Robust Design of a Manufacturing Network for Mass Personalization

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Abstract

Robust Design of a Manufacturing Network for Mass Personalization

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The Fourth Industrial Revolution (Industry 4.0 or I4.0) is transforming manufacturing through the integration of cyber-physical systems, artificial intelligence, and the Internet of Things. At its core is mass personalization (MP), enabling the production of customized products, particularly in high-tech sectors such as aerospace, medical devices, and precision optics. These industries require resilient supply networks to handle low-volume, high-complexity production and uncertainties in customer demands and supplier performance. Traditional supply chain models fall short in addressing these challenges, calling for advanced optimization frameworks.

This thesis explores the design of resilient and reconfigurable supply networks tailored to MP under I4.0. It makes three primary contributions. First, a strategic mixed-integer programming (MIP) model is proposed for optimizing supplier selection and order allocation, balancing design complexity with economies of scale. Second, a two-stage stochastic programming (2SP) model is developed for platform-based manufacturing networks, integrating crowdsourcing to enhance resilience by assigning primary and backup suppliers under uncertain capabilities. Third, an adjustable robust optimization (ARO) model is introduced for multi-echelon networks, addressing variability in supplier capacity and bill-of-material complexity, supported by an efficient math-heuristic algorithm.

Extensive numerical experiments and sensitivity analyses validate the models' effectiveness in mitigating risk and improving resilience. This research offers actionable insights for high-tech manufacturers aiming to build agile, cost-efficient supply networks that meet the evolving demands of mass personalization in the era of Industry 4.0.

Preface

This thesis has been prepared in “Manuscript-based” format under the supervision of Dr. Masoumeh Kazemi Zanjani from the Department of Mechanical, Industrial and Aerospace Engineering at Concordia University. This research was financially supported by the Natural Sciences and Engineering Research Council of Canada (NSERC). All articles included in this thesis were co-authored and reviewed prior to submission for publication by Dr. Masoumeh Kazemi Zanjani. The author of this thesis served as the primary researcher, developing mathematical models, programming solution methods, analyzing and validating results, and composing the initial drafts of the articles.

The thesis comprises three articles that contribute to the field of supply chain optimization. The first article, entitled “Supply Network Design for Mass Personalization in Industry 4.0 Era,” was co-authored with Dr. Kazemi Zanjani and published in the ”International Journal of Production Economics” in February 2022. It presents the foundational model for supply chain design in mass customization. The revised version of the second article, “Design of Resilient, Platform-based Manufacturing Networks for Highly-Customized Production,” co-authored with Dr. Kazemi Zanjani, has been submitted to the ”Journal of the Operational Research Society”, extends the model to a two-stage stochastic framework and proposes an algorithmic solution. The third article, “Adjustable Robust Optimization for the Design of a Manufacturing Network for Mass Customization”, co-authored with Dr. Kazemi Zanjani and submitted to the ”Annals of Operations Reserach, integrates robust optimization model and math-heuristic solution algorithm to address advanced challenges in supply chain design.

To my beloved parents

Abolhasan & Shahnaz

Acknowledgments

This PhD journey has been a transformative chapter, and I am deeply grateful to those who have supported me along the way.

My heartfelt thanks go to my supervisor, Dr. Masoumeh Kazemi Zanjani, whose insightful guidance, mentorship, and unwavering support shaped this thesis and my growth as a researcher.

I am immensely grateful to my family: my parents, Abolhasan and Shahnaz, for their endless love and encouragement; my brothers, Behnam and Behzad, and my sister-in-law, Sedi, for their steadfast presence. A special mention goes to my nephew, Karen, though not yet met in person, who has been a source of joy and inspiration.

I express deep appreciation to Siavash, whose encouragement and support during my academic journey were invaluable to me during this chapter of my life. To my dear friends in Canada—Behzad, Rojin, Hana and Heja—thank you for becoming my chosen family. Your kindness, companionship, and support, especially during difficult moments, made this journey brighter and more bearable. My colleagues at Concordia University, particularly Elaheh Iraj and Shayan Tavakoli, deserve thanks for their camaraderie and collaboration.

I also would like to express my deepest gratitude to my best friend, Tina, whose enduring support and presence in my life have been a constant source of strength. Though far away, she has always been there for me.

To all those who have contributed to this milestone, thank you for making this achievement possible.

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Chapter 1

Introduction

1.1 Overview

The Fourth Industrial Revolution, or Industry 4.0 (I4.0), has transformed global manufacturing by integrating cyber-physical systems (CPS), artificial intelligence (AI), and the Internet of Things (IoT) to enable flexible, sustainable, and customer-centric production (Shrouf, Ordieres, & Miragliotta, 2014). A key pillar of I4.0 is mass personalization (MP), which shifts from mass customization (MC) to a market-of-one, where products are tailored to individual customer specifications (Kumar, 2007; Wang, Ma, Yang, & Wang, 2017). This trend is particularly pronounced in high-tech industries such as aerospace, medical devices, and precision optics, where low-volume, highly customized products require sophisticated manufacturing processes and significant research and development (R&D) efforts. MP demands reconfigurable and resilient supply networks capable of managing complex, customizable components while maintaining cost efficiency and short lead times.

Traditional vertically integrated supply chains are increasingly replaced by collaborative networks of specialized suppliers, third-party logistics providers, and manufacturers, interconnected through cloud-based platforms (Chien, Chen, & Peng, 2010). However, the dynamic nature of MP introduces challenges, including uncertain customer requirements, variable supplier capabilities, and high production costs for small-batch, complex designs. These challenges necessitate advanced decision-support tools to optimize supply network design (SND) and ensure resilience against uncertainties. Motivated by these requirements, this thesis focuses on developing quantitative decision models for designing reconfigurable and resilient supply networks in the context of MP under I4.0, addressing the gap in practical, data-driven tools for smart supply chain management.

1.2 Literature Review and Research Gaps

Despite extensive work on traditional supply chain design for high-volume, standardized production (Beamon, 1998; Garcia & You, 2015; Sha & Che, 2006), Industry 4.0's shift toward mass personalization exposes several critical gaps. First, while smart supply chain studies highlight dynamic meta-structures and modular platforms (Dolgui, Ivanov, & Sokolov, 2020; Min, Zacharia, & Smith, 2019), they lack quantitative decision models that simultaneously integrate network reconfiguration, modular product design, and stochastic supplier performance (Jamrus, Wang, & Chien, 2020; Oh & Jeong, 2019). Second, mass customization frameworks offer strategies for modular design and simultaneous product–network optimization (F. Salvador, 2004; Gupta & Krishnan, 1999; J. H. Mikkola, 2004; Lamothe, Hadj-Hamou, & Aldanondo, 2006; Zhang, Huang, & Rungtusanatham, 2008), yet they assume fixed product catalogues and deterministic supplier readiness, overlooking individualized BOMs and uncertain technological capabilities central to mass personalization (Baud-Lavigne, Agard, & Penz, 2012). Third, research on customized supply chain design has begun to address complexity and integrated supplier selection (Changbai Tan & Freiheit, 2022; Inman & Blumenfeld, 2014; Katoozian & Zanjani, 2022), but typically assumes in-house production or neglects stochastic resilience for outsourced, complex modules. Finally, robust and stochastic optimization techniques have advanced supply chain resilience under uncertainty (Ben-Tal, Goryashko, Guslitzer, & Nemirovski, 2004; Ben-Tal & Nemirovski, 2002; Bertsimas, Brown, & Caramanis, 2011; Birge & Louveaux, 2011; Pishvaee, Rabbani, & Torabi, 2011). However, existing applications to multi-echelon, customizable networks are scarce and computationally prohibitive due to overlooking scalability.

1.3 Scope and Objectives

To address the gap in decision-support tools for MP in I4.0, this thesis develops a comprehensive framework for designing resilient supply networks. More specifically, it investigates the design of supply networks for manufacturing modular, customizable high-tech products in I4.0. The specific objectives are:

(1) To propose a strategic planning model for designing a reconfigurable supply network that supports MP, optimizing supplier selection and order allocation while considering design complexity and economy of scale.

(2) To evaluate the impact of market conditions and supplier readiness on network configuration and profitability through sensitivity analysis.

(3) To develop a decision model for the design of a platform-based manufacturing network, enhancing resilience against uncertain technological capabilities of external suppliers.

(4) To formulate a robust decision model for the design of a multi-echelon manufacturing network, ensuring robustness against supplier capacity variability and BOM complexity.

(5) To devise a computationally efficient math-heuristic algorithm to solve the robust model for large-scale instances.

(6) To create a benchmark dataset and a scenario sampling technique to validate and efficiently solve the above decision models.

(7) To conduct extensive numerical experiments, including Monte Carlo simulations, to compare robust and deterministic approaches and derive managerial insights.

The above objectives are structured into three key problems, each addressed in a core chapter based on a published paper. First, we consider the strategic formation of a reconfigurable supply network to support MP, where customers specify individualized product designs, leading to variable bills-of-material (BOM). The goal is to select a pool of suppliers capable of delivering standard and customizable components, optimizing profit and service level while accounting for design complexity and economies of scale. Second, we explore platform-based manufacturing networks (PBMNs) that leverage crowdsourcing to enhance resilience against supplier failures.

This involves selecting primary and backup suppliers and determining production quantities under uncertain technological capabilities, using a cloud-based platform to coordinate stakeholders. Third, we address the design of a multi-echelon manufacturing network resilient to supplier capacity variability, incorporating uncertainty in production rates due to BOM complexity and supplier performance.

Each problem is formulated using advanced optimization techniques: mixed-integer programming (MIP) for reconfigurable network design, two-stage stochastic programming (2SP) for platform-based resilience, and adjustable robust optimization (ARO) for multi-echelon robustness. These models account for real-world complexities such as piecewise linear cost functions, uncertain supplier capabilities, and varying design complexities, ensuring applicability to industries like optics, LiDAR, and biomedical instrumentation. The research also develops efficient solution methods, including scenario sampling and math-heuristic algorithms, to address computational challenges in large-scale instances.

1.4 Organization of the Thesis

This thesis is structured into five chapters. Chapter 1 provides the introduction, setting the I4.0 and MP context, defining the research scope, and summarizing contributions. Chapter 2 presents a strategic MIP model for designing a reconfigurable supply network for MP, analyzing the impact of design complexity and supplier capabilities. Chapter 3 introduces a 2SP model for a platform-based manufacturing network, incorporating crowdsourcing and resilience against supplier failures, along with a benchmark dataset and solution heuristic. Chapter 4 develops an ARO model for a robust multi-echelon manufacturing network, supported by a math-heuristic algorithm and numerical experiments. Chapter 5 concludes the thesis, synthesizing findings, discussing practical implications, and suggesting future research directions.

Chapter 2

Supply Network Design for Mass Personalization in Industry 4.0 Era

Abstract

The manufacturing industry is confronted with the growing demand of personalized products of small batch sizes. In other words, the producers are faced with the satisfaction of heterogeneous customer needs through individualization and the realization of scale effects along the value chain. This study is among the first that proposes a mixed-integer programming model to obtain the optimal configuration of a supply network comprising of a pool of suppliers to satisfy the demand of highly-customized and modular-structured products. The product individualization is incorporated into the model by considering different design complexity levels for the components/subassemblies in the bill-of-material. Furthermore, the impact of batch size is modeled by considering piece-wise production cost functions in different echelons of the network. Our numerical results inspired by the case of tunable lasers indicate that the configuration of supply network varies as a function of the demand at different design complexity levels. Whereas, the profitability of supply network is closely tied to the market condition as well as the production capacity, flexibility of processes, and cost structure of manufacturers.

2.1 Introduction

Align with the paradigm shift to the 4th Industrial revolution, the manufacturing sector has recently witnessed major supply and market challenges. Industry 4.0 (I4.0) revolves around an industrial production that is highly flexible in production volume and customization. It is also sustainable and relies on an extensive integration between the main producer, suppliers, 3rd-party logistics (3PL) providers, and customers by the application of cyber-physical systems (CPS) (Shrouf et al., 2014). Mass customization (MC) is the use of flexible processes to produce varied and often individually customized products and services at the price of standardized, mass-produced alternatives. There has been a transition from MC to Mass Personalization (MP) from mid 90s, as customers have been further involved into the design of individualized products. MP, as one of the key pillars of I4.0, is a paradigm shift from a market segment of few in MC to a market-of-one Kumar (2007); Wang et al. (2017). Making the customer involved in the design stage in MP is equivalent to offering a product family with a high degree of flexibility (and variability) in the bill-of-material (BOM). In other words, the customer has the possibility to alter both the structure of the product (e.g., height of BOM) and the design of its components. Nonetheless, this high level of individualization in product structure calls for a flexible and reconfigurable supply network. This is in particular crucial when the manufacturing of components and sub-assemblies are outsourced to external suppliers/sub-contractors. More specifically, the successful implementation of MP heavily relies on establishing a network of suppliers who are willing to share their scares technological resources and manufacturing capacities to manufacture individually designed components at a low price and a short lead-time.

Faced with the dynamic business ecosystem in the context of I4.0 revolution, supply chain (SC) managers strive to improve the agility and flexible decision capabilities to meet the challenges of smart and mass-personalized production Ivanov, Dolgui, and Sokolov (2019); Ivanov, Tsipoulanidis, and Schönberger (2019). Due to seamless integration via emerging technologies such as artificial intelligence (AI) and the Internet of Things (IoT), supply chain management (SCM) has been undergoing a dramatic paradigm shift Jamrus et al. (2020). In particular, the visualization of SCs by the aid of Cyber-Physical-Systems (CPS) ensures smooth inter-company operations, providing real-time access to relevant product and production for all stakeholders in the network Brettel, Friederichsen, Keller, and Rosenberg (2017). Consequently, global manufacturing paradigm has shifted from conventional vertically integrated SCs towards collaborative value chains consisting of many complementary and specialized production and distribution companies in value constellations. In the same vein, global manufacturing competition is no longer between individual companies but among supply chains and manufacturing networks, in which collaboration among and vertical integration of horizontally specialized value providers are critical for the success of individual companies and the entire business ecosystem Chien et al. (2010).

Connection and collaboration are among the key attributes of future-generation SCs that enable them to be agile in adequately responding to market uncertainties. The recent advances in information and communication technologies, hence, can be leveraged towards virtually connecting the SC stakeholders on a cloud-based information platform, where those members can collaborate with each other via sharing their real-time data. The concept of smart supply chain can be interpreted as a large-scale business strategy that brings as many links of the chain as possible into a closer working relationship with each other. The goal is to improve response time, production time, and reduce costs and waste (Sun, Yamamoto, & Matsui, 2020).

Despite the increasing number of research publications on smart SCs in the context of I4.0, the majority of existing contributions are mainly focused on the conceptual design of such cloud-based manufacturing networks. This study is thus among the first that proposes a quantitative decision model for the design of a reconfigurable supply network (SN) in the context of MP. More precisely, we propose a strategic-level decision support tool for the formation of a pool of component suppliers and sub-assembly manufacturers that enable the manufacturing of a set of customizable modular-structured products to maximize the profit and service level. To adapt supply network design (SND) model in the context of MP, we assume that a certain number of sub-assemblies and components in the BOM can be customized by the customers. More precisely, we categorize the items on the BOM as the standard and customizable ones. While the former category entails the elements that are essential in product configuration, the latter group provide the possibility of individualized (technical) features to the customers. Furthermore, to capture the uncertainty inherent in the design features provided by different clients, we categorize the customer requirements into different design complexities. The aforementioned assumptions are valid in the context of advanced technical devices such as tunable filters and lasers that are in general ordered in small batch sizes and are featured with several customization options. For instance, the center wave-length, tuning range and linewidth are customizable in tunable lasers that could substantially differ from one category of customers (e.g, research centres) to another (e.g., manufacturing firms). Depending on the requested features, the design and manufacturing of these devices would fall between relatively complex to very complex categories. It is noteworthy that the above-mentioned approach to incorporate individualized designs in SND problem is substantially distinct from the common assumption in the literature of SC design models for MC (e.g., Baud-Lavigne et al. (2012); Lamothe et al. (2006)), where the customization is modeled as a catalogue comprising of a predetermined product configurations.

Under a cloud manufacturing framework, we further assume that the focal company that receives individualized orders (e.g., the manufacturer of tunable lasers) have access to a bank of suppliers and manufacturers that are qualified to supply components and sub-assemblies at different complexity levels. In other words, the proposed SND model aims to determine the optimal choice of suppliers along with the order assignment to the selected pool while considering the design complexity and quantity of the demand for different products as well as the technological capability, capacity and cost of suppliers. The objective is to maximize the profit by considering a piece-wise linear cost function for the supply of customizable components in the BOM. More precisely, due to the considerably increased amount of time and resources involved for the design and manufacturing of products with complex features, their manufacturing cost is assumed to be a function of order quantity. Furthermore, in order to introduce the notion of service level in this problem, we consider the option of rejecting part of the demand (as lost-sale) due to lack of technological capabilities and/or high price of certain requested designs/product features. The SND problem is formulated as a mixed-integer programming (MIP) model after linearizing the piece-wise linear cost functions.

The proposed SND model is implemented on a set of test instances with the goal of investigating the impact of key parameters unique to the context of MP on the configuration of the supply network along with the profitability of the supply network. In particular, our sensitivity analysis experiments aim to study the network structure and profit by varying parameters pertaining to market condition for MP as well as industry readiness to offer highly-customized products at a reasonable cost. To the best of authors' knowledge, the SND model in this study is among the first proposed in the context of MP that explicitly takes into account individual product designs via introducing different design complexities. It is also unique in the sense that it provides a reconfigurable network comprising a pool of suppliers that can vary based on the demand structure in terms of design complexity, suppliers' cost structure as well as the targeted service level. Furthermore, the proposed model is among the very few that incorporates the economy of scale when modeling suppliers' cost structure for manufacturing custom-designed components. The managerial insights on the network configuration of the provided based on the sensitivity analysis results are among other contributions of this study.

The remainder of this article is structured as follows. Section 2 summarizes the review of literature relevant to this study. The problem description and formulation is provided in section 3. Section 4 entails our numerical experiments followed by concluding remarks in section 5.

2.2 Literature review

Supply chain design in the context of traditional manufacturing processes have been well established since 1990s; however, the problem of SND in the context of I4.0 is suffering from lack of quantitative decision models. According to Min et al. (2019), faced with the diversification of customer needs, companies would require an Omni-channel strategy that covers different SC configurations ranging from a direct SC to a globally extended value chain. Furthermore, the adoption of additive manufacturing technologies (e.g., 3D printing) could lead to less complex SC structures comprising of a focal farm, its immediate supplier, and customer. In the same vein, an open platform enables the company to interact with a massive volume of customers and suppliers, which result in reducing the SC complexity. In a recent study, Dolgui et al. (2020) argue that reconfigurability can be considered as the central direction to adapt the SCs to ever changing environments in the presence of climate changes, frequent natural disasters, digitalization and CPS. The authors also provide frameworks at the macro and micro levels for the design of SCs via introducing the concepts of “dynamic SC meta-structures” and “dynamic autonomous services”. Malladi, Erera, and III (2020) study the utilization of transportable modular production capacity along with the inventory control to increase dynamic SC reconfiguration.

The research on decision-support models for tactical or operational planning in smart SCs is also limited to a very few recent studies. The notion of smart manufacturing supply chains was investigated in Oh and Jeong (2019), where the authors provide a single-period tactical planning model to determine production and transportation quantities along with the transportation routes and adjusted capacities for each entity of the value chain on a pseudo real-time basis. Ivanov, Dolgui, Sokolov, Werner, and Ivanova (2016) propose a mathematical model and algorithm for supply chain dynamic scheduling in the context of industry 4.0 smart factories. The coordinated scheduling in supply chains is investigated in Jamrus et al. (2020) by considering the changing demands of dynamic environments to empower smart production. The authors propose an integrated hybrid particle swarm optimization and genetic algorithm to minimize the uncertain makespan.

SC design problem in a MC framework has been investigated by a handful of researchers. According to J. H. Mikkola (2004), designing modular components that can be configured into a wide variety of end products and services seems to be the best way to achieve MC. Through standardization of interfaces, modularization permits components to be produced separately and used interchangeably in different configurations without compromising system integrity. Postponement is another strategic decision involved in MC, where the assembly process of components is postponed until specific customer requirements are known. Depending on the level of modularization and postponement, the authors in J. H. Mikkola (2004) define four types of supply chain structure that enable MC implementation. The authors in F. Salvador (2004) propose different supply chain configurations for different customization levels (i.e., soft vs. hard customization). For a moderate level of customization, the authors propose a moderately long distribution network; on the contrary, a more direct distribution network is suggested for a hard MC strategy.

The notion of product family has been used by several authors in the context of product design for MC. It refers as a set of module options to choose among in order to obtain different variants of the product family and design their BOM in order to satisfy customers’ demand. Gupta and Krishnan (1999) are among the first authors who investigated the simultaneous design of product family and the corresponding SC. Lamothe et al. (2006) investigate a similar problem by considering a generic BOM (G-BOM) in order to cover a set of predetermined customer requirements for the final products. The proposed MIP model in this study provides the optimal product configurations that cover all customer requirements in addition to the optimal configuration of the corresponding SC. In a similar study, Zhang et al. (2008) investigate the simultaneous design of platform product based on the G-BOM concept and the corresponding supply network. Baud-Lavigne et al. (2012) demonstrate that the challenge in designing a product family is how to precisely define the BOM for each final product that covers all product features that might be required by the customer. To overcome the modeling challenge in designing such BOMs that in general leads to a large number of binary decision variables, the authors provide an alternative modeling approach for the simultaneous product and SC design that relies on considering substitutable sub-assemblies and components.

It is noteworthy that the proposed MIP programming models proposed in the literature for simultaneous design of product family and SC are limited to a MC context, where a limited number of design options in the framework of a product catalogue is offered to the customer to choose. This is essentially distinct from a MP context where the customer has the option to request individualized features/design for certain components in the BOM. In other words, none of the existing studies takes into account the uncertainty in terms of design features as well as the technological capabilities of suppliers in manufacturing those individually designed components. This study aims to fill this gap by proposing a generic SND model that is applicable in the context of MP and cloud manufacturing networks.

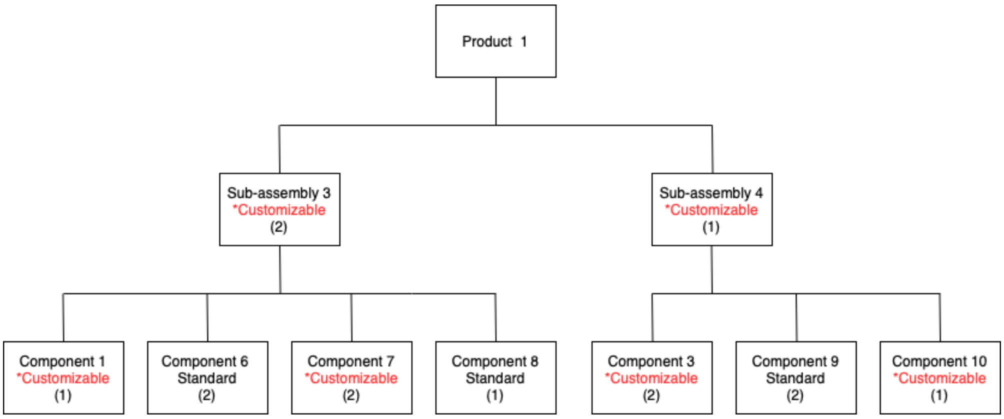
2.3 Problem description and formulation

2.3.1 Problem description

In this study, we confine our attention to the case of advanced technical devices with a modular structure that can be represented as a BOM, similar to one depicted in Figure 2.1. In this figure, the numbers indicated in brackets correspond to the number of components/sub-assemblies involved in the upper level item. We further assume that a sub-set of components and sub-assemblies in the BOM are customizable depending on the individualized product features requested by the customers. The rest of the items in the BOM are assumed to be standard that are common in all designs. In the case of tunable lasers, for instance, the tunable filter is one of the customizable sub-assemblies with a relatively complex to very complex design features. In the same vein, the active and passive fibres are among the customizable components that should be chosen correctly from the available products on the market and need further customization to meet the requirements. On the contrary, the laser pump and stepper motor are among the standard sub-assemblies for each category of lasers. To further integrate an MP paradigm into our decision model, we categorize the customizable items in the BOM into different design complexity levels (e.g., low, moderate, and high). We further assume that the same complexity level is inherited by the customizable sub-assemblies and components in the BOM of a product. For instance, if the product's design complexity level is 3, all of its corresponding customizable sub-assemblies and components are also featured with highly-complex designs. It is worth noting that the manufacturing cost of each complexity category increases with its complexity level due to additional R&D efforts involved in the design of products with complex (personalized) features as well as adjusting corresponding manufacturing processes. Consequently, the manufacturing cost of customizable items is modeled as a piece-wise linear function of order quantity, where the cost drops as the order size increases. This would also implicitly incorporate industry readiness for MP in the proposed model. More precisely, if the manufacturing processes in a company are flexible enough to adjust to complex designs at a relatively low cost, the order (production) quantity intervals for incremental cost reduce are assumed to be short. In other words, such companies are ready to embrace the manufacturing of highly customized products with small lot-sizes at the cost of mass production. In contrast, when the industry is not ready for MP, such cost interval are expected to be longer given that the production cost of complex designs at small scale is very high due to significantly higher set-up costs incurred to adjust the manufacturing processes.

For each item in the BOM, we consider a pool of qualified suppliers that have adequate technological capabilities to manufacture those items at different design complexities. In other words,

Figure 2.1: Example of a BOM with design personalization options



we assume a horizontal collaboration among stakeholders in different echelons of the supply network, similar to the network provided in Figure 2.2. Furthermore, it is assumed that suppliers' information in terms of technological capabilities, manufacturing capacity and cost is available on an open platform similar to the one in a cloud-manufacturing environment. By considering a focal company that receives a given demand portfolio of final products, featured with different design complexities and batch sizes, our goal is to construct the optimal network configuration that maximizes the profit and customer service level. In other words, depending on the design features, we aim to identify the optimal sub-set of partnering suppliers in the pool along with their order quantity such that a high service level and profit is guaranteed. It is worth to mention that this SN is a reconfigurable manufacturing network, where the mix of suppliers at different echelons can vary according to the quantity of demand at different design complexity levels; hence, it can facilitate SC transformation towards a mass personalization paradigm. The mathematical formulation of the SND problem described above is provide in the next section.

