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Concurrent Product and Supply Chain Design: Framework, Process, Methods, and Application

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Content

Abstract

Product design and supply chain design are two key determinants of manufacturers’ competitiveness. This is especially important to manufacturers with complex products and globalised supply chains. However, product design and supply chain design follow different design objectives and thus require systematic trade-off between them to ensure competitiveness for the manufacturers.

This dissertation provides an extensive literature review on past research in methodology related to product design, supply chain design and concurrent design that specifically addresses the design trade-off between product and supply chain. The review finds that even though methodology for product design and supply chain design is well established within each domain in research and industry, an integrated methodology that enables the concurrent design of both domains is still lacking.

Building on relevant theories, frameworks and the methodology identified in the literature review, this dissertation first introduces a novel framework that structures product and supply chain design attributes onto three design levels, which are differentiated between two domains (architectural-strategic, detailed-tactical and dynamic-operational). The framework unravels the intricacy of how design attributes interact with one another, which is used to derive four propositions for concurrent product and supply chain design with the focus on improving efficacy and efficiency.

The framework and four propositions provide the theoretical foundation for the development of a new conceptual process for concurrent product and supply chain design. This conceptual process includes a novel method for generating design tradespace between product design and supply chain design. The tradespace is characterised by a set of curves that show the individual and combined values of a common design attribute of both designs. The referential points that are located at the intersection of the individual curves and at the peak of the combined curve further characterise the tradespace. These referential points are not only useful for identifying the most important region for design trade-off, hereby allowing greater efficacy and efficiency when conducting concurrent design, but also useful for defining product-supply chain system archetypes, which offer novel perspectives for the analysis of industries.

Next, this dissertation shows how the conceptual process is operationalised with product design and supply chain design methods that are specifically developed for modularity and sourcing flexibility. This operationalised process is then applied to an automotive case study involving a battery system for the purpose of demonstrating its

efficacy and efficiency during the concurrent design of the battery system and its supply chain.

Finally, this dissertation extends its supply chain design method for modularity and sourcing flexibility to consider supplier integration risks, which are important for complex products such as aircraft with convergent global supply chains. Three distinct approaches of incorporating supplier integration risks are employed in this method to explore the effect of this risk on supply chain designs. This method considers integration risks as key decisional factors when selecting suppliers, determining their tier levels and required level of sourcing flexibility. Robust optimisation is then used to study the effect of uncertainty over baseline risk values. This method is applied to a case study of a major aerospace manufacturer.

Zusammenfassung

Produktdesign und Lieferkettendesign sind zwei Bestimmungsfaktoren der Wettbewerbsfähigkeit der Hersteller. Sie sind vor allem wichtig für Hersteller mit komplexen Produkten und globalisierten Lieferketten. Dennoch folgen Produkt- und Lieferkettendesign unterschiedlichen Auslegungszielen und benötigen deshalb einen systemischen Ausgleich, um die Wettbewerbsfähigkeit der Hersteller zu gewährleisten.

Diese Arbeit beinhaltet eine umfassende Auswertung vorangegangener Forschung an der Methodiken Produkt- und Lieferkettendesign sowie für simultanes Design, das spezifisch den Ausgleich zwischen beiden Auslegungsgebieten adressiert. Obwohl die Methodiken sowohl des Produkt- auch als des Lieferkettendesigns in Forschung und in Industrie bereits als eigene Gebiete etabliert sind, mangelt es dennoch an integrierter Methodik, um das simultane Design beider Auslegungsgebiete ermöglichen zu können.

In Anlehnung an relevante Theorien, Rahmen und Methodiken aus der Literaturauswertung führt diese Arbeit zunächst einen neuartigen Rahmen ein, der Produkt- und Lieferkettendesignattribute auf drei Auslegungsebenen und in zwei Auslegungsgebiete (architektonisch-strategisch, detailliert-taktisch, und dynamisch-operational) strukturiert. Dieser Rahmen entschlüsselt die komplexe Weise, wie diese Designgebiete aufeinander einwirken. Basierend auf diesem Rahmen leitet die Arbeit vier Theoreme für die simultane Auslegung von Produkt- und Lieferkettendesign mit dem Fokus auf Effektivität und Effizienz ab.

Dieser Rahmen und die vier Theoreme bilden die theoretische Grundlage für die Entwicklung eines neuen konzeptuellen Prozesses für simultanes Produkt- und Lieferkettendesign. Der konzeptuelle Prozess verfügt über einen neuartigen Ansatz zur Abbildung eines Auslegungsfeldes, das von Attributkurven charakterisiert wird, die die individuellen und kombinierten Werte eines gemeinsamen Designattributs von sowohl Produkt- als auch Lieferkettendesign darstellen. Die Referenzpunkte, die an den Schnittpunkten der individuellen Attributkurven beziehungsweise am Scheitelpunkt der kombinierten Attributkurve liegen, charakterisieren das Auslegungsfeld weiter. Diese Referenzpunkte sind nicht nur nützlich für die Identifizierung des wichtigsten Zielkonfliktgebiets, das zur größeren Effektivität und Effizienz bei der Zielkonfliktlösung beiträgt, sondern auch für die Definition von Produkt- und Lieferkettensystemarchetypen, die eine neuartige Perspektive auf die Analyse der Industrie bieten.

Des Weiteren wurde der konzeptuelle Prozess zur Anwendung operationalisiert, der auf Modularität und Lieferungsflexibilität fokussiert ist. Dafür wurden spezifische Clustering-Methoden für Produkt- und Lieferkettendesign entwickelt und eingeführt.

Dieser operationalisierte Prozess wurde dann in einer Fallstudie auf ein Batteriesystem angewendet, um seine Effektivität und Effizienz bei der simultanen Auslegung des Batteriesystems und dessen Lieferkette zu demonstrieren.

Abschließend erweitert diese Arbeit die Lieferkettendesignmethode für Modularität und Flexibilität auf das Forschungsfeld Lieferkettenrisikomanagement, um auf Lieferantenintegrationsrisiken einzugehen, die für komplexe Produkte mit konvergierenden Lieferketten, wie Flugzeuge, von großer Bedeutung sind. Drei unterschiedliche Ansätze zur Berücksichtigung der Lieferantenintegrationsrisiken wurden dafür eingesetzt. Unsere Methode betrachtet das Integrationsrisiko als einen entscheidenden Faktor bei der Auswahl von Lieferanten und deren vertikaler Einstufung sowie bei der Entscheidung über die erforderliche Lieferungsflexibilität. Die Robust-Optimierungsmethode wurde dann für die Analyse der Auswirkungen der Risikowerteunsicherheit auf die Ergebnisse eingesetzt. Diese neue Methode wurde dann in einer Luftfahrtfallstudie eines führenden Flugzeugbauers angewendet.

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List of abbreviations

3DCE	Three-Dimensional Current Engineering
AHP	Analytic Hierarchy Process
CDA-TOP	Concurrent Design Attribute Trade-Off Pyramid
CDM	Clustered Decision Matrix
C-DSM	Combined DSM
CGF	Cumulant Generating Function
CP-SCD	Concurrent Product - Supply Chain Design
DOP	Design Optimum Point
DSM	Design Structure Matrix
DSP	Design Symmetry Point
ELECTRE	ELimination Et Choix Traduisant la REalité
EV	Electric Vehicle
IRM	Integration Risk Matrix
M	Modularity level
MCDA	Multi-Criteria Decision Analysis
MGF	Moment Generating Function
MAUT	Multi-Attribute Utility Theory
MOP	Multi-Objective Programming
NSC-DSM	Normalised Supply Chain – Design Structure Matrix
NSC-M	Normalised Supply Chain Modularity Level
OEM	Original Equipment Manufacturer
OPL	Optimisation Programming Language
PD	Product Design
PDA	Product Design Architecture
PD-DSM	Product Design – Design Structure Matrix
PD-M	Product Design Modularity Level
PROMETHEE	Preference Ranking Organization Method for Enrichment of Evaluations
PSM	Part Supplier Matrix
P-SC	Product-Supply Chain
RO	Robust Optimisation
SC	Supply Chain
SCA	Supply Chain Architecture
SCD	Supply Chain Design
SC-DSM	Supply Chain – Design Structure Matrix
SC-M	Supply Chain Modularity Level
SCRM	Supply Chain Risk Management
W_{PD}	Weight of Product Design
W_{SCD}	Weight of Supply Chain Design

List of symbols

Chapter 2

M	Modularity level of a product-supply chain system
M_P	Modularity level of a product design
M_S	Modularity level of a supply chain design

Chapter 3

WS_i	Seeding function
r_{ij}	Interaction strength between part i and part j
c_{ij}	Number of interactions between seed part i and part j
P	Set of parts in PSM
p	Index of part in PSM
I	Set of seed parts i ($I \subseteq J$) in DSM
i	Index of seed part P in DSM
J	Set of all parts j in DSM
j	Index of part P in DSM
n	Minimum size of a cluster
N	Maximum size of a cluster
x_{ij}	Decision variable assigning part j to seed part i
h	Sourcing flexibility constant
k	Upper limit to the number of modules that can be assigned to a supplier
l	Upper limit to the number of parts in a module
q_{ps}	Decision variable assigning part p to supplier s in the PSM
y_{ms}	Decision variable assigning module m to supplier s
x_{pm}	Decision variable assigning part p to module m
t_s	Decision variable to select supplier s
c_m	Decision variable to select module m
W_{PD}	Weight of interactions in PD-DSM for C-DSM
W_{SC}	Weight of interactions in SC-DSM for C-DSM
u_{pm}	Decision variable assigning part p to module m in CDM

Chapter 4

S	Set of supplier candidates
i	Index of supplier
j	Index of supplier ($\neq i$)
P	Set of parts sourced

p	Index of part in PSM
S'	Pairs of suppliers with overlapping part portfolios
PS'	Suppliers s capable of producing parts p
$APSS'$	Parts that can be jointly integrated by both supplier i and j
$NPSS'$	Parts that cannot be jointly integrated by both supplier i and j
$x_{(i,j)}$	Decision variable assigning supplier i and j in the same module
$y_{(p,s)}$	Decision variable assigning part p to supplier s
$h_{(i,j)}$	Parameter indicating if module is single sourced or double sourced
Γ	Uncertainty budget for the overall risk budget approach
$\Gamma_{(p,s)}$	Uncertainty budget for each part-supplier pair in the weakest link approach
Γ_s	Uncertainty budget for each supplier in the additive approach
$\bar{r}_{(p,s)}$	Maximum deviation of integration risk for pair (p, s)
$\tilde{r}_{(p,s)}$	Integration risk considering uncertainty
$\xi_{(p,s)}$	Normalised deviation of the integration risk for (p, s)
λ	Auxiliary dual variable for the overall risk budget approach
λ_s	Auxiliary dual variable for all suppliers s for the additive approach
$\mu_{(p,s)}$	Auxiliary dual variable for all pairs (p, s)

1. Introduction

"Manufacturing gets involved from Day 1 and they are not 2nd class citizens"

Steve Jobs, 1992, Cambridge, Massachusetts

1.1 Motivation and background

The coordination effort, physical footprint and technologies that are needed to create products and their supply chains are epitomes of major human achievements (Economist, 2021a). A product is a configuration of elements, material and components that give a product its attributes of function, appearance, durability, and safety (Walsch et al., 1988). A supply chain consists of suppliers, manufacturing centres, warehouses, distribution centres, and retail outlets, as well as raw materials, work-in-process inventories, and finished products that flow between the facilities (Simchi-Levi et al., 2008). The contrast between the physical size a product, such as a smartphone, and its massive supply chain that stretches over millions of kilometres across countless mines, farms, warehouses, and factories around the world cannot be overstated. Product design (PD) influences its supply chain design (SCD) and vice versa. For example, the selection of materials for a product has an impact on its SCD as certain materials can only be sourced from certain regions in the world. Titanium used in lightweight aerostructures is sourced mostly from China and Russia. Cobalt for batteries is sourced mostly from the Democratic Republic of Congo. Conversely, the selection of suppliers based on their capabilities (e.g., technologies and processes) has an impact on how the product is modularised for outsourcing (e.g., number of modules and the contents within the modules). Manufacturing companies need to manage trade-off topics between PD and SCD effectively and efficiently to ensure their competitive advantages such as costs, flexibility, and efficiency. However, this capability is still underdeveloped in research and in industries. The development and application of this capability are becoming even more important in view of the emerging global trends, risks, and opportunities, which are presented in this section.

1.1.1 Geo-politics

The recent spikes in supply chain disruption incidents (e.g., global automotive electronic chips shortage, the Suez Canal blockage, Covid-19 pandemic, Russo-Ukrainian War) and their massive impact on the global economy and geo-politics have highlighted the vulnerability of the global supply chain and the importance of supply chain design and risk management. The Economist (2021a), a major British business magazine, stated that "*Supply chain resilience comes not from autarky but from diverse*

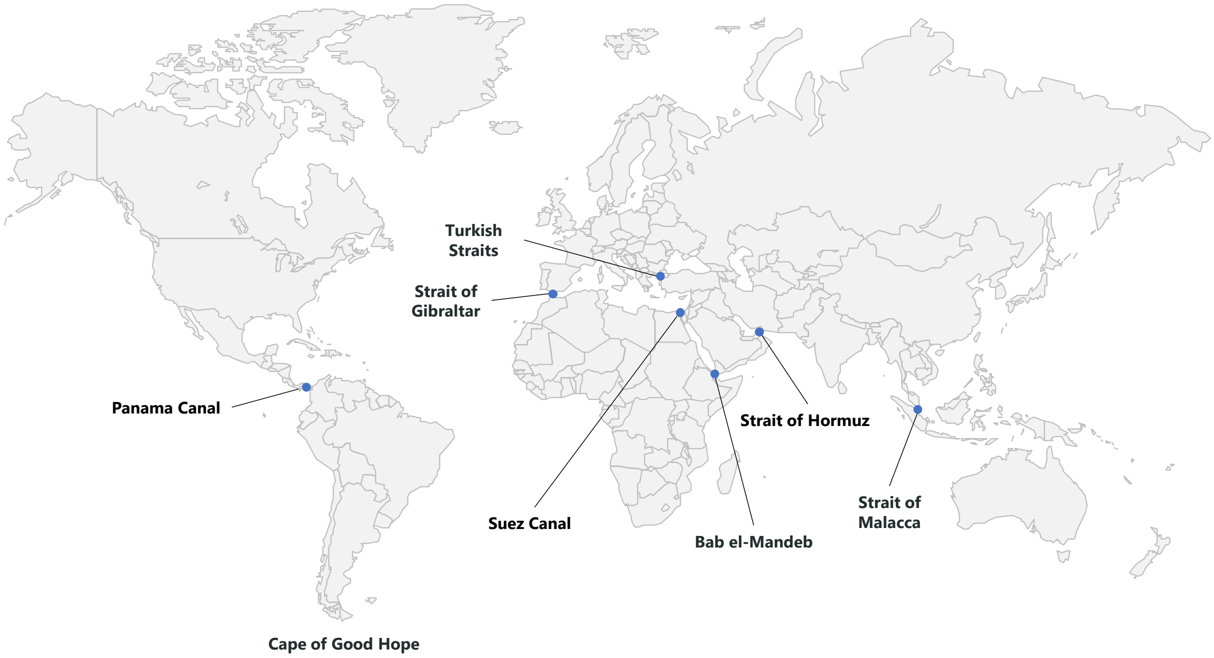

Figure 1: Global shipping routes and chokepoints (Data: ARGIS, 2021)

sources of supply." It highlighted a supply chain vulnerability caused by globalisation, which has forged global networks of geographically specialised production locations and overly lean global supply chains. For example, the iPhone relies on Apple's manufacturing network that covers 49 countries, and Pfizer, a global pharmaceutical multinational company (MNC) that supplies Covid-19 vaccines, has more than 5,000 suppliers. However, the relentless pursuit of efficiency has led to low inventories and chokepoints. The world economies have been hit dramatically due to shortages of various critical supplies to these globalised supply chains. For example, over half of advanced semiconductors are made in a few plants in Taiwan and South Korea. Recent chip shortages from these countries have stopped automotive production operations for months resulting in financial losses of several billion dollars. Another example is the fact that China processes 72% of the world's cobalt that is used in electric-car batteries, which are critically needed by all automotive OEMs in the coming years and decades. This global reliance on a few countries for critical raw materials is a major supply chain risk that has not yet unravelled into a global supply chain crisis.

A leading news agency, Reuters, reported that the recent Suez Canal blockage by the grounded ship, Ever Given, could cost global trade $6 billion to $10 billion a week (Reuters, 2021). Besides such logistics accidents, blockages of major shipping conduits (e.g., Suez Canal and the Straits of Malacca) can also be caused by natural disasters (e.g., Fukushima Earthquake 2011) and military conflicts (e.g., the Gulf of Aden and the South China Sea) (Figure 1). Rising trade barriers (e.g., Brexit, US-China trade war) as well as the tightening border restrictions on the movement of goods and people further exacerbate the challenges of global supply chains (Economist, 2020). Hence, we need to rethink the supply chain designs of future products in view of how such geo-politics could impact global supply chains, economies, and the livelihoods of everyone.

1.1.2 New technologies

Over recent years, technological advancements such as multi-material additive-layer manufacturing (ALM) and artificial intelligence (AI) that are used in production systems have changed the way products are developed, manufactured, and sourced. ALM enables product designs to eliminate unnecessary materials that incur cost, weight, and complexity, which have an impact on supply chain designs. AI technology allows higher automation level using more precise and reliable robots for automated assembly and visual sensors for quality inspection. Furthermore, AI technology has disrupted the century-old (Ford era) flow-line production system by enabling a modular and flexible production system that uses autonomous ground vehicles instead of fixed conveyor lines to manage highly customised products while shortening their production lead times and lowering inventories. AI technology is already being used to optimise global supply chain operation performance by continuously improving transportation, inventory, sourcing policies. All these technologies have a significant impact on supply chain designs. Moreover, new technologies have been constantly transforming the architecture of both products and their supply chains. For example, the emergence of automotive electric drive systems could potentially compel OEMs to increase their outsourcing by up to 20% in value (Fleming et al., 2019; Küpper et al., 2020), which has significant organisational and business implications such as relative bargaining powers between OEMs and suppliers (Henkel and Hoffmann, 2018). Electric drive systems enable more innovative and optimised product architecture such as using a more distributed positioning of electrical motors in automobiles and aircraft. This allows for more numerous but smaller electrical components that can have a significant impact (e.g., costs, inventory, replacement) on their supply chains (Fleming et al., 2019). There is a need to challenge conventional thinking on how future products and their supply chains can be designed to harness these emerging technological trends while mitigating the associated risks.

1.1.3 Environment and sustainability

The recent advancement of global environmental regulations (e.g., Paris Agreement) and greater consumer awareness of sustainable products have created new paradigms for PD and SCD. The carbon-emission regulations on transportation systems and manufacturing industries have driven manufacturers to foray into using new or alternative technologies as well as the deployment of appropriate supply chain strategies. For example, the European Union (EU) carbon regulation has motivated incumbent automotive OEMs to shift from using internal combustion engines to electrical powertrains. This change has a major impact on vehicle architectural design. Electric vehicles (EV) have fewer parts and are more modular and scalable. However, this has shifted the value chain in favour of Tier 1 suppliers, which are not located in the EU. Most incumbent automotive OEMs have already announced their intentions to develop mainly or solely EVs, while many emerging OEMs are offering EVs exclusively. Similarly, the aerospace industry has taken steps towards complying with the regulation by means of major initiatives to develop more environmentally friendly propulsion systems using hydrogen and synthetic fuels, as well as pure or hybrid electrical powertrains. These propulsion systems use electrical energy from fuel cells, batteries, or both (European Union, 2020). In the same way, these new propulsion systems have similar impacts on aircraft architectural designs such as that of EVs. We need to find new approaches to concurrently consider sustainability in both PDs and SCDs for future products.

This combination of recent geo-political, environmental, and technological developments highlights the need to review existing methods that design products and their supply chains in order to mitigate emerging supply chain risks as well as to exploit the emerging technological potential to the fullest so that supply chain management practices and research can be advanced.

1.2 Research scope

Fisher (1997) highlights that a critical success factor of manufacturers is their capability to match the right SCD to the PD. The matching process between PD and SCD requires a trade-off between innovative and efficiency factors. At around the same time, Fine (1998) introduces the theoretical framework Three-Dimensional Concurrent Engineering (3DCE) for the concurrent design of products, processes, and supply chains in his seminar book *Clockspeed* (Figure 2). His work has unravelled new ways of classifying different industries by using their industrial *clockspeeds* as well as their product, process and supply chain designs for formulating business strategies. Both seminal works emphasise the importance of conducting design trade-offs between product and supply chain designs, such as considering the right degree of product-supply chain modularity, make-buy, sourcing, and business strategies. Building on his theoretical and empirical studies, Fine (2005) provides quantitative evidence that indicates a strong alignment between product and supply chain architectures. While

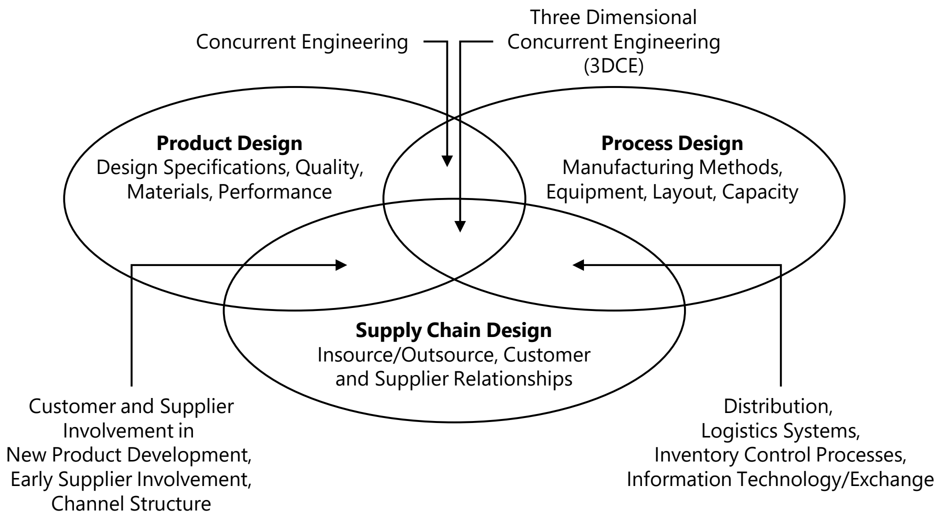

Figure 2: Adapted 3DCE Framework by Ellram et al. (2008) from Fine (1998).

the 3DCE framework provides a powerful notion on how products, processes and supply chains should be aligned and designed concurrently, it lacks both a theoretical and operational methodology to support its widespread use and offer an understanding of the interfaces between the three design domains (Ellram et al., 2007). The 3DCE framework has however sparked a new area of research that has since attracted strong interest from PD and SCD research communities and inspired a steep increase in their research activities over the last decade (Pashaei and Olhager, 2015; Gan and Grunow, 2016; Yao and Askin, 2019).

This dissertation builds on the 3DCE framework as well as the knowledge from numerous research papers that followed (e.g., Ellram et al., 2007; Khan et al., 2009; Pashaei and Olhager, 2015; Gan and Grunow, 2016; Yao and Askin, 2019), which have collectively paved the way for many interesting and unexplored areas of research in concurrent product and supply chain design (CP-SCD). It is important to note that the interfaces between product and process design domains have already been extensively researched and have achieved widespread use in industries (Fine, 1998), such as Toyota's Set-based Concurrent Engineering (Durward et al., 1999) shown in Figure 3. Figure 3 shows how product designers and manufacturing engineers can collaborate to achieve a product that meet both functional and manufacturability requirements. Concurrent product and process design methodology has helped manufacturing companies to shorten their product development and industrialisation duration. This methodology shortens the time-to-market of products and reduces the cost of development by reducing the iterations and rework needed in a sequential (waterfall)

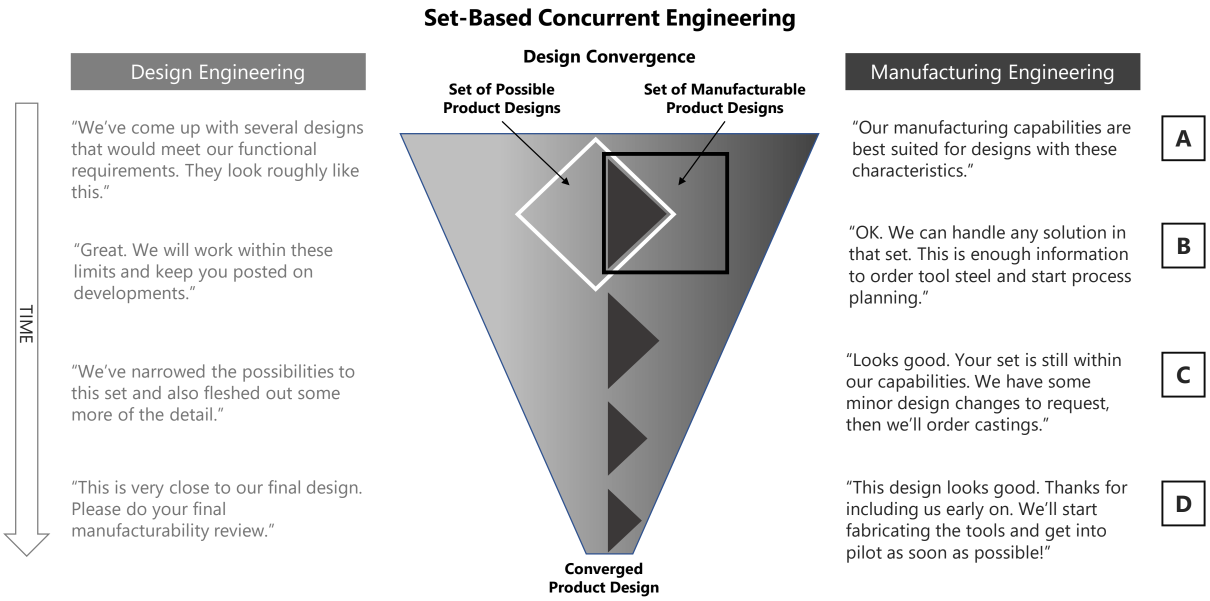

Figure 3: Set-Based Concurrent Engineering from Toyota (Durward et al., 1999)

development methodology. The concurrent product and process methodology is especially useful when the product is fully manufactured in house and not outsourced to suppliers. In contrast to working with suppliers, in-house product and process development allows for faster coordination, alignment, trade-off and learning. However, this is much more complex if the products and processes are developed in collaboration with suppliers, which requires significant effort to manage the complex interfaces between the manufacturers and the suppliers. Examples of such complexity include differences in processes, technical and management capabilities, company goals, language, and culture. With the globalisation of supply chains, along with the associated complexity highlighted earlier in this section, a methodology that allows concurrent product and supply chain design is, however, lacking. These interfaces between PD and SCD domains are still under-explored (Khan et al., 2009; Pashaei and Olhager, 2015; Yao and Askin, 2019).

Modularity has been an intensive area of research in both PD and SCD domains. Fine (2005) introduces the notion of modularity as a common design attribute between PD and SCD domains. Even through modularity has been extensively researched and documented in the PD domain (Mikkola and Gassmann, 2003, Gershenson, Prasad, and Zhang, 2004, Hölttä, Suh, and de Weck, 2005, Jung and Simpson, 2017), research in modularity in the SCD domain has only recently attracted greater attention (Pashaei and Olhager, 2015; Yao and Askin, 2019). Pashaei and Olhager (2015) provide a literature review on the relationship between product and supply chain architecture, highlighting the relevance of the modularity to PD and SCD. Yao and Askin (2019)

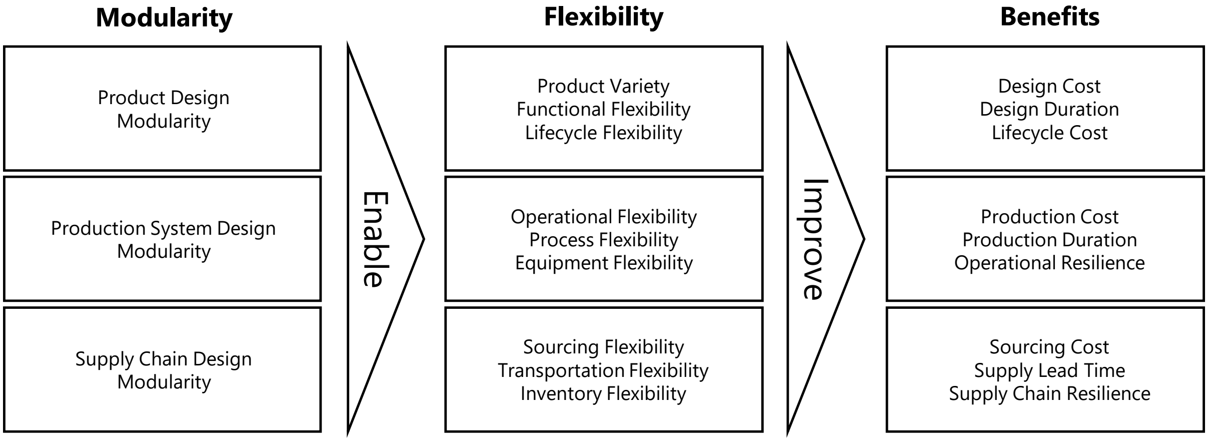

Figure 4: The impact of modularity on flexibility and the potential benefits for product, production, and supply chain designs

provide an in-depth literature review of how PD impacts supply chain configuration, another dimension that is strongly linked to its modularity. Most recently, Hackl et al. (2020) introduce a dependency network model that shows the qualitative impact of modularity decisions on a company's operations and its economic objectives. Based on a literature review and their survey, they highlight the significant influence of modularity on the three types of operations, namely product development, production, and procurement, of companies and their suppliers. Within each type of operation, the impacts of different modularity properties (e.g. decoupling, standardised interfaces, commonality, reuse parts) on operational attributes (e.g. variety, flexibility, "ilities") and the company's economic benefits (e.g. costs, lead time, risk) are mapped.

Highlighting the key elements of the dependency network model from Hackl et al. (2020), Figure 4 shows how modularity enables different types of flexibility as well as their potential benefits for product, production system and supply chain designs.

Product design modularity enables greater product variety without the need to completely redesign each variant through the use common parts and standardised interfaces. This saves design cost and time. In the same way, these benefits apply to products with different functionalities. Moreover, product modularity can reduce the lifecycle costs by increasing the changeability for replacement of obsolete or worn parts without incurring significant costs and time.

Production system design modularity enables operational flexibility by allowing multiple routing possibilities in production flows as compared to fixed flow lines (e.g. mixed-product production cells used in automotive industries). Production process modularity allows greater process flexibility in the manufacture of parts that need different processes (e.g. multi-purpose 3D printing machines that can use different feedstock materials). Production equipment modularity offers similar benefits by allowing the use of flexible components (e.g. CNC machine with interchangeable milling heads). All these flexibilities have the potential benefits of reducing production costs and duration as well as having a greater operational resilience against disruptions.

Supply chain design modularity enables sourcing flexibility (e.g. single, double or multiple sourcing), a greater flexibility in the choice of transportation modes (e.g. air, sea and land) and inventory strategies (e.g. pooling versus decentralisation). All these flexibilities offer the potential benefits of lowering sourcing and inventory costs, shortening lead time and having a greater supply chain resilience against supply chain disruptions.

Even though past research has extensively investigated how modularity can affect products, processes and their supply chains, an approach towards the quantitative design trade-off between PD and SCD domains using modularity as the common design attribute remains elusive.

Sourcing flexibility has been identified as a key SCD attribute for mitigating global supply chain risks, as highlighted by the recent supply chain incidents in Section 1.1. Even though sourcing flexibility has been subjected to extensive research in the past (De Boer et al., 2001; Gosling et al., 2010), approaches that allow the integration of sourcing flexibility into CP-SCD has been lacking. In addition to assessing and selecting suppliers by manufacturers for mitigating their direct suppliers' risks, the capability of their suppliers' capabilities in managing and integrating lower-tier suppliers is often overlooked in research and industry. Supplier integration risks have been major causes of supply chain disruptions (Tang et al., 2009), especially at the converging part of the supply chains such as those from automotive and aerospace industries. There is currently a lack of methodology that define supply chain integration risks and how they can be integrated into CP-SCD methodology.

This dissertation thus focuses on exploring and unravelling the details of the interfaces between PD and SCD within the 3DCE framework, as well as developing a new methodology for CP-SCD and supply chain integration risk mitigation. This use of architectural and strategic design attributes (modularity and flexibility), which have been emphasised in past research as imperative for this cross-disciplinary research domain, are cornerstones of the developed methodology.

1.3 Problem statements

Based on the identified research areas and industrial trends in the last section, the problem statements for this dissertation have been formulated as follows:

1) What are the research gaps in the field of CP-SCD?
2) How can incumbent PD and SCD processes be integrated to allow for CP-SCD?
3) How can the trade-off between PD and SCD be structured and conducted for more efficiency and efficacy?
4) How can the CP-SCD methodology consider supplier integration risks?
5) What are the industrial strategies and managerial recommendations from the research in CP-SCD?

1.4 Research contributions

This dissertation addresses the lack of research on the interfaces between PD and SCD domains in the 3DCE and other CP-SCD frameworks (Fisher, 1997; Fine, 1998; Fine 2005). It advances existing theories in CP-SCD, introduces new methodology and demonstrates its applications. It first provides an extensive literature review of past research on CP-SCD (Gan and Grunow, 2016).

Secondly, based on this literature review, it introduces a new exploratory framework CDA-TOP (Concurrent Design Attribute Trade-Off Pyramid), for classifying and structuring design attributes in both PD and SCD domains according to the different levels of design trade-off (architectural-strategic, detailed-tactical, and dynamic-operational).

Thirdly, it introduces a conceptual methodology that specifically addresses the underexplored tradespace between integral and modular product and supply chain architectures. This methodology centres on the use of a high-impact design attribute, *modularity*, which is considered the most important architectural design attribute in past research (Ulrich, 1995; Mikkola and Gassmann, 2003; Hackl et al., 2020).

Fourthly, this dissertation introduces a new approach towards quantifying modularity and its design space, which is used for developing a novel framework that quantifies the relative modularity level and alignment of product and supply chain architectures using a design structure matrix (DSM). This framework classifies product-supply chain (P-SC) systems into six different archetypes, which are used for representing the intrinsic properties of the PD and SCD strategies of different industries. Building on this approach, this dissertation then introduces an operationalised version of the conceptual methodology (Gan et al., 2022).

Fifthly, as parts of this operationalised methodology, the dissertation introduces a new DSM clustering method, a SCD method for sourcing flexibility for mitigating supply chain risks and a method for transforming the generated SCD into a SC-DSM that can be commensurate with a PD-DSM. This new methodology is then applied to an industrial case study from the automotive industry, involving a new electric vehicle battery system, which is lacking in past research (Yao and Askin, 2019).

Finally, the dissertation contributes to the research area of supply chain risk management (SCRM) by extending the CP-SCD method for mitigating supplier integration risk, which this dissertation introduces for addressing a gap in research for designing the convergent supply chains of complex products (Tang et al., 2009). A case study of a major aerospace OEM is used to demonstrate the use of our SCD methods for supplier integration risk mitigation.

1.5 Dissertation outline

This dissertation is structured to provide a progressive representation of my individual and collaboration works with other researchers. Chapter 1 provides the motivation, scope, problem statements and contributions of my research work.

In Chapter 2, an extensive literature review of past research in PD, SCD, and CP-SCD, focusing on their design frameworks, processes, and methodology, is presented. This literature review is based on the work done in the first part of Gan and Grunow (2016). The review highlights research gaps and summarises key findings, which are used for creating an exploratory framework CDA-TOP for structuring design attributes, trade-off levels between PD and SCD domains and four propositions for CP-SCD. In the second part of Gan and Grunow (2016), the way these four propositions are used to develop a conceptual process for CP-SCD for modularity is presented. This new conceptual process shows how it uses DSMs to model PD and SCD architectures as well as presents the methods and approach for the quantification of their modularity levels. To derive managerial insights from these architectures, a novel framework is introduced, showing how the DSM alignment levels and the relative quantified modularity levels between PD and SCD are used to derive six archetypes of different product-supply chain (P-SC) systems. A thorough discussion of the managerial implications, PD, and SCD strategies of these archetypes and the relevant industries is presented at end of this chapter.

