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Tadeusz Sawik

Stochastic Programming in Supply Chain Risk Management

Resilience, Viability, and Cybersecurity

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To Bartek,
Siasia,
Diana Demi and Joanna Rokimi,
Kalinka, Aleksander, Kajetan Ragnar,
and to the Memory of my Parents

Preface

Scope

This purpose of this book is to present applications of stochastic programming for stochastic combinatorial optimization problems in supply chain risk management, with a particular focus on the pandemic type crisis management in the global supply chains. The optimization problems are modeled using scenario-based stochastic MIP (mixed integer programming) to address risk-neutral, risk-averse, and mean-risk decision-making in the presence of supply chain disruption risks. Stochastic MIP is an exact mathematical modeling approach that allows for the inclusion of uncertainty by probabilistic scenarios of disruptive events and for finding the optimal solutions with respect to multiple objective functions. However, the deep uncertainty stemming from the pandemic-type disruptions may sometimes question the suitability of the stochastic models. The predictions and generations of disruption scenarios for possible long-term crises may not be easy due to the lack of sufficient historical data. Nevertheless, after the COVID-19 pandemic, the low availability of past data to forecast future disruptions scenarios and their probabilities is no longer a significant issue. Now, in the post-COVID era, we are well aware of the ripple effect impact on the recovery processes at the times of long-term crises. Moreover, the optimization objectives under long-term crises may often focus on supply chain survival and viability rather than on minimizing performance deviations after a disruption. One of the main objectives of this book is to present computationally efficient multi-portfolio approach to integrated and coordinated decision-making in global supply chains subject to propagated disruption risks. In the context of supply chain disruptions, the portfolio is defined as the allocation of demand for different part types among suppliers and the allocation of demand for different product types among production facilities (e.g., assembly plants) of the final manufacturer. The allocation of demand for parts among suppliers is defined as a supply portfolio, whereas the allocation of demand for products among production facilities of the final manufacturer is defined as a demand or capacity portfolio. Unlike most of reported research on the supply chain risk management which mainly focuses on the risk mitigation decisions taken prior to a disruption, the proposed multi-portfolio approach combines decisions made before, during, and after the disruption. When a disruption occurs, the primary portfolios determined prior to a disruption are replaced by recovery portfolios. The selection of portfolios will be combined with management of disrupted material flows, i.e., supply, production, and distribution scheduling under disruption risks. The integration and coordination of supply chain preparedness and recovery is similar to the integration and coordination of innate and adaptive capabilities of the immune system. Therefore, the multi-portfolio approach applied for optimization of supply chain resilience may resemble an immunization mechanism in the biological systems. The multi-portfolio approach can be particularly useful for material flow coordination in contemporary supply chain networks, which are cyber-physical systems, where integrated and coordinated decision-making and control across the entire network are of the utmost importance.

The proposed multi-portfolio approach allows the two popular financial engineering percentile measures of risk, VaR (Value-at-Risk) and CVaR (Conditional Value-at-Risk), to be applied for managing the risk of supply chain disruptions. For a finite number of disruption scenarios, CVaR allows the evaluation of worst-case costs (or worst-case service levels) and shaping of the resulting cost (service level) distribution by selection of optimal portfolios. The book demonstrates that the multi-portfolio approach leads to the integrated decision-making models and, owing to embedded network flow structures, to computationally efficient stochastic mixed integer programs with a strong LP (Linear Programming) relaxation. The main features of this book are listed below:

- Integrated vs. hierarchical decision-making is applied depending on the available information on the future disruption events
- Multi-objective decision-making models for the global supply chains are proposed to optimize trade-off between: cost vs. service level objective function, business-as-usual vs. worst-case performance, etc.
- Multi-period decision-making is considered to capture dynamics of disruption mitigation and recovery processes, i.e., static vs. dynamic portfolios, scheduling of supply chain operations under propagated disruption risks, uncertain and time-varying market demands, uncertain and time-varying capacities of suppliers and manufacturers, etc.
- Multilevel disruptions are modeled to capture partially disrupted flows, partially fulfilled orders, partially recovered facilities, partially available capacities, etc.
- Multi-tier resilient and viable supply portfolios are modeled to compare resilience and viability of the multi-tier supply chain networks.

