Supply Chain Network Strategy for Consumer Medical Device Introduction

by

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S.B., Harvard University (2009)

Submitted to the MIT Sloan School of Management and the Department of Mechanical Engineering
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Abstract

This thesis presents an optimization framework to model the trade-offs in strategic supply chain decision-making for a new product introduction in a real-world setting. The focus of the thesis is on a consumer medical device that Johnson & Johnson's Calibra business will launch in the future. As with any new product introduction, the launch exposes the J&J business to risk and uncertainty. We develop a mixed-integer optimization model to guide the optimal design of a global consumer medical device supply chain network comprising component suppliers, assembly facilities, sterilizers, and distribution centers. The model evaluates strategic decisions over a seven-year time horizon related to the location and capacities of various supply chain facilities and partners, transportation costs, and strategic inventory required to satisfy global demand. We developed a stochastic optimization extension of the model to protect the supply chain decision maker from demand uncertainty. Comparison of the output of the model assuming deterministic demand to a managerial heuristic resulted in total supply chain network cost reductions of 19% - 27%, amounting to hundreds of millions in present-value dollars. The stochastic optimization solution reduces infeasibility related to either not meeting the demand or transportation lead time constraints. The two models presented in this thesis enable J&J supply chain decision makers to gauge the additional costs and benefits of different network design concepts, develop a network strategy that can adapt to uncertain demand, and create a strong strategic foundation for future tactical and operational decisions.

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Chapter 1

Introduction

1.1 Project Motivation

The purpose of this project is to develop a seven-year supply chain strategy coinciding with the introduction of a new consumer medical device being launched by the Calibra business at Johnson & Johnson's Diabetes Care Franchise (DCF). The device is a wearable bolus insulin delivery patch (IDP) that is used directly by persons with diabetes. The launch of the IDP creates an entirely new market category focused on bolus-only insulin delivery patches. As with any new product introduction, the launch of the IDP exposes the supply chain organization at J&J to risk and uncertainty. It also provides the organization with an immense opportunity to evaluate and develop strategic supply chain initiatives. J&J aimed to create a customer-centric, end-to-end supply chain strategy. Looking across a seven-year time horizon, the project objective was to develop strategic planning, sourcing, manufacturing, and delivery process designs to ensure that the supply chain could efficiently and rapidly respond to changes in customer demand in the future.

In contrast to previous product launches at J&J, this project viewed the supply chain as a strategic asset that could be leveraged to gain a competitive advantage in the insulin delivery market. Traditionally, J&J, a manufacturer renowned for high quality manufactured goods, deployed preexisting supply chain assets and capabilities and incrementally improved on them over the product life-cycle to reduce cost and improve profitability through process improvement and economies of scale. The focus was always on the utility derived by customers from product features and functionality. This project aimed to shift that focus towards the strategic selection and configuration of supply chain capabilities and assets that could create value for customers beyond product functionality.

1.2 Problem Statement

If supply chain strategy is developed in such a way so as to confer a competitive advantage, then decisions about internal business systems and processes, assets and capabilities have to align with the business's basis of competition. This decision-making process is complicated by demand-side and supply-side uncertainties when introducing a new consumer medical device product.

On the demand side, one difficulty is understanding the unique supply chain requirements for customers in various regions of the world. Consumers' supply chain preferences and expectations have changed over the last decade, particularly with the rise of e-commerce [5], improvements in the speed and accuracy of order fulfillment by retailers such as Amazon, and the growth of on-demand services such as Uber [6]. For medical devices, global differences in reimbursement make it imperative to demonstrate value to price-conscious payers through an excellent patient experience encompassing not only product features, but also the supply chain capabilities that enable patients to attain improved clinical outcomes through better therapeutic adherence [7]. This adherence derives from high product quality (including usability and Garvin's eight dimensions of quality [8]), availability, as well as rapid response to emergency needs. The difficulty lies in knowing which of the new customer-centric processes or technologies should be implemented, and how each maximizes device adoption and end-user retention.

At the supply chain network level, the desire to have facilities that are in close proximity to customers may result in the dispersion of facilities and supply chain partners around the world. This introduces complexity at a time when close collaboration is necessary to reduce cost and time to market. It is estimated that 80% of supply chain costs are determined by facility locations and the flow of products between them [9]. Nevertheless, the design of the supply chain network is usually done with a short-term focus, with tactical and operational decisions predominating during the accelerated production ramp-up phase that precedes new product introduction. Furthermore, functional managers within the supply chain organization may have limited visibility to the impact of their decisions on the long-term, end-to-end profitability of the supply chain. The desire for cost reduction by managers focusing on the upstream portion of the supply chain could result in increasing costs downstream. These trade-offs are usually invisible to the functional manager. If visible, they are usually only qualitatively addressed. This makes it imperative to employ optimization techniques during strategic supply chain network planning to ensure that the organization can profitably satisfy global demand in the long-run.

1.3 Thesis Overview and Contribution

This thesis presents an optimization framework to explicitly model the trade-offs in strategic supply chain network design for a new product introduction. The centerpiece of the thesis is a mixed-integer linear optimization model that guides the optimal design of a global consumer medical device supply chain network comprising component suppliers, assembly facilities, sterilizers, and distribution centers. Taking a resource view of the supply chain [10], the model helps managers determine the optimal location and capacities of various supply chain facilities and partners, transportation modes, and strategic inventory required to satisfy global demand over a seven-year period at minimal cost.

The model builds on data provided by a cross-functional team within the supply chain organization, and thus serves to deepen managerial insight into the value of each strategic network configuration. The results provide a prescriptive roadmap to help profitably scale the supply chain for a new product introduction from a small regional launch in a beachhead market, to a complex, multi-layered global supply chain. Since strategic planning focuses on the decisions that have a long-term impact on the supply chain, the underlying hypotheses were that 1) an optimized supply chain network could serve as a solid foundation on which the Calibra business could develop medium to short-term tactical and operational decisions, and 2) that a network optimization model could outperform managerial heuristics used in the design of the supply chain network in terms of the end-to-end supply chain cost.

It is important to note here that this quantitative framework complements, and does not replace, the qualitative frameworks of industry-level, firm-level, or corporate-level strategic analysis [11][12]. A comprehensive assessment of Calibra's competitive advantage, industry positioning, and customer supply chain requirements was conducted as part of this supply chain project. This helped guide the configuration of the supply chain network. Nevertheless, this thesis omits details from that strategic analysis, and instead focuses on the design of the supply chain network.

1.4 Thesis structure

This thesis is organized into six chapters:

- Chapter Two provides background about diabetes, insulin therapy, the Calibra IDP launch, and previous literature on end-to-end supply chain network optimization.
- Chapter Three details the formulation of a deterministic mixed integer optimization (MIO) network design model focused on the case of J&J's Calibra business.
- Chapter Four describes a stochastic revision to the MIO model to handle the demand uncertainty that was ignored in the deterministic model, with the goal of minimizing the expected

cost of the end-to-end supply chain network based on a set of global demand scenarios.

- Chapter Five provides the numerical results for both the deterministic and stochastic models.
- Chapter Six provides final recommendations and conclusions.

Chapter 2

Background on Johnson & Johnson and Diabetes

2.1 Overview

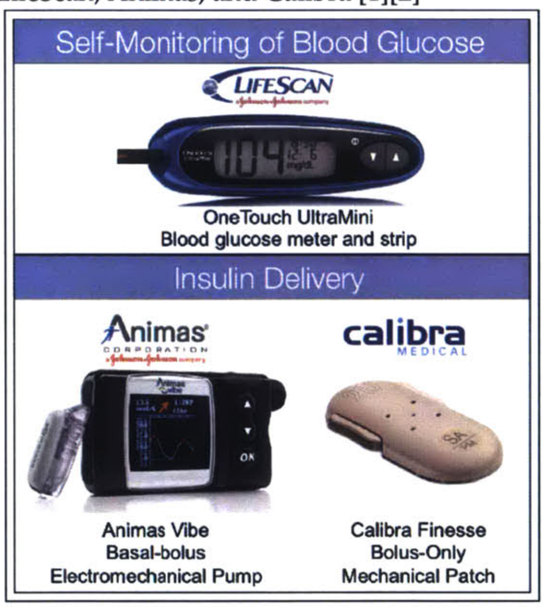
This Chapter introduces the Johnson & Johnson company and its Diabetes Care Franchise (DCF). It presents a short overview of diabetes and the salient characteristics of Calibra's new wearable insulin delivery patch (IDP). The Chapter ends with a discussion of the Six Sigma DMADV design excellence methodology used to carry out this supply chain strategy project and the rationale for the use of mathematical optimization in the development of the supply chain network strategy. Prior literature focused on the use of optimization techniques in multi-layered, multi-period supply chain network design projects are also discussed.

2.2 The Johnson & Johnson Business

Johnson & Johnson (J&J) is one of the world's largest healthcare companies by revenue, with worldwide sales of $74 billion in 2014. The company comprises three product segments: 1) pharmaceuticals, 2) consumer products, and 3) medical devices. [13]

This thesis focuses on the Calibra business, which is one of three businesses within J&J's Diabetes Care Franchise (DCF). DCF is based in Chesterbrook, Pennsylvania, and is part of J&J's medical devices segment. Besides Calibra, DCF comprises the LifeScan and Animas businesses. LifeScan produces glucose meters and electrochemical strips for self-monitoring of blood glucose (SMBG). Animas manufactures electromechanical insulin delivery pumps that deliver both basal and bolus insulin. The Calibra business plans to introduce a new wearable bolus-only patch device into the market. The DCF products are explored in Figure 2-1 and are described further in Section 2.5. Along with the Vision Care Franchise (VCF), which produces the Acuvue brand of contact lenses, DCF forms the *Consumer Medtech* category of medical devices at J&J. Consumer medical devices are designed for use directly by the end-user (the patient), unlike traditional medical devices that are operated by healthcare professionals (e.g. ultrasound transducers, MRIs, suction catheters, and others) or implanted into patients by healthcare professionals (e.g. pacemakers or hip implants).

Figure 2-1: Self-monitoring of blood glucose (SMBG) and insulin delivery consumer medical devices produced by DCF's LifeScan, Animas, and Calibra [1][2]



While the pharmaceuticals and consumer products segments lagged behind the medical devices segment prior to 2010, the pharmaceutical segment has seen increasing sales in the period 2012-2014. [14]. DCF has seen a decrease in sales from \$2.6 billion in 2012 to \$2.142 billion in 2014 [14]. This has been attributed to lower prices resulting from competitive bidding [15] [16]. The launch of the Calibra IDP could significantly boost DCF revenues. Nevertheless, it is expected that price-conscious payers will continue to apply pricing pressure, even in the case of an innovative new medical device with improved clinical efficacy compared to pre-existing products. This requires the strategic design of a supply chain network that can ensure product availability and that meets the end-users' and payers' requirements, but that also leverages resources efficiently.

2.3 An Overview of Diabetes and Insulin

Diabetes mellitus is a metabolic disorder characterized by chronically elevated blood sugar levels (hyperglycemia) resulting from insufficient production of insulin in the pancreas or from reduced response to insulin by the body. Based on a 2014 estimate, there are approximately 25 million people with diabetes in the United States [17]. This number includes 18 million people with a diabetes diagnosis, as well as 7 million people that are estimated to have diabetes but are undiagnosed. There are approximately 382 million people with diabetes worldwide [18]. The incidence of diabetes has increased in the United States over the past 25 years, but has shown a decline between the period of 2008 and 2014. There were 1.4 million new cases of diabetes reported in 2014 in the United States, compared to 1.7 million in 2008. [19].

There are three main types of diabetes:

- Type 1: Formerly known as *juvenile diabetes*, this is a condition in which there is a severe deficiency in the amount of insulin produced by the pancreas. This results from the body's immune system attacking the insulin-producing beta-islet cells in the pancreas. Type 1 diabetes patients must take insulin. Ten to fifteen percent of diabetics have Type 1 diabetes.
- Type 2: Formerly known as *adult-onset diabetes*, this is a condition where the pancreas does not produce a sufficient amount of insulin and/or where body's tissues do not respond as well to insulin, a phenomenon known as *insulin resistance*. Type 2 accounts for 85 to 90% of diabetic patients.
- Gestational Diabetes: Occurs in approximately 4% of pregnant women around week 24 of pregnancy, when the body cannot produce enough insulin due to hormone production from the placenta that reduces tissue response to insulin (increasing insulin resistance)[20]. It is seen as a mechanism through which the mother's body channels more glucose to the developing fetus [20][21].

Diabetes results in increased chance of complications including blindness, limb amputations, kidney failure as well as two to four-fold increased risk of heart disease (e.g. coronary artery disease) and stroke [22] [23]. Cardiovascular disease results in 68% of deaths for people with diabetes over the age of 65, with stroke accounting for 16%. [24]. The high prevalence of diabetes costs the US healthcare system approximately $220 billion annually, with an average lifetime cost of $283,000 [25]. The global cost of diabetes was estimated at $376 billion in 2010 [26].

2.4 Insulin Therapy

The goal of diabetes treatment is to ensure control of blood glucose levels, or *glycemic control*. To gauge treatment efficacy, a patient's glycated hemoglobin, or hemoglobin A1C (HbA1C), is measured. HbA1C results from plasma glucose attaching non-enzymatically to hemoglobin in the blood. The higher the blood glucose level, the higher the HbA1C. The HbA1C level constitutes the weighted average of blood glucose levels over the last 120 days, and is a powerful indicator of glycemic control. The American Diabetes Association (ADA) suggests a target level of 7% HbA1C for patients with diabetes, although this goal is individualized based on patient's age, comorbid conditions, and their risk of hypoglycemia [27].

Since patients with Type 1 diabetes do not produce sufficient insulin, they are introduced to insulin therapy from the moment that they are diagnosed. Type 1 patients may be given long-acting insulin which mimics low-level, *basal* insulin secretion from a normal pancreas.[1]. At mealtime, Type 1 patients take rapid-acting insulin to mimic the pancreas's *bolus* insulin secretion that helps the body process the carbohydrates in food [30]. An alternative therapeutic strategy involves the use of an electromechanical pump that delivers rapid-acting insulin at a precisely controlled flow rate to mimic basal insulin. These pumps additionally provide the user with the ability to deliver a bolus dose at mealtime [31]. Electromechanical pumps have an average list price of $6,500 [32].

Glycemic control is addressed differently in Type 2 patients. Patients are provided with lifestyle coaching upon diagnosis which emphasizes weight control, healthy eating, and exercise. If HbA1C goals are not met through lifestyle changes alone, then the American Council of Endocrinologists' (ACE) glycemic control algorithm provides a useful therapeutic guideline for physicians. Based on the patient's HbA1C levels, monotherapy usually commences with metformin. If the patient is not at the HbA1C goal in 3 months, then dual therapy commences which combines the first-line agent (usually metformin) with a second-line agent. If glycemic control continues to be elusive, dual therapy is followed by triple therapy, introduction of basal (long-acting) insulin, and finally the introduction of prandial, or mealtime (rapid-acting) insulin [27].

One-third of the diagnosed diabetic population in the U.S. uses insulin (approximately 7 million people). One-third of those insulin users use mealtime insulin, with 250,000 new patients introduced to rapid-acting insulin (RAI) annually [33]. As a mealtime insulin delivery device, the Calibra IDP is labeled for use with rapid-acting insulin analogs NovoLog (Novo Nordisk) and Humalog (Eli Lilly).

The incredible toll that the diabetes epidemic has on our society highlights the importance of delivering solutions that improve therapeutic outcomes. This includes a focus on new pharmaceutical treatments or medical devices for controlling blood glucose, as well as awareness and education about the long-term risks of diabetes and the importance of therapeutic adherence.

[1] There are four major categories of insulin in the market, grouped by their pharmacokinetics, which defines their absorption by the body, their onset of action, and the duration of activity in the body. [28][29]. These categories are long-acting, intermediate-acting, short-acting, and rapid-acting insulin. Details about these categories, along with major brand names, are presented in Appendix A, A.1

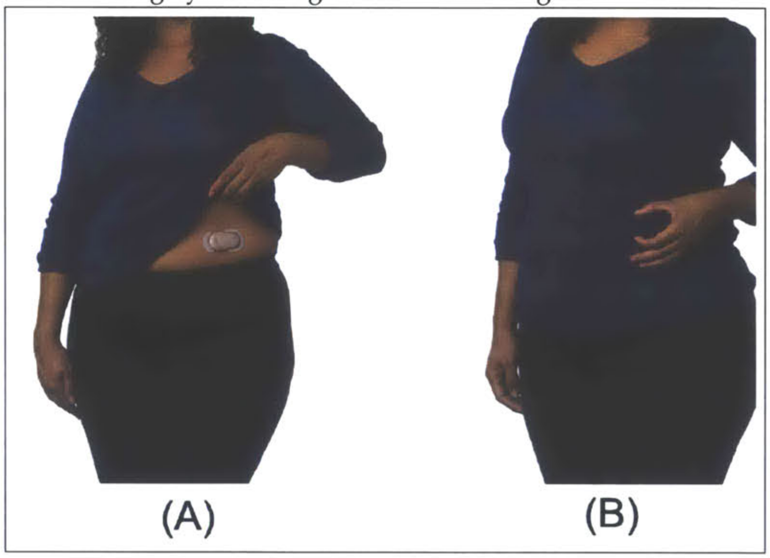
2.5 Calibra IDP Launch

The launch of Calibra IDP will create a new category of insulin delivery devices that will enable Type 1 and Type 2 diabetes patients to maintain glycemic control. Approximately two-thirds of patients on rapid-acting insulin therapy do not maintain good glycemic control (defined as $\leq 7\%$ glycated hemoglobin) with the use of pre-existing bolus-only insulin delivery devices [34]. There are numerous reasons suggested, including 1) the fear of hypoglycemic events, which discourages aggressive insulin treatment or 2) improper adherence to pharmacologic treatment in real-world settings[35]. Mean adherence to insulin therapy was measured at 63% in one study [35]. A patient's level of stress or dietary habits may impact non-adherence, but there is also clear evidence of intentional insulin ommission by more than half of diabetes patients on insulin [36]. Intentional insulin omission usually results from anxiety about insulin injection, as many patients note that injection interferes with daily activities, causes pain, and results in fear of public embarrassment [37][36]. This suggests that a device strategy targeting injection-related omission problems could improve adherence.

The Calibra IDP is filled with rapid-acting insulin by the user, and an adhesive layer on the back of the patch enables attachment to a user's abdominal area. The patch can be worn for three days. After three days, it is disposed and replaced with a new patch. When the patch is attached to the abdomen, a tiny, flexible cannula is inserted into the subcutaneous tissue, which provides the path for insulin to enter the body. The use of a flexible cannula means that no needle stick is necessary for mealtime dosing. The IDP is designed to release precisely 2 units of rapid-acting insulin when two buttons on the device are clicked simultaneously. Empty reservoirs or occluded channels disable the buttons. The buttons are accessible from beneath a layer of clothing, allowing the user to deliver a bolus dose discreetly (Figure 2-2).

The device's success will hinge on the ability to re-engage diabetic patients with their bolus therapy and reduce the risk of insulin omission after failure to maintain glycemic control using conventional bolus insulin delivery devices, such as 1) insulin pens or 2) syringes. Rapid-acting insulin pens for bolus delivery include disposable pens that are pre-filled with insulin, such as the Flexpen (Novo Nordisk) or Kwikpen (Eli Lilly) [38][39]. There are also reusable insulin pens, such as the Novopen Echo (Novo Nordisk) [40] that enable users to load disposable insulin cartridges into the pen. Syringes and needles have also been used traditionally for insulin delivery. For insulin pens and syringes, the economies of scale, coupled with simpler design [41] makes them a low-cost insulin delivery solution. The downsides of both pens and syringes is that they 1) require a needle for each subcutaneous bolus delivery and 2) have to be used in the open, which as mentioned above may result in injection-related anxiety [42]. The IDP delivers multiple doses of bolus insulin discreetly over a three-day period through a flexible cannula, without the need for needle injections.

Figure 2-2: (A) Attachment of the wearable Insulin Delivery Patch (IDP) to the user's abdominal area. (B) Discreet bolus dosing by activating the buttons through the user's clothing



In determining coverage and payment with payers, J&J will emphasize the quality dimensions of the new wearable patch, including performance, features, aesthetics, and usability that help satisfy the functional, emotional, and social needs of the user. Furthermore, unlike the more complex and expensive basal-bolus electro-mechanical durable pumps that DCF's Animas produces, the Calibra IDP is made of only mechanical parts. The original rationale for a mechanical device lacking electrical parts is that it would reduce the cost per patch [43], making discreet mealtime insulin delivery affordable. Clinical outcome studies will demonstrate how these added features could help improve adherence and ensure glycemic control at an affordable price.

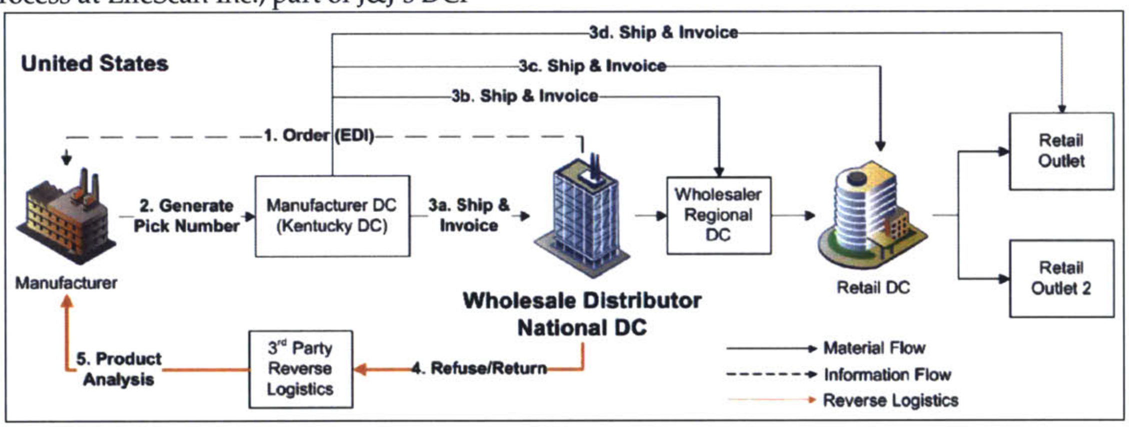
2.6 Methodology

Given the characteristics of the new device, Calibra's end-to-end supply chain strategy team used the DMADV[2] process design framework to develop the supply chain strategy and process design. The cross-functional membership in the team mirrored the structure of the supply chain organization at J&J. J&J's supply chain organization is structured using a process-oriented view of activities that connect upstream suppliers to downstream customers. The process structure of the supply chain organization parallels that developed by the Supply Chain Operations Reference (SCOR) model, which divides supply chain functions into distinct, but interlinked management processes that resemble the material flow in a typical manufacturing supply chain: Plan, Source, Make, Deliver, and Return [3] [4]. This is described further in Table A.2 of Appendix A.

