Technology optimization and change management for successful digital supply chains

Chapter 10: Digital inventory optimization:
A practitioner’s guide to transform your organization
Technology Optimization and Change Management for Successful Digital Supply Chains

Ehap Sabri
KPMG LLP, USA & University of Texas at Dallas, USA

A volume in the Advances in Logistics, Operations, and Management Science (ALOMS) Book Series
Chapter 10
Digital Inventory Optimization:
A Practitioner’s Guide to Transform Your Organization

Andreas Werner
KPMG LLP, USA

ABSTRACT
This chapter provides an overview of select inventory optimization (IO) techniques for single and multi-echelon optimization. The main goal is to familiarize the reader with various IO models by providing a clearly structured approach, improving the reader’s understanding of the mathematical concepts, and by providing an ample number of examples. Furthermore, the guaranteed service model for a three stage serial supply chain is introduced to show the effects of keeping inventory at different echelons in the supply chain in regards to total cost. Lastly an inventory planning maturity model is presented to show actionable next steps to the practitioner.

INTRODUCTION
Inventory reduction remains one of the key targets of companies to reduce working capital and its associated costs which leads to improved cash flow. At the same time customers are demanding higher service levels and increased convenience for example shorter lead times. To achieve these seemingly conflicting objectives is a great challenge for many companies on their digital journey, however, inventory optimization (IO) has proven that it can achieve an increase in customer service while reducing safety stock (Farasyn et al., 2011). Surprisingly, most companies are not yet taking advantage of inventory optimization, especially of multi-echelon inventory optimization (MEIO). Only 21% of consumer goods companies surveyed reported that they perform multi-echelon inventory optimization to some extent (Romanow, 2014). Another study found that a MEIO implementation can increase service levels by 3% while reducing the cash-to-cash cycle by 15% (Aberdeen group, 2012).

DOI: 10.4018/978-1-5225-7700-3.ch010
The main value proposition of the following chapter is providing the reader and supply chain practitioner an overview of the IO basics including mathematical concepts which enables them to understand important details for a digital transformation journey. MEIO is the focus of the main chapter since the author feels that the greatest opportunity for many companies exists in this area. The target audience for this chapter is knowledgeable in supply chain management and undergraduate level statistics but not an expert in inventory optimization. Most existing literature can be categorized into either of the following.

- Academic articles focused on the mathematical aspect of inventory optimization, e.g. operations research
- Articles focusing on the qualitative aspects of inventory optimization, e.g. defining the approaches, best practices and laying out the observed benefits of an inventory optimization implementation

This chapter seeks to strike a balance between both worlds and is structured in the following way. Firstly, select literature is reviewed that provides the foundation to understand the further sections. After that, the main section explains the mathematical background of single- and multi-echelon inventory optimization. The goal of which is to provide the mathematical basics and an understanding of the general IO concepts and common formulas. After this, the context of inventory optimization within the overall supply chain planning function is explained to help the reader understand the big picture and the fit of IO within their organization’s supply chain functions. Lastly, a maturity model for inventory planning is introduced to enable the reader to articulate the gaps and opportunities within their organization and help with the next steps.

**BACKGROUND**

The following will provide a literature review on select articles that the author deems important to understand the main section of this chapter. Table 1 shows an overview of the sources reviewed in the literature review alongside for their reasoning of being included in the background section.

<table>
<thead>
<tr>
<th>Literature reviewed</th>
<th>Category</th>
<th>Reasoning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farasyn et al. (2011)</td>
<td>Case study of inventory optimization</td>
<td>Qualitative study to showcase results of single- and multi-echelon optimization.</td>
</tr>
<tr>
<td>Graves and Willems (2003)</td>
<td>Mathematical modeling of MEIO</td>
<td>Comparison of MEIO techniques: GSM and SSM. Includes details of GSM that are used later in the chapter. Also explains solving the supply chain configuration problem which simultaneously makes sourcing and inventory decisions</td>
</tr>
<tr>
<td>Klosterhalfen, Minner and Willems (2014)</td>
<td>Mathematical modeling of MEIO</td>
<td>Example of an extension to the GSM model (dual supply) and its benefits</td>
</tr>
<tr>
<td>Eruguz et al. (2016)</td>
<td>Mathematical modeling of MEIO</td>
<td>Overview of various GSM models</td>
</tr>
</tbody>
</table>
Farasyn et al. (2011) describe the benefits of applying inventory optimization at Procter and Gamble. Procter and Gamble (P&G) is a large consumer packed goods (CPG) company with a revenue of more than 65 billion USD in 2017. The author describes a decision framework that P&G uses to decide between deploying a single or multi-echelon approach across their different businesses. The framework promotes the use of single echelon optimization in the form of spreadsheets for their simpler supply chains in terms of number of SKUs and network stages.

The company achieved between 10% and 50% in total inventory reduction with the help of single echelon inventory optimization. Farasyn, Perkoz and Van de Velde (2008) go into more detail on the single echelon spreadsheet approach. Multi-echelon optimization is deployed in their more complex businesses, for example, Beauty & Grooming. An average network model is described as having 4,000 – 5,000 stages and 6,000 – 10,000 arcs. Based on a guaranteed service (GS) multi-echelon algorithm, the realized benefits are described as a total inventory reduction of 7% across their North America cosmetics supply chain while simultaneously increasing service levels.

