Automotive supply chain logistics: container demand planning using Monte Carlo simulation

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Abstract: Car manufacturers are continuously examining ways to reduce logistics costs combined with higher performance in inbound delivery. The increasingly important role of packaging in the efficient and effective operation of multi-site car manufacturing needs to develop a planning model of container demand that better fulfils the prerequisites posed by dynamic supply chains in automotive industry. The paper analyses critical issues in container demand planning of the product development phase of a new car model before start of production. A quantitative methodology with Monte Carlo simulations is used to incorporate the uncertainty of valuation parameters. The research is based on real case study data of European auto industry in a multi-tier inbound transport network. The proposed methodology contributes to the current demand for computational support for logistics planning. In addition, it may reveal potential weakness in standard approaches for container demand planning.

Keywords: automotive supply chain planning; totes investment; Monte Carlo simulation; container demand; inbound delivery; packaging; transport network; logistics planning.

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1 Introduction

This paper investigates a dynamic container demand model that better fulfils the requirements posed by sophisticated supply chains found in practice. The paper focuses on the supply of components and sub-assemblies in automotive industry upstream of the car manufacturer. Container demand planning is a task that has to be both economically efficient and provide viable planning results (Seidel, 2008). The objective is to calculate the number of containers needed for a new product in inbound, in-house and outbound logistics, taking into consideration the supply chain strategy, supplier and customer relationships and locations for production and logistics. Therefore, the requirement placed on container demand planning is for modelling methods that rapidly and efficiently provide indicators for the supply networks assessed to a desired level of granularity and to a sufficient degree of realism. Today's supply chains are becoming more complex and dynamic. One consequence is that visibility of container flows across organisational boundaries is declining (Bartlett et al., 2007).

Containerisation has a fundamental and significant impact on the success of logistics operations. Container utility is concerned with how packaging impacts logistical productivity and efficiency. All logistical operations are affected by containerisation – from truck loading and unloading, truck utilisation, warehouse handling to storage cube. The automobile industry uses returnable containers extensively. Returnable containers like reusable plastic totes, bulk containers and pallets protect parts better than disposables, are normally cheaper if used over product lifecycle and restricted shipment distance, and are friendlier to the environment (Wu, 2003; Baudin, 2004). Although low-cost country sourcing of parts leads to the trend that suppliers are further away, which constrains the use of returnable containers on the long-distance hauls (Lowson, 2002).

For every new car model that is launched in the automotive industry, packaging costs, and particularly inbound packaging, can run into millions of Euros. Therefore, logistics planning is involved much earlier in the new product development process. Forward planning starts years before start of production (SOP) of a new car model. An important supply chain consideration is whether a component is packaged and transported in the most efficient manner, which makes product design and development an important precursor to supply chain decisions and highlights the need for a better design-supply chain co-ordinated effort (van Hoek and Chapman, 2006; van Hoek and Chapman, 2007; Khan et al., 2008). Container design influences a huge number of factors like cube efficiency (cubing out), environmental impact, part quality, ergonomic lineside handling and production efficiency. According to Design for Logistics (DFL) which is aimed at making the product more logistics-friendly, there must be a close link between container and parts planning (Mather, 1992; Dowlatshahi, 1999). Therefore, packaging engineers look at parts as far as three years prior to SOP and making decisions on the packaging in an attempt to reduce the overall investment. Size, standard pack and the number of containers purchased are key issues in packaging planning at a tactical level. Container design depends on each individual supplier relation and the planning process has to verify which packaging is best suited to each link in the supply chain. Packaging has to be considered as an integral part of component design and specification to match product and supply chain design (Appelqvist et al., 2004).

2 Standard approach

To calculate the number of containers needed for a new component, the automotive industry uses different approaches, which vary slightly but they are all generally based on one approach. This standard model takes into account average daily container demand