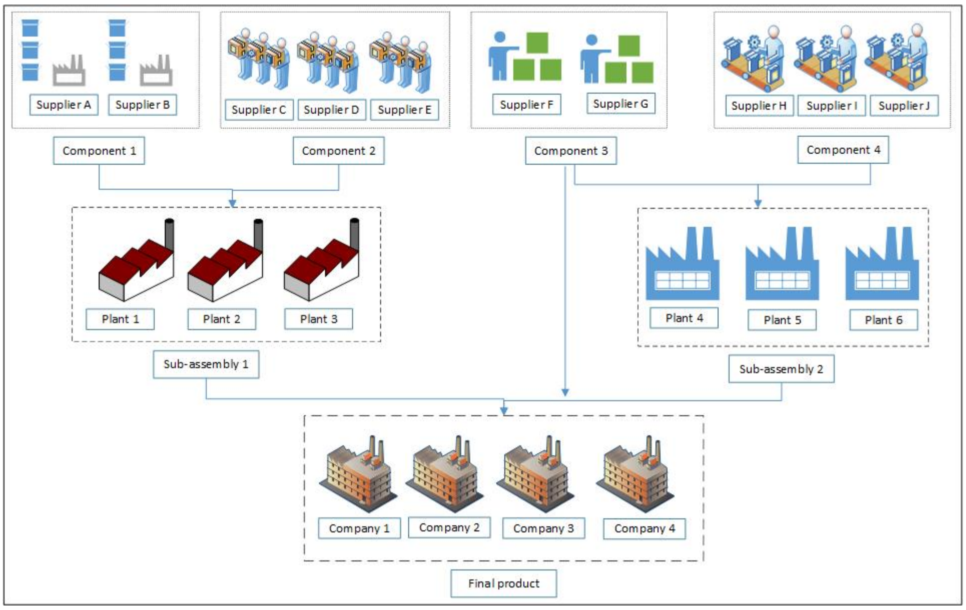


Figure 2.2: Supply network horizontal collaboration for mass personalization

2.3.2 Problem formulation

In this section, we describe the mathematical notation used to formulate the SND problem, followed by the corresponding MIP model.

Notation

I Sets

P: Set of final products indexed by **p**.
I: Set of product complexity levels indexed by **i**.
N: Set of sub-assemblies indexed by **n**.
M: Set of components indexed by **m**.
H: Set of sub-assembly producers indexed by **h**.
K: Set of component suppliers indexed by **k**.
J: Set of incremental production quantity intervals indexed by **j**.
M^s: Sub-set of standard components.
M^c: Sub-set of customizable components.
N^s: Sub-set of standard sub-assemblies.
N^c: Sub-set of customizable sub-assemblies.
N^s_m: Sub-set of standard sub-assemblies that contain component **m**.
N^c_m: Sub-set of customizable sub-assemblies that contain component **m**.

II Parameters

<u>*Final products:*</u>
D_{pi}: Demand of final product **p** at complexity level **i**.
FC_{pi}: Production capacity of final product **p** at complexity level **i**.
C_{pi}: Cost of producing one unit of final product **p** at complexity level **i**.
α_{pi}: Capacity consumption corresponding to one unit of final product **p** at complexity level **i**.
CL_{pi}: Cost of losing one unit of sale for final product **p** at complexity level **i**.
L^j_{pi}: Upper limit of the **jth** production quantity interval corresponding to product **p** at complexity level **i**.
S^j_{pi}: Selling price of each unit of final product **p** produced at complexity level **i** within the **jth** production quantity interval, where $S^1_{pi} > S^2_{pi} > ... > S^J_{pi}$ and

$$S^j_{pi}: \begin{cases} S^1_{pi}, & q_{pi} \leq L^1_{pi} \\ S^2_{pi}, & L^1_{pi} < q_{pi} \leq L^2_{pi} \\ . & \\ . & \\ S^J_{pi}, & L^{J-1}_{pi} < q_{pi} \leq L^J_{pi} \end{cases}$$

<u>*Sub-assemblies:*</u>
PC_{hn}: Production capacity of producer **h** for standard sub-assembly **n** ($n \in N^s$).
PC_{hni}: Production capacity of producer **h** for customizable sub-assembly **n** ($n \in N^c$)
C^s_{hn}: Cost of producing one unit of standard sub-assembly **n** ($n \in N^s$) by producer **h**.
η_{np}: Units of sub-assembly **n** ($n \in N$) needed to produce one unit of final product **p**.
F_h: Fixed cost of having a contract with producer **h**.
β^s_{hn}: Capacity consumption corresponding to one unit of standard sub-assembly **n** ($n \in N^s$)

at producer **h**.

β^c_{hni}: Capacity consumption corresponding to one unit of customizable sub-assembly **n** ($n \in N^c$) at complexity level **i** at producer **h**.

θ^s_{hn}: $\begin{cases} 1, & \text{If producer } \mathbf{h} \text{ is capable of producing standard sub-assembly} \\ & \mathbf{n}\ (n \in N^s). \\ 0, & \text{otherwise} \end{cases}$

θ^c_{hni}: $\begin{cases} 1, & \text{If producer } \mathbf{h} \text{ is capable of producing customizable sub-assembly} \\ & \mathbf{n}\ (n \in N^c) \text{ at complexity level } \mathbf{i}. \\ 0, & \text{otherwise} \end{cases}$

L^j_{hni}: Upper limit of $\mathbf{j}^{\mathbf{th}}$ production quantity interval corresponding to sub-assembly **n** ($n \in N^c$) at complexity level **i** for producer **h**.

C^j_{hni}: Cost of producing one unit of customizable sub-assembly **n** ($n \in N^c$) by producer **h** at complexity level of **i** within the $\mathbf{j}^{\mathbf{th}}$ production quantity interval, where $C^1_{hni} > C^2_{hni} >$ ... $> C^J_{hni}$, and

$$C^j_{hni}: \begin{cases} C^1_{hni}, & q_{hni} \leq L^1_{hni} \\ C^2_{hni}, & L^1_{hni} < q_{hni} \leq L^2_{hni} \\ . & \\ . & \\ C^J_{hni}, & L^{J-1}_{hni} < q_{hni} \leq L^J_{hni} \end{cases}$$

<u>*Components:*</u>

SC_{km}: Capacity of supplier **k** for standard component **m** ($m \in M^s$).

SC_{kmi}: Capacity of supplier **k** for customizable component **m** ($m \in M^c$).

C^s_{km}: Cost of purchasing one unit of standard component **m** ($m \in M^s$) from supplier **k**.

λ_{mn}: Units of component **m** ($m \in M$) needed to produce one unit of sub-assembly **n** ($n \in N$).

F_k: Fixed cost of having a contract with supplier **k**.

γ^s_{km}: Capacity consumption corresponding to one unit of standard component **m** ($m \in M^s$) at supplier **k**.

γ^c_{kmi}: Capacity consumption corresponding to one unit of customizable component **m** ($m \in M^c$) at at complexity level **i** at supplier **k**.

σ^s_{km}: $\begin{cases} 1, & \text{Supplier } \mathbf{k} \text{ is capable of offering standard component} \\ & \mathbf{m}\ (m \in M^s). \\ 0, & \text{otherwise} \end{cases}$

σ^c_{kmi}: $\begin{cases} 1, & \text{Supplier } \mathbf{k} \text{ is capable of offering customizable component} \\ & \mathbf{m}\ (m \in M^c) \text{ at complexity level } \mathbf{i}. \\ 0, & \text{otherwise} \end{cases}$

L^j_{kmi}: Upper limit of $\mathbf{j}^{\mathbf{th}}$ procurement quantity interval corresponding to component **m** ($m \in M^c$) at complexity level **i** for supplier **k**.

C^j_{kmi}: Cost of purchasing one unit of customizable component **m** ($m \in M^c$) from supplier **k** at complexity level **i** within the $\mathbf{j}^{\mathbf{th}}$ order quantity interval, where $C^1_{kmi} > C^2_{kmi} >$ ... $>$ C^J_{kmi}, and

$$C^j_{kmi}\colon \begin{cases} C^1_{kmi}, & q_{kmi} \leq L^1_{kmi} \\ C^2_{kmi}, & L^1_{kmi} < q_{kmi} \leq L^2_{kmi} \\ . \\ . \\ C^J_{kmi}, & L^{J-1}_{kmi} < q_{kmi} \leq L^J_{kmi} \end{cases}$$

III Decision Variables

q^{cj}_{kmi}: Total units of customizable component **m** ($m \in M^c$) purchased at complexity level **i** from supplier **k** within the **j^th^** interval.
q^s_{km}: Total units of standard component **m** ($m \in M^s$) purchased from supplier **k**.
q^{cj}_{hni}: Total units of customizable sub-assembly **n** (n $\in N^c$) produced by producer **h** at complexity level **i** within the **j^th^** production quantity interval.
q^s_{hn}: Total units of standard sub-assembly **n** (n $\in N^s$) produced by producer **h**.
q^j_{pi}: Total quantity of final product **p** produced at complexity level **i** within the **j^th^** production quantity interval.
w_{pi}: Total units of lost sale for product **p** at complexity level **i**.

$$x_k\colon \begin{cases} 1, & \text{If supplier } \mathbf{k} \text{ is selected.} \\ 0, & \text{otherwise} \end{cases}$$

$$y_h\colon \begin{cases} 1, & \text{If producer } \mathbf{h} \text{ is selected.} \\ 0, & \text{otherwise} \end{cases}$$

$$z^j_{pi}\colon \begin{cases} 1, & \text{If the production quantity of product } \mathbf{p} \text{ at complexity} \\ & \text{level } \mathbf{i} \text{ is within the } \mathbf{j^{th}} \text{ interval.} \\ 0, & \text{otherwise} \end{cases}$$

$$u^j_{hni}\colon \begin{cases} 1, & \text{If the production quantity of sub-assembly } \mathbf{n} \text{ by producer } \mathbf{h} \\ & \text{at complexity level } \mathbf{i} \text{ is within the } \mathbf{j^{th}} \text{ interval.} \\ 0, & \text{otherwise} \end{cases}$$

$$v^j_{kmi}\colon \begin{cases} 1, & \text{If the purchased quantity of component } \mathbf{m} \text{ from supplier } \mathbf{k} \\ & \text{at complexity level } \mathbf{i} \text{ is within the } \mathbf{j^{th}} \text{ interval.} \\ 0, & \text{otherwise} \end{cases}$$

Mathematical formulation

$$\textit{Maximize} \sum_p \sum_i \sum_j S^j_{pi} q^j_{pi} - \sum_p \sum_i \sum_j C_{pi} q^j_{pi} - \sum_h \sum_n C^s_{hn} q^s_{hn} - \sum_h \sum_n \sum_i \sum_j C^j_{hni} q^{cj}_{hni} - \sum_k \sum_m C^s_{km} q^s_{km} - \sum_k \sum_m \sum_i \sum_j C^j_{kmi} q^{cj}_{kmi} - \sum_h F_h y_h - \sum_k F_k x_k - \sum_p \sum_i CL_{pi} w_{pi} \tag{2.1}$$

Subject to

$$\sum_j q^j_{pi} + w_{pi} = D_{pi}, \qquad \forall p \in P, \forall i \in I \tag{2.2}$$

$$\sum_j \alpha_{pi} q_{pi} \leq FC_{pi}, \qquad \forall p \in P, \forall i \in I \tag{2.3}$$

$$\beta^s_{hn} q^s_{hn} \leq PC_{hn} \theta^s_{hn} y_h, \qquad \forall h \in H, \forall n \in N^s \tag{2.4}$$

$$\sum_j \beta^c_{hni} q^c_{hni} \leq PC_{hni} \theta^c_{hni} y_h, \qquad \forall h \in H, \forall n \in N^c, \forall i \in I \tag{2.5}$$

$$\gamma^s_{km} q^s_{km} \leq SC_{km} \sigma^s_{km} x_k, \qquad \forall k \in K, \forall m \in M^s \tag{2.6}$$

$$\sum_j \gamma^c_{kmi} q^c_{kmi} \leq SC_{kmi} \sigma^c_{kmi} x_k, \qquad \forall k \in K, \forall m \in M^C, \forall i \in I \tag{2.7}$$

$$q^j_{pi} \leq L^j_{pi} z^j_{pi}, \qquad \forall p \in P, \forall i \in I, \forall j \in J \tag{2.8}$$

$$z^j_{pi}(L^{j-1}_{pi} + 1) \leq q^j_{pi}, \qquad \forall p \in P, \forall i \in I, \forall j \in J \backslash \{1\} \tag{2.9}$$

$$\sum_j z^j_{pi} = 1, \qquad \forall p \in P, \forall i \in I \tag{2.10}$$

$$q^{cj}_{hni} \leq u^j_{hni} L^j_{hni}, \qquad \forall h \in H, \forall n \in N^c, \forall i \in I, \forall j \in J \tag{2.11}$$

$$u^j_{hni}(L^{j-1}_{hni} + 1) \leq q^{cj}_{hni}, \qquad \forall h \in H, \forall n \in N^c, \forall i \in I, \forall j \in J \backslash \{1\} \tag{2.12}$$

$$\sum_j u^j_{hni} = 1, \qquad \forall h \in H, \forall n \in N^c, \forall i \in I \tag{2.13}$$

$$q^{cj}_{kmi} \leq v^j_{kmi} L^j_{kmi}, \qquad \forall k \in K, \forall m \in M^c, \forall i \in I, \forall j \in J \tag{2.14}$$

$$v^j_{kmi}(L^{j-1}_{kmi} + 1) \leq q^{cj}_{kmi}, \qquad \forall k \in K, \forall m \in M^c, \forall i \in I, \forall j \in J \backslash \{1\} \tag{2.15}$$

$$\sum_j v^j_{kmi} = 1, \qquad \forall k \in K, \forall m \in M^c, \forall i \in I \tag{2.16}$$

$$\sum_h q^s_{hn} = \sum_i \sum_j \eta_{np} q^j_{pi}, \qquad \forall n \in N^s, \forall p \in P \tag{2.17}$$

$$\sum_h \sum_j q^{cj}_{hni} = \sum_j \eta_{np} q^j_{pi}, \qquad \forall n \in N^c, \forall p \in P, \forall i \in I \tag{2.18}$$

$$\sum_k q^s_{km} = \sum_h \sum_{n \in N^s_m} \lambda_{mn} q^s_{hn} + \sum_h \sum_{n \in N^s_m} \sum_i \sum_j \lambda_{mn} q^{cj}_{hni}, \forall m \in M^s \tag{2.19}$$

$$\sum_k \sum_j q^{cj}_{kmi} = \sum_h \sum_{n \in N^c_m} \sum_j \lambda_{mn} q^{cj}_{hni}, \qquad \forall m \in M^c, \forall i \in I \tag{2.20}$$

$$q^{cj}_{kmi}, q^s_{km}, q^{cj}_{hni}, q^s_{hn}, q^j_{pi}, w_{pi} \in \mathbb{Z}^+,$$

$$\forall k \in K, \forall m \in M^c, \forall m \in M^S, \forall h \in H, \forall n \in N^c, \forall n \in N^S, \forall i \in I, \forall j \in J, \forall p \in P \tag{2.21}$$

$$x_k, y_h, z^j_{pi}, w^j_{hni}, v^j_{kmi} \in \{0,1\}, \quad \forall k \in K, \forall h \in H, \forall p \in P, \forall i \in I, \forall j \in J, \forall n \in N^c, \forall m \in M^c \tag{2.22}$$

The objective function 2.1 maximize the profit calculated as the difference between the revenue earned from selling products and the cost incurred to: i) choose producers/suppliers; ii) produce final products and sub-assemblies; iii) purchase components from suppliers; and iv) the cost of not satisfying the demand (lost-sale cost). It is noteworthy that the fixed cost of producer/supplier selection entails: i) the cost of signing contracts with those parties; ii) the transportation cost, as a direct function of geographical distances; and iii) the investment costs incurred by the focal company to upgrade the manufacturing processes and/or train operators in the suppliers'/producers' facilities. Furthermore, the unit production cost incorporates both the R&D costs incurred for the product design and the cost of adjusting the manufacturing processes to customized designs; hence, it is increasing with the product complexity level. Constraint 2.2 ensures that the demand is (fully) satisfied by manufacturing the products or a partial lost-sale occurs. It is evident that a high lost-sale level is an indicator of a low customer service level in the network. Constraint 2.3 limits the production quantity of final products at different design complexity levels to the maximum production capacity. Constraints 2.4-2.7 correspond to similar capacity restrictions for the production of sub-assemblies and components by producers and suppliers, differentiated for standard and customizable items. Constraints 2.8-2.10 are provided to linearize the step-wise linear selling price of final products by considering corresponding price intervals defined for different production quantity intervals. In particular, 2.8-2.9 correspond to disjunction constraints ensuring that the production quantity and its corresponding selling price are assigned to the appropriate interval; whereas constraint 2.10 ensures that only one interval is selected. Constraints 2.11-2.13 and 2.14-2.16 correspond to similar linearization conditions for customizable sub-assemblies and components, respectively. Constraints 2.17-2.20 enforce the flow balance between the production quantity of final products, (standard and customizable) sub-assemblies and components based on the structure of the BOM. Constraints 2.21 and 2.22 are the domain constraints.

2.3.3 Complexity of the model

The proposed SND model 2.1-2.22 is a complex MIP model with $(|K| + |H| + |P||I||J| + |H||N||I||J|+|K||M||I||J|)$ binary decision variables, $(|K||M||I||J|+|K||M|+|H||N||I||J|+|H||N|+|P||I||J|+|P||I|)$ integer decision variables and $(3\times|P||I|+|H||N^s|+2\times|H||N^c||I|+|K||M^s|+2\times|K||M^c||I|+(2\times|P||I||J|-|J|)+(2\times|H||N^c||I||J|-|J|)+(2\times|K||M^c||I||J|-|J|)+|N^s||P|+|N^c||P||I|+|M^s|+|M^c||I|)$ constraints. It's obvious when the number of components, sub-assemblies, supplier, and/or producers increases the size of the model will increase drastically. In practice, solving such a large-scale model by commercial solvers will be challenging.

2.4 Numerical experiments

In this section, we aim to validate the proposed SND model 2.1-2.22 by the aid of a case study inspired by a tunable laser manufacturer in Canada that produces a wide range of customized lasers and filters with different batch sizes while collaborating with suppliers from China, Germany, US, and Canada. Our second goal is to analyze the impact of several key model parameters on the configuration and profitability of the supply network. All problem instances are solved by CPLEX

12.9 on a Core i7 CPU 3.40 GHz computer equipped with 8:00 GB RAM under Windows 7. The CPU time of solving these instances did not exceed a few seconds. In what follows, we first describe our experimental settings and case study data, followed by the results of sensitivity analysis experiments as well as some managerial insights.

2.4.1 Experimental design

We consider a tunable laser as an example of a highly customizable and complex product to manufacture. The main laser parameters are the center wave-length, tuning range, linewidth, stability, single-frequency operation and mode-hop free tuning that are in general customizable. For instance, the center wavelength might vary between 780 to 3000 nano-meters (nm), whereas the tuning range can be between 60 to 90 nm. The design of a customized tunable laser is a demanding step carried-out by the manufacturer that involves the design of laser structure (e.g., linear, loop, etc.) according to the features requested by the customer. Among major sub-assemblies of this product, we might refer to the gain medium and tunable filter that can be both custom-designed according to the customer specifications. The gain medium, on its turn, is a design-intensive sub-assembly that encompasses active fibres, laser pump and passive fibres. While the laser pump is a relatively standard component for each specific category of tunable lasers, the active and passive fibres should be chosen correctly from the available products manufactured by a limited number of suppliers and need to be customized to meet the requirements. The tunable filter is the other major customizable sub-assembly of this product that can be also sold as a separate product. It is composed of standard mechanical parts, such as a stepper motor, electronics, such as a stepper motor driver, in addition to optical components that require custom design. These components are comprised of several customizable elements such as lenses, prisms, gratings and collimators, some of which are purchased from external suppliers, and some are custom-designed in-house. Finally, the manufacturing of the tunable filter involves an implementation phase followed by calibration and final testing.

In our numerical experiments, we consider two type of products that belong to the family of tunable filters and lasers. Due to confidentiality issues in this highly competitive market, the name of products, components and sub-assemblies are not provided. To keep the size of the SND model manageable, only the most expensive and design-intensive sub-assemblies and components are considered in the corresponding BOMs, depicted in figures 2.1 and 2.3. Among the 4 sub-assemblies and 10 components, 3 sub-assemblies and 4 components are customizable, where two of the customizable components are required for two different sub-assemblies (components 1 and 3).

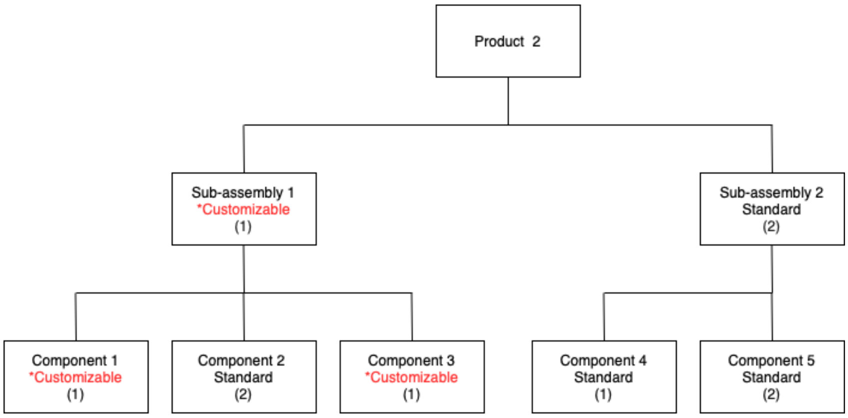


Figure 2.3: BOM for Product 2

Two different classes of producers/suppliers for standard sub-assemblies/components are taken into consideration in our experiments, including local and international ones. Local producers/suppliers have a lower fixed cost and capacity and a higher production cost as compared with the international ones that are active in low-wage countries (e.g. China). We also consider three classes of producers/suppliers that differ in terms of their technological capabilities to manufacture different design complexity levels, cost, and capacity. The list of producers/suppliers for different sub-assemblies/components along with their manufacturing capabilities are provided in table 2.1. Among these entities, producers 1, 6, and 9 are the ones that manufacture all design complexity levels. These producers represent the group of local or international high-tech companies active in high-wage, industrialized countries (e.g., Canada, US, Germany, etc.) that do not require high investment cost to adapt their facilities for MP; hence a low fixed cost is associated with them. These companies typically incur a relatively higher production cost for the manufacturing of sub-assemblies at design complexity levels (1) (relatively complex) and (2) (moderately complex) as compared to manufacturers that cannot manufacture highly complex products. Nevertheless, these companies are very efficient at manufacturing sub-assemblies at design complexity level (3) (highly complex) at a high capacity and relatively low production cost.

Producers 2, 7, and 10 can only produce sub-assemblies at design complexity levels (1) and (2). They represent international companies active in low-wage countries (e.g., China) that have low labor/production cost but a higher fixed cost due to their distant geographical locations. Finally, producers 3, 8, and 11 represent North American research centers that are able to design and manufacture highly complex items (i.e., level (3) sub-assemblies) at a significantly higher production cost and lower capacities as compared with the first category of producers (2, 7, and 10). However, they incur low transportation and fixed cost for signing contracts. In the same vein, suppliers 1, 6, 15, and 22 belong to the first category that provide components at all complexity levels. Suppliers 2, 7, 16, and 23 correspond to the second category that only supply components at complexity levels (1) and (2). Suppliers 3, 8, 17, and 24 can only provide components at the highest complexity level.

Producers	SA 1			SA 3			SA 4		
	i=1	i=2	i=3	i=1	i=2	i=3	i=1	i=2	i=3
P 1	✓	✓	✓						
P 2	✓	✓							
P 3			✓						
P 6				✓	✓	✓			
P 7				✓	✓				
P 8						✓			
P 9							✓	✓	✓
P 10							✓	✓	
P 11									✓

Suppliers	C 1			C 3			C 7			C 10		
	i=1	i=2	i=3	i=1	i=2	i=3	i=1	i=2	i=3	i=1	i=2	i=3
S 1	✓	✓	✓									
S 2	✓	✓										
S 3			✓									
S 6				✓	✓	✓						
S 7				✓	✓							
S 8						✓						
S 15							✓	✓	✓			
S 16							✓	✓				
S 17									✓			
S 22										✓	✓	✓
S 23										✓	✓	
S 24												✓

Table 2.1: Producers and suppliers capability matrix

Case study data

This section illustrates how data corresponding to different parameters of model 2.1-2.22 are generated. Table 2.2 summarizes different intervals from which the data corresponding to final products are generated. It is noteworthy that the demand, selling quantity interval, and the maximum capacity of highly-complex products (i=3) are assumed lower than their counterparts for products at the lowest complexity level (i=1). On the contrary, the production and lost-sale cost along with the selling price of highly-customized products (i=3) are assumed higher as compared with the ones for low-customized products (i=1). It should be also noted that three selling price intervals are considered in our numerical experiments as demonstrated in this table.

Parameter	Demand(D_{pi})	Capacity(FC_{pi})	Production Cost(C_{pi})	Lost-sale Cost(CL_{pi})
Interval	(70, 425)	(315, 700)	(140, 450)	(2400, 5280)
Parameter	**Selling Price(S^j_{pi})**		**Production Quantity Interval(L^j_{pi})**	
Interval (j=1)	(2000, 4400)		(150, 250)	
Interval (j=2)	(1800, 3960)		(300, 500)	
Interval (j=3)	(1600, 3520)		(315, 700)	

Table 2.2: Final product data

Table 2.3 summarized data corresponding to the producers/suppliers standard sub-assemblies/components.

Parameters	Fixed Cost(F_h, F_k)	Capacity(PC_{hn}, SC_{hn})	Production Cost(C_{hn}, C_{km})
Interval	(1000, 2000)	(1000, 3000)	(50, 350)

Table 2.3: Data on producers/suppliers of standard sub-assemblies/components

The fixed costs (F_h and F_k) of producers/suppliers of customizable items are set to values in the interval of (1000, 3000). More precisely, the fixed cost for category 2 companies are considered twice as the one for the two other categories. The production costs (C^j_{hni},C^j_{kmi}) and capacities (PC_{hni},SC_{kmi}) of suppliers/producers of customizable items are presented in table 2.4.

Parameter	Sub-assemblies (i=1)	Sub-assemblies (i=2)	Sub-assemblies (i=3)	Parameter	Components (i=1)	Components (i=2)	Components (i=3)
Capacity(PC_{hn})	(300, 750)	(400, 1000)	(160, 525)	Capacity(SC_{kmi})	(300, 1500)	(400, 2000)	(160, 1050)
Production Cost(C^j_{hni}, j=1)	(150, 220)	(180, 275)	(315, 770)	Procurement Cost(C^j_{kmi},j=1)	(130, 200)	(195, 300)	(480, 1200)
Production Cost(C^j_{hni}, j=2)	(120, 176)	(144, 220)	(252, 616)	Procurement Cost(C^j_{kmi}, j=2)	(98, 150)	(147, 225)	(360, 900)
Production Cost(C^j_{hni}, j=3)	(90, 132)	(108, 165)	(189, 462)	Procurement Cost(C^j_{kmi}, j=3)	(65, 100)	(98, 150)	(240, 600)
Production quantity Interval(L^j_{hni}, j=1)	(100, 250)	(134, 334)	(54, 175)	Procurement quantity Interval(L^j_{kmi}, j=1)	(100, 500)	(134, 667)	(54, 350)
Production quantity Interval(L^j_{hni},j=2)	(200, 500)	(268, 668)	(108, 350)	Procurement quantity Interval(L^j_{kmi}, j=2)	(200, 1000)	(268, 1334)	(108, 700)
Production quantity Interval(L^j_{hni}, j=3)	(300, 750)	(400, 1000)	(160, 525)	Procurement quantity Interval(L^j_{kmi}, j=3)	(300,1500)	(400, 2000)	(160,1050)

Table 2.4: Data on producers/suppliers of customizable sub-assemblies/components

2.4.2 Sensitivity analysis experiments

The goals of our sensitivity analysis experiments are two-fold. We first aim to obtain a threshold value for the unit lost-sale cost that maximizes customer service level (minimizes the total lost-sale cost). Afterwards, we confine our attention to investigate the impact of key model parameters, that represent market condition and industry readiness for MP, on the network configuration (pool of suppliers), profit, revenue, and production cost.

