Models for Flexible Supply Chain Network Design

by

Nima Salehi Sadghiani

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Industrial and Operations Engineering)
in the University of Michigan
2018

Doctoral Committee:

Professor Mark S. Daskin, Chair
Professor Pascal Van Hentenryck
Associate Professor Long Nguyen
Assistant Professor Cong Shi
Dr. Don Zhang

Nima Salehi Sadghiani
nsalehi@umich.edu
ORCID iD: 0000-0003-0726-3236

To my parents Nahid and Mahmoud with deepest gratitude
for their endless love and continuous support.

Acknowledgements

I would like to express my sincere gratitude to my advisor, Prof. Mark S. Daskin for his continuous support, guidance, and for everything he has taught me throughout the tenure of my Ph.D. study, without which this dissertation would not have been completed.

I would also like to thank my other committee members Prof. Pascal Van Hentenryck, Prof. Long Nguyen, Prof. Cong Shi, and Dr. Don Zhang who have been supportive of my work and provided valuable comments, suggestions and guidance during the course of this dissertation.

During the past four years, I have had the privilege to work with several collaborators from Ford Motor Company. In particular, I would like to acknowledge the contribution and support of Dr. Don Zhang.

I gratefully acknowledge the financial support from the Department of Industrial and Operations Engineering at the University of Michigan, and the Ford-University of Michigan Alliance. These supports enabled me to conduct the research within this dissertation.

Finally, I would also like to thank my family, friends, officemates, and classmates. I am especially grateful to Ece, Ehsan and Shadi, Pooyan, Amir, and Selin. You have encouraged me throughout these years, and you made me look forward to coming into the office every day.

Table of Contents

List of Figures

List of Tables

List of Appendices

Abstract

Arguably Supply Chain Management (SCM) is one of the central problems in Operations Research and Management Science (OR/MS). Supply Chain Network Design (SCND) is one of the most crucial strategic problems in the context of SCM. SCND involves decisions on the number, location, and capacity, of production/distribution facilities of a manufacturing company and/or its suppliers operating in an uncertain environment. Specifically, in the automotive industry, manufacturing companies constantly need to examine and improve their supply chain strategies due to uncertainty in the parameters that impact the design of supply chains. The rise of the Asian markets, introduction of new technologies (hybrid and electric cars), fluctuations in exchange rates, and volatile fuel costs are a few examples of these uncertainties.

Therefore, our goal in this dissertation is to investigate the need for accurate quantitative decision support methods for decision makers and to show different applications of OR/MS models in the SCND realm. In the first technical chapter of the dissertation, we proposed a framework that enables the decision makers to systematically incorporate uncertainty in their designs, plan for many plausible future scenarios, and assess the quality of service and robustness of their decisions. Further, we discuss the details of the implementation of our framework for a case study in the automotive industry. Our analysis related to the uncertainty quantification, and network's design performance illustrates the benefits of using our framework in different settings of uncertainty. Although this chapter is focused on our case study in the automotive industry, it can be generalized to the SCND problem in any industry.

We have outline the shortcomings of the current literature in incorporating the correlation among design parameters of the supply chains in the second technical chapter. In this chapter, we relax the traditional assumption of knowing the distribution of the uncertain

parameters. We develop a methodology based on Distributionally Robust Optimization (DRO) with marginal uncertainty sets to incorporate the correlation among uncertain parameters into the designing process. Further, we propose a delayed generation constraint algorithm to solve the NP-hard correlated model in significantly less time than that required by commercial solvers. Further, we show that the price of ignoring this correlation in the parameters increases when we have less information about the uncertain parameters and that the correlated model gives higher profit when exchange rates are high compared to the stochastic model (with the independence assumption).

We extended our models in previous chapters by presenting capacity options as a mechanism to hedge against uncertainty in the input parameters. The concept of capacity options similar to financial options constitute the right, but not the obligation, to buy more commodities from suppliers with a predetermined price, if necessary. In capital-intensive industries like the automotive industry, the lost capital investment for excess capacity and the opportunity costs of underutilized capacity have been important drivers for improving flexibility in supply contracts. Our proposed mechanism for high tooling cost parts decreases the total costs of the SCND and creates flexibility within the structure of the designed SCNs. Moreover, we draw several insights from our numerical analyses and discuss the possibility of price negotiations between suppliers and manufacturers over the hedging fixed costs and variable costs.

Overall, the findings from this dissertation contribute to improve the flexibility, reliability, and robustness of the SCNs for a wide-ranging set of industries.

Chapter 1.

Introduction

Managing uncertainty is one of the challenging issues in supply chains. In the automotive industry, numerous factors require manufacturing companies to constantly analyze and improve their supply chain strategies. The rise of the Asian markets, introduction of new technologies (hybrid and electric cars), mergers and acquisitions, fluctuations in exchange rates, and volatile fuel costs are a few examples of these uncertainties. To be successful in the competitive markets, manufacturing companies must strive to reduce supply chain costs and improve quality of service while accounting for the uncertainties. Using only the expected value of the uncertain parameters when designing a supply chain network can be risky due to the uncertainties that threaten both the optimality and feasibility of the decisions. Deviations from expected values of the key input parameters can make the deterministic formulations infeasible and/or inefficient much of the time. An interesting example of this fact can be found the book of *The Flaw of Averages* [77, 78]. Consider the position of a drunk person, wandering around on a busy highway. His average position is the center line of the highway, so the state of the drunk person at his average position is alive, however, considering his shivering, the average state of the drunk person is dead.

Problem Context and Motivation

Supply chain network design (SCND) is the strategic planning of supply chains involving the number, location, and capacity of suppliers, and the management of the flows throughout the whole network over future years. These strategic decisions typically involve high investments and are not easily reversible. Having made these decisions, the manufacturing company needs to fulfill the demands at all markets while remaining competitive. This is why designing a flexible and cost-efficient network is crucial to the long term success of any manufacturing company.

The current practice to deal with uncertainty in many industries is through observing the sensitivity of the deterministic model's objective function and decision variables to the key inputs. Then, the decisions from such models will be refined through a subjective process by other criteria (such as technical limitations, law and regulations, and financial targets). Although this approach is straightforward, there are a number of important limitations associated with this approach. First, planning against one single future scenario is risky and naive. The risk analysis process is manual and lacks a systematic approach to study the effect of multiple plausible future scenarios in the decision process. Finally, this process cannot determine the performance measures of the proposed designs like the quality of service, expected unmet demand, and expected costs or profits. It is worth noting that unless systems are truly linear, the expected value of an outcome is not the same as the outcome evaluated at the expected value of the input parameters.

In this dissertation, we investigate the need for incorporating uncertainty in designing supply chains and creating flexibility within their structures. In our models, we include multiple sources of uncertainty in demand, exchange rate, and freight cost parameters.

These parameters has been identified as the key inputs for making sourcing decisions in the automotive industry.

Summary of Contributions and Dissertation Overview

Chapter 2 summarizes a two-year research engagement project with the Ford Motor Company. In this chapter, we addressed the need for an effective tool to incorporate potential uncertainties associated with the model parameters into sourcing decisions. This model enables Ford to plan for many alternative future scenarios, incorporate uncertainties into their decision making process, assess the robustness of their decisions, and analyze the tradeoff between their unmet demand and tooling expenditures.

The objective of this model is the Net Present Value (NPV) of the total landed cost. Decision variables include supplier selection, production volume assignment for each selected supplier, and shipping volumes. Inspired by the current practice at Ford, we presented the stochastic version of the NPV of the total landed cost model. Our model is a two-stage stochastic programming model. In the first stage, the model makes supplier and capacity decisions. These decisions are sent to the second stage which evaluates the first stage decisions with respect to a large number of future scenarios. The second stage of the model minimizes the purchasing and logistic costs for each realization (or each future scenario), while the first stage of the models minimizes the tooling costs and the expected purchasing and logistic costs over all possible realizations (or future scenarios).

Through our numerous experiments we have shown the impacts of uncertainty from 3 major sources (demand, fuel costs, and exchange rates) on Ford's sourcing decisions. By comparing the forecast data in 2013 and the actual realizations in 2016, we were able to demonstrate the benefits associated with using our modeling framework. In particular, potential savings and cost of uncertainty were investigated through two case studies.

We contribute to the literature by presenting an extensive data analysis related to uncertainty quantification for the Ford sourcing model. Our analyses are based on Ford's network structure, but they can be generalized to any supply chain network design problem in the literature. Finally, this chapter helps managers in different industries develop a framework to assess the benefits and costs of incorporating uncertainty in their modeling process.

Chapter 3 investigates the effect of correlations among input parameters and the costs of ignoring such correlations. In this chapter, we relax the conventional assumption of independence among the input parameters. Traditional models assume that demand values at different markets and for different products are independent and the demand distributions are given. These assumptions are not accurate when correlation among the demand of different products exists. In this research, we propose a decision model for designing flexible supply chain networks operating under correlated uncertainties. We extend the current models by coordinating several supply chain networks of common commodities of different products.

To do so, we employ distributionally robust optimization to coordinate the supply chain networks against the worst-case distribution with given marginal probabilities for demand, exchange rate, and freight cost uncertainties. Moreover, we investigate the price of correlation in the design parameters against the traditional methods in which the independence of the uncertain parameters is an assumption. To the best of our knowledge, our model is different from other approaches found in the literature and contributes in the following ways. (1) We include multiple sources of uncertainty in the model (demand, exchange rate, and freight cost). (2) Capacity planning (as opposed to holding inventory) is proposed to create flexibility in designing supply chains. In particular, holding inventory to create flexibility is not feasible in the automotive industry. (3) Distributionally robust optimization frameworks is used to coordinate the supply chain networks of different products and parts against the worst-case joint distribution of the uncertain parameters with given marginal probabilities.

Our results indicate that our model often deploys more capacity than the traditional stochastic models for a profit-maximization problem where positive correlations can lead to profit loss, if inadequate capacity limits potential sales.

Chapter 4 presents another strategy to create flexibility in supply chain network design problems. In this chapter, we propose buying capacity options in combination with reserved capacity as a mechanism to hedge against uncertainty and create flexibility in designing supply chains networks. Our results from the case study for parts with high tooling costs suggest that reserving capacity and buying capacity options can decrease the expected costs of designs up to 10%. We extensively analyze the sensitivity of the designs for the key input parameters of the capacity option model. In particular, we discuss the possibility of price negotiation between suppliers and the manufacturers. Finally, we propose a Bender's decomposition algorithm to solve the MIP model in significantly less time than the time required by commercial solvers.

In this chapter, we contribute to the SCND literature by: (1) the development of capacity option models that allow manufacturers to hedge against uncertainty and we demonstrate its application for the automotive industry; (2) analyzing the sensitivity of the models under mean-excess regret risk and demonstrating conditions under which capacity option models are beneficial.

The remainder of this dissertation presents the details of the research described above in chapters 2 - 4. The dissertation concludes in chapter 5 with a summary of the most important findings and an outline of future research opportunities.

Chapter 2.

Global Sourcing under Uncertainty

2.1. Introduction

2.1.1. Global Sourcing Decision Process

The *One Ford* initiative is Ford's key strategy to optimize their global sourcing program. Under One Ford, it is possible to optimize global supplier locations, reduce initial (tooling) investments, and take advantage of economies of scale through global sourcing. All regions need to work together to take advantage of the global manufacturing network, tooling efficiency, and economies of scale. Making decisions in a global sourcing environment is the new norm at Ford. For a given common part, global sourcing decisions include the following:

- Determine the number of regions involved in the sourcing decision. The regions here refer to the five major markets and/or manufacturing bases for Ford. Throughout this chapter, we refer to this regions by A-E letters. Each region can have more than one supplier and assembly plant

- Determine the numbers of tools required to meet global demand for the regions
- Select the tooling locations and suppliers to source parts
- Determine production volumes for the selected suppliers
- Determine shipping volumes to satisfy all demand

2.1.2. Scope of the Model

Sourcing decisions deal with many aspects of suppliers, such as quality, cost, reliability, capacity, legacy contracts, business strategy, risks etc. The model described here does not deal with the full spectrum of criteria in supplier selection. Instead, the model complements the existing supplier selection process and emphasizes the cost side of the selection. That is, buyers need to select a group of suppliers that are qualified for quality, capacity, and other criteria. These suppliers submit quotes to compete for the business. The model processes these quotes and recommends the proper sourcing strategy and supplier(s) based on selected financial criteria.

2.1.3. Contribution and Highlights

In this chapter, we contribute to the literature by presenting an extensive data analysis related to uncertainty quantification for the Ford sourcing model. Our analyses are based on Ford's network structure, but they can be generalized to any supply chain network design problem in the literature. Finally, this chapter helps managers in different industries develop a framework to assess the benefits and costs of incorporating uncertainty in their modeling process.

2.2. Literature Review

We take advantage of two streams of research in this work. The first stream is related to Supply Chain Network Design (SCND) problems. The second stream of scholarship pertains to a more in-depth analysis of the performance metrics for SCNs operating under uncertainties.

2.2.1. The evolution of SCND problems

Deterministic SCND formulations are built upon facility location models, in particular discrete facility location models [65]. Facility location problems consider flows of a single commodity/product among the selected facilities and demand nodes. One of the basic discrete facility location problems is the *Fixed Charge Location Problems* (FCLP). In the FCLP there is a finite set of demand locations that will be served by a finite set of facility locations. In these problems two sets of decisions must be made. The first set of decisions is the location decisions that determine where to locate the facilities. The second set is the allocation decisions that dictate how to satisfy the demand [30]. In these models, the facilities can be capacitated or uncapacitated [89]. The original formulation of these models goes back to Balinski [9]. Since then several researchers have proposed extensions of these problems. Further discussions about developments in FCLPs can be found in Owen and Daskin [70], and Snyder [89].

SCND is considered to be an extension of *Capacitated Fixed Charge Location Problems* (CFCLP). Capacity decisions were added to Fixed Charge Location Problems by Elson [40]. Eppen et al. 1989 described a capacity expansion model in the auto industry. The capacity expansion models in the SCND literature are relatively more recent [3, 5]. In their models, the amount of expansion, and time of expansion were key decision variables.

In comparison with the current models in the SCND literature, we propose capacity planning as opposed to holding inventory to create flexibility in designing Supply Chain Networks (SCNs). Moreover, the structure of our optimization model captures more details than have previously been reported in the literature.

2.2.2. Uncertainties in SCN and performance metrics

The future under which a SCN will operate is non-deterministic (uncertain) or in some cases unknown. "Uncertain" refers to cases in which the possible outcomes are known with some probabilities and "unknown" refers to situations in which the associated probabilities of the outcomes are not known a priori [25]. Uncertainty is usually defined as a perturbation in the input data in optimization problems [19]. A scenario can be defined as a combination/ realization of the uncertain parameters [38]. The future environments under which SCNs operate are shaped by uncertainties; these uncertainties can be captured by the scenario structure modeling in SCND [12, 56].

Uncertainties are divided into random uncertainties and interdictions. Random uncertainties divide into natural and man-made categories owing to the nature of the uncertainty. Interdictions refer to events having an element of human intent/intelligent (targeted attacks). Fluctuations in demanded products and terrorist attacks are the common examples of these two categories, respectively [92]. Planning for random uncertainties requires different modeling and solution techniques than is required for the analysis of interdictions. Here, we only focus on random uncertainties. The majority of the literature has classified the source of the uncertainty in two broad groups [93] as follows:

- **Demand-side uncertainties** (also known as operational risks [96]): instability in demand or inexact demand forecasts.
- **Supply-side uncertainties**:
  - **Long-term** (also known as disruption risks [96] and supply disruptions [93]): congestion, disruptions, faults or delays in the suppliers deliveries.
  - **Short-term** (also known as yield uncertainty [93]): the quantity produced or received differs from the quantity ordered due to shortfalls and manufacturing defects.

In addition, we add a third source of uncertainty:

- **Environmental uncertainties**: including changes in the regulatory and macro-economic environment; for example, exchange rates.

Decision-making under uncertainty often requires using large-scale optimization models. We briefly review frequently used techniques in the literature:

- **Sensitivity analysis (SA)**: sensitivity analysis is a technique used to determine the impact of changes in a parameter on the objective function and decision variables [87]. In this technique, usually small changes in one parameter are studied. One of the drawbacks of this technique is its limited capability to study the combined effect of multiple changes in independent parameters at the same time. In addition, a very limited range for parameters is often used in practice.

- **Robust optimization (RO)**: considering a pre-defined set for the uncertain parameter (could be the range), robust optimization finds the best solution which is feasible for any realization of the uncertainty in the given set [14]. Robust solutions are known to be overly conservative [16].

- **Stochastic programming (SP)**: In SP, the probability distributions of the random parameters are usually known a priori [19]. Using these probabilities, we can generate and define alternative future scenarios. The major concern with discrete SP techniques is the *curse of dimensionality*. In other words, the number of scenarios can be extremely large or infinite in some cases. The *Sample Average Approximation* (SAA) method was developed by Santoso et al. [76] to overcome this difficulty for supply chain network design under uncertainty.

Several scholars have proposed hybrid techniques (such as robust stochastic programming [91], and chance-constrained programming [66]). In summary, we consider several aspects of the SCND problems, modeling frameworks, and uncertainty modeling in the literature to show the scope of our proposed approach:

In table 3.1 we compare the literature using three different major criteria: (1) SCND Structure, (2) Modeling Framework, (3) Uncertainty Modeling. The first criterion focuses on different features of SCND problems including whether capacity planning, inventory decisions, multi-stage/dynamic planning, multi-commodity/multi-product, and exchange rate effects are considered. The second criterion focuses on the framework used to model

Table 2.1: Qualitative comparison of SCND Literature

Literature	SCND Structure					Modeling Framework	Uncertainty Modeling
	CP	I	MS/DY	MC/MP	ER	D/SP/RO/DRO	D/S/E
Tsiakis et al. [100]		*		*		D/SP	D
Daskin et al. [32]		*				D/SP	D
Ahmed et al. [3]	*	*	*	*		D/SP	D
Bertsimas and Thiele [17]		*	*			D/RO	D
Guillén et al. [44]	*	*	*	*		D/SP	D
Martel [60]	*	*	*	*	*	D/SP	D
Shen [85]		*		*		D/SP	D
Amiri [5]	*					D	
Melo et al. [63]	*		*	*		D	
Shen [86]		*	*	*		D	
You and Grossmann [103]		*	*	*		D/SP	D
Altiparmak et al. [4]				*		D	
Klibi and Martel [52]	*		*		*	SP	D/S/E
Badri et al. [8]		*	*	*		D	
Sawik [79]		*		*	*	SP	S
Jafarian and Bashiri [48]		*	*	*		D	
Maass et al. [58]	*	*	*			D	
Current Work	*			*	*	D/SP	D/E

SCND Structure: CP: Capacity Planning, I: Inventory Decisions, MS/DY: Multi-stage/Dynamic, MC/MP: Multi-commodity/Multi-product, ER: Exchange Rate
Modeling Framework: D: Deterministic, SP: Stochastic Programming, RO: Robust Optimization
Uncertainty Modeling: D: Demand-side, S: Supply-side, E: Environmental

the SCNs. Deterministic models ignore the effect of uncertainty into the modeling process while the other techniques consider uncertainty in different ways. Finally, the last criterion focuses on the source of the uncertainty and divides it into three categories: demand-side, supply-side, and environmental. Table 3.1 shows that most researchers focus on holding inventory rather than capacity planning. However, this may not be feasible for the automotive industry.

2.3. The Current Approach: A Deterministic Model

Ford used a linear Mixed Integer Programming (MIP) model to optimize global sourcing decisions across all regions. The objective function of this model is the Net Present Value (NPV) of the total landed cost. Decision variables include supplier selection, production volume for each selected supplier, and shipping volumes. After finding optimal solutions different sourcing scenarios, they conducted financial evaluations to make final sourcing decision.

2.3.1. The Total Landed Cost NPV Model

Ford's SCN consists of three main elements: parts, suppliers, and demand zones. Suppliers are the exogenous sources of parts in the network. The model deals with only one part/-commodity and one time period. A supplier is called *Global*, if (1) it has enough capacity to satisfy the global demand, (2) the optimal sourcing decision indicates only that supplier should be selected. A *regional* supplier has only enough capacity to satisfy local demand in the region it serves. All suppliers competing for the business have quality and business practices that meet Fords' requirements. Ford's supply chain network is depicted in figure 2.1:

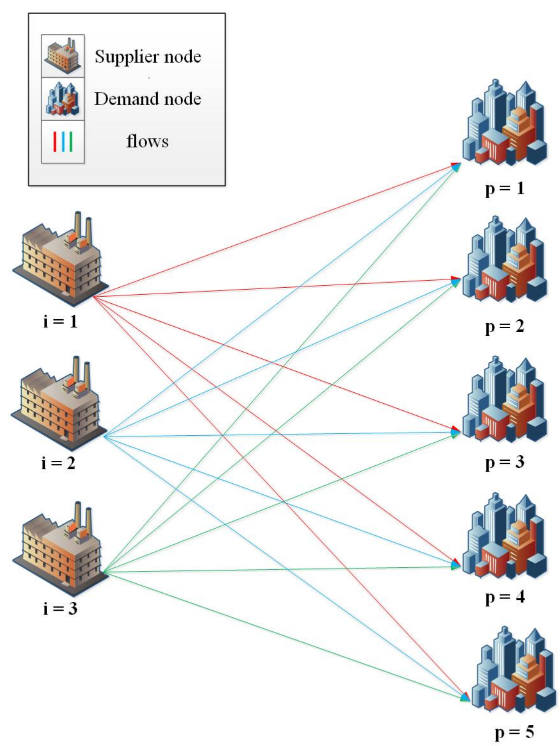

Figure 2.1: Scheme of Ford's supply chain network

In figure 2.1 supply facilities are on the left side of the figure represented by plant-shaped icons and indexed by i and demand regions are on the right side of the figure represented by city-shaped icons and indexed by p. The demand regions represent the aggregated demand of a specific part at an assembly plant in the region. The flow of the vehicle parts among supply and demand nodes are represented with solid lines with different colors.

Deciding the optimal level of capacity allocation, plays a crucial role in strategic level decision making models. Capacity levels in this case are the number of production lines (modules) required in the plants. Therefore, the capacity decisions are involved with commitment of capital resources for the period of the contracts with the suppliers. The capacity of the suppliers depends on the number of modules (production lines) which will be referred to as *Modular Capacity*. Each module has a specific capacity; thus, the total capacity can be expressed by the number of modules at each supplier. The upfront fees for reserving capacity are proportional to the number of modules at each supplier.

All sets, indices, and parameters used in the model are described in detail in the following table.

Sets	Description
I	Set of supplier locations indexed by i
P	Set of Ford vehicle assembly plant locations indexed by p
K	Set of currencies indexed by k
T	Time horizon in years indexed by t
L_i	Set of capacity levels at supplier i indexed by l
Parameter	**Description**
n	Number of sourcing suppliers
h	Inventory holding rate
r_t	Discount rate at year t
c_i	Unit part cost at location i independent of time
d_p	Annual part demand in assembly plant p
e_k	Exchange rate for currency k in USD per unit local currency
θ_{il}	Tooling cost at location i for capacity level l
ψ_{il}	Annual maximum supplier capacity levels at supplier location i at level l
f_{ip}	Freight cost from supplier location i to assembly plant p in USD
δ_{ip}	Numbers of days in transit from supplier location i to plant p
η_{ip}	Duty rates from supplier location i to plant p

Finally, the decision variables are:

Variable	Description
X_i	The binary variables for supplier selection decisions. 1 if supplier i is selected; 0 otherwise
Y_{il}	The binary variables for capacity decisions. 1 if supplier i operates at capacity level l; 0 otherwise
V_{ip}	Global production volume in supplier i and shipped to assembly plant p

The objective function of the model is to minimize the NPV of the total landed cost. The NPV of the total landed cost includes tooling costs, part turnover or part costs (piece price times volume), logistical costs (regular and premium freight cost, packaging cost, duty, inventory holding cost). We use bold face to denote decision vectors to distinguish them from individual decision variables. By defining $a_{il} = \theta_{il} e_i$, and $b_{ip} = R^{-1}\left(c_i e_i + f_{ip} + \delta_{ip} c_i e_i h/365 + c_i e_i \eta_{ip}\right)$, and $R = \sum_{t \in T} (1 + r_t)^t$, the formulation of the total landed cost NPV model is as follows:

$$\min_{\mathbf{X},\mathbf{Y} \in \{0,1\}; \mathbf{V} \in \Re^+} \left(\sum_{i \in I} \sum_{l \in L_i} a_{il} Y_{il} \right) + \left(\sum_{i \in I} \sum_{p \in P} b_{ip} V_{ip} \right) \tag{2.1}$$

subject to:

$$\sum_{i \in I} X_i \leq n \tag{2.2}$$

$$\sum_{l \in L_i} Y_{il} \leq X_i, \quad \forall i \in I \tag{2.3}$$

$$\sum_{i \in I} V_{ip} \geq d_p, \quad \forall p \in P \tag{2.4}$$

$$\sum_{p \in P} V_{ip} \leq \sum_{l \in L_i} \psi_{il} Y_{il}, \quad \forall i \in I \tag{2.5}$$

The objective function (2.1) minimizes the NPV of the total landed cost with discount rate r_t in each period $t \in T$. Constraints (2.2) stipulate that the number of selected suppliers is less than or equal to n. Constraints (2.3) state that each used supplier can be selected for at most one capacity level. Constraints (2.4) ensure that total number of parts produced and shipped to plant $p \in P$ is greater than or equal to its demand. Constraints (2.5) are capacity constraints.

In some countries, especially developing countries, the government imposes minimum Local Content Restrictions (LCRs) for the vehicles assembled there. In this case, a minimum annual capacity level can be considered for each supplier to address the minimum local content issue as follows:

$$\sum_{p \in P} V_{ip} \geq \sum_{l \in L_i} \underline{\psi}_{il} Y_{il}, \quad \forall i \in I \tag{2.6}$$

where $\underline{\psi}_{il}$ represents the minimum annual capacity level at supplier $i \in I$ operating at capacity level $l \in L_i$.

2.3.2. Financial Analysis

After obtaining the optimal sourcing strategy from the NPV of the total landed cost model, a financial analysis is performed to evaluate ROI for capital investment. The information is used for final sourcing decisions. Thus, the actual sourcing strategy may differ from the one recommended by this model.

2.3.3. The Freight Model

One of the challenges of using the NPV of the total landed cost model for optimizing sourcing decisions is to estimate the freight cost of a particular part, because of the complexity in packaging, conveyance used, etc. For a given conveyance type and packaging requirement for a commodity, packing density is determined by either part volume or part weight. Combining packing density and conveyance rate for given origin and destination pairs, we can calculate freight cost per part. Using this technique, the estimated freight costs are proportional to the length of a route and the fuel cost.

2.3.4. Risk Analysis

Although global sourcing can reduce tooling investment, it also brings in higher risks to Ford because of a longer supply chain, and increased currency exchange rate risk. It is important to identify and estimate risks for globally sourced parts to allow balancing of risks and benefits. The objective of estimating risks is to provide decision-makers with quantitative risk information in global sourcing to avoid the potential for taking high-risk sourcing decisions with small gains.

Ford's experts currently identified three sources of uncertainty in their decision making process: (1) Freight cost, (2) Exchange rate, and (3) Demand. The uncertainty in the freight rate (premium freight, inventory obsolescence, delayed shipment, etc.) is taken care of by using a significant uplift factor. The uplift factor is a conservative approach to ensure that the estimations are on the safe side. Since freight costs are a relatively small part of the total landed costs (for the parts considered here), the heavy uplift factor in freight rates has a limited impact on final sourcing decisions, especially when aggressive financial criteria are applied frequently in practice.

Moreover, Ford considers risk in exchange rates. Because the decision here is between global sourcing and regional sourcing, they restrict risk estimates to global sourcing only and assume zero currency risks for region sourcing. In practice, all part prices are converted to USD using projected exchange rates defined by Program Finance. The exchange rates are fixed throughout the sourcing process. Then, they study the effects of different realizations of the exchange rates in their decision making process.

Ford runs simulations to study the effects of up/downlift in global demand and imbalance demand on sourcing decisions. Considering discrete values for different parameters, Ford considers the sensitivity of the sourcing decisions with regard to different realizations of the parameters through a scenario generation process. Designing scenarios in this fashion is very beneficial when the mixed effect of parameters is considered.

2.3.5. Drawbacks of the Current Approach

Ford's current approach consists of single point estimations/forecasts of the input parameters from other sections, optimizing a deterministic model, and analyzing the sensitivity of the decisions through designed scenarios and finalizing them through their financial analysis process. Although this process is fairly straightforward, there are a number of important limitations associated with this approach. First, the one-point estimation of inputs threatens both the optimality and feasibility of the sourcing decisions much of the time.

Planning against one future scenario is naive. This is one reason Ford's experts designed alternative future scenarios. However, this process is manual and they lack a systematic approach to study the effect of multiple plausible future scenarios in their decision process. Another drawback of their approach is that it is not clear how robust the obtained sourcing decisions are with respect to perturbations in uncertain parameters.

Finally, the current approach cannot determine their quality of service, expected unmet demand, and expected costs. A more systematic approach will enable them to consider all possible scenarios (instead of a subset of plausible future scenarios), the behavior of the uncertain parameters simultaneously (as opposed to sensitivity analysis in which one single parameter is studied at the time), the trade-off between unmet demand and tooling expenditures and the robustness of the decisions (instead of one decision from the optimization model and analyze it through an accepting/rejecting process).

2.4. Our Approach: A Scenario-based Stochastic Programming Model

Ford's SCN was described in the previous sections. In a two-year research engagement project with Ford, we addressed the issue of uncertainty in their demand, exchange rates, and freight costs parameters by designing a scenario-based stochastic programming model. Our approach enabled Ford to plan for many alternative future scenarios, incorporate uncertainties into their decision making process, assess the robustness of their decisions, and analyze the tradeoff between their unmet demand and tooling expenditures.

Most decisions in supply chains are demand-driven. The demand parameters are uncertain much of the time due to instability in demand, inexact demand forecasts, or seasonality effects. Environmental uncertainties including changes in the regulatory and macroeconomic environment can also affect the parameters of the supply chain models. Exchange rates or fuel costs are two well-known examples of this type of uncertainty. Here we assume unknown-but-bounded uncertainty for these parameters. The joint distribution of the uncertain parameters is known. We use bold face to denote random variables (random vectors) to distinguish them from their particular realizations. In particular, $(\boldsymbol{f}, \boldsymbol{e}, \boldsymbol{d})$ represents the random data vector for freight costs, exchange rates, and demands parameters. The new objective function is to minimize the sum of tooling costs (deterministic) and the expected future purchasing and logistic costs. Given demand uncertainty, it may be impossible to meet the demand for certain realizations, we include an additional variable for the unmet demand represented by τ_p for demand region $p \in P$.

2.4.1. The Stochastic NPV of the Total Landed Cost Model

To model the stochastic version of the NPV of the total landed cost model, we use two-stage stochastic programming. In the first stage, the model makes supplier and capacity decisions. These decisions are sent to the second stage which evaluates the first stage decisions with respect to all possible realizations of the uncertain parameters $\boldsymbol{f}$, $\boldsymbol{e}$ and $\boldsymbol{d}$. The second stage of the model minimizes the purchasing and logistic costs for each realization, while the first stage of the models minimizes the tooling costs and the *expected* purchasing and logistic costs over all possible realizations. Furthermore, we restrict the unmet demand over all possible scenarios to a fraction of the total expected demand. Here we superscript each scenario with $w \in W$ and W is the set of all possible scenarios. The formulation of the stochastic NPV of the total landed cost model is as follows:

$$(1st - stage)$$

$$\min_{\mathbf{X},\mathbf{Y} \in \{0,1\}} \left(\sum_{i \in I} \sum_{l \in L_i} a_{il} Y_{il} \right) + E_w \left[\mathcal{Q}(\boldsymbol{Y}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) \right] \tag{2.7}$$

subject to:

$$\sum_{i \in I} X_i \leq n \tag{2.8}$$

$$\sum_{l \in L_i} Y_{il} \leq X_i, \quad \forall i \in I \tag{2.9}$$

$$(2nd - stage)$$

$$\mathcal{Q}(\boldsymbol{Y}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) = \min_{\boldsymbol{V^w}, \boldsymbol{\tau^w} \in \Re^+} \left(\sum_{i \in I} \sum_{p \in P} b_{ip}^w V_{ip}^w \right) \tag{2.10}$$

subject to:

$$\sum_{i \in I} V_{ip}^w + \tau_p^w \geq d_p^w, \quad \forall p \in P, w \in W \tag{2.11}$$

$$\sum_{w \in W} Pr^w \sum_{p \in P} \tau_p^w \leq \gamma E_w \left[\sum_{p \in P} d_p^w \right] \tag{2.12}$$

$$\frac{\tau_p^w}{d_p^w} \leq \varphi \sum_{p \in P} \frac{\tau_p^w}{d_p^w}, \quad \forall p \in P, w \in W \tag{2.13}$$

$$\sum_{p \in P} V_{ip}^w \leq \sum_{l \in L_i} \psi_{il} Y_{il}, \quad \forall i \in I, w \in W \tag{2.14}$$

where Pr^w and $E_w(.)$ represent the probability of the scenario w, and expected value over all the scenarios in Wm, respectively. Furthermore, γ is the maximum allowed percent of expected unmet demand and φ is the equity parameter. The equity parameter ensures that the distribution of the unmet demand is fair among all demand regions based on their demand. This constraint is necessary since the model tends to source to demand regions with lower transportation costs and ignores the demand of regions with higher transportation costs. In scenarios with positive unmet demands, the equity parameter establishes a fair distribution of parts among all demand regions proportional to the demand of that region, while in other scenarios this constraint does not add any restriction. A reasonable choice of φ is $\varphi = \frac{1}{|P|}$ and the $|.|$ operator shows the size of a set.

Constraints (2.11) ensure that total number of parts produced and shipped to plant $p \in P$ in addition to the unmet demand at the same plant is greater than or equal to its demand. Constraint (2.12) guarantees that the expected total unmet demand is less than or equal to the expected total demand. Constraints (2.13) are equity constraints to avoid imbalanced unmet demand over demand regions.

Furthermore, Constraints (2.12) and (2.14) guarantees $\mathcal{Q}(\boldsymbol{Y}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) < \infty$ and the non-negativity constraints and non-negative nature of the input parameters makes $\mathcal{Q}(\boldsymbol{Y}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) \geq 0$. Therefore, the objective function is finite valued and its expected value is well-defined.

2.4.2. Curse of Dimensionality

The complexity in solving the stochastic model comes from taking the expected value functions. In particular, the expected value of the second stage objective function for a given set of suppliers and capacity levels ($\boldsymbol{Y}$) involves solving a large number of linear programs for discrete distributions. This phenomenon is known as the *Curse of Dimensionality.*

To overcome this difficulty, data-driven approximation methods have been developed to solve the model with fewer scenarios [20]. These methods are divided into two broad groups: scenario generation and scenario reduction. Scenario generation methods generate a subset of scenarios and solve the model optimally for that subset. The most famous method in this group is called Sample Average Approximation (SAA) technique. In SAA, we generate a subset of scenarios randomly and solve the model for the randomly generated subset of scenarios. Kleywegt et al. [51] proved that by repeating this experiment for a predetermined number of iterations, the decisions variables and objective function go to the optimal decisions and optimal objective value on average. The other techniques in this category are Moment Matching Problem (MMP) or Distribution Matching Problem (DMP) in which we try to preserve the moments of the distribution of the uncertain parameters or their cumulative distribution function [20].

The second category of approximations is scenario reduction techniques in which we try to reduce the number of scenarios. The most well-known technique in this category is Stochastic Dynamic Programming (SDP) that eliminates the scenarios in multi-stage stochastic models by going backward through the different stages in the model [20]. Another heuristic scenario reduction technique tries to preserve the margins of the distribution functions of the uncertain parameters [50].

2.4.3. Sample Average Approximation (SAA)

Consider the stochastic model formulated above. Assuming discrete possible values for the uncertain parameters, the number of possible realizations is finite. However, this number will grow exponentially with the number of uncertain parameters in the model. The SAA is a Monte Carlo simulation-based approach to stochastic discrete optimization problems. The basic idea of such methods is that a random sample is generated and the expected value function is approximated by the corresponding sample average function. The sample average optimization problem is solved, and the procedure is repeated several times until a stopping criterion is satisfied.

Consider $\mathcal{Q}(\boldsymbol{Y}, w)$ to be the objective function of the stochastic problem under the realization of scenario $w = (\boldsymbol{f}, \boldsymbol{e}, \boldsymbol{d})$. Therefore, $\mathcal{Q}(\boldsymbol{Y}, w)$ is a random variable and $\sum_{w \in W} f(w) = 1$ where $f(w)$ is probability mass function for the distribution of w and W is the support. In SAA, a random sample of N realizations $w^1, w^2, \ldots, w^N$ is generated from W. The probability of a w to be selected in the random sample depends on $f(w)$. Then, the objective function of the first stage is approximated by:

$$\hat{Z}^N = \min_{\mathbf{X}, \mathbf{Y} \in \{0,1\}} \left(\sum_{i \in I} \sum_{l \in L_i} a_{il} Y_{il} \right) + \frac{1}{N} \sum_{n=1}^{N} \mathcal{Q}(\boldsymbol{Y}, w^n) \tag{2.15}$$

where N is the sample size and $\hat{Z}^N$ is an approximation of the first stage objective function (total cost). Although $\hat{Z}^N$ and $(\hat{\boldsymbol{X}}^N, \hat{\boldsymbol{Y}}^N)$ are random variables (functions of a random sample), for a particular realization of w the problem is deterministic. The SAA steps to generate a lower bound and an upper bound for the optimal value of the true problem are illustrated in Santoso et al. [76]. We review the SAA steps in here:

Algorithm 1 SAA algorithm for stochastic total landed cost NPV model

1: Generate M independent samples each of size N. w_j^n represents the random sample $n = 1, \dots, N$ for replication $j = 1, \dots, M$.

2: For each sample solve the corresponding SAA problem:

$$\hat{Z}_j^N = \min_{\mathbf{X},\mathbf{Y} \in \{0,1\}} \left(\sum_{i \in I} \sum_{l \in L_i} a_{il} Y_{il} \right) + \frac{1}{N} \sum_{n=1}^{N} \mathcal{Q}(\boldsymbol{Y}, w_j^n)$$

subject to:

$$\sum_{i \in I} X_i \leq n$$

$$\sum_{l \in L_i} Y_{il} \leq X_i, \quad \forall i \in I$$

3: Let $\hat{Z}_j^N$ and $\left(\hat{\boldsymbol{X}}_j^N, \hat{\boldsymbol{Y}}_j^N\right)$ be the corresponding optimal objective value and an optimal solution of the approximation model, respectively. Then, compute the lower bound:

$$\bar{Z}_{LB} = \frac{1}{M} \sum_{j=1}^{M} \hat{Z}_j^N$$

4: Select $\left(\bar{\boldsymbol{X}}, \bar{\boldsymbol{Y}}\right)$ from $\left(\hat{\boldsymbol{X}}_j^N, \hat{\boldsymbol{Y}}_j^N\right)$, $j = 1, \dots, M$ in previous section and estimate the upper bound for $N' >> N$ new samples:

$$\bar{Z}_{UB} = \sum_{i \in I} \sum_{l \in L_i} a_{il} \bar{Y}_{il} + \frac{1}{N'} \sum_{n=1}^{N'} \mathcal{Q}(\bar{\boldsymbol{Y}}, w^n)$$

5: Compute the optimality gap:

$$\text{gap} = \bar{Z}_{UB} - \bar{Z}_{LB}$$

To design an iterative algorithm with a stopping criterion, we can start with smaller values of N and by increasing N gradually, we can improve the optimality gap. The stopping criterion can be met when the $gap \leq \epsilon$ for a solution.

