Designing and Managing Manufacturer Distribution Systems

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German abstract

Diese kumulative Dissertation besteht aus drei Forschungsartikeln, von denen zwei bereits in wissenschaftlichen Fachzeitschriften veröffentlicht wurden und der dritte derzeit bei einer renommierten Fachzeitschrift begutachtet wird. Alle drei Arbeiten befassen sich mit der Gestaltung und dem Management eines Herstellervertriebssystems in unterschiedlichen Szenarien. Im Gegensatz zur traditionellen Literatur im Bereich des Marketings, die Vertriebsstrategien oder Vertriebsintensität (d.h. die breite Verfügbarkeit von Produkten) meist aus der Sicht des Einzelhandels untersucht, konzentriert sich diese Arbeit auf die Perspektive des Herstellers. Der technologische Fortschritt und die sich ändernden Kundenbedürfnisse haben viele Hersteller dazu veranlasst, mehrere Vertriebskanäle zu nutzen, die direkt oder indirekt mit den Endkunden verknüpft sein können. Hersteller, die sich für einen direkten Vertriebsweg entscheiden, konkurrieren möglicherweise mit ihren bestehenden unabhängigen Zwischenhändlern (Einzelhändler, Großhändler), so dass es zu einem Vertriebskanalkonflikt zwischen den Parteien kommen kann. Diese Art von Wettbewerb wird gemeinhin als Übergriff des Herstellers (engl.: Manufacturer Encroachment) bezeichnet. In diesem Zusammenhang bietet der erste Artikel (Kapitel B) eine systematische und umfassende Literaturübersicht über Mehrkanalvertriebssysteme, bei denen der Hersteller mit seinen

unabhängigen Zwischenhändlern konkurriert. Es wird ein konzeptioneller Rahmen für die Analyse von Szenarien entwickelt, in denen ein Hersteller in den Markt der Einzelhändler eindringt. Hierbei werden die Faktoren untersucht, die den Hersteller dazu veranlassen, einen direkten Vertriebsweg einzuschlagen. Außerdem werden mögliche Mechanismen analysiert, die der Hersteller einsetzen kann, um den Vertriebswegkonflikt zu entschärfen. Des Weiteren werden betriebliche Entscheidungsprobleme in einem Mehrkanalvertriebssystem näher beleuchtet. Darüber hinaus werden mögliche Forschungslücken untersucht und zukünftige Forschungsrichtungen vorgeschlagen.

Vor dem Hintergrund der in Kapitel B identifizierten Forschungslücken wird in Kapitel C die Ausgestaltung eines Vertriebsnetzes auf der letzten Meile für einen Hersteller untersucht, der mehrere Produkte an unterschiedliche Kundensegmente verkauft. Die heute entwickelten Informationstechnologien und der Sektor der Third-Party-Logistics ermöglichen es den Herstellern, ihre Vertriebskanäle zu modifizieren, um die steigenden Kundenerwartungen zu erfüllen und Wettbewerbsvorteile zu erlangen. Daher müssen neben strategischen, taktischen und operativen Entscheidungen auch die Präferenzen der Kunden hinsichtlich der Vertriebskanäle und der Lieferdienste ausdrücklich berücksichtigt werden, damit die Hersteller eine kosteneffiziente Lieferkette realisieren können. In Anbetracht des begrenzten Umfangs früherer

Forschungsarbeiten werden im zweiten Artikel drei Möglichkeiten der Gestaltung des Vertriebsnetzes eines Herstellers (Single-Channel-, Multi-Channel- und Omni-Channel-Vertrieb) unter dem Aspekt der Standort- und Routingentscheidungen analysiert. Insbesondere das für das Omni-Channel-Vertriebsnetz formulierte Modell füllt eine bedeutende Lücke und trägt zur einschlägigen Literatur bei. Hier wird ein integriertes Optimierungsmodell vorgeschlagen, das ein Standort-Routing-Problem für die Gestaltung einer kombinierten zweistufigen Lieferkette für ein Omni-Channel-Distributionssystem mit fragmentierter Kundennachfrage, die über mehrere Einkaufs- und Lieferoptionen befriedigt wird, beinhaltet. Außerdem wird eine Nebenbedingung für das Kundenservicelevel berücksichtigt. Zur Lösung des Problems wird ein Dekompositionsverfahren entwickelt, um große Instanzen effizient zu lösen. Aufbauend auf einer computergestützten Studie lässt sich schlussfolgern, dass ein Omni-Channel-Vertriebssystem eine geeignete Strategie ist, mit der mehr Kundensegmente zu niedrigen Logistikkosten erreicht werden können. Die Ergebnisse zeigen auch, dass eine Erhöhung der Anzahl der "Buy Online Pick-Up In-Store"-Kunden (BOPIS) einen positiven Einfluss auf die gesamten Logistikkosten hat.