Sensitivity analysis on the lost-sale cost

The results of sensitivity analysis on the impact of changing unit lost-sale cost (CL_{pi}), as a percentage of selling price (S^j_{pi}), on the profit, revenue and production cost are presented in figures 2.4, 2.5, and 2.6. As it can be observed in these figures, when the unit lost-sale cost is below 75% of the selling price, the model choose to produce less in order to reduce the production cost and maximize the profit. In contrast, by considering this cost equal to or above this value, it is more beneficial to produce up to capacity rather than losing the orders. It is evident that a high unit lost-sale cost is an indicator of a higher customer service level; therefore, the model enforces higher production quantities (and higher revenue) to minimize the total lost-sale cost. Nevertheless, as a consequence of increasing the production cost, the profit is reduced as compared with the former case. Finally, our results indicate that increasing the unit lost-sale cost above 75% of the selling price will not change the optimal solution. Therefore, this can be considered as an appropriate threshold value for the unit lost-sale cost that guarantees a maximum service level.

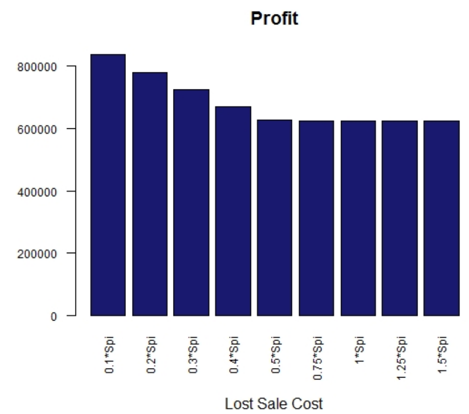


Figure 2.4: Profit Values Results

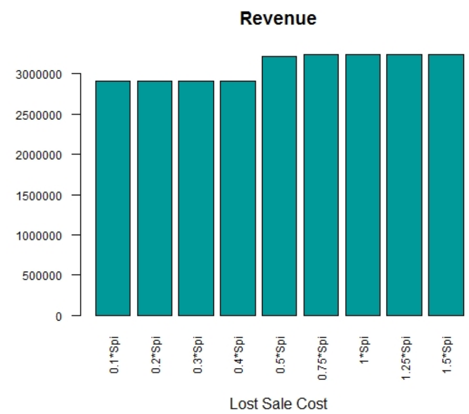


Figure 2.5: Revenue Values Results

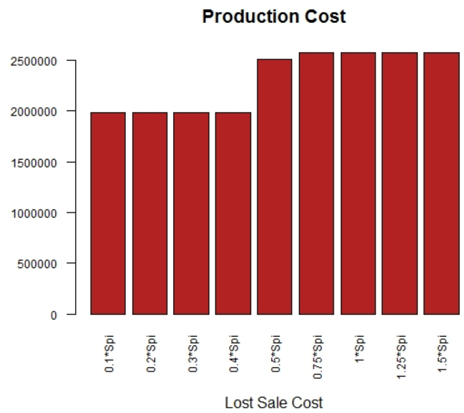


Figure 2.6: Production Cost Values Results

Analysis of the impact of market condition and industry readiness on supply network configuration and profitability

In this section, we aim to investigate the impact of four key parameters, including the demand of customized products with high design complexity level, unit lost-sale cost, production capacity for high design complexity level, and incremental production cost interval (PCI) for the same design complexity level on the optimal solution of the SND model. It is noteworthy that the demand of highly complex designs and unit lost-sale cost for these products represent market condition for MP; whereas, capacity and PCI are the indicators of industry readiness for embracing a MP paradigm. By considering 2 extreme levels for these parameters, 16 scenarios are generated to run the sensitivity analysis experiments. We also consider the primary scenario described in section 4.1 as the the base case; hence the low/high level for the above parameters are considered as a percentage of the base case. More precisely, the demand, capacity, and PCI levels are defined as $\pm 40\%$ of base value, whereas, low/high levels for the unit lost-sale cost are considered as $\pm 33\%$ of the base value. The aforementioned scenarios are summarized in table 2.5. We further consider a benchmark case, denoted as "scenario 0" where the demand for design complexity level 3 is set to zero. This case can be interpreted as a mass customization paradigm. The main key performance indicators in our experiments incorporate profit, revenue, and production cost. We also investigate the impact of changing these parameters on the pool of suppliers (network configuration).

Scenarios	Demand	Lost Sale Cost	Capacity	PCI	Scenarios	Demand	Lost Sale Cost	Capacity	PCI
1	Low	Low	Low	Low	9	High	Low	Low	Low
2	Low	Low	Low	High	10	High	Low	Low	High
3	Low	Low	High	Low	11	High	Low	High	Low
4	Low	Low	High	High	12	High	Low	High	High
5	Low	High	Low	Low	13	High	High	Low	Low
6	Low	High	Low	High	14	High	High	Low	High
7	Low	High	High	Low	15	High	High	High	Low
8	Low	High	High	High	16	High	High	High	High

Table 2.5: Scenario settings

The optimal decisions in terms of selection of sub-assemblies producers and components suppliers for different items in the BOM are summarized in the tables 2.6 and 2.7, respectively. The results indicate that under the primary and other scenarios where the demand for highly-customized products is low and/or production capacity for the manufacturing of such products is high, the third category of producers and suppliers (i.e. research centers) that only produce design complexity level (3) are not selected. On the contrary, under scenarios 9, 10, 13, and 14, where the market for MP is thriving but industry is not ready to respond (i.e. under high demand and low capacities for the production of highly-complex products), the expensive research centres are selected to satisfy the demand of complex sub-assemblies and avoid lost-sale. In the same vein, suppliers 3 and 8 are selected under scenarios 13 and 14 as a response to a highly demanding market and high lost-sale cost. The proposed suppliers'/producers' category of highly equipped research centers is an excellent illustration of redundancy. As the results show, this group of suppliers/producers is not selected when the conditions are not extreme (when market is very demanding and/or industry is not ready). When the situation is complicated, however, these redundant sources are chosen to meet the surplus demand. As expected, under scenario 0, featured by zero demand for design complexity level (3), only the second category of producers/suppliers that provide design complexity levels (1) and (2) are selected. This is mainly due to considerably lower manufacturing costs in these facilities as compared with the first category of suppliers that produces all design complexities levels. These results indicate that the (cost) competitive advantage of second-category suppliers is only effective when the demand for highly-customized designs is zero. In other words, manufacturers in the first category (high-wage countries) can capture the market of highly-complex personalized products by further investing in capacity expansion and enhancing flexibility of their manufacturing processes. It is noteworthy that the pool of suppliers/producers represents the flexibility and reconfigurability of the proposed SND model. More precisely, as the results show, when market condition and industry readiness indicators change, the configuration of the selected pool of suppliers/producers will change accordingly.

Sub-assemblies	Producers	Primary Scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12	Scenario 13	Scenario 14	Scenario 15	Scenario 16	Scenario 0
SA 1	P1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
	P2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	P3										✓	✓			✓	✓			
SA 3	P6	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
	P7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	P8																		
SA 4	P9	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
	P10	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	P11																		

Table 2.6: Optimal producer selection

Components	Producers	Primary Scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12	Scenario 13	Scenario 14	Scenario 15	Scenario 16	Scenario 0
C 1	S1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
	S2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	S3														✓	✓			
C 3	S6	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
	S7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	S8														✓	✓			
C 1	S15	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
	S16	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	S17																		
C 1	S22	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
	S23	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	S24																		

Table 2.7: Optimal supplier selection

Figure 2.7 represents the changes in profit under generated scenarios. It is interesting to observe that the maximum profit is attained under the benchmark "Scenario 0", featured with zero demand for highly-complex designs. This can be attributed to the lower production cost of sub-assemblies/components with relatively to moderately-complex designs, manufactured by the second category of suppliers, as compared with the third category of items that can only be manufactured by the first and third group of suppliers. Therefore, if the focal company aims to extend its market towards MP, efforts must be exerted to enhance the productivity of the aforementioned suppliers to manufacture highly-customized products at a lower cost. For instance, investments must be made to transform suppliers' manufacturing technology towards more flexible and automated processes. In a similar fashion, scenarios 1 to 8, featured with low demand for highly-customized products, have higher profit compared to the primary scenario. In other words, given that the market is not demanding for such products, the production quantity (and cost) remains low as compared to the base case; hence the profit is increased.

In contrast, under scenarios 9 to 16 that represent a demanding market for highly-customized products, the model considers a trade-off between production and lost-sale cost. In other words, the profitability of manufacturing these products depends on industry readiness, modeled as the capacity of production and the PCI. As anticipated, scenarios 11 and 15, where suppliers have the highest capacity and consider shorter order quantity intervals to decrease the cost (shorter PCI), lead to highest profit compared to other scenarios in this group. As a consequence, scenarios 9, 10, 13, and 14, featuring low industry readiness, result the lowest profit among all scenarios. Scenarios 13 and 14, in particular, correspond to the least profitable circumstances given that the major portion of demand cannot be fulfilled (and goes to lost-sale) due to low production capacity for highly-complex designs.

The production revenue and cost under different scenarios are, respectively, shown in figures 2.8 and 2.9. As expected, scenarios 9 to 16, corresponding a demanding market, lead to higher revenue (and a higher production cost) as compared to low-demand scenarios 1 to 8. As mentioned earlier, the readiness of the industry plays an important role in determining the production quantity. Consequently, scenarios 11, 12, 15, and 16 result in higher revenue (and higher production cost) as compared with the primary scenario due to higher readiness level of the industry. Vice versa, under scenarios 9, 10, 13, and 14, the production revenue (and cost) are lower compared to the primary scenario; Nevertheless, the revenue (and cost) under these scenarios are still higher than the scenarios with low and zero demand for design complexity level (3). Furthermore, the production revenue (and cost) for scenarios 1 to 8 do not vary as a response to changes in the lost-sale cost and industry readiness factors. These results indicate that under low-demand scenarios, it is always beneficial to produce and satisfy the demand rather than incurring lost-sale cost. In scenarios 9, 10, 13, and 14, featured with a demanding market, the revenue is lower compared to the primary scenario since industry is not sufficiently ready to satisfy the demand.

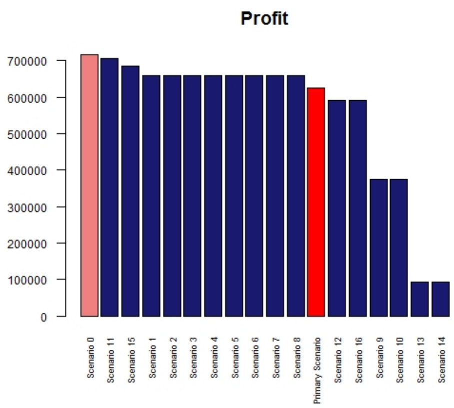


Figure 2.7: Profit Values Results

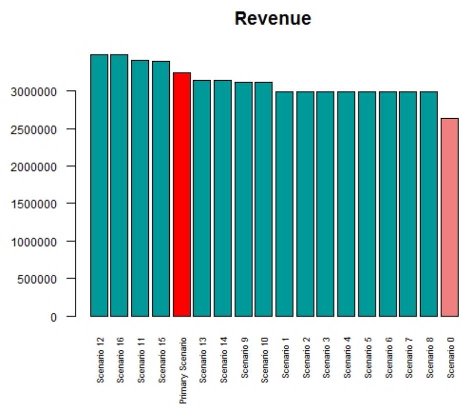


Figure 2.8: Revenue Values Results

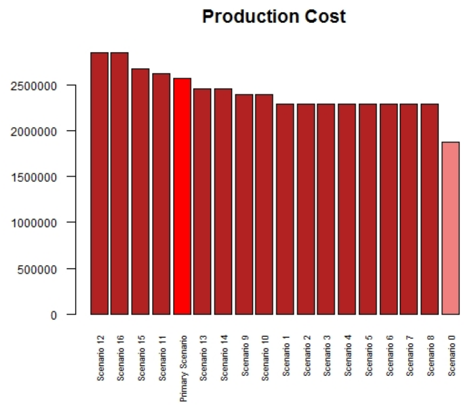


Figure 2.9: Production Cost Values Results

2.4.3 Managerial insights

Our numerical results indicate that transforming traditional manufacturing processes to more automated, smart and reconfigurable systems would be an effective strategy for the manufacturers in high-wage, industrialized countries to compete with international manufacturers (e.g. China) that are not equipped with such advanced manufacturing technologies; yet have considerably lower production cost for the manufacturing of standard and mass-customized products. In particular, when the market is in high demand for personalized products, some of which featured with highly-complex designs, the focal company is expected to increase its capacity of production for this category of products. Furthermore, given that such orders typically arrive at small batch sizes, the company requires to decrease the incremental price interval to accommodate MP. In other words, the selling price of products with high design complexity levels must be reduced as close as possible to the price of standard products. To this end, the manufacturing cost must be decreased by promoting automation in the production line and upgrading the manufacturing technology towards more flexible and reconfigurable processes, in-line with I4.0 paradigm. Furthermore, similar investments must take place in the manufacturing facilities of the sub-assembly producers and component suppliers to guarantee the profitability of manufacturing mass-personalized products. The goal is to enhance customer service level and avoid lost-sale when the market is thriving for this category of products. In addition, excess demand can be also fulfilled via close collaboration with research centers that are equipped with state-of-the-art technologies for the design and manufacturing of complex components.

2.5 Concluding remarks

Motivated by the concepts of mass-personalization (MP) and cloud-manufacturing in the framework of I4.0, in this study, a MIP model was proposed for SND while explicitly considering the uncertain nature of personalized product designs and non-linear production cost of such products that is a function of design complexity level and batch size. By assuming the availability of suppliers' information in terms of technological capabilities, capacities and prices on a cloud manufacturing platform, the model seeks the best combination of suppliers for the manufacturing of sub-assemblies and components constituting the BOM of personalized products to satisfy the demand. The objective is to maximize the profit and service level while maintaining the cost of manufacturing at a minimum level. By conducting a set of sensitivity analysis experiments, we demonstrated that the configuration of the network in terms of pool of suppliers can change as a response to the nature of demand in terms of design complexity level. Therefore, the proposed model provides a decision support tool for designing a reconfigurable SN for MP. Furthermore, our numerical results indicate that the transition towards MP is an effective action plan for high-tech manufacturers to compete with the producers active in low-wage countries. Nevertheless, the success of such initiative is tied to investing in upgrading the manufacturing facilities in different echelons of the SN to facilitate manufacturing of personalized products with small batch sizes at low cost.

The proposed SND model can be modified in a straightforward manner to include product family design while considering individualized design options for customizable components in the BOM. Nevertheless, efficient decomposition algorithms needs to be developed to overcome the increased computational complexity. Current study can be further extended by incorporating various uncertain parameters plausible to the manufacturing of highly-customized products, such as the technological capabilities of suppliers and the volume of demand for complex designs. Finally, given that the suppliers and producers in the network are independent entities that aim for maximizing their own profit, designing efficient collaboration mechanisms among these partners to facilitate information sharing would be another important research direction to pursue.

Chapter 3

Design of Resilient, Platform-based Manufacturing Networks for Highly-Customized Production

Abstract

Inspired by the growing interest in enhancing the lead time and cost of mass personalization in the industrial sector, this study investigates the design of a Platform-based manufacturing network in the context of highly customized production. The uncertain technological capabilities of suppliers in manufacturing customized components with intricate design specifications have been explicitly addressed by establishing a stochastic decision framework. The proposed two-stage stochastic programming model determines the optimal choice of suppliers, producers, and logistics carriers, in addition to the quantities of production and transportation in a platform-based network. Two types of corrective actions, namely emergency orders to backup entities and purchasing from the open market, have been foreseen to mitigate the risk of suppliers' failure in delivering customized items. The objective is to maximize the expected profit under uncertain scenarios. In addition, a scenario sampling heuristic is developed to overcome the computational complexity of the proposed model. Our numerical experiments underline the effectiveness of the proposed decision framework in identifying more reliable entities as the primary partners in the network. Moreover, the results emphasize the critical role of accurate supplier failure prediction and a broader selection of suppliers in enhancing network profitability and resilience.

3.1 Introduction

Customers in today's unpredictable and swiftly changing markets seek options that suit their specific needs; consequently, the demand for highly customized and personalized products has been constantly growing (Pallant, Sands, & Karpen, 2020). This trend is particularly pronounced in the advanced technology sector, such as aerospace/avionic systems, Light Detection and ranging (LiDAR) scanners, medical imaging devices, optical devices, and sensors. Such products typically involve intensive Research & Development (R&D) efforts and require advanced manufacturing processes while being produced at low volumes. For instance, LiDAR development requires expertise in many fields such as optics, artificial intelligence, computer vision, hardware design, embedded software, and much more (Singer, 2025). While there is a core design, LiDAR's design must be elaborated in different applications (e.g., autonomous vehicles). The low volume of production and complexity of manufacturing customized modules significantly drive up the production cost. To overcome this challenge, companies typically outsource the manufacturing of intricate modules (e.g., lasers, lenses, sensors, etc.) while maintaining the core elements, assembly, and testing in-house to ensure compliance with extremely challenging performance requirements.

Outsourceing R&D and manufactruing activities to external suppliers, on the other hand, is prone to various challenges, such as supplier reliability in delivering the highly customized modules within the promised lead-time and design specifications. The competitiveness of the highly customized manufacturing sector thus steadily relies on establishing efficient, flexible, and resilient supply chains (SCs) to improve quality and shorten the delivery time at minimum cost. In particular, the selection of reliable suppliers that possess the capability to deliver customizable items with a high degree of design complexity is of vital importance for ensuring the financial viability of such industries.

To address the aforementioned challenges in SCs, several studies, like Kohler (2015), Chida, Kaihara, Fujii, and Kokuryo (2019), and Xu, He, Zhou, and Cheng (2023) have proposed crowdsourcing as a promising strategy. By embracing the concept of an open company, this approach seeks to overcome organizational boundaries and leverage the resources and capabilities of dispersed stakeholders across the SC. Aligned with the concept of Platform-Based Supply Chains (PBSCs) (Veile, Schmidt, Müller, & Voigt, 2024), the cyber platform for crowdsourcing enables a manufacturer to explore external knowledge and resources by coordinating the design and manufacturing activities among the stakeholders through a cooperative manufacturing network.

Despite the increasing market trend for highly-customized manufacturing, the research on developing decision-support tools that adequately tackle the particular challenges of this industrial sector remains insufficient thus far. The main target of this study is to promote the crowdsourcing concept in PBSCs to enhance the financial viability of manufacturing advanced customizable products (e.g., optical devices). We develop a robust decision model for the design of a manufacturing network that is resilient against the uncertain capabilities of external suppliers in delivering intricate customized modules involved in the manufacturing of such custom-made products. The idea is to establish a platform-based manufacturing network (PBMN) that harnesses the combined R&D, design, manufacturing, and logistics resources operating by various entities to effectively meet the demand of such products. The proposed model, specifically, enhances network resilience by recommending corrective actions such as selecting back-up or emergency suppliers in response to the failure of the initial supplier pool to deliver the customized modules within the design specifications.

Our first original contribution is centered on proposing a two-stage stochastic (2SP) mixed-integer programming (MIP) model that identifies the optimal choice of primary and secondary (backup) network partners, along with determining their respective production/transportation quantities.The 2SP approach (Birge & Louveaux, 2011), is a suitable methodology to incorporate the uncertain supplier failure into the proposed network design model as it allows the inclusion of recourse (corrective) actions to hedge against excessive lost sales. In addition, it overcomes the conservative nature of the robust optimization (Ben-Tal & Nemirovski, 2002) approach by modeling the uncertainty as a discrete scenario set with a known probability distribution. By assuming a Bernoulli distribution for uncertain suppliers' technological capabilities, the proposed 2SP model designates a group of companies as the primary partners in the corresponding PBMN without full knowledge of their technical capabilities. A set of corrective actions, such as resorting to backup suppliers and outsourcing the orders to open markets, are also envisaged to mitigate the risk of suppliers' failure to produce customized items. The objective is to maximize the expected revenue while simultaneously minimizing the expected costs associated with production, emergency orders, and lost sale penalties. This model is distinct from the existing robust SC design model in the literature as it specifically accounts for various design complexity levels of product components in the bill-of-material (BOM) as well as increased production cost incurred for manufacturing highly complex items with small batch sizes.

Considering the novelty of this type of decision model in the literature, there is a clear need for generating benchmark problem instances for validation purposes. Our second contribution is, hence, focused on proposing a procedure for the systematic generation of random problem instances of varying sizes that provide reasonable outcomes. Generating such data sets is not a trivial task owing to the large number of parameters involved in formulating the proposed decision model, reflecting the challenges of designing a resilient PBMN for customized manufacturing.

Our third contribution revolves around addressing the computational complexity of the model, which becomes increasingly challenging due to the exponential growth in the number of uncertain scenarios corresponding to suppliers' failure in real-size problem instances. A scenario sampling heuristic is developed that relies on a new scenario sampling procedure that overcomes the shortcomings of a Monte Carlo sampling technique in underestimating the impact of suppliers' failure in the proposed 2SP model. More specifically, the proposed sampling method ensures the generation of more conservative scenarios as compared with a pure random sampling technique, commonly used in the Sample-Average-Approximation (SAA) scheme (Shapiro & Homem-de Mello, 2000). It, thus, enhances the robustness of the manufacturing network structure when confronted by suppliers's failure. Finally, we conduct computational experiments to assess the effectiveness of the proposed model and the efficiency of the solution method and ultimately provide some managerial insights. Monte-Carlo simulation experiments have been particularly designed to highlight the advantages of the proposed model and solution method in terms of protecting the manufacturing network under extreme scenarios and ultimately increasing its resilience.

The rest of this article is organized as follows. Section 3.2 describes the review of relevant literature. Section 3.3 contains the problem description and formulation. Section 3.4 describes the solution algorithms. The numerical results are discussed in Section 3.5 and concluding remarks are exposed in Section

3.2 Literature review

The supply chain design (SCD) problem has been broadly studied in the literature. The majority of existing studies are focused on the mass production of standard products. The studies in Fragoso and Figueira (2021); Pan and Nagi (2013); Sha and Che (2006) are among several studies that focus on the design of multi-echelon production value chains. A literature review on SC design and optimization is provided in (Garcia & You, 2015). Within the same mass production paradigm, numerous studies have also incorporated uncertainty into SCD problems to enhance SC performance and resilience (See, e.g., Masruroh, Putra, Mulyani, and Rifai (2023); Omrani, Adabi, and Adabi (2017); Şen, Yaman, Güler, and Körpeoğlu (2014)). Two-stage stochastic programming (Birge & Louveaux, 2011) and robust optimization (Ben-Tal & Nemirovski, 2002) approaches are among the most prevalent methodologies that have been explored in this context. Several studies (e.g., Simchi-Levi et al. (2015)) specifically focus on assessing the resilience of multi-echelon SCs in the manufacturing sector. Taghizadeh, Venkatachalam, and Chinnam (2021) provide a framework relying on discrete-event simulation for the resilience assessment of deep-tier supply networks. The study in Sanci, Daskin, Hong, Roesch, and Zhang (2022) provides a variety of mitigation strategies against automobile parts supply disruption risks, such as reserving backup capacity from the primary and secondary suppliers, and holding backup inventory. Nonetheless, none of the above-mentioned studies incorporate the challenges of customized manufacturing into the SCD problem.

SCD optimization within the scope of highly customized manufacturing has only recently been studied by a handful of researchers. Inman and Blumenfeld (2014) are among the first to study the impact of product design complexity on SC disruptions and delays. The authors develop mathematical models for estimating the SC reliability based on the availability of components in the BOM of complex products and the probability of delayed deliveries from the suppliers of those components to assembly facilities. Nonetheless, they do not provide any network design model that incorporates uncertain suppliers' failure in producing complex modules in the BOM. Changbai Tan and Freiheit (2022) develop a concurrent optimization framework that integrates the selection of manufacturing processes and suppliers into the architectural design of personalized products. By considering a cost model based on product architecture, process, and supplier portfolio, a MIP model is formulated that maximizes the potential profit of a product family based on customer preferences. By assuming that all product modules are manufactured in-house, this study does not address the optimal configuration of the SC when some complex, customized modules are outsourced to external producers with limited technological resources. To facilitate mass personalization, Katoozian and Zanjani (2022) develop an MIP model for determining the optimal selection of a pool of suppliers to satisfy the demand for highly customized products. Although this study touches upon several challenges involved in producing modular products at different customization levels and small batch sizes, it does not fully capture the uncertain factors inherent in personalized manufacturing.

The above literature survey reveals the increasing trend of research on the efficient design of SCs for facilitating customized manufacturing. Nonetheless, the existing studies do not thoroughly capture the intricate design complexity and technological challenges involved in manufacturing highly customized product modules prevalent in the advanced technology sector. In the same vein, they do not discuss the need for the design of a crowd-sourced manufacturing network that provides flexibility in terms of supplier selection to mitigate the risk of suppliers' failure in producing customized parts. The present study fills this research gap by proposing a stochastic decision framework that relies on crowd-sourcing the manufacturing of intricate customized modules in a PBMN while explicitly integrating the uncertain technological capabilities of external suppliers.

3.3 Problem description and formulation

In this section, we first present a formal description of the PBMN design problem under investigation. We then elaborate on modeling the uncertain manufacturing capability of suppliers/producers and develop a 2SP formulation.

3.3.1 Problem description

We consider a multi-echelon manufacturing network comprised of *i)* a main company that manufactures highly-customized, modular-structured products (e.g., LiDAR scanners); *ii)* a pool of producers/suppliers at the upstream echelons, differentiated in terms of capacity, technological capabilities, and cost; and *iii)* a group of logistics carriers, at the downstream echelon, distinguished in the sense of their cost and delivery lead time. We further assume that the above entities in the network are connected to a digital platform where the main company shares the design specification of custom orders while the suppliers and logistics carriers provide quotes for the manufacturing and delivery of those orders. The customizable nature of the end products has been captured by considering different customization options (e.g. low, moderate, and high) for a subset of sub-assemblies and components in the BOM. In the case of complex customization levels, the quotes would also include the preliminary technical analysis as proof of suppliers' technological capabilities.

To reflect the technical limitation of suppliers in the PBMN, we consider a technological capability matrix (TCM) with binary values representing the qualification/disqualification (1/0) of each entity in manufacturing a given customizable item at a certain customization level. This matrix can be prepared by the main company based on the historical performance of suppliers. In addition, a piece-wise linear cost function for the manufacturing of customizable items is considered to better reflect the cost implications of producing these components at small batch sizes. Finally, we consider different modes of delivery (e.g., expedited and regular) for customizable end products. A similar matrix is also considered for logistics carriers, where a value of 1 is equivalent to the possibility of a given delivery option (e.g., expedited).

In this context, the PBMN design problem consists of determining the optimal choice of sub-assembly producers, part suppliers, and logistics carriers (among the available pool) in addition to the production/transportation quantities at different echelons of the network to satisfy the demand of customizable final products at different design customization levels and delivery options. More precisely, the objective is to maximize revenue while minimizing the costs invoked by production, transportation, and lost sales. The mathematical formulation of the problem in a deterministic context is provided in A.1.