In Chapter 3, the conceptual process from Gan and Grunow (2016) is further developed for application. This chapter presents the work from Gan et al. (2022), which focuses on the operationalisation of the conceptual process for modularity and sourcing flexibility. An industrial case study involving a newly designed automotive battery is used to demonstrate the new process and methods.

In Chapter 4, the CP-SCD method for sourcing flexibility from Gan et al. (2022) is extended to consider multiple types of sourcing policies (e.g., single, double) for supply chain risk mitigation under risk uncertainty. This chapter presents my work in Cunha et al. (2022), which enhances the computational efficiency of the SCD method from Gan et al. (2022) and includes a new research contribution of considering supplier integration risks in a CP-SCD method. Supplier integration risk is a type of supply chain risk that is important to convergent type of supply chain but has so far been underexplored. The application of this new method is demonstrated using a case study from a major aerospace OEM as well as random instances.

Finally, Chapter 5 provides a summary of the results, contributions, and limitations of this dissertation. The managerial implications and an orientation for future research are outlined.

2. Concurrent product and supply chain design: a literature review, an exploratory research framework, and a process for modularity design

This chapter is based on
T.-S. Gan and M. Grunow (2016)
International Journal of Computer Integrated Manufacturing 29(12):1255–1271

The capability to concurrently design the product and its supply chain is a key competence in manufacturing companies. However, this crucial capability is still underdeveloped because of the lack of practical methodology for concurrent product and supply chain design in the industries. Moreover, research has not been able to fill this industrial capability gap partly because there is a lack of convergence of methodologies in the product design and supply chain design research communities. This paper provides a literature review that unravels undiscovered aspects and gaps of past research in concurrent product and supply chain design (CP-SCD). The findings from the literature review are synthesised into a novel exploratory research framework termed Concurrent Design Attribute – Trade-Off Pyramid that provides propositions for research on CP-SCD methodology. The practicality of this framework is demonstrated by the development of a CP-SCD methodology, which is applied to modularity design. Based on an innovative use of the design structure matrix in modularity design, this methodology also generates useful managerial insights in design trade-off analysis and the classification of product-supply chain systems.

Keywords: product design, supply chain design, concurrent design, trade-off methodology, modularity

2.1. Introduction

2.1.1. Motivation

For a manufacturing company to be successful in today's competitive, complex and globalised world, the capability to design products has to be complemented by the capability to manage a complex supply chain (encompassing suppliers, manufacturing sites and a distribution system) that delivers the product to the market. Many researchers have identified the benefits of concurrent design of products and supply chains (SCs), such as greater SC performance and risk-mitigating flexibility as well as lower SC costs. Some have even systematically quantified these benefits by using complex industrial cases (e.g., Blackhurst et al., 2005; Ellram et al., 2007; Ellram and Stanley, 2008; ElMaraghy and Mahmoudi, 2009; Gokhan et al., 2010). However, concurrent product and supply chain design (CP-SCD) is complex because of the scope and multi-disciplinary nature of the design space. Hence, a structured approach for CP-SCD is needed.

2.1.2. Product and supply chain design

For various reasons, such as complexity of cross-disciplinary research and unexhausted mono-disciplinary research potentials, researchers in product design (PD) and supply chain management have stayed mainly within their domains (Ellram et al., 2007; Zhang et al., 2008). Research in PD has been documented for more than a century (Krishnan and Ulrich, 2001; Tomiyama et al., 2009). As PD sub-disciplines are not always quantifiable or intuitive, PD remains a combination of art and science (Fixson, 2005). Tomiyama et al. (2009) have provided a comprehensive review of PD methodologies and theories.

PD methodologies are product-centric and are still not effectively integrated with other non-PD methodologies such as those for SCD. One possible explanation is that the majority of PD processes have been introduced before the era of globalisation of supply chains, during which in-house production depth was relatively high and suppliers were mostly local or at most regional. A few PD processes consider design factors beyond the PD domain, such as production processes (e.g., manufacturing, assembly) and cost factors (e.g., future need to outsource). However, these factors are often considered at later phases of these processes (Tomiyama et al., 2009). More recent concurrent engineering methodologies such as Design for X exist but do not adequately address SCD in terms of method, tool and metric (Chiu and Kremer, 2011). All these approaches are not sufficiently specific towards CP-SCD and in particular do not provide a detailed prescriptive procedure to do CP-SCD.

Several PD methodologies have highlighted that PD can be represented by PD attribute levels (architectural, detailed and dynamic) (Tomiyama et al., 2009). This classification of PD attributes is based on the concepts and principles found in Ulrich (1995), Hofer and Halman (2005) and Liu et al. (2010). PD architectural attributes describe any form of spatial and functional arrangement of product elements (e.g., modularity, commonality and configuration). PD detailed attributes can be extrinsic (e.g., design cost, innovation level, quality, market factors) or physical (e.g., geometry, material) attributes of a product. In comparison, dynamic attributes describe PD lead time, the functional performance of the product as well as product changes with respect to its form and function over time (e.g., product lifecycle factors). These levels enable a systematic top-down approach in PD. Among these three PD attribute levels, the product architecture has recently received strong attention in the research community because of its impact on downstream design as well as product lifecycle and the SC. Cornerstones of product architectural design are the axiomatic design theorems, according to which PD has to generally account for design for manufacturability and design-manufacturing interfaces. Ground-breaking research using architectural attributes such as modularity and commonality (e.g., Suh, 1998; Suh et al., 1998) resulted and much more qualitative and quantitative attributes followed (e.g., Gershenson et al., 2004; Thevenot and Simpson, 2006).

PD theories and methodologies are more established than those for SCD. A possible explanation for this is the transformation of industry. The need for systematic PD methodologies predates the need for SCD. Contemporary research in SCD usually assumes a defined PD before considering the design of SC, hence leaving very limited design space for SCD. Useful for the purposes of our research are the SCD frameworks using a hierarchy to structure SC attributes. Shapiro (2006), Simchi-Levi, Kaminsky, and Simchi-Levi (2008), Günther and Tempelmeier (2014) and Meyr and Stadtler (2010) use three-level structures (strategic, tactical and operational) that are dependent on the differences in decision horizons and the impact on the SC performance. These structures go back to the seminal work of Anthony (1965) and Hax and Meal (1973). Examples of strategic attributes are locations, SC network and supply flexibility (Duclos et al., 2003). Examples of tactical attributes are capacities and inventory policies. Finally, operational attributes are more short-term types (e.g., scheduling related and operational flexibility; Duclos et al., 2003). Table 1 summarises the design levels for both domains. We will use this structure in the following to discuss the literature and develop a framework for CP-SCD.

Table 1: Levels in product and supply chain design.

Design Level	Product	Supply Chain
Top	Architectural (A)	Strategic (S)
Intermediate	Detailed (D)	Tactical (T)
Bottom	Dynamic (Y)	Operational (O)

Table 2: Overview of selected case study papers related to CP-SCD (in order of publication year), design attributes discussed and industry contexts.

		PD Attributes										**SCD Attributes**												
Year	Authors (Year of Publication)	Modularity	Commonality	Configuration	Design Cost	Quality	Geometry	Material	Innovation	Market Factors	Lifecycle Factors	Lead Time	Operation Flexibility	Inventory cost	Transportation cost	Procurement cost	Production cost	Fixed cost	Quality	Supplier Relationship	Location	Assembly Sequence	Supply Flexibility	Industry / Product Context
2001	Eppinger and Novak (2001)	x		x					x												x		x	Automotive
2003	Mikkola and Skjoett-Larsen (2003)	x																		x			x	Medical/Audio/Visual
2004	Appelqvist et al. (2004)			x			x					x					x					x		Aerospace
2004	Krikke et al. (2004)	x	x	x							x			x			x					x		Industrial/Auto/ Printing
2005	Lau and Yam (2005)	x							x											x			x	Electronic
2005	Fixson (2005)	x	x	x								x		x		x					x		x	Discrete Products
2005	Petersen et al. (2005)				x	x														x				General
2007	Humphrey et al. (2007)	x	x		x								x						x	x				Telecommunication
2008	Khan et al. (2008)				x	x		x	x	x		x	x		x	x							x	Textile
2009	Khan and Creazza (2009)		x		x								x							x			x	Textile/Ceramic/ Polymer plastic
2010	Lau et al. (2010)	x																					x	Electronics / Plastics
2010	Pero et al. (2010)	x	x						x			x		x	x	x	x	x	x	x			x	Discrete Products

A number of papers dealt with CP-SCD based on case studies. Table 2 shows some recent examples and provides information on the industries and attributes according to the product and SC domains. These publications highlight the growing interest in an integrated approach towards product and supply chain design. However, none of these papers provided detailed information on the methodology used for CP-SCD.

Similarly, there is also a significant amount of literature in the operations management community on early supplier involvement (e.g., Dowlatshahi, 1998; Zsidisin and Smith, 2005; McIvor and Humphreys, 2004) and supplier contributions to PD (e.g., Tracey and Tan, 2001; Petersen et al., 2005). While supplier cooperation is important in leveraging SC potentials connected to PD, this research generally takes critical SCD decisions such as make-or-buy and supplier selection as given. In addition, most of this work is based on empirical methodology such as case studies and does not propose a detailed methodology for decision-making on PD and SCD attributes as well as for trading off objectives from both domains.

2.1.3. Design trade-off methodology

The search for global design optimality of both the product and the SC requires methodology to support trade-off decisions between conflicting design objectives. Trade-off methodology is a pivotal for CP-SCD. Trade-off methodology can be defined as an analytical approach for evaluating and comparing competing design solutions based on stakeholder-defined criteria (Bahill, Daniels and Werner, 2001). For design trade-off, Multi-Criteria Decision Analysis (MCDA) methodologies are particularly relevant. Colson and Bruyn (1989) classify MCDA into compensatory, non-compensatory or partially compensatory types. For compensatory type, the value of one criterion can be used to compensate the performance of the other (i.e., a trade-off is possible). This requires criteria to be commensurable. For non-compensatory types, trade-off is not possible because of their lack of direct commensurability. Guitouni and Martel (1998) state the need for aggregation of criteria in decision trade-off. Aggregation allows compensation between different criteria and hence enables trade-off to occur. In the context of our review, trade-off methodology is defined as the process of finding the best overall solution (global solution) to a problem based on a set of target objectives, evaluation criteria and constraints using commensuration, compensation and aggregation. MCDA methodologies that are of particular interest to trade-off are those of compensatory and partially compensatory types such as Weighted-Sum, MAUT, ELECTRE, PROMETHEE, Analytic Hierarchy Process (AHP) and Multi-Objective Programming (MOP). Detailed descriptions of the algorithms and a comparison between the methodologies can be found in Guitouni and Martel (1998) and Ehrgott et al. (2010).

Simulation is another type of methodology that can be used to support trade-off analysis. Simulation is not a trade-off methodology *per se* but can be used with other methodologies (e.g., MCDA, Design of Experiment) to analyse more complex trade-off (e.g., over time) and with stochastic model attributes (e.g. Su et al., 2005; Izui et al., 2010).

2.1.4. Paper contributions and structure

The key contributions of this paper are the following:

- a literature review of work on design methodology for CP-SCD analysing the design attributes used in both domains and the employed trade-off methodologies,
- a new exploratory research framework, which structures CP-SCD and is used to derive potential areas for further research on the development of CP-SCD methodology,
- a CP-SCD process for modularity design and alignment as well as new concepts for quantifying the design modularity level using a modularity index,
- a classification of different product-supply chain (P-SC) systems in archetypes, for which standard strategies are derived.

In the next section, we present the literature review methodology. Our paper goes beyond existing review papers that link product and supply chain design domains (Beamon, 1998; Rungtusanatham and Forza, 2005; Forza et al., 2005; Ellram et al., 2007;

Chiu and Kremer, 2011). Beamon (1998) provides an overview on the SCD methods and performance attributes but has limited insights on how PD attributes can be integrated into SCD. Rungtusanatham and Forza (2005) and Forza et al. (2005) summarise relevant papers and propose research agenda for CP-SCD such as the need for an integrative framework. Ellram et al. (2007) highlight the obstacles hindering the adoption of the three-Dimensional Current Engineering (3DCE) framework, which covers interactions between product and its ecosystem (e.g., process, SC, organisation, strategy) and propose research methods in gaining understanding of the 3DCE practices. Chiu and Kremer (2011) provide a detailed review of the "Design-for-X" PD methods for product value chain and also suggest the need of an integrative framework. Our paper includes the analysis of the interdependence between PD and SCD attributes and has a more focused review scope that provides more detailed insights into CP-SCD trade-off analysis than these past review papers, which offer more generic discussions of the research trends and potentials of CP-SCD.

In section 2.3, we use findings from the literature review to develop a novel exploratory research framework termed Concurrent Design Attribute – Trade-Off Pyramid (CDA-TOP). This framework presents a high-level taxonomy of concurrent design attributes and interfaces between the product and SC domains. In addition, the CDA-TOP framework introduces the concept of design trade-off asymmetry between PD and SCD.

In section 2.4, the CDA-TOP framework is used to develop the CP-SCD process with a focus on the architectural design phase. In the architectural design phase, we focus on modularity design of product and SC and introduce a novel method for conducting modularity design trade-off using Design Structure Matrix (DSM). Moreover, we introduce a topology of P-SC system archetypes for classifying P-SC system modularity. These archetypes are useful for formalising characteristics of P-SC system for future research.

In section 2.5, we bridge CP-SCD theory with practice by generating managerial insights from these P-SC system archetypes. Standard strategies for the PD and the SC are derived and structured into a managerial framework to support outsourcing decision process. In the last section, we provide a synthesis and analysis of our findings and highlight future research potentials in CP-SCD.

2.2. Literature review

2.2.1. Scope and methodology

The literature review methodology is designed such that it addresses specifically the cross-disciplinary research boundary between PD and SCD. Hence, the criterion for inclusion in our literature review is the presence of design concurrency and trade-off methodology across the PD and SCD domains. This also means that the design attributes used in the literature must possess the elements of commensurability, compensation and aggregation.

With this scope in mind, a search has been conducted using university and other databases (Google Scholar, Scopus, EBSCO, Science Direct, ProQuest, Taylor & Francis, Springer, etc.) that cover major journals in PD, engineering, supply chain, operations management and management science. In order to efficiently and effectively filter relevant papers from the vast amount of product and supply chain related papers, our search procedure uses exhaustive combinations of different key words to capture relevant papers. The key words such as *product design, supply chain design, concurrent design, simultaneous engineering, architecture, trade-off, modularity, configuration, optimisation, methodology,* etc., are used to filter the enormous collection of product and supply chain management papers. In order to identify additional relevant papers, we conducted extensive backward and forward search based on references and citations. Based on the extrapolated trend, the review period was restricted to publications which appeared after 1992. On this basis, 19 relevant papers were identified.

2.2.2. CP-SCD methodology: an underexplored and emerging research area

The papers within the review scope are listed in Table 3. The low number of CP-SCD relevant papers over the last two decades indicates that research in CP-SCD methodology is still an emerging research area. Most papers were in fact published after 2005 (Lamothe et al., 2006; Ellram et al., 2007; Seliger and Zettl, 2008; ElMaraghy and Mahmoudi, 2009; Gokhan et al., 2010; El Hadj Khalaf et al., 2011; Ülkü and Schmidt, 2011; Baud-Lavigne et al., 2012; Nepal, Monplasir, and Famuyiwa, 2012; Shidpour et al., 2013; Chiu and Okudan, 2014).

Table 3: Overview of quantitative papers (in order of publication year), design attributes and product contexts.

		PD Attributes											**SCD Attributes**												
Year	Authors (Year of Publication)	Modularity	Commonality	Configuration	Design Cost	Quality	Geometry	Material	Innovation	Market Factors	Design Lead Time	Lifecycle Factors	SC Lead Time	Operational	Inventory cost	Transportation cost	Procurement cost	Production cost	Fixed cost	Quality	Supplier Relationship	Location	Assembly Sequence	Supply Flexibility	Industry Product Context
1995	Lee and Sasser (1995)		X		X							X	X		X	X				X		X			Computer (printer)
2003	Krikke et al. (2003)	X										X				X		X	X			X			Household (refrigerator)
2005	Blackhurst et al. (2005)							X					X		X										Aerospace (electronic)
2005	Fine et al. (2005)	X											X				X	X	X	X	X		X		Elevator
2005	Huang et al. (2005)	X	X	X									X		X	X	X	X						X	Computer
2005	Su et al. (2005)	X	X		X								X		X			X	X						Discrete Products
2006	Lamothe et al. (2006)	X		X						X					X	X		X	X			X			Automotive (wiring)
2008	Zhang et al. (2008)	X	X	X	X					X				X	X		X								Discrete Products
2008	Seliger and Zettl (2008)	X	X	X				X	X	X		X						X				X	X		Cellphone
2009	ElMaraghy and Mahmoudi (2009)	X													X	X	X	X							Automotive
2010	Gokhan et al. (2010)			X						X		X	X		X	X		X						X	Discrete Products
2010	El Hadj Khalaf et al. (2011)	X		X												X		X				X			Automotive
2010	Izui et al. (2010)				X		X						X		X	X	X	X							Energy (Electrical Switch)
2011	Jiang et al. (2011)			X									X		X			X							Automotive (Tractor)
2011	Ülkü and Schmidt (2011)	X			X	X				X											X				Discrete Products
2012	Nepal et al. (2012)	X								X			X		X			X			X			X	Heavy Machineries
2012	Baud-Lavigne et al. (2012)		X		X					X						X		X							Discrete Products (Ind. Case)
2013	Shidpour et al. (2013)					X				X	X		X				X	X	X	X				X	Mobile device
2014	Chiu and Okudan (2014)	X											X		X	X	X	X					X		Bicycle

2.2.3. Asymmetrical CP-SCD design trade-off

An analysis of the PD and SCD attributes that appear in the reviewed papers reveals some interesting insights. Table 3 shows the different PD and SCD attributes used in reviewed papers. While on aggregate the numbers of attributes in each domain are similar, most individual papers do not have a balanced number of attributes for modelling the design space in both domains. As introduced in section 2.1.2, the design attributes are classified into three levels: architectural, detail and dynamic on the PD side and strategic, tactical, and operational on the SCD side.

Table 4 aggregates the classified PD and SCD attributes and highlights the following analysis. The PD attributes used in these papers are mostly of product architectural types. Also, 16 out of 19 papers use product architectural attributes for the trade-off. One explanation is that PD architectural attributes have greater impact on SC performance than other lower-level PD attributes. Also, the difficulty in modelling the relationship between product detailed and dynamic attributes to SC attributes leads to a focus on architectural attributes. Only two papers use solely PD detailed attributes with SC attributes (Blackhurst et al., 2005; Izui et al., 2010).

Table 4: Overview of papers (in order of publication year), trade-off design attributes (Architectural (A), Detailed (D), Dynamic (Y) for PD; Strategic (S), Tactical (T), Operational (O) for SCD and their trade-off methodologies.

	Product			**Supply Chain**			
	A	**D**	**Y**	**S**	**T**	**O**	**Trade-off Method**
Lee & Sasser (1995)	1	1	1	1	3	1	Optimisation
Krikke et al. (2003)	1		1	1	3		MILP
Blackhurst et al. (2005)		1			1	1	Simulation
Fine et al. (2005)	1			1	5	1	WGP
Huang et al. (2005)	3			1	4	1	GA
Su et al. (2005)	2	1			3	1	Simulation
Lamothe et al. (2006)	2	1		1	4		MILP
Zhang et al. (2008)	3	2			2	1	MILP
Seliger & Zettl	3	3	1	2	1		MILP
ElMaraghy & Mahmoudi (2009)	1				4		MILP
Gokhan et al. (2010)	1	1	1	1	3	1	MILP
El Hadj Khalaf et al. (2011)	2			1	2		MILP
Izui et al. (2010)		2			4	1	Simulation
Jiang et al. (2011)	1				2	1	GA
Ülkü & Schmidt (2011)	1	3			1		Simulation
Nepal et al. (2012)	1	1		1	3	1	WGP
Baud-Lavigne et al. (2012)	1	2			2		MILP
Shidpour et al. (2013)		2	1	1	4	1	MILP / TOPSIS / FAHP
Chiu & Okudan (2014)	1			1	4	1	NLP

In contrast, the SC attributes used are mostly of detailed type. Only 11 out of 19 papers use SC strategic attributes. This comes as no surprise as modelling SC using detailed attributes (e.g., production and sourcing costs) and operational attributes (e.g., lead time) is a common approach in SC research, while the numerical characterisation of supply network structures (e.g., in terms of complexity) is less proliferated in management science.

Interestingly, only four papers have been found to address non-greenfield SCD (Lee and Sasser, 1995; ElMaraghy and Mahmoudi, 2009; Gokhan et al., 2010; Nepal et al., 2012). These papers consider existing SC by using penalties of deviation from existing designs (costs of integrating new suppliers [Gokhan et al., 2010]) and constraints (existing locations [ElMaraghy and Mahmoudi, 2009]) or by comparing between existing and alterative SCD (Lee and Sasser, 1995; Nepal et al., 2012). This small number of non-greenfield analyses in CP-SCD trade-off does not reflect industrial requirements as the reuse of existing assets for new products reduces new investment and is hence a necessity. In addition, the papers are classified based on their trade-off symmetry according to the highest level used on either side (i.e., if architectural and detailed attributes are used – it is shown as architectural level) (number of papers shown in parenthesis):

- PD architectural-SC strategic trade-off (10)
- PD architectural-SC tactical trade-off (6)
- PD detailed-SC strategic trade-off (2)
- PD detailed-SC tactical trade-off (2)
- PD dynamic-SC operational trade-off (0)

Interestingly, only one of the 19 quantitative papers has been found to compare between sequential and simultaneous CP-SCD processes (Gokhan et al., 2010).

2.2.4. CP-SCD trade-off methodologies

In section 2.1.3, the different types of MCDA methodologies have been outlined. Table 4 shows the types of trade-off methodologies used in the 19 papers that have been highlighted in the previous section. Among them, 15 papers use at least one of the MCDA methodologies. These papers use MOP-type (e.g., MILP, GP, GA) methodologies, with the majority using cost functions and one using a utility function (Seliger and Zettl, 2008). One paper uses a unique 2-step CP-SCD process that combines MOP and TOPSIS-FAHP (Technique for Order of Preference by Similarity to Ideal Solution – Fuzzy Analytical Hierarchy Process) methodologies to capture both quantitative and quality attributes respectively. Four papers use simulation. We believe that the complex relationships of trade-off attributes and the ease of quantifying certain target objectives (e.g., cost, utility, quality) favour the use of MOP and simulation over other types of MCDA methodologies. Other MCDA methodologies using either pairwise comparison (e.g., AHP) or scoring are only suitable for selecting discrete design options and not suitable for continuous attribute trade-off. Discretisation of continuous attributes by ranking or scoring is required for aggregation, which can be unwieldy if there is large number of attributes with complex relationships.

2.3. Concurrent design attribute – trade-off pyramid

In order to synthesize the findings from the literature review, an exploratory research framework termed CDA-TOP (Figure 5) is proposed. It maps and links the key relationships and interactions between PD and SC attributes. The CDA-TOP framework is structured as a multi-level pyramid for illustrating the concurrent design trade-off domains with the following main features:

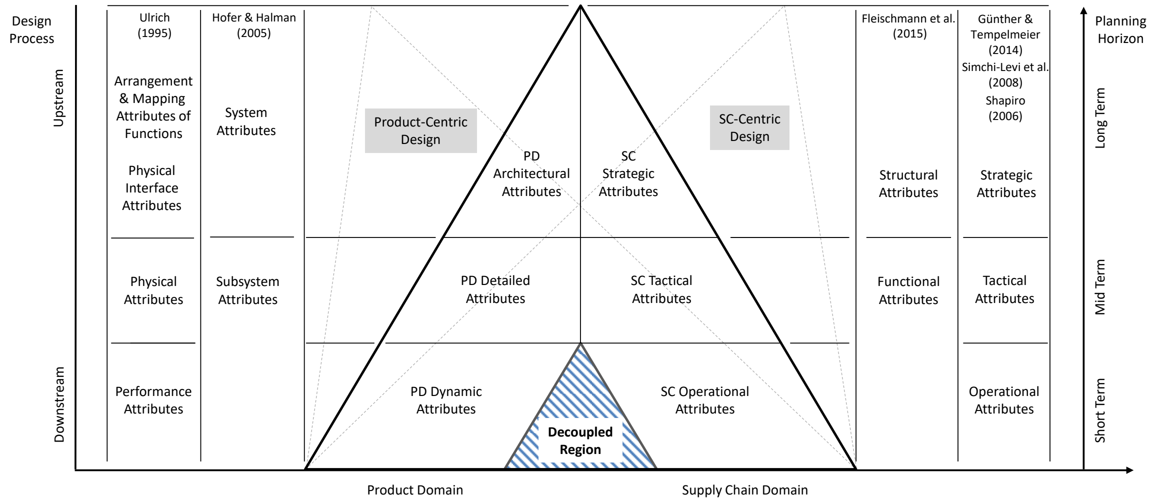

Figure 5: The Concurrent Design Trade-Off Pyramid (CDA-TOP) framework.

- a three-level hierarchy of the PD and SC attributes
- a positioning of attributes along the design process and the horizon of the SC planning decisions
- a boundary between the PD and SC domains indicating the coupling-decoupling of attributes in different domains

CDA-TOP uses a three-level hierarchy, which is (as outlined in section 2.1.3) well-established in both domains, to classify different types of design attributes according to their relative leverage on the product and the SC. Similar structures have often been used as an effective way to represent attributes in trade-off studies (Bahill et al., 2001). The triangular shape of the trade-off pyramid indicates that a few very central decisions are taken at the top level and numerous diverse decisions are made on the bottom level.

At the centre, CDA-TOP shows the trade-off boundary between the PD and the SC domains. More importantly, this trade-off boundary not only marks the coupled region at the architectural-strategic and detailed-tactical level, but also the decoupled region at the dynamic-operational level. No direct linkage exists between the PD dynamic and the SCD operational attributes. Accordingly, no paper involving direct trade-off between PD dynamic and SCD operational attributes has been found in the literature review. In order to bridge terminology used in CDA-TOP and terminology in the PD and SCD research domains (Ulrich, 1995; Hofer and Halmann, 2005; Shapiro, 2006; Günther and Tempelmeier, 2014; Simchi-Levi et al., 2008; Meyr and Stadtler, 2010), further terms are shown on both sides of CDA-TOP for comparison (Figure 5).

2.3.1. Significance of the CDA-TOP framework

CDA-TOP provides a holistic view of the different types of design attributes and their conceptual relationship between them. CDA-TOP has been created to be conceptually useful to product and SC designers. CDA-TOP is shown as a symmetrical pyramid with balanced design attributes in product and SC domains for optimum trade-off. However, our literature review shows that asymmetrical design dominates. The number of design attributes used in the product and supply chain domains is unbalanced and even mixed across different levels. In practice, this asymmetry also occurs as the design processes are usually skewed either in favour of the PD engineers (PD-centric) or the SC managers (SC-centric). For high-mix/low-volume and complex products such as aircrafts, PD engineers have typically very compelling reasons to dominate over SC managers. In comparison, high-volume/low-mix and low-value products such as packaged products for which SC attributes are more important, SC managers take the lead in concurrent design. This is in line with contemporary view that SC designs of innovative and non-innovative products are different (Krishnan and Ulrich, 2001). However, such practices of asymmetrical trade-off are suboptimal as they narrow designers' view of the CP-SCD design space and may limit hinder designers' ability to find design optimality for the P-SC system.

CDA-TOP offers a conceptual visualisation of the design trade-off asymmetry when one of the abovementioned trade-off scenarios occurs (see dotted lines in Figure 5). In the event of design trade-off symmetrical level change (illustrated by a horizontal shift of the pyramid peak towards either ends of the two domains), the greatest impacts of such a shift are on the architectural level, followed by the detailed level and lastly the dynamic level of the other design domain. These impacts are graphically represented by the change of the overlapping areas between the symmetrical and shifted asymmetrical pyramids. For example, a change of the automotive SC make-buy architecture will impact the product modular architecture (e.g., modularisation to enable outsourcing Nepal et al., 2012). Consequently, the choice of material (product detail) may have an impact on maximum speed, for example because of material weight changes (product dynamic). Conversely, a change of the product modular architecture (e.g., product standardisation; Lee and Sasser, 1995) will impact the SC push-pull boundary (SC strategic), the replenishment policy (SC tactical) and the lead time (SC operational). As represented in the CDA-TOP framework, this top-down relationship can also be derived from the fact that SC operational attribute is a function of upper-level tactical and strategic attributes (e.g., lead time depends on inventory policies and the push-pull decoupling point). This impact on the SC tactical and operational attributes also affects the choice of production technology and infrastructure, which are reflected in SC attributes such as lead times and costs. Such dominating influences of upstream design attributes over downstream design attributes have been widely accepted by many PD and SC researchers (Ulrich, 1995; Salvador et al., 2002; Fine et al., 2005; Hofer and Halman, 2005; Jiang et al., 2011). It is important to note that there is always a direct interdependence between PD architectural and SC strategic attributes (Fine et al., 2005), but there may not always be a linkage between PD detailed and SC tactical design attributes (e.g., replenishment policy, choice of material) and hardly any direct relationship between PD dynamic and SC operational attributes (e.g. completion time, product speed).

2.3.2. The four propositions of the CDA-TOP framework

Four propositions can be derived from the CDA-TOP framework relating to the design of a CP-SCD trade-off methodology.

Proposition 1: A concurrent design process for PD and SCD can bring greater value than a sequential design process due to an improvement of trade-off leverage and quality. Concurrent consideration of product and SC design attributes increases the design space early in the PD process in order to avoid costly redesign. Numerous papers support the practice of CP-SCD (see section 2.1.1).

Proposition 2: Symmetrical design trade-off at architectural-strategic and detailed-tactical levels should be pursued to ensure higher trade-off quality. Symmetrical design entails balanced inclusion of design attributes from both domains. This widens the design space of the P-SC system during the decision process before determination of design orientation (PD or SCD oriented). As a result, symmetrical design also increases the chance of finding optimal P-SC system designs than in asymmetrical design case. As it is possible to conduct concurrent design without ensuring design symmetry, it is also important to note that symmetrical design goes beyond concurrent design (proposition 1). The practices and methodologies in the reviewed papers have been found to be asymmetric. The development of new methodology must therefore significantly advance the state of the art to obtain design trade-off symmetry.

Proposition 3: The design trade-off should be pursued at architectural-strategic level first before other levels to ensure greatest trade-off leverage on the PD and the supply chain in the early stages of the concurrent design process. As explained in the two aforementioned conceptual examples in the previous section, the coupling between attributes weakens across hierarchical levels (e.g., architectural-tactical) because of the need for cross-hierarchical abstraction in the trade-off model. In contrast, design trade-off on the same hierarchical level allows for more accurate modelling of attribute relationships and hence higher trade-off quality. However, none of the previous research provides a methodology for CP-SCD in which the trade-off is made by addressing the hierarchical levels systematically one after the other. Substantial research effort is therefore required.

Proposition 4: The lack of direct linkage between PD dynamic and SCD operational attributes illustrated by the framework suggests that new methodology should avoid direct dynamic-operational trade-off. This is in line with previous research on CP-SCD methodology.

These four propositions form the foundation of the CP-SCD process, which will be introduced in the next section.

2.4. Development of the CP-SCD process based on the CDA-TOP framework

2.4.1. Procedural concept based on the CDA-TOP propositions

Based on the CDA-TOP framework and its propositions, we propose a procedure for the development of the CP-SCD process. Figure 6 shows the trade-offs and linkages between the different design domains and hierarchical levels identified in the reviewed papers. Figure 6 also shows the CP-SCD process that has been developed from the CDA-TOP framework propositions (concurrent design, symmetrical design trade-off, top-down design approach and decoupled dynamic-operational level attributes). The CP-SCD process consists of two fundamental steps. Step 1 involves architectural-strategic level trade-off between product and SC design. Step 2 involves trade-offs between PD and SCD domains at both detailed-tactical and dynamic-operational levels. The sequential two-step procedure reflects the first and third propositions, which state the need for concurrent design and a top-down design approach respectively. In each step shown in Figure 6, the trade-off linkages reflect the second and the fourth proposition, which state the need for symmetrical design trade off and for avoiding direct trade-off between dynamic and operational attributes respectively. This ensures design trade-off quality and leverage.

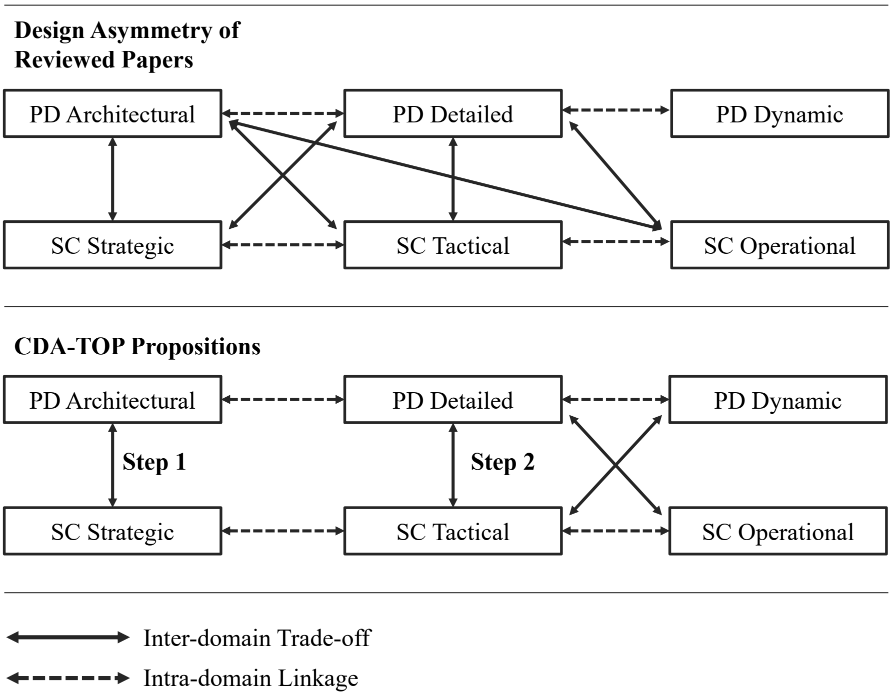

Figure 6: Comparison between the trade-off approaches of the reviewed papers and the CDA-TOP propositions.

2.4.2. Development of the CP-SCD process for modularity design

In this paper, modularity has been chosen as it is one of the most widely discussed and important architectural attributes. The benefits of modularity are far-reaching and are well documented in Gershenson et al. (2003) and Chiu and Okudan (2014). The importance and shortcomings of modern modularity research provide us with two strong impetuses for the development of the CP-SCD process. First, the CP-SCD architectural design phase focuses on finding the best overall modular design for the product and the SC. While modularity is useful for the product (e.g., design cost reduction by modular standardisation) and the SC (e.g., transaction costs reduction by SC simplification), modularity comes at a price for both (e.g., loss of product performance and SC control; Simchi-Levi, 2010). Hence, the modularity levels of the PD and the SCD have to be analysed and determined. Second, as the optimal modularity level of the product and the SC may or may not coincide, the trade-off between the product and the SC domains to find the best overall modularity for the whole P-SC system deserves deeper analysis.