As such, the strategy team included representatives from marketing as well as planning, sourcing, manufacturing, and distribution. After the project scope was defined by the team, Voice of

Customer (VOC) data was collected using interviews and surveys with four customer segments: persons with diabetes, healthcare professionals, wholesale distributors and retailers. This enabled mapping of these customers' supply chain journeys and illumination of their supply chain needs (refer to Figure 2-3 for an example of the process involved in fulfilling wholesale distributors' or retailers' orders). VOC needs were translated into the supply chain design's functional requirements, which detail what the supply chain needs to do to meet the customers' needs. These requirements were used to evaluate current state processes and metrics, and to develop future state supply chain design concepts.

Figure 2-3: Process outlining the receipt of an order by J&J, and delivery of product from J&J's distribution center to a wholesale distributor or retailer's distribution centers in the United States. In case of product damage during delivery, the product may be returned. This flow is based on the process at LifeScan Inc., part of J&J's DCF



The strategy team reasoned that meeting the supply chain's functional requirements, such as on-time delivery, continuity of supply, or responsiveness depends fundamentally on how the supply chain network is configured. For example, placing manufacturing facilities close to customers increases the likelihood of on-time delivery and fast responsiveness. But this also comes at a cost. The supply chain network may be *strategically* designed and optimized in order to ensure sufficient proximity to global customers, while reducing its overall cost. Strategic supply chain network design focuses on decisions that have a long-term (multi-year) impact on the manufacturing organization [44]. This includes decisions regarding the optimal location and purpose of supply chain facilities, allocation of capacity to those facilities, and the optimal flow of product across the network [45] [9] [44]. For Calibra, an optimized end-to-end global supply chain network could benefit all stakeholders. It ensures that patients can readily access the product with limited supply disruptions. For J&J, it boosts profitability through the efficient use and timely deployment of assets to satisfy demand. Reducing cost through network optimization also ensures long-term market competitiveness as the product matures and struggles to maintain premium pricing.

2.7 Literature Review

This section provides a brief discussion of previous literature focused on supply chain network design and optimization. A manufacturing supply chain network is defined as the flow of materials, information, and money through a set of suppliers, manufacturing facilities, distribution centers, ending with delivery of the finished good to the customer [9]. The application of optimization techniques to supply chain network design are explored in several texts and reviews [9] [46][47] [48] [49].

In addition to reviews, we would like to highlight those studies that have looked at strategic decision-making in network design and optimization. Sabri and Beamon [50] conducted an integrative strategic and operational analysis of procurement, production, and transportation decisions in supply chain design by building a strategic level sub-model whose material flow outputs are then used for operational-level decision-making under uncertainty of demand, production, and delivery. ElMaraghy and Majety [51] focus on minimizing the total cost for a multi-stage, multi-level, multi-customer automotive powertrain manufacturing supply chain using a multi-criteria mixed-integer linear programming model. Hasani, Zegordi, and Nikbaksh [52] look at the real-world case of a medical device manufacturer by constructing a robust mathematical programming model to aid in the design of a multi-period, multi-echelon global supply chain under uncertainty. These constitute just a portion of the hundreds of studies dedicated to mathematical optimization techniques in the context of supply chain network design.

Chapter 3

Supply Chain Network Design and Optimization

3.1 Overview

Chapter 3 presents the mathematical optimization model for Calibra's global supply chain network. The chapter begins by exploring qualitative decision-making frameworks used by decision makers in supply chain design. A quantitative, mathematical optimization framework is then used to build a simple facility location-capacity allocation model. The model is expanded to include multiple periods and the multiple layers seen in a medical device supply chain, including components suppliers, assembly facilities, sterilizers, and distribution centers. Transportation modes and strategic inventory are later incorporated to enable holistic assessment of all the important strategic levers in network design.

3.2 Portfolio approach to supply chain design

In order to evaluate the strategic decision levers available for supply chain design, a strategic planning team may resort to a strategy table similar to the one shown in Table 3.1 (adapted from [53]). This table includes all the important strategic levers for supply chain network design: the location of manufacturing facilities, the mode of international shipping, and the inventory stocking model. If the supply chain design emphasizes responsiveness, with very low order-to-delivery time, the table provides a concise graphical representation that allows managers to select compatible strategic lever options that reflect the overall supply chain strategy.

Table 3.1: Strategic table for supply chain design. Cells are highlighted only to illustrate how managers may select different options to ensure alignment with the organization's strategic objectives

Lever	**Fast/High $**	**Intermediate Design**	**Slow/Low $**
Manufacturing Location	In Country	Regional	Global
Sterilization	In Country	Regional	Global
Final Packaging	In Country	Regional	Global
International Shipping	Air	Truck	Ship
Order Fulfillment location	In Country	Regional	Global
Inventory Stocking Model	Build to Stock	Configure to Order	Build to Order

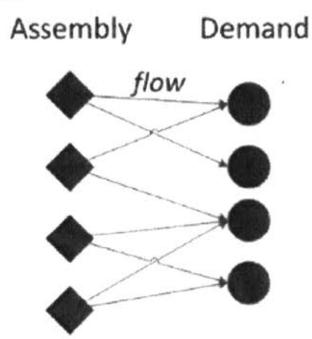
This table is a very useful tool for initiating a discussion about the strategic design of a supply chain network. Nevertheless, it is unclear what magnitude of difference exists between the three options for each strategic lever. Apart from a qualitative insight, it is unclear how the different levers interact, and how different configurations impact the total end-to-end cost or responsiveness of the supply chain. To complement these qualitative decision-making tools, this thesis developed an end-to-end network optimization model to quantify the impact of strategic choices in supply chain network design for a consumer medical device.

3.3 Manufacturing facility location-allocation problem

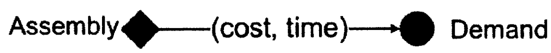
The facility location and capacity allocation problem for the Calibra manufacturing lines is addressed first. This is a simplified subset of the end-to-end model of the supply chain network, but is the most critical, since it ensures that the supply chain network is able to satisfy the forecasted demand. The goal is to locate an undetermined number of manufacturing facilities and their capacities in order to minimize the 1) fixed cost of establishing these facilities, 2) the cost of acquiring capacity, and 3) the variable cost of transporting product to customers in a given set of countries (the demand nodes in Figure 3-1).

Manufacturing in the IDP supply chain refers to the component *assembly* process. Components are *fabricated* at selected suppliers and shipped to the assembly facilities.

Figure 3-1: Simplified network model illustrating the flow of finished goods along arcs between assembly facilities and demand nodes



Each arc in this network has an associated transportation cost and transportation lead time. The lead time could also incorporate the cycle time at the preceding node, to provide managerial insight into the total of production and delivery lead times to the customer.



When the mode of transportation is consistent across all arcs (a preliminary assumption in this model), such that the cost is proportional to the distance between the nodes, then minimizing the cost of the network minimizes the distance and lead time. If this simplification is forgone, the model provides an opportunity to explore the impact of transportation as a strategic lever. As demand and production volumes increase later in the product life cycle, lower-cost transportation modes such as sea freight or trucking may be preferred over air freight. These lower-cost modes are associated with greater lead times, and that trade-off can be explicitly modeled, as shown in Section 3.7. For now, the model assumes one mode of transportation.

The notation and formulation of the simplified network model is provided below.

Notation

Sets

J Set of manufacturing facilities, indexed by j

M Set of countries, indexed by m

Parameters

F_j Fixed cost of setting up manufacturing plant j,

k_j Variable capacity acquisition cost for manufacturing plant j,

D_m Demand in country m,

f_{jm} Transport cost per unit from facility j to demand node m,

M Arbitrarily large constant (capacity constraint)

Variables

C_j Capacity of manufacturing facility j,

y_{jm} Quantity of product shipped from facility j to demand node m,

$$x_j = \begin{cases} 0, & \text{if manufacturing site } j \text{ is not chosen,} \\ 1, & \text{if manufacturing site } j \text{ is chosen,} \end{cases}$$

Mathematical Formulation

Objective

$$minimize \sum_j (F_j x_j + k_j C_j) + \sum_{jm} f_{jm} y_{jm} \tag{3.1}$$

subject to

$$\sum_j y_{jm} \geq D_m \,;\, \forall m \in M \tag{3.2}$$

$$\sum_m y_{jm} \leq C_j \,;\, \forall j \in J \tag{3.3}$$

$$0 \leq C_j \leq M x_j \,;\, \forall j \in J \tag{3.4}$$

$$0 \leq y_{jm} \,;\forall j \in J, \forall m \in M \tag{3.5}$$

$$x_j \in \{0, 1\} \tag{3.6}$$

This simplified model assumes that the capacity C_j can take on any value in the set of non-negative real numbers. [1] Constraint (3.2) ensures that production volumes satisfy the forecasted demand. Constraint (3.3) ensures that the sum of production volumes $\sum_m y_{j,m}$ in plant j do not exceed the chosen plant capacity, C_j. Constraint (3.4) restricts the capacity C_j to be less than zero if a plant is not selected. Otherwise, it is set to be smaller than an arbitrarily large constant M (this constraint may not be so arbitrary, as it really represents the ceiling of the allowable capacity acquisition). Finally, constraints (3.5) and (3.6) are non-negativity and binary constraints, respectively.

3.4 Model expansion to include suppliers, sterilizers, and distribution centers

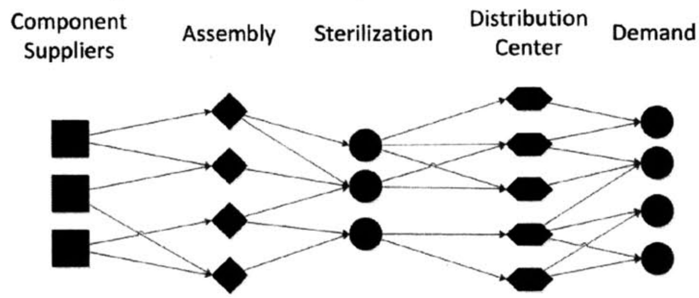
With the goal of developing an end-to-end view of the supply chain, the model was expanded to include supplier selection, sterilization, and distribution centers. These are the layers within a traditional medical device supply chain. The nodes and arcs shown in Figure 3-2 form a directed graph, or network. A description of each of the stages in the Calibra IDP network is provided below.

Suppliers

Supplier selection is a multi-step process, usually beginning with 1) determining criteria with which to judge the suppliers (e.g. quality, cost, technical ability, financial quality, etc.), 2) qualifying suppliers to ensure they meet certain standards, and 3) final selection. Further, within the medical

[1] The next section shows that this is not particularly the case for the Calibra capacity allocation problem.

Figure 3-2: Representation of the end-to-end network inclusive of first-tier component suppliers, assembly facilities, sterilizers, distribution centers, and demand nodes



device world, supplier switching sometimes requires gaining additional approval from the FDA. There is extensive literature devoted to decision models that support the selection process [54] [55] [56].

Suppliers in the model are selected so as to minimize 1) the variable cost of transporting components from the suppliers to the manufacturing facilities and 2) the variable costs of purchasing components from a supplier. This is contingent on all suppliers within the set of feasible suppliers meeting the technical, quality, and financial guidelines adopted by the sourcing team.

Expanding the set of suppliers constitutes a challenge for a strategic network design project focused on new product introduction. The supply chain organization usually defaults to preferred suppliers that are part of an approved supplier list (ASL). This aligns with the supply chain's habitual focus on efficiency and economies of scale. Larger volumes from suppliers working with several businesses within J&J usually results in lower procurement costs, while also reducing the cost and lead time of qualifying a new supplier. Nevertheless, reaching out beyond the ASL may provide benefits in technical expertise that may reduce time to market or enable new product innovation that offsets the higher cost.

This model focuses on a *strategic* subset of suppliers that provide critical components. Critical components 1) contribute significantly to the overall cost of the device, 2) are essential for meeting the device's functional requirements, and 3) are difficult to manufacture, thereby making it challenging to find a replacement supplier. This then restricts the analysis to four types of components defined by the set C of components indexed by $c \in \{1, 2, 3, 4\}$. The set of four component types includes injection molded plastic parts, plastic films, and two types of rubber parts. All of these parts are *detail-controlled parts*, meaning that the assembler (J&J) developed the functional specification and conducted detailed engineering of the components, while the supplier is expected to deliver parts that are built to specifications [57].

If the supplier network is assumed to be fixed (supplier selection is not a decision variable), then the goal of the network optimization is to choose assembly facility locations that balance between proximity to the demand and proximity to the suppliers. On the other hand, given that there are one or two alternative suppliers for each component in the set C, supplier switching may be permitted, but this incurs a cost (both money and time). Establishing a new supplier partnership requires added time for supplier qualification, added cost of supplier management (i.e. the additional project management or engineering resources to ensure supplier meets project goals and time line) or regulatory penalties for supplier switching. This switching cost is discussed in Section 3.5.

Maintaining two concurrent supplier relationships for one component type incurs additional fixed costs. Since the model aims to minimize cost, it may select only one supplier for each component. Given the risk associated with single-sourced components, the model could determine the added cost of mitigating supplier disruption by forcing it to select two or more suppliers for specific components c. A binary decision variable, $x_{c,i} \in \{0,1\}$, is used to represent whether a supplier i in a set of I suppliers, producing component c in a set C of components, is chosen. This is similar to the notation used for assembly facilities in Equation 3.6.

Assembly

A pilot line was created in Redwood City, California by the Calibra business prior to its acquisition by J&J. This is a very low throughput line (500 units/week) that relies on manual assembly of the components into the final device, with the intention of designing and optimizing the assembly process. A low volume line was designed in collaboration with an external automation partner to automate the manual processes. This line is located in Aguadilla, Puerto Rico. The aim of this automated line is to increase throughput to meet the forecasted launch demand and to further optimize the assembly process. Once assembled, each individual device is packaged into a plastic blister pack (primary packaging) with a Tyvek peal-off cover. Ten blister packs are combined into one *refill* kit. Refill kits are stacked onto pallets. The pallets are then transported for sterilization. The flow of finished goods in this network model tracks the flow of pallets of one particular SKU, which is the IDP refill kit.[2].

In strategic global network design projects, there is always a question about the optimal extent of assembly facility dispersion. This can sometimes be guided by the marketing strategy. Obtaining permission to commercialize a medical device in some countries, such as Russia, requires setting up manufacturing activities within those countries. The scope of these manufacturing activities varies. For example, sterilization or final kitting could be sufficient to meet those requirements. There are also supply chain advantages to localization: 1) the ability to respond quickly to customers, 2) the ability, through regional localization, to aggregate country demand and delay differentiation of products, and 3) the ability to use operational hedging in order to mitigate demand or exchange

[2] Additional SKUs that could be considered are 1) kits that healthcare professionals use to demonstrate the product to patients or 2) kits that enable patients to immediately commence therapy after training on using the patch in a healthcare professional's office. These SKUs are neglected in this model

rate risk [58].

Product design changes introduce an interesting challenge to the dispersion of manufacturing facilities around the world. A device such as the IDP will have a unique design history file (DHF), mandated by the Food and Drug Administration (FDA), which documents the history of the product development process for that medical device [59]. If the device is produced by several assembly locations around the world, a change introduced to the DHF (e.g. a component change, or a new assembly process improvement) would have to be adopted by all assembly sites. This synchronization becomes difficult as some sites are more capable of responding to a process change than others. One solution to the synchronization problem is to create two or three design history files, one for each assembly site catering to a unique set of demand nodes. However, creating and maintaining these sets of files becomes costly and difficult.

In the simplified facility location and capacity allocation model, the capacity of the assembly lines could take on any non-negative real value. Given the high degree of automation in the Calibra assembly lines, this assumption is forgone. Instead, there are five discrete blocks of capacity that can be allocated across the different manufacturing facilities. Low volume lines (LVL) have the lowest production capacity, while high volume lines (HVL) have the highest:

(1) Line 1: Low Volume Line (LVL)

(2) Line 2: Medium Volume Line (MVL)

(3) Line 2: MVL Capacity Increase

(4) Line 3: High Volume Line (HVL)

(5) Line 4: High Volume Line 2 (HVL2)

This alters decision variable C_j to $C_{j,p} \in \{0,1\}$ where P is the set of five capacities indexed by $p \in \{1,2,3,4,5\}$, for the four manufacturing lines indicated above. As such, the decision is whether or not a manufacturing facility j adds the assembly line with the associated capacity p. An assembly line incurs a capital investment cost $A_{j,p}$, a scale-up operating fixed cost $SC_{j,p}$, and a steady-state operating fixed cost $SS_{j,p}$. The notation $x_j \in \{0,1\}$ representing the choice of manufacturing facility j remains the same.

An important, but difficult notion to quantify is the estimate of the organization's ability to *incrementally* improve the production capacity of pre-existing lines in lieu of investing in a new lines. This is referred to internally as a "capacity acceleration" initiative. This can be incorporated into the model by assuming that a small, discrete block of capacity $c_{j,p}$ could be added to a block of assembly line capacity p, once that line is established. The cost per unit of incremental capacity, $k_{j,p}$, is greater, however, than the bulk purchase represented by the set P of capacities. The value of this incremental capacity could impact the timing of line investments under different demand scenarios. This additional capacity can be built through learning and added investment in automation engineers or technologists, and constitutes part of the annual operating costs of operating the line.

Sterilization

The IDP product requires ethylene oxide (EtO) sterilization due to the use of a PTFE (Teflon) insulin-delivery cannula in the device. PTFE provides a low coefficient of friction and biocompatibility, but exposure to gamma irradiation degrades PTFE [60] [61]. High temperature steam sterilization is also not an option as it degrades the other plastics in the device and the primary packaging plastic blister packs that hold the device [61].

Ethylene oxide sterilization can be conducted externally at sterilization suppliers, or a new greenfield project could be erected in close proximity to the assembly facility. EtO is an explosion hazard, and hazard risk minimization in medical device sterilization requires ensuring inertness of the EtO, either by mixing it with gases such as CO_2 or hydrochlorfluorocarbons (HCFCs), or by using 100% EtO in combination with N_2 within the sterilization chamber. The high cost of HCFC mixtures makes the 100% EtO option more favorable, but the capital investments in equipment or reinforcement to ensure facility safety when using 100% EtO become more costly.

During sterilization, entire pallets are introduced into the sterilization chamber, up to a certain capacity of pallets per day. The EtO permeates through the secondary packaging and penetrates the Tyvek cover in the primary packaging. Once the sterilization cycle is complete, the pallets are removed from the sterilization chamber and transported to the J&J distribution centers. One scenario under consideration couples manufacturing with the sterilization facility in an attempt to reduce the transport cost of shipping pallets to a sterilizer.

Mathematically, the decision to choose a sterilizer is represented by similar notation to assembly, with $x_k \in \{0, 1\}$ representing the binary choice of whether or not sterilization facility k is chosen out of a set of K possible options.

Distribution centers

After the sterilizer ships the pallets of sterilized product to the distribution center (DC), the DC stores the pallets. Operators in the DC break apart a small subset of the refill kits, extracting the blister packs and creating new secondary packaging. The remaining refill kits are untouched. When an order from a customer is received, the warehouse management system (WMS) sends a pick, pack, and ship request to the DC. Depending on each individual customer's demand, the distribution center transports full truckloads (FT), less-than-truckloads (LTL), or parcels of product. FT incurs the lowest cost per unit, while parcel delivery incurs the highest cost per unit.

Mathematically, the decision to choose a DC is represented by similar notation to assembly and sterilization, with $x_l \in \{0, 1\}$ representing the binary choice of whether or not DC l is chosen out of a set of L possible options.

Demand

Commercial launch of the IDP will commence in countries where J&J 1) has strong commercial operations and 2) can attain prices that ensure profitability. There remains some uncertainty about regulatory approval of the product in several national markets. There is also uncertainty about how much payers might reimburse for the patch (this is seen in the United States as the sequence of coverage, coding, and payment [62]). For example, in the United States there is a question about whether the patch will be covered as a pharmacy (Rx) benefit or as durable medical equipment (DME), which impacts J&J's revenue per patch. [3] In single-payer systems of healthcare, the government's delay or refusal to grant reimbursement for a consumer medical device means that J&J may decide to stay out of the market, or enter with the expectation that patients will pay for the product out of pocket. This is known as a *cash pay* model, and is appealing in countries where a significant fraction of patients are willing to pay for the functional and social features of the IDP.

Since this is a new product introduction, there is no historical demand data that can be used in the model. Instead, demand forecasts are used, knowing that the demand realized in the future may vary considerably from the demand forecasted today. These parameters are therefore subject to *prediction errors*. To ensure network design robustness in light of this demand uncertainty, different demand scenarios are developed, and a stochastic mixed-integer linear program is formulated to address this uncertainty. This is discussed in Chapter 4. For now, the focus will be on the deterministic demand problem using the demand forecasts provided by J&J's commercial team.

The demand notation for the model remains the same, with D_m representing the demand at country m in a set of M total countries.

Vertical Integration

Vertical integration impacts the types of goods or services procured. In the case of the Calibra business, this leads to the question: is it beneficial to source raw materials, convert those internally into components and assemble them (backward integration)? On the other side of the spectrum, is it worthwhile to outsource raw material procurement, component manufacturing, and device assembly to a supply chain partner? Would a supplier's relocation of physical fabrication assets (e.g. injection molding machines) closer to the assembly process help ensure faster problem resolution and process improvement? The qualitative factors going into this assessment are discussed below:

- *Brownfield space availability:* underutilized space at pre-existing J&J manufacturing facilities makes the internal assembly option appealing from a cost perspective. In this case, the financial analysis would have to account for the efficiency gains from producing another J&J product in the same facility.

[3] This is an interesting device coverage challenge because the device does not have all the characteristics of durable medical equipment, but also does not conform to what would traditionally be considered a pharmaceutical

- *Intellectual property protection:* both the device design and assembly process can be compromised in countries with lax legal enforcement of IP rights. This significant risk would have to be weighed against improvements in labor and material costs. If the risk is severe, then those options would be removed from the set of possible suppliers in the network model.

- *Technological readiness of the assembly partner:* In the case of partnering with an external assembly supplier, the supplier must have the technical and project management capabilities to successfully deliver on the project objectives. The supplier must show willingness to invest in the equipment and space necessary for the assembly operations. One advantage of outsourcing would be the expected knowledge spillovers from the supplier's prior success with assembling similar types of medical devices at a comparable throughput, a form of external agglomeration [63]. On the other hand, shifting injection molding capabilities into near proximity of assembly allows for internal agglomerations, inter-firm learning, enhancing the ability of the J&J organization to surface and solve problems. This type of inter-firm learning has been explored previously in the automotive industry [57].

  For the case of Calibra, the reliance would be primarily on the external supplier's *capacity*, as the system assembly process is worked out internally.