Graves and Willems (2003) compare the guaranteed service model (GSM) and stochastic service model (SSM) in their chapter on supply chain design. They derive the respective models based on the following assumptions:

- The supply chain represents a generic network as opposed to a distribution network or assembly system. This assumption makes the models applicable to most real-world supply chains.
- The focus is on finding an optimized safety stock placement in the supply chain based on demand uncertainty. Other variables for example lead time, lead time variability or capacity uncertainties are not considered.
- The authors further assume that placement of safety stock is not constrained by e.g. warehouse space at different nodes since the safety stock problem falls under supply chain design in the authors’ framework.
- Stages place a replenishment order to the supplier equal to the demand which means that there are no hedging or lot sizing effects in place
- Every stage has a deterministic processing time

The above represents the most important assumptions based on which the GSM and SSM models are derived. The SSM takes a service target level for the external customer as an input and provides service target levels for internal customers as an output when used in an optimization context. The replenishment time $\tau_j$ at any stage $j$ of the network is equal to the constant processing lead time $L_j$ plus any delay from upstream stages. The following equation for the expected replenishment lead time is derived, assuming a maximum of one supplier will experience a stock-out per period and defining $\pi_{ij}$ as the probability of stage $i$ causing a stock-out at stage $j$.

$$E[\tau_j] = L_j + \sum_{i \in (j) \in A} \pi_{ij} L_i$$

Graves and Willems further derive the objective function for the SSM assuming normally distributed demand and considering holding costs.
Digital Inventory Optimization

The main part of this chapter focuses on the GSM, so it will be explained in more detail based on the definition in Graves and Willems (2003). The key characteristic of the GSM is that it eliminates probability by assuming a 100% service level if demand stays within the defined boundary. In case of a normally distributed demand, the boundary $D_j$ can be set by defining a customer service level with an appropriate $z$ score.

$$D_j(t) = t\mu_j + k_j \sigma_j \sqrt{t}$$

where

$t =$ Number of time periods

$\mu_j =$Mean demand per period

$k_j =$ z score of customer service level

$\sigma_j =$Standard deviation of the demand per period

Every stage $j$ will quote an outgoing service time $s^{\text{out}}_j$ to their customers and receive incoming goods with a service time $s^{\text{in}}_j$ and processing lead time $L_j$. Then the replenishment time $\tau_j$ equals

$$\tau_j = s^{\text{in}}_j + L_j$$

Since this is a deterministic equation it is easy to define the net replenishment lead time as $s^{\text{in}}_j + L_j - s^{\text{out}}_j$. The base stock $B_j$ of a node $i$, which is the inventory at time 0, needs to cover the demand within the replenishment lead time. Using the demand bound equation from earlier we can see that

$$B = (s^{\text{in}}_j + L_j - s^{\text{out}}_j) \mu_j + k_j \sigma_j \sqrt{s^{\text{in}}_j + L_j - s^{\text{out}}_j}$$

Using this formula Graves and Willems define an objective function with the goal of minimizing the inventory holding costs per unit $C_j^s$ for the network.

$$\min_j \sum_{j=1}^{N} C_j^s k_j \sigma_j \sqrt{s^{\text{in}}_j + L_j - s^{\text{out}}_j}$$

Later in this chapter, we will see examples that use the formulas and definitions of this basic GSM model. After deriving the models, they are applied to two real-world examples: Bulldozer assembly and Battery manufacturing and distribution. A simplified network is depicted for both supply chains and the underlying modeling assumptions are highlighted. In contrast to the assumptions listed earlier, these assumptions are related to the specific supply chains. The total supply chain costs are then compared. The SSM leads to higher costs across all end customer service levels less than 100%. The authors explain this behavior with the different underlying assumptions of GSM and SSM. While the SSM’s
countermeasure to stockout is more inventory, the GSM assumes that demand that exceeds the defined boundary is considered either lost or is being fulfilled by taking extraordinary measures, e.g. premium freight or overtime.

The chapter continues with a modified version of the safety stock problem called supply chain configuration problem. Configuration decisions are sourcing decisions in the Graves and Willems’ model. The example is that a local high-cost supplier has a shorter lead time compared to a global, low-cost supplier which reduces safety stock costs. Other costs that are considered in the model are the cost of goods sold and pipeline stock costs. The GSM is used as a basis and expanded with the sourcing options. The resulting non-linear mixed integer programming problem is solved in the bulldozer supply chain example. The sourcing options and their related costs are created based on observations from the industrial manufacturing industry. After solving the example the authors conclude that significant additional cost savings can be realized by looking at supply chain configuration and safety stock placement holistically.

Klosterhalfen, Minner and Willems (2014) extend the GSM framework with an exact model for static dual supply in general acyclic N-echelon network structure. The author can show a 9.1% cost savings compared to approximate results from previously published solutions. Dual- or multi-sourcing can be an important part of a companies’ supply chain strategy to mitigate the risk of being dependent on a single supplier. Another consideration is that supply chain agility is increased when sourcing from multiple suppliers by being able to secure upside demand. The trade-off compared to single sourcing is usually increased costs since smaller order quantities are placed with the different suppliers.

The model presented in the paper is based on the following assumptions:

- Stages place a replenishment order to the supplier equal to the demand which means that there are no hedging or lot sizing effects
- Every stage has a deterministic processing time
- Allocations between the suppliers are static, e.g. one supplier receives 30% of the demand another one receives 70%.

Eruguz et al. (2016) provide an overview of the various extensions to the original GSM while looking at three different angles:

- Modeling assumptions such as deterministic vs. stochastic lead times
- Solution methodologies and optimality/network configuration/objective function
- Industry applications and results

The author of this chapter recommends a review of Eruguz et al. (2016) to anyone planning to implement a GSM in their organization since it provides guidance on the mathematical models that are currently available.

**TYPES AND PURPOSES OF INVENTORY**

The lean principle taught us that unnecessary inventory is one of the seven types of waste. The question arises what constitutes as unnecessary inventory and what does not, in other words: What is the purpose of inventory?
Digital Inventory Optimization

To answer this question the following types of inventory or stock are defined and examples are given:

- Cycle stock
- Safety stock (sometimes: Buffer stock)
- Tactical and Strategic stock

All the inventory types shown in figure 1 can be present at any level in the supply chain, e.g. at raw material, sub-assembly, or finished good level.

Cycle Stock

The American Production and Inventory Control Society (APICS) defines cycle and safety stock as follows.

One of two main conceptual components of any item inventory, the cycle stock is the most active component. The cycle stock depletes gradually as customer orders are received and is replenished cyclically when supplier orders are received. The other conceptual component of the item inventory is the safety stock, which is a cushion to protect against uncertainty in the demand or in the replenishment lead time. (Pittman, P., Blackstone, J.H., & Atwater, J.B., 2016)

So cycle stock represents the amount of inventory that is kept to fulfill the demand of the downstream stage until the product is replenished.