In Kapitel D wird schließlich ein internes Distributionsproblem in einem Lager untersucht, das Retouren von online verkauften Artikeln bearbeitet. Ein Unternehmen, das hauptsächlich Bekleidung verkauft, bearbeitet

Retouren an zwei Arten von Stationen: Aufarbeitung und Recycling. Um die Bearbeitung von Retouren zu verbessern, plant das Unternehmen den Einsatz von spurgeführten Transportfahrzeugen (engl.: lane-guided transport, LGT), die Kartons mit zurückgesendeten Artikeln in einem Depot abholen und sie zu den Stationen bringen, indem sie optischen Markierungen auf dem Boden folgen. In diesem Zusammenhang wird ein Modell der gemischt-ganzzahligen Programmierung (engl.: mixed-integer program, MIP) formuliert, das eine optimale Lösung für ein Routing-Problem mit einer gegebenen Menge an Stationen und mehreren Depots ermittelt: Das Modell optimiert dabei die Zuordnung der verschiedenen Arbeitsgänge zu den verschiedenen Stationen, die Anzahl von LGT-Fahrzeugen sowie deren Routen. Da das MIP-Modell ein NP-schweres Problem ist, wird eine dreistufige heuristische Dekompositionsmethode entwickelt, die aus Industriedaten abgeleitete Instanzen in einer angemessenen Lösungszeit nahezu optimal löst. Um zu prüfen, inwieweit diese Erkenntnisse aus dem MIP-Modell, insbesondere die Anzahl der Fahrzeuge, für den realen Betrieb optimal sind, wird zusätzlich eine Simulationsstudie durchgeführt. Die Ergebnisse zeigen, dass die Anzahl der Depots einen bemerkenswerten Einfluss auf die Gesamtleistung des Systems hat, während der Standort des Depots nur einen geringen Einfluss auf die Effizienz des Systems hat.

Abstract

This cumulative dissertation consists of three research articles, two of which have already been published in scientific journals. The third one is currently under review at another renowned scientific journal. All three articles address the design and management of a manufacturer distribution system in various contexts. Unlike the traditional marketing literature that investigates distribution strategies or distribution intensity (i.e., wide spread availability of products) generally from the retailers' point of view, this thesis focuses on the manufacturer's perspective. Technology advancement and changing customer requirements have driven many manufacturers to utilize multiple distribution channels that use both direct and indirect sales channels. Manufacturers that adopt a direct channel may compete with their existing independent intermediaries (retailers, wholesalers), and thus a channel conflict may emerge between the parties. This type of competition is referred to as manufacturer encroachment. The first paper (Chapter B) responds by providing a systematic and exhaustive literature review of multi-channel distribution systems wherein the manufacturer competes with its independently-owned intermediaries and develops a conceptual framework for analyzing scenarios where a manufacturer intrudes into the retailers' market, investigates determinant factors that induce the

manufacturer to adopt a direct channel, explores possible mechanisms that the manufacturer may use to mitigate the channel conflict, and studies operational decision problems in a multi-channel distribution setting. Moreover, it explores potential research gaps and proposes future research directions.