3.5 Incorporating time into the model

The model so far has not accounted for the seven-year time horizon of the strategy. One approach that may be used could have the model iterate through the forecasted demand in years $t \in \{1, 2, ..., 7\}$, creating a network design for each year. There are two problems with this approach:

1. Decisions made during time period t are not linked to the decisions in time $t+1$. For example, in year $t = 5$, the model may decide to open the assembly candidate facility in Germany, but given the demand in $t = 6$ it may find that the assembly plant in Ireland is preferable. When the model is re-run in each time iteration t, it is oblivious to the decisions and costs associated with period $t-1$.

2. Point (1) above may be solved by ensuring that as the model iterates through t, the optimal first year $t = 1$ decisions are set as constraints for the next time period $t = 2$. This is a greedy approach that does not guarantee optimality.

Adding the time index

To reflect the time horizon of the decision-making process, the decision variables are all associated with a time period $t \in \{1, 2, ...7\}$. For example, the decision to choose sterilizer k in period t can be represented as $x_{k,t} \in \{0,1\}$. Similarly, the cost parameters are indexed by t to reflect price inflation and the time value of money. This is to ensure that future cost improvements, while potentially significant, when discounted to their present value still warrant the undertaking of this plan in the present.

Adding a time index to the model helps tighten the intuition about facilities and their longevity. This is especially important in the manufacturing world, where the construction of facilities and purchase, placement, and set-up of expensive, highly automated manufacturing equipment is usually an irreversible decision. As such, constraints can be added to enforce the continuity of the assembly line capacity decision from one period to the next:

$$C_{j,p,t} \geq C_{j,p,t-1};\ \forall\, j \in J, \forall\, p \in P, \forall\, t \in T. \tag{3.7}$$

Introducing period-to-period switching costs

Alternatively, instead of forcing the model to perpetuate a facility decision, a period-to-period switching cost can be included in the model. This can be done by using the fixed costs $R_{j,t}$ for launching a new facility j (where j here could represent assembly, sterilizer, or DC) in time t, and a lower fixed cost $r_{j,t}$ for maintaining the facility j in time t. For an assembly facility, $r_{j,t}$ can be seen as the fixed plant operating costs including depreciation, manufacturing overhead, or property taxes among others. This prevents the model from opening one facility in year t, and then opening a second facility in year $t+1$ that is closer to demand (and improves transportation cost), while leaving the first facility idle.[4]

The period-to-period switching cost requires comparison of decisions in period t to period $t-1$, for $t \in \{2,3,...,7\}$. Using the example of the sterilizer above, creating a new relationship with a sterilizer incurs a cost:

$$max\{(x_{k,t} - x_{k,t-1}), 0\} * R_{k,t}; \forall\, k \in K, t \in \{2,3,...,7\}. \tag{3.8}$$

For a pre-existing relationship with a sterilizer k, the associated cost is:

$$(x_{k,t} * x_{k,t-1}) * r_{k,t}; \forall\, k \in K, t \in \{2,3,...,7\}. \tag{3.9}$$

These are nonlinear terms that can be linearized with the introduction of two new variables $Z1_{k,t} \in \{0,1\}$ and $Z2_{k,t} \in \{0,1\}$ and some additional constraints:

[4]While idle capacity is expensive, it can be seen as a form of production *flexibility*. Production flexibility is the difference between theoretical capacity and the forecasted demand. The trade-off here lies between maximizing the flexibility while minimizing the cost of idle capacity. This may not be that important in the deterministic formulation of the problem, but becomes more important when exploring the stochastic version of the problem in Chapter 4.

$$min\,(max\{(x_{k,t} - x_{k,t-1}), 0\}) \implies min\,Z1_{k,t}\,;\,\forall\,k \in K, t \in \{2, 3, \ldots, 7\},$$

subject to

$$Z1_{k,t} \geq (x_{k,t} - x_{k,t-1}). \tag{3.10}$$

$$min(x_{k,t} * x_{k,t-1}) \implies min\,Z1_{k,t}\,;\,\forall\,k \in K, t \in \{2, 3, \ldots, 7\},$$

subject to

$$Z2_{k,t} \leq x_{k,t} \tag{3.11}$$

$$Z2_{k,t} \leq x_{k,t-1} \tag{3.12}$$

$$Z2_{k,t} \geq x_{k,t} + x_{k,t-1} - 1. \tag{3.13}$$

3.6 Revised End-to-End Model

This Section provides the revised end-to-end model inclusive of the time index, as well as the facility switching and maintenance costs. The sets of assembly facilities, sterilizers, and distribution centers, with their locations, are presented in Tables A.5, A.6, and A.7 in Appendix A.

Sets

- I Set of suppliers, indexed by $i \in \{1, 2, 3, 4\}$
- J Set of assembly facilities, indexed by $j \in \{1, 2, \ldots, 15\}$
- K Set of sterilization facilities, indexed by $k \in \{1, 2, \ldots, 13\}$
- L Set of distribution centers, indexed by $l \in \{1, 2, \ldots, 5\}$
- M Set of demand countries, indexed by $m \in \{1, 2, \ldots, 15\}$
- C Set of components, indexed by $c \in \{1, 2, 3, 4\}$
- P Set of capacities, indexed by $p \in \{1, 2, \ldots, 5\}$
- T Set of time periods, indexed by $t \in \{1, 2, \ldots, 7\}$

Parameters

$A_{j,p,t}$	Capital investment for assembly line with capacity p in manufacturing facility j in time period t
$A_{k,t}$	Capital investment for establishing internal greenfield sterilizer k in time period t
$k_{j,p,t}$	Additional operating cost for incremental capacity in manufacturing plant j with capacity p in time period t
$F_{j,t}$; $F_{k,t}$	Facility overhead cost for manufacturing facility j, or sterilization facility k, in time period t
$SC_{j,p,t}$	Fixed assembly line scale-up operating cost in time period t
$SS_{j,p,t}$	Fixed assembly line steady-state operating cost in time period t
$f_{c,i,j,t}$	Transport cost per unit of component c from supplier i to manufacturing facility j
$f_{j,k,t}$; $f_{k,l,t}$; $f_{l,m,t}$	Transportation cost per unit from facility j to k, k to l, and l to m in time period t
$R_{c,i,t}$; $R_{k,t}$; $R_{l,t}$	Fixed cost of establishing relationship with supplier i, sterilizer k, or DC l in time period t
$r_{c,i,t}$;$r_{k,t}$;$r_{l,t}$	Fixed cost of maintaining relationship with supplier i, sterilizer k, and DC l in time period t
$D_{m,t}$	Demand in country m in time period t
n_c	Number of component c per patch
$p_{c,i,t}$	Cost of procuring component c from supplier i in time period t
$p_{k,t}$	Sterilization cost per unit at sterilizer k in time period t
$p_{l,t}$	Processing cost per unit at DC l in time period t
M_p	Magnitude of capacity in capacity block p
$M2$	Maximum limit to added incremental capacity
M	Arbitrarily large constant

Decision Variables

$$x_{c,i,t} = \begin{cases} 0, & \text{if supplier } i \text{ for component } c \text{ is not chosen in time period } t, \\ 1, & \text{if supplier } i \text{ for component } c \text{ is chosen in time period } t, \end{cases}$$

$$C_{j,p,t} = \begin{cases} 0, & \text{if assembly line with capacity } p \text{ in facility } j \text{ is not chosen in time period } t, \\ 1, & \text{if assembly line with capacity } p \text{ in facility } j \text{ is chosen in time period } t, \end{cases}$$

$$x_{j,t}\ ;\ x_{k,t}\ ;\ x_{l,t} = \begin{cases} 0, & \text{if manufacturing facility } j\text{, sterilizer } k\text{, or DC } l \text{ are not chosen in time period } t, \\ 1, & \text{if manufacturing facility } j\text{, sterilizer } k\text{, or DC } l \text{ are chosen in time period } t, \end{cases}$$

$y_{j,k,t}; y_{k,l,t}; y_{l,m,t}$	Quantity of product shipped from from j to k, k to l, and l to m,
$y_{c,i,j,t}$	Quantity of component c shipped from supplier i to manufacturing facility j,
$c_{j,p,t}$	Added incremental capacity of facility j with original capacity p,
$Z1_{c,i,t}$	Establishing new relationship with supplier i for component c in time period t,
$Z1_{j,p,t}$	Establishing new assembly line with capacity p in facility j in time period t,
$Z1_{j,t}; Z1_{k,t}; Z1_{l,t}$	Establishing new relationship with manufacturing facility j, sterilizer k, or distribution center l in time period t,
$Z2_{c,i,t}$	Maintaining relationship with supplier i for component c from time period $(t-1)$ to time period t,
$Z2_{j,p,t}$	Maintaining assembly line with capacity p in facility j from time period $(t-1)$ to time period t,
$Z2_{j,t}; Z2_{k,t}; Z2_{l,t}$	Maintaining relationship with manufacturing facility j, sterilizer k, or distribution center l from time period $(t-1)$ to time period t

Mathematical Formulation

The mathematical program incorporates the changes made to the end-to-end network problem: Capital investment costs

$$A = \sum_{jpt} A_{j,p,t} Z1_{j,p,t} + \sum_{kt} A_{k,t} Z1_{k,t}. \tag{3.14}$$

Operating and Relationship Fixed Costs

$$B_{oper} = \sum_{jt} F_{j,t} x_{j,t} + \sum_{jpt} \left[k_{j,p,t} c_{j,p,t} + SC_{j,p,t} Z1_{j,p,t} + SS_{j,p,t} Z2_{j,p,t} + k_{j,p,t} c_{j,p,t} \right] \tag{3.15}$$

$$B_{rel} = \sum_{cit} \left[R_{c,i,t} Z1_{c,i,t} + r_{c,i,t} Z2_{c,i,t} \right] + \sum_{kt} \left[R_{k,t} Z1_{k,t} + r_{k,t} Z2_{k,t} \right] + \sum_{lt} \left[R_{l,t} Z1_{l,t} + r_{l,t} Z2_{l,t} \right] \tag{3.16}$$

Transport costs

$$TC = \sum_{cijt} f_{c,i,j,t} y_{c,i,j,t} + \sum_{jkt} f_{j,k,t} y_{j,k,t} + \sum_{klt} f_{k,l,t} y_{k,l,t} + \sum_{lmt} f_{l,m,t} y_{l,m,t} \tag{3.17}$$

Variable Costs

$$VC = \sum_{cijt} p_{c,i,t} y_{c,i,j,t} + \sum_{klt} p_{k,t} y_{k,l,t} + \sum_{lmt} p_{l,t} y_{l,m,t} \tag{3.18}$$

Objective

$$minimize(A + B_{oper} + B_{rel} + TC + VC) \tag{3.19}$$

subject to

$$\sum_l y_{l,m,t} \geq D_{m,t} \qquad ; \forall\, m \in M, \forall\, t \in T \tag{3.20}$$

$$\sum_k y_{j,k,t} \leq \sum_p M_p Z2_{j,p,t} + \sum_p c_{j,p,t} \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.21}$$

$$C_{j,p,t} \leq x_{j,t} \qquad ; \forall\, j \in J, \forall p \in P, \forall\, t \in T \tag{3.22}$$

$$0 \leq c_{j,p,t} \leq M2 * Z2_{j,p,t} \qquad ; \forall\, j \in J, \forall\, p \in P, \forall\, t \in T \tag{3.23}$$

$$\sum_i y_{c,i,j,t} \geq \sum_k n_c y_{j,k,t} \qquad ; \forall\, c \in C, \forall\, j \in J, \forall t \in T \tag{3.24}$$

$$\sum_j y_{j,k,t} \geq \sum_l y_{k,l,t} \qquad ; \forall\, k \in K, \forall\, t \in T \tag{3.25}$$

$$\sum_k y_{k,l,t} \geq \sum_m y_{l,m,t} \qquad ; \forall\, k \in K, \forall\, t \in T \tag{3.26}$$

$$\sum_j y_{c,i,j,t} \leq M x_{c,i,t} \qquad ; \forall\, c \in C, \forall i \in I, \forall\, t \in T \tag{3.27}$$

$$\sum_k y_{j,k,t} \leq M x_{j,t} \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.28}$$

$$\sum_l y_{k,l,t} \leq M x_{k,t} \qquad ; \forall\, k \in K, \forall\, t \in T \tag{3.29}$$

$$Z1_{c,i,t} \geq x_{c,i,t} - x_{c,i,t-1} \qquad ; \forall\, c \in C, \forall\, i \in I, \forall\, t \in T \tag{3.30}$$

$$Z2_{c,i,t} \leq x_{c,i,t} \qquad ; \forall\, c \in C, \forall\, i \in I, \forall\, t \in T \tag{3.31}$$

$$Z2_{c,i,t} \leq x_{c,i,t-1} \qquad ; \forall\, c \in C, \forall\, i \in I, \forall\, t \in T \tag{3.32}$$

$$Z2_{c,i,t} \geq x_{c,i,t} + x_{c,i,t-1} - 1 \qquad ; \forall\, c \in C, \forall\, i \in I, \forall\, t \in T \tag{3.33}$$

$$Z1_{c,i,t} \in \{0,1\}, Z2_{c,i,t} \in \{0,1\} \qquad ; \forall\, c \in C, \forall i \in I, \forall\, t \in T \tag{3.34}$$

$$Z1_{j,p,t} \geq C_{j,p,t} - C_{j,p,t-1} \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.35}$$

$$Z2_{j,p,t} \leq C_{j,p,t} \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.36}$$

$$Z2_{j,p,t} \leq C_{j,p,t-1} \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.37}$$

$$Z2_{j,p,t} \geq C_{j,p,t} + C_{j,p,t-1} - 1 \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.38}$$

$$Z1_{j,p,t} \in \{0,1\}, Z2_{j,p,t} \in \{0,1\} \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.39}$$

$$Z1_{j,t} \geq x_{j,t} - x_{j,t-1} \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.40}$$

$$Z2_{j,t} \leq x_{j,t} \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.41}$$

$$Z2_{j,t} \leq x_{j,t-1} \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.42}$$

$$Z2_{j,t} \geq x_{j,t} + x_{j,t-1} - 1 \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.43}$$

$$Z1_{j,t} \in \{0,1\}, Z2_{j,t} \in \{0,1\} \qquad ; \forall\, j \in J, \forall\, t \in T \tag{3.44}$$

$$Z1_{k,t} \geq x_{k,t} - x_{k,t-1} \qquad ; \forall\, k \in K, \forall\, t \in T \tag{3.45}$$

$$Z2_{k,t} \leq x_{k,t} \qquad ; \forall\, k \in K, \forall\, t \in T \tag{3.46}$$

$$Z2_{k,t} \leq x_{k,t-1} \qquad ; \forall\, k \in K, \forall\, t \in T \tag{3.47}$$

$$Z2_{k,t} \geq x_{k,t} + x_{k,t-1} - 1 \qquad ; \forall\, k \in K, \forall\, t \in T \tag{3.48}$$

$$Z1_{k,t} \in \{0,1\}, Z2_{k,t} \in \{0,1\} \qquad ; \forall\, k \in K, \forall\, t \in T \tag{3.49}$$

$$Z1_{l,t} \geq x_{l,t} - x_{l,t-1} \qquad ; \forall\, l \in L, \forall\, t \in T \tag{3.50}$$

$$Z2_{l,t} \leq x_{l,t} \qquad ; \forall\, l \in L, \forall\, t \in T \tag{3.51}$$

$$Z2_{l,t} \leq x_{l,t-1} \qquad ; \forall\, l \in L, \forall\, t \in T \tag{3.52}$$

$$Z2_{l,t} \geq x_{l,t} + x_{k,t-1} - 1 \qquad ; \forall\, l \in L, \forall\, t \in T \tag{3.53}$$

$$Z1_{l,t} \in \{0,1\}, Z2_{l,t} \in \{0,1\} \qquad ; \forall\, l \in L, \forall\, t \in T \tag{3.54}$$

$$\sum_j C_{j,p,t} \leq 1 \qquad ; \forall\, p \in P, \forall t \in T \tag{3.55}$$

$$y_{c,i,j,t} \geq 0, y_{j,k,t} \geq 0, y_{k,l,t} \geq 0, y_{l,m,t} \geq 0 \qquad ; \forall C, I, J, K, L, M, P, T \tag{3.56}$$

$$x_{c,i,t} \in \{0,1\}, x_{j,t} \in \{0,1\}, x_{k,t} \in \{0,1\}, x_{l,t} \in \{0,1\} \qquad ; \forall C, I, J, K, L, T \tag{3.57}$$

Constraint (3.20) ensures that the production level satisfies customer demand. Constraint (3.21) ensures that a manufacturing facility will not produce more than its capacity. The use of $Z2_{j,p,t}$ ensures that production cannot commence until one time period after the line capacity has been established. Constraint (3.22) prevents adding capacity to a manufacturing facility if the facility is not selected ($x_{j,t}$). Constraint (3.23) ensures that incremental capacity cannot be added until *at least one time period* after the line is established. Constraints (3.24-3.26) are conservation of flow constraints. Constraints (3.27-3.29) ensure that flow is not enabled out of a facility that is not selected. Constraint (3.55) ensures that only one block of each capacity p can be chosen. Finally, (3.56) and (3.56) are non-negativity and binary constraints, respectively.

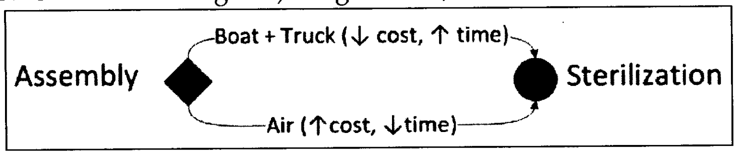
The way that 3.14 is currently written implies that the capital investment is expensed immediately in the model. An alternative would be to depreciate the assets over their lifetime, leading to a different form:

$$A = \sum_{jpt} Dep_{j,p,t} C_{j,p,t} + \sum_{kt} Dep_{k,t} x_{k,t}. \tag{3.58}$$

Here, $Dep_{j,p,t} = A_{j,p,t}/EL_p$ and $Dep_{k,t} = A_{k,t}/EL_k$, where EL equals the expected lifetime of the assets p and k, which we define as equal to seven years based on industry standards.

3.7 Revising the transportation modes

Incorporating the variety of possible transportation modes is an important part of the network strategy. This can be implemented using new binary decision variables representing two transportation arcs, giving the model the choice between 1) a low cost, longer lead time mode such as sea transport combined with trucking or 2) a higher cost, shorter lead time mode such as air freight.



This changes the network into a directed multigraph, with multiple directed arcs (two arcs in this case) connecting the nodes. This also transforms the model into a *multi-objective* model, where the goal is to balance two competing objectives: minimize the total cost of the supply chain, while also minimizing the total lead time. Different solution techniques may be used for multi-objective optimization, including scalarization (weighted-sum), ϵ-constraints, goal optimization, or multi-level optimization methods [64]. In the case of the ϵ-constraints method, the original objective of minimizing cost is maintained, and the lead time objective is added as a constraint. The constraint ensures that the value of the lead time objective is less than or equal to a given target, ϵ. Here, the value of ϵ can be 1) the mean lead time across the network, or 2) the maximum lead time. The value of ϵ can be chosen to conform to a customer-specified target level, knowing well however, that different global customers have different delivery lead time requirements.

A new index, $r \in \{1(lowcost), 2(highcost)\}$, is introduced to the product and component flow y to reflect the mode of transportation, as well as two new binary decision variables that determine if the model picks a mode: S, for longer lead time, lower cost sea and truck freight, and A, for shorter lead time, higher cost air freight. For simplicity, the model picks only one mode of transportation between two nodes. The new decision variables are:

$$S_{j,k,t} = \begin{cases} 0, & \text{if low cost transportation mode is not selected between } j \text{ and } k \text{ at time } t, \\ 1, & \text{if low cost transportation mode is selected between } j \text{ and } k \text{ at time } t, \end{cases}$$

$$A_{j,k,t} = \begin{cases} 0, & \text{if high cost transportation mode is not selected between } j \text{ and } k \text{ at time } t, \\ 1, & \text{if high cost transportation mode is selected between } j \text{ and } k \text{ at time } t, \end{cases}$$

$y_{j,k,r,t}$ Quantity of product shipped from j to k using transport mode r at time t.

Parameters are:

$s_{j,k,r,t}$ Transportation lead time from j to k using transportation mode r in time t,

M_{trans} Arbitrarily large constant (transportation capacity).

An additional set of constraints ensure that if the binary variables S or A for mode selection are zero, then the flow using that mode is also zero (Equations 3.59 and 3.60). Furthermore, we limit the model to the choice of only one transportation mode between different nodes (Equation 3.61):

$$y_{j,k,r=low\,cost,t} \leq M_{trans} * S_{j,k,t} \,;\, \forall j \in J, k \in K, t \in T \tag{3.59}$$

$$y_{j,k,r=high\,cost,t} \leq M_{trans} * A_{j,k,t} \,;\, \forall j \in J, k \in K, t \in T \tag{3.60}$$

$$S_{j,k,t} + A_{j,k,t} \leq 1 \,;\, \forall j \in J, \forall k \in K. \tag{3.61}$$

The updated transport costs become:

$$B = \sum_{cijrt} f_{c,i,j,r,t} y_{c,i,j,r,t} + \sum_{jkrt} f_{j,k,r,t} y_{j,k,r,t} + \sum_{klrt} f_{k,l,r,t} y_{k,l,r,t} + \sum_{lmrt} f_{l,m,r,t} y_{l,m,r,t} \tag{3.62}$$

Average lead time ϵ constraint

Setting the ϵ constraint for the average lead time case looks at the flows weighted by their transportation lead time. The greater the component or product flow associated with a longer lead time, the greater the average lead time. The end-to-end average transportation lead time that we are interested in calculating allows us to envision how long the product spends in transport from suppliers all the way through to customers. Due to flow conservation within the network, the average end-to-end transportation lead time equals the sum of all flows, weighted by their lead time, divided by the flow to the demand nodes. Rearranging produces the linear form in Equation 3.63:

$$\sum_{c,i,j,r} \left[\frac{y_{c,i,j,r,t} s_{c,i,j,r,t}}{n_c} \right] + \sum_{j,k,r} y_{j,k,r,t} s_{j,k,r,t} + \sum_{k,l,r} y_{k,l,r,t} s_{k,l,r,t} + \sum_{l,m,r} y_{l,m,r,t} s_{l,m,r,t} \leq \sum_{l,m,r} y_{l,m,r,t} * \epsilon \,;\, \forall t \in T \tag{3.63}$$

Inventory impacts the conservation of flow in the network. For example, this occurs if assembly plants produce more than what is required to satisfy demand for time period t in order to build up inventory for a future time period $t + 1$ (refer to Section 3.8). Since inventory is stored at the DCs, inflow into a DC for a particular year may not equal outflow. Nevertheless, conservation of flow still applies to the flow from suppliers all the way through to the DCs. As such, the network may be broken up into two parts to evaluate the end-to-end transportation lead time: 1) the average lead time for flows extending from suppliers through distribution centers, constrained by $\epsilon_{ave,1}$ and 2) the average lead time for flows from distribution centers to demand nodes, constrained by $\epsilon_{ave,2}$. Two equations, similar in form to Equation 3.63, are introduced:

$$\sum_{c,i,j,r} \left[\frac{y_{c,i,j,r,t} s_{c,i,j,r,t}}{n_c} \right] + \sum_{j,k,r} y_{j,k,r,t} s_{j,k,r,t} + \sum_{k,l,r} y_{k,l,r,t} s_{k,l,r,t} \leq \left[\sum_{k,l,r} y_{k,l,r,t} \right] * \epsilon_{ave,1} \,;\, \forall t \in T \tag{3.64}$$

$$\sum_{l,m,r} y_{l,m,r,t} s_{l,m,r,t} \leq \left[\sum_{l,m,r} y_{l,m,r,t} \right] * \epsilon_{ave,2} \,;\, \forall t \in T \tag{3.65}$$

Equations 3.64 and 3.65 could be solved by leaving them independent, or they may be combined into one equation: [5]

$$\sum_{c,i,j,r} \left[\frac{y_{c,i,j,r,t}s_{c,i,j,r,t}}{n_c}\right] + \sum_{j,k,r} y_{j,k,r,t}s_{j,k,r,t} + \sum_{k,l,r} y_{k,l,r,t}s_{k,l,r,t} + \sum_{l,m,r} y_{l,m,r,t}s_{l,m,r,t} \leq \left[\sum_{k,l,r} y_{l,m,r,t}\right] * \epsilon_{ave,1} + \left[\sum_{l,m,r} y_{l,m,r,t}\right] * \epsilon_{ave,2}\,;\ \forall t \in T \tag{3.66}$$

Maximum lead time ϵ constraint

Setting the constraint according to a maximum acceptable end-to-end transportation lead time requires assessment of all possible continuous paths leading from suppliers i to demand nodes m.

$$S_{c,i,j,t}s_{c,i,j,1,t} + A_{c,i,j,t}s_{c,i,j,2,t} + S_{j,k,t}s_{j,k,1,t} + A_{j,k,t}s_{j,k,2,t} + S_{k,l,t}s_{k,l,1,t} + A_{k,l,t}s_{k,l,2,t} + S_{l,m,t}s_{l,m,1,t} + A_{l,m,t}s_{l,m,2,t} \leq \epsilon_{max}\,;\ \forall c \in C, i \in I, j \in J, k \in K, l \in L, m \in M, \forall t \in T \tag{3.67}$$

The constraints in 3.67 ensure that all continuous paths conform to the maximum allowable end-to-end lead time, ϵ_{max}. We can vary this parameter to assess the impact on the total cost and location of supply chain facilities. Since 3.67 generates a significant number of constraints that increase the model solution speed, the total number of constraints may be reduced by focusing only on the injection-molded components instead of all the components in the set C.