Ideally the cycle stock amount matches the replenished stock. This requires the future demand picture or forecast to be 100% accurate to avoid stock-outs. Since this is not achievable in reality, safety stock is kept. Figure 1 shows the relationship between replenishment time and cycle stock. The longer it takes to replenish the inventory, the more amount of cycle stock is necessary to be kept. In practice the cycle stock quantity is often calculated using the Economic Order Quantity (EOQ) formula which provides a solution for the purchasing and manufacturing lot size problem.

Figure 1. Idealized sawtooth pattern showing the three types of inventory over time
In case of a manufactured product choosing the cycle stock quantity or lot size is often a trade-off between changeover costs and inventory holding costs. Changeover cost represents the cost it takes to manufacture a different product on the same machine. They can vary widely depending on the type of products. Inventory holding cost consists of two main components: The first component of inventory holding cost is the cost of capital tied up in inventory. This represents the opportunity cost of not being able to invest the money elsewhere. Typically, it is calculated by multiplying the standard cost of the product with the cost of capital percentage of the organization.

The second component of inventory holding cost are the warehousing costs. Depending on the size and shape of the product a different portion of personnel costs to handle the product, rent costs of the facility, utility costs, inventory shrinkage, insurance costs, taxes etc. can be assigned to a product. Due to the difficulty of this calculation, some implementations only consider the cost of capital to optimize their inventory. Implicitly, this assumes that the warehousing costs are proportional to the cost of the product which might not be true for all products, e.g. bulky low-cost products like bottled water.

**Safety Stock**

Safety stock is used as a buffer against uncertainty. Without safety stock at the customer facing echelon of the supply chain, a decrease of the anticipated supply or an increase of the anticipated demand of the product would lead to a guaranteed stock-out and a decrease in customer service level – unless extraordinary measures like premium freight are taken. Demand-side uncertainties typically account for the largest portion of the total safety stock. Examples of demand changes are inaccurate forecast or changing customer orders. Examples on the supply-side are variability in the manufacturing process, e.g. a lower than expected yield of a production run. Another supply-side example could be variability in the lead time of the incoming products needed to manufacture the outgoing products. E.g. bad weather causes a shipment from overseas to be delayed. However, if there was no uncertainty on both the supply- and demand-side no safety stock would be necessary. Make-to-order products represent another scenario where no safety stock of the finished good is kept. The decision of where in the supply chain make to order or make to stock should be used is one of the questions that MEIO can help answer.

An important concept is that safety stock only has to cover for the net replenishment lead time. If a customer’s expectation is to receive an order within 10 days of placing it and it only takes 9 days for the supplier to order and receive materials, manufacture the product, and transport it, then there is no need to keep any inventory (make to order). But if the customer requires the product to arrive within 6 days, inventory needs to be kept to account for 9 - 6 = 3 days’ worth of demand plus demand and supply variability.

**Tactical and Strategic Stock**

Tactical and strategic stock is inventory build on top of cycle and safety stock. It can serve a multitude of purposes. Tactical inventory is build up in the short- to mid-term for a specific purpose. An example of tactical stock is when a supply planner decides to build up enough inventory to conduct a full machine shutdown and maintenance without impacting the customer service levels. Similarly, strategic inventory can fulfill business purposes that are relevant in the mid- to long-term, such as hedging raw material to counteract an anticipated price increase.
Digital Inventory Optimization

To summarize inventory is kept for a variety of reasons that are legitimate. Any inventory on top of the described purposes is excess inventory that does not serve any purpose and reduces the working capital of the organization. Furthermore, inventory needs to be kept at the right stage in the supply chain. To answer these two questions of where to store inventory and how much of it, the optimization piece of this book chapter will focus on the latest research in safety stock optimization. However, the other components of inventory shall not be underestimated as there can also be significant benefits in optimizing cycle stock and tactical/strategic stock.

Figure 2 depicts the author’s view of an inventory optimization maturity model. In contrast to a maturity model presented later in this chapter it focuses only on the optimization piece of the whole inventory planning process.

SINGLE ECHELON INVENTORY OPTIMIZATION

The calculation of single echelon safety and cycle stock quantities will be the primary topic of discussion in the following sections. The author sees a lot of importance in the understanding of the mathematical background for anyone implementing supply chain inventory optimization (IO). In its core every IO transformation will be based on a mathematical model and even though there are many other aspects to a successful transformation, the proper design of the IO software represents one of the most important ones.

In the following paragraphs definition and examples of these important IO concepts will be given:

1. Economic order quantity (EOQ) calculation
2. Type 1 and type 2 service level definition
3. Type 1 service level calculation
4. Type 2 service level calculation
5. Type 1 service level calculation including lead time variability

Figure 2. Inventory optimization maturity model
Applying single echelon optimization techniques in an organization can be realized with spreadsheets or specialized software. One example for a successful spreadsheet implementation is shown in the literature research part of this chapter (Farasyn et al. 2008).

The Economic Order Quantity

The economic order quantity (EOQ) is a very popular rule of thumb to quantify the reorder amount. It optimizes the relationship of ordering cost and holding cost. Ordering costs are the fixed costs per order and typically include the cost of transportation and handling. The formula to determine the EOQ is the following:

\[
Q = \sqrt{\frac{2DK}{h}}
\]

where

- \(Q\) = Economic Order quantity
- \(D\) = Demand quantity over the reviewed period
- \(K\) = fixed cost per order
- \(h\) = holding cost per unit over the reviewed period

The formula assumes that the demand stays constant within the reviewed period and each replenishment is delivered on time and in full (OTIF). As a result the optimal quantity \(Q\) is independent of the unit cost. The resulting order quantity is generally considered a robust solution, however research has shown that it can be sensitive to forecast errors (Mykytka and Ramberg, 1984).

The EOQ is a highly researched topic and various extensions to the EOQ formula exist to consider quantity discounts, one-time discounts, stochastic lead time, finite replenishment (Zipkin 2000), fuzzy costs (Vujošević, Petrović and Petrović, 1996) and more.