The book also addresses the issue of fundamental understanding of business-as-usual and worst-case performance of the global supply chains in the presence of propagated disruption risks, understanding of mitigation and recovery mechanisms as well as understanding of the supply chain resilience and viability.

A straightforward computational approach used in this book is to solve the deterministic equivalent mixed integer programs of the two-stage stochastic mixed integer programs with recourse, which allows for a direct application of commercially available software for mixed integer programming. In the computational experiments reported throughout the book, an advanced algebraic modeling language AMPL (see, Fourer et al. 2003) and the CPLEX and Gurobi solvers have been applied.

Content

The book is divided into an introductory Chap. 1, where an overview of supply chain risk modeling and management is provided with a particular emphasize on an innovative multi-portfolio approach, and the three main parts. Parts I, II, and III address supply chain resilience, supply chain viability, and supply chain cybersecurity, respectively.

Part I (Chaps. 2 to 4) introduces portfolio approach for optimization of supply chain resilience by determining resilient supply portfolios, i.e., selection and fortification of suppliers, pre-positioning of RMI (Risk Mitigation Inventory) of parts, and allocation of order quantities to mitigate the impact of supply chain disruption risks.

Part I is comprised of these chapters:

- Chapter 2, Supply Chain Resilience: Supply Portfolio. In this chapter, the portfolio approach and stochastic MIP (mixed integer programming) models are presented for the combined selection and protection of part suppliers and order quantity allocation in a supply chain with disruption risks. The protection decisions include the selection of suppliers to be fortified against disruptions and the allocation of RMI (Risk Mitigation Inventory) of parts to be pre-positioned at the fortified suppliers so as to maintain uninterrupted supplies in case of natural or man-made disruptive events. Both, single- and multilevel protection of suppliers are considered. The problem objective is to achieve a minimum cost of suppliers protection, RMI pre-positioning, parts ordering, purchasing, transportation and shortage, and to mitigate the impact of disruption risks by minimizing the potential worst-case cost. As a result, resilient supply portfolio is identified with protected suppliers capable of fully or partially supplying parts in the face of disruptive events.
- Chapter 3, Supply Chain Resilience: Multi-tier Supply Portfolio. This chapter presents a multi-portfolio approach to disruption mitigation and recovery in a multi-tier supply chain network. The supply chain network is geographically dispersed across multiple regions, where in each region suppliers of the same and/or of different tiers are located. In addition to multi-sourcing and recovery and transshipment supplies, to strengthen the network resilience, pre-positioning of RMI at primary suppliers of parts of different tiers and at primary OEM (Original Equipment Manufacturer) assembly plant is considered. Owing to the embedded network flow structure, computationally efficient stochastic mixed

integer programs with a very strong LP relaxation are developed. In addition to the developed optimization model with an embedded network flow problem, the findings emphasize the supply chain end-to-end visibility as a crucial prerequisite for a multi-tier supply chain resilience.

- Chapter 4, Supply Chain Resilience under Ripple Effect. In this chapter, a multi-portfolio approach and scenario-based stochastic MIP models for optimization of supply chain operations under the ripple effect are provided. The ripple effect is caused by regional pandemic disruption risks propagated from a single primary source region and triggering delayed regional disruptions of different durations in other regions. The propagated regional disruption risks are assumed to impact both primary and backup suppliers of parts, OEM assembly plants as well as market demand. The resulting simultaneous disruptions in supply, demand, and logistics across the entire supply chain are modeled. The mitigation and recovery decisions made to optimize the supply chain resilience include pre-positioning of RMI at OEM assembly plants and ordering recovery supplies from backup suppliers of parts, located outside the primary source region. The decisions are spatiotemporally integrated. The findings indicate that the resilient measures commonly used to mitigate the impacts of region-specific disruptions can be successfully applied for mitigation the impacts of multi-regional pandemic disruptions and the ripple effect.

Part II (Chaps. 5 to 7) deals with supply chain viability and provides stochastic programming models to establish viability space and determine viable supply portfolio.