Method

Transforming the problem from one mode of transportation to two introduces a technical challenge. Whereas with one mode of transport we can assume the total great circle distance from one {latitude, longitude} pair to another, for two modes we need to understand what percentage of the track connecting two nodes happens over land and water. Land transportation in the form of trucking generally has a significantly higher (an order of magnitude or more) cost per ton mile than sea transportation. Further, the speed of sea freight could be two to four times slower than trucking speed.

A solution can be developed by following the steps:

1. Cities or countries in the model are geocoded (represented as latitudes and longitudes), and the Haversine formula is used to determine the distance, d between two nodes.

2. A direct path connecting each node in the network to another node is created. This is called a *track*. Each track is a vector composed of n entries: the first entry is the origin's latitude,

[5]Note that the way in which Equation 3.66 is written allows either one of the $\epsilon_{ave,1}$ or $\epsilon_{ave,2}$ constraints to be violated, while preserving the *total* end-to-end transportation lead time constraint represented by $(\epsilon_{ave,1} + \epsilon_{ave,2})$

longitude pair, followed by a series of $n-2$ {latitude, longitude} pairs, and ending with the destination's {latitude, longitude} pair. This creates $n-1$ equal segments. We choose n to be 20. The sum of the lengths of all $n-1$ segments equals d.

3. A determination is made about whether the position for each entry in the track vector is located over land or water. This is done by generating a 5x5 pixel static map through Google that is centered on the {latitude, longitude} coordinates. The 5x5 pixel image is analyzed, and if the color of the central region is blue, then the point is classified as water. Otherwise, it is classified as land.

    - For example, a track can be developed to connect an assembly plant in Aguadilla, Puerto Rico {18.427445, -67.15407} to a sterilizer in Charlotte, North Carolina {35.227087,-80.843127}. This represents a path directed to the northwest (increase in latitude, decrease in longitude). We confirm using the Google Maps query that the first point in Aguadilla lies on land, which is shown as point **1** in Figure 3-3.
    - Close to the midpoint of the journey (point **2** in Figure 3-3) is {28.3183,-74.5659}. We confirm with Google Maps that this point is over water.
    - If the point happens to lie over water, assume that the entire segment connecting the previous point to this point in the track is over water. As such, a distance $\frac{d}{n-1}$ is assumed to cover water. The accuracy increases with larger n.
    - We iterate through the remaining points in the track vector, and similarly assign each segment to water or land. The final destination point, point **3** in Figure 3-3, is over land.

Figure 3-3: Constructing a track between geocoded points in the network. A map is centered over each location, with the pixel color helping discriminate land from sea.

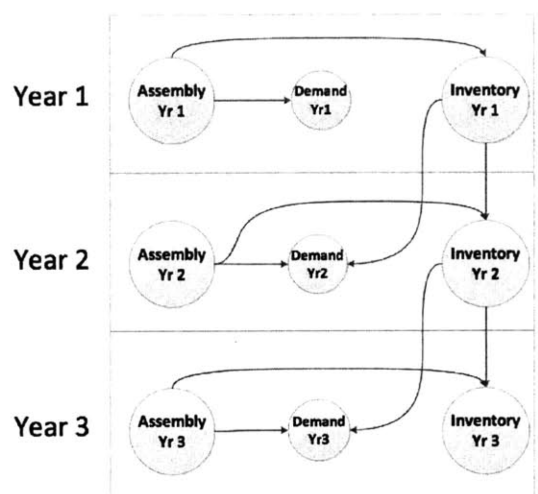
This method allows the model to determine the total distance over land and water connecting two nodes in the supply chain network. The distance helps determine both the transport cost (assuming a cost per ton-mile) and transportation lead times (assuming a given speed for each mode).

3.8 Integrating strategic inventory positioning

After determining yearly capacity allocation, transportation modes, and optimal flows, the focus turns to the remaining strategic lever of inventory. Inventory has a critical effect on balancing supply and demand in a supply chain network, particularly due to 1) variability in production and transportation lead times and 2) prediction errors in demand forecasts. Inventory helps ensure that the organization can satisfy demand at satisfactory service levels. Generally, inventory policies are considered to be more tactical or operational in nature. In this network design model, the focus will be on *strategic inventory*, which is important in the context of capacity allocation problems. It is a means for the network to cope with demand uncertainty and unexpected shocks to the supply chain network. Given a yearly inventory holding cost at a DC at location l, represented by $H_{l,t}$, the model may opt to build up inventory in years where capacity exceeds demand, to satisfy next year's demand in lieu of investing in additional capacity. This is captured in a new variable $I_{l,t}$.

At the strategic level, an inventory node can be used for each time period, with associated inbound and outbound arc costs. This is shown in Figure 3-4, where arcs connect assembly to the year's demand nodes, but also to the year's inventory node, which can be used to supply future demand. Assuming a 2 year shelf life, it may be possible for inventory produced in one year to transfer to the next.

Figure 3-4: Simplified network model accounting for inventory flow between different years



The inventory is stored at the distribution centers l, and is available for satisfying demand in the next year. In this case, the inventory equals the product inflow into the DC minus the outflow used to satisfy the demand from that DC:

$$I_{l,t} = \sum_{k,r} y_{k,l,r,t} - \sum_{m,r} y_{l,m,r,t}\,; \forall k \in K, \forall t \in T. \tag{3.68}$$

The network begins with zero inventory in year 1. Inventory incurs an entire year's worth of holding cost. The value of the holding cost is discussed in Section 3.10. As such, a holding cost HC is added to the objective function, equal to:

$$HC = \sum_{lt} H_{l,t} I_{l,t}. \tag{3.69}$$

This in turn changes the objective function in 3.19 to the following:

Objective

$$minimize(A + B_{oper} + B_{rel} + TC + VC + HC). \tag{3.70}$$

While $I_{l,t}$ represents the total inventory created in year t, a flow decision variable $i_{l,m,r,t}$ is added to the model for years $t \in \{2, 3, \ldots, 7\}$ representing the amount of the inventory stored at DC l that is used to meet demand in year t through transportation mode r. This flow is constrained by the total inventory on hand for that year (Equation 3.71). Similarly, the combination of flows of inventory and newly manufactured product from a DC l are limited by the choice of transportation mode out of that DC (Equations 3.72-3.73):

$$\sum_{m,r} i_{l,m,r,t} \leq I_{l,t-1}\,; \forall l \in L, \forall t \in T \tag{3.71}$$

$$y_{l,m,r=lowcost,t} + i_{l,m,r=lowcost,t} \leq M * S_{l,m,t}\,;\ \forall l \in L, m \in M, t \in T \tag{3.72}$$

$$y_{l,m,r=highcost,t} + i_{l,m,r=highcost,t} \leq M * A_{l,m,t}\,;\ \forall l \in L, m \in M, t \in T. \tag{3.73}$$

3.9 A note on the tax strategy

J&J aims to benefit patients throughout the world with the sale of its new product, and the revenues earned in different countries are subject to different levels of taxation. Large companies with a global reach such as Johnson & Johnson aim to maximize the net after-tax profit. As such, taxes are important in the design of global supply chain networks. Tax considerations can be incorporated into the model by adding new tax parameters that would recognize the increased cost of a facility option in a country with higher taxes. The model would use an option only when the benefit from transportation cost and/or facility costs outweighs the added tax costs. With the inclusion of revenues from the various global markets, the objective of the network optimization problem changes from a cost minimization to a profit maximization.

The tax parameters would account for:

- Marginal tax rates and cash grants for the purchase of manufacturing equipment
- Transfer prices

There are several methods for establishing transfer prices, including comparable uncontrolled method, cost plus, or the profit split method. Transfer pricing must comply with the arm's length standard, which requires related parties, such as international subsidiaries of an organization, to "set their inter-company pricing policies as if they were unrelated parties dealing with one another in the open market." [65] What marginal tax rates are used depends on the profit earned by the legal entity within each location, based on functions performed, risks borne (inventory, currency, product liability, etc.) and assets employed (IP and hard assets).

Although important, a rationale is provided below for why taxes are not included in this model:

1. Corporate tax rates and cash grants are subject to change over the seven to ten-year horizon of this strategic network design model (see for example [66]), while facility location and capacity allocation decisions are usually irreversible.

2. Most importantly, as this is a launch of a new medical device, regulatory approval of the product in many of the markets remains uncertain. There is also uncertainty about reimbursement as mentioned in Section 3.4. Enumerating the vast number of reimbursement and cash pay possibilities, as well as their likelihood is extremely difficult. Here, a robust optimization approach could be used to address revenue parameter uncertainty. We will neglect this in the model.

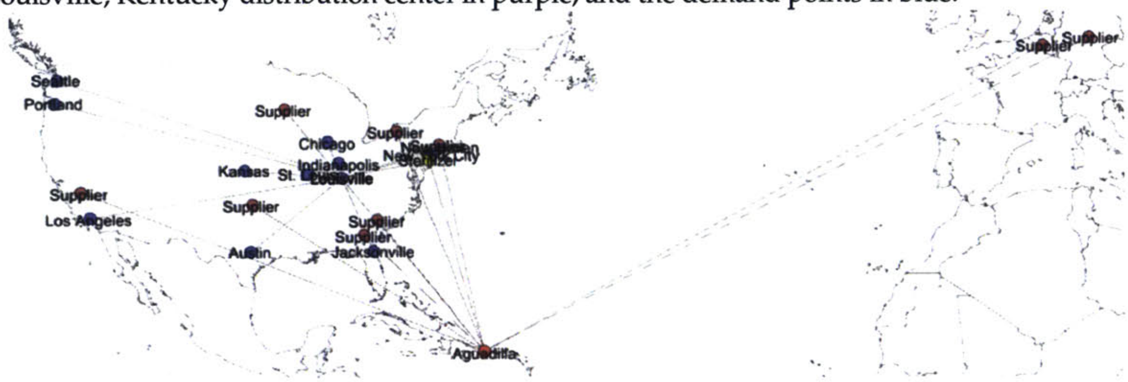
3.10 Modeling Assumptions and Scenarios

Several assumptions are incorporated into the model to account for some of the data and decisions that have already been made by the Calibra organization for the early years.

An image of the anticipated network configuration for 2016 is shown in Figure 3-5 (using Gephi software). This map represents the initial conditions of the supply chain network. The network changes as the model minimizes cost over the 7-year time horizon.

- One of the most important assumptions is that the design of the device does not change. This assumes a mature device design where the number and types of components remain the same throughout the seven-year period. Through the design transfer process, the mature product design is committed to production in the manufacturing environment. Therefore, an associated assumption is that the technologies for all assembly lines are similar. This allows for only incremental improvements after the assembly line capacities are determined (discussed above).

Figure 3-5: Anticipated network map for Calibra, 2016. Suppliers, as well as the assembly plant in Aguadilla, Puerto Rico, are shown in red. The New Jersey sterilizer is shown in yellow, the Louisville, Kentucky distribution center in purple, and the demand points in blue.



- Cost assumptions for sea, truck, and air freight are made (shown in Table A.3 in Appendix A), resulting in a transportation cost per mile. The transportation cost and lead time are both functions of the distance traveled and the mode of transportation used.

- The first two lines (LVL and MVL), and their associated capacities, are set to Aguadilla, Puerto Rico, to reflect decisions that have already been made by the Calibra business. This is done by setting the capacity decision variable $C_{j,p,t}$ for the first three capacity increments in non-Aguadilla locations to zero:

$$C_{j \neq Aguadilla, p=\{1,2,3\},t} = 0\,; \forall t \in T \tag{3.74}$$

- Lines 3 and 4, the two high volume lines, do not have to be placed in the same facility.

- Incremental capacity cannot be added until *at least one time period* after the line is established):

$$c_{j,p,t} \leq M2 * Z2_{j,p,t}; \forall j \in J, \forall p \in P, \forall t \in T \tag{3.75}$$

- The holding cost equals 20% of the product's unit cost. The product unit cost is the total assembly line and facility operating costs, plus inbound transportation and sterilization costs, divided by the total production volume. Because of the division, this cost is nonlinear. However, it is possible to maintain linear terms by instead using an alternative estimate of the holding cost per unit. Since production during year t may exceed demand due to the desire for strategic inventory buildup, an upper bound of the unit cost could be attained by dividing the operating costs by that year's total demand. While this may represent a higher per unit cost, this holding cost estimate can be varied.

Chapter 4

Stochastic Network Optimization

4.1 Overview

After introducing the supply chain network optimization model in Chapter 3, Chapter 4 outlines the development of a stochastic optimization model that enables the supply chain decision maker to cope with future demand uncertainty during the strategic planning of a global supply chain network for a new product introduction. We modify the deterministic network optimization model by first defining the stochastic demand as a set of three demand scenarios: low, medium, or high levels of future demand. We then break the decision-making process down into multiple stages in which some decisions are made prior to demand realization, and others after. The model helps identify optimal strategic decisions that can be made by the decision maker in the current period to ensure that the network is able to cope with uncertain demand in future periods.

4.2 Rationale for Stochastic Optimization

In Chapter 3, we assumed that future demand values are known with certainty (they are not random). This deterministic demand assumption was made initially for two reasons. First, the deterministic model is easier to build and work with than a stochastic model. Second, the use of only one set of country demand values enables alignment of the various functions, such as marketing, manufacturing, or engineering, on one demand target. This reduces friction during the modeling and planning process. Since many functional plans are designed based on the nominal demand values, proposing that the demand is stochastic introduces additional complexity and uncertainty that could result in greater managerial indecision. This could impede a large organization's progress towards a final plan that fully aligns the different functions.

Nevertheless, in the real-life implementation of the supply chain network, the deterministic model is not very realistic. The extent of patch adoption in the global markets is uncertain. The demand that is realized could differ significantly from the forecasted numbers. In the case of realizing lower-than-expected demand, this would mean that capital is tied up in expensive equipment and facilities that are underutilized. In the case of greater-than-expected demand, insufficient capital investment in capacity results in the loss of customer sales and goodwill.

In case of greater-than-expected demand, the optimal capacity allocation and supplier/facility selection decisions obtained using the deterministic model may become infeasible. Constraint (3.20) in Chapter 3 guarantees that for any feasible solution, production satisfies all demand. But when the supply chain network is implemented in real-life, this constraint may be violated if the demand that is realized in the first period exceeds the allocated capacity. In addition to not being able to satisfy demand, another infeasibility may arise when we consider the second objective of the multi-objective model: ensuring that the average or maximum lead-time does not exceed some ϵ-constraint. Having already selected the transportation mode between different nodes in the network, greater-than-expected demand from distant demand nodes may increase the average lead time, thereby violating the ϵ constraint of the deterministic problem.

Stochastic optimization protects the decision maker against uncertainty by ensuring that the optimal decisions remain feasible for different realizations of the stochastic demand parameter. Stochastic optimization is described in several texts and reviews [67][68]. To address the demand uncertainty, we transform the deterministic model developed in Chapter 3 into a stochastic optimization model.

4.3 Representing the demand uncertainty

The first step in building the stochastic network optimization model is to characterize the demand uncertainty. One possibility involves creating demand scenarios that obey a known probability distribution. For example, we can specify a set, $\Omega = \{\omega_1, \omega_2, ...\omega_n\}$, of n demand scenarios ω, where each scenario ω_n occurs with some probability p_n. Here, $\sum_n p_n = 1$. Using this set of scenarios, we modify slightly the notation of the deterministic model introduced in Chapter 3. The demand parameter, $D_{m,t}$, which represents the demand in country m in time period (t), transforms into $D_{m,t}(\omega_n)$, which represents the demand in country m in time period (t), under demand scenario ω_n.

The multiperiod problem described in Chapter 3 introduces additional complexity because the demand realized in period $(t+1)$ is generally thought to depend on the demand realized in period (t). These product adoption dynamics are explored in several diffusion models [69], which posit that the probability of adoption by non-adopters in period $(t+1)$ is a function of the number of previous adopters in periods $\{t, t-1, ..., 1\}$. For example, if demand in period one is stochastic with three possible scenarios of low, medium, and high demand equal to {100, 200, 300} units, then the realization of the low scenario of 100 units of demand means that the demand scenarios for period 2 would more likely have lower magnitude (e.g. $\{200, 300, 400\}$ in year 2) than the demand scenarios if the demand realized in period 1 was the high of 300 units (e.g. $\{400, 500, 600\}$ in year 2).

This requires adding scenarios for each subsequent period of the model, which grows the scenario tree exponentially. The total number of scenarios equals ($n^{|T|}$) if there are n scenarios for each period of the set of T periods. Adding scenarios increases the total number of variables in the model. Specifically, if the deterministic model has M variables, then the stochastic optimization model with S scenarios results in a total of $\approx M * S$ variables. To maintain tractability, only three scenarios are considered for the Calibra IDP supply chain network, reflecting the possibility of realizing low, medium, or high levels of demand.

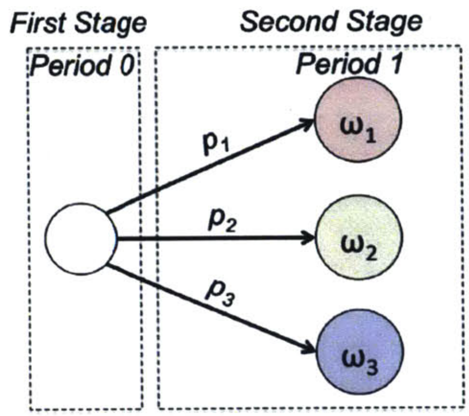
4.4 Multi-stage structure of stochastic optimization

In the stochastic optimization model, the decision-making process is broken into several decision-making stages, with some decisions being made by the decision maker before the stochastic demand is realized, and others after. Through this *multi-stage* approach, the decision maker determines the optimal set of decisions that can be made today in preparation for the uncertain demand that arises in the future. For example, for a two-stage problem with only two time periods, the decision maker allocates capacity and selects strategic suppliers in the current period. These first stage decisions are equivalent for all three scenarios. In the next period, the demand is realized from a set of n possible scenarios, and production commences. The objective then becomes to minimize the current period's capacity investment costs and the subsequent period's expected operating and transportation costs. This is shown in Figure 4-1 for a set of three possible demand scenarios.

In the second stage, the amount of IDP produced depends on the scenario, but it cannot exceed the capacity allocated by the first stage decisions. As such, the optimal first stage capacity allocation and supplier selection decisions that are common to all three scenarios ensure that production volumes in the second stage can satisfy the realized demand for all three scenarios. This demonstrates how the stochastic optimization model bolsters solution feasibility and protects the decision maker from demand uncertainty.

As we expand the multi-stage process into additional stages, we see that a common pattern emerges. New demand information is revealed at the beginning of each stage. Production quantities are then determined through the flow decision variables $y_{o,d,r,t}$ where o represents an origin facility, d represents a destination facility or demand country, and r represents the transportation mode at year t. Only outcomes of the current stage and previous stages are known. We can ad-

Figure 4-1: In the two stage decision-making process, decisions are made in period zero (the first stage). In this example, three demand scenarios could be realized in period one (the second stage). The probability of realizing each scenario $\{\omega 1, \omega 2, \omega 3\}$ is $\{p_1, p_2, p_3\}$ respectively, where $p_1 + p_2 + p_3 = 1$.



dress this more concretely by assuming for simplicity that an assembly plant j produces the IDP that flows to a sterilizer k, satisfying demand at country nodes m in year t. The notation of the flow and facility/supplier selection variables is modified in a similar way to the demand parameter described earlier, with $x(\omega_n)$ representing decision variable x under demand scenario ω_n. The sequence of demand realizations and decisions is shown in Table 4.1.

4.5 Incorporating multiple periods into a two-stage process

In Section 4.3, we limited the number of demand scenarios to three in order to maintain model tractability. As such, instead of constructing T stages and exponentially growing the scenario tree, the stochastic model comprises only two stages and T periods. Period $T = 0$ coincides with the first stage, and periods $T = \{1, 2, \ldots, 7\}$ coincide with the second decision-making stage. This implies that once we branch into one of the three demand scenarios in period 1, the demand that follows in subsequent periods is deterministic. This is shown in Figure 4-2.