Single Echelon Optimization for a (Q,R) Inventory Policy

The (Q,R) or continuous review inventory policy is widespread in industry and is the basis of many commercial inventory systems. \(Q\) equals the reorder quantity and \(R\) equals the reorder point. To define a calculation for the safety stock quantity with the goal of achieving a certain service level goal, one must first define the meaning of service level. Two common definitions are being presented. The first one defines service level as the probability of having a stockout during the replenishment duration. This definition is called \(\alpha\) or type 1 service level.

\[
\alpha = P\left(\text{Cum. demand in replenishment period} \leq \text{Inventory at beginning of repl. period}\right)
\]

The second common definition of service level considers the fill rate instead of a binary stock-out situation. So, it gives more weight to a stock-out that results in a significant backlog quantity and less
weight to a stock-out that results in only a few units of backlog. The β- or type 2 service level measures the portion of the demand that is met on time:

$$\beta = 1 - \frac{\text{Demand not filled during repl. period}}{\text{Demand during repl. period}}$$

The choice of service level measurement is important because it changes the calculation methods and the level of safety stock kept. Comparing the definitions makes it clear that $\alpha \leq \beta$ and sometimes they can differ considerably. Even if a single unit of product is missed during the period, the service level is set to zero in the case of the α-service level. So the same (Q,R) inventory policy could lead to an 85% α-service level, but a 99% β-service level.

The α-service level is more appropriate if a stock-out has severe consequences regardless of quantity. An example is an automotive tier 1 supplier that needs to make sure not to run out of stock to avoid disrupting the OEM production line or inventory of a life-saving medicine. However, in the consumer-packaged goods (CPG) industry the β-service level might be more appropriate since the consequences of missing an order are mostly missed revenue which is proportional to the quantity missed.

In case of the α-service level it can be shown that the EOQ provides the optimal reorder order quantity $Q$. Considering only demand variability for normally distributed demand the reorder point R can be determined by applying the following formula

$$R = k\sigma + \mu$$

where

- $k = z$ score of customer service level
- $\sigma$ = standard deviation of the total demand within the replenishment lead time
- $\mu$ = mean of the total demand within the replenishment lead time

The safety stock portion of the reorder point equals $k\sigma$.

**Example 1:** Type 1 service level and random demand:

A product has normally distributed weekly demand with mean $\mu = 100$ units and standard deviation $\sigma = 20$. The lead time is 1 week. The fixed cost per order $K = $20, the product cost equals $5 and the holding costs $h$ are based on a 10% annual interest rate. The α-service customer service level should be 95%. First, the EOQ is computed to

$$Q = \sqrt{\frac{2DK}{h}} = \sqrt{\frac{2 \times 100 \times 52 \times $20}{5 \times 0.1}} \approx 645$$

Second, the reorder point R is computed.
The total inventory policy is (645,133) for a type $\alpha$-service level and the safety stock equals 33 units.

**Example 2:** Type 2 service level and random demand:

Looking at the $\beta$-service level we must use a different formula. The approach presented by Silver et al. (1998, pp.269) is to calculate the inventory policy iteratively although alternative, approximate calculations are available, see for example Vasconcelos and Marques (2000), that might be easier to implement. The increased complexity stems from the fact that $Q$ and $R$, or cycle stock and safety stock, are no longer independent of each other. Intuitively, this becomes clear by looking at the implicitly assumed shortage cost. Every time a stock-out occurs shortage cost are proportional to the shortage quantity. The bigger $Q$, the lower the shortage costs become and thus $R$ can be set lower while achieving the same service level.

The calculation uses the standard loss function $L(z)$ and assumes the same service level as in the type 1 example above. Starting off with a $Q_0$ equal to the EOQ, $R$ is calculated with the following formula:

$$L\left(z_0\right) = \frac{(1-\beta)Q_0}{\sigma} = \frac{(1-0.95) \times 645}{20} \Rightarrow z_0 = -1.6$$

$$R_0 = z_0\sigma + \mu = -1.6 \times 20 + 100 = 68$$

Now $Q_1$ is calculated based on $R_0$. $F\left(z\right)$ represents the standard cumulative distribution.

$$Q_1 = \frac{(1-\beta)Q_0}{1 - F\left(z_0\right)} + \sqrt{\frac{2Kd}{h} + \left[\frac{1-\beta}{1 - F\left(z_0\right)}\right]^2} = \frac{(1-0.95) \times 645}{1 - F\left(-1.6\right)} + \sqrt{\frac{2 \times 100 \times 52 \times 20}{5 \times 0.1} + \left[\frac{(1-0.95) \times 645}{1 - F\left(-1.6\right)}\right]^2} \approx 680$$

For the next iteration $Q_1$ is used to calculate $z_1$ and then computed as in the example above. See table 2 for the results of the iterative calculations.

**Table 2. Iterations for a type 2 service level continuous review policy**

<table>
<thead>
<tr>
<th>Iteration $i$</th>
<th>$Q_i$</th>
<th>$R_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>645 (EOQ)</td>
<td>68</td>
</tr>
<tr>
<td>1</td>
<td>680</td>
<td>66</td>
</tr>
<tr>
<td>2</td>
<td>681</td>
<td>66</td>
</tr>
</tbody>
</table>
After two iterations $R$ is converging to 66. This results in the final inventory policy of (681,66). As expected compared to the type 1 service level of (645, 133) $R$ decreased drastically and $Q$ slightly increased. This example shows that choosing a type 1 or type 2 service type definition results in significantly different outcomes of the required safety stock quantity.

The standard deviation has been used in the examples above. Organizations of a certain maturity level will provide a forecasted demand picture instead of assuming the demand will follow the average demand for past periods. Only demand quantities that are deviating from the provided forecast need to be considered for safety stock purposes. In this case the standard deviation of forecast and actual demand should be provided for safety stock calculation purposes. Some software vendors use an approximation by applying a conversion factor to the forecast accuracy metric MAD (mean absolute deviation) to come up with the standard deviation of the forecast (Silver et al, 1998). The following formula is an estimate for the standard deviation assuming the normal distribution is appropriate.

$$\sigma = \sqrt{\pi / 2} \times \text{MAD}$$

Another choice that presents itself to the practitioner is the choice of forecast lag. The question is which cycle’s forecast should be used to determine the deviation between forecast and actuals. A common practice is to set the forecast lag equal to the top 5% lead time of purchased goods in the supply chain.

