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Synthesis of Optimization and Simulation for Multi-Period Supply Chain Planning with Consideration of Risks

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A Dissertation Submitted to The Graduate School at the University of Missouri – St. Louis in partial fulfillment of the requirements for the degree
Doctor of Philosophy in Business Administration with an emphasis in Logistics and Supply Chain Management

December 2016

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Table of Contents

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Table of Figures

 Copyright, Liang Xu, 2016

Table of Tables

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Abstract

Solutions to deterministic optimizing models for supply chains can be very sensitive to the formulation of the objective function and the choice of planning horizon. We illustrate how multi-period optimizing models may be counterproductive if traditional accounting of revenue and costs is performed and planning occurs with too short a planning horizon. We propose a “value added” complement to traditional financial accounting that allows planning to occur with shorter horizons than previously thought necessary.

This dissertation presents a simulation model with an embedded optimizer that can help organizations develop strategies that minimize expected costs or maximize expected contributions to profit while maintaining a designated level of service. Plans are developed with a deterministic optimizing model and each of the decisions for the first period in the planning horizon are implemented within the simulator. Random deviations in demands and in upstream and downstream shipping times are imposed and the state of the system is updated at the end of each simulated period of activity. This process continues iteratively for a chosen number of periods (90 days for this research). Multiple replications are performed using unique random number seeds for each replication. The simulation model generates detailed event logs for each period of simulated activity that are used to analyze supply-chain performance and supply-chain risk. Supply-chain performance is measured with eleven key

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performance indicators that reveal system behavior at the overall supply-chain level, as well as performance related to individual plants, warehouses, and products.

There are three key findings from this research. First, a value-added complement in an optimization model's objective function can allow planning to occur effectively with a significantly shorter horizon than required when traditional accounting of costs and revenues is employed. Second, solutions with the value-added complement are robust for situations where supply-chain disruptions cause unexpected depletions in inventories at production facilities and warehouses. Third, *ceteris paribus,* the hybrid multi-period planning approach generates solutions with higher service levels for products with greater revenue per average production-minute, shorter average upstream lead times, and lower coefficients of variation for daily demand.

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Chapter 1 Introduction

1.1 Overview

Competition, globalization, shortened product lives and lean production systems have led managers to focus on efficiency and cost reduction in the design and management of supply chains (Ghadge et al., 2012; Tang et al., 2012; Wagner and Bode, 2006; Blackhurst et al., 2005). Greater efficiency, however, does not guarantee greater effectiveness (Heckmann et al. 2015). Implementing various cost effective strategies such as outsourcing, global sourcing, lean production, etc. can reduce safety stocks and time buffers. This exposes enterprises to a higher level of supply chain (SC) risk and acquires even greater significance for organizations involved in multi-mode transportation across international boundaries.

Empirical studies conducted by Hendricks and Singhal (2003, 2005a, b) revealed that SC disruptions can have a significant impact on both shareholder value and operating performance. The Wall Street Journal reported that a Hong Kong port strike in 2013 cost Hongkong International Terminals $644,000 per day (Chiu 2013). Disruption of production for a few days, caused by a custom employees strike, resulted in a million dollar lost for a consumer packaged goods firm located in South America (Schmitt and Singh, 2012). The National Retail Federation (NRF) and National Association of Manufacturers (NAM) revealed that the 10-day stoppage at the West Coast ports in 2002 cost the U.S. economy about $1 billion a day and months to recover. Moreover, the NRF-NAM study estimates that a 5-day stoppage at U.S. West Coast ports will cause a daily reduction of GDP by $1.9 billion and affect 73,000 jobs, while a 20-day stoppage will result in a daily loss of $2.5 billion and disrupt 405,000 jobs (Elenstar, 2014).

As the likelihood, frequency and magnitude of SC disruptions increase (Blackhurst et al., 2005; Coleman, 2006; Okubo et al., 2013; Cardoso et al., 2015), supply chain risk management (SCRM) attracts the attention of both researchers and practitioners. Adding to the complexity of supply chain risk management is the fact that strategies needed to mitigate one type of risks may simultaneously increase other risks (Chopra and Sodhi, 2004). Deep relationships with a single supplier, for example, may reduce the risks of receiving incompatible parts but increase the risk of shutdowns due to major disruptions at the supplier's facilities. Thus, a holistic approach is advocated and organizations should adopt SCRM practices at strategic, tactical, and operational levels. At the tactical and operational levels, SCRM (Hsieh and Wu, 2008; Kara and Kayis, 2004; Pitty *et al*., 2008; etc.) emphasizes reactive actions to diminish negative impacts once disruptions occur. At the strategic level, SCRM focuses on dealing with risks in a proactive way, thereby reducing or preventing the negative impacts caused by anticipated disruptions (Muckstadt *et al*., 2003; Rice and Caniato, 2003a; Norrman *et al*., 2004; Herroelen and Leus, 2005; Kleindorfer and Saad, 2005; Hendricks and Singhal, 2005a; Hendricks *et al*, 2008; Ji and Zhu, 2008; etc.). When supply chain disruptions or unusual events occur, managerial short-term interests may shift, depending on delays in flows of the supply chain. Reactions may cause abnormal patterns in production, distribution and procurement, leading to a dilemma where decisions to optimize performance in a normal time frame may become counterproductive (to be illustrated in Chapter 3 of this dissertation).

Organizations plan based on expectations, often with a rolling horizon whereby they implement decisions according to plan early in the planning horizon, experience events that cause the state of the system to differ from expectations, and revise the plan as new information becomes available. When planning with a rolling horizon, organizations confront the question of how long the horizon should be. This question has been ignored in most supply chain management (SCM) studies that employ optimization models for tactical and operational decisions (e.g., Ciarallo et al., 1994; Wang and Gerchak, 1996; You et al., 2009; Cardoso et al., 2015 etc.). The first question we address in this dissertation is therefore:

> Q1: What rolling horizon length should be adopted in order to achieve higher SC performance for a given objective function and performance metrics?

At face, it seems that to consider the consequences of decisions connected with activities in the supply chain, the planning horizon would need to encompass the longest lead time for procurement of materials, the production cycle times at the manufacturing facilities, and the longest lead time downstream for goods to reach consumers. This seems necessary to avoid decisions from short-term optimization that could harm long-term performance. A planning horizon that encompasses the longest lead times upstream and downstream plus the production cycle time may not be practicable, however, especially for organizations managing international logistics and supply chains. We therefore experiment with a value-added planning objective that enables an organization to recognize the effects of decisions for which the benefits and costs will accrue beyond the planning horizon. We explore the use of such value-added planning objective in a stochastic environment with discrete-event simulation. We apply the research model on a rolling horizon over 90 days, generate 11 key performance measures, impose normal SC variations (product demand, upstream and downstream lead time), and analyze resulting SC performance via different combination of the length of the planning horizon and the approach in the objective function to address our second research question:

> Q2: Can a "value-added" complement to the SCM objective function mitigate the sub-optimization that occurs when the planning horizon is shorter than the time required to capture the effects of all relevant events (procurement, production and deliveries) upstream and downstream?

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After addressing Q2, we next consider the effects of uncertainty by imposing random disruptions that result in inventory shortages, apply the same multi-period SC planning settings (a rolling horizon over 90 days and different combination of the planning horizon and the approach in the objective function), and evaluate the resulting SC performance on the same 11 key metrics to address our third research question:

> Q3: Does any advantage derived from the value-added complement to the objective function persist when SC disruptions occur?

After recognizing the benefits of the value-added complement to the objective function, we compare results derived from addressing Q2 and Q3 to address our fourth and fifth research question:

> Q4: How sensitive is SC performance to the choice of planning horizon and addition of the value-added complement to the objective function?
>
> Q5: What product characteristics are associated with the differential service levels that result from application of the SC optimization model on a rolling horizon?

1.2 Research Methodology

Analytical modeling is employed by researchers and practitioners to support managerial decision making while recognizing interdependencies of activities in a supply chain. These models can be even more beneficial when probabilistic and/or random variations are incorporated. To capture the stochastic elements in the SC, this research presents a simulation model with an embedded optimizer to address the research questions. This hybrid model is constructed on the Statistical Analysis System (SAS) 9.4 platform.

The hybrid model presented in the research is aimed at solving multi-period SC planning problems. Each replication consists 90 days of activity with a rolling optimization horizon. Solutions for the chosen planning horizon at the end of each revision period are extracted and saved in a dataset that stores in a specified SAS library. The simulation model reads the extracted solutions from the SAS library and updates the dataset with stochastic demands and stochastic transit times for flows in the supply chain network during the revision period. It schedules arrivals of goods and materials accordingly and imposes the results as boundary conditions for re-solution of the planning model. Then the optimization model reads the information from the updated dataset as the new initial conditions and solves the problem for the chosen planning horizon. This iterative process continues until it reaches the last day in the experimental period and last replication. Figure 1-1 illustrates the interactive process of the hybrid model.

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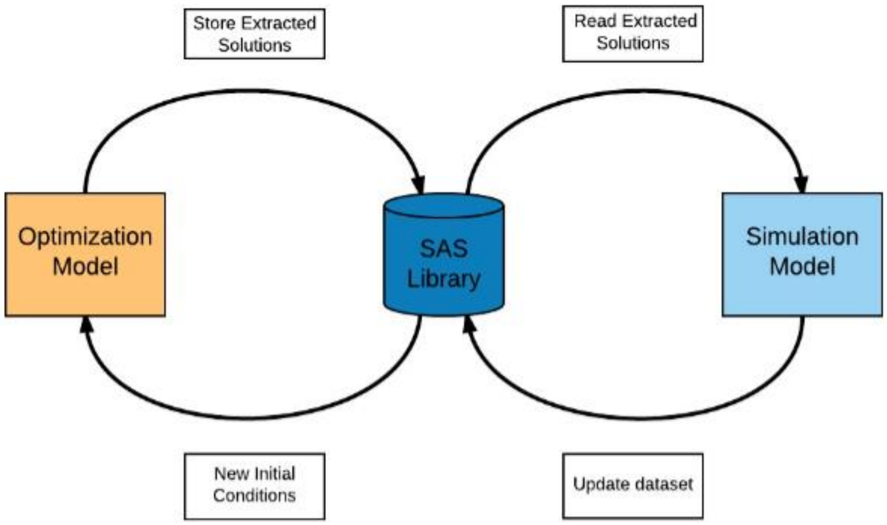

Figure 1-1 Interaction Between Simulation and Optimization

Statistical analysis is performed at the end to generate insights and provide foundations for research findings.

1.3 Research Outline

The remainder of this dissertation is presented in five chapters. Chapter 2 contains a review of the relevant literature and identifies the literature gaps which motivate the purposes of this research. Chapter 3 presents the design and methodological underpinnings of the deterministic optimization model. Chapter 4 illustrates characteristic behaviors of the analytical model. Chapter 5 addresses Q1 and Q2. Q1: What rolling horizon length should be adopted in order to achieve higher SC performance for the given objective function and performance metrics? Q2: Can a “value-added” complement to the SCM objective function mitigate the sub-optimization that occurs when the planning horizon is shorter than the time required to capture the effects of all relevant events (procurement, production and deliveries) upstream and downstream? This is investigated through scenario one under the circumstances that there are no major disruptions in the supply chain. In Chapter 6, section 6.2 addresses question Q3: Does any advantage derived from the value-added complement to the objective function persist when supply chain disruptions occur? This is investigated via scenario two where outages occur randomly with 20% of product-warehouse combination which represent disruptions or unusual events that deplete product inventories at the warehouse. In section 6.3, SC performance from scenario one and scenario two are compared to address Q4: How sensitive is SC performance to the choice of planning horizon and addition of the value-added complement to the objective function? Product service level derived from scenario one and scenario two are evaluated to address Q5: What product characteristics are associated with the differential service levels that result from application of the SC optimization model on a rolling horizon? Chapter 7 summarizes the research findings, provides managerial insights, discusses the limitations of the research, and identifies areas for future research.

Chapter 2 Literature Reviews

2.1 Supply Chain Risk

General sources of SC risk that have been discussed in the academic literature are summarized in Figure 2-1. They can be classified as Supply Risk, Demand Risk, Process Risk, Network Risk, Organizational Risk, and Environmental Risk. The numbers in Figure 2-1 indicate the number of subtopics identified in each category in this research. Details for each of the subtopics are provided in Appendix A. Particular sources of SC risk include market capacity (Zsidisin, 2003), uncertain variable cost (Tang, 2006 b; Bilsel and Ravindran, 2011), resources (talent, technology, and capital) risk (Ghoshal, 1987), product variety (Thun and Hoenig, 2011), and general SC risk caused by single sourcing, globalization, Just-In-Time production, centralized distribution and production (Juttner, 2005; Thun and Hoenig, 2011).

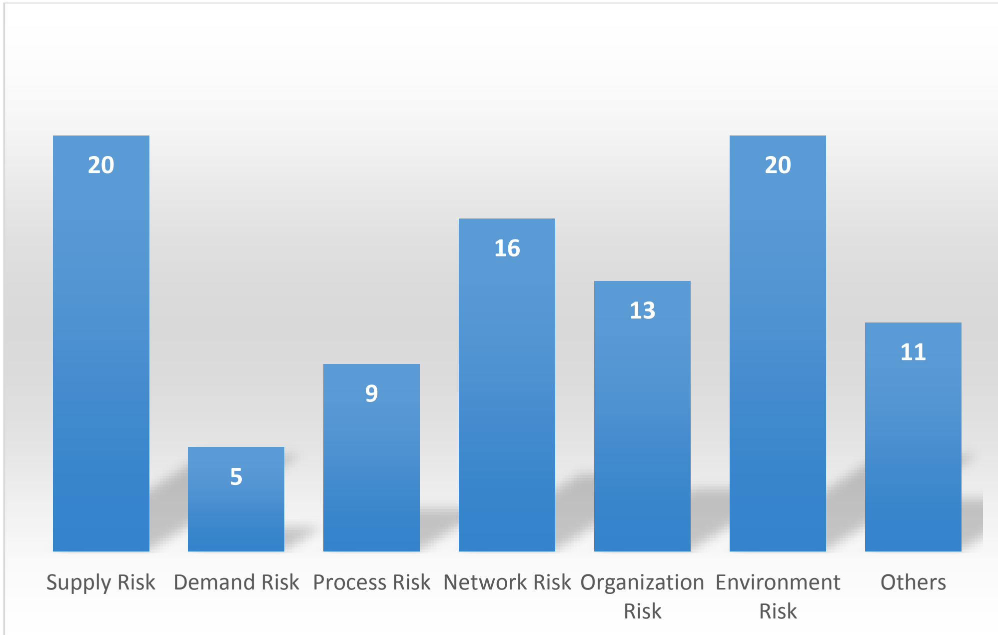

Figure 2-1 Major Sources of SC Risk

Depending on the magnitude of negative impact, SC risk may be described as “disruption”, “disturbance”, “crisis”, “vulnerability”, “uncertainty”, “adverse events”, “disaster”, “peril”, “glitch”, “hazard”, and “perturbations” (Harland et al., 2003; Christopher and Peck, 2004; Christopher and Lee, 2004; Blackhurst et al., 2005; Hendricks and Singhal, 2005a; Tang, 2006a, b; Wagner and Bode, 2006; Ghadge et al., 2012; Wu et al., 2007; and Azevedo et al., 2008). Most of the literature discusses SC risk in two dimensions: probability and severity (March and Shapira, 1987; Mitchell, 1995; Harland et al., 2003; Kleindorfer and Saad, 2005; Wagner and Bode, 2008; Manuj and Mentzer, 2008; Thun and Hoenig, 2011; Wang, 2014; etc.). More recent works argue that the duration of SC risk should also be considered (Klibi and Martel, 2012; Schmitt &

Singh, 2012) as an important dimension. On one hand, minor disruptions in production due to machine breakdowns may be considered as a glitch and probably ignored due to small magnitude associated. Major disruptions, on the other hand, such as those caused by a tsunami can be classified as a "disaster" because they may affect an entire industry or economy. Although SC risk has a multifaceted and multidimensional construct (Wagner and Bode, 2006), in this research, probability, magnitude and duration are used to capture key characteristics of a SC risk. Using these three dimensions, Figure 2-2 illustrates the differences between aforementioned SC risks.

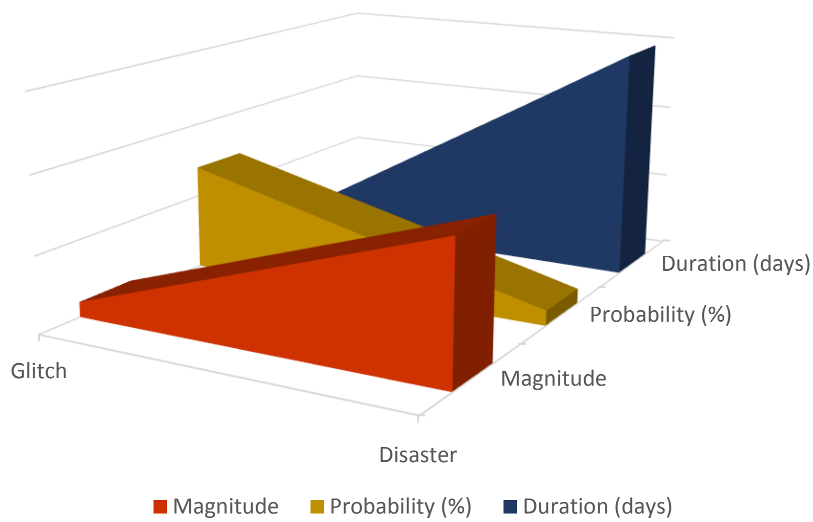

Figure 2-2 Key Factors to Describe SC Risk

2.2 Supply Chain Risk Management

If achieving greater SC efficiency through various cost reduction strategies is important for organizations to increase competitiveness and improve performance, then ensuring the continuous flows of goods, services, and related information, which is the effectiveness of a SC, is equally important. However, assuring the effectiveness of a SC is a challenging task, and even more so for a global supply chain (GSC). As an organization spans national boundaries to further exploit opportunities and reduce costs, the SC becomes longer and more complex. Managing a GSC requires the assistance of advanced information technology. Decision makers face challenges in collaborating with SC partners that have different cultural backgrounds, speak different languages, and reside in different time zones. Companies experience changes in governmental regulations, customs delays, varying exchange rates, strikes, and political instability.

Unexpected disruptions can result in stockouts and the inability to meet customer demand, decrease the efficiency of SCs (Blackhurst et al., 2005), and have negative effects on stock prices (Hendricks and Singhal, 2005a). Despite all these challenges, there is evidence that a GSC presents opportunities that can be explored with good risk management. Hauser (2003) posits that risk adjusted supply chain management (SCM) leads to improved financial performance and competitive advantage. An empirical study conducted by Thun and Hoenig (2011) in the German automotive industry revealed that integrated SCRM tends to improve the performance of a SC, as companies with the lowest degree of SCRM, on average, had the lowest values for all performance criteria.

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Narasimhan and Talluri (2009) view SCRM as “a strategic management activity in firms given that it can affect operational, market and financial performance of firms” and argue that the essence of SCRM is to optimally align organizational processes with decisions to exploit opportunities while simultaneously minimizing risk (Miles et al., 1978; Venkatraman and Camillus, 1984). However, this perspective on SCRM focuses on individual organizations while omitting the collaboration with SC partners to cope with SC risks. Tang (2006 b) defined SCRM as “the management of SC risks through coordination or collaboration among the supply chain partners so as to ensure profitability and continuity”. The importance of coordination and collaboration in SCRM is also stressed by Juttner et al. (2003), Norrman and Lindroth (2004), and Olson and Swenseth (2014).

Although SCRM is a growing research area, Sodhi et al. (2012) stated that SCRM can be very subjective with varying definitions and interpretations among researchers. Focusing on quantitative approaches in SCRM, this research believes that SCRM should be integrated into modern SCM with the primary responsibility to assure the continuous flows of goods, services, and related information, thus fostering a high-performance business model.

2.3 Quantitative research in Supply Chain Risk Management

Various methodologies have been applied in managing SC risks. Fahimnia et al. (2015) identified eight primary research clusters (Table 2-1) in SCRM.

Table 2-1 Primary Research Clusters in SCRM

Literature classification: the primary research clusters.

Cluster	No. of papers	Research area
1	61	Upstream supply chain risks (supply uncertainty and supplier evaluation issues)
2	29	Downstream supply chain risks (demand uncertainty issues)
3	39	Uncertainty modeling in supply chain network design and facility location
4	20	Uncertainty modeling in tactical/operational supply chain planning
5	22	Supply and demand forecasting analysis
6	18	Uncertainty modeling in inventory management and process control
7	14	Sustainability risks (focus on energy/biomass/biofuel/ethanol supply chains)
8	24	Uncertainty in purchasing and retail sourcing (case studies)

(Source: Fahimnia et al., 2015)

Among these clusters, "uncertainty modeling in tactical/operational supply chain planning" is the most relevant one to this research. Lead papers in cluster 4, plus additional quantitative approaches in SCRM have been reviewed in this research.

2.3.1 Supply Chain Planning

Deleris and Erhun (2005) developed a Monte Carlo simulation model to assess the impact of SC disruptions on network flow. With an interest in system downtime and recovery time, Schmitt and Singh (2012) used Arena to simulate a multi-echelon consumer packaged goods SC to examine how risk flows in the SC

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and how disruptions affect each node in the SC network. This research, using customer fulfillment as a performance metric, illustrates that SC risk assessment at the network level can best reveal the true level of risk exposure. They further show how flexibility through redundancy can increase SC resilience and reduce the risk of failure. Redundancy is realized through buffer inventories and backup capacities. The cost structure (holding costs of raw materials, work-in-process, and finished goods) determines where buffer inventories should be positioned and the source of disruptions in the SC network affects the selection of appropriate mitigation strategies. Importantly, the research demonstrates that the magnitude of SC disruptions varies through time and the impacts can be amplified and outlast the disruptions themselves as events propagate through the SC.

You et al. (2009) proposed a stochastic model that incorporates demand and freight rate uncertainty to examine the tradeoffs between cost and risk in multi-period planning. The research revealed that for different risk management methods (managing the variance, the variability index, the probabilistic financial risk, and the downside risk), total expected cost will increase after risk management. Bode et al. (2011) confirmed that buffering (building safeguards such as inventory) and bridging (collaborating with SC partners) are two generic strategies adopted by firms to cope with SC risk. Their empirical study revealed that organizations regard these two strategies as equally effective alternatives. Cardoso et al. (2015) developed a MILP model for SC design and planning to investigate system resilience associated with different SC structures when considering demand uncertainty in a fixed time period (t=3). Their research concluded that, depending on the existing SC network structure, adding redundancy does not always lead to a more resilient SC.

Lee and Kim (2002) adopted a hybrid approach, iterating between a deterministic optimization model and a discrete-event simulation model, to address the integrated production-distribution problems with consideration of production and distribution uncertainty. Operation time uncertainties, including machine and vehicle breakdown, queuing, and transportation delays, were captured by the simulation model. To hedge against variations in demand, Lin and Chen (2009) developed a stochastic model to explore the benefit of flexibility in coordinated replenishment and shipment policies for a fixed planning horizon (30 days). Sabri and Beamon (2000) developed sets of model to simultaneously address strategic and operational SC planning problems. A deterministic model (MILP) was constructed for strategic planning. To incorporate uncertainties in production, delivery, and demand, a stochastic model was developed at the operational level. The research adopted an iterative approach between deterministic and stochastic models to assist in strategic and operational planning. Sodhi (2005) presented a deterministic model and a stochastic model to solve the replenishment schedule for an electronics company. He used information from these two models as a guide for managers to reallocate capacity among different products to mitigate inventory and demand risk. A stochastic model was developed by Leung et al., (2006) to address the production planning problem with consideration of uncertain demand for a given 3-month planning horizon. Variation in demand is not directly incorporated into the model. Instead, uncertain demand is realized through changes in probability distributions of economic scenarios.

In order to achieve desired customer service level in all demand regions, Jung et al., (2004) developed sets of models to investigate safety stocks needed to cope with demand uncertainty for a given planning period (3 months). A stochastic planning and scheduling model incorporates buffer inventories to deal with demand uncertainty, while simulation with an embedded optimization model was used to address safety stock levels needed in order to achieve desired customer service level. The planning and scheduling problem was employed with a rolling horizon (increase one period at a time until the end of planning period), however, the length of the rolling planning horizon is not clarified in their research. Instead, their assumption pertains to the length of the rolling planning horizon considers downstream longest lead time (delivery from each production facility to each customer takes less time than the chosen horizon). Although the model proposed in this research is robust, it is almost impossible to allow any tactical analysis to react to SC disruptions because of the computation time required (100 hours).

Wang and Gerchak (1996) developed a stochastic model to investigate the production planning problem with consideration of uncertain production processes and uncertain demand. The research revealed (not surprisingly) that for a multi-period production planning problem, the optimal policy depends upon the initial inventory level at each period. Schmitt and Singh (2009) presented a simulation model (Monte Carlo with Arena) to investigate the impact of disruptions on SC and assess strategies for coping with SC risk in pursuit of a targeted service level. Their research showed how customer service depends on inventory levels in the system at the beginning of a disruption and the nature of uncertainty in demand and production operation. They assert that it is important to monitor and evaluate SC risk through time.

2.3.2 Correlations among Supply Chain Risk Sources

Monte Carlo simulation was applied to investigate outsourcing risks in the SC by Lee et al. (2012). The research revealed that although total average lead time and total average SC costs were both reduced after outsourcing, the variation of cost was increased due to exposure to risk or uncertainty. Bode and Wagner (2015) did an empirical study to investigate the relationship between conceptualized upstream SC complexity and the frequency of disruptions experienced by buying firms. These conceptualized structures are horizontal complexity (number of direct suppliers), vertical complexity (number of ties), and spatial complexity (global sourcing). Their findings suggested that each of aforementioned dimensions of upstream SC complexity is a source of disruption risk.

Wu and Olson (2008) proposed three different models to assist in vendor selection with consideration of risks: chance constrained programming, data envelopment analysis, and multi-objective programming. Risks were incorporated with probability distributions and risk profiles were generated through Monte Carlo simulation, then embedded into the aforementioned models. Kull and Closs (2008) developed a discrete-event simulation model to investigate the disruption impacts associated with second-tier supply failure. Multi-regression analysis was used to assess the impact of inventory level and ordering policy on supply risk. The researchers concluded that ordering policies can have significant impact on firm's exposure to supply risk, and that inventory in the system is not an adequate indicator of SC resilience. Empirical studies conducted by Wagner et al., (2009, 2011) focused on investigating default dependence between suppliers and concluded that such interdependencies can have significant detrimental impacts on the buying firm. Costantino and Pellegrino (2010) developed a Monte Carlo simulation model to explore the tradeoffs between single sourcing and dual sourcing and indicated that the additional costs of using than one supplier may be offset by reduction in supply risk. More importantly, their research stated that if the default probability of all suppliers is correlated, managers should consider having an additional supplier in a foreign country or carrying more buffer inventory. Guertler and Spinler (2015) used Monte Carlo simulation to investigate the interrelationships among various supply risks mentioned in the literature and concluded that such interdependencies can significantly affect the total risk originated from SC upstream.

Tsiakis et al. (2001) developed a mixed integer linear programming (MILP) to assist in designing a multiproduct, multi-echelon SC network with consideration of demand uncertainty. Vaagen and Wallace (2008) developed a multidimensional stochastic optimization model to assess the impact of uncertainties and demand correlations on system performance for fashion SCs. The research concluded that ignoring demand correlations of fashion products can lead to inferior trade-offs between risk and expected profit. Ciarallo et al. (1994) constructed a stochastic model to solve the production planning problem with consideration of uncertain demand and uncertain capacity. The variation in demand and uncertain production capacity were captured by random variables with a general distribution. The research indicated that an order-up-to inventory policy may be used effectively for multiple-period production planning problem but suggested that a more realistic production planning model should consider nonzero correlations between random demands in different periods. Focusing on SC design problems, Azaron et al. (2008) developed a stochastic model with consideration of uncertain costs in production. The objectives were to minimize the expected total costs, the variance of total cost, and the financial risk when configuring a SC. Sets of scenarios with given probabilities of occurrence were considered. Demands, supplies, processing costs, transportation costs, and shortage and capacity expansion costs were modeled as random variables. The study illustrated correlations between the expected total SC cost and financial risk. Lim et al. (2005) adopted a hybrid approach, iterating between genetic algorithm (GA) and simulation, to solve a distribution planning problem. The GA is used to find near optimal solutions, while simulation captures uncertainty associated with machine and transportation vehicles. Moreover, research conducted by Lium et al. (2007) via stochastic programming revealed that the correlation structure of demand (positive, mixed, negative) affects the optimal truck routes (less-than-truckload).

Petrovic et al. (1998) developed fuzzy models and a simulation model, to investigate the tradeoffs between stock levels, order quantities, and total delivery costs. Uncertain demand and uncertain supply of raw materials were modeled using fuzzy sets. Simulation was used to assess the impact of decisions derived from fuzzy models on system performance. Petrovic (2001) constructed sets of models to analyze SC behavior and performance with consideration of uncertainties. Uncertain demand, uncertain raw materials supply, and uncertain lead time were again modeled using fuzzy sets. Simulation was used to assess the impact of decisions derived from fuzzy models on system performance. However, correlations among demands were not considered in Petrovic et al., 1998 and Petrovic, 2001.

Giannakis and Louis (2011) proposed a conceptual multi-agent based framework to facilitate SCRM. Okubo et al. (2013) used scenario-based simulation to investigate the impact of disruptions on a given SC and evaluate the effectiveness associated with different restoration plans (considering time to restore full capacity versus time to restart production). Talluri et al. (2013) used discrete-event simulation to test the appropriateness and effectiveness of conceptual SCRM framework proposed by Chopra and Sodhi (2004). The study revealed that the appropriateness and effectiveness of risk mitigation strategies are contingent on the internal and external environments. Their research suggested that SCRM needs to consider risk category, risk source, and SC configuration and there is no one-size-fits-all strategy. Their research does not consider the correlations of SC risk sources and does not allow multiple risks or strategies to interact simultaneously. Tomlin (2009) developed a stochastic model to investigate various supply chain risk mitigation strategies (SCRMS) to cope with the supply disruption with considerations of uncertainties derived from upstream and downstream activities. The research concluded that a supply diversification strategy is preferred to contingent sourcing if demand risk is high, while contingent sourcing becomes more effective than supply diversification if supply failure probability increases. Furthermore, the study revealed that demand switching tactics can be used to cope with variations in demand. However, if products are sourced from the same set of suppliers, demand switching is not an effective antidote to supply risk.

With various perspectives on SCRM, researchers have recognized that correlations among sources of risk impinge on sourcing strategies (Wagner et al., 2009, 2011; Costantino and Pellegrino, 2010), vehicle routing solutions (Lium et al., 2007), and financial performance (Vaagen and Wallace, 2008). However, analytical models (such as stochastic programming) that incorporate risk, generally assume that supply chain risk components, such as variation of demand in different markets, transportation delays, etc. are independent of each other (Ciarallo et al., 1994; Wang and Gerchak, 1996; Sodhi, 2005; Wu and Olson, 2008; Lin and Chen, 2009; Schmitt and Singh, 2012; Cardoso et al., 2015 etc.). This may cause a significant underestimation of the impact of adverse events (Zhang and Li, 2010; Liberatore et al, 2012).

2.4 Supply Chain Event Management

An important aspect of risk mitigation involves dealing with adverse events when they occur. Following Bearzotti et al, 2012; Giannakis and Louis, 2011; Bodendorf and Zimmermann, 2005; and Otto 2003, we call this supply chain risk event management (SCEM). It is the combination of supply chain risk mitigation strategies and supply chain risk event management that determines the ultimate performances of the system. Examples of actions which might be taken in response to adverse events occurred in the SC are the use of overtime or alternative supplies of raw materials and components when production must be intensified. Such reactive actions may include the use of faster (usually more expensive) modes of transportation when there is an urgent need for supplies at manufacturing facility, goods at warehouse, or final delivery to a customer.