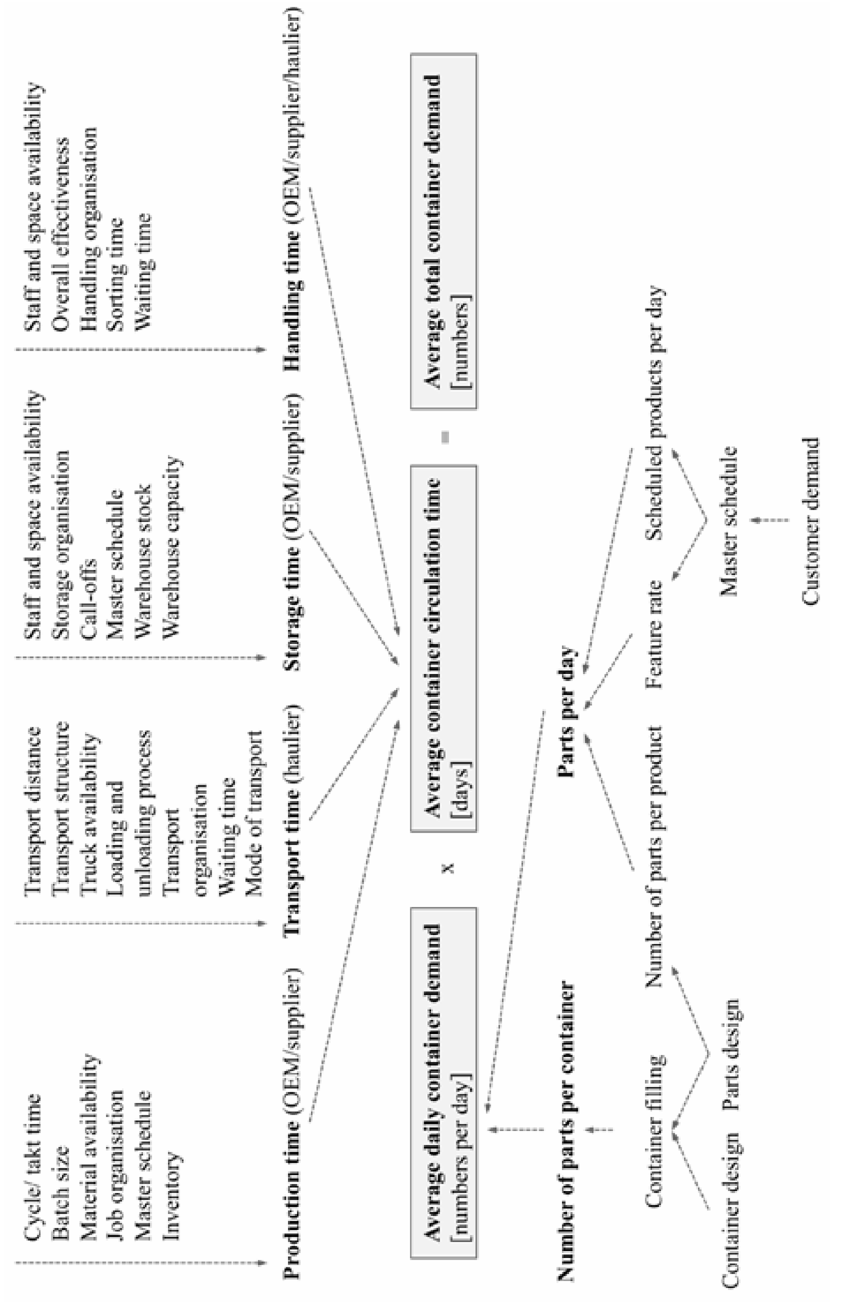
and average container circulation time (Figure 1). The average container demand per day is calculated on the basis of scheduled cars per day, parts per car, number of parts per container and the planned feature rate, which is less than 1 (100%) when a part is not standard feature. The standard method is using static average parameters plus a supplement factor α to take into account that real container circulation process fluctuates. Accordingly, the standard approach the average total container demand is given by

$$\begin{matrix}\text{Average total}\\ \text{container demand}\end{matrix} = \frac{\text{Scheduled cars per day} \bullet \text{Parts per car} \bullet \text{Feature rate}}{\text{Number of parts per container}} \bullet \begin{matrix}\text{Average container}\\ \text{circulation time}\end{matrix} \bullet (1+\alpha) \quad (1)$$

This approach is well accepted by practitioners in supply chain planning. The consensus derives from the model's simplicity, making it easy for the logistics planner to use. Although the standard method plays a crucial role in container planning, it suffers from at least three pitfalls.