Extensive research in modularity design has been observed in the last decades. However, the definitions of modularity are still diverse and many of them are not easily quantifiable (Ulrich, 1995; Salvador et al., 2002; Mikkola and Gassmann, 2003;

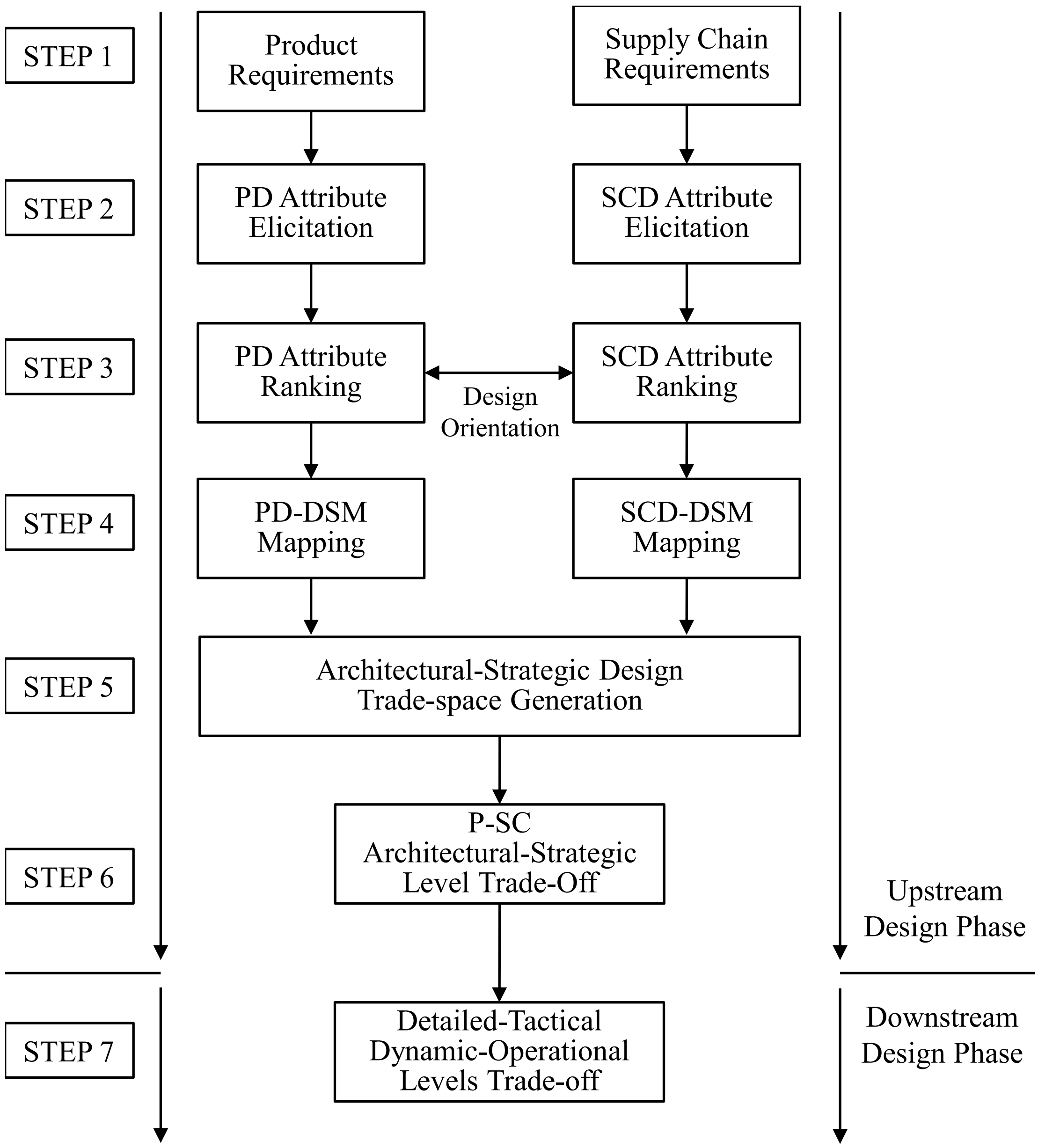

Figure 7: The CP-SCD process (architectural-strategic phase).

Gershenson et al., 2004; Hölttä-Otto and De Weck, 2007; Sosa et al., 2007). Here, we follow the definition of modularity by Gershenson et al. (2004), who define modularity as the ratio of component intra-module dependencies and similarities to all possible dependencies and similarities. In our approach, DSM (Design Structure Matrix) is used for the quantification of the modularity levels of the PD and the SCD. DSM is an established method for mapping architectural attributes and is well-documented in Eppinger and Browning (2012). DSM is chosen over mathematical and graph models because of its flexibility to map different attributes and the ease of aggregating quantitative attribute values. The modularity level is defined by the index M, which is the weighted sum of intra-module design component interactions in the PD and SCD

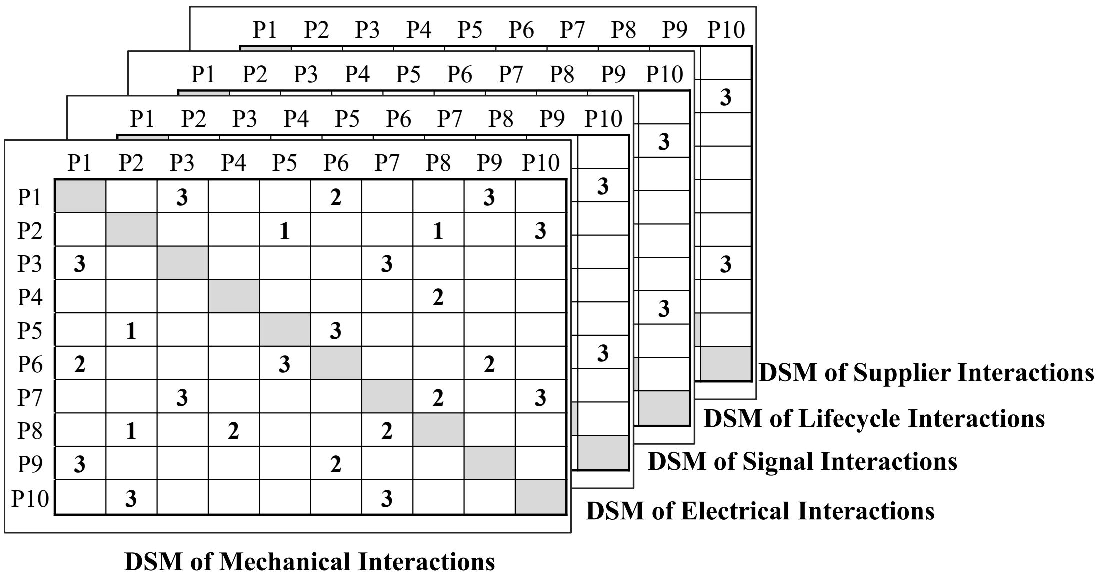

Figure 8: Mapping of different PD and SCD attribute interactions using DSM.

DSM after clustering. An overview of the CP-SCD process for architectural-strategic level design described in the remaining part of this section is shown in Figure 7.

STEP 1: Derivation of the product and supply chain requirements

This step includes procedures for the definition of PD requirements using established methodologies (e.g., ISO15288). The preliminary product concept and its major components at the architectural level are defined. Also, the SC requirements are derived. Based on empirical research, Simchi-Levi (2010) proposes 36 operational rules for SCD, including some that relate SCD to PD. The configuration diversity (mix) of products, for example, affects the required SC flexibility. Also, existing product and SC structures may significantly constraint design freedom. In non-greenfield situations, it is typical to consider the reuse level of product technology and of the capital infrastructure (plant, property and equipment) of the company and its suppliers. Also, requirements relating to environmental impact are included.

STEP 2: Elicitation of design attributes

Design attributes are elicited from the stakeholders using the following four guidelines. First, the elicited attributes should relate to the PD and SCD requirements. Second, there should be a balanced mix of stakeholders from all relevant functional areas, who have the relevant experience and expertise to contribute to the process.

P-DSM	P1	P2	P3
P1			3
P2			1
P3	3	1	

Meaning of PD-DSM Mapping	Example
Product component P3 is strongly interacting with P1	P2 is structurally supporting P1 (statically critical) P3 is electrical energy source for P1 (primary source)
Product component P2 is weakly interacting with P1	P2 is structurally supporting P1 (statically non-critical) P3 is electrical energy source for P1 (alternative source)

S-DSM	P1	P2	P3
P1			3
P2			1
P3	3	1	

Meaning of SCD-DSM Mapping	Example
Product component P3 is strongly interacting with P1	P3 and P2 can be delivered from the same supplier(s) P3 and P2 are can be sourced from the same country
Product component P2 is weakly interacting with P1	P3 and P2 can be delivered from partnering supplier(s) P3 and P2 are can be sourced from the same geographical region

Figure 9: Examples of types of DSM Interactions between product components.

Third, in order to limit the complexity of the process, the number of design attributes per domain should be scoped down to the most unique and important. This can be done by elimination of less relevant attributes and grouping of similar attributes. The literature review has revealed that it is not typical to have more than seven attributes per domain in CP-SCD. Such limit is also in accordance with general recommendations on MCDM derived from an analysis of the cognitive capability of humans.

Based on the CDA-TOP framework and the literature review, the number of architectural-strategic level attributes has also been found to always be lower than the number of detailed-tactical and dynamic-operational level attributes. This finding can be explained by the fact that there are more ways to characterize products and SCs using detailed-tactical and dynamic-operational level attributes than using architectural-strategic level attributes.

STEP 3: Ranking of design attributes and determination of the design orientation

CP-SCD involves both subjective judgments and objective criteria in the decision-making process. The ranking of design attributes using MCDA methods is subjective. It is important to state that the ranking of attributes from both domains provides the *design orientation* of the stakeholders. The design orientation is defined as the collective preference of all stakeholders when determining the trade-off between PD and SCD. The overarching objective is to compare design leverages of the architectural-strategic design attributes (e.g., modularity, supply flexibility), not

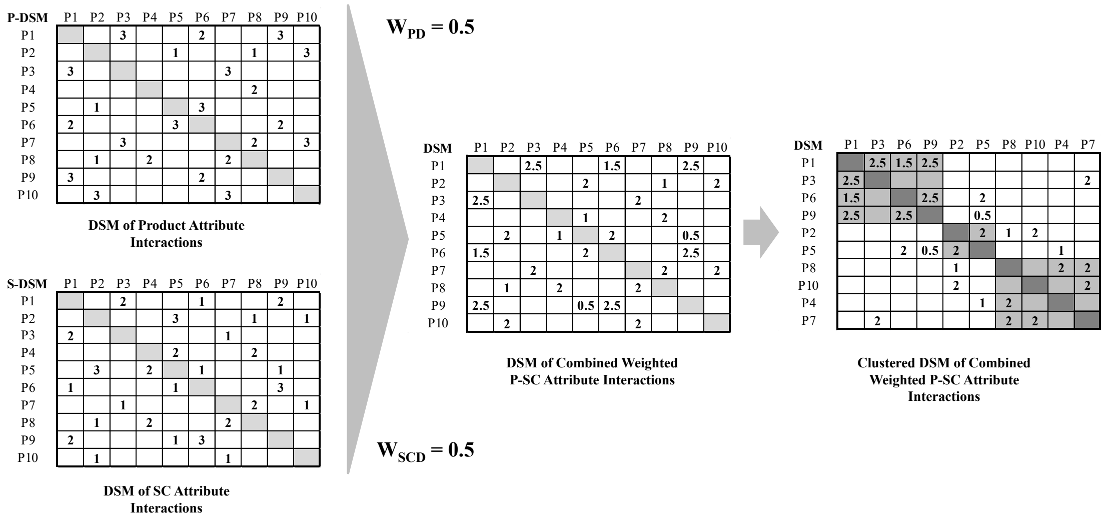

Figure 10: Process from DSMs to clustered modules.

leverages of attributes, which may not be measurable at this design level (e.g. profitability, cost).

Using the same group of stakeholders from step 2, the ranking of design attributes is done using MCDA methods such as the AHP, which help establish the relative importance of the attributes. This relative importance can in turn be translated into aggregate weights for the product and the SC domain (W_{PD} and W_{SCD}).

STEP 4: Mapping of PD and SCD attributes into DSM

The major functional components of the product are compiled and mapped in a separate DSM for each design attribute. For PD, functional interactions are captured in the DSM. For SCD, for example, inter-supplier interactions in logistic and production are captured in the DSM using supplier-component relationships. Figure 8 shows different types of PD and SCD DSMs. The scale used for quantifying the strength of interactions is selected according to the fidelity level of the elicited attribute data. To ensure comparability, the interaction scales for all DSMs are normalised. Figure 9 shows examples of different types of product component interactions that can be used to map the DSMs.

STEP 5: Generation of design modularity trade-space

The DSMs are aggregated separately for the PD and for the SCD domain using the weights obtained in step 3, yielding two combined weighted DSMs (Figure 10). Both are then further integrated into a single weighted P-SC DSM that is then used for finding the modules of the P-SC system using any known clustering algorithm (e.g.,

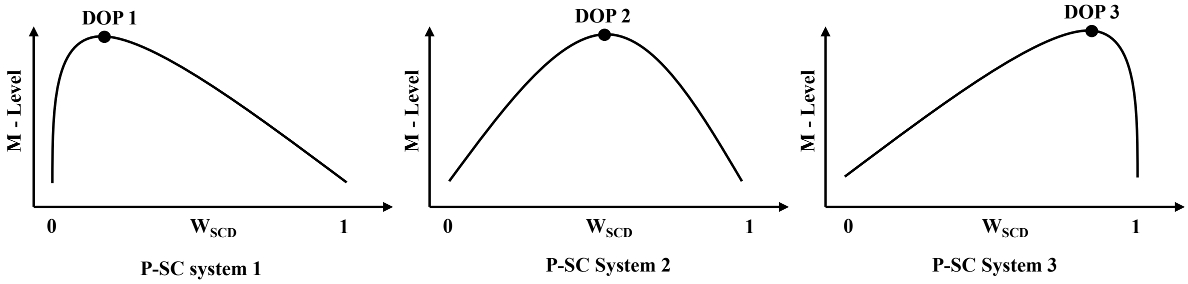

Figure 11: Examples of M curve shapes and their DOPs.

Huang and Kusiak, 1998; Zakarian, 2008). Using the example of the P-SC DSM in figure 10, the combined weighted interaction level between P3 (column) and P1 (row) is the sum of the PD and SCD interaction values multiplied with the respective weights (i.e., $3 \cdot 0.5 + 2 \cdot 0.5 = 2.5$). Figure 10 also shows the result after clustering the P-SC DSM and identifies three different modules with their respective module boundaries and sizes (two or four components in each module). This result represents one possible modularity design based solely on the interaction levels and the weights of the PD and SCD attributes.

The sum of the component interactions within the modules is used to quantify the modularity level (index *M*). The index *M* provides a quantitative measurement of the component integration level of the P-SC design at the architectural-strategic level. Hence, by summing the interactions in all three modules, a modularity index *M* of 34 (18+4+12) can be calculated. It is important to note that the modularity index *M* is by itself not an intrinsic but an extrinsic value that is only useful for comparison between different design concepts (Gershenson, Prasad and Zhang, 2004).

In section 2.3.1, our CDA-TOP framework has highlighted the concept of design symmetry in CP-SCD design. By varying the relative weights of the PD and SCD DSMs, a curve that shows the corresponding M values across the relative weights ($W_{PD} + W_{SCD} = 1$) (i.e., product-oriented to SC-oriented) can be plotted (Figure 11).

In this paper, the point of design symmetry is defined by the design optimal point (DOP), which is the maximum point of the *M*-curve (i.e., the point on the *M*-curve where the joint modularity of the product and its SC is the greatest). Figure 11 shows the DOPs of three different P-SC systems. DOP 1 characterises a P-SC system with higher product modularity potential. DOP 2 indicates a balanced modularity potential between the P-SC system domains. DOP 3 indicates a P-SC system with higher SC modularity potential. Together, the *M*-curve and the DOPs provide a unique representation of the trade-off in the design of the specific P-SC system. They complement the results from step 3 (design orientation based on the ranking between the PD and SCD attributes). This combination of design orientation (a subjective reference derived by MCDA methods) and DOP (an objective reference point derived by DSM clustering) provides product and SC designers with greater appreciation of the design trade-space, hence enabling higher design trade-off quality.

STEP 6: Modularity Design Trade-off (Architectural-Strategic Level)

After creating the set of possible P-SC architectural design alternatives, further product technical feasibility and SC operational analyses are conducted before selecting the best design(s). In the product case, the technical analysis includes a feasibility check of clustered components from the perspectives of the identified design attributes (e.g., functional, spatial, energy, thermal and lifecycle) in step 2. In the SC case, the operational analysis includes feasibility checks of clustered components from the perspectives of SCD attributes (e.g., supplier capability, compatibility). In accordance to set-based engineering practice, reducing the various alternatives to a set of possible best designs instead of a single design offers greater design flexibility for unexpected changes at later phases of the CP-SCD process (Step 7) for the detailed-tactical and dynamic-operational levels.

2.5. Product-supply chain system archetypes and their managerial implications

2.5.1 Product and supply chain system archetypes

Besides measuring the modularity level of P-SC systems and identifying the trade-space, the modularity index *M* can further be used to classify different type of P-SC systems. Figure 12 shows six different *M*-curves, each defining a unique *archetype* of the underlying P-SC system.

Archetypes 1 and 4 have equal modularity index *M* values in both the product and the SC domain. This means that in the DSMs, which are clustered individually for each of the two domains, the interaction strengths between the product components in the modules are identical. However, the alignment levels are different between archetypes 1 and 4. For archetype 1, the horizontal *M*-curve characterises a combination of identical and aligned modularity of the PD and the SCD. No matter which weight is assigned to the domains, the modules do not change. Hence, archetype 1 can be conceptually considered as the ideal archetype of modularity design. The symmetrical convex curve of archetype 4 shows the variation of the

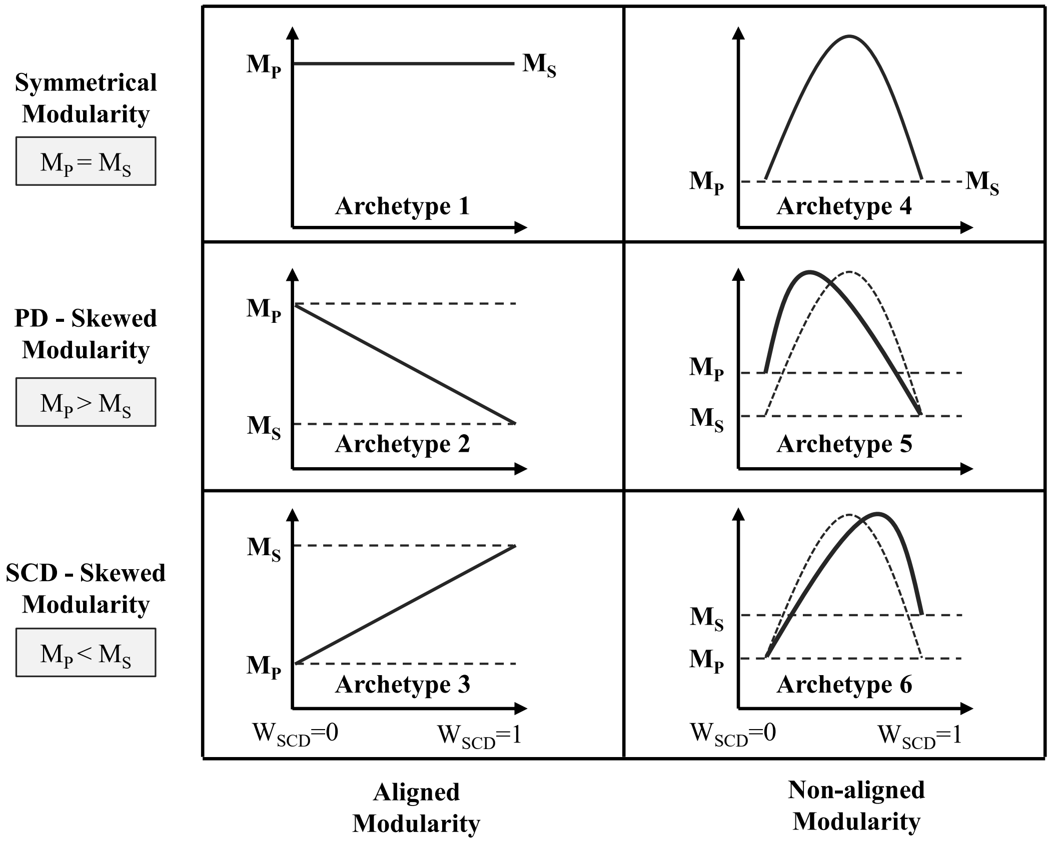

Figure 12: Modularity Alignment Matrix – the definition of the P-SC system archetypes.

modularity index *M* when there is a combination of identical but non-aligned modularity of the PD and the SCD. For this archetype, the modules depend on the weights assigned to the domains. The *M*-curve is convex if the DOP (highest point on the *M*-curve) is higher than the product modularity (M_P) and SC modularity (M_S). At the DOP, the overall system modularity is higher than the individual modularity of the product and the SC.

Archetypes 2 and 5 differ from archetypes 1 and 4 by having higher product modularity than SC modularity. The characteristic downward sloping *M*-curve in archetype 2 and the skewed convex curve in archetype 5 result. Archetypes 3 and 6 have the reverse characteristic of upward sloping *M*-curves. These six archetypes form a topology of P-SC systems.

2.5.2 The value of product-supply chain system archetypes in CP-SCD

The P-SC system archetypes are defined by the relative modularity difference and the modularity alignment between the PD and the SCD. It is important to know the relative modularity difference between the product and the SC in order to evaluate their difference in modularity design potential, which defines the design trade-space.

Knowing this difference allows designers to conduct a better design trade-off by broadening the architectural-strategic design trade-space.

The P-SC system archetypes offer new perspectives in the way P-SC systems can be classified and analysed. They provide a standardised cardinal structure for the CP-SCD process. Similar to the way product designers classify different types of modular designs (Ulrich, 1995; Salvador et al., 2002) as well as the way building architects classify architectures (e.g., gothic, renaissance, baroque), product and SC architects need a "common language" for the CP-SCD process. This structure provides a consolidated and common understanding of the P-SC system for all design decision stakeholders. Moreover, it rationalises the process of the identification of the P-SC system characteristics and the analysis of their implications, which can be generalised for the archetypes.

2.5.3 Derivation of standard strategies

Knowing the modularity alignment and modularity difference between the PD and the SCD summarised in the P-SC system archetypes helps in determining the standard P-SC strategy for the manufacturer.

Archetype 1 has product and SC architectures with equal modularity level. In addition, the PD and SCD DSMs are also aligned, meaning that the module boundaries of the product and the SC are fully aligned. For this archetype, it is easy to be a system integrator for the product and the SC by focusing only on the PD interface definition and the product final assembly. Due to the high modularity level and alignment, the manufacturer should effectively outsource all detailed design and production to the suppliers and focus only on coordinating design and assembly. Personal computer manufacturers are examples of this archetype.

Archetype 2 has stronger product modularity than SC modularity. However, the modularity of both domains is aligned, which means that the module boundaries of the product and the SC are also fully aligned. For this archetype, it is relatively more difficult to outsource the SC than the PD work. The manufacturer should outsource design work, focusing on the product interface definition and manufacture in-house. Outsourcing of production will incur effort in strengthening SC modularity (e.g., increasing compatibility among suppliers and with the manufacturer). Hence, such manufacturers should focus on horizontally integrated production of externally designed parts, components and modules. Subcontracted manufacturers of mobile devices are examples of this archetype.

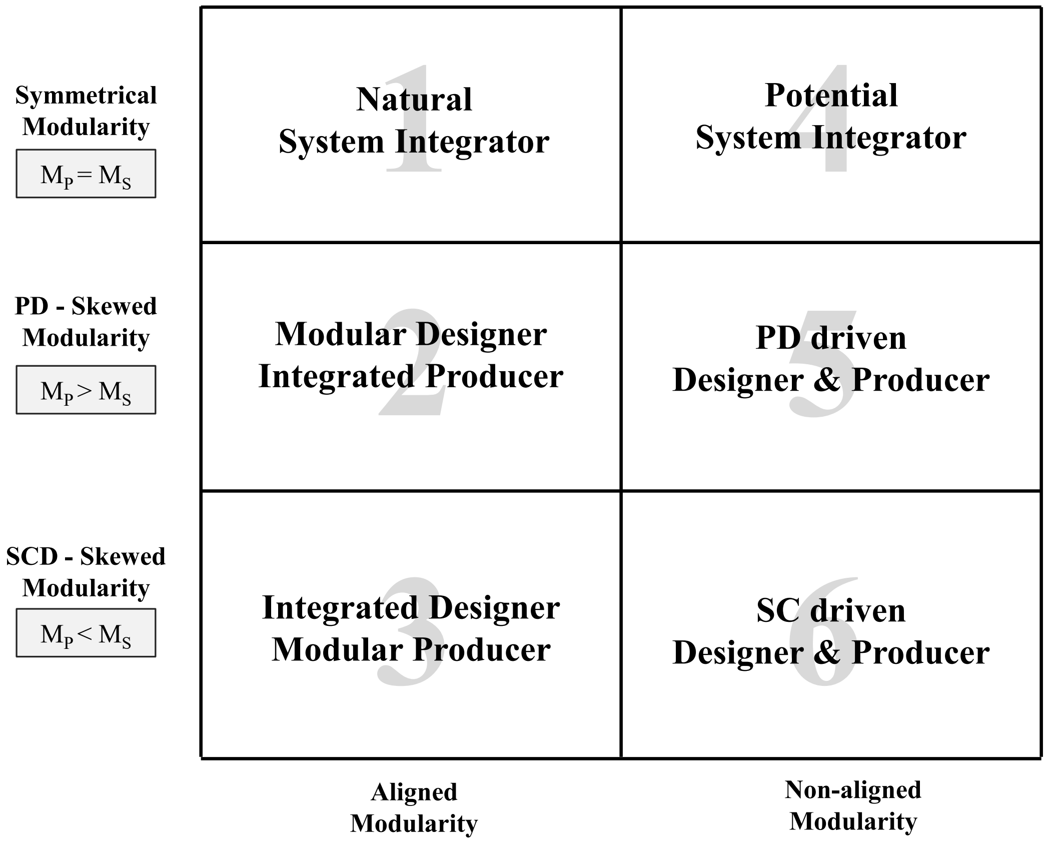

Figure 13: The managerial framework of the P-SC system archetypes.

Archetype 3 has stronger SC modularity than product modularity. The SC and product modularity are aligned. Archetype 3 faces relatively greater difficulty in outsourcing product module design work than the SC. On the one hand, such manufacturer faces the challenge of finding suppliers who are capable of designing integrated product modules. On the other hand, such manufacturer can easily find suppliers that can deliver product component in kits (e.g., unrelated components delivered in a box). Automotive OEMs today have suppliers that are capable of supplying different automotive components that have limited or no product functional interaction (e.g., windshield wiper and braking system). One strategy for this archetype must be to limit the supplier concentration by outsourcing production to sufficient number of suppliers and limiting the outsourcing scope for an individual supplier to a limited number of technologies.

The remaining archetypes (4-6) are derivatives of the archetypes 1-3. Different from archetypes 1-3, archetypes 4-6 have a non-aligned product and SC modularity, resulting in a requirement for more complex strategies. Archetype 4 represents a manufacturer having complementary product and SC modularity. The strategy must be to increase the alignment between product and supply chain modularity by enhancing supplier capabilities. For example, aircraft manufacturers, which have been aligning their product and SC architectures over the last few decades to increase their P-SC modularity, can be characterised by this archetype. An example of archetype 5 is a manufacturer of a new modular product with few or no existing suppliers (e.g., specialised military equipment). Here, the strategy focus must be on best exploiting the benefits of the modular products internally and outsourcing the more standard modules. Archetype 6 represents a manufacturer of integrated by-products made in established SCs (e.g., a manufacturer of aftermarket products like computer accessories with USB interfaces and cloned products). The strategy emphasises the design efficient use of the supply chain resources, e.g., by using excess capacity in the SC.

These six archetypes are synthesised into a framework that matches the P-SC system archetypes to an idealised operational model of manufacturing companies (Figure 13). This framework provides managers with a useful cardinal reference of the possible P-SC system archetypes when they design their products and SCs.

2.6. Conclusion

Our literature review has highlighted diverging trade-off methodologies and design asymmetries in the scientific work on CP-SCD. In addition, this paper has introduced three novel ideas and concepts to the emerging research field of CP-SCD. First, we have introduced a new exploratory research framework CDA-TOP, which structures CP-SCD trade-off by classifying different types of design attributes according to the different design levels and domains. The CDA-TOP framework was also used for deriving four research propositions for future research on CP-SCD methodologies. Second, we have proposed a CP-SCD process for modularity design and highlighted the new concept of using the modularity level (the index M) for quantifying modularity design. Third, using the modularity level and the alignment between PD and SC modularity, we have shown how different P-SC system archetypes and corresponding standard CP-SCD strategies can be identified.

We have identified the following areas for further research. First, the design process of CP-SCD deserves a closer look. Only one of the 19 reviewed papers compares between sequential and simultaneous CP-SCD processes (Gokhan, Needy, and Norman, 2010). Second, it is still unclear to what extent design asymmetry affects the leverage and quality of the CP-SCD trade-off. Empirical and experimental research to validate this question is needed. We have also not identified any existing process that provides prescriptive and holistic guidance for CP-SCD trade-off analysis. We have introduced the CP-SCD process to address this gap for the architectural-strategic design level. We aim to develop this process further to be more holistic, especially with respect to downstream design phases. Most importantly, the application of this CP-SCD process on real cases is needed to validate its usefulness.

Third, the mapping of SCD attributes into a SCD-DSM is another area for further research. While mapping of the product components into the PD-DSM is straightforward, this may not be the case for mapping the SCD-DSM. The mapping of the SCD-DSM can be challenging if the relationship between the SC attributes (e.g., supply scope, capability, inter-supplier compatibility) and the product components is not known. Nevertheless, many new development products in the practice are further evolution of existing products and companies do have existing knowledge of these SC attributes and their relationship to product elements and functions (e.g., technological capability and capacity of supplier to deliver a product function or component). Furthermore, the approaches of mapping and clustering of SCD attribute interactions in the DSM warrants further investigation, especially regarding modularisation for SC flexibility (e.g., sourcing policy - single, double or multiple sourcing), which cannot be achieved using conventional DSM. Approaches to consider non-greenfield situations also deserve more attention. Using the CP-SCD process, we have demonstrated the potential of mapping a non-greenfield SCD into SCD-DSM for trade-off with the PD.

Fourth, the development of an arbitration process to explore the design space between the asymmetrical design, which is defined by the stakeholders' design orientation of the stakeholders, and the DOP will contribute significantly to an improvement of the CP-SCD process. Finally, we believe that the P-SC archetypes have contributed to the foundation for the relatively new research area of CP-SCD. The logical next step is an empirical investigation of the characteristics and implications of the P-SC archetypes.

3. Concurrent design of product and supply chain architectures for modularity and flexibility: process, methods, and application

This chapter is based on
T.-S. Gan, M. Steffen, M. Grunow, and R. Akkerman (2022)
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Product design and supply chain design are two key determinants of company competitiveness. However, they follow different design objectives and thus require a systematic trade-off. Although methodologies for product design and supply chain design are well established within each domain in research and industry, an integrated methodology that bridges both design domains is still lacking. Based on a recently introduced concurrent product and supply chain design process, we contribute to this underdeveloped research area with a generic approach towards exploring design tradespace. We introduce a detailed operational process for the concurrent design of product and supply chain architectures. To apply this generic process to the specific trade-off between the product-related objective of modularity and the supply-chain-related objective of sourcing flexibility, we also develop new methods for key steps of the process. We demonstrate the application of the process and the developed methods using an industrial case study of a new product (electric-vehicle battery module). The case shows that our methodology was able to structure the concurrent design process. It hereby ensured an efficient trade-off and led to high-quality designs.

Key words: concurrent design, product modularity, sourcing flexibility, DSM, electric-vehicle battery.

3.1. Introduction

Manufacturing companies can be classified by product type: niche products, differentiated products, and commodities. Niche product manufacturers' competitiveness depends mainly on product design (PD) attributes such as aesthetics, functional performance, and customisability. In contrast, commodity manufacturers' competitiveness depends mainly on supply chain design (SCD) attributes such as cost, flexibility, and lead time. As most companies produce differentiated products, they have to consider both types of design attributes to ensure overall competitiveness. This reflects the key ideas in the seminal work by Fisher (1997), highlighting the importance of matching the right supply chain (SC) to the product. While this is relatively easy for niche and commodity products, it is less so for differentiated products due to the lack of trade-off methodologies between PD and SCD (Gan and Grunow, 2016).

PD and SCD are strategic decisions in two central but different functions in manufacturing companies. Traditionally, the product is designed first, and the appropriate SC structure is then chosen with the typical aim of finding the best possible trade-off between efficiency and responsiveness (Fisher, 1997). However, a sequential approach unduly limits the design space for SCD. For example, the overwhelming focus on a highly customisable PD in the development of the NH90 European military helicopter led to an inferior SCD, consisting of a myriad of small, inefficient, and redundant suppliers. This SCD contributed to more than ten years of delivery delays and cost overruns (Uiterwijk et al., 2013). More recently, CNBC (2018) reported that the decision of electric car manufacturer Tesla to use type 2170 battery cells (optimised for high energy density and supplied by a single supplier) instead of the commonly available but less efficient type 18650 battery cells resulted in severe SC delays due to its single-sourcing strategy. In both examples, the emphasis on PD undermined the efficiency and the responsiveness of the SCD.

3.1.1. Concurrent product and supply chain design

Concurrent product and supply chain design (CP-SCD), in contrast, explores the two design spaces simultaneously. Using this method, SC efficiency and SC responsiveness can be considered earlier in the design process, potentially at the expense of the PD. The understanding of such trade-offs between PD and SCD is so far underdeveloped (Pashaei and Olhager, 2015). Increasingly complex products and SCs do however require systematic concurrent approaches to characterise the tradespace between optimal PD and optimal SCD. Here, the design tradespace is defined as the set of combinations of product and SC designs optimised with varying relative importance of PD and SCD objectives. Research on such methodologies is unfortunately lacking (Ellram and Stanley, 2008; Khan and Creazza, 2009; Gokhan et al., 2010; Baud-Lavigne et al., 2012; Gan and Grunow, 2016; Yao and Askin, 2019).

In the development of CP-SCD approaches, different design levels could be addressed. PD can be done at architectural, detailed, or dynamic level while SCD can be done at strategic, tactical, or operational level. Any CP-SCD method must address attributes from similar hierarchy levels (Gan and Grunow, 2016) and must be able to allow design attributes of both domains to be commensurable, aggregable, and compensable (Colson and Bruyn, 1989; Guitouni and Martel, 1998). The higher the hierarchy level, the higher the impact on the design of the product and its SC. We therefore focus on the architectural-strategic level. Amongst the design attributes on this level, modularity and flexibility are widely considered to be the most important for both domains (Fine, 1998; Simchi-Levi, 2013).

3.1.2. Product and supply chain modularity

In PD, modularity is widely considered to be the most important architectural attribute because of the distinct advantages that it provides (e.g., configurability) and enables (e.g., flexibility, replaceability) (Ulrich, 1995; Mikkola and Gassmann, 2003). Modularity enables flexibility for product reconfiguration as well as replaceability for repairs and upgrades, both of which affect product lifecycle performance (Ross et al., 2008). Product modularity is well-documented in e.g., Mikkola and Gassmann (2003), Gershenson et al. (2004), Hölttä et al. (2005), and Jung and Simpson (2017).

The concept of modularity can also be applied to SCD (Pashaei and Olhager, 2015). SCD modularity is also considered one of the most important strategic design attributes (Duclos et al., 2003; Zhang et al., 2008; Khan and Creazza, 2009; Simchi-Levi, 2013; Jayaram and Vickery, 2018). It is important for lowering transaction costs by simplifying SC structures and reducing associated complexity. Furthermore, it increases efficiency by enabling standardisation of production, shorter lead times, and reduced inventories (Feng and Zhang, 2013).

SC modularity leads to sourcing flexibility, which is defined as the ability to reconfigure the SC according to supply and demand changes (Duclos et al., 2003). This is vital for the mitigation of risks associated with demand fluctuations, SC disruptions, and supplier quality problems (Tang and Tomlin, 2008; Saleh et al., 2009; Simchi-Levi, 2013). Moreover, sourcing flexibility has far-reaching implications for manufacturing companies: it enables multiple sourcing, which in turn ensures sourcing price stability and the sustainability of a competitive, non-monopolistic industrial ecosystem. For example, automotive companies commonly use different suppliers for the same components in different final products. This enables these companies to mitigate disruption risks. Also, it improves the bargaining power over suppliers (Henkel and Hoffmann, 2018).