The shape of the three demand scenarios appears in Figure 4-3. The average curve will be used for the deterministic model implementation in Chapter 5. These scenarios reinforce the idea that once one scenario is realized in period 1, the demand in subsequent periods is known with complete certainty (it is deterministic). The shape of the aggregate demand curves mirrors that seen in S-shaped product adoption curves, with the low scenario showing early maturity in years 6 and 7, the medium scenario emphasizing continued growth, and the high scenario representing a very successful product.

Table 4.1: The sequence of production and capacity allocation decisions with respect to the timing of the demand. For simplicity, the aggregate demand D_t is considered instead of the country-level demand, $D_{m,t}$.

Year 0	1. Decide on manufacturing capacity $C_{j,p,0}$, as well as facility and supplier selection $x_{j,0}$,$x_{k,0}$,$x_{l,0}$, and $x_{c,i,0}$
Year 1	2. Realize year 1 aggregate demand, $D_1(\omega_n)$ 3. Produce $y_{j,k,r,1}(\omega_n)$ product to satisfy demand 4. Left-over inventory at DC = $I_{l,1}(\omega_n)$ 5. Decide on capacity $C_{j,p,1}(\omega_n)$
Year 2	6. Realize year 2 aggregate demand, $D_2(\omega_n)$ 7. Produce $y_{j,k,r,2}(\omega_n)$ product 8. Satisfy demand with new product and left-over inventory from Year 1 = $y_{j,k,r,2}(\omega_n) + I_{l,1}(\omega_n)$ 9. Left-over inventory at DC = $I_{l,2}(\omega_n)$ 10. Decide on capacity $C_{j,p,2}(\omega_n)$
...	...

4.6 Formulating the two-stage model

We now formulate the two-stage, multi-period stochastic linear optimization model with three demand scenarios. For three demand scenarios, our set of scenarios, $\Omega = \{\omega_1, \omega_2, \omega_3\}$. The probability of each scenario is equal to p_1, p_2, p_3, respectively. To provide a more compact representation of the decision variables in time t, we use the vector of decisions:

$$X_t = \{C_{j,p,t}, Z1_{j,p,t}, Z2_{j,p,t}, x_{o,t}, Z1_{o,t}, Z2_{o,t}, y_{o,d,r,t}, i_{l,m,t}, I_{l,t}\} \tag{4.1}$$

To maintain concision, the variables $x_{o,t}$ and $y_{o,d,r,t}$ are used to represent all possible facility or partnership decisions and flow decisions in period (t). The objective function becomes a function of our decision variables and the realized demand, $f(X_t, D_t(\omega))$, similar to the objective function shown in 3.19. For the current period, (t), the objective function costs reflect the production, inventory, transportation, and capacity decisions of that period. These current period decisions are constrained by the capacity, supplier, and inventory decisions made in the prior period, ($t-1$), as well as the constraints of the current period (t). This dependency appears in the constraints of the optimization model below. Once again, for concision, the constraints are grouped into a matrix, A_t, with m columns equal to the number of variables in X_t, and n rows equal to the number of

Figure 4-2: In the two stage, multi-period decision-making process, decisions are made in period zero (the first stage). Three possible demand scenarios are possible in period one (the second stage), with the demands in subsequent periods depending on the Period 1 scenario.

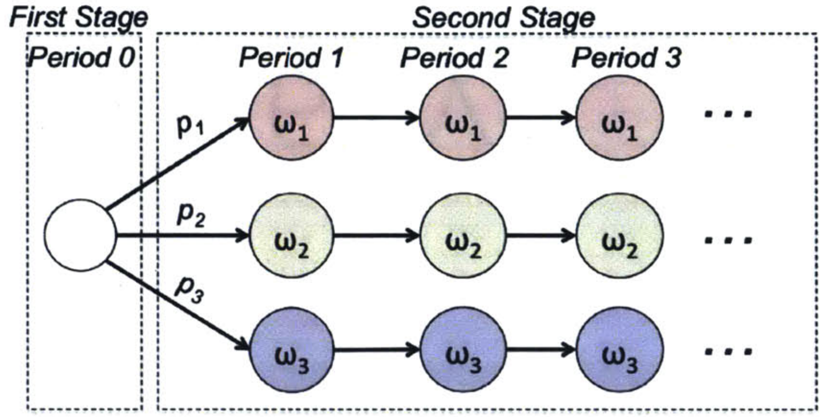
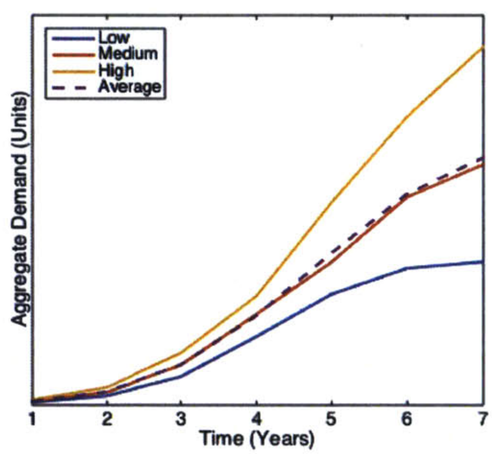


Figure 4-3: Low, medium, and high aggregate demand scenarios for Calibra IDP



constraints. The right-hand side of the constraints is represented by a vector of parameter values, B_t, representing the flow . The objective function can then be represented as the expected value of the costs under different scenarios:

Notation

Sets

Ω Set of demand scenarios ω_n, for $n \in \{1, 2, 3\}$

Parameters

p_n	Probability of realizing demand scenario ω_n
$D_t(\omega_n)$	Aggregate demand in year t under demand scenario ω_n
B_t	Vector representing right-hand side of constraints

Variables

$\boldsymbol{X_t}$ Vector of decision variables in time period t

Mathematical Formulation

Objective:

$$\begin{aligned} \textit{minimize}\, f(\mathbf{X_0}) &+ p_1[f(\mathbf{X_1}, D_1(\omega_1)) + f(\mathbf{X_2}, D_2(\omega_1)) + \ldots + f(\mathbf{X_7}, D_7(\omega_1))] + \ldots \\ &+ p_2[f(\mathbf{X_1}, D_1(\omega_2)) + f(\mathbf{X_2}, D_2(\omega_2)) + \ldots + f(\mathbf{X_7}, D_7(\omega_2))] + \ldots \\ &+ p_3[f(\mathbf{X_1}, D_1(\omega_3)) + f(\mathbf{X_2}, D_2(\omega_3)) + \ldots + f(\mathbf{X_7}, D_7(\omega_3))] \end{aligned} \tag{4.2}$$

subject to

$$A_0\mathbf{X_0} \leq B_0 \tag{4.3}$$

$$-B_0\mathbf{X_0}(D_1(\omega)) + A_1\mathbf{X_1}(D_1(\omega)) \leq B_1(D_1(\omega));\ \forall\, \omega \in \Omega \tag{4.4}$$

$$-B_1\mathbf{X_1}(D_2(\omega)) + A_2\mathbf{X_2}(D_2(\omega)) \leq B_2(D_2(\omega));\ \forall\, \omega \in \Omega \tag{4.5}$$

$$\ldots$$

$$-B_6\mathbf{X_6}(D_7(\omega)) + A_7\mathbf{X_7}(D_7(\omega)) \leq B_7(D_7(\omega));\ \forall\, \omega \in \Omega \tag{4.6}$$

$$\mathbf{X_t}(D_t(\omega)) \geq 0;\ \forall\, t \in T,\ \omega \in \Omega \tag{4.7}$$

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Chapter 5

Network Optimization Model Results

5.1 Overview

After introducing the deterministic supply chain network optimization model in Chapter 3 and the stochastic optimization model in Chapter 4, Chapter 5 presents the numerical results from solving the two supply chain network optimization models. The models comprise tens of thousands of variables and tens to hundreds of thousands of constraints and can be solved to optimality within a reasonable amount of time. We demonstrate the value of the deterministic model by comparing its objective value to that of a managerial heuristic. Significant cost savings on the orders of hundreds of millions of dollars can be attained. Similarly, numerical results are presented for the stochastic model to demonstrate how the decision maker is protected from demand uncertainty.

5.2 Model Tractability

5.2.1 Size of the network problem

One of the characteristics that determines the ability to algorithmically solve a problem in an acceptable amount of time is the size of the mixed integer optimization model. The mixed integer optimization models were implemented using the Julia for Mathematical Programming (JuMP) language [70], and solved using the commercial solver Gurobi (version 6.5.0) [71].

Deterministic Problem

The deterministic demand model includes 19,952 variables (10,512 binary variables) and 18,385 linear constraints for the $\epsilon_{average}$ transportation lead time problem. The ϵ_{max} problem features the same number of variables, but includes 400,708 linear constraints. This problem includes a significantly greater number of constraints as it ensures that all possible combinations of continuous paths connecting upstream injection molding suppliers to downstream demand nodes have lead time less than ϵ_{max}.

Stochastic Problem

The stochastic optimization model with three demand scenarios includes 59,856 variables (31,536 binary variables) and 52,787 linear constraints for the $\epsilon_{average}$ transportation lead time problem. Table 5.1 below compares the variable and constraint counts for the deterministic and stochastic models.

Table 5.1: Number of total variables, binary variables, and linear constraints associated with each of the models.

Model	Total Variables	Binary Variables	Linear Constraints
Deterministic ϵ_{ave}	19,952	10,512	18,385
Deterministic ϵ_{max}	19,952	10,512	400,708
Stochastic ϵ_{ave}	59,856	31,536	52,787

5.2.2 Solution Speed

After comparing the sizes of the deterministic and stochastic models, this section explores the speed at which these models can be solved. Generally, the decision maker may find models that require too much time to solve to be unacceptable if the frequency at which decisions need to be made surpasses the model's decision throughput (the system's bandwidth). Given that this is a strategic network optimization model, decisions need to be made annually or at most, bi-annually, so the speed of the solution becomes less critical. Nevertheless, it is important to determine if these models can be solved within a reasonable amount of computation time, and if the solver solution strategy can be tuned to improve the computation time.

All of the computations were conducted on a desktop computer with an Intel Core i7-3970X CPU (6-core, 12-threads, 64 GB RAM). All threads were used during computation to help reduce the solution time. The mixed integer optimization (MIO) gap is used as a solution speed metric. The MIO gap indicates the difference in the objective value of the best integer-valued solution – the upper bound – and the objective value of all current leaf nodes – the lower or best bound resulting from the continuous relaxation of the mixed-integer problem. The MIO Gap is indicative of the quality of the current integer solution, or how far away it is from the optimum. An MIO Gap of ≈ 0 (default value of 0.01% in most commercial solvers) indicates that the problem has been solved to optimality.

In real world problems with estimation errors in the data, such levels of precision may not be necessary, and the termination criteria – the relative MIO Gap at which the optimization stops – may be adjusted. Interestingly, for a strategic decision-making process, estimation errors in the parameters will undoubtedly exist, which may drive the modeler to terminate early if the model is large and slow to solve. On the other hand, the infrequency of decisions at the strategic level affords the decision maker days or weeks to solve the problem, which minimizes the need to terminate early.

Figure 5-1: Mixed Integer Optimization (MIO) Gap for the Deterministic ϵ_{ave} transportation lead time constraint problem. Providing the model with initial condition constraints significantly reduces the solution time (top panel). If initial conditions are not provided, the solution time increases, but parameter tuning may significantly reduce the solution time (in this case by almost 1/2) as seen in the bottom panel.

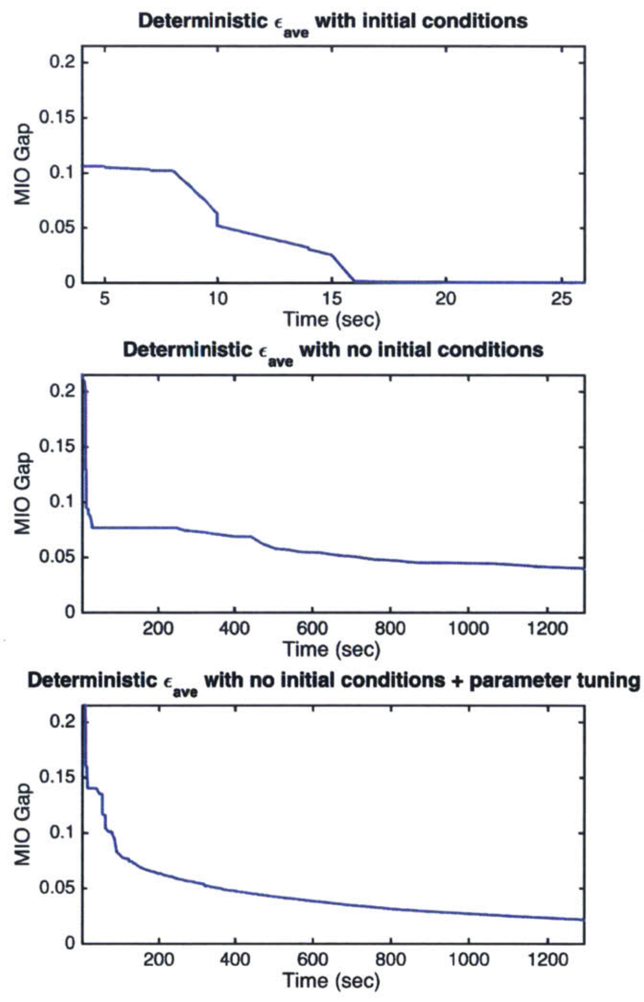
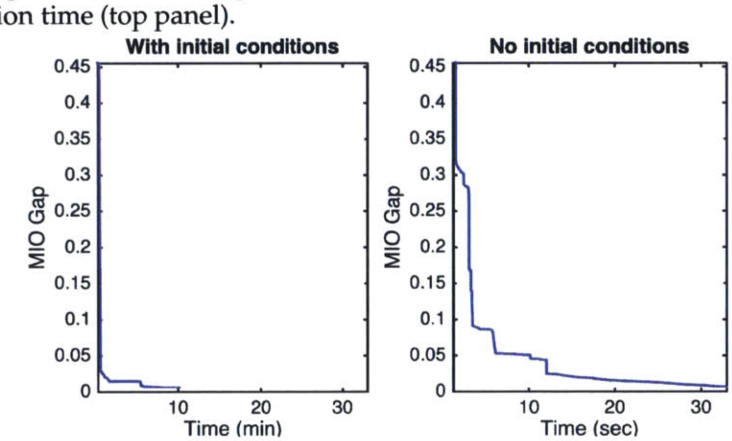


Figure 5-1 demonstrates that the deterministic ϵ_{ave} problem can be solved in approximately 15 seconds for a model with initial conditions, or in 1500-3000 seconds (25-50 minutes) for a problem with no initial conditions. The initial conditions refer to the decisions already made by the supply chain decision makers at J&J, as mentioned in Section 3.10. These decisions appear as constraints that set the capacity or facility options that are *not* selected by the decision maker to zero for the initial two periods of the model. Adding these constraints accelerates the solution time as it forces the model to build a supply chain network around those decisions that have already been made, without expending the time to determine the optimal starting point. We present the solution time for the scenario with no initial conditions to demonstrate how this network model could generalize to other strategic network optimization projects and still solve in a reasonable time.

The Gurobi solver parameters play an important role in determining how fast a mixed integer optimization problem can be solved. Tuning of these parameters resulted in significant improvements in solution time – almost halving the time – for the model without initial conditions (Figure 5-1, lower panel). The most difficult challenge was in having a lower bound that was moving very slowly. Focusing the *MIPFocus* parameter, which controls the high-level solution strategy, on moving the bound yielded improvements. Another significant solution time improvement came from shutting off cuts by setting the *Cuts* parameter to 0. Combining a focus on finding feasible solutions quickly and reducing cuts also resulted in performance improvements.

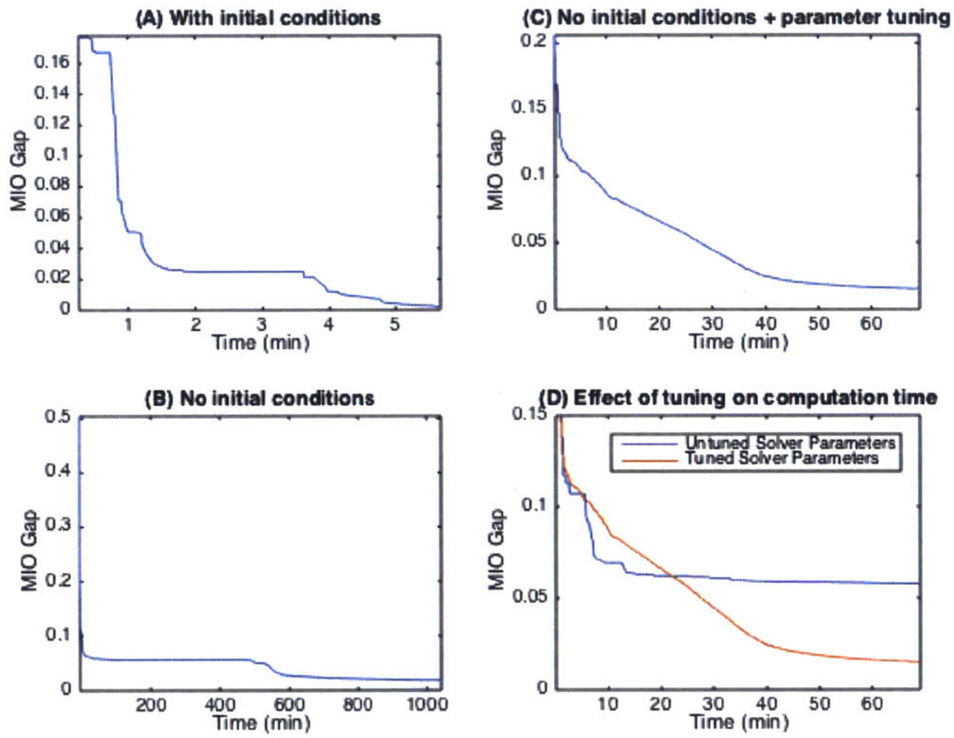
In the case of the deterministic ϵ_{max} transportation lead time problem, Gurobi parameter tuning did not significantly reduce the solution time. The MIO Gap and solution time are shown in Figure 5-2.

Figure 5-2: Mixed Integer Optimization (MIO) Gap for the Deterministic ϵ_{max} transportation lead time constraint problem. Providing the model with initial condition constraints significantly reduces the solution time (top panel).



The solution time for the stochastic optimization problem exceeds that of the deterministic problem. The stochastic problem has approximately three times the number of variables and constraints. The model with initial conditions can be solved to an MIO gap of 0.01% within 340 seconds (approximately 6 minutes). The model without initial conditions requires approximately 17 hours for termination at an MIO gap of 1.6%. This suggested that there may be room for improvement through solver parameter tuning in the case of the stochastic optimization model, which tends to feature a slowly moving bound. By varying the solver parameters (primarily by setting the Cuts parameter to zero), the model without initial conditions requires approximately 70 minutes to terminate at an MIO gap of 1.5%, a significant improvement over the original computation time. With tuning, the computation time is approximately 10 hours for termination at an MIO gap of 0.5%. The MIO Gap result for the stochastic optimization model is shown in Figure 5-3.

Figure 5-3: Mixed Integer Optimization (MIO) Gap for the Stochastic ϵ_{ave} transportation lead time constraint problem. Providing the model with initial condition constraints significantly reduces the solution time (panel A). Providing no initial solution results in increased solution time (panel B), while parameter tuning significantly reduces the solution time (panels C and D).



5.3 Comparing the Deterministic model to a managerial heuristic

To understand the value of the deterministic optimization model, the model's decision outputs are compared to a heuristic decision-making technique employed by managers. Heuristics provide efficient decision-making rules for finding satisfactory solutions to large, complex problems such as the design of a global supply chain network. As discussed in Section 1.2, managers may use their extensive supply chain experience to guide the network design, but in doing so they may give considerably more weight to one dimension of the problem at the expense of others. The value of the deterministic model lies in understanding the interdependencies between the strategic decision levers and their impact on cost and lead time.

We compare the cost and lead time outputs of the model to the cost and lead times of the managerial decision-making heuristic. The heuristic represents decisions that the supply chain planner would have made *without* access to the strategic network optimization model. The heuristic is outlined in the section below.

5.3.1 Managerial Heuristic

1. Each distribution center is assigned to a set of countries. As such, a country demand node can only receive the finished good from one distribution center. The rationale for this heuristic is that it compartmentalizes each geographic region, placing fulfillment responsibility on one DC and simplifying communication between logistics and the country business managers. This approach also reduces the number of transportation 'lanes' that need to be set up by the logistics managers on the tactical and operational level.

2. Assembly operations are concentrated in one location. The rationale for this heuristic is that concentrating assembly operations in one location allows the organization to leverage economies of scale and spread the fixed facility costs and overhead over a larger production output.

3. The transportation modes between different layers in the supply chain are pre-determined. This heuristic perpetuates the decisions made in the early phase of the supply chain network design, where the network can afford to ship small volumes of components using the high cost transport mode to expedite experimentation in product design and manufacturing. This high cost transportation mode of shipping is extended to the first four years of the network strategy as an attempt by managers to ensure that customers receive product in a timely manner.

We focus first on the difference in the objective value between the heuristic and the deterministic model. To make the comparison a fair one, we ensure that the deterministic model's average transportation lead time approximately matches that obtained by the heuristic. The next question is whether we add the supply chain's initial conditions, which were mentioned in Section 3.10, as constraints to the deterministic model. This includes the location of the low volume and medium volume assembly lines, as well as the selection of the sterilizer and distribution center facilities. These analysis scenarios are presented below:

5.3.2 Scenarios for Analysis

- Scenario 1: All three managerial heuristics are respected and the deterministic model is run without adding the supply chain's initial conditions.
- Scenario 2: Only the first two managerial heuristics are respected: 1) the assignment of demand nodes to DCs, and 2) the concentration of assembly in only one location. Strict ϵ-constraints are enforced to ensure very short transportation lead time to safeguard the 'spirit' of the third heuristic. The deterministic model is run without adding initial conditions.
- Scenario 3: Only the first two managerial heuristics are respected, but the deterministic model is run with the initial conditions.
- Scenario 4: Assume lower transportation cost parameters per mile for both the low cost and high cost modes (deeply discounted/highly negotiated costs). Assume only the first two managerial heuristics are respected, and that the deterministic model is run without adding initial conditions.
- Scenario 5: Assume lower transportation cost parameters per mile for both the low cost and high cost modes (deeply discounted/highly negotiated costs). Assume only the first two managerial heuristics are respected, and that the deterministic model is run with initial conditions.

Table 5.2: Percent difference for deterministic model versus the heuristic decision-making process. Here, average lead time 1 equals $\epsilon_{ave,1}$, while average lead time 2 equals $\epsilon_{ave,2}$.