Part II has three chapters:

- Chapter 5, Supply Chain Viability: Risk-Neutral Decision-Making. This chapter presents a novel quantitative approach and stochastic quadratic optimization model to maintain supply chain viability under the ripple effect. Instead of viability kernel commonly used in the viability theory, this chapter establishes the boundaries on acceptable production states for which the production can be continued under the ripple effect, with no severe losses. For a given implementable portfolio of controls, the boundaries on acceptable production trajectories associated with the two conflicting objectives, cost and customer service level, are determined. The decision maker selects a viable production trajectory in-between the two boundary trajectories: the cost-optimal and the service-optimal. The selection depends on the decision maker preference, represented by a chosen weight factor in the optimized quadratic objective function that minimizes weighted deviations from the cost-optimal and from the service-optimal production schedules under the ripple effect. The findings indicate that for the extreme values of the weight factor, the viable production trajectory is inclined toward the corresponding boundary trajectory and remains in-between the two boundaries, when both objectives are equally important. Keeping production trajectory in-between the two boundaries makes the supply chain more resilient to disruption risks, while the supply chain resilience diminishes as the production trajectory approaches a boundary trajectory. Then, a more severe disruption may push the production outside the viability space and cause greater losses.

- Chapter 6, Supply Chain Viability: Risk-Averse Decision-Making. In this chapter, stochastic optimization of CVaR is applied to maintain risk-averse viability and optimize resilience of a supply chain under propagated disruptions. In order to establish the risk-averse boundaries on supply chain viability space, two stochastic optimization models are developed with the two conflicting objectives: minimization of Conditional Cost-at-Risk and maximization of Conditional Service-at-Risk. Then, the risk-averse viable production trajectory between the two boundaries is selected using stochastic mixed integer quadratic programming model. The proposed approach is applied to maintain the supply chain viability in the smartphone manufacturing and the results of computational experiments are provided. The findings indicate that when the decision-making is more risk-aversive, the size of viability space between the two boundaries is greater. As a result, more room is available for selecting viable production trajectories under severe disruptions. Moreover, the larger is viability space, the higher is both worst-case and average resilience of the supply chain. Risk-neutral, single-objective decision-making may reduce the supply chain viability. A single objective supply chain optimization, which moves production to the corresponding boundary of the viability space, should not be applied under severe disruption risks to avoid greater losses.
- Chapter 7, Supply Chain Reshoring: Risk-Neutral vs Risk-Averse Decision-Making. This chapter presents a scenario-based stochastic MIP model for risk-neutral or risk-averse optimization of supply chain reshoring to domestic region, under the ripple effect propagated from a foreign disruption source region. The reshoring decisions with respect to tier-one suppliers of parts and tier-zero OEM assembly plants are considered under disruptions in supply, manufacturing, logistics, and demand rippling across the entire supply chain. The proposed innovative approach integrates strategic supply chain reshoring and operational supply chain scheduling, which allows the decision maker to evaluate the operational impact of the strategic decision. Results of computational experiments, partially modeled after a supply chain reshoring problem in the smartphone manufacturing, are provided. The findings indicate that reshoring decisions are strongly dependent on the level of government subsidy for capital expenditure and for risk-neutral reshoring, a portfolio of supply chain nodes with positive expected net savings can be considered only. In general, the reshored supply chain can better meet domestic market demand. Moreover, full reshoring of a supply chain improves its business-as-usual performance and even partial reshoring mitigates the impact of the ripple effect. However, for the risk-averse decision-making, if reshoring is incapable of reducing worst-case cost, in particular, worst-case lost sales, no reshoring is selected.

Part III (Chaps. 8 to 10) addresses management of cyber risks in supply chains and optimization of cybersecurity investments. The portfolio approach applied to mitigate the impact of supply disruptions has been modified to select portfolio of security controls and optimize the cybersecurity investments to mitigate the impact of information flow disruptions in supply chains caused by cybersecurity incidents.

