Figure 4: Comparison of SKU lean/agile segmentation at different holding cost (synthetic data)

We start by studying the impact of holding cost, by comparing the segmentation under four holding cost rate scenarios $h = \{0, 0.25, 0.50, 1\}$. Figure 4a shows the result when $h = 0$, i.e. we omit inventory decisions from the network design phase. A vertical cut-off limit, corresponding to a volume of 209,000 units, separates the two segments, this means that in this case, 39% of SKUs belong to the agile segment. Figure 4b displays how the agile segment changes as h increases. The red dots are products allocated to the agile segment when $h = 0$, while the pink, green and light green dots represent additional products allocated to the agile segment as h increases. Figure 4b illustrates how the segmentation boundaries evolve. The percentage of SKUs in the agile segment rises from 39% when $h = 0$, to 45%, 50%, and 56% as h increases.

The main advantage of an agile supply chain is its ability to react to changes in demand, reducing the need to hold safety stocks. As the holding cost increases the gains from agile operations also increase, resulting in a larger number of products assigned to this segment. When $h = 0$, a significant number of products remain assigned to this segment due to the lower manufacturing fixed costs of agile facilities. For values of cv around zero, the cut-off limits for different h values in the volume dimension are approximately equal. However, as cv increases, the slope of the boundary between the two segments changes, and it becomes non-linear. The real case shows the same pattern although the relationship is less clear.

Next, we compare the optimal policy under different manufacturing costs for the agile segment, with inventory holding cost rate set to the base case value, $h = 25\%$. As in the discussion above, Figure 5 demonstrates how the product allocations to the agile segment change for the scenarios where the agile variable manufacturing cost reduces by 20% and 40% and the agile fixed manufacturing cost increases by 40%. The red dots in Figures 5a and 5b represent the optimal agile allocation using the base values for the manufacturing costs for the agile segment. The pink, green, and light green dots represent additional products allocated to the agile segment as the agile manufacturing costs change.



(a) Change in the agile segment for different agile variable manufacturing cost

(b) Change in the agile segment for different agile fixed manufacturing cost

Figure 5: Sensitivity of manufacturing costs in the agile segment using synthetic parameters

As shown in both figures, when the variable or fixed cost changes the line separating the two segments moves in the volume dimension even when cv is almost zero. Demonstrating the impact of cv on the trade-off between variable and fixed costs for the lean and agile segments. However, the slope of the dividing line remains the same for a change in the fixed cost while it significantly decreases for a decrease in the variable cost. In the total cost calculation, the variable manufacturing cost impacts on both the mean and cv of demand, a change in the fixed cost affects only the mean demand. The reason for this difference is the way that holding cost is charged. The inventory holding cost is calculated based on the accumulated variable costs up to the stock holding node, see Equations (6) and (7). Therefore, as the variable manufacturing cost decreases, holding cost also decreases. We observe similar results for the analysis of the transport costs.

In Figures 4 and 5 we observe the change in the agile segment as the cost parameters change, with the proportion of SKUs assigned to the agile segment differing significantly based on these parameters. This implies that a predefined segmentation rule based on a proportional allocation of SKUs to segments, e.g. the 80-20 rule, cannot perform well without considering the economic parameters.

5.3. Impact of integrating safety stock and network optimisation

Finally, one question remains: Is it at all meaningful to integrate safety stock optimisation into the network design problem? As we follow the current literature on supply chain segmentation strategies, we use volume and variability as the allocation criteria of SKUs to either segment. However, in a purely deterministic network model without safety stock optimisation, the variability of demand would not have any impact. As is easily seen from Equation (1), the safety stock term SSC^*_{ijsp} is the only term that contains σ_p. If removed, the remaining network model is purely deterministic.

To quantify the impact on the cost of including safety stock optimisation in the model, we modify the objective Equation (1) as follows

$$TC' = \min_{X_{ijsp}} \sum_{p\in P}\sum_{s\in S}\sum_{i\in N}\sum_{j\in R} X_{ijsp}\left(\frac{\mu_p}{Q_p} f_{is} + \mu_p c^{\text{fac}}_{is} + \mu_p c^{\text{up}}_{ijs} + \mu_p c^{\text{dn}}_{jsp} + \mu_p r_j\right), \tag{11}$$

subject to the constraints Equations (2), (3) and (4). Optimal safety stocks $SSC^{*'}_{ijsp}$ for the network resulting from optimising Equation (11) are then added to the total cost TC'.

We simulate the optimal policy using different holding cost rates in the range $h = \{0.25, 0.50, 1\}$ and compare the results to the joint optimisation under each of the holding cost rates used in Section 5.2. Our results show that using the real data and jointly optimising the network structure and safety stock levels, total costs can be decreased by between 5% and 18%. Therefore, we find that it is important to include safety stock considerations when performing network optimisation for Type III segmented supply chains. Significant improvements are achieved by optimising inventory and network design simultaneously.

6. Conclusion

To the best of our knowledge, this is the first study which proposes an optimal approach to the supply chain segmentation problem. The literature on supply chain segmentation to date uses rules of thumb to allocate SKUs to supply chain segments, for example, the well-known Pareto 80-20 rule. This paper contributes to the existing body of knowledge in two ways, i) by proposing a mathematical model to optimise the allocation of SKUs to supply chain segments and ii) by including safety stock optimisation as a joint optimisation problem. Our analysis shows that adopting a Type III supply chain leads to significant cost improvements compared to a Type II or an unsegmented supply chain. We further show that introducing the safety stock optimisation problem into the network problem and optimising both simultaneously, leads to significant cost benefits.

Comparing Type II and Type III supply chains allows us to evaluate the impact of segmentation criteria. We establish a set of Type II scenarios based on a Pareto segmentation, i.e. 80-20 rule, and determine the optimal supply chain structure based on predefined SKU segments. The results show that such a two-step approach to supply chain segmentation has the potential to give good results and a volume-variability based categorisation is a viable basis for segmentation. However, the results highlight that the costs are sensitive to the parameters chosen for the segmentation rules, and these must be chosen carefully to avoid significant cost penalties. Adopting a Type III supply chain, however, avoids these issues and outperforms the Type II supply chain significantly.

To model the impact of demand variability, we include inventory control decisions in our model in the design phase. Our results confirm that the inclusion of inventory holding costs can change the optimal supply chain design significantly. The supply chain configuration of the motivating case company, i.e. a serial supply chain system, forms the basis for our modelling. Such a setup applies to companies where the product, for reasons of manufacturing efficiency, product authenticity or market regulation is produced and packaged specifically for the local market at the source. This includes products such as tobacco and pharmaceuticals. Obviously, the assumption of a serial supply chain restricts the applicability of our approach, in particular, it is not possible to take advantage of inventory pooling in this context as each product is only sold in one market. However, the model has the potential to be generalised further.

An immediate extension of our model could be to consider settings where inventory pooling comes into play. The main challenge in such a setting is to incorporate the pooling effect and solve the nonlinearity of the inventory control model. One might then consider expanding the model in the supply dimension, i.e. from a single sourcing setting to dual sourcing. Another research direction would be to model the manufacturing and transport processes in more detail. Currently, these are modelled at an aggregate level ignoring the interaction with the assignment of products. For example, the lead times and costs will differ based on the number and the demand characteristics of the products assigned to a factory. To see the detailed transport and manufacturing processes in such a complex system simulation modelling would be an appropriate approach.

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