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AN OPTIMIZATION MODEL FOR STRATEGIC SUPPLY CHAIN DESIGN UNDER STOCHASTIC CAPACITY DISRUPTIONS

A Record of Study

by

JAIME LUNA CORONADO

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF ENGINEERING

December 2007

Major Subject: Engineering
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ABSTRACT

An Optimization Model for Strategic Supply Chain Design under Stochastic Capacity Disruptions. (December 2007)

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This Record of Study contains the details of an optimization model developed for Shell Oil Co. This model will be used during the strategic design process of a supply chain for a new technology commercialization. Unlike traditional supply chain deterministic optimization, this model incorporates different levels of uncertainty at suppliers' nominal capacity. Because of the presence of uncertainty at the supply stage, the objective of this model is to define the best diversification and safety stock level allocated to each supplier, which minimize the total expected supply chain cost. We propose a Monte Carlo approach for scenario generation, a two-stage non-linear formulation and the Sample Average Approximation (SAA) procedure to solve the problem near optimality. We also propose a simple heuristic procedure to avoid the nonlinearity issue. The sampling and heuristic optimization procedures were implemented in a spreadsheet with a user's interface. The main result of this

development is the analysis of the impact of diversification in strategic sourcing decisions, in the presence of stochastic supply disruptions.

DEDICATION

To my wife

To my parents

Without you, I would not be here.

ACKNOWLEDGMENTS

I want to thank my Co-Chairs, Dr. Gary Gaukler and Dr. Antonio Arreola-Risa, for their guidance and coaching through my doctoral studies. Special thanks to Dr. Antonio Arreola-Risa for giving me the opportunity of working in this project. Also, I would like to express my gratitude to my committee members, Dr. Bickel and Dr. Smith, for their support during my graduate studies.

A special acknowledgement goes to Barry Keys, at Shell Oil Co., who I thank for giving me the opportunity of collaborating on his team. Working under his supervision was an enjoyable learning experience. My gratefulness also to Jeremy Brann, from the Texas A&M / Shell Oil Co. team. Jeremy played a crucial role during the spreadsheet implementation of this model.

I would like to thank Dr. Guy L. Curry and the rest of the faculty and staff in the Industrial and Systems Engineering Department at Texas A&M University, who provided me with the most invaluable knowledge I could have ever obtained. I also want to express my gratitude to Dr. Bryan L. Deuermeyer, my mentor during the first half of my graduate studies at Texas A&M.

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NOMENCLATURE

CV	Coefficient of variation
FA	Final assembly
LP	Linear programming
NLP	Nonlinear programming
MTBF	Mean time between failures
MTTR	Mean time to repair
QAEC	Quality adjusted effective capacity
VBA	Visual Basic for Applications

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1. INTRODUCTION

A supply chain is defined as a network of facilities, distribution centers and warehouses that perform the functions of procurement of materials, transformation of these materials into intermediate and finished products and distribution of these products to customers. In complex and competitive environments, supply chains should be managed in the most efficient way, with the objectives of (i) minimization of costs, lead-times, inventories and investments, (ii) maximization of throughput, profit, return on investment (ROI) and customer service level. The presence of variability either at the supply or demand brings the importance of the design of robust supply chain networks. The impact of variability on supply chain performance has been well studied by researchers and understood by practitioners, with the common acceptance that any kind of variability or disruption degrades the performance of the system. Several mechanisms have been proposed as hedge to minimize the impact of variability: capacity, lead-time, inventory and recently, information sharing. New managerial trends such as Six Sigma and Lean Manufacturing have focused their attention on variability as a form of waste and how to identify and reduce it. Information flows between supply chain stages have recently been studied in the literature, and their impact and value have been identified on different variables: capacity, lead-time and inventory. Literature has focused on information sharing as a way to maximize the whole supply chain profit, instead of concentrating in local optimization.

This record of study follows the style of *Management Science.*

Most of the supply chain models in the literature and in practice assume either reliable supply and / or a single supplier per process. Although 80's manufacturing tendencies such as JIT and now Lean Manufacturing propose the reduction of suppliers, they do not imply working with only one. Practical literature has made a strong case for single sourcing, citing benefits such as improved quality and service resulting from a long-term relationship (Anupindi and Akella 1993). However, qualitative and quantitative issues may affect this relationship: defects, capacity, price variations and lead-time, among others. Then, common sense calls to have a backup supplier or a pool of suppliers in case of a disruption in the main supplier; or assigning different pieces of the demand to each potential supplier, in order to reduce risk in the case of a failure at any of the suppliers.

Bozarth and Handfield (2006) provide a definition for different sourcing strategies. In a *single sourcing* strategy, the buying company depends on a single company for all or nearly all of a particular item. This strategy was heavily followed by North American organizations in the past, primarily because of the example set by new manufacturing strategies and Japanese companies who have used single sourcing to achieve continuous price, quality and lead-time improvements. Pochard (2003) presents some examples of how large companies reduced their suppliers' base:

- Xerox went from 5,000 suppliers in 1985 to 4,000 in 1987, reducing its lead-time from 52 to 18 weeks

- Merck reduced from 40,000 to 30,000 suppliers between 1992 and 1997
- Allied Signal reduced from 10,000 suppliers to 2,000 from 1992 to 1997

In a *multiple sourcing* strategy, the buying firm shares its business across multiple suppliers. In a *cross sourcing strategy*, a company uses a single supplier for a certain part or service in one part of the business, and another supplier with the same capabilities for a similar part in another area of the business. A fourth sourcing strategy is *dual sourcing*. Here, two suppliers are used for the same component or service. Usually, 70% of the total business is allocated to one of the suppliers, and the rest to the second supplier. The performance of both suppliers will be reflected in this performance. Bozarth and Handfield also compare the advantages and disadvantages for both single and multiple sourcing strategies. See Tables 1 and 2.

Table 1 Advantages – disadvantages of single sourcing

Single Sourcing	
Advantages	**Disadvantages**
Results in volume leveraging-when volume goes up, cost per unit decreases as the supplier spreads fixed costs over larger volume	Can result in higher cost when the supplier, knowing it has the business decides it can actually increase prices in the short term
Reduces transportation costs, with fewer shipments and lower per-unit transportation costs	Increase supply risk - if a dissater occurs, the buyer can be left without a souce of supply
Reduces quality variability and provides a standardized product	Can result in the buyer becoming "captive" to the supplier's technology - while other suppliers are surging ahead with newer technology that has better performance
Builds stronger relationship with the supplier and provides access to its design and engieering capabilities	Does not enable buyer to know if it has the "best" supplier available
Is required when the supplier has a propietary product	Is a dangerous strategy if the supplier has limited capacity - it may "shut down" the buyer if it takes on too much business
Is required if the purchased volume is too small to split between two suppliers	

Table 2 Advantages – disadvantages of multiple sourcing

Multiple Sourcing	
Advantages	**Disadvantages**
Creates competition	Reduces supplier loyalty-suppliers may not be willing to "go extra mile" for the purchaser
Spreads risk (in the event of fire, strike, etc at one supplier)	Can increase risk in the event of a shortage-suppliers may only supply preferred customers
Is requiered if the purchased volume is too great for one supplier	May result in different product attributes with varying quality
Is desired if the buyer wishes to meet obligations to support minority suppliers	Can actually result in increased prices over time as suppliers are reclutant to provice cost-savings ideas
Can ensure that suppliers do not become "complacent"	Suppliers can let performance slide if volume is not high enough to merit their attention

Even though single sourcing presents some advantages with respect to cost against multiple sourcing, the risk imbedded in case of any supply disruption might impact significantly the performance of the supply chain. Some examples of supply disruptions in single sourcing are described below (Bartholomew 2006, Sheffi and Rice 2005):

- Toyota lost production of 20,000 cars ($200 million in revenue) after the 1995 earthquake in Kobe, Japan, when its only supplier of brake shoes, Sumitomo Metal Industries Ltd, lost all water and gas.

- Phillips N.V. suffered a fire at the chip plant in Albuquerque, New Mexico in 2000. The company lost $40 million in sales. Ericsson, its main customer, came up short of million of chips needed for its latest generation of cell phones. Ericsson lost $2.34 billion in its mobile phone division.

- Land Rover almost had to shut down its total operation in 2001 due to a dispute with his single chassis supplier, UPF Thomson, after they declared bankruptcy. UPF stopped supplying chassis to and went to a legal dispute with Land Rover.

Usually, in both sourcing strategies, supplier selection was based on cost, quality, lead-time and, in some cases, capacity. Nowadays, because companies face globalization and a much more competitive environment, the analysis of supply chain disruptions has gained an important role during the design of supply chain networks. Traditionally, the first thing that usually comes to mind about uncertainty in supply chains is demand uncertainty (Tajbakhsh et al. 2007). Recently, supply uncertainty has gained the attention and concern of supply chain managers, practitioners and academics, especially because of the vulnerability due to modern manufacturing tendencies and complex supply networks. Supply chain risk can become full fledge supply chain problems, causing unanticipated changes in flow due to disruptions. These disruptions can be frequent or infrequent; short or long term, causing problems from minor to serious (Chopra and Sodhi 2004). The MIT Research Group on "Supply Chain Response to Global Terrorism" identifies six different levels of disruption in the context of supply chain management (Porch 2003). See Table 3.

Table 3 Categories of supply chain disruptions

Failure Mode	Description
Disruption in Supply	Delay or unavailability of materials from suppliers leading to a shortage of inputs that could paralyze the activity the activity of the company
Disruption in Transportation	Delay or unavailability of the transportation infraestructure leading to the impossibility to move goods, either inbound and outbound
Disruption at Facilities	Delay or unavailability of plants, warehouses and office buildings hampering the ability to continue operations
Freight breaches	Violation of the integrity of cargoes and products, leading to the loss or adulteration of goods (can be due either to theft or tampering with criminal purpose, e.g. smuggling weapons inside conteiners)
Disruptions in communications	Delay or unavailability of the information and communication infrastructiure, either within or outside the company, leading to the inability to coordinate operations and execute transactions
Disruption in Demand	Delay or disruption downstream can lead to the loss of demand temporarily or permanently, thus affecting all the companies upstream

An alternative definition for multiple sourcing as a hedging mechanism to the impact of supply disruption is the concept of Diversification, which, like the portfolio theory (where the objective is to design the best combination of stocks to minimize risk while maximizing revenue), tries to define the best allocation of the “business” among a pool of possible suppliers, with the main objective of minimizing the risk of stock-outs due to the failure of some vendors (Cohen and Lee 1989). We can define total business as the total production order of each component needed in the Final Assembly process. Diversification, including supplier selection and lot-size allocation, might not be an easy task, especially in the presence of supplier's capacity disruptions. In this case, the traditional cost approach does not give enough information and might mislead important strategic decisions.

Although supplier's capacity is subject to random fluctuations due to normal business variability, it is also affected by random disruptions inherent to its operation (machine breakdowns, strikes, maintenance, etc.) and by unexpected catastrophic events such as snow storms, floods, earthquakes, etc. Besides the main challenges that a company faces when trying to select suppliers and allocate "business" among them, it is necessary to first define the kind and amount of information required about each supplier in order to make the selection and allocation decision. As already addressed, in the traditional sourcing strategy, only cost and promised capacity were the parameters considered in this crucial strategic decision.

This Record of Study addresses the problem of a supply chain with three assembly plants which require five strategic components. Each component has a pool of three potential suppliers with different capacities, costs and supply reliability. The objective is to identify the best diversification level or allocation of "business" for each supplier, (order or lot-size) as well as the safety stock level required, so to minimize the whole supply chain system cost.

The model was constructed using the concept of Two-Stage Stochastic Optimization. This technique considers that there are two types of decisions: First Stage decisions, (sometimes known as “design decisions” or, more simply, “here and now” decisions) and Second Stage decisions (also known as “wait and see” or control decisions). Unlike first stage decisions, which are taken in the presence of uncertainty, second stage decisions are taken later in response to events happening. Both allocation and safety stocks are modeled as 1^{st} stage variables, while production quantities and inventories are considered as 2^{nd} stage.

We propose a Monte Carlo approach to generate scenarios of possible supplier’s capacities outcomes. Each possible capacity outcome is the combination of several stochastic disruptions such as nominal capacity, reliability, quality and catastrophic events (also known as Acts of God), each disruption with a different probability distribution.

We also propose a nonlinear programming (NLP) formulation with the objective function of minimizing the total expected monthly cost, which include production, holding and penalty costs. A Sample Average Approximation (SAA) introduced in Kleywegt et al. (2001) is proposed as the solution approach. However, given the complexity of NLP problems and taking advantage of simplicity to compute expected values using MS Excel, we proposed a simple heuristic procedure. This heuristic decomposed the NLP problem into two easy-to solve LP models, where the first LP model is solved to obtain the allocation, and then, using the optimal value of the 1^{st} stage variable, the second model is solved for the next 1^{st} stage variable. Using this approach, we obtain 1^{st} stage variables which provide a robust solution to a wide variety of possible scenario outcomes.

It is important to point out that the major purpose of this work is to propose a supply chain design framework rather than the development of efficient solution algorithms.

From the managerial point of view, this model can answer the following questions:

1. Given reliabilities and yields for each supplier, what is the optimal diversification between suppliers, and what is the optimal safety stock level to carry at each supplier to manage risk vs. expected cost?

2. Given the supplier diversification ranges / limits, what is the recommended capacity for each vendor?

3. What is the impact of performance (service level) improvements on expected cost and risk?

4. What is the impact of maintenance (MTBF / MTTR) improvements on expected cost and risk?

5. What is the impact of six sigma and lean manufacturing improvements on expected cost and risk?

The work presented here is the result of one and a half years of development at Shell Oil Company, in the Unconventional Oil unit, which is part of the Exploration and Production division. This model is a component of a pool of modeling tools currently used by SURE during the strategic planning processes for the commercialization of a new technology. The importance of this development lies on the fact that, because the complexity and heavy content of intellectual property of this technology, only few suppliers would be able to manufacture some of the components and would be constrained in capacity.

Given the nature of the commercialization project, all information related to intellectual property will not be included in this document.

2. LITERATURE REVIEW

In this section, we provide a brief overview of the current literature state on the following research streams:

- Supply chain design under risk and uncertainty
- Supplier selection and diversification

Chakravarty (1979) proposes a framework to define the best order allocation among a group of competing suppliers. Using the primary supplier performance indicators (price, quality and lead-time), they propose a dynamic programming model that tries to allocate using the costs associated with excess of stock caused by quality and lead-time.

Gerchak and Parlar (1990) analyze the problem of diversification in an EOQ setting random yield. They show that, if the manufacturer diversifies, the ratio of the Q order size to each supplier is equal to the ratio of the mean demand times the variance of each supplier. Anupindi and Akella (1993) study the effect of diversification under supply uncertainty. They point out that, despite the benefits cited for single sourcing in the popular literature, there is enough evidence of industries having two or three sources. They address the problem of quantity allocation between two suppliers and its effects on the inventory policies. In this case, supply uncertainty depends on the type of delivery contracts (single or multiple deliveries). Anupindi and Akella also provide an excellent review of literature on diversification with inventory models.

Yano and Lee (1995) provide an excellent literature review of different production and procurement models with random yields. Guo and Ganeshan (1995) study the effect on the expected lead-time and variability by adding more suppliers. By splitting the order quantity Q among n suppliers and assuming uniform and exponential lead-times, they show that adding more suppliers will reduce both expected lead-time and variability.

Agrawal and Nahimias (1997) consider random yield with multiple and different suppliers. Assuming deterministic demand, they address the issue of order splitting and supplier selection with the newsboy model. The trade-off in this problem is the reduction of the yield uncertainty against the increase in ordering fixed cost. Arreola-Risa and De Croix (1998) model a company that faces stochastic supply and demand. The supply experiences random disruptions of random duration. The inter-arrival times of the disruptions and the duration of the disruptions are modeled as exponential random variables. The demand is modeled as a Poisson process. Arreola-Risa and DeCroix assume a modified *(s,S)* inventory, where replenishment orders are only paced when the supply is available. They determine the optimal values of s and S. In addition, they explore the behavior of the optimal values of s and S as the disruptions become more / less frequent and of longer / shorter duration.

Ghodsypour and O'Brien (2001) propose a deterministic mixed nonlinear programming model to solve the multi-sourcing problem, considering transportation, storage and ordering costs. The suppliers are capacity constrained and subject to quality yield. The model incorporates multiple objectives for supplier selection such as: on-time delivery, after sales service and response to change. Santoso et al. (2003) also propose a stochastic MILP formulation and solution procedure for large supply chain design problems. They point out the fact that the existing stochastic programming approaches for supply chain design under uncertainty are suited only for a small number of scenarios. They present a solution methodology which incorporates the Sample Average Approximation as the sampling strategy with an accelerated Bender's decomposition. With this solution framework, the authors were able to obtain high quality solutions for realistic size problems. In this work, transportation costs, demands, supplies and capacities are stochastic.