The research gaps identified in Chapter B pave the way for Chapter C which investigates the configuration of a last-mile distribution network for an encroaching manufacturer who sells multiple products to different customer segments. Today's developed information technologies and the third-party logistics sector enable manufacturers to modify their distribution channels to meet rising customer expectations and gain from potential competitive advantages. Therefore, there is a need to explicitly consider customer channel preferences and delivery services in addition to strategic, tactical, and operational decisions to help manufacturers realize a cost-effective supply chain. Given the limited scope of earlier research, the second article analyzes three distribution network design choices of a manufacturer (single channel, multi-channel, and omni-channel) through the lens of location and routing decisions. In particular, the model formulated for the omni-channel distribution network fills a significant gap and contributes to the related literature. Here, we propose an integrated optimization model that includes a location-routing problem for designing of a combined two-echelon supply chain for an omni-channel distribution system with fragmented customer demand met via multiple shopping and delivery options. We also incorporate a customer service-level constraint. We further develop a decomposition solution method to solve large-scale instances efficiently. Based on our computational study, we conclude that an omni-channel distribution system is a feasible strategy that can reach more customer segments at low logistics costs. Our findings also show that an increase in the number of ‘buy online pick-up in-store’ (BOPIS) positively impacts the total logistics cost.

Finally, Chapter D investigates an internal distribution problem in a warehouse handling returns of items sold online. A case company selling mainly apparel processes returns at two types of workstations: refurbishing and recycling. To improve the processing of returned items, the company plans to implement lane-guided transport (LGT) vehicles that pick up boxes of returned items at a depot and drop them off at workstations by following optical markers on the floor. In this context, we formulate a mixed-integer programming (MIP) model seeking an optimal solution to the following routing problem: Given a set of stations and multiple depots, which station should do what type of work, and what is the optimal number of LGT vehicles and their routes? Since the MIP model is an NP-hard problem, we develop a three-stage heuristic decomposition scheme that solves instances obtained from industry data to near-optimality in a reasonable solution time. Furthermore, to test to what extent our findings from the MIP model, particularly the number of vehicles, are optimal for real-world operations, we conduct a simulation study in addition. Our results show that the number of depots has a notable impact on the overall system performance, while the depot location has only a small influence on system efficiency.

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List of Abbreviations

AGV	Automated guided vehicle
BOPIS	Buy online pick-up in-store
CPU	Central processing unit
CVRP	Capacitated vehicle routing problem
DC	Distribution center
DS	Dark store
GB	Gigabyte
GHz	Gigahertz
h	Hour
km	Kilometer
L	Large
LB	Lower bound
LGT	Lane-guided transport
LKH	Lin-Kernighan heuristic
LRP	Location-routing problem
LTSRP	Lane-guided transport system routing problem
m	Meter
M	Medium
m/s	Meter per second
MC	Multi-channel
MD-R	Single manufacturer distributing products directly and through a retail channel

MD-R-3PL	Manufacturer collects the returned items over third party logistics providers
MD-R-3PL&M	Manufacturer collects the returned items directly and over third party logistics providers
MD-R-M	Manufacturer collects the returned items directly
MD-R-R	Manufacturer collects the returned items over retailers
MD-Rs	Single manufacturer distributing products through direct and multiple retail channels
min	Minute
MIP	Mixed integer programming
MILP	Mixed integer linear programming
MsD-R	Multiple manufacturers selling products directly and through a common retailer
MsD-Rs	Multiple manufacturers distributing products both directly and through multiple retail channels
NP	Nondeterministic polynomial time
OC	Omni-channel
PC	Personal computer
RAM	Random-Access Memory
RQ	Research question
s	Second
S	Small
SC	Single channel
SCM	Supply chain management

TS	Tabu search
TSP	Traveling salesman problem
UB	Upper bound
UTM	Universal Transverse Mercator
2E-LRP	Two echelon location routing problem

Chapter A. Introduction and Overview

A.1. Distribution channel design and management in the context of changing customer requirements and technology advancement