First, the traditional approach is performed under deterministic assumptions. In other word, one does not take into account uncertainty in the circulation and parts demand process properly. Figure 1 shows root causes of the average total container demand. Some planning figures like parts per product are technically fixed according to the bill of material of a new car. These endogenous variables can vary but depend on internal decisions of the company. Most of the planning parameters are exogenous variables, which depend on customer demand (e.g. parts per day) and future logistics processes (e.g. transport time). All process steps are indicated as static in the standard approach whilst real activities of production, transport, storage and handling are dynamic. Taking a longer term perspective of some years before start of production in container demand planning the static consideration in modelling is adequate. By contrast, nearer term a realistic mid- and short-term depiction of the logistics operations is called for, in order to minimise uncertainties in decision-making and to ensure the feasibility for implementation of the planned supply chain process. Uncertainty occurs when packaging planners cannot estimate the root causes of container demand properly. Galbraith (1973) defines uncertainty as the difference between the amount of information required to perform a task and the amount of information already possessed. This uncertainty increases the risk as a consequence of the external and internal uncertainties that affect the container demand (Sanchez-Rodrigues et al., 2008). Risk is stated here as the probability that a wrong container demand is planned, while uncertainty is a probability distribution of container demand representing a range of possible values (Simpson et al., 2000). In the standard model uncertainty is taken into account with the security supplement α, which is assumed to be constant through time. Not only the average daily container demand is important, but also the question of variance of container demand. When such parameters are not determined very rigorously, the estimated value of circulation time can be far off its actual dynamic value. The overall effect can lead to a substantial reduction in reliability of container delivery (α is too low) or an overinvestment in containers (α is too high). Both facts would be considered as a less than perfect situation (waste) under a lean supply perspective (Lamming, 1996). Far-reaching container investment decisions have to consider process dynamics and variance, in order to assure their feasibility, adequacy and efficiency.

Figure 1 Analysis of the root causes of average total container demand (see online version for colours)



Another drawback of the standard method is that container circulation is not a continuous flow. Throughout the closed container loop transfer and process batching takes place. In production parts and therefore containers have to wait while processed before the workstation. Also transport of full and empty containers is determined by economic transport quantities, so a number of containers are accumulated before being shipped (Monden, 1998). Even when circulation times themselves are constant, variability can occur when moving containers in batches. According to the Process Batching Law of Factory Physics average container circulation time grows proportionally with batch size (Hopp and Spearman, 2008). In addition, circulation time is linked to total pipeline inventory in the supply chain, including in-transit inventory and at holding points en route (Baker, 2007).

Finally, the container usage is implicitly assumed to be 100%. Real container usage lies below this value according to lost, forgotten or misplaced containers.

3 Research design

3.1 Methods used

For a detailed research of the described problem a Monte Carlo simulation is used. The name Monte Carlo was coined by physicist Nicholas Metropolis during the Manhattan Project of Word War II, because of the similarity of statistical simulation to games of chance, and because the capital of Monaco is a centre for gambling and similar pursuits (Metropolis and Ulam, 1949). Monte Carlo simulation is a technique of analysis based on artificially recreating a chance process, running it many times, and directly observing the results. With Monte Carlo simulation, which is based on statistical measures and probability distributions of the variables we address the stochastic (aleatory) uncertainty issue. Uncertainty exists at every echelon in the supply chain (Lee and Billington, 1995), impacts logistics operations like transport and is known to impact the effectiveness and responsiveness of a supply chain (Davis, 1993; Mason-Jones and Towill, 1998; Geary et al., 2002; Childerhouse and Towill, 2004).

The basis of modelling is the root cause relationships in Figure 1, extended by temporal system development achieved through dynamic modelling. Our chance processes are the container circulation time in a given logistics supply process and the container demand per day. Monte Carlo simulation generates a series of replications of the dynamic figures and analyses the results of the experiment. Because spreadsheet software can be used very effectively for analysing logistics and supply chain issues (Smith, 2003), the simulation workbench to model and evaluation of stochastic processes in a multi-echelon supply chain is developed using Microsoft Excel with an add-in for Monte Carlo simulation.

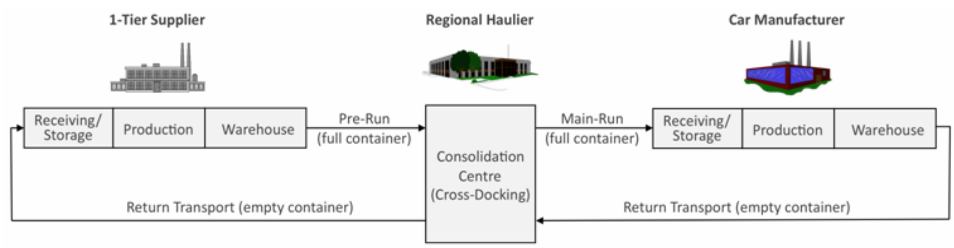
3.2 Container circulation model

The first step is to define and model the planned container circulation process. For further investigations a closed loop multi-stage logistics cycle is chosen. Therefore, we use a three-tier container supply chain in serial interactions. Returnable containers are provided solely by the automaker.