Taking reactive actions in a timely manner is crucial for organizations to recover and, most importantly, to survive (Simchi-Levi, 2015).

2.5 Summary

Because the initial state of the system directs the optimal policy, it is essential to capture changes in the state of the system at the beginning of each period when dealing with multi-period SC planning. The importance of adopting rolling planning horizon and adequately updating the initial conditions to capture changes in the state of the system can never be overstressed. However, regardless the consideration of uncertainties, there has been limited research employing a rolling planning horizon and capturing changes in the state of the system to solve multi-period SC planning problems. Meanwhile, it is generally recognized that short term optimization can actually hurt long term performance. But, when disruptions or unusual events occur, depending on the magnitude and the duration of the risk events, SC may experience abnormal patterns in procurement, production and distribution etc., and managerial short-term interests may also shift. The same SC planning toolbox or analytical model utilized before the risk events may be counterproductive and unable to reveal the true SC performance. A robust analytical toolbox requires excessive time to generate results (100 hours in Jung et al., 2004) and is likely unable to satisfy managerial short-term needs to cope with risk events occurred, especially when reaction in a timely manner is the essence to mitigate risk effects. However, rarely discussed in the literature is the different approach in the objective function of the analytical models to deal with such a dilemma. Last but not least, in the field of SCM, sporadic studies utilize multi-criteria to assess the overall SC performance and assist managerial decision making by providing the “whole picture” (upstream and downstream) of the SC.

This dissertation investigates the effects of using a combination of strategies for SCRM and SCEM by employing a discrete-event simulation model with an embedded optimizer. A rolling horizon planning with consideration of the initial conditions for each period is adopted to solve multi-period SC planning problems. The hybrid model produces 11 key SC performance measures to assist managers in making procurement, production and distribution decisions and assessing the effects of different risk-mitigation strategies such as redundancy and flexibility. We propose a value-added complement to traditional deterministic objective functions to improve SCRM and assess its robustness with the hybrid model. We investigate how changes in the length of rolling planning horizons and the approach in analytical model’s objective function for developing and implementing production schedules may affect system performance. Meanwhile, the hybrid approach proposed in this research is intended to meld the strengths of mathematical optimization (pursuit of a goal while adhering to constraints) and simulation (incorporating uncertainty) in an analytically tractable manner.

Chapter 3 Analytical Model

In the supply chain management field, hybrid approaches which combine simulation and optimization are gaining more attention. Simulated decisions can be formed with help from optimizing models and constraints imposed in the optimization process can be guided by simulation results. Beginning with an integrated simulation and optimization model constructed on the Statistical Analysis System (SAS) platform by Smith et al. (2016), this research incorporates additional elements of upstream activities, sets production system-wide inventory level for each product across all plants, and experiments with different methods of establishing production priorities (Note that the terms “plant”, “facility”, and “production facility” will be used interchangeably in the remaining of this research).

3.1 Model analysis framework

This research studies a three-echelon supply chain for bulk products that are distributed through warehouses in several different regions. The supply chain under investigation is predefined and has m suppliers, n production facilities, p products, and w warehouses. Customers’ demands are aggregated and allocated to the warehouses. The locations of suppliers, production facilities, and warehouses are hypothetically given and the transportation of raw materials and finished goods is assumed to be done by third-party logistics (3PL) providers (thus avoiding the issues of consolidating shipments and related delay due the shipment consolidation process). Research data were adapted from the literature (Tsiakis et al., 2001) with amendments made to accommodate the purposes of this research. Figure 3-1 illustrates the supply chain structure examined by this research.

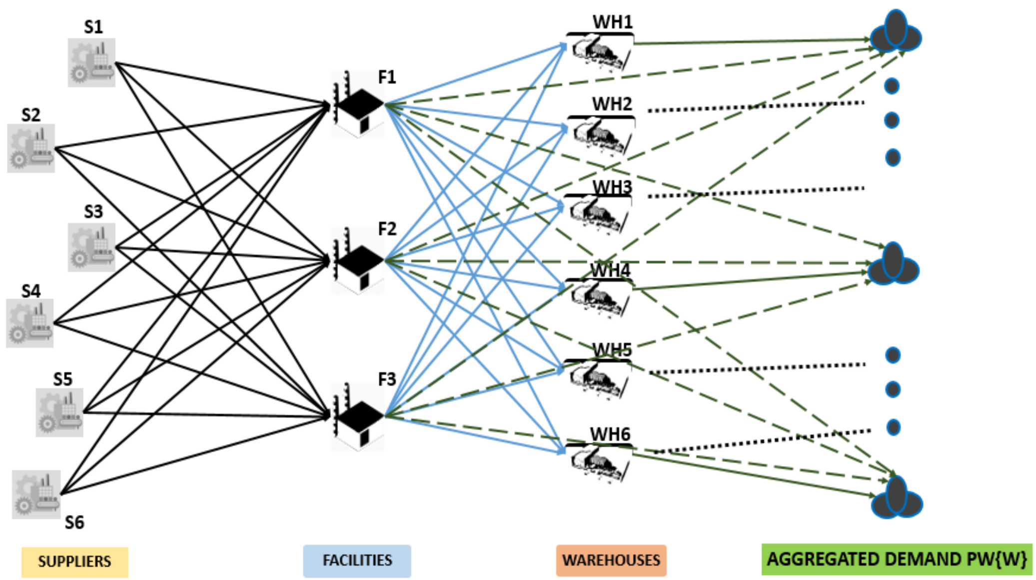

Figure 3-1 Research Supply Chain Structure

With an interest in maximizing net profit contribution, major decisions resulted from the optimization model in each planning period include procurement, production, and distribution plans. Buffer inventories (raw materials, finished goods at plants and products at warehouses) are built into supply chain as part of the risk mitigation strategies. Supply chain risk event management is represented by allowing finished goods to be shipped directly to customers when shortages occur at customer service centers (warehouses) or by adding additional shifts when production must be intensified (possibly due to disruptions that have occurred in the supply chain).

3.2 Model description

The analytical model is developed with the following assumptions:

1) The managerial goal is to maximize net contribution to profit.
2) The profit contribution net of shipping costs is realized when customer demand is satisfied from the warehouses or directly from the plant.
3) Inventory replenishment is recognized at the end of each business day.
4) Aggregate customer demands for products are registered at the beginning of each day at the warehouses.
5) Suppliers who provide the same raw material are geographically separated (and therefore subject to different disruption risks).
6) Each production facility can produce all products, ship products to all warehouses, and perform alternative delivery of finished goods via expedited shipping to satisfy customer demand as alternatives to deliveries from warehouses.
7) Customer demand of products is aggregated and assigned to designated warehouse every day. Alternative deliveries from other warehouses are not considered in this research.

Description of the notation used in this research is presented in the following table.

Table 3-1 Optimization Model Parameters and coinciding description

Parameter	*Description*
mrR_rP_p	Units of raw material r required to produce one unit of product p
$mininvP_pF_f$	Minimum inventory of product p desired at production facility f
$maxinvP_pF_f$	Maximum inventory of product p desired at production facility f
$mininvR_rF_f$	Minimum inventory of raw material r desired at production facility f
$maxinvR_rF_f$	Maximum inventory of raw material r desired at production facility f
$ShtPenaltyR_rF_f$	Daily penalty ($ per unit) for shortage of raw material r inventory at production facility f
$ShtPenaltyP_pF_f$	Daily penalty ($ per unit) for shortage of product p inventory at production facility f
$ShtPenaltyP_pW_w$	Daily penalty ($ per unit) for shortage of product p inventory at warehouse w

$OvrPenaltyR_rF_f$	Daily penalty ($ per unit) for excess raw material r inventory at production facility f
$OvrPenaltyP_pF_f$	Daily penalty ($ per unit) for excess of product p inventory at production facility f
$OvrPenaltyP_pW_w$	Daily penalty ($ per unit) for excess of product p inventory at warehouse w
$mininvP_pW_w$	Minimum inventory of product p desired at warehouse w (including outstanding orders)
$maxinvP_pW_w$	Maximum inventory of product p desired at warehouse w (including outstanding orders)
dem_pwhse_w	Assigned aggregated average daily demand for product p at warehouse w
$shiptimeF_fW_w$ δ (f, w)	Shipping time (days) from production facility f to warehouse w
$shiptimeS_sF_f$ θ (s, f)	Shipping time (days) from supplier s to production facility f
$spcF_f$	Production setup costs at production facility f incurred each day that production occurs (including idle cost associated with set up time)
pcP_pW_w	Unit profit contribution of product p delivered from warehouse w

$scP_pF_fW_w$	Supply cost per unit of product p from production facility f to warehouse w (including variable production cost at production facility f and shipping cost from production facility f to warehouse w, but excluding raw material and goods in transit costs)
$scR_rS_sF_f$	Supply cost per unit of raw material r from supplier s to production facility f (including ordering and shipping costs, but excluding raw material in transit costs)
scP_pW_w	Shipping cost per unit of product p from warehouse w to customer
icP_pF_f	Inventory carrying cost for finished product p at production facility f
icR_rF_f	Inventory carrying cost of raw material r at production facility f
$itcP_pF_fW_w$	Unit cost of carrying product p in transit from production facility f to warehouse w
$itcR_rS_sF_f$	Unit cost of raw material r in transit from supplier s to production facility f
$acP_pF_fW_w$	Unit cost of alternative supply from production facility f for product p at warehouse w
icP_pW_w	Inventory carrying cost for product p at warehouse w

$opcostP_pW_w$	Unit opportunity cost of lost sales for product p at warehouse w
$DemP_pW_wD_d$	Demand for product p (units) at warehouse w on day d
$sutimeP_pF_f$	Product p production setup time at production facility f
$idlePenF_f$	Idle penalty cost per hour at production facility f
$MXprodF_f$	Maximum daily throughput (units) at production facility f
$minsysinvP_p$	Desired minimum system inventory of product p (across all production facilities)
$maxsysinvP_p$	Desired maximum system inventory of product p (across all production facilities)

Table 3-2 Set Notation Employed

Set	*Description*
R{r}	Set of raw materials
S{s}	Set of suppliers
F{f}	Set of production facilities
P{p}	Set of products
W{w}	Set of warehouses
D{d}	Set of days in planning horizon
SR{r}	Set of suppliers for raw material r
RP{p}	Set of raw materials used in producing product p
PF{f}	Set of products produced in production facility f
PR{r}	Set of products require raw material r for production
RF{f}	Set of raw materials used in producing products at production facility f
PW{w}	Set of products distributed through warehouse w
WP{p}	Set of warehouses to which product p is delivered
DRMS {r, s, f}	Set of days on which raw material r from supplier s is scheduled to arrive at production facility f
DFGS {p, f, w}	Set of days on which product p from production facility f is scheduled to arrive at warehouse w

Parameters are set for individual products to allow experiments from which conclusions may be generalized according to product type (where product type is characterized by product value, level of demand, and variability of demand). As Fisher (1997) indicated that the supply chain strategy of a product must be aligned with the demand characteristics of that product and Talluri et al. (2013) stated that more realistic supply chain risk mitigation strategies should consider demand variations. Among all six products produced across production facilities, product 1 (P1) and product 2 (P2) have high demand, product 3 (P3) and product 4 (P4) have medium demand, while product 5 (P5) and product 6 (P6) share low demand. However, the variability in demand differs among products. Table3-3 summarizes demand characteristics of all six products considered in this research and presents unit profit contribution associated with each product.

Table 3-3 Product Demand Characteristics

Product	Demand	Demand Variation	Unit Profit Contribution
P1	High	High	$9.15
P2	High	Low	$8.26
P3	Medium	High	$11.44
P4	Medium	Low	$10.48
P5	Low	High	$28.85
P6	Low	Low	$26.78

Three different raw materials are consumed at production facilities to produce all products. Each raw material has two suppliers with one supplier offering a shorter lead time at a higher cost than the other. Supplier 1 (S1) and supplier 2 (S2) provide raw material 1 (R1), supplier 3 (S3) and supplier 4 (S4) supply raw material 2 (R2), and supplier 5 (S5) and supplier 6 (S6) sell raw material 3 (R3). Table 3-4 presents information about average lead time and standard deviation of lead time from supplier to production facility (F1 to F3 denotes production facility 1 to production facility 3 correspondingly).

Table 3-4 Average Lead Time from Supplier to Production Facility

Supplier	Average Lead Time			Standard Deviation of Lead Time		
	F1	F2	F3	F1	F2	F3
S1	10	12	15	1	2	2
S2	16	17	20	2	3	5
S3	9	7	15	1	1	2
S4	13	11	20	2	2	5
S5	10	13	10	1	2	1
S6	16	17	15	2	3	3

P1 and P2 require R1, P3 and P4 require R2, and P5 and P6 require R3. However, units of raw materials required to produce each unit of product can be different. Material requirements for production of all products are given in Table 3-5.

Table 3-5 Raw Material Utilization Summary for Production

Product	Raw Material Consumption	Material Requirements
P1	R1	1.6
P2	R1	1.5
P3	R2	2.5
P4	R2	2
P5	R3	3
P6	R3	3

Table 3-6 Summary of Production Rate across Production Facilities

Product	Production Rate (unit/hour)		
	F1	F2	F3
P1	138	126	145
P2	161	146	168
P3	70	81	77
P4	80	92	88
P5	52	50	45
P6	58	55	50

Although products can be produced at different plants, production capacity differs among products and plants. Production facilities can ship products to all warehouses with varying costs and lead time. Table 3-6 illustrates the production rate (unit per hour) across production facilities and Table 3-7 provides information about average lead time and standard deviation of lead time from production facility to warehouse (WH1 to WH6 denotes warehouse 1 to warehouse 6 in order).

Information presented in Table 3-6 and Table 3-7 indirectly indicates that the unit supply cost of products from production facility to warehouse are set to depend on the combination of profit contribution of individual products, lead time from plant to warehouse, and the level of economies of scale at each individual plant.

Table 3-7 Average Lead Time from Production Facility to Warehouse

	Average Lead Time			Standard Deviation of Lead Time		
	F1	F2	F3	F1	F2	F3
WH1	7	9	15	2	2	3
WH2	7	10	17	2	3	4
WH3	8	7	17	2	2	5
WH4	9	7	19	3	2	6
WH5	13	15	7	5	5	2
WH6	15	15	8	5	6	2

The supply chain is generally demand driven. Information of product demands collected from warehouses dictates the quantity that the production scheduling model should produce, units of products to ship, and the amount of raw materials to purchase. Meanwhile, production of products, delivery of products, and procurement of raw materials take into consideration the minimum inventories of raw materials to maintain at plants, minimum inventories of finished products to maintain at plants, minimum system-wide inventories of finished products, and minimum inventories of finished goods at warehouses. Table 3-8 and table 3-9 summarize the aggregated demand information through warehouses in this research. Table 3-10 presents coefficients of variation for demands of products at warehouses. As some products exhibit high coefficients of variation, these product demands are being truncated in the simulation model to avoid any negative values.

Table 3-8 Warehouse Aggregated Product Demand

	Average Daily Demand						Total Demand per Day
	WH1	WH2	WH3	WH4	WH5	WH6	
P1	137	106	120	125	102	112	702
P2	128	160	200	160	176	160	984
P3	45	54	54	48	32	40	273
P4	75	66	65	63	48	64	381
P5	11	18	14	14	8	13	78
P6	21	21	14	15	16	18	105

Table 3-9 Standard Deviation of Product Demand

	Standard Deviation of Daily Demand					
	WH1	WH2	WH3	WH4	WH5	WH6
P1	21	16	18	19	15	17
P2	6	8	10	8	9	8
P3	16	19	19	17	12	14
P4	19	17	17	16	12	16
P5	6	9	7	7	4	7
P6	9	9	6	6	7	8

Table 3-10 Product Demand Coefficient of Variation

	Product Demand Coefficient of Variation					
	WH1	WH2	WH3	WH4	WH5	WH6
P1	0.15	0.15	0.15	0.15	0.15	0.15
P2	0.05	0.05	0.05	0.05	0.05	0.05
P3	0.36	0.35	0.35	0.35	0.38	0.35
P4	0.25	0.26	0.26	0.25	0.25	0.25
P5	0.55	0.50	0.50	0.50	0.50	0.54
P6	0.43	0.43	0.43	0.40	0.44	0.44

3.3 Model construction

Daily production at plants, shipments to warehouses, and deliveries to customers are planned with consideration of production capacities across plants, lower and upper inventory limits at plants and in warehouses, transit times to warehouses, and the possibility of expedited shipping from production facilities directly to the customer (at higher cost) or accepting lost sales in the event of stockouts at the warehouses. A mixed-integer mathematical programming model (with options of planning over different horizons considering current system status, expected future demands, shipping times etc.) is employed to determine “optimal” allocations of production capacity each day and shipments to warehouses from which customer demand is satisfied. Decision variables are presented in table 3-10, followed with optimization model’s objective and constraints.

Table 3-11 Optimization Model Decision Variables

Decision Variables	*Description*
$ProdP_pF_fD_d$	Units of product p produced at production facility f at the end of day d
$USP_pF_fD_d$	Units short of safety stock of product p at production facility f at the end of day d
$OSP_pF_fD_d$	Units over max desired inventory of product p at production facility f at the end of day d
$ShpP_pF_fW_WD_d$	Units of product p shipped out of production facility f to warehouse w at the end of day d
$ItsP_pF_fW_WD_d$	Units of product p in transit and scheduled to arrive at warehouse w from production facility f at the end of day d
$USR_rF_fD_d$	Under-stock (shortage from reorder point) of raw material r at production facility f at the end of day d
$OSR_rF_fD_d$	Over-stock (above max desired inventory) of raw material r at production facility f at the end of day d
$ShpR_rS_sF_fD_d$	Units of raw material r shipped out of supplier s to production facility f at the end of day d
$ItsR_rS_sF_fD_d$	Units of raw material r in transit and scheduled to arrive at production facility f from supplier s at the end of day d

$USP_pW_wD_d$	Under-stock (shortage from reorder point) of product p at warehouse w at the end of day d
$OSP_pW_wD_d$	Over-stock (above max desired inventory) of product p at warehouse w at the end of day d
$DelP_pW_WD_d$	Units of product p delivered from warehouse w to customers by the end of day d
$AltP_pF_fW_WD_d$	Units of product p shipped directly from production facility f at the end of day d to satisfy demand
$LSP_pW_WD_d$	Lost sales (in units) of product p at warehouse w at the end of day d
$InvP_pF_fD_d$	Inventory of product p in production facility f at beginning of day d
$InvP_pW_wD_d$	Inventory of product p in warehouse w at beginning of day d
$TrP_pF_fW_wD_d$	Units of Product p in transit from production facility f to warehouse w at beginning of day d
$TrR_rS_sF_fD_d$	Units of Raw material r in transit from supplier s to production facility f at beginning of day d
SUF_fD_d	1 if production facility f is activated for production on day d; 0 otherwise
$SUP_pF_fD_d$	Extend to which setup time at production facility f on day d is attributed to the production of product p

$IdleF_fD_d$	Total idle hours at production facility f during day d
$OR_rS_sF_fD_d$	Units of raw material r ordered at supplier s for delivery to production facility f at beginning of day d
$OOR_rS_sF_fD_d$	Outstanding orders of raw material r for delivery from supplier s to production facility f at beginning of day d
$OP_pF_fW_wD_d$	Units of product p ordered at production facility f for delivery to warehouse w at beginning of day d
$OOP_pF_fW_wD_d$	Outstanding orders of product p at production facility f for delivery to warehouse w at beginning of day d

The objective of the optimization model is to maximize net contribution to profit from meeting customer demand with supplies of finished products from warehouses and alternative supplies from production facilities.

Net Profit Contribution = (Profit contribution from warehouse deliveries + Profit contribution from alternative deliveries – Costs of lost sales – Product inventory holding costs at plants and warehouses – Raw material inventory holding costs at plants – Product inventory shortage costs at plants and warehouses – Raw material inventory shortage costs at plants – Product inventory overstocking costs at plants and warehouses – Raw material inventory overstocking costs at plants – Product shipping costs – Product in transit costs – Raw material shipping costs – Raw material in transit costs – Plant setup costs – Plant idle costs)

The algebraic formulation of the problem is presented below:

$$Max \sum_{d\in D\{d\}} \left\{ \sum_{w\in W\{w\}} \sum_{p\in PW\{w\}} \left[\left(pcP_pW_w - scP_pW_w \right) * DelP_pW_wD_d \right.\right.$$

$$+ \sum_{f\in F\{f\}} \left(pcP_pW_w - acP_pF_fW_w\right) * AltP_pF_fW_wD_d - opcostP_pW_w * LSP_pW_wD_d - icP_pW_w * Inv\,P_pW_wD_d$$

$$\left. - ShtPenaltyP_pW_w * USP_pW_wD_d - OvrPenaltyP_pW_w * OSP_pW_wD_d \right]$$

$$- \sum_{f\in F\{f\}} \left[\sum_{p\in P\{p\}} \left(icP_pF_f * InvP_pF_fD_d + ShtPenaltyP_pF_f * USP_pF_fD_d + OvrPenaltyP_pF_f * OSP_pF_fD_d \right.\right.$$

$$\left. + \sum_{w\in W\{w\}} \left(scP_pF_fW_w * ShpP_pF_fW_wD_d + itcP_pF_fW_w * TrP_pF_fW_wD_d\right) \right) + spcF_f * SUF_fD_d + idlePenF_f$$

$$* idleF_fD_d$$

$$+ \sum_{r\in RP\{p\}} \left(icR_rF_f * InvR_rF_fD_d + ShtPenaltyR_rF_f * USR_rF_fD_d + OvrPenaltyR_rF_f * OSR_rF_fD_d \right.$$

$$\left.\left.\left. + \sum_{s\in SR\{r\}} \left(scR_rS_sF_f * ShpR_rS_sF_fD_d + itcR_rS_sF_f * TrR_rS_sF_fD_d\right) \right) \right] \right\}$$

Subject to the following constraints:

Product p can't be produced at production facility f on day d unless the necessary set up is completed (constraint $STP_pF_fD_d$). For each production facility and day for each $p \in PF\{f\}$,

$$ProdP_pF_fD_d \ \le \ MxprodP_pF_f \ * \ SUP_pF_fD_d. \tag{1}$$

Consumption of raw materials r at production facility f on day d cannot exceed the quantities available at beginning of day d (constraint $UBR_rF_fD_d$). For each production facility and day for each $p \in PR\{r\}$ and each $r \in RF\{f\}$,

$$\sum_{p \in PR\{r\}} mrR_rP_p * ProdP_pF_fD_d \le InvR_rF_fD_d. \tag{2}$$

Notice that if units of raw material r required to produce each unit of product p are significantly different across production facilities because of labor, technology or machinery etc., then raw material conversion rates could be defined as $mrR_rP_pF_f$. For this research, we assume that there is no significant difference or bill of materials for product p produced at each production facility. This constraint also assumes that raw materials received during the day will not be available for production until the next day.

Sum of production times used on day d at production facility f cannot exceed total available operating time (constraint $TPRODF_fD_d$). For each production facility and day,

$$\sum_{p \in PF\{\mathrm{f}\}} \left(\left(\frac{1}{unitperhr} \right) * ProdP_p F_f D_d + sutimeF_f * SUF_f D_d + IdleF_f D_d \right) \tag{3}$$
$$= 8 * maxshifts$$

SUF_fD_d = [0,1]. If setup times are negligible, these binary constraints may be relaxed.

Production of product p at production facility f on day d cannot occur unless the production facility is activated for production on that day (constraint $FSUF_fD_d$). For each production facility and day for each $p \in PF\{f\}$,

$$\sum_{p \in PF\{f\}} SUP_p F_f D_d \leq SUF_f D_d. \tag{4}$$

$SUP_pF_fD_d$ values attribute set up time to the production of individual product. If separate set up were required for each product, these equations would be replaced with sets of equations for set up of individual product. For this research, we assume that there is a single setup required if a production facility is to be activated for production during the day. $SUP_pF_fD_d$ in this formulation allocates production capacity to individual products. We, therefore, add a constraint that creates a single binary variable for each production facility during the day that accounts for setup to activate and shut down the production at production facility.

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Raw materials inventory balance at production facility f (constraint $IBR_rF_fD_d$). For each production facility and day for each $r \in RF\{f\}$ and each $s \in SR\{r\}$,

$$InvR_rF_fD_{d+1} = InvR_rF_fD_d - \sum_{p \in PR\{r\}} mrR_rP_p * ProdP_pF_fD_d + \sum_{s \in SR\{r\}} (ShpR_rS_sF_fD_{d-\theta(s,f)} + ItsR_rS_sF_fD_d). \tag{5}$$

Note that the $ItsR_rS_sF_fD_d$ variables are defined only for (r, s, f, d) combinations where there are raw materials in transit at beginning of the planning horizon and are scheduled to arrive at production facility f on day d for each $d \in DRMS\{r, s, f\}$.

Place order of raw material r at beginning of day d to ensure safety stock at production facility f (constraint $MNOR_rF_fD_d$). For each production facility and day for each $r \in RF\{f\}$ and each $s \in SR\{r\}$,

$$\sum_{s \in SR\{r\}} \left(OR_rS_sF_fD_d + OOR_rS_sF_fD_d\right) + InvR_rF_fD_d \geq mininvR_rF_f - USR_rF_fD_{d-1}. \tag{6}$$

Note that under storage of raw materials could occur at the beginning of Day 1.

Restrict order of raw material r at beginning of day d to prevent overstock at production facility f (constraint $MXOR_rF_fD_d$). For each production facility and day for each $r \in RF\{f\}$ and each $s \in SR\{r\}$,

$$\sum_{s \in SR\{r\}} \left(OR_r S_s F_f D_d + OOR_r S_s F_f D_d \right) + InvR_r F_f D_d \\ \leq maxinvR_r F_f + OSR_r F_f D_{d-1}. \tag{7}$$

Note that over storage of raw materials could occur at the beginning of Day 1.

Update under storage (constraint $AUSR_rF_fD_d$) and overstocking (constraint $AOSR_rF_fD_d$) of raw material r at production facility f at the end of day d. For each production facility and day for each $r \in RF\{f\}$ and each $s \in SR\{r\}$,

$$InvR_r F_f D_d + USR_r F_f D_d - \sum_{p \in PR\{r\}} mrR_r P_p * ProdP_p F_f D_d \\ + \sum_{s \in SR\{r\}} (ShpR_r S_s F_f D_{d-\theta(s,f)} + ItsR_r S_s F_f D_d) \\ \geq minInvR_r F_f. \tag{8}$$

$$InvR_r F_f D_d - OSR_r F_f D_d - \sum_{p \in PR\{r\}} mrR_r P_p * ProdP_p F_f D_d \\ + \sum_{s \in SR\{r\}} (ShpR_r S_s F_f D_{d-\theta(s,f)} + ItsR_r S_s F_f D_d) \\ \leq maxInvR_r F_f. \tag{9}$$

Note that the $ItsR_rS_sF_fD_d$ variables are defined only for (r, s, f, d) combinations where there are raw materials in transit at beginning of the planning horizon and are scheduled to arrive at production facility f on day d for each $d \in DRMS\{r, s, f\}$.

Total units of raw material r shipped from supplier s at the end of day d to satisfy orders acknowledged from production facility f at beginning of that day (constraint $DLVR_rS_sF_fD_d$). For each day and each $s \in \mathrm{SR}\,\{r\}$ for each production facility,

$$ShpR_rS_sF_fD_d \geq \; OR_rS_sF_fD_d. \tag{10}$$

Update outstanding orders of raw material r at production facility f at beginning of day d (constraint $OOUR_rS_sF_fD_d$). For each production facility and day for each $r \in \mathrm{RF}\,\{f\}$ and each $d \in DRMS\{r, s, f\}$,

$$\begin{aligned} OOR_rS_sF_fD_{d+1} & \\ &= OOR_rS_sF_fD_d + OR_rS_sF_fD_d - ShpR_rS_sF_fD_{d-\theta(s,f)} \\ &- ItsR_rS_sF_fD_d. \end{aligned} \tag{11}$$

Note that the $ItsR_rS_sF_fD_d$ variables are defined only for (r, s, f, d) combinations where there are raw materials in transit at beginning of the planning horizon and are scheduled to arrive at production facility f on day d for each $d \in DRMS\{r, s, f\}$. $OOR_rS_sF_fD_1$ should include sum of the $ItsR_rS_sF_FD_d$ values for each day with scheduled arrivals.

Update raw materials in transit from supplier s to production facility f (constraint $RITR_rS_sF_fD_d$) at beginning of day d. For each production facility and day for each $r \in \mathrm{RF}\,\{f\}$ and each $d \in DRMS\{r, s, f\}$,

$$TrR_rS_sF_fD_{d+1}$$
$$= TrR_rS_sF_fD_d + ShpR_rS_sF_fD_d - ShpR_rS_sF_fD_{d-\theta(s,f)} - ItsR_rS_sF_fD_d. \quad (12)$$

Note that the $ItsR_rS_sF_fD_d$ variables are defined only for (r, s, f, d) combinations where there are raw materials in transit at beginning of the planning horizon and are scheduled to arrive at production facility f on day d for each $d \in DRMS\{r, s, f\}$. TrRrSsFFD$_1$ is set to sum of the $ItsR_rS_sF_fD_d$ values for each day with scheduled arrivals of raw materials.

Place order for product p at the beginning of day d to ensure desired safety stock at warehouse w (constraint $MNOP_pW_wD_d$). For each warehouse and day for each $p \in PW\{w\}$,

$$\sum_{f \in F\{f\}} (OP_pF_fW_wD_d + OO\,P_pF_fW_wD_d) + InvP_pW_wD_d \geq mininvP_pW_w - USP_pW_wD_{d-1}. \quad (13)$$

Note that under storage of products can occur with associated penalty.

Restrict order of product p at the beginning of day d to prevent overstock at warehouse w (constraint $MXOP_pW_wD_d$). For each warehouse and day for each $p \in PW\{w\}$,

$$\sum_{f \in F\{f\}} (OP_p F_f W_w D_d + OO\, P_p F_f W_w D_d) + InvP_p W_w D_d \le maxinvP_p W_w + OSP_p W_w D_{d-1}. \tag{14}$$

Note that over storage of products can occur with associated penalty.

Produce sufficient product p across plants to cover orders and provide production system-wide safety stocks (constraint $MNSYSP_pD_d$). For each day for each product across all plants,

$$\sum_{f \in F\{f\}} (Prod\, P_p F_f D_d + InvP_p F_f D_d) \ge \sum_{f \in F\{f\}} \sum_{w \in PW\{w\}} OP_p F_f W_w D_d + minsysinvP_p. \tag{15}$$

Restrict production of product p across plants on day d to prevent overstock in the production system (constraint $MXSYSP_pD_d$). For each day for each product across all plants,

$$\sum_{f \in F\{f\}} (Prod\, P_p F_f D_d + InvP_p F_f D_d) \le \sum_{f \in F\{f\}} \sum_{w \in PW\{w\}} OP_p F_f W_w D_d + maxsysinvP_p. \tag{16}$$

Ship sufficient finished goods from production facility f to cover orders placed at warehouse w on day d (constraint $DLVP_pF_fW_wD_d$). For each production facility and day for each $\mathrm{p} \in \mathrm{PF}\{\mathrm{f}\}$ and each $p \in PW\{w\}$,

$$ShpP_pF_fW_wD_d \;\geq\; OP_pF_fW_wD_d. \tag{17}$$

Update over storage (constraint $AOSP_pF_fD_d$) and under storage (constraint $AUSP_pF_fD_d$) of product p at production facility f at the end of day d. For each production facility and day for each $p \in PF\{f\}$ and each $p \in PW\{w\}$,

$$\begin{aligned} &InvP_pF_fD_d - OSP_pF_fD_d + ProdP_pF_fD_d \\ &\qquad - \sum_{w \in WP\{p\}} \left(ShpP_pF_fW_wD_d + AltP_pF_fW_wD_d\right) \\ &\qquad \leq maxInvP_pF_f. \end{aligned} \tag{18}$$

$$\begin{aligned} &InvP_pF_fD_d + USP_pF_fD_d + ProdP_pF_fD_d \\ &\qquad - \sum_{w \in WP\{p\}} \left(ShpP_pF_fW_wD_d + AltP_pF_fW_wD_d\right) \\ &\qquad \geq minInvP_pF_f. \end{aligned} \tag{19}$$

Limit shipments of product p from production facility f to warehouses on day d to the amount available in production facility inventory (constraint $SLP_pF_FD_d$). For each production facility and day for each $p \in PF\{f\}$ and each $p \in PW\{w\}$,

$$\sum_{w \in WP\{p\}} \left(ShpP_pF_fW_wD_d + AltP_pF_fW_wD_d\right) \leq InvP_pF_fD_d. \tag{20}$$

This also implies that production of product p during day d will not be available for delivery until the next day.