In addition to offering goods, sellers' customer value propositions involve a broad set of peripheral elements, such as the provision of detailed product information, assortment variety, high service levels, fast delivery, lenient return policies, and a distinctive store ambience. These peripheral service elements pose various tradeoffs to sellers as well as customers. A customer, for example, may face a tradeoff in experiencing an appealing store ambience versus incurring a high transportation cost to visit the store. From a firm's perspective, in order to increase its sales revenue, market penetration rate, and overall customer satisfaction, it may try to increase the number of such peripheral services, which often depends on its existing sales channel's structure. Usually, a firm that operates multiple sales channels can offer additional services to customers more efficiently. As such, sales channels have changed over recent years due to changing customer shopping behaviours and the development of information technology. Many firms have operated a single sales channel through brick-and-mortar stores until about two decades. Examples of new channel structures that emerged are telemarketing and sales, which began in the 1980s (e.g., Home Shopping Network), and internet retailing (e.g., Amazon), which became dominant after 2000. Technology development triggered companies to introduce a new direct-to-customer channel (online) in addition to the existing traditional retail channel (offline) from which the dual- or multi-channel phenomenon emerged. To further enhance the customers' shopping experience, many companies continue to think of new sales channels.

In the last decade, multi-channel retailing has been dominant. Today, rapid digitalization of sales and marketing strategies (i.e., mobile channels, VR, social media, and live streaming sales) made it easier for firms to promote their products and increase sales, thus pushing the retail industry in favour of omni-channel business models. Furthermore, the COVID-19 pandemic provided a strong impetus for this transformation.

The formal definitions and taxonomies of multi- and omni-channel retailing (or distribution systems) have been proposed in several studies. In a nutshell, multi-channel retailing sells products through more than one distinct channel (e.g., online and offline channels), whereas an omni-channel sells products through multiple available channels and customer touchpoints (Verhoef et al. 2015; Beck et al. 2015). From an operational decision point of view, in multi-channel distribution systems, the firms perform physical store replenishments and e-commerce shipments through separate warehouses and distribution systems concurrently, while in omni-channel systems, they integrate all facilities (Millstein et al., 2018). Furthermore, an omni-channel relies on improving the customers' shopping experience, which is a primary concept behind this phenomenon. Consider the case where one can buy a product via a mobile channel and prefer either home delivery, delivery to automated packaging systems, or in-store pickup, and with the same options for returns (Hübner et al. 2016; Paul et al. 2019). Bonobos and Indochino, for example, are apparel retailers that use their stores as showrooms, where customers place orders on their website, and with orders fulfilled through home delivery or pickup stores. Walmart and Tesco offer a "free in-store pickup" option that customers utilize when purchasing online and picking up the order at the store (Chopra, 2018).

Managing multiple sales channels gives rise to new challenges for firms. These challenges include data integration, channel coordination, product consistency, and inventory tracking across channels (e.g., see Beck et al. 2015; Neslin et al. 2006; Berman et al. 2004). For a firm to move from adopting a multi-channel to an omni-channel distribution system carries many operational challenges (Hübner et al. 2016). In an omni-channel setting, the management of order fulfilment and tracking inventory require effective coordination between conventional (brick-and-mortar) and virtual (online) channels (Ishfaq et al. 2015). For example, last-mile delivery services bring about routing complexity and extra cost for companies (Janjevic et al. 2020). With a well-configured omni-channel supply chain, the chain can become more cost-efficient and responsive to customer service (Chopra, 2016). To this end, companies need to integrate offline (physical stores) and online channels as well as mobile touchpoints, and they also need to manage them in a synchronized fashion.

The above survey studies saw the chain from the eyes of the retailer, implying that an omni-channel is a retail concept. This dissertation advocates that there is a significant value in examining the design and management of various types of distribution channels also from a manufacturer's perspective. Technological advancements and customers preferring online over brick-and-mortar channels enticed many manufacturers to enter the online sales market by selling directly to customers. For example, the U.S. Census Bureau reports that in 2019, e-commerce shipments of U.S. manufacturers accounted for 67.8% of all manufacturing shipments, up from 67.4% in 2018 (E-Stats 2019). Those statistics resulted in the opening of new venues in supply chain research. In the following subsection, we address this in more detail.