From a very strategic point of view, Chopra and Sodhi (2004) explain the importance of identifying and managing risk at the supply chain to avoid any type of breakdown. They point out that, by understanding the variety and interconnectedness of supply chain risk, managers can tailor balanced, effective risk–reduction strategies for their companies. They identify various types of risk drivers and mitigation strategies.

Sheffi and Rice (2005) address the problem of supply chain disruptions. According to the authors, companies are no longer subject only to the uncertainty of the demand, but also to uncertainty within complex supply chain networks, with factors such as disruptions on supply, capacity, quality and manufacturing yields, and recently, the menace of terrorist attacks. Sheffi and Rice point out the importance of risk management as part of the strategic initiative of building resilient enterprises. They also provide a framework to classify several types of disruptions and ways to understand and manage them (Vulnerability Assessment).

Berger et al. (2004) propose a decision model to select the number of suppliers needed in the presence of risks. Using conditional probabilities and a decision-tree approach, the authors show how to obtain the optimum number of suppliers.

Guillen et al. (2005) propose a multi-period MILP formulation for supply chain design, where they incorporate production capacity uncertainty. They transform the model into a two-stage stochastic optimization model, with an objective function of maximizing supply chain profit, demand satisfaction and minimizing financial risk. They use Monte Carlo sampling techniques for scenario generation.

Erdem et al. (2006) also analyze an EOQ setting with multiple suppliers having random capacities (this might be due to unreliable equipment and unplanned maintenance). In a more empirical approach, Hendricks and Singhal (2005) investigate the impact of supply chains disruptions on the long-run price of the firm’s stocks and equity risk. Using a sample of 827 disruptions publicly announced during 1989-2000, they tested several hypotheses about the abnormal stock price before and after the announcing, increase in the equity risk, financial leverage and asset risk. Tomlin (2006) studies a supply chain model with a single product and two capacitated suppliers, where one of them is unreliable and lacks flexibility. In this case, the reliable and flexible supplier is more expensive. Using a Markovian base stock model, Tomlin focuses on supply-side tactics of inventory, sourcing and rerouting as a mitigation and contingency tactic in the case of supply disruptions. This paper shows that inventory is not an attractive strategy in the case of rare but long disruptions.

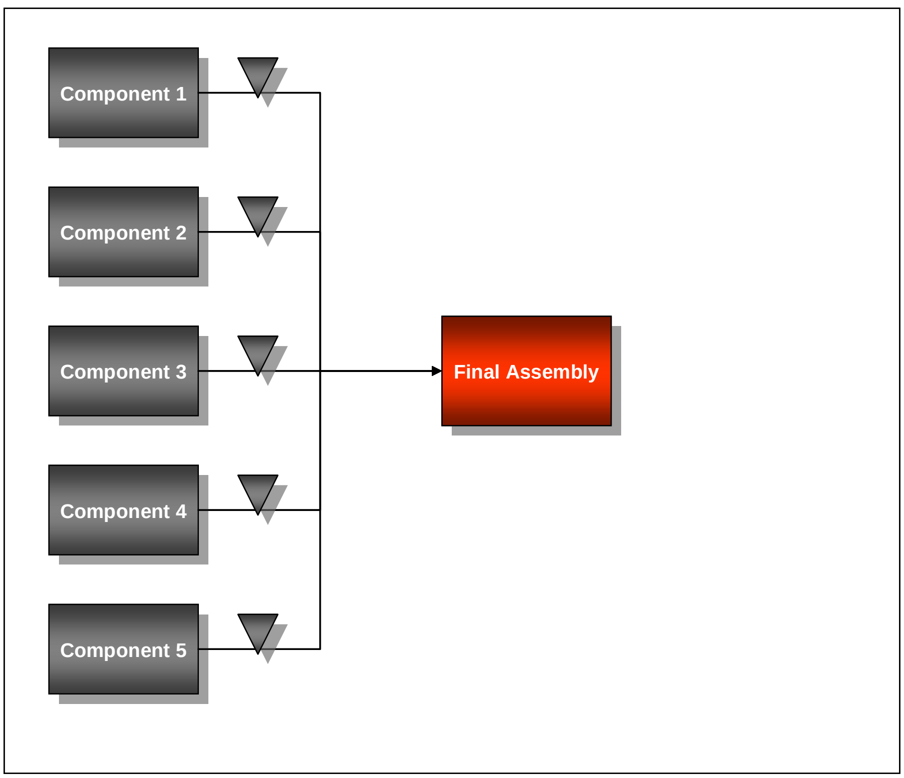
Kleindofer and Saad (2005) provide a conceptual framework that reflects the joint activities of risk assessment and risk mitigation that are fundamental to disruption risk management. The authors identify two types of broad categories of risk affecting supply chain design and management: risk arising from problems of coordinating supply and demand, and risk arising from disruptions to normal activities. This work focuses on the second category (natural disasters, strikes, economic disruptions and terrorist attacks). Burke et al. (2006) analyze the impact of single versus multiple supplier sourcing strategies under demand uncertainty. Using a newsboy framework, they incorporate supplier cost, capacities, historical reliability and holding costs into the decision of supplier selection and order allocation. They conclude that single sourcing is a dominant strategy only when supplier capacities are large relative to customer demand.

Qi and Max Shenn (2007) propose a model for a supply chain design with unreliable supply. They analyze a multi-period problem, with multiple retailers, multiple intermediate facilities and a single supplier. Because each intermediate facility might have random yield (reliability coefficient), the amount of final product delivered on time to the final customer may not be the same amount requested. They propose a nonlinear formulation with the objective function of maximizing the whole supply chain profit, by selecting the best allocation of facilities, demand allocation and inventory policy. They also propose to use the Sub-gradient Algorithm to solve the problem. Tajbakhsh et al. (2007) provide an excellent introduction and literature review to supply uncertainty and diversification. In specific, they focus in three main aspects: uncertainty in supply timing, uncertainty in supply quantity and uncertainty in the purchase price.

3. MODEL OVERVIEW

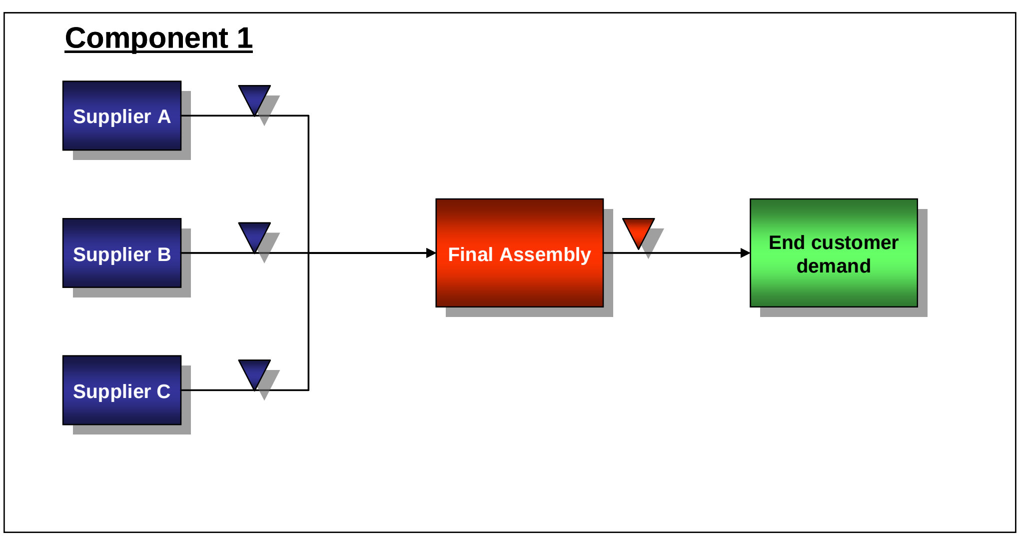
We assume a two-stage supply chain network with a single product formed by five different components. The components are assembled into a single product in a final assembly operation. There is a deterministic monthly demand for the single item T, with a penalization of $\$\pi$ per product stock out-occurrence, with no backlog allowed (lost sales). The Bill of materials (BOM) structure is 1:1 for each component in relation to the final product. See Figure 1.

Figure 1 Supply chain structure



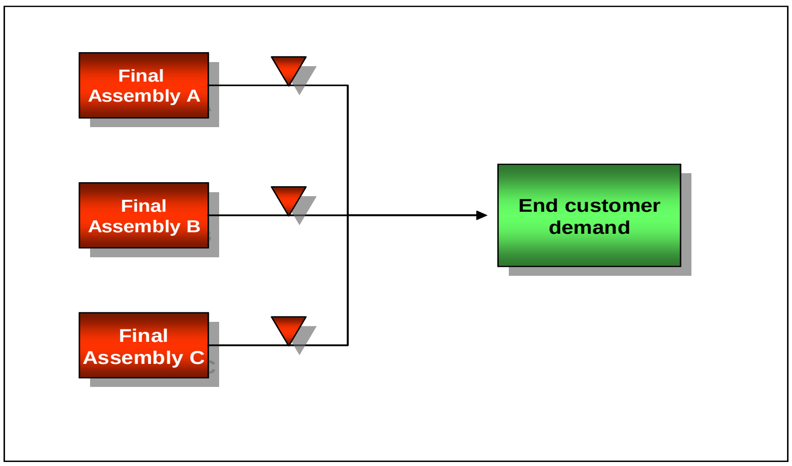
Each component might have up to three possible suppliers with the same lead-time but with different throughput and cost. Following the definition provided in Hopp and Spearman (2000), *throughput* is the average output of a production process per unit time, while *capacity* is the upper limit on the throughput of a production process. Here, we introduce the concept of *Quality Adjusted Effective Capacity* (QAEC) which is the final, real or observable monthly capacity after all possible disruptions have occurred. As we already specified, monthly supplier's QAEC will be the only source of uncertainty in the model. We assume that suppliers for each component are independent and do not have knowledge of each other's current capabilities and cost information. Besides of the penalization π at the final stage, there is also a second penalization θ at the component stage, where every supplier will be penalized for the difference between the production order allocated by the Final Assembly operation and total component availability (production plus inventory). See Figure 2.

Figure 2 Supplier structure per component



We also consider three alternatives for the Final Assembly (FA) operation. Each FA operation will be allocated certain order-size Q, where Q is a function of the total demand and the percentage assigned to that FA plant. The supply of components assigned to each FA plant will be a function of that allocation. Like the component stage, each FA operation might have a different production cost. See Figure 3.

Figure 3 Final assembly structure



Since the nominal capacity for each supplier is going to be affected by several random disruptions, the suppliers are allowed to carry a safety stock of each component. Because we want to design a lean supply operation, this safety stock will be used only when the supplier can not deliver the order size Q allocated to him. We assume that every component not delivered to FA will be lost (no backlogging allowed) and penalized by θ per item occurrence. Every period, the supplier will produce the minimum of its capacity and its order size plus the difference between the on-hand inventory and the order-up-to level in case some material was consumed from the stock during the last period. Similarly, for each period, the inventory at the component stage will be the result of how much was produced plus the on-hand final inventory from the previous period, minus what FA consumed.

We assume a similar structure for the FA operation: each plant might carry its own safety stock of final product. However, the final production rate for each period at each FA plant will be a function of how many components are available, and its QAEC in the period. In this case, the safety stock will not only buffer against the variability of the FA own operation (where its capacity is a random variable), but also against the variability at the supply stage.

Because suppliers are capacity constrained and subject to random fluctuations, we would face a big risk by assigning only one supplier per component. Here, we use the concept of *diversification*, which we already defined as how production is allocated among all suppliers for each component and FA operations. Since we assume a deterministic demand, every month (or time period defined) each component stage must deliver the same amount of material needed to satisfy the target demand at the FA operations (i.e. if the target is 50 units / month, every component stage should supply 50 units / month). The level of diversification is represented as a decimal continuous non-negative variable, where the sum of the levels for each component should equal to one. We can see this variable as the percentage of the total business allocated to each supplier. A simple example is presented next: assume a supply chain with two components and a FA operation, with three possible suppliers per stage and a monthly demand of 200 units. Table 4 shows how for each component and FA, we diversify the demand or the production order. Therefore, supplier 1 for component 1 will produce every month 65 units of the total demand (or 32.6% of 200), while suppliers 2 and 3 will produce 87 and 47 units respectively. The total sum for each component is 100% (or 200 units).

Table 4 Example of diversification

Component	Supplier	Diversification	Order
1	1	32.6%	65
	2	43.6%	87
	3	23.7%	47
2	1	50.3%	101
	2	49.7%	99
	3	0.0%	0
Final Assembly	1	70.0%	140
	2	15.0%	30
	3	15.0%	30

We assume that the diversification level assigned will stay constant for the planning period. This means that this variable must be defined before any uncertainty is resolved. In the presence of capacity constraints and uncertainty for all components and FA operations, and because of the large cost penalty for stock-out occurrence, we need to find the best diversification level configuration which minimizes the risk of stock-out.

We can clearly see how the flow of time can be divided into two stages. At stage-one ("here and now decisions"), at time zero, before any uncertainty has been resolved, there are only two decisions to be made: the diversification level and safety stock allocated to each component and FA suppliers. Once the uncertainty has been resolved (monthly QAEC), we can define production quantities and inventory levels (stage-two decision variables).

The model obtained here is a stochastic two-stage optimization model with recourse. Higle (2005) defines recourse models as those in which some decisions must be fixed before information relevant to the uncertainties is available, while some of them can be deferred. In our case, we fix the values of the order-size and safety stock to each supplier before we observe the real capacity. So, our objective is to find the best set of first stage variables, such that we obtain the best solution that is well positioned overall against all possible scenario realizations.

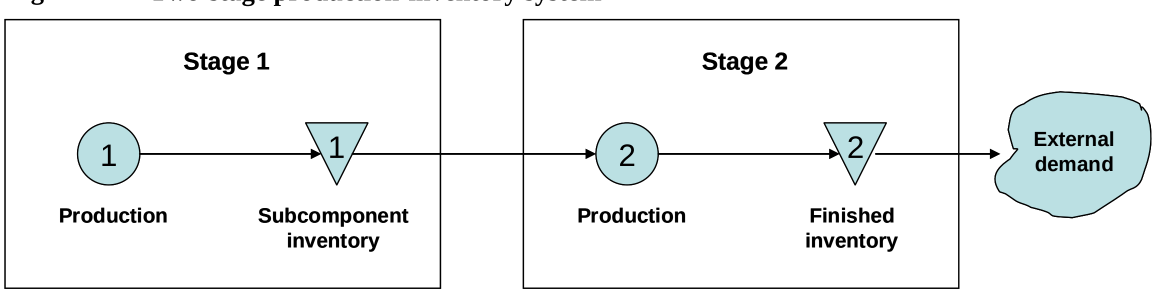
The objective function of the model is to minimize the total supply chain system cost, which includes production, inventory holding and penalization cost at each supplier, plus production, inventory holding and penalization cost at the final assembly stage, subject to capacity constraints. In this model, the capacity parameter will turn into a random variable.

4. MODEL FORMULATION

The supply chain structure studied here is formed of two main stages: a component stage and a Final Assembly stage. As we have already described, the component stage is composed of five different components. Each of these components has three different potential suppliers. For the Final Assembly stage we also have three potential suppliers.

Johnson and Montgomery (1974) present a LP formulation for a simplified version of this model. Figure 4 shows the situation for a two-stage production-inventory system for a single product. The first stage is the supplier of a subcomponent that will be delivered to a Final Assembly operation in the second stage. Both stages carry its own inventory (subcomponents and finished product). The model assumes a deterministic and dynamic demand. Each stage will call for overtime in any period to produce in excess of its regular time capacity. The main objective is to find the best production plan that minimizes the regular time, overtime and holding cost.

Figure 4 Two-stage production-inventory system



Defining the following notation:

X_{it} = regular time production at stage *i* in period *t*, (*i* = 1 , 2 ; *t* = 1, 2,…, T)

Y_{it} = overtime production at stage *i* in period *t*

I_{it} = inventory at stage *i* at the end of period *t*

P_{it} = regular time production capacity at stage *i* in period *t*

P'_{it} = overtime production capacity at stage *i* in period *t*

c_{it} = unit variable cost of regular time production at stage *i* in period *t*

c'_{it} = unit variable cost of overtime production at stage *i* in period *t*

h_{it} = cost of carrying a unit in inventory from period *t* to *t+1* at stage *i*

Z = total cost of production and inventory during the planning horizon

D_t = demand for finished product in period *t*

The objective function is to minimize the total cost of production (regular and overtime) plus the holding cost, such that the demand at each period is satisfied.