Account for inventory balance of products at production facility f at the end of day d (constraint $IBP_pF_fD_d$). For each production facility and day for each $p \in PF\{f\}$ and each $p \in PW\{w\}$,

$$InvP_pF_fD_{d+1} = InvP_pF_fD_d + ProdP_pF_fD_d - \sum_{w \in WP\{p\}} \left(ShpP_pF_fW_wD_d + AltP_pF_fW_wD_d\right). \tag{21}$$

Deliver goods from warehouse or alternative source (production facility) to satisfy customer demand and acknowledge lost sales if inventory is insufficient (constraint $DLVP_pW_wD_d$). For each warehouse and day for each $p \in PW\{w\}$,

$$DelP_pW_wD_d + LSP_pW_wD_d + \sum_{f \in F\{f\}} AltP_pF_fW_wD_d = DemP_pW_wD_d. \tag{22}$$

Account for inventory balance of product p at warehouse w recognizing inbound shipping delays (constraint $IBP_pW_wD_d$) at the end of day d. For each warehouse and day for each $p \in PW\{w\}$,

$$InvP_pW_wD_{d+1} = InvP_pW_wD_d - DelP_pW_wD_d + \sum_{f \in F\{f\}} (ShpP_pF_fW_wD_{d-\delta(f,w)} + ItsP_pF_fW_wD_d). \tag{23}$$

Note that the $ItsP_pF_FW_WD_d$ variables are defined only for (p, f, w, d) combinations where there are finished goods in transit at the beginning of the planning horizon and are scheduled to arrive at warehouse w on day d for each $d \in DFGS\{p, f, w\}$.

Update over storage (constraint $AOSP_pW_wD_d$) or under storage (constraint $AUSP_pW_wD_d$) of product p at warehouse w at the end of day d. For each warehouse and day for each $p \in PW\{w\}$,

$$
\begin{aligned}
InvP_pW_wD_d &+ USP_pW_wD_d - DelP_pW_wD_d \\
&+ \sum_{f \in F\{f\}} (ShpP_pF_fW_wD_{d-\delta(f,w)} + ItsP_pF_fW_wD_d) \\
&\geq mininvP_pW_w.
\end{aligned}
\tag{24}
$$

$$
\begin{aligned}
InvP_pW_wD_d &- OSP_pW_wD_d - DelP_pW_wD_d \\
&+ \sum_{f \in F\{f\}} (ShpP_pF_fW_wD_{d-\delta(f,w)} + ItsP_pF_fW_wD_d) \\
&\leq maxinvP_pW_w.
\end{aligned}
\tag{25}
$$

Note that the $ItsP_pF_FW_WD_d$ variables are defined only for (p, f, w, d) combinations where there are finished goods in transit at the beginning of the planning horizon and are scheduled to arrive at warehouse w on day d for each $d \in DFGS\{p, f, w\}$.

Update outstanding orders for product p at warehouse w at the end of day d (constraint $OOUP_pF_FW_wD_d$). For each warehouse and day for each $p \in PW\{w\}$ and each $d \in DFGS\{p, f, w\}$,

$$OOP_pF_fW_wD_{d+1}$$

$$= OOP_pF_fW_wD_d + OP_pF_fW_wD_d - ShpP_pF_fW_wD_{d-\delta(f,w)} \qquad (26)$$

$$- ItsP_pF_fW_wD_d.$$

Note that the $ItsP_pF_FW_WD_d$ variables are defined only for (p, f, w, d) combinations where there are finished goods in transit at the beginning of the planning horizon and are scheduled to arrive at warehouse w on day d for each $d \in DFGS\{p, f, w\}$. $OOP_pF_FW_wD_1$ should include sum of the $ItsP_pF_FW_WD_d$ values for each day with scheduled arrivals.

Update finished goods in transit to reflect shipments and receipts (constraint $GITP_pF_fW_wD_d$) at the end of day d. For each warehouse and day for each $p \in PW\{w\}$ and each $d \in DFGS\{p, f, w\}$,

$$TrP_pF_fW_wD_{d+1}$$

$$= TrP_pF_fW_wD_d + ShP_pF_fW_wD_d - ShpP_pF_fW_wD_{d-\delta(f,w)} \qquad (27)$$

$$- ItsP_pF_fW_wD_d.$$

Note that the $ItsP_pF_FW_WD_d$ variables are defined only for (p, f, w, d) combinations where there are finished goods in transit at the beginning of the planning horizon and are scheduled to arrive at warehouse w on day d for each $d \in DFGS\{p, f, w\}$. $TrP_pF_fW_wD_1$ is set to sum of the $ItsP_pF_fW_WD_d$ values for each day with scheduled arrivals.

As formulated with the warehouse inventory balance constraint (23), products that arrive in a day may be cross-docked and shipped out immediately if there is demand for them on that day rather than putting them into inventory. Such shipments could be delayed until the next day by adding a constraint (constraint $CDP_pW_WD_d$) that delivery of product p at warehouse w in a day can't exceed the beginning inventory of that product in that day. For each warehouse and day for each $p \in PW\{w\}$,

$$DelP_pW_wD_d \ \leq \ InvP_pW_wD_d. \tag{28}$$

All variables are nonnegative. To facilitate extraction of the solution in the report generator, we define variable $ARRP_pF_fW_WD_d$ to be the finished goods shipped from all production facilities that arrive at the warehouse in day d which will be shipped in this planning horizon and establish their equality in constraints that define inbound freight (constraint $IBP_pF_fW_WD_d$). We also define variable $ARRR_rS_sF_fD_d$ to be the amount of raw material r shipped from supplier s to arrive at production facility f on day d. They are set equal to the corresponding outbound shipments as follows (constraint $IBR_rS_sF_fD_d$),

$$ARRP_pF_fW_wD_d = ShpP_pF_fW_wD_{d-\delta(f,w)}. \tag{29}$$

$$ARRR_rS_sF_fD_d = ShpR_rS_sF_fD_{d-\theta(s,f)}. \tag{30}$$

Note that variables of $ItsP_pF_fW_WD_d$ and ItsRrSsFfDd represent goods in transit to arrive as a result of initial conditions, while that of $ShpPpFfW_WDd$ and

$ShpR_rS_sF_fD_d$ indicate when goods arrive from shipments in the current planning frame. We also provide the examination of the characteristic behaviors of the optimization model in Appendix C.

Chapter 4 Investigating the Optimizing Model's Behavior

The purpose of this chapter is to demonstrate how solutions from the optimizing model may vary when different planning horizons are used and when initial inventories are set at different levels. We investigate the average daily net profit contribution (NPC) projected over the planning horizon, and the character of procurement plans, production schedules and distribution plans that result. Most importantly, this chapter demonstrates that an optimizing model that recognized revenues according to standard accounting practice (i.e., when goods are sold to customers rather than when they are produced) can be counterproductive when too short a planning horizon is employed.

4.1 Problem Description

This chapter considers three cases where initial inventories are at minimum levels (Case A), maximum levels (Case B), and values distributed uniformly at random between min and max but also with a random 20% of outages at warehouses (Case C). All cases were developed under the assumptions that product demands are normally distributed (with truncation of negative values to 0) with constant means and assuming that no disruptions will occur in the supply chain during the chosen planning horizon. Actual demand is known only for the first period. Because revenues are realized only when products are sold, the optimizing model ignores revenues that will be realized from deliveries to warehouses that would support sales of product beyond the planning horizon. This can be a major problem when long lead times are required to replenish warehouse inventories. The procurement of raw materials, production schedules, and distribution plans at production facilities in the first period of the model's planning solution (which is implemented on a rolling horizon before revising the schedule with new information) might differ dramatically with varying lengths of planning horizon.

4.2 Inventory Reorder Points

The optimizing model determines the acquisition of raw materials, production at plants, distribution of goods to warehouses, and shipments from warehouses in response to customer demand. It incorporates parameters for provision of safety stocks and safety times. The optimization model may also incorporate variables that represent responses for event management (alternative deliveries of products directly from plants to satisfy customer demand or adding shifts when production must be intensified). The production module considers setup times for production lots, availability of productive resources (raw materials, equipment and/or labor), and production rates for different products.

As stated in Chapter 3, this research considers five key characteristics in the supply chain: minimum inventory levels of raw materials at plants, minimum inventory levels of finished products at plants, minimum inventory levels of products at warehouses, minimum system-wide inventories of finished goods, and the length of production planning horizon.

Because demand and lead time both vary, the calculation of product re-order points (ROP) at warehouses is done in three steps. In the first step, this research uses a ROP model with safety stocks to set minimum inventory levels with independent demand for each product at each warehouse (Heizer and Render, 2014). In the second step, the research allocates warehouse demands at plants with a gravity model (Smith and Moses, 1996) based on plant's unit supply cost. Table 4-1 contains the resulting inventory requirements at selected warehouse under different desired customer service levels. The complete table for products' minimum inventories associated with different customer service level at all warehouses can be found in Appendix B "ROP Calculation Steps".

Table 4-1 Warehouse Minimum Product Inventories in Days of Expected Demand

	Warehouse 1 (95% Service Level)	**Warehouse 1 (98% Service Level)**	**Warehouse 1 (99% Service Level)**
P1	17	19	19
P2	17	18	19
P3	18	19	20
P4	18	19	19
P5	18	20	21
P6	18	19	20

In the optimization model, warehouse orders will be placed with the most economical alternatives under the present conditions and constraints, including consideration of shortage penalties imposed in the model. Since the warehouses will not always get finished products from the cheapest source, certain portion of a period's orders are placed with the second or the third sources. The gravity model, without considering supply constraints at the production facilities, is used as a crude mechanism for allocating demand when setting safety stocks.

The expected production every day determines the daily raw material requirements at each production facility. The minimum inventory level of a raw material at each plant is set to a weighted average of what would be required if solely procured from each supplier, where the weight is the volume of business assigned to a supplier based on the gravity model. Table 4-2 presents the calculated lower bounds of raw material across plants.

Table 4-2 Minimum Raw Material Inventories in Days of Expected Production

	F1	F2	F3
R1	21	23	23
R2	14	11	25
R3	22	27	18

For this exercise, we shall assume that the minimum inventory equals zero and the maximum inventory of finished products at each plant equals to one day of its corresponding expected production quantities from the gravity model. To cope with SC risks, buffer inventories can be strategically placed across production and distribution facilities. The optimization model utilizes maxsysinv and minsysinv to allocate finished product inventories across plants as buffers to cope with disruptions or unusual events in the supply chain. Table 4-3 displays inventory boundary conditions of finished products at each plant in days of expected production quantities and Table 4-4 presents production system-wide inventory requirements of finished products in corresponding units. Note that in Table 4-4, the maximum system-wide inventory for each product equals to one day of total assigned average demand of that product at all warehouses.

Table 4-3 Product Inventory Limits at Plant

	Individual Plant (Days of expected production)
mininvfp	0
maxinvfp	1

Table 4-4 Production System-wide Product Inventory Limits

	minsysinv	maxsysinv
P1	0	702
P2	0	984
P3	0	273
P4	0	381
P5	0	78
P6	0	105

We assume that limited space also restricts the maximum level of raw material inventories at each plant to supply no more than 30 days of expected production and the maximum amount of product inventories carried at each warehouse to satisfy no more than 30 days of expected demand. Of course, this restriction would have to be set according to the physical constraints and costs structures in a practical setting.

We vary initial conditions to reflect different safety times incorporated in the supply chain as buffers to cope with supply chain risks. In a practical matter, the varying initial conditions at beginning of the planning horizon can also capture changes in the state of the system when events occur in the supply chain as these conditions can affect the optimality of the MILP model (Wang and Gerchak, 1996). Two cases with opposite (minimum and maximum) initial conditions are presented in the next section, along with a special case in which initial inventory is set at zero for 20% of product-warehouse combinations that are randomly chosen. Each of the three cases will be investigated with long and short planning horizons as we study the character of procurement plans, production schedules and distribution plans that emerge from the optimization model.

4.2 Scenario Analysis

In Case A, raw material inventories at production facilities, finished product inventories across plants, production system-wide finished product inventories, and product inventories at warehouses are all set at their corresponding minimum values. Desired customer service level at warehouses for all products is set at 95% when determining lower bounds on inventory. With a 5-day production planning horizon, the model yields a total NPC of $78,685.94 with $15,737.19 NPC per day. Daily NPC associated with the length of planning horizons is presented in Figure 4-1 below.

Starting with all inventories at their minimum levels, daily NPC deteriorates drastically at first when increasing the length of planning horizon and reaches the lowest with 15-day planning horizon. Increasing the length of planning horizon further along, daily NPC starts to increase (start with 20-day planning horizon). Although NPC per day variates with different length of planning horizon, total NPC increases with longer planning horizon because more demands are being satisfied. Note, however, that the daily NPC from the optimizing model is not an indication of the expected NPC per day that would be achieved when the solutions are implemented in practice (Next chapter will

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simulate the implementation of the solution with a rolling horizon to determine the latter). It reveals, however, the extent to which the optimizing model, with a given planning horizon, is taking into consideration future revenues versus production and distribution costs.

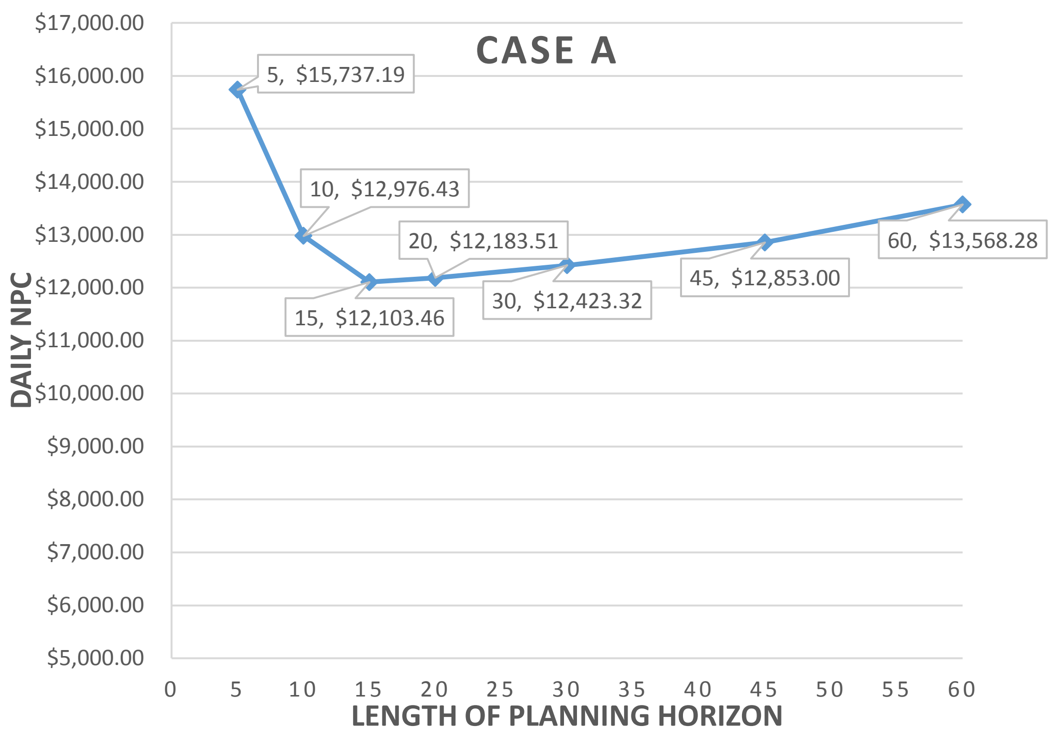

Figure 4-1 Case A Daily NPC Outcomes

To take the advantage of longer planning horizon and achieve higher total NPC, orders of raw materials are placed with a mix of suppliers as shown in Table 4-5. For selected plants and raw materials in Table 4-5, the left panel shows the procurement of raw materials with a 10-day planning horizon, while the right panel illustrates such raw material purchasing activities with a 15-day planning horizon.

Production and distribution schedules are affected dramatically by choice of planning horizon, as revealed in Table 4-6. Table 4-6 shows how production capacity is allocated among products each day (with .125 *8 =1 hour allocated for set-up and shut down in each plant). For a 5-day planning horizon, because all inventories are at their corresponding lower limits, all products are being produced at Plant 1 and Plant 2 as shown in the left panel of Table 4-6. However, for longer planning horizons, production schedules are similar as presented in the right panels of Table 4-6. Note that P3 is not produced with 45-day planning horizon because production capacity can be allocated to more profitable products and these products can be delivered in time (within 45 days) to realize revenues.

Although production schedules are similar when longer planning horizons are incorporated, distribution plans differ significantly as shown in Table 4-7. With initial inventories all at minimum level, short planning horizons result in low order fulfillment at warehouses (left panel in Table 4-7). Increasing the length of planning horizon, more shipments are made in response to warehouse orders (right panels in Table 4-7).

Table 4-5 Case A Procurement of Raw Materials

Obs	Raw Material	Facility	Day	INV	RM INV Shortage	Outstanding Orders	At Supplier	Order Placed	At Supplier	Old Order Arriv	From Supplier	New Order Arriv	From Supplier
29	1	3	7	17704	5738	.	.	.	.	.	.	.	.
30	1	3	8	16481	6962	.	.	.	.	.	.	.	.
31	1	3	9	15257	6962	.	.	.	.	.	.	.	.
32	1	3	10	15257	7548	.	.	.	.	.	.	.	.
33	1	3	11	14671	.	.	.	.	.	.	.	.	.
34	2	1	1	6300	315	.	.	3150	3	.	.	.	.
35	2	1	2	5985	630	3150	3	.	.	.	.	.	.
36	2	1	3	5670	1056	3150	3	.	.	.	.	.	.
37	2	1	4	5244	1656	3150	3	.	.	.	.	.	.
38	2	1	5	4644	2256	3150	3	.	.	.	.	.	.
39	2	1	6	4044	2862	3150	3	.	.	.	.	.	.
40	2	1	7	3438	3444	3150	3	.	.	.	.	.	.
41	2	1	8	2856	3759	3150	3	.	.	.	.	.	.
42	2	1	9	2541	3759	3150	3	.	.	.	.	.	.
43	2	1	10	2541	1239	3150	3	.	.	.	.	3150	3
44	2	1	11	5061	.	.	.	.	.	.	.	.	.
45	2	2	1	4784	605	.	.	4784	3	.	.	.	.
46	2	2	2	4180	1228	4784	3	.	.	.	.	.	.
47	2	2	3	3557	1983	4784	3	.	.	.	.	.	.
48	2	2	4	2801	2715	4784	3	.	.	.	.	.	.
49	2	2	5	2069	3314	4784	3	.	.	.	.	.	.
50	2	2	6	1470	3865	4784	3	.	.	.	.	.	.
51	2	2	7	919	4416	4784	3	.	.	.	.	.	.
52	2	2	8	368	.	4784	3	.	.	.	.	4784	3
53	2	2	9	4784	.	.	.	.	.	.	.	.	.
54	2	2	10	4784	83	.	.	.	.	.	.	.	.
55	2	2	11	4701	.	.	.	.	.	.	.	.	.
56	2	3	1	15240	.	.	.	.	.	.	.	.	.

From 10-day Solution

Obs	Raw Material	Facility	Day	INV	RM INV Shortage	Outstanding Orders	At Supplier	Order Placed	At Supplier	Old Order Arriv	From Supplier	New Order Arriv	From Supplier
57	2	1	9	3287	3083	4658	3	.	.	.	.	.	.
58	2	1	10	3217	.	4658	3	.	.	.	.	3150	3
59	2	1	11	6300	.	1508	3	.	.	.	.	315	3
60	2	1	12	6300	.	1193	3	.	.	.	.	371	3
61	2	1	13	6300	.	822	3	.	.	.	.	601	3
62	2	1	14	6300	.	221	3	.	.	.	.	.	.
63	2	1	15	6300	409	221	3	.	.	.	.	221	3
64	2	1	16	5891	.	.	.	.	.	.	.	.	.
65	2	2	1	4784	714	.	.	4784	3	.	.	.	.
66	2	2	1	.	.	.	.	705	4	.	.	.	.
67	2	2	2	4070	1607	4784	3	1104	3	.	.	.	.
68	2	2	2	.	.	705	4	.	.	.	.	.	.
69	2	2	3	3177	2322	5888	3	1104	3	.	.	.	.
70	2	2	3	.	.	705	4	166	4	.	.	.	.
71	2	2	4	2462	2787	6992	3	776	3	.	.	.	.
72	2	2	4	.	.	871	4	404	4	.	.	.	.
73	2	2	5	1997	3333	7768	3	.	.	.	.	.	.
74	2	2	5	.	.	1275	4	.	.	.	.	.	.
75	2	2	6	1451	3882	7768	3	368	3	.	.	.	.
76	2	2	6	.	.	1275	4	.	.	.	.	.	.
77	2	2	7	902	4416	8136	3	32	3	.	.	.	.
78	2	2	7	.	.	1275	4	.	.	.	.	.	.
79	2	2	8	368	.	8168	3	.	.	.	.	4784	3
80	2	2	8	.	.	1275	4	.	.	.	.	.	.
81	2	2	9	4784	.	3384	3	.	.	.	.	1104	3
82	2	2	9	.	.	1275	4	.	.	.	.	.	.
83	2	2	10	4784	.	2280	3	.	.	.	.	1104	3
84	2	2	10	.	.	1275	4	.	.	.	.	.	.

From 15-day Solution

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Table 4-6 Case A Allocation of Production Capacity

Obs	Facility	Day	Product	Proportion of Time Available	Cum. Prop. of Time Available
1	1	1	1	0.14402	0.14402
2	1	1	2	0.40200	0.54603
3	1	1	3	0.10357	0.64960
4	1	1	4	0.13281	0.78241
5	1	1	5	0.04087	0.82328
6	1	1	6	0.05172	0.87500
7	2	1	1	0.18155	0.18155
8	2	1	2	0.22774	0.40929
9	2	1	3	0.19290	0.60219
10	2	1	4	0.15940	0.76159
11	2	1	5	0.04750	0.80909
12	2	1	6	0.06591	0.87500
13	3	1	1	0.26552	0.26552
14	3	1	2	0.24330	0.50882
15	3	1	4	0.11951	0.62833
16	3	1	5	0.11667	0.74500
17	3	1	6	0.13000	0.87500

From 5-day Solution

Obs	Facility	Day	Product	Proportion of Time Available	Cum. Prop. of Time Available
1	1	1	1	0.24437	0.24437
2	1	1	2	0.53804	0.78241
3	1	1	5	0.04087	0.82328
4	1	1	6	0.05172	0.87500
5	2	1	1	0.31131	0.31131
6	2	1	2	0.22774	0.53905
7	2	1	3	0.08803	0.62708
8	2	1	4	0.13451	0.76159
9	2	1	5	0.04750	0.80909
10	2	1	6	0.06591	0.87500
11	3	1	1	0.31034	0.31034
12	3	1	2	0.31799	0.62833
13	3	1	5	0.11667	0.74500
14	3	1	6	0.13000	0.87500

From 30-day Solution

Obs	Facility	Day	Product	Proportion of Time Available	Cum. Prop. of Time Available
1	1	1	1	0.24437	0.24437
2	1	1	2	0.53804	0.78241
3	1	1	5	0.04087	0.82328
4	1	1	6	0.05172	0.87500
5	2	1	1	0.35994	0.35994
6	2	1	2	0.22774	0.58768
7	2	1	4	0.17391	0.76159
8	2	1	5	0.04750	0.80909
9	2	1	6	0.06591	0.87500
10	3	1	1	0.31034	0.31034
11	3	1	2	0.31799	0.62833
12	3	1	5	0.11667	0.74500
13	3	1	6	0.13000	0.87500

From 45-day Solution

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Table 4-7 Case A Distribution Plans

Obs	Variable Name	Product	Facility	Warehouse	Day	Amount shipped
1	SHPP2F1W1D1	2	1	1	1	18
2	SHPP2F1W2D2	2	1	2	2	39

From 15-day Solution

Obs	Variable Name	Product	Facility	Warehouse	Day	Amount shipped
1	SHPP1F1W1D2	1	1	1	2	137
2	SHPP1F1W2D2	1	1	2	2	21
3	SHPP1F1W2D3	1	1	2	3	25
4	SHPP1F1W2D4	1	1	2	4	58
5	SHPP1F1W2D9	1	1	2	9	59
6	SHPP1F2W3D2	1	2	3	2	84
7	SHPP1F2W4D5	1	2	4	5	10
8	SHPP1F2W4D6	1	2	4	6	10
9	SHPP1F3W5D3	1	3	5	3	102
10	SHPP1F3W5D4	1	3	5	4	102
11	SHPP1F3W5D5	1	3	5	5	102
12	SHPP1F3W5D6	1	3	5	6	102
13	SHPP1F3W5D7	1	3	5	7	52

From 30-day Solution

Obs	Variable Name	Product	Facility	Warehouse	Day	Amount shipped
1	SHPP1F1W1D3	1	1	1	3	69
2	SHPP1F1W1D6	1	1	1	6	18
3	SHPP1F1W1D9	1	1	1	9	127
4	SHPP1F1W1D10	1	1	1	10	37
5	SHPP1F1W2D2	1	1	2	2	106
6	SHPP1F1W2D7	1	1	2	7	22
7	SHPP1F1W2D15	1	1	2	15	0
8	SHPP1F2W3D2	1	2	3	2	120
9	SHPP1F2W3D3	1	2	3	3	120
10	SHPP1F2W3D4	1	2	3	4	81
11	SHPP1F2W4D5	1	2	4	5	10
12	SHPP1F2W4D6	1	2	4	6	100
13	SHPP1F2W4D7	1	2	4	7	87
14	SHPP1F2W4D8	1	2	4	8	81
15	SHPP1F3W5D2	1	3	5	2	65
16	SHPP1F3W5D3	1	3	5	3	81
17	SHPP1F3W5D4	1	3	5	4	102
18	SHPP1F3W5D5	1	3	5	5	102
19	SHPP1F3W5D7	1	3	5	7	74
20	SHPP1F3W5D8	1	3	5	8	102
21	SHPP1F3W5D9	1	3	5	9	102
22	SHPP1F3W5D10	1	3	5	10	102

From 45-day Solution

To further evaluate the impact of initial conditions on system performance in terms of daily NPC and the impact of planning horizons on procurement plans, production schedules, and distribution plans, Case B was developed. While keeping all other initial settings the same as Case A (95% service level and one shift), Case B sets beginning raw material inventories at production sites, finished product inventories at plants, production system-wide finished product inventories, and product inventories at warehouses all at maximum level. NPC per day associated with different length of planning horizon is presented in Figure 4-2.

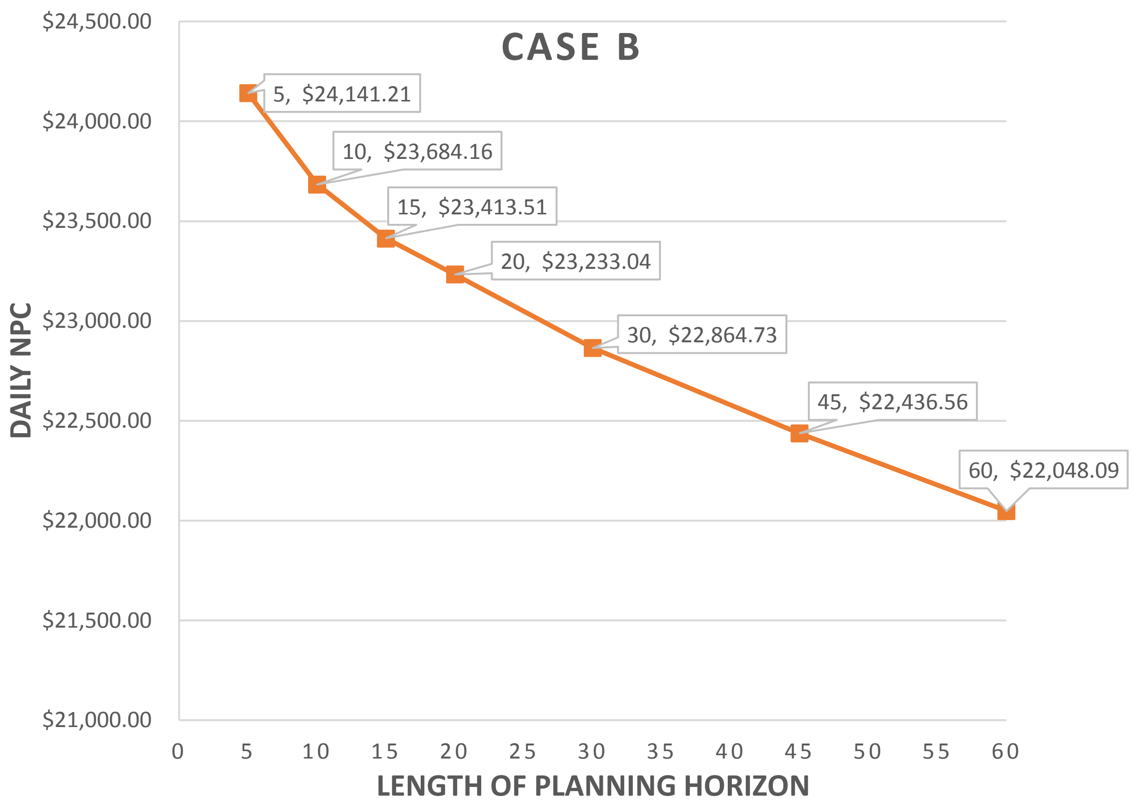

Figure 4-2 Case B Daily NPC Outcomes

With maximized safety stock incorporated into the system, under a 5-day planning horizon, there is no motivation to set up plants for production because current product inventories at warehouses are sufficient to satisfy customer demands. Raw material inventories are also sufficient for production of corresponding products if the planning horizon is short (up to 15 days for R1, R2 and up to 10 days for R3 across production facilities in ICB). Longer planning horizons stimulate production activities and trigger the procurement of raw materials as shown in Table 4-9. However, when to place the order of raw materials at what quantity with which supplier vary with the length of planning horizon (right panel in Table 4-9).

Table 4-10 presents warehouse activities for the same problem that differs only with the length of planning horizon. The left panel in Table 4-10 shows warehouse activities with a 15-day planning horizon. Corresponding activities with 45-day planning horizon are presented in the right panel. Increasing the length of planning horizons in Case B triggers orders to satisfy future customer demand and avoid future inventory shortage penalties. Orders are made in the early periods with anticipated benefits from delivery of goods with long shipping delays. However, how many units of products to order, when orders are placed, and where orders are placed, all vary over the planning horizon. Note, for example, the outstanding orders of product 3 at warehouse 2 on day 8 with relatively short planning horizon (15-day as the left panel in Table 4-10). More orders are placed at the plant with shorter lead time but higher supply costs to avoid lost sales and inventory shortage penalty. With the longer planning horizon (45-day as the right panel in Table 4-10), more orders are placed at the plant with lower supply costs but long shipping delays. Order patterns at the warehouse reflect "consolidation" strategies intended to reduce costs when longer planning horizons are used. More production is consolidated at the plant that can most economically supply the warehouse. Additionally, "flexibility" is exercised as deliveries to a warehouse are allowed to occur from alternative plants. Initial raw material inventories at plants and the length of planning horizon together affect plants' production schedules, procurement of raw materials and distribution plans.