Examples 1 and 2 only considered demand variation as an input factor to safety stock. However often supply variability represents a challenge as well as shown in figure 3 b) and c). Supply variability can occur at every echelon. At the raw material level the supply variability includes the lead time it takes the supplier to respond to the order and ship a product. Transportation processes can include significant variability, especially overseas shipments. If the supplier operates make to order, the supplier manufacturing lead time and lead time variability also needs to be considered. At finished good level the internal manufacturing lead time might vary as well, sometimes considerably in case of machine outages.

**Figure 3. Inventory patterns with and without variability**
The following formula applies to normally distributed and independent demand and supply variability for a type 1 service level. The first sum inside the square root accounts for lead time variability and the second part accounts for the demand variability as illustrated in figure 3.

\[ SafetyStock = k \cdot \sqrt{\mu_D^2 \cdot \sigma_L^2 + \mu_L \cdot \sigma_D^2} \]

where

- \( k \) = z score of customer service level
- \( \mu_D \) = mean of the demand in each period
- \( \sigma_L \) = standard deviation of the lead time duration
- \( \mu_L \) = mean of the lead time duration
- \( \sigma_D \) = standard deviation of the demand in each period

**Example 3:** Type 1 service level and random demand & lead time:

A product has normally distributed weekly demand with mean \( \mu_D = 100 \) units and standard deviation \( \sigma_D = 20 \) as in example 1. The lead time is now a random variable. To be able to compare it to example 1 we set the lead time to \( \mu_L = \text{1 week} \). The standard deviation of the lead time shall be \( \sigma_L = 2 \text{ days} = 2/7 \text{ weeks} \). The \( \alpha \)-service customer service level should be 95%.

\[ SafetyStock = 1.64 \cdot \sqrt{100^2 \cdot \left(\frac{2}{7}\right)^2 + 1 \cdot 20^2} \approx 57 \]

The reorder point \( R \) is computed to

\[ R = \mu_D \cdot \mu_L + SafetyStock = 100 \cdot 1 + 57 = 157 \]

Comparing this result to the inventory policy from example 1 we see that there is an increase of 24 units or 72% in safety stock when considering lead time variability.

It should be noted that the calculations presented in this section apply mostly to fast-moving items for which normally distributed demand is a reasonable assumption. Other distributions need to be taken into consideration for slower moving items, e.g. the gamma distribution (Burgin, 1975).

**Multi-Echelon Inventory Optimization**

Optimizing the inventory levels locally will always result in sub-optimization. Each echelon is focused on maintaining a customer service level that their immediate downstream customer demands, but for an optimized solution the focus should be on the end customer and inventory decisions should be made.
Digital Inventory Optimization

based on the end customer service requirements. For that reason, multi-echelon inventory optimization can achieve significant cost savings, especially in complex supply chains, even if a sophisticated single echelon optimization is already in place.

Generally, MEIO is not implemented in the form of spreadsheets, but instead with the help of specialized software since the model and calculations can be too complex and the data volume too big for spreadsheet software to handle. That means to achieve the next level of inventory optimization maturity an investment must be made by the company including an underlying business case. Businesses might have a different set of requirements and being able to understand and challenge the software vendor’s proposed solution can be advantageous to the success of the project. It also becomes important during the vendor selection process to inquire about specific capabilities on the IO software.

There are mainly two different approaches to MEIO. The guaranteed service model (GSM) and the stochastic service model (SSM). The differences are discussed in more detail in Graves and Willems (2003) and also in the background section of this chapter. The following section will give the reader an overview and understanding of the basic GSM as presented in the literature review (Graves and Willems, 2000). The GS service model was the focus of extensive research in the last decade. Multiple extensions to the basic GS have been made in recent years and it has been applied at many large companies, e.g. Procter and Gamble, Eastman Kodak, Hewlett Packard, Intel, and Microsoft (Eruguz et al., 2016). For this chapter, two GS spreadsheet models are developed and the results are presented with different input values. Each of these scenarios will serve to increase the reader’s understanding of the basic GSM and the factors and decisions to make as part of MEIO in general.

Model 1: 2 Stage GSM

In the first example a 2-step manufacturing process is analyzed. This is common in the CPG industry. Typically, the first step is the bulk production of a product and the second step is packaging the bulk product into the final product that is shipped to the distribution center or retail store. Looking at the example in Figure 4 the following parameters are given.

Looking at the service times, \( s_{1}^{in} \) equals the total supplier lead time of the product that is transformed in the manufacturing process. As per the assumptions of the basic GSM, all service times are deterministic in nature and the only decision variable in our 2 stage model is \( s_{1}^{out} \) which is equal to \( s_{2}^{in} \). The customer service time is \( s_{2}^{out} \). The GSM will determine the optimal inventory level at stages 1 and 2 given all these constraints. This is done by solving for \( s_{1}^{out} \). This becomes clear by looking at low and
high values for $s_{1}^{out}$. In case of a low value for $s_{1}^{out}$, a higher amount of inventory has to be stocked at stage 1 in order to be able to fulfill the demand with a shorter service time. Similarly, if the optimal $s_{1}^{out}$ value turns out to be a high value, a small amount of inventory has to be kept.

Note that there are no transportation stages modeled. Stages 1 and 2 have deterministic processing times $L_{1}$ and $L_{2}$. This is the time it takes from receiving the incoming product to making the product available to the downstream stage. Thus, all lead times that are modeled at a stage $i$ need to be summed and included in $L_{i}$ such as goods received time, manufacturing lead time, transportation lead time, etc.

In the basic GSM, the demand from the customer is stationary. This means that the mean demand $\mu$ and standard deviation $\sigma$ do not vary over time. $k$ represents the $z$ score of the service level which the model is achieving by calculating the upper demand bound. For a given value of customer service lead time $s_{2}^{out}$, the model will achieve 100% service level as long as the demand is not exceeding the demand bound. As explained in (Graves and Willems 2000), if the demand increases beyond this upper limit, extraordinary measures have to be taken to fulfill the demand. The usual ways that an organization can avoid lowering their customer service level in this case are expediting freight, run overtime, and ad-hoc subcontracting, all of which incur a premium cost.

$C_{1}$ and $C_{2}$ represent the inventory holding costs. The input parameters shown in table 3 are used in the first scenario for model number 1.