3.3.2 Modeling the uncertain technological capabilities

In the scope of manufacturing advanced technology products (e.g., LiDARs) with complex, customized features, it is not always straightforward to deliver the product according to the design specifications. This is mainly attributed to the technological limitations of the producers/suppliers of complex sub-assemblies (e.g., lasers) and parts (e.g., lenses). The higher the design customization level, the lower the chance of manufacturing those items by the suppliers that are not equipped with state-of-the-art technologies and R&D resources. Therefore, the elements of suppliers' TCM are random binary variables following a Bernoulli distribution. To model this uncertainty, for each entity in the pool of producers/suppliers, we assume a random failure probability for manufacturing each customizable item at a given design customization level. In other words, a 0/1 value is assigned to a given entity in the TCM at a given probability (e.g., 80%/20%). This indicates that the supplier won't be able to manufacture the item with the probability of 80% and only in 20% of the cases the item at the desired design customization level might be delivered by that supplier. It is worth mentioning that the probability of failure for those suppliers is, in general, estimated by the main company based on historical data.

To incorporate the uncertain TCM into the PBMN design model, we define a (finite) set of scenarios with known probabilities. Each scenario represents a possible outcome in terms of suppliers' technological capabilities. For instance, by considering 2 customizable items (P1/P2) with a very complex design, two potential suppliers for each item (S1 & S2 for P1 and S3 & S4 for P2), and the probability of failure for all suppliers equal to 80%, 2^4 scenarios with their corresponding probabilities can be defined as summarized in Table 3.1.

Scenario	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
P1/S1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
P1/S2	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0
P2/S3	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0
P2/S4	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
Probability	0.0016	0.0064	0.0064	0.0256	0.0064	0.0256	0.0256	0.1024	0.0064	0.0256	0.0256	0.1024	0.0256	0.1024	0.1024	0.4096

Table 3.1: Example of TCM scenarios

As can be observed in this table, the scenarios represent all possibilities in terms of the success/failure of the supplier in manufacturing the items. The number of such scenarios grows exponentially by increasing the number of items with complex designs in the BOM and the size of the pool of potential suppliers.

3.3.3 Two-stage stochastic programming formulation

Two-stage stochastic programming (2SP) (Birge & Louveaux, 2011) is a viable approach for reformulating linear programming (LP) models that include random parameters into a single deterministic equivalent model and has been applied in a variety of SC planning problems (see, e.g., (Kazemi Zanjani, Nourelfath, & Aït-Kadi, 2011; Leung, Wu, & Lai, 2006)). This approach is particularly suitable when the uncertain parameters can be represented as a finite number of scenarios (outcomes) with known probabilities. In addition, it provides a flexible decision framework by designating corrective actions to compensate for the constraints violation under some scenarios. In this method, the decision variables are categorized as the first (here-and-now) and second stage (recourse) decisions that are determined, respectively, before and after the outcome of uncertainty is revealed to the decision maker. Therefore, the stages are distinguished in terms of the availability of information on random parameters. The objective is to optimize an expected performance measure over all scenarios. A more detailed description of this approach is provided in section A.2. This method is, in particular, suitable for the problem investigated in this study as the random TCM is modeled as a finite scenario set. Furthermore, a PBMN is supposed to provide a flexible platform where the focal company can modify the supplier pool as a response to the failure of the existing partners.

In the PBMN design problem, the choice of (primary) producers/suppliers and logistic carriers must be made without complete knowledge of their technological capabilities. Therefore, the first-stage decisions correspond to assigning an initial set of producers and logistics careers. This is primarily driven by the contractual terms established with the key upstream and downstream partners that serve as the main collaborators of the company. Upon designating an initial pool of suppliers, the main company shares the statement of work (SOW) with them (on the interface of the manufacturing platform) based on the orders received for customized products. Thereafter, those entities submit their detailed technical proposals for the design and manufacturing of customizable items along with the quote (cost estimation and manufacturing lead time).

After receiving the quotes from the main partners and reviewing the initial R&D analysis, the company gains a clear picture of suppliers' capabilities for the delivery of custom items. At this (second) stage, critical decisions are made, including assigning the actual orders to the upstream entities (i.e., issuing purchase orders (POs)), determining optimal production quantities within the (main) company's facilities, and planning the flow of final products to transportation carriers. If some (primary) suppliers prove to be incapable of delivering items on time or meeting the requested design specifications, the company considers two types of corrective (recourse) actions to mitigate the risk of significant lost sales. The first action involves engaging backup suppliers/producers on an emergency basis. To this end, the focal company shares the SOW with a list of backup suppliers on the platform and finalizes the potential pool based on the submitted proposals/quotes. Signing a contract with these entities during the second stage incurs a higher fixed cost compared to first-stage contracts, due to the urgent nature of these late orders. Under some scenarios, where none of the partners provide an adequate proposal, the second type of recourse action involves purchasing the item from the open market, if available. This option allows the company to acquire items with complex designs, albeit at a significantly higher cost. If neither of these corrective actions is feasible, the orders are classified as lost sales.

Within the decision framework described above, the 2SP approach would be a natural choice to formulate the PBMN design problem. The objective of this 2SP model is to maximize the expected profit of the main company under a set of scenarios that represent the random manufacturing capability of producers/suppliers. It is noteworthy that this modeling framework is expected to propose the most reliable suppliers (featured with the lowest chance of failure) as the primary partners. This is typically achievable by considering the cost of recourse actions (i.e., resorting to emergency suppliers, open market, and lost sale) significantly higher than the first-stage costs. In other words, even though the cost of signing contracts with more reliable manufacturers might be initially high, to minimize the expected cost of emergency orders and lost sales under worst-case scenarios, the model is expected to favor the most reliable partners. The proposed 2SP model is described as follows. The corresponding notations are provided in section A.3.

Two-stage Stochastic Programming Model

Maximize

$$
\begin{aligned}
&\sum_{\omega} p(\omega) \Bigg(\sum_{p}\sum_{i}\sum_{j}\sum_{l} S^{j}_{pil} q^{j}_{pil}(\omega) - \sum_{p}\sum_{i}\sum_{j}\sum_{l} C_{pi} q^{j}_{pil}(\omega) - \sum_{p}\sum_{i}\sum_{l}\sum_{g} \\
&C_{pigl} r_{pigl}(\omega) - \sum_{h}\sum_{n}\sum_{l} C^{s}_{hn} q^{s}_{hnl}(\omega) - \sum_{h}\sum_{n}\sum_{i}\sum_{j}\sum_{l} C^{j}_{hni} q^{cj}_{hnil}(\omega) - \sum_{h}\sum_{n} \\
&\sum_{i}\sum_{j}\sum_{l} C^{j}_{hni} q'^{cj}_{hnil}(\omega) - \sum_{k}\sum_{m}\sum_{l} C^{s}_{km} q^{s}_{kml}(\omega) - \sum_{k}\sum_{m}\sum_{i}\sum_{j}\sum_{l} C^{j}_{kmi} q^{cj}_{kmil}(\omega) \\
&- \sum_{k}\sum_{m}\sum_{i}\sum_{j}\sum_{l} C^{j}_{kmi}\, q'^{cj}_{kmil}(\omega) - \sum_{n}\sum_{i}\sum_{l} C^{open}_{ni} q^{open}_{nil}(\omega) - \sum_{m}\sum_{i}\sum_{l} C^{open}_{mi} \\
&q^{open}_{mil}(\omega) - \sum_{p}\sum_{i}\sum_{l} CL_{pi} w_{pil}(\omega) - \sum_{h} F'_{h} y'_{h}(\omega) - \sum_{k} F'_{k} x'_{k}(\omega)\Bigg) - \sum_{h} F_{h} y_{h} \\
&- \sum_{k} F_{k} x_{k} - \sum_{g} F_{g} o_{g} \Bigg)
\end{aligned}
\tag{3.1}
$$

Subject to

Demand constraints:

$$\sum_j q_{pil}^j(\omega) + w_{pil}(\omega) = D_{pil}, \qquad \forall p \in P, \forall i \in I, \forall l \in L, \forall \omega \in \Omega \tag{3.2}$$

Capacity constraints:

$$\sum_j \sum_l \alpha_{pi} q_{pil}^j(\omega) \leq FC_{pi}, \qquad \forall p \in P, \forall i \in I, \forall \omega \in \Omega \tag{3.3}$$

$$\sum_l \beta_{hn}^s q_{hnl}^s(\omega) \leq PC_{hn} \theta_{hn}^s y_h, \qquad \forall h \in H, \forall n \in N^s, \forall \omega \in \Omega \tag{3.4}$$

$$\sum_l \gamma_{km}^s q_{kml}^s(\omega) \leq SC_{km} \sigma_{km}^s x_k, \qquad \forall k \in K, \forall m \in M^s, \forall \omega \in \Omega \tag{3.5}$$

$$\sum_j \sum_l \beta_{hni}^c q_{hnil}^{cj}(\omega) \leq PC_{hni} \theta_{hni}^c(\omega) y_h, \qquad \forall h \in H, \forall n \in N^c, \forall i \in I, \forall \omega \in \Omega \tag{3.6}$$

$$\sum_j \sum_l \beta_{hni}^c q_{hnil}^{\prime cj}(\omega) \leq PC_{hni} \theta_{hni}^c(\omega) y_h^\prime(\omega), \qquad \forall h \in H, \forall n \in N^c, \forall i \in I, \forall \omega \in \Omega \tag{3.7}$$

$$\sum_j \sum_l \gamma_{kmi}^c q_{kmil}^{cj}(\omega) \leq SC_{kmi} \sigma_{kmi}^c(\omega) x_k, \qquad \forall k \in K, \forall m \in M^C, \forall i \in I, \forall \omega \in \Omega \tag{3.8}$$

$$\sum_j \sum_l \gamma_{kmi}^c q_{kmil}^{\prime cj}(\omega) \leq SC_{kmi} \sigma_{kmi}^c(\omega) x_k^\prime(\omega), \qquad \forall k \in K, \forall m \in M^C, \forall i \in I, \forall \omega \in \Omega \tag{3.9}$$

$$\sum_p \sum_i r_{pigl}(\omega) \leq M \mu_{gl} o_g, \qquad \forall l \in L, \forall g \in G, \forall \omega \in \Omega \tag{3.10}$$

Price/Cost linearization constraints:

$$q_{pil}^{j}(\omega) \leq L_{pi}^{j} z_{pil}^{j}(\omega), \qquad \forall p \in P, \forall i \in I, \forall j \in J, \forall l \in L, \forall \omega \in \Omega \tag{3.11}$$

$$z_{pil}^{j}(\omega)(L_{pi}^{j-1} + 1) \leq q_{pil}^{j}(\omega), \qquad \forall p \in P, \forall i \in I, \forall j \in J \backslash \{1\}, \forall l \in L, \forall \omega \in \Omega \tag{3.12}$$

$$\sum_{j} z_{pil}^{j}(\omega) = 1, \qquad \forall p \in P, \forall i \in I, \forall l \in L, \forall \omega \in \Omega \tag{3.13}$$

$$q_{hnil}^{cj}(\omega) + q_{hnil}^{\prime cj}(\omega) \leq u_{hnil}^{j}(\omega) L_{hni}^{j}, \qquad \forall h \in H, \forall n \in N^{c}, \forall i \in I, \forall j \in J, \forall l \in L, \forall \omega \in \Omega \tag{3.14}$$

$$u_{hnil}^{j}(\omega)(L_{hni}^{j-1} + 1) \leq q_{hnil}^{cj}(\omega) + q_{hnil}^{\prime cj}(\omega),$$

$$\forall h \in H, \forall n \in N^{c}, \forall i \in I, \forall j \in J \backslash \{1\}, \forall l \in L, \forall \omega \in \Omega \tag{3.15}$$

$$\sum_{j} u_{hnil}^{j}(\omega) = 1, \qquad \forall h \in H, \forall n \in N^{c}, \forall i \in I, \forall l \in L, \forall \omega \in \Omega \tag{3.16}$$

$$q_{kmil}^{cj}(\omega) + q_{kmil}^{\prime cj}(\omega) \leq v_{kmil}^{j}(\omega) L_{kmi}^{j},$$

$$\forall k \in K, \forall m \in M^{c}, \forall i \in I, \forall j \in J, \forall l \in L, \forall \omega \in \Omega \tag{3.17}$$

$$v_{kmil}^{j}(\omega)(L_{kmi}^{j-1} + 1) \leq q_{kmil}^{cj}(\omega) + q_{kmil}^{\prime cj}(\omega),$$

$$\forall k \in K, \forall m \in M^{c}, \forall i \in I, \forall j \in J \backslash \{1\}, \forall l \in L, \forall \omega \in \Omega \tag{3.18}$$

$$\sum_{j} v_{kmil}^{j}(\omega) = 1, \qquad \forall k \in K, \forall m \in M^{c}, \forall i \in I, \forall l \in L, \forall \omega \in \Omega \tag{3.19}$$

Flow balance constraints:

$$\sum_{j} q_{pil}^{j}(\omega) = \sum_{g} r_{pigl}(\omega), \qquad \forall p \in P, \forall i \in I, \forall l \in L, \forall \omega \in \Omega \tag{3.20}$$

$$\sum_h q^s_{hnl}(\omega) = \sum_p \sum_i \sum_j \eta_{np} q^j_{pil}(\omega),$$

$$\forall n \in N^s, \forall l \in L, \forall \omega \in \Omega \quad (3.21)$$

$$q^{open}_{nil}(\omega) + \sum_h \sum_j q^{cj}_{hnil}(\omega) + \sum_h \sum_j q'^{cj}_{hnil}(\omega) = \sum_p \sum_j \eta_{np} q^j_{pil}(\omega),$$

$$\forall n \in N^c, \forall i \in I, \forall l \in L, \forall \omega \in \Omega \quad (3.22)$$

$$\sum_k q^s_{kml}(\omega) = \sum_h \sum_{n \in N^s_m} \lambda_{mn} q^s_{hnl}(\omega) + \sum_h \sum_{n \in N^s_m} \sum_i \sum_j \lambda_{mn} q^{cj}_{hnil}(\omega) +$$

$$\sum_h \sum_{n \in N^s_m} \sum_i \sum_j \lambda_{mn} q'^{cj}_{hnil}(\omega) + \sum_{n \in N^s_m} \sum_i \lambda_{mn} q^{open}_{nil}(\omega), \qquad \forall m \in M^s, \forall l \in L, \forall \omega \in \Omega \quad (3.23)$$

$$q^{open}_{mil}(\omega) + \sum_k \sum_j q^{cj}_{kmil}(\omega) + \sum_k \sum_j q'^{cj}_{kmil}(\omega) = \sum_h \sum_{n \in N^c_m} \sum_j \lambda_{mn} q^{cj}_{hnil}(\omega) +$$

$$\sum_h \sum_{n \in N^c_m} \sum_j \lambda_{mn} q'^{cj}_{hnil}(\omega) + \sum_{n \in N^c_m} \lambda_{mn} q^{open}_{nil}(\omega), \qquad \forall m \in M^c, \forall i \in I, \forall l \in L, \forall \omega \in \Omega \quad (3.24)$$

Primary/Secondary supplier constraints:

$$y_h + y'_h(\omega) \leq 1, \qquad \forall h \in H, \forall \omega \in \Omega \quad (3.25)$$

$$x_k + x'_k(\omega) \leq 1, \qquad \forall k \in K, \forall \omega \in \Omega \quad (3.26)$$

Open market constraints:

$$q^{open}_{nil}(\omega) = 0, \qquad \forall n \notin N'^c, \forall i \in I', \forall l \in L, \forall \omega \in \Omega \quad (3.27)$$

$$q^{open}_{mil}(\omega) = 0, \qquad \forall m \notin M'^c, \forall i \in I', \forall l \in L, \forall \omega \in \Omega \quad (3.28)$$

Domaine constraints:

$q^{open}_{mil}(\omega), q^{cj}_{kmil}(\omega), q'^{cj}_{kmil}(\omega), q^s_{kml}(\omega), q^{cj}_{hnil}(\omega), q'^{cj}_{hnil}(\omega), q^{open}_{nil}(\omega), q^s_{hnl}(\omega), q^j_{pil}(\omega),$

$$w^j_{pil}(\omega) \geq 0, \qquad \forall k \in K, \forall m \in M^c, \forall m \in M^S, \forall h \in H, \forall n \in N^c, \forall n \in N^S, \forall i \in I,$$

$$\forall j \in J, \forall p \in P, \forall l \in L, \forall \omega \in \Omega \tag{3.29}$$

$$x_k, x'_k, y_h, y'_h, o_g, z^j_{pil}(\omega), u^j_{hnil}(\omega), v^j_{kmil}(\omega) \in \{0,1\}, \qquad \forall k \in K, \forall h \in H, \forall p \in P,$$

$$\forall i \in I, \forall j \in J, \forall n \in N^c, \forall m \in M^c, \forall l \in L, \forall \omega \in \Omega \tag{3.30}$$

The objective function (3.1) maximizes the expected profit over all scenarios. This equation comprises the expected revenue from selling the end products minus the expected costs of i) transportation of end products; ii) manufacturing end products and sub-assemblies along with purchasing components from the primary/secondary producers/suppliers and the open market; iii) lost sales; and iv) the fixed cost of signing contracts with the primary and backup producers/suppliers and logistics carriers. It is worth mentioning that the unit production/procurement cost of sub-assemblies/components heightens as the customization level is increased. The idea is to adjust producers'/suppliers' costs to the elevated design and manufacturing resources engaged to deliver the desired customization level.

Constraint (3.2) ensures that demand is either satisfied by manufacturing the end products or goes to a lost sale. Constraint (3.3) imposes capacity restrictions on producing end products at different customization levels. Constraints (3.4)-(3.5) enforce capacity limitations for standard sub-assemblies/components provided by producers/suppliers; whereas Constraints (3.6)-(3.9) guarantee that the production quantities of customizable sub-assemblies and components do not exceed the maximum available capacity of primary and backup producers and suppliers. Constraint (3.10) is a capacity limitation constraint for logistic carriers. It must be noted that constraints (3.3)-(3.10) ensure that items can be manufactured/delivered by different entities only if they are qualified to provide items with corresponding customization levels/delivery options (according to the TCM) and have been selected as primary or secondary partners.

By considering different pricing intervals set by the main company for various manufacturing quantity intervals and customization levels, constraints (3.11)-(3.13) are provided to linearize the step-wise linear selling price of end products. More precisely, constraints (3.11)-(3.12) ensure that the production amount and its corresponding selling price are assigned to the proper interval, while constraint (3.13) ensures that only one interval is selected. Similar linearization criteria for customizable sub-assemblies and components are represented by constraints (3.14)-(3.16) and (3.17)-(3.19), respectively based on the cost intervals set by the upstream partners for customizable items.

Constraints (3.20) imply the flow balance conditions for the delivery of manufactured end products. Constraints (3.21)-(3.24) impose flow balance conditions based on the structure of BOM. In other words, they formulate the logical flow between the production quantity of end products, sub-assemblies, and components according to the corresponding BOM.

Constraints (3.25)-(3.26) ensure that each producer and supplier is selected either as a primary or backup provider. Nonetheless, these constraints would be redundant if two separate sets of companies are considered as primary and backup suppliers. Constraints (3.27)-(3.28) state that only a subset of customizable sub-assemblies and components are available for purchase from the open market. Constraints (3.29)-(3.30) are the domain constraints.

3.4 Solution Methodology

3.4.1 Complexity Analysis of the 2SP PBMN Design Problem

The 2SP model (3.1)-(3.30) is a MIP model that contains $(|K| + |H| + |G| + |K||\Omega| + |H||\Omega| + |P||I||J||L||\Omega| + |H||N||I||J||L||\Omega| + |K||M||I||J||L||\Omega|)$ binary variables. The majority of these variables are indexed by scenarios. As highlighted in section 3.2, the number of TCM scenarios ($|\Omega|$) grows exponentially as the number of customizable items in the BOM and their corresponding pool of suppliers is increased. Therefore, the number of binary variables in model (3.1)-(3.30) would grow exponentially when considering multiple customizable modules and a large supplier pool. Consequently, it becomes excruciatingly challenging to solve this model when considering all TCM scenarios. This motivated us to propose a scenario sampling heuristic (SSH) that relies on solving the original 2SP model by considering a sample of scenarios randomly generated from the underlying probability distribution.

3.4.2 Scenario Sampling heuristic

When adopting a sampling approach for approximating the original uncertainty set to a smaller scenario set, the choice of scenarios in the sample would be crucial considering that some 2SP models are highly sensitive to these scenarios (Shapiro & Homem-de Mello, 2000). Our preliminary numerical experiments revealed the shortcomings of a Monte-Carlo sampling approach, commonly applied within the Sample Average Approximation (SAA) algorithm (Mak, Morton, & Wood, 1999; Shapiro & Homem-de Mello, 1998, 2000). More specifically, even at large samples (500 scenarios), a random sampling technique generates optimistic scenarios for the technological capabilities of suppliers that are featured with a high failure probability. This leads to the selection of unreliable (cheaper) suppliers in the 2SP model, which is not a desirable outcome as this category is prone to higher failure rates for manufacturing complex custom items. When the chance of suppliers' failure is high (above 60 %), the worst-case scenarios (i.e., the ones corresponding to the failure of the majority of unreliable suppliers) should have a higher chance of occurrence in the scenario set. Nevertheless, the Monte-Carlo sampling method is not capable of generating such worst-case scenarios unless a very large scenario sample is generated which is not practical.

To fix this drawback, we propose a heuristic scenario sampling approach that guarantees a more realistic occurrence of suppliers' failure scenarios in the sample based on the corresponding failure probability. Considering a sample of size N, this procedure ensures that each producer/supplier, featured with $X\%$ probability of failure, would receive zero values for corresponding TCM elements (i.e., fails to deliver the item) under $X\%$ of scenarios in the sample. For instance, let us assume 70% and 90% failure probabilities for suppliers S1 and S2. By considering the sample size equal to 100, this approach ensures that in 70 and 90 scenarios, S1 and S2, respectively, receive zero values. Nonetheless, the choice of scenarios where zero TCM elements appear for each supplier is randomized within the sample. As such, for each supplier, the algorithm randomly selects the scenario subset $S' \subset S$ in which that supplier would fail to deliver the customized item and sets the corresponding TCM element to zero. For other scenarios that do not belong to S', the TCM elements are set to 1 for that supplier. The scenario sample S is completed by repeating this step for all suppliers.

Proposition: The worst-case TCM scenarios for suppliers with high failure probability have a higher chance of occurrence in the proposed SSH as compared to the Monte-Carlo sampling method.

Proof: When sampling from a Bernoulli distribution, the failure probability of suppliers can not be explicitly incorporated into a Monte-Carlo sampling framework. To generate a scenario by this method, for each supplier, a random number between (0,1) is generated (based on their corresponding Bernoulli distribution) to represent their failure/success. Since equal probabilities are considered for the generated scenarios, this method does not guarantee an adequate occurrence of failures for unreliable suppliers (with high failure probabilities) in the scenario set when considering small to medium sample sizes. The SSH, on the contrary, explicitly incorporates the probability of failure when generating scenarios; hence, it generates (identical) worst-case scenarios in the sample more frequently. Therefore, even though the individual scenarios have equal probabilities in the sample, by cumulating the probabilities of identical counterparts, such worst-case scenarios would ultimately receive a higher probability.

According to the above proposition, the worst-case scenarios have a higher weight in the objective function of the 2SP model when applying the SSH method as compared to pure random sampling. This is a desirable feature in the PBMN design model as it provides more protection (robustness) against worst-case scenarios and ultimately enhances network resilience. This characteristic will be further validated in our numerical experiments.

3.5 Numerical Results

In this section, we describe the results of numerical experiments carried out to evaluate the effectiveness of the proposed 2SP-PBMN design model and the efficiency of the solution algorithm. First, we present the experimental setup and data structure corresponding to the parameters of the proposed 2SP model. Thereafter, we thoroughly analyze the outcomes of this model under different parameter settings and shed light on some interesting managerial insights. In addition, the superiority of a stochastic programming approach versus a deterministic one is underscored by assessing the value of stochastic solution (VSS) across the problem instances. Finally, we showcase the efficiency of the SSH algorithm in solving larger problem sets. All numerical experiments are coded/run in Python using the Callable Library of CPLEX 12.9 on a Core i7 CPU 3.40 GHz computer equipped with 8.00 GB RAM under Windows 10.

3.5.1 Experimental Design

Considering the lack of benchmark instances in the literature, we propose a procedure to systematically generate random problem instances of varying sizes, ensuring reasonable optimal solutions are obtained. The generated instances differ in terms of the total number of finished products ($|P|$), sub-assemblies ($|N|$), components ($|M|$), and producers/suppliers for each customization level of sub-assemblies/components ($|H|$ and $|K|$). Without loss of generality, we consider three different customization levels for non-standard (customizable) components, sub-assemblies, and final products as low, moderate, and highly customized. Moreover, two categories of producers/suppliers are considered for subassemblies/components, namely local and the ones located overseas, that differ in terms of their fixed and variable production costs and capacity. For highly customizable sub-assemblies/components (level 3), the two categories of producers/suppliers also differ in terms of their technological capabilities. More specifically, the following two classes of producers/suppliers have been considered:

(1) Reliable Suppliers/producers: featured with higher fixed and variable production costs, but a lower chance of failing to deliver customized orders.

(2) Unreliable Suppliers/producers: featured with lower fixed and variable costs, but a higher probability of failing to fulfill customized orders.

In our numerical experiments, we only consider uncertain technological capabilities for the producers/suppliers of subassemblies/components with the highest level of design customization (level 3) to reflect the challenging nature of manufacturing items in this category. However, this parameter can be also considered random for lower customization levels. Additionally, we consider regular and expedited delivery as two distinct types of delivery options. Accordingly, two classes of logistic carriers are distinguished: one is more expensive and offers both types of delivery, while the other is cheaper and only offers a regular delivery option.

Table 3.2 provides an overview of various intervals from which data for final products is derived. It's worth noting that the production and lost-sale costs and selling price of highly customized products are anticipated to be higher than ones with a lower customization level. The idea is to reflect the challenging nature of highly customized manufacturing as well as the priority of delivering products with complex customized designs to the customers. Additionally, as shown in the table, three selling price and production cost intervals are considered that are reliant on the order quantity. It is noteworthy that transportation costs are considered lower for regular delivery compared to fast delivery options.

Parameter	customization Level	Interval	Parameter	customization Level	Interval	Parameter	customization Level	Quantity Interval	Interval	Parameter	customization Level	Production Quantity Interval	Interval
	1	(50 - 220)		1	(200 - 300)			1	(2000 - 3500)			1	(300 - 462)
Demand	2	(100 - 350)	Production Cost	2	(400 - 600)		1	2	(1200 - 2100)		1	2	(616 - 924)
	3	(150 - 600)		3	(800 - 1200)			3	(720 - 1260)			3	(1232 - 1848)
	1	(840 - 1260)		1	(3000 - 4000)			1	(2500 - 5250)			1	(185 - 278)
Capacity	2	(1200 - 1800)	Lost Sale Cost	2	(4000 - 6000)	Selling Price	2	2	(1500 - 3150)	Production Quantity Interval	2	2	(370 - 555)
	3	(1512 - 2268)		3	(6000 - 8000)			3	(900 - 1890)			3	(739 - 1109)
Parameter	Delivery Mode	Interval	Parameter	Delivery Mode	Interval			1	(3750 - 7000)			1	(112 - 169)
Transportation	Regular	(50 - 125)	Transportation	Regular	(1000 - 1500)		3	2	(2250 - 4200)		3	2	(222 - 337)
Variable Cost	Fast	(125 - 200)	Fixed Cost	Fast	(2000 - 3000)			3	(1350 - 2520)			3	(442 - 673)

Table 3.2: Final Products Data Intervals

Table 3.3 demonstrates the data corresponding to the capacity and production cost of producers/suppliers of standard sub-assemblies/components.