Part III has three chapters:

- Chapter 8, Supply Chain Cybersecurity: A Linear Optimization Model. This chapter presents a mixed integer linear programming formulation for optimization of cybersecurity investment in the global supply chains. Using a recursive linearization procedure, a complex nonlinear stochastic combinatorial optimization model with a classical exponential function of breach probability is transformed into its linear equivalent. The obtained linear optimization model is capable of selecting optimal portfolio of security controls to minimize cybersecurity investment and expected cost of losses from security breaches in a supply chain. The new efficiency measures of cybersecurity investment are introduced: cybersecurity value and cybersecurity ratio. In addition, the proposed linear model has been enhanced for the Hurwicz-type, best-worst criterion to minimize a convex combination of the minimal and the maximal supply chain node vulnerability, under limited budget. The resulting compromise cybersecurity investment aims at balancing vulnerability across the entire supply chain, independent of cyberattack probabilities and potential losses by security breaches, thereby hardening the weaker critical nodes. The findings indicate a crucial role of intrinsic vulnerability, determined by the architecture of supply chain information system and highlight "design-for-cybersecurity" as an important emerging area of research.
- Chapter 9, Supply Chain Cybersecurity: Direct and Indirect Cyber Risks. In this chapter, a stochastic MIP formulation is presented for optimization of cybersecurity investment and selection of security controls to mitigate the impact of direct and indirect (propagated) cyber risks in a supply chain. Using a recursive network transformation to compute the reduced vulnerabilities of secured supply chain nodes and the first-order Taylor series approximation of natural logarithm to linearize the nonlinear constraints, a nonlinear stochastic combinatorial optimization model is approximated by its linear equivalent. The problem objective is to determine an optimal cybersecurity investment under limited budget and portfolio of security controls for each supply chain node to balance the cybersecurity across the entire supply chain. The minmax objective functions are applied to minimize either the maximum breach probability or the maximum loss of supply chain nodes. Alternatively, maxmin objectives are used to maximize the minimum non-breach probability or the minimum savings of loss.
- Chapter 10, Supply Chain Cybersecurity: Security Controls with Maximum Cybersecurity Value. This chapter deals with optimization of cybersecurity investment in the supply chains. A classical exponential function of breach probability and the intuitive idea of expected net benefits were applied to introduce the concept of cybersecurity value. The cybersecurity value of security control is defined as the value gained by implementing a single control to secure a subset of components. The cybersecurity value of a control can be seen as a measure of its efficiency in reducing vulnerability of a secured system or component. A mixed binary optimization problem, next transformed into an unconstrained

binary program, is developed to maximize total cybersecurity value of security control portfolio. The optimal solution to the binary program provides a simple formula to immediately obtain the portfolio of security controls with maximum total cybersecurity value and determines a rough cut cybersecurity investment. This study also shows that portfolio of security controls with maximum total cybersecurity value reduces the losses from security breaches and mitigate the impact of cyber risk.

Each chapter ends with a table summarizing major managerial insights and the end-of-chapter problems to help the reader a self-check of material comprehension and to encourage for a further self-study.

The book can be considered a follower of my two previous monographs on supply chain disruption management using stochastic mixed integer programming (Sawik 2017, 2020), where the multi-portfolio approach and scenario-based stochastic MIP approaches were developed for the integrated decision-making in global supply chains. The reader interested in knowing more about stochastic programming is referred to the monographs by Birge and Louveaux (2011) or Kall and Mayer (2011). For a general introduction to mixed integer programming models and techniques, the reader is referred to the seminal work in the field by Nemhauser and Wolsey (1999) or to the application-oriented book by Chen et al. (2010). The books by Sawik (1999, 2011) are devoted to application of mixed integer programming in production planning and scheduling in flexible manufacturing and assembly systems and in supply chains. The fundamentals of supply chain theory are well presented by Snyder and Shen (2011), and for an engineering-oriented general reference work on supply chains, the reader is referred to the book by Dolgui and Proth (2010). Finally, some books cover supply chain risk management in general, e.g., Kouvelis et al. (2011), Sodhi and Tang (2012), Khojasteh (2018), Ivanov (2018), Ivanov et al. (2019), Khojasteh et al. (2022); and some of these emphasize supply chain disruption management, e.g., Gurnani et al. (2012).