The main types of returnable containers used in automotive industry can be split up in standard and special containers. Standard containers, like reusable plastic totes and stillages, follow predefined size and weight standards, specified by national (e.g. VDA) and international (e.g. ODETTE) authorities. Special containers are purpose built for specific parts and therefore existing in a variety of different types and shapes. Common types used in automotive industry are steel racks (un-foldable and foldable) and durable plastic boxes with foam-tooth-systems, inserts and separators.

The total container circulation is split up in a full and empty container process based on special containers. No container pooling system is used, where standard containers or pallets are shared by multiple and changing supply chain partners. As main collection and delivery strategy a cross-dock consolidation and delivery is taken as widely used in European automotive industry (Miemczyk and Holweg, 2004). Load consolidation is one of the key ways in which costs in logistics can be lowered (Harrison and van Hoek, 2008). The full container shipping is divided into a pre- and main run. Figure 2 depicts a typical container circulation process in automotive industry from 1-tier supplier to car manufacturer via regional haulier.

Figure 2 Process chain container circulation (see online version for colours)



We start the container circulation loop with the receiving and storage of empty containers at the 1-tier supplier production site. After container filling in production and finished goods storage in warehouse the supplier delivers via a regional haulier system. First a collecting truck transports full containers either directly or indirectly via a milk-run system to a consolidation centre. Multi-stage transport is used where volumes do not justify dedicated full trucks or suppliers have components destined for several plants of the same manufacturer. The consolidation point allows for ingoing deliveries to be unloaded, sorted and consolidated together with deliveries from other pre-run collections into new outgoing loads (Stefansson, 2006). Load units are shifted from an incoming dock to an outgoing dock and consolidated with other load units that have arrived from other suppliers in the same region. From the cross-docking consolidation terminal the full truckload (FTL) is shipped to a specific car manufacturer site. While the pre-run is relatively short from supplier to consolidation centre the main run concerns deliveries over a longer distance from the material consolidation centre to automotive manufacturing facility. After receiving and storage of full containers at the car manufacturer full containers are called off and placed at the shop floor where containers are emptied. Empty containers go back to empty container storage area where they get cleaned and sorted. According to supplier delivery notes, empty containers will be loaded at original equipment manufacturer (OEM) site and returned via consolidation centre to the 1-tier supplier.

For each closed loop container activity an empirical-based probability density function is defined and verified. The main inputs are data related to a German car manufacturer. The regional haulier manages and operates a consolidation centre in the northern region of Germany. The logistics service provider is responsible to manage and operate a consolidation centre for around 80 suppliers in the region. Container bundling, sorting and shipping takes place in its own consolidation centre, which supplies the OEM site in Southern Germany via direct main runs. The container collection in the consolidation area of the regional haulier is realised by direct and milk-run collections, carried out partially by subcontractors. Subsequently the recorded stochastic distributions have been validated, by using various data from European automotive industry to ensure that the behaviour of the model replicates a real-life logistics scenario. Such probability distributions allow us to assume that the circulation time is not constant through time and that it depends on a variety of different factors. In order to model all the echelons and the structure of the supply loop, the simulation workbench is designed to contain main circulation activities starting with the empty container delivery for the first tier supplier. Table 1 depicts all used model distributions with their statistical parameters. Means and standard deviations (SD) of normal and exponential distributions are based on the non-truncated distributions. All probability density functions are restricted by minimum and maximum values, according to their empirical validation.