To obtain the tightest upper bound, we can choose:

$$(\bar{\boldsymbol{X}}, \bar{\boldsymbol{Y}}) \leftarrow \arg \min_{j=1}^{M} \left(\sum_{i \in I} \sum_{l \in L_i} a_{il} (\hat{Y}_j)_{il} + \frac{1}{N'} \sum_{n=1}^{N'} \mathcal{Q}(\hat{\boldsymbol{Y}}_{\boldsymbol{j}}, w^n) \right)$$

2.5. Implementation at Ford

In a two-year research engagement with Ford, we studied the effect of uncertainty of demand, exchange rate, and freight cost on their global sourcing strategies (One Ford initiatives). For this study we consider two common parts. Throughout this chapter we refer to them as the LT with lower tooling costs (Low Tooling) and the HT with higher tooling costs (High Tooling). We consider A-E as the demand regions for these parts, since Ford has assembly plants in these locations. For the LT three potential suppliers are considered. We will refer to them as SLT-1-A (located in region A), SLT-2-B (located in region B), and SLT-3-B (located in region B). For the HT part, four potential suppliers are considered: SHT-1-A, SHT-2-B, SHT-3-F (located in a different region than A-E), and SHT-4-E. All other details about the parts and suppliers are removed due to confidentiality concerns. The demand values, suppliers' capacities, and all costs are masked. A production module at each supplier has a capacity of one and demand values are scaled according to the modules' actual capacities.

For the deterministic case we use the 2013 forecasts of demand, exchange rates, and freight costs (one-point estimation). For the stochastic models, we discretize the distribution of the uncertain parameters into a three-point estimation distribution arbitrary. For our set of experiments in this section, we fixed the lower and higher values to be 0.75 and 1.50 times the middle value. According to the historic data obtained from the company, these bounds cover most of the range of previous fluctuations. For comparison purposes, the probabilities are set in a way that the expected values of the uncertain parameters are equal to the value of the middle outcome. The mid-value of probabilities are provided in Tables 2.3 and 2.4. Here we assume perfect correlation among freight costs. In other words, if the fuel cost is high, all freight costs will be realized at their high levels and vice versa. Since different parts can have suppliers in the same country (same currency), it is logical to assume the exchange rate of these suppliers are perfectly correlated. We assume all other uncertain parameters fluctuate independently from each other.

2.5.1. The Impact of Different Sourcing Policies on the Network Structure

In our first set of experiments, we run the deterministic model with the 2013 forecasts of demand, exchange rates, and freight costs. Figures 2.2 and 2.3 present the optimal solution from the model on the Ford's SCN for both parts:

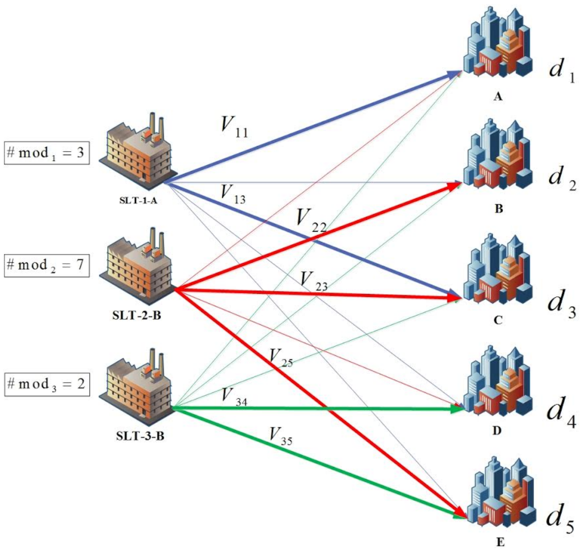

Figure 2.2: LT part

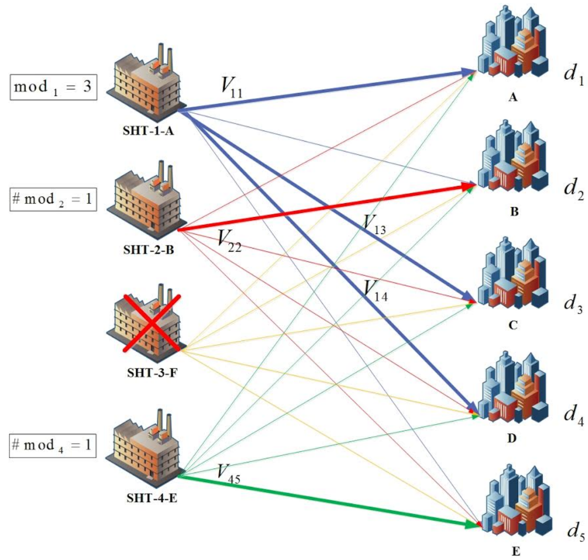

Figure 2.3: HT part

Figures 2.2 and 2.3 show the sourcing decisions from the deterministic model for the LT and HT parts respectively. All suppliers are selected for the LT part. Therefore, we have a 3−region sourcing policy for this part. For the HT part the model did not select the supplier in region F, and therefore, we again have a 3−region sourcing policy. The supplier in region F has the most expensive part cost. The reserved modular capacity for each supplier is written next to the name of supplier. The bold lines show the optimal shipping routes from each supplier. Due to confidentiality concerns, the actual production volumes and demand values are omitted from the plots.

Table 2.2: The impact of different sourcing policies on the network structure

Policy	LT			HT		
	Capacities	Tooling	Total	Capacities	Tooling	Total
1-Global Supplier	$Inf^{\dagger}$	$N/A^{\ddagger}$	N/A	$(4,0,0,0)$	1.16%	100%
2-Region Suppliers	$(3,0,9)$	1.22%	100%	$(3,1,0,0)$	1.21%	97.33%
3-Region Suppliers	$(3,7,2)$	0.99%	99.8%	$(3,1,0,1)$	1.65%	96.01%
4-Region Suppliers	N/A	N/A	N/A	$(3,1,0,1)$	1.65%	96.01%

All costs in Table 2.2 are normalized by the largest cost for each part. Table 2.2 gives us an important insight into the sourcing policies. For the LT (i.e. low tooling) part, the tooling cost is about 1% of the total cost. The model focuses on minimizing production, purchasing and logistic costs rather than tooling costs. In the 3−region policy, the model selected the second supplier with its maximum capacity. This supplier has the second smallest tooling cost per module (very close to the cheapest one) and the second smallest part cost (very close to the cheapest one). The rest of the capacity is divided between the first and third suppliers in manner that the total cost is minimized. In the 2−region policy, we have a more expensive tooling strategy than the 3−region policy. This is due to the fact that the third supplier has the lowest part cost and ordering a large quantity of parts from this supplier compensates for its more expensive tooling cost. For HT (i.e. high tooling), the tooling cost is around 2% of the total cost. The model never selected the most expensive supplier in terms of part cost (the third supplier). The first supplier has the cheapest tooling and part costs, therefore, the model selected three modules from the first supplier. The last supplier has the most expensive tooling and second cheapest part cost. Thus, in the 4−region and 3−region policies the model selected one module from the last supplier and one module from the second supplier (second cheapest tooling and part costs) to minimize the total cost. Finally, for 1−global supplier, the model selected the first supplier with the maximum capacity, since it has the cheapest tooling and part costs.

2.5.2. The Impact of Uncertainty on Sourcing Decisions

In this section, we report on the impact of imperfect knowledge of some input parameters on the tooling and sourcing decisions. In particular, we are interested in the impact of demand uncertainty (*Demand Model*), exchange rate uncertainty (*Exchange Rate Model*), freight cost uncertainty (*Freight Cost Model*), and the combined impact of all three sources of uncertainty simultaneously (*Full Model*). Similar to the previous section, we use the 3−point discrete distribution for the uncertain parameters in which the estimations of the low and high values are equal to 0.75 and 1.50 times the middle value respectively (*Base Case*). Again, similar to the previous section, the probabilities are set in a way that the expected values of the uncertain parameters are equal to the value of the middle outcome. The selected ranges of the uncertain parameters and their probability distributions are presented in table 2.3.

Table 2.3: The estimates of the uncertain parameters and their probability distributions for the Base Case

Parameters		Values			Probabilities		
		Low	**Med.**	**High**	**Low**	**Med.**	**High**
Demand	**A**	75%	100%	150%	0.133	0.8	0.067
	B	75%	100%	150%	0.2	0.7	0.1
	C	75%	100%	150%	0.133	0.8	0.067
	D	75%	100%	150%	0.2	0.7	0.1
	E	75%	100%	150%	0.2	0.7	0.1
Exchange Rate	**A**	75%	100%	150%	0.2	0.7	0.1
	B	75%	100%	150%	0.133	0.8	0.067
	C	75%	100%	150%	0.133	0.8	0.067
	D	75%	100%	150%	0.133	0.8	0.067
	E	75%	100%	150%	0.133	0.8	0.067
	F	75%	100%	150%	0.133	0.8	0.067
Freight Cost	**Oil**	75%	100%	110%	0.133	0.8	0.067

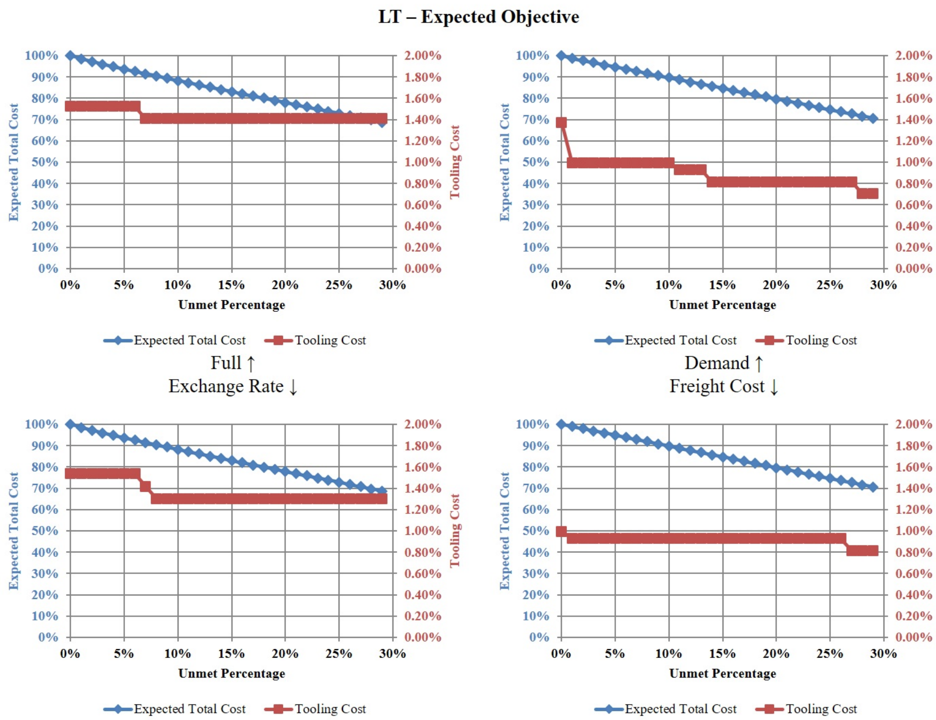

Figure 2.4: The total cost vs. tooling cost for four different models with base case uncertainty level

Figure 2.4 illustrates the relationship between total cost and tooling cost for different values of unmet demand (γ). The unmet demand parameter can be interpreted as the quality of service Ford intends to provide to their customers around the world. Increasing the unmet percentage leads to a drop in both total and tooling costs. However, the most important observation from these graphs is that the exchange rate uncertainty dominates other sources of uncertainty in the model. This is why the graphs for the full and exchange rate models are very similar. All numbers are normalized by the largest cost. The optimal capacity decisions under different settings are illustrated in Figure 2.5.

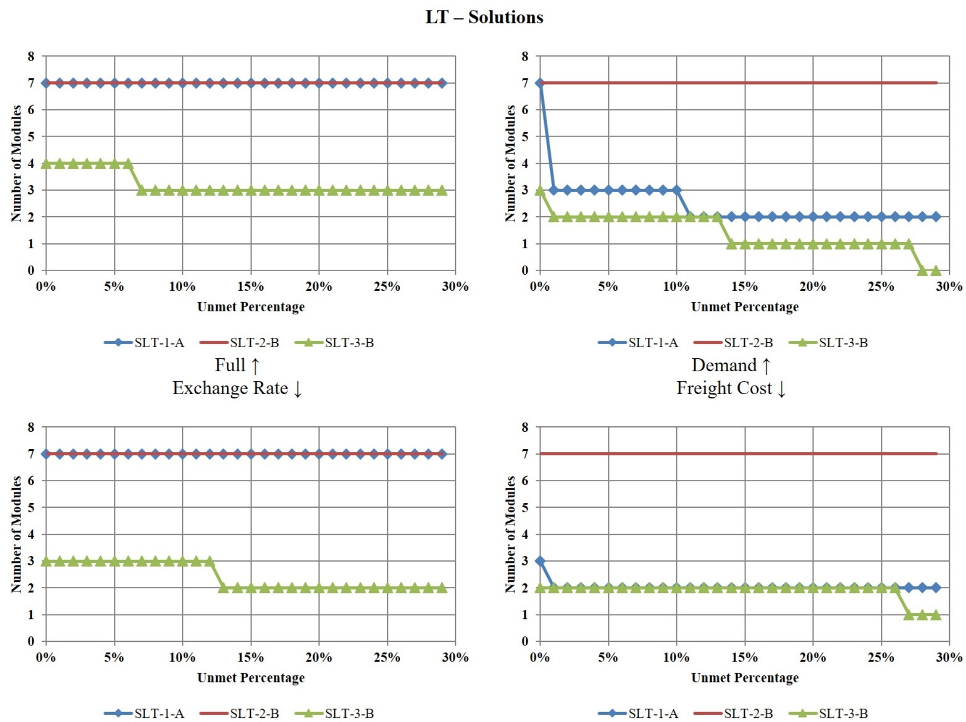

Figure 2.5: The capacity decisions for four different models with base case uncertainty level

There are two important observations related to these graphs. The most important is that the model tends to add extra capacity to hedge against uncertainty. In other words, the idle capacity can be used to create flexibility in the structure of the network. This is as opposed to holding inventory which is not a feasible strategy in the automotive industry. Furthermore, the optimal overall capacity with full uncertainty exceeds optimal capacity from the deterministic model. In other words, the optimal capacity decisions from the deterministic model are infeasible for some realizations of the uncertain parameters, particularly for lower values of the unmet demand percentage. Finally, we can observe that the capacity decisions from deterministic model are optimal in the demand model for unmet demand percentages between $1\% - 10\%$.

Reduced Exchange Rate uncertainty

The dominant effect of exchange rate uncertainty makes us believe the base case uncertainty level (0.75 low and 1.50 high) may mask the effect of other types of uncertainty in the decision making process. Therefore, we designed another set of experiments with reduced exchange rate uncertainty to study the behavior of the optimal capacity decisions from the stochastic model. We reduced the range of the exchange rate distributions to 0.90 and 1.15 times of the middle value (*Reduced Exchange Rate*). Below, we only focus on the Full model and the new ranges of the exchange rates and their probability distributions are provided in table 2.4

Table 2.4: The new ranges of the exchange rates and their probability distributions

Parameters		**Values**			**Probabilities**		
		Low	**Med.**	**High**	**Low**	**Med.**	**High**
Exchange Rate	**A**	90%	100%	115%	0.18	0.7	0.12
	B	90%	100%	115%	0.12	0.8	0.08
	C	90%	100%	115%	0.12	0.8	0.08
	D	90%	100%	115%	0.12	0.8	0.08
	E	90%	100%	115%	0.12	0.8	0.08
	F	90%	100%	115%	0.12	0.8	0.08

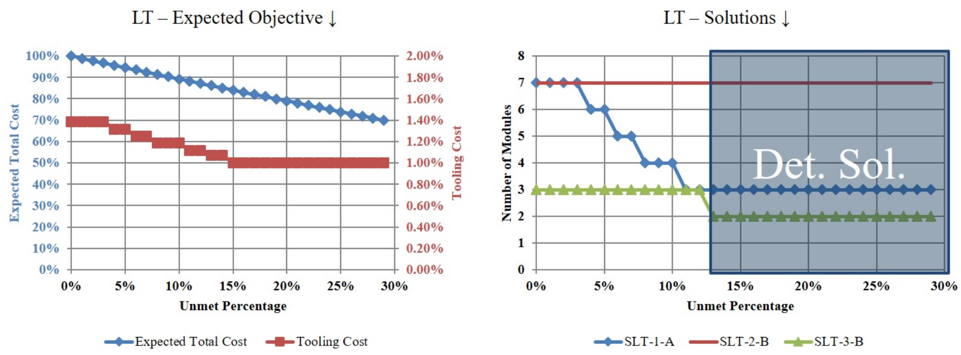

Figure 2.6: The objective and capacity decisions for full model with reduced uncertainty level

Based on the results of our experiments shown in Figure 2.6, more alternative solutions appeared after reducing the effect of the range of exchange rate uncertainty. The optimal capacity decisions introduced by the stochastic model converge to the deterministic solution for large values of the unmet demand percentage. If Ford sets its unmet demand percentage (quality of service) to high values, it seems the deterministic model is sufficient under reduced uncertainty levels for the uncertain parameters, especially the exchange rate. Finally, decreasing the unmet demand percentage leads to the use of local suppliers.

An interesting statistic for the obtained capacity solutions is the distribution of the unmet demand (under production):

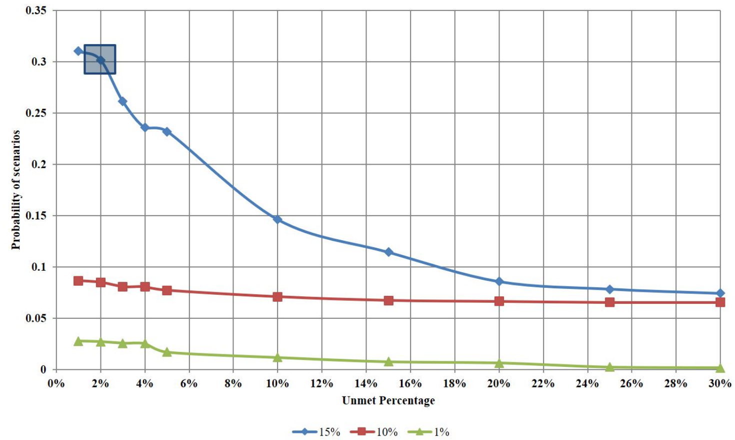

Figure 2.7: The distribution of the unmet demand for the full Model with $\gamma = 1, 10, 15\%$

Every point in figure 2.7 can be interpreted as the probability of having at least $X\%$ unmet demand by solving the model for different values of expected unmet demand (γ). The expected unmet demand parameter is fixed in the model and then we solve the model for optimal sourcing decisions. Then, we find the probability of scenarios in which we have at least $X\%$ unmet demand. For example, the highlighted point in this figure shows fixing the optimal capacity decisions for 15% unmet demand, leaves 30% probability of having 2% *expected* unmet demand or more. This probability decays as we increase the expected unmet percentage. Similarly, we can observe that fixing the unmet percentage parameter γ at lower levels, gives more conservative solutions. This is true because lower values of unmet demand lead to overcapacity tooling and more flexibility for future perturbations in the design parameters of the model. Finally, we ran the same experiments with the high tooling part (HT). Again, we only focus on the full model.

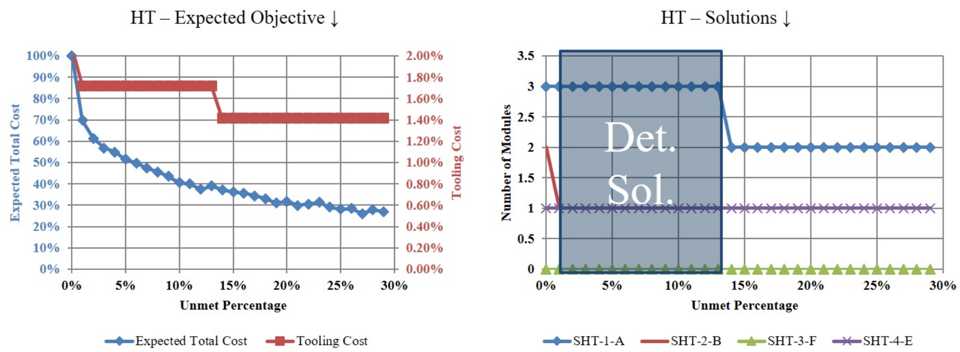

Figure 2.8: The objective and capacity decisions from the SAA for the full model with reduced uncertainty level

There is one major difference between this part and the LT. Because the size of the problem increased (for the LT we have $3^8 = 6,561$ scenarios and for the HT we have $3^{10} = 59,049$ scenarios), we cannot enumerate all the scenarios and solve the problem in a timely manner using CPLEX. For these experiments we used a personal computer with an Intel(R) Xeon(R) 2.80 Hz CPU and 32.0 GBs of RAM. Thus, we need to use the SAA scheme. We have tuned the SAA for this problem following the procedure described in previous section (the number of replications is set to 10 and the number of samples ranges between 5000 to 10000 for different experiments). As we can see in the left graph of figure 2.8 the convex form of the total cost is due to the fact that the SAA estimator of the expected cost is a lower bound of the true cost. For this part, the deterministic solution performs better, especially for lower levels of the unmet demand percentage.

Higher Tooling Costs

To study the impact of tooling costs on the capacity decisions, we increased the tooling costs for the low tooling cost part to five times their original values (*Higher Tooling*). These experiments give us the capability to compare the capacity decisions with previous sections for the low tooling part.

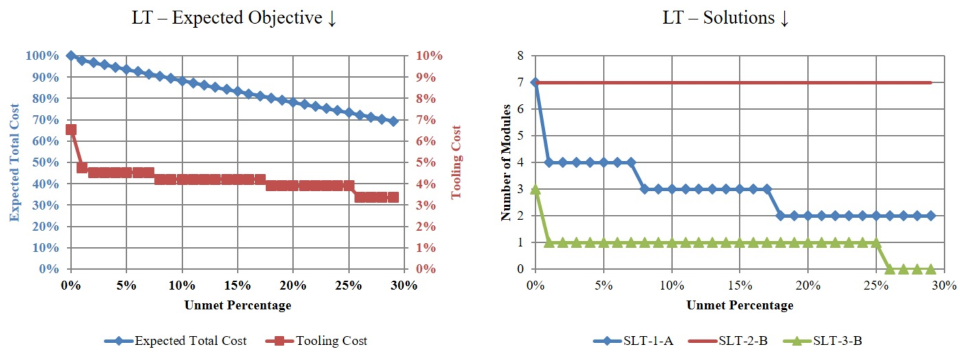

Figure 2.9: The objective and capacity decisions for full model with high tooling cost

Figure 2.9 suggests the total number of suppliers drops faster for higher tooling costs. Thus, tooling is only added when it is absolutely needed. We can conclude that as the tooling costs increase, the extra idle reserved capacity drops.

Comparisons and Discussions

In this section we compare the capacity decisions resulting from different uncertainty and cost input conditions for the low tooling cost part (LT). In figure 2.10 (left), we compare the different capacity decisions for the base case uncertainty level, reduced exchange rate uncertainty case, and the higher tooling cost case for the full model. In figure 2.10 (right), we compare the capacity decisions of different models in terms of the uncertain parameters (demand, exchange rate, freight cost, and full models).

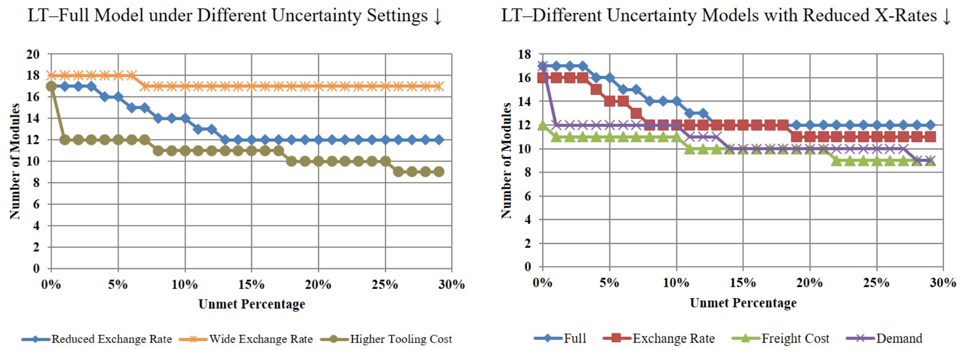

Figure 2.10: Comparisons of capacity decisions among different uncertainty settings and models

The graph on the left shows that the model with higher tooling cost (purple) uses a lower total number of modules (capacity) than do the other two cases. This fact is similar to our previous experiments: tooling is only added when it is absolutely needed when tooling costs are high. The graph on the right illustrates that we need more idle capacity to hedge against several sources of uncertainty (blue). Finally, we can clearly see exchange rate uncertainty drives localization of suppliers more than other sources of the uncertainty.

2.6. Realized Benefits for Ford

In the previous section, we used Ford's 2013 forecasts of demand, exchange rates, and freight costs. These forecasts are made three years in advance. In this section, we compare the forecasts vs. actual realizations of the uncertain parameters and highlight the realized benefits of our approach compared to Ford's previous approach. In particular, we are interested in the actual realized demands at these five demand regions and to follow the trends of exchange rates and freight cost since 2013.

2.6.1. Actual Realizations in 2016 vs. 2013 Forecasts for 2016

In this section we show how accurate the point estimations of the uncertain parameters are and how risky it is to use these estimates in the deterministic model. First, we look at the actual realized demands at the five different demand regions. The actual values are disguised due to confidentiality concerns. We used the demand data for LT. Figure 2.11 depicts the demand forecasts and actual demand realizations in 2013 and 2016 as polyhedrons. The forecasts for regions A and B are accurate but in other cases they are far from the actual values. The inexact forecasts (especially in the region C) can be due to a variety of reasons including changes in the vehicle designs, transportation difficulties, and fluctuations of the exchange rates rates, and freight costs.

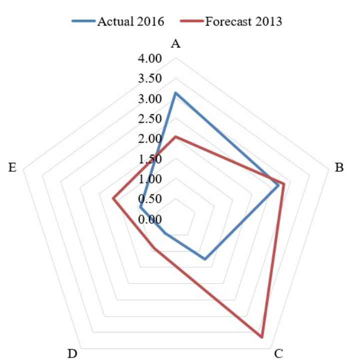

Figure 2.11: Demand Forecasts vs. Actual Realizations

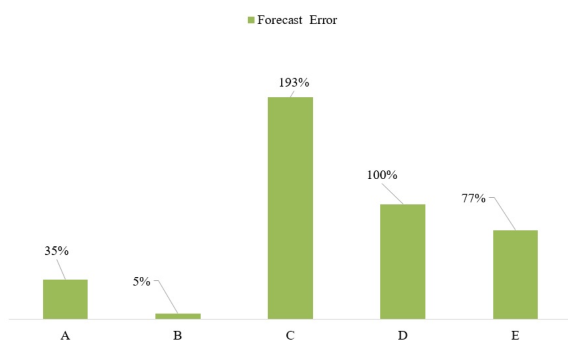

Figure 2.12: Demand Forecasts Errors

Figure 2.12 shows the relative demand errors. The interesting cases are the 35% lost opportunities for Ford in region A and 193% and 77% excess capacity in the regions C and E. Finally, it is worth noting that in 2013 Ford overestimated the total demand for this part by 31%.

For exchange rates and freight costs we used the monthly data of the relevant currencies (currencies for regions A-E) and the oil price by barrel of a specific oil company.

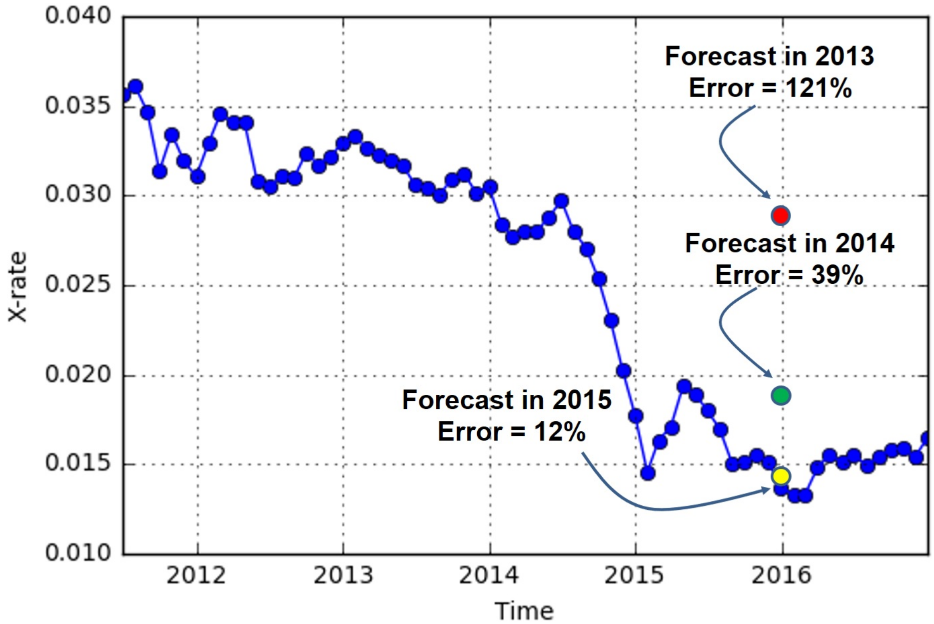

Figure 2.13: Forecasts vs. Actual Realizations of X-rate for region D

Figure 2.13 illustrates the monthly exchange rate value of the region D currency to the USD from 2012 to the end of 2016. Ford's forecasts in 2013-15 are added by red, green, and yellow dots. The 2013 forecasts were off by 121%, although the accuracy improved in the following years.

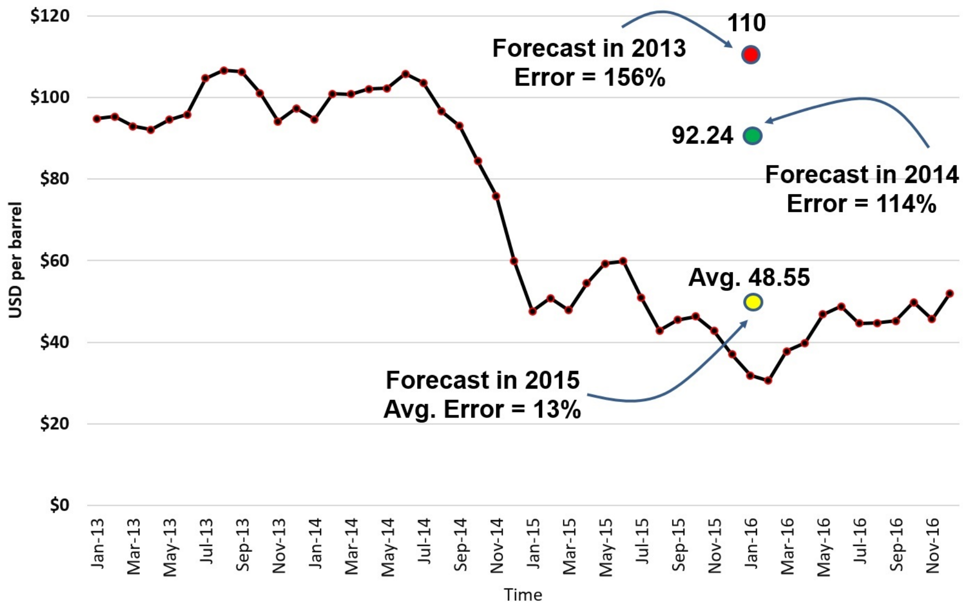

Figure 2.14: Oil Price Forecasts vs. Actual Realizations

Figure 2.14 shows the oil price forecasts over time. Again, Ford's forecast for 2016 were significantly higher than the realized values.

In summary, Ford's forecasts in 2013 were off by $5\% - 193\%$ for demand, $12\% - 121\%$ for exchange rates, and on average 156% for fuel cost. Ford overestimated the total demand by 31%. The results of this analysis show the inadequacy of the current practice considering the inexact forecasts.

2.6.2. Methods for Estimating the Distribution of Uncertain Parameters

In this section we discuss methods by which Ford can estimate the distributions of the uncertain parameters in the optimization model:

- If we know the distribution, sampling from the distribution and generating scenarios is a good approach.

- If we have limited historic data, we can form an $n - point$ discrete distribution. In this study we used a $3 - point$ distribution for all parameters due to limited information. It is easier to understand the $3 - point$ estimation of the uncertain parameters, since we can interpret them as low, medium, and high realizations of the parameters.

Finally, to have interpretable results, we suggest setting the expected value of the distributions to the middle value. This way, we can more easily compare the results of the stochastic model with the deterministic models. To do that, we need some estimates of the low and high values for the $3 - point$ estimations distributions and then need to estimate their probabilities.

Methods for Estimating Low and High Values

For the $3 - point$ distribution, we set the middle value to the expected value of the forecast parameters. Due to the sensitivity of the outputs of the model to the range of the uncertain parameters, in particular the exchange rate uncertainty (discussed in previous sections), we need the tightest possible estimates for the low and high values of the distributions. Since we have very limited information for demand parameters, we propose using a *wide* range to model demand uncertainty. Our proposed *wide* range is 50% of the middle value for the low value and 150% of the middle value for the high value. For exchange rates and fuel cost, since we have monthly information, we can follow their trends and suggest a tighter range for uncertainty. In this chapter, we suggest 80% of the middle value for the low value and 150% of the middle value for the high value for *increasing* trends, 50% of the middle value for the low value and 110% of the middle value for the high value for *decreasing* trends, 80% of the middle value for the low value and 110% of the middle value for the high value for *stable* trends, and 50% of the middle value for the low value and 150% of the middle value for the high value for *wild* fluctuations with no trend. For example, Figure 2.15 depicts the trend of the currency in region A from 2012 to 2016. The actual realizations during 2012 show a very mild decreasing trend, therefore, we can use the *stable* uncertainty range for the exchange rate of region A.

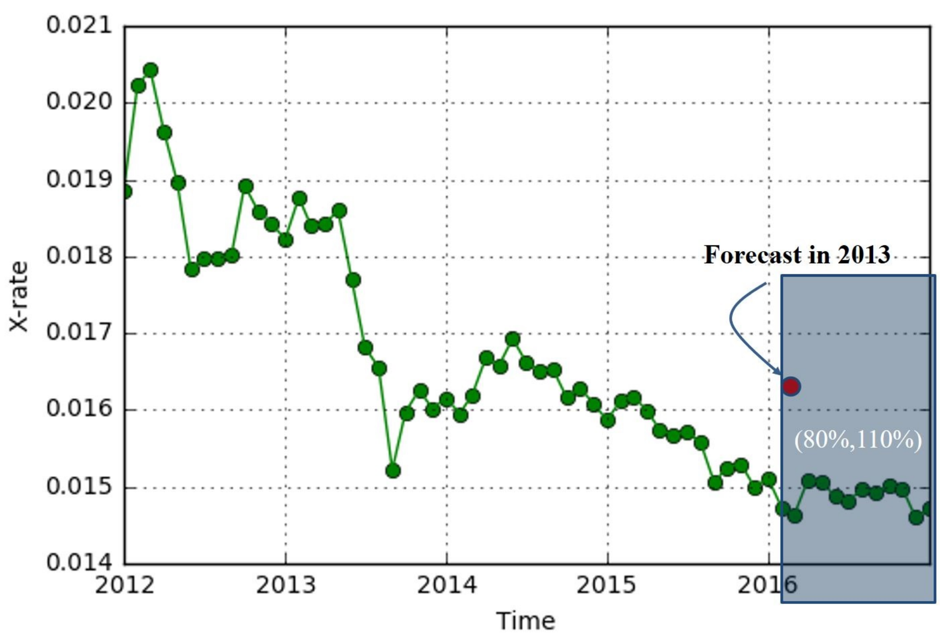

Figure 2.15: The actual realizations of the currency in region A over time

It is worth noting that although the 2013 forecast of the currency in region A for 2016 is slightly higher than the actual realization, the 2016 realizations are in fact inside the 80% to 110% range.

2.6.3. Comparisons with Deterministic Models

The deterministic model was introduced in section 3.1. We compare the results of the full model with 2013 forecasts of demand, exchange rates, and freights costs (*Det. 2013*) with the 2016 actual realizations of these parameters (*Det. 2016*). Finally, we compare the optimal capacity decisions for these two settings with Ford's actual implementation (*Act. 2016*). The actual capacity decisions are different from the optimal ones. This is due to the fact that the optimal decisions are evaluated and modified by financial criteria and sensitivity analysis at Ford. The chosen ranges for the uncertain parameters in the stochastic model are presented in table A.2.

Table 2.5: The selected ranges of the uncertain parameters for the stochastic model and their probabilities

Parameters		Values			Probabilities		
		Low	**Med.**	**High**	**Low**	**Med.**	**High**
Demand	**A**	50%	100%	150%	0.1	0.8	0.1
	B	50%	100%	150%	0.05	0.9	0.05
	C	50%	100%	150%	0.15	0.7	0.15
	D	50%	100%	150%	0.05	0.9	0.05
	E	50%	100%	150%	0.05	0.9	0.05
Exchange Rate	**A**	80%	100%	110%	0.033	0.9	0.067
	B	80%	100%	150%	0.214	0.7	0.086
	C	50%	100%	110%	0.017	0.9	0.083
	D	50%	100%	110%	0.017	0.9	0.083
	E	50%	100%	110%	0.017	0.9	0.083
	F	80%	100%	150%	0.214	0.7	0.086
Freight Cost	**Oil**	50%	100%	110%	0.033	0.8	0.167

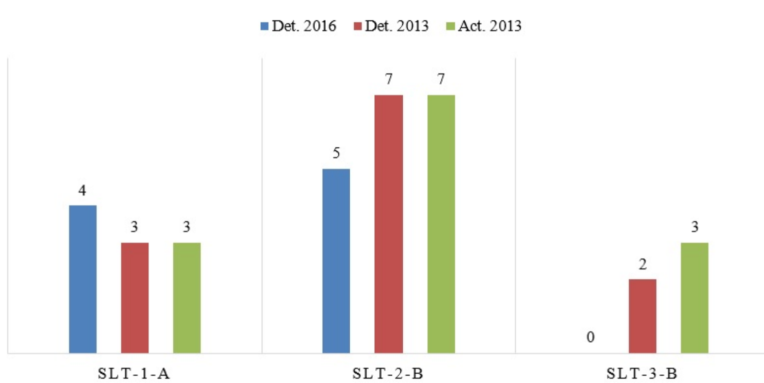

Figure 2.16: Tooling comparison for different settings of the deterministic model

In Figure 2.16, the bars represent the number of modules in three different settings. The optimal tooling for the *Det. 2016* case uses 4 modules in region A and 5 modules in region B, if we knew the actual realizations. In particular, the total realized demand is 30% less than the forecast demand in 2013. Thus, we only need 9 modules instead of 12. Furthermore, Ford's actual implementation used 13 modules.