3.1.3. Sourcing flexibility

The role of sourcing flexibility in supplier selection and its dependency on the buyer-supplier relationship has received much attention in past research. De Boer et al. (2001) reviewed methods for supplier selection and sourcing decisions, highlighting the complexity of the procurement process before supplier selection and sourcing decisions are made. They also argue that the purchasing situation is an important factor for selecting the right decisional method for sourcing strategy. Gosling et al. (2010) highlight the lack of consideration of SC flexibility in supplier selection research. They suggest that SC flexibilities are key criteria for supplier selection and supplier relationship development. While the literature stresses the impact of many criteria on sourcing decisions, they consider product architectures fixed, hereby overlooking the impact of product architectures on the sourcing decisions.

Decisions on product modularity and SC modularity are strongly interconnected and have an impact on sourcing flexibility. For instance, in PD, it might be beneficial to combine some components in a module, but it might not be possible to source the resulting module from a sufficient number of suppliers, thus reducing sourcing flexibility. Similarly, in SCD, simple SC structures with low transaction costs are preferred, but they may lead to fewer and larger modules, which in turn may lead to combinations of components that are impossible to integrate in a product design. Hence, CP-SCD approaches should facilitate discussions between product designers and SC designers early in the design process.

3.1.4. Contributions

In this paper, we pursue four aims. Firstly, we aim at building an understanding of the interaction between PD and SCD by showing how the tradespace between the optimal PD and the optimal SCD can be generically characterised at the architectural-strategic level. Secondly, we aim to develop a detailed CP-SCD process for the generation of the design tradespace. Thirdly, we aim to introduce new methods to generate PD and SCD architectures. For the PD architecture a clustering method is used in the creation of product modules. The SCD method focusses on supplier selection and sourcing flexibility, which need to be considered early in the CP-SCD process. These PD and SCD methods specifically focus on modularity and flexibility but could be adapted to consider other attributes such as various cost factors, responsiveness, or environmental footprints. Finally, we aim to demonstrate the application of the CP-SCD process using an industrial case study (of a new electric-vehicle battery) that characterises a typical CP-SCD situation. With this, we also aim to show how the systematic exploration of the design space can lead to a range of solutions that provide a better understanding of the trade-off between PD and SCD objectives.

3.1.5. Paper organisation

This paper is structured as follows. In Section 3.2, we provide a literature review on methodologies for CP-SCD, architectural PD, and strategic SCD. In Section 3.3, we introduce the case study (electric vehicle battery system). In Section 3.4, we use introduce detailed procedures for architectural-strategic design in the CP-SCD process and specific clustering methods using data from the case study. Moreover, we explain the key concepts for the characterisation of design tradespace for CP-SCD, a cornerstone of this paper. Finally, in Section 3.5, we discuss our contributions, limitations, and the potential improvements to our methodology for future research.

3.2. Literature review

3.2.1. Architectural design of products and supply chains

Methods for architectural PD are well established in research and industry. Some examples are Axiomatic Design Method, Object Process Methodology, and Design Structure Matrix (DSM) (Suh, 1998; Dori, 2002; Fixson, 2005; Tilstra et al., 2012; Jung and Simpson, 2017). DSM is more commonly used in industry because of its flexibility in modelling different PD and non-PD attributes and visualising the clustering results (e.g., Behncke et al., 2014). DSM can either use binary or numerical values in a matrix to map functional or relational interactions between parts. In industry, the functionalities of DSM have been further developed and used in specialised software tools (e.g., METUS) that provide advanced user interfaces as well as connections to data analytics tools.

Several methods of strategic SCD exist. Examples of qualitative methods are frameworks for core-competence analysis, make-or-buy analysis, and supplier integration to support decision making in strategic SCD (Fine and Whitney, 1996; De Boer et al., 2001; Novak and Eppinger, 2001; Noori and Georgescu, 2008; Gosling et al., 2010). Quantitative methods of strategic SCD are typically model-based methods that mathematically link interactions between SCD attributes for optimisation (Beamon, 1998; Meixell and Gargeya, 2005; Melo et al., 2009).

Both PD and SCD are fields with a large body of literature that has introduced various methods dedicated to the architectural-strategic design level of the individual field. In the following, we discuss research on concurrent approaches.

3.2.2. Concurrent product and supply chain design

CP-SCD is recognised by many as an important research area and a vital industrial capability (Blackhurst et al., 2005; Zhang et al., 2008; Elmaraghy and Mahmoudi, 2009; Gokhan et al., 2010; Chiu and Okudan, 2014). Despite this recognition, it is still an emerging research field, which is also clear from three recent review papers that highlight the state-of-the-art research on CP-SCD (Pashaei and Olhager, 2015; Gan and Grunow, 2016; Yao and Askin, 2019). Published around the same time, Pashaei and Olhager (2015) and Gan and Grunow (2016) find that there is limited understanding of how design decisions for PD and SCD interact with each other. While the impact of PD on SCD is well studied, the impact of SCD on PD is unexplored, and little work is done on the development of methodologies for CP-SCD. Pashaei and Olhager (2015) further note that there is a lack of case studies in CP-SCD. Past research focusses on extreme PD cases (either modular or integral) and the design tradespace between these extremes is underexplored. More recently, Yao and Askin (2019) review and identify different representation schemes (e.g., BOM, DSM) used for CP-SCD and note a lack of studies on matrix representations (e.g., DSM) and clustering efficiency. Gan and Grunow (2016) additionally summarise their findings in a conceptual framework, synthesising existing design hierarchical structures from both domains, classifying the different types of design attributes, and laying the foundation for fundamental propositions on the quality of CP-SCD methodologies. Using these propositions, they further propose a conceptual CP-SCD process at architectural-strategic level. However, this conceptual process remains to be operationalised and applied to industrial cases, which are the aims of our current paper.

CP-SCD-related frameworks that analyse the relationship between PD and SCD attributes exist. Fine and Whitney (1996) include relationships between PD attributes (e.g. product architecture, modularity) and SCD attributes (e.g. make-or-buy decision). Fine (1998) extends this by linking product, process, and SC designs. Appelqvist et al. (2004) map data exchange processes between the PD and SCD activities of an aerospace company. Pero et al. (2010) analyse the relationships between PD attributes (modularity, variety, innovativeness) and SCD attributes (structure, configuration) in several case studies. Gokhan et al. (2010) introduce the process of Design for Supply Chain as an improvement to sequential design processes. This contributes to methodological CP-SCD research by analysing the procedural aspect of CP-SCD. Although all these frameworks provide multifaceted perspectives on CP-SCD methodology, they do not specify approaches for the exploration of design tradespace and for design trade-off, which are imperative for ensuring the quality of design decision.

While previous literature does not provide CP-SCD methodologies that explore the interaction between PD and SCD, literature on Multi-Criteria Decision Analysis (MCDA) does provide a basis for the development of such methodologies. CP-SCD methodology needs to identify the interdependency between PD and SCD attributes and provide an approach to balance between conflicting design objectives of PD and SCD. For the purpose of linking these design domains and their attributes, the principles of *compensability, commensurability,* and *aggregation* between PD and SCD attributes need to be ensured (Colson and Bruyn, 1989; Guitouni and Martel, 1998). Adherence to these principles allows the use of MCDA methods (Ehrgott et al. 2010) to model and search for optimal solutions in the tradespace.

3.2.3. Key findings of the literature review

In summary, we identify the following literature gaps:

- Past research focussed only on the impact of PD on SCD. There is a lack of understanding of the impact of SCD on PD. It lacks the more comprehensive exploration of the design tradespace for different module configurations formed under product and supply chain objectives.

- Past frameworks for CP-SCD are of a conceptual nature and are not sufficiently specific to be applied in practice. Methodologies that systematically and hierarchically integrate PD and SCD methods are lacking. Particularly at the architectural-strategic level, methodologies supporting a systematic assessment of the design tradespace are missing.

- There is an abundance of qualitative and quantitative methods for product architectural and strategic SCD. However, they are dedicated to the specific domain. Matrix representations, widely used in PD, have not been developed sufficiently for use in CP-SCD. Also, even though MCDA methods are well established, they have not been used to bridge the domains.

- Finally, there is a lack of case studies in CP-SCD that explore the design tradespace between product – supply chain (P-SC) system architectures.

Our review thus highlights the immature status of literature on CP-SCD. These findings motivate us to develop a detailed CP-SCD process and methods that together address the aforementioned issues and translate conceptual frameworks into an operational methodology for the architectural-strategic design level. We also introduce a case study to demonstrate the application of the CP-SCD process.

3.3. Introduction to the case study

In this section, we introduce the case study that is used to explain the procedure and methods of the operationalised CP-SCD process. The case study focusses on a battery system named Conchifera, which is being developed by a Munich-based company (Invenox GmbH). Conchifera has been selected as it is a differentiated product that is still under development. The company has a green-field SC situation that suits the application of the CP-SCD process. The objective of this case study is to find the best design trade-off between the product design architecture (PDA) and the supply chain architecture (SCA) of Conchifera using modularity as the common design attribute.

In general, case study research is useful for research stage exploration, theory building, theory testing, as well as theory refinement (Voss et al., 2002). Moreover, case study research is useful when it is relevant to the understanding of the interactions between organisations and methodologies (e.g., Eisenhardt and Graebner, 2007; Ketokivi and Choi, 2014). Our work is in the early research stages, in which a single case study approach is often chosen since this allows for an in-depth analysis (Voss et al., 2002). Our methodology is applied in its natural setting and its effectivity observed in practice, which is important for evaluating the complex interactions between the different functional (PD and SCD) teams of Invenox when using our methodology.

In the case study, two of the authors participated in numerous meetings, which involved the product designers and SC managers from the company, to observe their discussions and to gather direct feedbacks. All data and company documentation required for our methodology were collected in these meetings. For example, the DSMs, Part-Supplier Matrices (PSM) and design tradespace were created together with the product designers and SC managers.

Conchifera is being developed in pursuit of higher PD and SCD performance (e.g., energy density and assembly cost, respectively). The main advantages of Conchifera are twofold: the scalability of mass assemblies of battery cells with short lead times, and the configurability using common cylindrical cells (type 18650) for diverse applications. These advantages are made possible using a proprietary contact material that connects battery cells, unlike welded connectors used in other battery systems. This material minimises part quantity, weight, and cost. Moreover, it allows

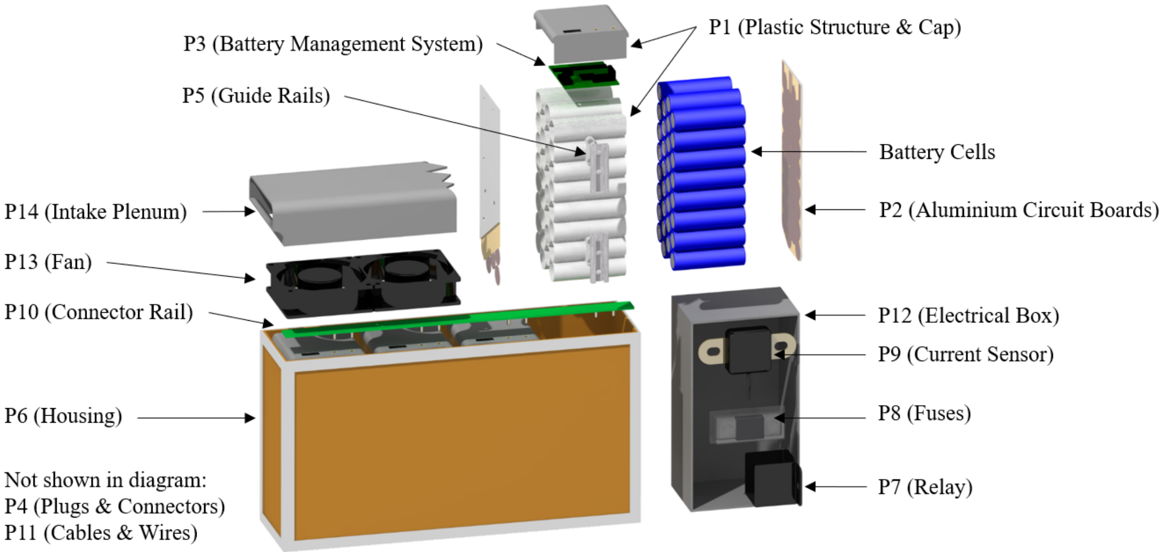


Figure 14: Conchifera electrical vehicle battery system (quadruple variant).

faulty cells to be replaced individually and easily to restore the system lifespan as well as ensuring a high level of safety (Hammer et al. 2014).

Conchifera's main components are shown in Figure 14. There is a total of 14 unique parts in the quadruple variant of Conchifera. These components are defined by the functions derived from the PD requirements and can be sourced from different suppliers who have overlapping supply scope. While simpler components (e.g., plastic housing) can be sourced from several suppliers with similar quality and functional performance, it is more difficult for relatively more complex components (e.g. circuit boards).

Some components can only be sourced from a few specialised suppliers. 14 potential suppliers have been identified based on their capabilities and supply scope (Appendix A3). The battery cells and contact material components are excluded from our case study due to quality and proprietary reasons. Although battery cells are considered commodities, the quality of battery cells from different suppliers can differ significantly. The contact material is a core proprietary component and is therefore manufactured in-house.

3.4. Methodology: The CP-SCD process

3.4.1. Overview of the CP-SCD process for architectural design

Gan and Grunow (2016) derive a conceptual CP-SCD process for modularity design. This process is derived from four propositions for CP-SCD, which are grounded in an extensive literature review. These propositions can be summarised as follows:

1. A concurrent design process for PD and SCD can bring greater value than a sequential design process.
2. A concurrent design process should have a balanced inclusion of design attributes from both domains to ensure higher trade-off quality.
3. A concurrent design process should pursue design trade-offs at the same hierarchical level (starting from the architectural-strategic level) to allow for more accurate modelling of attribute relationships and a higher trade-off quality.
4. A concurrent design process should avoid trade-offs at the lowest hierarchical levels due to the lack of trade-off opportunities between PD and SCD attributes on those levels.

Here, we build on the conceptual model that Gan and Grunow (2016) derived from these propositions and develop a detailed operational process, consisting of three different phases: *strategic alignment*, *concurrent product and SC architectural design*, and *design trade-off* (illustrated in Figure 15 and further described below). The concurrent consideration of PD and SCD in our process results from Proposition 1. The hierarchical, top-down approach of our process, which starts with the architectural-strategic phase before the detailed design phase, follows Proposition 3. The choice of an architectural PD attribute (product modularity) and a strategic SCD attribute (sourcing flexibility) follows Propositions 2 and 4, as these attributes are at the same, relatively high hierarchical design level, enabling the commensuration, aggregation, and compensation of design attributes. The detailed design level following the three phases of our process is not considered, as trade-off opportunities would be limited on that level and concurrency is not required anymore (following Proposition 4).

Our process is applicable for PD and SCD under different objectives. It has a hierarchical structure with open interfaces to specific methods (the grey boxes in Figure 15). In the remainder of this section, we first discuss the general procedure for each of the three phases. We then develop methods for the specific trade-off between product modularity and SC sourcing flexibility.

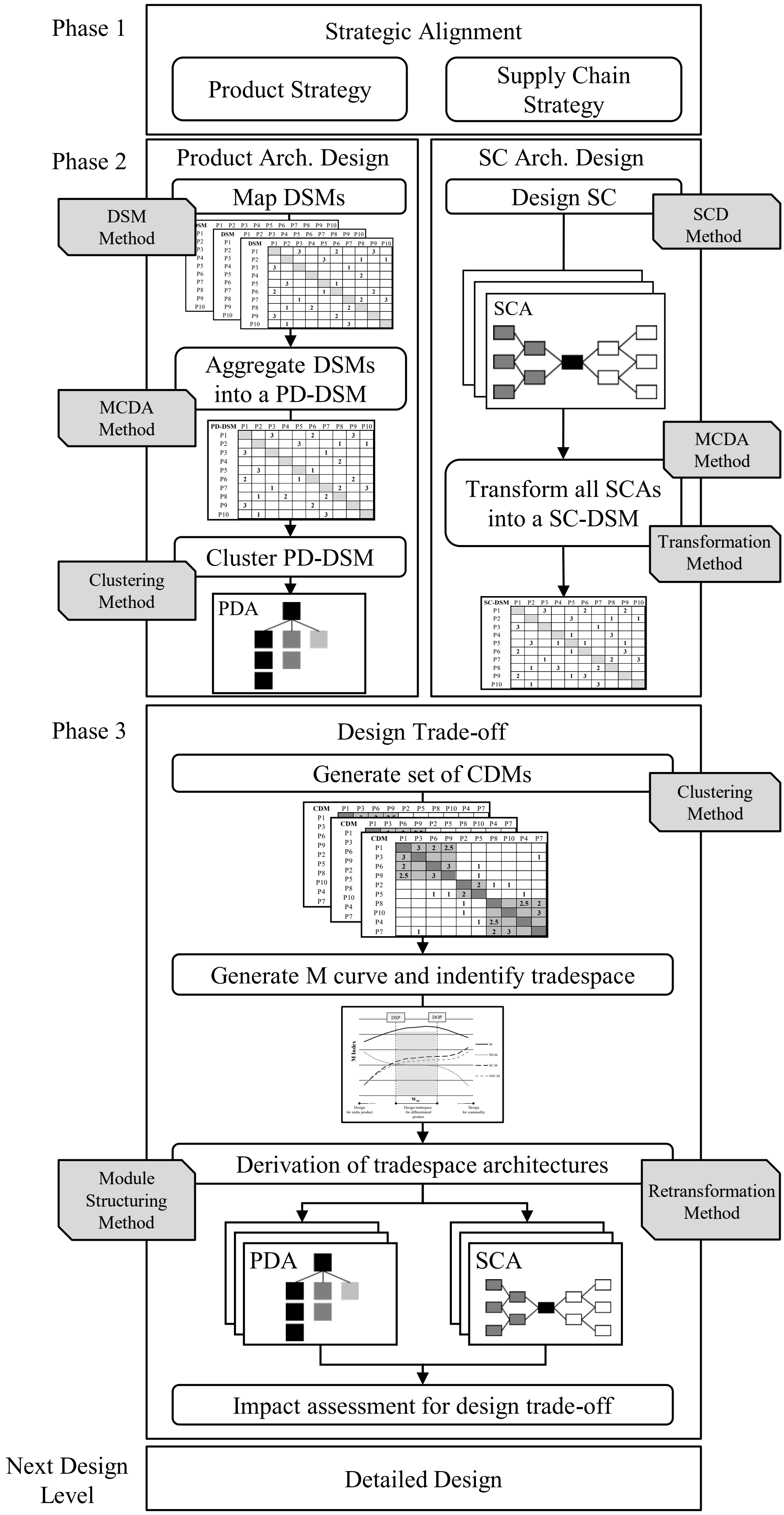


Figure 15: Overview of the CP-SCD process.

In Phase 1, product and SC designers align the product and SC strategies (e.g., target number of modules and required sourcing flexibility) based on the PD and SCD requirements. Examples of product strategy can be found in Ulrich (1995), who focuses on the linkages between product architectures and different PD strategies such as product change, product variety, component standardisation, product performance, and product development management. Examples of SC strategy can be found in Fisher (1997), who focuses on matching the right products to the right SCD. He outlines that functional and innovative products need different types of SCD (i.e. efficient versus responsive). PD and SCD requirements are elicited from the market (e.g., customers, users) and the SC (e.g., suppliers, partners). Next, PD and SC design attributes are defined from the elicited PD and SCD requirements. Established methods for requirement elicitation can be found in Walden et al. (2015).

In Phase 2, the procedures for PD and SCD are described in two concurrent streams. Each stream involves an independent procedure of numerical matrix operations. In contrast to past studies that are mostly sequential (e.g., Nepal et al. 2012; Chiu and Okudan 2014) and that assume the PD to be given (or limited to a very small number of PD options) in the SCD, we explore both PD and SCD concurrently based on the broad requirements resulting from the strategic alignment. Where past studies thus only show the impacts of different PD scenarios on the SCD, we avoid limiting the design trade-offs in this part of the design process. The concurrent design streams in Phase 2 allow designers to build up the product architecture (PDA) and supply chain architecture (SCA) independently and supported their convergence to a commensurable, aggregated, and compensable set of design data structures using matrices (DSM and PSM).

For the product architectural design stream, DSMs are used to map the PD attributes. These DSMs are then weighted based on the prioritisation of the PD attributes using a suitable MCDA methodology and aggregated to generate the PD-DSM. This stream ends after the generation of the PDA, which represents a clustered PD-DSM (for which a variety of clustering methods may be used).

For the SC architectural design stream, the SCA is first derived. This may be done using a variety of SCD methods and objectives (e.g., costs, speed, or sustainability), possibly resulting in multiple SCAs. However, the SCAs are based on SC attributes other than parts (e.g., supplier, delivery lead times, location, or manufacturing technologies). As SCA representations that allow design trade-offs in relation to the PDA are lacking, our approach introduces a transformation of the SCA into a part-to-part SC-DSM to link the PD and SCD domains. For PD, DSM is an established methodology. For SCD, working with a matrix representation is still uncommon. For this transformation, additional operations using specific methods are required. Note that the main difference between the PD and SCD streams is the procedural sequence. In the product architectural design stream, the architectural design is the last step of the procedure. The DSMs are weighted and aggregated into a PD-DSM and then clustered into a PDA. In the SC architectural design stream, the architectural design is the first step of the procedure. The SCAs are aggregated into an SC-DSM.

Following Propositions 2 and 3, the specific design trade-off we consider in our case (product modularity vs sourcing flexibility) concerns attributes on the same hierarchical level (i.e., the architectural-strategic level). Past studies have often considered design trade-offs between attributes at different hierarchical levels, reducing the quality of the design trade-off in CP-SCD. For example, non-strategic SCD attributes are often traded off against architectural PD attributes (Nepal, Monplaisir and Famuyiwa, 2012; Chiu and Okudan, 2014).

In Phase 3, the PD-DSM and the SC-DSM are normalised, weighted, and aggregated into a single DSM which is then clustered to form the Clustered Decision Matrix (CDM). The CDM represents the architecture of the respective P-SC system at different points in the design tradespace. By varying the relative weights between the PD-DSM and the SC-DSM, CDMs are generated and used to compute the corresponding PD-M, SC-M and M values. These values are used to plot the three curves to represent the design tradespace of the P-SC system. For an in-depth analysis of every selected CDM, the corresponding PDA and SCA are generated for impact assessment. While the PDA is derived directly from the CDM, the SCA has to be retransformed from the CDM using a specific SCD retransformation method. The PDAs and SCAs are assessed according to specific criteria before the transition to the next step for detailed design.

The fundamental contributions to the practice of CP-SCD resulting from our methodology lie in the structuring of the concurrent design interactions, design trade-offs, as well as discussions between the product designers and the SC designers in the design process. It shows in a novel hierarchical way how PD and SCD strategies are defined and linked to a symmetrical design trade-off at architectural-strategic level using modularity as the common design attribute. As Phase 1 is elaborated in Gan and Grunow (2016), we focus on Phase 2 and Phase 3 in the following.

PD-DSM	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14
P1		1.17	0.66	0.68	1.17	0.02				0.28	0.02	0.04	0.56	0.60
P2	1.17		1.57	1.33	0.10		0.24	0.24	0.24	0.26	0.24		0.02	
P3	0.66	1.57		1.77	0.10		1.32		1.10		0.44		0.66	
P4	0.68	1.33	1.77		0.10		0.24	0.24	0.24	1.47	0.47		0.02	
P5	1.17	0.10	0.10	0.10		1.09						0.02		0.56
P6	0.02				1.09		0.10	0.10	0.10	0.38	0.66	0.98	0.10	0.96
P7		0.24	1.32	0.24		0.10		0.84	0.86	0.56	0.62	0.94	0.12	0.10
P8		0.24		0.24		0.10	0.84		0.84	0.56	0.62	0.94	0.12	0.10
P9		0.24	1.10	0.24		0.10	0.86	0.84		0.56	0.62	0.94	0.12	0.10
P10	0.28	0.26		1.47		0.38	0.56	0.56	0.56		1.18	0.59	0.84	0.10
P11	0.02	0.24	0.44	0.47		0.66	0.62	0.62	0.62	1.18		0.96	0.32	0.10
P12	0.04				0.02	0.98	0.94	0.94	0.94	0.59	0.96		0.12	0.12
P13	0.56	0.02	0.66	0.02		0.10	0.12	0.12	0.12	0.84	0.32	0.12		0.68
P14	0.60				0.56	0.96	0.10	0.10	0.10	0.10	0.10	0.12	0.68	

Definition of rating scheme
Empty - No interaction
1 – Weak functional / relational interaction
2 – Medium functional / relational interaction
3 – Strong functional / relational interaction

PDA	M1	M2	M3	M4
P1				
P5				
P6				
P11				
P13				
P14				
P2				
P3				
P4				
P7				
P8				
P9				
P10				
P12				

Figure 16: Phase 2 result showing the PD-DSM and the PDA.

3.4.2. Product architectural design

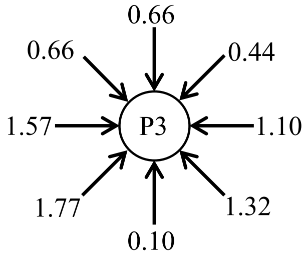
3.4.2.1. General procedure

The product architectural design stream of Phase 2 involves mapping of DSMs, aggregation of DSMs into a PD-DSM, and clustering of the PD-DSM to create the PDA.

The first step maps the interactions of the PD attributes (e.g., electrical, structural, thermal, spatial, signal, compatibility, lifecycle factors) between product parts in a set of numerical DSMs. We use a numerical DSM method because of its higher information content as compared to a binary DSM method. The upper right-hand side of the DSM indicates feed-back interaction and the lower left-hand side of the DSM indicates feed-forward interaction. Before mapping PD attributes in the DSM, the product needs to be broken down into parts. The granularity of the parts depends on the required depth of analysis and the complexity of the product. The PD-DSM of the case study is shown in Figure 16.

The second step aggregates DSMs into a single DSM (PD-DSM). In order to map all functional and relational interactions between the parts, the DSM of each PD attribute is weighted and aggregated. The weights of the PD attributes can be determined by any MCDA method that elicits the relative importance of the design attributes from all CP-SCD process stakeholders (e.g., Analytical Hierarchical Process or PROMETHEE).

The third step clusters the PD-DSM to form modules which define the PDA. Clustering methods either use a predefined number of clusters or determine the



$$\sum_j r_{3j} = 7.62$$

$$\sum_j c_{3j} = 8$$

Search direction in the Filtered Matrix

WS_i	Part	Coupled Parts													
75.00	P11			P3	P4		P6	P7	P8	P9	P10		P12		
74.58	~~P10~~				P4		P6	P7	P8	P9		P11	P12	P13	
65.60	~~P4~~	P1	P2	P3							P10	P11			
65.34	~~P7~~			P3					P8	P9	P10	P11	P12		
62.92	~~P9~~			P3				P7	P8		P10	P11	P12		
60.96	~~P3~~	P1	P2		P4			P7		P9		P11		P13	
56.50	~~P12~~						P6	P7	P8	P9	P10	P11			
54.10	P2	P1		P3	P4										
52.00	~~P1~~		P2	P3	P4	P5								P13	P14
46.00	~~P8~~							P7		P9	P10	P11	P12		
44.90	~~P6~~					P5					P10	P11	P12		P14
44.16	P13	P1		P3							P10				P14
34.20	~~P14~~	P1				P5	P6							P13	
21.98	P5	P1					P6								P14

Identified seed parts in the Filtered Matrix
at F-level = 0.13 (P11, P2, P13, P5)

Figure 17: The Filtered Matrix for an F-level of 0.13 (case study data).

number of clusters as a part of the method (e.g., Kusiak and Chow, 1987; Helmer et al., 2010; Jung and Simpson, 2017). Figure 16 shows the results at the end of Phase 2.

3.4.2.2. Specific clustering method for modularisation

One of the key features of the product architectural design procedure is its modular interface to the clustering method for the identification of modules. This allows a flexible use of different clustering methods to cater to different CP-SCD situations, which may have different clustering objectives and constraints. It also allows for the use of new clustering methods that may be developed in the future.

Existing clustering methods employed for DSMs are found to be inadequate for our case study due to their lack of control over the number and size of identified modules. These are important to the CP-SCD process as the number and size of the modules are key constraints for the PDA (e.g., design teams' workshares) and the SCA (e.g., number of potential suppliers). This motivates us to develop a new heuristic clustering method.

There are two advantages of this new method with respect to design-thinking. Firstly, it uses *seed parts* in the product modularisation process. Using a search algorithm in this method, designers can identify and select seed parts that are best suited for clustering other parts to form modules (e.g., key interfacing components like product housing and electrical wiring). Secondly, it utilises the designers' knowledge by allowing them to predefine the number and size of modules. The number of

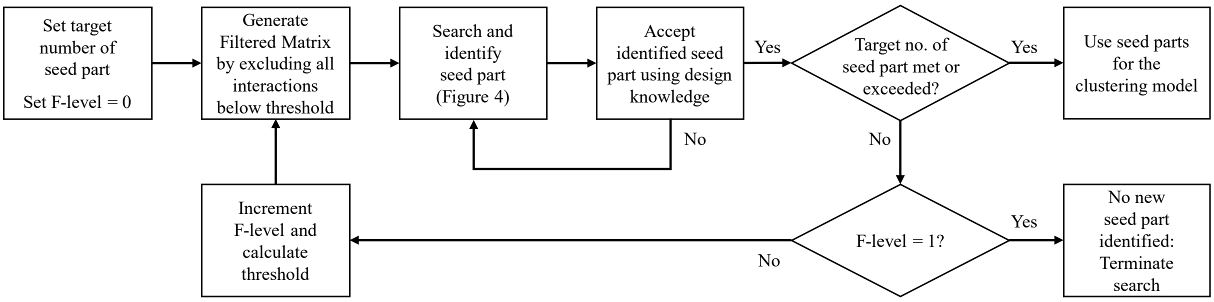


Figure 18: Procedure of the heuristic algorithm for the selection of seed parts.

predefined clusters often has limited possible values which are determined by internal and external constraints such as organisation, production locations, and manufacturing processes. If required, the method can also be applied for different parametrisations.

Jung and Simpson (2017) introduce the use of interaction strength and number as part of a mathematical approach to cluster DSMs. Our method differs from theirs in the following ways. Firstly, our method is based on the identification of seed parts using interaction numbers for weighting the interaction strengths. The choice of seed parts depends on their *strength* and *number* of interactions with other parts. Secondly, we propose a heuristic algorithm that facilitates the integration of additional design knowledge.

Heuristic algorithm. Seed parts are identified in the PD-DSM by an algorithm using two criteria. Firstly, a seed part i shall have a high number of interactions c_{ij} and high interaction strengths r_{ij} with other parts j (Figure 17). To ensure that both the number of interactions and the interaction strength are considered, the algorithm starts the search from the part i with the highest value for the seeding function WS_i, defined as the product of both values:

$$WS_i = \sum_{j \in J} c_{ij} \sum_{j \in J} r_{ij} \tag{1}$$

where:

r_{ij} Interaction strength between part i and part j

c_{ij} Binary parameter indicating an interaction between part i and part j (c_{ij} = 1, iff $r_{ij} > 0$)

Secondly, a seed part shall have low interaction strengths with other seed parts. For the identification of seed parts, the algorithm uses a filter (*F-level*) to differentiate weak interactions from strong interactions.

The procedure of the heuristic algorithm is shown in Figure 17 and pseudocode is included in Appendix A1. Firstly, the target number of seed parts and the initial *F-level* are set (default value = 0). This is followed by conversion of the DSM to a Filtered Matrix (Figure 17). This Filtered Matrix decouples the parts by suppressing DSM interactions that are below the *F-value*, with $F\text{-}value = F\text{-}level \cdot \max_{i,j} r_{i,j}$.

In the next step, the parts in the Filtered Matrix are sorted in descending order according to their WS_i values. Next, the part with the highest WS_i value is assigned as the first seed part. The algorithm then searches downwards, row-by-row, for the next seed part. A part is identified as a seed part if it is not coupled with the preceding seed parts (e.g., P11→P2→P13→P5 in Figure 17). However, if any of these parts should not be chosen based on additional design knowledge, they can be skipped. This additional knowledge is used to determine the suitability of the part as seed parts due to certain physical (e.g., spatial location) and non-functional attributes (e.g., value) that are not captured in the DSM. For instance, a low-value commodity part would not be chosen as a seed part. This algorithm terminates once the target number of seed parts has been reached or if the *F-level* has reached the value of one. Otherwise, the *F-level* is incremented, and the abovementioned steps are repeated.

After the identification of seed parts, a quadratic integer programming model is used to determine the modules. It maximises the interactions between the identified seed parts and the non-seed parts assigned to them, while ensuring the number and size constraints of the modules.

Sets:

J Set of all parts *j*

I Set of seed parts i ($I \subseteq J$)

Parameters:

n Minimum size of a cluster

N Maximum size of a cluster

Decision variables:

$$x_{ij} = \begin{cases} 1, & \text{part } j \text{ is assigned to seed part } i \\ 0, & \text{part } j \text{ is not assigned to seed part } i \end{cases}$$

Module formation model:

$$Max\left(\sum_{i\in I}\sum_{j\in J\backslash I} x_{ij}r_{ij} + \frac{1}{2}\sum_{i\in I}\sum_{j\in J\backslash I}\sum_{k\in J\backslash I, k\neq j} x_{ij}x_{ik}r_{jk}\right) \qquad (2)$$

Subject to:

$$\sum_{i\in I} x_{ij} = 1 \qquad \forall\, j \in J\backslash I \qquad (3)$$

$$n - 1 \leq \sum_{j\in J\backslash I} x_{ij} \leq N - 1 \qquad \forall\, i \in I \qquad (4)$$

The objective function (2) maximises the interactions between the seed parts i and the non-seed parts *j* (first expression) as well as the interactions between all non-seed parts *j* and *k* in all clusters (second expression). Constraints (3) ensure that each part *j* is assigned to exactly one seed part i. Constraints (4) ensure minimum and maximum cluster sizes. The quadratic assignment problem (Equations (2)-(4)) can be solved by a non-linear solver such as a quadratic and general reduced gradient solver or a meta-heuristic such as a genetic algorithm depending on the size of model. For the case study (Figure 4), we set the target number of seed parts as four and the minimum cluster size as two. The seed parts are determined at *F-level* = 0.13. The four resulting modules consist of the seed parts (P2, P5, P11 and P13) and their assigned parts (Figures 3 and 4). Using a laptop with Intel® Core i7 processor and 16GB RAM, the mode of the clustering method is solved by the genetic algorithm in Frontline Solver Pro (60 sec).

3.4.3. Supply chain architectural design

3.4.3.1. General procedure

The general procedure for the SC architectural design stream of Phase 2 comprises an SCD step and a transformation step which generate SCAs and convert the SCAs into an SC-DSM respectively. In comparison to PD attributes mapped in a part-to-part DSM, SCD may use other attributes (e.g., suppliers, delivery lead times, location, or manufacturing technologies) to consider certain SC objectives (e.g., costs, speed, or sustainability). An SC-DSM also needs to map parts to parts to be able to link the PD and SCD domains. Hence, an SCA has to be transformed into an SC-DSM. For cases that involve multiple SCAs, this transformation includes a weighting and aggregation procedure based on a MCDA methodology.

As in the case of the PD stream, a key characteristic of the SCD stream is its capability to use different SCD methods. While there are numerous SCD methods, transformation methods to convert the resulting SCAs into representations that are commensurable with PDAs have not been developed.

SC architectures can be designed with many different objectives. In the next section, we introduce a specific optimisation-based method for generating the SCA when aiming at an efficient supply base with a minimum number of suppliers and supply modules that still allow for flexible sourcing. In general, the SC architecture could however be constructed with different objectives in mind, and with different methods. For instance, the SCD could involve typical location-allocation decisions on what parts to assemble at which locations. These decisions can be supported in many ways, ranging from simple scenario analyses to optimisation models that quantify expected production, transportation, and inventory costs in detail. Such models could also include richer information such as the restriction of the allocation of parts based on sensitive intellectual property to certain locations.