Table 4-8 Case B Facility Production Set up

Obs	Variable Name	Facility	Day	idlehrs	idlecost	setupFacility	setupco
1	IDLEF1D1	1	1	8	400	.	
2	SUF1D2	1	2	0	0	1	1
3	SUF1D3	1	3	0	0	1	1
4	SUF1D4	1	4	0	0	1	1
5	SUF1D5	1	5	0	0	1	1
6	SUF1D6	1	6	0	0	1	1
7	IDLEF1D7	1	7	8	400	.	
8	IDLEF1D8	1	8	8	400	.	
9	IDLEF1D9	1	9	8	400	.	
10	IDLEF1D10	1	10	8	400	.	
11	IDLEF1D11	1	11	8	400	.	
12	IDLEF1D12	1	12	8	400	.	
13	SUF1D13	1	13	0	0	1	1
14	SUF1D14	1	14	0	0	1	1
15	SUF1D15	1	15	0	0	1	1
16	IDLEF2D1	2	1	8	400	.	
17	SUF2D2	2	2	0	0	1	1
18	SUF2D3	2	3	0	0	1	1
19	SUF2D4	2	4	0	0	1	1
20	SUF2D5	2	5	0	0	1	1
21	SUF2D6	2	6	0	0	1	1
22	SUF2D7	2	7	0	0	1	1
23	SUF2D8	2	8	0	0	1	1
24	IDLEF2D9	2	9	8	400	.	
25	IDLEF2D10	2	10	8	400	.	
26	SUF2D11	2	11	8	400	0	
27	IDLEF2D12	2	12	8	400	.	
28	SUF2D13	2	13	8	400	0	
29	SUF2D14	2	14	0	0	1	1

From 15-day Solution

Obs	Variable Name	Facility	Day	idlehrs	idlecost	setupFacility	setupcost
1	IDLEF1D1	1	1	8	400	.	.
2	SUF1D2	1	2	0	0	1	150
3	SUF1D3	1	3	0	0	1	150
4	SUF1D4	1	4	0	0	1	150
5	SUF1D5	1	5	0	0	1	150
6	SUF1D6	1	6	0	0	1	150
7	SUF1D7	1	7	0	0	1	150
8	SUF1D8	1	8	0	0	1	150
9	SUF1D9	1	9	0	0	1	150
10	SUF1D10	1	10	0	0	1	150
11	SUF1D11	1	11	0	0	1	150
12	SUF1D12	1	12	0	0	1	150
13	SUF1D13	1	13	0	0	1	150
14	SUF1D14	1	14	0	0	1	150
15	SUF1D15	1	15	0	0	1	150
16	SUF1D16	1	16	0	0	1	150
17	SUF1D17	1	17	0	0	1	150
18	SUF1D18	1	18	0	0	1	150
19	SUF1D19	1	19	0	0	1	150
20	SUF1D20	1	20	0	0	1	150
21	SUF1D21	1	21	0	0	1	150
22	IDLEF1D22	1	22	8	400	.	.
23	IDLEF1D23	1	23	8	400	.	.
24	IDLEF1D24	1	24	8	400	.	.
25	IDLEF1D25	1	25	8	400	.	.
26	IDLEF1D26	1	26	8	400	.	.
27	SUF1D27	1	27	0	0	1	150
28	IDLEF1D28	1	28	8	400	.	.
29	SUF1D29	1	29	0	0	1	150

From 30-day Solution

Obs	Variable Name	Facility	Day	idlehrs	idlecost	setupFacility	setupcost
1	IDLEF1D1	1	1	8	400	.	.
2	SUF1D2	1	2	0	0	1	150
3	SUF1D3	1	3	0	0	1	150
4	SUF1D4	1	4	0	0	1	150
5	SUF1D5	1	5	0	0	1	150
6	SUF1D6	1	6	0	0	1	150
7	SUF1D7	1	7	0	0	1	150
8	SUF1D8	1	8	0	0	1	150
9	SUF1D9	1	9	0	0	1	150
10	SUF1D10	1	10	0	0	1	150
11	SUF1D11	1	11	0	0	1	150
12	SUF1D12	1	12	0	0	1	150
13	SUF1D13	1	13	0	0	1	150
14	SUF1D14	1	14	0	0	1	150
15	SUF1D15	1	15	0	0	1	150
16	SUF1D16	1	16	0	0	1	150
17	SUF1D17	1	17	0	0	1	150
18	SUF1D18	1	18	0	0	1	150
19	SUF1D19	1	19	0	0	1	150
20	SUF1D20	1	20	0	0	1	150
21	SUF1D21	1	21	0	0	1	150
22	SUF1D22	1	22	0	0	1	150
23	SUF1D23	1	23	0	0	1	150
24	SUF1D24	1	24	0	0	1	150
25	SUF1D25	1	25	0	0	1	150
26	SUF1D26	1	26	0	0	1	150
27	SUF1D27	1	27	0	0	1	150
28	SUF1D28	1	28	0	0	1	150
29	SUF1D29	1	29	0	0	1	150

From 45-day Solution

Table 4-9 Case B Procurement of Raw Materials

Obs	Raw Material	Facility	Day	INV	RM INV Shortage	Outstanding Orders	At Supplier	Order Placed	At Supplier	Old Order Arriv	From Supplier	New Order Arriv	From Supplier
169	2	1	25	.	.	754	4	.	.	.	.	.	.
170	2	1	26	6300	.	374	3	.	.	.	.	.	.
171	2	1	26	.	.	754	4	.	.	.	.	.	.
172	2	1	27	6300	.	374	3	.	.	.	.	372	3
173	2	1	27	.	.	754	4	.	.	.	.	.	.
174	2	1	28	6300	.	2	3	.	.	.	.	.	.
175	2	1	28	.	.	754	4	.	.	.	.	.	.
176	2	1	29	6300	.	2	3	.	.	.	.	2	3
177	2	1	29	.	.	754	4	.	.	.	.	439	4
178	2	1	30	6300	.	315	4	.	.	.	.	315	4
179	2	1	31	6300	.	.	.	.	.	.	.	.	.
180	2	2	1	11040	.	.	.	.	.	.	.	.	.
181	2	2	2	11040	.	.	.	.	.	.	.	.	.
182	2	2	3	10462	.	.	.	625	4	.	.	.	.
183	2	2	4	9838	.	625	4	577	4	.	.	.	.
184	2	2	5	9280	.	1202	4	467	4	.	.	.	.
185	2	2	6	8680	.	1669	4	433	3	.	.	.	.
186	2	2	6	.	.	.	.	258	4	.	.	.	.
187	2	2	7	8202	.	433	3	2	3	.	.	.	.
188	2	2	7	.	.	1927	4	485	4	.	.	.	.
189	2	2	8	7596	.	435	3	588	4	.	.	.	.
190	2	2	8	.	.	2413	4	.	.	.	.	.	.
191	2	2	9	6980	.	435	3	625	4	.	.	.	.
192	2	2	9	.	.	3000	4	.	.	.	.	.	.
193	2	2	10	6316	.	435	3	186	3	.	.	.	.
194	2	2	10	.	.	3625	4	478	4	.	.	.	.
195	2	2	11	5863	.	621	3	453	4	.	.	.	.
196	2	2	11	.	.	4103	4	.	.	.	.	.	.

From 30-day Solution

Obs	Raw Material	Facility	Day	INV	RM INV Shortage	Outstanding Orders	At Supplier	Order Placed	At Supplier	Old Order Arriv	From Supplier	New Order Arriv	From Supplier
253	2	1	33	6300	.	2900	3	.	.	.	.	370	3
254	2	1	34	6300	.	2530	3	326	3	.	.	318	3
255	2	1	35	6300	.	2538	3	.	.	.	.	437	3
256	2	1	36	6300	.	2101	3	.	.	.	.	541	3
257	2	1	37	6300	.	1559	3	.	.	.	.	491	3
258	2	1	38	6300	.	1069	3	.	.	.	.	395	3
259	2	1	39	6300	.	674	3	.	.	.	.	.	.
260	2	1	40	6300	.	674	3	.	.	.	.	.	.
261	2	1	41	6300	.	674	3	.	.	.	.	348	3
262	2	1	42	6300	.	326	3	.	.	.	.	.	.
263	2	1	43	6300	.	326	3	.	.	.	.	326	3
264	2	1	44	6300	.	.	.	.	.	.	.	.	.
265	2	1	45	6300	.	.	.	0	3	.	.	.	.
266	2	1	46	6300	.	.	.	.	.	.	.	.	.
267	2	2	1	11040	.	.	.	.	.	.	.	.	.
268	2	2	2	11040	.	.	.	.	.	.	.	.	.
269	2	2	3	10135	.	.	.	676	3	.	.	.	.
270	2	2	3	.	.	.	.	229	4	.	.	.	.
271	2	2	4	9158	.	676	3	752	3	.	.	.	.
272	2	2	4	.	.	229	4	67	4	.	.	.	.
273	2	2	5	8317	.	1428	3	686	3	.	.	.	.
274	2	2	5	.	.	295	4	313	4	.	.	.	.
275	2	2	6	7626	.	2114	3	709	3	.	.	.	.
276	2	2	6	.	.	609	4	.	.	.	.	.	.
277	2	2	7	6980	.	2823	3	579	3	.	.	.	.
278	2	2	7	.	.	609	4	49	4	.	.	.	.
279	2	2	8	6289	.	3402	3	691	3	.	.	.	.
280	2	2	8	.	.	658	4	.	.	.	.	.	.

From 45-day Solution

Table 4-10 Case B Warehouse Activities

Prod	W.H.	Day	W.H. Inventory	Demand	Delivered from W.H.	W.H. Inventory Shortage	Delivered from Facility	From Facility	Outstanding Orders	AT Facility	Order Placed	At Facility	Old Order Arriv	From Facility	New Order Arriv	From Facility	Lost Sales
3	2	2	1566	54	54	.	.	.	.	.	28	2	.	.	.	.	.
3	2	3	1512	54	54	.	.	.	28	2	54	1	.	.	.	.	.
3	2	3	.	.	.	.	.	.	.	.	26	2	.	.	.	.	.
3	2	4	1458	54	54	.	.	.	54	1	28	1	.	.	.	.	.
3	2	4	.	.	.	.	.	.	54	2	.	.	.	.	.	.	.
3	2	5	1404	54	54	.	.	.	82	1	26	1	.	.	.	.	.
3	2	5	.	.	.	.	.	.	54	2	54	2	.	.	.	.	.
3	2	6	1350	54	54	.	.	.	108	1	54	1	.	.	.	.	.
3	2	6	.	.	.	.	.	.	108	2	.	.	.	.	.	.	.
3	2	7	1296	54	54	.	.	.	162	1	28	1	.	.	.	.	.
3	2	7	.	.	.	.	.	.	108	2	4	2	.	.	.	.	.
3	2	8	1242	54	54	.	.	.	190	1	.	.	.	.	.	.	.
3	2	8	.	.	.	.	.	.	112	2	23	2	.	.	.	.	.
3	2	9	1188	54	54	.	.	.	190	1	.	.	.	.	.	.	.
3	2	9	.	.	.	.	.	.	134	2	.	.	.	.	.	.	.
3	2	10	1134	54	54	.	.	.	190	1	.	.	.	.	54	1	.
3	2	10	.	.	.	.	.	.	134	2	.	.	.	.	.	.	.
3	2	11	1134	54	54	.	.	.	136	1	.	.	.	.	28	1	.
3	2	11	.	.	.	.	.	.	134	2	.	.	.	.	26	2	.
3	2	12	1134	54	54	.	.	.	108	1	.	.	.	.	26	1	.
3	2	12	.	.	.	.	.	.	108	2	.	.	.	.	28	2	.
3	2	13	1134	54	54	.	.	.	82	1	.	.	.	.	54	1	.
3	2	13	.	.	.	.	.	.	80	2	.	.	.	.	26	2	.
3	2	14	1160	54	54	.	.	.	28	1	.	.	.	.	28	1	.
3	2	14	.	.	.	.	.	.	54	2	.	.	.	.	.	.	.
3	2	15	1134	54	54	.	.	.	0	1	.	.	.	.	0	1	.
3	2	15	.	.	.	.	.	.	54	2	.	.	.	.	54	2	.
3	2	16	1134	.	.	.	.	.	.	.	.	.	.	.	.	.	.

From 15-day Solution

Prod	W.H.	Day	W.H. Inventory	Demand	Delivered from W.H.	W.H. Inventory Shortage	Delivered from Facility	From Facility	Outstanding Orders	AT Facility	Order Placed	At Facility	Old Order Arriv	From Facility	New Order Arriv	From Facility	Lost Sales
3	2	3	1512	54	54	.	.	.	53	1	1	1	.	.	.	.	.
3	2	3	.	.	.	.	.	.	.	.	54	2	.	.	.	.	.
3	2	4	1458	54	54	.	.	.	54	1	54	2	.	.	.	.	.
3	2	4	.	.	.	.	.	.	54	2	.	.	.	.	.	.	.
3	2	5	1404	54	54	.	.	.	54	1	44	1	.	.	.	.	.
3	2	5	.	.	.	.	.	.	108	2	10	2	.	.	.	.	.
3	2	6	1350	54	54	.	.	.	98	1	54	2	.	.	.	.	.
3	2	6	.	.	.	.	.	.	118	2	.	.	.	.	.	.	.
3	2	7	1296	54	54	.	.	.	98	1	27	2	.	.	.	.	.
3	2	7	.	.	.	.	.	.	172	2	.	.	.	.	.	.	.
3	2	8	1242	54	54	.	.	.	98	1	44	1	.	.	.	.	.
3	2	8	.	.	.	.	.	.	199	2	37	2	.	.	.	.	.
3	2	9	1188	54	54	.	.	.	142	1	54	2	.	.	53	1	.
3	2	9	.	.	.	.	.	.	236	2	.	.	.	.	.	.	.
3	2	10	1187	54	54	.	.	.	90	1	27	1	.	.	1	1	.
3	2	10	.	.	.	.	.	.	290	2	27	2	.	.	.	.	.
3	2	11	1134	54	54	.	.	.	115	1	17	1	.	.	64	2	.
3	2	11	.	.	.	.	.	.	317	2	37	2	.	.	.	.	.
3	2	12	1144	54	54	.	.	.	132	1	54	2	.	.	44	1	.
3	2	12	.	.	.	.	.	.	290	2	.	.	.	.	.	.	.
3	2	13	1134	54	54	.	.	.	88	1	27	1	.	.	54	2	.
3	2	13	.	.	.	.	.	.	344	2	27	2	.	.	.	.	.
3	2	14	1134	54	54	.	.	.	115	1	17	1	.	.	54	2	.
3	2	14	.	.	.	.	.	.	317	2	37	2	.	.	.	.	.
3	2	15	1134	54	54	.	.	.	132	1	36	2	.	.	44	1	.
3	2	15	.	.	.	.	.	.	300	2	.	.	.	.	10	2	.
3	2	16	1134	54	54	.	.	.	88	1	27	1	.	.	54	2	.
3	2	16	.	.	.	.	.	.	326	2	16	2	.	.	.	.	.

From 45-day Solution

To further investigate the impact of inventories and planning horizon on planned system performance for the given objective function, Case C was developed. In Case C, initial inventories (raw materials, finished products at plants and in warehouses) are set between the lower and upper limits using a uniform probability distribution. In addition, this research randomly chooses 20% of product-warehouse combinations for which initial inventory is set at zero. Given the cost structure of the optimizing model, the main purpose of Case C is to demonstrate that an "expediting trap" can occur when inventory is exhausted and too short a time horizon is used in optimizing flows in the supply chain. Such random outages can occur with a disruption or unusual event which depletes inventories at the warehouse. Figure 4-3 illustrates NPC per day resulted from different planning horizons for Case C.

Compared with other cases, daily NPC in Case C drops significantly when short planning horizons (up to 30 days) are employed. This dramatic reduction in NPC per day is driven by the combination of inventory shortage costs at the warehouse and changes in the distribution plans (as shown in Table 4-11). The new distribution pattern illustrates that when disruption or unusual event alters the state of the system, the short planning horizon leads to an "expediting trap" whereby customer demands are satisfied solely from high-cost alternative deliveries made directly from the plant, because there is insufficient time in the planning horizon to capture revenues from products delivered to the warehouse (due to long shipping times).

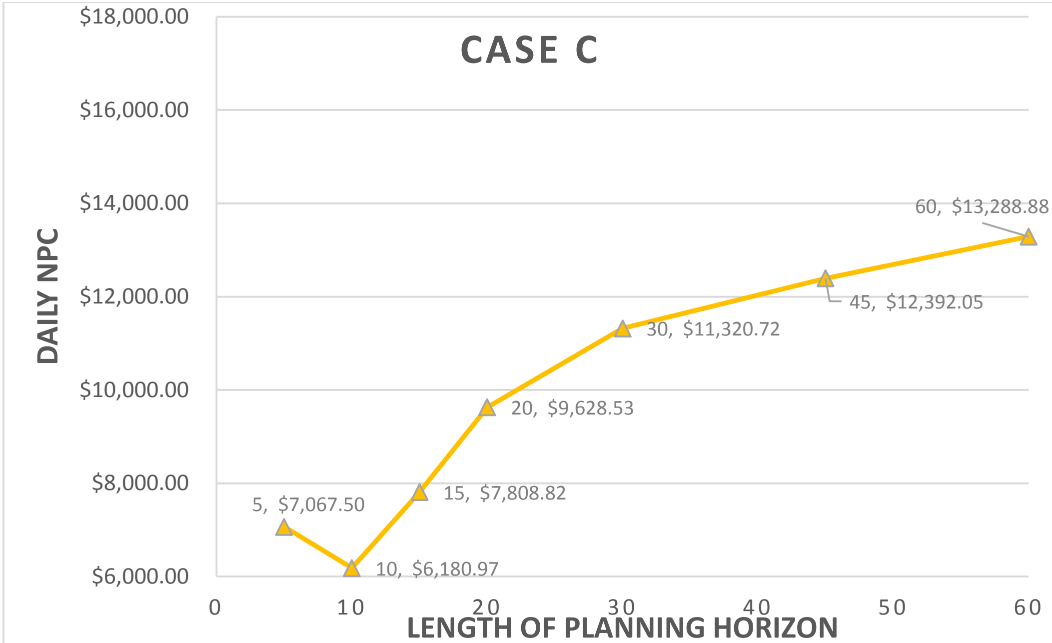

Figure 4-3 Case C Daily NPC outcomes

If a 15-day horizon were used instead for planning in the period following the stockouts (see the right panel of Table 4-11), warehouses place orders, goods are shipped to warehouses to satisfy later demands and the expediting trap is at least partially avoided. Note how WH3 partially restore the inventory of product 3.

Table 4-11 Case C Warehouse Activities

Prod	W.H.	Day	W.H. Inventory	Demand	Delivered from W.H.	W.H. Inventory Shortage	Delivered from Facility	From Facility	Outstanding Orders	AT Facility	Order Placed	At Facility	Old Order Arriv	From Facility	New Order Arriv	From Facility	L S
3	2	3	1322	54	54	.	.	.	.	.	.	.	.	.	.	.	
3	2	4	1268	54	54	.	.	.	.	.	.	.	.	.	.	.	
3	2	5	1214	54	54	.	.	.	.	.	.	.	.	.	.	.	
3	2	6	1160	.	.	.	.	.	.	.	.	.	.	.	.	.	
3	3	0	.	.	.	1188	.	.	.	.	.	.	.	.	.	.	
3	3	1	.	54	.	1188	54	3	.	.	.	.	.	.	.	.	
3	3	2	.	54	.	1188	54	1	.	.	.	.	.	.	.	.	
3	3	3	.	54	.	1188	54	1	.	.	.	.	.	.	.	.	
3	3	4	.	54	.	1188	54	1	.	.	.	.	.	.	.	.	
3	3	5	.	54	.	1188	54	3	.	.	.	.	.	.	.	.	
3	4	1	1280	48	32	.	16	3	.	.	.	.	.	.	.	.	
3	4	2	1248	48	48	.	.	.	.	.	.	.	.	.	.	.	
3	4	3	1200	48	.	.	48	1	.	.	.	.	.	.	.	.	
3	4	4	1200	48	.	.	48	1	.	.	.	.	.	.	.	.	
3	4	5	1200	48	48	48	.	.	.	.	.	.	.	.	.	.	
3	4	6	1152	.	.	.	.	.	.	.	.	.	.	.	.	.	
3	5	1	762	32	26	.	6	3	.	.	.	.	.	.	.	.	
3	5	2	736	32	32	.	.	.	.	.	.	.	.	.	.	.	
3	5	3	704	32	.	.	32	1	.	.	.	.	.	.	.	.	
3	5	4	704	32	.	.	32	1	.	.	.	.	.	.	.	.	
3	5	5	704	32	32	32	.	.	.	.	.	.	.	.	.	.	
3	5	6	672	.	.	.	.	.	.	.	.	.	.	.	.	.	
3	6	0	.	.	.	920	.	.	.	.	.	.	.	.	.	.	
3	6	1	.	40	.	920	40	1	.	.	.	.	.	.	.	.	
3	6	2	.	40	.	920	22	1	.	.	.	.	.	.	.	.	
3	6	2	.	.	.	.	18	3	.	.	.	.	.	.	.	.	
3	6	3	.	40	.	920	40	1	.	.	.	.	.	.	.	.	
3	6	4	.	40	.	920	40	1	.	.	.	.	.	.	.	.	

From 5-day Solution

Prod	W.H.	Day	W.H. Inventory	Demand	Delivered from W.H.	W.H. Inventory Shortage	Delivered from Facility	From Facility	Outstanding Orders	AT Facility	Order Placed	At Facility	Old Order Arriv	From Facility	New Order Arriv	From Facility	Lost Sales
3	2	10	1134	54	.	.	18	1	.	.	.	.	.	.	.	.	.
3	2	10	.	.	.	.	20	2	.	.	.	.	.	.	.	.	.
3	2	10	.	.	.	.	16	3	.	.	.	.	.	.	.	.	.
3	2	11	1134	54	.	.	20	2	.	.	.	.	.	.	.	.	.
3	2	11	.	.	.	.	34	3	.	.	.	.	.	.	.	.	.
3	2	12	1134	54	.	.	54	2	.	.	.	.	.	.	.	.	.
3	2	13	1134	54	.	.	54	2	.	.	.	.	.	.	.	.	.
3	2	14	1134	54	1	1	53	3	.	.	.	.	.	.	.	.	.
3	2	15	1133	54	54	55	.	.	.	.	.	.	.	.	.	.	.
3	2	16	1079	.	.	.	.	.	.	.	.	.	.	.	.	.	.
3	3	0	.	.	.	1188	.	.	.	.	.	.	.	.	.	.	.
3	3	1	.	54	.	1188	12	1	.	.	104	1	.	.	.	.	.
3	3	1	.	.	.	.	42	3	.	.	136	2	.	.	.	.	.
3	3	2	.	54	.	1188	54	3	104	1	17	1	.	.	.	.	.
3	3	2	.	.	.	.	.	.	136	2	127	2	.	.	.	.	.
3	3	3	.	54	.	1188	54	3	121	1	58	1	.	.	.	.	.
3	3	3	.	.	.	.	.	.	263	2	204	2	.	.	.	.	.
3	3	4	.	54	.	1188	54	3	179	1	134	1	.	.	.	.	.
3	3	4	.	.	.	.	.	.	467	2	204	2	.	.	.	.	.
3	3	5	.	54	.	1188	54	3	313	1	204	2	.	.	.	.	.
3	3	5	.	.	.	.	.	.	671	2	.	.	.	.	.	.	.
3	3	6	.	54	.	1188	54	2	313	1	.	.	.	.	.	.	.
3	3	6	.	.	.	.	.	.	875	2	.	.	.	.	.	.	.
3	3	7	.	54	.	1188	54	2	313	1	.	.	.	.	.	.	.
3	3	7	.	.	.	.	.	.	875	2	.	.	.	.	.	.	.
3	3	8	.	54	.	1052	54	1	313	1	.	.	.	.	136	2	.
3	3	8	.	.	.	.	.	.	875	2	.	.	.	.	.	.	.
3	3	9	136	54	.	821	54	3	313	1	.	.	.	.	104	1	.

From 15-day Solution

4.3 Summary

The primary purpose of this chapter has been to illustrate the character of procurement plans, production schedules and distribution plans that result when different planning horizons are used for the optimization model and when initial inventories are at different levels. Although NPC per day from the optimizing model is not an indication of the expected daily NPC that would be achieved under different planning horizons, it illustrates that how the optimizing model with an objective function of maximizing net contribution to profit takes into account future revenues versus costs for a given planning horizon. Case A and Case B both demonstrate the importance of using a sufficiently long planning horizon to avoid counterproductive effects of short-term optimization for the given objective function. As planning horizon lengthens, NPC per day associated with Case A and Case B in Figure 4-4 clearly reveal a tendency to converge.

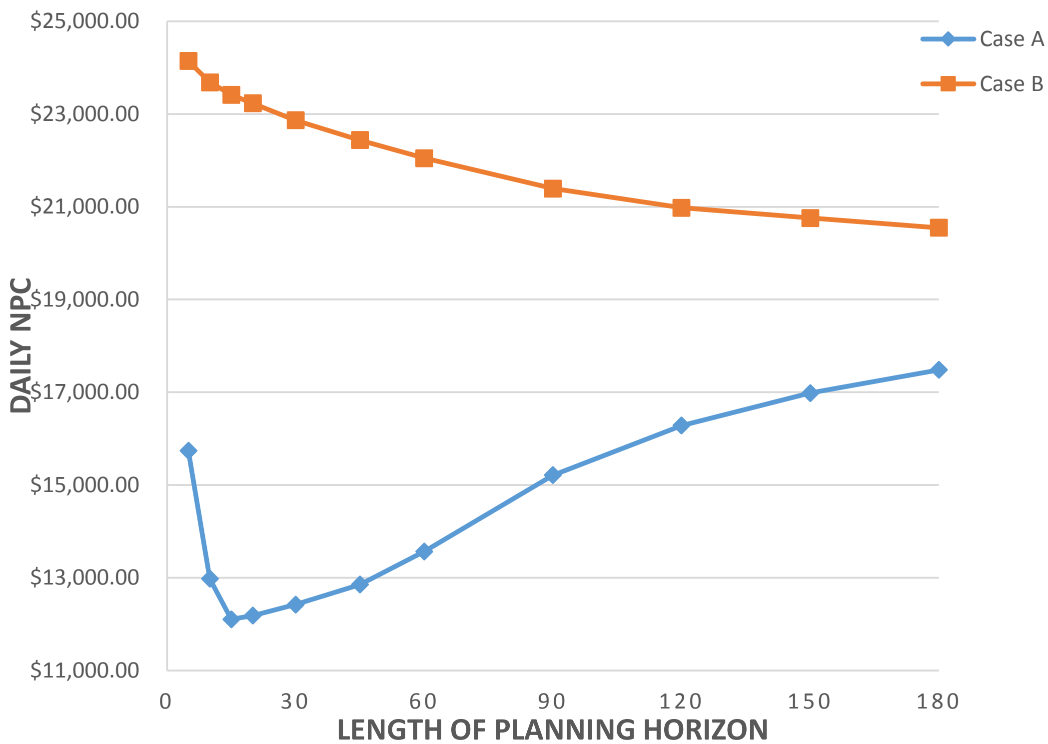

Figure 4-4 Comparison of Daily NPC Outcomes

Though the ideal situation is to show the convergence of daily NPC derived from Case A and Case B when the system reaches steady state, with 180-day planning horizon, the MILP model as formulated contained 165,240 rows and 194,230 columns with 540 binary variables, it takes SAS 9.4 over 26 hours to achieve integer optimality for a single solution. For the computational burden of long planning horizons, even for this relatively simple supply chain, motivate our investigation of how changes in planning horizons and the choices of re-planning cycle (time between schedule revisions) affect the performance and risk profiles of a supply chain.

In the course of these experiments, it became apparent that solutions from the MILP model regarding procurement, production and distribution can be very sensitive to small changes in cost parameters even when values to the objective function overall are not. In developing the optimizing model, the researcher observed how minuscule differences in costs associated with goods in transit could cause goods either to be retained at the plant until the latest possible moment or shipped out at the earliest possible moment. This has obvious implications for “postponement” strategies intended to reduce risk.

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Table 4-12 Allocations of Production Capacity in Production Schedules

Obs	Facility	Day	Product	Proportion of Time Available	Cum. Prop. of Time Available
1	1	1	1	0.40036	0.40036
2	1	1	2	0.32877	0.72914
3	1	1	5	0.06971	0.79885
4	1	1	6	0.07615	0.87500
5	2	1	1	0.24306	0.24306
6	2	1	2	0.51854	0.76159
7	2	1	5	0.04750	0.80909
8	2	1	6	0.06591	0.87500
9	3	1	1	0.28103	0.28103
10	3	1	2	0.36235	0.64339
11	3	1	5	0.06389	0.70727
12	3	1	6	0.16773	0.87500

From 90-day Solution

Obs	Facility	Day	Product	Proportion of Time Available	Cum. Prop. of Time Available
1	1	1	1	0.40036	0.40036
2	1	1	2	0.35320	0.75356
3	1	1	5	0.06971	0.82328
4	1	1	6	0.05172	0.87500
5	2	1	1	0.24306	0.24306
6	2	1	2	0.51153	0.75459
7	2	1	5	0.05450	0.80909
8	2	1	6	0.06591	0.87500
9	3	1	1	0.28103	0.28103
10	3	1	2	0.36235	0.64339
11	3	1	5	0.05833	0.70172
12	3	1	6	0.17328	0.87500

From 120-day Solution

Obs	Facility	Day	Product	Proportion of Time Available	Cum. Prop. of Time Available
1	1	1	1	0.43207	0.43207
2	1	1	2	0.28497	0.71704
3	1	1	5	0.06971	0.78675
4	1	1	6	0.08825	0.87500
5	2	1	1	0.24306	0.24306
6	2	1	2	0.51153	0.75459
7	2	1	5	0.05450	0.80909
8	2	1	6	0.06591	0.87500
9	3	1	1	0.31034	0.31034
10	3	1	2	0.36235	0.67270
11	3	1	5	0.05833	0.73103
12	3	1	6	0.14397	0.87500

From 150-day Solution

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In summary, as researchers and practitioners construct optimizing model to optimize the flows in the supply chain, they will find that the length of the planning horizon and the initial inventory levels can both have profound effects on solutions. In practice, a 20-day planning horizon, considering ocean shipping times, may be too short for an international supply chain and may cause an optimizing model to be counterproductive. The organization may fall into an expediting trap whereby goods are expedited perpetually to compensate for outages at warehouses after a major disruption or unexpected surge in demand. This raises a series of research questions as stated in the following:

1. What rolling planning horizon should be adopted in order to achieve high SC performance for a given objective function and performance metrics?
2. Can a different approach in formulating the objective function counter the effects associated with too short a planning horizon?
3. How might different approaches in formulating the objective function affect various SC performance metrics?
4. How sensitive is the supply chain performance resulted from the optimizing model to the choice of the length of rolling planning horizon or the approach in the objective function?

In an effort to search answers for these research questions and explore optimal choices to facilitate managerial decision making in planning procurement, production and distribution, and also to achieve better

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performance, experiments will be conducted in the following chapters. The simulation model with an embedded optimizer is introduced to consider the effects of random operational variations that normally occur.