The Linear Programming formulation is:

$$Z = \sum_{t=1}^{T} \sum_{i=1}^{2} \left[c_{ij} X_{it} + c'_{it} Y_{it} + h_{it} I_{it} \right] \qquad (4.1)$$

subject to

$$I_{1t} = I_{1,t-1} + X_{1t} + Y_{1t} - X_{2t} - Y_{2t} \quad (4.2)$$
$$I_{2t} = I_{2,t-1} + X_{2t} + Y_{2t} - D_t \quad (4.3)$$
$$X_{it} \le P_{it} \quad (4.4)$$
$$X_{it} \le P_{it}^{'} \quad (4.5)$$
$$X_{it}, Y_{it}, I_{it} \ge 0 \quad (4.6)$$

Equation 4.2 is the material balance constraint for the subcomponent stage. This constraint links the performance of the second stage with the inventory of the first stage. Because of the nonnegative constraint of 4.6, the model ensures that no shortages will be planned for the inventory between stages.

4.1 Model Formulation

Although formulation 4.1 - 4.6 does not assume multiple subcomponents and multiple sources options, linking equations 4.2 and 4.3 did help us in the modeling of the interactions between the component and the Final Assembly stage.

Since we assume infinite supply of raw material to the component stage and we allow stock-outs in both stages, we need to modify the previous formulation considering the following factors:

1. How much of the production and inventory of each supplier for each component is available to each FA operation?

2. What is the demand that each supplier at each component stage observes?

3. How should each stock-out be penalized?

The first issue is related to the availability of components for each FA operation. We can define this availability as how much material, including production and safety stock, is ready to be delivered to each FA operation. The problem here is to define how to allocate that amount among the set of FA operations. A simple assumption in this model is that each FA operation will have assigned a certain percent of the total availability of components. We can define that percentage as the level of diversification allocated to each FA. Although in practice a central planner will make decisions about the allocation of components in almost real time, we found out that this pre-assigned level was a reasonable modeling assumption. For modeling, we can differentiate two types of demand at the component stage: planned and real. We define the production plan as the amount that each FA operation should produce every period.

$$\text{Production plan in } t = \mathit{min} \begin{cases} \text{QAEC in } t \\ \text{Order size} + (\text{Order up-to-level} - \text{Inventory in } t\text{-}1) \end{cases}$$

However, this production plan could be affected by the availability of components. So, the real production is a function not only of capacity and production requirements, but also of the level of diversification.

$$\text{Production in } t = \ min \begin{cases} \text{Production plan in t} \\ \text{Level of diversification * Availability of each component} \end{cases}$$

Question two is basically for inventory considerations. Here, for modeling purposes, it is important to define what will be the demand that each supplier, at each component stage, will observe coming from the total FA operation. For any FA operation, its inventory level at each period will be:

Inventory in *t* = Production in *t* + Inventory in *t-1* – Order assigned

Opposite to the FA operation, where the demand observed is just the fraction of the target monthly demand (since a deterministic demand is assumed), the demand observed at the stage component is a function of the variability on the capacity that each FA observes, plus what their replenishment requirements are.

Based of this, the total demand that will be observed at the component stage is not longer deterministic. Now the problem lies in the definition of what percentage of the total demand each supplier will be responsible for. Similar to our previous assumption, we define that percentage as the diversification level assigned to each supplier at the component stage. For any supplier, its inventory level at each period will be:

Inventory in *t* = Production in *t* + Inventory in *t-1* – (Level of diversification * Total Production plan in FA in *t*

A third important issue to be considered here is regarding how to penalize for every unit of component or finished product not deployed to the final customer. In the case of the FA stage, the demand observed is a stationary deterministic quantity, so the penalization will be on the difference between demand and production.

$$\text{Penalization in } t = \begin{cases} \text{(Order-size – Availability in } t \text{) * penalty cost,} \\ \text{if Order-size > Availability} \\ \\ \text{0 otherwise} \end{cases}$$

For modeling purposes, the penalization for each component supplier will be on the difference between the fraction of the total production plan of FA assigned to each supplier and its material availability.

$$\text{Penalization in } t = \begin{cases} \text{(Total FA production plan * level of diversification –} \\ \text{Availability in } t\text{) * penalty cost, if Total FA production} \\ \text{plan * level of diversification > Availability,} \\ \\ \text{0 otherwise} \end{cases}$$

An important assumption of this model is that we do not consider fixed costs related to supplier selection. This assumption will facilitate the analysis. The objective function will be the minimization of the total average cost which includes:

Production cost + Inventory holding cost + Stock-out cost of component + Stock-out of finished product.

4.2 Mathematical Formulation

4.2.1 Sets

I = set of suppliers (1,..3)

J = set of stages (1,..6)

T = time period (1,..,12)

4.2.2 Parameters

D = Target monthly demand of finished product (units / month) at assembly plant

CAP_{ijt} = QAEC of supplier i of component j in period t

π = Penalty cost for every unit not supplied to final customer

θ_{ij} = Penalty cost for every component j from supplier i not supplied to Final Assembly

c_{ij} = Production cost per unit for supplier i of component j

h_{ij} = Inventory holding cost per unit for supplier i of component j

4.2.3 Variables

P_{ij} = Diversification level for supplier i of component *j*

Q_{ij} = Order size allocated to supplier *i* of component *j*

S_{ij} = Base-stock level for supplier *i* of component j in period *t*

Y_{ijt} = Production Plan quantity of supplier *i* of component *j* in period *t*

X_{ijt} = Production quantity of supplier *i* of component j in period *t*

I_{ijt} = Inventory level for supplier *i* of component j at the end of period *t*

B_{ijt} = Lost sales level for supplier *i* of component j at the end of period *t*

A_{ijt} = Available quantity from supplier *i* of component *j* in period *t*

4.2.4 Formulation

$$\text{Minimize} \quad \frac{1}{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} c_{ij}X_{ijt} + \frac{1}{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} h_{ij}I_{ijt} + \frac{1}{T}\sum_{i=1}^{I}\sum_{j=1}^{J-1}\sum_{t=1}^{T} B_{ijt}\theta_{ij} + \frac{1}{T}\sum_{i=1}^{I}\sum_{j=6}^{J}\sum_{t=1}^{T} B_{ijt}\pi \tag{4.7}$$

subject to

$$Q_{ij} = D * P_{ij} \qquad \forall i, j, t \tag{4.8}$$

$$\sum_{i=1}^{I} P_{ij} = 1 \qquad \forall j \tag{4.9}$$

$$X_{ijt} \le CAP_{ijt} \qquad \forall i, j = 1,..5, t \qquad (4.10)$$

$$X_{ijt} \le Q_{ij} + S_{ij} - I_{ijt-1} \qquad \forall i, j = 1,..5, t \qquad (4.11)$$

$$I_{ijt} - B_{ijt} = X_{ijt} + I_{ijt-1} - P_{ij} * \sum_{i=1}^{I} Y_{i6t} \qquad \forall i, j = 1,..5, t \qquad (4.12)$$

$$A_{ijt} = X_{ijt} + I_{ijt-1} \qquad \forall i, j = 1,..5, t \qquad (4.13)$$

$$Y_{ijt} \le CAP_{ijt} \qquad \forall i, j = 6, t \qquad (4.14)$$

$$Y_{ijt} \le Q_{ij} + S_{ij} - I_{ijt-1} \qquad \forall i, j = 6, t \qquad (4.15)$$

$$X_{ijt} \le Y_{ijt} \qquad \forall i, j = 6, t \qquad (4.16)$$

$$X_{ijt} \le P_{ij} * \sum_{i=1}^{I} A_{ijt} \qquad \forall i, j = 6, t \qquad (4.17)$$

$$I_{ijt} - B_{ijt} = X_{ijt} + I_{ijt-1} - Q_{ij} \qquad \forall i, j = 6, t \qquad (4.18)$$

$$A_{ijt} = X_{ijt} + I_{ijt-1} \qquad \forall i, j = 6, t \qquad (4.19)$$

$$P_{ij} \le 1 \qquad \forall i, j, t \qquad (4.20)$$

$$I_{ij0} = 0 \qquad \forall i, j \qquad (4.21)$$

$$P_{ij}, S_{ij}, X_{ijt}, Y_{ijt}, I_{ijt}, I_{ijt}, A_{ijt}, Q_{ij} \ge 0 \qquad \forall i, j, t \qquad (4.22)$$

Equation 4.7 is the total sum of the averages of the production, holding and penalty at both component and FA stage.

Equations 4.8 – 4.9 correspond to the level of diversification and order-size allocated to each supplier. Since we define P_{ij} as a continuous variable between 0 and 1, equation 4.9 ensures that we assign 100% to each component. Equations 4.10 – 4.11 restrict the component production to the minimum of the QAEC and the sum of the order-size allocated plus the replenishment in that period. In these equations, we set an upper-bound to the total production. So, for any period, the supplier will not produce more than Q+S. This bound turns to be a very effective way to avoid the model trying to foresee any capacity breakdown in the next periods.

Equation 4.12 is the material balance constraint. As we already specified, the demand faced by each supplier is a fraction of the total production plan of FA. This fraction is the diversified level assigned to each supplier. Equation 4.13 just specifies how much material is available to the FA stage. Equation 4.13 is similar to equation 4.10 but for the FA stage. Equations 4.14 – 4.15 are related to the production plan for each FA operation. Equation 4.17 constrains this plan on the availability of materials for each component. The fraction of material available for each component is a function of the diversification level allocated to each FA operation.

Equation 4.18 is the material balance for the FA stage. However, opposite to equation 4.12, the demand included here is just the target demand allocated to each FA operation. Equation 4.19 defines how much of finished product is available for deployment. Equation 4.20 restricts the value of the diversification level between 0 and 1.

Because of equations 4.12 and 4.17 we obtain a nonlinear programming formulation, where the level of diversification and the base-stock level are modeled as the 1^{st} stage variables, while the rest of the decision variables (2^{nd} stage) are inherent to each scenario.

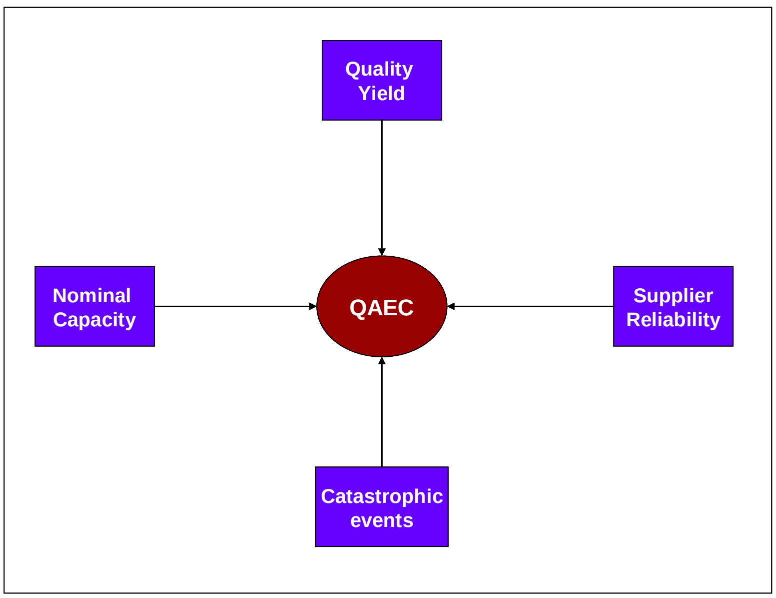
Although we consider discrete demand, for simplicity we will consider all the decision variables as continuous to avoid the integer complexity. This assumption seems to be reasonable since some of the components might have different units (feet, lbs, tons, etc.).

5. SCENARIO GENERATION

In this model, we assume that the only source of variability is in the supplier's monthly capacity. Although decision makers might have an estimate of the average or expected nominal capacity for each supplier at component-stage, it could be significantly modified by normal business variability, equipment reliability, process yield and external disruptions (usually called catastrophic events) such as strikes and natural disasters. Usually, practitioners are tempted to use simple averages on decision making models ignoring any kind of uncertainty. However, as explained in the previous sections of this Record of Study and largely mentioned in the literature, the risk of not considering variability in either supply or demand might drive to erroneous conclusions. Because of the nature of the supply chain structure studied here, the only source of uncertainty will be on the supplier's capacity.

In this section, we introduce in detail the procedure for the generation of scenarios. Starting from the main assumption that the monthly capacity for each supplier is a random variable, we need to generate sets of several months of capacity for each supplier at each component stage. We define scenario as a random vector or combination of several uncertainty factors. A more formal definition of scenario is given in Higle (2005), where scenario is defined as one, complete, realization of the stochastic elements that might appear during the course of the problem. In our case, each vector ξ^i or scenario is a sequence of twelve monthly possible capacity outcomes per supplier. Also, for each ξ^i , i = 1,…, N all scenarios have the same probability distribution and are independent (the sample is iid). The sample size of N = 500 scenarios was defined to try to catch all extreme events. Four different kinds of variability are considered to define the expected effective capacity (Figure 5). The main scenario generation procedure was implemented using Visual Basic, with a user's interface for parameters input.

Figure 5 Supply disruption factors



- **Normal variability**: The random fluctuations that the supplier's capacity will have under normal conditions. Normal and Gama distributions with parameters μ and coefficient of variation (CV).

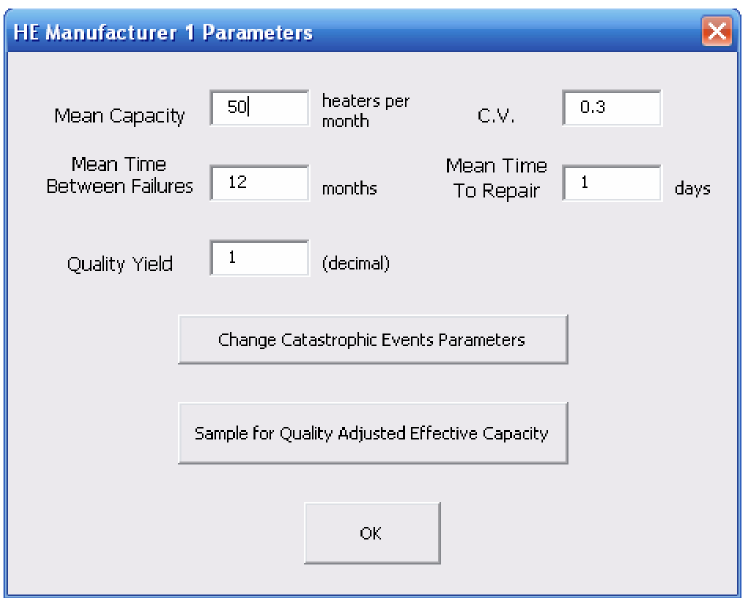
- **Supplier reliability**: Any kind of disruption that the supplier will have because of any factor under its control, such as: machine failure, maintenance, labor strikes and raw material supply (internal factors). In this case, any kind of shutdown at the supplier will have a certain number of effective production days lost. This will impact the nominal capacity already affected by normal fluctuations. For this kind of disruption, we propose the concept of *Mean Time Between Failures* (MTBF), which is the average time elapsed between two consecutive events. A reasonable assumption is to use the exponential distribution with parameter $\lambda = 1 / \text{MTBF}$. A second parameter to represent the duration of the failure, or how long it will take to repair it, is the *Mean Time to Repair* (MTTR), which can be defined as the average time that a device will take to recover from a non-terminal failure. Similar to MTTB, an exponential distribution is used to model failure's duration.

- **Process yield**: Defined as the average percentage of good parts produced each month. A Binomial distribution is used to model the behavior of process yield. A sequence of independent Bernoulli trials with parameter p is used here to generate the number of good parts per month, where p is the average percentage of good parts.

- **Catastrophic events or Acts of God**: This is the kind of disruption out of supplier's control (also known as external factors): snow storms, flooding, earthquakes, etc. Like the supplier reliability, any shutdowns because of a catastrophic event will affect the nominal capacity. The procedure to model this kind of disruption is similar to the one used for supplier reliability, therefore, an exponential distribution is used for both the inter-arrival time of disruptions and its duration.

The final or effective capacity that the supplier will have every period (month) will be the result of the normal variability, supplier reliability, process yield and catastrophic events. Because the service level at the Final Assembly plants is subject to the supplier's performance, the main challenge will be on how to allocate the order size given that every supplier is subject to all these forms of disruptions. Figure 6 shows parameters required for each supplier.

Figure 6 Supplier capacity parameters



5.1 Procedure to Generate Quality Adjusted Effective Capacity (QAEC)

For each supplier of each component:

For scn=1 to 500 (scenarios)

For n = 1 to 12 (months)

Sample nominal capacity NC(n,scn)

Sample the number of days that supplier will be off due failures = Duration1(n,scn)

Sample number of days that supplier will be shutdown due catastrophic events = Duration2(n,scn)

Sample quality yield q(n,scn)

Tduration(n,scn) = duration1(n,scn)+duration2(n,scn)

If the Tduration(n,scn) > 30 then Tduration(n,scn)=30

$$\mathrm{QAEC}(n, scn) = \left(1 - \frac{\mathrm{Tduration}(n, scn)}{30}\right) * \mathrm{NC}(n, scn) * q(n, scn)$$

Next n

Next scn

The result is a set of m vectors per scenario, where each scenario contains twelve months of QAEC. Table 5 shows the result of one scenario for four suppliers.