A. 2. Manufacturer encroachment and channelling strategies

To reach more customer segments and increase profits, many manufacturers (e.g., Apple, Nike, and DELL) switch their distribution channels from single channels to multi- or omni-channel distribution systems. A manufacturer's distribution channels can be categorized as *direct* and *indirect sales channels*: in the direct sales channels, a manufacturer vends products via its website or outlet stores, whereas in indirect sales channels, the manufacturer markets products through independent intermediaries (i.e., retailers, wholesalers, e-tailers). By adding a wholly-owned direct sales channel, a manufacturer enters the market and competes with its intermediaries. In the literature, this is termed *manufacturer encroachment* (Arya et al. 2007).

In terms of timeline, the manufacturer's process of formulating a distribution strategy can be divided into two distinct phases: the *pre-adoption* phase, where strategies for distribution systems are developed, and the *post-adoption* phase, where the designed distribution systems are managed. Adding a new direct sales channel to the existing indirect sales channel is a strategic decision that may affect the performance of the entire distribution system. Therefore, the manufacturer should evaluate all possible tradeoffs and prioritize determinant factors by considering all affected supply chain members. For instance, incorrectly assessing customer preferences or overriding market conditions may incur additional costs and even a failed channel adoption initiative.

Unsound decisions taken in the pre-adoption phase could lead to managerial challenges in the post-adoption phase. In the latter phase, the manufacturer has to make effective *tactical* and *operational decisions.*

Tactical decisions pertain to utilizing different mechanisms (e.g., pricing, coordination, product differentiation) that consolidate the manufacturer-retailer interaction. The most notable managerial challenge that damages the manufacturer-retailer relationship is a *channel conflict.* From the retailer's point of view, manufacturer encroachment is a threat that may prevent the retailer from achieving its goals such as profit maximization or market dominance. The manufacturer should consider this issue seriously and take corrective actions to mitigate the channel conflict. Otherwise, in the long run, the rising competition could make both the manufacturer and retailer worse off. From the manufacturer's perspective, employing both indirect and direct sales channels provides a set of advantages. More specifically, manufacturers are interested in selling both through online and the retailers' physical stores simultaneously, rather than bypassing the independent retailers who can provide advantages to the manufacturer. For example, the retailers undertake sales effort activities such as brand building, customer education, or building product awareness, which simplify the manufacturer's marketing and sales tasks (see Kaya et al. 2008; Tsay et al. 2004a). In an omni-channel setting, manufacturers use retailers' stores as order picking, fulfilment, and product return locations, making direct and indirect channels part of the distribution channel strategy.

In terms of *operational decisions*, the channel transition and managing multi- and omni-channels changes existing operational decisions problems in the areas of inventory control, order and delivery management, and return/refund management. For example, the manufacturer needs to minimize return/refund cost while considering a tradeoff between (the cost of the) return policy and customer satisfaction. A problem with online channels is that product returns increased to unprecedented levels adding complexity when making decisions on the type of refund policy and managing returns. An omni-channel offers customers more flexible product purchasing and returning options than what they get from going to physical stores alone that can expand the options to “buy online, pick up in-store” or “buy online, return in-store”. Operating such a channel structure requires the manufacturer and retailers to make joint decisions regarding inventory management practices, product return policy, and forward and reverse logistics. In addition, the growing online customer segment has driven manufacturers to plan their last-mile delivery routings efficiently. Besides minimizing logistic costs, the manufacturers should also consider the *city logistics* concept, which aims at reducing some environmental and social effects of freight distribution (e.g., pollution, congestion, restrictive city regulation) for better sustainability and quality of city life.