Chapter 5 Supply Chain Optimization on a Rolling Horizon

Research questions Q1 and Q2 are addressed in this chapter:

- Q1: What rolling horizon length should be adopted in order to achieve higher SC performance for a given objective function and performance metrics?
- Q2: Can a "value-added" complement to the SCM objective function mitigate the sub-optimization that occurs when the planning horizon is shorter than the time required to capture the effects of all relevant events (procurement, production and deliveries) upstream and downstream?

5.1 Problem Descriptions

As stated in the previous chapter, an optimization model may be counterproductive if too short a planning horizon is used. To answer Q1, theoretically, the length of the rolling planning horizon should include at least the longest lead time upstream and downstream plus the revision period (in practice, the revision period can refer to the production cycle time). However, this length of planning horizon may require excessive computational time to generate a solution and may not be practical for a real business setting. In order to conduct the experiments more efficiently and reach a comprehensive understanding of the impacts associated with the length of the planning horizon, we revise the upstream and downstream lead times and present them in Table 5-1 and Table 5-2. Note that ROPs for raw materials across plants and finished products at warehouses are revised accordingly.

Table 5-1 Shortened Upstream Lead Time with CV

Supplier	Average Lead Time			Lead Time Coefficient of Variation		
	F1	F2	F3	F1	F2	F3
S1	7	7	7	0.15	0.15	0.15
S2	10	10	10	0.15	0.15	0.15
S3	5	5	7	0.15	0.15	0.15
S4	7	7	10	0.15	0.15	0.15
S5	5	7	5	0.15	0.15	0.15
S6	10	10	7	0.15	0.15	0.15

Table 5-2 Shortened Downstream Lead Time with CV

	Average Lead Time			Lead Time Coefficient of Variation		
	F1	F2	F3	F1	F2	F3
WH1	3	5	5	0.15	0.15	0.15
WH2	3	5	7	0.15	0.15	0.15
WH3	5	3	7	0.15	0.15	0.15
WH4	5	3	7	0.15	0.15	0.15
WH5	5	5	3	0.15	0.15	0.15
WH6	5	5	3	0.15	0.15	0.15

These changes result the longest average downstream lead time at 7 days and that in upstream at 10 days. Thus, the SC performance associated with a 10-day rolling planning horizon (H10) and a 20-day rolling planning horizon (H20) will be both examined in this chapter.

When Jung et al., 2004 employed the rolling optimization horizon to investigate safety stocks needed to cope with demand uncertainty, one important assumption they made is that the downstream lead time (from plant to each custom) is less than the chosen length of rolling horizon. This assumption indicates their chosen length of the rolling planning horizon only considers the longest downstream lead time. Their analytical toolbox is considered “robust”; however, it does not take into account upstream activities which may pose constraints on production and alter the “optimal” production schedule significantly. To address this shortcoming, this research takes into account upstream activity in the SC.

Scenario 1 is developed in which the initial raw material inventories at each plant, the finished product inventories at each plant and finished products in each warehouse are all placed at 5% above their corresponding lower bounds. Scenario 1 sets the initial inventories close to targets of the popular lean environment, and, more importantly, assures that there will be no significant confounding of statistical results for product characteristics, plants, and warehouses due to differential amounts of the initial inventories.

5.2 Analytical Model Description

A hybrid model that consists of a simulation model and an integrated optimization model is developed on a SAS 9.4 platform to solve the multi-period SC planning problems. Each replication plans 90 days (an entire season) of activities with a rolling optimization horizon. Twenty-five (25) replications are conducted for each scenario and the results are analyzed to determine the extent to which differences in performance metrics are attributable to systematic versus random variation. For the purpose of this research, the planning revision period is fixed at one day to offer maximum responsiveness to immediate demands. Solutions from the optimizing model for the first day are extracted and saved in a SAS dataset used by the simulation model to induce production, flows of finished goods, orders from warehouses and orders of raw material in the optimization model. These solutions contain the following information:

1) Raw material inventory level at each plant.
2) Outstanding orders of raw materials at each plant.
3) Raw materials in transit to each plant.
4) Amount of each product produced at each plant.
5) Finished product inventories at each plant.
6) Finished product inventories at each warehouse.
7) Outstanding orders of products at each warehouse.
8) Finished products in transit at each warehouse.

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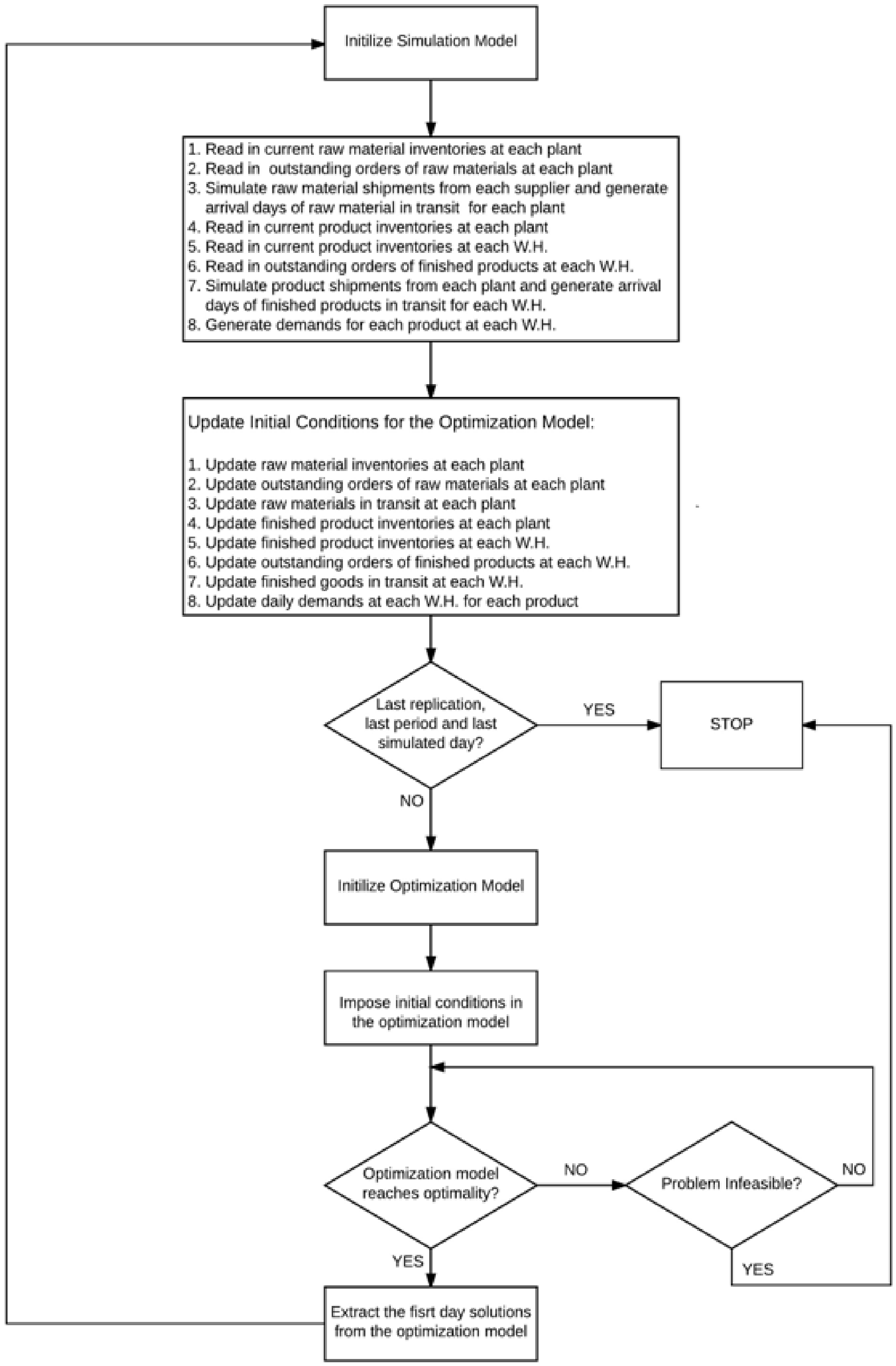
Product demands are revealed at the beginning of each day of simulated supply-chain activity. Therefore, the first period's demand is presumed to be known with certainty, but knowledge of subsequent demands is restricted to their means and standard deviations. The simulation model generates product demands and delivery dates according to specified distributions, reads the extracted solutions from the library of SAS datasets (tables or spreadsheets generated by the optimizing model, and updates datasets that represent the new states of the system including finished goods in transit and raw materials in transit. Randomly generated delivery dates for raw materials and finished goods are set when orders are placed and goods are shipped. They are not altered as successive iterations occur on the rolling horizon. The optimization model reads information from the updated datasets at the end of the simulated day as its new initial conditions and solves the problem for the fixed number of days in the planning horizon (e.g., Day2 to Day 16 in the second iteration of a 15-day planning horizon). This iterative process continues until it reaches the end of the planning horizon (where the solution is developed for Day 90 to Day 104 and just implemented for Day 90). The optimization model and simulation models are thus used in concert to develop SC plans that attempt to maximize the net profit contribution while controlling for risk. Note that the simulation results are used to compute NPC per day with traditional measures (excluding the value-added component which is intended to shape solutions that guarantee a successful ongoing enterprise). Figure 5-1 illustrates the interactive process between the simulation model and the optimization model.

Figure 5-1 Interactive Process of Simulation and Optimization Models



5.3 Simulation Verification

The simulation model is intended to capture the daily operational variations in the SC. These variations include upstream and downstream shipping times and product demands. In this research, upstream and downstream lead times, as well as product demands are assumed to follow normal distributions with constant means.

5.3.1 Steps in the simulation model

1. Set number of replications and number of days to be simulated
2. Read in optimization model initial conditions
    a. Product-Warehouse information
        i. Current product inventory
        ii. Average daily demand
        iii. Standard deviation of daily demand
        iv. Average lead time for delivery from plant to warehouse
        v. Standard deviation of delivery time from plant to warehouse
        vi. Current amount of finished products in transit from each plant
    b. Inventories at the plant
        i. Current product inventories at each plant
        ii. Current raw material inventories at each plant
        iii. Average lead time for delivery from supplier to plant
        iv. Standard deviation of delivery time from supplier to plant

v. Current amount of raw materials in transit from each supplier

3. Generate daily demands at each warehouse for each product for the current day.
4. Simulate product shipments from each plant to each warehouse and assign the arrival day randomly (with fixed mean and standard deviation) for each shipment.
5. Simulate raw material shipments ordered from the supplier on the current day from each supplier by generating arrival days of raw material that will be in transit to each plant. Terminate the simulation if Day 90 has been completed. If not, proceed to Step 6.
6. Update initial conditions for the optimization model according to the state of the system at the end of the previous day's simulated activity.
7. Return to step 2 to re-plan using the chosen planning horizon.

To verify the logic and behavior of the simulation model, a scenario is developed in which no adverse events occur in the supply chain and beginning inventories (raw materials and finished products at plants and finished goods at warehouses) are randomly set between lower bounds and upper bounds. For simplification, 2 replications of 5 days of simulated activity with a 20-day rolling planning horizon are conducted. In a full replication, the first planning interval is from Day 1 to Day 20, the second planning interval is from Day 2 to Day 21, …, and the last planning interval is from Day 90 to Day 109.

5.3.2 Raw Material Inventory Verification

The initial raw materials in transit with scheduled arrival dates are given in Table 5-3.

Table 5-3 Period One Initial Raw Materials in Transit (Day 1 to Day 20)

Initial Raw Materials in Transit				
Raw Material	Supplier	Facility	Arrival Day	Amount (units)
1	2	1	1	2000
1	2	3	2	2000
3	6	1	3	500
3	6	3	1	500

The time between schedule revisions is set at one day. The first day's decisions are extracted from the optimization model and read by the simulation model. Relevant records are updated – including arrival dates for materials and finished goods that are placed in transit. As seen in Table 5-3, at the end of simulated day one (first day of the first planning interval), 2000 units of raw material 1 from supplier 2 arrived at facility 1 and 500 units of raw material 3 from supplier 6 arrived at facility 3. At the end of simulated day two (first day of the second planning horizon), 2000 units of raw material 1 from supplier 2 are scheduled to arrive at facility 3. Similarly, 500 units of raw material 3 from supplier 6 are scheduled to arrive at facility 1 by the end of simulated day three, which is the first day in the third planning horizon.

Facilities' raw material inventories at the beginning of day one in replication one are illustrated in Table 5-4. Table 5-5 shows the production across facilities at the end of simulated day one.

Table 5-4 Period One Beginning Raw Material Inventories (Day 1 to Day 20)

Replication NO.	Simulate	Day	Raw Material	Facility	Min RM Inv.	Initial Raw Material Inventory	Max RM Inv.	Random Initial Inv Seed	Upstream LT Random Seed
1	Y	1	1	1	7200	14797	18000	7654	34068
1	Y	1	1	2	5528	6425	20730	7654	34068
1	Y	1	1	3	14366	20699	39180	7654	34068
1	Y	1	2	1	3465	6081	9450	7654	34068
1	Y	1	2	2	2944	10603	11040	7654	34068
1	Y	1	2	3	8371	20644	22830	7654	34068
1	Y	1	3	1	1353	3602	3690	7654	34068
1	Y	1	3	2	1584	3139	4320	7654	34068
1	Y	1	3	3	2256	3022	8460	7654	34068

Table 5-5 Simulated Day One Production Summary

Obs	Variable Name	Day	Facility	Product	Produced
1	PRODP1F1D1	1	1	1	226
2	PRODP2F1D1	1	1	2	288
3	PRODP3F1D1	1	1	3	39
4	PRODP4F1D1	1	1	4	85
5	PRODP5F1D1	1	1	5	78
6	PRODP6F1D1	1	1	6	26
7	PRODP1F2D1	1	2	1	299
8	PRODP2F2D1	1	2	2	267
9	PRODP3F2D1	1	2	3	54
10	PRODP4F2D1	1	2	4	99
11	PRODP6F2D1	1	2	6	58
12	PRODP1F3D1	1	3	1	177
13	PRODP2F3D1	1	3	2	204
14	PRODP3F3D1	1	3	3	147
15	PRODP4F3D1	1	3	4	197
16	PRODP6F3D1	1	3	6	21

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For simplification, Facility 1 is selected to demonstrate how raw material inventories are calculated and updated in our model. Relevant information from Table 3-5 shows that 226 units of P1 and 288 units of P2 consumed 794 units of raw material one (226*1.6 + 288*1.5, rounded to the nearest whole number), 2000 units of R1 from S2 arrived at F1 (from table 5-3) on day one, and the initial R1 inventory at F1 was 14797 units. Thus, at the end of simulated day one (and beginning of day 2), R1 inventory at F1 equals 16003 units (14797 + 2000 – 794). Producing 39 units of P3 and 85 units of P4 reduced R2 inventory by 268 units, while 78 units of P5 and 26 units of P6 decreased R3 inventory by 312 units. Neither R2 nor R3 has any deliveries on day one, thus, F1 has 5813 units of R2 and 3290 units of R3 by the end of simulated day one. Extracted from the simulation report are the updated initial raw material inventories for the planning period Day 2 to Day 21. They are illustrated in Table 5-6 to verify the aforementioned raw material inventory balance.

Table 5-6 Period Two Beginning Raw Material Inventories (Day 2 to Day 21)

Replication NO.	Simulate	Day	Raw Material	Facility	Min RM Inv.	Initial Raw Material Inventory	Max RM Inv.	Random Initial Inv Seed	Upstream LT Random Seed
1	Y	2	1	1	7200	16003	18000	7654	60840
1	Y	2	1	2	5528	5546	20730	7654	60840
1	Y	2	1	3	14366	20110	39180	7654	60840
1	Y	2	2	1	3465	5813	9450	7654	60840
1	Y	2	2	2	2944	10270	11040	7654	60840
1	Y	2	2	3	8371	19883	22830	7654	60840
1	Y	2	3	1	1353	3290	3690	7654	60840
1	Y	2	3	2	1584	2965	4320	7654	60840
1	Y	2	3	3	2256	3459	8460	7654	60840

Note that a stipulated number seed is used to generate initial raw material inventories across facilities. This seed changes from one replication to another, thus generating different initial raw material inventories for each replication. The random seed used to generate upstream lead time is changing not only by replications, but also by simulated day. Table 5-7 shows random seeds used in simulated day one in replication two.

At the beginning of each planning period, the simulation model generates product demands across warehouses and arrival dates for goods in transit according to the specified distributions. The random number generator in the simulation model ensures there is no correlations of product demands, upstream lead times, and downstream lead times from one period to another.

Table 5-7 Replication Two Random Seeds Illustration (Day 1 to Day 20)

Replication NO.	Simulate	Day	Raw Material	Facility	Min RM Inv.	Initial Raw Material Inventory	Max RM Inv.	Random Initial Inv Seed	Upstream LT Random Seed
2	Y	1	1	1	7200	12047	18000	32090	70044
2	Y	1	1	2	5528	7760	20730	32090	70044
2	Y	1	1	3	14366	23348	39180	32090	70044
2	Y	1	2	1	3465	4078	9450	32090	70044
2	Y	1	2	2	2944	4779	11040	32090	70044
2	Y	1	2	3	8371	9963	22830	32090	70044
2	Y	1	3	1	1353	1824	3690	32090	70044
2	Y	1	3	2	1584	4285	4320	32090	70044
2	Y	1	3	3	2256	7779	8460	32090	70044

Raw material orders were placed across facilities on simulated day one. Raw material shipments are assumed to occur as soon as the order is placed.

Table 5-8 provides shipment information that is used by the simulation model to generate arrival dates of raw material in transit, shown in Table 5-9, for the next planning period (Day 2 to Day 21).

Table 5-8 Raw Material Shipment Summary by the End of Simulated Day One

Obs	Variable Name	Day	Raw Material	Supplier	Facility	Amount shipped
1	SHPR1S1F2D1	1	1	1	2	1085
2	SHPR1S2F2D1	1	1	2	2	692
3	SHPR1S2F3D1	1	1	2	3	1307

Table 5-9 Period Two Initial Raw Materials in Transit (Day 2 to Day 21)

Raw Material	Supplier	Facility	Shipped On Day	Arrival Day	Total Received	Lead Time	replication	Simulate	simulated_day
1	1	2	1	9	1085	8	1	Y	2
1	2	2	1	11	692	10	1	Y	2
1	2	3	.	1	2000	.	1	Y	2
1	2	3	1	9	1307	8	1	Y	2
3	6	1	.	2	500	.	1	Y	2

Recall Table 5-3 indicates that at the beginning of period one (Day 1 of the planning period Day 1 to Day 20), 2000 units of R1 from S2 are scheduled to arrive at F3 on day 2 and 500 units of R3 from S6 are scheduled to deliver to F1 on day 3. Note that the planning revision period is one day and that the randomly generated delivery dates for raw materials and finished goods are not altered in successive planning periods. Thus, 2000 units of R1 from S2 are scheduled to arrive at F3 on the first day of the second planning horizon (Day 2 to Day 21). Arrival day indices for raw materials in transit at the beginning of the current planning period are reduced by one day at the beginning of next planning period as shown in Table 5-9.

5.3.3 Production Facilities Finished Product Inventory Verification

Table 5-10 displays the initial finished product inventories at each production facility. Note that equation (20) presented in Chapter 3 stipulates that any products produced during a day cannot be used for deliveries until the next day. Thus, by the end of simulated day one, the amount shipped of each product at each production facility cannot exceed the initial finished product inventory at that facility. Execution of this logic is verified in Table 5-11.

Table 5-10 Period One Initial Finished Product Inventory at Facilities

Replication NO.	Simulate	Day	Product	Facility	Min Product Inv.	Initial Product Inventory	Max Product Inv.	Random Initial Inv Seed	Downstream LT Random Seed
1	Y	1	1	1	0	17	159	22962	79492
1	Y	1	2	1	0	72	231	22962	79492
1	Y	1	3	1	0	51	58	22962	79492
1	Y	1	4	1	0	42	85	22962	79492
1	Y	1	5	1	0	10	17	22962	79492
1	Y	1	6	1	0	4	24	22962	79492
1	Y	1	1	2	0	32	183	22962	79492
1	Y	1	2	2	0	223	266	22962	79492
1	Y	1	3	2	0	47	68	22962	79492
1	Y	1	4	2	0	19	99	22962	79492
1	Y	1	5	2	0	13	19	22962	79492
1	Y	1	6	2	0	20	29	22962	79492
1	Y	1	1	3	0	275	360	22962	79492
1	Y	1	2	3	0	266	487	22962	79492
1	Y	1	3	3	0	54	147	22962	79492
1	Y	1	4	3	0	22	197	22962	79492
1	Y	1	5	3	0	7	42	22962	79492
1	Y	1	6	3	0	8	52	22962	79492

Table 5-11 Period One Plant to Warehouse Shipment Summary

Obs	Variable Name	Day	Facility	Warehouse	Product	Amount shipped
1	SHPP1F1W2D1	1	1	2	1	7
2	SHPP1F1W3D1	1	1	3	1	10
3	SHPP1F2W2D1	1	2	2	1	32
4	SHPP1F3W2D1	1	3	2	1	155
5	SHPP1F3W3D1	1	3	3	1	120
6	SHPP2F1W1D1	1	1	1	2	71
7	SHPP2F1W6D1	1	1	6	2	1
8	SHPP2F2W1D1	1	2	1	2	64
9	SHPP2F2W6D1	1	2	6	2	159
10	SHPP2F3W1D1	1	3	1	2	63
11	SHPP2F3W6D1	1	3	6	2	203
12	SHPP3F1W3D1	1	1	3	3	51
13	SHPP3F2W2D1	1	2	2	3	47
14	SHPP3F3W2D1	1	3	2	3	54
15	SHPP4F1W3D1	1	1	3	4	42
16	SHPP4F2W3D1	1	2	3	4	19
17	SHPP4F3W3D1	1	3	3	4	22
18	SHPP5F1W3D1	1	1	3	5	10
19	SHPP5F2W6D1	1	2	6	5	13
20	SHPP5F3W3D1	1	3	3	5	7
21	SHPP6F1W3D1	1	1	3	6	4
22	SHPP6F2W2D1	1	2	2	6	13
23	SHPP6F2W3D1	1	2	3	6	7
24	SHPP6F3W2D1	1	3	2	6	8

Information presented in Table 5-10 and 5-11 implies that by the end of simulated day one, all initial finished product inventories at each production facility were used to replenish warehouses, indicating that initial finished product inventories at each production facility for the next planning period is equal to what has been produced at each production facility during simulated day one. This is illustrated in Table 5-12. Note that maximum inventories are exceeded in Day two for some products in F1 and F2. This is because the over storage penalty is low enough that carrying the extra inventory enables profitable deliveries in later periods.

Table 5-12 Period Two Initial Finished Product Inventory at Facilities

Replication NO.	Simulate	Day	Product	Facility	Min Product Inv.	Initial Product Inventory	Max Product Inv.	Random Initial Inv Seed	Downstream LT Random Seed
1	Y	2	1	1	0	226	159	22962	141960
1	Y	2	2	1	0	288	231	22962	141960
1	Y	2	3	1	0	39	58	22962	141960
1	Y	2	4	1	0	85	85	22962	141960
1	Y	2	5	1	0	78	17	22962	141960
1	Y	2	6	1	0	26	24	22962	141960
1	Y	2	1	2	0	299	183	22962	141960
1	Y	2	2	2	0	267	266	22962	141960
1	Y	2	3	2	0	54	68	22962	141960
1	Y	2	4	2	0	99	99	22962	141960
1	Y	2	5	2	0	0	19	22962	141960
1	Y	2	6	2	0	58	29	22962	141960
1	Y	2	1	3	0	177	360	22962	141960
1	Y	2	2	3	0	204	487	22962	141960
1	Y	2	3	3	0	147	147	22962	141960
1	Y	2	4	3	0	197	197	22962	141960
1	Y	2	5	3	0	0	42	22962	141960
1	Y	2	6	3	0	21	52	22962	141960

Information obtained from Table 5-12 indicates that at the beginning of the second planning horizon (Day 2 to Day 21), neither F2 nor F3 has any inventories of P5. This information is consistent with the first period production summary presented in Table 5-5 where no production of P5 occurred at either F2 or F3. Meanwhile, Table 5-11 provides information about finished goods in transit at the end of first planning horizon and Table 5-12 shows the random seed used in the downstream to generate arrival dates for these finished goods in transit. Such information is also used to verify warehouse product inventory balance in the next section.

5.3.4 Warehouse Product Inventory Verification

The initial finished products in transit with scheduled arrival dates are given in Table 5-13.

Table 5-13 Period One Initial Finished Products in Transit

Initial Finished Products in Transit				
Product	Facility	Warehouse	Arrival Date	Amount (units)
1	3	6	3	250
2	2	4	1	300
3	2	1	2	100
4	3	1	1	100

Information presented in Table 5-13 indicates that, at the end of simulated day one, 300 units of product 2 from facility 2 arrived at warehouse 4 and 100 units of product 4 from facility 3 arrived at warehouse 1. Additionally, 100 units of product 3 from facility 2 are scheduled to arrive at warehouse 1 by the end of simulated day 2, which is the first day in the second planning period (Day 2 to Day 21). In a similar fashion, by the end of the first day in the third planning horizon, 250 units of product 1 from facility 3 are scheduled to arrive at warehouse 6.

Table 5-14 displays the initial product inventories at each warehouse at the beginning of the first planning horizon, product demands at each warehouse for simulated day one, as well as random seeds used by simulation model to generate such demands and initial product inventories. Note that unique random numbers were used (Table 5-14 and Table 5-15) in the simulation model to generate product demands to avoid any correlations of demands between planning periods.

Table 5-14 Period One Warehouse Product Inventory and Demand Status

Replication NO.	Day	Simulate	Warehouse	Product	Min Product Inv	Initial Product Inventory	Max Product Inv	Demand	Random Initial Inv Seed	Random Demand Seed
1	1	Y	1	1	959	1889	4110	124	38270	11356
1	1	Y	2	1	954	1368	3180	103	38270	11356
1	1	Y	3	1	960	1604	3600	131	38270	11356
1	1	Y	4	1	1250	3355	3750	158	38270	11356
1	1	Y	5	1	816	1942	3060	118	38270	11356
1	1	Y	6	1	896	2189	3360	140	38270	11356
1	1	Y	1	2	896	1348	3840	139	38270	11356
1	1	Y	2	2	1440	3499	4800	162	38270	11356
1	1	Y	3	2	1600	4270	6000	203	38270	11356
1	1	Y	4	2	1600	3016	4800	163	38270	11356
1	1	Y	5	2	1408	3240	5280	170	38270	11356
1	1	Y	6	2	1280	1716	4800	159	38270	11356
1	1	Y	1	3	360	1005	1350	27	38270	11356
1	1	Y	2	3	540	816	1620	61	38270	11356
1	1	Y	3	3	486	828	1620	45	38270	11356
1	1	Y	4	3	480	1168	1440	75	38270	11356
1	1	Y	5	3	256	554	960	37	38270	11356
1	1	Y	6	3	360	963	1200	37	38270	11356
1	1	Y	1	4	525	2016	2250	88	38270	11356
1	1	Y	2	4	660	1638	1980	71	38270	11356
1	1	Y	3	4	585	836	1950	60	38270	11356
1	1	Y	4	4	630	1562	1890	73	38270	11356
1	1	Y	5	4	384	746	1440	55	38270	11356
1	1	Y	6	4	512	1867	1920	63	38270	11356
1	1	Y	1	5	88	266	330	4	38270	11356
1	1	Y	2	5	180	513	540	20	38270	11356
1	1	Y	3	5	126	267	420	3	38270	11356
1	1	Y	4	5	140	391	420	17	38270	11356
1	1	Y	5	5	64	134	240	9	38270	11356
1	1	Y	6	5	117	192	390	6	38270	11356
1	1	Y	1	6	168	440	630	20	38270	11356
1	1	Y	2	6	210	301	630	17	38270	11356
1	1	Y	3	6	126	171	420	10	38270	11356
1	1	Y	4	6	150	339	450	11	38270	11356
1	1	Y	5	6	128	421	480	15	38270	11356
1	1	Y	6	6	162	373	540	15	38270	11356

As presented in Table 5-14, the initial inventory of P2 at WH4 is 3016 units, demand of P2 at WH4 during the simulated day one is 163 units, in addition, 300 units of P2 from F2 arrived at WH4 on simulated day one (from

Table 5-13). Thus, at the end of simulated day one, WH4 has 3153 units (3016 + 300 – 163) of P2. This becomes the initial inventory of P2 at WH4 for the second planning horizon (Day 2 to Day 21) is 3153 units. Calculated in a similar manner, the initial inventory of P4 at WH1 for the second planning horizon is 2028 units. For all other products, the initial inventory at warehouses for the second planning horizon equals to the beginning inventory at warehouses of simulated day one minus corresponding demand in simulated day one. The information presented in Table 5-15 verifies such inventory balance at warehouses.

Note that in Table 5-15, product demands are changing because different random seeds are used to generate the demands. This random demand seed is changes for each replication and day. The random seed used by the simulation model to generate initial product inventory at warehouses, however, only needs to change from one replication to another. Table 5-16 illustrates these random seed values and the resulting initial product inventories at warehouses.

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Table 5-15 Period Two Warehouse Product Inventory and Demand Status

Replication NO.	Day	Simulate	Warehouse	Product	Min Product Inv	Initial Product Inventory	Max Product Inv	Demand	Random Initial Inv Seed	Random Demand Seed
1	2	Y	1	1	959	1765	4110	94	38270	20280
1	2	Y	2	1	954	1265	3180	89	38270	20280
1	2	Y	3	1	960	1473	3600	156	38270	20280
1	2	Y	4	1	1250	3197	3750	120	38270	20280
1	2	Y	5	1	816	1824	3060	111	38270	20280
1	2	Y	6	1	896	2049	3360	121	38270	20280
1	2	Y	1	2	896	1209	3840	124	38270	20280
1	2	Y	2	2	1440	3337	4800	168	38270	20280
1	2	Y	3	2	1600	4067	6000	201	38270	20280
1	2	Y	4	2	1600	3153	4800	155	38270	20280
1	2	Y	5	2	1408	3070	5280	182	38270	20280
1	2	Y	6	2	1280	1557	4800	168	38270	20280
1	2	Y	1	3	360	978	1350	19	38270	20280
1	2	Y	2	3	540	755	1620	23	38270	20280
1	2	Y	3	3	486	783	1620	60	38270	20280
1	2	Y	4	3	480	1093	1440	75	38270	20280
1	2	Y	5	3	256	517	960	0	38270	20280
1	2	Y	6	3	360	926	1200	30	38270	20280
1	2	Y	1	4	525	2028	2250	93	38270	20280
1	2	Y	2	4	660	1567	1980	71	38270	20280
1	2	Y	3	4	585	776	1950	98	38270	20280
1	2	Y	4	4	630	1489	1890	43	38270	20280
1	2	Y	5	4	384	691	1440	59	38270	20280
1	2	Y	6	4	512	1804	1920	62	38270	20280
1	2	Y	1	5	88	262	330	5	38270	20280
1	2	Y	2	5	180	493	540	28	38270	20280
1	2	Y	3	5	126	264	420	17	38270	20280
1	2	Y	4	5	140	374	420	19	38270	20280
1	2	Y	5	5	64	125	240	7	38270	20280
1	2	Y	6	5	117	186	390	17	38270	20280
1	2	Y	1	6	168	420	630	17	38270	20280
1	2	Y	2	6	210	284	630	14	38270	20280
1	2	Y	3	6	126	161	420	13	38270	20280
1	2	Y	4	6	150	328	450	12	38270	20280
1	2	Y	5	6	128	406	480	6	38270	20280
1	2	Y	6	6	162	358	540	15	38270	20280

Table 5-16 Replication Two Random Seeds Illustration

Replication NO.	Day	Simulate	Warehouse	Product	Min Product Inv	Initial Product Inventory	Max Product Inv	Demand	Random Initial Inv Seed	Random Demand Seed
2	1	Y	1	1	959	3273	4110	120	160450	23348
2	1	Y	2	1	954	2095	3180	73	160450	23348
2	1	Y	3	1	960	2414	3600	112	160450	23348
2	1	Y	4	1	1250	3592	3750	146	160450	23348
2	1	Y	5	1	816	2169	3060	107	160450	23348
2	1	Y	6	1	896	958	3360	101	160450	23348

Recall in the previous section when verifying finished product inventory at production facilities, Table 5-11 provides information about shipments made from each facility to each warehouse at the end of simulated day one. These shipments, as well as initial finished products in transit (after subtracting arrivals at the end of simulated day one), provide initial finished products in transit for the second planning period (Day 2 to Day 21) as displayed in Table 5-17.