Costs	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Average Lead Time 1 (hours)	+24	+24	+24	+24	+24
Average Lead Time 2 (hours)	+12	+12	+12	+12	+12
Objective Value Difference	-27%	-25%	-19%	-18%	-13%
Capital Investment	-6%	+6%	+7%	-5%	-5%
Facility Operating Costs	+53%	+53%	+94%	+41%	+81%
Transport Cost Low Mode	+138%	+40%	+34%	+43%	+34%
Transport Cost High Mode	-73%	-71%	-56%	-68%	-52%
Transport Cost DC to Demand Low Mode	+48%	-1%	+0%	+0%	+4%
Transport Cost DC to Demand High Mode	+24%	+64%	+62%	+73%	+51%
Assembly Line Startup Costs	+3%	+3%	+5%	-1%	-1%
Assembly Line Steady State Costs	+11%	+11%	+19%	-3%	-3%
Unit Costs Material	-1%	-1%	-1%	+1%	+1%
Unit Costs Sterilization	-11%	-11%	-9%	-8%	-7%
Holding Costs	-17%	-17%	-42%	+49%	+52%

Table 5.2 outlines the difference in the objective value between the deterministic model and the managerial heuristic for the five scenarios. A negative objective value difference indicates that the

deterministic model costs *less* than the managerial heuristic. Optimization through the deterministic model results in significant cost savings, on the order of hundreds of millions in present-value dollars. The relative cost improvement ranges from 27% for Scenario 1, where all three managerial heuristics are respected and the deterministic model is free to set the initial conditions, to 19% in Scenario 3, which assumes that only the first two heuristics are respected and that the deterministic model is constrained by the initial conditions. Aggressively reducing the transportation cost parameters (assuming negotiated rates) reduces the magnitude of the relative difference, but still reduces the total supply chain cost by 13 to 18%, which represents tens to hundreds of millions in present-value dollars.

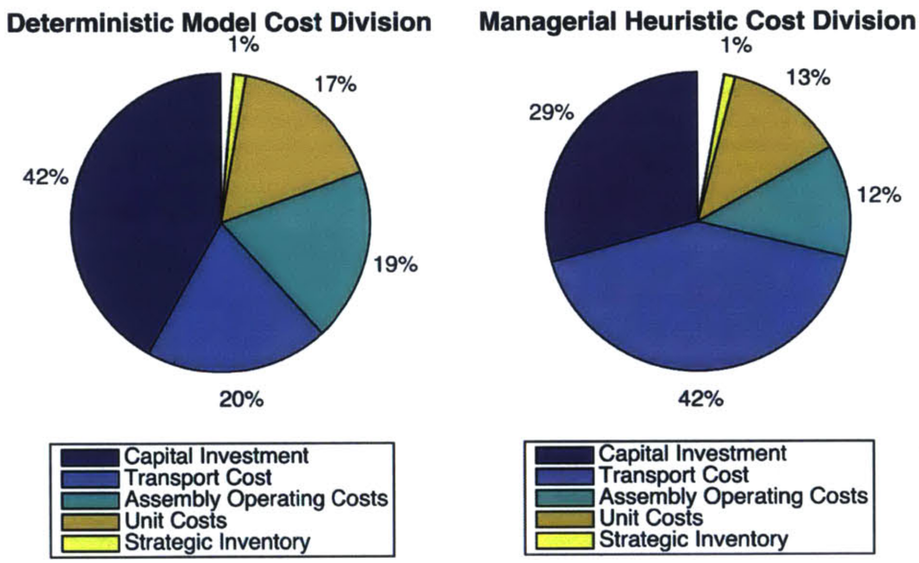
The deterministic model's facility location and transportation strategy is markedly different from the manager's heuristic. Table 5.2 demonstrates how the deterministic model elects to pay about 50%-90% more in operating costs in order to run additional facilities that are closer to the demand. In doing so, the model dramatically reduces the transportation costs. Interestingly, the model in Scenario 3 has significantly higher operating costs because it is constrained by the initial conditions for the low volume and medium volume assembly lines. It elects to add the two additional high volume lines in two separate facilities located on two different continents in order to increase proximity to the demand. Furthermore, the deterministic model assigns country demand nodes to distribution centers that lie outside the country's region in order to balance the transportation costs and lead times over all countries in the model. Note that by selecting assembly and distribution facilities that are closer to the demand, the model is able to meet the aggressive ϵ_{ave}-constraint by spending more money shipping through the high cost transportation mode from the DCs to the customers (represented by Transport Cost DC to Demand High Mode), because these usually constitute shorter distances compared to the long distances connecting a single global assembly site to the downstream sterilizers and DCs.

This idea is further emphasized in Figure 5-4, where a greater percentage of the deterministic model's cost lies in facility operating costs, while a substantial portion of the managerial heuristic cost lies in the transportation costs. This exemplifies how the decision maker opting to reduce supply chain cost by leveraging economies of scale using a global manufacturing facility may inadvertently increase costs by emphasizing only one strategic supply chain cost driver or lever.

5.4 Effect of transportation lead time on supply chain costs

After comparing the results of the deterministic model to those of the managerial heuristic, we start to see that the model affords the decision maker an opportunity to evaluate the cost and impact of reducing the average or maximum transportation lead time constraints. Meeting a customer's transportation lead time requirements is important, but at what point does the transportation lead

Figure 5-4: Distribution of costs in the deterministic model compared to the managerial heuristic in Scenario 2. The deterministic model elects to operate multiple regional assembly facilities, which increases the fraction of assembly operating cost, but substantially decreases the transportation cost relative to the heuristic.

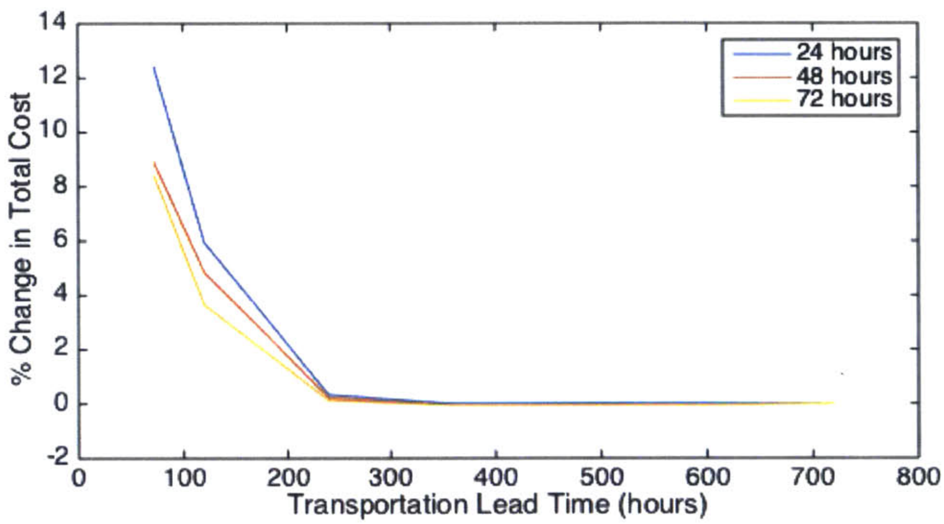


time requirement start having a significant impact on the objective function value, and what is the magnitude of that impact? Furthermore, how does the transportation lead time constraint impact the facility site selection?

The impact of reducing the transportation lead time on the objective value is shown in Figure 5-5. We notice that the objective value does not change significantly until $\epsilon_{ave,1}$ is set to 120 hours or lower, meaning that the average time transporting components, assembled devices, and sterilized kits should not exceed 120 hours. This results in a 4-6% increase in the objective function value, depending on where the customers are required to be from the distribution centers ($\epsilon_{ave,2}$).

In other data, we show that the transportation cost for the 24 hours line does not actually increase when the $\epsilon_{ave,1}$ falls to 120 hours. The model opts to 1) reroute flows, 2) alter and re-balance the choice of transportation modes, or 3) adjusts to the lead time requirement by opening additional facilities. This is part of the flexibility of the model that can be leveraged extensively by the supply chain decision maker.

Figure 5-5: Impact of transportation lead time $\epsilon_{ave,1}$ reduction in the supply chain network on the objective function value given constraints on the proximity of DCs to customers, $\epsilon_{ave,2}$ = { 24,48,72 hours}.



5.5 Value of the Stochastic Model

After demonstrating the value of the deterministic model, we now focus on how the stochastic model protects the decision maker from infeasibility and demand uncertainty by comparing the performance of the stochastic model's stage one decisions to those of the deterministic model under a series of different test scenarios.

A set of n test scenarios is generated by multiplying the average demand forecast by a uniformly distributed random variable, $X_{rand} \sim \mathcal{U}(0.7, 1.5)$:

$$D_{scen,n} = \{Demand_{t=1,2,...,7} * X_{rand}\} \tag{5.1}$$

We set (n = 30). Equation 5.1 implies that the demand scenario generated could have demand that is 30% lower to 50% higher than the average demand shown in Figure 4-3. We set the first stage outputs of the deterministic and stochastic models as the decisions for the first period in the test. The subsequent periods are then solved, assuming that each demand test scenario is deterministic. As discussed in Section 4.2, under certain test scenarios, the deterministic solution may become infeasible. The allocated capacity may be insufficient to satisfy the demand, or the transportation lead times may not satisfy the average lead time constraint.

One approach is to tabulate the scenarios in which infeasibility occurs. Alternatively, we could allow the model to *recover* from the infeasibility through the addition of a recourse variable. This recourse variable represents the organization's ability to access patches from an external source – a contract manufacturer for example – through which the supply chain network satisfies the realized demand.[1] The cost of these recourse patches is greater, however, than the per unit cost, c, of patches attained through the regular manufacturing operations. This higher cost equals $c(1+\delta)$, where δ represents the added fractional expense (e.g. 20%-60% or more) per patch from sourcing through the contract manufacturer. Furthermore, these patches can be shipped through the high cost transportation mode from any DC in order to meet the lead time constraint. In the real world of the Calibra supply chain, there will be no contract manufacturer that will provide this capability. This is a feature that we add to the model to provide the decision-maker with insight into the value of the stochastic model.

An uncapacitated recourse variable REC, in the set of non-negative real numbers, is then added to ensure that we satisfy demand for period two:

$$\sum_{lr} y_{l,m,r,t} + \sum_{lr} REC_{l,m,r,t} \geq D_{m,t} \qquad ; \forall\, m \in M, t = 2 \tag{5.2}$$

$$REC_{r,l,m,t} \geq 0 \qquad ; \forall\, r \in R, \forall\, l \in L, \forall\, m \in M, t = 2. \tag{5.3}$$

5.5.1 Results

We now compare the two models' first and second period costs for the thirty test scenarios, assuming that the supply chain decision maker implements either the deterministic or stochastic model's first stage decisions. As discussed in Section 4.4, the first stage decisions impact the suppliers, assembly facility locations, assembly facility capacities, sterilizers, and distribution centers for the second period. Since only the first period decisions are fixed, the model can solve for the optimal decisions in subsequent periods.

We see in Figure 5-6 and in Table 5.3 that the stochastic model's average objective function value for the first two periods is less than the deterministic model's. Further, the coefficient of variation – a measure of the dispersion of the data – is also smaller.

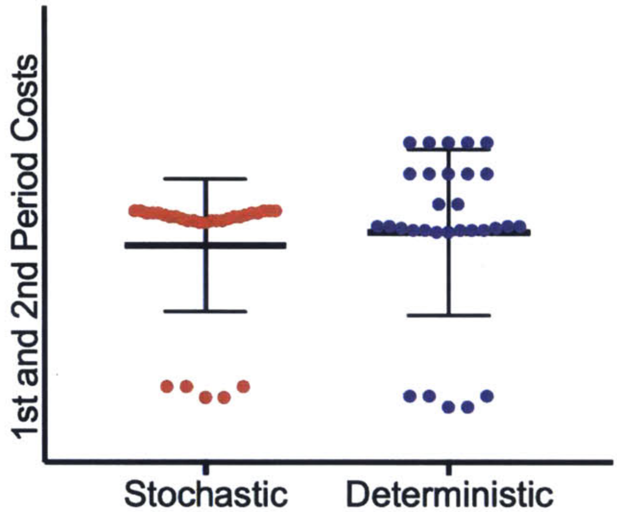
Table 5.3: Mean and coefficient of variation of second period objective function value for the deterministic and stochastic model first period decisions.

Model	Mean	Coefficient of Variation
Deterministic	1	1
Stochastic	0.97	0.98

We observe that the stochastic model protects the decision maker from demand uncertainty by investing in additional "buffer" capacity in the first period. This comes at an added cost in capital investment and labor. This cost represents the price that the supply chain decision maker pays in order to maximize the chances of satisfying the realized demand in the future. In test scenarios where the realized demand is lower than the average demand, or slightly higher (up to 20% higher),

[1] An alternative way to think about the recourse variable is to see it as a penalty incurred for not satisfying demand, similar to the *underage* cost seen in a two-stage newsvendor model

Figure 5-6: Combined first and second period costs for thirty test scenarios assuming implementation of the first stage deterministic or stochastic decisions. The deterministic model's first period decisions result in a higher average cost and greater standard deviation and coefficient of variation than the stochastic model's first period decisions.}.

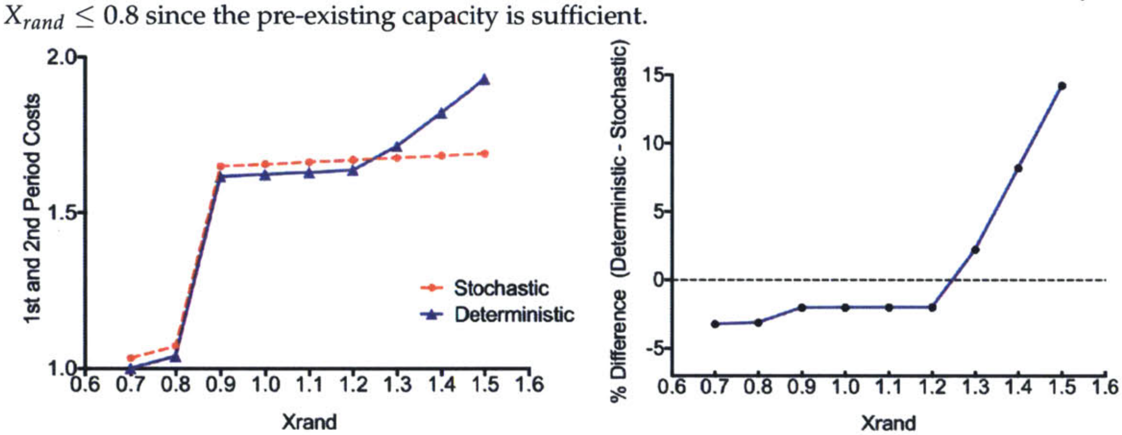


implementing the stochastic solution means that we have essentially purchased excess capacity, and the combined first and second period costs of the stochastic model's decisions exceed that of the deterministic model. This difference in capital investment cost can be seen in the gap between the stochastic and deterministic lines in the left panel of Figure 5-7 for X_{rand} less than 1.2.

On the other hand, when the realized demand is more than 20% larger than the average forecast, implementing the deterministic model's first stage decisions results in infeasibility: we don't have the necessary capacity in period two to satisfy demand. To recover from infeasibility, the model has recourse in the second period to the more expensive patches. Purchasing these patches increases the second period cost, especially as the realized demand increases from X_{rand} = 1.3 to 1.5, as shown in Figure 5-7. The total cost of the supply chain over all periods is similarly lower for the stochastic decision implementation when $X_{rand} \geq 1.2$ (data not shown).

The results of this section support the investment in additional capacity. Period two in this multi-period model is a critical one for the dynamics of IDP adoption. Lost sales resulting from inadequate capacity during this period could have a detrimental long-term impact on the ramp-up of user adoption if we assume adoption in later periods is a function of pre-existing adopters.

Figure 5-7: Combined first and second period costs as a function of realized demand, assuming implementation of the deterministic or stochastic models' decisions for the first period. The deterministic model's decisions cost less when demand is near or lower than the average forecast (when X_{rand} lies between 0.7 and 1.2). Obtaining expensive recourse patches to recover from infeasibility means that the deterministic model's decisions become more expensive as the realized demand grows. The jump from $X_{rand} = 0.8$ to 0.9 is due to the investment in an additional assembly line in period two in preparation for the demand in period three. This investment is not necessary when $X_{rand} \leq 0.8$ since the pre-existing capacity is sufficient.



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Chapter 6

Conclusions

6.1 Overview

This thesis utilized a mathematical optimization model to evaluate the trade-offs in strategic supply chain decision-making for a new product introduction in a real-world setting. The optimization model focused on strategic decisions related to the location and capacities of various supply chain facilities and partners, transportation costs, and strategic inventory required to satisfy global demand. The model significantly reduces the cost of the multi-period global supply chain network compared to a managerial heuristic decision-making process. Further, the stochastic optimization model protects the decision-maker against infeasibility – or the inability to satisfy demand within the specified transportation lead time – due to demand uncertainty. This section highlights recommendations and opportunities for implementing and developing modeling capabilities at J&J.

6.2 Recommendations

1. **Deployment of optimization models**

   After demonstrating the value of the deterministic and stochastic optimization models, the next step is to deploy these modeling tools in a format that is easy to access and use by Calibra's supply chain decision makers. This would include creating an interface for parameter, constraint, or variable (e.g. demand nodes) modification in the model so that managers can incorporate new assumptions or developments.

2. **Developing a cross-functional modeling culture**

   The introduction of optimization models could have a significant impact on organizational decision-making processes. Currently, qualitative and semi-quantitative strategic decision-making tools are used by managers to reduce the global supply chain network problem into smaller, tractable subsets focused on capacity allocation, supplier selection, facility location, transportation, or strategic inventory. Managerial heuristics are then used to reduce the solution space for each problem subset (e.g. assembly facility location) to two or three feasible scenarios that are analyzed quantitatively. On the other hand, the model provides a more holistic view of the end-to-end supply chain, selecting an optimal solution that conforms to the decision maker's constraints from thousands of different supply chain configurations. The transition from reliance on managerial heuristics to accepting the model's prescriptive output has a significant impact on the organization's decision-making culture. As such, building optimization models requires tight cooperation between functional decision-makers, since cross-functional acceptance of the model's output presupposes cross-functional acceptance of the model's inputs and assumptions.

The utilization of optimization models also impacts the way that data is collected and shared across the organization. Data on supplier selection, assembly facility location, or transportation resides in disparate parts of the organization under different functional managers. The success of this project depended heavily on the functions' ability to share data and insights. One recommendation is to streamline data collection and institute new data management practices. For data collection, it becomes imperative to enable faster data sharing with the modeler. This in turn depends on the data management practices. Having a central depository of data organized by a data manager that constantly revises the necessary permissions helps reduce data collection, model implementation, and decision-making lead times. The data manager has the responsibility of balancing between safeguarding the privacy needs of critical projects in the planning stage, and new projects that desire access to information from projects that have already been considered or implemented. This enables an incremental transformation into a data-driven organization.

3. **Cross-franchise learning**

   J&J is a very large global company with incredibly sophisticated capabilities in medical device design, manufacturing and distribution. Since the company employs a decentralized organizational model, business units within J&J have the autonomy to make their own business decisions. This autonomy sometimes results in locking important capabilities or best practices internally within the business units. Future supply chain projects could benefit from information sharing across the business units. Managers from other business units may join the cross-functional supply chain strategy teams as new product introduction consultants. This may help in developing synergies through the shared use of supply chain assets, processes, and capabilities.

4. **Strategy implementation**

Donald Sull at the MIT Sloan School of Management emphasizes that a great strategy is of little use without proper execution [72]. The supply chain network strategy with its resource-based focus is a critical strategic dimension of the overall supply chain strategy, which also includes organizational processes and capabilities. We recommend that a steering team comprising supply chain leadership maintain year-to-year oversight over the supply chain strategy, revise the strategy when necessary by incorporating new information, and create project teams led by managers from the different supply chain functions to develop the more detailed tactical or operational implementation plans.

5. **Multi-product model improvement**

   Since the current model focuses on one product, J&J may benefit from expanding the model in future iterations to look at the trade-offs involved in implementing global supply chain networks for multiple SKUs within the Calibra organization, or multiple products from different business units within consumer medical devices.

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Appendix A

Tables

Table A.1: The four major categories of insulin. The Calibra IDP is labeled for use with Novolog and Humalog

Insulin Name	Duration	Brand	Onset of Action	Peak
Insulin glargine	Long-Acting	Lantus	1.5 hrs	Flat (Max at 5 hrs)
Insulin detemir	Long-Acting	Levemir	1 hr	Flat (Max at 5 hrs)
Insulin NPH	Intermediate-Acting	NPH (N)	2-4 hrs	4-12 hrs
Regular Human Insulin	Short-Acting	Humulin R,Novolin R	30 min	2-3 hrs
Insulin lyspro (analog)	Rapid-Acting	Humalog	15 min	1-2 hrs
Insulin aspart (analog)	Rapid-Acting	Novolog	15 min	1-2 hrs
Insulin glulisine (analog)	Rapid-Acting	Apidra	15 min	1-2 hrs

Table A.2: The five major process areas of the SCOR model [3] [4]

Plan	The matching of aggregate demand and supply in order to develop optimal process plans for sourcing, manufacturing, and delivery.
Source	The procurement of goods or services from external vendors to meet demand.
Make	The manufacturing of the finished good. In the case of Calibra, this involves the assembly of various fabricated components procured from suppliers. This involves management of the production facilities.
Deliver	Distributing the finished goods to customers. This includes order management, warehousing, and transportation management.
Return	Return of defective or used product as well as product packaging. This is becoming more critical with the rise of sustainable supply chains.

Table A.3: Cost and speed assumptions for different modes of transportation. FT refers to full truckload.