Table 1 Statistical parameters container circulation

Loop Activity	*Loop Partner*	*Used Distribution*	*Mean*	*SD*	*Min*	*Max*	*λ*
Receiving/ Storage (empty) Empty Container	1-Tier	Normal	4.00	2.00	1.00	7.00	
Container Filling Time (empty/full)	1-Tier	Uniform	0.55	0.26	0.10	1.00	
Storage Finished Goods (full)	1-Tier	Normal	3.00	2.00	0.00	11.00	
Pre-Run (full)	Haulier	Exponential	0.13	0.13	0.10	0.50	8.00
Handling Consolidation Centre (full)	Haulier	Normal	0.20	0.10	0.10	0.50	
Main-Run (full)	Haulier	Exponential	0.50	0.50	0.50	1.00	2.00
Receiving/Storage (full)	OEM	Normal	2.00	1.00	0.00	6.00	
Container Clearing (full/empty)	OEM	Uniform	0.26	0.14	0.02	0.50	
Storage Empty Container (empty)	OEM	Normal	5.00	3.00	0.50	10.00	
Return Transport to CC (empty)	Haulier	Exponential	0.50	0.50	0.50	1.00	2.00
Handling CC (empty)	Haulier	Normal	0.20	0.10	0.10	0.50	
Return Transport to 1-Tier (empty)	Haulier	Exponential	0.13	0.13	0.10	0.50	8.00

The activities used are briefly described as followed:

- *Goods receiving and storage empty container*: Therefore, a normal distribution is assumed with mean of 4.00 days and a standard deviation of 2.00 days. The distribution is restricted to a minimum (maximum) of 1.0 (7.0) day(s), which depends mainly on delivery time frame, free docking station/ramp, available personnel in goods receiving and empty container inventory.

- *Container filling time at 1-tier supplier*: Therefore, a uniform distribution is assumed with a mean of 0.55 days and a standard deviation of 0.26 days. The distribution is restricted to a minimum (maximum) of 0.1 (1.0) day(s), which depends mainly on container size, internal handling, master schedule and cycle time.
- *Storage in finished goods warehouse*: Therefore, a normal distribution is assumed with a mean of 3.00 days and a standard deviation of 2.00 days. The distribution is restricted to minimum (maximum) of 0.0 (11.0) days, which depends mainly on OEM call-offs, warehouse stock and warehouse capacity.
- *Pre-run transport from supplier to consolidation centre*: Therefore, an exponential distribution is assumed with a mean of 0.13 days and a standard deviation of 0.13 days. The distribution is restricted to a minimum (maximum) of 0.10 (0.50) days, which depends mainly on transport distance and organisation, loading and unloading time, free docking ramp and available personnel.
- *Handling in consolidation centre*: Therefore, a normal distribution is assumed with a mean of 0.20 days and a standard deviation of 0.10 days. The distribution is restricted to a minimum (maximum) of 0.10 (0.50) days, which depends mainly on inbound unloading, in-house sorting and outbound loading time.
- *Main-run transport from consolidation centre to OEM*: Therefore, an exponential distribution is assumed with a mean of 0.50 days and a standard deviation of 0.50 days. The distribution is restricted to a minimum (maximum) of 0.50 (1.00) day(s), which depends mainly on transport distance and organisation, loading and unloading time, free docking ramp and available personnel.
- *Goods receiving and storage full container*: Therefore, a normal distribution is assumed with a mean of 2.00 days and a standard deviation of 1.00 day. The distribution is restricted to a minimum (maximum) of 0.0 (6.0) days, which depends mainly on delivery time frame, free docking station/ramp, available personnel in goods receiving, finished goods stock, OEM master schedule and cycle time.
- *Container clearing in OEM production*: Therefore, a uniform distribution is assumed with a mean of 0.26 days and a standard deviation of 0.14 days. The distribution is restricted to a minimum (maximum) of 0.02 (0.5) days, which depends mainly on container size, internal handling, master schedule and cycle time.
- *Storage empty container*: Therefore, a normal distribution is assumed with a mean of 5.00 days and a standard deviation of 3.00 days. The distribution is restricted to a minimum (maximum) of 0.5 (10.0) days, which depends mainly on OEM call-offs, empty container stock, empty container area capacity, handling and service time that includes collection, cleaning, sorting and maintenance.
- *Return transport to consolidation centre*: Therefore, an exponential distribution is assumed with a mean of 0.50 days and a standard deviation of 0.50 days. The distribution is restricted to a minimum (maximum) of 0.50 (1.00) day(s), which depends mainly on transport distance and organisation, loading and unloading time, free docking ramp, available handling personnel and redistribution structures.
- *Handling in consolidation centre*: Therefore, a normal distribution is assumed with a mean of 0.20 days and a standard deviation of 0.10 days. The distribution is restricted to a minimum (maximum) of 0.10 (0.50) days, which depends mainly on inbound unloading, in-house sorting and outbound loading time.