Table 5-17 Period Two Finished Products in Transit (Day 2 to Day 21)

Product	Facility	Warehouse	Shipped On Day	Arrival Day	Total Received	Lead Time	replication	Simulate	simulated_day
1	1	2	1	3	7	2	1	Y	2
1	1	3	1	6	10	5	1	Y	2
1	2	2	1	6	32	5	1	Y	2
1	3	2	1	8	155	7	1	Y	2
1	3	3	1	6	120	5	1	Y	2
1	3	6	.	2	250	.	1	Y	2
2	1	1	1	3	71	2	1	Y	2
2	1	6	1	4	1	3	1	Y	2
2	2	1	1	5	64	4	1	Y	2
2	2	6	1	6	159	5	1	Y	2
2	3	1	1	5	63	4	1	Y	2
2	3	6	1	3	203	2	1	Y	2
3	1	3	1	6	51	5	1	Y	2
3	2	1	.	1	100	.	1	Y	2
3	2	2	1	5	47	4	1	Y	2
3	3	2	1	7	54	6	1	Y	2
4	1	3	1	5	42	4	1	Y	2
4	2	3	1	4	19	3	1	Y	2
4	3	3	1	5	22	4	1	Y	2
5	1	3	1	6	10	5	1	Y	2
5	2	6	1	5	13	4	1	Y	2
5	3	3	1	7	7	6	1	Y	2
6	1	3	1	6	4	5	1	Y	2
6	2	2	1	4	13	3	1	Y	2
6	2	3	1	3	7	2	1	Y	2
6	3	2	1	8	8	7	1	Y	2

Since the revision period is one day and randomly generated delivery dates for raw materials and finished goods are set and not altered in successive planning periods, arrival days of finished products in transit are reduced by one day from one planning horizon to the next.

In summary, section 5.3 verifies the logic and behavior of the simulation model, illustrates how product demands are generated from one period to another, and demonstrates how raw material inventory and finished product inventory at production facilities are calculated. It also demonstrates the calculation of finished goods inventory at warehouses, and displays how initial conditions are updated at the beginning of each planning horizon and each replication. With this foundation, we conduct our analysis of SC performance associated with different planning horizon and different objective function.

5.4 Scenario One Analysis

As mentioned in section 5.1, H10 and H20 are both employed to assess SC performance. We begin with the observation of detailed financial performance derived from H10. Note that all average statistics in the following are computed for the 90-days of simulated activity. With H10, Table 5-18 presents average daily gross profit contribution of each product at each warehouse. Table 5-19 provides finished product inventory costs and finished product in transit costs at each plant. Table 5-20 includes raw materials related costs at each plant and Table 5-21 summarizes idle costs and setup costs at each plant.

Table 5-18 Average Daily Product Gross Profit Contribution (H10)

Product	W.H.	Avg. Daily Gross Profit Contrib.	Avg. Daily Profit Contrib. from W.H. Deliv.	Avg. Daily Profit Contrib. from ALT. Deliv	Avg. Daily Lost Sales Costs	Avg. Daily Shipping Costs	Avg. Daily W.H. Inv. Costs
1	1	668.41	799.41	178.44	185.66	123.05	0.74
1	2	469.59	594.74	132.43	169.88	87.01	0.69
1	3	805.20	982.67	39.19	60.13	155.28	1.25
1	4	861.37	1,016.30	51.11	48.67	155.91	1.46
1	5	653.59	781.18	58.16	63.18	121.25	1.32
1	6	712.04	845.95	65.67	71.08	127.01	1.49
2	1	616.70	731.41	127.70	129.47	112.22	0.72
2	2	806.78	958.94	141.01	148.31	143.67	1.19
2	3	1,169.80	1,371.22	114.25	99.92	214.52	1.23
2	4	964.13	1,122.61	78.45	69.87	165.63	1.43
2	5	1,054.79	1,262.18	73.01	80.63	197.49	2.28
2	6	948.96	1,149.90	57.91	77.60	179.10	2.14
3	1	370.13	441.50	23.84	26.88	67.77	0.56
3	2	433.71	527.14	31.22	43.20	80.76	0.69
3	3	259.92	395.60	63.32	140.32	58.15	0.53
3	4	275.82	358.23	63.85	93.62	52.08	0.56
3	5	184.98	191.97	73.06	52.00	27.83	0.22
3	6	220.65	243.09	90.21	77.62	34.72	0.29
4	1	553.49	674.03	40.39	54.76	105.44	0.72
4	2	510.90	609.93	30.88	35.74	93.39	0.77
4	3	364.83	510.41	44.52	112.93	76.36	0.80
4	4	376.67	483.33	53.90	88.19	71.47	0.89
4	5	295.76	319.14	81.12	55.86	48.34	0.31
4	6	408.11	427.21	108.91	62.82	64.78	0.41
5	1	205.84	262.82	12.00	28.13	40.33	0.50
5	2	340.21	433.69	20.11	46.21	66.34	1.04
5	3	202.02	217.55	77.77	62.28	30.74	0.27
5	4	234.32	221.81	85.80	42.40	30.57	0.33
5	5	179.27	213.93	2.29	1.44	35.01	0.50
5	6	292.00	349.05	2.92	2.62	56.44	0.92
6	1	323.07	427.63	32.92	71.07	65.83	0.58
6	2	324.83	431.60	34.04	75.54	64.58	0.69
6	3	132.53	145.07	90.14	84.24	18.28	0.16
6	4	189.30	162.59	109.00	62.00	20.09	0.20
6	5	346.63	412.00	4.06	2.41	66.24	0.78
6	6	400.84	475.05	7.10	4.91	75.45	0.95
		17,157.20					

Table 5-19 Average Daily Product Inventory Costs (H10)

Product	Facility	Sum of Avg. Daily Prod. Inv. Related Costs	Avg. Daily Prod. Inv. Costs	Avg. Daily Finished Prod. in Transit Costs
1	1	1.70	0.53	1.18
1	2	2.77	1.02	1.75
1	3	2.13	0.71	1.42
2	1	2.10	0.65	1.45
2	2	3.24	1.10	2.14
2	3	3.26	1.14	2.12
3	1	1.40	0.56	0.84
3	2	0.94	0.31	0.63
3	3	0.57	0.18	0.39
4	1	1.80	0.67	1.13
4	2	1.24	0.41	0.83
4	3	0.94	0.31	0.63
5	1	0.86	0.27	0.60
5	2	0.50	0.15	0.35
5	3	0.90	0.36	0.54
6	1	1.06	0.33	0.73
6	2	0.33	0.10	0.23
6	3	1.33	0.53	0.80
		27.08		

Table 5-20 Average Daily Raw Material Inventory Costs (H10)

Raw Material	Facility	Sum of Avg. Daily R.M. Inv. Related Costs	Avg. Daily R.M. Inv. Costs	Avg. Daily R.M. in Transit Costs	Avg. Daily R.M. Shipping Costs
1	1	45.24	4.70	2.99	37.55
1	2	80.26	2.76	5.66	71.84
1	3	74.29	9.51	4.79	59.99
2	1	82.71	2.58	2.76	77.37
2	2	43.03	1.90	1.38	39.74
2	3	30.01	5.95	1.33	22.74
3	1	54.19	1.32	1.10	51.78
3	2	17.79	1.65	0.61	15.52
3	3	78.00	2.73	1.85	73.43
		505.52			

Table 5-21 Average Daily Plant Idle Costs and Setup Costs (H10)

Facility	Sum of Avg. Daily Costs	Avg. daily Idle Costs	Avg. Daily Setup Costs
1	157.97	7.97	150.00
2	163.86	13.86	150.00
3	186.28	36.28	150.00
	508.11		

We also generate quarterly reports closely approximating accounting income statements and present daily net profit contribution statement for 90-day period in Table 5-22. For simplicity, the SC financial performance derived from different scenarios in the remainder of this research will be presented with the daily net profit contribution statement.

Table 5-22 Daily Net Profit Contribution Statement (H10)

Daily Net Profit Contribution Statement for 90-day period with H10		
	$	$
GROSS PROFIT CONTRIBUTION		17,154.10
Products sold at warehouses	17,154.10	
PLANT EXPENSES		1,040.18
Finished Product Inventory Costs	9.34	
Finished Product in Transit Costs	17.70	
Raw Material Inventory Costs	33.11	
Raw Material in Transit Costs	22.44	
Raw Material Shipping Costs	449.50	
Idle Costs	58.49	
Setup Costs	449.60	
NET PROFIT CONTRIBUTION		16,113.92

We present the daily net profit contribution statement resulted from 20-day rolling planning horizon in Table 5-23. Increasing the length of planning horizon from 10-day to 20-day results in an improvement of overall SC financial performance by more than 13% and average daily net profit contribution rises from $16,113.92 to $18,299.38.

Table 5-23 Daily Net Profit Contribution Statement (H20)

Daily Net Profit Contribution Statement for 90-day period with H20		
	$	$
GROSS PROFIT CONTRIBUTION		19,269.27
Products sold at warehouses	19,269.27	
PLANT EXPENSES		969.89
Finished Product Inventory Costs	10.26	
Finished Product in Transit Costs	22.40	
Raw Material Inventory Costs	39.37	
Raw Material in Transit Costs	31.64	
Raw Material Shipping Costs	416.22	
Idle Costs	0.00	
Setup Costs	450.00	
NET PROFIT CONTRIBUTION		18,299.38

To further assess the impacts associated with the length of planning horizon, we focus our analysis at the product level in this research. Average daily simulated demand for each product is computed and compared with expected demand to assess the variations in the product demands. Average daily gross profit contribution (after adjusting lost sales costs and warehouse replenishment shipping costs) is calculated to analyze financial performance associated with different types of product. Average daily NPC is driven mainly by profit contribution derived from warehouse deliveries and alternative sources. We report the costs associated with lost sales, average daily demand satisfied from warehouse deliveries (in units), average daily demand satisfied from plants' direct shipping (in units), as well as average daily lost sales (in units). The percent of demand satisfied from warehouse deliveries reflects the product service level at warehouse. The SC product service level takes into account total demand being satisfied from all sources. Average total units produced (across all plants), average total warehouse product inventories (in days of demands), average total warehouse end (at the end of day 90) product inventories (in days of demands), average total plant product inventories (in days of demand), and average total plant end product inventories (in days of demands) are all computed and reported to assess the product flows in the SC. These performance metrics are summarized in the following:

- GPC – average daily gross profit contribution
- WHDELV – average daily product deliveries from warehouses
- PLDELV – average daily product shipments to customers from plants
- LOSTSALE – average daily lost sales for each product
- WHPCT – percentages of product demands satisfied from warehouse deliveries
- SCSL – average supply chain service level for individual products
- PLPRODUCED – average daily production of each product

- WHINV – average daily warehouses inventory in days of demand for each product
- ENDWHINV – average ending inventory (in days of demand for each product) upon completion of simulated activity
- PLINV – average total plant finished inventory (in days of total demand for each product)
- ENDPLINV – average total plant end finished product inventory in days of demand for each product

Together, these performance metrics reveal SC performance measures in five dimensions summarized in Table 5-24. GPC is used to measure the overall daily gross profit contribution by product. WHDELV, PLDELV, and LOSTSALE are aggregate measures of satisfied demands from warehouses, satisfied demands from plants and lost sales. WHPC and SCSL express the same information as a percentage of total customer demand. PLPRODUCED shows daily production (across all production facilities) of each product. WHINV, ENDWHINV, PLINV, and ENDPLINV summarize inventory levels during and at the end of the simulated period. Ending inventories are important to consider because they position the firm for ongoing operations beyond the simulated period.

Table 5-24 Summary of Supply Chain Performance Metrics

Performance Metrics	Dimensions
GPC	Profit Contribution
WHDELV	Demand Satisfaction
PLDELV	
LOSTSALE	
WHPCT	Service Level
SCSL	
PLPRODUCED	Production
WHINV	Finished Product Inventories
ENDWHINV	
PLINV	
ENDPLINV	

With this background, we next compare the SC performance resulting from H10 and H20 in Table 5-25. The top panel presents the quarterly product-level supply chain metrics associated with 10-day planning horizon and the bottom panel shows the complementary information resulted from 20-day planning horizon.

Table 5-25 Scenario One Summary Statistics for Quarterly Product-level SC Metrics in 25 Replications

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	549.2	95.6	53.9	4,179	78.6	92.3	606.5	2.7	1.0	0.9	0.8
2	984.0	980.0	796.6	121.0	62.5	5,539	81.3	93.6	863.1	2.7	0.9	0.9	0.8
3	273.0	269.7	188.6	50.4	30.7	1,754	70.0	88.9	226.6	2.3	1.1	0.8	0.8
4	381.0	378.1	289.4	56.8	31.9	2,523	76.6	91.7	326.1	2.5	1.1	0.9	0.8
5	78.0	75.7	58.0	12.3	5.4	1,438	76.7	92.9	66.0	3.7	1.8	0.9	0.8
6	105.0	102.7	76.5	17.3	8.9	1,722	74.6	91.4	88.5	3.1	1.5	0.9	0.8
	2,523.0	2,505.1	1,958.4	353.4	193.3	17,154			2,176.7				

10-Day Rolling Planning Horizon

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	649.5	26.2	23.0	4,869	93.0	96.7	675.8	5.0	4.9	1.0	1.0
2	984.0	980.0	924.4	28.3	27.4	6,245	94.3	97.2	957.9	5.2	5.1	1.0	1.0
3	273.0	269.7	173.4	55.1	41.2	1,487	64.3	84.8	222.8	3.6	3.1	0.8	0.7
4	381.0	378.1	313.7	41.6	22.8	2,744	83.0	94.0	340.4	2.8	1.9	0.9	0.9
5	78.0	75.7	73.9	0.7	1.1	1,744	97.6	98.5	77.2	7.6	7.9	1.0	1.0
6	105.0	102.7	100.5	0.5	1.8	2,180	97.8	98.3	104.5	7.1	7.8	1.0	1.0
	2,523.0	2,505.1	2,235.4	152.3	117.3	19,269			2,378.7				

20-Day Rolling Planning Horizon

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As the planning horizon increases, the overall average daily demand satisfied from warehouse deliveries increases and that from plants deliveries decreases, along with drop in the overall lost sales, thus, improving the overall daily gross profit contribution. Larger inventories are held in the system, increasing of the SC service level for most of the products.

To investigate reasons for the differential product service levels (SCSL), we focus on the characteristics associated with individual products that may drive such differences. We first calculate the average (across all plants) of the unit production minutes needed for each product, then divide product's revenue per unit by the average production minutes required per unit to get the revenue per average production minute associated with each product. This metric reflects the return from scarce resources (production time) if allocated to the respective products. We also consider the demand coefficient of variation (across all warehouses) and average upstream (raw material) lead time for each product. Note that initial inventories in scenario one are all set at 5% above their corresponding lower limits, thus, the initial inventory level doesn't have confounding effects on service level. Meanwhile, average downstream lead time at the product level is constant at 4.67 days. Therefore, the initial inventory level and average downstream lead time are both omitted from the statistical model in this instance. Table 5-26 presents characteristics associated with each of the products.

Table 5-26 Product Service Level Influential Characteristics

Product	Average Unit Production Minutes Needed	Revenue per Average Production Minute	Demand Coefficient of Variation	Average Upstream Lead Time
P1	0.4416	41.4413	0.0620	8.5000
P2	0.3803	43.4442	0.0206	8.5000
P3	0.7924	28.8755	0.1468	6.8333
P4	0.6947	30.1729	0.1048	6.8333
P5	1.2291	46.9465	0.2145	7.3333
P6	1.1085	48.3191	0.1774	7.3333

Multiple regression analysis is performed upon replication results for the 20-day horizon to obtain better knowledge about the joint impacts of these influential characteristics on product service level. In Table 5-27 we indicate how each of these characteristics is correlated with product service level and present corresponding basic statistics. We also provide the magnitudes of the multiple regression coefficients when all of these influential characteristics is included in the model. The regression model for product service level is:

Product Service Level = 99.75 + 0.79 * (revenue per average production minute) – 4.06 * (average upstream lead time) – 48.22 * (demand coefficient of variation) + unexplained variation.

This model explains 76.5% of the variation in product service level and the coefficients for each of the independent variables are statistically significant at 0.0001 level. The regression model indicates that, ceteris paribus, the higher revenue per average production minute the higher product service level, or the shorter the average upstream lead time the higher product service level, or the lower the demand coefficient of variation the higher the product service level.

Table 5-27 Scenario One Drivers of Product Service Level

	Corr. With SCSL	Min	Max	Mean	Std. Dev.	t Value	Multiple Regression Coeff.
Product Service Level in pct (SCSL)	1	82.11	100	94.91	4.88	N.A.	N.A.
Rev. per avg. production minute (REVPERPRODM)	0.83	28.88	48.32	39.87	7.68	14.01	0.79
Demand Coefficient of Variation (DEMCV)	-0.03*	0.02	0.21	0.12	0.07	-6.24	-48.22
Avg. Upstream Lead Time (AVGRMLT)	0.51	6.83	8.50	7.56	0.70	-4.83	-4.06

*not significant at 0.5 level.

Although, theoretically, the length of the rolling horizon planning should cover, at minimum, the sum of the longest lead time upstream and downstream plus the production cycle time, this length of the planning horizon may not be practicable for organizations involved in multi-modal transportation across international boundaries. This length of the planning horizon may also require excessive time for analytical models to reach optimality. We therefore next investigate a possible alteration to the optimizing model that may mitigate the negative effects associated with too short a planning horizon.

5.4 Analytical model with the Value-added Complement

The optimization model presented in Chapter 3 recognizes revenue only when products are sold, in accordance with standard accounting practice. There is no incentive in the optimizing model to ship goods to a warehouse if they do not reach the destination in time to realize revenue from sales at the warehouse. To mitigate the negative effects of this, we could recognize expected revenue from future sales when we ship the goods to the warehouse (though facing, of course, the risk that the sales may not materialize). Thus, we consider an alternative "value added" approach to production and flows of product in the supply chain and propose the following hypotheses:

- ❖ H1: Value-added complement in the optimization model's objective function counters the negative effects associated with short planning horizon.
- ❖ H2: Value-added complement in the optimization model's objective function improves the overall SC performance.

With the value-added approach, the optimization model recognizes revenues when finished goods are shipped out at plants but only for those that have insufficient time to reach the warehouse to satisfy demands that materialize during the planning horizon. It also recognizes revenues from sales of product at warehouses attributed to goods in place at the beginning of the planning horizon. The objective function is revised to the following:

Net Profit Contribution = (Profit contribution from replenish shipments + Profit contribution from alternative deliveries + Profit contribution from warehouse deliveries up to minimum downstream lead time plus one day – Costs of lost sales – Product inventory holding costs at plants and warehouses – Raw material inventory holding costs at plants – Product inventory shortage costs at plants and warehouses – Raw material inventory shortage costs at plants – Product inventory overstocking costs at plants and warehouses – Raw material inventory overstocking costs at plants – Product shipping costs – Product in transit costs – Raw material shipping costs – Raw material in transit costs – Plant setup costs – Plant idle costs)

The model is subject to the same set of constraints presented in Chapter 3, the mathematical formulation of the objective function is revised and presented mathematically below:

$$
\begin{aligned}
Max \sum_{d\in D\{d\}} \Bigg\{ & \sum_{w\in W\{w\}} \sum_{p\in PW\{w\}} \Bigg[\sum_{f\in F\{f\}} \Big(\big(pcP_pW_w - scP_pF_fW_w \big) * ShP_pF_fW_wD_d + \big(pcP_pW_w - acP_pF_fW_w \big) \\
& * AltP_pF_fW_wD_d \Big) - opcostP_pW_w * LSP_pW_wD_d - icP_pW_w * Inv\ \ P_pW_wD_d - ShtPenaltyP_pW_w * USP_pW_wD_d \\
& - OvrPenaltyP_pW_w \\
& * OSP_pW_wD_d \Bigg] - \sum_{f\in F\{f\}} \Bigg[\sum_{p\in P\{p\}} \Bigg(icP_pF_f * InvP_pF_fD_d + ShtPenaltyP_pF_f * USP_pF_fD_d + OvrPenaltyP_pF_f \\
& * OSP_pF_fD_d + \sum_{w\in W\{w\}} \big(scP_pF_fW_w * ShpP_pF_fW_wD_d + itcP_pF_fW_w * TrP_pF_fW_wD_d \big) \Bigg) + spcF_f * SUF_fD_d \\
& + idlePenF_f * idleF_fD_d \\
& + \sum_{r\in RP\{p\}} \Bigg(icR_rF_f * InvR_rF_fD_d + ShtPenaltyR_rF_f * USR_rF_fD_d + OvrPenaltyR_rF_f * OSR_rF_fD_d \\
& + \sum_{s\in SR\{r\}} \big(scR_rS_sF_f * ShpR_rS_sF_fD_d + itcR_rS_sF_f * TrR_rS_sF_fD_d \big) \Bigg) \Bigg] \Bigg\} \\
& + \sum_{d=1}^{t} \Bigg(\sum_{w\in W\{w\}} \sum_{p\in PW\{w\}} \big(pcP_pW_w - scP_pW_w \big) * DelP_pW_wD_d \Bigg)
\end{aligned}
$$

Notice that the last term in the objective function is used to register revenues of warehouse deliveries up to the minimum downstream lead time plus one day (t=4 in this case) within the optimization model for each rolling planning horizon. To differentiate approaches in the analytical models presented in this research, the “standard objective function (STDOBJ)” and “value-added objective function (VAOBJ)” will be used. Scenario one with 10-day planning horizon and 20-day planning horizon are both solved with the analytical model that adopts VAOBJ.

Table 5-28 presents information about the cross comparison of SC financial performance derived from STDOBJ_H10, VAOBJ_H10, STDOBJ_H20, and VAOBJ_H20. The cross comparison of SC performance on each of the eleven metrics is included in Table 5-29.

Table 5-28 Scenario One Cross Comparison of SC Financial Performance

Daily Net Profit Contribution Statement for 90-day period								
	STDOBJ_H10		VAOBJ_H10		STDOBJ_H20		VAOBJ_H20	
	$	$	$	$	$	$	$	$
GROSS PROFIT CONTRIBUTION		17,154.10		19,629.55		19,269.27		19,748.32
Product sold at warehouses	17,154.10		19,629.55		19,269.27		19,748.32	
PLANT EXPENSES		1,040.18		1,045.27		969.89		987.97
Finished Product Inventory Costs	9.34		10.32		10.26		10.47	
Finished Product in Transit Costs	17.70		22.93		22.40		24.37	
Raw Material Inventory Costs	33.11		38.04		39.37		39.25	
Raw Material in Transit Costs	22.44		26.00		31.64		30.82	
Raw Material Shipping Costs	449.50		497.98		416.22		433.06	
Idle Costs	58.49		0.00		0.00		0.00	
Setup Costs	449.60		450.00		450.00		450.00	
NET PROFIT CONTRIBUTION		16,113.92		18,584.28		18,299.38		18,760.35

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Table 5-29 Scenario One Product Level SC Metrics Cross Comparison

Summary Statistics for Quarterly Product-level Supply-Chain Metrics in 25 Replications
Scenario One 10-Day Planning Horizon and STD_Objective

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	549.2	95.6	53.9	4,179	78.6	92.3	606.5	2.7	1.0	0.9	0.8
2	984.0	980.0	796.6	121.0	62.5	5,539	81.3	93.6	863.1	2.7	0.9	0.9	0.8
3	273.0	269.7	188.6	50.4	30.7	1,754	70.0	88.9	226.6	2.3	1.1	0.8	0.8
4	381.0	378.1	289.4	56.8	31.9	2,523	76.6	91.7	326.1	2.5	1.1	0.9	0.8
5	78.0	75.7	58.0	12.3	5.4	1,438	76.7	92.9	66.0	3.7	1.8	0.9	0.8
6	105.0	102.7	76.5	17.3	8.9	1,722	74.6	91.4	88.5	3.1	1.5	0.9	0.8
	2,523.0	2,505.1	1,958.4	353.4	193.3	17,154			2,176.7				

Summary Statistics for Quarterly Product-level Supply-Chain Metrics in 25 Replications
Scenario One 10-Day Planning Horizon and VA _Objective

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	655.5	21.0	22.2	4,918	93.8	96.8	681.0	5.1	5.2	1.0	1.0
2	984.0	980.0	924.4	27.0	28.7	6,263	94.3	97.1	959.2	5.2	5.3	1.0	1.0
3	273.0	269.7	190.1	44.1	35.5	1,675	70.5	86.9	221.1	2.6	1.9	0.8	0.8
4	381.0	378.1	319.9	36.7	21.5	2,796	84.6	94.3	344.7	3.4	2.4	0.9	0.9
5	78.0	75.7	74.6	0.2	0.9	1,767	98.6	98.8	78.1	7.3	8.0	1.0	1.0
6	105.0	102.7	100.6	0.1	2.0	2,211	97.9	98.1	106.5	6.6	7.6	1.0	1.0
	2,523.0	2,505.1	2,265.1	129.1	110.8	19,630			2,390.7				

Summary Statistics for Quarterly Product-level Supply-Chain Metrics in 25 Replications
Scenario One 20-Day Planning Horizon and STD_Objective

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	649.5	26.2	23.0	4,869	93.0	96.7	675.8	5.0	4.9	1.0	1.0
2	984.0	980.0	924.4	28.3	27.4	6,245	94.3	97.2	957.9	5.2	5.1	1.0	1.0
3	273.0	269.7	173.4	55.1	41.2	1,487	64.3	84.8	222.8	3.6	3.1	0.8	0.7
4	381.0	378.1	313.7	41.6	22.8	2,744	83.0	94.0	340.4	2.8	1.9	0.9	0.9
5	78.0	75.7	73.9	0.7	1.1	1,744	97.6	98.5	77.2	7.6	7.9	1.0	1.0
6	105.0	102.7	100.5	0.5	1.8	2,180	97.8	98.3	104.5	7.1	7.8	1.0	1.0
	2,523.0	2,505.1	2,235.4	152.3	117.3	19,269			2,378.7				

Summary Statistics for Quarterly Product-level Supply-Chain Metrics in 25 Replications
Scenario One 20-Day Planning Horizon and VA _Objective

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	690.4	0.0	8.4	5,236	98.8	98.8	702.0	5.3	5.7	1.0	1.0
2	984.0	980.0	970.1	0.0	9.9	6,652	99.0	99.0	984.6	5.2	5.5	1.0	1.0
3	273.0	269.7	186.4	0.0	83.3	684	69.1	69.1	176.2	3.6	3.1	0.6	0.6
4	381.0	378.1	368.2	0.0	9.9	3,175	97.4	97.4	388.2	5.2	5.1	1.0	1.0
5	78.0	75.7	74.8	0.0	0.9	1,778	98.8	98.8	78.8	7.3	7.8	1.0	1.0
6	105.0	102.7	101.5	0.0	1.2	2,224	98.8	98.8	105.2	6.6	7.4	1.0	1.0
	2,523.0	2,505.1	2,391.4	0.0	113.6	19,748			2,435.1				

Information derived from Table 5-28 and Table 5-29 illustrates that the value-added complement in the objective function eliminates the dramatic differences in average daily NPC derived from STDOBJ_H10 and STDOBJ_H20 and improves warehouse product service level. Table 5-29 displays that, when using VAOBJ_H10, total product demands satisfied from warehouse deliveries (2265.1 units) are even slightly higher than that derived from STDOBJ_H20 (2235.4 units). For short planning horizon (H10), the value-added approach also reduces the alternative deliveries and increases the average daily total inventories carried at warehouses. More products are produced at plants and more product inventories are available at the end of planning period, thus helping to sustain SC financial performance in the next planning period or the near future.

To further assess the effects of the choice of planning horizon and the structure of the analytical model's objective function, we performed ANOVA analysis with Duncan's multiple range tests in which the combination of planning horizon and objective function approach is the designated experimental treatment. With this analysis, we can determine the extent to which differences in simulated performance metrics are attributable to systematic versus random variation.

Consider first our results at the overall SC level (Table 5-30 through Table 5-32) and then the performance measures at the product level in the SC (Table 5-33 to Table 5-35).