Parameter (Sub-assembly)	Interval	Parameter (Component)	Interval
Production Cost	(50 - 150)	Production Cost	(30 - 100)
Fixed Cost	(1000 - 3000)	Fixed Cost	(1000 - 3000)

Table 3.3: Standard Suppliers/Producers Data Intervals

In our numerical settings, we considered the unit capacity consumption rates for the sub-assemblies and components equal to their level of customization. The number of sub-assemblies/components required to make one unit of its upper-level part in the BOM is represented by an integer generated randomly from the set $\{1,2\}$. The capacity of each supplier or manufacturer to produce standard and customizable products (for the base cases) is determined by multiplying the unit capacity consumption rates and the number of units required at the upper-level item by the demand in each generated instance. The idea is to strike a balance between capacity and demand in base instances. In addition, the production/procurement quantity intervals are generated such that the third interval for each design customization level (and delivery option) is equal to the total capacity of the suppliers/producers. The first and second intervals are set as half of the second and third intervals, respectively. The open market prices have been considered twice the highest variable cost among the suppliers of customizable items.

Table 3.4 summarizes the cost intervals for the first category of suppliers (located overseas) for the low and moderate customized parts as well as the unreliable suppliers for highly customized parts:

Parameter (Sub-assembly)		customization Level	Interval	Parameter (Component)		customization Level	Interval
Variable Production Cost	Overseas Supplier	1	(100 - 200)	Variable Production Cost	Overseas Supplier	1	(50 - 100)
	Overseas Supplier	2	(200 - 300)		Overseas Supplier	2	(150 - 250)
	Reliable Supplier	3	(350 - 500)		Reliable Supplier	3	(250 - 400)
Fixed Cost	Overseas Supplier	1	(1000 - 1500)	Fixed Cost	Overseas Supplier	1	(1000 - 1500)
	Overseas Supplier	2	(1000 - 1500)		Overseas Supplier	2	(1000 - 1500)
	Reliable Supplier	3	(3000 - 4500)		Reliable Supplier	3	(3000 - 4500)

Table 3.4: Customizable Suppliers/Producers Data Intervals

The variable and fixed cost structure for customizable sub-assemblies/components have been generated randomly for different suppliers/producers as follows. For the suppliers/producers of customizable items, the variable cost for the second category of suppliers (local/reliable) is considered 20% higher than the first category (overseas/unreliable). Furthermore, since the production costs are considered piece-wise linear in these instances, the cost of the third and second intervals is considered to be 60% of the costs of the second and first intervals for all suppliers/producers and all customization levels, respectively. Finally, the fixed cost for all local/reliable suppliers/producers (for all customization levels) is considered twice higher than the overseas/unreliable ones. The second-stage fixed cost of signing contracts with backup entities is three times higher than the first-stage ones for all suppliers and producers.

3.5.2 Analysis of the 2SP-PBMN design model

This section presents the results of sensitivity analysis experiments conducted on small problem instances generated based on the procedure described in the previous section. In these instances, we consider one customizable end product, two subassemblies, and four components. The corresponding BOM for this product is shown in figure 3.1. Only one subassembly and one component are considered customizable; the other items are standard. In the base case, we assume 10% and 90% failure probabilities for reliable and unreliable suppliers/producers, respectively. It is also assumed that only the customizable sub-assemblies/components at the third customization level (highly customized parts) are available for purchase from the open market. One of the advantages of examining small instances is the opportunity to closely analyze the structure of the optimal solution, thereby gaining insights into the impact of influential model parameters on this solution.

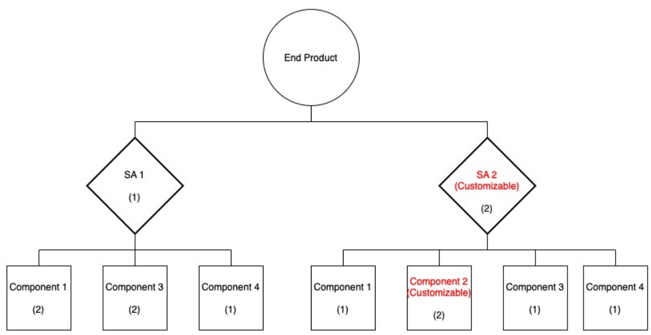


Figure 3.1: BOM in Small Problem Instances

The goal of our sensitivity analysis experiments is to examine the solutions obtained from the 2SP model, particularly in terms of the choice of first-stage and backup suppliers under different supplier failure probability, demand levels, and supplier selection fixed costs. The selection of parameters for sensitivity analysis is guided by their influence on the supplier pool selection. This process is informed by an initial set of parameter screening tests, along with the potential managerial insights these parameters can provide. Within these experiments, we further analyze the benefits of adopting a stochastic programming approach versus a deterministic one to address the PBMN design problem by assessing the VSS that can be calculated as follows.

Let us denote the optimal objective function value of the stochastic model as $2SP$ and the expected profit of the deterministic solution as EDS. The latter is calculated by fixing the value of first-stage decisions in model (3.1)-(3.30) as their optimal value obtained from solving the deterministic model (A.1). Thereafter, EDS is calculated accordingly as the objective function of this model. The VSS (for the maximization problem under investigation) is calculated as the difference between EDS and $2SP$, as indicated in the following equation:

$$VSS(\%) = \frac{2SP - EDS}{2SP} \times 100 \tag{3.31}$$

It can be easily proved that $VSS \geq 0$ (Birge & Louveaux, 2011). In fact, in a complete recourse 2SP model, where the recourse actions are defined such that the model remains feasible for all scenarios, the optimal (first-stage) solution of the deterministic model is a feasible solution to the 2SP model; hence provides a sub-optimal objective function value. However, the VSS is highly sensitive to the model parameters, specifically, the choice of scenarios (and their probabilities) in addition to the cost of first- and second-stage decision variables.

The number of TCM scenarios in small instances is 16 as only two items in the BOM are considered customizable and for each item (at the highest level of customization), two potential providers with uncertain TCM are available. The structure of such scenarios is similar to the example provided in Table 3.1; however, their probabilities are different since a significantly larger failure probability (90%) is assumed for the unreliable suppliers versus a small probability (10%) for the reliable ones. Table 3.5 summarizes the results of 8 problem instances by considering different failure probabilities for unreliable suppliers of customizable items (at the highest level of customization) where the failure probability for the reliable ones is set to 10%. In this table, the optimal objective value ("OBJ"), as well as supplier assignment decisions (in terms of the choice of reliable/unreliable ones), are reported for the deterministic and 2SP models. Furthermore, the optimal solution of the 2SP model is presented separately for the first and second stage (backup) supplier selections. Under the "EDS" column, we also report the assignment of backup suppliers under different scenarios based on the initial assignment obtained from the deterministic model. Finally, the $VSS(\%)$ and its absolute value are reported in the last two columns of this table. The CPU time of CPLEX for solving small problem instances does not exceed a few seconds.

Instance	Unreliable suppliers/producers failure percentage	Deterministic			2SP					EDS					VSS%	VSS Value
					OBJ	First Stage Suppliers		Backup Suppliers		OBJ	First Stage Suppliers		Backup Suppliers			
		OBJ	Reliable	Unreliable		Reliable	Unreliable	Reliable	Unreliable		Reliable	Unreliable	Reliable	Unreliable		
Base	90	354,787		✓	219,970	✓			✓	196,929		✓	✓		10.48%	23,041
1	80	354,787		✓	232,073	✓			✓	214,469		✓	✓		7.58%	17,604
2	70	354,787		✓	244,176	✓			✓	232,009		✓	✓		4.98%	12,167
3	60	354,787		✓	257,574		✓	✓		249,548		✓	✓		3.12%	8,026
4	50	354,787		✓	271,619		✓	✓		267,088		✓	✓		1.67%	4,531
5	40	354,787		✓	285,663		✓	✓		284,628		✓	✓		0.36%	1,035
6	30	354,787		✓	302,167	✓			✓	302,167		✓	✓		0	0
7	20	354,787		✓	319,707	✓			✓	319,707		✓	✓		0	0
8	10	354,787		✓	337,247	✓			✓	337,247		✓	✓		0	0

Table 3.5: Sensitivity Analysis on Suppliers' Technological Capabilities

As anticipated, the deterministic model consistently selects unreliable suppliers, featured with lower production costs, to maximize the profit by relying on their full capability to deliver customized items. However, companies typically strive to minimize lost sales by contracting with reliable suppliers. The 2SP model, on the contrary, assigns the items to reliable suppliers in the first stage when the probability of failure for the unreliable ones is high ($\geq$ 70%). The goal is to minimize the expected cost of resorting to more expensive suppliers in the second stage, which incurs a significantly higher fixed cost for signing the contract on an emergency basis. On the other hand, this model selects unreliable suppliers as the first stage optimal decisions under a moderate chance of failure (40%-60%). This is primarily due to the relatively low expected cost of resorting to backup suppliers in the second stage under these circumstances. In other words, the probabilities of scenarios where unreliable suppliers are unavailable are quite low in such circumstances. Finally, under the low probability of supplier failure ($\leq$ 30%), the model arbitrarily chooses reliable ones as there is not much difference between the two categories when it comes to the choice of first and second-stage decisions. We also note that in all of the experiments, the 2SP model resorts to an open market under some scenarios, where none of the suppliers are available, to satisfy the demand and avoid lost sales. As anticipated, the $VSS\%$ is declined as the probability of supplier failure is reduced and it reaches zero under low failure probabilities.

Table 3.6 compares the optimal objective value ("OBJ"), supplier assignment decisions, as well as $VSS\%$ obtained from the deterministic and 2SP models under different demand profiles. The supplier failure probability for unreliable suppliers is set to 90% (base case) in all these experiments. In this table, the demand profiles are expressed as a percentage of base demand described in section 3.5.1.

Instance	Demand	Deterministic			2SP					EDS					VSS%	VSS Value
					OBJ	First Stage Suppliers		Second Stage Suppliers		OBJ	First Stage Suppliers		Second Stage Suppliers			
		OBJ	Reliable	Unreliable		Reliable	Unreliable	Reliable	Unreliable		Reliable	Unreliable	Reliable	Unreliable		
Base		354,787		✓	219,970	✓			✓	196,929		✓	✓		10.48%	23,069
1	-40%	218,575		✓	127425	✓			✓	104,356		✓	✓		18.10%	23,040
2	-20%	194,700		✓	74,187	✓			✓	51,147		✓	✓		31.06%	12,167
3	+10%	361,246		✓	213,788	✓			✓	190,748		✓	✓		10.77%	23,040
4	+20%	45,199		✓	-114,898	✓			✓	-137,938		✓	✓		20.053%	23,040

Table 3.6: Sensitivity Analysis on Demand

As can be observed in this table, the value of adopting a stochastic programming (SP) approach is more emphasized when the demand is lower than the capacity (less than the base case). This implies that when the capacity is too tight (base case), the negative consequences of the unavailability of suppliers can be mitigated by adopting a stochastic approach only to some extent. Nevertheless, when the model has more flexibility, better results are obtained from the 2SP model which is significantly more advantageous to the deterministic approach. On the contrary, when the capacity is over-committed, the increasing trend of VSS is less significant. It is notable that, when the demand is significantly higher than the maximum manufacturing capacity (+120%), the SC won't be profitable anymore (negative profit). Finally, the results of these experiments indicate that under all demand settings, the deterministic model selects the unreliable suppliers as the optimal decisions whereas, the 2SP selects the reliable ones in the first stage.

Table 3.7 compares the optimal objective value ("OBJ"), supplier assignment decisions, as well as $VSS\%$ obtained from the deterministic and 2SP models under different fixed supplier selection costs. All other parameters are set at their base level. The results indicate the consistency of the 2SP model in including the more reliable suppliers in the pool despite the increase in the fixed cost of signing contracts with them. The cost increase, as expected, does not force the deterministic model to select the more expensive category of reliable suppliers. The value of adopting a stochastic solution is, hence, following the fixed cost trend.

Instance	Fixed Cost	Deterministic			2SP					EDS					VSS %
		OBJ	Reliable	Unreliable	OBJ	First Stage Suppliers		Second Stage Suppliers		OBJ	First Stage Suppliers		Second Stage Suppliers		
						Reliable	Unreliable	Reliable	Unreliable		Reliable	Unreliable	Reliable	Unreliable	
1	+30%	354,787		✓	148,152	✓	✓			147,115		✓	✓		0.70%
2	+50%	354,787		✓	169,067	✓	✓			167,543		✓	✓		0.90%
3	+70%	354,787		✓	192,800	✓			✓	177,456		✓	✓		7.96%
4	+100%	354,787		✓	219,970	✓			✓	196,929		✓	✓		10.48%

Table 3.7: Sensitivity Analysis on Fixed Supplier Selection Cost

3.5.3 Performance Analysis of the SSH algorithm

In this section, larger problem instances of the 2SP-PBMN design model are solved with the aid of a commercial solver, whenever possible, and the proposed SSH algorithm. Table 3.8 summarizes the features of different families of instances in terms of the number of standard and customizable sub-assemblies and components. We consider one final product and three potential producers/suppliers per MOB item across all instances. The size of these instances is realistic enough within the motivational context of this study (customized optical devices). As can be observed in this table, by increasing the number of customizable items in the BOM, the number of TCM scenarios and consequently, the number of binary variables in the corresponding 2SP model grows exponentially. Table 3.9 summarizes the results of applying this algorithm on 5 problem instances in each family, distinguished by the scenario set generated by the SSH algorithm. The 2SP models corresponding to all problem instances, except for the last group, incorporate all TCM scenarios and are solved by a commercial solver (CPLEX), and the optimal objective value ("OBJ") and CPU time are reported under the "2SP Results" column. Solving the last group of problem instances by an off-the-shelf solver is not possible due to the very large number of binary variables. It is noteworthy that these difficult instances correspond to extreme cases where six items in the BOM are featured with very complex design specifications. This is justified by the fact that the sub-assemblies in the BOM could represent complex modules of advanced optical devices, such as tunable lasers, and sensors, that are typically outsourced, and suppliers' failure is more prevalent for extremely complex product modules.

All problem instances are also solved by the SSH algorithm by considering sample sizes equal to 50 and 100 for families 1 to 3 and 500 for family 4 for 5 independent samples. The CPU time does not exceed a few seconds for solving these instances. The objective function values ("OBJ") of the five instances are reported under the "SSH Results" column for 50 scenarios. It is worth mentioning that increasing the sample size from 50 to 100 has a negligible impact on the Mean values. Moreover, the SD of objective values among the 5 batches of scenario samples is small enough (less than 1% of the average). Therefore, 50 seems to be a reasonable sample size for these problem instances. Column ("GAP") represents the optimality gap, i.e., the difference between the objective function of the 2SP model (by considering all scenarios) and the average objective value across the 5 instances of SSH results. The average VSS value and % across the five sample batches are also reported in this table. Due to the computational challenge of estimating EDS for the last group of instances under all scenarios, the VSS has been approximated by solving the 2SP model with 1000 scenarios after fixing the first-stage decisions by their optimal value from the deterministic model.

Family	# of Sub-assembly ($\|N\|$)		# of Component ($\|M\|$)		# of Scenarios	# of Binary Decision Variables
	Standard ($\|N^s\|$)	Customizable ($\|N^c\|$)	Standard ($\|M^s\|$)	Customizable ($\|M^c\|$)		
1	1	1	2	2	64	29,126
2	1	2	2	2	256	45,632
3	1	2	1	3	1024	72,836
4	1	3	2	3	4096	101,144

Table 3.8: Description of Problem Family Instance

Family	Instance	2SP Results		SSH Results	Gap	VSS	
		OBJ	CPU TIME (s)	OBJ		VSS Value	VSS%
1	1	$ 1,827,100	10	$ 1,683,936	7.22 %	$ 92,674	5.47 %
	2			$ 1,712,718			
	3			$ 1,691,018			
	4			$ 1,697,034			
	5			$ 1,690,671			
2	1	$ 3,215,723	74	$ 3,114,108	2.95 %	$ 54,449	1.74 %
	2			$ 3,131,209			
	3			$ 3,135,295			
	4			$ 3,114,122			
	5			$ 3,110,421			
3	1	$ 2,667,114	300	$ 2,454,337	7.9 %	$ 155,458	6.33 %
	2			$ 2,463,821			
	3			$ 2,456,242			
	4			$ 2,436,411			
	5			$ 2,472,201			
4	1	NA	NA	$ 7,003,836	*	$ 49,250	0.7 %
	2			$ 7,004,756			
	3			$ 7,016,836			
	4			$ 7,017,342			
	5			$ 7,005,017			

Table 3.9: Performance Analysis of the SSH Algorithm

The results indicate that approximating the original 2SP model by considering a very small sample size provides optimal first-stage solutions. This significant advantage is mainly attributed to the effectiveness of the proposed scenario generation procedure within the SSH framework which serves as an alternative to Monte Carlo sampling. Nonetheless, the reported optimality gaps (% Gap) (average of 6% across the 3 instances) reflect the difference between the expected second-stage revenues/costs calculated by the commercial solver and SSH. As expected, the conservative scenario generation approach adopted in SSH assigns high probabilities to the worst-case scenarios. Therefore, the expected profit estimated by this algorithm underestimates the profit of the network. In the same vein, the VSS is also underestimated for the last family of instances when considering 1000 scenarios among the full scenario set when estimating the EDS. Nonetheless, the results of all instances highlight the advantages of the 2SP model when it comes to the selection of primary SC partners as compared with a deterministic model that invariably prioritizes cheaper producers/suppliers despite being less reliable.

Monte-Carlo simulation experiments are conducted to highlight the underestimation of expected profit in the SSH approach. By using the same scenario generation technique adopted in this algorithm, a significantly larger scenario set (e.g., 1000 as compared to 50 used by SSH) is generated to obtain a more realistic estimation of the expected profit in the 2SP model. Afterward, the choice of primary suppliers determined by the SSH algorithm is fixed in the 2SP model, corresponding to the randomly generated scenarios, and the expected profit is calculated. Table 3.10 summarizes the average expected profit obtained from the simulation experiments across the 4 problem instances. For problem instance families 1 to 3, the expected profit is calculated by considering the full scenario set. For the last group (4), solving the 2SP model for all scenarios is not possible; hence, we solve the 2SP model for 1000 scenarios. The CPU times for calculating the expected profit in the simulation runs are also reported. In addition, the (relative) gap between the simulation results and the optimal objective function value of the 2SP model is reported for family instances

1 to 3 under the "GAP%" column. The negligible gaps across these instances demonstrate that the SSH algorithm provides optimal first-stage and almost optimal second-stage (recourse) decisions by only considering a small scenario sample. This is mainly attributed to the effectiveness of the proposed scenario generation approach within this algorithm. For the largest instances, this gap is calculated as the relative difference between the simulation results and the expected profit reported by the SSH Algorithm in Table 3.9. This positive gap for the largest problem instances further reveals the conservative (pessimistic) estimation of profit by the SSH algorithm.

Instance	Simulation Results		
Family	Expected Profit	CPU TIME (s)	GAP%
1	1,827,143	2	0.0024
2	3,215,822	40	0.0031
3	2,667,702	210	0.0220
4	7,069,317	93	0.84*

Table 3.10: Monte-Carlo Simulation Results

3.5.4 Managerial Insights

The numerical experiments conducted in this study demonstrate the significance of incorporating uncertain technological capabilities of suppliers for manufacturing highly customized modules when designing a PBMN. This is more critical when the main company offers individualized designs with high complexity levels and the manufacturing of some key intricate modules is outsourced to external producers. The superiority of the proposed stochastic PBMN design model versus a deterministic one is mainly attributed to the incorporation of random suppliers' failure in the model and considering the possibility of resorting to backup suppliers and/or open markets as corrective actions. Specifically, as confirmed by the sensitivity analysis, the suggested decision framework is most effective in situations where the network capacity is slightly higher than the demand. In this context, the R&D and technological resources of the sub-assembly producers and component suppliers must be considered as the primary factors for entering into a contract with them. In other words, the manufacturing cost should play a secondary role in choosing SC partners. Relatedly, our results demonstrated the high sensitivity of the proposed model to the failure probability of suppliers. Therefore, exploring advanced analytics approaches, such as machine learning and deep learning algorithms would be a promising path to accurately predict suppliers' technical limitations and/or estimate a more precise probability for such undesirable events. Finally, identifying a set of best-in-class manufacturers and initiating collaboration with them as the backup suppliers via establishing an efficient supplier development program would be utterly crucial.

3.6 Concluding remarks

In this study, we developed a two-stage stochastic mixed-integer-programming model for the design of a PBMN designated for the manufacturing of highly customized products with heterogeneous individualized design intricacy levels and various delivery speeds. To the best of our knowledge, the proposed model is among the first that explicitly addresses the unpredictable manufacturing capabilities of entities in different echelons of the network when responding to the highest degree of complexity in product features. More specifically, it seeks the optimal pool of primary and backup suppliers, producers, and logistics carriers in a platform-based value chain to maximize the expected profit under a scenario set plausible to uncertain suppliers' failure. One of the main differences between this model with its deterministic counterpart revolves around providing various corrective actions when the main suppliers fail to manufacture customized items due to technological limitations. Emergency orders to back up suppliers and resorting to open markets, if available, are among such recourse actions. The proposed decision framework, thus, provides flexibility in terms of choosing producers and logistics carriers. This could ultimately lead to significant cost and time savings in the value chains when confronting suppliers' failure in producing items with intricate design features.

We further established a procedure for generating benchmark test instances of the problem that could serve as a testbed for its future extensions. To overcome the computational complexity of the model, we also developed a scenario sampling heuristic that can efficiently solve large-scale problem instances. Our numerical experiments, conducted in a Monte-Carlo simulation scheme, highlighted the advantages of the proposed decision model and solution algorithm over a deterministic approach across various problem settings.

Our computational experiments have provided valuable insights into the benefits of incorporating uncertain suppliers' defaults into the PBMN design problem. In particular, this model gives priority to the most reliable suppliers as the primary entities even though they have higher manufacturing costs. As a result, the expected cost of corrective actions in the presence of unfavorable scenarios in this model is significantly lower as compared with a deterministic model that designates cheaper, but less reliable suppliers. Therefore, the proposed stochastic decision framework can potentially address the concerns regarding the cost and time associated with changing producers in an SC. From a methodological perspective, the proposed scenario-generation procedure, embedded within the heuristic, proves to be quite effective in terms of identifying the most reliable suppliers in the pool and ultimately enhancing the network resilience under extreme suppliers' failure scenarios.

This study has the potential for extension from different perspectives. Notably, decomposition-based algorithms could be developed to overcome the computational complexity of the proposed decision model in the context of manufacturing custom products with complex BOMs. Furthermore, the model can be extended to a dynamic decision framework for the design of manufacturing platforms where the composition of suppliers in different echelons needs to be dynamically reconfigured as a response to the ongoing flow of individualized orders with unique features and BOM structures. In addition, other uncertain factors such as suppliers' capacity and manufacturing lead time could be also encapsulated into the network design model. Finally, exploring the state-of-the-art artificial intelligence algorithms to accurately estimate suppliers' failure is another interesting avenue of research.

Chapter 4

Adjustable Robust Optimization for the Design of a Manufacturing Netwrok for Mass Customization

Abstract

Motivated by the growing interest in customized manufacturing in the high-tech sector, this study investigates the design of a multi-echelon manufacturing network that integrates the uncertain production rate (and capacity) of external suppliers in manufacturing intricate product modules. An adjustable robust optimization (ARO) model is established based on an uncertainty budget that determines the optimal choice of suppliers, in addition to their order quantities such that the profit under worst-case scenarios in terms of suppliers' capacities is maximized. A scenario sampling approach is adopted to approximate the nonlinear ARO model into a linear mixed-integer-program (MIP). In addition, a math-heuristic algorithm is developed to overcome the computational complexity of the MIP model when considering multiple products with several customizable modules. Our numerical experiments showcase the effectiveness of the proposed decision framework in establishing a robust network configuration that is protected against suppliers' capacity fluctuations. Furthermore, the results emphasize the efficiency of the proposed math-heuristic in solving large-scale problem instances.

4.1 Introduction

In today's dynamic and fast-evolving markets, customers increasingly demand products tailored to their unique preferences and requirements. As a result, the need for highly specialized and customized manufacturing has seen consistent growth (Pallant et al., 2020). This trend is especially evident in advanced technology industries such as robotics, satellite communication systems, biomedical instrumentation, and precision measurement tools. These products often require significant investment in Research and Development (R&D) and involve sophisticated manufacturing techniques, despite typically being produced in small quantities. For example, the development of dental scanners (Mangano, Gandolfi, Luongo, & Logozzo, 2017) demands cross-disciplinary expertise in precision optics, sensitive electronics, and user-centric software. While a foundational architecture exists, each scanner must be customized in terms of scan resolution, interface design, integration with CAD/CAM systems, and more. The combination of low production volume and technical complexity substantially increases manufacturing costs and lead time. To manage these challenges, companies often delegate the fabrication of complex components (e.g., inertial sensors, lasers, etc.) to specialized suppliers, while retaining control of core integration, final assembly, and quality testing to meet stringent performance and regulatory standards.

Outsourcing R&D and manufacturing tasks to external companies presents its own set of challenges—the most notable being the volatile capacity of suppliers in delivering highly customized components depending on the complexity of design requirements. In this context, the sustained competitiveness of the custom manufacturing sector hinges on the development of a resilient manufacturing network that is cost-effective and adaptable. This is essential for achieving shorter lead times and improved product quality at a controlled cost. Above all, the ability to identify and collaborate with dependable suppliers—those capable of managing intricate designs and delivering tailored solutions—is critical to maintaining the operational and financial sustainability of such high-mix, low-volume industries.

Although demand for highly customized manufacturing continues to grow, research aimed at developing decision-support tools tailored to the unique challenges of this sector remains relatively scarce. This study seeks to address that gap by developing a robust decision model for the design of a multi-echelon manufacturing network that produces modular customizable high-tech products with standard and customizable components, while resilient to the uncertain production capacity of external suppliers, particularly in delivering sophisticated, custom-built components.

Our first contribution revolves around the formulation of the above-mentioned network design problem as an adjustable robust optimization (ARO) model. This model integrates an interval-based uncertainty set with an uncertainty budget to capture production rate uncertainty (capacity consumption) due to supplier technological variability and BOM complexity. It further optimizes supplier and producer selection, production and procurement quantities, and lost sales to maximize profit under the worst-case outcomes of uncertainty. By incorporating a piecewise linear cost function to model economies of scale and employing a two-stage framework, the model determines the strategic choice of suppliers before uncertainty realization and adjusts the order quantities and lost sales based on the worst-case suppliers' performance outcomes within the uncertainty set, ensuring a resilient and cost-efficient manufacturing network. It is noteworthy that the two-stage framework aligns with practical decision-making environments, where commitments to external partners are often established under incomplete information regarding their operational capabilities. Subsequent operational decisions are then made once the true characteristics of resource requirements are disclosed. In addition, the ARO approach ensures the feasibility of the network configuration by explicitly accounting for suppliers' capacity constraints under uncertainty.