Table 5 Scenario for 4 suppliers

Supplier 1 QAEC

Scn	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
1	63.4	61.5	59.9	63.4	63.9	56.6	63.1	61.9	58.9	61.1	53.9	62.0

Supplier 2 QAEC

Scn	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
1	43.3	38.2	47.5	36.4	57.5	46.4	45.8	44.5	43.2	54.1	49.8	62.9

Supplier 3 QAEC

Scn	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
1	57.3	58.4	45.7	26.2	41.7	39.0	52.8	50.3	62.1	30.4	53.4	18.8

Supplier m QAEC

Scn	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
1	7.1	16.8	11.6	23.4	30.3	15.8	24.6	23.4	8.6	14.3	9.6	28.5

5.2 Nominal Capacity

We define nominal capacity as the theoretical monthly capacity only subject to business variations (also called natural variability), without any kind of internal or external disruptions. For nominal capacity, we assume a Normal distribution when the CV is below 0.2 and a GAMMA distribution when CV is above 0.2. The reason for doing this is that in the case of Normal distribution is very likely to obtain negative capacities for suppliers with large CV's. Since both distributions are very similar for small CV's, we consider it a reasonable assumption. Two parameters are required for the sampling procedure: μ and CV.

When CV is below 0.2, we use the polar method described in Law and Kelton (1999). Figures 7 and 8 show the probability distribution for nominal capacity of two suppliers with a μ = 200 and a CV of 0.2 and 0.4 (Normal and Gamma respectively).

Figure 7 Normal probability distribution for capacity with CV < 0.2

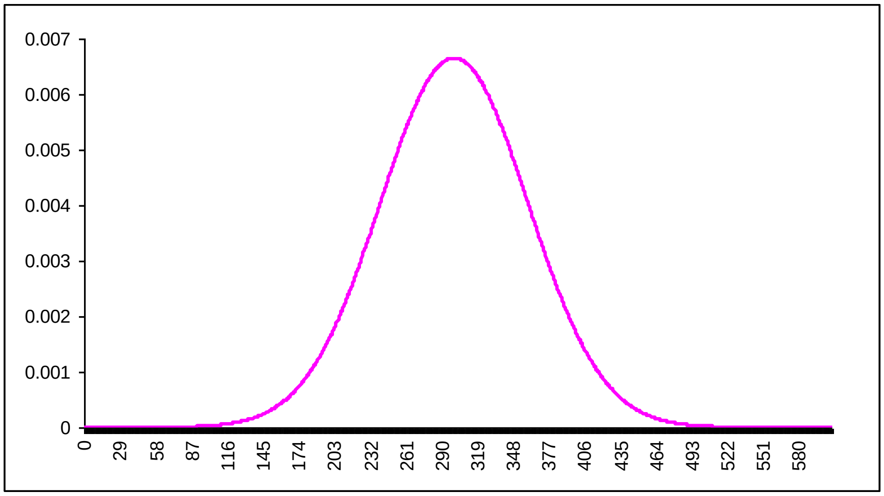
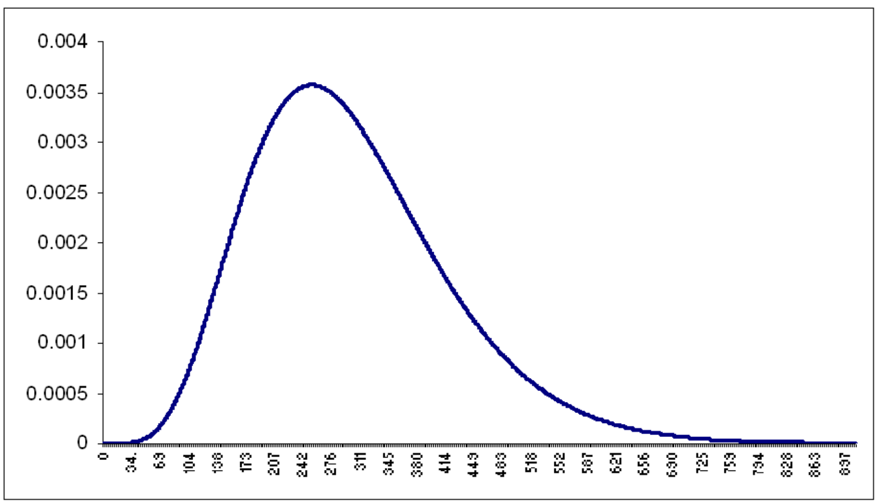


Figure 8 Gamma probability distribution for capacity with CV > 0.2



5.2.1 Nominal Capacity Generation Procedure

For each supplier of each component:

For scn=1 to 500 (scenarios)

For n = 1 to 12 (months)

1.- RN_1 = random uniform number between 0 and 1

RN_2 = random uniform number between 0 and 1

$V_1 = 2 * RN_1 - 1$

$V_2 = 2 * RN_2 - 1$

$r = V_1^2 + V_2^2$

if $r > 1$ then go to 1

$$Y = \sqrt{\frac{-2 * LN(r)}{r}}$$

$NC(n, scn) = \mu + (Y * V_2 * \sigma)$

Next n

Next scn

For Gamma sampling (CV's > 0.2), although there exist efficient methods for random variates generation (Law and Kelton 1999), we decided to use the already Excel built-in function *Gammainv (RN,α,β)* with the following change in parameters:

$$\alpha = \frac{\mu^2}{\sigma^2}$$

$$\beta = \frac{\sigma^2}{\mu}$$

To verify that the distribution generated by the sampling procedure was indeed a Normal or Gamma, we used BestFit (part of Palisade decision tools suite) to run a chi-square test for a different set of possible scenarios:

- Nominal capacity = 200, CV = 0.5
- Nominal capacity = 200, CV = 0.1
- Nominal capacity = 200, CV = 0.05

Figure 9 BestFit output for a nominal capacity with μ = 200 and CV = 0.5

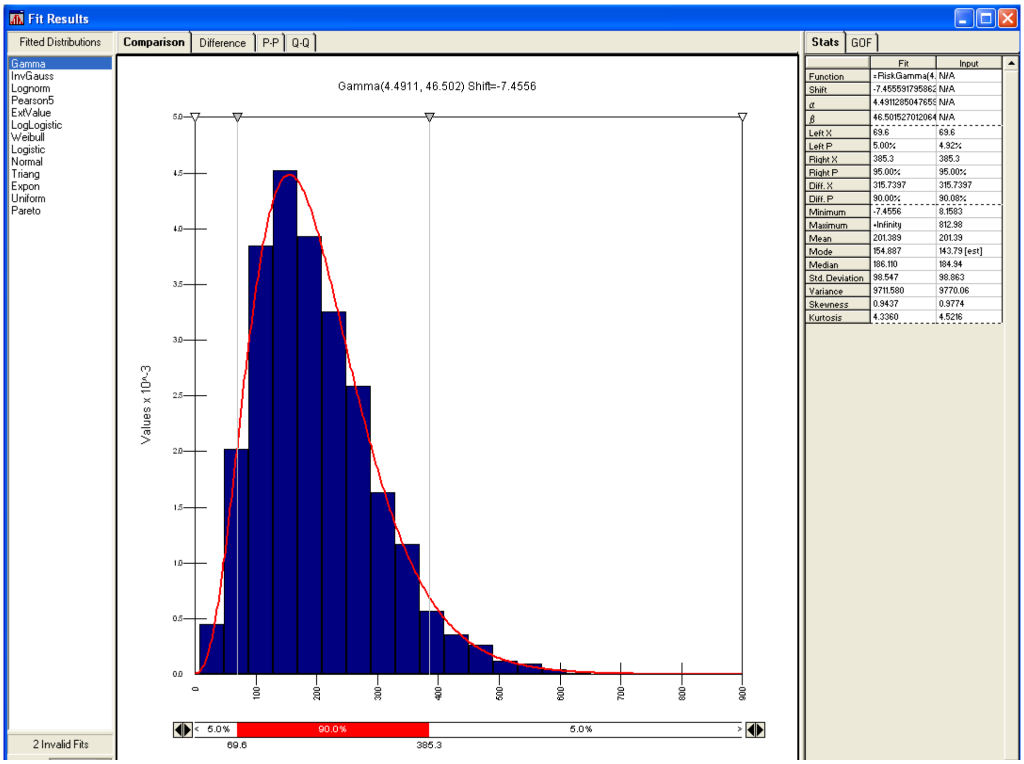


Figure 10 BestFit output for a nominal capacity with μ = 200 and CV = 0.1

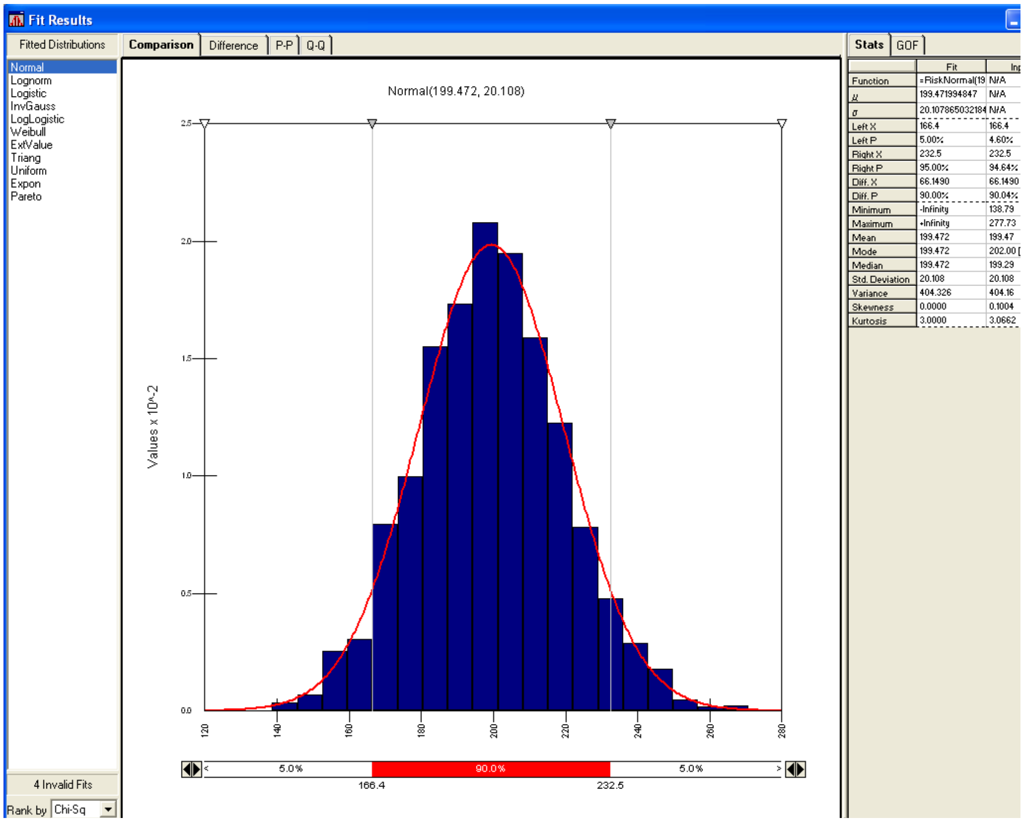
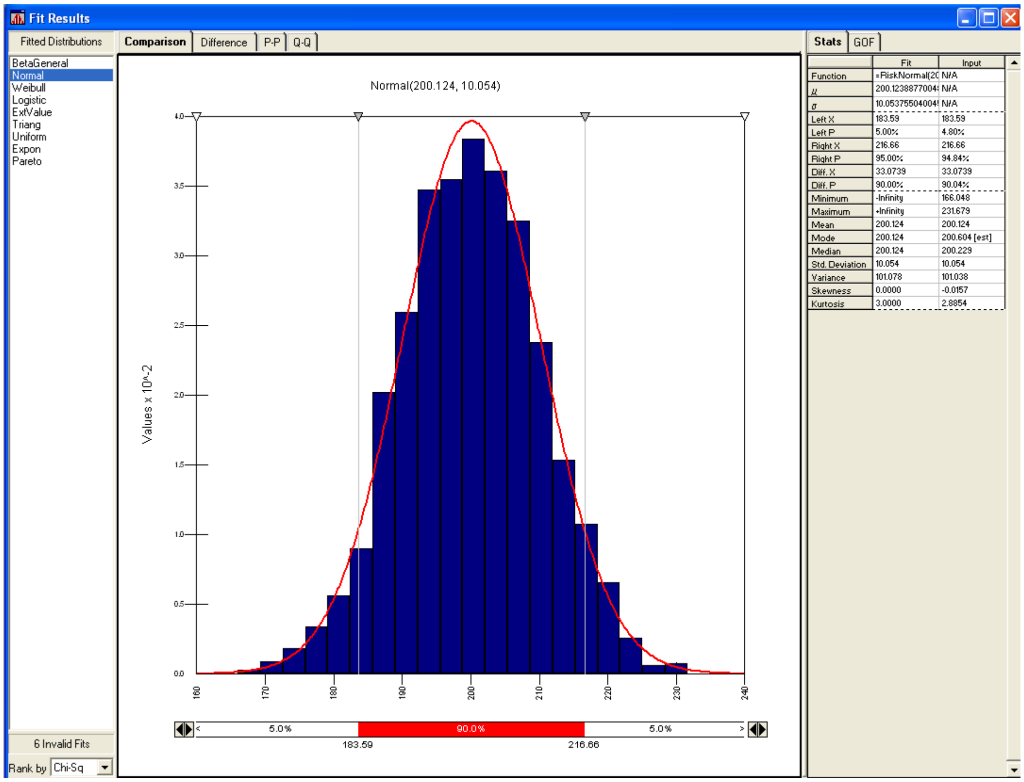


Figure 11 BestFit output for a nominal capacity with μ = 200 and CV = 0.05



Figures 9, 10 and 11 show the goodness-of-fit test for the distribution obtained from a sample of 2,500 nominal capacities for each scenario described above. After several experiments, we can conclude that the procedure proposed here produces, depending on the value of the CV, well defined Normal and Gamma distributions.

5.3 Supplier Reliability

Once the nominal capacity for a given month has been sampled from the Gamma-Normal distribution, the next step is sampling for the number of days the supplier will loose from its nominal capacity (zero production) for each month. Two parameters are required:

- Mean time between failures (MTBF): on average, how frequently a failure will occur (days)
- Mean time to repair (MTTR): on average, how long the failure will last (in days)

Assuming exponential inter-arrival times of failures with mean MTBF, we compute the probability of not having a failure from the first to the last month of the year (scenario) using the Poisson distribution:

$$P(N_t = x) = \frac{(\lambda t)^x e^{-\lambda t}}{x!} \text{ for } x = 0,1,..$$

For x=0, the pdf is reduced to

$$P(N_t = 0) = e^{-\lambda * t}$$

Using the Poisson distribution with x = 0, we generate a vector Pr(t) of twelve probabilities or chances of not having a failure per month. To produce failure events, we propose to generate a random number in a sequential way every month. If the random number generated in month *t* is greater than the probability stored in Pr(t), we then generate an event. Table 6 illustrates a Pr vector for a MTBF = 3 months.

Table 6 Probability vector for supplier reliability

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
0.7165	0.5134	0.3679	0.2636	0.1889	0.1353	0.0970	0.0695	0.0498	0.0357	0.0256	0.0183

Two important assumptions are considered here. First, we assume that only one failure can occur in a single month. Second, if a failure has occurred in month t, we reset the time index to t=1 in vector Pr(t). Because the probabilities in vector Pr are in a decreasing way as t increases, this assumption helps to avoid generating extra failures. From the practical point of view, this means that, after a failure has occurred, the machine or equipment would have been replaced or repaired, so its probability of failing again in the next months has been updated.