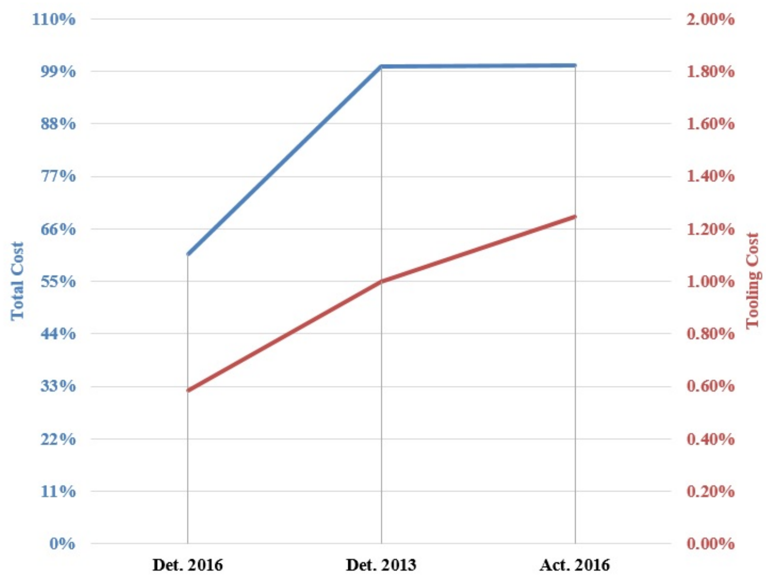

Figure 2.17: Total cost and the tooling cost for different settings of the deterministic model

Figure 2.17 shows the total cost and the tooling cost for three different settings. Numbers are all normalized by the total cost in *Det. 2013* models. If we knew the actual realizations, we could have reduced the total cost for %39. However, we can see Ford's strategy was to increase the tooling cost for a part with low tooling cost, but decrease the freight cost. In this manner, the total cost remains about the same as the *Det. 2013*. The reasoning behind this decision might be complex (due to other layers of decision making at Ford such as financial criteria), but we can see its effect on tooling and total cost. Similarly, for the high tooling cost part, we have the following comparisons.

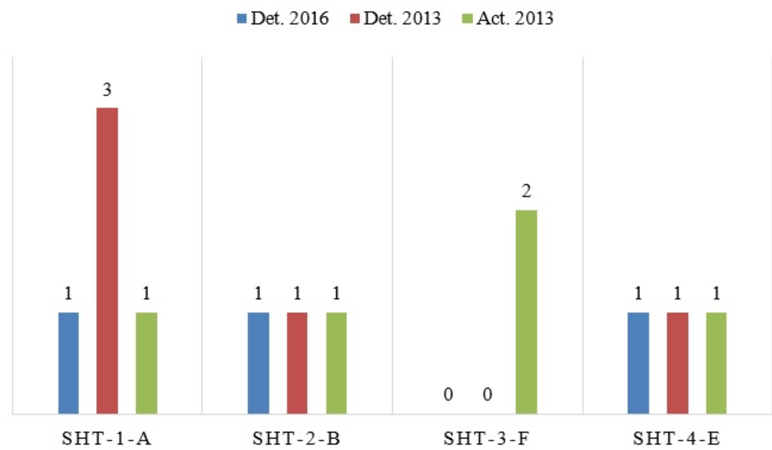

Figure 2.18: Tooling comparison for different settings of the deterministic model

Figure 2.18 shows that Ford decided to equip the third supplier in region F with two modules, although the *Det. 2013* model recommended otherwise. This supplier has the most expensive part cost; however, it has the second cheapest tooling cost.

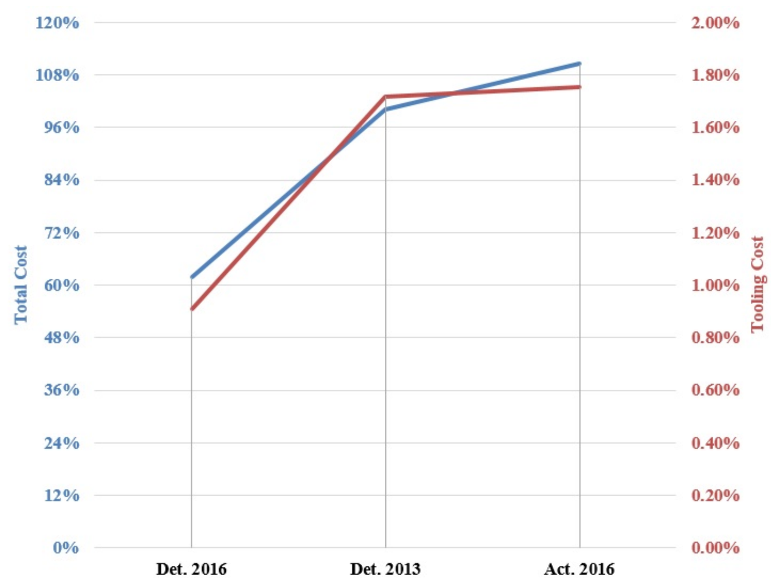

Figure 2.19: Total cost and the tooling cost for different settings of the deterministic model

Figure 2.19 also suggests Ford's strategy for this part was to spend more money to move the capacity to region F (higher total cost, same tooling cost). Shipping difficulties might have been the reason behind this decision for the HT part.

2.6.4. Comparison of the Stochastic and Deterministic Models

In this section we compare the capacity decisions and costs obtained from the stochastic approach (*Stoch. 2013*) with the *Det. 2013* and *Det. 2016* models. To do these comparisons, first we run the stochastic model over all possible scenarios (or selected scenarios in the SAA scheme) to find the optimal total and tooling costs when demand, exchange rates, and freight costs are uncertain. Although we have abundant data for exchange rates and fuel costs, fitting a distribution might be impossible since the behavior of these parameters change over time. We used the the $3-point$ estimates for the uncertain parameters with low, medium, and high values for each. This is due to the fact that we only have very limited historic data for demand. Next, we compare the optimal tooling and total costs of the stochastic models with the tooling and total costs of the stochastic model with fixed capacity decisions to the optimal values in *Det. 2013* and *Det. 2016* models. In this way, we can show how much better our proposed approach (stochastic) does than what Ford was doing traditionally (*Saving from Det. 2013*) and how much we are off from the optimal decisions knowing all the realizations (*Cost of Uncertainty from Det. 2016*).

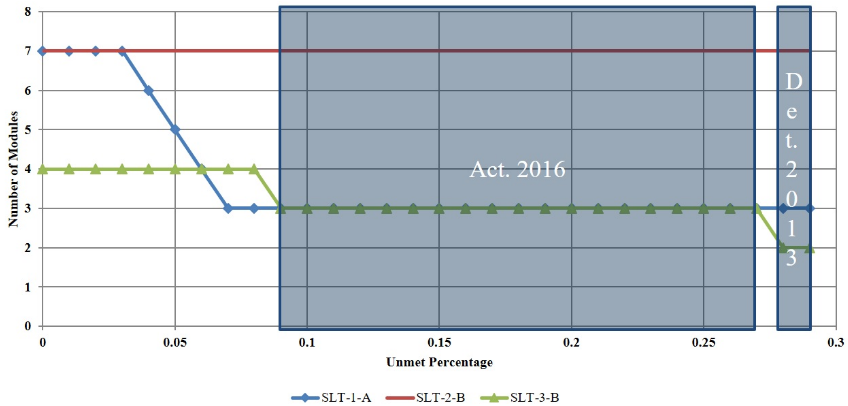

Figure 2.20: Comparisons of capacity decisions between stochastic and deterministic models for LT

Figure 2.20 compares the optimal capacity decisions from the stochastic model with those of the optimal capacity decisions from *Det. 2013* and *Act. 2016* models. 12 modules are selected in the *Det. 2013* setting while 13 modules were implemented in *Act. 2016*. Ford can guarantee an optimal sourcing for the expected value of at least 28% under *Det. 2013* and at least 9% under *Act. 2016*. Ford can serve even more demand (less unmet demand) but at higher costs than optimal. It is worth mentioning that due to low realizations of the demand parameters, we only needed 9 modules to satisfy all demand. However, this is only one possible realization from numerous others we are considering in the stochastic models.

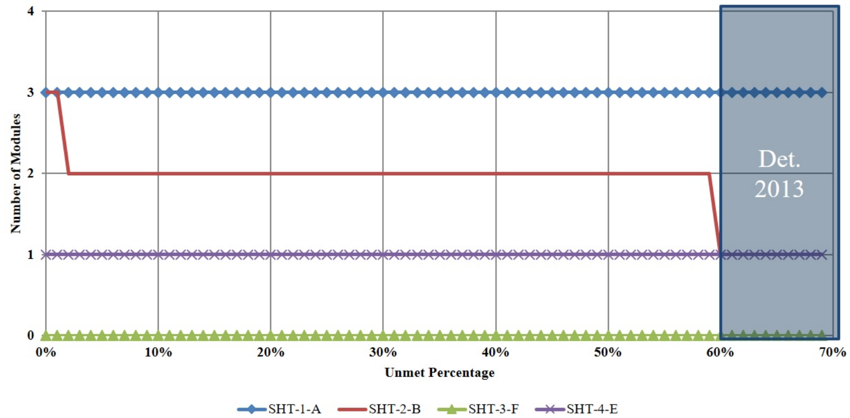

Figure 2.21: Comparisons of capacity decisions between stochastic and deterministic models for HT

For the high tooling cost part, Figure 2.21 shows that the decisions obtained from *Det. 2013* are optimal, only if Ford considers 60% unmet demand or more, although lower unmet demand is possible at higher cost than optimal. It is worth noting that the capacity decisions from the *Act. 2016* are $(1, 1, 2, 1)$. In terms of total capacity this solution is similar to any other solution with 5 production modules. Therefore, we can conclude that Ford's strategy for this part was to move their capacity to a more expensive supplier due to other considerations from their financial criteria or excessive transportation costs for this part. Next, we fix the capacity decisions from the *Det. 2013* and *Det. 2016* models and compare the expected costs with the expected costs obtained from the *Stoch. 2013* model. Figures 2.22 and 2.23 illustrate the *Saving* and *Cost of Uncertainty* of the stochastic model in compare to the two settings for the LT part:

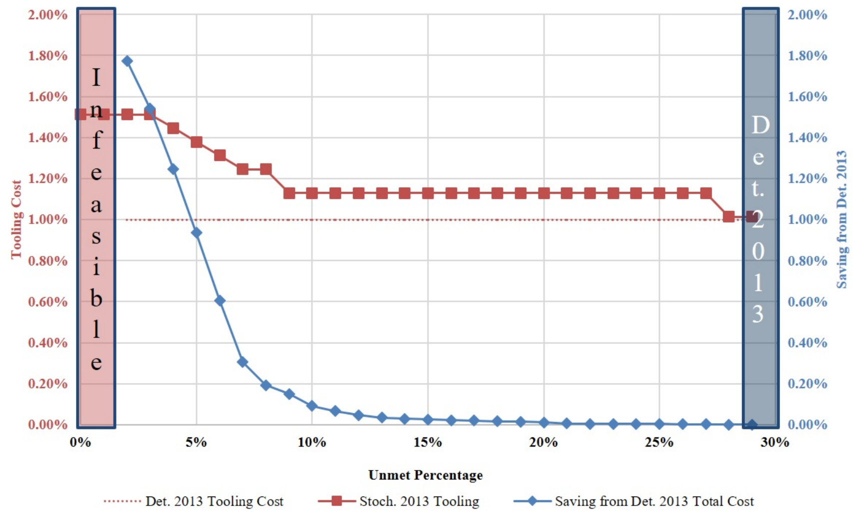

Figure 2.22: Savings from *Stoch. 2013* compared to *Det. 2013*

In figure 2.22 the tooling cost of the *Stoch. 2013* for different percentages of the unmet demand is shown with a solid red line and the tooling cost of the fixed solution of the *Det. 2013* is shown with a red dotted line. The difference between the total cost of these two settings is shown with a blue solid line. Similar to the results of figure 2.20 the stochastic model suggests excess capacity for lower values of the unmet demand percentage and the tooling decisions converge to the *Det. 2013* as the unmet percentage increases. Thus, savings from the stochastic model go to zero as the unmet demand percentage increases, since both models suggest the same tooling at that point. For the lower values of the unmet demand percentage, we are able to save up to %1.80 by adding more capacity and creating more flexibility into sourcing. It is worth noting that the fixed decisions from the *Det. 2013* setting are infeasible for 0% and 1% unmet demand percentages.

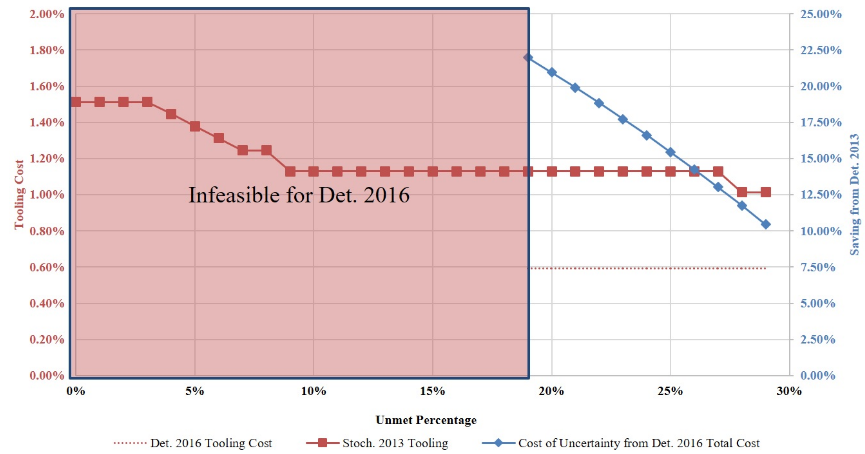

Figure 2.23: Cost of uncertainty of *Stoch. 2013* compared to *Det. 2016*

Figure 2.23 illustrates the extra cost of using the stochastic model compared to the *Det. 2016* model. Similar to the previous comparison, we fixed the capacity decisions from the *Det. 2016* and ran the stochastic model for all scenarios. In this graph the blue solid line represents the extra cost of the stochastic model (*Cost of Uncertainty*). It is worth noting that the *Det. 2016* solution is infeasible for unmet demand percentages of 19% and less. In figure 2.23 the maximum extra cost of the stochastic model compared to the *Det. 2016* is about %22 which is significantly less than the difference between the total costs of the *Det. 2013* and *Det. 2016* (about %39). This fact implies that the capacity decisions from the *Stoch. 2013* model would perform better under all possible realizations of the uncertain parameters compared to the decisions from *Det. 2013* model.

We repeated the same set of experiments with the high tooling part (HT). Since we used sampling for this part the solid blue line representing the savings is wavy. However, it still converges to zero, similar to figure 2.22.

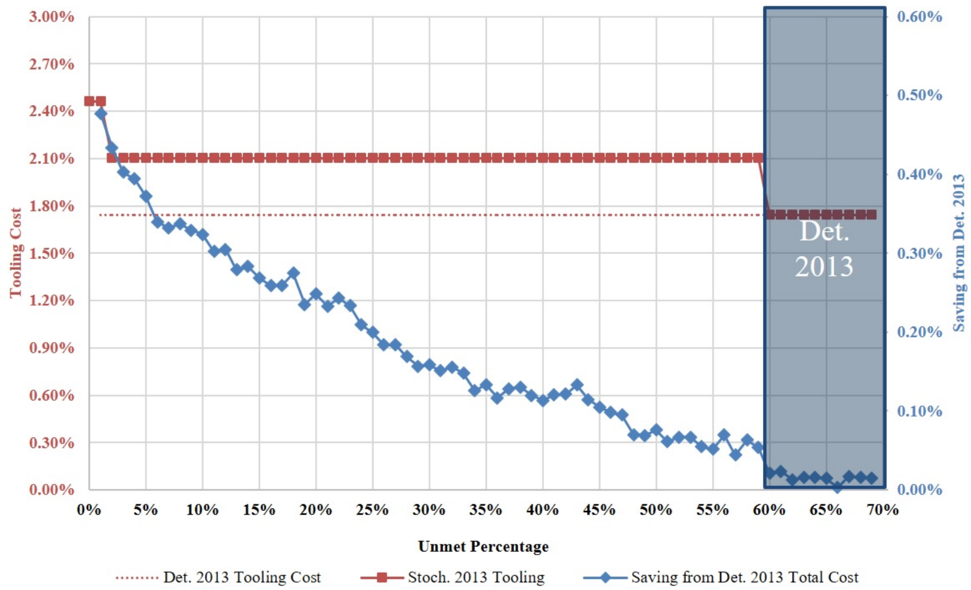

Figure 2.24: Savings from *Stoch. 2013* compared to *Det. 2013*

In figure 2.24, the *Det. 2013* is infeasible for 0% expected unmet demand and the capacity decisions of the *Stoch. 2013* converge to the *Det. 2013* solution for 60% expected unmet demand. Although it is not economical to add excess capacity for high tooling cost parts, in general, we can see in figure 2.24 that adding one more module in HT (region B) is optimal for unmet demand values as low as 2%. The *Stoch. 2013* model exhibits more savings compared to the *Det. 2013* for lower values of the expected unmet demand (higher quality of service). Finally, the capacity decisions obtained from the *Det. 2016* model are infeasible for any value of the expected unmet demand under the stochastic assumptions. In other words, the *Det. 2016* solution is only feasible for the realized scenario (low realization of demand). Therefore, we skip plotting the *Cost of Uncertainty* for this part.

2.6.5. Discussion and Recommendations

Uncertainties are threatening the efficiency and optimality of supply networks and the lack of comprehensive models that can assist planners in designing networks operating under uncertainties is becoming more obvious every day. Models that do not consider uncertainty may obtain sub-optimal solutions or result in infeasible solutions for practical applications. Moreover, 3-year and 2-year forecasts are often very inexact and Sensitivity Analysis (SA) may not be adequate as a decision support tool. For low tooling cost parts buying extra tooling to mitigate uncertainties might be a good strategy. But with high tooling cost parts, it might be more economical to work with suppliers to build in more flexibility.

2.7. Concluding Remarks

Supply chain networks play an important role in today's business environment. Uncertainty threatens the efficiency and optimality of the supply chains more than ever and the lack of comprehensive models that can assist planners in designing robust networks has become more obvious. The need for accurate quantitative decision support methods is becoming an increasing critical subject for managers. Managing uncertainty is one of the challenging issues in supply chains. This is why addressing uncertainty issues in optimization is of importance and it has received a great deal of attention in both academia and industry. In this chapter, we addressed the issue of optimizing supply networks under uncertainty and compared the decisions obtained from the stochastic model with the decisions from deterministic models under different settings. Our proposed approach will enable Ford to plan for many alternative future scenarios, incorporate uncertainty in their decision making process, and assessing the quality of service and robustness of their decisions. Moreover, the stochastic approach has the capability to deal with both symmetric and asymmetric distributions. We have shown the scalability of our approach with the SAA scheme. Finally, through our numerous experiments with the data from two case studies (low and high tooling parts), we investigated the impact of uncertainty from 3 major sources (demand, fuel cost, and exchange rate). By comparing the forecast data in 2013 and the actual realizations in 2016, we were able to demonstrate the benefits associated with using our modeling framework.

Chapter 3.

Flexible Supply Chain Network Design under Correlated Uncertainty

3.1. Introduction

Planning in the face of uncertainty is a challenging issues in supply chains. Recently, a significant increase in *Supply Chain Network* (SCN) risks has been observed by business owners [29]. As a result, designing SCNs that can handle risks has emerged as one of the top priorities for managers [29]. Ford Motor Company announced that they expect a weak exchange rate to hurt sales in the United Kingdom following the Brexit vote in June 2016 [61]. The German car company BMW stated that despite rising sales revenues, they conceived that their profit would be eroded by changes in exchange rates. The company's own calculations in its annual reports suggest that the negative effect of exchange rates were summed up to €2.4bn between 2005 and 2009 [18]. Another example of these uncertainties is the growing demand in the car industry after the 2009 recession. As the economy moves from recession to recovery, car companies are expanding their production lines and their demand is growing annually [94]. Proper tooling is required to satisfy this growing demand; otherwise, lost sales will be inevitable.

Designing a SCN is a complex task. This complexity is compounded by the multinational coverage of the SCNs and uncertainties in the key inputs [54]. Exchange rates vary continuously creating opportunities for car companies to import/export their production from/to their demand markets. However, inexact forecasts of exchange rates and their significant influence on decisions regarding localization/globalization of the production lines make them primary sources of uncertainties in SCNDs. Additionally, capacity decisions are made 2-3 years before production begins and remain unchanged during the production period. Fluctuations in demands for different vehicles consuming common parts can lead to idling of capacity or demand loss for those vehicles. Although this is an inevitable fact, the financial loss can be minimized by incorporating uncertainty into demand trends and planning models.

This chapter extends the literature on Supply Chain Network Design (SCND) models operating under uncertainty by incorporating correlations among uncertain parameters (demand, exchange rate, freight cost) and introducing a profit maximization model in which we use capacity planning as opposed to holding significant amounts of inventory to create flexibility. In this model, we consider competition among multiple products sharing similar parts for the capacity within the network structure.

The remainder of this chapter is organized as follows. In Section 2, we review the literature on the foundation of SCND problems and uncertainties in SCN and performance metrics. Section 3 provides the problem description and formulation for a SCN in auto industry. In section 4, the deterministic version of the described model is first developed and then it is extended to stochastic models to capture the uncertainties of input data in the original model. In Section 5, a solution methodology is proposed to solve the developed models efficiently. In Section 6, the developed models are validated through a real case study in auto industry. Managerial insights evolved from this study are provided in this section as well. Finally, Section 7 concludes the final remarks from developed models and introduces avenues for further research.

3.2. Literature Review

We take advantage of two streams of research in this work. The first stream is related to variations of the SCND models. The second stream pertains to a more in-depth analysis of uncertainty modeling in SCNs.

3.2.1. The review of SCND models

Deterministic SCND formulations are built upon facility location models, in particular discrete facility location models [31, 65]. Facility location problems consider flows of a single commodity/product among the selected facilities and demand nodes. One of the basic discrete facility location problems is the *Fixed Charge Location Problems* (FCLP). In the FCLP there is a finite set of demand locations to be served by a finite set of facility locations. In these problems two sets of decisions must be made: facility location and demand allocation decisions [9]. In these models, the facilities can be capacitated or uncapacitated [89]. The original formulation of these models goes back to Balinski [9]. Since then several researchers have proposed extensions of these problems in different aspects. Further discussions about developments in FCLPs can be found in Owen and Daskin [70] and Snyder [89].

SCND is considered to be an extension of *Capacitated Fixed Charge Location Problems* (CFCLP) models. Capacity decisions were added to Fixed Charge Location Problems by Elson [40]. Eppen et al. 1989 described a capacity expansion model in the auto industry. The capacity expansion models in the SCND literature are relatively more recent [3, 5]. In their models, the amount of expansion, and the time of expansion were key decision variables.

Multi-stage and dynamic SCND problems were proposed in the literature by Daskin et al. [34] and Dogan and Goetschalckx [39] and Martel [60]. In multi-stage models, the location decisions were made only at the beginning of the planning horizon while the dynamic models allow revision of the location decisions in each time period Melo et al. [64].

Multi-commodity and multi-product problems were discussed by Shen [85] and Melo et al. [63] in the SCND literature. In these papers, a commodity refers to either the parts or the final products in the SCN. A thorough review of the multi-commodity models within the SCND literature can be found in Melo et al. [64].

In comparison with the current models in the SCND literature, the structure of our optimization model captures more details than have previously been reported in the literature. In particular, we consider competition among multiple products sharing similar parts for the capacity within the network structure. Moreover, we propose capacity planning and pricing (as opposed to holding inventory) to create flexibility in designing SCNs.

3.2.2. Uncertainty modeling in SCN

A large number of problems in location, transportation, and SCND require decisions to be made in the presence of uncertainty. Davis [36] was among the first scholars to explicitly consider uncertainty as a strategic issue for supply chains. Uncertainties are random and they can be divided into natural and man-made categories owing to the nature of the uncertainty. Fluctuations in demanded products and terrorist attacks are the common examples of these two categories, respectively [92].

The majority of the literature has classified the source of the uncertainty in two broad groups [93]:

- **Demand-side uncertainties** (also known as operational risks [96]): instability in demand or inexact demand forecasts.
- **Supply-side uncertainties**:
  - **Long-term** (also known as disruption risks [96] and supply disruptions [93]): congestion, disruptions, faults or delays in the suppliers deliveries.
  - **Short-term** (also known as yield uncertainty [93]): the quantity produced or received differs from the quantity ordered due to shortfalls and manufacturing defects.

In addition, we add a third source of uncertainty:

- **Environmental uncertainties**: including changes in the regulatory and macroeconomic environment; for example, exchange rates.

There are several measures to model the uncertainty in the SCNs operating under uncertainty. While the majority of the literature considers measures of central tendency (e.g. nominal values [17], expected value [76], etc.) and measures of dispersion (e.g. variance or approximations of the variance [67], etc.), some scholars proposed different approaches such as regret [91], mean-excess regret [23], and Conditional Value at Risk (CVaR) [21]. The choice of modeling highly depends on the decision makers' risk attitude. A risk-neutral decision maker would prefer a central tendency measure whereas a risk-averse decision maker would prefer variability and the worst-case-scenarios [53].

Several scholars proposed different performance measures for SCNs operating under uncertainty. While most of them have overlapping definitions, Klibi et al. [54] argue that a combination of robustness and resilience is sufficient to improve the performance of SCNs under different types of uncertainty. Robustness is defined as how well the SCN performs with respect to uncertainty [90] while resilience is defined as the capability of a SCN to recover from disruptions [26]. Resilience can be achieved by building flexibility [49] and redundancy [84] within the structure of the systems. While much of the literature considers safety stock inventory and backup suppliers as effective strategies to hedge against uncertainty [90], in many industries (like the auto industry) keeping inventory for long periods is not possible. It is worth mentioning that some scholars proposed safety stock inventory for short periods [82, 88] to deal with supply-side uncertainties. However, we still need to exploit other strategies for strategic decisions. Thus, we believe capacity planning (as opposed to holding inventory) is a more effective strategy in practice for automotive supply chains.

Decision-making under uncertainty often requires using large-scale optimization models. A comprehensive review of optimization techniques under uncertainty is provided in Sahinidis [75] and Govindan et al. [43]. Here, we briefly review frequently used techniques in the literature:

- **Parametric Programming (PP)**: parametric programming is the study of the effect of uncertain parameters on the output of the optimization model [87]. In general, the following optimization problem is considered,

  $$\min_{\boldsymbol{x} \in \mathcal{X}(\boldsymbol{\xi})} f(\boldsymbol{x}, \boldsymbol{\xi}), \qquad \forall \boldsymbol{\xi} \in \Xi$$

  where $\boldsymbol{x}$ are the decision variables, $\boldsymbol{\xi}$ are the uncertain parameters. The set $\mathcal{X}(\boldsymbol{\xi})$ is the feasible set for a realization of $\boldsymbol{\xi}$ and Ξ is the parameters space.

- **Robust Optimization (RO)**: considering a pre-defined set for the uncertain parameter (could be the range), robust optimization finds the best solution which is feasible for any realization of the uncertainty in the given set [13, 14, 15]. In other words, in this approach we optimize against the worst case outcome. The general form of a RO problem is,

  $$\min_{\boldsymbol{x} \in \mathcal{X}} \max_{\boldsymbol{\xi} \in \Xi} f(\boldsymbol{x}, \boldsymbol{\xi})$$

  Robust solutions are known to be overly conservative [16].

- **Stochastic Programming (SP)**: If the uncertainty is from the random nature of the parameters, SP approaches can be used. In SP, the probability distributions of the random parameters are usually known a priori [19]. If the underlying distribution is not known a priori, then the decision maker needs to estimate it (assumes that the distribution has a closed form). The general form of a SP problem is as follows,

$$\min_{\boldsymbol{x}\in\mathcal{X}} E_{p_{\boldsymbol{\xi}}\in\mathcal{P}} f(\boldsymbol{x},\boldsymbol{\xi})$$

  where $p_{\boldsymbol{\xi}}$ is the probability of a realization $\boldsymbol{\xi}$ from probability function $\mathcal{P}$. The major concern with discrete SP techniques is the *curse of dimensionality*. In other words, the number of scenarios can be extremely large or infinite in some cases. The *Sample Average Approximation* (SAA) method was developed by Kleywegt et al. [51] to overcome this difficulty and applied for supply chain network design under uncertainty by Santoso et al. [76].

- **Distributionally Robust Optimization (DRO)**: to address the limitations of the previous methods, DRO is proposed as an intermediate step between RO and SP. The DRO model (also known as minimax stochastic programs) was proposed by Scarf et al. [81]. In general, the DRO problem can be modeled as,

$$\min_{\boldsymbol{x}\in\mathcal{X}} \max_{\mathcal{P}\in\mathbb{P}} E_{p_{\boldsymbol{\xi}}\in\mathcal{P}} f(\boldsymbol{x},\boldsymbol{\xi})$$

where $\mathbb{P}$ is the set of possible distribution given limited information. Delage and Ye [37] extended applications of DRO under moment uncertainty. Different variations of the DRO is applied for facility location models with disruption risks [57], demand location uncertainty [21], and more recently demand uncertainty [22].

Several authors have proposed hybrid techniques (such as robust stochastic programming [91], and chance-constrained programming [66]).

In this research we include multiple sources of uncertainty in the model (demand, exchange rate, and freight cost) and implement DRO to coordinate SCNs of different products and parts against the worst-case joint distribution of the uncertain parameters with given marginal probabilities. Our model relaxes the traditional assumption of knowing the distribution of the uncertain parameters. The assumption of knowing the distribution of the uncertain parameters is reasonable when we have many historical data points to construct the joint distribution. However, for new products, newly implemented networks, or for parameters for which obtaining data is expensive, historical data is scarce and therefore, the traditional models are not practical [22]. In the DRO model developed below, we consider the distribution of the uncertain parameters to plan against the worst-case joint distribution.

In summary, we consider several aspects of the SCND problems to compare our proposed model with similar studies in the literature. Our comparison is based on the elements of SCND structure, modeling framework, uncertainty modeling, and the type of objective functions. SCND structure includes capacity planning and inventory decisions, if the models consider multiple stages or if they make decisions dynamically, if they can handle multiple commodities/products, or whether authors incorporated exchange rate and Bill of Material (BOM) in their models. We also review how authors took into account the effect of uncertainty in their models. To do so, we consider multiple sources of uncertainty including demand-side, supply-side, and environmental uncertainty, possible correlation among different sources of uncertainty, and multiple possible modeling frameworks including deterministic, stochastic programming, robust optimization, and distributionally robust optimization. Finally, we report if authors used a cost minimization approach by fixing the revenues or a profit maximization approach. For this comparison, we compare our proposed model with 20 other proposed models in the literature that are similar to ours in 3.1.

Table 3.1: Qualitative comparison of SCND Literature

Literature	SCND Structure						Modeling Framework	Uncertainty Modeling		Objective Function
	CP	I	MS/DY	MC/MP	ER	BOM	D/SP/RO/DRO	D/S/E	(W-)COR	P/C
Tsiakis et al. [100]		*		*			D/SP	D		C
Daskin et al. [32]		*					D/SP	D	*	C
Ahmed et al. [3]	*	*	*	*			D/SP	D		C
Bertsimas and Thiele [17]		*	*				D/RO	D		C
Guillén et al. [44]	*	*	*	*			D/SP	D		P
Martel [60]	*	*	*	*	*	*	D/SP	D		P
Shen [85]		*		*			D/SP	D	*	C
Amiri [5]	*						D			C
Melo et al. [63]	*		*	*			D			C
Shen [86]		*	*	*			D			P
You and Grossmann [103]		*	*	*			D/SP	D		P
Altiparmak et al. [4]				*		*	D			C
Klibi and Martel [52]	*		*		*		SP	D/S/E	*	C
Badri et al. [8]		*	*	*		*	D			P
Sawik [79]		*		*	*		SP	S		C
Jafarian and Bashiri [48]		*	*	*		*	D			P
Chan et al. [21]							SP/DRO	D	*	C
Chen [22]				*			D/SP/DRO	D	*	C
Qiu and Wang [72]				*			RO/DRO	D/S		P
Nakao et al. [68]				*			D/SP/DRO	D	*	C
Current Work	*			*	*	*	D/SP/DRO	D/E	*	P

SCND Structure: CP: Capacity Planning, I: Inventory Decisions, MS/DY: Multi-stage/Dynamic, MC/MP: Multi-commodity/Multi-product, ER: Exchange Rate, BOM: Bill of Material

Modeling Framework: D: Deterministic, SP: Stochastic Programming, RO: Robust Optimization, DRO: Distributionally Robust Optimization

Uncertainty Modeling: D: Demand-side, S: Supply-side, E: Environmental, (W-)COR: (Worst Case -) Correlation

Objective: P: Profit maximization, C: Cost Minimization

Table 3.1 shows that most researchers focus on holding inventory than capacity planning. However, this may not be feasible in many industries. The profit maximization models received less attention in this literature and most scholars assume the revenue is stable and fixed. Finally, more sophisticated techniques such as DRO are very new in this literature.

3.3. Problem Description

A simplified SCN in the auto industry consists of four main elements: commodities/products, suppliers, plants, and demand markets. Commodities are the raw materials or unassembled parts. Final products are a set of assembled commodities, in this case a specific model of an automobile. Suppliers are the exogenous sources of commodities in the network. Commodities will be assembled in the plants and the final products will be sent to the demand markets.

The efficient flow of commodities from suppliers to assembly plants and the distribution of finished products to demand markets are critical in today's competitive environment. SCND entails decisions not only about the flow of commodities and the distribution pattern of the final products, but also decisions regarding the location of the suppliers, tooling at the suppliers, the quantity of the commodities ordered from the suppliers, and inventory of the commodities [35].

Planning for one single final product (vehicle) with several commodities (parts) might not be efficient for a manufacturing company with many products. In this manner, coordinating the SCNs of the common commodities among the different products is beneficial for all the suppliers, the manufacturing company, and the demand markets. In such a model, we need to extend the SCN of the manufacturing company, so that the suppliers of the same commodities can share their capacities to produce different commodities. The SCN model in this study consists of the following elements:

Nodes of the network:

- **First-tier suppliers:** manufacturing companies or providers of raw materials providing the network exogenously.
- **Casting and forging plants:** raw steel, aluminum, and other metal alloys bought from first-tier suppliers are shipped to these plants. Some of the vehicle parts such as gears and valves are cast and forged in these plants.
- **Engine assembly plants:** the vehicle engines are assembled in these plants.
- **Stamping plants:** some of vehicle parts such as ignition components, fuel systems components, accelerator modules, doors, and exterior sheet metal are stamped in these plants.
- **Transmission plants:** the vehicle transmission systems are built in these plants.
- **Vehicle assembly plants:** the final assembly of the other plants and other commodities sent from suppliers is done in these plants.
- **Demand markets:** any country that is targeted for selling final products.

Types of flows:

- **Commodities (parts):** the first-tier suppliers send their raw materials or sub-assembled parts (from second-tier suppliers) to assembly plants. These raw materials or sub-assembled parts are called commodities.
- **Final products (vehicles):** different models of vehicles are called products.

Each supplier has the capability of providing some of the commodities conditional on the appropriate tooling. The capacity of the suppliers depends on the number of modules (production lines) which will be referred to as *Modular Capacity*. Each module has a specific capacity; thus, the total capacity cane be expressed by the number of modules at each supplier. The upfront fees for reserving capacity are proportional to the number of modules at each supplier. This capacity will be divided among different types of commodities that a supplier is providing. The number of selected suppliers for different commodities will determine the sourcing policy of that commodity. If only one supplier is chosen from the available suppliers then it is called a global sourcing policy and if more than one supplier is chosen it is called a regional sourcing policy. Commodities may have different policies. If a supplier is chosen, it can be equipped for one commodity or more. Figure 3.1 depicts the scheme of the SCN:

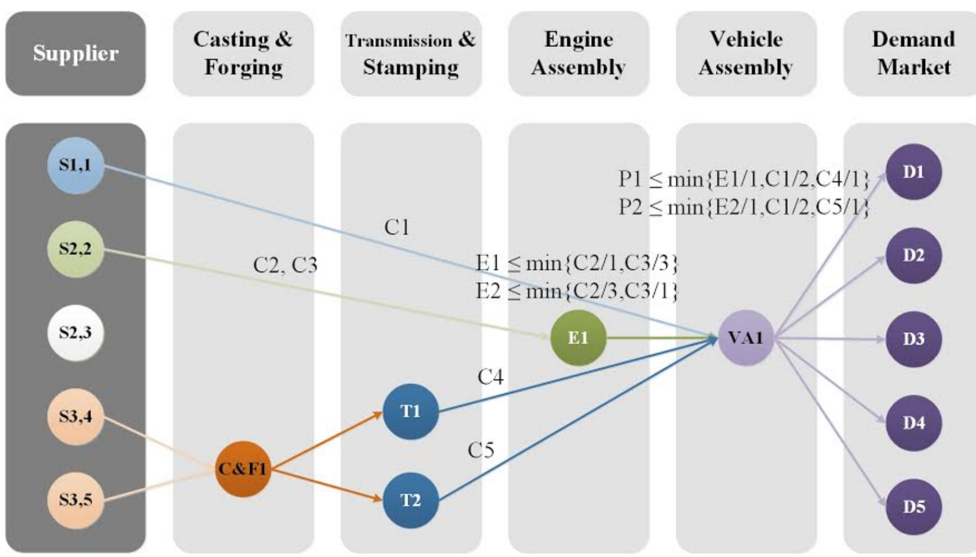

Figure 3.1: An example of the production process with BOM information

In this network, if a supplier is chosen to produce some types of commodities, we will reserve some of its capacity in terms of modules. Different colors for arrows in Figure 3.1

represent the flow of different types of commodities from selected suppliers. In this model, different suppliers produce different commodities for different products and different plants share capacities to increase the production rate of a specific commodity.