Our second contribution is centered on the development of a computationally efficient solution methodology to address the complexity of the ARO model. A scenario sampling approach is adopted to approximate the nonlinear ARO model into a linear mixed-integer-program (MIP). Additionally, we propose a math-heuristic algorithm that fixes the binary variables in the MIP model and solves the resulting linear programming (LP) subproblem using a commercial solver. The algorithm operates in two phases: first, it constructs an initial feasible solution and a lower bound (LB) for the original MIP model using a greedy heuristic; second, it improves the quality of the initial LB through a local search (LS) heuristic - an approach that has been proved significantly efficient in enhancing the performance of math-heuristics (see, e.g., Borreguero Sanchidrián et al. (2024); Lu, Zhang, Kong, and Fathollahi-Fard (2025); Mischek and Musliu (2021)).

We also conduct extensive numerical experiments to investigate the performance of the ARO model across a variety of scenarios and uncertainty budgets, highlighting its effectiveness in mitigating the risks associated with supplier performance inconsistencies within the network. The advantage of robustness is further illustrated through Monte Carlo simulation experiments, where we compare the outcomes of the robust and deterministic models across a broad spectrum of uncertainty realizations. Finally, we assess the scalability and computational efficiency of the proposed math-heuristic algorithm, demonstrating its capability to solve large-scale instances that are otherwise intractable for commercial solvers.

The remainder of the paper is organized as follows. Section 4.2 reviews the recent literature relevant to this study. Section 4.3 briefly describes the fundamentals of the ARO approach. Section 4.4 details the problem definition, uncertainty modeling, and mathematical formulation. Section 4.5 describes the solution methodology, including the math-heuristic algorithm. Section 4.6 presents computational experiments. Finally, the concluding section summarizes our findings and discusses the practical implications of the proposed robust network design framework.

4.2 Literature Review

In this section, we first provide a brief review of recent studies on the design of manufacturing networks and highlight their shortcomings in addressing the challenges of producing intricate customized products. Afterward, we briefly review several applications of ARO approach in supply chain planning problems.

Mass production, focused on standardized high-volume production, has been extensively studied since the 1990s, establishing well-founded manufacturing network design (MND) frameworks aimed at network configuration, cost minimization, and performance optimization Beamon (1998); Fattahi, Mahootchi, and Moattar Husseini (2016); Garcia and You (2015); Sha and Che (2006). Over time, these foundational models have been extended to incorporate uncertainty, with a predominant focus on supply and demand variations Dong, Zhang, Yan, and Nagurney (2005); Jeihoonian, Zanjani, and Gendreau (2017); Rezaee, Dehghanian, Fahimnia, and Beamon (2017); Zanjani, Bajgiran, and Nourelfath (2016). The challenges of MND in the context of mass customization (MC) Da Silveira, Borenstein, and Fogliatto (2001), on the contrary, have been only investigated in a handful of studies. In the MC paradigm that introduces dynamic customer design inputs, resulting in complex, customizable BOM structures, the studies in Baud-Lavigne, Bassetto, and Agard (2016); Nepal, Monplaisir, and Famuyiwa (2012) are among the first that address MND by matching product architectures with supply chain (SC) configurations for customizable products. Inman and Blumenfeld (2014) discuss the impact of product design complexity on SC disruptions and delays. The authors develop models for estimating the SC reliability based on the availability of components in the BOM of complex products. The challenges of designing the manufacturing network that incorporates uncertain suppliers' failure in producing complex modules have not been investigated in this study. Changbai Tan and Freiheit (2022) develop an integrated optimization framework that combines the selection of manufacturing processes and suppliers into the architectural design of personalized products. By assuming that all product modules are manufactured in-house, this study does not address the optimal configuration of the SC when some complex, customized modules are outsourced to external producers with limited technological resources. Katoozian and Zanjani (2022) developed a supply network design model focusing on supplier selection for the manufacturing of modular products that can be customized at different design complexity levels. Although this study has included several complicating aspects of MC, it does not explicitly address the uncertainty associated with the fluctuating capacity of external suppliers in the delivery of complex custom-made modules.

Robust optimization (RO) approach Bertsimas et al. (2011); Bertsimas and Sim (2004) has garnered significant attention in incorporating uncertainty into optimization models due to its ability to generate solutions that remain feasible under worst-case scenarios, thus ensuring performance even when key parameters such as cost, demand, or supply reliability deviate from their nominal values. This approach has been also explored to manage uncertainties in SC design problems (see, e.g., Pishvaee et al. (2011); Prakash, Kumar, Soni, Jain, and Rathore (2020); Zokaee, Jabbarzadeh, Fahimnia, and Sadjadi (2017)). However, static RO models often produce overly conservative solutions, limiting their adaptability in dynamic environments Bertsimas et al. (2011). ARO, on the contrary, addresses these limitations by employing a two-stage framework, where strategic decisions are fixed before uncertainty realization, and tactical adjustments adapt to revealed conditions Ben-Tal et al. (2004). This method has been applied in several network design problems (see, e.g., Kafiabad, Zanjani, and Nourelfath (2022); Zeng and Zhao (2013)). Although effective in reducing the degree of conservatism of the decision models, this approach suffers from significant computational challenges, specifically when dealing with MIP models. Several exact and heuristic algorithms have been proposed in the literature to overcome this drawback Bertsimas, Litvinov, Sun, Zhao, and Zheng (2012); Gabrel, Murat, and Thiele (2014); Kafiabad et al. (2022).

Despite some recent advances in supply chain design for MC, significant gaps persist in addressing uncertain technological limitations of external suppliers that impact their capacity for manufacturing complex, customized product modules. This study aims to fill this gap by proposing a novel ARO model, relying on an interval-based uncertainty set moderated by an uncertainty budget, that facilitates a robust supplier selection to mitigate their capacity variability.

4.3 Adjustable Robust Optimization

The adjustable robust optimization (ARO) approach Zeng and Zhao (2013) relies on determining the optimal first-stage (here-and-now) decisions such that the cost of second-stage decisions under worst-case scenarios within a given uncertainty set/budget is minimized. First-stage decisions are established prior to the realization of uncertain parameters, whereas second-stage decisions are executed with complete awareness of uncertainty outcomes. Let x and y represent the first-stage and second-stage decision variables, respectively, and let Ω signify the uncertainty set. An ARO model in a general form can be formulated as follows:

$$U(x,y) = \min_{x} c^T x + \max_{\omega \in \Omega} \min_{y \in F(x,\omega)} b^T y \tag{4.1}$$

$$\text{s.t.} \quad Ax \geq d, \quad x \in P_x \tag{4.2}$$

where $F(x,\omega) = \{y \in P_y : Gy \geq h - Ex - M\omega\}$ with $P_y \subseteq \mathbb{R}_+^{m''}$ and $P_x \subseteq \mathbb{R}_+^{m'}$.

The model defined by (4.1)-(4.2) constitutes a nonlinear program that integrates a max-min term associated with the second-stage problem in the objective function. Two types of methodologies have been proposed in the literature to reduce the computational complexity linked to this category of models. The initial technique involves representing the second-stage decision variables as affine functions of uncertain parameters, followed by the resolution of the ARO model as illustrated in Bertsimas et al. (2011). The alternative approach reformulates model (4.1)–(4.2) into a bi-linear programming model by discretizing the original uncertainty set into a scenario set. Benders-dual cutting plane Bertsimas et al. (2012); Gabrel, Lacroix, Murat, and Remli (2014) and column-and-constraint generation (Zeng and Zhao (2013)) algorithms have been widely accepted methods proposed for the efficient resolution of the resulting bi-linear model.

Although effective for addressing specific categories of RO models, the aforementioned algorithms rely on the dual of the second-stage decisions across separate iterations; therefore, they are not applicable for solving ARO models that include binary and/or integer second-stage variables. Considering that the uncertainty set Ω comprises a finite number of scenarios, another alternative could be accounting for all such scenarios. Nevertheless, this would significantly increase the complexity of the associated ARO model. As a result, some studies (e.g., Kafiabad et al. (2022)) propose to approximate this model by examining a subset of scenarios, randomly selected from the uncertainty set Ω. This equates to loosening restrictions related to situations excluded from the chosen sample, thus offering a legitimate relaxation (and, subsequently, a lower bound) of the optimal objective value of the original ARO model. By using ω_s as a potential result of the uncertain parameter in scenario s, model (4.1)–(4.2) can be approximated as a MIP as follows:

$$\hat{U}(x, y_s, \theta) : \min_x c^T x + \theta \tag{4.3}$$

s.t.

$$Ax \geq d \tag{4.4}$$

$$\theta \geq b^T y_s, \quad s = 1, \ldots, p \tag{4.5}$$

$$Ex + Gy_s \geq h - M\omega_s, \quad s = 1, \ldots, p \tag{4.6}$$

$$x \in P_x, \quad y_s \in P_y \tag{4.7}$$

By introducing variable θ in the objective function that captures the maximum of $b^T y_s$ over all scenarios based on restrictions (4.5), the non-linear max-min term in (4.1) is linearized in models (4.3)– (4.7). Additionally, set $F(x, \omega)$ in (4.1) is clearly expressed as restrictions (4.6), where scenarios serve as indexes for the second-stage decision variables.

4.4 Problem Description and Formulation

In this section, we first present a comprehensive overview of the manufacturing network design (MND) problem under investigation, emphasizing the impact of supplier performance uncertainty on the on-time delivery of highly customized products. Subsequently, we introduce a framework for modeling the uncertainty in supplier performance, specifically focusing on variations in unit capacity consumption, which directly affects their ability to deliver custom-made parts by the delivery due dates. Finally, we present an ARO model for the MND problem.

4.4.1 Problem Description

This study focuses on the design of a multi-echelon manufacturing network that facilitates the production of highly customized, modular-structured products. The products are featured with a BOM encompassing both standard and custom components at different customization levels. The network consists of a main manufacturer, in charge of final assembly, and a pool of upstream semi-finished items producers and part suppliers. The MND problem under investigation seeks the optimal choice of upstream partners in addition to the optimal production quantities at different entities of the network. The primary goal is to maximize profit while ensuring the efficient and reliable fulfillment of customer demand. The non-homogeneity of the upstream partners in terms of technological capabilities, production rates/capacities, as well as cost structures critically impacts the choice of producers/suppliers for the main manufacturer.

Customizable parts in the BOM (e.g., advanced sensors) present unique challenges, as higher complexity levels demand advanced technologies, substantial research and development (R&D) efforts, and longer production cycles. These requirements increase variability in supplier performance and elevate production costs. To model these dynamics, the study employs a piecewise linear cost function. This cost structure captures economies of scale, where larger batch sizes benefit from reduced unit costs, while smaller, specialized orders incur higher costs due to inefficiencies in setup and resource utilization.

The variability in production rates for customizable parts, particularly at higher complexity levels adds further complexity to the MND problem. Facing technological constraints and/or extended R&D timelines required to produce intricate custom items, the producers in the network typically experience variable resource capacity consumption rates. The latter represents the amount of resource usage required by suppliers and producers to fulfill production demands, influenced by the complexity of products, resource availability, and operational constraints. Such variabilities could reduce the production capacity of producers and consequently lead to high lost sales. Therefore, a robust optimization framework would be a suitable modeling approach to control the lost sales and ensure the resilience of the manufacturing network under worst-case outcomes of uncertainty.

4.4.2 Modeling the Uncertainty

To address the variability inherent in the capacity consumption of customized items across different producers, this study adopts an interval-based approach for modeling the uncertainty. Let $\tilde{\beta}^c_{hni}$ and $\tilde{\gamma}^c_{kmi}$ denote the unit capacity consumption parameters for customizable sub-assemblies and components per item, complexity level, and producer/supplier, respectively. In a deterministic context, these parameters are assumed to be fixed and equal to the nominal values, $\bar{\beta}^c_{hni}$ and $\bar{\gamma}^c_{kmi}$. However, to account for their variability, a (positive) drift value for the capacity consumption per item, complexity level, and producer/supplier is considered as Δ_{hni}/Δ_{kmi}. Therefore, the uncertain capacity consumption factors can be modeled within predefined bounds as follows:

$$\tilde{\beta}^c_{hni} = \bar{\beta}^c_{hni} + \Delta_{hni}, \quad \tilde{\gamma}^c_{kmi} = \bar{\gamma}^c_{kmi} + \Delta_{kmi},$$

To avoid excessive conservatism, the budget of uncertainty Γ_{ni} and Γ_{mi} are introduced to control the number of producers or suppliers that can experience capacity consumption deviations per each customizable item and complexity level. The uncertainty set is therefore defined as:

$$\Omega_{\Gamma_{ni}\Gamma_{mi}} = \begin{Bmatrix} \tilde{\beta}^c_{hni} \in \mathbb{R}^+_0 := \bar{\beta}^c_{hni} + \zeta_{hni}\Delta_{hni}, \quad \tilde{\gamma}^c_{kmi} \in \mathbb{R}^+_0 := \bar{\gamma}^c_{kmi} + \rho_{kmi}\Delta_{kmi}, \\ \zeta_{hni}, \rho_{kmi} \in \{0,1\}, \quad \sum_{h \in H^c} \zeta_{hni} \leq \Gamma_{hni}, \quad \sum_{m \in M^c} \rho_{kmi} \leq \Gamma_{kmi}, \\ \forall n \in N^c, \forall h \in H^c, \forall m \in M^c, \forall k \in K^c \end{Bmatrix} \tag{4.8}$$

4.4.3 Adjustable Robust Optimization Model

We formulate the MND problem as an ARO model by leveraging the framework outlined in Section 4.3 and a sample of scenarios randomly generated from the uncertainty set $\Omega_{\Gamma_{ni}\Gamma_{mi}}$, defined in Section 4.4.1. As such, we define the first-stage decisions as the selection of suppliers (x_k) and producers (y_h). These decisions are established before the acknowledgment of uncertainty and remain constant in all scenarios within the uncertainty set. The second-stage decisions, comprised of production quantities ($q^j_{pi}(\omega)$, $q^j_{hni}(\omega)$), procurement quantities ($q^j_{kmi}(\omega)$), and lost sales ($w_{pi}(\omega)$), are established after the actual capacity of suppliers is revealed to the focal company. This division guarantees that the model maintains a balance between resilience in strategic choices and adaptability in tactical modifications. The objective function of this problem aims to maximize the profit under worst-case scenarios within the uncertainty set. This formulation ensures that decisions remain robust against the worst-case realizations of uncertain parameters, mitigating potential excessive lost sales. The ARO mathematical formulation of the MND problem under consideration is introduced in the next subsection, with the associated notations detailed in A.4.

Mathematical Formulation

The scenario-based ARO model is formulated as follows:

$$\text{maximize} \quad \nu \tag{4.9}$$

Subject to:

Worst-case Profit

$$\begin{aligned}\nu \leq & \sum_p \sum_i \sum_j S^j_{pi} q^j_{pi}(\omega) - \sum_p \sum_i \sum_j C_{pi} q^j_{pi}(\omega) - \sum_p \sum_i CL_{pi} w_{pi}(\omega) - \sum_h \sum_n C^s_{hn} q^s_{hn}(\omega) \\ & - \sum_h \sum_n \sum_i \sum_j C^j_{hni} q^{cj}_{hni}(\omega) - \sum_k \sum_m C^s_{km} q^s_{km}(\omega) - \sum_k \sum_m \sum_i \sum_j C^j_{kmi} q^{cj}_{kmi}(\omega) \\ & - \sum_h F_h y_h - \sum_k F_k x_k \qquad \forall \omega \in \Omega\end{aligned} \tag{4.10}$$

Demand Satisfaction Constraints

$$\sum_j q^j_{pi}(\omega) + w_{pi}(\omega) = D_{pi}, \quad \forall p \in P, \forall i \in I, \forall \omega \in \Omega \tag{4.11}$$

Capacity Constraints

$$\sum_j q^j_{pi}(\omega) \leq \frac{FC_{pi}}{\alpha_{pi}}, \quad \forall p \in P, \forall i \in I, \forall \omega \in \Omega \tag{4.12}$$

$$q^s_{hn}(\omega) \leq \frac{PC_{hn}}{\beta^s_{hn}} \theta^s_{hn} y_h, \quad \forall h \in H, \forall n \in N^s, \forall \omega \in \Omega \tag{4.13}$$

$$\sum_j q^c_{hni}(\omega) \leq \frac{PC_{hni}}{\beta^c_{hni}(\omega)} \theta^c_{hni} y_h, \quad \forall h \in H, \forall n \in N^c, \forall i \in I, \forall \omega \in \Omega \tag{4.14}$$

$$q^s_{km}(\omega) \leq \frac{SC_{km}}{\gamma^s_{km}} \sigma^s_{km} x_k, \quad \forall k \in K, \forall m \in M^s, \forall \omega \in \Omega \tag{4.15}$$

$$\sum_j q^c_{kmi}(\omega) \leq \frac{SC_{kmi}}{\gamma^c_{kmi}(\omega)} \sigma^c_{kmi} x_k, \quad \forall k \in K, \forall m \in M^c, \forall i \in I, \forall \omega \in \Omega \tag{4.16}$$

BOM Flow Conservation Constraints

$$\sum_h q^s_{hn}(\omega) = \sum_p \sum_i \sum_j \eta_{np} q^j_{pi}(\omega), \quad \forall n \in N^s, \forall \omega \in \Omega \tag{4.17}$$

$$\sum_h \sum_j q^{cj}_{hni}(\omega) = \sum_p \sum_j \eta_{np} q^j_{pi}(\omega), \quad \forall n \in N^c, \forall i \in I, \forall \omega \in \Omega \tag{4.18}$$

$$\begin{aligned} \sum_k q^s_{km}(\omega) = & \sum_h \sum_{n \in N^s_m} \lambda_{mn} q^s_{hn}(\omega) \\ & + \sum_h \sum_{n \in N^s_m} \sum_i \sum_j \lambda_{mn} q^{cj}_{hni}(\omega), \quad \forall m \in M^s, \forall \omega \in \Omega \end{aligned} \tag{4.19}$$

$$\sum_k \sum_j q^{cj}_{kmi}(\omega) = \sum_h \sum_{n \in N^c_m} \sum_j \lambda_{mn} q^{cj}_{hni}(\omega), \quad \forall m \in M^c, \forall i \in I, \forall \omega \in \Omega \tag{4.20}$$

Cost Linearization Constraints

$$q^j_{pi}(\omega) \leq L^j_{pi} z^j_{pi}(\omega), \quad \forall p \in P, \forall i \in I, \forall j \in J, \forall \omega \in \Omega \tag{4.21}$$

$$z^j_{pi}(\omega)(L^{j-1}_{pi} + 1) \leq q^j_{pi}(\omega), \quad \forall p \in P, \forall i \in I, \forall j \in J \setminus \{1\}, \forall \omega \in \Omega \tag{4.22}$$

$$\sum_j z^j_{pi}(\omega) = 1, \quad \forall p \in P, \forall i \in I, \forall \omega \in \Omega \tag{4.23}$$

$$q^{cj}_{hni}(\omega) \leq u^j_{hni}(\omega) L^j_{hni}, \quad \forall h \in H, \forall n \in N^c, \forall i \in I, \forall j \in J, \forall \omega \in \Omega \tag{4.24}$$

$$u^j_{hni}(\omega)(L^{j-1}_{hni} + 1) \leq q^{cj}_{hni}(\omega), \quad \forall h \in H, \forall n \in N^c, \forall i \in I, \forall j \in J \setminus \{1\}, \forall \omega \in \Omega \tag{4.25}$$

$$\sum_j u^j_{hni}(\omega) = 1, \quad \forall h \in H, \forall n \in N^c, \forall i \in I, \forall \omega \in \Omega \tag{4.26}$$

$$q_{kmi}^{cj}(\omega) \leq v_{kmi}^{j}(\omega)L_{kmi}^{j}, \quad \forall k \in K, \forall m \in M^c, \forall i \in I, \forall j \in J, \forall \omega \in \Omega \tag{4.27}$$

$$v_{kmi}^{j}(\omega)(L_{kmi}^{j-1}+1) \leq q_{kmi}^{cj}(\omega), \quad \forall k \in K, \forall m \in M^c, \forall i \in I, \forall j \in J \setminus \{1\}, \forall \omega \in \Omega \tag{4.28}$$

$$\sum_{j} v_{kmi}^{j}(\omega) = 1, \quad \forall k \in K, \forall m \in M^c, \forall i \in I, \forall \omega \in \Omega \tag{4.29}$$

Domain Constraints

$$\nu, q_{kmi}^{cj}(\omega), q_{km}^{s}(\omega), q_{hni}^{cj}(\omega), q_{hnl}^{s}(\omega), q_{pi}^{j}(\omega), w_{pi}^{j}(\omega) \geq 0,$$
$$\forall k \in K, \forall m \in M^c, \forall m \in M^S, \forall h \in H, \forall n \in N^c, \forall n \in N^S, \forall i \in I, \forall j \in J, \forall p \in P, \forall \omega \in \Omega \tag{4.30}$$

$$x_k, y_h, z_{pi}^{j}(\omega), u_{hni}^{j}(\omega), v_{kmi}^{j}(\omega) \in \{0,1\},$$
$$\forall k \in K, \forall h \in H, \forall p \in P, \forall i \in I, \forall j \in J, \forall n \in N^c, \forall m \in M^c, \forall \omega \in \Omega \tag{4.31}$$

The objective function (4.9) maximizes the worst-case profit. Constraints (4.10) define the profit across worst-case capacity consumption scenarios and incorporate revenue from selling final products while deducting costs associated with production, procurement, lost sales, and establishing contracts with external manufacturers. The demand satisfaction constraints (4.11) ensure that the total demand for each product and customization level is either met through production or recorded as lost sales.

Capacity constraints (4.12)–(4.16) impose limits on production and procurement quantities to ensure feasibility within the capacity of selected suppliers and manufacturers. Constraint (4.12) restricts the production of final products to their available manufacturing capacities. Constraint (4.13) applies capacity limits to standard sub-assemblies, while constraint (4.14) extends these restrictions to customizable sub-assemblies, explicitly incorporating uncertainty in the capacity consumption factor. Similarly, constraints (4.15) and (4.16) govern the procurement of standard and customizable components, respectively, ensuring that procurement remains feasible under all scenarios. The material flow conservation constraints (4.17)–(4.20) enforce consistency across the network. These constraints ensure that the production of sub-assemblies and procurement of components align with the requirements of final products, as defined in the BOM. Constraint (4.17) ensures sufficient production of standard sub-assemblies, while constraint (4.18) guarantees that customizable sub-assemblies meet the demand for final products. Constraints (4.19) and (4.20) regulate the procurement of standard and customizable components to maintain logical material flows. Cost linearization constraints (4.21)–(4.29) improve computational tractability by representing production and procurement costs as piece-wise-linear functions. Constraints (4.21)–(4.23) assign production quantities of final products to appropriate price intervals, reflecting economies of scale and capturing cost structure variations. Similarly, constraints (4.24)–(4.26) apply linearization to customizable sub-assemblies, and constraints (4.27)–(4.29) extend this logic to customizable components. Finally, (4.30) and (4.31) represent the domain constraints.

4.5 Math-Heuristic Algorithm

The ARO model (4.9)-(4.31) is a MIP model that includes two classes of binary variables corresponding to the network configuration (choice of suppliers/producers) and production volume intervals. Solving this model becomes challenging when considering a large pool of manufacturers in the network and a large scenario set for uncertain resource consumption factors. To tackle this computational complexity, a math-heuristic algorithm is proposed that revolves around fixing the above-mentioned binary variables and solving the remaining linear programming (LP) model by a commercial solver. More specifically, the algorithm includes two phases corresponding to constructing an initial feasible solution, and a lower bound (LB) to the original MIP model with the aid of a greedy heuristic, followed by enhancing the quality of the initial LB with the aid of a local search heuristic.

Phase 1: Constructing the Initial Feasible Solution. The objective of this phase is to construct an initial network configuration by systematically identifying a pool of producers/suppliers (x_k, y_h) for all items of the BOM, in addition to fixing the corresponding production volume interval (u^j_{hni}, v^j_{kmi}) for customizable items, while ensuring operational feasibility. To this end, the algorithm sorts the entities by ascending variable production cost. Considering that the standard items are featured with a fixed capacity consumption factor, the algorithm determines the minimum number of required entities by dividing the demand for items at different BOM levels over the average capacity of suppliers/producers. It then assigns the necessary entities to standard items starting from the highest-ranked item in the sorted list.

For customizable items, the algorithm initializes a set $\mathcal{U}$ for all customizable items and selects the cheapest entities to them from the sorted list. For the initial set of assigned entities, it then sets the production intervals to their maximum level and solves the resulting ARO model (an LP) by a commercial solver (e.g., CPLEX). If the model becomes infeasible, the algorithm commands the solver to identify the suppliers/producers whose production intervals cause violations of capacity constraints. The infeasibility is then resolved by reducing those intervals until a feasible solution is obtained. The list of assigned entities for customizable items is gradually expended by adding entities to the network for all items until the selected entities are assigned a production volume above a minimum threshold (τ). If adding the next entity results in an allocation below (τ), the algorithm fixes the pool to the previously selected feasible configuration and removes the corresponding item from $\mathcal{U}$. This continues until $\mathcal{U}$ is empty, ensuring all customizable items have received sufficient suppliers/producers.

The outcome of this phase is an initial feasible solution and an LB to the optimal objective value of ARO model. While this step fixes the size of the suppliers/producers pool for all items, the choice of entities within the pool is further refined in phase 2 to increase the LB.

Phase 2: Solution Refinement and Improvement. This step corresponds to a local search (LS) procedure within the vicinity of the initial feasible solution. The LS seeks alternative network configurations by randomly swapping suppliers from the available pool per customizable item while maintaining the size of the pool based on the outcome of phase 1. Similar to the previous phase, the local search is implemented per customizable item of BOM. After fixing the choice of suppliers and the production intervals, the remaining LP model is solved by a commercial solver. As such, the production volume intervals for the customizable items are also adjusted to maintain the feasibility of the new configuration. If the new configuration results in an improved objective value, it is recorded as the best-known feasible solution (and LB). For small and medium instances, the algorithm exhaustively evaluates all possible swaps of entities to guarantee optimality. For large instances, the process is terminated after a predefined number of iterations (T_{stop}) without improvement in the LB, striking a balance between computational efficiency and solution quality.

The pseudocode for the math-heuristic algorithm is presented in Algorithms 1 and 2, detailing the steps involved in both phases.