In relation to failure durations, a common practice is to model them as exponential random variables. The method proposed here is the inverse transformation method for the exponential distribution, where λ is the 1 / MTTR. Defining the expected value of E(t) = MTTR = 1 / λ, and the probability density and cumulative function, we can generate random failure durations following an exponential distribution:

$$f(t) = \lambda e^{-t\lambda}, t > 0$$

$$F(t) = \int_0^x e^{-x\lambda} dx = 1 - e^{-\lambda t}, t > 0$$

Setting F(t) = random uniform number(0,1), we can solve for t:

$$F(t) = RND$$

$$t = -\frac{1}{\lambda}\ln(1 - Rnd)$$

5.3.1 Failure Generation Procedure

For each supplier of each component:

λ = 1 / MTTB

For n = 1 to 12 (months)

$F(n) = P(\text{no failure at month n}) = e^{-\lambda * n}$

Next n

For scn=1 to 500 (scenarios)

For n = 1 to 12 (months)

RN = random uniform number between 0 and 1

If (RN > Pr and Pr(n-1) =0) then Generate Duration

Else Pr(n) = 0

Next n

5.3.2 Failure Duration Procedure

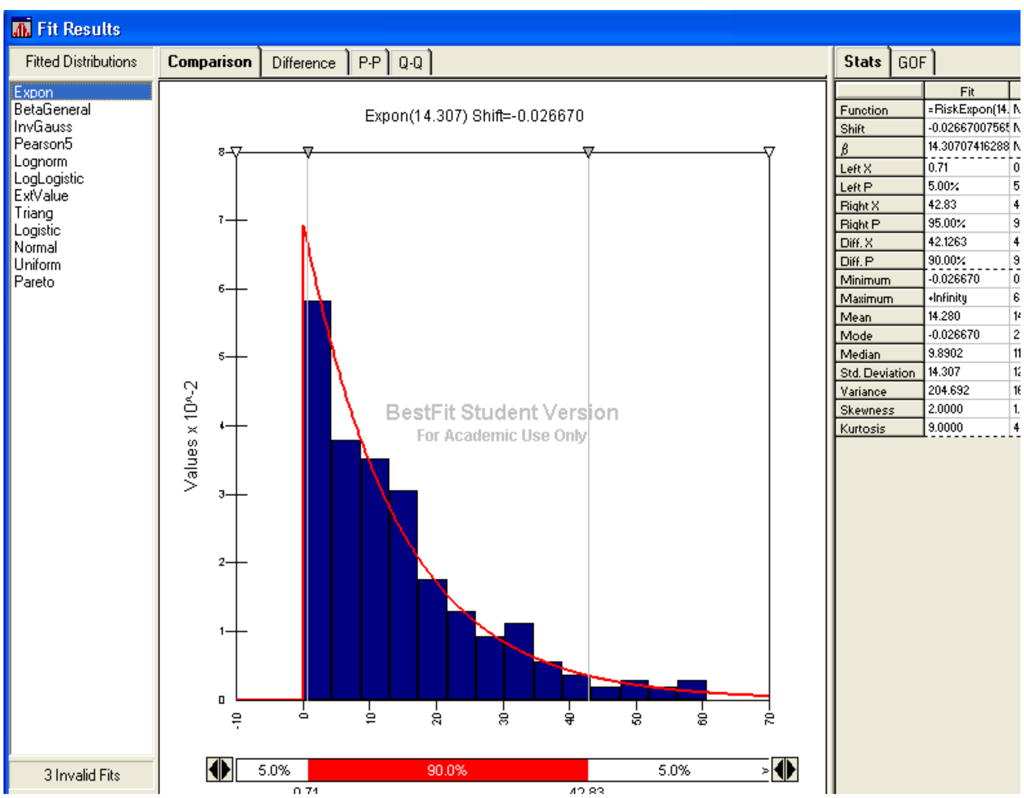
For each failure occurrence

RN = random uniform number between 0 and 1

Duration1(n,scn) = - MTTR * LN(1-RN)

To verify that the procedure indeed produces random failure durations following an exponential distribution, we used again BestFit for a sample of 2,500 observations with a MTTR of 15 days. See Figure 12.

Figure 12 BestFit output for a exponential random variable with λ = 1/15



5.4 Catastrophic Events

Machine and equipment breakdowns are not the only source of capacity disruptions. As described before, external factors such as strikes, natural disasters, sabotages and extreme situations like terrorist attacks are another source of disruptions that must be considered. Based on managerial input, we came with ten different categories:

- Tornado
- Earthquake
- Flood
- Snow Storm
- Hurricane
- Labor strike
- Terrorist attacks
- Sabotage
- HSSE
- Other

For sampling purposes, we follow an approach similar to the one we used for Supplier Reliability. However, in the case of catastrophic events, we have ten possible sources of operations breakdown, each with a different duration, so we will need to come up with a total λ. One easy way to do this is by just adding the reciprocal of frequency for each event (λ_i or occurrences per year). Once we have the total λ, we can assign a probability of occurrence to each event based on its frequency. Following this simple logic, we can generate events, and then define its duration. The superposition of renewal Poisson events each with parameter λ_i is a Poisson process with parameter:

$$\lambda = \sum_{i=1}^{n} \lambda_i$$

In addition, the probability of and events in the superposition being from process i is

$$P(i) = \frac{\lambda_i}{\lambda}$$

Table 7 illustrates how to set the probability of occurrence for each catastrophic event.

Table 7 Probability assignment for Acts of God

Description	Frequency	Duration	Prob	Acum
Earthquake	0.5	5	0.043	0.043
Flooding	1	4	0.087	0.130
Snowstorm	2	3	0.174	0.304
Hurricane	1	2	0.087	0.391
Strike	2	1	0.174	0.565
Tornado	1	0.5	0.087	0.652
Terrorist Attack	2	10	0.174	0.826
Sabotage	1	1	0.087	0.913
EHS	1	1	0.087	1.000
λ	**11.5**			

From the procedure above, using λ_t we can generate exponential arrivals per month (i.e. we might have more than one event per month). Once we have computed the total number of events per month, we generate their duration (exponential) using the discrete distribution obtained in the previous procedure.

5.4.1 Catastrophic Event Duration Procedure

Let's define Duration2(n,scn) as the total number of days-off in month n, scenario scn due to catastrophic events.

```
For scn = 1 To 500 (scenarios)
   For n = 1 To 12 (months)
      Y = number of events in month j
      Duration(scn, n)  = 0
      For k = 1 to Y
      RN = random uniform number between 0 and 1
        For i = 1 to n (number of defined events)
                 If RN < CDF(d) then
                          Duration2(scn,n) =  Duration2(scn,n) + MDCE * LN(1-RN)
      Next i
      If duration2(scn,n) > 30 then duration2(scn,n) =30
      Next j
      Next scn
```

5.5 Quality Process Yield

Based on the assumption that no manufacturing process is 100% reliable in terms of good parts, it is necessary to include this source of uncertainty into our scenario generation. Using the average value of good parts (*p*) for each supplier, we follow the approach suggested in Ross (2004), to invert the Binomial distribution based on a sequence of independent Bernoulli trials. In this method, at each month we assign to the variable *n* the round up value of the capacity obtained from the previous procedure (after adjusting reliability and Acts of God events). Then, we generate a random number RN that is compared to *p*. If RN > *p*, then we increase the counter by one; otherwise, we continue to the next step. At the end of the procedure, we just subtract the quantity on the counter from the capacity.

5.5.1 Quality Process Yield Procedure

```
For scn = 1 To 500 (scenarios)
    For n = 1 To 12 (months)
        EC(scn, n) = Effective capacity in month n scenario scn
        total = 0
        b = Round(EC(scn,n), 0)
        For k = 1 to b
            RN = random uniform number between 0 and 1
```

```
        If (RN > p) Then
        total = total + 1
        End If
      Next k
      Q(scn,,n) = 1 – total / cap
Next n
Next scn
```

5.6 Numerical Example

The following example illustrates the impact of stochastic disruptions into a supplier nominal capacity through time. With this example, we try to demonstrate two main concepts. First, we show how Monte Carlo sampling procedures can help to obtain and model random variables, which would be very difficult to obtain in a closed analytical form by methods such as convolution, or another statistical procedures.

Second, we exemplify the risk of not considering variability in the supplier's capacity when assigning production orders. Using the parameters on Table 8, we generate 500 possible scenarios of monthly QAEC.

Table 8 Supplier capacity parameters for scenario generation

Nominal Capacity	**Mean**	**CV**
	200	0.15
Reliability	**MTBF**	**MTTR**
	3	2
Yield	**Quality Yield**	
	97%	

	Category	**Freq**	**Duration**
Catastrophic Events	**Tornado**	1	2
	Earthquake		
	Flood	0.5	3
	Snow Storm	1	4
	Hurricane		
	Labor Strike		
	Terrorist Acts		
	Sabatoge		
	HSSE		
	Other	0.3	1

Figure 13 shows the resulting histogram for the sampled nominal capacity, which, as we assumed, follows a Normal distribution. However, after adding the remaining disruption factors, we obtain the QAEC showed in Figure 14. The effective capacity has a mean of 179.8 with a CV of 0.187, following a Beta distribution with parameters α = 48.93 and β = 36.18. As we can see, supplier reliability, quality yield and catastrophic events not only affected the parameters of the nominal capacity, but also changed the probability distribution.

Figure 13 BestFit output for a nominal capacity with μ = 200 and CV = 0.15

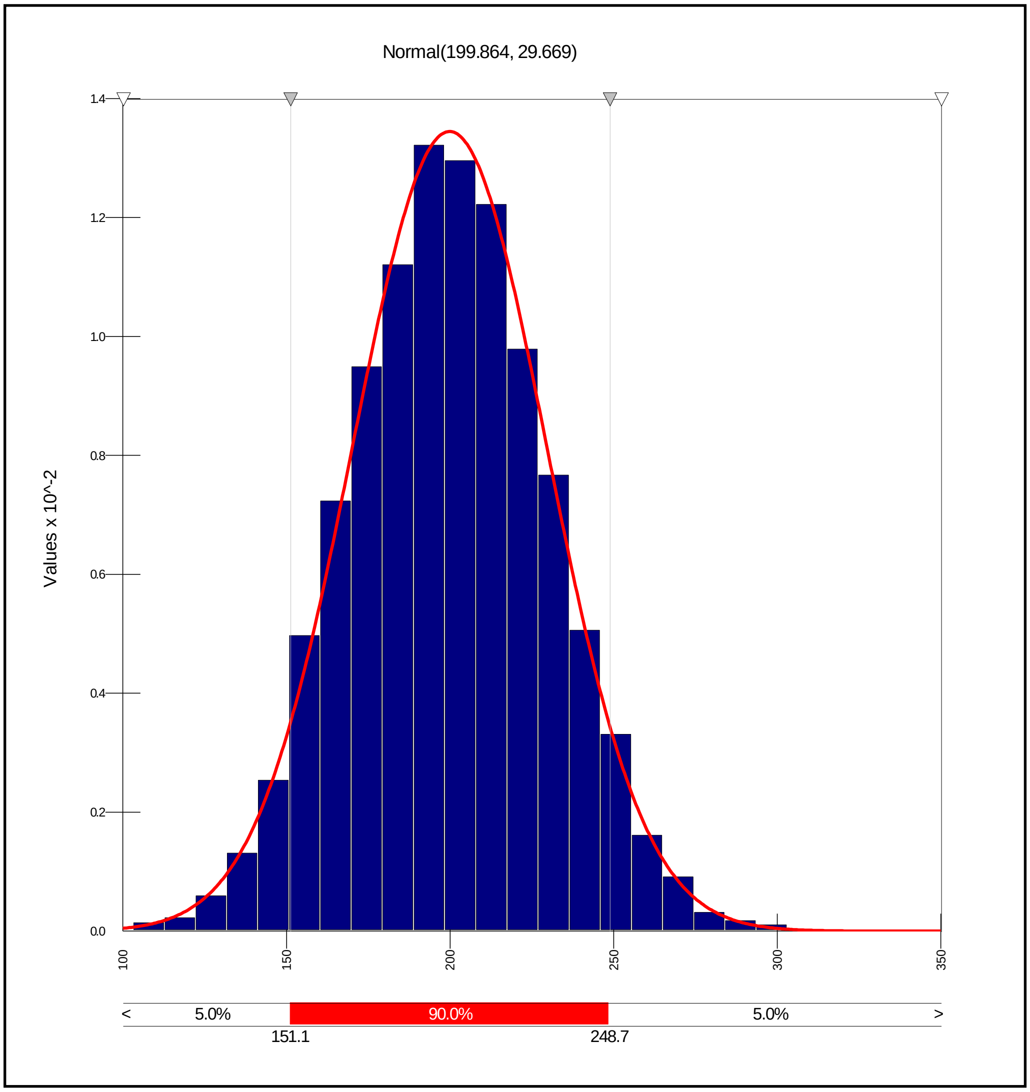
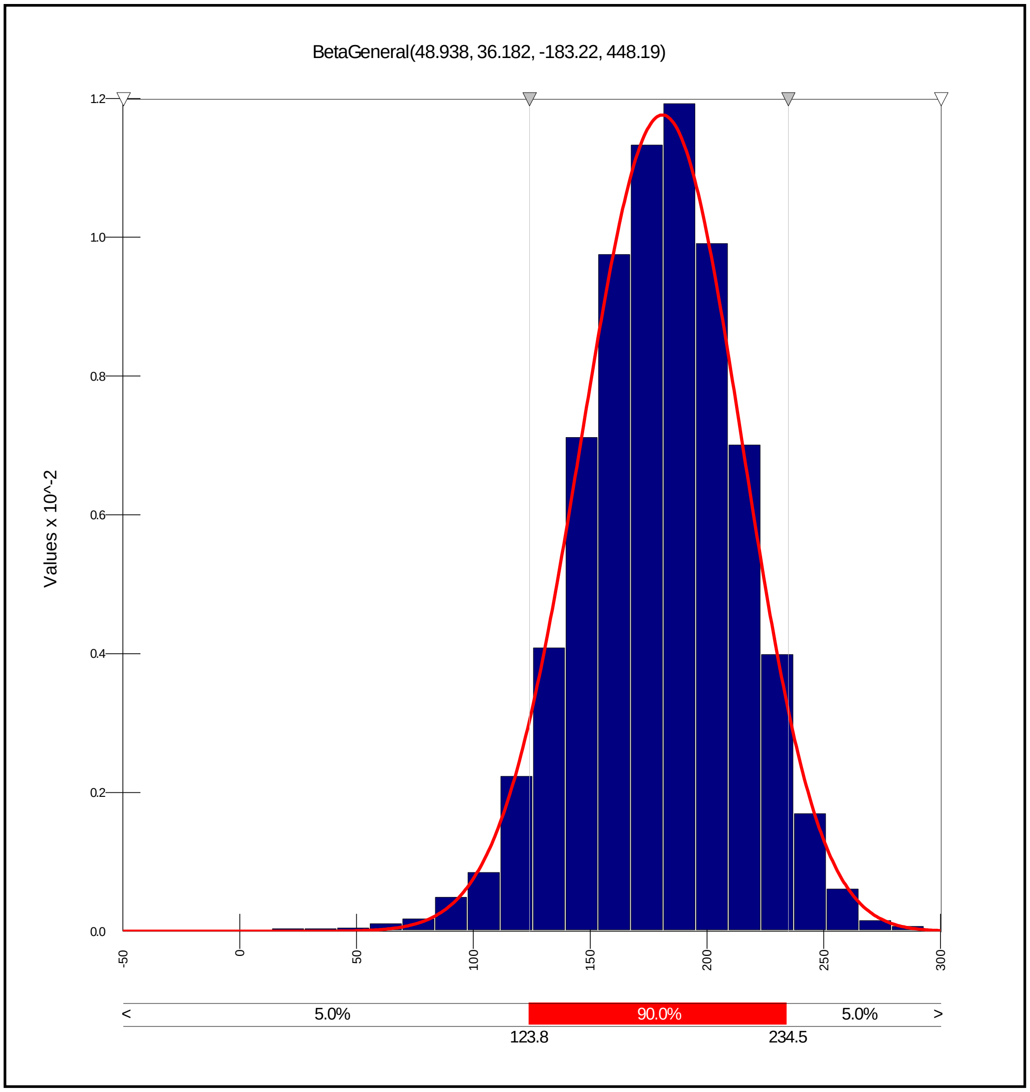
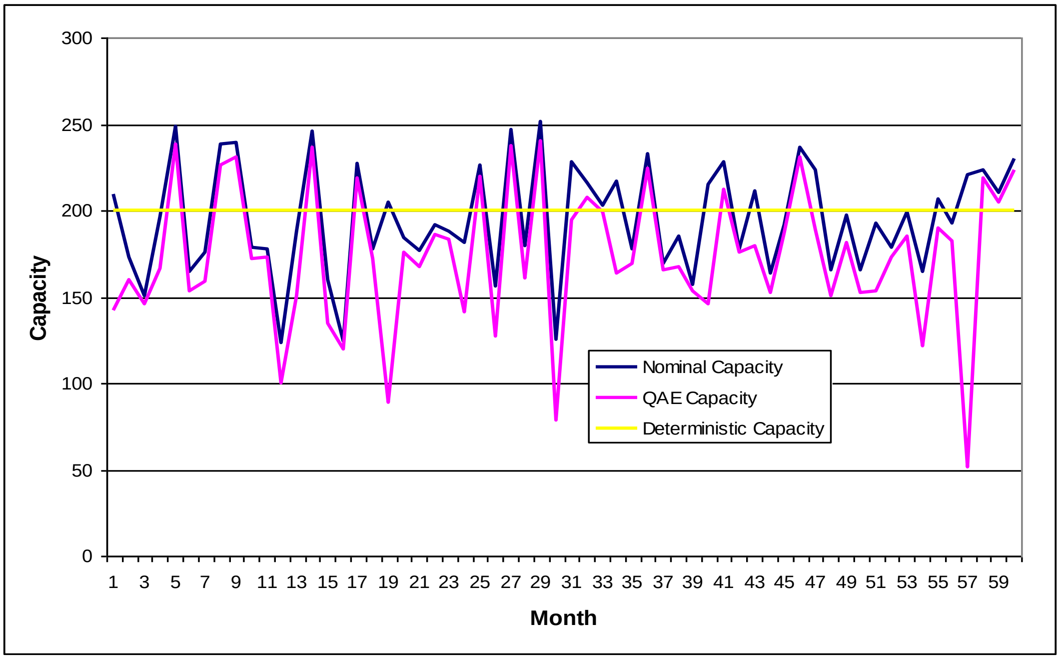


Figure 14 **BestFit output for a nominal capacity after random disruptions**



Continuing with the same numerical example, we now show the risk of order allocation without considering the impact of disruptions on supplier's capacity. Assume that in time 0, without full knowledge of a supplier's capacity (the only information we have is its nominal mean capacity of 200 units), a contract for 170 units per month is signed with the supplier. Figure 15 shows 5 years of possible outcomes of both nominal and QAE capacity for the supplier.