Based on the demand parameters, the upper demand bound calculates to

$$D_{j}\left(s_{2}^{out}\right) = s_{2}^{out} \mu_{j} + k_{j} \sigma \sqrt{t} = 1 \times 10 + 1.64 \times 4 \times \sqrt{1} = 16.56 \text{ units per day.}$$

Only 1 decision variable exists in this two-stage network which is the service time $s_{1}^{out}$. Based on the parameters above, $s_{1}^{out}$ is bounded by 0 on the low end since service times cannot be negative. The upper

---

### Table 3. Input parameters for model 1, scenario 1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_{1}^{in}$</td>
<td>8</td>
</tr>
<tr>
<td>$s_{2}^{out}$</td>
<td>1</td>
</tr>
<tr>
<td>$L_{1}$</td>
<td>5</td>
</tr>
<tr>
<td>$L_{2}$</td>
<td>2</td>
</tr>
<tr>
<td>$C_{1}$</td>
<td>1</td>
</tr>
<tr>
<td>$C_{2}$</td>
<td>1.2</td>
</tr>
<tr>
<td>$\mu$</td>
<td>10</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>4</td>
</tr>
<tr>
<td>$k$</td>
<td>1.64</td>
</tr>
</tbody>
</table>
Digital Inventory Optimization

bound equals 13 days because having a service time of 13 days means that stage 1 operates as make to order \( (s_1^{in} + L_1) \). Additional service lead time on top of the 13 days is unnecessary.

Computing all possible combinations results in the safety stock quantities and costs at stages 1 and 2 pictured in figure 5.

The optimum safety stock configuration in this network is achieved by setting \( s_1^{out} = 13 \). As a result all safety stock is kept at stage 2 and stage 1 becomes a make to order process without any safety stock.

A second scenario is created in figure 6 by increasing the inventory holding costs \( C_2 \) to $1.4.

In this case it is most cost-effective to set \( s_1^{out} = 0 \). However, there is still safety stock kept at stage 2. This is necessary because the lead time \( L_2 \) is smaller than the customer service time \( s_2^{out} \), so some inventory needs to be kept at stage 2 to achieve the service level. The last scenario for this supply chain network will now look at the effect of a decreased lead time \( L_2 \). All other input parameters are the same as in scenario 2.

Figure 7 shows the result. As expected the optimal \( s_1^{out} \) is still 0, however, now no inventory is required at stage 2 as it becomes a make to order process. This strategy is also called postponement. In this example it means that the product is stored in bulk and only packed once the order has been placed by the customer. In this example it results in significant inventory holding cost savings going from $32.84 to $23.65 (28%).

Figure 5. Costs and safety stock quantities for scenario 1

<table>
<thead>
<tr>
<th>( s_1^{out} )</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS Qty Stage 1</td>
<td>23.65</td>
<td>22.72</td>
<td>21.76</td>
<td>20.74</td>
<td>19.68</td>
<td>18.55</td>
<td>17.36</td>
<td>16.07</td>
<td>14.67</td>
<td>13.12</td>
<td>11.36</td>
<td>9.28</td>
<td>6.56</td>
<td>0.00</td>
</tr>
<tr>
<td>Costs</td>
<td>$31.52</td>
<td>$33.86</td>
<td>$35.39</td>
<td>$36.49</td>
<td>$37.28</td>
<td>$37.84</td>
<td>$38.18</td>
<td>$38.33</td>
<td>$38.28</td>
<td>$38.01</td>
<td>$37.47</td>
<td>$36.55</td>
<td>$34.94</td>
<td>$29.45</td>
</tr>
</tbody>
</table>

Figure 6. Costs and safety stock quantities for scenario 2

<table>
<thead>
<tr>
<th>( s_1^{out} )</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS Qty Stage 1</td>
<td>32.84</td>
<td>35.71</td>
<td>37.66</td>
<td>39.11</td>
<td>40.22</td>
<td>41.05</td>
<td>41.65</td>
<td>42.04</td>
<td>42.22</td>
<td>42.16</td>
<td>41.82</td>
<td>41.09</td>
<td>39.67</td>
<td>34.36</td>
</tr>
<tr>
<td>Costs</td>
<td>$32.84</td>
<td>$35.71</td>
<td>$37.66</td>
<td>$39.11</td>
<td>$40.22</td>
<td>$41.05</td>
<td>$41.65</td>
<td>$42.04</td>
<td>$42.22</td>
<td>$42.16</td>
<td>$41.82</td>
<td>$41.09</td>
<td>$39.67</td>
<td>$34.36</td>
</tr>
</tbody>
</table>

Figure 7. Costs and safety stock quantities for scenario 3

<table>
<thead>
<tr>
<th>( s_1^{out} )</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS Qty Stage 1</td>
<td>23.65</td>
<td>22.72</td>
<td>21.76</td>
<td>20.74</td>
<td>19.68</td>
<td>18.55</td>
<td>17.36</td>
<td>16.07</td>
<td>14.67</td>
<td>13.12</td>
<td>11.36</td>
<td>9.28</td>
<td>6.56</td>
<td>0.00</td>
</tr>
<tr>
<td>Costs</td>
<td>$23.65</td>
<td>$31.91</td>
<td>$34.75</td>
<td>$36.65</td>
<td>$38.05</td>
<td>$39.09</td>
<td>$39.85</td>
<td>$40.37</td>
<td>$40.64</td>
<td>$40.67</td>
<td>$40.40</td>
<td>$39.74</td>
<td>$38.37</td>
<td>$33.11</td>
</tr>
</tbody>
</table>
Model 2: 3-Stage GSM

A 3-stage supply chain network is examined next. The 2-stage model is extended by including a warehouse process with a lead time $L_3$ shown in figure 8.

Now two decision variables are present in the model. In addition to $s_{1\text{out}}$, the internal service time of stage 2 serving stage 3, namely $s_{2\text{out}}$, is to be determined.

The customer service time commitment has been lowered to zero. This means that inventory must be immediately available at stage 3 to fulfill the customer demand. The bounds for $s_{1\text{out}}$ are the same as in the previous model. For $s_{2\text{out}}$ the upper bound depends on the choice of $s_{1\text{out}}$ plus $L_2$. The results of the cost calculation with all instances within the bound are displayed in figure 9.