- *Return transport from consolidation centre to 1-tier supplier*: Therefore, an exponential distribution is assumed with a mean of 0.13 days and a standard deviation of 0.13 days. The distribution is restricted to a minimum (maximum) of 0.10 (0.50) days, which depends mainly on transport distance and organisation, loading and unloading time, free docking ramp, available handling personnel and redistribution structures.

The range and shape of restricted probability density functions reflect the uncertainty issues related to the valuation of real container circulation. The cumulative effect of variations in each circulation step over the closed loop will be investigated with the simulation model. The variables used are completely independent from each other (no autocorrelation).

The second step is to define and model a realistic case for container demand per day. The sales department has to estimate a realistic number of cars sold and feature rates, which determine that not each part is standard and some features are just available with extra charges. Therefore, a uniform distribution is assumed for scheduled cars per day with a minimum (maximum) of 800 (1000) cars. Furthermore, we assume a fixed parts number per container (30) and a given feature rate (0,3). The number of parts per car (2) is set by construction and development. It can change during the car development phase but is presumed to be fixed in our case concerning a certain planning phase.

3.3 Monte Carlo simulation

The use of continuous Monte Carlo simulation is based on the ability to experiment and therefore to obtain better insights into the dynamic behaviour of the container demand process without excessive computation (Walters, 1975). Because Monte Carlo simulation is grounded on repeatedly sampling from a chance process, it stands to reason that random numbers are a crucial part of the modelling process (Barreto and Howland, 2006). According to the problems with random number generation (hidden structure), which may completely invalidate the results, we will use a random number algorithm based on a fast multiple recursive generator (FMRG) (Deng and Lin, 2000). They use the previous output to generate the next number, but instead of using just the previous number like a linear congruential generator (LCG), an FMRG uses a linear combination of the past random numbers generated. The recursive generator produces 18 random numbers per each run, which are used to generate the necessary density functions in Table 1. All following random variate generations are based on a continuous standard uniform distribution of pseudorandom numbers.

The standard distribution used in the simulation model is generated by Box-Muller transform of random numbers uniformly distributed. Let (U_1, U_2) be a pair of independent random variables from the same uniform density function on the interval [0,1]. Then (Z_0, Z_1) will be a pair of independent random variables from the same normal distribution with mean 0 and standard deviation 1 (Box and Muller, 1958) according to:

$$Z_0 = \sqrt{-2\ln U_1}\ \cos(2\pi U_2) \tag{2}$$

$$Z_1 = \sqrt{-2\ln U_1}\ \sin(2\pi U_2) \tag{3}$$

Given that the family of normal distributions is closed under linear transformations we can relate the standard normal random variate Z to the more general normal random variate X with specific mean μ and standard deviation σ as shown in Table 1 according to equations (2) and (3).

$$X = \sigma Z + \mu \tag{4}$$

The uniform distribution with the two boundaries a and b used in the simulation model is generated by a standard uniform distribution. If U_s is a value sampled from the standard uniform distribution, then the general uniform distribution sample U_g is parametrised by a and b according to:

$$U_g = a + (b - a)\, U_s \tag{5}$$

The exponential distribution used in the simulation model is calculated by inverse transform sampling. We generate the exponential random variate T with an arbitrary continuous standard uniform distribution by the following equation (Devroye, 1986):