Audience

The book is addressed to practitioners and researchers on supply chain risk management and disruption management, and to students in supply chain management, industrial engineering, operations research, applied mathematics, computer science, and the like at masters and PhD levels. It is not necessary to have a detailed knowledge of stochastic programming and integer programming in order to go through this book. The knowledge required corresponds to the level of an introductory course in operations research and supply chain management for engineering, management, and economics students.

Kraków, Poland
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Tadeusz Sawik

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Acronyms

ABC_EC	Model for risk-neutral decision-making to minimize expected cost
ABC_ES	Model for risk-neutral decision-making to maximize expected service
ABC_CCR	Model for risk-averse decision-making to minimize conditional cost-at-risk (CVaR of cost)
ABC_CSR	Model for risk-averse decision-making to maximize conditional service-at-risk (CVaR of service)
ABC_ECCR	Model for mean-risk decision-making to minimize cost
ABC_ECSR	Model for mean-risk decision-making to maximize service
CVaR	Conditional value-at-risk
CVaR^c	Conditional cost-at-risk
CVaR^{sl}	Conditional service-at-risk
E^c	Expected cost
E^{sl}	Expected service level
MIP	Mixed integer programming
OEM	Original equipment manufacturer
RMI	Risk Mitigation Inventory
VaR	Value-at-risk
VaR^c	Cost-at-risk
VaR^{sl}	Service-at-risk

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Chapter 1
Introduction

Abstract In this introductory chapter an overview of supply chain risk modeling and management is provided with a particular emphasis on supply chain resilience, viability, and cybersecurity. The innovative multi-portfolio approach and scenario-based stochastic MIP formulations are proposed as efficient optimization tools for integrated and coordinated decision-making. The multi-portfolio approach is capable of spatially and temporally integrating and coordinating the proactive and reactive decisions in the multi-regional supply chains under propagated regional disruptions. Illustrative real-world examples of contemporary global supply chains and supply chain preparedness and recovery strategies are described.

Keywords Supply chain resilience · Viability · Cybersecurity · Conditional value-at-risk · Multi-portfolio approach · Two-level vs. multilevel disruptions · Risk-neutral · Risk-averse · Mean-risk

1.1 Overview of Supply Chain Risk Management

In the contemporary global supply chains a significant increase in supply chain risks is observed. The global supply chains are complex networks of multiple part suppliers, final producers, distribution centers, retailers, and customers, all dispersed across many geographical regions. A schematic diagram of a typical multi-tier supply chain network is shown in Fig. 1.1, where each vertical level (suppliers, producers, distribution centers, customers) is called a tier or an echelon, and the arcs represent material flows. The major sources of the supply chains disruption risks can be linked to:

- Outsourcing and offshoring that result in geographically more diverse supply chains, lead to the global factory and externalize the firm activity.
- Lean manufacturing leading to just-in-time manufacturing and low inventory levels.

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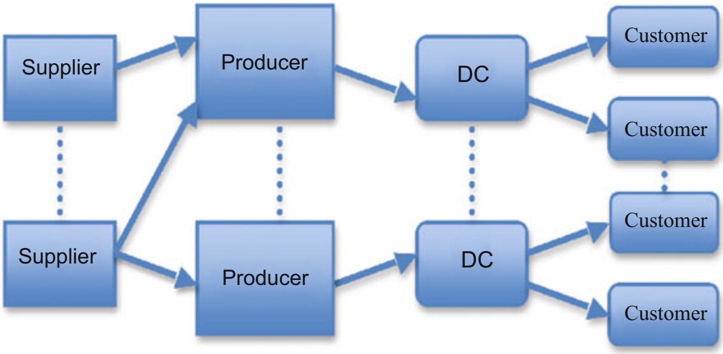

Fig. 1.1 A supply chain network

- Pandemic-type crises that may have a long-lasting impact with simultaneous disruptions in supply, demand, and logistics.
- Highly volatile demand, supply, and capacities.

Outsourcing refers to restructuring the firm ownership by subcontracting, joint ventures, strategic alliances, etc., and offshoring refers to relocating of production to foreign countries and restructuring the supply chain across many geographical regions.