Information about the number of different types of commodities that are used in the final products can be obtained from the BOM of different models of products. This information will be used in the production process. Figure 3.1 also depicts a small example of the production process of two models of vehicles P1 and P2. The BOM of these two vehicles is as follows:

	C1	C2	C3	C4	C5	E1	E2
E1		1	3				
E2		3	1				
P1	2			1		1	
P2	2				1		1

In Figure 3.1, the selected suppliers are equipped to produce the commodities types C1, C2, and C3 and to procure the raw material/sub-assemblies for commodities types C4 and C5. Commodities C2 and C3 are used in the engine. According to the information from the BOM, for E1 (engine of P1) one unit of C2 and three units of C3 are necessary in this example and for the E2 three units of C2 and one unit of C3 are used. One engine, two units of C1, and one unit of C4 are used for the final assembly of the product P1 and similarly for P2, one engine, two units of C1, with one unit of C5 are used.

In assembly plants, it is crucial that we receive the right ratio of commodities for different products. This ratio can be calculated using the BOM information. In this manner, the output of each plant is less than or equal the minimum of the ratios of the received commodities divided by the ratio parameter. In figure 2, E1 and E2 compete for the common commodities (C2 and C3). Similarly, P1 and P2 also compete for a common commodity (C1). Thus, the outputs of the assembly plants cannot be calculated independently of each other. This is another fact that adds to the complexity of this model. Having limited commodities, we have to prioritize the products based on their profits. Therefore, information about the demand of different products in each market as well as the prices of each product in each market should be available.

All engine, transmission, casting and forging, stamping, and vehicle assembly plants are shown in the big box in Figure 3.1 and are subject to capacity constraints. The operating capacity of a plant is the maximum number of outputs that can be produced. Finally, we assume that the demand estimates are in the maturity life cycle of the product. In other words, the mean of demand is stationary throughout the planning horizon.

3.4. Model Formulation

The SCND problem is formulated on a directed connected graph $G(N, A)$, where N is the set of the nodes and $A \subseteq N \times N$ denotes the set of arcs/flows. The sets of commodities are denoted by C. The set N consists of exogenous suppliers (set S_c) for commodity type c, the demand nodes (set D_c for commodity type c), and all the plants (set $N' = N \setminus \bigcup_{c \in C} \{S_c \cup D_c\}$). The set A consists of all different types of commodity flows including raw materials, sub-assemblies, and final products. The set of arcs directed out of a node $i \in N$ is the forward star of i, denoted by $FS(i)$. Similarly, set of arcs directed into node $i \in N$ is the reverse star of i, denoted by $RS(i)$. Finally, the set L_{ic} represents the capacity levels (modular capacity) at supplier $i \in S_c$ for commodity type $c \in C$. Similarly, we define set C_i as the set of commodities that can be produced at node i. Other parameters are introduced in appendix I. In this work, we assume the exchange rates remain the same during the planning horizon (independent of time) and therefore, we have a static model. Finally, the decision variables are:

Variable	**Description**
X_{ilc}	The binary variables for location and capacity decisions. 1 if supplier $i \in S_c$ is selected to produce commodity type $c \in C$ at capacity $l \in L_{ic}$; 0 otherwise
$Y_{(i,j)c}$	The non-negative continuous variables for allocation decisions (flows) on arc $(i, j) \in A$ for commodity type $c \in C$
U_{ic}	The non-negative continuous variables for unmet demand in demand market $i \in D_c$ for commodity type $c \in C$

The deterministic formulation of the SCN model is as follows:

3.4.1. Deterministic Formulation with unmet demand

($FSCND - u - det$)

$$\max_{\mathbf{X}\in\{0,1\};\mathbf{Y},\mathbf{U}\in\Re^+} \left(\sum_{c\in C} \sum_{\substack{(j,i)\in A;\\ i\in D_c}} \rho_{ic} Y_{(j,i)c} \right) - \left(\sum_{c\in C} \sum_{i\in S_c} \sum_{l\in L_{ic}} a_{ilc} X_{ilc} + \sum_{c\in C} \sum_{(i,j)\in A} b_{(i,j)c} Y_{(i,j)c} \right) \tag{3.1}$$

subject to:

$$\sum_{l\in L_{ic}} X_{ilc} \leq 1, \quad \forall i \in S_c; c \in C \tag{3.2}$$

$$\sum_{j\in FS(i)} Y_{(i,j)c} \leq \sum_{l\in L_{ic}} \psi_{ilc} X_{ilc}, \quad \forall i \in S_c; c \in C \tag{3.3}$$

$$\sum_{\substack{c\in C_i;\\ \beta_{c'c}\neq 0}} \sum_{j\in FS(i)} \beta_{c'c} Y_{(i,j)c} \leq \sum_{j\in RS(i)} Y_{(j,i)c'}, \quad \forall i \in N'; c' \in C_j, j \in RS(i) \tag{3.4}$$

$$\sum_{c\in C} \sum_{j\in RS(i)} \tau_{ic} Y_{(j,i)c} \leq \phi_i, \quad \forall i \in N'; c \in C \tag{3.5}$$

$$\sum_{j\in RS(i)} Y_{(j,i)c} + U_{ic} = d_{ic}, \quad \forall i \in D_c; c \in C \tag{3.6}$$

The objective function (3.1) maximizes the discounted net profit of the SCN. The positive cash flows (revenues) are the total discounted revenue of selling the final products across all demand markets. The negative cash flows (costs) are the total fixed costs of locating and tooling suppliers $i \in S_c$ with capacity levels $l \in L_{ic}$ for commodities $c \in C$ at time 0, discounted transportation and unit costs of commodities $c \in C$ within the network. Constraints (3.2) ensure at most one capacity level is assigned to each supplier for each commodity $c \in C$. Constraints (3.3) stipulate that the production capacity of suppliers (total flows going out of supplier $i \in S_c$ for commodities $c \in C$) to be less than or equal their selected capacity levels $l \in L_{ic}$ for commodities. Constraints (3.4) are the flow balance constraints for all plants. Detailed description of constraints (3.4) and the diagram are attached in Appendix III (Figure A.1). Constraints (3.5) are operating capacity constraints. They stipulate that the total amount/number of commodities received by any plant is less than or equal to its operating capacity. Constraints (3.6) state that the number of final products sent to demand market $i \in D_c; c \in C$ is plus the unmet demand is equal to the demand of that product in that market.

Theorem 3.1. *The $FSCND - u - det$ is $\mathcal{NP}$-hard.*

Remark 3.1. *Sometimes it is required to distribute unmet demand fairly among all demand nodes. Therefore, we can add equity constraints to the above model as follow:*

$$\frac{U_{ic}}{d_{ic}} \leq \Upsilon_c \sum_{i \in D_c} \frac{U_{ic}}{d_{ic}}, \quad \forall i \in D_c; c \in C \tag{3.7}$$

where Υ_c is the commodity-specific equity parameter in the model. These parameters can be set by the decision makers to avoid imbalanced unmet demand over demand regions. Basically, these constraints enforce that the ratio of unmet demand over the actual demand for each demand region is less than or equal to the $100\Upsilon_c\%$ of the sum of all the ratios of unmet demand over the actual demand of all demand regions for each commodity.

3.4.2. Stochastic Formulation ($FSCND - u - stoch$)

The future under which a SCN will operate is non-deterministic (uncertain) or in some cases unknown. In $FSCND - u - det$ problem, we assume all parameters were deterministic, however, in reality, uncertainty can be seen in demand parameters, freight costs, and exchange rates. Here we formulate both cases with (w)/without (w/o) knowing the probability distributions of the uncertain parameters a priori.

Stochastic Formulation ($FSCND - u - stoch - w$)

A scenario can be defined as a possible combination or realization of the uncertain parameters [38]. Assuming uncertainty in exchange rates, freight costs, and demands, we assume the uncertain parameters in the model $(\boldsymbol{b}, \boldsymbol{d}) \in \Xi_b \times \Xi_d$ have independent support. For notational brevity, we show this support by Ξ. One common assumption in the literature is the box-shape support given by $\Xi = \{\underline{b}_{(i,j)c} \leq b_{(i,j)c} \leq \bar{b}_{(i,j)c}, \forall (i,j) \in A, c \in C, \underline{d}_{ic} \leq d_{ic} \leq \bar{d}_{ic}, \forall i \in d_c, c \in C\}$. The lower bound and upper bound can be obtained from historic data. Since for continuous distributions, exact computation of the expected values involves taking integrals [76], the discrete support assumption to generate scenarios is another common assumption in the literature. It is worth mentioning that we are not considering any uncertainty in parameters $\boldsymbol{a}$, since the exchange rates are known at the beginning of the planning horizon. The probability of scenarios over the support Ξ are known a priori. The recourse decisions after observing the uncertain parameters are flow decisions and unmet demand decisions. Therefore, we have:

$(1st - stage)$

$$\max_{\mathbf{X}\in\{0,1\}} \left(-\sum_{c\in C}\sum_{i\in S_c}\sum_{l\in L_{ic}} a_{ilc}X_{ilc} + \sum_{(\boldsymbol{b},\boldsymbol{d})\in\Xi} p(\boldsymbol{b},\boldsymbol{d})h(\mathbf{X},\mathbf{b},\mathbf{d}) \right) \tag{3.8}$$

subject to:

$$\sum_{l\in L_{ic}} X_{ilc} \leq 1, \quad \forall i\in S_c; c\in C \tag{3.9}$$

$(2nd - stage)$

$$h(\mathbf{X},\mathbf{b},\mathbf{d}) = \max_{\mathbf{Y},\mathbf{U}\in\Re^+} \left(\sum_{c\in C}\sum_{\substack{(j,i)\in A;\\ i\in D_c}} \rho_{ic}Y_{(j,i)c} \right) - \left(\sum_{c\in C}\sum_{(i,j)\in A} b_{(i,j)c}Y_{(i,j)c} \right) \tag{3.10}$$

subject to:

$$\sum_{j\in FS(i)} Y_{(i,j)c} \leq \sum_{l\in L_{ic}} \psi_{ilc}X_{ilc}, \quad \forall i\in S_c; c\in C \tag{3.11}$$

$$\sum_{\substack{c\in C_i;\\ \beta_{c'c}\neq 0}}\sum_{j\in FS(i)} \beta_{c'c}Y_{(i,j)c} \leq \sum_{j\in RS(i)} Y_{(j,i)c'}, \quad \forall i\in N'; c'\in C_j, j\in RS(i) \tag{3.12}$$

$$\sum_{c\in C}\sum_{j\in RS(i)} \tau_{ic}Y_{(j,i)c} \leq \phi_i, \quad \forall i\in N'; c\in C \tag{3.13}$$

$$\sum_{j\in RS(i)} Y_{(j,i)c} + U_{ic} = d_{ic}, \quad \forall i\in D_c; c\in C \tag{3.14}$$

where $p(\boldsymbol{b},\boldsymbol{d})$ is the vector of probabilities belonging to the joint distribution of $(\boldsymbol{b},\boldsymbol{d})$, i.e. π.

Stochastic Formulation (FSCND-u-stoch-w/o)

If the underlying distributions of the input parameters are unknown, then the decision-maker needs to estimate them by either parametric or non-parametric approaches. However, these models are suitable only when a sufficient amount of data are accessible. DRO is an alternative approach in which after defining a set of probability distributions that is assumed to include the true distribution, the objective function is reformulated with respect to the expected worst-case over the choice of a distribution. We consider the case when only the marginal distributions of the uncertain parameters are known, but the correlations among them are not available.

$$\pi = \left\{ p(\boldsymbol{b}, \boldsymbol{d}) \geq 0 \left| \begin{array}{l} \sum_{(\boldsymbol{b},\boldsymbol{d}) \in \Xi} \mathbb{I}\left(b_{(i,j)c} = \varepsilon_{(i,j)c}\right) p(\boldsymbol{b}, \boldsymbol{d}) = q_{b_{(i,j)c}}(\varepsilon_{(i,j)c}), \forall (i,j) \in A, c \in C \\ \sum_{(\boldsymbol{b},\boldsymbol{d}) \in \Xi} \mathbb{I}\left(d_{ic} = \varepsilon^{'}_{ic}\right) p(\boldsymbol{b}, \boldsymbol{d}) = q_{d_{ic}}(\varepsilon^{'}_{ic}), \forall i \in D_c, c \in C \\ \sum_{(\boldsymbol{b},\boldsymbol{d}) \in \Xi} p(\boldsymbol{b}, \boldsymbol{d}) = 1 \end{array} \right. \right\} \tag{3.15}$$

where $q_{b_{(i,j)c}}$ and $q_{d_{ic}}$ are the marginal probabilities of $b_{(i,j)c}$ and d_{ic} at some values $\varepsilon_{(i,j)c}$ and $\varepsilon^{'}_{ic}$ respectively in support Ξ. The system of equations in (3.15) forms the generic shape of the joint distribution of the uncertain parameters given the margins. The first row forces the sum of the probabilities over the support of the uncertain parameters for each $b_{(i,j)c}$ to be equal to the margin of that parameter ($q_{b_{(i,j)c}}$) for all possible values of $b_{(i,j)c}$ (i.e. $\varepsilon_{(i,j)c}$). The second row is similar to the first one, but it holds the margins of the demand parameters (d_{ic}). The last row makes sure all probabilities sum to one. Thus, the SCND model can be reformulated as follows:

$$(1st - stage)$$

$$\max_{\mathbf{X}\in\boldsymbol{\chi}} \left(-\sum_{c\in C}\sum_{i\in S_c}\sum_{l\in L_{ic}} a_{ilc}X_{ilc} + \min_{p(\boldsymbol{b},\boldsymbol{d})\in\pi} \sum_{(\boldsymbol{b},\boldsymbol{d})\in\Xi} p(\boldsymbol{b},\boldsymbol{d})h(\mathbf{X,b,d}) \right) \tag{3.16}$$

$$(2nd - stage)$$

$$h(\mathbf{X,b,d}) = \max_{\mathbf{Y,U}\in\mathcal{F}(\mathbf{X,b,d})} \left(\sum_{c\in C} \sum_{\substack{(j,i)\in A;\\ i\in D_c}} \rho_{ic}Y_{(j,i)c} \right) - \left(\sum_{c\in C}\sum_{(i,j)\in A} b_{(i,j)c}Y_{(i,j)c} \right) \tag{3.17}$$

where χ is the feasible region for variables $\boldsymbol{X}$ and $\mathcal{F}(\mathbf{X,b,d})$ is the feasible region for variables $\mathbf{Y}$ and $\mathbf{U}$ given $\mathbf{X,b,d}$.

Remark 3.2. *The major concern with large-scale SP models is the curse of dimensionality. In other words, the number of scenarios can be extremely large or infinite in some cases. The SAA framework is described in [76] to overcome this problem. However, this framework is not applicable for max-min objectives.*

3.5. Solution Methodology

The first stage of $FSCND{-}u{-}stoch{-}w/o$ model is a max-min problem. In this section, we develop methodologies for reformulating and solving this model using the marginal-based ambiguity set defined in previous section. We begin by dualizing the second stage problem:

Proposition 3.1. *For any given* $\boldsymbol{X,b,d}$*, the second stage problem can be restated as:*

$$h(\boldsymbol{X,b,d}) = \min_{\boldsymbol{G},\boldsymbol{H},\boldsymbol{V},\boldsymbol{W}\in\Re^{+}} \sum_{c\in C}\sum_{i\in S_c} G_{ic}\left(\sum_{l\in L_{ic}} \psi_{ilc}X_{ilc}\right) + \sum_{i\in N'} \phi_i V_i + \sum_{c\in C}\sum_{i\in D_c} d_{ic}W_{ic} \quad (3.18)$$

subject to:

$$G_{ic} - H_{jc} + \tau_{jc}V_j \geq -b_{(i,j)c}, \quad \forall i \in S_c; j \in FS(i); c \in C \quad (3.19)$$

$$\sum_{\substack{c' \in C_j, j\in RS(i);\\ \beta_{c'c}\neq 0}} \beta_{c'c}H_{ic'} - H_{jc} + \tau_{jc}V_j \geq -b_{(i,j)c}, \quad \forall i \in N'; j \in FS(i); c \in C_i \quad (3.20)$$

$$\sum_{c' \in C_j, j\in RS(i)} H_{ic'} + W_{jc} \geq (\rho_{jc} - b_{(i,j)c}), \quad \forall i \in RS(j); j \in D_c; c \in C_i \quad (3.21)$$

where $\boldsymbol{G}, \boldsymbol{H}, \boldsymbol{V}, \boldsymbol{W}$ *are the dual variables corresponding to the second stage constraints (3.11)-(3.14) respectively. The feasible region will be referred to as* $\digamma^D(\boldsymbol{X,b,d})$*.*

Next, we dualize the inner min problem to obtain a maximization problem that can be merged with the first-stage objective.

Lemma 3.1. *For any given marginal-based ambiguity set, the optimal objective value of the inner* min *problem is equal to:*

$$\max_{\boldsymbol{\theta_b},\boldsymbol{\theta_d},\varpi} \left(\varpi + \sum_{c\in C}\sum_{(i,j)\in A} q_{b_{(i,j)c}}\theta_{b_{(i,j)c}} + \sum_{c\in C}\sum_{i\in D_c} q_{d_{ic}}\theta_{d_{ic}}\right) \quad (3.22)$$

subject to:

$$\varpi + \sum_{c\in C}\sum_{(i,j)\in A} \theta_{b_{(i,j)c}} + \sum_{c\in C}\sum_{i\in D_c} \theta_{d_{ic}} \leq h(\boldsymbol{X,b,d}), \quad \forall(\boldsymbol{b}, \boldsymbol{d}) \in \Xi \quad (3.23)$$

where $\boldsymbol{\theta_b}, \boldsymbol{\theta_d}, \varpi$ *are the dual variables corresponding to the marginal constraints on the probability sets.*

Next, we replace the min problem in (3.18)-(3.21) with equations (3.22) and (3.23) in $FSCND-u-stoch-w/o$ and merge the maximization objective of the dualized problem with the maximization objective of the first-stage problem to obtain the reformulation of $FSCND-u-stoch-w/o$:

$$\max_{\mathbf{X}\in\boldsymbol{\chi},\boldsymbol{\theta_b},\boldsymbol{\theta_d},\varpi}\left(-\sum_{c\in C}\sum_{i\in S_c}\sum_{l\in L_{ic}}a_{ilc}X_{ilc}+\varpi+\sum_{c\in C}\sum_{(i,j)\in A}q_{b_{(i,j)c}}\theta_{b_{(i,j)c}}+\sum_{c\in C}\sum_{i\in D_c}q_{d_{ic}}\theta_{d_{ic}}\right) \quad (3.24)$$

subject to:

$$\varpi+\sum_{c\in C}\sum_{(i,j)\in A}\theta_{b_{(i,j)c}}+\sum_{c\in C}\sum_{i\in D_c}\theta_{d_{ic}}\leq h(\mathbf{X},\mathbf{b},\mathbf{d}),\quad \forall(\boldsymbol{b},\boldsymbol{d})\in\Xi \quad (3.25)$$

However, this reformulation still remains intractable due to the large number of constraints in equation (3.23) even for discrete supports. Next proposition provides us a tractable reformulation of $FSCND-u-stoch-w/o$:

Proposition 3.2. *For any given* $\boldsymbol{X},\boldsymbol{b},\boldsymbol{d}$, *the* $FSCND-u-stoch-w/o$ *problem can be restated as:*

$(Master)$

$$\max_{\boldsymbol{X}\in\boldsymbol{\chi},\boldsymbol{\theta_b},\boldsymbol{\theta_d},\varpi}\left(-\sum_{c\in C}\sum_{i\in S_c}\sum_{l\in L_{ic}}a_{ilc}X_{ilc}+\varpi+\sum_{c\in C}\sum_{(i,j)\in A}q_{b_{(i,j)c}}\theta_{b_{(i,j)c}}+\sum_{c\in C}\sum_{i\in D_c}q_{d_{ic}}\theta_{d_{ic}}\right) \quad (3.26)$$

subject to:

$$\varpi+\sum_{c\in C}\sum_{(i,j)\in A}\theta_{b_{(i,j)c}}+\sum_{c\in C}\sum_{i\in D_c}\theta_{d_{ic}}\leq f(\boldsymbol{X}) \quad (3.27)$$

Where $f(\boldsymbol{X})$ *is:*

(*Subproblem*)

$$f(\boldsymbol{X}) = \min_{\boldsymbol{G},\boldsymbol{H},\boldsymbol{V},\boldsymbol{W}\in\digamma^D(\boldsymbol{X},\bar{\boldsymbol{b}},\boldsymbol{d}),\boldsymbol{\lambda}\in\Re^+,\boldsymbol{\varrho}\in\{0,1\}} \sum_{c\in C}\sum_{i\in S_c} G_{ic}\left(\sum_{l\in L_{ic}} \psi_{ilc}X_{ilc}\right) + \sum_{i\in N'} \phi_i V_i + \sum_{c\in C}\sum_{i\in D_c}\sum_{n\in\mathfrak{N}_{ic}} \lambda_{icn}\hat{d}_{icn} \tag{3.28}$$

subject to:

$$\sum_{n\in\mathfrak{N}_{ic}} \varrho_{icn} = 1, \quad \forall i\in D_c, c\in C \tag{3.29}$$

$$\lambda_{icn} \geq W_{ic} - M(1-\varrho_{icn}), \quad \forall n\in\mathfrak{N}_{ic}, i\in D_c, c\in C \tag{3.30}$$

$$\lambda_{icn} \leq W_{ic}, \quad \forall n\in\mathfrak{N}_{ic}, i\in D_c, c\in C \tag{3.31}$$

$$\lambda_{icn} \leq M\varrho_{icn}, \quad \forall n\in\mathfrak{N}_{ic}, i\in D_c, c\in C \tag{3.32}$$

Where $\boldsymbol{\lambda},\boldsymbol{\varrho}$ *are the McCormick [62] and auxiliary variables respectively. Moreover,* $\bar{\boldsymbol{b}}$ *means all parameters* $b_{(i,j)c}, \forall(i,j)\in A, c\in C$ *are set at their higher values. It is worth noting that the worst-case distribution does not have a general parametric form, but it can be obtained by solving the system of linear equations (3.15) for non-zero* $\boldsymbol{\theta}$*s.*

Proposition 3.3. *A special case of the marginal-based confidence set can be obtained by relaxing the marginal constraints (3.15); therefore, the* $\pi = \left\{p(\boldsymbol{b},\boldsymbol{d})\geq 0, \sum_{(\boldsymbol{b},\boldsymbol{d})\in\Xi} p(\boldsymbol{b},\boldsymbol{d}) = 1\right\}$. *Then, we have:*

$$\max_{\boldsymbol{X}\in\boldsymbol{\chi}} \left(-\sum_{c\in C}\sum_{i\in S_c}\sum_{l\in L_{ic}} a_{ilc}X_{ilc} + f(\boldsymbol{X})\right) \tag{3.33}$$

In other words, ϖ *is less than or equal to the second-stage objective function over all pos-*

sible scenarios (combinations of $(\boldsymbol{b}, \boldsymbol{d})$*). Therefore, the* $\boldsymbol{X}^*$*,* $\boldsymbol{Y}^{*s}$*, and* $\boldsymbol{U}^{*s}$ *are the optimal solutions for the robust counterpart when we have no margins. The worst-case distribution under these conditions is singleton and can be obtained by setting the probabilities such that* $p^{(\bar{\boldsymbol{b}}, \boldsymbol{d}^*)} = 1$ *and* $p^{(\boldsymbol{b}, \boldsymbol{d})} = 0, \forall (\boldsymbol{b}, \boldsymbol{d}) \neq (\bar{\boldsymbol{b}}, \boldsymbol{d}^*)$*.*

Finally, we present a variant of a cutting-plane algorithm (similar to the delayed constraint generation algorithm in Chen [22]) that is significantly more efficient than enumerating all constraints defined by Constraints (3.20). Roughly speaking, the algorithm starts with a similar formulation, but only a subset of constraints (Relaxed Problem). At each iteration, the algorithm adds a separating hyperplane (in the form of Constraints (3.27)), if the current location decisions lead to a set of profits that is infeasible for any $(\boldsymbol{b}, \boldsymbol{d}) \in \Xi$. Algorithm 2 describes the outline of the cutting-plane algorithm.

Algorithm 2 cutting-plane algorithm for $FSCND - u - stoch - w/o$ in Proposition 2

Set tolerance level $\epsilon \leftarrow (0, 1)$

Initialize iteration counter $k \leftarrow 0$

Initialize cuts list $cuts \leftarrow \emptyset$

Set $f(\boldsymbol{X}^0) \leftarrow \infty$

Set stop condition $newCuts \leftarrow$ True

while $newCuts$ **do**

  $k \leftarrow k + 1$

  Solve *(Master)*:

$$\max_{\mathbf{X} \in \boldsymbol{\chi}, \boldsymbol{\theta_b}, \boldsymbol{\theta_d}, \varpi} \left(- \sum_{c \in C} \sum_{i \in S_c} \sum_{l \in L_{ic}} a_{ilc} X_{ilc} + \varpi + \sum_{c \in C} \sum_{(i,j) \in A} q_{b_{(i,j)c}} \theta_{b_{(i,j)c}} + \sum_{c \in C} \sum_{i \in D_c} q_{d_{ic}} \theta_{d_{ic}} \right)$$

  subject to:

$$\varpi + \sum_{c \in C} \sum_{(i,j) \in A} \theta_{b_{(i,j)c}} + \sum_{c \in C} \sum_{i \in D_c} \theta_{d_{ic}} \leq f(\boldsymbol{X}^k), \quad k = 0, 1, \ldots, K$$

  Let $\bar{\boldsymbol{X}}^k, \bar{\boldsymbol{\theta_b}}^k, \bar{\boldsymbol{\theta_d}}^k, \bar{\varpi}^k$ be the optimal solution for *(Master)*, then solve *(Subproblem)*:

$$f(\bar{\mathbf{X}}^k) = \min_{\mathbf{G},\mathbf{H},\mathbf{V},\mathbf{W} \in \mathcal{F}^D(\mathbf{X}, \bar{b}, \mathbf{d}), \boldsymbol{\lambda} \in \Re^+, \boldsymbol{\varrho} \in \{0,1\}} \sum_{c \in C} \sum_{i \in S_c} G_{ic} \left(\sum_{l \in L_{ic}} \psi_{ilc} \bar{X}^k_{ilc} \right) + \sum_{i \in N'} \phi_i V_i + \sum_{c \in C} \sum_{i \in D_c} \sum_{n \in \mathfrak{N}_{ic}} \lambda_{icn} \hat{d}_{icn}$$

  subject to:

$$\sum_{n \in \mathfrak{N}_{ic}} \varrho_{icn} = 1, \forall i \in D_c, c \in C$$

$$\lambda_{icn} \geq W_{ic} - M(1 - \varrho_{icn}), \quad \forall n \in \mathfrak{N}_{ic}, i \in D_c, c \in C$$

$$\lambda_{icn} \leq W_{ic}, \quad \forall n \in \mathfrak{N}_{ic}, i \in D_c, c \in C$$

$$\lambda_{icn} \leq M \varrho_{icn}, \quad \forall n \in \mathfrak{N}_{ic}, i \in D_c, c \in C$$

10: **if** $\bar{\varpi}^k + \sum_{c \in C} \sum_{(i,j) \in A} \bar{\theta}^k_{b_{(i,j)c}} + \sum_{c \in C} \sum_{i \in D_c} \bar{\theta}^k_{d_{ic}} > (1 - \epsilon) f(\bar{\boldsymbol{X}}^k)$ **then**
11: $\quad cuts \leftarrow cuts \cup \{\varpi + \sum_{c \in C} \sum_{(i,j) \in A} \theta_{b_{(i,j)c}} + \sum_{c \in C} \sum_{i \in D_c} \theta_{d_{ic}} \leq f(\bar{\boldsymbol{X}}^k)\}$
12: **else**
13: $\quad newCuts \leftarrow$ False

Since the main problem has exponentially many constraints, we need to generate and add them progressively. In this algorithm, we solve a relaxed version of the main problem with fewer constraints and then, we check the feasibility of the obtained optimal solutions for all the possible realizations in set Ξ. Then, a randomly selected subset of violated constraints is added to the relaxed problem. While our algorithm does not guarantee polynomial running time, in our computational experiments, we stop the procedure long before the constraints are all generated. The main difficulty in the implementation of Algorithm 2 is to solve the optimization problem defined in Step 4. Even the restricted $FSCND - u - stoch - w/o$ is NP-hard, since it can be reformulated as an extension of the capacitated FCLP, which is itself known to be NP-hard [42].

Finally, considering the difficulty of computing the worst-case distribution, it is necessary to assess the risks involved in simply ignoring the correlations and assuming independence in parameters.

Definition 3.1. ***Price of Correlation (POC) [1].*** *POC is defined as:*

$$POC = \left\{ \frac{g(\boldsymbol{X}_C^*)}{g(\boldsymbol{X}_I^*)} \right\} \tag{3.34}$$

Where $\boldsymbol{X}_I^*$ is the optimal solution of the stochastic problem (where independence in parameters is assumed) and $\boldsymbol{X}_C^*$ is the optimal solution of the above model. Finally, $g(\boldsymbol{X}_I)$ is the objective value of $FSCND - u - stoch - w$ problem and $g(\boldsymbol{X}_C)$ is the objective *value of $FSCND - u - stoch - w/o$ problem. Since for a profit maximization problem, $FSCND - u - stoch - w/o$ needs to satisfy more constraints, its corresponding objective value $g(\boldsymbol{X}_C^*)$ is less than or equal to $g(\boldsymbol{X}_I^*)$ and thus, $POC \leq 1$.*

3.6. Case Study and Computational Efforts

In a two-year research engagement project with the largest automakers in the United States, we identified and categorized the sources of uncertainty in their complex and lengthy supply chain into three categories of demand, exchange rate, and freight cost uncertainty. Most decisions in supply chains are demand-driven and demand parameters are uncertain much of the time due inexact demand forecasts, or even seasonality effects. Environmental uncertainties including changes in the regulatory and macro-economic environment can also affect the parameters of the supply chain models operating globally. Exchange rates or fuel costs are two well-known examples of this type of uncertainty. For the deterministic case we use the the most probable estimation (one-point estimation).

For the stochastic models, we discretize the distribution of the uncertain parameters into a three-point estimation distribution arbitrary. Due to the sensitivity of the outputs of the model to the range of the uncertain parameters, in particular the exchange rate uncertainty, we need the tightest possible estimates for the low and high values of the distributions. Since we have very limited information for demand parameters, we used a wide range to model demand uncertainty. The proposed range is 50% of the middle value for the low value and 150% of the middle value for the high value. For exchange rates and fuel cost, since we have monthly information, we can follow their trends and suggest a tighter range for uncertainty. The proposed range for the input parameters is attached in table A.2 in appendix III. According to the historic data obtained from the company, these bounds cover most of the range of previous fluctuations. For comparison purposes, the probabilities are set in a way that the expected values of the uncertain parameters are equal to the value of the middle outcome. Then, we construct scenarios (different realizations of the uncertain parameters) with a specific order of uncertain parameters, i.e. freight costs, exchange rates, and demands. We sort scenarios from the lowest realization of the all uncertain parameters to the highest realization of them. Therefore, we have:

$$\begin{aligned}
\Xi = \{\boldsymbol{\xi_1} : \quad & (\overbrace{low}^{\text{1 freight cost}}, \overbrace{low, \ldots, low}^{\text{6 exchange rates}}, \overbrace{low, \ldots, low}^{\text{5 demands}}), \\
\boldsymbol{\xi_2} : \quad & (low, low, \ldots, medium), \\
\boldsymbol{\xi_3} : \quad & (low, low, \ldots, high), \\
\ldots, & \\
\boldsymbol{\xi_{3^{12}}} : \quad & \underbrace{(high, high, \ldots, high)}_{\text{12 uncertain parameters}}\}
\end{aligned}$$

We assume perfect correlation among freight costs. In other words, if the fuel cost is high, all freight costs will be realized at their high levels and vice versa. Moreover, since different parts can have suppliers in the same country (same currency), it is logical to assume the exchange rate of these suppliers are perfectly correlated. Since we do not know the joint distribution of the uncertain parameters, we assume the worst-case correlation can happen in other cases. The correlation structure among the parameters is shown in figure 3.2:

	Demand	Exchange Rate	Freight cost
Demand	**Worst-case (1: if same)**	0	0
Exchange Rate	0	**Worst-case**	0
Freight cost	0	0	**1**

Figure 3.2: Structure of the correlation among the uncertain parameters

In figure 3.2, 0 represents no correlation and 1 represents perfect correlation. Furthermore, we have synthetic data for two parts, 1 and 2. Part 1 has three suppliers located in India, China, and China respectively. The second part has four suppliers located in India, China, Germany, and Brazil. Therefore, we are dealing with four different exchange rates for the purchasing cost. The demand markets of the vehicle are in India, China, UK, Russia, and Brazil. This accounts for two more exchange rates on the demand side (totally 6 different exchange rates are involved).

According to the BOM, part 1 is part of the Transmission System of the vehicle and has to be sent to the Transmission Plants. There are three Transmissions plants available in India, China, and China. Part 2 needs to be sent to the Casting and Forging Plants first and then the Stamping Plants. We consider two Casting plants both located in Germany for this part and one Stamping plant in UK. Both parts will be sent to five available Vehicle

Assembly plants in India, China, UK, Russia, and Brazil. Finally, the final product (vehicle) will be sent from Vehicle Assembly plants to the demand markets. In this case study we do not have information about engine parts. The BOM and the production process of these parts is depicted in figure 3.3:

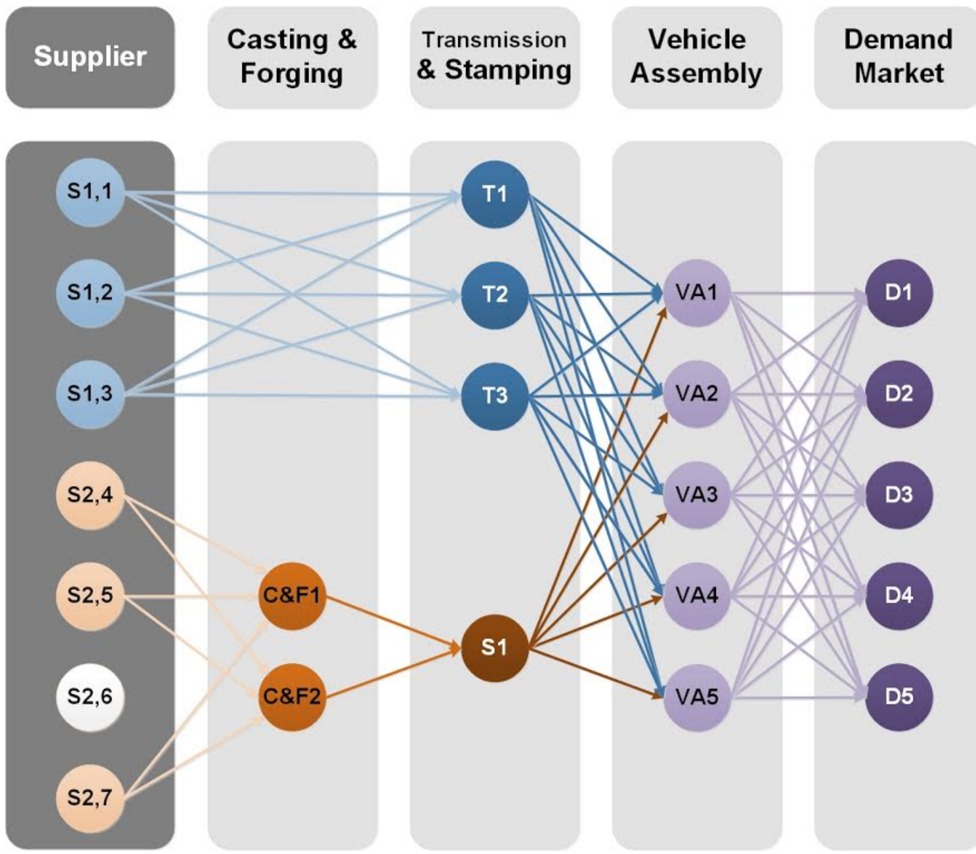

Figure 3.3: The process sheets of parts 1 and 2

On the left side of this network we have the suppliers denoted by $S1$ and $S2$ for parts 1 and 2 respectively ($S1\_X$ is supplier number X for part 1). The arrows show the feasible flows for each part. The color of the arrow changes when the parts are processed in different nodes. The nodes C&F, T, E, S, and VA represent the Casting and Forging, Transmission, Engine, Stamping, and Vehicle Assembly plants respectively. Finally, demand markets are shown by D nodes.

We ran all the models on a computation server with 12 cores and 128 GBs of RAM. More specifically, the machine has 2 CPU's which are Xeon $E5-2643$ $v4$ chips running at 3.4 GHz (i.e. each chip has 6 cores). We used Gurobi 7.0 MIP solver package for Python to solve the developed MILP models. The MIP solver parameters for tuning, generating cuts, and tolerances are all set to default values. To force for multi-threading, the "Threads" parameter (controls the number of threads used by the parallel MIP solver to solve the model) is set to the maximum.

The deterministic model yields a solution with no unmet demand. The tooling decisions (capacity) along with the flows on each arc are depicted in figure A.2 attached to supplementary files. The results obtained from the models are summarized in table 3.2:

Table 3.2: Comparison of the solutions from different models

Models	Capacities/Supplier	Tooling (Modules)	Objective	POC
FSCND-u-det	$(3, 7, 2, 4, 4, 1, 0)$	$(12, 9)$	$504, 598, 311$	N/A
FSCND-u-stoch-w	$(7, 7, 4, 4, 2, 0, 4)$	$(18, 10)$	$502, 263, 180$	1
FSCND-u-stoch-w/o[1]	$(7, 7, 3, 4, 4, 0, 4)$	$(17, 12)$	$491, 065, 297$	0.97
FSCND-u-stoch-w/o[2]	$(3, 6, 0, 3, 0, 0, 4)$	$(9, 7)$	$229, 061, 767$	0.45

[1]The model with margins for each uncertain parameter.

[2]The model without margins (Proposition 3.3).

In the deterministic model we are only planning against the mean values of the parameters. The profit obtained under this condition is very close to the expected profit in the $FSCND-u-stoch-w$. In the $FSCND-u-stoch-w/o^1$ model we used the probabilities for the uncertain parameters as the marginal probabilities of the actual joint distribution and the results suggest under the worst-case distribution the correlation among demand parameters and the exchange rates can reduce the profitability. However, by keeping 24 margins (we have 12 uncertain parameters and we keep 2 margins for each) for uncertain parameters the reduced profit might not be significant. Finally, the $FSCND-u-stoch-w/o^2$ has a significantly lower profit in comparison with other models and this is due to the fact that we are only planning against one scenario (the worst-case scenario) and basically this is the lowest profit we can obtain conditioning on the suggested tooling.