$$T = \frac{-\ln U_s}{\lambda} \tag{6}$$

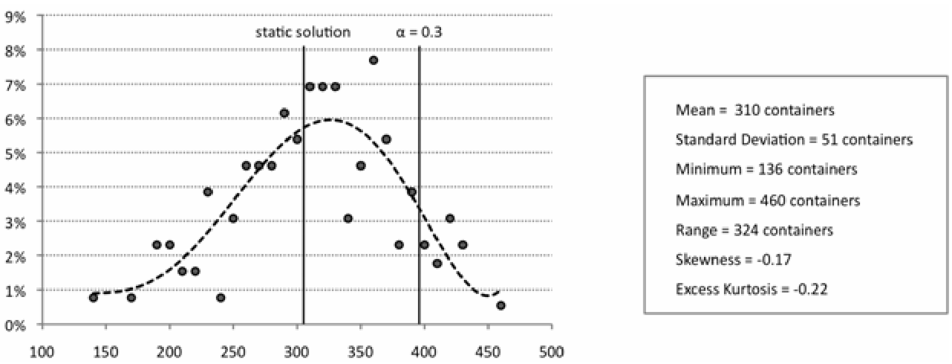
A practical procedure is used for determining the appropriate sample size, which is a worthwhile strategy in terms of both research goals and practical problem solutions (Bienstock, 1996). The container circulation model is projected over a life cycle period of returnable containers related to a life-span equivalent to an automobile model of five to seven years. According to our container circulation model in Figure 2 the aggregated mean values for container circulation are 17 days. If we assume an average circulation time per container, each container circles on average 130 times in its life time. Research using computer simulation is an experimental process, with each run of the simulation model comprising a single experiment. Therefore, we will use 130 runs for each experimental condition. This technique will provide a logistics planner with the number of replications, which will yield the degree of precision necessary for drawing conclusions about the behaviour of the container demand under the various experimental conditions. Although an increased sample size would decrease the random error, a higher number of runs would neutralise the meaning of the used restricted and non-symmetric distributions. In total 13% of total container circulation time is determined by non-normal distributions, which contribute to distortions in the resulting container demand distribution based on Monte Carlo simulation.

3.4 Results

The first step is to simulate the current logistics operation in European automotive industry according to the container circulation model as described above (Figure 2). The response variable of interest in this model is average total container demand (Figure 1). Our verified and validated baseline model generates the results shown in Figure 3 and serves as the standard for comparison with alternative scenarios in the following sensitivity analysis.

We observe that the mean value for container demand is 310 and standard deviation is 51 containers with a minimum of 136 containers and a maximum container demand of 460. A normal distribution was the best fit for this distribution shown by the dotted line in Figure 3, which is generated by a polynomial interpolation. According to the use of non-normal distributions (uniform and exponential distributions account for 13% of the average container circulation time) and the restriction of random variables by minimum and maximum values (Table 1) in Monte Carlo simulation there is a slightly distortion of the resulting probability density function, which is indicated by an excess kurtosis of –0.22 and a skewness of –0.17 (normal distribution = 0). The container demand results span from a low of 136 to a high of 460 containers, which represents a range of 324 containers. This wide range indicates the high level of uncertainty in planning process.

Figure 3 Density distribution container demand



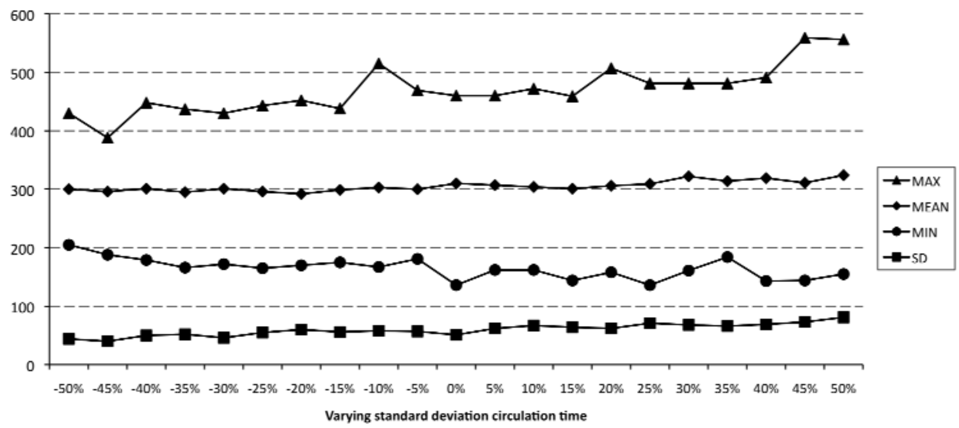
According to the standard model (1) we receive a static container demand of 306 containers without security supplement, which is slightly below the mean value of dynamic simulation.

$$\begin{array}{c}\text{Average total}\\ \text{container demand}\end{array} = \frac{900\text{ cars per day} \bullet 2\text{ parts per car} \bullet 0.3}{30\text{ parts per container}} \bullet 17\text{ days} = 306\text{ containers}$$

Logistics planning may be more interested by the whole range of container demand to analyse the likelihood that the value would fall below some threshold. A standard supplement α widely used in automotive industry is about 0,3 (plus 30%). According to this the threshold of container demand is 398 containers, which would be purchased in our base model case. This value counts for 91% of all possible container demands. The remaining 9% represent the likelihood of a container demand not being fulfilled. This relatively high percentage of container shortage corresponds well to empirical data in the automotive industry, where lack of container is common in container management.