For the process we propose in this paper, the only requirement is that the resulting SCA can be translated into a DSM, so that it can be consolidated with the results from the concurrently designed product architecture in Phase 3. For the above-mentioned location-allocation example, the parts being assembled at the same location would for instance receive positive entries in the SC-DSM.

3.4.3.2. Specific method for sourcing flexibility

Our SCD method allocates parts to supply modules that are assigned to suppliers. We define sourcing flexibility as the number of suppliers assigned to a supply module. The supply scope of a supplier is defined by the parts that it can supply. It is represented in a Part-Supplier Matrix (PSM). Each '1' in the PSM indicates that the part (row) can be sourced from the supplier (column) (cf. Appendix A2). Single-sourced parts are not considered in the PSM as they offer no sourcing flexibility to the SC design space. The creation of the PSM considers various determinants for supplier selection by using MCDA methods (Ho et al., 2010). Suppliers that do not meet those determinants, such as quality and performance, are not considered in the PSM. A bi-objective binary integer programming is used to first minimise the number of suppliers and then the number of supply modules using a lexicographic approach, while ensuring the required sourcing flexibility. We are using the following notation and model formulation:

Parameters:

h Sourcing flexibility constant

k Upper limit to the number of modules that can be assigned to a supplier

l Upper limit to the number of parts in a module

$$q_{ps} = \begin{cases} 1, & \text{Part } p \text{ can be sourced from the supplier } s \text{ in the PSM} \\ 0, & \text{Part } p \text{ cannot be sourced from the supplier } s \text{ in the PSM} \end{cases}$$

Decision variables:

$$y_{ms} = \begin{cases} 1, & \text{Module } m \text{ is assigned to a supplier } s \\ 0, & \text{Module } m \text{ is not assigned a supplier } s \end{cases}$$

$$x_{pm} = \begin{cases} 1, & \text{Part } p \text{ is assigned to a module } m \\ 0, & \text{Part } p \text{ is not assigned a module } m \end{cases}$$

$$t_s = \begin{cases} 1, & \text{Supplier } s \text{ is selected} \\ 0, & \text{Supplier } s \text{ is not selected} \end{cases}$$

$$c_m = \begin{cases} 1, & \text{Module } m \text{ is selected} \\ 0, & \text{Module } m \text{ is not selected} \end{cases}$$

Sourcing model:

$$Min \sum_{s \in S} t_s \tag{5}$$

$$Min \sum_{m \in M} c_m \tag{6}$$

Subject to:

$$\sum_{m \in M} x_{pm} = 1 \qquad \forall\, p \in P \tag{7}$$

$$x_{pm} \leq c_m \qquad \forall\, p \in P, \forall\, m \in M \tag{8}$$

$$y_{ms} \leq t_s \qquad \forall\, m \in M, \forall\, s \in S \tag{9}$$

$$\sum_{p \in P} x_{pm} \geq y_{ms} \qquad \forall\, m \in M, \forall\, s \in S \tag{10}$$

$$c_{m+1} \leq c_m \qquad \forall\, m \in M \backslash \{|M|\} \tag{11}$$

$$\sum_{p \in P} p \cdot x_{pm} \geq \sum_{p \in P} p \cdot x_{pm+1} \qquad \forall\, m \in M \backslash \{|M|\} \tag{12}$$

$$\sum_{s \in S} y_{ms} \geq h\, c_m \qquad \forall\, m \in M \tag{13}$$

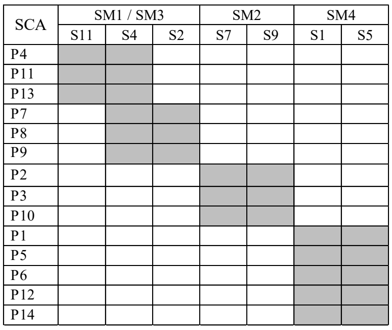
$$\sum_{m \in M} y_{ms} \leq k \qquad \forall\, s \in S \tag{14}$$

$$\sum_{p \in P} x_{pm} \leq l \qquad \forall\, m \in M \tag{15}$$

$$\sum_{s \in S^r} y_{ms} \geq 1 \qquad \forall\, m \in M \tag{16}$$

$$x_{pm} + y_{ms} \leq q_{ps} + 1 \qquad \forall\, p \in P, \forall\, m \in M, \forall\, s \in S \tag{17}$$

The first objective function (5) minimises the number of suppliers t_s and the second objective function (6) minimises the number of supply modules c_m to improve the efficiency of the SCD. Constraints (7) ensure that each part is assigned to a single module. Constraints (8) ensure that no part is assigned to a module if the module is not used. Constraints (9) ensure that no module is assigned to a supplier if the supplier is not selected. Constraints (10) ensure that no supplier is assigned to a module if the module has no assigned parts. Constraints (11) and (12) are symmetry-breaking constraints. Constraints (13) ensure the required sourcing flexibility, which is defined by the constant h (h = 2 for double sourcing; h = 3 for triple sourcing, etc.). Optionally, constraints (14)-(16) can be applied. To limit the suppliers' power over the OEM, constraints (14) ensure the maximum number of modules that can be assigned to the suppliers. Constraints (15) ensure the maximum size of the supply modules. Constraints (16) ensure that there is at least one responsive supplier in each supply module. Finally, constraints (17) ensure the feasibility of the result with respect to the PSM.



SC-DSM	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14
P1					5	5						5		5
P2			3							3				
P3		3								3				
P4											3		3	
P5	5					5						5		5
P6	5				5							5		5
P7								3	3					
P8							3		3					
P9							3	3						
P10		3	3											
P11				3									3	
P12	5				5	5								5
P13				3							3			
P14	5				5	5						5		

Figure 19: Phase 2 result showing the SCA defined by the Supply Modules (SM) and its transformation to an SC-DSM.

The output of this step defines the optimal assignment of the parts to the supply modules [x_{pm}] and the supply modules to the supplier groups with flexible sourcing [y_{ms}]. The result of the transformed SCA with double sourcing flexibility using data from the case study is shown in Figure 19. It is important to note that it is possible that the coupling of the supplier groups (e.g., S4 in Figure 19) can occur. This occurs if the PSM, which is the feasibility constraint of the clustering model, does not have sufficient flexibility to allow for completely disjunct supplier groups. Using the computational specification, the model of the SCD method is solved by CPLEX (0.1 sec).

The transformation method for the conversion of the SCA into an SC-DSM uses the sizes of the supply modules to identify the interaction strength between parts (Figure 19). The number of parts assigned to each supply module can be identified in the SCA. Fewer and bigger modules are beneficial due to lower transaction costs (e.g., managing suppliers) and final assembly lead time.

3.4.4. Design trade-off

Phase 3 of the CP-SCD process involves the generation of the set of CDMs and the M curve, the identification of the design tradespace, the derivation of design architectures, and the impact assessment for design trade-off.

3.4.4.1. Generation of the CDMs

The generation of the set of CDMs is based on the normalised PD-DSM and SC-DSM. The left side of Figure 20 shows the normalisation of the SC-DSM using the scale from the PD-DSM. This ensures that the PD-DSM and the normalised SC-DSM have interaction values that are on the same scale, thereby ensuring their aggregability.

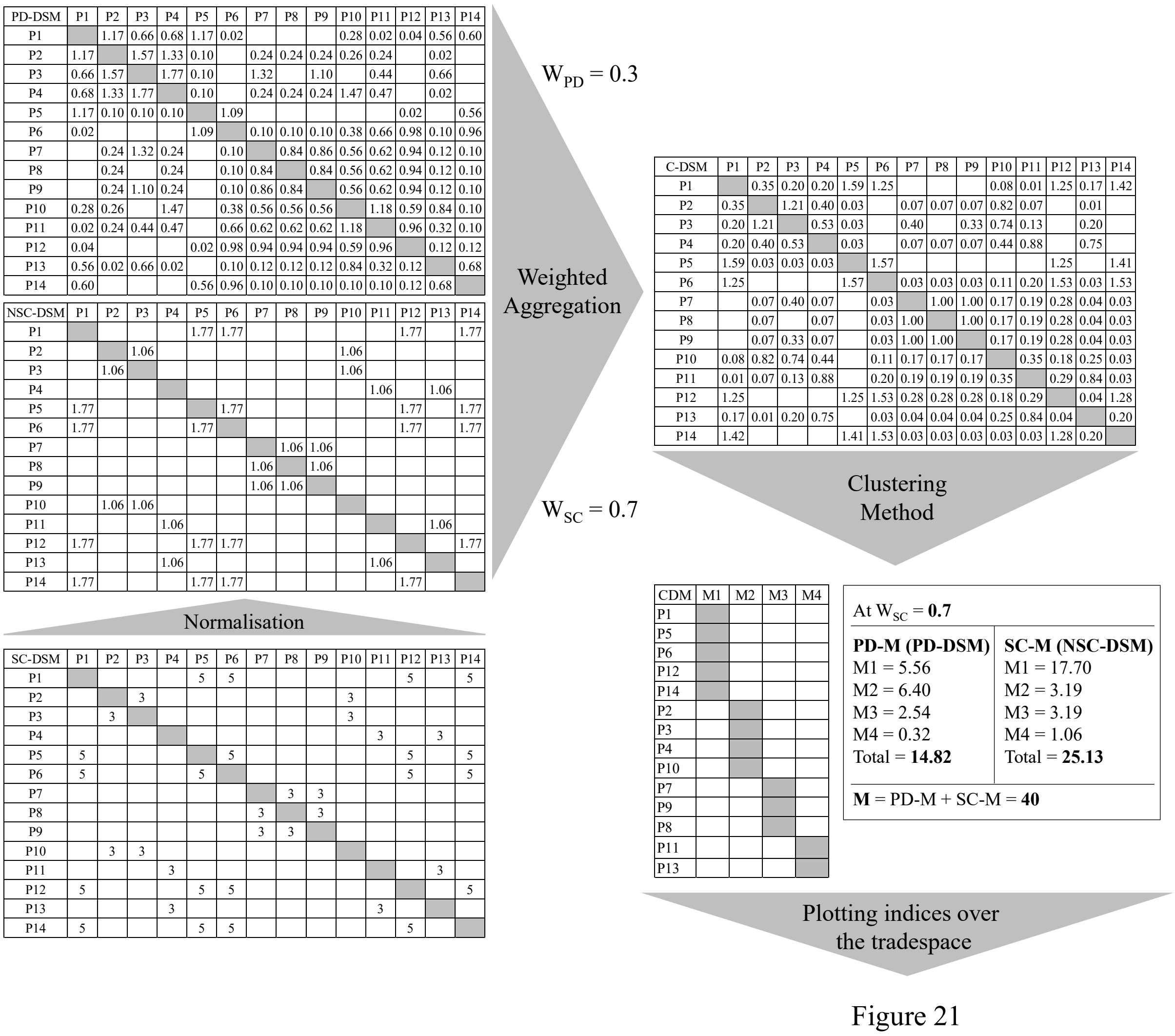


Figure 20: DSM operations for the generation of tradespace.

First, the interactions of the two DSMs are aggregated into a single DSM (C-DSM, top right of Figure 20), making the PDA and the SCA commensurable. Next, the C-DSM is clustered to generate the CDM, which represents the modules obtained from an integrated product and SC perspective. Any clustering method may be used, including the method proposed in Section 3.4.2.2. For the clustering of the PD-DSM and the C-DSM, the design team predefines a target of four modules, while keeping the number of supply modules and supplier groups in SCA unrestricted. Even though the number of supply modules identified in the SCA and the number of modules in the PDA are identical, the results are independent as they are clustered using different methods. The detailed results are found in Appendix A4.

To vary the relative importance of both domains, we introduce relative weights W_{PD} and W_{SC}, with $W_{PD} = 1 - W_{SC}$. These weights range from 0 to 1 and have the following design implications: if W_{SC} equals 0, the P-SC system is exclusively product-centric and if W_{SC} equals 1, the P-SC system is exclusively SC-centric. Varying weights avoids the need to predetermine the values of the weights. Instead, this typical MCDA approach generates and explores the design tradespace.

3.4.4.2. Generation of the tradespace

The CDM modules are assessed from the product perspective as well as the SC perspective by referring to the original DSMs. The following indices quantify the modularity level of the PDA and the SCA for the modules represented in the CDM:

- *PD-M* index: *non-weighted sum* of PD-DSM interactions captured by the CDM modules
- *SC-M* index: *non-weighted sum* of SC-DSM interactions captured by the CDM modules
- *NSC-M* index: normalised SC-M index
- *M* index: *Sum* of the *PD-M* and *SC-M* values

The modularity indices can subsequently be plotted over the entire range of W_{SC} to characterise the design tradespace of the P-SC system. The resulting PD-M, SC-M, NSC-M, and M curves presented in Figure 21 show the modularity levels of the PD, the SCD and the P-SC system respectively.

Here it can be seen that the potential designs for weights W_{SC} = 0.2 and W_{SC} = 0.3 are identical. The same holds true for the designs for weights W_{SC} ≥ 0.8. In total, eight different modules in the CDM were detected. If weights were varied at smaller intervals, even more potential designs might be identified. The PD-M curve has a generally negative gradient, and the SC-M curve has a generally positive gradient. The modularity curves thus illustrate a trade-off. The exception are cases in which the same modules are optimal from a product perspective as well as a supply chain perspective.

Gan and Grunow (2016) define the *Design Optimum Point* (DOP) as the point in the tradespace where the design attribute of a P-SC system is the highest. Graphically, the DOP is located at the apex of the M curve. This concept can be applied to all commensurable design attributes. The bottom right of Figure 20 shows the three indices at W_{SC} equals 0.7 (DOP). Here, we obtain values of PD-M = 14.82, SC-M = 25.13 and M ≈ 40.

The DOP by itself does not provide sufficient information to conduct a design trade-off. In this paper, we therefore introduce the *Design Symmetry Point* (DSP), defined as the point in the tradespace where the normalised values of the PD and the

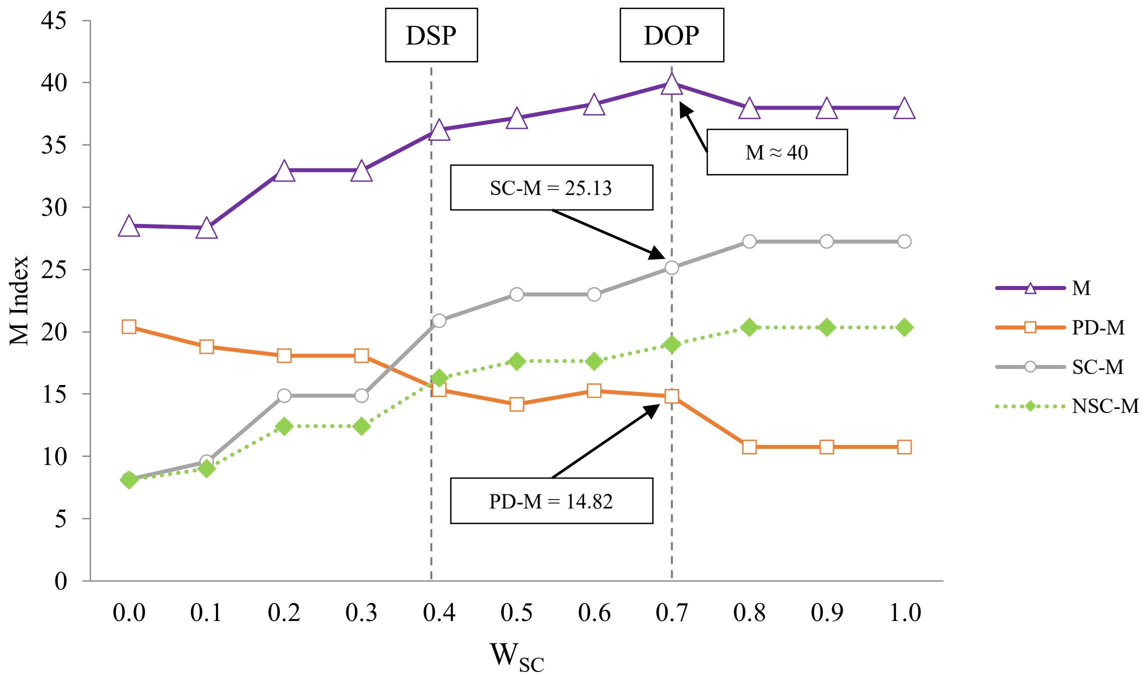


Figure 21: Representation of the tradespace by the PD-M, SC-M, NSC-M, and M curves.

SCD attributes are identical (with normalisation related to their maximum values). Hence, the DSP reflects an equitable trade-off point. It is important to note that the DOP and the DSP are always specific to the scope of design trade-off and that the DSP can be positioned on either side of the DOP, depending on the P-SC system. Together, these points help characterise the tradespace and enhance the trade-off process in the following ways:

- Quantification of the alignment level between the PD and the SCD as an endogenous characteristic of the P-SC system.
- Demarcation of different areas of the tradespace relevant for different types of products.
- Enrichment of design trade-off process using visual graphs.

For niche products and commodities, equitable consideration of both design domains is not necessary since one of the domains dominates the design process. For niche products, the part of the tradespace near the solution with exclusive consideration of PD requirements is relevant. Similarly, for commodities, the part of the tradespace near the solution with exclusive consideration of SCD requirements is relevant.

For differentiated products such as the battery system investigated in our case study, the DSP and the DOP provide relevant insights on the characteristics of the tradespace. The larger the distance between the DSP and the DOP, the larger the effort required for the design trade-off. Exploring the design space between the DOP and the DSP, we balance the optimality of the entire P-SC system with the equitable consideration of both domains. At every exploration step, feasibility studies are conducted to assess the impact of the designs. In Figure 21, the DOP is located to the right of the DSP. This indicates a higher P-SC system modularity when the P-SC system architecture is oriented towards the SCD. Between the DSP and the DOP is a gap of 0.3 in the tradespace, representing the tradespace between equitability and optimality in the P-SC system. In order to assess the impacts of these two points on the P-SC system architecture, we present the comparisons of their respective CDMs (CDM_{DSP} and CDM_{DOP}) with the CDM_0 (W_{SC} = 0) and the CDM_1 (W_{SC} = 1) in the following section.

For the designers in the case study, the generated tradespace (Figure 21) offered a concrete view of the design trade-off. This visual representation of the tradespace provided a common understanding of the P-SC system. By starting with the DSP and the DOP, the designers were quickly able to evaluate important points in the tradespace to be studied further in the impact assessment. We have not found any previous study that provides a method of generating a tradespace in CP-SCD.

3.4.4.3. Derivation of tradespace architectures

The next step in Phase 3 includes the derivation of PDAs and SCAs. The derivation of SCAs requires an additional step to retransform the selected CDMs into the corresponding SCA. The retransformation of the CDM to the SCA is needed to ensure the optimal grouping of the suppliers, which may differ from the supplier groups of the SCA derived from Phase 2. The retransformation method is a modification of the SCD method. The modification includes a new objective function (18) for maximising the similarity between the part-to-supplier group assignment x_{pm} of the SCA and the part-to-module assignment u_{pm} of the CDM. Constraints (12) are omitted to ensure the feasibility of the solutions.

$$u_{pm} = \begin{cases} 1, & \text{Part } p \text{ is assigned to the module } m \text{ in the CDM} \\ 0, & \text{Part } p \text{ is not assigned to the module } m \text{ in the CDM} \end{cases}$$

$$Max \sum_{p \in P} \sum_{m \in M} x_{pm} u_{pm} \tag{18}$$

3.4.4.4. Impact assessment for design trade-off

In the final step of Phase 3 of the CP-SCD process, the impact assessment focuses on the space between DSP and DOP. In our case study, this facilitated a discussion on the tangible design options constituting the tradespace. In the example presented in Figure 22, we compare the modules found for the DOP and the DSP with each other. For illustration purposes, we also contrast them against the modules generated for CDM_0 and CDM_1. These comparisons highlight the differences in the size and the content of the modules.

The differences between the CDMs and the CDM_0 are assessed directly with regards to product design impacts such as technical feasibility (e.g., functional degradation, weight, space). For example, the architecture of the CDM_{DSP} has a major impact on the functional integrity of the CDM_0 modules. The CDM_0 modules M1, M2 and M3 are disintegrated and distributed over all modules of the CDM_{DSP}. Only the CDM_0 module M4 remains integral. Major impacts of the CDM_{DSP} on the CDM_1 can similarly be observed as only the CDM_1 module M4 remains intact.

In comparison to the CDM_{DSP}, the CDM_{DOP} has similar impact on the CDM_0 and only a minor impact on the CDM_1. The CDM_0 module M3 is redistributed to three of the CDM_{DOP} modules, as in the case of the CDM_{DSP}. The CDM_1 modules M3 and M4 remain intact. M2 is almost unchanged except for the plugs & connectors, which are added from the M2. Another result of the impact assessment relates to the change of the SCA complexity. We highlight this result by focussing on the material flows within the SCA. These changes affect how the parts can be sourced (i.e., part, supply kit or module). A module is a set of assembled parts that can be further assembled. A supply kit is a set of parts delivered by the same supplier without any functional association (e.g., a box of loose parts). As such, the use of supplier type in the SCA has a different impact on the lead time, assembly and testing in production.

The increase in SC complexity is indicated by the flows of parts between the SCA modules at the DSP and the DOP shown in the hierarchy diagrams (Figures 26b and 26d). For the SCA at the DSP, the supplier group S4/S11 changes from a module supplier group to a mixed module and part supplier group, which delivers the part P4 to S7/S9 (Figure 23b). Furthermore, the supplier group S7/S9 changes from a module supplier group to a mixed module and kit supplier group, which delivers the kit (P2/P3) to S2/S4. As a result, both supplier groups become first tier and second tier supplier groups. This additional SC layer increases the lead time and the cost of production

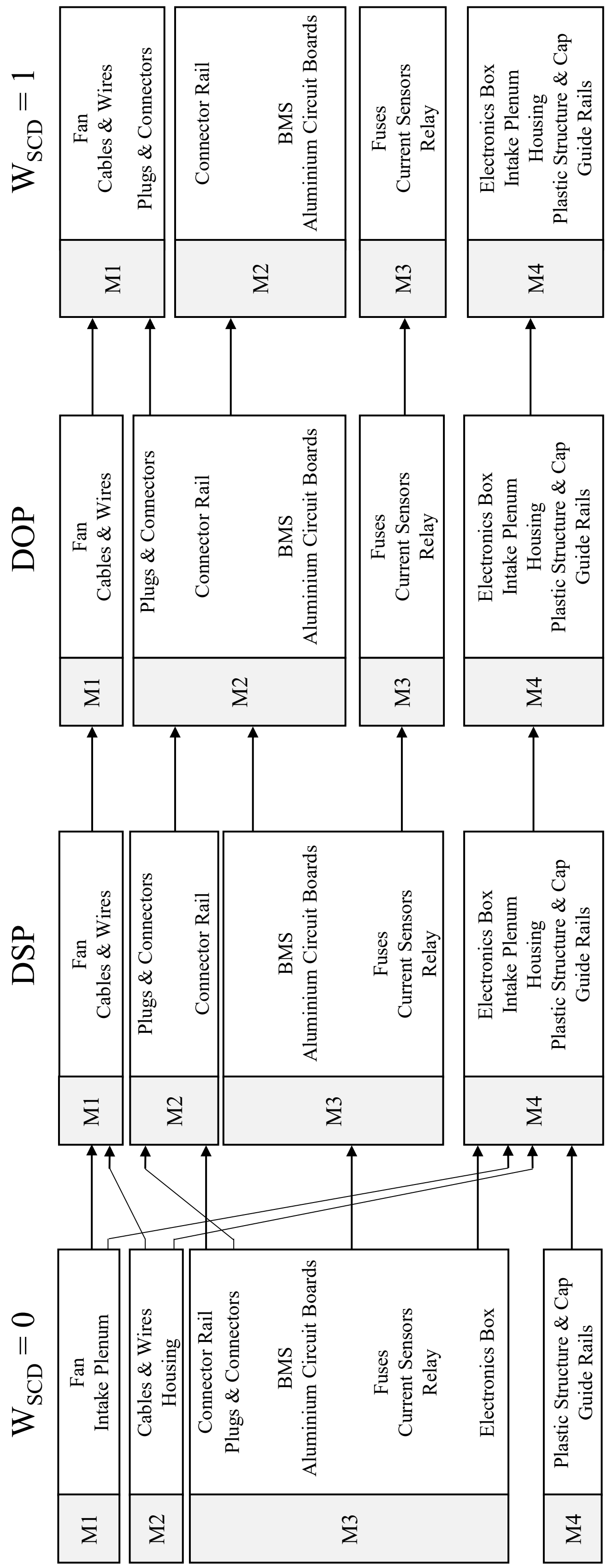


Figure 22: Impact assessment of the architectures at the DSP and the DOP.

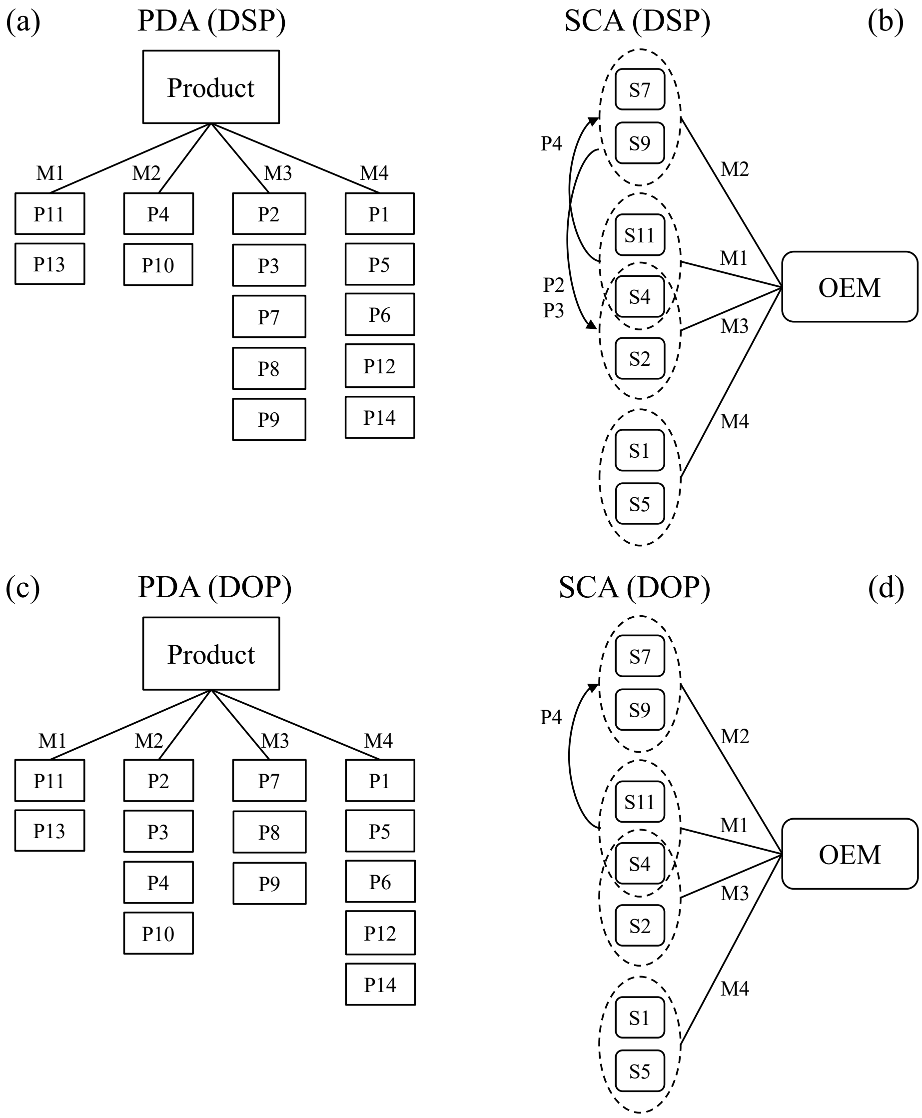


Figure 23: Hierarchy diagrams of PDA (a) and SCA (b) at DSP, and PDA (c) and SCA (d) at DOP.

(e.g. inventory and transportation). In comparison to the SCA at the DSP, the SCA at the DOP is less complex as it only has to additionally source P4 from S4/S11 to S7/S9 (Figure 23d).

Even though sourcing flexibility is ensured in the resulting SCAs, only seven out of the 14 potential suppliers were selected to supply the four modules (Figures 22 and 26). These modules are however very different from the modules that would be created for an optimal PD (as was shown in Figure 22).

Overall, the SCAs at the DSP and the DOP reduce the number of suppliers that are managed directly by Invenox and the associated transaction costs. Comparing the P-SC architectures at pure product orientation, DSP, DOP, and pure SC orientation, the designers found that the advantages of a more modular and flexible SCD obtained at DOP outweighed the technical disadvantages for the PD. The impact assessments supported by visualisations such as Figures 25 and 26 thus helped balance between PD and SCD objectives in the case.

3.5. Conclusion

This paper advances research in CP-SCD by linking theory and methodology to practice. Firstly, we built a better understanding of the interaction between PD and SCD by introducing a novel way to characterise the design tradespace between a PDA and an SCA. We introduced a new design term (DSP) and showed how it can be used together with the DOP to demarcate the relevant part of the tradespace. We are thus contributing to the state-of-the-art, which so far did not allow for a comprehensive exploration of the tradespace.

Secondly, we operationalised the conceptual CP-SCD process by introducing a detailed process for generating the tradespace between a PD and an SCD. The detailed process consists of three phases. The first phase aligns PD and SCD requirements and defines the relevant design attributes. The second phase consists of parallel processes to generate the PD and the SCD. The third phase generates the design tradespace and conducts impact assessments of the selected PDAs and SCAs. This methodology, consisting of a detailed process and methods, goes beyond past work that only proposes conceptual frameworks that are not sufficiently specific to be applied in practice.

Thirdly, we introduced new methods to generate PD and SCD architectures. The PD method goes beyond current clustering methods by allowing greater control of the number and the size of the modules. Our PD method includes a new heuristic algorithm that uses interaction numbers and interaction strengths to select independent seed parts for clustering the parts into modules. The SCD method differentiates itself from the current SCD methods by clustering parts to their suppliers while ensuring sourcing flexibility. More importantly, our SCD method ensures that the SCA is commensurable with its PDA, thereby facilitating design trade-off. Here, we contribute by using DSM representations for both the PD and SCD. In contrast to previous work, this also allows us to use common methods for PD and SCD and to apply MCDA methodology to bridge both domains.

Finally, we address the lack of cases highlighted in our literature review by demonstrating the application of the CP-SCD process and methods in a real case study in the electric-vehicle battery industry. The systematic exploration of the design tradespace in the case study showed how a range of solutions provide a better understanding of the trade-off between PD and SCD objectives.

We also realize that our methodology and case study have several possible limitations and areas for future research. Firstly, the result of the CP-SCD process is dependent on quality and promptness of input data. For example, the functional and SC interactions between components may not be fully known in Phase 1 of the PD process. This is especially true for more complex products. A way to address this issue is to update the data and iterate the process until an adequate level of architectural design maturity has been reached.

Secondly, the case study uses an unconstrained PDA with a green-field SCA. However, for cases such as product improvement, the PDA can be influenced by the PDAs of predecessor products. Similarly, the SCA can also be constrained by brown-field SC factors such as the reuse of existing suppliers. These considerations are not covered in our case study.

Finally, our methodology is applicable to PD and SCD under different objectives; our case study and the specific methods developed focus on two design attributes: modularity and flexibility. These are key attributes at the architectural level. Nonetheless, methods for optimising other design attributes (e.g., assembly locations) under different criteria (e.g., costs, responsiveness, or environmental footprints) can also be explored and developed for use in our CP-SCD process, which has been deliberately developed with open interfaces to other methods.

4. Robust supply chain design with suppliers as system integrators: an aerospace case study

This chapter is based on
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OEMs have sought new supply chain paradigms that allowed them to focus on core activities, i.e., overall product design and commercialisation. This pursuit led to partnerships with a new generation of tier-1 strategic suppliers that act as integrators. Integrators are not only responsible for system supply, but also for system design. However, critical integrators were not able to live up to their new roles, which led to costly delays in development and production. These failures highlight the ineptitude of current risk management practices of OEMs. To support OEMs in implementing a more differentiated and suitable approach to the use of integrators, this paper proposes a mathematical programming model for supply chain design (SCD). Instead of looking at the introduction of integrators as a dichotomous decision, the model suggests the optimal number of integrators, i.e., systems, and individual part suppliers. We propose new measures for integration risk, which build upon current risk assessment practices. Robust optimisation (RO) is used to study the effect of uncertainty over baseline risk values. All approaches were tested using both randomly generated instances and real data from a large European OEM in the aerospace industry.

Keywords: Aerospace Industry, Sourcing Flexibility, Supply Chain Design, Robust Optimisation, Supply Chain Risk Management

4.1. Introduction

High-tech industries with convergent supply chains have suffered heavily due to failures of critical system suppliers - i.e., integrators. For example, Boeing's attempt to partner with single source system suppliers in the 787 aircraft program resulted in almost four years of delay and billions of dollars in losses (Gates, 2015). Tesla's Model 3 encountered production delays due to delivery stoppages from its battery system supplier, resulting in losses of more than a billion dollars, while also damaging the trust from its investors and customers (Hull, 2017). Apple also faced delivery delays with the iPhone X from its system supplier Foxconn due to a mixture of production and supply chain issues (Wu et al., 2017).

These incidents have been caused by a new supply chain paradigm of OEMs focusing on core competences and outsourcing sub-system design and supply to a small set of suppliers. In this context, specialised partners are expected to deliver fully integrated systems to the final assembly site. This relieves OEMs from managing and coordinating lower-tier suppliers.

Tang et al. (2009) identify the main hurdles in making a complete transition towards this supply chain paradigm. First, there is the suppliers' inexperience in designing and integrating components combining a wide range of technologies. Second, the OEM relies on a perfect coordination between specifications, operations and the management of each integrator. Tang et al. (2009) also provide evidence that OEMs adopt the new paradigm lacking proactive supply chain risk management (SCRM). Specifically, a concurrent product design (PD), supplier selection and risk assessment is lacking. Traditional supply chain risk (SCR) types (such as supplier reliability, quality and capacity) used do not adequately address the transition of system suppliers now responsible for successful integration.

This work identifies this new risk type, integration risk, which measures the risk of combining multiple parts in sub-systems. An exploratory stance is adopted to model this SCR employing three distinct approaches for measuring and mitigating this risk across the supply chain. We impose risk thresholds across the entire supply chain, at each supply module, or for individual part-supplier associations. The characteristics of the three approaches make it possible to adapt the model to different supply chain contexts and objectives.

Sourcing flexibility can be used as a mechanism to mitigate integration risk. Ho et al. (2015) show that double sourcing reduces supply-related risks substantially. However, for manufacturers of safety relevant products, such as medical devices, automobiles and aircraft, having alternative suppliers (sourcing flexibility) requires additional effort. Suppliers require the needed certification for safety. Nevertheless, the choice between single and double sourcing represents a trade-off between supply chain complexity and risk exposure.

There is a need to support decision makers in addressing the complex task of integrating PD, supplier selection, and risk assessment. We develop a mathematical programming model for concurrent product system modularity - PD - and supplier selection with selective sourcing flexibility - SCD. The model minimises the number supply modules by assigning sets of parts to one or two suppliers considering the technologies required by the parts. However, OEMs have limited insights into suppliers' integration capabilities. Hence, we use uncertain parameters to model each supplier’s proficiency with the technical aspects in manufacturing and assembling the allocated parts, as well as their ability to independently manage their own supply chain. Since for the new product, statistical distributions for the integration risk are not available, we use RO to test the effect of uncertainty on the concurrent PD and SCD decisions. Here, the budget of uncertainty reflects the OEMs attitude towards the integration risk. Overall, the present work is organised around three core objectives.

This first objective is to contribute to SCR by formalising a new risk source. The integration risk consolidates the descriptive work of Tang et al. (2009), which outlines the potential supplier disruptions associated with increased systems design and integration responsibilities. We introduced a 3-level measurement scale for this risk, mirroring current practices. We propose three approaches to mitigate integration risk. These impose risk thresholds across the entire supply chain, at each supply node, or for each part-supplier association.