Algorithm 2 :Math-heuristic- Phase 2

1: **Input:** Stopping criterion (T^{stop}), LB= The objective function value obtained in Phase 1, Best solution=The solution obtained in Phase 1
2: Initialize $no\_improvement = 0$
3: **while** $no\_improvement < T^{\text{stop}}$ **do**
4:     **for** each customizable item n, m **do**
5:         Randomly select an entity from the pool of assigned suppliers/producers, and one from the pool of unassigned ones
6:         Swap the entities identified in step 5 and set the corresponding production intervals to the maximum level
7:         Solve the resulting ARO model by a commercial solver
8:         **while** infeasible **do**
9:             Identify the suppliers/producers, recently added to the pool that cause capacity violations, and reduce their production intervals by one level
10:             Resolve the ARO model by a commercial solver
11:         **end while**
12:         **if** objective value improves over the current LB **then**
13:             Update the pool of selected suppliers/producers accordingly
14:             Update LB and best solution
15:             $no\_improvement = 0$
16:         **else**
17:             $no\_improvement = no\_improvement + 1$
18:         **end if**
19:     **end for**
20: **end while**
21: **Output:** Best-known feasible solution

4.6 Numerical Experiments

In this section, we present the findings from a comprehensive series of numerical experiments conducted to evaluate the performance of the proposed ARO model and the efficiency of the math-heuristic algorithm. We begin by outlining the experimental setup, including the procedure for generating scenarios for the sample-based ARO model. In addition, we elaborate on the Monte-Carlo simulation framework adopted to analyze the out-of-sample performance of the ARO model and estimate the value of robustness in the MND problem under investigation. Subsequently, we analyze the performance of the ARO model under diverse scenarios and uncertainty budgets, emphasizing its ability to effectively address the risk of suppliers' performance inconsistencies in the network. The value of robustness is further demonstrated through Monte Carlo simulation experiments via comparing the performance of robust and deterministic models across a wide range of uncertainty realizations. Finally, we evaluate the scalability and computational efficiency of the math-heuristic algorithm, showcasing its ability to solve large-scale instances that are intractable for commercial solvers. All experiments are implemented in Python using the Callable Library of

Algorithm 1 :Math-heuristic - Phase 1

1: **Input:** Production Threshold (τ)
2: Sort all suppliers $h \in H$ for each $n \in N$ and producers $k \in K$ for each $m \in M$ by ascending variable production cost
3: Initialize the pool of selected suppliers and producers for standard items ($H_n = \emptyset$, $K_m = \emptyset$)
4: **for** each standard item $n \in M^s, m \in M^s$ **do**
5: Compute the demand at item level (D_n, D_m) based on BOM structure
6: Calculate the required number of suppliers/producers by dividing D_n, D_m over the average capacities of corresponding entities
7: Starting from the highest-ranked item on the sorted list in step 2, add the necessary suppliers/producers to sets H_n and K_n and fix the corresponding binary variables to 1 in the ARO model
8: **end for**
9: Initialize a set $U = \emptyset$ as the pool of selected suppliers/producers for all customizable items ($n \in M^c, m \in M^c$)
10: Add the cheapest supplier/producer from the list in step 2 to U for all customizable items and fix the corresponding binary variables to 1 in the ARO model
11: Set the production intervals to their maximum level for the suppliers/producers, selected in steps 7 and 10, and fix the corresponding binary variables to 1 in the ARO model
12: Solve the resulting ARO model (by a commercial solver) after fixing the binary variables in steps 7, 10, and 11
13: **while** infeasible **do**
14: Identify suppliers/producers causing capacity violations and reduce their production intervals by one level
15: Resolve the ARO model by a commercial solver
16: **end while**
17: **while** $U \neq \emptyset$ **do**
18: Add the next cheapest supplier to the selected pools for all items in U and fix the corresponding binary variables to 1 in the ARO model
19: Set corresponding production intervals to their maximum level and fix the associated binary variables to 1 in the ARO model
20: Solve the resulting ARO model (by a commercial solver) after fixing the binary variables in steps 18 and 19
21: **while** infeasible **do**
22: Identify the suppliers/producers, recently added to the pool that cause capacity violations, and reduce their production intervals by one level
23: Resolve the ARO model by a commercial solver
24: **end while**
25: **for** each item in U **do**
26: **if** t **then**he production quantities allocated to the most recent supplier/producer $< \tau$
27: Remove the entity and item from U
28: **end if**
29: **end for**
30: **end while**
31: **Output:** Initial LB and feasible solution

CPLEX 12.10 and executed on a Core i7 CPU 3.60 GHz server with 32 GB of RAM under Linux.

4.6.1 Data Generation and Experimental Settings

In the absence of benchmark instances in the literature, a systematic procedure is proposed to generate problem instances of varying sizes, ensuring realistic and meaningful optimal solutions. The generated instances vary in terms of the number of finished products ($|P|$), sub-assemblies ($|N|$), components ($|M|$), and producers/suppliers for each customization level of sub-assemblies/components ($|H|$ and $|K|$). To ensure general applicability, we consider two categories of suppliers, referred to as stable and volatile, distinguished by their production capacity, cost structure, and production rate uncertainty for customizable items. These differences are particularly relevant for highly customizable subassemblies/components, where the complexity of design and technological requirements is most pronounced. Stable suppliers are characterized by higher fixed and variable production costs, yet, they maintain consistent and reliable production rates (i.e., $1/\beta^c_{hni}$ and $1/\gamma^c_{kmi}$). In other words, their advanced R&D capabilities, coupled with sophisticated production systems, enable them to manufacture highly customized items with minimal variability on resource consumption factors. Volatile suppliers, in contrast, operate at lower fixed and variable costs but exhibit significant variability in production rates when producing highly customized items. In our numerical experiments, we specifically account for uncertain resource consumption factors (and production rates) for subassemblies/components with the highest level of design customization (level 3). However, the proposed MND model provides the possibility to consider production rate uncertainty for all customization levels.

Table 4.1 summarizes demand, capacity, price, and various unit cost categories for final products at different customization levels.

Table 4.1:Final Products Data Intervals

Parameter	**Customization Level**	**Interval**	**Parameter**	**Customization Level**	**Interval**
Demand	1–3	[300, 1500]	Production Cost	1–3	[200, 600]
Capacity	1–3	[1350, 2500]	Selling Price	1–3	[2000, 10000]
Lost Sale Cost	1–3	[3000, 8000]			

Tables 4.2 and 4.3 present the data intervals for the capacity and production costs of standard and customizable subassemblies and components, respectively.

Table 4.2:Standard Subassemblies and Components Data Intervals

Sub-assembly	**Interval**	**Component**	**Interval**
Variable Production Cost	[50, 150]	Variable Production Cost	[30, 100]
Fixed Cost	[1000, 3000]	Fixed Cost	[1000, 3000]

Table 4.3:Customizable Subassemblies and Components Data Intervals

	Sub-assembly	Complexity Level	Interval ($)	Components	Complexity Level	Interval ($)
Variable Production Cost	Volatile Producers	1	[50, 200]	Volatile Suppliers	1	[50, 100]
		2	[450, 600]		2	[200, 400]
		3	[850, 1000]		3	[500, 700]
	Stable Producers	1	[60, 240]	Stable Suppliers	1	[60, 120]
		2	[540, 720]		2	[240, 480]
		3	[1020, 1200]		3	[600, 840]
Fixed Cost	Volatile Producers	1	[1000, 1500]	Volatile Suppliers	1	[1000, 1500]
		2	[1500, 2000]		2	[2000, 3000]
		3	[2000, 3000]		3	[3000, 4000]
	Stable Producers	1	[1500, 2500]	Stable Suppliers	1	[2000, 3000]
		2	[2500, 3000]		2	[4000, 6000]
		3	[3000, 4500]		3	[6000, 8000]

Expanding on the parameter intervals provided in Tables 4.1 and 4.2, we consider the baseline (nominal) capacity consumption factor for each supplier equal to the complexity level of the parts being produced (i.e., levels 1, 2, and 3). To model the uncertainty, we consider a (positive) drift over the nominal capacity consumption factors. More specifically, stable suppliers are assumed to experience only minor fluctuations (+1 unit), while volatile ones are subject to larger deviations (+3 unit) when producing highly customizable items.

In all numerical experiments, we consider three categories of problem instances—small, medium, and large—each corresponding to varying sizes of manufacturing networks. Table 4.4 summarizes the structural characteristics of these instances, detailing the number of final products, subassemblies, components, and suppliers involved.

Table 4.4:Problem Sizes for Experimental Settings

Instance Size	**Final Products (Range)**	**Subassemblies (Total / Customizable)**	**Components (Total / Customizable)**	**Suppliers per Customizable Part**
Small	[2–4]	[4–8] / [2–4]	[8–10] / [4–5]	[6–8]
Medium	[4–8]	[8–10] / [4–5]	[10–20] / [5–10]	[8–10]
Large	[8–10]	[10–20] / [5–10]	[20–40] / [10–20]	[10–12]

Scenario Generation in the ARO model

Generating representative scenarios is a critical step in the proposed scenario-sampled ARO model to ensure the realistic modeling of suppliers' production rates within a given uncertainty budget and guarantee the robustness of manufacturing network configuration. Each scenario in the ARO model corresponds to one random realization of resource consumption factor drifts among the suppliers/producers of highly customized items. In addition, the uncertainty budget governs the proportion of entities that are going to be subject to resource consumption factor variability for producing such items under each scenario. To further guarantee the configuration robustness, when randomly selecting entities among the pool of suppliers/producers per custom item, the priority is given to volatile suppliers that experience higher drifts in capacity consumption factor. In our experiments, given a certain uncertainty budget Γ, 70% of suppliers that would randomly receive maximum drift are selected from the volatile category and only 30% are chosen from the stable group. For instance, in a pool of 10 suppliers with a budget $\Gamma = 50\%$, 5 out of 10 suppliers will be randomly assigned the maximum drift, among which, 3-4 are selected from the volatile category and 1-2 are from the stable ones.

Monte Carlo Simulation Framework

This section outlines a Monte Carlo simulation framework designed to compare the network configurations generated by the deterministic and ARO models under randomly generated scenarios corresponding to suppliers' capacity consumption variations for producing custom items with intricate design features. The primary objective is to compare the robustness of these network structures in terms of the expected profit under uncertain suppliers' performance.

The simulation process receives the optimal network configuration decisions (x_k, y_h) determined by the deterministic and ARO models as the inputs. Next, it fixes these variables in the ARO model, based on these inputs, and solves it by considering one scenario for suppliers' capacity consumption factors, randomly generated from the uncertainty set, defined in section 4.4.2. The optimal profit is then recorded for each scenario and model (deterministic/ARO). This Procedure is repeated for a large number of replications ($M = 1000$) and the expected profit of both models is calculated. The value of robust solution (VRS) is then estimated as the difference between the expected profit of network configurations determined by the ARO and deterministic models. Algorithm 3 outlines the detailed simulation procedure.

Algorithm 3 :Monte Carlo Simulation Framework

1: **Step 1:** Solve the deterministic model to obtain first-stage decision variables (x_k, y_h).
2: **Step 2:** Solve the ARO model, formulated based on a randomly generated scenario set (e.g., $N = 100$) and obtain the first-stage decision variables (x_k, y_h).
3: **Step 3:** Generate $M = 1000$ random capacity consumption scenarios ($M \gg N$) from the uncertainty set, defined in Section 4.4.2.
4: **for** each scenario $m \in \{1, \ldots, M\}$ **do**
5: **Step 4:** Fix the deterministic model's first-stage decisions and solve for second-stage decisions under scenario m to obtain the objective function value (f^m_{det}).
6: **Step 5:** Fix the robust optimization model's first-stage decisions and solve for second-stage decisions under scenario m to obtain the objective function value (f^m_{ro}).
7: **end for**
8: **Step 6:** Calculate the VRS based on the average objective function values obtained from steps 4 and 5 over all M scenarios:
9: $VRS = \mathbb{E}[f_{\text{ro}}] - \mathbb{E}[f_{\text{det}}]$

Math-heuristic Parameter Tuning

To optimize the performance of the proposed math-heuristic algorithm, we tuned two critical parameters: the minimum production allocation threshold (τ) in Phase 1 and the iteration limit for local search termination (T_{stop}) in Phase 2. We set $\tau = 10$ units for all customizable items, determined through preliminary experiments to ensure sufficient supplier/producer allocations while avoiding trivial assignments. It is worth noting that considering higher values (e.g., 15 units) restricts supplier selection in small instances while adopting lower values (e.g., 5 units) yields suboptimal solutions. We also set T_{stop} to 15 to balance exploration and efficiency. These settings ensure scalability across different families of problem instances.

4.6.2 Performance Analysis of ARO Model

This section provides an in-depth evaluation of the proposed robust optimization model, beginning with the analysis of its performance under different scenario sample sizes. This is followed by the comparison of network configuration (choice of suppliers) determined by the deterministic and ARO models. The first analysis examines how different scenario sizes influence the performance of the ARO model. Table 4.5 presents the results for medium-sized instances with scenario sample sizes of N =50, 100, 200. The scenarios are generated using the approach described in the section 4.6.1 by considering 70% budget of uncertainty. Generally speaking, increasing N improves the robustness of the solutions by capturing a wider range of uncertainty realizations. However, larger scenario sizes also significantly increase the CPU time required to solve the model. Considering that the difference between optimal objective value under $N = 100$ and $N = 200$ is negligible, $N = 100$ would be a computationally efficient and effective choice for subsequent evaluations. It is noteworthy that similar behavior is observed in the ARO model when considering other budgets of uncertainty.

Table 4.5: Results of ARO Model for Different Scenario Sample Sizes

Number of Scenarios (N)	**Objective Value (M$)**	**CPU Time (Minutes)**
Deterministic	$4.765	few seconds
50	$4.334	1.5
100	$4.248	8.3
200	$4.220	43.0

To further demonstrate the advantages of ARO model over a deterministic one, the optimal choice of producers/suppliers determined by these models are compared for medium- and large-sized problem instances under a 70% uncertainty budget, as summarized in Table 4.6. The results show that the robust model strategically diversifies supplier selection across stable and volatile categories by leveraging the uncertainty budget, while the deterministic model relies entirely on volatile suppliers. More specifically, in large problem instances, 70% of the suppliers selected by the robust model belong to the stable category, compared to none in the deterministic model. This demonstrates the robust model's adaptability in managing variability in terms of entities' capacity consumption factor when manufacturing highly customized items. This diversification is less pronounced in medium-sized instances due to the smaller number of customizable parts.

Table 4.6:Supplier Selection Comparison between Deterministic and Robust Models

Instance Size	**Entity**	**Entity Category**	**Deterministic Model**	**ARO Model** ($N = 100$)
Medium	Producers (Sub-Assemblies)	Stable	0	3
		Volatile	4	1
	Suppliers (Components)	Stable	0	5
		Volatile	9	4
Large	Producers (Sub-Assemblies)	Stable	0	7
		Volatile	5	5
	Suppliers (Components)	Stable	0	10
		Volatile	15	5

4.6.3 The Value of Robustness

In this section, we analyze the out-of-sample performance of ARO model through Monte Carlo simulation experiments. More precisely, we showcase the value of robust network configuration determined by the ARO model when compared with a deterministic approach. Comparing the profits reported by the deterministic and ARO models (Table4.5), the former may appear, at first glance, to perform better. However, this comparison is not entirely fair, as the deterministic model assumes nominal resource consumption factors and does not account for variability. In contrast, the robust model incorporates worst-case scenarios (under an uncertainty budget), making its objective inherently different. To provide a more balanced evaluation, the out-of-sample performance of both models is compared with the aid of Monte Carlo simulation framework described in Algorithm 3. The results, presented in Table 4.7 under different uncertainty budgets, highlight that the robust model consistently achieves higher and more stable expected profits across all instances, demonstrating its adaptability and effectiveness in managing uncertainties. Additionally, the column VRS (%) in Table 4.7 corresponds to the value of robust solution (VRS) that quantifies the (relative) profit improvement achieved by the robust model over the deterministic one. For instance, under a 50% uncertainty budget for large-sized instances, the robust model delivers a 29% improvement in expected profit compared to the deterministic model. The VRS is more significant at 70% uncertainty budget, emphasizing the important role of uncertainty budget in protecting the network configuration under worst-case uncertainty outcomes. These results underscore the robust model's ability to mitigate the impact of variability and ensure more reliable decision-making under uncertain conditions.

Table 4.7:Out-of-Sample Performance of Deterministic and Robust Models

Instance Size	Budget of Uncertainty	Expected Profit (Deterministic Model (M$))	Expected Profit (Robust Model (M$))	VRS (%)
Medium	50%	$4.00	$4.80	20%
Medium	70%	$3.70	$4.75	28%
Large	50%	$6.50	$8.40	29%
Large	70%	$5.80	$8.35	44%

The superior performance of the ARO model is attributed to the high quality of network configuration (in terms of pool of suppliers) set by this model that are designed to ensure resilience against production rate variability for highly customized items. In particular, by considering the entire uncertainty set rather than a single realization, the robust model demonstrates adaptability and effectiveness across various random outcomes. Therefore, suppliers are selected among stable and volatile categories, ensuring a balanced and reliable network configuration.

To further analyze the stability of the network structure determined by the ARO model under out-of-sample scenarios, Table 4.8 presents the average and standard deviation (SD%) of expected profits across five independent Monte Carlo simulation batches (each consisting 1000 scenarios). The results show minimal variability in expected profits for both medium-sized and large-sized instances, with standard deviations of 0.73% and 0.58%, respectively. This reflects the robust model's ability to consistently deliver stable solutions, even under diverse uncertainty realizations.

Table 4.8:Expected Profits Across Different Simulation Batches ($M = 1000$, $Gamma$ = 70%)

Instance Size	Batch 1 (M$)	Batch 2 (M$)	Batch 3 (M$)	Batch 4 (M$)	Batch 5 (M$)	SD (%)
Medium	4.23	4.31	4.24	4.32	4.29	0.73%
Large	8.21	8.29	8.25	8.30	8.27	0.58%

4.6.4 Performance of the Math-Heuristic Algorithm

The performance of the proposed math-heuristic algorithm is evaluated across three categories of problem instances, including small, medium, and large. Moreover, ten problem instances have been randomly generated under each category. The evaluation focuses on solution quality, computational efficiency, and scalability. Small and medium-sized instances are particularly important for analyzing the algorithm's performance, as they allow comparisons with a commercial solver. Large instances, on the other hand, are used to demonstrate the scalability and practicality of the heuristic under computationally challenging conditions. All problem instances in this section are solved by considering the uncertainty budget of 70% that represents a balanced level of conservatism in practice.

The results for small problem instances are summarized in Table 4.9 where "# iterations" and "Optimality Gap (%)" columns, respectively represent the number of local search iterations in the math-heuristic and the objective function gap between the solution of math-heuristic and a commercial solver. These instances, being solvable by a commercial solver (CPLEX) by considering 0.1% optimality gap, provide a basis for evaluating the quality and efficiency of the math-heuristic. According to these results, the math-heuristic achieves near-optimal solutions, with an average optimality gap of 1.9%. Furthermore, it demonstrates an average computational time improvement of 20% compared to the commercial solver. These findings confirm the efficiency of the proposed algorithm in solving small-scale problems while maintaining high solution quality. Additionally, the minimal variability in performance across instances highlights its robustness.

Table 4.9:Math-heuristic Performance Results for Small Instances

Instance	CPLEX Obj (M$)	CPLEX CPU Time (s)	Math-Heuristic Obj (M$)	Math-Heuristic CPU Time (s)	# Iterations	Optimality Gap (%)	CPU Time Improvement (%)
Small 1	2.87	151.95	2.78	116.15	20	3.23	23.59
Small 2	3.02	130.00	2.98	105.55	28	1.12	18.81
Small 3	2.99	121.63	2.94	98.09	20	2.45	19.33
Small 4	2.90	151.95	2.85	113.76	28	1.72	25.15
Small 5	3.01	123.96	2.95	102.41	26	1.99	17.41
Small 6	3.00	130.29	2.94	104.87	22	2.00	19.36
Small 7	2.97	138.34	2.93	109.22	23	1.35	21.12
Small 8	2.96	135.49	2.91	107.38	27	1.69	20.74
Small 9	2.92	145.17	2.87	113.21	21	1.71	22.03
Small 10	3.00	131.98	2.96	106.99	25	1.33	18.95
Average	2.96	136.88	2.91	107.66	24	1.91	20.15

Table 4.10 presents the results for medium-sized instances. These instances, while moderately complex, can still be solved within a reasonable timeframe by the commercial solver. The results indicate that the math-heuristic achieves an average optimality gap of 1.34% and a computational time reduction of 44%. As problem complexity increases, the heuristic becomes increasingly effective at improving computational efficiency. These results further demonstrate its scalability and ability to deliver high-quality solutions while saving significant time for medium-sized problem instances.

Table 4.10:Math-heuristic Performance Results for Medium Instances

Instance	CPLEX Obj (M$)	CPLEX CPU Time (s)	Math-Heuristic Obj (M$)	Math-Heuristic CPU Time (s)	# Iterations	Optimality Gap (%)	CPU Time Improvement (%)
Medium 1	6.37	378.77	6.22	167.93	20	2.38	55.69
Medium 2	6.48	297.67	6.40	81.84	20	1.20	72.54
Medium 3	6.44	549.85	6.37	222.90	28	1.09	59.47
Medium 4	6.42	617.09	6.35	340.08	28	1.15	44.88
Medium 5	6.50	725.73	6.42	285.73	28	1.23	60.64
Medium 6	6.46	314.72	6.38	236.42	28	1.25	24.93
Medium 7	6.47	307.77	6.39	231.89	29	1.23	24.47
Medium 8	6.45	322.73	6.36	239.12	27	1.40	25.74
Medium 9	6.44	317.18	6.36	237.45	28	1.24	25.16
Medium 10	6.49	306.42	6.41	233.89	30	1.23	23.71
Average	6.45	413.09	6.37	227.83	26.60	1.34	44.83

The results for large instances are shown in Table 4.11. These instances exceed the computational capacity of the commercial solver, making the math-heuristic the only viable solution method.

The algorithm solves all instances within an average computational time of 507 seconds. These outcomes underscore the scalability and practicality of the heuristic in solving large, complex MND problems.

Table 4.11:Math-heuristic Performance Results for Large Instances

Instance	CPLEX Obj (M$)[1]	CPLEX CPU Time (s)[2]	Math-Heuristic Obj (M$)	Math-Heuristic CPU Time (s)	# Iterations	Optimality Gap (%)[3]	CPU Time Improvement (%)[4]
Large 1	*	*	8.30	512.25	35	*	*
Large 2	*	*	8.63	498.11	33	*	*
Large 3	*	*	8.46	505.47	32	*	*
Large 4	*	*	8.51	510.32	34	*	*
Large 5	*	*	8.54	507.89	36	*	*
Large 6	*	*	8.48	504.15	33	*	*
Large 7	*	*	8.47	509.78	34	*	*
Large 8	*	*	8.52	506.89	32	*	*
Large 9	*	*	8.55	506.78	36	*	*
Large 10	*	*	8.50	510.52	34	*	*
Average	*	*	8.50	507.31	34.30	*	*

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In summary, the math-heuristic algorithm demonstrates significant versatility and effectiveness. It achieves high-quality solutions for small and medium-sized problems and scales efficiently to tackle large, computationally intensive instances. These results establish the proposed algorithm as a reliable tool for solving complex robust MND problems in a highly customized manufacturing environment.

4.7 Conclusion

In this study, we developed an ARO model for the design of a manufacturing network that facilitates the manufacturing of highly customized, modular-structured products. We specifically incorporated the uncertain production rate of the external suppliers for manufacturing complex product modules. This aspect has been neglected in the existing literature while long production lead time is one of the key challenges of MC. We modeled the uncertain resource utilization of complex modules as an interval and considered an uncertainty budget that limits the number of suppliers that might face the lowest production rate. The AOR model determines the optimal pool of external producers/suppliers as the first-stage decision and sets the production quantity and lost sale as a response the the outcome of uncertainty such that the profit under worst-case outcomes of uncertainty is maximized. The nonlinear ARO model is reformulated as a MIP model by approximating the uncertainty set as a scenario set. A math-heuristic algorithm was also developed to overcome the computational complexity of the MIP model when considering multiple products with several complex custom-made items.

Our numerical experiments highlighted the significant advantages of the ARO model over a deterministic network design model in terms of reducing the lost sale cost when the external suppliers fail to deliver complex product components on time due to insufficient production capacity. The model also strategically diversifies suppliers by incorporating both stable and volatile suppliers to mitigate the risks associated with production capacity fluctuations, thereby ensuring a more consistent performance under adverse conditions. The math-heuristic algorithm also proved effective in generating near-optimal solutions within reduced computational times, particularly for small- and medium-sized instances, and it scales well to tackle the more complex, large-scale problems that are beyond the reach of standard commercial solvers.

This study can be further extended by integrating adaptive uncertainty sets and/or leveraging data-driven techniques to refine the uncertain intervals. In addition, other sources of uncertainty involved in the manufacturing of high-tech customizable products can be incorporated into the network design problem. Finally, expanding the proposed ARO model into a multi-period setting where the configuration of the supply network can be dynamically adapted as a response to the changes in products' design specifications would be another avenue of research to explore.

Chapter 5

Conclusion and Research Directions

5.1 Conclusion

This thesis tackled the pressing challenge of designing resilient and reconfigurable supply networks to support mass personalization (MP) within the Industry 4.0 (I4.0) framework. Driven by the rising demand for customized high-tech products—such as those in aerospace, medical devices, and precision optics—the research introduced advanced optimization models to enhance strategic decision-making in supply network design (SND). The work was structured around three core contributions, each derived from a published paper, which collectively push the boundaries of supply chain management by addressing the unique complexities of MP in the I4.0 era.

In Chapter 2, a mixed-integer programming (MIP) model was developed for SND, explicitly addressing the uncertain nature of personalized product designs and the non-linear production costs tied to design complexity and batch size. Leveraging a cloud-manufacturing platform that provides real-time data on suppliers' technological capabilities, capacities, and costs, the model optimizes supplier selection and order allocation to maximize profit and service level while minimizing manufacturing costs. Sensitivity analyses reveal how network configurations adapt to varying demand complexities, underscoring the need for investments in advanced manufacturing facilities to enable cost-effective production of small-batch personalized products. This model not only serves as a decision-support tool for creating reconfigurable supply networks tailored to MP but also demonstrates the strategic importance of aligning supplier capabilities with customization demands, offering high-tech manufacturers a competitive edge in dynamic markets.

Chapter 3 presented a two-stage stochastic programming (2SP) model tailored for platform-based manufacturing networks (PBMNs), designed to produce highly customized products while ensuring resilience against supplier failures. By integrating crowdsourcing and backup suppliers, the model minimizes the expected costs of corrective actions and lost sales under uncertain supplier capabilities. A scenario sampling heuristic was introduced to efficiently handle large-scale instances, and Monte Carlo simulations validate its superiority over deterministic approaches, particularly in emphasizing the value of prioritizing reliable suppliers despite their higher initial costs. This contribution highlights the critical role of proactive risk mitigation in maintaining operational continuity, providing a flexible and scalable framework for managing the intricate uncertainties of MP within the I4.0 paradigm.

In Chapter 4, an adjustable robust optimization (ARO) model was proposed for multi-echelon manufacturing networks, ensuring robustness against supplier capacity variability. The model strategically diversifies suppliers to mitigate risks and employs a math-heuristic algorithm to solve complex instances effectively. Numerical experiments, including detailed sensitivity analyses, highlight its ability to reduce lost sales and enhance network resilience, offering a practical and computationally viable tool for managing uncertainty in modular, high-tech production systems. By balancing robustness and cost efficiency, the ARO approach equips manufacturers with a sophisticated mechanism to design supply networks capable of withstanding disruptions while meeting the stringent demands of personalized production.

Together, these models advance supply chain management by providing theoretically sound, data-driven, and practically viable solutions tailored to the challenges of MP in I4.0. The research delivers actionable insights—such as the benefits of supplier diversification, the adaptability of reconfigurable networks, and the necessity of proactive risk management—enabling high-tech manufacturers to thrive in competitive, customization-driven markets. Beyond their immediate applications, these contributions establish a comprehensive framework that integrates optimization techniques, real-time data, and resilience strategies, aligning with the transformative vision of I4.0 and setting a new standard for supply network design in the age of personalization.