To further discuss the differences among all models, we simulated $10,000$ random scenarios (sorted by index s) and compare the profit under different tooling. In this simulation we produced $10,000$ scenarios from the set Ξ without considering the probabilities of the uncertain parameters. In other words, we produced $10,000$ random numbers between 1 and $|\Xi| = 3^{12}$ and we sorted them in ascending order of the realizations (similar to the order of the whole Ξ). Then, we found the corresponding realizations of the uncertain parameters for each random number from set Ξ. As we can see in figure 3.4 the tooling for $FSCND-u-stoch-w/o^2$ shows a very robust performance with less variation. In fact, the Coefficient of Variation (CV) for the profit obtained in this model is around 18.59% and it is the lowest among all models. It is also worth noting that the solution of the $FSCND-u-stoch-w/o^1$ model has the highest mean and highest CV. Other means, standard deviations, and CVs are reported in table 3.3 below:

Table 3.3: **Comparison of means, standard deviations, and CVs for different tooling**

Models	**Mean**	**Standard Deviation**	**100%CV**
FSCND-u-det	$525,103,895$	$118,615,604$	22.59%
FSCND-u-stoch-w	$542,395,559$	$123,169,840$	22.71%
FSCND-u-stoch-w/o[1]	$545,186,324$	$128,993,201$	23.66%
FSCND-u-stoch-w/o[2]	$437,754,098$	$81,401,263$	18.59%

[1]The model with margins for each uncertain parameter.

[2]The model without margins (Proposition 3.3).

The scatter plot of the profits obtained for these models show a repeating pattern. The main pattern belongs to the three different values of the freight costs (gray highlights) and it has been repeated three times (Low (L), Medium (M), and High (H) freight costs). For each realization of the freight costs, we have another repeating pattern related to the exchange rates. The high peaks correspond to scenarios with high exchange rate realizations and low peaks correspond to low realizations of the exchange rates. In these scenarios the performance of the deterministic model is relatively poor in comparison with the stochastic models $FSCND-u-stoch-w$ and $FSCND-u-stoch-w/o^1$. In other words, the deterministic model is only reliable when we have low or medium realizations for the exchange rate uncertainty. Other variations in this plot correspond to demand uncertainty which is increasing gradually because we sorted these scenarios in ascending order of their index and therefore, the higher demand realizations are shown on the right hand side of each section of the plot.

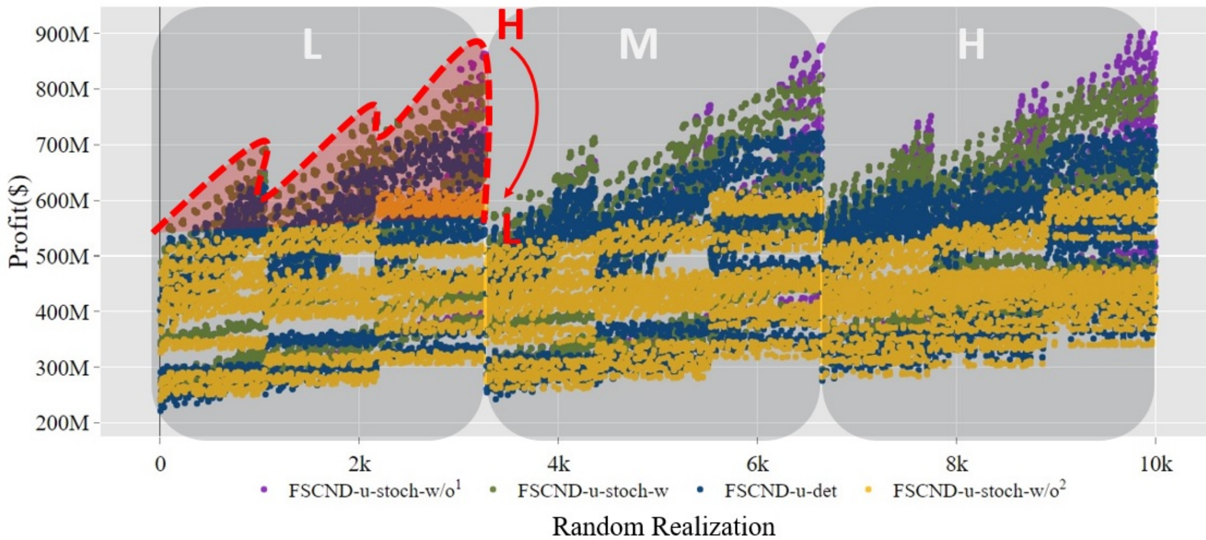

Figure 3.4: Comparison of the profit from simulated scenarios under different tooling

Finally, the $FSCND-u-stoch-w/o^1$ is giving the highest profit of all in most scenarios. The high and low peaks in $FSCND-u-stoch-w/o^1$ correspond to the scenarios with high and low realization of the exchange rates. The $FSCND-u-stoch-w/o^1$ model is giving a higher profit than the $FSCND-u-stoch-w$ model with similar tooling. This is due to the fact that we are reserving capacity to hedge against both demand and exchange rate uncertainties and therefore, higher tooling will yield higher profit in scenarios with high demand and high exchange rate realizations.

Comparing the worst, average, and best profits obtained from each tooling is also beneficial to describe the performance of these models. Figure 3.5 shows that on average (the blue line) the profits obtained from the $FSCND-u-stoch-w/o^1$ is higher than that of the other models (about 24% more than $FSCND-u-stoch-w/o^2$ and 4% more than the deterministic tooling). The worst profit (red line) obtained from all models is similar to each other. Finally, the best profit comes from $FSCND-u-stoch-w/o^1$ in comparison with others (about 46% more than $FSCND-u-stoch-w/o^2$, 23% more than the deterministic tooling, and about 9% more than stochastic tooling).

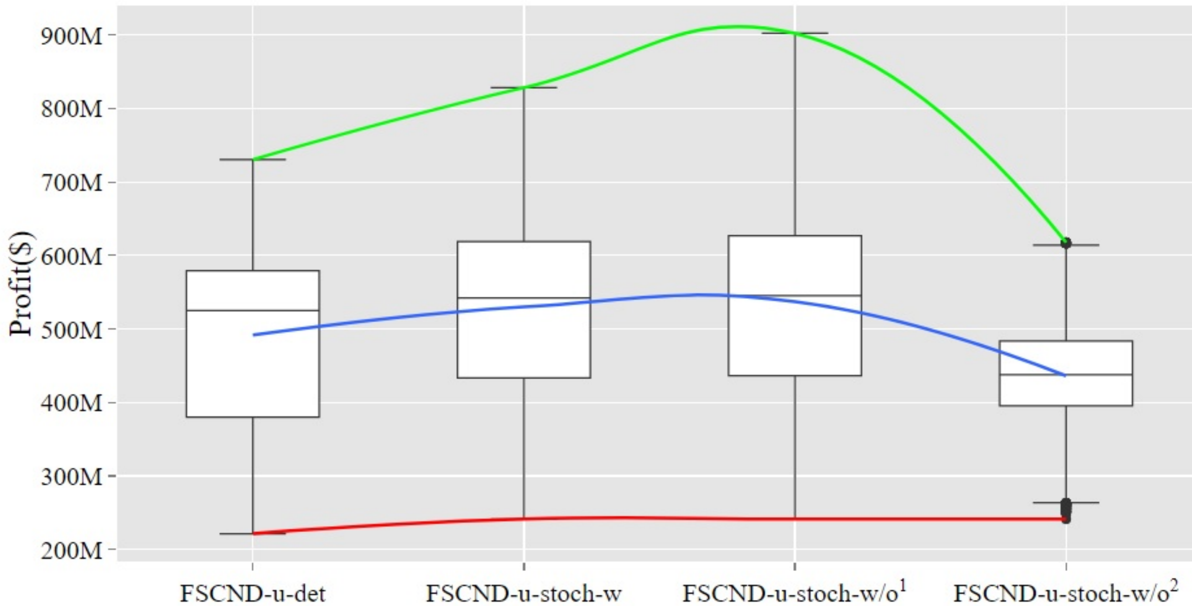

Figure 3.5: Box-plots from simulated scenarios under different tooling

The box-plots of the profits from simulated scenarios are also depicted in figure 3.5. The horizontal lines of the box are showing the first, second, and the third quartiles of the profits under different tooling. The lowest horizontal lines represent the 1.5 times Quartile Range (QR) from below the first quartile. Similarly, the highest horizontal lines represent the 1.5 times QR from above the third quartile. The filled dots represent the obtained profits outside this wider range. As we can see in figure 3.5 both $FSCND - u - stoch - w/o^1$ and $FSCND - u - stoch - w$ have similar QRs. However, the 1.5 times QR for the $FSCND - u - stoch - w/o^1$ model is wider. This fact indicates the profits obtained from $FSCND - u - stoch - w/o^1$ model has a higher variation. In fact, the coefficient of variation for this model is about 23.66% and it is the highest among all models.

3.6.1. Managerial Insights from The Correlated Models

In this section we discuss how the correlated stochastic models can result in solutions that are different than the corresponding solutions given by the independent stochastic model. In particular, we discuss differences in the tooling under the assumption that demand parameters are the only uncertain parameters in the models. The reason we chose demand parameters is that the feasible region of the uncertain models is only affected by demand. Then, we compare the results for different tooling in which all demands, exchange rates, and freight costs are uncertain (Full model) versus the models in which we only have demand uncertainty (Demand model). First, similar to the Full model, the results obtained from the models in which only demand was uncertain (Demand model) are summarized in table 3.4:

Table 3.4: Comparison of the solutions from different models under demand uncertainty only

Models	Capacities/Supplier	Tooling (Modules)	Objective	POC
FSCND-u-det	$(3,7,2,4,4,1,0)$	$(12,9)$	$504,598,311$	N/A
FSCND-u-stoch-w	$(5,7,2,4,4,1,1)$	$(14,10)$	$502,781,262$	1
FSCND-u-stoch-w/o[1]	$(7,7,3,4,4,3,1)$	$(17,12)$	$499,573,622$	0.99
FSCND-u-stoch-w/o[2]	$(3,6,0,4,3,0,0)$	$(9,7)$	$379,980,381$	0.75

[1]The model with margins for each uncertain parameter.
[2]The model without margins (Proposition 3.3).

From table 3.4, we can see similar number of modules for the $FSCND-u-stoch-w/o^1$ and $FSCND-u-stoch-w/o^2$ models (correlated models), but the breakdowns of the modules for the suppliers are different.The total tooling for the $FSCND-u-stoch-w$ has decreased. This is the result of having less uncertainty in the model. The larger POC

values for the Demand model indicate that the correlation across uncertain parameters has less impact on the corresponding decision problems with fewer uncertain parameters. We used the same simulated $10,000$ random scenarios to compare the performance of the tooling obtained from models under Full uncertainty and only Demand uncertainty conditions.

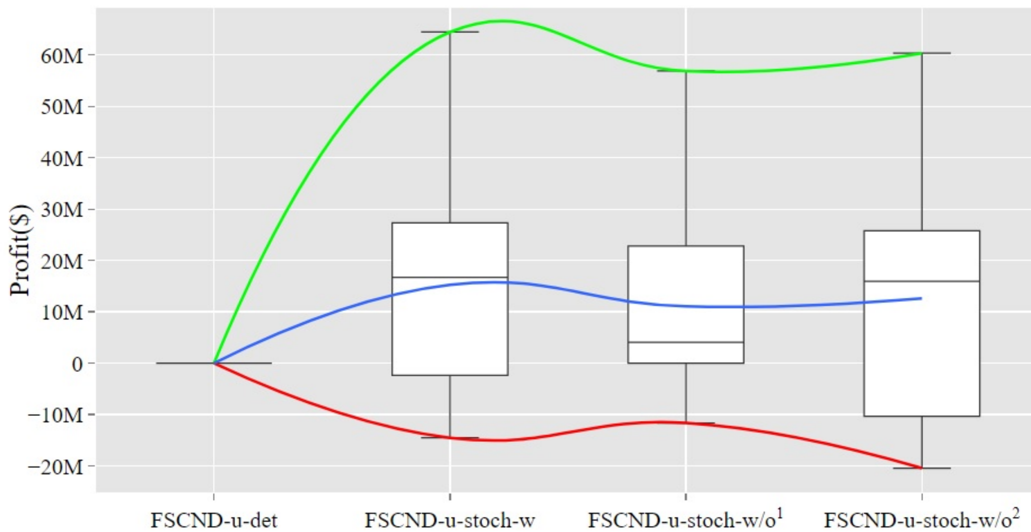

Figure 3.6: Box-plots for Full versus Demand model

Figure 3.6 illustrates the box-plot of differences between profits (profit gaps) where the tooling obtained under Full uncertainty and Demand only uncertainty for all models. For the deterministic model the solution is always the same, therefore, in all scenarios the obtained profits are the same. As we can see the profit gaps for the independent stochastic model has a wider QR and a slightly higher mean. The high gap values are related to simulated scenarios with high realizations of the freight costs and exchange rates. In these scenarios profitability of the tooling under the Demand only conditions is relatively small due to low tooling in the Demand only model. The low tooling leads to higher transportation costs. The lower QR belongs to the $FSCND-u-stoch-w/o^1$ model. By comparing the box-plots of all models we can conclude that the $FSCND - u - stoch - w/o^1$ model is slightly less sensitive to exchange rates and freight costs uncertainties and the exchange rate and freight cost uncertainties have a significant effect on tooling decisions in the independent model.

Finally, in the $FSCND - u - stoch - w/o^1$ model we set two margins for each uncertain parameter with three possible realization; low, medium, and high. This is the maximum number of margins we could fix independently from each other. In the $FSCND - u - stoch - w/o^2$, we did not fix any margins. In that sense these two model are the two ends of this range. We compare the value of POC for the Full model with different number of margins in Figure 3.7.

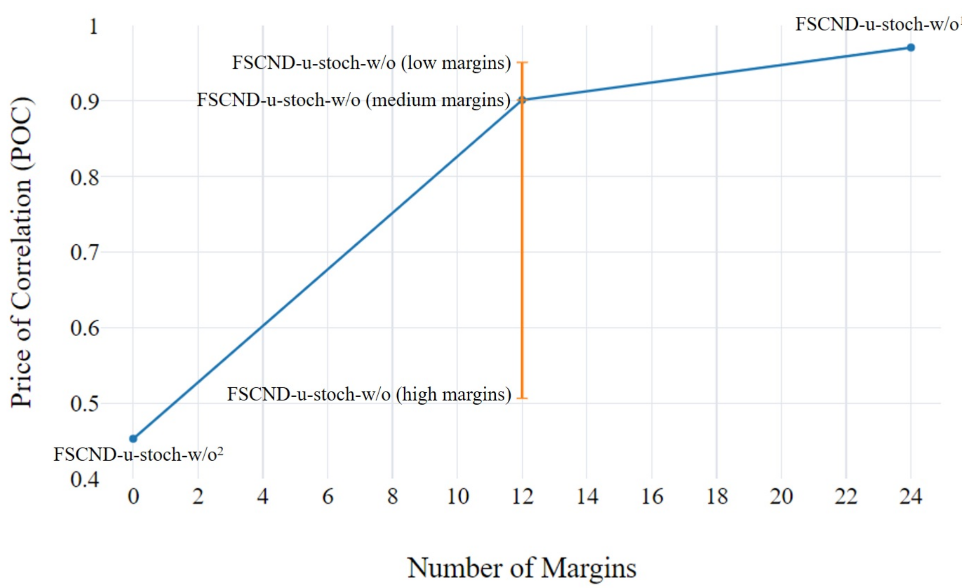

Figure 3.7: The effect of margins on POC

In Figure 3.7 the blue line shows the decrease in the POC value by reducing the number of margins. On the right side of this Figure, we kept all 24 margins and therefore, this model is in fact $FSCND - u - stoch - w/o^1$. On the left side of the Figure, we kept 0 margins and therefore, the no margin model is equivalent to $FSCND - u - stoch - w/o^2$. The middle point of the blue line is the POC value for a model in which we only kept 12 margins (the middle values of the distribution functions of the uncertain parameters). The orange line shows the range of the POC values for different possible combinations of the 12 margins (3^{12} combinations). The highest POC is from the model in which we kept 12 margins that are the low realizations of the uncertain parameters and the lowest POC belongs to the highest realizations of them.

Figure 3.7 suggests that by reducing the number of margins, the POC drops. In other words, having less information about the distributions of the uncertain parameters leads to relatively inefficient tooling and less profit. Thus, the correlation across uncertain parameters has more implications on the corresponding decision problems when we have less information about the uncertain parameters.

3.6.2. Complexity Analysis of The Correlated Models

The problem introduced in Proposition 3.2 has exponentially many constraints and therefore, we need to generate and add them progressively. Algorithm 2 describes the outline to generate and add the delayed constraints. In this section we compare the running times of the MILP solver for different models. Since the complexity of the models depends on the total number of scenarios, we represent the complexity of the different models with the size of scenario set for each model. For the $FSCND - u - stoch - det$ we only consider one scenario, the $FSCND - u - stoch - w$ has 3^n scenarios, and therefore its complexity is proportional to $\mathcal{O}(|\Xi|) = \mathcal{O}(3^n)$ for a problem with n uncertain parameters (each parameter is discretized into three low, medium, and high estimations). The complexity of the

$FSCND - u - stoch - w/o^1$ is proportional to $\mathcal{O}(3^{2n})$ since we have a constraint for each scenario. Finally, by proposition 3.3, the complexity of the $FSCND - u - stoch - w/o^2$ is reduced and it is proportional to $\mathcal{O}(3^n)$.

We compare the running time of the Gurobi 7.0 MIP solver for all models with different number of uncertain parameters. In Figure 3.8 the horizontal axis shows the number of uncertain parameters. In this axis 0 means no uncertain parameters (deterministic model). Then, we add the demand uncertainty, then exchange rates, and finally the freight cost. This comparison is presented in figure 3.8:

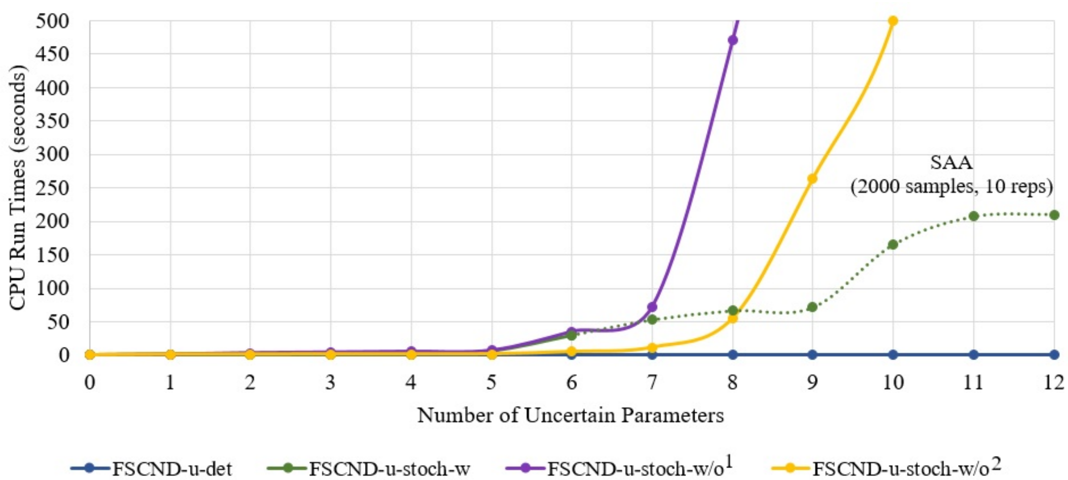

Figure 3.8: Comparison of the running times for different models

As expected the MILP deterministic model is very fast for different problem sizes. The convexity of the plots suggest that the running times increase exponentially by increasing the number of uncertain parameters for the stochastic models. For the $FSCND - u - stoch - w$, the solver was able to solve the problem sizes up to 5 uncertain parameters in an acceptable time, however, for larger problem instances we used the SAA scheme with $2,000$ samples and 10 reps. The solver was not able to solve the $FSCND - u - stoch - w/o^1$

model for problem sizes larger than 7 in less than 500 seconds. However, using Algorithm 2 we were able to solve these instances faster. Figure 3.9 compares the running times of the MILP solver with the cutting-plane algorithm 2 for $\epsilon = 0.1\%$:

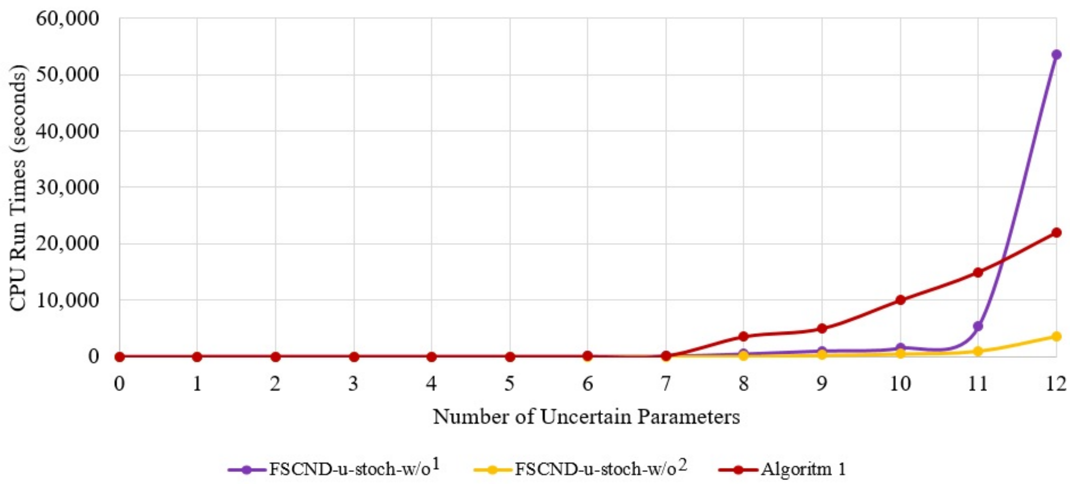

Figure 3.9: Comparison of the running times for MILP Solver and Cutting-plane Algorithm 2

The cutting-plane algorithm 2 was able to solve all instances. It seems the running time of the algorithm 2 is less sensitive to the problem size compared to that of MILP solver. The convexity of the curve for the running times of this algorithm suggests that algorithm 2 does not guarantee polynomial time solutions as we mentioned before. It is worth mentioning that we consider a relatively small ϵ for comparison purposes. Larger values of ϵ can lead to different (sub-optimal) solutions than the exact optimal solution.

3.7. Concluding Remarks

We propose an optimization model for designing flexible SCNs operating under uncertainty through capacity planning. First, we consider an extension of current SCN models by coordinating several SCNs of common commodities of different products. In practice, we cannot coordinate the SCNs of all the parts in different products (vehicles) due to different designs, specifications, and requirements for different products. However, we can optimize the global sourcing strategies of the common parts to reduce initial (tooling) investments, and take advantage of economies of scale. Although in our case study we did not consider any suppliers capable of producing more than one commodity, the capacity of the suppliers can be shared among different commodities for different products in our models. Second, we focus on the correlation among uncertain parameters (demands, exchange rates, and freight costs). To do so, we employ distributionally robust optimization to coordinate the SCNs against the worst-case distribution with given marginal probabilities for demand, exchange rate, and freight cost uncertainties. Moreover, we investigate the price of correlation in the design parameters against the traditional methods in which the independence of the uncertain parameters is an assumption. To the best of our knowledge, our model is different from other approaches found in the literature and contributes in the following ways. (1) We include multiple sources of uncertainty in the model (demand, exchange rate, and freight cost). (2) Capacity planning (as opposed to holding inventory) is proposed to create flexibility in designing SCNs. In particular, holding inventory to create flexibility is not feasible in auto industry. (3) *Distributionally Robust Optimization* (DRO) is used to coordinate SCNs of different products and parts against the worst-case joint distribution of the uncertain parameters with given marginal probabilities.

Our results show that correlation has an effect on the profit and the effect of the correlation increases when we have less information about the uncertain parameters. The deterministic model is only reliable when we have low or medium exchange rates. The correlated model (with full margins) gives higher profit when exchange rates are high compared to the stochastic model (independent). The worst-case analysis of all models return similar results, but the correlated model has a slightly higher mean profit. The results indicate the value of the correlated model compared to other variations. Finally, we proposed a tractable algorithm to solve the correlated model in less amount of time than required by the commercial solvers.

For the future research, we suggest the study of risks involved with under/over estimating the required tooling, specifically for parts with expensive tooling. Another interesting subject to investigate is the possibility of reserving capacity options. Finally, the study of the demand elasticity to the price in different markets can be another interesting subject.

Chapter 4.

Capacity Options to Hedge Against Uncertainty

4.1. Introduction

Supply Chain Network Design is a strategic problem that involves decisions not only about the flow of commodities and products, but also decisions regarding the number, location, capacity of the suppliers, tooling the suppliers, quantity of the commodities ordered to suppliers, and inventory of the commodities. Upon implementation it is difficult to reverse or alter some of these decisions. During the operation time when the decisions are in effect, many input parameters (such as demands, exchange rates, costs, etc.) can change dramatically from their originally assumed values. In fact, uncertainty in input parameters is always a constant threat to the optimality and feasibility of these decisions. This is why designing models that can address the inherent uncertainty of the design parameters of Supply Chain Networks (SCNs) has become a significant concern in different industries. The automotive industry is no exception from this. For example, Ford Motor Company announced that they expect a weak exchange rate to hurt sales in the United Kingdom following the Brexit vote in June 2016 [61]. This is an example of exchange rate uncertainty and how it can affect the previous decisions made by Ford to produce cars in the United Kingdom. This is due to the fact that the weaker pound makes it less attractive for suppliers to invest in that market. Another example of these uncertainties is the growing demand in the car industry after the 2009 recession. As the economy moves from recession to recovery, car companies are expanding their production lines and their demand is growing annually [94]. Proper tooling is required to satisfy this growing demand; otherwise, lost sales will be inevitable.

To deal with the uncertainty, researchers often define uncertainty sets over which the distribution of the uncertain parameters are known a priori [19]. By considering discrete distributions, discretization of the continuous distribution, or sampling from the distribution of the uncertain parameters one can form scenarios and optimize the model over the set of all possible scenarios. A scenario is defined as a realization of the uncertain parameters [38]. Scenario planning is also a common approach for SCND problems. Expected value and worst-case performance are the most common approaches to evaluate the performance of the designs in SCND problems. However, such approaches are not necessarily practical since, in practice, systems may not be typically designed for the average case or the worst-case scenario. For example, airports are never sized for an average day, since doing so would result in significant under-capacity much of the time. On the other hand, airports are never sized for the peak travel day, e.g., the Sunday of Thanksgiving weekend in the United States, since doing so would be prohibitively expensive [23].

Depending on the source of the uncertainty (demand-side, supply-side, or environmental) in the model, several mitigation strategies have been proposed by researchers in the literature. While much of the literature considers safety stock inventory and backup suppliers as effective strategies to hedge against uncertainty [90], in many industries (like the auto industry) keeping inventory for long periods is not possible. It is worth mentioning that some scholars proposed safety stock inventory for short periods [82, 88] to deal with supply-side uncertainties.

In this chapter, we proposed capacity planning combined with evaluation of capacity options as an effective strategy to hedge against uncertainty in the design of flexible SCNs. Capacity option contracts create more flexibility compared to fixed-commitment contracts and improve the expected costs of the SCNDs.

In what follows, we provide a motivational example to show the benefits of using capacity options along with reserved capacity in compare to the setting in which options are not available.

4.1.1. A Motivational Example: The Newsvendor Problem

The Newsvendor model addresses order quantity decisions under stochastic demand. The Newsvendor logic dates back as far as Arrow et al. [6]. The model has numerous applications, including advance sale of capacity [102], the purchase of high fashion or seasonal clothing and flexible spending accounts.

The simplest form of the Newsvendor model is a one-period one-product inventory model. The agent faces the problem of determining the optimal order quantity of a product that satisfies the following set of assumptions:

- The product is perishable; i.e., it can only last for one period.
- All items have to be purchased at the beginning of a period.
- Demand for the product is uncertain.
- All prices and cost parameters are deterministic and known a priori.

There are several extensions of this model in the literature, in this section, we examine an extension of the Newsvendor problem with an option to buy capacity. In the classic Newsvendor problem, an agent must determine how many items to purchase from a supplier (e.g., how many Newpapers to purchase from a publisher). The agent must do so in the face of uncertain demand. Demand is realized after the items are purchased from the supplier. If the realized demand falls short of the number of items the agent purchases, the extra items may (in some cases) be salvaged at a net loss to the agent. If the realized demand exceeds the number of items the agent purchases, there is a loss of potential profit.

In some cases, however, the agent may be able to reserve capacity at the supplier in the event demand exceeds the quantity initially purchased. The cost of purchasing an option for additional capacity must clearly be less than the cost of buying an item outright. Furthermore, the cost of exercising an option plus the cost of buying the option must exceed the cost of purchasing an item outright and less than the retail sales price of the item. We assume that any unused reserved capacity is lost; clearly, if there is a market for these options (as may be the case in the event of there being multiple agents), there may be a salvage value for the unused options as well.

To illustrate the advantages of allowing options or hedging, consider the following simple example. The demand for the item is given by the symmetric distribution shown in Figure 4.1.

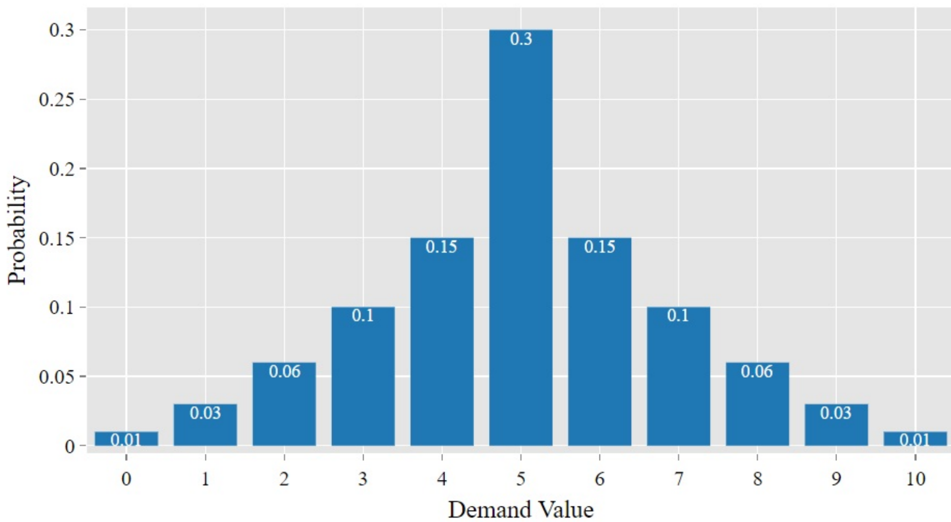

Figure 4.1: Example of demand distribution

The agent buys goods at \$100 per item. Items are sold at \$300 per item and the salvage value of unsold items is \$15. The optimal Newsvendor solution is to buy 6 items for an expected profit of \$815.25. The breakdown of this profit for each possible realization of demand is shown in Table 4.1.

Table 4.1: Classic Newsvendor Results

Dem.	Prob.	Cum. Prob.	Buy	Sell	Salvage	Buy Cost	Sales Revenue	Salvage Revenue	Net Profit
0	0.01	0.01	6	0	6	600	0	90	-510
1	0.03	0.04	6	1	5	600	300	75	-225
2	0.06	0.1	6	2	4	600	600	60	60
3	0.1	0.2	6	3	3	600	900	45	345
4	0.15	0.35	6	4	2	600	1200	30	630
5	0.3	0.65	6	5	1	600	1500	15	915
6	0.15	0.8	6	6	0	600	1800	0	1200
7	0.1	0.9	6	6	0	600	1800	0	1200
8	0.06	0.96	6	6	0	600	1800	0	1200
9	0.03	0.99	6	6	0	600	1800	0	1200
10	0.01	1	6	6	0	600	1800	0	1200
Expected Value			**6**	**4.65**	**1.35**	**600**	**1395**	**20.25**	**815.25**

If we can buy an option for additional items at $20 per option with an additional exercise cost of $90, the optimal policy is to buy 3 items outright and to purchase an option for an additional 5 items. The expected revenue is now $898.25, or an increase of $83 or over 10%.

Table 4.2: **Newsvendor Model with Options**

Dem.	Prob.	Cum. Prob.	Buy	Options Bought	Options Exercised	Sell	Salvage	Buy Cost	Option Cost	Exercise Cost	Sales Revenue	Salvage Revenue	Net Profit
0	0.01	0.01	3	5	0	0	3	300	100	0	0	45	-355
1	0.03	0.04	3	5	0	1	2	300	100	0	300	30	-70
2	0.06	0.1	3	5	0	2	1	300	100	0	600	15	215
3	0.1	0.2	3	5	0	3	0	300	100	0	900	0	500
4	0.15	0.35	3	5	1	4	0	300	100	90	1200	0	710
5	0.3	0.65	3	5	2	5	0	300	100	180	1500	0	920
6	0.15	0.8	3	5	3	6	0	300	100	270	1800	0	1130
7	0.1	0.9	3	5	4	7	0	300	100	360	2100	0	1340
8	0.06	0.96	3	5	5	8	0	300	100	450	2400	0	1550
9	0.03	0.99	3	5	5	8	0	300	100	450	2400	0	1550
10	0.01	1	3	5	5	8	0	300	100	450	2400	0	1550
Expected Value			**3**	**5**	**2.1**	**4.95**	**0.15**	**300**	**100**	**189**	**1485**	**2.25**	**898.25**

Below, we present two different models of a Newsvendor model with the option to buy additional items. The first model is based on a continuous distribution of demand. In this model, we develop purchasing rules for the Newsvendor. In other words, we identify the number of items to purchase and the size of the option to buy. The second model is a stochastic programming model of the Newsvendor problem with options.

We begin with a simple analytic model in which we assume that the demand is continuous with a density function given by $f(y)$. Additional inputs are below.

Parameter	Description
p	Unit sale price
c	Cost of a unit if purchased upfront
s	Salvage value per unit
o	Cost per unit optioned
e	Cost per unit to exercise the option
$f(y)$	Density function of demand
$F(y)$	Cumulative distribution of demand

Clearly we require $p > o + e > c > s$ for the problem to make sense. We also require $e < c$, since otherwise we would never want to use hedging. If $e \geq c$, it is always less expensive to simply buy items outright than it is to use hedging and then purchase the additional items by exercising an option. We also define the following decision variables.

Variable	Description
B	Number of units to buy
X	Number of units to option

With this notation, we can write down the expected revenue for a Newsvendor problem in which the agent buys B items outright at a cost per item of c and purchases the right to buy an additional X items at an option price of o per item. When the option is exercised, meaning one or more additional items are purchase following the realization of demand, an additional e dollars per unit must be paid. Items are sold at a unit price of p, and any unsold items from the original B items purchased outright can be salvaged at a unit price of s. The expected revenue is given by:

$$\begin{aligned}\pi(B,X) =& -cB \\ & -oX \\ & +\int_0^B pyf(y)dy \\ & +pB\int_B^{B+X} f(y)dy + \int_B^{B+X} (p-e)(y-B)f(y)dy \\ & +pB\int_{B+X}^{\infty} f(y)dy + (p-e)X\int_{B+X}^{\infty} f(y)dy \\ & +\int_0^B s(B-y)f(y)dy\end{aligned}$$

where $\pi(B,X)$ represents the expected profit. The first two terms in the revenue are the cost of purchased items and cost of options purchased. The next three rows are the expected revenue if demand is less than B, between B and $B+X$, and more than B. Finally, the last term is the expected revenue from the salvaged items.

Taking the derivatives of this function with respect to B and X, we obtain:

$$\begin{aligned}\frac{\partial\pi(B,X)}{\partial B} =& p-c+(e-p)F(B+X)+(s-e)F(B)=0 \\ \frac{\partial\pi(B,X)}{\partial B} =& -o+p-e-(p-e)F(B+X)=0\end{aligned}$$

or $F(B+X) = \frac{p-o-e}{p-e}$ and $F(B) = \frac{o+e-c}{e-s}$. These values need to be compared to the standard Newsvendor result which says that we should purchase a quantity W such that $F(W) = \frac{p-c}{p-s}$. If $W \geq B + X$, we should purchase W items and simply use the Newsvendor results; otherwise, we should purchase B items outright and an option for an additional X items. We can show that if $(p-s)o < (c-s)(p-e)$, we should use hedging; otherwise, we should use the standard Newsvendor results.

We now turn to a scenario-based approach to the problem. In addition to the inputs defined above, we define:

Parameter	**Description**
q_n	Probability of demand being equal to n

We also define the following decision variables:

Variable	**Description**
B	Number of units to buy
X	Number of units to option
Z_n	Number sold when demand is n
W_n	Number of options exercised when demand is n
V_n	Number of salvaged items when demand is n

With this notation, a scenario-based formulation of the problem is given below (where each scenario is a different realization of demand):

$$\max_{\mathbf{B,X,Y,Z,W,V}\in\Re^+} \left(\sum_{n=0}^{\infty} q_n p Z_n + \sum_{n=0}^{\infty} q_n s V_n\right) - \left(cB + oX + \sum_{n=0}^{\infty} q_n e W_n\right) \tag{4.1}$$

subject to:

$$Z_n \leq n, \quad \forall n \tag{4.2}$$

$$Z_n \leq B + X, \quad \forall n \tag{4.3}$$

$$W_n \geq Z_n - B, \quad \forall n \tag{4.4}$$

$$Z_{n+1} - Z_n \leq 1, \quad \forall n \tag{4.5}$$

$$Z_n + V_n \leq B + W_n, \quad \forall n \tag{4.6}$$

$$W_n \leq X, \quad \forall n \tag{4.7}$$

The constraint $Z_{n+1} - Z_n \leq 1$ is added simply to ensure that numerical issues do not violate this natural constraint.

To illustrate these results, consider the case in which we have Poisson demands with a mean of 15, a sale price (p) of 225, a purchase cost (c) of 100, an option cost (o) of 20, a cost to exercise an option (e) of 90, and a salvage cost (s) of 10. For this model we have $F(B) = 0.125$, $F(B+X) = 0.8519$, and $F(W) = 0.5814$. This results in $B = 11$ and $X = 8$, for the hedging model and $W = 9$ for the Newsvendor model, respectively. The expected profit for the hedging model is \$1,689.07 and \$1,547.51 for the standard Newsvendor model. The hedging model increases profit by \$141.56 or 9.15%.

4.1.2. Contributions and Highlights

The contributions of this chapter to the SCND literature are twofold and include:

- The development of the capacity option models that allow to hedge against uncertainty and its application for automotive industry,
- Analyzing the sensitivity of the developed models under mean-excess regret risk and demonstrating conditions under which capacity option models are beneficial.