The second objective is to introduce a model that enables the concurrent application of PD, SCD and SCRM. Our model extends the deterministic work from Gan and Grunow (2016) and Gan et al. (2022), which make part integration and horizontal supply chain consolidation decisions. Our approach derives the supply modules and sourcing flexibility based on integration risk exposure targets.

The third objective is to quantify the trade-off between integration risk exposure and supply chain complexity, i.e., the number of modules and suppliers. We study the influence of uncertainty on PD and SCD decisions using a case study from a large European OEM in the aerospace industry, and also using randomly generated instances.

The remainder of this paper is structured as follows. Section 4.2 reviews relevant contributions in PD, SCD, and SCRM. Section 4.3 presents a deterministic mathematical programming formulation for concurrent decisions on product system modularity, sourcing flexibility, and supplier selection. We develop a robust optimisation extension to handle uncertain supplier capabilities. It further introduces different measures for the integration risk. Section 4.4 includes tests on both a real aerospace case study and on randomly generated instances. This section also discusses the results, managerial implications and challenges for the aerospace industry. Section 4.5 concludes the paper.

4.2. Literature review

Introducing a new product demands a clear SCD strategy. Garcia and You (2015) and Calleja et al. (2018) provide comprehensive insight into the state of the art for SCD. Their work highlights the historical trend of having the New Product Development (NPD) process preceding SCD decisions. Exploring the interaction between NPD and SCD, Graves and Willems (2005) and Amini and Li (2011) explore how OEMs should configure their supply chains to maximise new product diffusion. An emerging extension to SCD is the cross-disciplinary research on concurrent PD and SCD. Pashaei and Olhager (2015) and Gan and Grunow (2016) review the interface between these fields and identify design attributes of both fields and methodologies suitable for integrated decision making. At the architectural level, previous work simultaneously decides on product modularity along the PD-dimension and supplier selection along the SCD-dimension. However, the risks originating from making suppliers responsible for large modules have been treated in a simple way by forcing double sourcing across all modules.

Klibi et al. (2010) review SCD literature and highlight the need for focused risk sources, adapted to specific design context. Furthermore, the authors claim that this field lacks in non-value-based models, with objective functions that don't focus on minimising costs. There is also a specific mention on the need to apply RO to this field, especially with a model that does not maximise expected value. They also mention that current research does not sufficiently tackle risk mitigation constructs as design decisions. Our work makes contributions on all these fronts.

Graves and Tomlin (2003) and Tomlin (2006) suggest that having a flexible supply base increases resiliency towards supply chain inefficiencies. Thus, SCRs can indeed be mitigated by increasing supply chain flexibility (Yang and Yang, 2010; Chiu et al., 2011; Talluri et al., 2015; Sreedevi and Saranga, 2017), i.e. increase the number of supply sources for each part. Ho et al. (2015) highlight that dual-sourcing outperforms single-sourcing in the presence of a supply disruption (Yu et al., 2009; Li et al., 2010; Xanthopoulos et al., 2012). Tang and Tomlin (2008) argue that even limited flexibility is sufficient to reduce process risks with other researchers indicating that using more than two suppliers brings marginal benefits (Fang et al., 2013). Our model adjusts the sourcing flexibility to the risks resulting from the product modularity. Although there is extensive literature about SCR (Hong et al., 2018; Hamdi et al., 2018), Ho et al. (2015) point out that past definitions are too specific to supply chain functions and do not cover the entire supply chain. Traditional risks that are considered include: demand risk (including lead time), logistics risk, supplier risk, manufacturing risk, supply risk, infrastructural risk. These risks are defined as disruptions that can be directly associated with each company's activities. For example, Li and Amini (2012) propose a SCD model for new product diffusion, with demand risk.

We formalise a new SCR, the integration risk, which does not only consider individual part conformity or delays, but also the technological and managerial capabilities of suppliers. This risk type builds on the descriptive analysis of Tang et al. (2019). Research such as Artzner et al. (1999) provide guidelines on how to measure risk, however, to potentiate seamless industrial application for our tools, we chose to mimic current measure practices from a large European OEM in the aerospace industry.

In general, SCD methods that consider SCR use fuzzy or stochastic programming in the form of mathematical and simulation models (Sabouhi et al., 2018; Jabbarzadeh et al., 2018). Other alternatives to deal with uncertainty, which leverage stochastic programming, were Rockafellar (2007), such as value-at-risk or conditional-value-at-risk approaches. When deciding about the modularity of new products, information on probability distributions required for tackling risk with such approaches is unavailable due to lack of historical data. Bertsimas and Sim (2004) proposed RO as an alternative approach to deal with uncertainty. Uncertain parameters are characterised by a simple set of potential values. While previous work applied this concept to SCD (e.g., Hahn and Kuhn (2012)), we use RO for merging SCD with PD and SCRM.

4.3. Problem statement and mathematical formulation

Building on the work of Gan et al. (2022), we introduce a problem that seeks an efficient and robust supply base with minimum number of product system modules, while considering the suppliers' integration risk. This decision is carried out during the planning stage for both product and supply chain. The model makes simultaneous decisions on the integration of parts into components and their assignment to a systems integrator supplier, in a module. For industries such as aerospace, demand is disregarded as a risk source at this stage.

Modules may have up to two suppliers and any number of parts. Suppliers are responsible for the design, production and pre-assembly of all parts in their module. The problem is to determine supply modules containing a set of parts and the suppliers that source them. Let $p \in P$ be the parts to be sourced and $s, i, j \in S$ the supplier candidates (see Appendix A5 for all the relevant notation used in this paper). Modules can be single or double sourced. Supply modules are built under the following assumptions:

1. Suppliers in each supply module integrate all parts assigned to them.
2. All parts $p \in P$ can be integrated together into a larger system.
3. Each supplier can only contribute to one module, but the same module may have up to two suppliers.

Assumptions (1) is self-explanatory and embodies the main goal of supply chain integration. Assumption (2) is a simplification to the problem by ignoring the physical compatibility between parts and enhancing the model's focus on part-supplier interactions. This assumption will prioritise SCD considerations over detailed PD insight. Gan et al. (2022) circumvents this limitation by defining a design structure matrix containing compatibility parameters for each part pair. We follow the same approach. Assumption (3) was made so both design and risk decisions for each supplier are directly linked to the supply chain's modularity.

The main input in this problem is the pool of supplier candidates, represented in a part-supplier matrix (PSM). The PSM contains a binary relation between parts and suppliers and indicates whether a part can be sourced from each potential supplier.

The two main binary decision variables are $x_{(i,j)}$ and $y_{(p,s)}$. $x_{(i,j)}$ decides if suppliers i and j are in the same supply module. To allow the application of these decision variables to both single and double sourcing, a virtual supplier with index 0 is also defined. For any supplier i, if $x_{(0,i)} = 1$, supplier i is in a single sourced module. Each module has an associated parameter $h_{i,j}$ which is equal to 0 if $i = 0$, meaning that the module is single sourced, and equal to 1 otherwise. To avoid redundancy and break symmetry, we define set S' with all possible (i, j) associations such that $j > i$. $y_{(p,s)}$ decides whether a part p is sourced from supplier s. Each part may be sourced from a maximum of two suppliers.

Beyond the incorporation of risk and uncertainty described along this section, another major improvement to the work of Gan et al. (2022) is the improved computational efficiency of the deterministic model. This is achieved by reducing the size of $x_{(i,j)}$ and $y_{(p,s)}$ to not consider (i, j) and (p, s) pairs that would be invalid from the onset, based on the information from the PSM (see Table 5 for details on how the number of decision variables decreases in our formulation).

4.3.1. Deterministic base model

Objective function (1) of the model is to achieve an optimal level of supplier integration by minimising the number of supply modules selected for sourcing the full range of parts. This goal represents the OEM's focus on reducing transaction costs through modularisation of its products and supply chain. An additional term with weight of α is used to break the symmetry between solutions with the same number of modules, but different sourcing flexibility. Choosing small values for α maintains the priority for integration while including a preference for single sourcing and reduced management effort. Later in our computational experiments we use a small value of α = 0.01 as a tie breaker between our two objectives to ensure that the minimisation of the number of modules remains our main goal.

$$\min \sum_{(i,j)\in S'} \left[1 + \alpha \cdot h_{(i,j)}\right] \cdot x_{(i,j)} \tag{1}$$

As mentioned above, decision variables $x_{(i,j)}$ and $y_{(p,s)}$ are binary:

$$x_{(i,j)} \in \{0,1\}, \qquad y_{(p,s)} \in \{0,1\} \tag{2}$$

Constraints (3) ensure that suppliers can only be in one module. Note that the virtual supplier 0 is not a part of set S and can be in multiple modules.

$$\sum_{(i,j)\in S'} x_{(i,j)} + \sum_{(j,i)\in S'} x_{(j,i)} \leq 1, \forall i \in S \tag{3}$$

Constraints (4) and (5) ensure that all parts must be assigned to at least one supplier, and a maximum of two. As mentioned in our literature review, building on the insight of Tang and Tomlin (2008) and Fang et al. (2013), sourcing flexibility is limited to two suppliers per module. However, despite the documented benefits of double sourcing, the model's objective is to select the least complex solution, both in number of modules and number of suppliers.

$$\sum_{(p,s)\in PS'} y_{(p,s)} \geq 1, \forall p \in P \tag{4}$$

$$\sum_{(p,s)\in PS'} y_{(p,s)} \leq 2, \forall p \in P \tag{5}$$

Constraints (6) activate decision variables $x_{(i,j)}$, ensuring that suppliers sourcing parts are assigned to a module. Where the set PS' contains the part-supplier allocations allowed by the PSM.

$$y_{(p,i)} \leq \sum_{(i,j)\in S'} x_{(i,j)} + \sum_{(j,i)\in S'} x_{(j,i)}\,, \forall (p,i) \in PS' \tag{6}$$

Constraints (7) and (8) relate decision variables $y_{(p,s)}$ and $x_{(i,j)}$, ensuring that if a given part is sourced from more than one supplier, those suppliers must be in the same module. The set $APSS'$ defined below contains parts that can be integrated by both suppliers, where $P'(i)$ is the set of parts that can be integrated by supplier i.

$$y_{(p,i)} \leq y_{(p,j)} + \left(1 - x_{(i,j)}\right), \forall (p,i,j) \in APSS' \tag{7}$$

$$y_{(p,j)} \leq y_{(p,i)} + \left(1 - x_{(i,j)}\right), \forall (p,i,j) \in APSS' \tag{8}$$

$$APSS' = \{(p,i,j) | (i,j) \in S', (p,i) \in PS' : p \in P'(j)\},$$

These constraints are not sufficient since they ignore parts that can be sourced from one supplier in the module, but not the other. The set $NPSS'$ lists parts that suppliers cannot be integrated together. Therefore, if suppliers in this list are in the same module, then neither can supply those parts, as defined in constraints (9) and (10).

$$y_{(p,i)} \leq 1 - x_{(i,j)}, \forall (p,i,j) \in NPSS' \tag{9}$$

$$y_{(p,i)} \leq 1 - x_{(j,i)}, \forall (p,i,j) \in NPSS' \tag{10}$$

$$NPSS' = \{(p,i,j) | (i,j) \in S', (p,i) \in PS' : p \notin P'(j)\}$$

Constraints (11) serve the opposite purpose, ensuring that suppliers that are not in the same module may not integrate the same parts.

$$y_{(p,i)} + y_{(p,j)} \leq 1 + x_{(i,j)}, \forall (p,i,j) \in APSS' \tag{11}$$

To improve the efficiency of the model, two sets of constraints are introduced to represent corollaries of previous assumptions. These constraints are not necessary, but they correspond to valid inequalities that squeeze the solution space. Firstly, constraints (12) and (13) ensure that if a supplier sources zero parts it cannot be in a module and, if it is in a module, then it must produce at least one part.

$$\sum_{(p,i)\in PS'} y_{(p,i)} \geq \sum_{(i,j)\in S'} x_{(i,j)}\,, \forall (i,j) \in S' \tag{12}$$

$$\sum_{(p,j)\in PS'} y_{(p,j)} \geq \sum_{(i,j)\in S'} x_{(i,j)}\,, \forall (i,j) \in S' \tag{13}$$

Additionally, using only the overlapping parts of each pair (i,j) in the set $APSS'$, if $x_{(i,j)} = 1$, then suppliers (i,j) must source at least one part from this list, as defined in constraints (14) and (15).

$$\sum_{(p,i,j)\in APSS'} y_{(p,i)} \geq x_{(i,j)}, \forall (i,j) \in S' \tag{14}$$

$$\sum_{(p,i,j)\in APSS'} y_{(p,j)} \geq x_{(i,j)}, \forall (i,j) \in S' \tag{15}$$

4.3.2. Incorporating risk measures

To incorporate a risk aversion component into the model, the integration risk matrix (IRM) is introduced containing an integration risk score for each part-supplier pair (p, s). Integration risk, denoted as $r_{(p,s)}$ for part p from supplier s, is represented in a 3-level scale: 'low', 'medium' or 'high', which are stored as 1, 2 or 3, respectively. While this represents a narrow range for analysis, this scale was chosen to mirror current practices from OEMs in the aerospace industry. These estimations are based on their knowledge of the suppliers' technical and supply chain management capabilities.

Since the OEM's motivation is to improve supply chain integration, risk measures are imposed as restrictions on the model and are not included in the objective function. Three risk measures are considered based on the OEM's feedback. Firstly, a limit on the *overall risk* of integration is imposed. The second approach improves the performance of the *weakest link* in modules by forbidding parts with risk above a certain threshold. Finally, the *additive approach* imposes an upper limit on the accrued risk of parts selected for each module. By introducing these constraints, the deterministic model's objective is still to maximise integration, via the objective function, but this will happen as a trade-off with risk exposure. As can be seen in the following approaches, the model increases supply chain complexity, by increasing the number of modules and suppliers, to ensure these restrictions are met.

Overall risk budget approach

One possible approach of quantifying risk is to consider it as a proxy for the engineering and management resources that the OEM must allocate to solve issues with suppliers. Constraints (16) introduce a budget Ψ for dealing with integration risk that OEMs will make available for their supply chain. The lowest Ψ value will restrict the solutions to exclusively single sourced modules with 'low' risk parts. The highest value $(6 \cdot p)$ represents complete freedom, including all 'high' risk parts from double sourced modules. The model has the flexibility to use additional modules and double sourcing while simultaneously limiting the total supplier development cost.

$$\sum_{(p,s)\in PS'} r_{(p,s)} \cdot y_{(p,s)} \leq \Psi \tag{16}$$

Weakest Link Approach

The second alternative imposes the threshold R_w on the part with the highest integration risk in a module, i.e., the weakest link. This setting assumes that a single part's risk can compromise the entire module. Constraints (17) defines the upper bound on the risk of each part sourced from a supplier. As an example, if R_w is 2, for a single sourced module, only suppliers with 'low' or 'medium' risk will yield a feasible design. Notably, R_w may only varying between 0.5 and 3. Since all parts must be sourced, R_w equal to 0.5 is the minimum feasible value for sourcing "low" risk parts, as the thresholds become 2 · (0.5), which is equivalent to 1, the nominal value assigned to "low" risk parts. For R_w equal to 3, all parts can be single-sourced, even high-risk parts which have a nominal risk value of 3. Higher values for R_w do not have a practical meaning in our model's context.

Approximating the findings of Fang et al. (2013), a linear improvement in tolerance to risk exposure is assumed from single to double sourcing.

$$r_{(p,i)} \cdot y_{(p,i)} \leq R_w \cdot \sum_{(i,j)\in S'} \left[x_{(i,j)} \cdot \left(1 + h_{(i,j)}\right)\right], \forall (p,i) \in PS' \tag{17}$$

Additive Approach

The additive approach evaluates the risk level of a module by adding individual risk contributions from each part and controlling exposure via the threshold R_a. Constraints (18) limit the amount of risk assigned to a module by summing up the integration risk of all the parts sourced by each supplier in that module. Selective sourcing flexibility within modules is used as an additional risk mitigation strategy by offsetting the threshold. As before, dual sourcing of a module also doubles the risk tolerance. Following the same principle used in the weakest link approach, the minimum feasible value of R_a for sourcing "low" risk parts is 1, despite only allowing a single supplier in this configuration. Selecting two suppliers with "low" risk parts would accrue a nominal risk value of 2, which would be over the threshold. The maximum meaningful value for R_a would allow the supplier that can source the most parts to integrate all of them, with "high" risk scores, i.e., 3 times the number of parts.

$$\sum_{(p,i)\in PS'} r_{(p,i)} \cdot y_{(p,i)} \le R_a \cdot \left(\sum_{(i,j)\in S'} \left[x_{(i,j)} \cdot \left(1 + h_{(i,j)}\right)\right] + \right.$$

$$\left. \sum_{(j,i)\in S'} \left[x_{(j,i)} \cdot \left(1 + h_{(j,i)}\right)\right] \right), \forall i \in S \quad (18)$$

4.3.3. Robust optimisation model

RO is used to immunise solutions against uncertainty. By applying RO to each risk approach, the SCD method can take into account the variability in the estimated performance of supplier candidates. Since the IRM values are estimates made by the OEM, it is possible that they may be incorrect or vary over the lifetime of the aircraft. Using robust optimisation, an uncertain dimension is associated to each value in the IRM. Take $\tilde{r}_{(p,s)}$ to be the uncertain parameter, such that $r_{(p,s)}$ is its nominal value, estimated by the OEM. Let $\bar{r}_{(p,s)}$ be its maximum deviation from the baseline estimation. $\tilde{r}_{(p,s)}$ can be written as follows: $\tilde{r}_{(p,s)} = r_{(p,s)} + \bar{r}_{(p,s)} \cdot \xi_{(p,s)}$, where $\xi_{(p,s)}$ is the scaled deviation $\xi = (\tilde{r} - r)/\bar{r}$, which takes values within the interval $[0,1]$.

For each of the three risk measures, an unique polyhedral uncertainty set is defined. Uncertainty sets U^o, $U^w_{(p,s)}$ and U^a_s define all uncertainty scenarios for the overall risk budget (o), weakest link (w) and additive (a) approaches, respectively. e represents a vector of ones with the appropriate dimensions for each uncertainty set.

$$U^o = \left\{ \xi^o \in \mathbb{R}_+^{|PS'|} : \xi^o \in [0, e], e^T \xi^o \in [0, \Gamma] \right\} \quad (19)$$

$$U^w_{(p,s)} = \left\{ \xi^w \in [0,1], \xi^w \in \left[0, \Gamma_{(p,s)}\right] \right\} \quad (20)$$

$$U^a_s = \left\{ \xi^a \in \mathbb{R}_+^{|P_s|} : \xi^a \in [0, e], e^T \xi^a \in [0, \Gamma_s] \right\} \quad (21)$$

Robust optimisation increases the values $\xi_{(p,s)}$ towards the worst possible scenario. The size of the uncertainty set is defined by the Γ parameters. By varying these integration risk evaluations, it will be possible to study the impact of the uncertainty on solutions. Let Γ, $\Gamma_{p,s}$ or Γ_s be the maximum number of deviations allowed to the IRM values. The realisations produced through higher uncertainty levels represent more pessimistic scenarios, meaning that the suppliers' performance increasingly deviates from the original assessment.

Comparing this extension that considers uncertainty with the deterministic model, the goal is still to maximise integration. However, the risk thresholds become harder to uphold as Γ-values go up. Thus, it is predictable that the price of robustness will increase, i.e., more modules and/or more suppliers.

Overall risk budget approach

$\tilde{r}_{ps}$ is introduced as the integration risk for each part-supplier pair under uncertainty. As such, the robust counterpart for constraints (16) is written in constraints (22). RO imposes an optimisation problem on the relevant constraints that must remain feasible for all realisations of ξ^o in the uncertainty set U^o, as described in constraints (23).

$$\sum_{(p,s)\in PS'} \left[\left(r_{(p,s)} + \bar{r}_{(p,s)}\xi^{o}_{(p,s)}\right) \cdot y_{(p,s)}\right] \leq \Psi, \forall \xi^o \in U^o \tag{22}$$

$$\sum_{(p,s)\in PS'} \left[r_{(p,s)} \cdot y_{(p,s)} + \max_{\xi^o \in U^o}\left(\bar{r}_{(p,s)} \cdot \xi^{o}_{(p,s)} \cdot y_{(p,s)}\right)\right] \leq \Psi \tag{23}$$

As shown by Bertsimas and Sim (2004) these constraints can be transformed into tractable robust counterparts. This transformation is outlined in Appendix A6. Thus, the overall risk budget approach produces equations (24) and (25), with the bounds on each decision variable defined in equation (26). $\mu_{(p,s)}$ and λ are variables used to write the robust counterpart of the risk constraints in the dual version.

$$\sum_{(p,s)\in PS'} \left[r_{(p,s)} \cdot y_{(p,s)}\right] + \left[\Gamma \cdot \lambda + \sum_{(p,s)\in PS'} \mu_{(p,s)}\right] \leq \Psi \tag{24}$$

$$\lambda + \mu_{(p,s)} \geq \bar{r}_{(p,s)} \cdot y_{(p,s)},\ \forall (p,s) \in PS' \tag{25}$$

$$\lambda,\ \mu_{(p,s)} \geq 0,\ \forall (p,s) \in PS' \tag{26}$$

Weakest link approach

Applying the same uncertainty parameters for r_{ps} to Constraints (17) yields Constraints (27).

$$\left(r_{(p,i)} + \bar{r}_{(p,i)} \cdot \Gamma_{(p,i)}\right) \cdot y_{(p,i)} \leq R_w \cdot \left(\sum_{(i,j)\in S'} \left[x_{(i,j)} \cdot \left(1 + h_{(i,j)}\right)\right] + \sum_{(j,i)\in S'} \left[x_{(j,i)} \cdot \left(1 + h_{(j,i)}\right)\right]\right), \forall (p,i) \in PS' \tag{27}$$

This formulation does not produce a RO problem. Since the Γ-values have the same dimensions as the constraints, these will not have robust counterparts. $\Gamma_{(p,s)}$ is defined for each part-supplier pair, with a maximum value of 1. Therefore, a study on the robustness of the solutions will consist of looking at snapshots of incremental deviations from the original IRM. If $\Gamma_{(p,s)}$ is the same for all pairs, then the variations are shared across original estimations of equal score. OEMs with access to historical data on suppliers' performance may assign individual $\Gamma_{(p,s)}$ to each supplier. Alternatively, $\bar{r}$ can be set for each part-supplier entry.

Additive approach

Re-writing Constraints (18) to incorporate the uncertain parameter $\tilde{r}_{(p,s)}$ and ensuring their feasibility for every value of $\xi^a_{(p,s)}$ over the uncertainty set U^a_s leads to Constraints (28). In the context of RO, these constraints are re-written as a new optimisation problem in Constraints (29).

$$\sum_{(p,i)\in PS\prime} \left[r_{(p,i)} + \bar{r}_{(p,i)} \cdot \xi^a_{(p,i)}\right] \cdot y_{(p,s)} \leq RHS_i, \forall \xi^a \in U^a_s$$

$$RHS_i := R_a \cdot \left(\sum_{(i,j)\in S'} \left[x_{(i,j)} \cdot \left(1 + h_{(i,j)}\right)\right] + \sum_{(j,i)\in S'} \left[x_{(j,i)} \cdot \left(1 + h_{(j,i)}\right)\right] \right), \forall \xi^a \in U^a_s \qquad (28)$$

$$\sum_{(p,s)\in PS'} \left[r_{(p,s)} \cdot y_{(p,s)} + \max_{\xi^o \in U^a_s}\left(\bar{r}_{(p,s)} \cdot \xi^a_{(p,s)} \cdot y_{(p,s)}\right)\right] \leq RHS, \forall s \in \mathrm{S} \qquad (29)$$

Using the same transformation described in Appendix A6, the tractable robust counterpart is obtained by incorporating the dual auxiliary problem as shown in Constraints (30) and (31). The bounds for λ_s and $\mu_{(p,s)}$ are described in Constraints (32). Γ_s ranges between 0 and the total number of parts that can be sourced by each supplier, i.e., it is the sum of the $\xi^a_{(p,s)}$ components for each supplier.

$$\sum_{(p,s)\in PS'} \left[r_{(p,s)} \cdot y_{(p,s)}\right] + \left[\Gamma_s \cdot \lambda_s + \sum_{(p,s)\in PS'} \mu_{(p,s)}\right] \leq RHS, \forall s \in S \qquad (30)$$

$$\lambda_s + \mu_{(p,s)} \geq \bar{r}_{(p,s)} \cdot y_{(p,s)},\ \forall (p,s) \in PS' \qquad (31)$$

$$\lambda_s,\ \mu_{(p,s)} \geq 0,\ \forall (p,s) \in PS' \qquad (32)$$

4.3.4. Assigning probabilities to constraint violation

Traditional RO methods deal with bounded uncertainty, i.e., they assume lower and upper bounds for the uncertain parameters. Then, as outlined above, worst-case robust counterparts are derived for each constraint. The uncertainty sets are defined under the assumption that uncertain parameters cannot realise values that render an optimal solution infeasible. One notable limitation has been the lack of information regarding the probabilities for the realisations of uncertain parameters. Ben-Tal and Nemirovski (2000) and Bertsimas and Sim (2004) were the first to use uncertainty sets with non-zero probabilities of constraint violation and derived a priori upper bounds for this probability. Models solved using this method yield less conservative solutions. The recent studies of Guzman et al. (2016, 2017a,b) have improved these bounds and suggested the introduction of Probability Distribution Functions (PDFs) for the sources of uncertainty. This method is valid provided the problem is based on uncertain and independent parameters, which have a known Cumulant Generating Function (CGF), and that the expected value for each distribution function is zero. Not only does this method stand to improve the model's solutions, but it also boosts the applicability of these tools by providing decision makers with a novel way to parametrise their decisions by assigning their tolerance for the probability of violating the risk constraints. In the context of our problem, integration risk values must be replaced for each part-supplier by PDFs.

Hesse (2000) indicates that triangular distributions are best suited for scenarios where uncertain parameters are based on an "educated guess". As the IRM values used by OEMs are qualitative assessments of each supplier's expected performance, triangular distributions seem to be the best fit for this analysis. Triangular distributions are defined via the lower and upper limits, and the mode. We assume separate asymmetric right triangular distributions for part-supplier pairs in the range between

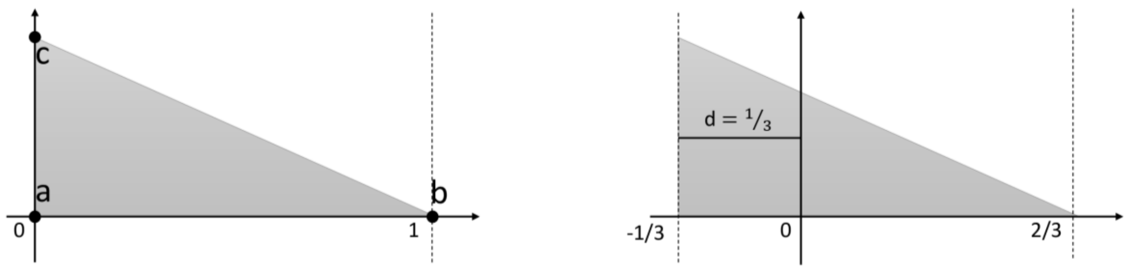


Figure 24: Non-symmetrical triangular distributions between 0 and 1 (left) and the necessary transformation to the range between -1/3 and 2/3 via the parameter d=1/3 (right). This ensures that the expected value of the distributions is zero, i.e., a+b+c=0.

Table 5. Number of decision variables for the deterministic SCD model with risk in comparison to the SCD model in Gan et al. (2021).

	Real OEM	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7
$x_{(i,j)}$	713	162	168	314	427	332	414	427
$y_{(p,s)}$	166	76	76	121	166	121	166	166
Gan et al. (2021)	82000	82000	82000	82000	82000	82000	82000	82000

$r_{(p,s)}$ and $r_{(p,s)} + \bar{r}_{(p,s)}$. An illustration of how this range can be normalised via $\xi_{(p,s)}$ is shown in Figure 24 (left). Since the IRM stems from the multivariate assessment of suppliers, it is also taken as the mode. The use of triangular distributions does not change the formulation of the robust counterparts.

Guzman et al. (2017a) define a theoretical bound for the probability of violation for constraints with uncertainty terms. To fit the aforementioned specifications, the distributions must be shifted by $d = 1/3$ so the expected value of the distribution is zero. New Moment Generating Function (MGF), M_{ps}, and CGF, Λ_{ij}, must be derived (see Appendix A8). This bound is given by the inequality shown below. The extra term $d\theta$ represents the offset in the distributions.

$$Pr\left\{\sum_{(p,s)} r_{(p,s)}\, y_{(p,s)} + \sum_{(p,s)\in PS'} \xi_{(p,s)}\, \bar{r}_{(p,s)} y_{(p,s)} > R_a\right\} \leq$$
$$exp\left(\min_{\theta>0}\left\{-\theta\Gamma_a + \sum_{(p,s)\in PS'} \left(d\theta + \Lambda_{(p,s)}(\theta)\right)\right\}\right)$$

Using Algorithm 1 in Guzman et al. (2017a) (see Appendix A7), Γ-values are calculated for different probabilities of constraint violation. By limiting the deviations from the baseline, Γ-values control the trade-off between performance and probability of violating risk constraints.

4.4. Computational experiments

Figure 25 illustrates a typical model solution in which suppliers hold integration responsibilities for larger modules and while others supply only single parts. For modules M1-M6, the model decides for double sourcing, while the remainder is only single sourced.

The computational experiments in this section analyse how the structure of the solution changes according to the three risk measures. For the additive approach, an

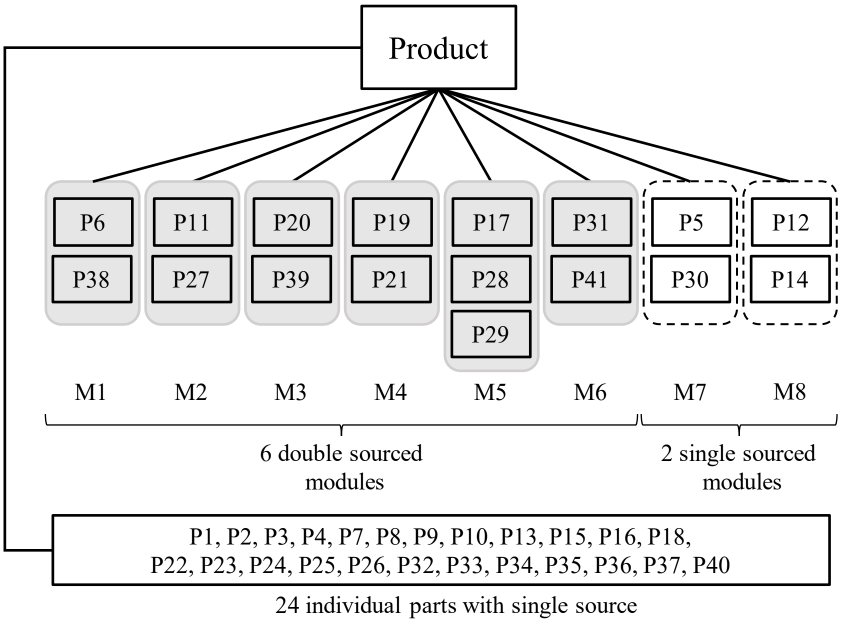


Figure 25: Result for case-study with aerospace OEM using the additive approach with $\Gamma_s = 0.4$. Solution yielded thirty-two modules with six double sourced modules M1-M6.

additional analysis on the probability of constraint violation is carried out. The first batch uses data from a large European OEM in the aerospace industry. The second set of tests is carried out on randomly generated instances. All computational experiments followed scripts implemented in OPL and were executed using the IBM ILOG CPLEX Optimization Studio 12.6.0.0 on an Intel(R) Core(TM) i7-4790 CPU @3.60GHz with 16.0Gb of RAM, under a Windows 8.1 Pro Operating System. The data sets that support the findings of this study are openly available in Mendeley Data at https://data.mendeley.com/datasets/m3rrb8tpfv/3.

4.4.1. Aerospace OEM instance

In this section, the model is applied to a setting provided by a large European OEM in the aerospace industry. The data set contains one hundred available suppliers and forty-one different parts. These parts represent partially assembled components, and the model will attempt further integration. The total number of parts in an aircraft is multiple orders of magnitude greater. In the following subsections, we show results for the three different risk approaches. Recall that the integration risk $r_{(p,s)}$ is represented in a 3-level scale: 'low', 'medium' or 'high', which are stored as 1, 2 or 3, respectively.

Results for the overall risk budget approach

Figure 26 shows the results for the overall risk budget approach for Γ values of 0 (deterministic solution), 0.05 and 0.1. The plot shows the ratio of modules to the number of parts. The lower this ratio is, the higher the integration level.

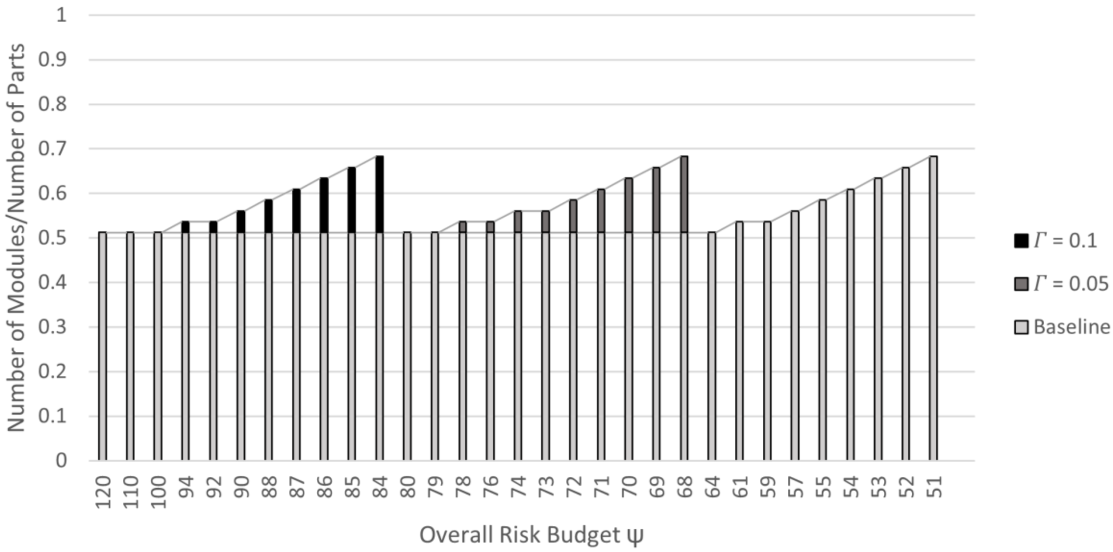


Figure 26: SCD solutions for case-study with aerospace OEM using the overall risk budget approach to risk management in supply modules.

Since not all parts have 'low' risk supplier candidates the minimum feasible, Ψ is 51 (68, 84), instead of 41, for Γ = 0 (0.05, 0.1). For each uncertainty level, we observe a sharp increase in the objective function for the lowest feasible values of Ψ. Given that the maximum allowed budget Ψ for this industry setting is 246 (cut off in the figure), there is a very narrow range in Ψ that considerably decreases the integration level.

The solution yielded by the model suggest nearly halving the number of supply nodes (21 modules/41 parts $= 0.51$). Further integration could be expected, were it not for the extreme specialisation found in suppliers. Among the 100 supplier candidates included in the PSM, 71 suppliers can only produce a single part. Therefore, if selected, they must be in a single-part module.

Results for the weakest link approach

Figure 27 shows model solutions for R_w equal to 2.5. This value was chosen since it means that double sourcing is only required for 'high' risk parts. This makes it possible to observe the dynamic sourcing flexibility risk mitigation mechanism without having an overwhelming number of double sourced parts. To extend this rule for 'medium' risk parts, $R_w$would have to be between 1 and 2. Having R_w between 0.5 and 1 would require double sourcing for 'low' risk parts as well.