Figure 8. 3-stage supply chain network

Table 4. Input parameters for model 2, scenario 1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_{1\text{in}}$</td>
<td>8</td>
<td>Total supplier lead time in days</td>
</tr>
<tr>
<td>$s_{2\text{out}}$</td>
<td>0</td>
<td>Customer service time commitment in days</td>
</tr>
<tr>
<td>$L_1$</td>
<td>5</td>
<td>Stage 1 lead time in days</td>
</tr>
<tr>
<td>$L_2$</td>
<td>2</td>
<td>Stage 2 lead time in days</td>
</tr>
<tr>
<td>$L_3$</td>
<td>1</td>
<td>Stage 3 lead time in days</td>
</tr>
<tr>
<td>$C_1$</td>
<td>1</td>
<td>Holding cost per unit at stage 1 in USD</td>
</tr>
<tr>
<td>$C_2$</td>
<td>1.2</td>
<td>Holding cost per unit at stage 2 in USD</td>
</tr>
<tr>
<td>$C_3$</td>
<td>1.3</td>
<td>Holding cost per unit at stage 3 in USD</td>
</tr>
<tr>
<td>$\mu$</td>
<td>10</td>
<td>Mean customer demand per day at stage 2 in units</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>4</td>
<td>Standard deviation of daily customer demand at stage 2 in units</td>
</tr>
<tr>
<td>$k$</td>
<td>1.64</td>
<td>Z score of a 95% customer service level</td>
</tr>
</tbody>
</table>
The optimal solution in this example occurs for \( s_{1}^{\text{out}} = 13 \) and \( s_{2}^{\text{out}} = 15 \). This means that all safety stock inventory of the supply chain is stored at stage 3. As seen in this example and the examples of model 1, the optimal solution seems to be an extreme point. That means that the optimal solution dictates that each stage either has a service time equal to its net replenishment lead time or a service time of zero. This has been established as true for all concave cost functions in the basic GSM (Humair and Willems, 2006). Figure 9 shows further the power of MEIO. If each stage is determining their own safety stock quantities in a single echelon calculation, sub-optimization will most likely occur (red area). Only a holistic view of the supply chain enables the supply chain manager to find the optimal solution.

In practice the extreme point property of the GSM can lead to some challenges especially if the organization is operating in silos. Let each stage in our example represent a different plant that belongs to a different business unit and thus reports to different management within an organization. If the results of the MEIO calculation were followed, then one stage would take all the burden of the inventory and would have significantly worse inventory key performance indicators (KPIs). On the other hand, the other stages would drastically reduce their customer service KPIs, e.g. on time in full (OTIF). As seen in the examples, MEIO can help to answer the strategic questions of push or pull. To achieve alignment, support for the MEIO initiative in an organization must be at the C-level in the organization. Furthermore, it requires a restructuring of the KPIs for plant management. Instead of focusing on lower inventory at a single echelon the new KPI could measure the adherence to the safety stock target instead and so ensure that the output of the MEIO calculation becomes reality.

So far, the examples have been simple serial supply chain networks. But real-world supply chains are often general acyclic networks or even cyclic networks as seen in following figure 10 a and b. Solving for cyclic networks has not been subject to much research so there might be a need to break up the supply chain model to avoid creating cyclic relationships.
Looking at node 3 in figure 10 a) one can see that it serves the two downstream nodes 4 and 5. This could be a common subassembly or component for a finished product. Now assume that the two downstream nodes are producing different products and the two products have independent demand. In this case it can be shown how through risk pooling the safety stock inventory can be lowered substantially.

Stages 4 and 5 have a demand random variable $X_4$ and $X_5$. Then the mean demand at stage 3 is

$$E(X_3) = E(X_4 + X_5) = E(X_4) + E(X_5)$$

This represents a simple addition of the mean demand at the downstream stages. It seems intuitive and does not contribute to the risk pooling effect. However, looking at the demand variance shows a different picture:

$$VAR(X_3) = VAR(X_4 + X_5) = VAR(X_4) + VAR(X_5) + 2Cov(X_4, X_5)$$

**Equation 1: Variance of Summation of Two Random Variables**

The total demand variability at stage 3 depends on the covariance of the downstream demand. Figure 12 shows two common cases of demand covariance.

If the demand for the two end products is positively correlated (positive covariance), for example, demand for pens and notebooks at a retail store, the positive effects of risk pooling are reduced. However, if the products are negatively correlated (negative covariance), e.g. 2 similar products that cannibalize each other, then the positive effect of risk pooling is increased. Going forward the assumption is that the random variables $X_4$ and $X_5$ are independent from each other which represents a neutral situation, i.e. the covariance equals zero and the covariance term in equation 1 can be ignored.

$$VAR(X_3) = VAR(X_4 + X_5) = VAR(X_4) + VAR(X_5)$$
To illustrate the implications of this equation an example is shown. Let $X_4$ and $X_5$ be normally distributed demand with standard deviations of $\sigma_4 = 5$ and $\sigma_5 = 6$. Then

$$\sigma_3 = \sqrt{\sigma_4^2 + \sigma_5^2} = \sqrt{25 + 36} \approx 7.81$$

So instead of having to account with safety stock for a standard deviation of the demand of 11 ($\sigma_4 + \sigma_5$) only 7.81 needs to be considered. This effect allows the company to carry significantly less safety stock while keeping the same customer service level. Practically the risk pooling effects need to be considered when making decisions on warehouse consolidation (Eppen, 1979) or postponement of the finished good assembly to keep inventory at a common subassembly stage.

**INVENTORY PLANNING PROCESS AND MATURITY MODEL**

Now that the reader is familiar with the basic mathematical concepts the broader scope of inventory optimization will be discussed in the form of the inventory planning process. The main goal of the inventory planning process is to provide the safety and sometimes cycle stock parameters to other planning functions, namely:

1. Production scheduling and material requirements planning (MRP)
2. Master planning and rough-cut capacity planning (RCCP)
3. Sales and operations planning (S&OP)
The following describes the general relationship between inventory planning and the planning functions above. It should be noted that the interconnection of these processes can vary by organization based on business model, maturity, and system architecture. The production scheduling and MRP processes have the goal to create a feasible, short-term production schedule for shop floor execution to fulfill the customer orders while balancing costs such as stock-out, overtime and inventory holding costs. The output of the inventory planning process has to be an input to this process or otherwise the computed safety and cycle stock targets will not be realized.