5.2 Future Research Directions

This thesis lays a robust foundation for several avenues of future research, offering opportunities to extend and refine the proposed methodologies while addressing emerging challenges in supply chain management. Potential directions include:

(1) Expanding the models to incorporate additional sources of uncertainty—such as demand volume fluctuations, supply chain disruptions due to natural disasters or geopolitical tensions, and variable lead times—to create a more holistic representation of real-world dynamics and enhance the practical applicability of the frameworks.

(2) Developing dynamic decision frameworks that enable real-time supply network reconfiguration in response to evolving customer demands, technological advancements, and market shifts, potentially integrating adaptive algorithms to ensure continuous optimization under changing conditions.

(3) Integrating artificial intelligence and machine learning techniques to predict supplier performance, assess failure risks, and recommend optimal network configurations, thereby improving the precision of uncertainty modeling and enabling more informed strategic decision-making.

(4) Designing collaboration mechanisms—potentially leveraging game theory, blockchain technology, or smart contracts—to enhance information sharing, trust, and coordination among supply chain partners, fostering a transparent and efficient ecosystem that supports the complexities of MP.

(5) Extending the proposed frameworks to other industries beyond high-tech manufacturing, such as fashion, consumer electronics, or automotive sectors, to evaluate their adaptability and generalizability across diverse customization-driven contexts.

(6) Investigating the incorporation of sustainable practices into supply network design, such as circular economy principles, green logistics, or carbon footprint minimization, to align with

environmental goals and emerging regulatory requirements while maintaining economic viability.

(7) Exploring the use of digital twins and advanced simulation tools to model and optimize supply network performance under a wide range of scenarios, providing deeper insights into resilience, adaptability, and long-term strategic planning.

(8) Examining the socio-economic implications of resilient supply networks, including their impact on workforce skill requirements, regional economic development, and global trade patterns, to broaden the scope of the research beyond technical optimization.

These extensions promise to further strengthen the resilience, adaptability, and sustainability of supply networks, ensuring their alignment with the evolving landscape of I4.0. By addressing these research directions, future work can build on this thesis to drive innovation in supply chain management, meeting the growing demand for personalized products while navigating the complexities of an increasingly interconnected and uncertain global economy.

Appendix A

My Appendix

A.1 Deterministic PBMN design Model for Highly-Customized Production

Table A.1Decision Variables

q^j_{pil}	Quantity of end product **p** produced at customization level **i** with delivery option **l** within the $\mathbf{j}^{\text{th}}$ production quantity interval.
w_{pil}	Quantity of lost sale for end product **p** at customization level **i** with delivery option **l**.
r_{pigl}	Quantity of end product **p** at customization level **i** with delivery option **l** assigned to logistic carrier **g**.
q^s_{hnl}	Quantity of standard sub-assembly **n** (n $\in N^s$) with delivery option **l** produced by producer **h**.
q^{cj}_{hnil}	Quantity of customizable sub-assembly **n** produced by producer **h** at customization level **i** with delivery option **l** within the $\mathbf{j}^{\mathbf{th}}$ production quantity interval.
q^s_{kml}	Quantity of standard component **m** ($m \in M^s$) purchased from supplier **k** with delivery option **l**.
q^{cj}_{kmil}	Quantity of customizable component **m** ($m \in M^c$) purchased at customization level **i** with delivery option **l** from supplier **k** within the $\mathbf{j}^{\mathbf{th}}$ interval.
z^j_{pil}	1 if the production quantity of product **p** at customization level **i** with delivery option **l** is within the $\mathbf{j}^{\mathbf{th}}$ interval, 0 otherwise.
u^j_{hnil}	1 if the production quantity of sub-assembly **n** by producer **h** at customization level **i** with delivery option **l** is within the $\mathbf{j}^{\mathbf{th}}$ interval, 0 otherwise.
v^j_{kmil}	1 if the purchased quantity of component **m** by supplier **k** at customization level **i** with delivery option **l** is within the $\mathbf{j}^{\mathbf{th}}$ interval, 0 otherwise.
y_h	1 if producer **k** is selected, 0 otherwise.
x_k	1 if supplier **k** is selected, 0 otherwise.
o_g	1 if logistic carrier **g** is selected, 0 otherwise.

Mathematical Model

Maximize $$\sum_p\sum_i\sum_j\sum_l S^j_{pil}q^j_{pil} - \sum_p\sum_i\sum_j\sum_l C_{pi}q^j_{pil} - \sum_h\sum_n\sum_l C^s_{hn}q^s_{hnl} - \sum_h\sum_n$$

$$\sum_i\sum_j\sum_l C^j_{hni}q^{cj}_{hnil} - \sum_k\sum_m\sum_l C^s_{km}q^s_{kml} - \sum_k\sum_m\sum_i\sum_j\sum_l C^j_{kmi}q^{cj}_{kmil} - \sum_h F_h y_h -$$

$$\sum_k F_k x_k - \sum_g F_g o_g - \sum_p\sum_i\sum_l\sum_g C_{pigl}r_{pigl} - \sum_p\sum_i\sum_l CL_{pi}w_{pil} \tag{A.1}$$

Subject to

Demand Constriants:

$$\sum_j q^j_{pil} + w_{pil} = D_{pil}, \qquad \forall p \in P, \forall i \in I, \forall l \in L \tag{A.2}$$

Capacity Constraints:

$$\sum_j\sum_l \alpha_{pi}q^j_{pil} \le FC_{pi}, \qquad \forall p \in P, \forall i \in I \tag{A.3}$$

$$\sum_l \beta^s_{hn}q^s_{hnl} \le PC_{hn}\theta^s_{hn}y_h, \qquad \forall h \in H, \forall n \in N^s \tag{A.4}$$

$$\sum_j\sum_l \beta^c_{hni}q^c_{hnil} \le PC_{hni}\theta^c_{hni}y_h, \qquad \forall h \in H, \forall n \in N^c, \forall i \in I \tag{A.5}$$

$$\sum_l \gamma^s_{km}q^s_{kml} \le SC_{km}\sigma^s_{km}x_k, \qquad \forall k \in K, \forall m \in M^s \tag{A.6}$$

$$\sum_j\sum_l \gamma^c_{kmi}q^c_{kmil} \le SC_{kmi}\sigma^c_{kmi}x_k, \qquad \forall k \in K, \forall m \in M^C, \forall i \in I \tag{A.7}$$

$$\sum_p\sum_i r_{pigl} \le M\mu_{gl}o_g, \qquad \forall l \in L, \forall g \in G \tag{A.8}$$

Price/Cost Linearization Constraints:

$$q_{pil}^{j} \leq L_{pi}^{j} z_{pil}^{j}, \qquad \forall p \in P, \forall i \in I, \forall j \in J, \forall l \in L \tag{A.9}$$

$$z_{pil}^{j}(L_{pi}^{j-1} + 1) \leq q_{pil}^{j}, \qquad \forall p \in P, \forall i \in I, \forall j \in J \backslash \{1\}, \forall l \in L \tag{A.10}$$

$$\sum_{j} z_{pil}^{j} = 1, \qquad \forall p \in P, \forall i \in I, \forall l \in L \tag{A.11}$$

$$q_{hnil}^{cj} \leq u_{hnil}^{j} L_{hni}^{j}, \qquad \forall h \in H, \forall n \in N^{c}, \forall i \in I, \forall j \in J, \forall l \in L \tag{A.12}$$

$$u_{hnil}^{j}(L_{hni}^{j-1} + 1) \leq q_{hnil}^{cj}, \qquad \forall h \in H, \forall n \in N^{c}, \forall i \in I, \forall j \in J \backslash \{1\}, \forall l \in L \tag{A.13}$$

$$\sum_{j} u_{hnil}^{j} = 1, \qquad \forall h \in H, \forall n \in N^{c}, \forall i \in I, \forall l \in L \tag{A.14}$$

$$q_{kmil}^{cj} \leq v_{kmil}^{j} L_{kmi}^{j}, \qquad \forall k \in K, \forall m \in M^{c}, \forall i \in I, \forall j \in J, \forall l \in L \tag{A.15}$$

$$v_{kmil}^{j}(L_{kmi}^{j-1} + 1) \leq q_{kmil}^{cj}, \qquad \forall k \in K, \forall m \in M^{c}, \forall i \in I, \forall j \in J \backslash \{1\}, \forall l \in L \tag{A.16}$$

$$\sum_{j} v_{kmil}^{j} = 1, \qquad \forall k \in K, \forall m \in M^{c}, \forall i \in I, \forall l \in L \tag{A.17}$$

Flow Balance Constraints

$$\sum_{j} q_{pil}^{j} = \sum_{g} r_{pigl}, \qquad \forall p \in P, \forall i \in I, \forall l \in L \tag{A.18}$$

$$\sum_{h} q_{hnl}^{s} = \sum_{p} \sum_{i} \sum_{j} \eta_{np} q_{pil}^{j}, \qquad \forall n \in N^{s}, \forall l \in L \tag{A.19}$$

$$\sum_{h} \sum_{j} q_{hnil}^{cj} = \sum_{p} \sum_{j} \eta_{np} q_{pil}^{j}, \qquad \forall n \in N^{c}, \forall i \in I, \forall l \in L \tag{A.20}$$

$$\sum_{k} q_{kml}^{s} = \sum_{h} \sum_{n \in N_{m}^{s}} \lambda_{mn} q_{hnl}^{s} + \sum_{h} \sum_{n \in N_{m}^{s}} \sum_{i} \sum_{j} \lambda_{mn} q_{hnil}^{cj}, \quad \forall m \in M^{s}, \forall l \in L \tag{A.21}$$

$$\sum_{k} \sum_{j} q_{kmil}^{cj} = \sum_{h} \sum_{n \in N_{m}^{c}} \sum_{j} \lambda_{mn} q_{hnil}^{cj}, \qquad \forall m \in M^{c}, \forall i \in I, \forall l \in L \tag{A.22}$$

Domain Constraints:

$$q_{kmil}^{cj}, q_{kml}^{s}, q_{hnil}^{cj}, q_{hnl}^{s}, q_{pil}^{j}, w_{pil}^{j} \geq 0,$$
$$\forall k \in K, \forall m \in M^{c}, \forall m \in M^{S}, \forall h \in H, \forall n \in N^{c}, \forall n \in N^{S}, \forall i \in I, \forall j \in J, \forall p \in P, \forall l \in L \tag{A.23}$$

$$x_{k}, y_{h}, z_{pil}^{j}, u_{hnil}^{j}, v_{kmil}^{j} \in \{0, 1\},$$
$$\forall k \in K, \forall h \in H, \forall p \in P, \forall i \in I, \forall j \in J, \forall n \in N^{c}, \forall m \in M^{c}, \forall l \in L \tag{A.24}$$

A.2 Two-Stage Stochastic Programming with Recourse

Consider the following linear programming (LP) model parameterized by the random vector $\omega \in \Omega$:

$$\mathit{Min}\ c^T x \tag{A.25}$$

Subject to

$$Ax = b \tag{A.26}$$

$$T(\omega)x = h(\omega) \qquad \forall \omega \in \Omega \tag{A.27}$$

$$x \geq 0 \tag{A.28}$$

where $T(\omega)$ and $h(\omega)$ correspond to the random technological coefficients and right-hand-side vector, respectively. This model is a semi-infinite optimization program that is not well-defined. The 2SP approach aims to transform this ill-defined model into to a deterministic equivalent (DE) model by modeling the uncertainty set Ω as a set of finite scenarios $s \in S$, each representing a possible outcome of uncertainty, with known probabilities p^s. The decision variables are then grouped as the first- and second-stage variables that must be determined, respectively, before and after the uncertain outcomes of uncertainty are revealed to the decision-maker. The first-stage variables correspond to the here-and-now decisions that must be taken without full knowledge of the uncertainty (e.g. choice of suppliers in a supply chain). The second-stage variables (e.g., order allocation to suppliers), on the contrary, are determined after the uncertain events (e.g., demand) take place and are indexed by scenarios. They are also denoted as the recourse (corrective) actions as their role is typically to compensate the infeasibility of the uncertain constraints (A.27) for random outcomes (scenarios). In other words, the uncertain constraints are assumed to be soft conditions that are allowed to be violated; however, their infeasibility, measured by the recourse variables, is penalized in the objective function, by considering a unit recourse cost vector q. The objective function of the 2SP approach is to optimize the expected performance measure over all scenarios. The DE of model (A.25)-(A.28) can be accordingly formulated as a single LP model as follows:

$$\mathit{Min}\ c^T x + \sum_s p^s q^T y^s \tag{A.29}$$

Subject to

$$Ax = b \tag{A.30}$$

$$T^s x + W y^s = h^s \qquad \forall s \in S \tag{A.31}$$

$$x \geq 0 \tag{A.32}$$

$$y^s \geq 0 \qquad \forall s \in S \tag{A.33}$$

where the objective function (A.29) minimizes the cost of first-stage decisions in addition to the expected cost of recourse actions. The uncertain constraints are also defined for each scenario. It is worth noting that the computational complexity of a 2SP model drastically increases as the size of the scenario set grows.

A.3 2SP Model Notations

Table A.2Sets

Sets:	
P	Set of end products indexed by **p**.
I	Set of product customization levels indexed by **i**.
I'	Sub-set of product customization levels available to purchase from the open market.
N	Set of sub-assemblies indexed by **n**.
M	Set of components indexed by **m**.
L	Set of delivery options indexed by **l**.
H	Set of sub-assembly producers indexed by **h**.
K	Set of component suppliers indexed by **k**.
G	Set of transportation carriers indexed by **g**.
J	Set of incremental production quantity intervals indexed by **j**.
M^s	Sub-set of standard components.
M^c	Sub-set of customizable components.
M'	Sub-set of customizable components available to purchase from the open market.
N^s	Sub-set of standard sub-assemblies.
N^c	Sub-set of customizable sub-assemblies.
N'	Sub-set of customizable sub-assemblies available to purchase from the open market.
N_m^s	Sub-set of standard sub-assemblies that contain component **m**.
N_m^c	Sub-set of customizable sub-assemblies that contain component **m**.
Ω	Set of TCM scenarios indexed by $\boldsymbol{\omega}$.

Table A.3Parameters

End Products:	
p(ω)	Probability of scenario $\boldsymbol{\omega}$.
D_{pil}	Demand for end product **p** at customization level **i** with delivery option **l**.
FC_{pi}	Available capacity for end product **p** at customization level **i**.
C_{pi}	Unit production cost of end product **p** at customization level **i**.
α_{pi}	Unit capacity consumption factor for producing end product **p** at customization level **i**.
μ_{gl}	1 if logistics carrier **g** is capable of delivering end product **p** by delivery option **l**; 0 otherwise.
CL_{pi}	Unit lost sale cost for end product **p** at customization level **i**.
F_g	Fixed contract cost of selecting logistic carrier **g**.
C_{pigl}	Unit delivery cost of end product **p** at customization level **i** with delivery option **l** by logistic carrier **g**.
L_{pi}^j	Upper limit of the **j$^{\text{th}}$** production quantity interval for end product **p** at customization level **i**.
S_{pil}^j	Unit selling price of end product **p** manufactured at customization level **i** with delivery option **l** within the **j$^{\text{th}}$** production quantity interval, where $S_{pil}^1 > S_{pil}^2 > ... > S_{pil}^J$ and
S_{pil}^j	$\begin{cases} S_{pil}^1, & q_{pil} \leq L_{pi}^1 \\ S_{pil}^2, & L_{pi}^1 < q_{pil} \leq L_{pi}^2 \\ . & \\ . & \\ S_{pil}^J, & L_{pi}^{J-1} < q_{pil} \leq L_{pi}^J \end{cases}$

Sub-assemblies:	
PC_{hn}	Capacity of producer **h** for standard sub-assembly **n** ($n \in N^s$).
PC_{hni}	Capacity of producer **h** for customizable sub-assembly **n** ($n \in N^c$) at customization level **i**.
C^s_{hn}	Unit production cost of standard sub-assembly **n** ($n \in N^s$) by producer **h**
η_{np}	Units of sub-assembly **n** ($n \in N$) required to manufacture one unit of end product **p**.
F_h	Fixed contract cost of selecting producer **h** as a primary (first-stage) producer.
F'_h	Fixed contract cost of selecting producer **h** as a backup (second-stage) producer.
β^s_{hn}	Unit capacity consumption factor for producing standard sub-assembly **n** ($n \in N^s$) at producer **h**.
β^c_{hni}	Unit capacity consumption factor for producing customizable sub-assembly **n** ($n \in N^c$) at customization level **i** at producer **h**.
θ^s_{hn}	1 if producer **h** is capable of manufacturing standard subassembly **n** ($n \in N^s$); 0 otherwise (elements of TCM).
$\theta^c_{hni}(\omega)$	1 if producer **h** is capable of manufacturing customizable sub-assembly **n** ($n \in N^c$) under scenario $\boldsymbol{\omega}$; 0 otherwise (elements of TCM).
L^j_{hni}	Upper limit of $\mathbf{j^{th}}$ production quantity interval for sub-assembly **n** ($n \in N^c$) at customization level **i** for producer **h**.
C^{open}_{ni}	Unit purchase cost of customizable sub-assembly **n** ($n \in N'^c$) at customization level of **i** from the open market.
C^j_{hni}	Unit production cost of customizable sub-assembly **n** ($n \in N^c$) by producer **h** at customization level of **i** within the $\mathbf{j^{th}}$ production quantity interval.

Components:	
SC_{km}	Capacity of supplier **k** for standard component **m** ($m \in M^s$).
SC_{kmi}	Capacity of supplier **k** for customizable component **m** ($m \in M^c$) at customization level **i**.
C^s_{km}	Unit purchase cost of standard component **m** ($m \in M^s$) from supplier **k**.
λ_{mn}	Units of component **m** ($m \in M$) required to manufacture one unit of sub-assembly **n** ($n \in N$).
F_k	Fixed contract cost of selecting supplier **k** as a primary (first stage) supplier.
F'_k	Fixed contract cost of selecting supplier **k** as a backup (second stage) supplier.
γ^s_{km}	Unit capacity consumption for standard component **m** ($m \in M^s$) at supplier **k**.
γ^c_{kmi}	Unit capacity consumption for customizable component **m** ($m \in M^c$) at customization level **i** at supplier **k**.
L^j_{kmi}	Upper limit of $\mathbf{j^{th}}$ procurement quantity interval corresponding to component **m** ($m \in M^c$) at customization level **i** for supplier **k**.
C^{open}_{mi}	Unit purchase cost of customizable component **m** ($m \in M'^c$) at customization level of **i** from the open market.
σ^s_{km}	1 if supplier **k** is capable of offering standard component **m** ($m \in M^s$); 0 otherwise (elements of TCM).
$\sigma^c_{kmi}(\omega)$	1 if supplier **k** is capable of offering customizable component **m** ($m \in M^s$) under scenario $\boldsymbol{\omega}$; 0 otherwise (elements of TCM).
C^j_{kmi}	Cost of purchasing one unit of customizable component **m** ($m \in M^c$) from supplier **k** at customization level **i** within the $\mathbf{j^{th}}$ order quantity interval.

Table A.4Decision Variables

Decision Variables:	
y_h	1 if producer **k** is selected as a primary producer; 0 otherwise.
x_k	1 if supplier **k** is selected as a primary supplier; 0 otherwise.
o_g	1 if logistic carrier **g** is selected; 0 otherwise.
$y_h{}'(\omega)$	1 if producer **h** is selected as a backup producer under scenario $\boldsymbol{\omega}$; 0 otherwise.
$x_k{}'(\omega)$	1 if supplier **k** is selected as a backup supplier under scenario $\boldsymbol{\omega}$; 0 otherwise.
$z^j_{pil}(\omega)$	1 if the production quantity of product **p** at customization level **i** with delivery option **l** is within the **j**$^{\mathbf{th}}$ interval under scenario $\boldsymbol{\omega}$; 0 otherwise.
$u^j_{hnil}(\omega)$	1 if the production quantity of customizable sub-assembly **n** ($n \in N^C$) by producer **h** at customization level **i** with delivery option **l** is within the **j**$^{\mathbf{th}}$ interval under scenario $\boldsymbol{\omega}$; 0 otherwise.
$v^j_{kmil}(\omega)$	1 if the purchased quantity of customizable component **m** ($m \in M^c$) by supplier **k** at customization level **i** with delivery option **l** is within the **j**$^{\mathbf{th}}$ interval under scenario $\boldsymbol{\omega}$; 0 otherwise.
$q^j_{pil}(\omega)$	Quantity of end product **p** produced at customization level **i** with delivery option **l** within the **j**$^{\text{th}}$ production quantity interval under scenario $\boldsymbol{\omega}$.
$w_{pil}(\omega)$	Quantity of lost sale for end product **p** at customization level **i** with delivery option **l** under scenario $\boldsymbol{\omega}$.
$r_{pigl}(\omega)$	Quantity of end product **p** at customization level **i** with delivery option **l** assigned to logistic carrier **g** under scenario $\boldsymbol{\omega}$.
$q^s_{hnl}(\omega)$	Quantity of standard sub-assembly **n** (n $\in N^s$) with delivery opti-on **l** produced by producer **h** under scenario $\boldsymbol{\omega}$.
$q^{cj}_{hnil}(\omega)$	Quantity of customizable sub-assembly **n** ($n \in N^C$) produced by primary producer **h** at customization level **i** with delivery option **l** within the **j**$^{\mathbf{th}}$ production quantity interval under scenario $\boldsymbol{\omega}$.
$q'^{cj}_{hnil}(\omega)$	Quantity of customizable sub-assembly **n** ($n \in N^C$) produced by backup producer **h** at customization level **i** with delivery option **l** within the **j**$^{\mathbf{th}}$ production quantity interval under scenario $\boldsymbol{\omega}$.
$q^{open}_{nil}(\omega)$	Quantity of customizable sub-assembly **n** (n $\in N'^c$) at custo-mization level **i** with delivery option **l** purchased from the open market under scenario $\boldsymbol{\omega}$.
$q^s_{kml}(\omega)$	Quantity of standard component **m** ($m \in M^s$) purchased from supplier **k** with delivery option **l** under scenario $\boldsymbol{\omega}$.
$q^{cj}_{kmil}(\omega)$	Quantity of customizable component **m** ($m \in M^c$) purchased at customization level **i** with delivery option **l** from primary suppli-er **k** within the **j**$^{\mathbf{th}}$ interval under scenario $\boldsymbol{\omega}$.

$q'^{cj}_{kmil}(\omega)$	Quantity of customizable component **m** ($m \in M^c$) purchased at customization level **i** with delivery option **l** from backup supplier **k** within the $\mathbf{j^{th}}$ interval under scenario $\boldsymbol{\omega}$.
$q^{open}_{mil}(\omega)$	Quantity of customizable component **m** (m $\in M'^c$) at customization level **i** with delivery option **l** purchased from the open market under scenario $\boldsymbol{\omega}$.

A.4 ARO Model Notations

Sets:

Set	Description	Index
P	Set of final products	p
I	Set of customization levels for products	i
N	Set of sub-assemblies	n
M	Set of components	m
H	Set of sub-assembly manufacturers	h
K	Set of component suppliers	k
J	Set of production or procurement quantity intervals	j
M^s	Subset of components classified as standard and non-customizable	–
M^c	Subset of components classified as customizable and adaptable to customer specifications	–
N^s	Subset of sub-assemblies that are standardized and uniform across product designs	–
N^c	Subset of sub-assemblies that are customizable for specific product configurations	–
Ω	Set of scenarios capturing the uncertainty in supplier performance	ω

Parameters:

Final Products:

Parameter	Description
D_{pi}	Demand for product p at customization level i.
FC_{pi}	Maximum production capacity available for product p at level i.
C_{pi}	Unit production cost for product p at level i.
CL_{pi}	Unit cost of unmet demand for product p at level i (lost sales).
L^j_{pi}	Upper limit of the j^{th} production interval for product p at level i.
S^j_{pi}	Unit selling price for product p at level i within the j^{th} interval.
η_{np}	Number of sub-assembly units n needed to produce one unit of product p.

Sub-assemblies:

Parameter	Description
PC_{hn}	Maximum production capacity of manufacturer h for standard sub-assembly n.
PC_{hni}	Maximum production capacity of manufacturer h for customizable sub-assembly n at level i.
C^s_{hn}	Unit production cost for standard sub-assembly n at manufacturer h.
C^j_{hni}	Unit production cost for customizable sub-assembly n at level i within the j^{th} interval at manufacturer h.
β^s_{hn}	Unit capacity required to produce standard sub-assembly n at manufacturer h.
$\beta^c_{hni}(\omega)$	Unit capacity required to produce customizable sub-assembly n at level i at manufacturer h under scenario ω.
θ^s_{hn}	Binary parameter; 1 if manufacturer h can produce standard sub-assembly n, 0 otherwise.
θ^c_{hni}	Binary parameter; 1 if manufacturer h can produce customizable sub-assembly n at level i, 0 otherwise.

Components:

Parameter	Description
SC_{km}	Maximum capacity of supplier k for standard component m.
SC_{kmi}	Maximum capacity of supplier k for customizable component m at level i.
C^s_{km}	Unit purchase cost for standard component m from supplier k.
C^j_{kmi}	Unit purchase cost for customizable component m at level i within the j^{th} interval from supplier k.
λ_{mn}	Number of component units m required to produce one unit of sub-assembly n.
γ^s_{km}	Unit capacity required for supplier k to provide standard component m.
$\gamma^c_{kmi}(\omega)$	Unit capacity required for supplier k to provide customizable component m at level i under scenario ω.
σ^s_{km}	Binary parameter; 1 if supplier k can supply standard component m, 0 otherwise.
σ^c_{kmi}	Binary parameter; 1 if supplier k can supply customizable component m, 0 otherwise.

Decision Variables:

Productions and Procurement:

Variable	Description
$w_{pi}(\omega)$	Quantity of lost sale for end product **p** at customization level **i** under scenario ω.
$q^{j}_{pi}(\omega)$	Quantity of final product p produced at level i in the j^{th} interval under scenario ω.
$q^{s}_{km}(\omega)$	Quantity of standard component m procured from supplier k under scenario ω.
$q^{j}_{kmi}(\omega)$	Quantity of customizable component m procured from supplier k at level i within the j^{th} interval under scenario ω.
$q^{s}_{hn}(\omega)$	Quantity of standard sub-assembly n manufactured by manufacturer h under scenario ω.
$q^{j}_{hni}(\omega)$	Quantity of customizable sub-assembly n produced by manufacturer h at level i within the j^{th} interval under scenario ω.

Binary Selection Variables:

Variable	Description
x_k	Binary variable; 1 if supplier k is selected, 0 otherwise.
y_h	Binary variable; 1 if manufacturer h is selected, 0 otherwise.
$z^{j}_{pi}(\omega)$	Binary variable; 1 if production quantity of product p at level i is within the j^{th} interval under scenario ω, 0 otherwise.
$v^{j}_{kmi}(\omega)$	Binary variable; 1 if procurement quantity of customizable component m from supplier k at level i is within the j^{th} interval under scenario ω, 0 otherwise.
$u^{j}_{hni}(\omega)$	Binary variable; 1 if production quantity of customizable sub-assembly n from producer h at level i is within the j^{th} interval under scenario ω, 0 otherwise.

Worst-case profit

Variable	Description
ν	Worst-case profit

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