Mode	Cost per ton mile	Cost per pallet per mile	Average Speed (mph)
Truck	\$0.08 (FT) - \$0.37	\$0.2-\$0.4	35
Air	\$0.6 - \$6.4	\$0.1-\$1.3	450
Ocean	\$0.02	\$0.044 - \$0.1	12.65

Table A.4: Set of supplier options

Component	Type	Option	Country
1	Injection Molded Parts	A	US
1	Injection Molded Parts	B	US
1	Injection Molded Parts	C	US
2	Rubber Parts	A	US
2	Rubber Parts	B	US
3	Plastic Film	A	Belgium
4	Rubber Parts	A	US
4	Rubber Parts	B	US
4	Rubber Parts	C	US

Table A.5: Set of assembly options

Option	State	Country	Internal/External
A	Puerto Rico	US	Internal
B	-	UK	Internal
C	-	Ireland	Internal
D	-	Singapore	Internal
E	Georgia	US	External
F	-	Germany	External
G	Illinois	US	External
H	-	Mexico	External
I	-	Romania	External
J	Arizona	US	External
K	Michigan	US	External
L	-	Ireland	External
M	New York	US	External
N	-	Ireland	External
O	Massachusetts	US	External

Table A.6: Set of global sterilizer options

Option	State	Country	Internal/External
A	New Jersey	US	External
B	North Carolina	US	External
C	New Mexico	US	External
D	Texas	US	External
E	-	Ireland	External
F	-	Netherlands	External
G	-	Belgium	External
H	-	China	External
I	-	China	External
J	Puero Rico	US	Internal
K	-	UK	Internal
L	-	Ireland	Internal
M	-	Singapore	Internal

Table A.7: Set of global distribution center options

Option	City	State	Country	Internal/External
A	Louisville	Kentucky	US	Internal
B	Franklin	New Jersey	US	Internal
C	Beerse	-	Belgium	Internal
D	Singapore	-	Singapore	Internal
E	Shanghai	-	China	Internal

Table A.8: Capital investment, fixed operating costs, and variable costs associated with suppliers

Capital Investment	Fixed Cost	Variable Cost	Decision Variables Impacted	Value
	Establish relationship		$Z1_{c,i,t}$	$R_{c,i,t}$
	Maintain relationship		$Z2_{c,i,t}$	$r_{c,i,t}$
		Component price per unit	$y_{c,i,j,r,t}$	$p_{c,i,t}$
		Transport cost per unit	$y_{c,i,j,r,t}$	$f_{c,i,j,r,t}$

Table A.9: Capital investment, fixed operating costs, and variable costs associated with assembly facilities

Capital Investment	Fixed Cost	Variable Cost	Decision Variables Impacted	Value
Assembly line capital investment			$Z1_{j,p,t}$	$A_{j,p,t}$
Incremental capacity			$c_{j,p,t}$	$k_{j,p,t}$
	Facility overhead cost		$X_{j,t}$	$F_{j,t}$
	Line scale-up operating cost		$Z1_{j,p,t}$	$SC_{j,p,t}$
	Line steady-state operating cost		$Z2_{j,p,t}$	$SS_{j,p,t}$
		Transport cost per unit	$y_{j,k,r,t}$	$f_{j,k,r,t}$

Table A.10: Capital investment, fixed operating costs, and variable costs associated with sterilizers

Capital Investment	Fixed Cost	Variable Cost	Decision Variables Impacted	Value
	Establish relationship		$Z1_{k,t}$	$R_{k,t}$
	Maintain relationship		$Z2_{k,t}$	$r_{k,t}$
		Sterilization price per unit	$y_{c,i,j,r,t}$	$p_{k,t}$
		Transport cost per unit	$y_{k,l,r,t}$	$f_{k,l,r,t}$

Table A.11: Capital investment, fixed operating costs, and variable costs associated with distribution centers

Capital Investment	Fixed Cost	Variable Cost	Decision Variables Impacted	Value
	Establish relationship		$Z1_{l,t}$	$R_{l,t}$
	Maintain relationship		$Z2_{l,t}$	$r_{l,t}$
		Pick and pack price per unit	$y_{l,m,r,t}$	$p_{l,t}$
		Transport cost per unit	$y_{l,m,r,t}$	$f_{l,m,r,t}$