The remainder of this chapter is organized as follows. In Section 2, we review the literature on the different uncertainty measures used in SCND literature, mitigation strategies, and capacity options. Section 3 provides the mathematical formulation of the problem in three different settings (deterministic, minimax regret, and mean-excess regret). In section 4, a modified Bender's decomposition is proposed to solve the developed models efficiently. In Section 5, the developed models are validated through a case study in for high tooling cost parts and the sensitivity of the designs are discussed extensively. Managerial insights evolved from this case study are provided in section 6. Finally, concluding remarks and future directions are presented in section 7.

4.2. Literature Review

This chapter surveys the strands of literature related to three topics: first, the literature on uncertainty measures for optimization under uncertainty that gives insight into the choice of reasonable criteria to evaluate the designs; second, the body of literature on different mitigation and hedging strategies is of interest; and third, shedding light on the capacity options and embedding this into the greater context of flexible SCND.

4.2.1. Uncertainty Measures

There are several measures to model the uncertainty in SCNs operating under uncertainty. The majority of the literature considers measures of central tendency (e.g. nominal value [17], expected value [76], etc.). The SCND problem under uncertainty is also traditionally modeled with the expected value criterion [89]. However, as we have mentioned before, this criterion might not be appropriate in all contexts (Airport example). Moreover, the obtained profit/costs in SCND problems are random variables whose distributions depend on the distribution of the random input and the decision variables. Therefore, in economic studies in which we are interested in quantifying the at-risk values of the profit/cost and limiting the at-risk values the expected value measure might not be adequate.

The most common risk measures after central tendency are measures of dispersion (e.g. variance [7] or approximations of the variance [67], etc.), standard deviation [46], absolute deviation [74]). Similar to the central tendency measure, most of the dispersion measures cannot provide the decision makers with a variety of solutions (portfolio of designs). Each such measure provides the decision maker with only a single design. A review of these measures and their frequencies in the literature is provided in Govindan et al. [43].

To overcome this issue, some scholars proposed different measures such as regret [91], α-minimax regret [33], mean-excess regret [23], and Conditional Value at Risk (CVaR) [21].

The choice of modeling depends on the decision makers' risk attitude. A risk-neutral decision maker would prefer a central tendency measure whereas a risk-averse decision maker would prefer variability and the worst-case-scenarios [53]. For more information about computational complexity of different risk measures, one can refer to Ahmed [2].

4.2.2. Mitigation Strategies

The performance of SCNs operating under uncertainty can be evaluated through several different metrics. Several scholars proposed different performance metrics such as robustness, flexibility, and resilience Klibi et al. [54]. Depending on the source of uncertainty (demand-side, supply-side, and environmental), one can adopt different mitigation strategies to minimize the effect of risks and improve the performance of the SCNs operating in uncertain environments.

Disruptions (also known as disruption risks [96]), congestion, and shortfalls (also known as yield uncertainty [93]) are examples of supply-side uncertainty.

Facility fortification, strategic stock, and sourcing strategy (multiple sourcing and backup sourcing) are examples of common strategies in the literature to deal with supply-side uncertainty. Tang [95], Tang and Tomlin [97], and Tang and Musa [98] proposed and surveyed mitigation strategies which could be utilized to supply-side risks. For more information about mitigation strategies for supply-side uncertainty, readers can refer to these papers.

Instability in demand or inexact demand forecasts are examples of demand-side uncertainty (also known as operational risks [96]). Moreover, volatility of exchange rates is an example of environmental uncertainty. Snyder and Shen [93] argued similarities between strategies to mitigate supply-side and demand-side uncertainties. Here is a short review of the most common mitigation strategies with focus on demand-side uncertainty.

- **Safety Stock:** In this strategy, decision makers can hold inventory for commodities and products within different layers of the SCN. This inventory is practical to satisfy demand volatility, if the products are not changing significantly over time or they are not perishable. Examples of the application of this strategy can be found in [99], Qi et al. [71], and Mak and Shen [59].

- **Multiple Sourcing:** In this strategy, sourcing is carried out by using multiple suppliers simultaneously. A good review and application of this strategy for global supply chain networks is presented in Sawik [80].

- **Improved Forecasts:** Demand forecasting is often difficult, and most demand forecasting conducted today is inaccurate. Understanding the underlying causes of demand variability and using new technologies to forecast demand is a must in SCND. Machine learning and deep learning algorithms can significantly help companies to address demand forecasting challenges. The application of these algorithms in SCND is in its infancy and very few papers exist in the literature including: Ban and Rudin [10] and Oroojlooyjadid et al. [69].

- **Demand Management:** The demand management process addressed the issue of balancing the customer's demand with the capabilities of the SCNs. This includes synchronizing the forecast demand with production and distribution capabilities. Croxton et al. [28] review the process of demand management and provide some practical details.

- **Capacity Planning:** Capacity planning in SCND is the process of determining the amount of reserved capacity required to produce any given products to satisfy the forecast demand in the future. Several scholars proposed different variations of this strategy in the literature, including Melo et al. [63] and Klibi and Martel [52].

In this chapter, we propose using flexible capacity contracts and capacity options to create flexibility in SCNs. Before moving to the review of flexible contracts, first we review the background of options from finance literature.

4.2.3. Capacity Options

A financial option is the right (but not the obligation) to purchase (call) or to sell (put) the underlying financial asset at (European option) or up to (American option) a certain date at a predetermined price (the strike price or exercise price) [47].

Capacity Options used in supply contracts likewise constitute the right, but not the obligation to buy more commodities from suppliers by a certain date and with a predetermined price. Quan [73] makes a connection between capacity reservations and financial options in the hotel room reservations context. In another context Hellermann [45] has shown the effectiveness of capacity options mechanism combined with pricing in air cargo industry.

From the perspectives of both suppliers and a manufacturing selling/buying company capacity options have some benefits. For the manufacturing company (buyer), capacity options can lower the total purchasing cost due to the opportunity to pay the fixed cost of renewing contracts less frequently, which implies economies of scale in production [27]. Furthermore, a manufacturing company can hedge against uncertainties in demand, exchange rate and product price. Serel et al. [83] investigate the optimal capacity that should be reserved by the manufacturer from preferred and alternative suppliers. The authors show that the amount of reserved capacity goes down if an alternative supplier is available. Cheng et al. [24] modeled flexible supply contracts for both the manufacturing company (the motivational example in section 1) and the suppliers considering capacity options for the Newsvendor problem. They have also shown that the integrated models with profit-sharing mechanisms can obtain higher profits for both parties. Barnes-Schuster et al. [11] investigate the contracts with options in a two period model with the same setting as the previous study. Van Delft and Vial [101] suggests using stochastic programing to solve the sequential decision-making problem developed initially by Barnes-Schuster et al. [11].

In summary, although designing SCNs under uncertainty is explored to a great extent, it seems to us the choice of uncertainty measures requires further investigation and it is ignored by the researcher in this field much of the time. Moreover, the synergy between reserved capacity and capacity options to create flexibility in the structure of the SCNs makes the hybrid mechanism very compelling to investigate. To the best of our knowledge, our model in this chapter differs from the SCND literature on considering capacity options for the manufacturer and allows to adjust the reliability level of the design.

4.3. Problem Formulation

The structure of the SCN described in this chapter is inspired from a major North American automotive manufacturing company. The manufacturing company's SCN consists of three main elements: parts, suppliers, and demand zones. Suppliers are the exogenous sources of parts in the network. The model deals with only one part/commodity and one time period. A supplier is called *Global*, if (1) it has enough capacity to satisfy the global demand, (2) the optimal sourcing decision indicates only that supplier should be selected. A *regional* supplier has only enough capacity to satisfy local demand in the region it serves. All suppliers competing for the business have quality and business practices that meet the manufacturing company's requirements.

The objective function of this model is the Net Present Value (NPV) of the total landed cost. Decision variables include supplier selection, production volume for each selected supplier, and shipping volumes. After finding optimal solutions for different sourcing scenarios, they conduct financial evaluations to make the final sourcing decision.

4.3.1. The Deterministic Model

Deciding the optimal level of capacity plays a crucial role in strategic level decision making models. Capacity levels in this case are the number of production lines (modules) required in the plants. Therefore, capacity decisions are involved with commitment of capital resources for the period of the contracts with the suppliers. The capacity of the suppliers depends on the number of modules (production lines) which will be referred to as *Modular Capacity*. Each module has a specific capacity; thus, the total capacity can be expressed by the number of modules at each supplier. The upfront fees for reserving capacity are proportional to the number of modules at each supplier. All sets, indices, and parameters used in the model are described in detail in the following table.

Sets	Description
I	Set of supplier locations indexed by i
P	Set of vehicle assembly plant locations indexed by p
K	Set of currencies indexed by k
T	Time horizon in years indexed by t
L_i	Set of capacity levels at supplier i indexed by l
Parameter	**Description**
n	Number of sourcing suppliers
h	Inventory holding rate
r_t	Discount rate at year t
c_i	Unit part cost at location i independent of time
d_p	Annual part demand in assembly plant p
e_k	Exchange rate for currency k in USD per unit local currency
θ_{il}	Tooling cost at location i for capacity level l
ψ_{il}	Annual maximum supplier capacity levels at supplier location i at level l
f_{ip}	Freight cost from supplier location i to assembly plant p in USD
δ_{ip}	Numbers of days in transit from supplier location i to plant p
η_{ip}	Duty rates from supplier location i to plant p

Finally, the decision variables are:

Variable	Description
X_i	The binary variables for supplier selection decisions. 1 if supplier i is selected; 0 otherwise
Y_{il}	The binary variables for capacity decisions. 1 if supplier i operates at capacity level l; 0 otherwise
V_{ip}	Global production volume in supplier i and shipped to assembly plant p

The objective function of the model is to minimize the NPV of the total landed cost. The NPV of the total landed cost includes tooling costs, part turnover or part costs (piece price times volume), logistical costs (regular and premium freight cost, packaging cost, duty, inventory holding cost). We use bold face to denote decision vectors to distinguish them from individual decision variables. By defining $a_{il} = \theta_{il} e_i$, and $b_{ip} = R^{-1}\left(c_i e_i + f_{ip} + \delta_{ip} c_i e_i h/365 + c_i e_i \eta_{ip}\right)$, and $R = \sum_{t \in T} (1 + r_t)^t$, the formulation of the total landed cost NPV model is as follows:

$$\min_{\mathbf{X},\mathbf{Y} \in \{0,1\}; \mathbf{V} \in \Re^+} \left(\sum_{i \in I} \sum_{l \in L_i} a_{il} Y_{il} \right) + \left(\sum_{i \in I} \sum_{p \in P} b_{ip} V_{ip} \right) \tag{4.8}$$

subject to:

$$\sum_{i \in I} X_i \leq n \tag{4.9}$$

$$\sum_{l \in L_i} Y_{il} \leq X_i, \quad \forall i \in I \tag{4.10}$$

$$\sum_{i \in I} V_{ip} \geq d_p, \quad \forall p \in P \tag{4.11}$$

$$\sum_{p \in P} V_{ip} \leq \sum_{l \in L_i} \psi_{il} Y_{il}, \quad \forall i \in I \tag{4.12}$$

The objective function (4.8) minimizes the NPV of the total landed cost with discount rate r_t in each period $t \in T$. Constraints (4.9) stipulate that the number of selected suppliers is less than or equal to n. Constraints (4.10) state that each used supplier can be selected for at most one capacity level. Constraints (4.11) ensure that total number of parts produced and shipped to plant $p \in P$ is greater than or equal to its demand. Constraints (4.12) are capacity constraints.

In some countries, especially developing countries, the government imposes minimum Local Content Restrictions (LCRs) for the vehicles assembled there. In this case, a minimum annual capacity level can be considered for each supplier to address the minimum local content issue as follows:

$$\sum_{p \in P} V_{ip} \geq \sum_{l \in L_i} \underline{\psi}_{il} Y_{il}, \quad \forall i \in I \tag{4.13}$$

where $\underline{\psi}_{il}$ represents the minimum annual capacity level at supplier $i \in I$ operating at capacity level $l \in L_i$.

Drawbacks of the Deterministic Model

Manufacturer's current approach consists of single point estimations/forecasts of the input parameters from other sections, optimizing a deterministic model, and analyzing the sensitivity of the decisions through designed scenarios and finalizing them through their financial analysis process. Although this process is fairly straightforward, there are a number of important limitations associated with this approach. First, the one-point estimation of inputs threatens both the optimality and feasibility of the sourcing decisions much of the time.

In this model, it is not clear how robust the sourcing decisions are with respect to perturbations in the uncertain parameters. Moreover, the deterministic model cannot determine the quality of service, expected unmet demand, and expected costs. A more systematic approach will enable the company to consider all possible scenarios, the impact of the uncertain parameters on the outputs, the trade-off between unmet demand and tooling expenditures, and the robustness of the decisions.

4.3.2. The α-Reliable Minimax Regret Model

The future under which a SCN will operate is non-deterministic (uncertain). In the previous model, we assumed all parameters were deterministic. However, in reality, uncertainty can be seen in demand parameters, freight costs, and exchange rates.

The α-Reliable minimax regret model was developed by Daskin et al. [33] for a p-median problem. In this model, the reliability set is defined by an endogenously selected subset of scenarios from the set of all possible scenarios, whose collective probability of occurrence is at least some user-defined value α. Then, the maximum regret is computed over the reliability set. In this model regret of a scenario is defined by the difference between the objective function value that results from having to source from compromise suppliers, and the best objective function value that we could attain if we could source from the best possible suppliers for that specific scenario alone.

By minimizing the α-reliable maximum regret, the decision maker can be $100\alpha\%$ sure that the regret realized will be no more than that found by the model. This is true because the α-reliable maximum regret only reflects the α-quantile of the regrets and does not assess the magnitude of the regrets associated with the scenarios that are not included in the reliability set (from the tail of the distribution of the regret).

Here we assume the demand, exchange rate, and freight cost parameters are uncertain but bounded. The joint distribution of the uncertain parameters is known. We use bold face to denote random variables (random vectors) to distinguish them from their particular realizations. In particular, $(\boldsymbol{f}, \boldsymbol{e}, \boldsymbol{d})$ represents the random data vector for freight costs, exchange rates, and demands parameters. Given demand uncertainty, it may be impossible to meet the demand for certain realizations, we include an additional variable for the unmet demand represented by τ_p for demand region $p \in P$.

Moreover, we introduce the new decision variables to buy and exercise capacity options in this model. We will use the same notation for these new variables superscribed by (h). Furthermore, we restrict the unmet demand over all possible scenarios to a fraction of the total expected demand. Here we superscript each scenario with $w \in W$ and W is the set of all possible scenarios. The formulation of the α-Reliable minimax regret model is as follows:

$(1st - stage)$

$$\min_{\boldsymbol{X},\boldsymbol{Y},\boldsymbol{Y^{(h)}},\boldsymbol{Z^w}\in\{0,1\},\boldsymbol{R^w},\beta} \left(\sum_{i\in I} \sum_{l\in L_i} a_{il} Y_{il} + \sum_{i\in I} \sum_{l\in L_i} a_{il}^{(h)} Y_{il}^{(h)} \right) + \beta \tag{4.14}$$

subject to:

$$\sum_{i\in I} X_i \leq n \tag{4.15}$$

$$\sum_{l\in L_i} Y_{il} \leq X_i, \quad \forall i \in I \tag{4.16}$$

$$\sum_{l\in L_i} Y_{il}^{(h)} \leq X_i, \quad \forall i \in I \tag{4.17}$$

$$\sum_{l\in L_i} l Y_{il}^{(h)} \leq \sum_{l\in L_i} l Y_{il}, \quad \forall i \in I \tag{4.18}$$

$$R^w = \mathcal{Q}(\boldsymbol{Y}, \boldsymbol{Y^{(h)}} \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) - \mathcal{Q}^*(\boldsymbol{Y^w}, \boldsymbol{Y^{(h)w}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}), \quad \forall w \in W \tag{4.19}$$

$$\sum_{w\in W} Pr^w Z^w \geq \alpha \tag{4.20}$$

$$\beta - R^w + M^w(1 - Z^w) \geq 0, \quad \forall w \in W \tag{4.21}$$

$(2nd - stage)$

$$\mathcal{Q}(\boldsymbol{Y}, \boldsymbol{Y^{(h)}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) = \min_{\boldsymbol{V^w},\boldsymbol{V^{(h)w}},\boldsymbol{\tau^w}\in\Re^+} \left(\sum_{i\in I} \sum_{p\in P} b_{ip}^w V_{ip}^w + b_{ip}^{(h)w} V_{ip}^{(h)w} \right) \tag{4.22}$$

subject to:

$$\sum_{i\in I} \left(V_{ip}^w + V_{ip}^{(h)w} \right) + \tau_p^w \geq d_p^w, \quad \forall p \in P, w \in W \tag{4.23}$$

$$\sum_{w\in W} Pr^w \sum_{p\in P} \tau_p^w \leq \gamma E_w \left[\sum_{p\in P} d_p^w \right] \tag{4.24}$$

$$\frac{\tau_p^w}{d_p^w} \leq \varphi \sum_{p\in P} \frac{\tau_p^w}{d_p^w}, \quad \forall p \in P, w \in W \tag{4.25}$$

$$\sum_{p\in P} V_{ip}^w \leq \sum_{l\in L_i} \psi_{il} Y_{il}, \quad \forall i \in I, w \in W \tag{4.26}$$

$$\sum_{p\in P} V_{ip}^{(h)w} \leq \sum_{l\in L_i} \psi_{il}^{(h)} Y_{il}^{(h)}, \quad \forall i \in I, w \in W \tag{4.27}$$

where α is the reliability level, Pr^w is the probability of scenario w, R^w represents the regret in scenario w, β is the maximum regret in all scenarios, Z^w is the binary variable indicating if a scenario is in the reliability set or not, and M^w is a large constant specific to scenario w such that $M^w > R^w$.

Furthermore, $E_w(.)$ represents the expected value over all the scenarios in W, γ is the maximum allowed percent of expected unmet demand and φ is the equity parameter. The equity parameter ensures that the distribution of the unmet demand is fair among all demand regions based on their demand. This constraint is necessary since the model tends to source to demand regions with lower transportation costs and ignores the demand of regions with higher transportation costs. In scenarios with positive unmet demands, the equity parameter establishes a fair distribution of parts among all demand regions proportional to the demand of that region, while in other scenarios this constraint does not add any restriction. A reasonable choice of φ is $\varphi = \frac{1}{|P|}$ and the $|.|$ operator shows the size of a set.

Constraints (4.18) enforces that the total hedging capacity (capacity options) is less than or equal to the reserved capacity in the model. This is a practical assumption we make in this model. Constraints (4.19) show the regret for all scenarios. Constraint (4.20) guarantees that the collective probability of occurrence of selected scenarios in the reliability set is at least α. Constraints (4.21) enforce that β is greater than or equal to the regret of all scenarios that are selected in the reliability set.

Constraints (4.23) ensure that total number of parts produced and shipped to plant $p \in P$ in addition to the unmet demand at the same plant is greater than or equal to its demand. Constraint (4.24) guarantees that the expected total unmet demand is less than or equal to the expected total demand. Constraints (4.25) are equity constraints to avoid imbalanced unmet demand over demand regions.

Additionally, constraints (4.24), (4.26), and (4.27) guarantee $\mathcal{Q}(.) < \infty$ and the non-negativity constraints and non-negative nature of the input parameters makes $\mathcal{Q}(.) \geq 0$. Therefore, the objective function is finite valued and its expected value is well-defined. Finally, $\mathcal{Q}^*(\boldsymbol{Y^w}, \boldsymbol{Y^{(h)w}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w})$ are the non-compromising objectives of the following optimization model:

$$\mathcal{Q}^*(\boldsymbol{Y^w}, \boldsymbol{Y^{(h)w}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) = \min_{\substack{\boldsymbol{V^w}, \boldsymbol{V^{(h)w}}, \boldsymbol{\tau^w} \in \Re^+, \\ \boldsymbol{Y^w}, \boldsymbol{Y^{(h)w}} \in \{0,1\}}} \sum_{w \in W} \sum_{i \in I} \sum_{p \in P} \left(b_{ip}^w V_{ip}^w + b_{ip}^{(h)w} V_{ip}^{(h)w} \right) \tag{4.28}$$

subject to:

$$\sum_{i \in I} \left(V_{ip}^w + V_{ip}^{(h)w} \right) + \tau_p^w \geq d_p^w, \quad \forall p \in P, w \in W \tag{4.29}$$

$$E_w \left[\sum_{p \in P} \tau_p^w \right] \leq \gamma E_w \left[\sum_{p \in P} d_p^w \right] \tag{4.30}$$

$$\frac{\tau_p^w}{d_p^w} \leq \varphi \sum_{p \in P} \frac{\tau_p^w}{d_p^w}, \quad \forall p \in P, w \in W \tag{4.31}$$

$$\sum_{p \in P} V_{ip}^w \leq \sum_{l \in L_i} \psi_{il} Y_{il}^w, \quad \forall i \in I, w \in W \tag{4.32}$$

$$\sum_{p \in P} V_{ip}^{(h)w} \leq \sum_{l \in L_i} \psi_{il}^{(h)} Y_{il}^{(h)w}, \quad \forall i \in I, w \in W \tag{4.33}$$

Drawbacks of the α-Reliable Minimax Regret Model

Although there are situations where it is appropriate to minimize the α-reliable maximum regret rather than the average or worst-case regret, computationally the α-reliable minimax regret is very difficult to obtain, which limits its use in real life.

Moreover, the α-reliable maximum regret model does not assess the magnitude of the regrets associated with the scenarios that are not included in the reliability set and does not distinguish between cases where the regrets in the tail are only a little bit worse than the α-reliable maximum regret and those in which the regrets in the tail are higher.

4.3.3. The α-Reliable Mean-Excess Regret Model

To over come the issues with α-Reliable minimax regret model, Chen et al. [23] present the α-Reliable mean-excess regret model. In contrast to the α-Reliable minimax regret model where the regret that defines the α-quantile of all regrets is minimized, in this model they minimize the expectation of the regrets associated with the scenarios in the tail, whose collective probability is $1-\alpha$. Therefore, the new metric explicitly accounts for the magnitude of the regrets in the tail. The new model is also computationally significantly less expensive, making it easier to apply to practical situations. The objective function of the α-Reliable mean-excess regret model is as follows:

$$(1st - stage) \tag{4.34}$$

$$\min_{\boldsymbol{X},\boldsymbol{Y},\boldsymbol{Y^{(h)}}\in\{0,1\},\boldsymbol{R^w},\beta} \left(\sum_{i\in I} \sum_{l\in L_i} a_{il} Y_{il} + \sum_{i\in I} \sum_{l\in L_i} a_{il}^{(h)} Y_{il}^{(h)} \right) + \beta + \frac{1}{1-\alpha} E_w \left[R^w - \beta \right]^+$$

subject to:

(4.15) – (4.19) and (4.22) – (4.27).

4.4. Bender's Decomposition for MIP Problems

The MIP problems in previous sections are sensitive to the problem size. We can sample the scenarios, but the model after sampling is still intractable. Therefore, we need to use Bender's decomposition to separate the first stage and second stage of the models. The first stage contains all the binary variables and β is the only continuous variable in this stage. The second stage consists of continuous variables and therefore it is an LP. However, we cannot decompose the second stage into several smaller problems for each scenario because of the bound on the expected unmet demand and fairness constraints.

We define non-negative continuous $\zeta^w \in \Re^+$ auxiliary variables:

$$\zeta^w \geq R^w - \beta, \quad \forall w \in W \tag{4.35}$$

where both ζ^w and R^w are second stage variables.

Proposition 4.1. *For any given* $\boldsymbol{Y}, \boldsymbol{Y^{(h)}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}$, *the second stage problem can be expressed as the following problem and it is always feasible.*

$$\mathcal{H}(\boldsymbol{Y}, \boldsymbol{Y^{(h)}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) = \max_{\boldsymbol{\rho} \in \Re^+} \sum_{p \in P} \sum_{w \in W} d_p^w \rho_p^{(23)w} - \gamma E_w \left[\sum_{p \in P} d_p^w \right] \rho^{(24)} - \sum_{i \in I} \left(\sum_{l \in L_i} \psi_{il} Y_{il} \right) \rho_i^{(26)}$$

$$- \sum_{i \in I} \left(\sum_{l \in L_i} \psi_{il}^{(h)} Y_{il}^{(h)} \right) \rho_i^{(27)} - \sum_{w \in W} \left(\beta + \mathcal{Q}^*(\boldsymbol{Y^w}, \boldsymbol{Y^{(h)w}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) \right) \rho^{(35)w} \tag{4.36}$$

subject to:

$$\rho_p^{(23)w} - \rho_i^{(26)w} - b_{ip}^w \rho^{(35)w} \leq p^w b_{ip}^w, \quad \forall i \in I; p \in P; w \in W \tag{4.37}$$

$$\rho_p^{(23)w} - \rho_i^{(27)w} - b_{ip}^{(h)w} \rho^{(35)w} \leq p^w b_{ip}^{(h)w}, \quad \forall i \in I; p \in P; w \in W \tag{4.38}$$

$$\rho_p^{(23)w} - \rho_i^{(24)w} - \frac{\varphi}{d_p^w} \sum_{p \in P} \rho_p^{(25)w} \leq \frac{1}{d_p^w}, \quad \forall i \in I; p \in P; w \in W \tag{4.39}$$

$$\rho_p^{(35)w} \leq \frac{1}{1-\alpha} p^w, \quad \forall p \in P; w \in W \tag{4.40}$$

where $\boldsymbol{\rho}$ are the dual variables corresponding to the second stage constraints (4.23)-(4.27) and (4.35), respectively.

Next, we use θ as the approximation of the expectation term in the first stage. The variables $\boldsymbol{u^i}$s and $\boldsymbol{\rho^i}$s are the dual variables of the constraints expressed in equation *4.i*. The proposed Bender's decomposition to solve the models is described in Algorithm 1. Note that all the continuous variables in the second stage are lower bounded by zero. The production and unmet demand variables are upper bounded by the demand parameters. Therefore, the dual of the second stage is always feasible or unbounded.

Algorithm 3 Bender's Decomposition for MIP Problems

Set tolerance level $\epsilon \leftarrow (0,1)$

Initialize iteration counter $k \leftarrow 0$

Initialize cuts list $cuts \leftarrow \emptyset$

Set $\boldsymbol{X} \leftarrow \bar{\boldsymbol{X}}, \boldsymbol{Y} \leftarrow \bar{\boldsymbol{Y}}, \boldsymbol{Y^{(h)}} \leftarrow \bar{\boldsymbol{Y}}^{(h)}, \boldsymbol{R^w} \leftarrow \bar{\boldsymbol{R}}^w,$ and $\beta \leftarrow \bar{\beta}$

Set $UB \leftarrow \infty$ and $LB \leftarrow -\infty$

while $UB - LB \geq \epsilon LB$ **do**

  $k \leftarrow k+1$

  Solve the *2nd-stage* problem for given $(\bar{\boldsymbol{X}}, \bar{\boldsymbol{Y}}, \bar{\boldsymbol{Y}}^{(h)}, \bar{\boldsymbol{R}}^w, \bar{\beta})$:

  if Primal Infeasible and Dual Unbounded **then**

    Get Farkas certificates $\boldsymbol{u}$ for unbounded rays of the Dual problem.

    Add the feasibility cut to *cuts*:

$$\sum_{p\in P}\sum_{w\in W} d_p^w \bar{u}_p^{(23)w} - \gamma E_w\left[\sum_{p\in P} d_p^w\right]\bar{u}^{(24)} - \sum_{i\in I}\left(\sum_{l\in L_i}\psi_{il}Y_{il}\right)\bar{u}_i^{(26)} \\ - \sum_{i\in I}\left(\sum_{l\in L_i}\psi_{il}^{(h)}Y_{il}^{(h)}\right)\bar{u}_i^{(27)} - \sum_{w\in W}\left(\beta + \mathcal{Q}^*(\boldsymbol{Y^w}, \boldsymbol{Y^{(h)w}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w})\right)\bar{u}^{(35)w} \geq 0$$

  else

    Get extreme points $\boldsymbol{\rho}$ of the Dual problem

    Add the optimality cut to *cuts*:

$$\sum_{p\in P}\sum_{w\in W} d_p^w \bar{\rho}_p^{(23)w} - \gamma E_w\left[\sum_{p\in P} d_p^w\right]\bar{\rho}^{(24)} - \sum_{i\in I}\left(\sum_{l\in L_i}\psi_{il}Y_{il}\right)\bar{\rho}_i^{(26)} \\ - \sum_{i\in I}\left(\sum_{l\in L_i}\psi_{il}^{(h)}Y_{il}^{(h)}\right)\bar{\rho}_i^{(27)} - \sum_{w\in W}\left(\beta + \mathcal{Q}^*(\boldsymbol{Y^w}, \boldsymbol{Y^{(h)w}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w})\right)\bar{\rho}^{(35)w} \leq \theta$$

$$\bar{\theta} \leftarrow \sum_{p\in P}\sum_{w\in W} d_p^w \bar{\rho}_p^{(23)w} - \gamma E_w\left[\sum_{p\in P} d_p^w\right]\bar{\rho}^{(24)} - \sum_{i\in I}\left(\sum_{l\in L_i}\psi_{il}\bar{Y}_{il}\right)\bar{\rho}_i^{(26)}$$
$$- \sum_{i\in I}\left(\sum_{l\in L_i}\psi_{il}^{(h)}\bar{Y}_{il}^{(h)}\right)\bar{\rho}_i^{(27)} - \sum_{w\in W}\left(\beta + \mathcal{Q}^*(\boldsymbol{Y^w}, \boldsymbol{Y^{(h)w}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w})\right)\bar{\rho}^{(35)w}$$

$UB \leftarrow \min\{UB, \left(\sum_{i\in I}\sum_{l\in L_i} a_{il}\bar{Y}_{il} + \sum_{i\in I}\sum_{l\in L_i} a_{il}^{(h)}\bar{Y}_{il}^{(h)}\right) + \bar{\theta}\}$

Solve the *1st-stage* problem with *cuts*

$LB \leftarrow \left(\sum_{i\in I}\sum_{l\in L_i} a_{il}\bar{Y}_{il} + \sum_{i\in I}\sum_{l\in L_i} a_{il}^{(h)}\bar{Y}_{il}^{(h)}\right) + \beta + \frac{1}{1-\alpha}E_w\left[\bar{R}^w - \bar{\beta}\right]^+$

Furthermore, we define the hedging ratio as:

Definition 4.1. *The Hedging ratio ($\boldsymbol{\Delta}$) is defined by:*

$$\boldsymbol{\Delta} = E_w\left[\frac{\sum_{i\in I}\sum_{p\in P} V_{ip}^{(h)w}}{\sum_{i\in I}\sum_{p\in P} V_{ip}^w + \sum_{i\in I}\sum_{p\in P} V_{ip}^{(h)w}}\right] \tag{4.41}$$

The hedging ratio gives the expected number of parts shipped from the hedging capacity divided by the total number of parts shipped from all suppliers.

Proposition 4.2. *For a feasible solution of $\boldsymbol{V}$ and $\boldsymbol{V^{(h)}}$, the hedging ratio is lower bounded by 0 and upper bounded by $\frac{1}{2}$, (i.e. $0 \leq \boldsymbol{\Delta} \leq \frac{1}{2}$).*

4.5. Case Study: High Tooling Cost Parts

In this section, we investigate the performance of our models through several numerical analysis from our case study with a major North American auto manufacturer. For this study, we consider a two-echelon network for part with a very high tooling cost. Throughout the chapter, we refer to this part as HT (High Tooling). We consider A-E as the demand regions for this part, since Ford has assembly plants in these locations. HT has three potential suppliers in different regions. We will refer to them as SHT-1-A (supplier 1 for high tooling cost part located in region A), SHT-2-B (located in region B), and SHT-3-B (located in region B). All other details about the parts and suppliers are provided in Appendix II Table B.1. The demand values, suppliers' capacities, and all costs are masked. A production module at each supplier has a capacity of one and demand values are scaled according to the modules' actual capacities.

For the deterministic model, we use the 2013 forecasts of demand, exchange rates, and freight costs (one-point estimation). We discretizie the distribution of the uncertain parameters into three point distributions for each uncertain parameter. All the three point distributions of the uncertain parameters are provided in Table 4.3 below.

Table 4.3: The selected ranges of the uncertain parameters for the stochastic models and their probabilities

Parameters		Values			Probabilities		
		Low	**Med.**	**High**	**Low**	**Med.**	**High**
Demand	**A**	50%	100%	150%	0.1	0.8	0.1
	B	50%	100%	150%	0.05	0.9	0.05
	C	50%	100%	150%	0.15	0.7	0.15
	D	50%	100%	150%	0.05	0.9	0.05
	E	50%	100%	150%	0.05	0.9	0.05
Exchange Rate	**A**	80%	100%	110%	0.033	0.9	0.067
	B	80%	100%	150%	0.214	0.7	0.086
Freight Cost	**Oil**	50%	100%	110%	0.033	0.8	0.167

Based on historic data from the company, these bounds cover most of the range of the previous fluctuations. For comparison purposes, the probabilities are set in a way that the expected values of the uncertain parameters are equal to the value of the middle outcome. The mid-value of probabilities are provided also in Table 4.3. Here we assume perfect correlation among freight costs. In other words, if the fuel cost is high, all freight costs will be realized at their high levels and vice versa. Since different parts can have suppliers in the same country (same currency), it is logical to assume the exchange rate of these suppliers are perfectly correlated. We assume all other uncertain parameters fluctuate independently from each other.

We ran all the models on a server with 16 logical processors and 128 GBs of RAM. More specifically, the machine has 2 CPU's which are Xeon(R) $E5-2640$ $v3$ chips running at 2.60

GHz (i.e. each chip has 8 cores). We used the Gurobi 7.0 MIP solver package for Python to solve the MILP models. The MIP solver parameters for tuning, generating cuts, and tolerances are all set to their default values. To force for multi-threading, the "Threads" parameter (which controls the number of threads used by the parallel MIP solver to solve the model) is set to its maximum value.

4.5.1. Comparison of The Models

Here we compare the results of the models for the fixed parameter setting. We set the hedging parameters to be $a_{il}^{(h)} = \sigma_1 a_{il}$ (fixed cost of tooling for hedging is σ_1 times of the fixed cost of the tools), $c_i^{(h)} = \sigma_2 c_i$ (unit part cost for hedging is σ_2 times of the unit part cost), and $\psi_{il}^{(h)} = \sigma_3 \psi_{il}$ (extra capacity for hedging is σ_3 times of the module capacity) where $\sigma_1 = 0.01$, $\sigma_2 = 1.2$, and $\sigma_3 = 1$, respectively. Later, we will show the sensitivity of the model to these parameters. We also fixed $\varphi = 0.2$ (fairness ratio). The results from different models are presented in Table 4.4. For each model, we also computed the expected total cost in $E-Tot.$ column and compare it with the objective of a base model in columns $S\%$. We chose a model with Risk-Neutral Regret (RNR) model for the base model. A common Risk-Neutral objective is the minimization of the expected value. Finally, we reports the Cap./Hedg. (capacity and hedging capacity decisions), Tooling (tooling cost), Δ (hedging ratio), Obj. (Objective function of the models), and β (VaR of the regrets) in other columns.

Table 4.4: **Comparison of the solutions from different models for $\alpha = 0.95$ and $\gamma = 0.1$**

Models	**Cap./Hedg.**	**Tooling**	$\boldsymbol{\Delta}$	**Obj.**	**E-Tot.**	$\boldsymbol{\beta}$	$\boldsymbol{S}\%$
Det[*]	$(7,3,0)/(0,0,0)$	$28,618,933$	0.00	$102,839,725$	N/A	N/A	N/A
RNR[+]	$(6,5,0)/(0,0,0)$	$32,588,472$	0.00	$104,555,355$	$104,555,355$	N/A	0.00%
H-RNR[++]	$(2,4,0)/(2,4,0)$	$18,790,831$	0.43	$94,045,328$	$94,045,328$	N/A	10.05%
$\boldsymbol{\alpha}$**-RMR**[†]	–	–	–	–	–	–	–
$\boldsymbol{\alpha}$**-RMER**[‡]	$(3,4,0)/(3,4,0)$	$21,483,922$	0.38	$27,950,538$	$98,112,171$	$6,466,616$	6.16%

[*] Det: Deterministic model from 3.1

[+] RNR: Risk-Neutral Regret Model without Hedging.

[++] H-RNR: Risk-Neutral Regret Model with Hedging

[†] α-RMR: α-Reliable Minimax Regret from 3.2

[‡] α-RMER: α-Reliable Mean-Excess Regret from 3.3.

As we see in Table 4.4, the deterministic model gives an optimal solution with 10 modules. However, assuming perfect knowledge of the parameters is naive. The stochastic model with expected regret and without hedging (RNR) has a slightly higher objective function with 11 modules. Without hedging variables, the regret for each scenario is equal to the objective function of the second stage. Therefore, the expected regret is equal to the expected value of the second stage in RNR. The objective function of the RNR model will be the base for comparison the saving columns ($S\%$). Assuming a 1% fixed cost to reserve and extra $20 to exercise the hedging capacity options, we were able to reduce the tooling to 6 modules and obtain about a 10.05% saving in the expected total costs ($E-Tot.$) of the expected regret model with hedging variables (H-RNR).

The α-RMR model has a very complicated structure and we were not able to use the decomposition techniques for it. Moreover, we were not able to solve the model optimally after running for 24 hours. Therefore, we are not reporting the results of this model here.

Finally, the α-RMER model returns a total of 7 modules and the expected costs from this model was about 6.16% less than the expected costs from the RNR model. Note that the CPU runtime of all these models are extremely high. However, using the Bender's decomposition described in Algorithm 3, we were able to solve all the instance in a couple of minutes. Therefore, the runtimes are insignificant and we skip reporting them in here.

4.5.2. Sensitivity Analysis of The α-RMER

In this section we investigate the sensitivity of the α-RMER model with regards to α, γ, σ_1, and σ_2 parameters respectively.

Sensitivity to α Parameter

The α parameter in the α-RMER shows the desired reliability level. In other words, in α-RMER the expectation of the regrets associated with the scenarios in the tail, which has a collective probability of $1-\alpha$ is minimized. Therefore, by increasing the α level from 0 to 1 we are adding more scenarios in the reliability set. Figure 4.2 illustrates the sensitivity of the hedging ratio (Δ), saving percentage ($S\%$) (both plotted on the right y-axis) and the total number of capacity modules, and hedging capacity modules (both plotted on the left y-axis).