The master planning and RCCP process has the goal to achieve a balance of demand and supply based on capacity constraints and planning parameters that have been deemed important to model for a mid-term horizon. As such it usually represents an input to the production scheduling process to bring in the information of a tactical buildup of inventory, level loading of production lines, etc. As such the computed safety and cycle stock targets need to be provided as an input as well. Similarly, the S&OP process seeks to balance demand and supply on a mid to long-term basis. The focus in the S&OP process is on strategic challenges and aligning all departments within an organization towards a common goal. Scenarios based on strategic investments, e.g. new production lines are created and evaluated on their financial KPI.

Figure 12 depicts the author’s view of an inventory planning maturity model. The higher levels of maturity encompass all positive characteristics of the lower levels. Governance, technology, and process are the three dimensions of inventory planning. It is possible to have a different maturity level in each of the dimensions, for example an organization might have a high technology, but a lower governance maturity. With any kind of business transformation, it is important to know what maturity level represents the starting point and then define what level should be achieved based on the business case.

Figure 12. Inventory planning maturity model
Thus, the first step is to take an unbiased look at the current inventory planning process, technology and governance to determine the current levels. Common techniques to achieve this first step is to analyze inventory parameter data and conducting interviews with the inventory planning stakeholders. The levels are described as the following.

The first level of the maturity model describes an ad-hoc or “no planning” state of inventory planning. There is no defined process to set inventory parameters in the system of record. Rules of thumb are used instead which leads to a circle of trial and error. Even the rules of thumb might vary across silos of the organization and the process cadence is not defined. As such the IO supporting technology is sparse to non-existent. In terms of governance, the KPIs are not established and tracking of actuals is not done consistently. Overall the importance of inventory is not well understood.

The second level is called “Limited Single Echelon Inventory Planning”. As improvements compared to level 1, the process is now defined, but might vary across business units. Inventory parameters are reviewed one by one since no exception capabilities are present. As a result the process is not scalable. The technology at this level consists of offline, non-standardized spreadsheets. They might include some of the formulas presented in the “Single Echelon Optimization for a (Q,R) inventory policy” section of this chapter. Since the IO system is not integrated with the ERP, simple day of cover policies are being used to avoid entering time-phased safety stock numbers. The governance includes tracking of inventory turns and a limited definition of roles and responsibilities.

The third level is still operating with a single echelon optimization model, but the overall maturity is improved in many ways. The inventory planning process and its cadence is fully standardized, documented, and adhered to. Portfolio segmentation exists to focus on the inventory issues of high value first. Technology-wise the single echelon approach can still be implemented as a spreadsheet solution or alternatively a specialized planning system is used. The output of the tool is integrated with the ERP system and exception reporting exists, which makes the solution scalable. Leadership is fully aware of the importance of inventory and KPI targets are being dictated.

The fourth level of inventory planning maturity adds the element of regular root cause analysis of stock out and excess inventory. MEIO enables the scientific application of postponement and inventory placement. The system is fully integrated with the source and target systems and allows for cost based optimization through mathematical programming. What-if scenarios are possible to model the inventory impact of new product introduction, inventory impact of a new sourcing method, changes in demand variability, etc. Inventory target adherence is tracked and root causes are identified, documented, and a plan is created on how to avoid non-adherence in the future. Cross functional initiatives on rationalizing the product portfolio might be included in the IO scope based on a total cost of ownership approach.

The final stage of inventory planning maturity is called “End-to-end strategic inventory planning”. The end-to-end supply chain is included in the maturity model including external suppliers, customers, and their suppliers and customers. The holistic approach requires sharing of information across the different organizations that could be achieved with incentivized contracts. Machine learning and data mining is used to predict the optimal future network configuration. The scope of IO is extended to also include network configuration aspects, for example sourcing decisions.
FUTURE RESEARCH DIRECTIONS

The author identifies research opportunities in the areas of

1. Inventory optimization surveys. The latest survey on IO tool and process adoption that the author was able to identify is from 2014. Given the rapid increased usage of digital technology, the numbers might look different at the present time. The survey should contain a variety of industries to show the differences in IO adoption.

2. SSM versus GSM. Although this chapter focused on the GSM, the SSM is a proven MEIO tool to provide safety stocks across the network. The different assumptions of both models might make one more applicable than the other depending on industry, supply chain network, computational costs, or other considerations. Developing a decision framework represents an opportunity for research. Other questions that could be answered in this framework are: Is the investment in MEIO worth it for a simple supply chain and what is the complexity threshold? What are industry best practices in terms of IO tool configuration?

3. Machine learning applied to inventory optimization. The traditional IO models are limited to a defined set of input parameters, for example demand and supply variability. Typically the historical variability is used as an indicator for the future. However each of these parameters could instead be predicted with machine learning techniques depending on input parameters such as the weather, port closure information, point of sales data, social media input, etc.

CONCLUSION

There is an opportunity for inventory optimization in many organizations that handle physical goods. Even the most advanced organizations that are known for their supply chain capabilities have not yet mastered all aspects of inventory planning maturity (Farasyn et al., 2011). The author is confident that using the inventory optimization tools presented in this chapter and combining them with transformation guidelines presented in the rest of this book will set up the supply chain practitioner for success and wishes the reader best of luck on their digital supply chain journey.

REFERENCES


Digital Inventory Optimization


KEY TERMS AND DEFINITIONS

**Arc:** Connection between stages/nodes. It can, for example, represent a relationship defined in a bill of material or a transportation network.

**BOM:** Bill of material.

**CPG:** Consumer packaged goods.

**EOQ:** Economic order quantity.

**GSM:** Guaranteed service model.
IO: Inventory optimization.
KPI: Key performance indicator.
MAD: Mean absolute deviation.
MEIO: Multi-echelon inventory optimization.
MRP: Material requirements planning.
OTIF: On time in full. It represents a KPI for delivery performance and is typically calculated by dividing the number of deliveries delivered on time in full by the total number of deliveries.
RCCP: Rough-cut capacity planning.
S&OP: Sales and operations planning.
SSM: Stochastic service model.
Stage/Node: A stage in the supply chain. It can represent a manufacturing operation or a warehousing process.