One key aspect in these results is the value of $\Gamma_{(p,s)} = 0.6$ where the number of parts per module decreases, thus decreasing the integration level. This is accompanied by a shift towards exclusively double sourced modules. Our results show that there is a narrow range in the tolerated realisations of uncertainty that causes a transition from

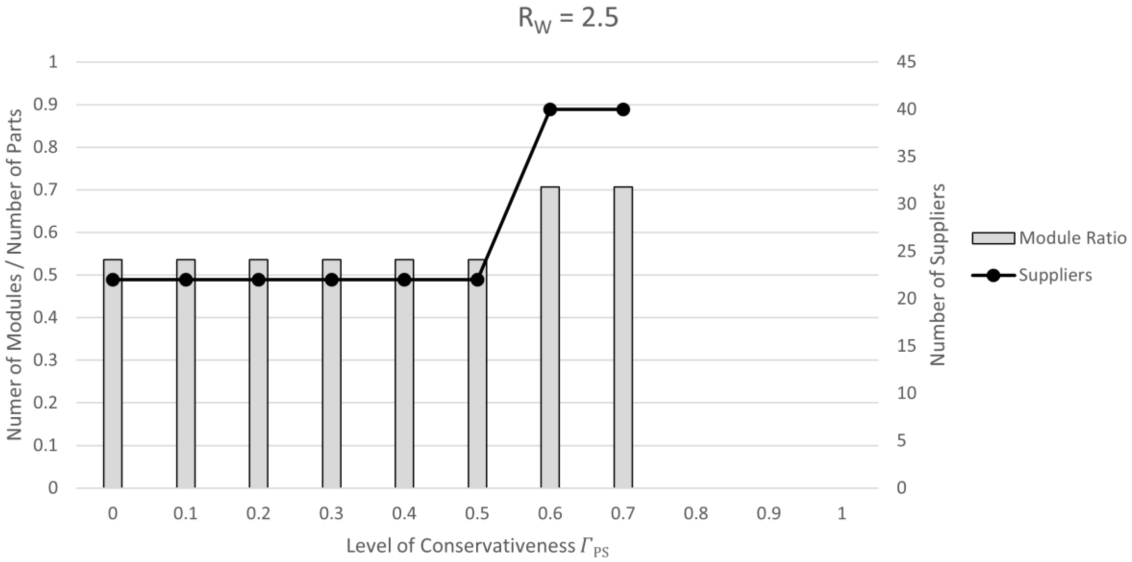


Figure 27: Solutions for case-study with aerospace OEM using the weakest link approach to risk management in supply modules.

a solution with full risk exposure to a solution with high degree of conservativeness. The incurred increase in both supplier modules and total number of suppliers represent the price of robustness for those uncertain scenarios.

No solution can be found beyond $\Gamma_{(p,s)} = 0.7$. The extreme specialisation of suppliers in the aerospace industry and the enforcement that suppliers can only participate in one supply module, means it is infeasible to double source all parts. This means that extreme levels of conservativeness cannot be reached.

Results for the additive approach

Figure 28 shows the results of the additive approach for different levels of conservativeness using a $R_a = 4$. For a level of conservativeness of $\Gamma_s = 0.4$, Figure 25 shows the resulting module structure and supply chain architecture. This approach achieved the least horizontal integration across all approaches, for the baseline values. For the high levels of conservativeness, the model yields a module ratio of 0.83 with 41 suppliers. This translates into thirty-four modules, seven of which are double sourced. The model thus achieves a final integration of only 1.2 parts per module. As with the weakest link approach, a prevalence of highly specialised suppliers considerably limits the integration potential. However, across the entire conservativeness range, ten alternatives with varying number of modules and sourcing flexibility are obtained. As previously stated, this nuanced outcome of the additive risk measure is one of the biggest advantages off using this approach.

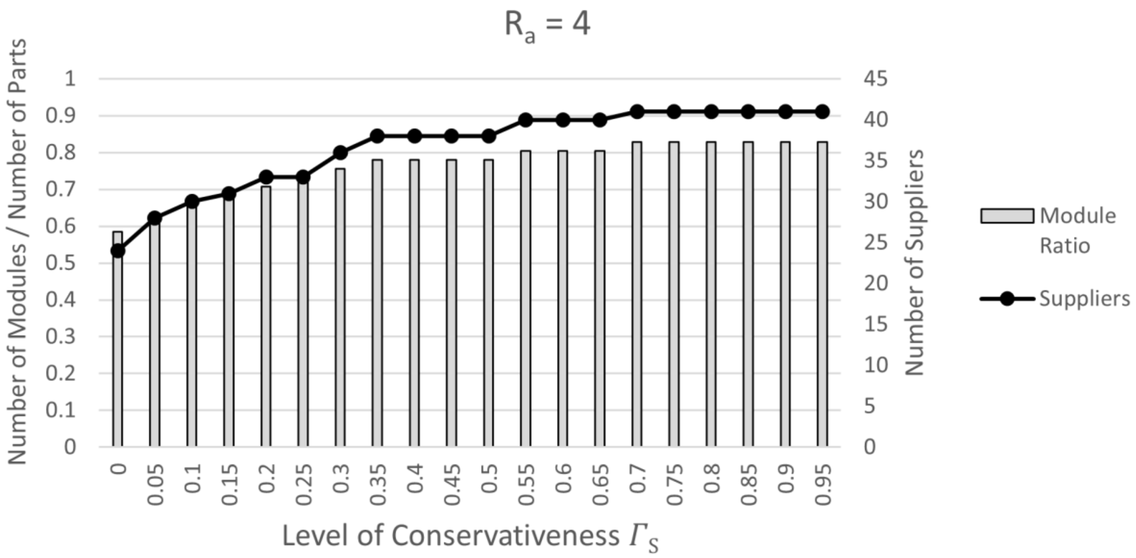


Figure 28: SCD solutions for case-study with aerospace OEM using the additive approach to risk management in supply modules, with $R_a = 4$.

Using the methodology proposed by Guzman et al. (2017a), the model was solved using RO with triangular distributions for each uncertain parameter. Notably, high values of Γ_S (above 0.65) correspond to probabilities of constraint violation close to 0%, which can be observed by comparing Figures 28 and 29.

4.4.2. Randomly generated instances

The randomly generated instances consider fifteen parts and thirty suppliers. Different instances were created by varying the number of available suppliers per part, and the range for the suppliers' integration risk. Recall that the integration risk $r_{(p,s)}$ is represented in a 3-level scale: 'low', 'medium' or 'high', which are stored as 1, 2 or 3, respectively.

The first randomly generated instance, which has the most constrained setting, has five suppliers per part and the total integration risk for each supplier is randomly chosen from the interval between 1 and 5. Hence, each supplier can supply at least one low risk part, and at most five low risk parts (or, for example, one high risk part and one medium risk part).

For the remainder randomly generated instances, the number of suppliers per part was increased in steps of three, and the upper and lower limit of the total integration risk were also increased by three. Five unique instances were generated for each such setting. Table 6 outlines the parameters for each randomly generated instance, and the labels used for the instances in this section. For the given number of

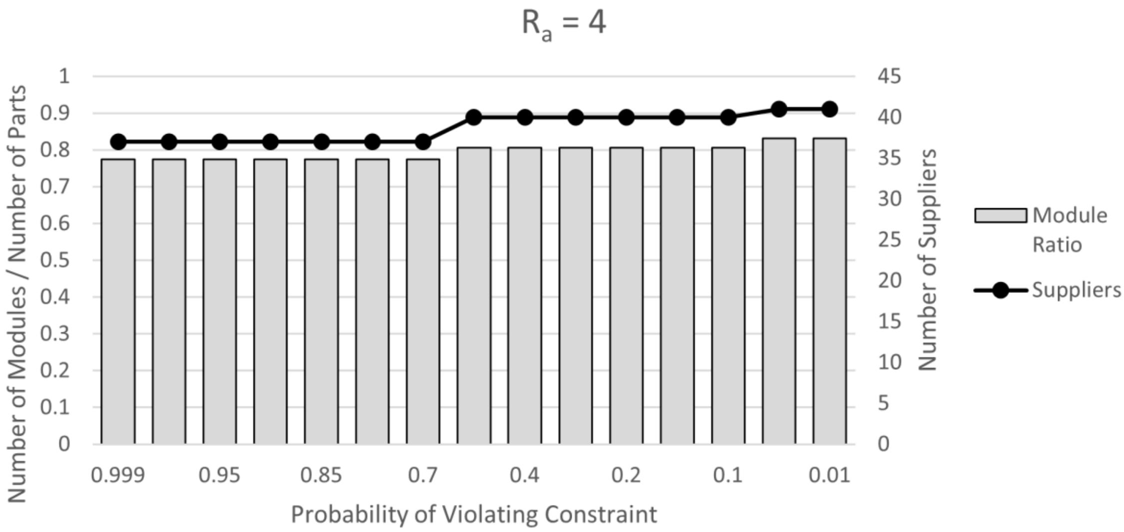


Figure 29: Solutions for case-study with aerospace OEM using robust optimisation with additive approach to risk management in supply modules, for varying values of probability of constraint violation.

parts, the indicated combinations of parameters settings yield meaningful problem instances.[1]

Results for overall risk budget approach

Figure 30 plots solutions for all randomly generated instances. For each instance set, the values for the number of modules were averaged, and the plot shows the ratio of modules to the number of parts. The lower this ratio is, the higher the integration level. Figures 30(a) and 30(b) show results for the IRM baseline values (deterministic solutions) and for 20% of the maximum Γ-value, respectively. Different solutions are presented for varying overall risk thresholds, Ψ. Notice that for tight risk thresholds no feasible solution can be found, which is why the lines discontinue for Instance Sets 2, 5, 6, and 7.

The different instance sets show how having more available suppliers for each part increases the likelihood of higher integration levels (observable by comparing Instance Sets 2, 3, and 4 and Instance Sets 5 and 6). Conversely, increasing the risk range per supplier leads to lower integration levels (observable by analysing Instance Sets 1 and 2, Instance Sets 3 and 5, and Instance Sets 4, 6, and 7). Since selecting two suppliers for the same part doubles the risk mitigation effort, this approach will never select double sourced modules. As outlined in Section 4.3.2, for our instances, Ψ can vary between 15 and 90. However, the overall risk constraints do not restrict solutions

[1] Parameters for randomly generated instances can be downloaded from: Cunha, Nuno (2020), "Theoretical Instance for SCD Model", Mendeley Data, V3. doi: 10.17632/m3rrb8tpfv.3

Table 6: Design parameters for randomly generated instances.

	Risk Per Supplier			
Suppliers Per Part	1 - 5	4 - 8	7 - 11	10 - 14
5	Instance Set 1	Instance Set 2	-	-
8	-	Instance Set 3	Instance Set 5	-
11	-	Instance Set 4	Instance Set 6	Instance Set 7

for large values of Ψ (observable by the constant ratio of modules to the number of parts for Ψ values larger than 33 in Figure 30(a) and larger than 35 in Figure 30(b)). This pattern occurs for the different instance set at varying thresholds. In some cases, the overall risk threshold does not impose a change in the solution structure (Instance Set 1 and 4). Because of the relatively low risk associated with the suppliers in these instances, the approach results in modules with a low integration risk even without a tight risk threshold. Overall, selecting lower values of Ψ forces OEMs to select new suppliers with lower risk evaluations, thus increasing the number of modules, and decreasing the integration level.

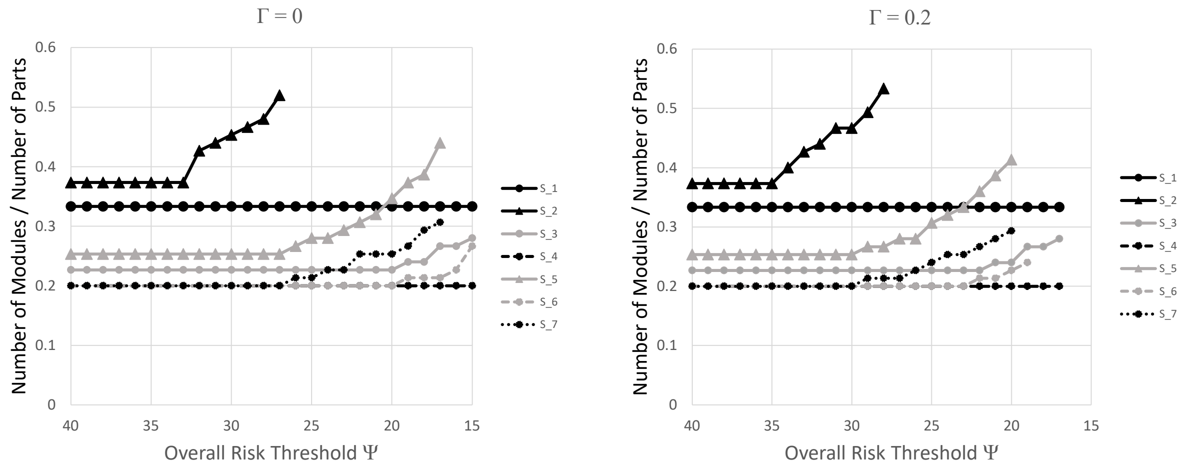
Figure 30(b) indicates that variations in 20% of the IRM values result in solutions that are shifted by one or two units of Ψ when compared to the baseline. Thus, if the suppliers' risk levels are uncertain, each value of Ψ will yield equal or lower integration levels, or even infeasible solutions.

Results for weakest link approach

Figures 31(a) and 31(b) show the module ratio and number of double sourced modules yielded by solutions for R_w = 2.5 for varying $\Gamma_{(p,s)}$ values, respectively. This means double sourcing is only required for 'high' risk parts. For every level of conservativeness $\Gamma_{(p,s)}$, the nominal value of $r_{(p,s)}$ has been increased by $\Gamma_{(p,s)} \cdot \bar{r}_{(p,s)}$, where $\bar{r}_{(p,s)}$ is the gap between the original risk value and its maximum, 3.

Analysing Figures 31(a) and 31(b) it is shown that an increasing level of conservativeness leads to less integration and more double sourcing. In some cases, even for baseline IRM values, the model selects double sourced modules (observable in Instance Sets 2, 5 and 7).

Based on the detailed results within each instance set, it is noticeable that the weakest link approach produces divergent solutions both in integration performance



(a) (b)

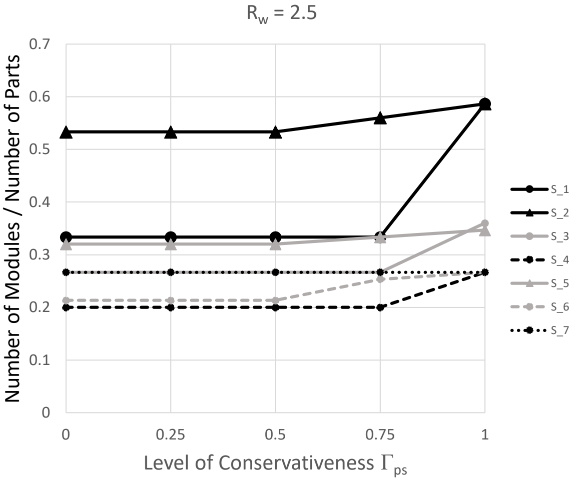
Figure 30: Solutions for randomly generated instances for the overall risk budget approach with (a) $\Gamma_s = 0$ and (b) $\Gamma_s = 0.2$.

and sourcing flexibility, even for instances with equivalent design attributes. This approach analyses the risk at the level of individual part-supplier assignments. Therefore, for a given R_w, the model guarantees that all parts will be double sourced, for which there are only suppliers with IRM values larger than this risk threshold. Building modules around such double sourced parts is difficult because it requires overlapping supplier capabilities. Therefore, the integration level for such instances is low. Instances with more suppliers per part are more likely to have at least one 'low' IRM supplier per part and achieve higher integration levels (observable when comparing Instance Set 4 against 2).

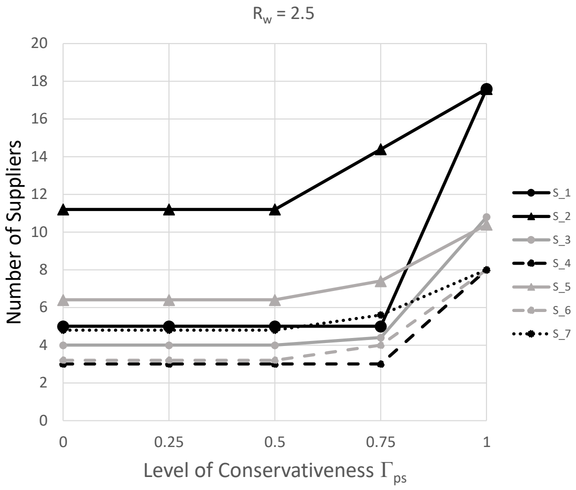
Results for additive approach

Figure 32 contains plots of the solution structure for all instance sets, using the additive approach. Figures 32(a) and 32(c) present the ratio of supply modules for $R_a = 5$ and $R_a = 6$, respectively. Figures 32(b) and 32(d) display the corresponding number of suppliers. From left to right, the level of conservativeness, Γ_s, for each supplier increases by the same percentage for each supplier. This normalisation makes it possible to track uncertainty levels across suppliers that can produce different number of parts.

Comparing the solutions in Figure 32, higher conservativeness levels require more supply modules, thus decreasing the integration level. As expected, the number of suppliers also increases. Predictably, increasing the amount of risk that can be accumulated at each module to $R_a = 6$ allows for greater integration levels with less suppliers, especially for higher levels of uncertainty. In the graphs, we just report the runs for which an optimal solution can be found. For Instance Sets 4, 6 and 7 the model



(a)



(b)

Figure 31: Solutions for randomly generated instances for the weakest link approach with R_w=2.5, (a) ratio of supply modules, (b) number of suppliers.

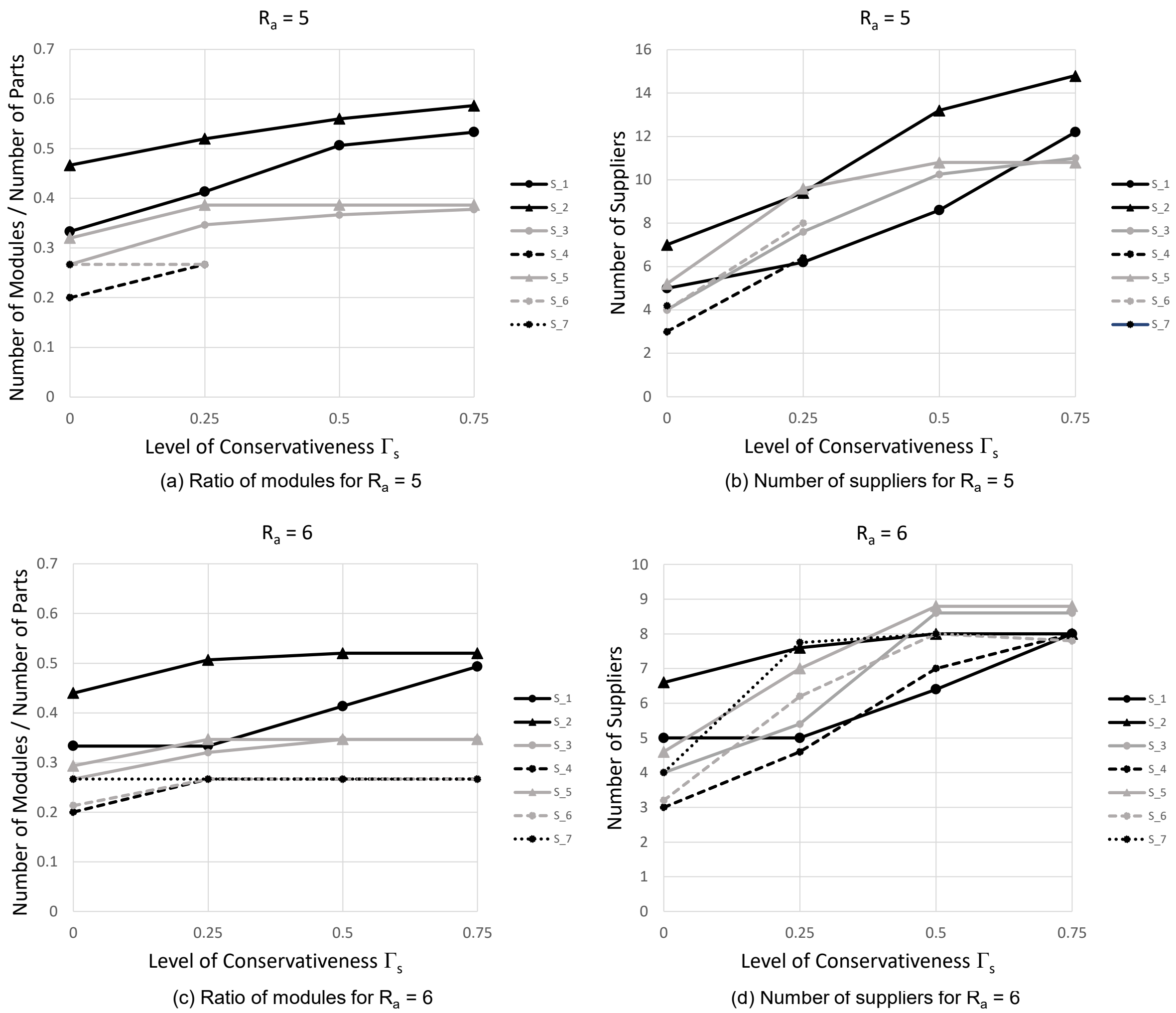
failed to find the optimal solution within three hours for high levels of conservativeness. This limitation does not jeopardise the previous insights.

Limits on probability of constraint violation

Similarly to the final analysis in Section 4.4.1, using the methodology from Guzman et al. (2017a), we assign an asymmetric triangular PDF for each risk value in the IRM. This approach adds a layer of complexity but allows to improve the accuracy in measuring the probability of constraint violation and the applicability of RO.

We apply this methodology to the additive approach. We choose this risk measure due to the superior performance outlined above. As before, the threshold R_a and the level of uncertainty, Γ_s, represent the decision maker's risk aversion. The association of PDFs to uncertainty values allows for a more intuitive adjustment of these two aversion parameters. Rather than estimating the number of incorrect values in the IRM, Γ_s, decision makers can directly represent their risk adverseness by deciding the probability of constraint violation. A lower probability corresponds to a larger risk adverseness.

Using Algorithm 1 in Guzman et al. (2017a) (see Appendix A7), we determined values of Γ_s for each supplier, for a given probability of constraint violation. Figure 33 shows the solutions for the first instance from Instance Set 3 using both methodologies. Implicitly, this methodology associates higher values of Γ_s with smaller probabilities of constraint violation.



(a) Ratio of modules for R_a = 5
(b) Number of suppliers for R_a = 5
(c) Ratio of modules for R_a = 6
(d) Number of suppliers for R_a = 6

Figure 32: Solutions for randomly generated instances for additive approach with R_a = 5 and R_a = 6.

By comparing the solution profiles, it is clear that this alternative methodology Guzman et al. (2017a) is more conservative than solving the model by iterating over Γ_s values. Indeed, the solutions for probabilities of constraint violation equal to 0.999, 0.99 and 0.95 are the same as for Γ_s equal to 0.35. Henceforth, this methodology rules out solutions with high integration level, such as the one found for Γ_s below 0.2, which correspond to four modules, but lead to an unacceptable probability of constraint violation.

On the other hand, the initial RO methodology suggests a solution with five modules, three of which double sourced, to cover most of the Γ_s range. However, the entirety of this range corresponds to a probability of constraint violation below 5%. This way, a decision maker solving exclusively for the entire range of Γ_s could overestimate the likelihood of this solution, thus hindering the integration potential and supplier effort for their supply chain. All other instances lead to similar insights.

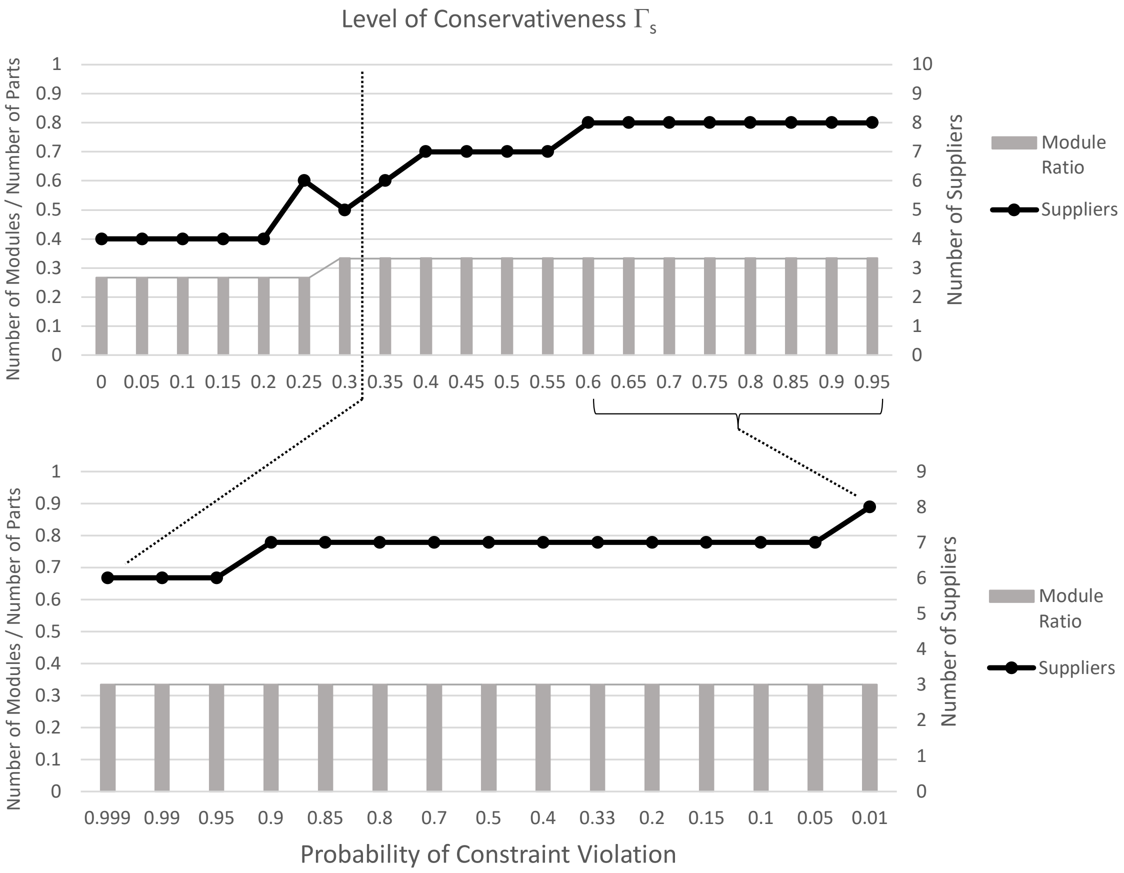


Figure 33: Solutions for a randomly generated instance using the additive approach for varying values of Γ_s and for different probabilities of constraint violation, for $R_a = 6$.

Appendix E after the References shows that the insights of our analysis hold irrespectively of the dimensions of the investigated problem instances.

4.5. Conclusion

Post-Covid/Post-Glasgow (COP26) aerospace industry, driven by both economic and environmental factors, is presented with the opportunity to develop new types of environmentally friendly aircrafts using new design and manufacturing technologies. This situation offers aerospace OEMs opportunities to also rethink their supply chain strategically. This paper provides a timely contribution to this endeavour by providing a method to design the supply chain, while considering the risk of selecting Tier 1 suppliers based on their capabilities to hold system integration responsibilities and manage lower-tier suppliers in their supply scope.

Supporting recent practices in OEMs with convergent supply chains, this paper presents an optimisation model for concurrent PD and SCD. As companies in several industries-built supply chains heavily reliant on outsourcing system design and integration responsibilities to a small set of suppliers, they were exposed to a new risk – *integration risk*.

This risk relates to the likelihood of disruptions associated with the increased technical and managerial capabilities demanded from key strategic suppliers that took on the role of 'integrators'. We base our approach on the industry practice of estimating supplier capabilities for individual parts. Three distinct approaches were employed to measure the effect of integration risk in concurrent PD and SCD: overall risk budget approach, weakest link approach and additive approach. These methodologies aim to reflect supplier management and development efforts (overall risk budget), to account for the risks involved in sourcing parts with high-risk scores (weakest link) and to prevent high risk exposure at individual modules (additive approach).

Our robust model optimises supply chain integration while mitigating the associated risk, yielding solutions that combine integrators with specialised suppliers. For a given supply base, we determine levels for module integration, the assignment of modules to suppliers, and the usage of double sourcing based on the risk estimations and decision-makers' levels of conservativeness. For each Γ-value, the price of robustness corresponds to the additional modules and additional suppliers, compared to the baseline of $\Gamma = 0$ when risk is not considered. Figures 27 through 29 and 31 through 34 all show that increasing the robustness of the solutions (by increasing the level of conservativeness Γ) "costs" more modules and more suppliers.

To provide decision makers with a more intuitive parametrisation of the model, uncertain risk estimates were modelled as asymmetric triangular distributions. The model was tested using both randomly generated instances and real supplier data from a large European OEM in the aerospace industry.

4.5.1. Managerial insights

The insights revealed by both the real case-study and the randomly generated instances are consistent. The results showed that our modelling approach is useful in determining solutions that shape modules and select the respective level of double sourcing. Furthermore, the solutions are tailored to the individual supply base and cannot be found by a simple policy or decision rule.

Unlike the findings of other papers in the field of SCD, such as Li and Amini (2012), we do not conclude that double sourcing outperforms single sourcing, regardless of the sourced part. Instead, we consider an increase in managerial effort arising from the interface with additional partners. Thus, we only select extra suppliers if it is necessary to comply with risk exposure thresholds while achieving greater integration performance.

Thus, we show how having suppliers that can manufacture more parts will enable higher levels of integration. Similarly, having more suppliers available for each part will sustain higher risk at modules and improve integration by potentiating double sourcing. OEMs should leverage this result to invest in developing their supplier base achieving more versatile suppliers and more redundancy for each part.

Moreover, the results provide a set of guidelines for each of the proposed risk approaches to mitigate integration risk. The overall risk budget approach is best suited for low uncertainty levels in the presence of low-risk suppliers. It cannot accommodate large uncertainty deviations. However, it is the only measure that represents management effort. Therefore, it presents the possibility of considering available risk management resources in the concurrent PD and SCD process.

The weakest link approach produces diverse solutions both in integration performance and sourcing flexibility, even for instances with equivalent design attributes. Building modules around high-risk, double sourced parts is difficult because it requires overlapping supplier capabilities. As a consequence, the integration level for this measure is low. However, the weakest link approach may be suited for individual, high-risk part-supplier profiles. For example, if the OEM is considering the introduction of a new material or technology into their aircraft programmes, these constraints can be defined exclusively for those parts.

The results from applying the additive approach showed a multitude of different PD and SCD configurations for different levels of conservativeness. This approach best exploits the possibilities to module sizing and double sourcing to respond to risk adverseness. However, a comparison with solutions guided by the probability of risk violation revealed that only a limited part of the solutions should be considered.

Compared to the overall risk budget and weakest link approaches, the additive approach is more sensitive towards changes in the level of conservativeness. On one hand, the first two approaches have a sharp change in integration performance caused by specific levels of conservativeness. On the other, the additive approach provides more alternatives to decision makers with distinct risk aversion profiles. This can be observed by compiling one of the solutions for a randomly generated instance (see Figure 34.

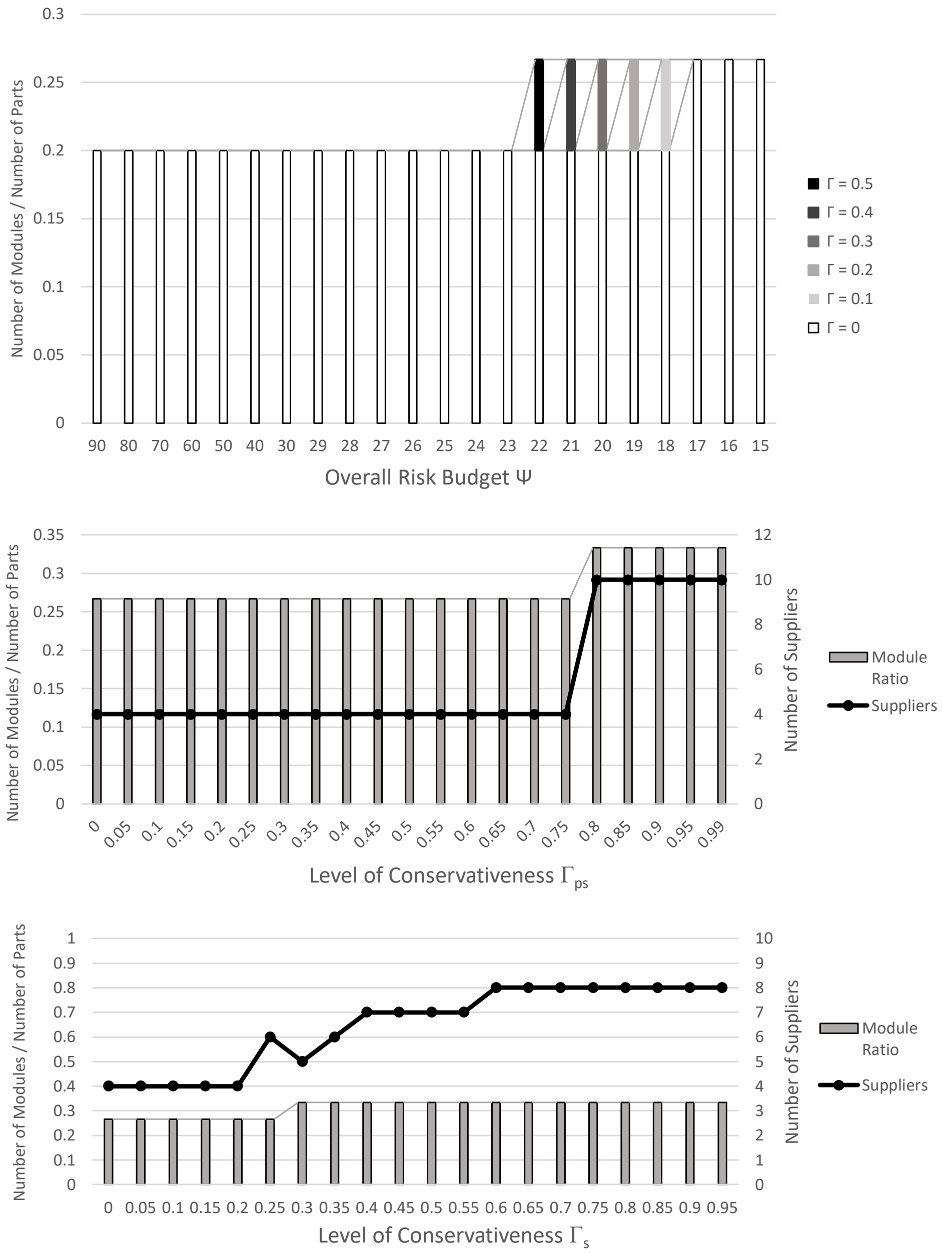


Figure 34: Solutions for a randomly generated instance using the overall risk budget, weakest link and additive approaches, for $R_a = 6$.

4.5.2. Limitations and future research

For simplicity, no restrictions to part-part associations are not considered. Future extensions of our approach should consider part compatibility. Additionally, contingency suppliers, as studied by Tomlin (2006), can be introduced as an alternative to increasing sourcing flexibility. This type of suppliers should require lower development efforts.

Our results show that the investigated risk measures are complementary. As future research, it would be interesting to combine them in an integrated approach. The sensitive additive approach could serve as a basis augmented by the overall risk budget measure that acts as an overarching set of constraints to capture supplier development effort. The weakest link approach could be added for individual parts to capture the risk related to new materials, technologies, or inexperienced suppliers.

5. Conclusion

"On engineering changes, we go out of our way to explain them to all who will be working on them. That carries through from the first line I draw on paper to completion of the airplane and its first flight."

Clarence Leonard (Kelly) Johnson

This chapter provides a summary of the research works presented in this dissertation. Section 5.1 presents the answers to the research questions. Section 5.2 summarises the academic contributions of this dissertation. Section 5.3 presents the managerial insights. Section 5.4 highlights the research limitations and provides an orientation for future research.