Table 5-30 Scenario One Overall SC Level Duncan Test Results Part I

The ANOVA Procedure

Duncan's Multiple Range Test for gpc

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	761.4838

Number of Means	2	3	4
Critical Range	15.49	16.30	16.84

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	3291.387	25	VAOBJ_H20
B	3271.592	25	VAOBJ_H10
C	3211.545	25	STDOBJ_H20
D	2859.017	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for whdelv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	3.457159

Number of Means	2	3	4
Critical Range	1.044	1.099	1.135

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	398.5693	25	VAOBJ_H20
B	377.5213	25	VAOBJ_H10
C	372.5713	25	STDOBJ_H20
D	326.3939	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for pldelv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	0.846363

Number of Means	2	3	4
Critical Range	.5165	.5435	.5615

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	58.8964	25	STDOBJ_H10
B	25.3859	25	STDOBJ_H20
C	21.5209	25	VAOBJ_H10
D	0.0000	25	VAOBJ_H20

The ANOVA Procedure

Duncan's Multiple Range Test for lostsale

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	2.260705

Number of Means	2	3	4
Critical Range	.8442	.8883	.9177

Means with the same letter are not significantly different.				
Duncan Grouping		Mean	N	treatment
	A	32.2205	25	STDOBJ_H10
	B	19.5537	25	STDOBJ_H20
	B			
C	B	18.9416	25	VAOBJ_H20
C				
C		18.4687	25	VAOBJ_H10

Table 5-31 Scenario One Overall SC Level Duncan Test Results Part II

The ANOVA Procedure

Duncan's Multiple Range Test for whpct

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	0.630427

Number of Means	2	3	4
Critical Range	.4458	.4691	.4846

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	93.6557	25	VAOBJ_H20
B	89.9597	25	VAOBJ_H10
C	88.3276	25	STDOBJ_H20
D	76.2834	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for scsl

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	0.276864

Number of Means	2	3	4
Critical Range	.2954	.3109	.3211

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	95.3255	25	VAOBJ_H10
B	94.9095	25	STDOBJ_H20
C	93.6557	25	VAOBJ_H20
D	91.8038	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for plproduced

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	1.434024

Number of Means	2	3	4
Critical Range	.6723	.7075	.7309

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	405.8469	25	VAOBJ_H20
B	398.4499	25	VAOBJ_H10
C	396.4436	25	STDOBJ_H20
D	362.7913	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for whinv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	0.039646

Number of Means	2	3	4
Critical Range	.1118	.1176	.1215

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	5.55148	25	VAOBJ_H20
B	5.20364	25	STDOBJ_H20
C	5.02903	25	VAOBJ_H10
D	2.80721	25	STDOBJ_H10

Table 5-32 Scenario One Overall SC Level Duncan Test Results Part III

The ANOVA Procedure

Duncan's Multiple Range Test for endwhinv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	0.082246

Number of Means	2	3	4
Critical Range	.1610	.1694	.1750

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	5.76296	25	VAOBJ_H20
B	5.12922	25	STDOBJ_H20
B			
B	5.05376	25	VAOBJ_H10
C	1.21567	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for plinv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	0.000052

Number of Means	2	3	4
Critical Range	.004033	.004245	.004385

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	0.948713	25	VAOBJ_H20
A			
A	0.948498	25	VAOBJ_H10
B	0.940944	25	STDOBJ_H20
C	0.855023	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for endplinv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	205.6448

Number of Means	2	3	4
Critical Range	8.051	8.473	8.752

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	402.267	25	VAOBJ_H20
A			
A	397.847	25	VAOBJ_H10
A			
A	395.407	25	STDOBJ_H20
B	346.707	25	STDOBJ_H10

Table 5-33 Scenario One Product Level Duncan Test Results Part I

The ANOVA Procedure

Duncan's Multiple Range Test for GPC

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	78763.21

Number of Means	2	3	4
Critical Range	63.65	67.01	69.26

Means with the same letter are not significantly different.				
Duncan Grouping		Mean	N	treatment
	A	3291.39	150	VAOBJ_H20
	A			
B	A	3271.59	150	VAOBJ_H10
B				
B		3211.54	150	STDOBJ_H20
	C	2859.02	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for PLDELV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	300.2481

Number of Means	2	3	4
Critical Range	3.930	4.137	4.276

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	58.896	150	STDOBJ_H10
B	25.386	150	STDOBJ_H20
B			
B	21.521	150	VAOBJ_H10
C	0.000	150	VAOBJ_H20

The ANOVA Procedure

Duncan's Multiple Range Test for WHDELV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	678.3494

Number of Means	2	3	4
Critical Range	5.907	6.218	6.427

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	398.569	150	VAOBJ_H20
B	377.521	150	VAOBJ_H10
B			
B	372.571	150	STDOBJ_H20
C	326.394	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for LOSTSALE

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	179.2931

Number of Means	2	3	4
Critical Range	3.037	3.197	3.304

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	32.221	150	STDOBJ_H10
B	19.554	150	STDOBJ_H20
B			
B	18.942	150	VAOBJ_H20
B			
B	18.469	150	VAOBJ_H10

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Table 5-34 Scenario One Product Level Duncan Test Results Part II

The ANOVA Procedure

Duncan's Multiple Range Test for WHPCT

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	21.38956

Number of Means	2	3	4
Critical Range	1.049	1.104	1.141

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	93.6557	150	VAOBJ_H20
B	89.9597	150	VAOBJ_H10
C	88.3276	150	STDOBJ_H20
D	76.2834	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for PLPRODUCED

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	490.3995

Number of Means	2	3	4
Critical Range	5.022	5.287	5.465

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	405.847	150	VAOBJ_H20
B	398.450	150	VAOBJ_H10
B			
B	396.444	150	STDOBJ_H20
C	362.791	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for SCSL

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	15.1593

Number of Means	2	3	4
Critical Range	.8830	.9296	.9608

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	95.3255	150	VAOBJ_H10
A			
A	94.9095	150	STDOBJ_H20
B	93.6557	150	VAOBJ_H20
C	91.8038	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for WHINV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	0.59623

Number of Means	2	3	4
Critical Range	.1751	.1844	.1905

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	5.55148	150	VAOBJ_H20
B	5.20364	150	STDOBJ_H20
B			
B	5.02903	150	VAOBJ_H10
C	2.80721	150	STDOBJ_H10

Table 5-35 Scenario One Product Level Duncan Test Results Part III

The ANOVA Procedure

Duncan's Multiple Range Test for ENDWHINV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	1.232489

Number of Means	2	3	4
Critical Range	.2518	.2651	.2740

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	5.7630	150	VAOBJ_H20
B	5.1292	150	STDOBJ_H20
B			
B	5.0538	150	VAOBJ_H10
C	1.2157	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for PLINV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	0.002785

Number of Means	2	3	4
Critical Range	.01197	.01260	.01302

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	0.948713	150	VAOBJ_H20
A			
A	0.948498	150	VAOBJ_H10
A			
A	0.940944	150	STDOBJ_H20
B	0.855023	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for ENDPLINV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	2430.865

Number of Means	2	3	4
Critical Range	11.18	11.77	12.17

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	402.267	150	VAOBJ_H20
A			
A	397.847	150	VAOBJ_H10
A			
A	395.407	150	STDOBJ_H20
B	346.707	150	STDOBJ_H10

Collectively, Table 5-30 through Table 5-35 clearly indicate that the value-added approach can counter the negative effects associated with a short planning horizon and provide strong support for H1 and H2.

5.5 Summary

When deriving solutions for multi-period SC planning problems, analytical models may be counterproductive if too short a planning horizon is employed and expected revenues are recognized only when goods are sold. The experiments conducted in this chapter reveal that increasing the length of the planning horizon can improve the overall SC performance.

Q1: What rolling horizon length should be adopted in order to achieve higher SC performance for a given objective function and performance metrics?

A1: With standard accounting practice in the objective function, the optimization model requires a planning horizon that is at least equals to the sum of the longest lead time upstream and downstream plus the production cycle time.

This planning horizon, however, may be too long for organizations that manage international supply chains with slow transit modes such as ocean liners. It may also result in large analytical models that require excessive amounts of times to generate “optimal” solutions. We therefore investigate whether a value-added complement in the objective function can allow planning to occur effectively with a short planning horizon.

With the value-added complement, the optimization model recognizes revenue for some products when they are shipped to warehouses. This counters the fact that they will not register in the model when the products are sold at the warehouse (because they would not reach the warehouse before the end of the planning horizon). The value-added complement improves the SC performance on almost all of the performance measures and achieves higher financial performance.

Q2: Can a “value-added” complement to the SCM objective function mitigate the sub-optimization that occurs when the planning horizon is shorter than the time required to capture the effects of all relevant events (procurement, production and deliveries) upstream and downstream?

A2: Yes. The value-added approach can mitigate the negative effects to a great extent. For the case on hand, value-added approach in the objective function can short the minimum planning horizon by at least 50%.

However, value-added approach in the objective function has its own “counterproductive” side if no consideration is given to revenues that will be derived from sales of goods in inventory at the warehouses (or plants) or from goods already in transit at the beginning of the planning horizon. To deal with this problem, we include (in the objective function for the optimizing model) any revenues from goods that shipped from the plant to warehouses and from the plant to customers in the current planning horizon (on the day that they are shipped, as with the value-added approach), but we also include revenues from goods in inventory or in transit at the beginning of the horizon when they are shipped to customers. In the current implementation, we simply include revenues for customer deliveries from warehouses only up to the minimum downstream lead time for warehouse replenishment.

How much inventory to carry in the system and where to place it is a complicated problem. Inventory placement affects SC performance and related risk. Decisions made to improve performance on one dimension may affect SC performance on other dimensions – beyond the obvious tradeoffs between short-term SC financial performance and the service level. Note that the average daily NPC resulted from VAOBJ_H20 is about 2.5% higher than that from STDOBJ_H20. This difference may be explainable by the fact that STDOBJ_H20 fails to recognize a number of future revenue possibilities.

Meanwhile, when disruptions or unusual events alter the state of the system, abnormal patterns may surface. In such instances, the time to recover and time to survive are critical to organizations (Simchi-Levi, 2015). Demands satisfied from alternative sources or expedited shipping may increase and managerial short-term interests may also shift, depending on the delay of the flows in the supply chain. This raises the question of whether value-added approach will outperform standard where disruptive events cause inventories to be lower than their planned levels. We developed scenario two in the next chapter to address this question.

Chapter 6 Supply Chain Risk Management

Research questions Q3, Q4, and Q5 are addressed in this chapter:

- Q3: Does any advantage derived from the value-added complement to the objective function persist when SC disruptions occur?
- Q4: How sensitive is SC performance to the choice of planning horizon and addition of the value-added complement to the objective function?
- Q5: What product characteristics are associated with the differential service levels that result from application of the SC optimization model on a rolling horizon?

6.1 Problem Description

In order to extend our analysis of the effects associated with choice of the length of rolling horizon and choice of objective function into the realm of risk management following disruptive events, we solve the multi-period supply chain planning problems in this chapter where random inventory outages are assumed to occurred (as perhaps with damage in processing or shipment or following surges in demand due to interruptions in supply chains of competitors).

For the purposes of this research, we focus on the risks downstream in the SC where disruptions or unusual events deplete some finished product inventories at the warehouse. To represent supply chain disruptions in such situations, we randomly set 20% of finished-product inventories at warehouses to zero, while keeping all other initial conditions the same as they were in scenario 1. Random changes in inventory and outages are imposed at the beginning of the planning period in each replication. Note that outages can occur in any product-warehouse combination and the amounts of other inventories held in the system can be any value between min and max at beginning of each replication.

Various strategies are proposed in the literature to cope with supply chain risks. In this research, buffer inventories of finished products, flexibility, and redundancy in the SC are used to cope with disruptions or unusual events that may occur. Shipments directly from plants to customers are allowed (at additional cost) when inventories are insufficient at the warehouse. (We do not presently allow product demands at one warehouse to be satisfied through deliveries from other warehouses, though this could easily be accommodated.) Some buffer inventories are provided at production facilities. This allows the SC to cope with variations in the product demands, but mitigates the risks associated with production process in the system as well. Redundancy is incorporated in the SC as dual sourcing for each raw material, flexibility allows plant to produce all products and shipments of finished products can occur from each plant to each warehouse. A “flexible” strategy is thus implemented by placing orders of finished products at either plant, purchasing raw materials from either one of the suppliers, and producing products at either plant.

6.2 Experiments under the Supply Chain Risk Environment

As illustrated in the preceding chapter, the analytical model can employ a standard accounting approach or a value-added approach when assigning coefficients to the objective function. The standard accounting approach in the objective function recognizes revenue only when goods are sold, while the value-added approach in the objective function register revenue when goods are shipped. The multi-period SC planning problem will be solved with these two approaches in the objective function (STDOBJ or VAOBJ) and with different planning horizons (H10 or H20). In total, four distinctive experiments are conducted, namely, STDOBJ_H10, STDOBJ_H20, VAOBJ_H10, and VAOBJ_H20.

We begin with employing optimization model using the standard objective function to solve the multi-period SC problem under the risk environment with H10 and H20. As expected, increasing the length of the planning horizon helps the SC to recover from the disruption via building up product inventories at the warehouse, thus, improving the overall product service level, decreasing the expensive expedited shipments from plants to customers, and resulting in better financial performance. Table 6-1 presents the daily net profit contribution statement for STDOBJ_H10 and STDOBJ_H20, while Table 6-2 compares the SC performance on all metrics resulted from STDOBJ_H10 and STDOBJ_H20.

Table 6-1 Scenario Two Cross Comparison of SC Financial Performance with STDOBJ

Daily Net Profit Contribution Statement for 90-day period with STDOBJ_H10 Scenario Two		
	$	$
GROSS PROFIT CONTRIBUTION		15,189.62
Product sold at warehouses	15,189.62	
PLANT EXPENSES		1,045.40
Finished Product Inventory Costs	9.19	
Finished Product in Transit Costs	17.03	
Raw Material Inventory Costs	33.94	
Raw Material in Transit Costs	22.46	
Raw Material Shipping Costs	444.50	
Idle Costs	68.48	
Setup Costs	449.80	
NET PROFIT CONTRIBUTION		14,144.22

Daily Net Profit Contribution Statement for 90-day period with STDOBJ_H20 Scenario Two		
	$	$
GROSS PROFIT CONTRIBUTION		18,127.16
Product sold at warehouses	18,127.16	
PLANT EXPENSES		971.10
Finished Product Inventory Costs	10.26	
Finished Product in Transit Costs	22.41	
Raw Material Inventory Costs	39.36	
Raw Material in Transit Costs	31.60	
Raw Material Shipping Costs	417.47	
Idle Costs	0.00	
Setup Costs	450.00	
NET PROFIT CONTRIBUTION		17,156.06

Table 6-2 Scenario Two Summary Statistics for Quarterly Product-level SC Metrics in 25 Replications

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	508.5	108.7	81.5	3,616	72.8	88.4	595.3	1.8	1.0	0.8	0.8
2	984.0	980.0	742.2	138.7	99.1	4,865	75.7	89.9	845.9	2.0	1.0	0.9	0.8
3	273.0	269.7	192.3	45.6	31.8	1,730	71.3	88.4	228.7	2.2	1.2	0.8	0.9
4	381.0	378.1	268.2	63.2	46.7	2,178	70.9	87.8	319.9	1.7	1.1	0.8	0.8
5	78.0	75.7	55.0	13.0	7.8	1,286	72.7	89.8	65.3	3.0	2.1	0.9	0.8
6	105.0	102.7	71.2	19.2	12.3	1,515	69.4	88.0	86.6	2.3	1.3	0.8	0.8
	2,523.0	2,505.1	1,837.4	388.4	279.3	15,190			2,141.7				

10-Day Rolling Planning Horizon

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	635.9	25.6	37.3	4,583	91.0	94.7	677.4	4.7	5.0	1.0	1.0
2	984.0	980.0	906.5	27.9	45.7	5,914	92.5	95.3	957.4	4.9	5.1	1.0	1.0
3	273.0	269.7	165.7	56.2	47.9	1,320	61.4	82.3	219.5	3.6	3.1	0.8	0.8
4	381.0	378.1	306.4	41.1	30.5	2,566	81.0	91.9	341.3	2.3	1.8	0.9	0.9
5	78.0	75.7	72.6	0.6	2.5	1,656	95.9	96.7	77.5	7.2	7.8	1.0	1.0
6	105.0	102.7	99.0	0.4	3.3	2,088	96.4	96.8	105.0	6.7	7.7	1.0	1.0
	2,523.0	2,505.1	2,186.1	151.8	167.2	18,127			2,378.2				

20-Day Rolling Planning Horizon

Information derived from Table 6-1 and Table 6-2 again indicates that too short a planning horizon can lead an analytical model to be counterproductive and produce sub-optimizing SC solutions. In scenario two, this counterproductive side of the optimization model associated with short planning horizon is amplified under the risk environment where SC financial performance differs by more than 21%. Longer planning horizon (H20) reduces the overall expedited shipping and lost sales by more than 60% and 40% respectively. More importantly, average daily total warehouse inventories are doubled for most of the products, while average total warehouse ending inventory is fortified, as are the plants' finished product inventories – thus leaving the enterprise in a better position for future business. Average daily total inventory and average total ending inventory are important determinants of SC resilience, affecting both "time to survive" and "time to recover".

To test the robustness of the value-added approach under the SC risk environment, the same problem is solved with VAOBJ_H10 and VAOBJ_H20. The full comparison of the SC financial performance and the overall product level SC performance on all eleven measures are presented in Table 6-3 and Table 6-4.

Table 6-3 Scenario Two Cross Comparison of SC Financial Performance

Scenario Two	Daily Net Profit Contribution Statement for 90-day period							
	STDOBJ and H10		VAOBJ and H10		STDOBJ and H20		VAOBJ and H20	
	$	$	$	$	$	$	$	$
GROSS PROFIT CONTRIBUTION		15,189.62		18,611.58		18,127.16		18,620.75
Products sold at warehouses	15,189.62		18,611.58		18,127.16		18,620.75	
PLANT EXPENSES		1,045.40		1,045.36		971.10		987.78
Finished Product Inventory Costs	9.19		10.33		10.26		10.49	
Finished Product in Transit Costs	17.03		23.15		22.41		24.53	
Raw Material Inventory Costs	33.94		38.00		39.36		39.27	
Raw Material in Transit Costs	22.46		26.02		31.60		30.79	
Raw Material Shipping Costs	444.50		497.86		417.47		432.70	
Idle Costs	68.48		0.00		0.00		0.00	
Setup Costs	449.80		450.00		450.00		450.00	
NET PROFIT CONTRIBUTION		14,144.22		17,566.22		17,156.06		17,632.97

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Table 6-4 Scenario Two Product Level SC Metrics Cross Comparison

Summary Statistics for Quarterly Product-level Supply-Chain Metrics in 25 Replications
Scenario Two 10-Day Planning Horizon and STD_Objective

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	508.5	108.7	81.5	3,616	72.8	88.4	595.3	1.8	1.0	0.8	0.8
2	984.0	980.0	742.2	138.7	99.1	4,865	75.7	89.9	845.9	2.0	1.0	0.9	0.8
3	273.0	269.7	192.3	45.6	31.8	1,730	71.3	88.4	228.7	2.2	1.2	0.8	0.9
4	381.0	378.1	268.2	63.2	46.7	2,178	70.9	87.8	319.9	1.7	1.1	0.8	0.8
5	78.0	75.7	55.0	13.0	7.8	1,286	72.7	89.8	65.3	3.0	2.1	0.9	0.8
6	105.0	102.7	71.2	19.2	12.3	1,515	69.4	88.0	86.6	2.3	1.3	0.8	0.8
	2,523.0	2,505.1	1,837.4	388.4	279.3	15,190			2,141.7				

Summary Statistics for Quarterly Product-level Supply-Chain Metrics in 25 Replications
Scenario Two 10-Day Planning Horizon and VA _Objective

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	645.0	19.1	34.6	4,679	92.3	95.1	684.1	4.7	5.2	1.0	1.0
2	984.0	980.0	913.2	23.3	43.5	6,002	93.2	95.6	962.1	4.9	5.3	1.0	1.0
3	273.0	269.7	181.9	48.3	39.5	1,563	67.5	85.4	222.0	2.4	1.8	0.8	0.8
4	381.0	378.1	307.2	39.7	31.2	2,573	81.2	91.7	342.2	2.3	2.0	0.9	0.9
5	78.0	75.7	73.1	0.5	2.2	1,685	96.5	97.2	77.8	6.6	7.4	1.0	1.0
6	105.0	102.7	98.6	0.4	3.7	2,111	96.0	96.4	106.2	6.2	7.2	1.0	1.0
	2,523.0	2,505.1	2,219.0	131.3	154.7	18,612			2,394.4				

Summary Statistics for Quarterly Product-level Supply-Chain Metrics in 25 Replications
Scenario Two 20-Day Planning Horizon and STD_Objective

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	635.9	25.6	37.3	4,583	91.0	94.7	677.4	4.7	5.0	1.0	1.0
2	984.0	980.0	906.5	27.9	45.7	5,914	92.5	95.3	957.4	4.9	5.1	1.0	1.0
3	273.0	269.7	165.7	56.2	47.9	1,320	61.4	82.3	219.5	3.6	3.1	0.8	0.8
4	381.0	378.1	306.4	41.1	30.5	2,566	81.0	91.9	341.3	2.3	1.8	0.9	0.9
5	78.0	75.7	72.6	0.6	2.5	1,656	95.9	96.7	77.5	7.2	7.8	1.0	1.0
6	105.0	102.7	99.0	0.4	3.3	2,088	96.4	96.8	105.0	6.7	7.7	1.0	1.0
	2,523.0	2,505.1	2,186.1	151.8	167.2	18,127			2,378.2				

Summary Statistics for Quarterly Product-level Supply-Chain Metrics in 25 Replications
Scenario Two 20-Day Planning Horizon and VA _Objective

Product	Expected Daily Demand	Avg. Simul. Daily Demand	Avg. Daily Shipped From Whses	Avg. Daily Shipped From Plants	Avg. Daily Lost Sales	Avg. Daily Gross Profit Contrib	Avg. Daily Whse Deliv (pct)	Avg. SC Service Level (pct)	Avg. Daily Total Plant Produced	Avg. Total Whse Inv (days demand)	Avg. Total Whse End Inv (days demand)	Avg. Total Plant Inv (days demand)	Avg. Total Plant End Inv (days demand)
1	702.0	698.8	676.6	0.0	22.2	4,957	96.8	96.8	702.0	5.1	5.7	1.0	1.0
2	984.0	980.0	952.2	0.0	27.8	6,331	97.2	97.2	985.2	5.0	5.4	1.0	1.0
3	273.0	269.7	180.5	0.0	89.2	535	66.9	66.9	176.0	3.5	3.1	0.6	0.7
4	381.0	378.1	360.3	0.0	17.8	2,994	95.3	95.3	389.0	5.0	5.1	1.0	1.0
5	78.0	75.7	73.4	0.0	2.3	1,688	96.9	96.9	78.8	7.0	7.7	1.0	1.0
6	105.0	102.7	99.7	0.0	3.0	2,116	97.1	97.1	105.7	6.5	7.3	1.0	1.0
	2,523.0	2,505.1	2,342.7	0.0	162.3	18,621			2,436.8				

To further evaluate the effectiveness associated with value-added approach, Duncan's multiple range tests are conducted at the overall SC level with results illustrated in Table 6-5, Table 6-6, and Table 6-7.

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Table 6-5 Scenario Two Overall SC Level Duncan Test Part I

The ANOVA Procedure

Duncan's Multiple Range Test for gpc

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	11225.88

Number of Means	2	3	4
Critical Range	59.49	62.60	64.67

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	3103.46	25	VAOBJ_H20
A			
A	3101.93	25	VAOBJ_H10
B	3021.19	25	STDOBJ_H20
C	2531.60	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for pldelv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	7.090041

Number of Means	2	3	4
Critical Range	1.495	1.573	1.625

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	64.7312	25	STDOBJ_H10
B	25.2978	25	STDOBJ_H20
C	21.8890	25	VAOBJ_H10
D	0.0000	25	VAOBJ_H20

The ANOVA Procedure

Duncan's Multiple Range Test for whdelv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	59.27539

Number of Means	2	3	4
Critical Range	4.323	4.549	4.699

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	390.456	25	VAOBJ_H20
B	369.838	25	VAOBJ_H10
C	364.349	25	STDOBJ_H20
D	306.235	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for lostsale

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	30.6042

Number of Means	2	3	4
Critical Range	3.106	3.268	3.376

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	46.544	25	STDOBJ_H10
B	27.864	25	STDOBJ_H20
B			
B	27.055	25	VAOBJ_H20
B			
B	25.784	25	VAOBJ_H10

Table 6-6 Scenario Two Overall SC Level Duncan Test Part II

The ANOVA Procedure

Duncan's Multiple Range Test for whpct

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	2.030178

Number of Means	2	3	4
Critical Range	.8000	.8418	.8696

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	91.7050	25	VAOBJ_H20
B	87.7943	25	VAOBJ_H10
C	86.3751	25	STDOBJ_H20
D	72.1290	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for scsl

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	0.952381

Number of Means	2	3	4
Critical Range	.5479	.5766	.5956

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	93.5539	25	VAOBJ_H10
B	92.9502	25	STDOBJ_H20
C	91.7050	25	VAOBJ_H20
D	88.7215	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for plproduced

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	7.549021

Number of Means	2	3	4
Critical Range	1.543	1.623	1.677

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	406.1334	25	VAOBJ_H20
B	399.0718	25	VAOBJ_H10
C	396.3682	25	STDOBJ_H20
D	356.9481	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for whinv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	0.069247

Number of Means	2	3	4
Critical Range	.1477	.1555	.1606

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	5.35580	25	VAOBJ_H20
B	4.91088	25	STDOBJ_H20
C	4.52019	25	VAOBJ_H10
D	2.16946	25	STDOBJ_H10

Table 6-7 Scenario Two Overall SC Level Duncan Test Part III

The ANOVA Procedure

Duncan's Multiple Range Test for endwhinv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	0.094608

Number of Means	2	3	4
Critical Range	.1727	.1817	.1877

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	5.74067	25	VAOBJ_H20
B	5.07682	25	STDOBJ_H20
C	4.81624	25	VAOBJ_H10
D	1.26335	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for endplinv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	194.4265

Number of Means	2	3	4
Critical Range	7.829	8.238	8.510

Means with the same letter are not significantly different.				
Duncan Grouping		Mean	N	treatment
	A	402.773	25	VAOBJ_H20
	A			
B	A	397.040	25	VAOBJ_H10
B				
B		394.500	25	STDOBJ_H20
	C	342.060	25	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for plinv

Alpha	0.05
Error Degrees of Freedom	96
Error Mean Square	0.000076

Number of Means	2	3	4
Critical Range	.004898	.005154	.005324

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	0.949780	25	VAOBJ_H20
A			
A	0.947950	25	VAOBJ_H10
B	0.941067	25	STDOBJ_H20
C	0.843487	25	STDOBJ_H10

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Information derived from Table 6-3 to Table 6-7 indicates that, when disruptions occurred in the SC, the value-added complement to the optimization model's objective function improves products' daily gross profit contribution, increases warehouse deliveries to satisfy customer demands, reduces alternative (more expensive) deliveries and lost sales, and improves warehouses' product service level. More products are being produced across production facilities. For the same length of planning horizon (H10 or H20), more buffer inventories are being held in the system when value-added complement to the objective function is used. To answer research question:

Q3: Does any advantage derived from the value-added complement to the objective function persist when SC disruptions occur?

A3: Yes. Information derived from Table 6-3 to Table 6-7 provide strong support that the value-added approach in the objective function can mitigate the "negative" impacts associated with too short a planning horizon, even under the supply chain risk environment. Moreover, the value-added approach facilitates the recovery process via building inventory more quickly up to the desired minimum level.

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6.3 Summary

We close this chapter by providing statistical analysis results at the product level from the ANOVA procedure. Duncan's Multiple range test outcomes on eleven performance measures are presented in Table 6-8, Table 6-9 and Table 6-10.

Table 6-8 Scenario Two Product Level Duncan Test Part I

The ANOVA Procedure

Duncan's Multiple Range Test for GPC

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	169180.5

Number of Means	2	3	4
Critical Range	93.3	98.2	101.5

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	3103.46	150	VAOBJ_H20
A			
A	3101.93	150	VAOBJ_H10
A			
A	3021.19	150	STDOBJ_H20
B	2531.60	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for PLDELV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	465.4152

Number of Means	2	3	4
Critical Range	4.892	5.151	5.324

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	64.731	150	STDOBJ_H10
B	25.298	150	STDOBJ_H20
B			
B	21.889	150	VAOBJ_H10
C	0.000	150	VAOBJ_H20

The ANOVA Procedure

Duncan's Multiple Range Test for WHDELV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	1388.656

Number of Means	2	3	4
Critical Range	8.451	8.897	9.196

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	390.456	150	VAOBJ_H20
B	369.838	150	VAOBJ_H10
B			
B	364.349	150	STDOBJ_H20
C	306.235	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for LOSTSALE

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	402.22

Number of Means	2	3	4
Critical Range	4.548	4.788	4.949

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	46.544	150	STDOBJ_H10
B	27.864	150	STDOBJ_H20
B			
B	27.055	150	VAOBJ_H20
B			
B	25.784	150	VAOBJ_H10

Table 6-9 Scenario Two Product Level Duncan Test Part II

The ANOVA Procedure

Duncan's Multiple Range Test for WHPCT

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	39.42229

Number of Means	2	3	4
Critical Range	1.424	1.499	1.549

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	91.7050	150	VAOBJ_H20
B	87.7943	150	VAOBJ_H10
B			
B	86.3751	150	STDOBJ_H20
C	72.1290	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for PLPRODUCED

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	654.8445

Number of Means	2	3	4
Critical Range	5.803	6.110	6.315

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	406.133	150	VAOBJ_H20
B	399.072	150	VAOBJ_H10
B			
B	396.368	150	STDOBJ_H20
C	356.948	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for SCSL

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	22.1962

Number of Means	2	3	4
Critical Range	1.068	1.125	1.163

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	93.5539	150	VAOBJ_H10
A			
A	92.9502	150	STDOBJ_H20
B	91.7050	150	VAOBJ_H20
C	88.7215	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for WHINV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	0.844748

Number of Means	2	3	4
Critical Range	.2084	.2194	.2268

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	5.3558	150	VAOBJ_H20
B	4.9109	150	STDOBJ_H20
C	4.5202	150	VAOBJ_H10
D	2.1695	150	STDOBJ_H10

Table 6-10 Scenario Two Product Level Duncan Test Part III

The ANOVA Procedure

Duncan's Multiple Range Test for ENDWHINV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	1.323354

Number of Means	2	3	4
Critical Range	.2609	.2747	.2839

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	5.7407	150	VAOBJ_H20
B	5.0768	150	STDOBJ_H20
B			
B	4.8162	150	VAOBJ_H10
C	1.2633	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for ENDPLINV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	2263.849

Number of Means	2	3	4
Critical Range	10.79	11.36	11.74

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	402.773	150	VAOBJ_H20
A			
A	397.040	150	VAOBJ_H10
A			
A	394.500	150	STDOBJ_H20
B	342.060	150	STDOBJ_H10

The ANOVA Procedure

Duncan's Multiple Range Test for PLINV

Alpha	0.05
Error Degrees of Freedom	591
Error Mean Square	0.003194

Number of Means	2	3	4
Critical Range	.01282	.01349	.01395

Means with the same letter are not significantly different.			
Duncan Grouping	Mean	N	treatment
A	0.949780	150	VAOBJ_H20
A			
A	0.947950	150	VAOBJ_H10
A			
A	0.941067	150	STDOBJ_H20
B	0.843487	150	STDOBJ_H10

Note that information presented in Table 6-8, Table 6-9, and Table 6-10 shows that, at product level, most key performance measures (10 out of 11) resulted from STDOBJ_H20 and VAOBJ_H10 are ranked in the same group, or don't have significant differences. This implies that, after SC disruptions occurred, the value-added complement to the objective function can completely counter the negative effects associated with too short a planning horizon at product level.

On one side, experiments conducted in this chapter illustrate that the "counterproductive" side of the optimization model is amplified under the SC risk environment when employed with too short a planning horizon. On the other side, SC financial performance and the overall multi-criteria SC performance prove the effectiveness and robustness of the value-added approach in countering the negative impacts from too short a planning horizon and improving the overall SC performance. To answer research question:

Q4: How sensitive is SC performance to the choice of planning horizon and addition of the value-added complement to the objective function?

A4: Supply chain performance is very sensitive to the choice of planning horizon with standard accounting practice. However, supply chain performance, relatively speaking, is much less sensitive to the length of planning horizon with value-added complement to the objective function.

We also focus on investigating what factors lead to the differential product service levels in this scenario. Besides influential characteristics associated with different products, in scenario 2, we also consider the average (across all warehouses) initial product inventory in days of expected demand for each product in each replication.

Replication results from experiments with the longer planning horizon (H20) are used to perform a multiple regression analysis to gain insights of what factors drive the differences in product service levels. The resulting regression model for product service level in scenario two is:

Product Service Level = 94.18 + 0.78 * (average initial warehouse inventory in days of expected demand) + 0.85 * (revenue per average production minute) – 4.51 * (average upstream lead time) – 56.09 * (demand coefficient of variation) + unexplained variation.

This model explains 76.7% of the variation in product service level and each of the explanatory variables is statistically significant at 0.0001 level with anticipated signs. In Table 6-11 we illustrate how each of these factors is correlated with product service level, along with corresponding summary statistics. Note that the magnitude of the multiple regression coefficient associated with product characteristics is greater than in those from scenario one. The most influential characteristic is still revenue per average production minute. *Ceteris paribus*, the higher revenue per average production minute, the higher the product service level; the more initial product inventory at warehouses, the higher product service level; the shorter the average upstream lead time, the higher product service level; and the lower the demand coefficient of variation, the higher the product service level.

Note that with STDOBJ_H20, the overall product service level is at 92.95% which indirectly indicates that the system is almost recovered from the disruptions and reaches desired service level. Although more initial inventories held in the warehouses, in general, lead to a higher overall service level, the small impact associated with this factor in scenario two also reflects the resilience of the SC when buffer inventories, flexibility, and redundancy as risk mitigation strategies are employed.

Table 6-11 Scenario Two Drivers of Product Service Level

	Corr. With SCSL	**Min**	**Max**	**Mean**	**Std. Dev.**	**t Value**	**Multiple Regression Coeff.**
Product Service Level in pct (SCSL)	1	76.82	99.40	92.95	5.34	N.A.	N.A.
Avg. Initial W.H. Inv. In Days Demand (INIDAYSINVWH)	0.22	2.83	9.60	7.40	1.55	5.43	0.77
Rev. per avg. production minute (REVPERPRODM)	0.81	28.88	48.32	39.87	7.68	13.73	0.85
Demand Coefficient of Variation (DEMCV)	-0.02*	0.02	0.21	0.12	0.07	-6.62	-56.09
Avg. Upstream Lead Time (AVGRMLT)	0.48	6.83	8.50	7.56	0.70	-4.91	-4.51

*not significant at 0.5 level.