In order to ensure the best supply chain performance, e.g., a high customer service level at a low cost, a variety of complex, interconnected decision-making problems need to be considered. The decision-making problems are strictly associated with the control and optimization of material flows (as well as financial and information flows) in the network, in particular, optimization of disrupted flows. Different types of material flows (e.g., flows of parts from suppliers to final producers, flows of finished products from the final producers to distribution centers and from the distribution centers to retailers and customers) should be coordinated in an efficient manner. In the global supply chains, the control and optimization of material flows are accomplished by coordinated planning and scheduling of manufacturing and logistics to fulfill customer demand in the presence of supply chain disruption risks. The schedule of customer orders immediately depends on the schedule of parts supplies, which in turn depends on supplier selection and order quantity allocation, that is, on supply portfolio. On the other hand, the schedule of customer orders implicitly defines the schedule of deliveries of finished products to customers, which in turn depends on customer order allocation among assembly plants, that is, on demand portfolio. In view of the recent trend of globalization, coordinated decision-making (e.g., selection of primary and recovery part suppliers and allocation of order quantities, selection of primary and recovery assembly plants and allocation of customer demand, and scheduling of customer orders in the assembly plants) may significantly improve the performance of a multi-tier supply chain under disruption risks. The research on computationally efficient quantitative approaches to coordinated scheduling of disrupted flows in global supply chains is nowadays of utmost importance.

In the global supply chains, disruption risk management has become a vital part of supply chain management strategy. Material flows in supply chains can be disrupted by unexpected natural or man-made disasters such as earthquakes, fires, floods, hurricanes or equipment breakdowns, labor strikes, economic crisis, and bankruptcy or by a deliberate sabotage or terrorist attack. The low-probability and high-impact flow disruptions and the resulting losses may threaten the financial state of firms. For example, the Taiwan earthquake of September 1999 created huge losses for many electronics companies supplied with components by Taiwanese manufacturers, e.g., Apple lost many customer orders due to supply shortage of DRAM chips (Sheffi 2005). The Philips microchip plant fire of March 2000 in New Mexico resulted in 400 million euros in lost sales by a major cell phone producer, Ericsson (Norrman and Jansson 2004). The well-known case of the Boeing 787 Dreamliner final assembly is an example of another type of disruption risks caused by the complexity of a global supply chain. Owing to the internal complexity of the aircraft design and the external complexity of outsourcing and offshoring of the multinational Boeing's global supply chain (e.g., over 50 tier-1 suppliers, of which 28 suppliers were located outside of the USA), the final assembly of the Boeing 787 Dreamliner, planned for 2–3 days, was delayed by 4 years, e.g., Celo et al. (2018).

Another example of the contemporary, complex global supply chains is a multi-tier supply chain network of the Toyota company. The supply chain has the following structure described below (see Kito et al. 2014):

- There are 580 firms in Tier-1, 1476 firms in Tier-2, and 136 firms in Tier-3.
- The supply chain is highly dependent on Japanese firms: 78% of Tier-1 suppliers, 65% of Tier-2 suppliers, and 69% of Tier-3 suppliers are located in Japan. In total there are 1517 suppliers in Japan, 126 suppliers in America, 207 suppliers in Europe, and 341 suppliers in Asia.
- A barrel-shaped (not a pyramidal shape) supply chain, where the second tier comprises 67% of the entire supply chain network.
- There are 3993 inter-tier ties (between firms in different tiers) and 1541 intra-tier ties (within a tier).
- In addition, Toyota suppliers also supply 12 other Japanese assemblers, 155 overseas assemblers, and 749 other clients.

In order to minimize losses caused by the shortage of material supplies, customer companies (firms) apply different disruption management strategies. When the Toyota supply chain and in particular supply chain of automotive semiconductors were hit by the Great East Japan Tohoku earthquake and tsunami, on March 11, 2011, Toyota supported the recovery of its suppliers (Fujimoto and Park 2013) to reduce the recovery time. The automotive semiconductors were manufactured by Renesas Electronics, who shares over 44% of worldwide automobile microcontroller units, and its main plant in Naka was severely damaged by the earthquake. The shipping of automotive semiconductors was expected to be stopped for 8 months. In order to shorten the expected recovery time, Toyota and other Japanese automotive,