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Appendix B

Network Optimization Code

```
## Supply chain strategy mixed integer optimization model
## Samer Haidar

using JuMP, AmplNLWriter
using DataArrays, DataFrames
using Formatting
using Gurobi


        # Define the model
        n = Model(solver=GurobiSolver(LogFile = "Log $(Int(now()))",Cuts=0,Threads = 12, MIPGap =
            ↪ 0.001))

        ##################################### Functions ##############################################
        #Inflation rate function
        function rep1(data, numperiods, inflation)

                arr1 = repeat([inflation], outer=[1,numperiods]);
                arr2 = reshape(collect(0:numperiods 1), 1, numperiods);

                temp = cell(1,1, numperiods)
                temp[1,1,:] = arr1 .^ arr2;
                matrix = repeat(temp[1,1,:], outer = [size(data)[1],size(data)[2],1]);
                return output = repeat(convert(Array,data), outer = [1,1,numperiods]).*matrix;

        end

        function rep2s(data, numperiods, inflation)
                arr1 = repeat([inflation], outer=[1,numperiods]);
                arr2 = reshape(collect(0:numperiods 1), 1, numperiods);
                matrix = repeat(convert(Array,data),outer=[1,periods]);
                temp = repeat(arr1 .^ arr2, outer = [size(matrix)[1],1]);
                return output = repeat(convert(Array,data),outer=[1,periods]).*temp;
        end

        #Discount rate function
        function discount(size, discrate, numperiods)
```

```
        numdims = length(size)
        arr1 = repeat([discrate], outer=[1,numperiods])
        arr2 = reshape(collect(0:numperiods 1), 1, numperiods)

        if (numdims == 2)
                temp = cell(1, numperiods)
                temp[1, :] = arr1 .^ arr2;
                return output = repeat(temp[1,:], outer = [size[1],1])
        end
        if (numdims == 3)
                temp = cell(1,1, numperiods)
                temp[1,1,:] = arr1 .^ arr2;
                return output = repeat(temp[1,1,:], outer = [size[1],size[2],1])
        end
        if (numdims == 4)
                temp = cell(1,1,1,numperiods)
                temp[1,1,1,:] = arr1 .^ arr2;
                return output = repeat(temp[1,1,1,:], outer = [size[1],size[2],size[3],1])
        end
end

#Timing function
function time(flow, timedata, nperiods,infrate, mode)
return output = rep1(timedata,nperiods,infrate).*squeeze(flow[mode,:,:,:],1);
end

#Unit Cost function
function unitcosts(flow,price,numperiods,discrate)
totsum = 0;
for(t=1:numperiods)
for(i=1:size(flow)[2])
        temp = sum(flow[:,i,:,t]*price[i,t])/discrate^(t 1);
        totsum = totsum + temp;
end
end
return output = totsum;
end

# Transport Cost function (low mode)
function tcostl(flow,cost,infrate,discount)
totsum = 0;
numperiods = size(flow)[4];
for(t=1:numperiods)
for(i=1:size(flow)[2])
for(j=1:size(flow)[3])
        temp = sum(flow[1,i,j,t]*cost[i,j]*infrate^(t 1))/discount^(t 1);
        totsum = totsum + temp;
 end
 end
 end
 return output = totsum;
end

# Transport Cost function (high mode)
```

```
function tcosth(flow,cost,infrate,discount)
totsum = 0;
numperiods = size(flow)[4];
for(t=1:numperiods)
for(i=1:size(flow)[2])
for(j=1:size(flow)[3])
        temp = sum(flow[2,i,j,t]*cost[i,j]*infrate^(t 1))/discount^(t 1);
        totsum = totsum + temp;
 end
 end
 end
 return output = totsum;
end


#################################### Data ######################################################

# Import cost data
df = readtable("geoloc5.csv");

## Suppliers
injmold = df[df[:SiteType] .== "InjMold", :];
rubber1 = df[df[:SiteType] .== "Rubber", :];
rubber2 = df[df[:SiteType] .== "Diaphragm", :];
film = df[df[:SiteType] .== "Film", :];

## Assembly, sterilizer, distribution centers and demand
man = df[df[:SiteType] .== "Man", :];
ster = df[df[:SiteType] .== "Ster", :];
dist = df[df[:SiteType] .== "Dist", :];
demand = df[df[:SiteType] .== "Dem", :];

infrate = 1.04;
Discount = 1.1;
# Number of transport modes
nmodes = 2; # Either air or combination of ocean plus trucking

## Set of Demands
k = 1;
Dema = cell(1)
for(i = 1:length(names(demand)))
        if(isequal(string(names(demand)[i])[1:4],"Dema") == true)
                if(k == 1)
                        Dema = names(demand)[i]
                        k = k+1
                else
                        Dema = vcat(Dema, names(demand)[i])
                        k = k+1
                end
        end
end

## Set of Capacities
r = 1;
```

```
Cap = cell(1)
for(i = 1:length(names(man)))
        if(isequal(string(names(man)[i])[1:4],"Capa") == true)
                if(r == 1)
                        Cap = names(man)[i]
                        r = r+1
                else
                        Cap = vcat(Cap, names(man)[i])
                        r = r+1
                end
        end
end

############### Facilities Parameters
# Number of facilities for each level of the supply chain

a= nrow(man); # manufacturing facilities
b= nrow(ster); # sterilization facilities
c= nrow(dist) # distribution sites
e = nrow(demand); # demand points
p = length(Cap); # size of assembly capacity set
inj = nrow(injmold); # injection molding suppliers
r1 = nrow(rubber1); # rubber part 1 suppliers
r2 = nrow(rubber2); # rubber part 2 suppliers
f = nrow(film); # plastic film suppliers

# Periods in model
periods = length(Dema);

############# Cost of establishing relationship
Ra = rep2s(injmold[:,:RCost],periods,infrate/Discount);
Rb = rep2s(rubber1[:,:RCost],periods,infrate/Discount);
Rc = rep2s(rubber2[:,:RCost],periods,infrate/Discount);
Rd = rep2s(film[:,:RCost],periods,infrate/Discount);
Rk = rep2s(ster[:,:RCost],periods,infrate/Discount);
Rl = rep2s(dist[:,:RCost],periods,infrate/Discount);

############ Cost of maintaining relationship
ra = rep2s(injmold[:,:rCost],periods,infrate/Discount);
rb = rep2s(rubber1[:,:rCost],periods,infrate/Discount);
rc = rep2s(rubber2[:,:rCost],periods,infrate/Discount);
rd = rep2s(film[:,:rCost],periods,infrate/Discount);
rk = rep2s(ster[:,:rCost],periods,infrate/Discount);
rl = rep2s(dist[:,:rCost],periods,infrate/Discount);

########### Manufacturing facility and line costs
Fj = rep2s(man[:,:OpCost],periods,1/Discount); # man facility operating cost
# assembly line scale up cost
SCjp = rep1(man[:,[:ScaleUp1,:ScaleUp2,:ScaleUp3,:ScaleUp4,:ScaleUp5]],periods,1.01/Discount);
# assembly line steady state cost
SSjp = rep1(man[:,[:Steady1,:Steady2,:Steady3,:Steady4,:Steady5]],periods,1.01/Discount);
# Incremental capacity cost

############ Capital Investment Parameters
```

```
CAPEX_assembly = rep1(man[: ,[:Capex1 ,:Capex2 ,:Capex3 ,:Capex4 ,:Capex5]] ,periods ,1/ Discount);
CAPEX_ster = rep2s(ster[: ,:Capex1],periods ,1/ Discount);

########## Variable Costs at Facilities/Suppliers
pa = rep2s(injmold[: ,:UnitCost],periods ,0.95);
pb = rep2s(rubber1[: ,:UnitCost],periods ,0.95);
pc = rep2s(rubber2[: ,:UnitCost],periods ,0.95);
pd = rep2s(film[: ,:UnitCost],periods ,0.95);
pk = rep2s(ster[: ,:UnitCost],periods ,0.99);
pl = rep2s(dist[: ,:UnitCost],periods ,0.99);

### Define demand
Demand1 = Array(demand[: , collect(Dema)]);

############### Transportation Parameters
# Transport mode speed in mph
air_speed = 450; #mph
truck_speed = 35; #mph
ocean_speed = 11 * 1.15; #16 knots * 1.15 miles/knot = mph

# Transport mode cost per mile
air_cost = 4/(2000/253);
truck_cost = 0.4;
ocean_cost = 0.1;

# Epsilon constraints
epsilon_ave1 = 240; # hours
epsilon_ave2 = 24; # hours
#epsilon_max = 150; # hours

# Import pre processed distances
#cd("/Users/samh/Documents/LGO/Spring2016/Thesis/Transport/");

## Pre calculated Distances in miles
injawater = convert(Array, readtable("water_case1.csv",header=false));
injaland = convert(Array,readtable("land_case1.csv",header=false));
injatotal = convert(Array,readtable("total_case1.csv",header=false));
r1awater = convert(Array,readtable("water_case2.csv",header=false));
r1aland = convert(Array,readtable("land_case2.csv",header=false));
r1atotal = convert(Array,readtable("total_case2.csv",header=false));
r2awater = convert(Array,readtable("water_case3.csv",header=false));
r2aland = convert(Array,readtable("land_case3.csv",header=false));
r2atotal = convert(Array,readtable("total_case3.csv",header=false));
fawater = convert(Array,readtable("water_case4.csv",header=false));
faland = convert(Array,readtable("land_case4.csv",header=false));
fatotal = convert(Array,readtable("total_case4.csv",header=false));
abwater = convert(Array,readtable("water_case5.csv",header=false));
abland = convert(Array,readtable("land_case5.csv",header=false));
abtotal = convert(Array,readtable("total_case5.csv",header=false));
bcwater = convert(Array,readtable("water_case6.csv",header=false));
bcland = convert(Array,readtable("land_case6.csv",header=false));
bctotal = convert(Array,readtable("total_case6.csv",header=false));
cewater = convert(Array,readtable("water_case7.csv",header=false));
celand = convert(Array,readtable("land_case7.csv",header=false));
```

```
cetotal = convert(Array,readtable("total_case7.csv",header=false));

## Transport Cost tables
cost1inja = injawater*ocean_cost + injaland*truck_cost;
cost2inja = injatotal*air_cost;
cost1r1a = r1awater*ocean_cost + r1aland*truck_cost;
cost2r1a = r1atotal*air_cost;
cost1r2a = r2awater*ocean_cost + r2aland*truck_cost;
cost2r2a = r2atotal*air_cost;
cost1fa = fawater*ocean_cost + faland*truck_cost;
cost2fa = fatotal*air_cost;
cost1ab = abwater*ocean_cost + abland*truck_cost;
cost2ab = abtotal*air_cost;
cost1bc = bcwater*ocean_cost + bcland*truck_cost;
cost2bc = bctotal*air_cost;
cost1ce = cewater*ocean_cost + celand*truck_cost;
cost2ce = cetotal*air_cost;

## Time tables
time1inja = injawater/ocean_speed + injaland/truck_speed;
time2inja = injatotal/air_speed;
time1r1a = r1awater/ocean_speed + r1aland/truck_speed;
time2r1a = r1atotal/air_speed;
time1r2a = r2awater/ocean_speed + r2aland/truck_speed;
time2r2a = r2atotal/air_speed;
time1fa = fawater/ocean_speed + faland/truck_speed;
time2fa = fatotal/air_speed;
time1ab = abwater/ocean_speed + abland/truck_speed;
time2ab = abtotal/air_speed;
time1bc = bcwater/ocean_speed + bcland/truck_speed;
time2bc = bctotal/air_speed;
time1ce = cewater/ocean_speed + celand/truck_speed;
time2ce = cetotal/air_speed;


################################ Variables ###################################################
## Facility/Partner Selection at time t
@defVar(n, Xa[i = 1:inj, t = 1:periods], Bin); # decision to use injection molding supplier i
@defVar(n, Xb[i = 1:r1, t = 1:periods], Bin); # decision to use rubber1 supplier i
@defVar(n, Xc[i = 1:r2, t = 1:periods], Bin); # decision to use rubber2 supplier i
@defVar(n, Xd[i = 1:f, t = 1:periods], Bin); # decision to use film supplier i
@defVar(n, Xj[i=1:a, t = 1:periods], Bin); # decision to open assembly facility a
@defVar(n, Cjp[i=1:a, j = 1:p, t = 1:periods], Bin); # add capacity p at facility a
@defVar(n, Xk[i=1:b, t = 1:periods], Bin); # decision to use sterilizer b
@defVar(n, Xl[i=1:c, t = 1:periods], Bin); # decision to use distribution center c

## Establish relationship with facility/partner
@defVar(n, Z1a[i = 1:inj, t = 1:periods], Bin); # establish inj molding partner
@defVar(n, Z1b[i = 1:r1, t = 1:periods], Bin); # establish rubber1 partner
@defVar(n, Z1c[i = 1:r2, t = 1:periods], Bin); # establish rubber2 partner
@defVar(n, Z1d[i = 1:f, t = 1:periods], Bin); # establish film partner
@defVar(n, Z1jp[i = 1:a,j = 1:p, t = 1:periods], Bin); # establish assembly line with capacity
    ↪ p in facility j
@defVar(n, Z1j[i = 1:a, t = 1:periods], Bin); # establish assembly facility relationship
```

```
@defVar(n, Z1k[i = 1:b, t = 1:periods], Bin); # establish sterilizer relationship
@defVar(n, Z1l[i = 1:c, t = 1:periods], Bin); # establish distribution center relationship

## Maintain relationship with facility/partner
@defVar(n, Z2a[i = 1:inj, t = 1:periods], Bin); # inj molding partner
@defVar(n, Z2b[i = 1:r1, t = 1:periods], Bin); # rubber1 partner
@defVar(n, Z2c[i = 1:r2, t = 1:periods], Bin); # rubber2 partner
@defVar(n, Z2d[i = 1:f, t = 1:periods], Bin); # film partner
@defVar(n, Z2jp[i = 1:a,j = 1:p, t = 1:periods], Bin); # assembly line with capacity p in
    ↪ facility j
@defVar(n, Z2j[i = 1:a, t = 1:periods], Bin); # assembly facility relationship
@defVar(n, Z2k[i = 1:b, t = 1:periods], Bin); # sterilizer relationship
@defVar(n, Z2l[i = 1:c, t = 1:periods], Bin); # distribution center relationship

## Inventory
@defVar(n, Ilt[i = 1:c, t = 1:periods] >= 0); # inventory at DC c at time t

## Flows
@defVar(n, Yaj[r = 1:nmodes, i = 1:inj, j = 1:a, t = 1:periods] >= 0); # flow of injection
    ↪ molded component to assembly a
@defVar(n, Ybj[r = 1:nmodes,i = 1:r1, j = 1:a, t = 1:periods] >= 0); # flow of component rubber
    ↪ 1 to assembly a
@defVar(n, Ycj[r = 1:nmodes,i = 1:r2, j = 1:a, t = 1:periods] >= 0); # flow of component rubber
    ↪ 2 to assembly a
@defVar(n, Ydj[r = 1:nmodes,i = 1:f, j = 1:a, t = 1:periods] >= 0); # flow of component film to
    ↪ assembly a
@defVar(n, Yjk[r = 1:nmodes,i = 1:a, j = 1:b, t = 1:periods] >= 0); # flow of product from
    ↪ manufacturing facility a to sterilizer b
@defVar(n, Ykl[r = 1:nmodes,i = 1:b, j = 1:c, t = 1:periods] >= 0); # flow of product from
    ↪ sterilizer b to DC c
@defVar(n, Ylm[r = 1:nmodes,i = 1:c, j = 1:e, t = 1:periods] >= 0); # flow of product from DC c
    ↪ to demand node e
@defVar(n, ilm[r = 1:nmodes,i = 1:c, j = 1:e, t = 1:periods] >= 0); # inventory flow from DC c
    ↪ to demand node e

## Transport Modes
@defVar(n, Saj[i=1:inj, j=1:a,t=1:periods],Bin); # Slow mode for flow from injection molder to
    ↪ assembly a
@defVar(n, Sbj[i=1:r1, j=1:a,t=1:periods],Bin); # Slow mode for flow from rubber 1 supplier to
    ↪ assembly a
@defVar(n, Scj[i=1:r2, j=1:a,t=1:periods],Bin); # Slow mode for flow from rubber 2 supplier to
    ↪ assembly a
@defVar(n, Sdj[i=1:f, j=1:a,t=1:periods],Bin); # Slow mode for flow from film supplier to
    ↪ assembly a
@defVar(n, Sjk[i=1:a, j=1:b,t=1:periods],Bin); # Slow mode for flow from assembly a to
    ↪ sterilizer b
@defVar(n, Skl[i=1:b, j=1:c,t=1:periods],Bin); # Slow mode for flow from sterilizer b to DC c
@defVar(n, Slm[i=1:c, j=1:e,t=1:periods],Bin); # Slow mode for flow from DC c to demand e

@defVar(n, Aaj[i=1:inj, j=1:a,t=1:periods],Bin); # Fast mode for flow from injection molder to
    ↪ assembly a
@defVar(n, Abj[i=1:r1, j=1:a,t=1:periods],Bin); # Fast mode for flow from rubber 1 supplier to
    ↪ assembly a
```

```
@defVar(n, Acj[i=1:r2, j=1:a,t=1:periods],Bin); # Fast mode for flow from rubber 2 supplier to
    ↪ assembly a
@defVar(n, Adj[i=1:f, j=1:a, t=1:periods],Bin); # Fast mode for flow from film supplier to
    ↪ assembly a
@defVar(n, Ajk[i=1:a, j=1:b, t=1:periods],Bin); # Fast mode for flow from assembly a to
    ↪ sterilizer b
@defVar(n, Akl[i=1:b, j=1:c,t=1:periods],Bin); # Fast mode for flow from sterilizer b to DC c
@defVar(n, Alm[i=1:c, j=1:e,t=1:periods],Bin); # Fast mode for flow from DC c to demand e

## Incremental Capacity
@defVar(n, AddCap[i=1:a, j = 1:p, t=1:periods] >= 0); # additional capacity option for
    ↪ manufacturing lines

#@defVar(n, Rec[1,i=1:c, j=1:e, t=1:periods] >= 0); # recourse variable


########################### FLOW TIME ###########################################################
#### 1 Transport Time
AJ = time(Yaj,time1inja,periods,1,1) + time(Yaj,time2inja,periods,1,2);
BJ = time(Ybj,time1r1a,periods,1,1) + time(Ybj,time2r1a,periods,1,2);
CJ = time(Ycj,time1r2a,periods,1,1) + time(Ycj,time2r2a,periods,1,2);
DJ = time(Ydj,time1fa,periods,1,1) + time(Ydj,time2fa,periods,1,2);
JK = time(Yjk,time1ab,periods,1,1) + time(Yjk,time2ab,periods,1,2);
KL = time(Ykl,time1bc,periods,1,1) + time(Ykl,time2bc,periods,1,2);
LM = time(Ylm,time1ce,periods,1,1) + time(Ylm,time2ce,periods,1,2);
ILM = time(ilm,time1ce,periods,1,1) + time(ilm,time2ce,periods,1,2);
#REC = time(Rec,time2ce,periods,1,1);

################################ Constraints ##################################################


######## DEMAND ######################################################

# Demand Constraint
for(t = 1:periods)
for(j = 1:e)
@addConstraint(n, sum(Ylm[:,:,j,t]) + sum(ilm[:,:,j,t]) >= Demand1[j,t]);
end
end

mult = 10;
############ FLOW ###################################################
##### Flow Constraints
# Injection molders to assemblers
for(t = 2:periods)
for(i = 1:a)
@addConstraint(n, sum(mult*Yaj[:,:,i,t]) >= sum(Yjk[:,i,:,t]));
end
end

# Rubber 1 to assemblers
for(t = 2:periods)
for(i = 1:a)
@addConstraint(n, sum(mult*Ybj[:,:,i,t]) >= sum(Yjk[:,i,:,t]));
```

```
end
end

# Rubber 2 to assemblers
for(t = 2:periods)
for(i = 1:a)
@addConstraint(n, sum(mult*Ycj[:,:,i,t]) >= sum(Yjk[:,i,:,t]));
end
end

# Rubber 2 to assemblers
for(t = 2:periods)
for(i = 1:a)
@addConstraint(n, sum(mult*Ydj[:,:,i,t]) >= sum(Yjk[:,i,:,t]));
end
end

# Assembly to sterilizers
for(t = 2:periods)
for(i = 1:b)
@addConstraint(n, sum(Yjk[:,:,i,t]) >= sum(Ykl[:,i,:,t]));
end
end

# Sterilizers to DCs
for(t = 2:periods)
for(i = 1:c)
@addConstraint(n, sum(Ykl[:,:,i,t]) >= sum(Ylm[:,i,:,t]));
end
end

# Mode Selection (ensure max of one arc connecting two nodes)
for(t = 2:periods)
@addConstraint(n, Saj[:,:,t] + Aaj[:,:,t] .<= ones(size(Aaj)[1:2]));
@addConstraint(n, Sbj[:,:,t] + Abj[:,:,t] .<= ones(size(Abj)[1:2]));
@addConstraint(n, Scj[:,:,t] + Acj[:,:,t] .<= ones(size(Acj)[1:2]));
@addConstraint(n, Sdj[:,:,t] + Adj[:,:,t] .<= ones(size(Adj)[1:2]));
@addConstraint(n, Sjk[:,:,t] + Ajk[:,:,t] .<= ones(size(Ajk)[1:2]));
@addConstraint(n, Skl[:,:,t] + Akl[:,:,t] .<= ones(size(Akl)[1:2]));
@addConstraint(n, Slm[:,:,t] + Alm[:,:,t] .<= ones(size(Alm)[1:2]));
end

# Stochastic problem has no flow in year 1
for(t = 1)
@addConstraint(n, Saj[:,:,t] + Aaj[:,:,t] .== 0);
@addConstraint(n, Sbj[:,:,t] + Abj[:,:,t] .== 0);
@addConstraint(n, Scj[:,:,t] + Acj[:,:,t] .== 0);
@addConstraint(n, Sdj[:,:,t] + Adj[:,:,t] .== 0);
@addConstraint(n, Sjk[:,:,t] + Ajk[:,:,t] .== 0);
@addConstraint(n, Skl[:,:,t] + Akl[:,:,t] .== 0);
@addConstraint(n, Slm[:,:,t] + Alm[:,:,t] .== 0);
end

# Flow possible only if mode selected
```

```
for(t=2:periods)
@addConstraint(n, squeeze(Yaj[1,:,:,t],1) .<= TransCap*Saj[:,:,t]);
@addConstraint(n, squeeze(Ybj[1,:,:,t],1) .<= TransCap*Sbj[:,:,t]);
@addConstraint(n, squeeze(Ycj[1,:,:,t],1) .<= TransCap*Scj[:,:,t]);
@addConstraint(n, squeeze(Ydj[1,:,:,t],1) .<= TransCap*Sdj[:,:,t]);
@addConstraint(n, squeeze(Yjk[1,:,:,t],1) .<= TransCap*Sjk[:,:,t]);
@addConstraint(n, squeeze(Ykl[1,:,:,t],1) .<= TransCap*Skl[:,:,t]);
@addConstraint(n, squeeze(Ylm[1,:,:,t],1) + squeeze(ilm[1,:,:,t],1) .<= TransCap*Slm[:,:,t]);
end

for(t=2:periods)
@addConstraint(n, squeeze(Yaj[2,:,:,t],1) .<= TransCap*Aaj[:,:,t]);
@addConstraint(n, squeeze(Ybj[2,:,:,t],1) .<= TransCap*Abj[:,:,t]);
@addConstraint(n, squeeze(Ycj[2,:,:,t],1) .<= TransCap*Acj[:,:,t]);
@addConstraint(n, squeeze(Ydj[2,:,:,t],1) .<= TransCap*Adj[:,:,t]);
@addConstraint(n, squeeze(Yjk[2,:,:,t],1) .<= TransCap*Ajk[:,:,t]);
@addConstraint(n, squeeze(Ykl[2,:,:,t],1) .<= TransCap*Akl[:,:,t]);
@addConstraint(n, squeeze(Ylm[2,:,:,t],1) + squeeze(ilm[2,:,:,t],1) .<= TransCap*Alm[:,:,t]);
end

# Inventory flow constraint
@addConstraint(n, ilm[:,:,:,1] .== 0);
for(t=2:periods)
for(i=1:c)
@addConstraint(n, sum(ilm[:,i,:,t]) <= Ilt[i,t 1]); # flow cannot exceed inventory on hand
end
end

######## LEAD TIME E constraint ##############
# Epsilon average constraint

for(t=2:periods)
@addConstraint(n, sum(AJ[:,:,t])+sum(BJ[:,:,t])+sum(CJ[:,:,t])+sum(DJ[:,:,t])+sum(JK[:,:,t])+
    ↪ sum(KL[:,:,t]) <= sum(Ykl[:,:,:,t])*epsilon_ave1);
end

for(t=2:periods)
@addConstraint(n, sum(LM[:,:,t])+sum(ILM[:,:,t]) <= (sum(Ylm[:,:,:,t])+sum(ilm[:,:,:,t]))*
    ↪ epsilon_ave2);
end

# # Epsilon max constraint
#  for(t=1:periods)
#  for(i=1:inj)
#  for(j=1:a)
#  for(k=1:b)
#  for(l=1:c)
#  for(m=1:e)
#        @addConstraint(n, Saj[i,j,t]*time1inja[i,j]+Aaj[i,j,t]*time2inja[i,j]+Sjk[j,k,t]*
    ↪ time1ab[j,k]+Ajk[j,k,t]*time2ab[j,k]+Skl[k,l,t]*time1bc[k,l]+Akl[k,l,t]*time2bc[k,l]+
    ↪ Slm[l,m,t]*time1ce[l,m]+Alm[l,m,t]*time2ce[l,m] <= epsilon_max);
# end
#      end
# end
```

```
# end
# end
# end

# for(t=1:periods)
# for(i=1:r1)
# for(j=1:a)
# for(k=1:b)
# for(l=1:c)
# for(m=1:e)
#         @addConstraint(n, Sbj[i,j,t]*time1r1a[i,j]+Abj[i,j,t]*time2r1a[i,j]+Sjk[j,k,t]*time1ab[
    ↪ j,k]+Ajk[j,k,t]*time2ab[j,k]+Skl[k,l,t]*time1bc[k,l]+Akl[k,l,t]*time2bc[k,l]+Slm[l,m,t
    ↪ ]*time1ce[l,m]+Alm[l,m,t]*time2ce[l,m] <= epsilon_max);
# end
# end
# end
# end
# end
# end

# for(t=1:periods)
# for(i=1:r2)
# for(j=1:a)
# for(k=1:b)
# for(l=1:c)
# for(m=1:e)
#         @addConstraint(n, Scj[i,j,t]*time1r2a[i,j]+Acj[i,j,t]*time2r2a[i,j]+Sjk[j,k,t]*time1ab[
    ↪ j,k]+Ajk[j,k,t]*time2ab[j,k]+Skl[k,l,t]*time1bc[k,l]+Akl[k,l,t]*time2bc[k,l]+Slm[l,m,t
    ↪ ]*time1ce[l,m]+Alm[l,m,t]*time2ce[l,m] <= epsilon_max);
# end
# end
# end
# end
# end
# end

# for(t=1:periods)
# for(i=1:f)
# for(j=1:a)
# for(k=1:b)
# for(l=1:c)
# for(m=1:e)
#         @addConstraint(n, Sdj[i,j,t]*time1fa[i,j]+Adj[i,j,t]*time2fa[i,j]+Sjk[j,k,t]*time1ab[j,
    ↪ k]+Ajk[j,k,t]*time2ab[j,k]+Skl[k,l,t]*time1bc[k,l]+Akl[k,l,t]*time2bc[k,l]+Slm[l,m,t]*
    ↪ time1ce[l,m]+Alm[l,m,t]*time2ce[l,m] <= epsilon_max);
# end
# end
# end
# end
# end
# end

######## CAPACITY ##################
# Injection molding capacity flow constraint
```

```
for(t = 2:periods)
for(i = 1:inj)
@addConstraint(n, sum(Yaj[:,i,:,t]) <= injmold[i,:Capacity1]*Z2a[i,t]);
end
end

# Rubber1 capacity flow constraint
for(t = 2:periods)
for(i = 1:r1)
@addConstraint(n, sum(Ybj[:,i,:,t]) <= rubber1[i,:Capacity1]*Z2b[i,t]);
end
end

# Rubber 2 capacity flow constraint
for(t = 2:periods)
for(i = 1:r1)
@addConstraint(n, sum(Ycj[:,i,:,t]) <= rubber2[i,:Capacity1]*Z2c[i,t]);
end
end

# Film capacity flow constraint
for(t = 2:periods)
for(i = 1:f)
@addConstraint(n, sum(Ydj[:,i,:,t]) <= film[i,:Capacity1]*Z2d[i,t]);
end
end

# Manufacturing line selection constraints
for(t = 1:periods)
for(i = 1:p)
@addConstraint(n, sum(Cjp[:,i,t]) <= 1)
end
end

# Capacity addition possible only if facility a is selected
for(t = 1:periods)
for(i = 1:a)
for(j = 1:p)
@addConstraint(n, Cjp[i,j,t] <= Xj[i,t]);
end
end
end

# Additional manufacturing capacity constraints
for(t = 1:periods)
for(i = 1:a)
@addConstraint(n, AddCap[i,:,t] .<= ceil(0.08*Array(man[i,collect(Cap)])).*Z2jp[i,:,t]); # No
    ↪ additional capacity permitted without opening line first
end
end

# Manufacturing capacity flow constraint
@addConstraint(n, sum(Yjk[:,:,:,1]) == 0);
for(t = 2:periods)
```

```
for(i = 1:a)
@addConstraint(n, sum(Yjk[:,i,:,t]) <= sum(Array(man[i,collect(Cap)]).*Z2jp[i,:,t]) + sum(
    ↪ AddCap[i,:,t 1]));
end
end

# Sterilizer capacity flow constraint
for(t = 2:periods)
for(i = 1:b)
@addConstraint(n, sum(Ykl[:,i,:,t]) <= ster[i,:Capacity1]*Z2k[i,t]);
end
end

# Dist capacity flow constraint
for(t = 2:periods)
for(i = 1:c)
@addConstraint(n, sum(Ylm[:,i,:,t]) + sum(ilm[:,i,:,t]) <= dist[i,:Capacity1]*Z2l[i,t]);
end
end

######## Relationship Establishment
# Injection molding supplier
@addConstraint(n, Z1a[:,1] .== Xa[:,1]);
for(t = 2:periods)
@addConstraint(n, Z1a[:,t] .>= (Xa[:,t] . Xa[:,t 1]));
end

# Rubber1 supplier
@addConstraint(n, Z1b[:,1] .== Xb[:,1]);
for(t = 2:periods)
@addConstraint(n, Z1b[:,t] .>= (Xb[:,t] . Xb[:,t 1]));
end

# Diaphragm supplier
@addConstraint(n, Z1c[:,1] .== Xc[:,1]);
for(t = 2:periods)
@addConstraint(n, Z1c[:,t] .>= (Xc[:,t] . Xc[:,t 1]));
end

# Film supplier
@addConstraint(n, Z1d[:,1] .== Xd[:,1]);
for(t = 2:periods)
@addConstraint(n, Z1d[:,t] .>= (Xd[:,t] . Xd[:,t 1]));
end

# Assembly line change
@addConstraint(n, Z1jp[:,:,1] .== Cjp[:,:,1]);
for(t = 2:periods)
@addConstraint(n, Z1jp[:,:,t] .>= (Cjp[:,:,t] . Cjp[:,:,t 1]));
end

# Assembly facility
@addConstraint(n, Z1j[:,1] .== Xj[:,1]);
for(t = 2:periods)
```

```
@addConstraint(n, Z1j[:,t] .>= (Xj[:,t] .  Xj[:,t 1]));
end

# Sterilizer facility
@addConstraint(n, Z1k[:,1] .== Xk[:,1]);
for(t = 2:periods)
@addConstraint(n, Z1k[:,t] .>= (Xk[:,t] .  Xk[:,t 1]));
end

# DC facility
@addConstraint(n, Z1l[:,1] .== Xl[:,1]);
for(t = 2:periods)
@addConstraint(n, Z1l[:,t] .>= (Xl[:,t] .  Xl[:,t 1]));
end



######## Relationship Maintenance

# Injection Molding Supplier
@addConstraint(n, Z2a[:,1] .== 0);
for(t = 2:periods)
@addConstraint(n, Z2a[:,t] .<= Xa[:,t])
@addConstraint(n, Z2a[:,t] .<= Xa[:,t 1])
@addConstraint(n, Z2a[:,t] .>= (Xa[:,t] .+ Xa[:,t 1] .  1))
end

# Rubber1 Supplier
@addConstraint(n, Z2b[:,1] .== 0);
for(t = 2:periods)
@addConstraint(n, Z2b[:,t] .<= Xb[:,t])
@addConstraint(n, Z2b[:,t] .<= Xb[:,t 1])
@addConstraint(n, Z2b[:,t] .>= (Xb[:,t] .+ Xb[:,t 1] .  1))
end

# Diaphragm Supplier
@addConstraint(n, Z2c[:,1] .== 0);
for(t = 2:periods)
@addConstraint(n, Z2c[:,t] .<= Xc[:,t])
@addConstraint(n, Z2c[:,t] .<= Xc[:,t 1])
@addConstraint(n, Z2c[:,t] .>= (Xc[:,t] .+ Xc[:,t 1] .  1))
end

# Film Supplier
@addConstraint(n, Z2d[:,1] .== 0);
for(t = 2:periods)
@addConstraint(n, Z2d[:,t] .<= Xd[:,t])
@addConstraint(n, Z2d[:,t] .<= Xd[:,t 1])
@addConstraint(n, Z2d[:,t] .>= (Xd[:,t] .+ Xd[:,t 1] .  1))
end

# Assembly facility
@addConstraint(n, Z2j[:,1] .== 0);
for(t = 2:periods)
```

```
@addConstraint(n, Z2j[:,t] .<= Xj[:,t])
@addConstraint(n, Z2j[:,t] .<= Xj[:,t 1])
@addConstraint(n, Z2j[:,t] .>= (Xj[:,t] .+ Xj[:,t 1] . 1))
end

# Assembly line
@addConstraint(n, Z2jp[:,:,1] .== 0);
for(t = 2:periods)
@addConstraint(n, Z2jp[:,:,t] .<= Cjp[:,:,t])
@addConstraint(n, Z2jp[:,:,t] .<= Cjp[:,:,t 1])
@addConstraint(n, Z2jp[:,:,t] .>= (Cjp[:,:,t] .+ Cjp[:,:,t 1]   1))
end

# Sterilizer
@addConstraint(n, Z2k[:,1] .== 0);
for(t = 2:periods)
@addConstraint(n, Z2k[:,t] .<= Xk[:,t])
@addConstraint(n, Z2k[:,t] .<= Xk[:,t 1])
@addConstraint(n, Z2k[:,t] .>= (Xk[:,t] .+ Xk[:,t 1] . 1))
end

# DC
@addConstraint(n, Z2l[:,1] .== 0);
for(t = 2:periods)
@addConstraint(n, Z2l[:,t] .<= Xl[:,t])
@addConstraint(n, Z2l[:,t] .<= Xl[:,t 1])
@addConstraint(n, Z2l[:,t] .>= (Xl[:,t] .+ Xl[:,t 1] . 1))
end

# Perpetuate incremental capacity decision
@addConstraint(n, AddCap[:,:,1] .== 0);
for(t = 2:periods)
@addConstraint(n, AddCap[:,:,t] .>= AddCap[:,:,t 1])
end

########### INVENTORY #######################
# Inventory constraint relating production to demand
for(t = 2:periods)
for(i = 1:c)
@addConstraint(n, Ilt[i,t]   sum(Ykl[:,:,i,t]) + sum(Ylm[:,i,:,t]) == 0) # inventory equals
    ↪ difference between production and demand
end
end

@addConstraint(n, Ilt[:,1] .== 0)


## Line Capacity increments
for(t=1:periods)
for(i=2:p)
@addConstraint(n, sum(Cjp[:,i,t]) <= sum(Cjp[:,i 1,t])) # ensures new line can't be used until
    ↪ previous line is open
end
end
```

```
## Line Capacity increments
for(t=1:periods)
for(i=1:a)
@addConstraint(n, Cjp[i,3,t] <= Cjp[i,2,t]) # ensures new line can't be used until previous
    ↪ line is open
end
end

# Initial Conditions constraints
@addConstraint(n, (sum(Yaj[:,:,:,1]) + sum(Ybj[:,:,:,1]) + sum(Ycj[:,:,:,1]) + sum(Ydj
    ↪ [:,:,:,1]) + sum(Yjk[:,:,:,1]) + sum(Ykl[:,:,:,1]) + sum(Ylm[:,:,:,1]) + sum(ilm
    ↪ [:,:,1])) == 0)

@addConstraint(n, (sum(Saj[:,:,1])+sum(Sbj[:,:,1])+sum(Scj[:,:,1])+sum(Sdj[:,:,1])+sum(Sjk
    ↪ [:,:,1])+sum(Skl[:,:,1])+sum(Slm[:,:,1])+sum(Aaj[:,:,1])+sum(Abj[:,:,1])+sum(Acj
    ↪ [:,:,1])+sum(Adj[:,:,1])+sum(Ajk[:,:,1])+sum(Akl[:,:,1])+sum(Alm[:,:,1])) == 0)
############################ COSTS #########################################################

########################## First Stage costs
### Capital Investment
FIRSTA = sum((Z1jp.*CAPEX_assembly)[:,:,1]) + sum((Z1k.*CAPEX_ster)[:,1]);

#### 2 Operating and Relationship Fixed Costs
FIRST_OPCOST = sum((Fj.*Xj)[:,1]);
FIRST_LINECOST1 = sum((SCjp.*Z1jp)[:,:,1]);
FIRST_LINECOST2 = sum((SSjp.*Z2jp)[:,:,1]);
FIRST_REL1 = sum((Ra.*Z1a)[:,1])+sum((Rb.*Z1b)[:,1])+sum((Rc.*Z1c)[:,1])+sum((Rd.*Z1d)[:,1])+
    ↪ sum((Rk.*Z1k)[:,1])+sum((Rl.*Z1l)[:,1]);
FIRST_REL2 = sum((ra.*Z2a)[:,1])+sum((rb.*Z2b)[:,1])+sum((rc.*Z2c)[:,1])+sum((rd.*Z2d)[:,1])+
    ↪ sum((rk.*Z2k)[:,1])+sum((rl.*Z2l)[:,1]);

######################## Second Stage Costs
### Transport Costs Slow Mode
TClow = tcostl(Yaj,costlinja,infrate,Discount)+tcostl(Ybj,costlr1a,infrate,Discount)+tcostl(Ycj
    ↪ ,costlr2a,infrate,Discount)+tcostl(Ydj,costlfa,infrate,Discount)+ tcostl(Yjk,costlab,
    ↪ infrate,Discount)+tcostl(Ykl,costlbc,infrate,Discount)+tcostl(Ylm,costlce,infrate,
    ↪ Discount)+tcostl(ilm,costlce,infrate,Discount);

#### Transport Cost Fast Mode
TChigh = tcosth(Yaj,cost2inja,infrate,Discount)+tcosth(Ybj,cost2r1a,infrate,Discount)+tcosth(
    ↪ Ycj,cost2r2a,infrate,Discount)+tcosth(Ydj,cost2fa,infrate,Discount)+ tcosth(Yjk,cost2ab
    ↪ ,infrate,Discount)+tcosth(Ykl,cost2bc,infrate,Discount)+tcosth(Ylm,cost2ce,infrate,
    ↪ Discount)+tcosth(ilm,cost2ce,infrate,Discount);


#### Capital Investment
A = sum((Z1jp.*CAPEX_assembly)[:,:,2:periods]) + sum((Z1k.*CAPEX_ster)[:,2:periods]);

#### 2 Operating and Relationship Fixed Costs
OPCOST = sum((Fj.*Xj)[:,2:periods]);
LINECOST1 = sum((SCjp.*Z1jp)[:,:,2:periods]);
LINECOST2 = sum((SSjp.*Z2jp)[:,:,2:periods]);
```

```
REL1 = sum((Ra.*Z1a)[:,2:periods])+sum((Rb.*Z1b)[:,2:periods])+sum((Rc.*Z1c)[:,2:periods])+sum
    ↪ ((Rd.*Z1d)[:,2:periods])+sum((Rk.*Z1k)[:,2:periods])+sum((Rl.*Z1l)[:,2:periods]);
REL2 = sum((ra.*Z2a)[:,2:periods])+sum((rb.*Z2b)[:,2:periods])+sum((rc.*Z2c)[:,2:periods])+sum
    ↪ ((rd.*Z2d)[:,2:periods])+sum((rk.*Z2k)[:,2:periods])+sum((rl.*Z2l)[:,2:periods]);


#Unit = sum(repeat(man[:,:UnitCost], outer = [1,1,periods]).*Yjk);
ACap = sum((1280*4.3*AddCap./discount(size(AddCap),Discount,periods))[:,:,2:periods]); #./
    ↪ discount(size(Z4), Discount, periods)

#### Unit Costs
UCa = unitcosts(Yaj*mult,pa,periods,Discount);
UCb = unitcosts(Ybj*mult,pb,periods,Discount);
UCc = unitcosts(Ycj*mult,pc,periods,Discount);
UCd = unitcosts(Ydj*mult,pd,periods,Discount);
UCk = unitcosts(Ykl,pk,periods,Discount);
UCl = unitcosts(Ylm,pl,periods,Discount);
UCi = unitcosts(ilm,pl,periods,Discount);
UNITCOST = UCa+UCb+UCc+UCd+UCk+UCl+UCi;

#### Holding Costs
HOLD = sum(rep2s(dist[:,:Holding],periods,1.01/Discount).*Ilt);

#cd("/Users/samh/Documents/LGO/Internship/Model/");
include("Model_V5_Stochastic_sub1_1.jl");
include("Model_V5_Stochastic_sub2_1.jl");


############################### Objective ################################################
@setObjective(n, Min, (FIRSTA + FIRST_OPCOST + FIRST_REL2 + FIRST_REL1 + FIRST_LINECOST2 +
    ↪ FIRST_LINECOST1 + (1/3)*(A + TClow + TChigh + OPCOST + LINECOST1 + LINECOST2 + REL1 +
    ↪ REL2 + ACap + UNITCOST + HOLD) + (1/3)*(A2 + TClow2 + TChigh2 + OPCOST2 + LINECOST12 +
    ↪ LINECOST22 + REL12 + REL22 + ACap2 + UNITCOST2 + HOLD2) + (1/3)*(A3 + TClow3 + TChigh3
    ↪ + OPCOST3 + LINECOST13 + LINECOST23 + REL13 + REL23 + ACap3 + UNITCOST3 + HOLD3)));

solve(n);

############################### Print Results ################################################
```

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