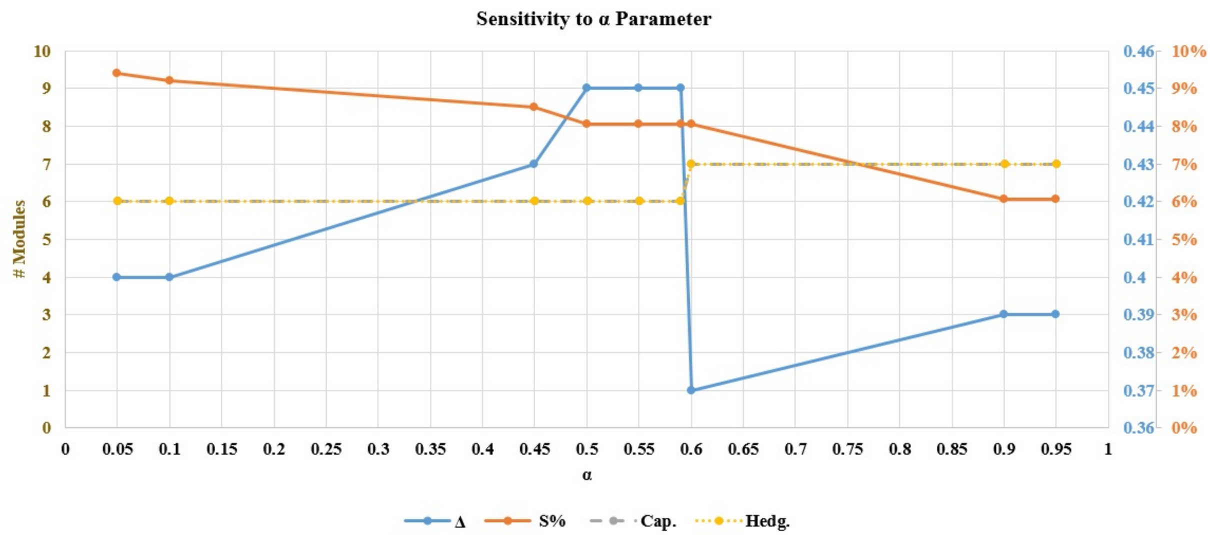

Figure 4.2: Sensitivity of α-RMER model to α parameter ($\gamma = 10\%, \sigma_1 = 0.01, \sigma_2 = 1.2$)

As we can see in Figure 4.2 the hedging ratio goes up when α is increased from 0 to 0.5 and stays at 0.45 and then drops. The reason is the model decides to increase the number of reserved modules from 6 to 7 at $\alpha = 0.60$. Therefore, we can source more parts through the actual reserved capacity. The saving percentage decreases continuously by increasing α, because we are considering more scenarios in the reliability set for higher values of α, and therefore, the expected cost of sourcing is higher.

The objective function of the α-RMER consists of the tooling cost and the CVaR of the regret. Therefore, by deducting the tooling cost from the objective we can compare the CVaR of the regret with VaR of the regret which is captured in β parameter. Figure 4.3 shows the convergence of the gap between CVaR and VaR for high values of α.

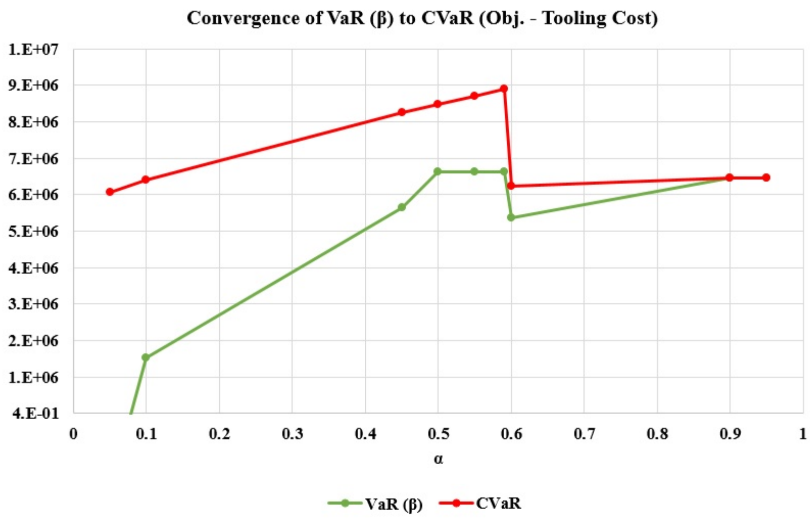

Figure 4.3: Convergence of the CVaR (Obj.-Tooling) to VaR (β) ($\gamma = 10\%, \sigma_1 = 0.01, \sigma_2 = 1.2$)

The intuition behind the convergence comes from the structure of the objective function in this model. Chen et al. [23] has shown that the stochastic part of the objective function of the α-RMER model is the weighted average between the α-quantile of the regrets (VaR) for a fixed set of decision variables and the conditional probability-weighted average of the regrets strictly exceeding the VaR. The balancing weight of these two parts in the objective function is α subtracted from the collective probability of those scenarios in which the regret does not exceed (for fixed decision variables), divided by the normalizer $1 - \alpha$. Therefore, by increasing α, there is a higher weight on VaR until the CVaR and VaR converge at some level. It is worth noting that for all values of α, $CVaR_{\alpha} \geq VaR_{\alpha}$. By intuition, we can argue that CVaR is the expected regret given that the regret exceeds VaR, and therefore it is obvious that CVaR should be higher than VaR for the same value of α. The complete table for the sensitivity analysis of the α parameter is attached in Appendix III Table B.2.

Sensitivity to γ Parameter

The γ parameter is the control parameter for the expected unmet demand across all scenarios in the developed models. In other words, γ is a variable to control the quality of service that is provided by the manufacturing company. Lower values of γ means less allowance for expected unmet demand in the sourcing. In particular, $\gamma = 0\%$ is a model in which no unmet demand is tolerated. Figure 4.4 represents the sensitivity of the hedging ratio (Δ), saving percentage ($S\%$) and the total number of capacity modules, and hedging capacity modules with respect to γ.

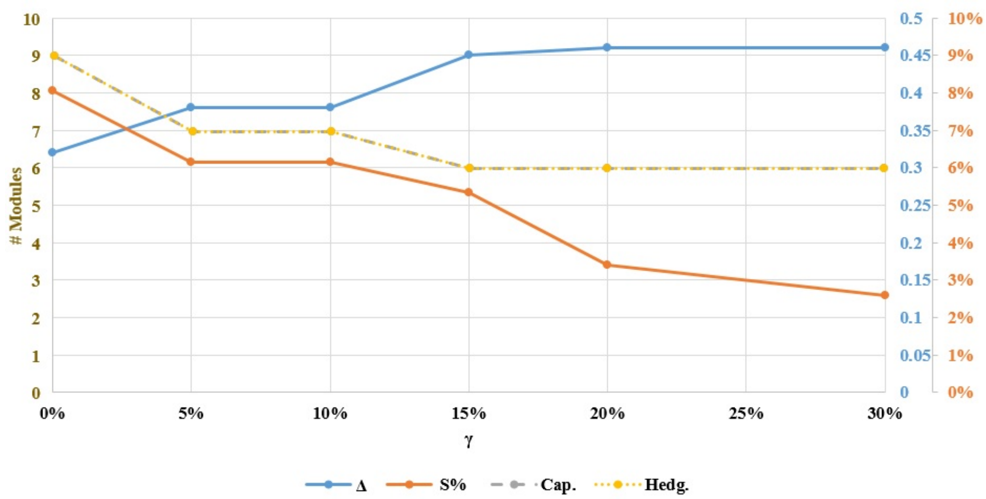

Figure 4.4: Sensitivity of α-RMER model to γ parameter ($\alpha = 0.95, \sigma_1 = 0.01, \sigma_2 = 1.2$)

In Figure 4.4, the hedging ratio increases while the saving percentage decreases when we allow for more expected unmet demand in the model. By increasing the value of γ we allow for more unmet demand (lower quality of service) and, therefore, the total number of capacity and hedging modules drops. From $\gamma = 0\%$ to 30% the total number of modules drops by 33% which leads to lower tooling cost and higher purchasing and transportation costs. The model also relies more on hedging for higher values of γ (about 50% more when we increase $\gamma = 0\%$ to 30%) since the total number of reserved capacity modules drops when we increase γ. This is why the saving percentage (sourcing through hedging is more expensive) decreases by increasing the γ value and for higher values of γ the savings due to hedging fades away. The complete table for the sensitivity analysis of the γ parameter is attached in Appendix III Table B.3.

Sensitivity to σ_1 parameter

σ_1 represents the fraction of the fixed cost of reserving modules that the manufacturer needs to pay upfront. As we increase this parameter from 0 (no extra charge for using capacity options) to 1 (equal to the fixed cost of reserving the capacity modules), it becomes less attractive for manufacturing company to pay for capacity options.

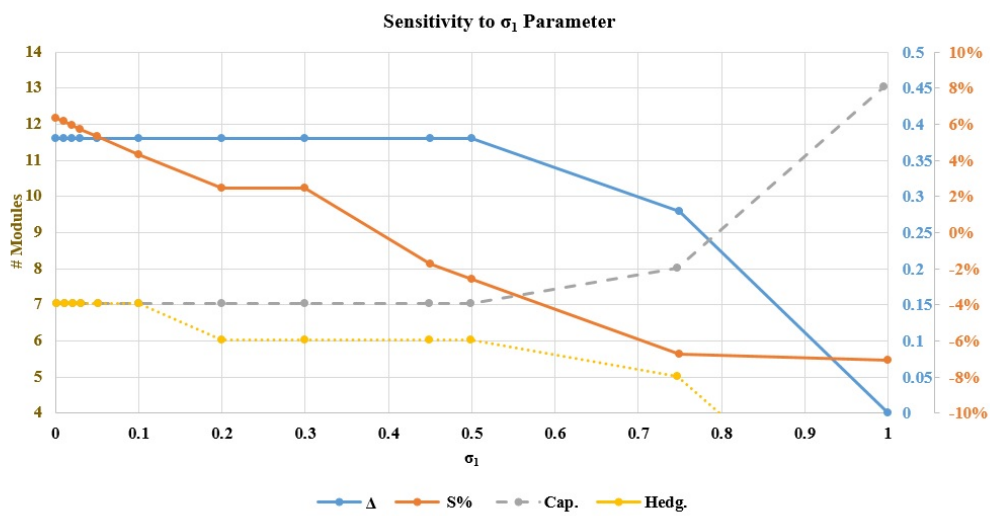

Figure 4.5: Sensitivity of α-RMER model to σ_1 parameter ($\alpha = 0.95, \gamma = 10\%, \sigma_2 = 1.2$)

In Figure 4.5, for lower values of the σ_1 the manufacturer reserves 7 capacity modules and satisfies the remaining demand through the capacity options. When $\sigma_1 \geq 0.45$, then there is no benefit for the manufacturer to buy capacity options. In particular, at $\sigma_1 = 1$ (fixed price for capacity options is equal to reserve capacity), the optimal decision from the manufacturer's perspective is to reserve enough capacity from the beginning and not to rely on options. The complete table for the sensitivity analysis of the σ_1 parameter is attached in Appendix III Table B.4.

Sensitivity to σ_2 parameter

We introduced σ_2 parameter as a multiplier for the unit part cost. Therefore, higher values of this parameter means more expensive parts for hedging. As we can see in Figure 4.6, by increasing the value of σ_2, the variable cost of hedging increases and therefore it is less desirable for the model to use the hedging capacity. This is why the hedging ratio (Δ) and the total number of hedging modules decrease when we increase σ_2. As we increase σ_2 model needs for reserved capacity to satisfy the demand. Thus, the total number of modules for the reserved capacity increases and saving percentage due to hedging fades away. For larger values of σ_2 the tooling cost and the total expected value of the purchasing and transportation costs exceeds the base costs from the RNR^+ model and, therefore, we can see negative saving percentage for those values. The complete table for the sensitivity analysis of the σ_2 parameter is attached in Appendix III Table B.5.

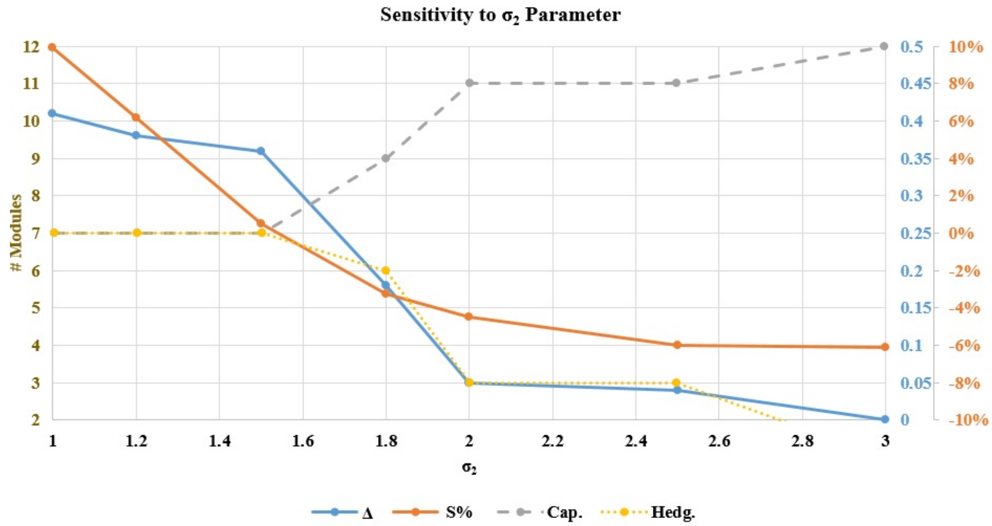

Figure 4.6: Sensitivity of α-RMER model to σ_2 parameter ($\alpha = 0.95, \gamma = 10\%, \sigma_1 = 0.01$)

4.6. Managerial Insights from α-RMER Model

Although the capacity option models stylize the contracts between the suppliers and the manufacturing company to the basic setting with fixed and given quotes from suppliers and limits the manufacturer decisions to the number of modular reserved and hedging capacity, sensitivity analysis of the key parameters of the model provides valuable insights for managers who actually negotiate capacity reservation contracts.

For parts with low tooling costs, buying extra tooling and localizing the supply sources is a cost-effective strategy to deal with uncertainty. However, with high tooling cost parts, reserving extra capacity and committing to specific suppliers might be risky. Through our numerous analysis in this chapter, we have shown it might be more economical to work with suppliers to build in more flexible capacity (hedging capacity).

Our results suggest that for the option contracts to be effective, the tooling cost should be high with respect to the total cost (in our examples the ratio was about 20%). Moreover, the negotiation over the fixed costs of hedging and the exercise price is crucial. The higher values of hedging fixed costs and exercise costs incentivized the suppliers to allow for capacity options; however, from the manufacturer's perspective, it is less interesting and less profitable to buy hedging options. As we can see from the Figure 4.5, for the manufacturer, it is beneficial to buy capacity options if the upfront price of the capacity options is less than 30% of the total cost while the variable cost is set to 20%. Any value for the fixed cost more than 30%, makes the savings zero or negative.

From Figure 4.6, we can see the negotiation power of the suppliers on the variable cost (unit cost of purchasing when the manufacturer exercise the options). Basically, if the extra fixed cost is set to 1% of the actual fixed cost, it makes sense for the manufacturer to buy capacity options if the variable cost is less than 50%. Any value for the variable cost more than 50%, makes the savings zero or negative.

The results of our sensitivity analysis on the expected unmet demand control parameter suggests that the capacity option mechanism can reduce the total cost of the sourcing decisions up to 10% for risk-neutral models and up to 8% for α-reliable models. Finally, the α-reliable models allows the mangers to design the supply chain networks with regards to their desirable amount of risk.

4.7. Concluding Remarks and Future Research

In this chapter, we proposed capacity planning combined with capacity options as an effective mechanism to hedge against uncertainty and to design flexible SCNs. Moreover, we suggest using the α-reliable mean-excess regret measure [23] for systems in which the average and the worst-case costs cannot describe the performance of the system and quantifying the at-risk values of the cost is of interest.

The major contribution of this chapter is the development of a capacity option model for long term capacity reservation contracts in the automotive industry. We show that capacity option contracts provide a mechanism to have more flexible supply contracts and consequently more flexible SCNs. Our results suggest that for parts with high tooling costs (in our case the tooling cost was about 20% of the total costs) reserving capacity and buying capacity options can decrease the costs up to 10%. We chose a stochastic model with expected costs and no hedging variable as the base of our comparisons for savings. Then, we investigated the sensitivity of the α-reliable mean-excess model with regards to the key parameters of the model. In particular, we have discussed the possibility of the price negotiation between suppliers and manufacturer and the elasticity of the manufacturer's decisions with regards to suppliers' quotes for hedging fixed costs and variable costs. Finally, we propose a Bender's decomposition algorithm to decompose the MIP models and solve them in significantly less time than the time required by commercial solvers.

For future research, we suggest the study of the capacity model with supplier's perspective. Then, the suppliers and manufacturer would pursue a Stackelberg game to come up with pricing, capacity, and hedging decisions. An alternative way of looking at this problem is the integrated supply chain holistic view in which the manufacturer tries to minimize its costs (consequently maximize its profit) while the suppliers try to maximize their profit. Therefore, all parties need to coordinate and maximize their combined profits.

Chapter 5.

Conclusions

In this dissertation, we have investigated the need for accurate quantitative decision support methods for supply chain network design in three technical chapters. The three chapters in this study are tied together in sense that we set the base of our modeling in chapter 2, then we extend the base model in the direction of modeling uncertainty in chapter 3, and in the direction of network structure and risk modeling in chapter 4.

Concluding Remarks

In chapter 2 we investigated the issue of optimizing supply networks under uncertainty and compared the designs from the stochastic model with the decisions from deterministic models under different settings. We proposed an end-to-end framework that enables the decision makers to systematically incorporate uncertainty in their designs, plan for many plausible future scenarios, and assess the quality of service and robustness of their decisions.

The framework includes incorporates identifying uncertain parameters, and estimating the distributions of them. Then, we optimize global sourcing decisions across all regions using a two-stage stochastic model. The objective of this model is the expected Net Present Value (NPV) of the total landed cost over all future scenarios.

We have shown the scalability of our approach with the SAA scheme. Further, through our numerous experiments, we have shown the impact of uncertainty from 3 major sources (demand, freight costs, and exchange rates) on SCN designs. Although this chapter is focused on our case study in the automotive industry, it can be generalized to supply chain network design problem in any industry.

Our results have shown that models that do not consider uncertainty may obtain sub-optimal solutions or result in infeasible solutions for practical applications. Moreover, 3-year and 2-year forecasts are often very inexact and sensitivity analysis of the key inputs may not be adequate for a decision support tool. Finally, our model suggests for low tooling cost parts buying extra tooling and localizing the production is a good strategy to mitigate uncertainty. But with high tooling cost parts, it might be more economical to work with suppliers to build in more flexibility. We discuss the latter approach in chapter 4.

In chapter 3, we addressed the question of how to incorporate correlation among uncertain parameters into decision making and developed a quantitative methodology for SCNDs under correlated uncertainty. This chapter is an extension of the chapter 2 in the sense that our modeling framework allows for planning multiple parts at the same time and incorporates the correlation into the decision process. To do so, we employ distributionally robust optimization to coordinate the SCNs of different parts against the worst-case distribution with given marginal probabilities for demand, exchange rate, and freight cost uncertainties.

Further, we have shown the price of ignoring the correlation in the parameters of the traditional methods in which the independence of the uncertain parameters is an assumption. Our methodology contributes to the literature by considering multiple sources of uncertainty into modeling and relaxing the assumption of independence among uncertain parameters. Finally, we proposed a tractable cutting-plane algorithm to solve the correlated model in less time than that required by commercial solvers.

Through our examples, we have shown that: (1) the effect of the correlation increases when we have less information about the uncertain parameters; (2) the deterministic model is only reliable when we have low or medium exchange rates; (3) the correlated model gives higher profit when exchange rates are high compared to the stochastic model (independent); and (4) the correlated model has a slightly higher mean profit than other models.

Finally, in chapter 4, we proposed capacity options as a mechanism to hedge against uncertainty in input parameters and show how to combine it with our proposed framework in chapter 2. Moreover, we suggest using the α-reliable mean-excess regret objective to evaluate the designs and create a variety of solutions for decision makers with different risk appetites. Our model is different from other approaches found in the literature.

We show in our numerical results that capacity option contracts provide a mechanism to have more flexible supply contracts and consequently more flexible SCNs. For high tooling cost parts in which localization through buying extra capacity is expensive, buying capacity options can decrease the total costs of SCND. Further, we have discussed the possibility of price negotiation between suppliers and the manufacturer over the hedging fixed costs and variable costs. Finally, we proposed a modified Bender's decomposition algorithm to decompose the MIP models and solve them in reasonable times.

Future Research

For future research, we propose 2 different avenues as extensions of the models in this dissertation:

- The study of the demand elasticity to the price in different markets: In chapter 2 we assumed the revenues generated from the SCN is fixed and we focused on minimizing the costs. In chapter 3, we discussed a profit maximization model. In this model, we introduced selling price as an input to the optimization model. However, it can be argued that the price of different vehicles are a function of the demand at different markets and the profit can change based on different realizations of the demand. In other words, in scenarios with high demand realizations, the manufacturer may be able to increase the selling price to balance its supply-demand curve. The new assumption will make the model harder to solve, since the decision makers need to make additional decisions about the prices.

- The intra-supply chain competition among the manufacturer and suppliers competing to maximize their profits: In chapter 4 we studied the capacity option model in which the manufacturer was assumed to be the dominant decision maker in the whole chain. However, considering the the competitive market for the automotive makers, the decisions' imposed by the manufacturer may not be rewarding for the suppliers. This gives the suppliers leverage to negotiate over the prices. For future research in this direction, we suggest the study of the capacity option model from the supplier's perspective. Then, the suppliers and manufacturer would pursue a Stackelberg game to come up with pricing, capacity, and hedging decisions.

Appendix A.

Supplements to Chapter 3

A.1. Appendix I: Nomenclature

All parameters used in the above models are described in detail in the following table:

Parameter	**Description**
h	Inventory holding rate
r_t	Discount rate at time t
e_i	Exchange rate of the foreign currency of the supplier i to USD
$\beta_{c'c}$	The required amount/number of commodity type c' in commodity type c (BOM)
$\delta_{(i,j)}$	Number of days in transit on arc (i, j)
τ_{ic}	Operating time required for each unit of commodity type c at node i
ϕ_i	Operating capacity of plant i
ψ_{ilc}	The modular capacity of supplier i operating at capacity level l to produce commodity type c
t_{ilc}	Tooling cost of supplier i for commodity type c at capacity level l
c_{ic}	Cost of purchasing one unit of commodity type c from supplier i
ρ'_{ic}	Price/value of commodity type c at node i
d_{ic}	Demand of commodity type c at node i
$f_{(i,j)c}$	Freight cost of commodity type c on arc (i, j)
$\eta_{(i,j)c}$	Duty rate of commodity type c on arc (i, j)

For convenience, we define the following parameters:

Parameter	
$a_{ilc} = t_{ilc}e_i$	$\forall i \in S_c, l \in L_{ic}, c \in C$
$b_{(i,j)c} = (1 + r_t)^{-t}(c_{ic}e_i + f_{(i,j)c} + \delta_{(i,j)}c_{ic}e_ih/365 + c_{ic}e_i\eta_{(i,j)c})$	$\forall (i, j) \in A, c \in C$
$\rho_{ic} = (1 + r_t)^{-t}\rho'_{ic}e_i$	$\forall i \in D_c, c \in C$

The a_{ilc} parameters represent the fixed costs of locating and tooling supplier $i \in S_c$ with capacity level $l \in L_{ic}$ for commodity $c \in C$. The $b_{(i,j)c}$ parameters represent the discounted logistical costs consists of purchasing costs, freight cost, inventory holding cost, and duty, respectively on arc $(i,j) \in A$ for commodity $c \in C$. The ρ_{ic} parameters represent the discounted selling price of commodity type $c \in C$ at demand market $i \in D_c$.

A.2. Appendix II: Proofs

Theorem 3.1

Proof. We consider the special case of $FSCND{-}u{-}det$ for only one type of commodity (no index for c). Moreover, we do not consider any plants, i.e. $N = \{S \cup D\}$ and suppliers are uncapacitated (no index for l and $\psi_i = \infty$). Here we also set $\rho_i = 0, \forall i \in D$. Therefore, the problem becomes a cost minimization problem and we need to remove variables $U_i, \forall i \in D$. This special case model is in fact the Uncapacitated Facility Location Problem (UFLP). Krarup and Pruzan [55] has shown the $\mathcal{NP}$-hardness of the UFLP by establishing its relationship with Set Packing-covering-partitioning problems. Since the special case of $FSCND - u - det$ is reduced to UFLP, the proof is complete.

□

Proposition 3.1

Proof. Recall that $h(\mathbf{X{,}b{,}d})$ is defined by equation (3.17). By strong duality of linear programming, $h(\mathbf{X{,}b{,}d})$ is equal to the optimal objective value of the dual problem of the second stage problem. Let us define $\boldsymbol{G}, \boldsymbol{H}, \boldsymbol{V}, \boldsymbol{W}$ as the dual variables corresponding to the second stage constraints stated in equations (3.11)-(3.14). We used $\mathcal{F}(\mathbf{X{,}b{,}d})$ to refer to the feasible region formed by these constraints:

$$h(\mathbf{X,b,d}) = \max_{\mathbf{Y,U}\in\Re^+} \left(\sum_{c\in C} \sum_{\substack{(j,i)\in A;\\ i\in D_c}} \rho_{ic} Y_{(j,i)c} \right) - \left(\sum_{c\in C} \sum_{(i,j)\in A} b_{(i,j)c} Y_{(i,j)c} \right) \tag{A.1}$$

subject to:

$$\sum_{j\in FS(i)} Y_{(i,j)c} \leq \sum_{l\in L_{ic}} \psi_{ilc} X_{ilc}, \quad \forall i \in S_c; c \in C \quad : \quad G_{ic} \tag{A.2}$$

$$\sum_{\substack{c\in C_i;\\ \beta_{c'c}\neq 0}} \sum_{j\in FS(i)} \beta_{c'c} Y_{(i,j)c} \leq \sum_{j\in RS(i)} Y_{(j,i)c'}, \quad \forall i \in N'; c' \in C_j, j \in RS(i) \quad : \quad H_{ic'} \tag{A.3}$$

$$\sum_{c\in C} \sum_{j\in RS(i)} \tau_{ic} Y_{(j,i)c} \leq \phi_i, \quad \forall i \in N'; c \in C \quad : \quad V_i \tag{A.4}$$

$$\sum_{j\in RS(i)} Y_{(j,i)c} + U_{ic} = d_{ic}, \quad \forall i \in D_c; c \in C \quad : \quad W_{ic} \tag{A.5}$$

Please note that $\boldsymbol{W}$ corresponds to the set of equality constraints (3.14) and therefore, it is unrestricted. However, The dual constraints of variables $\boldsymbol{U}$ enforce the non-negativity of $\boldsymbol{W}$. The other constraints are in their canonical forms and therefore, other variables are non-negative. The minimization problem in proposition 3.1 is exactly the dual of the second stage problem for a given $\mathbf{X,b,d}$. Constraints (3.19)-(3.21) form the feasible region of the dual problem that is referred to as $\mathcal{F}^D(\mathbf{X,b,d})$. □

Lemma 3.1

Proof. The minimization problem in equation (3.16) over the marginal-based ambiguity set π is restated here for convenience:

$$\min_{p(\boldsymbol{b},\boldsymbol{d})\in\Re^+} \sum_{(\boldsymbol{b},\boldsymbol{d})\in\Xi} p(\boldsymbol{b},\boldsymbol{d}) h(\mathbf{X},\mathbf{b},\mathbf{d}) \tag{A.6}$$

subject to:

$$\sum_{(\boldsymbol{b},\boldsymbol{d})\in\Xi} \mathbb{I}\left(b_{(i,j)c} = \varepsilon_{(i,j)c}\right) p(\boldsymbol{b},\boldsymbol{d}) = q_{b_{(i,j)c}}(\varepsilon_{(i,j)c}), \forall (i,j)\in A, c\in C \quad : \quad \theta_{b_{(i,j)c}} \tag{A.7}$$

$$\sum_{(\boldsymbol{b},\boldsymbol{d})\in\Xi} \mathbb{I}\left(d_{ic} = \varepsilon'_{ic}\right) p(\boldsymbol{b},\boldsymbol{d}) = q_{d_{ic}}(\varepsilon'_{ic}), \forall i\in D_c, c\in C \quad : \quad \theta_{d_{ic}} \tag{A.8}$$

$$\sum_{(\boldsymbol{b},\boldsymbol{d})\in\Xi} p(\boldsymbol{b},\boldsymbol{d}) = 1 \quad : \quad \varpi \tag{A.9}$$

Let us define $\varpi, \boldsymbol{\theta_b}, \boldsymbol{\theta_d}$ as the dual variables corresponding to the constraints of marginal-based ambiguity set defined in equation (3.15). Please note that all dual variables correspond to equality constraints and therefore, they are all unrestricted. The maximization problem in lemma 3.1 is exactly the dual of the this problem.

□

Proposition 3.2

Proof. By applying lemma 3.1, we can merge the first stage problem with the maximization problem to obtain equations (3.24) and (3.25). Therefore, we have:

$$\varpi + \sum_{c\in C}\sum_{(i,j)\in A} \theta_{b_{(i,j)c}} + \sum_{c\in C}\sum_{i\in D_c} \theta_{d_{ic}} \leq h(\mathbf{X},\mathbf{b},\mathbf{d}), \quad \forall (\boldsymbol{b},\boldsymbol{d})\in\Xi \tag{A.10}$$

$$\varpi + \sum_{c\in C}\sum_{(i,j)\in A} \theta_{b_{(i,j)c}} + \sum_{c\in C}\sum_{i\in D_c} \theta_{d_{ic}} \leq \min_{(\boldsymbol{b},\boldsymbol{d})\in\Xi} h(\mathbf{X},\mathbf{b},\mathbf{d}) \tag{A.11}$$

Next, by applying proposition 3.1 on equation (A.11), we have:

$$\varpi + \sum_{c\in C}\sum_{(i,j)\in A}\theta_{b_{(i,j)c}} + \sum_{c\in C}\sum_{i\in D_c}\theta_{d_{ic}} \le \min_{(\boldsymbol{b},\boldsymbol{d})\in\Xi}\ \min_{\boldsymbol{G},\boldsymbol{H},\boldsymbol{V}\in\Re^+,\boldsymbol{W}} \sum_{c\in C}\sum_{i\in S_c} G_{ic}\left(\sum_{l\in L_{ic}}\psi_{ilc}X_{ilc}\right) + \sum_{i\in N'}\phi_i V_i + \sum_{c\in C}\sum_{i\in D_c} d_{ic}W_{ic} \tag{A.12}$$

$$\varpi + \sum_{c\in C}\sum_{(i,j)\in A}\theta_{b_{(i,j)c}} + \sum_{c\in C}\sum_{i\in D_c}\theta_{d_{ic}} \le \min_{\boldsymbol{G},\boldsymbol{H},\boldsymbol{V}\in\Re^+,\boldsymbol{W}}\ \min_{(\boldsymbol{b},\boldsymbol{d})\in\Xi} \sum_{c\in C}\sum_{i\in S_c} G_{ic}\left(\sum_{l\in L_{ic}}\psi_{ilc}X_{ilc}\right) + \sum_{i\in N'}\phi_i V_i + \sum_{c\in C}\sum_{i\in D_c} d_{ic}W_{ic} \tag{A.13}$$

First, we noticed that the structure of the feasible region $\mathcal{F}^D(\mathbf{X,b,d})$ and the minimization objective enforce that all $b_{(i,j)c} = \bar{b}_{(i,j)c}$ and $\bar{b}_{(i,j)c}$ are the upper bounds for parameters $b_{(i,j)c}, \forall (i,j) \in A, c \in C$. This is possible, since we have assumed an independent and discrete support for these parameters $\boldsymbol{b} \in \Xi_b$ (finite number of levels). Next, the last term in equation (A.13) is bilinear. However, we have also assumed an independent and discrete support for demand parameters $\boldsymbol{d} \in \Xi_d$ (finite number of levels). Thus, we can consider different levels of demand $d_{ic}, i \in D_c, c \in C$ indexed by $n \in \mathfrak{N}_{ic}$ and replace d_{ic} with $\varrho_{icn}\hat{d}_{icn}$:

$$\sum_{n\in\mathfrak{N}_{ic}} \varrho_{icn} = 1, \quad \forall i \in D_c, c \in C \tag{A.14}$$

$$\varrho_{icn} \in \{0,1\}, \quad \forall i \in D_c, c \in C \tag{A.15}$$

Where demand value at level $n \in \mathfrak{N}_{ic}$ in market $i \in D_c$ for product $c \in C$ is shown with parameter $\hat{d}_{icn}$. Constraints (A.14) ensure that each demand parameter is selected at only one level. The decision variables $\varrho_{icn} = 1$ if the demand parameter in market $i \in D_c$ for product $c \in C$ is selected at level $n \in \mathfrak{N}_{ic}$. Since $\boldsymbol{W} \in \Re^+$, we know each

$W_{ic} \geq 0, \forall i \in D_c, c \in C$ (bounded from below by 0). Moreover, we assume there exist a large number (M) such that $W_{ic} \leq M, \forall i \in D_c, c \in C$ (can be bounded from above by a large number like M). Subsequently, we can reformulated the bilinear term in the objective function with auxiliary variables and the McCormick envelopes [62]. Let us define the McCormick auxiliary variables $\lambda_{icn} = \varrho_{icn} W_{ic}, \forall n \in \mathfrak{N}_{ic}, i \in D_c, c \in C$. Thus, we have:

$$f(\mathbf{X}) = \min_{\mathbf{G},\mathbf{H},\mathbf{V},\mathbf{W} \in F^D(\boldsymbol{X},\bar{\boldsymbol{b}},\boldsymbol{d}),\boldsymbol{\lambda},\boldsymbol{\varrho} \in \{0,1\}} \sum_{c \in C} \sum_{i \in S_c} G_{ic} \left(\sum_{l \in L_{ic}} \psi_{ilc} X_{ilc} \right) + \sum_{i \in N'} \phi_i V_i + \sum_{c \in C} \sum_{i \in D_c} \sum_{n \in \mathfrak{N}_{ic}} \lambda_{icn} \hat{d}_{icn} \tag{A.16}$$

subject to:

$$\sum_{n \in \mathfrak{N}_{ic}} \varrho_{icn} = 1, \forall i \in D_c, c \in C \tag{A.17}$$

$$\lambda_{icn} \geq 0, \quad \forall n \in \mathfrak{N}_{ic}, i \in D_c, c \in C \tag{A.18}$$

$$\lambda_{icn} \geq W_{ic} - M(1 - \varrho_{icn}), \quad \forall n \in \mathfrak{N}_{ic}, i \in D_c, c \in C \tag{A.19}$$

$$\lambda_{icn} \leq W_{ic}, \quad \forall n \in \mathfrak{N}_{ic}, i \in D_c, c \in C \tag{A.20}$$

$$\lambda_{icn} \leq M \varrho_{icn}, \quad \forall n \in \mathfrak{N}_{ic}, i \in D_c, c \in C \tag{A.21}$$

Where constraints (A.18)-(A.21) are the McCormick envelopes. McCormick envelopes bounds the bilinear term by the bounds of $\boldsymbol{\varrho}$ and $\boldsymbol{W}$ through a convex relaxation. Since $\boldsymbol{\varrho}$ are binary variables, the relaxation yields an exact solution [62]. Finally, we can replace equation (A.16) with equation (3.24) and add the new constraints (A.17)-(A.21) to obtain the subproblem. □

Proposition 3.3

Proof. The special case of the marginal-based confidence set was obtained by relaxing the marginal constraints; therefore $\pi = \left\{ p(\boldsymbol{b},\boldsymbol{d}) \geq 0, \sum_{(\boldsymbol{b},\boldsymbol{d})\in\Xi} p(\boldsymbol{b},\boldsymbol{d}) = 1 \right\}$. Then, we have:

$$\varpi \leq h(\boldsymbol{X}, \bar{\boldsymbol{b}}, \boldsymbol{d}), \quad \forall \boldsymbol{d} \in \Xi_d \tag{A.22}$$

$$\varpi = \min_{\boldsymbol{d}\in\Xi_d} h(\boldsymbol{X}, \bar{\boldsymbol{b}}, \boldsymbol{d}), \quad \forall \mathbf{X} \in \boldsymbol{\chi} \tag{A.23}$$

By applying proposition 3.2:

$$\max_{\mathbf{X}\in\boldsymbol{\chi}} \left(-\sum_{c\in C} \sum_{i\in S_c} \sum_{l\in L_{ic}} a_{ilc} X_{ilc} + f(\boldsymbol{X}) \right) \tag{A.24}$$

□

A.3. Appendix III: Inputs

Arc Costs

Table A.1: Input Parameters for Arc Costs

Flow Type	From	To	Origin	Destination	Part Cost	Transit Day	Freight Cost	Duty Rate
1	1	10	India	India	8.04	3	0.12	0.00
1	1	11	India	China	8.04	35	0.76	0.19
1	1	12	India	China	8.04	35	0.76	0.19
1	2	10	China	India	7.67	15	0.87	0.18
1	2	11	China	China	7.67	3	0.13	0.00
1	2	12	China	China	7.67	3	0.13	0.00
1	3	10	China	India	7.66	15	0.87	0.18
1	3	11	China	China	7.66	3	0.13	0.00
1	3	12	China	China	7.66	3	0.13	0.00
2	4	8	India	Germany	13.30	40	0.15	0.14
2	4	9	India	Germany	13.30	40	0.15	0.14
2	5	8	China	Germany	14.47	50	0.15	0.14
2	5	9	China	Germany	14.47	50	0.15	0.14
2	6	8	Germany	Germany	18.64	3	0.01	0.00
2	6	9	Germany	Germany	18.64	3	0.01	0.00
2	7	8	Brazil	Germany	14.47	35	0.14	0.14
2	7	9	Brazil	Germany	14.47	35	0.14	0.14
3	8	13	Germany	UK	0.00	3	0.15	0.00
3	9	13	Brazil	UK	0.00	35	0.14	0.14
4	10	14	China	India	0.00	15	0.87	0.18

4	10	15	China	China	0.00	3	0.13	0.00
4	10	16	China	UK	0.00	50	0.96	0.14
4	10	17	China	Russia	0.00	50	1.47	0.18
4	10	18	China	Brazil	0.00	44	0.95	0.18
4	11	14	Germany	India	0.00	44	0.95	0.14
4	11	15	Germany	China	0.00	44	0.95	0.18
4	11	16	Germany	UK	0.00	3	0.25	0.00
4	11	17	Germany	Russia	0.00	3	0.76	0.18
4	11	18	Germany	Brazil	0.00	44	0.95	0.13
4	12	14	Brazil	India	0.00	44	0.95	0.20
4	12	15	Brazil	China	0.00	44	0.95	0.20
4	12	16	Brazil	UK	0.00	35	0.76	0.14
4	12	17	Brazil	Russia	0.00	35	0.76	0.18
4	12	18	Brazil	Brazil	0.00	3	0.12	0.00
5	13	14	UK	India	0.00	44	0.15	0.14
5	13	15	UK	China	0.00	44	0.10	0.18
5	13	16	UK	UK	0.00	3	0.01	0.00
5	13	17	UK	Russia	0.00	3	0.21	0.18
5	13	18	UK	Brazil	0.00	44	0.10	0.13
6	14	19	India	India	0.00	3	0.13	0.00
6	14	20	India	China	0.00	35	0.88	0.19
6	14	21	India	UK	0.00	40	1.11	0.14
6	14	22	India	Russia	0.00	40	1.26	0.18
6	14	23	India	Brazil	0.00	44	1.11	0.19
6	15	19	China	India	0.00	15	1.01	0.18
6	15	20	China	China	0.00	3	0.15	0.00
6	15	21	China	UK	0.00	50	1.11	0.14

6	15	22	China	Russia	0.00	50	1.70	0.18
6	15	23	China	Brazil	0.00	44	1.10	0.18
6	16	19	UK	India	0.00	44	1.10	0.14
6	16	20	UK	China	0.00	44	1.06	0.18
6	16	21	UK	UK	0.00	3	0.14	0.00
6	16	22	UK	Russia	0.00	3	0.98	0.18
6	16	23	UK	Brazil	0.00	44	0.87	0.13
6	17	19	Russia	India	0.00	40	1.11	0.20
6	17	20	Russia	China	0.00	50	1.62	0.18
6	17	21	Russia	UK	0.00	3	0.47	0.14
6	17	22	Russia	Russia	0.00	3	0.14	0.00
6	17	23	Russia	Brazil	0.00	35	0.91	0.13
6	18	19	Brazil	India	0.00	44	1.18	0.20
6	18	20	Brazil	China	0.00	44	1.18	0.20
6	18	21	Brazil	UK	0.00	35	0.91	0.14
6	18	22	Brazil	Russia	0.00	35	0.94	0.18
6	18	23	Brazil	Brazil	0.00	3	0.13	0.00

Ranges for Uncertain Parameters

Table A.2: The selected ranges of the uncertain parameters for the stochastic model and their probabilities

Parameters		Values			Probabilities		
		Low	**Med.**	**High**	**Low**	**Med.**	**High**
Demand	**India**	50%	100%	150%	0.1	0.8	0.1
	China	50%	100%	150%	0.05	0.9	0.05
	UK	50%	100%	150%	0.15	0.7	0.15
	Russia	50%	100%	150%	0.05	0.9	0.05
	Brazil	50%	100%	150%	0.05	0.9	0.05
Exchange Rate	**India - INR**	80%	100%	110%	0.033	0.9	0.067
	China - CNY	80%	100%	150%	0.214	0.7	0.086
	UK - GBP	50%	100%	110%	0.017	0.9	0.083
	Russia - RUB	50%	100%	110%	0.017	0.9	0.083
	Brazil - BRL	50%	100%	110%	0.017	0.9	0.083
	Europe - EUR	80%	100%	150%	0.214	0.7	0.086
Freight Cost	**Oil - WTI**	50%	100%	110%	0.033	0.8	0.167

Diagram of Constraints (4)

Constraints (4) are the flow balance constraints for all plants. They restrict the sum of all outgoing flows for all commodities that can be produced in i ($c \in C_i$) to be less than or equal to the required amount/number of commodities $c^{'} \in C_j$ where j belongs to the set of all ingoing flows to i.