Figure 15 Time series of 5 years of monthly nominal and QAEC



Considering the first 20 months of the scenario just generated, we can see in Table 9 the risk associated with the allocation of a production order of 170 units / month.

Table 9 Example of the impact of QAEC for the allocation production order

Month	Order	QAEC	Production	Stockout
1	170	142	142	28
2	170	160	160	10
3	170	146	146	24
4	170	167	167	3
5	170	239	170	0
6	170	153	153	17
7	170	159	159	11
8	170	227	170	0
9	170	231	170	0
10	170	172	170	0
11	170	173	170	0
12	170	100	100	70
13	170	151	151	19
14	170	236	170	0
15	170	135	135	35
16	170	120	120	50
17	170	219	170	0
18	170	172	170	0
19	170	88	88	82
20	170	176	170	0
21	170	167	167	3
22	170	186	170	0
23	170	183	170	0
24	170	141	141	29

Although the supplier has a capacity of 200 units / month, there is a 55% risk of incurring in a stock-out if a production order of 170 units / month is allocated.

6. OPTIMIZATION PROCEDURE

Once the set of 500 scenarios realizations (i.e. a sequence of 500 years of monthly QAEC for each supplier) have been generated, the next step is the optimization of the stochastic formulation. Although Stochastic Linear Programming has existed since the 1950s, it was just recently that practitioners started incorporating it into their decision making process, thanks to the advent of more sophisticated computational resources and more efficient algorithms.

In this section, we introduce two solution methods for the stochastic problem already described. First, we propose the Sample Average Approximation (SAA) algorithm, introduced in Kleywegt et al. (2001), and described in Shapiro and Phipott (2007), as a more formal procedure for the optimization of this model. In this method, a relatively small number of scenarios is generated and used to run the stochastic model. After these series of designs are obtained, the 1st stage variables of each one are used as fixed numbers in the new stochastic model containing a much larger number of scenarios. The claim is that, if this procedure is run for a large number of scenarios, it can approximate the optimal solution.

Then, we propose a simple heuristic procedure as the solution method. This heuristic approach decomposed the NLP problem into two simple LP models that can be optimized in a sequential way. Since the objective function of the master problem is the minimization of expected value of monthly cost, we exploit the advantage that Excel and Solver provide when optimizing simple averages.

6.1 Sample Average Approximation (SAA)

To solve stochastic optimization problems, Kleywegt, Shapiro and Homem-de-Mello (2001) proposed the Sample Average Approximation (SAA) as an efficient method to solve large-scale problems, especially when the number of scenarios is considerable. The SAA method is based on Monte Carlo sampling procedures. In this method, the expected objective function of the stochastic problem is approximated by a sample average estimate derived from a random sample. The resulting sample average approximation problem is then solved by deterministic optimization techniques (Verweij et al. 2001). As pointed out before, the objective of any two-stage stochastic model is to minimize the sum of the 1st stage decisions and the expected recourse cost:

$$Z^* = \min_{x \in X} c^T x + \mathrm{E}_p[Q(x, \xi(w))]$$

Where x denotes the first-stage variable, w in Ω denotes a scenario that is unknown when the first-stage decision x has to be made, but it is known when the second-stage recourse decision y is made, Ω is the set of all scenarios and c denotes the cost parameter. The main claim of the SSA method is that by generating samples w^1,

$w^2,\ldots,w^N$ of N sample scenarios from Ω, the expected value function $E[Q(x,\xi(w))]$ is approximated by the sample average function:

$$\frac{\sum_{n=1}^{N} Q(x,\xi(w^n))}{N}$$

Obtaining the following problem:

$$Z^* = \min_{x\in X} c^T x + \frac{1}{N}\sum_{n=1}^{N} Q(x,\xi(w^n))$$

In the SAA technique, the expected second-stage profit in the objective function is approximated by an average estimate of NS independent random samples of the uncertain parameters, and the resulting problem is called the approximation problem. Each sample corresponds to a possible scenario and NS is the total number of scenarios considered. The resulting approximation problem is solved repeatedly for M different independent samples (each of size NS) as a deterministic optimization problem. In this case, the average of the objective functions of the approximation problems provides an estimate of the stochastic problem objective (this procedure may generate up to M different candidate solutions).

Once we have the M candidates, the next step is to determine which of these M candidates is optimal in the original problem. The values of the first-stage variables corresponding to each candidate solution are fixed and the problem is solved again using a large number of scenarios NS' >> NS to distinguish the candidates better. After solving these new problems, an estimate of the optimal solution of the original problem (x^*) is obtained. Therefore, x^* is given by the solution of the approximate problem that yields the highest objective value for the approximation problem with NS' samples. We present a simplified version of the algorithm included in Barbaro and Bagajewicks (2004).

SAA algorithm

Select NS, NS', M

For m = 1 to M

  For s = 1 to NS

    Use Monte Carlo sampling to generate an independent observation of the uncertain parameters *w*

  Next s

Solve the problem with NS scenarios. Let the x^{*m} be the optimal first-stage solution.

For m = 1 to M

  For s = 1 to NS'

    Use Monte Carlo sampling to generate an independent observation of the uncertain parameters *w*

  Next s

Solve problem with NS' scenario, fixing x^{*m} as the optimal first-stage solution.

Next m

Use x* = argmin{Obj(x*m) | m = 1, 2, …., M} as the estimate of the optimal solution to the original problem where Obj(x*) is the estimate of the optimal objective value.

End

A complete explanation of this algorithm can be found in Kleywegt et al. (2001), and excellent applications to logistics and supply chain problems in Verweij et al. (2001) and Santoso et al. (2003).

6.2 Heuristic Procedure

As previously explained in the scenario generation section, using a spreadsheet approach (i.e. Excel) provides a powerful set of statistical tools, such as covariance, probability distribution and random number generator. Also, spreadsheets are an easy way to compute expected values and variances form a large set of data in an almost instantaneous fashion. Additionally, Excel is well furnished with an optimization tool called Solver, which was designed to solve up-to medium scale optimization models (standard version included in Excel). Because our objective function is to minimize the expected monthly cost of the system, and since all scenarios have the same probability (1

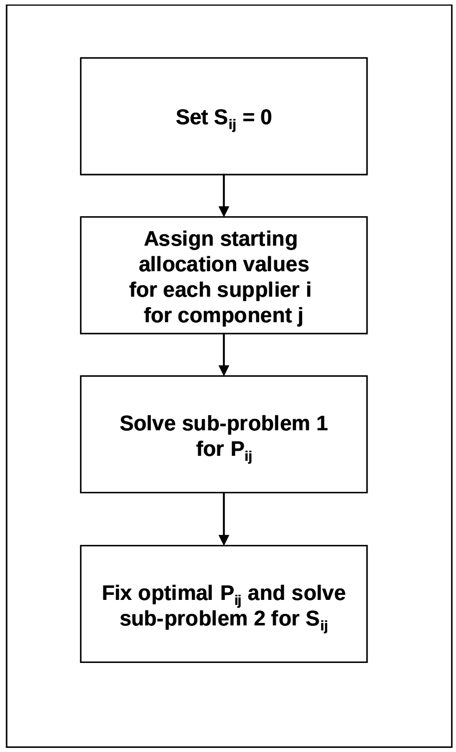
/ (500*12)), we can exploit these advantages and use Solver to minimize the average monthly cost function.

Unfortunately, because of the nonlinearity of the formulation proposed and the large number of scenarios, using Solver might not be the most efficient approach to solve the model in just one step. The Master Problem shows a NLP structure, but if we fix the value of the base-stock level (S) to zero, we then obtain a LP formulation. This sub-problem can be solved in an easier way than the master problem: fixing the optimal 1^{st} stage variables obtained from the 1^{st} sub-problem, and then solving the master problem again for the 1^{st} stage variable S.

It is important to note that even for simple LP models, Solver is very sensitive to the starting points in the optimization procedure. Keeping this in mind, we also propose two simple procedures to set starting points at the beginning of each optimization step.

The general procedure is described in Figure 16.

Figure 16 Heuristic procedure flow chart



6.3 Starting Point Solutions

Even though after the Master Problem decomposition we obtain two simply LP formulations, the problem is still difficult to solve in a reasonable computational time. The main cause of this issue is that we are using Excel functions within the model, such as MAX, IF-THEN, MIN and AVERAGE. Therefore, although we have a LP formulation, by using these functions we end up having an NLP problem. As we already pointed out, Solver is very sensible to starting points during the optimization process for NLP formulations (even for also large LP models with Max and Min functions), so we need to come up with an efficient way to define good starting solutions so Solver starts exploring the solution space neighborhood near the optimal solution. We propose two simple algorithms to set good initial points before each optimization step.

6.3.1 Starting Point Solutions for Allocation

The development of the staring points procedure proposed here entails concepts related to stochastic dominance of random variables along with the Karush-Kuhn-Tucker (KKT) conditions. For each component, using the mean and standard deviation of the QAEC for each supplier, we compute:

$$\mu_i = E(\text{QAEC supplier } \ i)$$
$$\sigma_i = \text{Standard deviation of QEAC supplier } i$$
$$\text{T} = \text{ Target demand}$$
$$\text{P}_\text{i} = \text{\% assigned to supplier } i$$

$$P_i = \frac{\mu_i + \dfrac{\sigma_i}{\sum_{i=1}^{n} \sigma_i}\left(T - \sum_{i=1}^{n} \mu_i\right)}{T}$$

A numerical example for a target demand of 15 units / month is showed in Table 10.

Table 10 Numerical example of the computation of diversification starting points

		Quality adjusted effective capacity		Diversification	
Component	**Suppliers**	**Mean**	**C.V.**	**% of Total**	**Order Quantity**
1	1	10.00	0.10	33.3%	5.00
	2	9.98	0.12	26.8%	4.02
	3	9.99	0.08	39.9%	5.99
2	1	9.97	0.10	32.8%	4.92
	2	10.05	0.12	27.8%	4.17
	3	0.98	0.08	40.0%	6.00
3	1	10.01	0.10	33.4%	5.01
	2	9.99	0.12	26.6%	4.00
	3	9.98	0.08	39.9%	5.99
4	1	10.01	0.10	32.7%	4.91
	2	9.99	0.12	27.4%	4.11
	3	10.00	0.08	39.9%	5.99
5	1	10.00	0.10	33.4%	5.01
	2	9.99	0.12	26.6%	3.98
	3	9.98	0.08	40.0%	6.00
Final Assembly	1	9.99	0.10	32.9%	4.94
	2	10.00	0.12	26.9%	4.04
	3	10.01	0.08	40.2%	6.02

6.3.2 Starting Point Solutions for Safety Stock

Before safety stock optimization (2^{nd} step), we propose to use basic inventory theory to set the starting solution points. Using the standard deviation of the QAEC for each supplier, we assume that the variability on the supply will represent the variability at the demand. Also, we assume a normal distribution approximation with a service level of 99% and a lead-time of 30 days for our computations. See Table 11 for an example.

For each component, including FA, we set the starting points as follows:

$\sigma_i = \text{Standard deviation of QEAC supplier } i$
$S_i = \text{Safety stock level at supplier } i$

$$S_i = 3 * \sigma_i$$

Table 11 Numerical example of the computation of safety stock starting points

		Quality adjusted effective capacity		
Component	**Suppliers**	**Mean**	**C.V.**	**Safety Stock**
1	1	200.00	0.20	120
	2	100.00	0.30	90
	3	250.00	0.10	75
2	1	300.00	0.05	45
	2	100.00	0.10	30
	3	45.00	0.00	0
3	1	100.00	0.40	120
	2	150.00	0.10	45
	3	150.00	0.00	0
4	1	100.00	0.23	69
	2	100.00	0.10	30
	3	100.00	0.30	90
5	1	200.00	0.01	6
	2	270.00	0.20	162
	3	300.00	0.10	90
Final Assembly	1	145.00	0.03	13
	2	200.00	0.01	6
	3	400.00	0.10	120

In special cases where the capacity at the FA stage is subject to a much larger variability in relation to the component stages, it is recommendable to use a little higher service level at the FA stage than the one used at the component stages (i.e. 99% for FA, 90% for components).

7. IMPLEMENTATION AND NUMERICAL EXAMPLES

As specified in the previous sections, this optimization model was completely implemented in Excel. Both the Monte Carlo approach for the scenario generation and the heuristic procedure were coded in several macros using Visual Basic for Applications (VBA), as well as direct formulas in different worksheets in the main file. Solver is called directly from the optimization macro. A friendly user's interface was also created for the control and visualization of the results from the sampling and optimization processes. Although we have been pointing out several of the advantages of using an spreadsheet approach such as the flexibility to generate stochastic variables, availability of logical and statistical functions (AVERAGE, MAX, MIN, IF-THEN, etc.), and an optimization engine (SOLVER), we need to be aware that for a very large problem instances, standard Solver might not be the most recommendable optimization tool. We consider that, for this problem instance (five components plus a FA stage with three alternatives each), standard Solver provides good solutions in a reasonable time. An excellent reference for the development of Decision Support Systems in Excel is Albright (2000).

In the first part of this section we show the main components of the spreadsheet model's implementation, explaining the different interfaces, dialog boxes and tables developed. Then, we present some numerical examples for possible supply chain scenarios. In these examples, the objective is to design a supply chain among a set of different supplier alternatives in the presence of different levels of capacity, variability and cost structures. We use those problem instances to show the impact of simple managerial decisions in the expected monthly cost (in relation to order and safety stock allocation), in the presence of supply uncertainty, against optimal values obtained using this model.

7.1 Model Implementation

We can divide the model into three main components:

1. User input / output interface
2. Tables with scenarios
3. Tables with formulation

In this section we will focus only in the User I/O interface, since it contains the most relevant information. The interface is showed in Figure 17. In this worksheet, the user will be able to perform the following actions:

- Enter target demand and penalization parameters
- Enter supplier's capacity and cost parameters
- Enter product dimensions
- Run scenario generation procedure
- Visualize expected QAEC for each supplier

- Perform manually diversification and safety stock levels
- Run optimization procedure
- Visualize expected monthly deployment, variability and service level
- Visualize expected monthly cost breakdown
- Perform risk analysis

The *Supplier Capacity Parameters* button is linked to a set of dialog boxes where the user will be able to enter each supplier's capacity information (i.e. nominal capacity, CV, MTBF, MTTR, etc.), cost structure and product specifications (see Figures 18, 19 and 20). In order to protect the confidentiality of the information, dialog boxes for cost and product specifications are not showed in this Record of Study.