We use information derived from Table 5-27 and Table 6-11 to answer our fifth research question.

Q5: What product characteristics are associated with the differential service levels that result from application of the SC optimization model on a rolling horizon?

A5: Revenue per average production minute, average upstream lead time, and demand coefficient of variation are factors contribute to the differential product service level. Drivers of product service level derived from scenario one and scenario two both reveal that, *Ceteris paribus*, the higher revenue per average production minute, the higher the product service level; the shorter the average upstream lead time, the higher product service level; and the lower the demand coefficient of variation, the higher the product service level.

Chapter 7 Summary

7.1 Overall Research Summary

Analytical models are widely used to inform managerial decision making. These models are more powerful and can provide practical insights when stochastic elements in the SC are considered. The analytical methodology developed in this research includes the integration of a deterministic model and a simulation model. Synthesis of optimization and simulation allows consideration of stochastic behavior in the supply chain and combines the advantages of the two modeling techniques to generate more practical insights when facilitating the decision making process. This research tests the efficacy of integrating a SC optimizer with stochastic simulations of rolling planning horizons, produces selected performance metrics that would emerge from use of the optimizer in a dynamic business setting over an entire season (quarter of the year), and identifies how the availability of newly revealed information affects these performance metrics. The synthetic approach also reveals SC performance on multiple dimensions and allows an analyst or manager to visualize status and behavior of the complete SC through time, covering procurement, production, and distribution.

Rarely discussed in the literature is the impact associated with the length of the planning horizon when employing an analytical model to solve various SC problems. As events unfold, organizations inevitably revise plans after completing only some of the work in the planning horizon. This makes it important to consider potential changes in the state of the system when solving multi-period SC planning problems. We began our research by illustrating the potentially counterproductive effects of using an optimization model using standard accounting for revenues with too short a planning horizon. Then we integrated the supply-chain optimizing model with a discrete-event simulation structure to accommodate stochastic behavior. SC planning reports reveal the counterproductive behavior of the SC when too short a planning horizon is used with standard accounting treatment for costs and revenues. Moreover, results from experiments conducted in scenario one indicate that the length of the planning horizon, at minimum, should consider the longest lead time upstream and downstream in the SC plus the production cycle time if revenues are recognized when goods are sold. However, this length of planning horizon may require excessive time for an analytical model to reach optimality and may not be practicable for organizations managing international logistics and supply chains. To resolve the dilemma, this research proposed a value-added objective function (with retention of standard accounting for revenue derived from goods in place at the beginning of the planning horizon) to allow planning with a shorter horizon. This novel method of recognizing value of SC activities in a SC optimizer allows effective planning to occur with much shorter and more practical planning horizons than required with standard accounting treatment. Results derived from experiments with this approach, along with statistical analysis, confirm its effectiveness in mitigating the negative impacts associated with too short a planning horizon. We also tested the robustness of the value-added approach under the SC risk environment where disruptions or unusual events occur downstream and deplete warehouses' inventories. These experiments also affirmed the effectiveness of the value-added approach (but with standard recognition of revenues for goods in place at the beginning of the planning horizon and for goods produced and shipped to consumers during the planning horizon).

The research also provides levers in the SC optimizer that help in shaping SC strategies to address specific problems revealed by comprehensive reports of SC performance such as profit contributions, product service levels, inventories, plant utilization, etc. The multi-dimensional SC performance report not only reveals the status and performance related to individual products, warehouses, plants and suppliers, but also the SC as a whole.

7.2 Limitations and Future Research

In this research, we focused on exploring methods to mitigate the counterproductive side of the optimization model when too short a planning horizon is employed to solve multi-period SC planning problems. In different scenarios, we illustrated the effectiveness of value-added approach in countering the negative effects associated with too short a planning horizon.

During the process, we deal with hazards that often accompany the use of SC optimizing models such as sensitivity of solutions to small changes in standard cost components and alternative optimal (or near-optimal) solutions. One of the limitations of this research is that the SC optimizer ignores some of the operational considerations such as sequence-dependent setup times, possibilities of shipment consolidations and priorities that should be given to orders according to order date or consumer characteristics. Another limitation of this dissertation is that the SC optimizer is capable of dealing with just a few products (or product groups) with relatively simple (or aggregated) bills of materials; otherwise the analytical model requires excessive computational time to reach optimality. Though techniques for improving efficiency of the SC optimizer are undoubtedly available, future research and practical applications may rely on a heuristic optimizer (which may be benchmarked against a corresponding MIP optimizer using deterministic test cases).

We stress-tested the modeled system by simulating the impact of disruptions or unusual events that deplete downstream inventories and deplete product inventories in warehouses randomly at the beginning of each planning period. We investigated how the addition of the value-added measures for some production and delivery activities facilitate the resilience of the SC in recovering from the disruptions. Of course, disruptions can occur anywhere in the SC, and in the future research, the SC under investigation can be further stressed by incorporating disruptions upstream or at plant/s. We could thus test the effectiveness of combining routine supply-chain risk reduction strategies with strategies for managing adverse events. In sum, the platform created in this dissertation for risk management can facilitate the investigation of possible changes in demand patterns, interrelationships among stochastic elements, and possibilities of disruptive events.

With various perspectives on SCRM, researchers have recognized that correlations among sources of risk impinge on sourcing strategies (Wagner et al., 2009, 2011; Costantino and Pellegrino, 2010), vehicle routing solutions (Lium et al., 2007), and financial performance (Vaagen and Wallace, 2008). However, analytical models (such as stochastic programming) that incorporate risk, generally assume that supply chain risk components, such as variation of demand in different markets, transportation delays, etc. are independent of each other (Ciarallo et al., 1994; Wang and Gerchak, 1996; Sodhi, 2005; Wu and Olson, 2008; Lin and Chen, 2009; Schmitt and Singh, 2012; Cardoso et al., 2015 etc.). This may cause a significant underestimation of the impact of adverse events (Zhang and Li, 2010; Liberatore et al, 2012). Future research should also consider the impact of correlations among supply chain risk sources on SC plans and investigate whether proper consideration of correlations among supply chain risk sources can cause significantly different solutions to emerge.

Appendix A Supply Chain Risk Sources Derived from the Literature

Supply Chain Risk Sources Derived from the Literature

Authors	SC Risk Elements	SC Risk Sources
Bilsel & Ravindran (2011)	Quality	Supply Risk
	Machine Performance	
	Delivery Delays	
	Transportation Disruptions	
Zsidisin (2003)	Inability to cope with demand fluctuation	
	Delivery delays	
	Quality	
	Cost/Pricing Variations	
	Inability to adopt new technologies	
Zsidisin et al. (2000)	Capacity	
	Quality	
	Inability to adopt new technologies	
	Product Design Changes	
Tang (2006)	Cost/Pricing Variations	
	Quality	
	Supply Commitment	
Wagner & Bode (2006)	Supplier Dependence	
	Single Sourcing	
	Global Sourcing	
Azevedo et al. (2008)	Delivery Delays	
	Quantity	
Narasimhan et al. (2009)	Contractual Risks	
	Cultural Risks	
	Loss of Knowledge	
	Process Change Risks	

Authors	SC Risk Elements	SC Risk Sources
Tuncle & Alpan (2010)	Quality	**Supply Risk**
Hallikas et al. (2004)	Inability to cope with demand fluctuation	**Supply Risk**
Hallikas et al. (2004)	Fulfillment	**Supply Risk**
Hallikas et al. (2004)	Cost/Pricing Variations	**Supply Risk**
Hallikas et al. (2004)	Weakness in resources, development, and flexibility)	**Supply Risk**
Tang & Tomlin (2008)	Demand Uncertainty	**Demand Risk**
Tuncle & Alpan (2010)	Demand Uncertainty	**Demand Risk**
Tuncle & Alpan (2010)	Change of Customer Tastes	**Demand Risk**
Bilsel & Ravindran (2011)	Consumer Preferences	**Demand Risk**
Bilsel & Ravindran (2011)	Competiotion	**Demand Risk**
Bilsel & Ravindran (2011)	Economic Uncertainty	**Demand Risk**
Tang (2006)	Demand Uncertainty	**Demand Risk**
Ghadge et al. (2012)	Uncertain Demand	**Demand Risk**
Bilsel & Ravindran (2011)	Capacity Uncertainty	**Process Risk**
Bilsel & Ravindran (2011)	Demand Uncertainty	**Process Risk**
Bilsel & Ravindran (2011)	Uncertain Cost	**Process Risk**
Tuncle & Alpan (2010)	Equipment Failure	**Process Risk**
Tang (2006)	Demand Uncertainty	**Process Risk**
Tang (2006)	Supply Uncertainty	**Process Risk**
Tang (2006)	Uncertain Cost	**Process Risk**
Tang & Tomlin (2008)	Quality	**Process Risk**
Tang & Tomlin (2008)	Time	**Process Risk**
Tang & Tomlin (2008)	Capacity	**Process Risk**
Tang & Tomlin (2008)	Delivery Delays	**Process Risk**

Authors	SC Risk Elements	SC Risk Sources
Juttner et al. (2003)	Suboptimal Interactions among SC members	SCN Risks
Klibi et al. (2010)	Endogenous Assets◆	
	Exogenous Geographical Factors●	
Ghadge et al. (2012)	Suboptimal Interactions among SC members	
Tversky & Kahneman (1974)	Individual Perspective	Organization Risk
March & Shapira (1987)	Incentives	
	Experience	
Manuj & Mentzer (2008)	Organization's Reward System	
Ghadge et al. (2012)	Unable to anticipate	
	Unable to react	
Juttner et al. (2003)	Labor	
	Production	
	IT System	
Ghadge et al. (2012)	Inventory Risk	
	Process/Operational Risk	
	Quality Risk	
	Management Risk	

Authors	SC Risk Elements	SC Risk Sources
Tang (2006)	Natural Disasters	**Environment Risk**
	Man-made Disasters	
	Exchange Rate Fluctuation	
	Strikes	
Rosenhead et al. (1972)	Competitors Behavior	
	Governmental Policies	
Juttner et al. (2003)	Accidents	
	Sociopolitical Risk	
	Natural Disasters	
Ghadge et al. (2012)	Natural Disasters	
	Politics	
	Governmental Policies	
	Market Forces	
	Uncertain Supply	
	Uncertain Demand	
	Global Sourcing	
	Short Product life cycles	
	Financial Instability	
	JIT outsourcing	
	Mergers and Acquisitions	
	New Technologies	
	E-business	
	Shorter time-to-market	

Authors	SC Risk Elements	SC Risk Sources
Ghoshal (1987)	Talent	Others
	Technology	
	Capital	
Bilsel & Ravindran (2011)	Transportation Cost	
	Other Costs	
Zsidisin (2003)	Single Sourcing	
	Market Capacity Constraints(shortage, concentration, and inflation)	
Juttner (2005)	Globalization	
	JIT production	
	Centralized distribution and production	
	Single Sourcing	
Thun & Hoeing (2011)	Globalization	
	Product Variety	

Endogenous Assets◆	Equipment
	Vehicles
	HR
	Inventories
	Distribution
	Recovery
	Revalorization & Service Center
	Customers
	Raw Materials
	Energy Suppliers
	Subcontractors
	3PL Provider
Exogenous Geographical Factors●	Nature
	Public Infrastructures
	Socio-economic-political Factors

Appendix B ROP Calculation Steps

This section illustrates steps used in calculating reorder points of products at warehouses. For simplicity reasons, the complete calculations are provided for warehouse one (WH1) only in Table B-0-1.

Step 1: Probabilistic ROP Model (Heizer and Render, 2014)

ROP = (Average daily demand x Average lead time) + $Z\delta_{dLT}$

Where Z is the value associated with desired service level (1.65 in this case with 95% service level).

Let δ_d = Standard deviation of demand per day

δ_{LT} = Standard deviation of lead time in days

then δ_{dLT} = SQRT ((Average lead time x δ_d^2) + (Average daily demand)$^2\delta^2_{LT}$)

Step 2: Gravity Model Used to assign Weight for each Production Facility

Let $CF_fP_pW_w$ = Unit supply cost of product *p* from plant *f* to warehouse *w*

$WF_fP_pW_w$ = Weight assigned to plant *f* to replenish *p* at warehouse *w*

$$WF_fP_pW_w = \frac{(CF_fP_pW_w)^2}{\sum_{f=1}^{3}(CF_fP_pW_w)^2}$$

Step 3: Convert Product Inventory to Days of Expected Demand

Table B-0-1 Warehouse One Product ROP Results

	WH1			Unit Supply Cost			Gravity				
	F1	F2	F3	F1	F2	F3	F1	F2	F3	Weighted Average	Days of avgdem
P1	1420	1697	2746	1.24719	0.96583	0.5795	0.14	0.23	0.63	2324	17
P2	1319	1575	2555	1.121	0.87189	0.52313	0.14	0.23	0.63	2160	17
P3	479	573	920	1.55257	1.20756	0.72453	0.14	0.23	0.63	779	18
P4	786	940	1516	1.42229	1.10622	0.66373	0.14	0.23	0.63	1283	18
P5	122	146	232	3.91536	3.04528	1.82717	0.14	0.23	0.63	197	18
P6	227	271	434	3.63443	2.82678	1.69607	0.14	0.23	0.63	368	18

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Appendix C Characteristic Behavior of the Optimization Model

The purpose of this section is to investigate the behavior of the deterministic optimizing model under different assumptions about the minimum product inventory at warehouses, minimum system-wide product inventory, and minimum raw material inventory at plants. This helps to verify that the MILP model is structurally sound and alert the researcher to characteristics that need to be considered when extracting production and distribution decisions to simulate the system with a rolling horizon.

C.1 Model Verification

When investigating the optimizing model's behavior, we must keep in mind the assumptions made when constructing it. As stated in the previous chapter, managerial interest in this research is to maximize net contribution to profit and profit is not realized until products are delivered. Demands for products are aggregated and assigned to designated warehouse every day. The alternative delivery from production facilities directly to customers may occur at higher cost, while the cost of delivering products from warehouse to customers is much lower, thus, result in higher profit. Alternative deliveries from other warehouses are not an option when designated warehouse does not have sufficient inventory.

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Three major cases were developed to verify the MILP model. In these cases, parameter values differ among initial raw material inventories (rminv) at plants, initial finished product inventories at plants (fpinv) and warehouses (wpinv), minimum raw material inventories at plants (minrminv), and minimum product inventories at plants (minfpinv) and warehouses (minwpinv). During the verification process, to better investigate the behavior of the optimization model, production planning horizon is fixed at three days. Once the model has been verified, the impact of using different production planning horizons for the optimization process will be examined in Chapter 5.

C.2 Model Verification Case Analysis

C.2.1 Model Verification Case 1

Case 1 is to verify that downstream activities are taking place in accordance with the minimum product inventory requirements imposed at warehouses. These activities include delivery of products from warehouses to satisfy customer demands, product inventory shortages at warehouses, and orders of products at warehouses. Table C-1 presents the parameter values used for model verification in Case 1.

In this case, production facilities have no initial inventory of finished products. Production at all plants is suppressed because no raw materials are available. Initial finished product inventories and the minimum finished product

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inventory requirements are both set to equal average daily demand (avgdem) assigned at warehouses.

Table C-0-1 Case 1 Parameters Value (in days of expected demand)

Case 1	rminv	minrminv	fpinv	minfpinv	wpinv	minwpinv
	0	0	0	0	1	1

Key Expected outcomes for Case 1:

1) Customer demand will be satisfied for the amount of one day only through deliveries made at assigned warehouse.
2) The amount of lost sales at warehouses equals two days of assigned average daily demand.
3) Product Inventory shortage will occur at warehouses.
4) No setup for production across all plants, thus idle costs will be incurred.

Solutions from Optimization Model for Case 1:

For model verification purpose, solutions from the optimization model for Case 1 are extracted and presented in Table C-2 and Table C-3. Table C-2 displays activities at production facilities which approve 4) in key expected outcomes. Table C-3 summarizes deliveries and orders of products at warehouses for selected products and warehouses to provide evidence for 1), 2) and 3) in key expected outcomes.

One shift results in total eight working hours. With no production activities across all plants and idle cost per hour at $50, total idle cost at each plant is $400 per day in Case 1 (idlecost in Table C-2).

Table C-0-2 Case 1 Idles Times, Idle Costs and Setup Indicators

Obs	Variable Name	Facility	Day	idlehrs	idlecost	setupFacility	setupcost
1	IDLEF1D1	1	1	8	400	.	.
2	IDLEF1D2	1	2	8	400	.	.
3	IDLEF1D3	1	3	8	400	.	.
4	IDLEF2D1	2	1	8	400	.	.
5	IDLEF2D2	2	2	8	400	.	.
6	IDLEF2D3	2	3	8	400	.	.
7	IDLEF3D1	3	1	8	400	.	.
8	IDLEF3D2	3	2	8	400	.	.
9	IDLEF3D3	3	3	8	400	.	.

Table C-0-3 Case 1 Sample of Warehouse Activities

Prod	W.H.	Day	W.H. Inventory	Demand	Delivered from W.H.	W.H. Inventory Shortage	Delivered from Facility	From Facility	Outstanding Orders	AT Facility	Order Placed	At Facility	Old Order Arriv	From Facility	New Order Arriv	From Facility	Lost Sales
1	1	1	137	137	.	.	.	.	.	.	.	.	.	.	.	.	137
1	1	2	137	137	.	.	.	.	.	.	.	.	.	.	.	.	137
1	1	3	137	137	137	137	.	.	.	.	.	.	.	.	.	.	.
1	2	1	106	106	.	.	.	.	.	.	.	.	.	.	.	.	106
1	2	2	106	106	.	.	.	.	.	.	.	.	.	.	.	.	106
1	2	3	106	106	106	106	.	.	.	.	.	.	.	.	.	.	.
1	3	1	120	120	.	.	.	.	.	.	.	.	.	.	.	.	120
1	3	2	120	120	.	.	.	.	.	.	.	.	.	.	.	.	120
1	3	3	120	120	120	120	.	.	.	.	.	.	.	.	.	.	.
1	4	1	125	125	.	.	.	.	.	.	.	.	.	.	.	.	125
1	4	2	125	125	.	.	.	.	.	.	.	.	.	.	.	.	125
1	4	3	125	125	125	125	.	.	.	.	.	.	.	.	.	.	.
1	5	1	102	102	.	.	.	.	.	.	.	.	.	.	.	.	102
1	5	2	102	102	.	.	.	.	.	.	.	.	.	.	.	.	102
1	5	3	102	102	102	102	.	.	.	.	.	.	.	.	.	.	.

With initial product inventories set equal to just one day of avgdem at warehouses, customer demands can be satisfied for only one day. To avoid additional inventory shortage costs for finished goods at warehouses, products are delivered at the end of the planning horizon (Day 3), leading to inventory shortages at warehouses by the end of Day 3. Since orders are placed at the beginning of a day, during 3-day planning horizon, no orders are placed.

C.2.2 Model Verification Case 2

Case 2 is to verify that the shortage of products at warehouses triggers alternative delivery from plant (or plants) in order to satisfy customer demands. In Case 2, initial product inventories at warehouses are set to zero. Production activities are still suppressed because no raw materials are available. However, product inventories at each plant are set to equal the daily throughput (maxprod) of corresponding products at that plant. Table C-4 presents optimization model parameters value incorporated in Case 2.

Table C-0-4 Case 2 Parameters Value

Case 2	rminv	minrminv	fpinv	minfpinv	wpinv	minwpinv
	0	0	1	0	0	1

Notes: 1) fpinv is as days of maxprod at plant. 2) minwpinv is as days of avgdem assigned at warehouse.

Note that initial product inventories at warehouses are less than the minimum level would typically cause the MILP model to be infeasible. However, because we allow shortage of products at warehouses and because customer demands can be satisfied via the combination of deliveries made from warehouses and plants, such settings will not trigger infeasibility of the optimization model.

Key Expected outcomes for Case 2:

1) No deliveries will be made at all warehouses.
2) To satisfy customer demands, only alternative deliveries from plants will occur.
3) No production activities will occur across plants.
4) The amount of customer demands can be satisfied depend on system-wide product inventories at the beginning of the planning horizon.
5) Warehouses place orders of products with an amount equal to their corresponding minimum requirement.
6) Inventory shortages will occur at warehouses each day because the planning horizon is too short for shipments to arrive.

Solutions from Optimization Model for Case 2:

In this case, production activities across plants are identical to Case 1 (see Table C-2). Lack of raw materials halts productions across plants, confirming key expected outcome 3) for Case 2.

Total system-wide inventories by product at the beginning of the day is summarized in Table C-5. For selected products, inventories at plants and activities at warehouses are presented in Table C-6 and Table C-7 respectively.

Table C-5 indicates that system-wide inventory of P2 at the beginning of day three is less than the total demand of P2 across warehouses (see Table 3-8), leading to lost sales of 136 units at warehouse/s by the end of day three. The table also suggests that demands across warehouses for all other products are satisfied since there are still inventories left in the system by the end of day three or at the beginning of day four. This information from Table C-5 verifies key expected outcome 4) for Case 2.

Table C-0-5 Case 2 Total Product Inventories across Plants

	Total System Inventory by Product at Beginning of the Day					
	Product 1	Product 2	Product 3	Product 4	Product 5	Product 6
Day						
1	3272	3800	1824	2080	1176	1304
2	1868	1832	819	1143	234	315
3	1166	848	546	762	156	210
4	464	.	273	381	78	105

Table C-0-6 Case 2 Sample of Production and Plant Inventories Summary

Obs	Variable Name	Product	Facility	Day	Produced	Inventory
1	INVP1F1D1	1	1	1	.	1104
2	INVP1F1D2	1	1	2	.	702
3	INVP1F1D3	1	1	3	.	357
4	INVP1F1D4	1	1	4	.	10
5	INVP1F2D1	1	2	1	.	1008
6	INVP1F2D2	1	2	2	.	702
7	INVP1F2D3	1	2	3	.	702
8	INVP1F2D4	1	2	4	.	453
9	INVP1F3D1	1	3	1	.	1160
10	INVP1F3D2	1	3	2	.	464
11	INVP1F3D3	1	3	3	.	107
12	INVP1F3D4	1	3	4	.	1
13	INVP2F1D1	2	1	1	.	1288
14	INVP2F1D2	2	1	2	.	984
15	INVP2F1D3	2	1	3	.	648
16	INVP2F2D1	2	2	1	.	1168
17	INVP2F2D2	2	2	2	.	656
18	INVP2F2D3	2	2	3	.	176
19	INVP2F3D1	2	3	1	.	1344
20	INVP2F3D2	2	3	2	.	192
21	INVP2F3D3	2	3	3	.	24

For selected product P4, Table C-7 shows that no lost sales occur at selected warehouses. Moreover, Table C-7 confirms aforementioned key expected outcomes 1), 2), 5) and 6) for Case 2 with the right amount of orders placed and inventory shortages at warehouses, and deliveries made only from plants.

Table C-0-7 Case 2 Sample of Warehouse Activities

Prod	W.H.	Day	W.H. Inventory	Demand	Delivered from W.H.	W.H. Inventory Shortage	Delivered from Facility	From Facility	Outstanding Orders	AT Facility	Order Placed	At Facility	Old Order Arriv	From Facility	New Order Arriv	From Facility	Lost Sales
4	1	4	.	.	.	.	.	.	75	3	.	.	.	.	.	.	.
4	2	1	.	66	.	66	66	2	.	.	66	3	.	.	.	.	.
4	2	2	.	66	.	66	66	2	66	3	.	.	.	.	.	.	.
4	2	3	.	66	.	66	66	2	66	3	.	.	.	.	.	.	.
4	2	4	.	.	.	.	.	.	66	3	.	.	.	.	.	.	.
4	3	1	.	65	.	65	65	2	.	.	65	3	.	.	.	.	.
4	3	2	.	65	.	65	65	3	65	3	.	.	.	.	.	.	.
4	3	3	.	65	.	65	65	1	65	3	.	.	.	.	.	.	.
4	3	4	.	.	.	.	.	.	65	3	.	.	.	.	.	.	.
4	4	1	.	63	.	63	63	2	.	.	63	3	.	.	.	.	.
4	4	2	.	63	.	63	63	3	63	3	.	.	.	.	.	.	.
4	4	3	.	63	.	63	63	1	63	3	.	.	.	.	.	.	.
4	4	4	.	.	.	.	.	.	63	3	.	.	.	.	.	.	.

C.2.3 Model Verification Case 3

Case 3 is to verify that raw materials usage and productions at plants are taking place in accordance with the amount of raw materials imposed in the optimization model. In Case 3, product inventories at plants, minimum product inventory requirements and initial product inventories at warehouses are all set equal to zero. Raw material inventories for productions of each product are set to be the amount needed for the throughput of that product at each plant(thrptrm). Table C-8 lists parameters value used for Case 3.

Table C-0-8 Case 3 Parameters Value

Case 3	rminv	minrminv	fpinv	minfpinv	wpinv	minwpinv
	1	1	0	0	0	0

Notes: rminv and minrminv are as days of thrptrm.

Key Expected outcomes for Case 3:

1) No deliveries will be made at warehouses.
2) To satisfy customer demands, only alternative deliveries from plants will occur.
3) Production activities will happen across plants.
4) The amount of customer demands can be satisfied during planning horizon, as well as lost sales, depend on units of products produced at plants.
5) Raw material inventory shortages will occur.

Solutions from Optimization Model for Case 3:

System-wide inventories would be zero at the beginning of day one in Case 3. This is represented as missing values for day one in Table C-9 because the report generator only extracts non-zero values from the optimization model's solution.

System-wide inventory of P2 equals 984 units at the beginning of day two. This implies that a total of 984 units of P2 are produced across plants at the end of day one (621 units at F1 and 363 units in F3 as shown in Table C-10). Moreover, deliveries of P2 directly from plants won't be made until day two, because products made in a day will not be available for delivery until the next day (constraint posted by equation 20). This constraint also implies that lost sales will occur at all warehouses on day one. System-wide inventory of P1 at the beginning of day four indicates that all 702 units of P1 are delivered by the end of day 3 (as presented in Table C-13).

Table C-0-9 Case 3 Total Product Inventories across Plants

	Total System Inventory by Product at Beginning of the Day					
	Product 1	Product 2	Product 3	Product 4	Product 5	Product 6
Day						
2	702	984	217	381	78	105
3	702	984	217	381	78	105
4	.	516	517	144	224	210

Table C-0-10 Case 3 Sample of Production and Plant Inventories Summary

Obs	Variable Name	Product	Facility	Day	Produced	Inventory
1	PRODP1F3D1	1	3	1	702	.
2	INVP1F3D2	1	3	2	702	702
3	INVP1F3D3	1	3	3	.	702
4	PRODP2F1D1	2	1	1	621	.
5	INVP2F1D2	2	1	2	621	621
6	INVP2F1D3	2	1	3	.	621
7	PRODP2F2D3	2	2	3	516	.
8	INVP2F2D4	2	2	4	.	516
9	PRODP2F3D1	2	3	1	363	.
10	INVP2F3D2	2	3	2	363	363
11	INVP2F3D3	2	3	3	.	363
12	PRODP3F1D3	3	1	3	273	.
13	INVP3F1D4	3	1	4	.	273
14	PRODP3F2D1	3	2	1	217	.
15	INVP3F2D2	3	2	2	217	217
16	INVP3F2D3	3	2	3	.	217
17	PRODP3F3D3	3	3	3	244	.
18	INVP3F3D4	3	3	4	.	244

For selected plants and products, plant productions and inventories summary, setup indicators at plants, and plant capacity utilizations are presented in Table C-10, Table C-11, and Table C-12 respectively.

Table C-0-11 Case 3 Idles Times, Idle Costs and Setup Indicators

Obs	Variable Name	Facility	Day	idlehrs	idlecost	setupFacility	setupcost
1	SUF1D1	1	1	0	0	1	150
2	SUF1D2	1	2	0	0	1	150
3	SUF1D3	1	3	0	0	1	150
4	SUF2D1	2	1	0	0	1	150
5	SUF2D2	2	2	0	0	1	150
6	SUF2D3	2	3	0	0	1	150
7	SUF3D1	3	1	0	0	1	150
8	SUF3D2	3	2	0	0	1	150
9	SUF3D3	3	3	0	0	1	150

Table C-0-12 Case 3 Sample of Production and Capacity Utilization

Obs	Facility	Day	Product	Proportion of Time Available	Cum. Prop. of Time Available
1	1	1	2	0.48242	0.48242
2	1	1	5	0.16629	0.64871
3	1	1	6	0.22629	0.87500
4	1	2	2	0.48242	0.48242
5	1	2	5	0.16629	0.64871
6	1	2	6	0.22629	0.87500
7	1	3	3	0.48750	0.48750
8	1	3	4	0.22489	0.71239
9	1	3	5	0.16261	0.87500
10	2	1	3	0.33528	0.33528
11	2	1	4	0.51766	0.85294
12	2	1	5	0.02206	0.87500

Note in Table C-12, the cumulative proportion of time utilized across all plants in production of products is 0.875 if no idle times occurred during a day.

This number is resulted from the fixed setup time of one hour across all production facilities, leading to total available production time equals 7 hours per day (0.875=7/8).

Table C-13 summarizes demands and delivery activities at warehouses for selected product and warehouses.

Table C-0-13 Case 3 Sample of Warehouse Activities

Prod	W.H.	Day	W.H. Inventory	Demand	Delivered from W.H.	W.H. Inventory Shortage	Delivered from Facility	From Facility	Outstanding Orders	AT Facility	Order Placed	At Facility	Old Order Arriv	From Facility	New Order Arriv	From Facility	Lost Sales
1	1	1	.	137	.	.	.	.	.	.	.	.	.	.	.	.	137
1	1	2	.	137	.	.	137	3	.	.	.	.	.	.	.	.	.
1	1	3	.	137	.	.	137	3	.	.	.	.	.	.	.	.	.
1	2	1	.	106	.	.	.	.	.	.	.	.	.	.	.	.	106
1	2	2	.	106	.	.	106	3	.	.	.	.	.	.	.	.	.
1	2	3	.	106	.	.	106	3	.	.	.	.	.	.	.	.	.
1	3	1	.	120	.	.	.	.	.	.	.	.	.	.	.	.	120
1	3	2	.	120	.	.	120	3	.	.	.	.	.	.	.	.	.
1	3	3	.	120	.	.	120	3	.	.	.	.	.	.	.	.	.
1	4	1	.	125	.	.	.	.	.	.	.	.	.	.	.	.	125
1	4	2	.	125	.	.	125	3	.	.	.	.	.	.	.	.	.
1	4	3	.	125	.	.	125	3	.	.	.	.	.	.	.	.	.
1	5	1	.	102	.	.	.	.	.	.	.	.	.	.	.	.	102
1	5	2	.	102	.	.	102	3	.	.	.	.	.	.	.	.	.
1	5	3	.	102	.	.	102	3	.	.	.	.	.	.	.	.	.
1	6	1	.	112	.	.	.	.	.	.	.	.	.	.	.	.	112
1	6	2	.	112	.	.	112	3	.	.	.	.	.	.	.	.	.
1	6	3	.	112	.	.	112	3	.	.	.	.	.	.	.	.	.

C.3 Summary

In Summary, solutions for Case 1, Case 2, and Case 3 verify that the optimization model behaves as it should for each test conditions. The MILP model verification process demonstrates that warehouses deliver products to satisfy customer demands registered at the beginning of a day if finished product inventories are sufficient at warehouses. Alternative deliveries of products directly from plants at higher costs may occur if warehouses experience inventory shortages. Warehouses place orders to maintain desired minimum inventory level and plants place orders of raw materials to support production. Production takes place at plants to replenish warehouses and maintain system-wide product inventories, while raw material inventories pose restrictions on production quantities at plants.

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