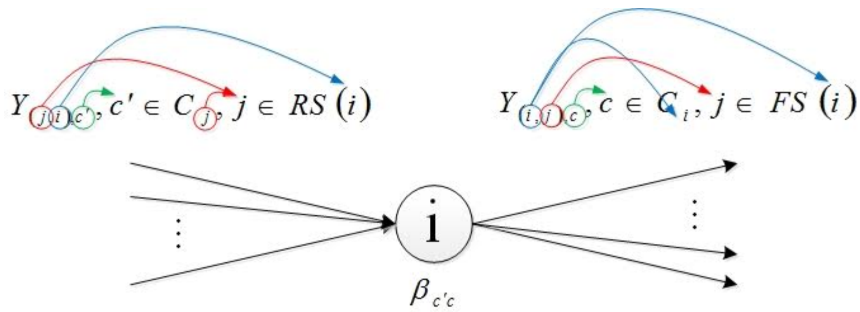

Figure A.1: The diagram of Constraints (4)

$FSND - u - det$ **solution**

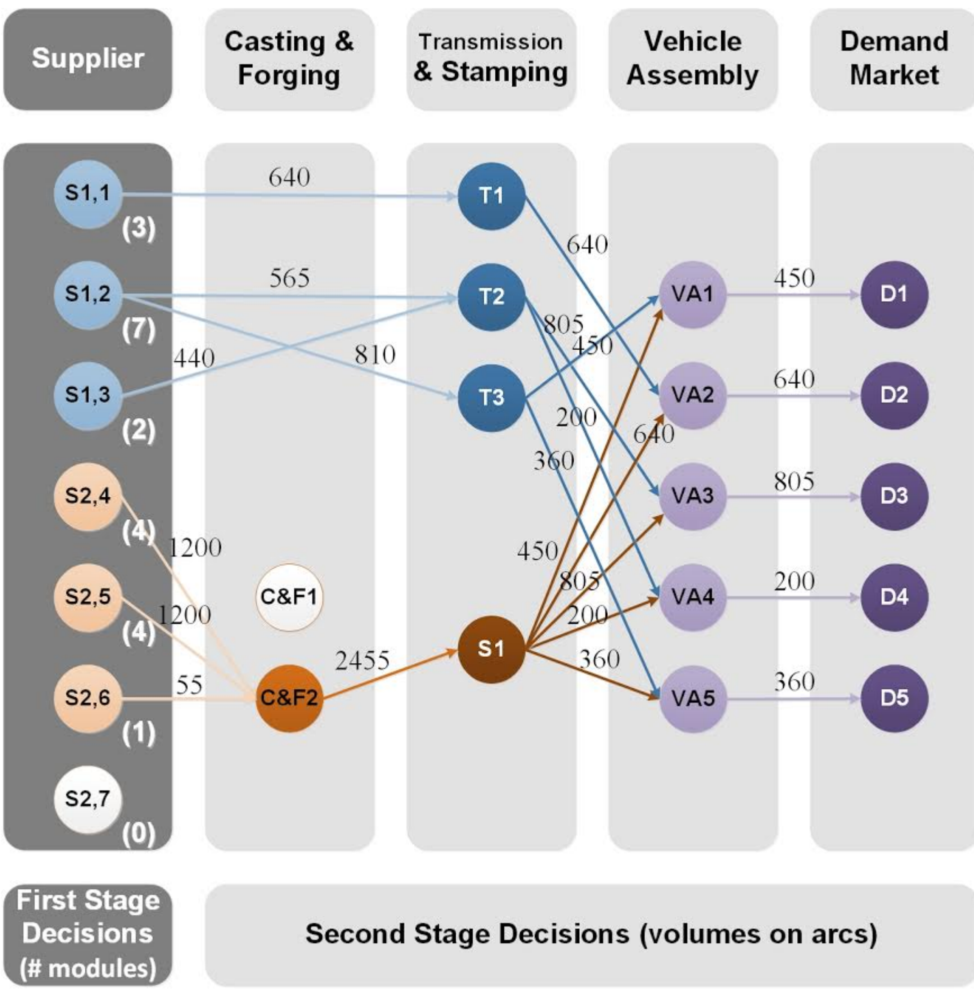

Figure A.2: The tooling and flows for the $FSCND - u - det$

Appendix B.

Supplements to Chapter 4

B.1. Appendix I: Proofs

Proposition 4.1

Proof. Let us define $\boldsymbol{\rho} \in \Re^+$ as the dual variables corresponding to the second stage constraints. The second stage problem can be restated as follows:

$$\mathcal{Q}(\boldsymbol{Y}, \boldsymbol{Y^{(h)}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) = \min_{\boldsymbol{V^w}, \boldsymbol{V^{(h)w}}, \boldsymbol{\tau^w} \in \Re^+} \sum_{w \in W} p^w \left(\sum_{i \in I} \sum_{p \in P} b^w_{ip} V^w_{ip} + b^{(h)w}_{ip} V^{(h)w}_{ip} \right) + \frac{1}{1-\alpha} \sum_{w \in W} p^w \zeta^w \tag{B.1}$$

subject to:

$$\sum_{i \in I} \left(V^w_{ip} + V^{(h)w}_{ip} \right) + \tau^w_p \geq d^w_p, \quad \forall p \in P, w \in W \quad : \rho^{(23)w}_p \tag{B.2}$$

$$-E_w \left[\sum_{p \in P} \tau^w_p \right] \geq -\gamma E_w \left[\sum_{p \in P} d^w_p \right] \quad : \rho^{(24)} \tag{B.3}$$

$$\varphi \sum_{p \in P} \frac{\tau^w_p}{d^w_p} - \frac{\tau^w_p}{d^w_p} \geq 0, \quad \forall p \in P, w \in W \quad : \rho^{(25)w}_i \tag{B.4}$$

$$-\sum_{p \in P} V^w_{ip} \geq -\sum_{l \in L_i} \psi_{il} Y_{il}, \quad \forall i \in I, w \in W \quad : \rho^{(26)w}_i \tag{B.5}$$

$$-\sum_{p \in P} V^{(h)w}_{ip} \geq -\sum_{l \in L_i} \psi^{(h)}_{il} Y^{(h)}_{il}, \quad \forall i \in I, w \in W \quad : \rho^{(27)w}_i \tag{B.6}$$

$$\zeta^w - \left(\sum_{i \in I} \sum_{p \in P} b^w_{ip} V^w_{ip} + b^{(h)w}_{ip} V^{(h)w}_{ip} \right) \geq -\mathcal{Q}^*(\boldsymbol{Y^w}, \boldsymbol{Y^{(h)w}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}) - \beta, \forall w \in W : \rho^{(35)w} \tag{B.7}$$

All constraints are in their canonical forms and therefore, all $\boldsymbol{\rho}$ variables are non-negative. By strong duality of linear programming, $\mathcal{H}(.)$ is equal to the optimal objective value of the dual problem of the second stage problem. The maximization problem in proposition 4.1 is exactly the dual of the second stage problem for a given $\boldsymbol{Y}, \boldsymbol{Y^{(h)}}, \boldsymbol{f^w}, \boldsymbol{e^w}, \boldsymbol{d^w}$ and $\boldsymbol{\rho} = 0$ is always a feasible solution.

□

Proposition 4.2

Proof. For a feasible solution $\bar{\boldsymbol{V}}^{w}, \bar{\boldsymbol{V}}^{(h)w} \in \Re^{+}$, we have:

$$0 < \sum_{i \in I} \sum_{p \in P} \bar{V}^{w}_{ip}, \quad \forall w \in W \tag{B.8}$$

This is true because the unmet demand is bounded and one supplier is at least selected. Moreover, from the constraints of the model, we have:

$$0 \le \sum_{p \in P} \bar{V}^{w}_{ip} \le \sum_{l \in L_i} \psi_{il} \bar{Y}_{il}, \quad \forall i \in I, w \in W \tag{B.9}$$

$$0 \le \sum_{p \in P} \bar{V}^{(h)w}_{ip} \le \sum_{l \in L_i} \psi^{(h)}_{il} \bar{Y}^{(h)}_{il}, \quad \forall i \in I, w \in W \tag{B.10}$$

$$0 \le \sum_{l \in L_i} l \bar{Y}^{(h)}_{il} \le \sum_{l \in L_i} l \bar{Y}_{il}, \quad \forall i \in I \tag{B.11}$$

From the last equation, it is easy to see:

$$0 \le \sum_{l \in L_i} \psi^{(h)}_{il} \bar{Y}^{(h)}_{il} \le \sum_{l \in L_i} \psi_{il} \bar{Y}_{il}, \quad \forall i \in I \tag{B.12}$$

Therefore,

$$0 \leq \sum_{i\in I}\left(\frac{\sum_{p\in P} V_{ip}^{(h)w}}{\sum_{p\in P} V_{ip}^{w} + \sum_{p\in P} V_{ip}^{(h)w}}\right) \leq \left(\frac{\sum_{i\in I}\sum_{l\in L_i}\psi_{il}^{(h)}\bar{Y}_{il}^{(h)}}{\sum_{i\in I}\sum_{l\in L_i}\psi_{il}\bar{Y}_{il} + \sum_{i\in I}\sum_{l\in L_i}\psi_{il}^{(h)}\bar{Y}_{il}^{(h)}}\right)$$

$$\leq \left(\frac{\sum_{i\in I}\sum_{l\in L_i}\psi_{il}\bar{Y}_{il}}{2\sum_{i\in I}\sum_{l\in L_i}\psi_{il}\bar{Y}_{il}}\right) \leq \frac{1}{2}, \quad \forall w \in W \tag{B.13}$$

Thus, $0 \leq \mathbf{\Delta} \leq \frac{1}{2}$, because it is the average of all the fractions weighted by the scenario probabilities. We can also intuitively argue that $\mathbf{\Delta}$ is upper bounded by $\frac{1}{2}$, because for any reserved capacity unit we prefer to ship with the regular cost first, and then, use the hedging capacity. $\mathbf{\Delta} = 0$ means no shipment was made from the hedging capacity. □

B.2. Appendix II: Inputs

Arc Costs, Suppliers, and Demands

Table B.1: Input Parameters

From	To	Part Cost	Transit Day	Freight Cost	Duty Rate	Masked Capacity	Max. Modules	Masked Demand	Module Cost
SHT-1-A	A	8.04	3	0.12	0.00	1.00	7	2.04	2666426
SHT-1-A	B	8.04	35	0.76	0.19	1.00	7	2.81	2666426
SHT-1-A	C	8.04	40	0.96	0.14	1.00	7	3.65	2666426
SHT-1-A	D	8.04	40	1.93	0.18	1.00	7	0.90	2666426
SHT-1-A	E	8.04	44	1.00	0.19	1.00	7	1.63	2666426
SHT-2-B	A	7.67	15	0.87	0.18	1.00	7	2.04	3317982
SHT-2-B	B	7.67	3	0.13	0.00	1.00	7	2.81	3317982
SHT-2-B	C	7.67	50	0.96	0.14	1.00	7	3.65	3317982
SHT-2-B	D	7.67	50	1.47	0.18	1.00	7	0.90	3317982

SHT-2-B	E	7.67	44	0.95	0.18	1.00	7	1.63	3317982
SHT-3-B	A	7.66	15	0.87	0.18	1.00	11	2.04	4635570
SHT-3-B	B	7.66	3	0.13	0.00	1.00	11	2.81	4635570
SHT-3-B	C	7.66	50	0.96	0.14	1.00	11	3.65	4635570
SHT-3-B	D	7.66	50	1.47	0.18	1.00	11	0.90	4635570
SHT-3-B	E	7.66	44	0.95	0.18	1.00	11	1.63	4635570

B.3. Appendix III: Outputs

Sensitivity to α Parameter

Table B.2: Sensitivity of α-RMER model to α parameter ($\gamma = 10\%, \sigma_1 = 0.01, \sigma_2 = 1.2$)

$\boldsymbol{\alpha}$ **Level**	**Cap./Hedg.**	**Tooling**	$\boldsymbol{\Delta}$	**Obj.**	**E-Tot.**	$\boldsymbol{\beta}$	$\boldsymbol{S}\%$
0.05	(2,4,0)/(2,4,0)	18,790,832	0.40	24,865,281	94,721,148	-2,103,495	9.40
0.10	(2,4,0)/(2,4,0)	18,790,832	0.40	25,192,130	94,911,791	1,517,752	9.22
0.45	(2,4,0)/(2,4,0)	18,790,832	0.43	27,056,943	95,661,339	5,637,362	8.50
0.50	(2,4,0)/(2,4,0)	18,790,832	0.45	27,279,916	96,122,444	6,630,069	8.06
0.55	(3,4,0)/(3,4,0)	18,790,832	0.45	27,486,469	95,925,098	6,630,069	8.05
0.90	(3,4,0)/(3,4,0)	21,483,923	0.39	27,950,539	98,204,200	6,466,617	6.07
0.95	(3,4,0)/(3,4,0)	21,483,923	0.38	27,950,539	98,112,171	6,466,616	6.06

Sensitivity to γ Parameter

Table B.3: Sensitivity of α-RMER model to γ parameter ($\alpha = 0.95, \sigma_1 = 0.01, \sigma_2 = 1.2$)

γ **Level**	**Cap./Hedg.**	**Tooling**	$\boldsymbol{\Delta}$	**Obj.**	**E-Tot.**	$\boldsymbol{\beta}$	$\boldsymbol{S}$%
0%	(5,4,0)/(5,4,0)	26,870,103	0.32	36,463,550	112,817,375	8,191,531	8.06
5%	(4,3,0)/(4,3,0)	20,825,850	0.38	29,516,529	103,252,708	8,690,678	6.15
10%	(3,4,0)/(3,4,0)	21,483,922	0.38	27,950,538	98,112,171	8,689,616	6.16
15%	(3,3,0)/(3,3,0)	18,132,759	0.45	26,821,106	92,868,390	8,688,346	5.33
20%	(3,3,0)/(3,3,0)	18,132,759	0.46	25,367,591	87,708,879	7,234,831	3.41
30%	(3,3,0)/(3,3,0)	18,132,759	0.46	23,843,872	78,666,511	5,711,113	2.59

Sensitivity to σ_1 Parameter

Table B.4: Sensitivity of α-RMER model to σ_1 parameter ($\alpha = 0.95, \gamma = 0.1, \sigma_2 = 1.2$)

$\boldsymbol{\sigma_1}$ **Values**	**Cap./Hedg.**	**Tooling**	$\boldsymbol{\Delta}$	**Obj.**	**E-Tot.**	$\boldsymbol{\beta}$	$\boldsymbol{S}$**%**
0.00	(3,4,0)/(3,4,0)	21,271,210	0.38	27,737,827	97,920,410	6,466,616	6.34
0.01	(3,4,0)/(3,4,0)	21,483,922	0.38	27,950,538	98,112,171	6,466,616	6.16
0.02	(3,4,0)/(3,4,0)	21,696,634	0.38	28,163,251	98,334,738	6,466,616	5.94
0.03	(3,4,0)/(3,4,0)	21,909,346	0.38	28,375,963	98,590,110	6,466,616	5.7
0.05	(3,4,0)/(3,4,0)	22,334,770	0.38	28,801,386	98,979,075	6,466,616	5.33
0.10	(3,4,0)/(3,4,0)	23,398,331	0.38	29,864,950	100,060,859	6,466,618	4.29
0.20	(4,3,0)/(3,3,0)	24,210,299	0.38	31,877,221	101,940,346	7,666,922	2.5
0.30	(4,3,0)/(3,3,0)	26,005,622	0.38	31,877,221	101,940,346	7,666,922	2.5
0.45	(4,3,0)/(3,3,0)	28,698,606	0.38	36,365,527	106,385,200	7,666,921	-1.75
0.50	(4,3,0)/(3,3,0)	29,596,267	0.38	37,263,189	107,258,807	7,666,921	-2.59
0.75	(5,3,0)/(2,3,0)	34,751,181	0.28	41,604,340	111,561,672	6,853,159	-6.71
1.00	(7,6,0)/(0,0,0)	38,572,881	0.00	4,301,832	111,920,733	4,445,447	-7.05

Sensitivity to σ_2 Parameter

Table B.5: Sensitivity of α-RMER model to σ_2 parameter ($\alpha = 0.95, \gamma = 0.1, \sigma_1 = 0.01$)

$\boldsymbol{\sigma_2}$ **Values**	**Cap./Hedg.**	**Tooling**	$\boldsymbol{\Delta}$	**Obj.**	**E-Tot.**	$\boldsymbol{\beta}$	$\boldsymbol{S}$%
1.0	(4,3,0)/(4,3,0)	20,825,850	0.41	24,611,606	94,166,163	3,785,756	9.93
1.2	(3,4,0)/(3,4,0)	21,483,922	0.38	27,950,538	98,112,171	6,466,616	6.16
1.5	(3,4,0)/(3,4,0)	21,483,922	0.36	33,953,686	104,048,415	12,469,764	0.48
1.8	(6,3,0)/(3,3,0)	26,132,039	0.18	38,445,729	107,973,754	12,313,689	-3.27
2.0	(7,4,0)/(1,2,0)	32,029,939	0.05	39,831,216	109,235,417	7,801,276	-4.48
2.5	(7,4,0)/(1,2,0)	32,029,939	0.04	41,004,511	110,810,474	8,974,571	-5.99
3.0	(7,5,0)/(0,1,0)	35,288,078	0.00	41,477,507	109,900,126	6,189,429	-6.12

Bibliography

[1] S. Agrawal, Y. Ding, A. Saberi, and Y. Ye. “Price of correlations in stochastic optimization”. In: *Operations Research* 60.1 (2012), pp. 150–162.

[2] S. Ahmed. “Convexity and decomposition of mean-risk stochastic programs”. In: *Mathematical Programming* 106.3 (2006), pp. 433–446.

[3] S. Ahmed, A. J. King, and G. Parija. “A multi - stage stochastic integer programming approach for capacity expansion under uncertainty”. In: *Journal of Global Optimization* 26.1 (2003), pp. 3–24.

[4] F. Altiparmak, M. Gen, L. Lin, and I. Karaoglan. “A steady-state genetic algorithm for multi-product supply chain network design”. In: *Computers & Industrial Engineering* 56.2 (2009), pp. 521–537.

[5] A. Amiri. “Designing a distribution network in a supply chain system: Formulation and efficient solution procedure”. In: *European journal of operational research* 171.2 (2006), pp. 567–576.

[6] K. J. Arrow, T. Harris, and J. Marschak. “Optimal inventory policy”. In: *Econometrica: Journal of the Econometric Society* (1951), pp. 250–272.

[7] A. Azaron, K. Brown, S. Tarim, and M. Modarres. “A multi-objective stochastic programming approach for supply chain design considering risk”. In: *International Journal of Production Economics* 116.1 (2008), pp. 129–138.

[8] H. Badri, M. Bashiri, and T. H. Hejazi. “Integrated strategic and tactical planning in a supply chain network design with a heuristic solution method”. In: *Computers & Operations Research* 40.4 (2013), pp. 1143–1154.

[9] M. L. Balinski. “Integer programming: methods, uses, computations”. In: *Management Science* 12.3 (1965), pp. 253–313.

[10] G.-Y. Ban and C. Rudin. “The big data newsvendor: Practical insights from machine learning”. In: (2017).

[11] D. Barnes-Schuster, Y. Bassok, and R. Anupindi. “Coordination and flexibility in supply contracts with options”. In: *Manufacturing & Service Operations Management* 4.3 (2002), pp. 171–207.

[12] B. M. Beamon. “Supply chain design and analysis: Models and methods”. In: *International journal of production economics* 55.3 (1998), pp. 281–294.

[13] A. Ben-Tal and A. Nemirovski. “Robust convex optimization”. In: *Mathematics of operations research* 23.4 (1998), pp. 769–805.

[14] A. Ben-Tal and A. Nemirovski. “Robust optimization–methodology and applications”. In: *Mathematical Programming* 92.3 (2002), pp. 453–480.

[15] A. Ben-Tal and A. Nemirovski. “Robust solutions of linear programming problems contaminated with uncertain data”. In: *Mathematical programming* 88.3 (2000), pp. 411–424.

[16] D. Bertsimas and M. Sim. “The price of robustness”. In: *Operations research* 52.1 (2004), pp. 35–53.

[17] D. Bertsimas and A. Thiele. “A robust optimization approach to supply chain management”. In: *International Conference on Integer Programming and Combinatorial Optimization*. Springer. 2004, pp. 86–100.

[18] X. Bin and L. Ying. *The case study: How BMW dealt with exchange rate risk*. Ed. by T. F. Times. [Online; 28 Nov. 2017]. Oct. 2012. URL: `https://www.ft.com/content/f21b3a92-f907-11e1-8d92-00144feabdc0`.

[19] J. R. Birge and F. Louveaux. *Introduction to stochastic programming*. 2011.

[20] B. A. Calfa, A. Agarwal, I. E. Grossmann, and J. M. Wassick. “Data-driven multi-stage scenario tree generation via statistical property and distribution matching”. In: *Computers & Chemical Engineering* 68 (2014), pp. 7–23.

[21] T. C. Chan, Z.-J. M. Shen, and A. Siddiq. “Robust facility location under demand location uncertainty”. In: *arXiv preprint arXiv:1507.04397* (2015).

[22] Chen. “Strategic Network Planning Under Uncertainty with Two-Stage Stochastic Integer Programming”. PhD thesis. University of Michigan, 2016.

[23] G. Chen, M. S. Daskin, Z.-J. M. Shen, and S. Uryasev. “The α-reliable mean-excess regret model for stochastic facility location modeling”. In: *Naval Research Logistics (NRL)* 53.7 (2006), pp. 617–626.

[24] F. Cheng, M. Ettl, G. Y. Lin, M. Schwarz, and D. D. Yao. “Flexible supply contracts via options”. In: *IBM TJ Watson Research Center Working Paper* (2003).

[25] C. C. Chow and R. K. Sarin. “Known, unknown, and unknowable uncertainties”. In: *Theory and Decision* 52.2 (2002), pp. 127–138.

[26] M. Christopher and H. Peck. “Building the resilient supply chain”. In: *The international journal of logistics management* 15.2 (2004), pp. 1–14.

[27] M. A. Cohen and N. Agrawal. “An analytical comparison of long and short term contracts”. In: *IIE transactions* 31.8 (1999), pp. 783–796.

[28] K. L. Croxton, D. M. Lambert, S. J. García-Dastugue, and D. S. Rogers. “The demand management process”. In: *The International Journal of Logistics Management* 13.2 (2002), pp. 51–66.

[29] S. Culp. *Supply Chain Disruption A Major Threat to Business*. Ed. by F. Magazine. [Online; 24 Oct. 2016]. Feb. 2013. URL: http://www.forbes.com/sites/steveculp/2013/02/15/supply-chain-disruption-a-major-threat-to-business/%5C#327fc0df7757.

[30] M. S. Daskin. *Network and discrete location: models, algorithms, and applications*. John Wiley & Sons, 2011.

[31] M. S. Daskin. *Network and discrete location: models, algorithms, and applications*. John Wiley & Sons, 2013.

[32] M. S. Daskin, C. R. Coullard, and Z.-J. M. Shen. "An inventory-location model: Formulation, solution algorithm and computational results". In: *Annals of operations research* 110.1-4 (2002), pp. 83–106.

[33] M. S. Daskin, S. M. Hesse, and C. S. Revelle. "α-reliable p-minimax regret: A new model for strategic facility location modeling". In: *Location Science* 5.4 (1997), pp. 227–246.

[34] M. S. Daskin, W. J. Hopp, and B. Medina. "Forecast horizons and dynamic facility location planning". In: *Annals of Operations Research* 40.1 (1992), pp. 125–151.

[35] M. S. Daskin, L. V. Snyder, and R. T. Berger. "Facility location in supply chain design". In: *Logistics systems: Design and optimization*. Springer, 2005, pp. 39–65.

[36] T. Davis. "Effective supply chain management". In: *Sloan management review* 34.4 (1993), p. 35.

[37] E. Delage and Y. Ye. "Distributionally robust optimization under moment uncertainty with application to data-driven problems". In: *Operations research* 58.3 (2010), pp. 595–612.

[38] R. S. Dembo. "Scenario optimization". In: *Annals of Operations Research* 30.1 (1991), pp. 63–80.

[39] K. Dogan and M. Goetschalckx. "A primal decomposition method for the integrated design of multi-period production–distribution systems". In: *Iie Transactions* 31.11 (1999), pp. 1027–1036.

[40] D. Elson. "Site location via mixed - integer programming". In: *Journal of the Operational Research Society* 23.1 (1972), pp. 31–43.

[41] G. D. Eppen, R. K. Martin, and L. Schrage. "OR practice - a scenario approach to capacity planning". In: *Operations research* 37.4 (1989), pp. 517–527.

[42] E. Fernández and M. Landete. "Fixed-charge facility location problems". In: *Location Science*. Springer, 2015, pp. 47–77.

[43] K. Govindan, M. Fattahi, and E. Keyvanshokooh. "Supply chain network design under uncertainty: A comprehensive review and future research directions". In: *European Journal of Operational Research* (2017).

[44] G. Guillén, F. Mele, M. Bagajewicz, A. Espuna, and L. Puigjaner. "Multiobjective supply chain design under uncertainty". In: *Chemical Engineering Science* 60.6 (2005), pp. 1535–1553.

[45] R. Hellermann. *Capacity options for revenue management: theory and applications in the air cargo industry*. Vol. 575. Springer Science & Business Media, 2006.

[46] E. Huang and M. Goetschalckx. "Strategic robust supply chain design based on the Pareto-optimal tradeoff between efficiency and risk". In: *European Journal of Operational Research* 237.2 (2014), pp. 508–518.

[47] J. C. Hull and S. Basu. *Options, futures, and other derivatives*. Pearson Education India, 2016.

[48] M. Jafarian and M. Bashiri. "Supply chain dynamic configuration as a result of new product development". In: *Applied Mathematical Modelling* 38.3 (2014), pp. 1133–1146.

[49] W. C. Jordan and S. C. Graves. "Principles on the benefits of manufacturing process flexibility". In: *Management Science* 41.4 (1995), pp. 577–594.

[50] R. Karuppiah, M. Martin, and I. E. Grossmann. "A simple heuristic for reducing the number of scenarios in two-stage stochastic programming". In: *Computers & chemical engineering* 34.8 (2010), pp. 1246–1255.

[51] A. J. Kleywegt, A. Shapiro, and T. Homem-de-Mello. "The sample average approximation method for stochastic discrete optimization". In: *SIAM Journal on Optimization* 12.2 (2002), pp. 479–502.

[52] W. Klibi and A. Martel. "Scenario-based supply chain network risk modeling". In: *European Journal of Operational Research* 223.3 (2012), pp. 644–658.

[53] W. Klibi and A. Martel. "The design of robust value-creating supply chain networks". In: *OR spectrum* 35.4 (2013), pp. 867–903.

[54] W. Klibi, A. Martel, and A. Guitouni. "The design of robust value-creating supply chain networks: a critical review". In: *European Journal of Operational Research* 203.2 (2010), pp. 283–293.

[55] J. Krarup and P. M. Pruzan. "The simple plant location problem: survey and synthesis". In: *European journal of operational research* 12.1 (1983), pp. 36–81.

[56] S. Lakhal, A. Martel, O. Kettani, and M. Oral. "On the optimization of supply chain networking decisions". In: *European journal of operational research* 129.2 (2001), pp. 259–270.

[57] M. Lu, L. Ran, and Z.-J. M. Shen. "Reliable facility location design under uncertain correlated disruptions". In: *Manufacturing & Service Operations Management* 17.4 (2015), pp. 445–455.

[58] K. L. Maass, M. S. Daskin, and S. Shen. “Mitigating hard capacity constraints with inventory in facility location modeling”. In: *IIE Transactions* 48.2 (2016), pp. 120–133.

[59] H.-Y. Mak and Z.-J. Shen. “Risk diversification and risk pooling in supply chain design”. In: *IIE transactions* 44.8 (2012), pp. 603–621.

[60] A. Martel. “The design of production-distribution networks: A mathematical programming approach”. In: *Supply chain optimization*. Springer, 2005, pp. 265–305.

[61] M. Martinez. *Ford expects UK sales to fall following Brexit vote*. Ed. by T. D. News. [Online; 24 Oct. 2016]. July 2016. URL: `http://www.detroitnews.com/story/business/autos/ford/2016/07/15/ford-europe-sales-rise/87126498/`.

[62] G. P. McCormick. “Computability of global solutions to factorable nonconvex programs: Part I - Convex underestimating problems”. In: *Mathematical programming* 10.1 (1976), pp. 147–175.

[63] M. T. Melo, S. Nickel, and F. S. Da Gama. “Dynamic multi-commodity capacitated facility location: a mathematical modeling framework for strategic supply chain planning”. In: *Computers & Operations Research* 33.1 (2006), pp. 181–208.

[64] M. T. Melo, S. Nickel, and F. Saldanha-da-Gama. “Facility location and supply chain management–A review”. In: *European journal of operational research* 196.2 (2009), pp. 401–412.

[65] P. B. Mirchandani and R. L. Francis. *Discrete location theory*. 1990.

[66] K. Mitra, R. D. Gudi, S. C. Patwardhan, and G. Sardar. “Midterm supply chain planning under uncertainty: a multiobjective chance constrained programming framework”. In: *Industrial & Engineering Chemistry Research* 47.15 (2008), pp. 5501–5511.

[67] J. M. Mulvey, R. J. Vanderbei, and S. A. Zenios. “Robust optimization of large-scale systems”. In: *Operations research* 43.2 (1995), pp. 264–281.

[68] H. Nakao, S. Shen, and Z. Chen. “Network design in scarce data environment using moment-based distributionally robust optimization”. In: *Computers & Operations Research* 88 (2017), pp. 44–57.

[69] A. Oroojlooyjadid, L. V. Snyder, and M. Takác. “Stock-out Prediction in Multi-echelon Networks”. In: *CoRR* abs/1709.06922 (2017). arXiv: `1709.06922`. URL: `http://arxiv.org/abs/1709.06922`.

[70] S. H. Owen and M. S. Daskin. “Strategic facility location: A review”. In: *European Journal of Operational Research* 111.3 (1998), pp. 423–447.

[71] L. Qi, Z.-J. M. Shen, and L. V. Snyder. “The effect of supply disruptions on supply chain design decisions”. In: *Transportation Science* 44.2 (2010), pp. 274–289.

[72] R. Qiu and Y. Wang. "Supply Chain Network Design under Demand Uncertainty and Supply Disruptions: A Distributionally Robust Optimization Approach". In: *Scientific Programming* 2016 (2016).

[73] D. C. Quan. "The price of a reservation". In: *Cornell Hotel and Restaurant Administration Quarterly* 43.3 (2002), pp. 77–86.

[74] N. S. Sadghiani, S. Torabi, and N. Sahebjamnia. "Retail supply chain network design under operational and disruption risks". In: *Transportation Research Part E: Logistics and Transportation Review* 75 (2015), pp. 95–114.

[75] N. V. Sahinidis. "Optimization under uncertainty: state-of-the-art and opportunities". In: *Computers & Chemical Engineering* 28.6 (2004), pp. 971–983.

[76] T. Santoso, S. Ahmed, M. Goetschalckx, and A. Shapiro. "A stochastic programming approach for supply chain network design under uncertainty". In: *European Journal of Operational Research* 167.1 (2005), pp. 96–115.

[77] S. Savage. "The flaw of averages". In: *Harvard Business Review* 80.11 (2002), pp. 20–22.

[78] S. L. Savage and H. M. Markowitz. *The flaw of averages: Why we underestimate risk in the face of uncertainty.* John Wiley & Sons, 2009.

[79] T. Sawik. "Selection of resilient supply portfolio under disruption risks". In: *Omega* 41.2 (2013), pp. 259–269.

[80] T. Sawik. "Single vs. multiple objective supplier selection in a make to order environment". In: *Omega* 38.3-4 (2010), pp. 203–212.

[81] H. Scarf, K. Arrow, and S. Karlin. "A min-max solution of an inventory problem". In: *Studies in the mathematical theory of inventory and production* 10 (1958), pp. 201–209.

[82] W. Schmidt, D. Simchi-Levi, Y. Wei, P. Y. Zhang, K. Combs, Y. Ge, O. Gusikhin, M. Sanders, and D. Zhang. "Identifying Risks and Mitigating Disruptions in the Automotive Supply Chain". In: *Interfaces Forthcoming* (2015).

[83] D. A. Serel, M. Dada, and H. Moskowitz. "Sourcing decisions with capacity reservation contracts". In: *European Journal of Operational Research* 131.3 (2001), pp. 635–648.

[84] Y. Sheffi et al. "The resilient enterprise: overcoming vulnerability for competitive advantage". In: *MIT Press Books* 1 (2005).

[85] Z. .-.-. J. M. Shen. "A multi - commodity supply chain design problem". In: *IIE Transactions* 37.8 (2005), pp. 753–762.

[86] Z.-J. M. Shen. "A profit-maximizing supply chain network design model with demand choice flexibility". In: *Operations Research Letters* 34.6 (2006), pp. 673–682.

[87] L. Simar and P. W. Wilson. "Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models". In: *Management science* 44.1 (1998), pp. 49–61.

[88] D. Simchi-Levi, H. Wang, and Y. Wei. "Increasing supply chain robustness through process flexibility and inventory". In: *Available at SSRN 2433175* (2015).

[89] L. V. Snyder. "Facility location under uncertainty: a review". In: *IIE Transactions* 38.7 (2006), pp. 547–564.

[90] L. V. Snyder. "Supply chain robustness and reliability: Models and algorithms". PhD thesis. Northwestern University, 2003.

[91] L. V. Snyder and M. S. Daskin. "Stochastic p-robust location problems". In: *IIE Transactions* 38.11 (2006), pp. 971–985.

[92] L. V. Snyder, M. P. Scaparra, M. S. Daskin, and R. L. Church. "Planning for disruptions in supply chain networks". In: *Tutorials in operations research* 2 (2006), pp. 234–257.

[93] L. V. Snyder and Z.-J. M. Shen. "Supply and demand uncertainty in multi-echelon supply chains". In: *Submitted for publication, Lehigh University* 15 (2006).

[94] M. Spector, J. Bennett, and J. Stoll. *U.S. Car Sales Set Record in 2015*. Ed. by T. W. S. Journal. [Online; 24 Oct. 2016]. Jan. 2016. URL: `http://www.wsj.com/articles/u-s-car-sales-poised-for-their-best-month-ever-1451999939`.

[95] C. S. Tang. "Perspectives in supply chain risk management". In: *International journal of production economics* 103.2 (2006), pp. 451–488.

[96] C. S. Tang. "Robust strategies for mitigating supply chain disruptions". In: *International Journal of Logistics: Research and Applications* 9.1 (2006), pp. 33–45.

[97] C. Tang and B. Tomlin. "The power of flexibility for mitigating supply chain risks". In: *International journal of production economics* 116.1 (2008), pp. 12–27.

[98] O. Tang and S. N. Musa. "Identifying risk issues and research advancements in supply chain risk management". In: *International journal of production economics* 133.1 (2011), pp. 25–34.

[99] B. Tomlin. "On the value of mitigation and contingency strategies for managing supply chain disruption risks". In: *Management Science* 52.5 (2006), pp. 639–657.

[100] P. Tsiakis, N. Shah, and C. C. Pantelides. "Design of multi-echelon supply chain networks under demand uncertainty". In: *Industrial & Engineering Chemistry Research* 40.16 (2001), pp. 3585–3604.

[101] C. Van Delft and J.-P. Vial. "A practical implementation of stochastic programming: an application to the evaluation of option contracts in supply chains". In: *Automatica* 40.5 (2004), pp. 743–756.

[102] L. Weatherford and P. Pfeifer. “The economic value of using advance booking of orders”. In: *Omega* 22.1 (1994), pp. 105–111.

[103] F. You and I. E. Grossmann. “Design of responsive supply chains under demand uncertainty”. In: *Computers & Chemical Engineering* 32.12 (2008), pp. 3090–3111.