Figure 17 Main user I/O interface

Deployment parameters

Target	100	units per month
Delayed deployment cost	$ 0.500	$MM per heater

Supplier capacity parameters

Optimization

Suppliers	Quality adjusted effective capacity (units per month)		Deployment target allocation (units per month)		Safety Stock		Service Level
	Mean	C.V.	% of total	Order quantity	SS (units)	SS (units)	
Component 1							
Supplier 1	95.69	0.21	47.80%	47.80	15	30000	99.97%
Supplier 2	111.18	0.30	45.21%	45.21	20	40000	100.00%
Supplier 3	119.15	0.02	7.00%	7.00	0	0	100.00%
Component 2			100.00%				
Supplier 1	144.94	0.21	37.21%	37.21	2	4000	99.98%
Supplier 2	96.46	0.20	62.79%	62.79	10	20000	99.47%
Supplier 3	145.19	0.10	0.00%	0.00	0	0	100.00%
Component 3			100.00%				
Supplier 1	150.03	0.01	0.00%	0.00	0	0	100.00%
Supplier 2	150.01	0.01	100.00%	100.00	0	0	100.00%
Supplier 3	149.99	0.01	0.00%	0.00	0	0	100.00%
Component 4			100.00%				
Supplier 1	47.96	0.22	29.22%	29.22	5	11560	99.17%
Supplier 2	95.62	0.26	59.20%	59.20	20	46240	99.73%
Supplier 3	104.26	0.16	11.58%	11.58	0	0	99.02%
Component 5			100.00%				
Supplier 1	197.78	0.15	0.00%	0.00	0	0	100.00%
Supplier 2	47.78	0.13	0.00%	0.00	0	0	100.00%
Supplier 3	150.00	0.01	100.00%	100.00	0	0	100.00%
Final Assembly			100.00%				
Supplier 1	149.99	0.01	0.00%	0.00	0	0	100.00%
Supplier 2	150.01	0.01	100.00%	100.00	0	0	99.53%
Supplier 3	149.97	0.01	0.00%	0.00	0	0	100.00%
			1				

Component	units
Componet 1	feet
Componet 2	feet
Componet 3	feet
Componet 4	feet
Componet 5	units
Final Assembly	units

Actual deployment

	Mean	C.V.	S.L.
Units per month	99.9798	0.004	99.53%

Total monthly cost (in $MM)

	Mean	C.V.
Production	$ 50.3968	0.01
Inventory holding	$ 0.03663	0.05
Delayed deployment	$ 0.01925	17.92
Total	$ 50.45266	0.0061

Risk analysis (total monthly cost)

Aspiration level in $M	50.50
Risk of exceeding aspiration level	10.17%

Figure 18 Dialog box to select supplier

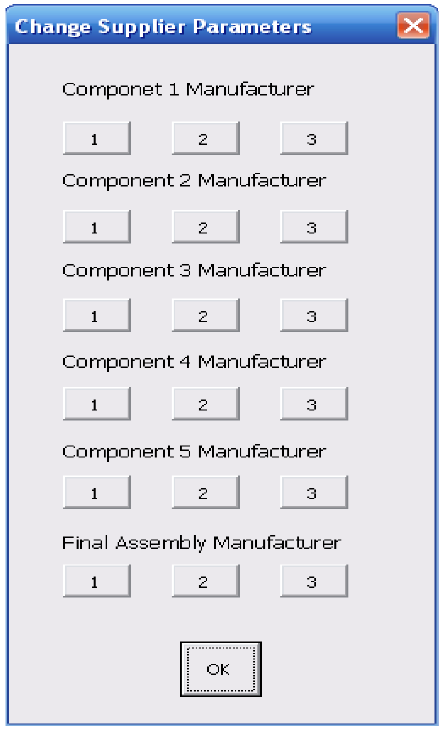


Figure 19 Dialog box to enter supplier capacity parameters

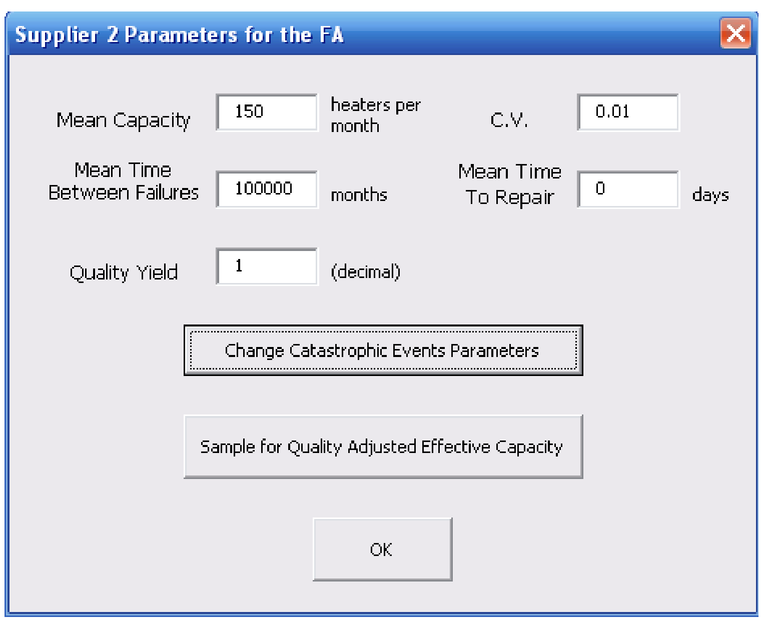
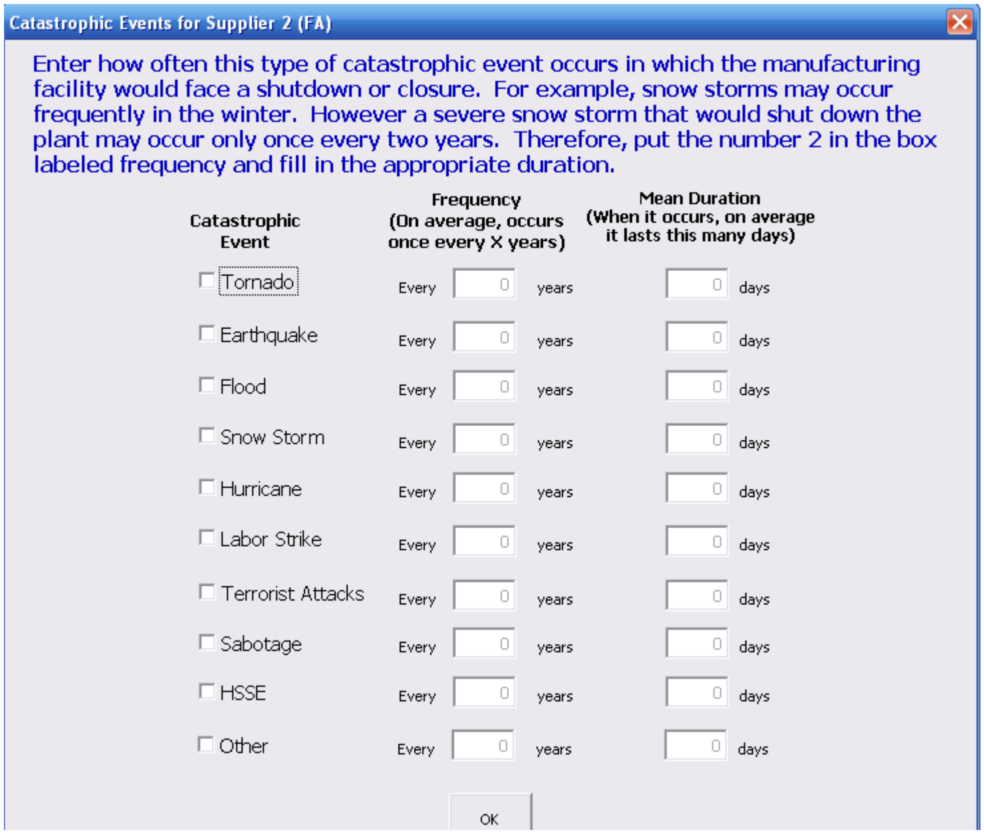


Figure 20 Dialog box to enter supplier's catastrophic events parameters



Once the user has entered all the information required, the *Sampling for QAEC* button will call a set of VBA macros that contains the sampling algorithms for each disruption factor. After generating the capacity scenarios for all suppliers and components, the next step is to obtain the best diversification and safety stock levels. For this, the user will be able to explore manually different configurations, trying to maximize the average deployment, minimize the total cost (already showed in this interface) or run the optimization procedure to obtain the best allocation and inventory configuration. By clicking the *Optimization* button, a VBA macro will generate starting solution points for the allocation variable, and then it will call Solver with the first LP formulation. Once Solver has finished the optimization of the first formulation, the macro will generate starting solution points for the safety stock level. After that, it will call Solver with the second LP formulation. The approximate running time for the whole optimization process is around 4:30 minutes (using a processor Intel Centrino-Duo T2050 1.60 Ghz).

Tables with scenarios are the set of 500 years of possible monthly QAEC outcomes. The VBA macro coded in the I/O interface generates this table for each supplier and component. Table 12 shows the first nine years of possible capacity outcomes for a supplier with a QAEC of 145 and a CV of 0.2.

Table 12 Table with scenario output for a supplier with QAEC = 145 and CV = 0.2

Scn	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
1	115	98	118	218	152	84	131	156	154	165	188	167
2	154	172	175	111	150	113	136	120	207	107	107	142
3	133	175	204	183	145	132	195	177	112	208	127	117
4	159	99	166	140	101	182	105	153	126	116	126	174
5	140	142	113	149	159	171	138	166	115	173	161	130
6	155	100	204	132	198	151	100	122	135	166	103	180
7	153	159	141	205	145	148	144	241	144	153	158	70
8	126	89	173	146	184	192	95	197	108	110	170	157
9	155	198	113	130	119	78	128	159	124	109	132	106

Tables with formulation include all the set of 2nd stage variables and constraints. Tables 13 and 14 show the production and inventory constraints information for a supplier with an assigned order size of 29.2 units / month and a safety stock of 5 units.

Table 13 Table with constraints for production variable Q = 29.5

Scn	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
1	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2
2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2
3	29.2	29.2	29.2	29.2	29.2	29.2	19.9	34.2	29.2	29.2	29.2	29.2
4	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2
5	29.2	28.9	29.5	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2
6	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2
7	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2
8	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2
9	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2

Table 14 Table with constraints for inventory variable S = 5

Scn	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
1	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
2	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
3	5.0	5.0	5.0	5.0	5.0	5.0	0.0	5.0	5.0	5.0	5.0	5.0
4	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
5	5.0	4.7	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
6	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
7	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
8	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
9	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0

7.2 Numerical Examples

In this section, we present two numerical problem instances, which will help illustrate the impact of supplier diversification in complex supply chain structures. For each problem instance, we first applied what we call “common sense” when selecting suppliers. Then, we use the optimization model to find the best supplier selection and order allocation. By doing this comparison, we show the risk of supplier selection by just considering nominal capacity and cost structure. To simplify our analysis, we do not consider catastrophic events for any supplier.

For the first example, we suppose a target demand of 100 units / month, with a penalization of $135,000 for every unit not deployed to the final customer and a penalization of $50,000 for every component stock-out. The parameters for each supplier are showed in Table 15.

Table 15 Suppliers parameters for numerical example 2

		Nominal		Reliability		Quality	Cost		
Component	**Suppliers**	**Mean**	**C.V.**	**MTBF**	**MTTR**	***p***	**Production**	**Holding**	**Penalty**
1	Supplier 1	100	0.2	4	2	98%	$ 18,400	11%	$ 50,000
	Supplier 2	120	0.3	2	2	96%	$ 16,560	11%	$ 50,000
	Supplier 3	120	0.0	100,000	0	100%	$ 20,240	11%	$ 50,000
2	Supplier 1	150	0.01	100,000	0	100%	$ 120,000	11%	$ 50,000
	Supplier 2	150	0.01	100,000	0	100%	$ 108,000	11%	$ 50,000
	Supplier 3	150	0.01	100,000	0	100%	$ 132,000	11%	$ 50,000
3	Supplier 1	150	0.01	100,000	0	100%	$ 58,956	11%	$ 50,000
	Supplier 2	150	0.01	100,000	0	100%	$ 53,060	11%	$ 50,000
	Supplier 3	150	0.01	100,000	0	100%	$ 64,852	11%	$ 50,000
4	Supplier 1	50	0.20	10	4	99%	$ 92,364	11%	$ 50,000
	Supplier 2	100	0.25	5	2	98%	$ 83,128	11%	$ 50,000
	Supplier 3	110	0.02	100,000	0	100%	$ 101,601	11%	$ 50,000
5	Supplier 1	150	0.01	100,000	0	100%	$ 53,770	11%	$ 50,000
	Supplier 2	150	0.01	100,000	0	100%	$ 48,393	11%	$ 50,000
	Supplier 3	150	0.01	100,000	0	100%	$ 59,147	11%	$ 50,000
Final Assembly	Supplier 1	150	0.01	100,000	0	100%	$ 46,016	11%	$ 135,000
	Supplier 2	150	0.01	100,000	0	100%	$ 41,415	11%	$ 135,000
	Supplier 3	150	0.01	100,000	0	100%	$ 50,618	11%	$ 135,000

By just considering nominal mean capacity and production cost, “common sense” will indicate to allocate 100% of the demand (or an order of 100 units / month) to the cheapest supplier for each component, since all of them have a capacity greater than the order size of 100 units. By using the sampling procedure with the rest of the supplier’s information, we generate scenarios of possible QAEC outcomes to analyze the impact of the previous allocation decision.

Figure 21 Main user I/O interface for example 1 with initial solution

	Quality adjusted effective capacity (units per month)		Deployment target allocation (units per month)		Safety Stock		
Suppliers	Mean	C.V.	% of total	Order quantity	SS (units)	SS (units)	Service Level
Component 1							
Supplier 1	95.69	0.21	0.00%	0.00		0	100.00%
Supplier 2	114.61	0.30	100.00%	100.00		0	63.90%
Supplier 3	119.97	0.01	0.00%	0.00		0	100.00%
Component 2			100.00%				
Supplier 1	149.97	0.01	0.00%	0.00		0	100.00%
Supplier 2	150.03	0.01	100.00%	100.00		0	100.00%
Supplier 3	150.00	0.01	0.00%	0.00		0	100.00%
Component 3			100.00%				
Supplier 1	150.03	0.01	0.00%	0.00		0	100.00%
Supplier 2	150.01	0.01	100.00%	100.00		0	100.00%
Supplier 3	149.99	0.01	0.00%	0.00		0	100.00%
Component 4			100.00%				
Supplier 1	47.95	0.22	0.00%	0.00		0	100.00%
Supplier 2	95.95	0.25	100.00%	100.00		0	40.45%
Supplier 3	110.01	0.02	0.00%	0.00		0	100.00%
Component 5			100.00%				
Supplier 1	149.99	0.01	0.00%	0.00		0	100.00%
Supplier 2	150.04	0.01	100.00%	100.00		0	100.00%
Supplier 3	150.01	0.01	0.00%	0.00		0	100.00%
Final Assembly			100.00%				
Supplier 1	149.99	0.01	0.00%	0.00		0	100.00%
Supplier 2	150.01	0.01	100.00%	100.00		0	25.70%
Supplier 3	149.97	0.01	0.00%	0.00		0	100.00%
			1				

Figure 21 shows the resulting QAEC after the sampling procedure. We can see also the impact of the allocation of 100% to the cheapest supplier per component. For components 2, 3, 5 and FA, the allocation selected proved to be the right decision, since their suppliers have plenty of capacity, no variability and different cost. However, for component 1 and 4, although their nominal capacities are greater than 100 units / month, the effect of variability impacts their service levels (63% and 40%). The service level at the FA operation is also affected by the unreliability of components 1 and 4. Figure 22 shows the result of this allocation in the total average throughput of the system (final deployment) and total average cost.

Figure 22 Output for deployment and cost for example 1 with initial solution

Actual deployment

	Mean	C.V.	S.L.
Units per month	83.6326	0.181	25.70%

Total monthly cost (in $MM)

	Mean	C.V.
Production	$ 48.9849	0.03
Inventory holding	$ -	#DIV/0!
Delayed deployment	$ 3.15724	0.93
Total	$ 52.14219	0.0381

We now run the optimization tool using the scenarios already generated by the sampling procedure. Figures 23 and 24 now show the optimal allocation among all suppliers. As we expected, the optimal allocation for component 2, 3, 5 and FA did not change (allocated to the cheapest supplier). For the unreliable components, the optimal decision is to use two suppliers, allocating 47% to supplier 1 and 52% to supplier 2 for component 1, and 30% and 69% to suppliers 1 and 2 respectively for component 4. Basically, the optimization model allocated an order-size to the cheapest supplier such that its service level is maximized. Then, it tried to allocate the rest of the order to the second cheapest supplier. Just by changing the allocation among component 1 and 4, the average deployment rate moves from 83 to 98 units / month. Because the total average stock-out decreased, the total average cost went down from $52.14 M to $48.81 M.