Dynamic behaviour as discussed in this paper is a function of the structure of the container system. To obtain a better insight into container demand structure and the dynamic contribution of individual probability density functions to total system behaviour, a sensitivity analysis is used. By systematically varying model parameters in repeated simulation runs, a pointedly quantitative investigation of model behaviour is undertaken. Sensitivity analysis acts as a surrogate for uncertainty, as we test the implications of varying the most likely factors to have a strong influence on container demand by a certain percentage of error (Lalwani et al., 2006). We tested the sensitivity to standard deviations of container circulation time to identify container demand structure. We varied this target and compared the container demand to the baseline model (Figure 3). For the whole container circulation process, we examine the impact of standard deviation increase/decrease by +/–50% in steps of 5%. Figure 4 presents numerical comparisons of the output, providing the average container demand. The sensitivity analysis results show that a change in the standard deviation of container circulation time has a strong impact on the standard deviation of the total container demand. For example if the standard deviation of the circulation time increases by 50% compared to baseline model (0%), this translates as an increase of standard deviation of average container demand by 59%. This result underlines the importance of variety reduction in logistics systems to plan more accurately at lower costs, as production can be run on a lower container inventory level in this special case (Holweg, 2001; Disney and Towill, 2006; Boute et al., 2007).

Figure 4 Sensitivity analysis container demand model



Not surprisingly, we observe lower maximum and higher minimum values for container demand when the standard deviation of circulation time is reduced. The range of container demand (maximum container demand – minimum container demand) is reduced by 176 containers comparing the worst (+50%) and best (–50%) case scenarios, which counts for massive container investment according to the high investment costs for special containers.

4 Conclusions and future research opportunities

One main contribution of this research is in improving accuracy of container demand planning and therefore reducing container investment for new car models. This is achieved by using differentiated security supplements generated dynamically by Monte Carlo simulation according to the individual supply process rather than general static estimates.

Furthermore, there has been some debate in literature about valuation variation in a supply chain system. Higher variances in container lead-times decrease the financial performance of the organisation. An ongoing challenge in this area is operationalisation of measures and data collection techniques that go beyond a single company and examine a network of organisations (Christensen et al., 2007). Container activities not under the direct control of an individual company have to be measured and controlled, making the container chain transparent (van Hoek, 1998). Containers are better used in reducing container circulation time variance than in solely reducing average circulation times. Clearly, reductions in average container demand alone are ineffective in increasing organisation’s financial performance and more attention must be paid to circulation time variance. The appeal of incorporating uncertainty in the valuation process is that the analysis does not merely yield a point estimate of the entire distribution of values, but rather the distribution of values. The approach advocated in this paper should help contribute to this debate.

As is the case of all techniques, the quality of outputs from a Monte Carlo simulation largely depends on the quality of inputs. With this in mind, further research should focus on the stability of the model that we use when other container processes are used. Further research is required to understand these elements more fully and to develop this framework as a useful tool for practitioners. This research was concentrated on the inbound logistics in automotive industry to gain an understanding of the interrelationships involved. In addition, the research should be extended to a wider supply network including outbound distribution, further industries and regions. Therefore, the Monte Carlo approach has to be enlarged to standard container systems, which can be used in a wider supply network. In doing so, a better understanding of the linkages between different circulation channels of the same tier and container in a supply network should emerge (Wilding, 1998). Parallel interactions, contrary to the serial interactions investigated in this paper, result in poor container delivery from some suppliers in the network affecting the efficiency of the good suppliers (Jones, 1990).

Finally, it might be fruitful to further investigate the relation between single circulation time variances. Not only is the absolute variance important, but also the relation between single variances, which determines the container demand. An analogy often used in lean logistics involves a boat floating down a rock-infested river. The water level in the river is analogous to container demand and the rocks represent circulation time variances over the closed container loop of full and empty containers. As rocks are made smaller, the boat is able to navigate the river at a much lower water level. Likewise, supply chain partners are able to maintain more effective operations (production, transport, storage, handling) at much lower container pool levels and with shorter circulation time (Suzaki, 1987).

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