5.1. Summary and discussion of research

This dissertation comprises two published journal papers and a paper that has been submitted to a journal for a peer review. The first paper (Gan and Grunow, 2016) provides an extensive literature review on CP-SCD, introduces a conceptual framework CDA-TOP, derives design propositions and develops a conceptual methodology for CP-SCD. The second paper (Gan et al., 2022) operationalises this conceptual methodology, introduces new methods for PD (DSM clustering method) and SCD (supplier selection and clustering for sourcing flexibility) and applies them to an automotive case study. The third paper (Cunha et al., 2022) extends the SCD method from the second paper to address a new type of SCR (supplier integration risk) as well as risk uncertainty using robust optimisation. A case study of a major aerospace OEM is used to validate this new SCD method and derive managerial insights. The ways these research papers address the four research questions are elaborated below.

1) What are the research gaps in the field of CP-SCD?

Chapter 2 (Gan and Grunow, 2016) presents an extensive literature review of past research in PD, SCD, CP-SCD and SCRM. This literature review covers more than a hundred research papers that were published after 1992. A total of 12 qualitative and 19 quantitative papers have been identified as relevant to CP-SCD. These papers were then reviewed in detail and classified according to their attributes, industries, and methodology. The literature review highlights the lack of CP-SCD methodology and quantitative case studies. There is also a lack of convergence of design trade-off methodology and the issues of design asymmetries in past research on CP-SCD are commonly found.

Chapter 4 (Cunha et al., 2022) highlights the lack of research in linking SCRM in CP-SCD and supplier integration risks. Furthermore, the use of robust optimisation for analysing the risk uncertainty in SCD has not been found in past research.

2) How can incumbent PD and SCD processes be integrated to allow for CP-SCD?

Chapter 2 (Gan and Grunow, 2016) uses the findings from the literature review to derive a conceptual CDA-TOP framework to structure design trade-off by classifying different types of design attributes according to the different design levels and domains. This CDA-TOP framework is then used to derive four design propositions and to develop a conceptual process for CP-SCD, addressing the lack of a CP-SCD methodology. The conceptual process facilitates the exploration of an approach to integrate PD and SCD for CP-SCD and to conduct a design trade-off. Furthermore, this paper introduces a new approach of using DSM to integrate PD and SCD for CP-SCD in modularity design, a key architectural design attribute, as well as the novel concept of characterising design tradespace, using modularity curves and the referential point DOP.

3) How can the trade-off between PD and SCD be structured and conducted for more efficiency and efficacy?

Chapter 3 (Gan et al., 2022) operationalises the conceptual CP-SCD process from Gan and Grunow (2016) and introduces new specific methods for PD (DSM clustering) and SCD (supplier selection and clustering for sourcing flexibility). This operationalised process focuses on the concurrent architectural PD and strategic SCD for modularity and sourcing flexibility. This chapter also operationalises and extends the concept of design tradespace between PD and SCD from Gan and Grunow (2016). The tradespace is generated by the operationalised CP-SCD process by plotting a set of the pareto curves using a common design attribute (e.g., modularity level). The extension includes the introduction of DSP, which is used together with the DOP introduced to characterise a design tradespace. DSP and DOP are design reference points in the tradespace that can be identified respectively through the intersection and peaks of these curves. These reference points help both product and supply chain designers to efficiently identify the most relevant part of the design tradespace and thereby significantly shorten the design exploration process. An automotive case study involving an EV battery system is used to demonstrate the efficacy and efficiency of this new process and the specific methods.

4) How can the CP-SCD methodology consider supplier integration risks?

Chapter 4 (Cunha et al., 2022) improves and extends the SCD method in Gan et al (2022) for sourcing flexibility to address supplier integration risks under risk uncertainties. This paper highlights the underexplored research area of supplier integration risks, which are especially relevant for complex products with convergent supply chains such as those from automotive and aerospace industries. This modified SCD method includes three new modelling approaches towards considering supplier integration risks in deciding the level of sourcing flexibility as a mitigation measure. These modelling approaches are namely the overall risk budget (limits total supply chain risk), weakest link (limits risk level for individual parts) and additive approaches (limits risk for each supply node). Robust optimisation method is used to address risk uncertainty, which is prevalent in industries with long development duration over many years. This method analyses the effect of uncertainty over baseline risk values and the confidence level of the results. The results provide new insights for supply chain risk management practices in the industries. SCDs suggested by the model indicate that the additive approach led to the most tailored solutions to different occurrences of uncertainty. Solutions using the overall risk budget approach suggest it is best suited to dealing with supplier development effort, while weakest link constraints manage risk exposure from new technologies and inexperienced suppliers.

5) What are the industrial strategies and managerial recommendations from the research in CP-SCD?

Chapter 2 (Gan and Grunow, 2016) introduces the use of DSM alignment and relative quantified modularity levels of PDA and SCA to create a novel classification framework for six P-SC archetypes, which generalises P-SC systems in industry. These P-SC archetypes provide cardinal references for difference types of make-buy architecture for both design and manufacturing works. A thorough discussion of the managerial implications of these six P-SC archetypes and the corresponding industrial strategies are presented.

5.2. Academic contribution (framework and methodology)

This dissertation highlights the lack of research on CP-SCD methodology based on an extensive literature review (Chapter 2). This review identifies the common issues of design trade-off asymmetries, the lack of research at architectural-strategic level and the lack of an effective and efficient design trade-off methodology for CP-SCD. While there have been case studies that investigate the impact of PD on SCD, case studies that investigate the impact of SCD on PD are lacking. For SCD, this review also identifies a lack of consideration of supplier integration risks, which are especially relevant to complex products and convergent supply chains, when selecting suppliers. This dissertation addresses these research gaps and contributes to academic research in the following three ways.

Firstly, this dissertation (Chapter 2) contributes by conceptualising a novel CDA-TOP framework, which structures CP-SCD trade-off by classifying different types of design attributes according to their design levels (architectural-strategic, detailed-tactical, and dynamic-operational) and domains (PD and SCD). The CDA-TOP framework is then used for deriving four design propositions that improve the efficacy and efficiency of CP-SCD. These propositions serve as the basis for developing a conceptual process for CP-SCD. To address the lack of research at the architectural-strategic design level, this conceptual CP-SCD process is developed into CP-SCD for modularity, which uses DSMs to map the interaction between product parts and to quantify the modularity level. Moreover, using relative modularity levels and DSM alignment levels between the PD and the SCD, P-SC systems can be classified by the six archetypes using the introduced classification framework. Standard theory and research focus for PDA and SCA can be derived for each archetype. This framework of P-SC systems has potential for future research in CP-SCD.

Secondly, this dissertation (Chapter 3) contributes by using the CDA-TOP framework and conceptual process to develop a CP-SCD methodology. It first introduces a novel approach towards representing design tradespace between a PD and an SCD. This is done by defining tradespace reference points (DOP and DSP) and showing how they can be used together to demarcate the relevant part of the tradespace, which is the most important part for designers. Next, the conceptual CP-SCD process is operationalised by introducing a detailed process for generating the design tradespace between a PD and an SCD for different types of products (niche, differentiated and commodity). New specific methods for PD and SCD that address modularity and sourcing flexibility are developed. The PD method uses a combination of the heuristic method and a binary integer programming model to modularise product parts. This method considers predefined clustering parameters (module quantity and size) as well as specific designer knowledge, which are not found in existing DSM clustering methods. The SCD method applies a lexicographical method to a binary integer programming model to select suppliers and to determine the right level of sourcing flexibility based on design space that is defined by a PSM. This SCD method has not been found in past research. Overall, the contributions of this CP-SCD methodology lie in the structuring of the concurrent design interactions as well as the facilitation of an efficient and high-quality design trade-off. Chapter 3 also contributes to addressing the lack of CP-SCD case studies in past research by providing an automotive case study involving EV batteries.

Thirdly, Chapter 4 of this dissertation addresses the lack of consideration of supplier integration risk in past research on SCRM methodology by extending the new SCD method from Chapter 4 to include this risk type in the model. This new SCD method uses binary integer programming to select suppliers, decide on the need for dual sourcing as a mitigation against supplier integration risks, which are mapped between parts and suppliers. Three new modelling approaches, namely the overall risk budget (limits total supply chain risk), weakest link (limits risk level for individual parts) and additive approaches (limits risk for each supply node), are compared for different SCD objectives. Moreover, the robust optimisation method is used to address risk uncertainty, which is prevalent in industry, in the SCD method by studying the effect of uncertainty over baseline risk values and by analysing the confidence level of the results. These new modelling approaches and the use of robust optimisation for supplier integration risk mitigation have not been found in past research.

5.3. Managerial insight (strategy and practice)

This dissertation has generated managerial insights for industry and practice. Chapter 2 provides new industry insights into the understanding of the interactions between PDA and SCA using a novel classification framework of P-SC system archetypes. The six P-SC system archetypes are defined by the relative modularity and the DSM alignment levels between PDA and SCA. These P-SC system archetypes offer new perspectives in which P-SC systems can be classified and analysed. These six archetypes represent the idealised operation models of manufacturing companies. This framework provides managers with useful cardinal references of the possible P-SC system archetypes when they design their products and SCs, especially towards make-buy and vertical-horizontal integration decisions of product development and manufacturing activities. This is useful to managers when selecting the most appropriate PD and SCD in view of the technological, environmental, and economic trends that are highlighted in Chapter 1.

Chapter 3 applies the operationalised CP-SCD process, as well as PD and SCD methods to an automotive case study involving an EV battery system. This case study provides managerial insights into the values and challenges of applying such a methodology to a real product and its supply chain. These insights are drawn from the in-depth involvement of the researchers during the product development process. This case study provided the following three managerial insights.

Firstly, the CP-SCD process provided an approach for structuring concurrent design work between product and SC designers. In Phase 1, the joint sessions for deriving design strategies and defining design attributes enriched discussions between the designers. In Phase 2, the concurrent design streams allowed the designers to build up the PDA and the SCA independently and supported their convergence to a commensurable, aggregated, and compensable set of design data structures using DSMs. In Phase 3, the generated design tradespace offered an objective perspective of the design trade-off. The respective impact assessments at the selected points in the tradespace help to minimise the likelihood of decision impasse among the designers.

Secondly, the methodology allowed the designers to conduct the design trade-off efficiently. It provided a common design language for design trade-off, as well as a visual representation of the P-SC system. By using the DSP and the DOP, the designers were able to identify the tradespace without needing to explore the entire design space, hence saving time and effort. Furthermore, the methodology reduced the product redesign and rework loops by considering SC factors early in the PD. The early inclusion of SC factors led to a shorter time-to-market of the product.

Finally, the methodology was able to help the designers to obtain a high-quality trade-off between the modularity levels of the PDA and the SCA. Comparing the P-SC architectures at pure product orientation, DSP, and DOP, the designers found that the advantages of a more modular and flexible SCA obtained at DOP outweighed the technical impact on the PDA.

Chapter 4 highlights the three managerial insights for OEMs (system integrators) and their suppliers (modules integrators) in the aerospace industry with regards to supplier integration risk, risk uncertainty, sourcing flexibility, and the relative power structure between OEMs and their suppliers.

Firstly, it highlights that risk assessment is a challenge for manufacturing companies, especially aerospace OEMs, due to the technical complexity of the products and their global supply chains. Here, supplier integration risk, which measures suppliers' risks in integrating different parts from within the supplier and from other lower-tier suppliers, is of particular importance for SCD. The failure to consider such risk in SCD may result in SC disruption. Supplier integration risk can be mitigated by having a sufficient level of sourcing flexibility at the OEM to ensure that there are sufficient alternative sources in case of SC disruption. Our research has shown that, on one hand, a higher supplier integration risk level leads to smaller supply modules and higher average sourcing flexibility. On the other hand, a greater number of supply modules and suppliers have higher transaction costs for the OEMs.

Secondly, it highlights the impact of risk uncertainty on SCD. Determining an accurate understanding of suppliers' risk level can be challenging. The inclusion of risk uncertainty in SCD can help in exploring the best SCDs early in the CP-SCD process and in planning for sufficient mitigation measures (e.g., sourcing flexibility) in the event of an inaccurate risk assessment.

Finally, the relative power between OEMs and suppliers in the aerospace industry is also a major concern. To manage the power of certain suppliers (e.g., engine and battery suppliers), OEMs can design their SC by determining the optimal number of supply modules as well as their sourcing flexibility levels (e.g., exclusivity). However, such an increase in sourcing flexibility may lead to a price increase due to the lower sourcing volume per supplier and unwillingness to share financial risk, which is currently being practised (e.g., risk-sharing partnership). Our SCD method with robust optimisation allows the exploration of different SCDs for more balanced and informed managerial decisions.

5.4. Limitations and orientation for future research

In Chapter 2, three limitations and their research orientation have been identified. Firstly, design asymmetry affects the quality of design trade-off between PD and SCD by having an imbalance in the selection and quantity of design attributes on both sides. However, the extent to which quality can be affected has not yet been quantified. Empirical and experimental research to validate this impact is an area for future research.

Secondly, the mapping of SCD attributes using an SCD-DSM is another area for further research. While the mapping of product parts using DSM is a well-established method, this is still a comparatively new for mapping SCD attributes. We have developed an SCD method that maps SCD attributes to SC-DSM, based on common supply scopes. Other approaches of mapping and clustering of SCD attribute interactions warrant further research.

Finally, we believe that the classification framework of the six P-SC archetypes has contributed to the theoretical nucleus for advancing the research area of CP-SCD. These archetypes are, however, based on collective industrial knowledge and observation of the authors. Future research can include qualitative and empirical studies of the characteristics and implications of these P-SC archetypes for generalisation and theory building.

In Chapter 3, four limitations and their orientation for future research have been identified. Firstly, the result of the CP-SCD process is dependent on the quality and promptness of input data. For example, the functional and SC interactions between components may not be fully known in Phase 1 of the PD process. This is especially true for more complex products. A way to address this issue is to update the data and iterate the process until an adequate level of architectural design maturity has been reached. This provides an impetus for research for CP-SCD in new products using novel technologies, which manufacturers do not have data and take reference from past products.

Secondly, the case study uses an unconstrained PDA with a greenfield SCA. However, for cases such as product improvement, the PDA can be influenced by the PDAs of predecessor products. Similarly, the SCA can also be constrained by brownfield SC factors such as the reuse of existing suppliers. These considerations are not covered in our case study and offer potential for future research.

Thirdly, our methodology is applicable to PD and SCD under different objectives; our case study and the specific methods developed focus on two design attributes: modularity and flexibility. These are key attributes at the architectural level. Nonetheless, methods for optimising other design attributes (e.g., assembly locations) under different criteria (e.g., cost, responsiveness, or environmental footprints) can also be explored and developed for use in our CP-SCD process, which has been deliberately developed with open interfaces to other methods.

Finally, the use of the details in the introduced design tradespace is still an uncharted research area. Together with the six P-SC archetypes, which only focus on the relative modularity levels, the utilisation and generalisation of other characteristics (e.g., DSP, PD-M and SC-M curves) are potential topics for future research. Moreover, we have demonstrated our methodology on a product, which is considered a differentiated commodity in the automotive industry. Even though this CP-SCD process can be applied to other products and industries in our view, the application and validation of this CP-SCD process using other case studies is meaningful for revealing other insights and experience from other industries.

In Chapter 4, the sets of parts used in the model are not characterised and there are no restrictions to part-part associations. Future enhancements of this model should consider part compatibility and be capable of defining which parts can be integrated with each other. Furthermore, additional lower-tier suppliers have not been considered. Backup suppliers, which should require lower development effort, can be introduced as an alternative to increasing sourcing flexibility. The results from the three approaches for integration risks in the SCD model are complementary. For future research, it would be interesting to combine them in an integrated approach. The sensitive additive approach could serve as a basis augmented by the overall risk budget approach that acts as an overarching set of constraints to capture supplier development effort. The weakest link approach could be used to capture the risk related to new materials, technology, or inexperienced suppliers.

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7. Appendices

Appendix A1: Pseudocode of the seeding algorithm

```
1:  Set TargetSeedQty            // < total number of parts
2:  Set F_level = 0.00
3:  Set F_step = 0.01            // step value depends on DSM interaction distribution
4:   j ← all parts in DSM
5:   i ← all candidate seed parts in DSM
6:  Calculate the WS_i for each part in the DSM (Eq. 1)
7:  Do While F_level ≤ 1
8:  // Generate the Filter Matrix (FM):
9:  F_value = F_level * Max (R)
10: Identify all filtered interactions between the parts in the DSM using the F_value
11: For i← 1 to I in the DSM
12:   For j← 1 to J in the DSM
13:     If r(i, j) > F_value Then
14:       Filtered_r(i, j) = Part Name    // Show part name in the Filtered Matrix
15:     Else Filtered_r(i, j) = Null      // Show blank space in the Filtered Matrix
16: Map the filtered interactions into the FM
17: // Search and identify the seed parts in the FM:
18: Sort the parts from the strongest to the weakest based on their WS_i
19: Set the strongest part as the 1st seed part
20: For i ← 1 to I in the FM
21:     Find the next strongest part that does not directly interact with the previous seed part(s)
22:     If a new seed part i is found Then
23:       If ∑ i < TargetSeedQty Then
24:         GoTo Step 21
25:       Else Exit
26:     Else F_level = F_level + F_step
27: Loop back to Step 7
```

Appendix A2: Example of a Part-Supplier Matrix (PSM).

PSM	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
P1	1	1	1					1		1
P2	1					1	1			1
P3	1	1	1	1			1		1	1
P4						1	1	1	1	1
P5	1		1		1	1	1		1	
P6	1		1	1	1		1	1	1	
P7		1	1			1	1	1		1
P8		1			1				1	
P9	1		1					1	1	
P10		1	1					1		

Appendix A3. PSM - Conchifera

PSM	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14
Plastic Structure & Cap	1				1			1		1		1		
Guide Rails							1		1	1				
Housing							1		1	1				1
Electronics Box				1		1					1			1
Intake Plenum	1				1			1				1		
Relay	1				1									
Fuses		1	1	1									1	1
Current Sensor		1		1										
Plugs & Connectors		1	1	1									1	
Cables & Wires							1		1	1				1
Fan				1		1					1			1
Aluminium Circuit Board	1				1			1		1		1		
BMS				1							1			
Connector Rail	1				1			1				1		

Appendix A4. CDMs for WSC = 0, WSC = 1, the DSP and the DOP

PDA	Cables & Wires	Aluminium Circuit Boards	Fan	Guide Rails
Housing	**0.66**			
BMS		**1.57**		
Plugs & Connectors		**1.33**		
Connector Rail		**0.26**		
Relay		**0.24**		
Fuses		**0.24**		
Current Sensor		**0.24**		
Electronics Box		**0.00**		
Intake Plenum			**0.68**	
Plastic Structure & Cap				**1.17**

SCA	Plastic Structure & Cap	Aluminium Circuit Boards	Plugs & Connectors	Relay
Guide Rails	**1.77**			
Housing	**1.77**			
Electronics Box	**1.77**			
Intake Plenum	**1.77**			
BMS		**1.06**		
Connector Rail		**1.06**		
Cables & Wires			**1.06**	
Fan			**1.06**	
Fuses				**1.06**
Current Sensor				**1.06**

Figure A4.1. CDM (W_{SC} = 0) and CDM (W_{SC} = 1) (seed parts shown in the headers).

DSP	Electronics Box	BMS	Connector Rail	Fan
Housing	**1.31**			
Intake Plenum	**0.81**			
Plastic Structure & Cap	**0.77**			
Guide Rails	**0.76**			
Aluminium Circuit Boards		**1.36**		
Relay		**0.77**		
Current Sensor		**0.64**		
Fuses		**0.00**		
Plugs & Connectors			**0.85**	
Cables & Wires				**0.63**

DOP	Electronics Box	Connector Rail	Relay	Fan
Housing	**1.53**			
Intake Plenum	**1.28**			
Plastic Structure & Cap	**1.25**			
Guide Rails	**1.25**			
Aluminium Circuit Boards		**0.82**		
BMS		**0.74**		
Plugs & Connectors		**0.44**		
Current Sensor			**1.00**	
Fuses			**1.00**	
Cables & Wires				**0.84**

Figure A4.2. CDM (DSP) and CDM (DOP) (seed parts shown in the headers).

Appendix A5. Notation (Chapter 4)

Indices and Sets

$s, i, j \in S$	Supplier candidates
$p \in P$	Parts sourced
$(i, j), i < j \in S' \subset S \times S$	Pairs of supplier with overlapping part portfolios
$(p, s) \in PS' \subset P \times S$	Suppliers s capable of producing parts p
$(p, i, j) \in APSS' \subset P \times S \times S$	Parts that can be jointly integrated by both supplier i and j
$(p, i, j) \in NPSS' \subset P \times S \times S$	Parts that cannot be jointly integrated by both supplier i and j

Decision Variables

$x_{(i,j)}$ 1, if supplier i and j are in the same module ($= 0$ otherwise)

$y_{(p,s)}$ 1, if part p is sourced from supplier s ($= 0$ otherwise)

Parameters

$h_{(i,j)}$ 0, if module is single sourced

1, if module is double sourced

Input Parameters

Γ Uncertainty budget for the overall risk budget approach

$\Gamma_{(p,s)}$ Uncertainty budget for each part-supplier pair in the weakest link approach

Γ_s Uncertainty budget for each supplier in the additive approach

$\bar{r}_{(p,s)}$ Maximum deviation of integration risk for pair (p, s)

Uncertain Variables

$\tilde{r}_{(p,s)}$ Integration risk considering uncertainty

$\xi_{(p,s)}$ Normalised deviation of the integration risk for (p, s)

Decision Variables

λ Auxiliary dual variable for the overall risk budget approach

λ_s Auxiliary dual variable for all suppliers s for the additive approach

$\mu_{(p,s)}$ Auxiliary dual variable for all pairs (p, s)

Appendix A6 : Transformation of robust optimisation constraints into dual version

In order to use RO on the overall risk budget and additive approaches, the constraints dealing with risk need to be transformed into tractable problems. The robust counterpart for the constraints dealing with risk for the additive approach were shown to be given by Constraints (33), re-stated below. They take into account the uncertain parameter $\tilde{r}_{(p,s)}$ and hold feasibility over an uncertainty set U_s^a.

$$\sum_{(p,s)\in PS'} \left[\tilde{r}_{(p,s)}\right] \cdot y_{(p,s)} \leq RHS, \forall s \in S$$

$$\sum_{(p,s)\in PS'} \left[r_{(p,s)} + \bar{r}_{(p,s)} \cdot \xi^a_{(p,s)}\right] \cdot y_{(p,s)} \leq RHS, \forall s \in S \tag{33}$$

$$RHS_i := R_a \cdot \left[\sum_{(i,j)\in S'} \left[x_{(i,j)} \cdot \left(1 + h_{(i,j)}\right)\right] + \sum_{(j,i)\in S'} \left[x_{(j,i)} \cdot \left(1 + h_{(j,i)}\right)\right]\right], \forall i \in S$$

$\bar{r}_{(p,s)}$ represents the maximum variation for each risk estimate $r_{p,s}$ from the IRM. The above semi-infinity constraints can then be re-written as follows:

$$\sum_{(p,s)\in PS'} \left(r_{(p,s)} \cdot y_{(p,s)}\right) + \max_{\xi^o \in U_s^a} \sum_{(p,s)\in PS'} \left(\bar{r}_{(p,s)} \cdot \xi_{(p,s)} \cdot y_{(p,s)}\right) \leq RHS, \forall s \in \mathrm{S} \tag{34}$$

It should be noted that a quadratic optimisation problem has to be solved in (34). To produce a tractable robust counterpart we first formulate the primal sub-problem (35) for every supplier ($\forall s \in S$) and transform it into its dual version (36):

$$\begin{aligned} \max \quad & \sum_{(p,s)\in PS'} \bar{r}_{(p,s)} \cdot \xi^a_{(p,s)} \cdot y_{(p,s)} \\ \text{s.t.:} \quad & \sum_{(p,s)\in PS'} \xi^a_{(p,s)} \leq \Gamma_s, \forall s \in S \\ & 0 \leq \xi^a_{(p,s)} \leq 1,\ \forall (p,s) \end{aligned} \tag{35}$$

$$\begin{aligned} \min \quad & \Gamma_s \cdot \lambda_s + \sum_{(p,s)\in PS'} \mu_{(p,s)} \\ \text{s.t.:} \quad & \lambda_s + \mu_{(p,s)} \geq \bar{r}_{(p,s)} \cdot y_{(p,s)}, \forall (p,s) \\ & \lambda_s,\ \mu_{(p,s)} \geq 0,\ \forall (p,s) \end{aligned} \tag{36}$$

Finally, as show in Bertsimas and Sim (2004), the tractable robust counterpart is obtained in constraints (37) by incorporating the dual auxiliary problems (36) into constraints (33).

$$\text{s.t.:} \quad \sum_{(p,s)\in PS'} \left[r_{(p,s)} \cdot y_{(p,s)} \right] + \left[\Gamma_s \cdot \lambda_s + \sum_{(p,s)\in PS'} \mu_{(p,s)} \right] \leq RHS, \forall s \in S \tag{37}$$

$$\lambda_s + \mu_{(p,s)} \geq \bar{r}_{(p,s)} \cdot y_{(p,s)},\ \forall (p,s) \in PS' \tag{38}$$

$$\lambda_s,\ \mu_{(p,s)} \geq 0,\ \forall (p,s) \in PS' \tag{39}$$

This transformation produces a tractable set of constraints so RO can be applied on the additive approach to risk. A similar transformation can be obtained for the overall risk budget approach by using general parameters for Γ and λ that are not indexed by supplier.

Appendix A7: Algorithm 1 from Guzman et al. (2017a)

Algorithm 1 Search algorithm to find Γ_i which satisfies ϵ_i^{prio}.

function MATCHPROBTHETABISECTION($\epsilon_i^{prio}, B(\theta, \Gamma_i), \Gamma_i(\theta), tol$)
    input:
        desired probability of constraint violation ϵ_i^{prio} for constraint i
        probability bound $B(\theta, \Gamma_i)$ ▷ Equation (35)
        function Γ_i (see Equation 54)
        convergence tolerance tol
    output:
        uncertain set parameter Γ_i which guarantees ϵ_i^{prio}
    ►Initialisation
    Set θ^U such that $B(\theta^U, \Gamma_i(\theta^U)) > \epsilon_i^{prio}$
    $\theta^L \leftarrow 0, \theta \leftarrow (\theta^L + \theta^U)/2, \Gamma_i \leftarrow \Gamma_i(\theta), p_i \leftarrow B(\theta, \Gamma_i)$
    ►Iterate until convergence
    while $\left|\epsilon_i^{prio} - p_i\right| > tol$ **do**
        if $p_i < \epsilon_i^{prio}$ **then**
            $\theta^U \leftarrow 0$
        else
            $\theta^L \leftarrow \theta$
        end if
        $\theta \leftarrow (\theta^L + \theta^U)/2, \Gamma_i \leftarrow \Gamma_i(\theta), p_i \leftarrow B(\theta, \Gamma_i)$
    end while
    return Γ_i
end function

Appendix A8: Implementing right triangular distributions in RO

Guzman et al. (2017a) use Equation (40) as the MGF associated with the PDF for an asymmetric triangular distribution with $a + b + c = 0$. There are two issues with fitting the proposed distributions for $\tilde{r}_{(p,s)}$ to this formulation. First, with $a = c$, the denominator in the MGF is equal to zero, so the MGF must be rewritten for a right triangular distribution. Furthermore, the parameters require an offset of $-1/3$ to satisfy the condition $a+b+c=0$. For this purpose, each distribution has been initially defined with $a=c=-1/3$ and $b=2/3$, and then corrected back to the original range, which will also produce an effect on the MGF.

$$M_{\xi}(\theta)=\frac{2T(\theta)}{(b-a)(b-c)(c-a)} \tag{40}$$

Therefore, consider a triangular distribution with lower bound $a=0$, upper bound $b=1$ and mode $c=0$. For any given distribution, the MGF is determined using equation (41).

$$M_X(\theta)=E\left[e^{\theta X}\right]=\int_{-\infty}^{+\infty}e^{\theta x}f_X(x)dx \tag{41}$$

$$f_X(x)=\begin{cases}0 & x<a\\ \dfrac{2(x-a)}{(b-a)(b-c)} & a\le x<c\\ \dfrac{2}{(b-a)} & x=c\\ \dfrac{2(b-x)}{(b-a)(b-c)} & c<x\le b\\ 0 & x=b\end{cases} \tag{42}$$

Using the PDF for a triangular distribution found in equation (42), the integral for the MGF can be written for the range between a and b. Note that for a right triangular distribution with $a=c$, only the range $c<x\le b$ yields a non-zero integral. As such, equations (43) – (45) show the steps necessary to achieve the MGF shown in equation (46).

$$M_X(\theta)=\int_c^b e^{\theta x}\frac{2(b-x)}{(b-a)(b-c)}dx \tag{43}$$

$$M_X(\theta)=2\int_c^b\frac{be^{\theta x}}{(b-a)(b-c)}dx-2\int_c^b\frac{xe^{\theta x}}{(b-a)(b-c)}dx \tag{44}$$

$$M_X(\theta)=\left[\frac{2be^{\theta x}}{\theta(b-a)(b-c)}\right]_c^b-\left[\frac{2e^{\theta x}(\theta x-1)}{\theta^2(b-a)(b-c)}\right]_c^b \tag{45}$$

$$M_X(\theta)=2\frac{e^{b\theta}-e^{ct}(b\theta-c\theta+1)}{\theta^2(b-a)(b-c)} \tag{46}$$

From this expression, the CGF, which is given by the natural logarithm of the MGF becomes:

$$\Lambda_X(\theta) = ln\left(2\frac{e^{b\theta} - e^{ct}(b\theta - c\theta + 1)}{\theta^2(b-a)(b-c)}\right) \tag{47}$$

The necessary correction to the MGF is given by equation (48), where d is the offset between the two distributions. To estimate the probability of violation in the constraints dealing with uncertainty, the CGF is defined as the natural logarithm of the MGF. Since the logarithm of a product is the sum of the logarithms of the factors, CGF is defined by equation (49).

$$M_{X+d}(\theta) = \ exp(b\theta)M_X(\theta) \tag{48}$$

$$\Lambda_{X+d}(\theta) = ln[exp(d\theta)M_X(\theta)] = d\theta + ln\left(2\frac{e^{b\theta} - e^{ct}(b\theta - c\theta + 1)}{\theta^2(b-a)(b-c)}\right) \tag{49}$$

The algorithm developed by solves the optimisation problem found on the right-hand side of equation (50) and requires four inputs: the desired probability of constraint violation, the probability bound (equation (50)), the function for $\Gamma_s(\theta)$ given by equation (51), and the convergence tolerance. A bisection algorithm is employed using values of θ, finding at each point the corresponding value of Γ_s and then calculating the probability of constraint violation. This probability is then compared with the desired probabilistic bound. The algorithm runs while the difference between the probability found and the one desired exceeds the chosen tolerance.

$$Pr\left\{\sum_j r_{ij}\, y_j + \sum_{j\in J_i} \xi_{ij}\, \bar{r}_{ij} y_j > R_i\right\} \leq exp\left(\min_{\theta>0}\left\{-\theta\Gamma_i + \sum_{k\in K_i}\left(d\theta + \Lambda_{ij}\left(g_{ij}\theta\right)\right)\right\}\right) \tag{50}$$

$$\Gamma_s(\theta^\star) = \sum_{p\in P}\left(\left.\frac{d\Lambda_{ps}(\theta)}{d\theta}\right|_{\theta^\star} + d\right) \tag{51}$$

Appendix A9 : Dimensions for randomly generated instances

Our model has been tested with larger randomly generated instances, of the same dimensions as the real case from a large European OEM in the aerospace industry, i.e., forty parts and one hundred suppliers. The conclusions drawn from these tests were in line with the results found Section 4.4.2. Figures A9(a), A9(b) and A9(c) show one of these tests, which preceded the extensive battery of tests in the paper. Figure A9(a) showcases the same discontinuity in solutions as the minimum feasible Φ increases with higher Γ-values. The weakest link approach shown in Figure A9(b) also displays an abrupt transition zone from the improved integration performance to a solution with exclusively double sourced modules. Finally, the additive approach shown in Figure A9(c) presents multiple alternative solutions, with a dynamic response to uncertainty, despite a worse initial solution than the one obtained for the weakest link approach.

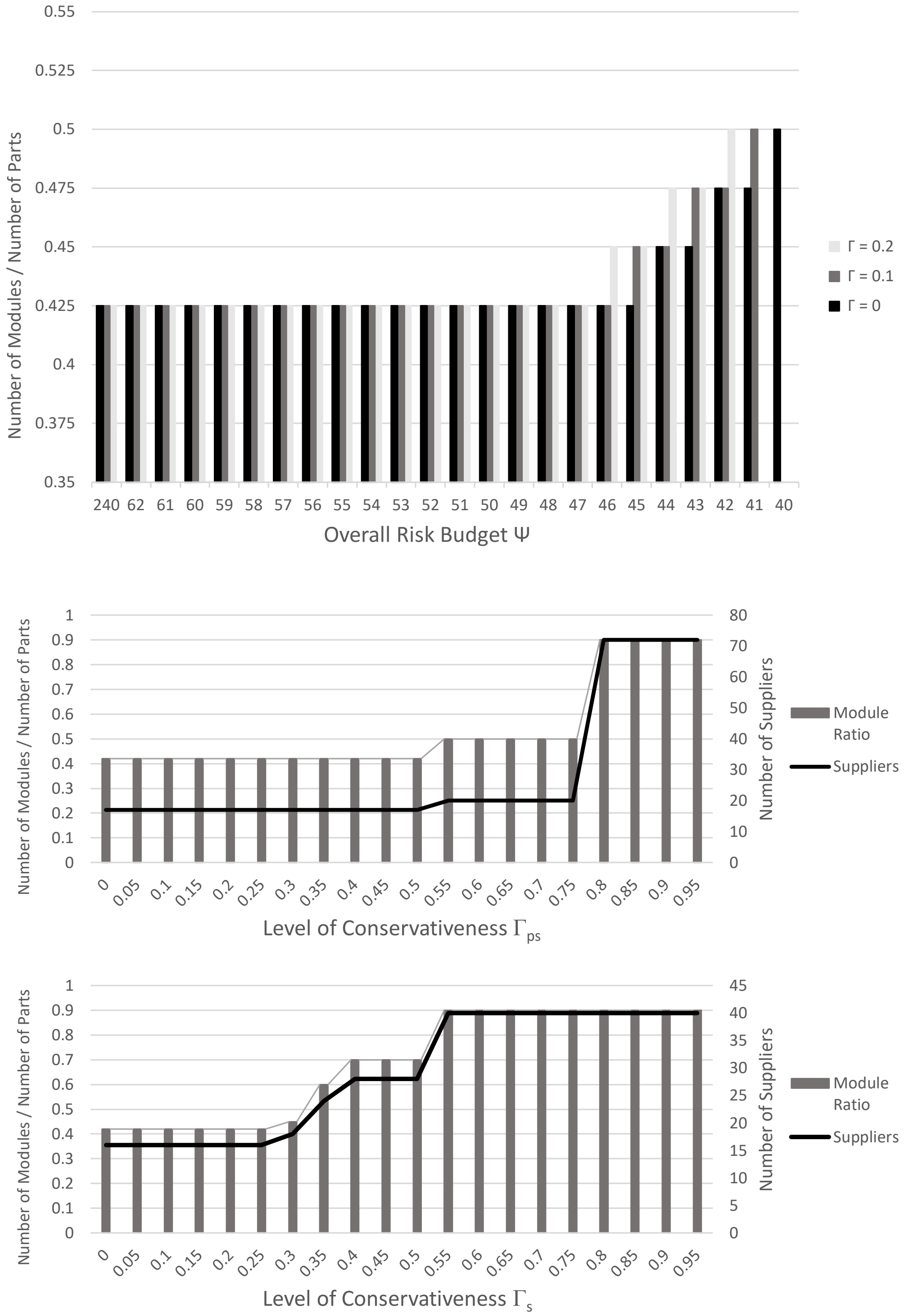

Figure A9. Solutions for randomly generated instance with forty parts and one hundred suppliers.