Figure 23 Main user I/O interface for example 1 after 1st optimization

	Quality adjusted effective capacity (units per month)		Deployment target allocation (units per month)		Safety Stock		
Suppliers	Mean	C.V.	% of total	Order quantity	SS (units)	SS (units)	Service Level
Component 1							
Supplier 1	95.69	0.21	47.61%	47.61		0	99.70%
Supplier 2	114.61	0.30	52.39%	52.39		0	98.65%
Supplier 3	119.97	0.01	0.00%	0.00		0	100.00%
Component 2			100.00%				
Supplier 1	149.97	0.01	0.00%	0.00		0	100.00%
Supplier 2	150.03	0.01	100.00%	100.00		0	100.00%
Supplier 3	150.00	0.01	0.00%	0.00		0	100.00%
Component 3			100.00%				
Supplier 1	150.03	0.01	0.00%	0.00		0	100.00%
Supplier 2	150.01	0.01	100.00%	100.00		0	100.00%
Supplier 3	149.99	0.01	0.00%	0.00		0	100.00%
Component 4			100.00%				
Supplier 1	47.95	0.22	30.45%	30.45		0	96.27%
Supplier 2	95.95	0.25	69.55%	69.55		0	87.53%
Supplier 3	110.01	0.02	0.00%	0.00		0	100.00%
Component 5			100.00%				
Supplier 1	149.99	0.01	0.00%	0.00		0	100.00%
Supplier 2	150.04	0.01	100.00%	100.00		0	100.00%
Supplier 3	150.01	0.01	0.00%	0.00		0	100.00%
Final Assembly			100.00%				
Supplier 1	149.99	0.01	0.00%	0.00		0	100.00%
Supplier 2	150.01	0.01	100.00%	100.00		0	82.82%
Supplier 3	149.97	0.01	0.00%	0.00		0	100.00%
			1				

Figure 24 Output for deployment and cost for example 1 after 1st optimization

Actual deployment

	Mean	C.V.	S.L.
Units per month	98.5369	0.045	82.82%

Total monthly cost (in $MM)

	Mean	C.V.
Production	$ 48.5480	0.01
Inventory holding	$ 0.00000	0.07
Delayed deployment	$ 0.27127	3.00
Total	$ 48.81923	0.0096

However, an average deployment of 98 units / month might not be enough (especially for critical products or large penalization costs). Using the optimal allocation, we now proceed to optimize for the safety stock levels. Figure 25 shows the optimal allocation and safety stock level.

Figure 25 Main user I/O interface for example 1 after 2nd optimization

	Quality adjusted effective capacity (units per month)		Deployment target allocation (units per month)		Safety Stock		
Suppliers	**Mean**	**C.V.**	**% of total**	**Order quantity**	**SS (units)**	**SS (units)**	**Service Level**
Component 1							
Supplier 1	95.69	0.21	47.61%	47.61	5	10000	99.87%
Supplier 2	114.61	0.30	52.39%	52.39	15	30000	99.78%
Supplier 3	119.97	0.01	0.00%	0.00	0	0	100.00%
Component 2			100.00%				
Supplier 1	149.97	0.01	0.00%	0.00	0	0	100.00%
Supplier 2	150.03	0.01	100.00%	100.00	0	0	100.00%
Supplier 3	150.00	0.01	0.00%	0.00	0	0	100.00%
Component 3			100.00%				
Supplier 1	150.03	0.01	0.00%	0.00	0	0	100.00%
Supplier 2	150.01	0.01	100.00%	100.00	0	0	100.00%
Supplier 3	149.99	0.01	0.00%	0.00	0	0	100.00%
Component 4			100.00%				
Supplier 1	47.95	0.22	30.45%	30.45	5	11560	98.77%
Supplier 2	95.95	0.25	69.55%	69.55	20	46240	98.37%
Supplier 3	110.01	0.02	0.00%	0.00	0	0	100.00%
Component 5			100.00%				
Supplier 1	149.99	0.01	0.00%	0.00	0	0	100.00%
Supplier 2	150.04	0.01	100.00%	100.00	0	0	100.00%
Supplier 3	150.01	0.01	0.00%	0.00	0	0	100.00%
Final Assembly			100.00%				
Supplier 1	149.99	0.01	0.00%	0.00	0	0	100.00%
Supplier 2	150.01	0.01	100.00%	100.00	0	0	99.05%
Supplier 3	149.97	0.01	0.00%	0.00	0	0	100.00%
			1				

By allowing unreliable suppliers to carry some safety stock, we can take the total average deployment from 98.53 to 99.87 units / month, with a decrease in the total monthly cost of $128,700. Figure 26 shows the optimal objective function.

Figure 26 Output for deployment and cost for example 1 after 2^{nd} optimization

Actual deployment

	Mean	C.V.	S.L.
Units per month	99.9785	0.005	99.62%

Total monthly cost (in $MM)

	Mean	C.V.
Production	$ 48.6550	0.01
Inventory holding	$ 0.02687	0.13
Delayed deployment	$ 0.00864	22.59
Total	$ 48.69051	0.0098

For the second example, we assume a target demand of 100 units / month, but now with a penalization of $500,000 per every unit not deployed to the final customer. The information for each supplier is on Table 16.

Table 16 Suppliers parameters for example 2

		Nominal		Reliability		Quality	Cost		
Component	**Suppliers**	**Mean**	**C.V.**	**MTBF**	**MTTR**	***p***	**Production**	**Holding**	**Penalty**
1	Supplier 1	100	0.2	4	2	98%	$ 18,400	11%	$ 50,000
	Supplier 2	120	0.3	2	2	96%	$ 16,560	11%	$ 50,000
	Supplier 3	120	0.0	12	1	100%	$ 20,240	11%	$ 50,000
2	Supplier 1	150	0.20	11	3	99%	$ 120,000	11%	$ 50,000
	Supplier 2	100	0.20	9	1	97%	$ 108,000	11%	$ 50,000
	Supplier 3	150	0.01	14	5	100%	$ 132,000	11%	$ 50,000
3	Supplier 1	150	0.01	100,000	0	100%	$ 58,956	11%	$ 50,000
	Supplier 2	150	0.01	100,000	0	100%	$ 53,060	11%	$ 50,000
	Supplier 3	150	0.01	100,000	0	100%	$ 64,852	11%	$ 50,000
4	Supplier 1	50	0.20	10	4	99%	$ 92,364	11%	$ 50,000
	Supplier 2	100	0.25	5	2	98%	$ 83,128	11%	$ 50,000
	Supplier 3	110	0.02	24	10	99%	$ 101,601	11%	$ 50,000
5	Supplier 1	200	0.15	5	1	100%	$ 53,770	11%	$ 50,000
	Supplier 2	50	0.11	5	3	99%	$ 48,393	11%	$ 50,000
	Supplier 3	150	0.01	100,000	0	100%	$ 59,147	11%	$ 50,000
Final Assembly	Supplier 1	150	0.01	100,000	0	100%	$ 46,016	11%	$ 500,000
	Supplier 2	150	0.01	100,000	0	100%	$ 41,415	11%	$ 500,000
	Supplier 3	150	0.01	100,000	0	100%	$ 50,618	11%	$ 500,000

In the presence of a large penalization cost at the FA stage, we might be tempted to allocate part of the total order size to the cheapest supplier (which shows a more unreliable operation) and the rest to the second cheapest supplier, which presents a more stable operation. Figures 27 and 28 show the result of this allocation.

Figure 27 Main user I/O interface for example 2 with initial solution

	Quality adjusted effective capacity (units per month)		Deployment target allocation (units per month)	
Suppliers	**Mean**	**C.V.**	**% of total**	**Order quantity**
Component 1				
Supplier 1	95.69	0.21	50.00%	50.00
Supplier 2	111.18	0.30	50.00%	50.00
Supplier 3	119.15	0.02	0.00%	0.00
Component 2			100.00%	
Supplier 1	144.94	0.21	50.00%	50.00
Supplier 2	96.46	0.20	50.00%	50.00
Supplier 3	145.19	0.10	0.00%	0.00
Component 3			100.00%	
Supplier 1	150.03	0.01	0.00%	0.00
Supplier 2	150.01	0.01	100.00%	100.00
Supplier 3	149.99	0.01	0.00%	0.00
Component 4			100.00%	
Supplier 1	47.96	0.22	50.00%	50.00
Supplier 2	95.62	0.26	50.00%	50.00
Supplier 3	104.26	0.16	0.00%	0.00
Component 5			100.00%	
Supplier 1	197.78	0.15	50.00%	50.00
Supplier 2	47.78	0.13	50.00%	50.00
Supplier 3	150.00	0.01	0.00%	0.00
Final Assembly			100.00%	
Supplier 1	149.99	0.01	0.00%	0.00
Supplier 2	150.01	0.01	100.00%	100.00
Supplier 3	149.97	0.01	0.00%	0.00
			1	

Figure 28 Output for deployment and cost for example 2 with initial solution

Actual deployment

	Mean	C.V.	S.L.
Units per month	92.3789	0.071	15.87%

Total monthly cost (in $MM)

	Mean	C.V.
Production	$ 49.0357	0.01
Inventory holding	$ 0.00000	0.09
Delayed deployment	$ 4.27393	0.86
Total	$ 53.30963	0.0571

Using the optimization model, we found the best allocation and safety stock level. Contrary to our "common sense" approach, the optimization process allocated a part of the total demand to the supplier with the highest cost. In components 1 and 4, a small order-size was allocated to the expensive suppliers. However, in component 5, the 100% of the demand was allocated to the supplier with the highest cost (this supplier does not present any kind of variability). With the optimal allocation and safety stock level, we could improve the total average deployment from 92.3 to 99.98 units / month, and we reduced the total average cost by almost $3 M. See Figures 29 and 30 for the optimal solution for this problem.

Figure 29 Main user I/O interface for example 2 after 2nd optimization

	Quality adjusted effective capacity (units per month)		Deployment target allocation (units per month)		Safety Stock		
Suppliers	Mean	C.V.	% of total	Order quantity	SS (units)	SS (units)	Service Level
Component 1							
Supplier 1	95.69	0.21	47.80%	47.80	15	30000	99.97%
Supplier 2	111.18	0.30	45.21%	45.21	20	40000	100.00%
Supplier 3	119.15	0.02	7.00%	7.00	0	0	100.00%
Component 2			100.00%				
Supplier 1	144.94	0.21	37.21%	37.21	5	10000	100.00%
Supplier 2	96.46	0.20	62.79%	62.79	10	20000	99.47%
Supplier 3	145.19	0.10	0.00%	0.00	0	0	100.00%
Component 3			100.00%				
Supplier 1	150.03	0.01	0.00%	0.00	0	0	100.00%
Supplier 2	150.01	0.01	100.00%	100.00	0	0	100.00%
Supplier 3	149.99	0.01	0.00%	0.00	0	0	100.00%
Component 4			100.00%				
Supplier 1	47.96	0.22	29.22%	29.22	5	11560	99.17%
Supplier 2	95.62	0.26	59.20%	59.20	20	46240	99.73%
Supplier 3	104.26	0.16	11.58%	11.58	0	0	99.02%
Component 5			100.00%				
Supplier 1	197.78	0.15	0.00%	0.00	0	0	100.00%
Supplier 2	47.78	0.13	0.00%	0.00	0	0	100.00%
Supplier 3	150.00	0.01	100.00%	100.00	0	0	100.00%
Final Assembly			100.00%				
Supplier 1	149.99	0.01	0.00%	0.00	0	0	100.00%
Supplier 2	150.01	0.01	100.00%	100.00	0	0	99.68%
Supplier 3	149.97	0.01	0.00%	0.00	0	0	100.00%
			1				

Figure 30 Output for deployment and cost for example 2 after 2nd optimization

Actual deployment

	Mean	C.V.	S.L.
Units per month	99.9862	0.003	99.68%

Total monthly cost (in $MM)

	Mean	C.V.
Production	$ 50.3968	0.01
Inventory holding	$ 0.03993	0.05
Delayed deployment	$ 0.01606	20.73
Total	$ 50.45279	0.0060

Summarizing the results from the two numerical examples, we can conclude that even for small problems such as the ones presented here, it might not be an easy task trying to define the best allocation (and safety stock level) by just using "common sense" or by manually exploring different alternatives. In the presence of different levels of variability, capacities and cost structures, it is necessary to recur to modeling tools such as the one proposed in this work.

8. SUMMARY AND CONCLUSIONS

In this Record of Study, we have presented the details of an optimization model for a strategic supply chain design. This model was developed during a one and a half year internship with Shell Oil Company, SURE unit. The objective of this model is to define the best diversification and safety stock level among a set of possible suppliers for a product formed of five different components. Unlike traditional supply chain optimization models, the approach presented here considers variability and stochastic disruptions into supplier's capacity.

We considered normal variability, equipment failure, quality yield and catastrophic events as the sources of disruptions that affect each supplier's capacity. In order to incorporate these stochastic factors into the optimization model, we propose to use Monte Carlo sampling techniques to generate scenarios of possible capacity outcomes. In order to model these disruptions, we use probability distributions such as Normal, Gamma, Exponential and Binomial.

We also proposed a non-linear formulation which minimizes the total expected monthly cost. This model is formulated as a two-stage stochastic problem, where the first-stage decisions are the level of diversification and safety stock at each supplier for each component. Although there are efficient methods to solve large-scale stochastic problems, such as Sample Average Approximation (SAA), we propose a simple heuristic which decomposes the original NLP formulation into two easy-to-solve LP problems, where the solution of the first is used as an input to the second problem. This heuristic also takes advantage of the flexibility of Excel to optimize average functions. Both the sampling procedure and the heuristic were implemented as a Decision Support System in a spreadsheet.

Thorough some numerical examples, we showed the advantage of using modeling and optimization tools like the one presented here. For the strategic design of complex supply chains, this model can provide the decision maker with general guidelines regarding the level of diversification. The course of action suggested by the model could be very helpful during the supplier engagement process and contract design. Another possible application of this model is to measure the impact of different supplier development initiatives.

As we have mentioned before, the main objective of this development is not to propose efficient sampling and optimization algorithms, but rather to offer a general framework for the strategic design of supply chains in the presence of stochastic supply disruptions.

The future work for this model will be in two main improvements. First, the implementation of a more robust optimization process (i.e. SAA). Second, a redefinition of the main formulation is necessary to avoid the nonlinear issue. We believe that it is possible to obtain a main LP formulation by redefining some of the 1st stage variables.

Besides the two main improvements just described, the model proposed here might also be furbished with new features, such as fixed costs by selecting a supplier, quantity discounts, stochastic supplier's price, different probability distribution for nominal capacity and failure occurrence and duration. In case the model gets expanded for more stages or components, it is recommended to migrate to a more robust optimization engine such as Professional Solver or CPLEX.

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APPENDIX A

INTERNSHIP FINAL OBJECTIVES

The following are the final internship objectives approved by the committee on June 20, 2007.

Project objective

The technical objective of the project is to develop a linear, stochastic programming model that captures the risks involved in the supply chain design of the innovative technology commercialization. This model will be implemented as a Decision Support System (DSS) for the supplier's engagement process. The managerial objective of the project is to assist in the strategic planning process of designing supplier's contracts.

Model characteristics

The main objective is the development of an optimization model based on Excel. This model must contain the following characteristics:

1. The model must consider at least four components or stages and a final assembly operation. Each of these stages will have two suppliers, with a production and

inventory costs associated to them. Each supplier's monthly capacity will be subject to several disruptions.

2. A robust sampling procedure for nominal capacity, supplier failure, quality yield and catastrophic events, for each supplier. This procedure should have different probability distributions for each disruption factor (normal, gamma, exponential, binomial). At least 100 scenarios of twelve months final capacity will be generated for each supplier at each stage.

3. Using the scenarios created in the sampling procedure, the model should be able to optimize for two 1^{st} stage variables: % of demand allocated to each supplier at each stage and the level of safety stock to carry out. Additional 1^{st} stage variables might be considered in the future. 2^{nd} stage variables are production and backlog amounts at each period.

4. The model should show a histogram of the total monthly's optimal cost for risk analysis purposes.

5. The model should have a compact and efficient Linear Programming formulation with a reasonable computational solution time.

6. This model will be expanded to include another four product configurations.

APPENDIX B

SUPERVISOR'S FINAL REPORT

Shell Exploration & Production

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November 15, 2007

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The purpose of this document is to provide a final evaluation of the internship project conducted by Jaime Luna-Coronado at Shell Oil Co. The internship objective was to develop an optimization model for strategic supply chain design of a new technology commercialization by Shell. This model would incorporate elements from deterministic and stochastic optimization, as well as advanced sampling techniques. The model had to be implemented on a spreadsheet environment as a Decision Support System.

Jaime did an excellent job during the development process of this optimization tool, by providing the perfect mix between academic research and practical application. For every phase of this project, Jaime not only interacted with me, but also with other members of the team (supply chain, operations, engineering), always meeting project milestones. I consider that this internship helped Jaime to improve his technical and managerial skills.

The model is being implemented and it is in the testing phase. This model will play an important role within our strategic planning process.

I would like to conclude this evaluation expressing that Jaime's performance during this one-year internship went far beyond expectations, the internship objectives were completely satisfied and Shell benefited greatly from this experience.

Sincerely,

Barry Keys
Heater Manufacturing Systems Manager

VITA

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Jaime Luna Coronado obtained his Bachelor of Science Degree in Industrial and Systems Engineering from Instituto Tecnologico y de Estudios Superiores de Monterrey (ITESM), Monterrey, Mexico in 1997. He received his M.E. Degree in Industrial Engineering in December, 2004 and his D. En. Degree in December, 2007, both from Texas A&M University. Before graduate school, Mr. Luna spent 4 years in General Electric in Mexico as an industrial and operations engineer. Mr. Luna may be reached at jlunacoronado@gmail.com.