A. 3. Thesis scope and overview

This thesis investigates the design and management of manufacturer distribution systems in a multi-channel context. To this end, Chapter B first provides a systematic and exhaustive literature review of multi-channel distribution systems in a combined forward and reverse supply chain where the manufacturer competes with its independently-owned intermediaries (retailers or wholesalers). The chapter develops a conceptual framework to classify related analytical and empirical studies and explores research gaps that could be addressed in the future. In this context, we aim to explore both “what” (i.e., what induces the manufacturer to introduce a direct sales channel) and “how” (i.e., how does the manufacturer manage multi-channel distribution systems) questions arising in the pre-adoption and post-adoption phases of omni-channels. To answer the scope of the first research question, we report several factors to be considered when a manufacturer intends to develop its channel strategy, which are *customer preference, information asymmetry, market environment, environmental concerns, manufacturer’s preemptive strategy* and *empirical specific factors.* The second research question relates to mechanisms (i.e., *pricing, coordination, information sharing, incentive schemes, product differentiation, empirical specific mechanisms*) that a manufacturer uses to mitigate emerging channel conflicts with retailers as well as methods (i.e., *inventory control, production planning, returns management, delivery management*) used for handling operational decision problems. The results of this review suggest that customer preferences for direct online channels differ by product category and shopping practice (e.g., online or in-store captive customers), and that customer preferences have a strong impact on the manufacturer's channel design strategy. In terms of supply chain configuration, most works study a two-tier supply chain network that comprises one manufacturer and a retailer selling a single product. This is usually referred to as a *dual-channel* supply chain in which the manufacturer distributes the products both directly and through a retailer. The results also reveal that designing a more complex and realistic (e.g., omni-channel) supply chain network flow has largely been overlooked in the literature. Our findings also report that operational problems have received much less attention in a multi-channel distribution context. Chapter B has been published as Tahirov, N., Glock, C. H. (2022): Manufacturer encroachment and channel conflicts: A systematic review of the literature. *European Journal of Operational Research* 302 (2), 403–426. The definitive publisher authenticated version is available online at https://doi.org/10.1016/j.ejor.2021.12.006.

Chapter C addresses designing distribution networks, identified as a research gap in Chapter B, i.e., a design reflective of what one observes in practice. It thus investigates a manufacturer who considers various distribution systems for selling multiple products to more customers of different segments. Thus, there is a need to consider the granular features of customer demand and delivery services in addition to strategic, tactical, and operational decisions to help the manufacturer achieve a cost-effective supply chain. To the best of the author's knowledge, the existing literature has not investigated a manufacturer's distribution network design in the context of channel transition yet, i.e., from single-channel to multi-channel and from multi-channel to omni-channel by considering customer preferences for various shopping/pick-up options, multiple products, and incorporation of a customer service-level constraint. Chapter C presents the formulation of an integrated optimization model that includes a location-routing problem (LRP). The developed model will help to design a combined two-echelon supply chain for an omni-channel distribution system to achieve a cost-effective supply chain and meet the expectations of various customer segments in terms of shopping and product preferences. Chapter C also proposes a decomposition metaheuristic technique for performing a computational study on large realistic instances. We investigate the effect of buy-online-pickup-in-store (BOPIS) customers on the distribution network and identify a percentage decrease in the total logistics cost in the number of BOPIS customers. Our findings confirm that an omni-channel distribution system is a feasible channel that can reach more customer segments at low logistics costs. We further find that the transportation costs decrease in the number of dark stores, as offering a BOPIS option to customers reduces the average distance for last-mile deliveries. Chapter C is based on the submitted manuscript Tahirov, N., Akhundov, N., Emde, S., Glock, C. H. (2022): Configuration of last-mile distribution networks for an encroaching manufacturer.

Chapter D addresses the importance of investing in novel transportation systems and operational (internal) logistics and how they impact managing the return of items sold online, identified as a research gap in Chapter B. It considers the case encountered at a major European apparel company that faces high return rates for online purchases. The company decided to install a lane-guided transport (LGT) system in a newly constructed warehouse to handle returns and reduce the time returned items spend in warehouse. An LGT system consists of small electric vehicles following optical markers on the floor, picking up boxes of returned items at a depot and dropping them off at workstations. Chapter D presents the formulation of an optimization problem that determines the optimal number of vehicles, their routes, and the assignment of roles (recycling and refurbishing) to the stations that are visited. This problem is fundamentally different from classic multi-depot routing problems, as it considers multiple vehicles serving the same route, the flexibility of stations in handling defective or refurbished items and longer routes requiring more vehicles to serve demand. Investment and operating costs depend on the number of LGT vehicles. Thus, the goal of the proposed model is to minimize the total vehicle fleet (i.e., primary objective) and the route travel times (i.e., secondary objective). The reason for that is that a shorter route duration reduces energy consumption and increases service frequencies for a given LGT vehicle. Owing to the complexity of the problem, a heuristic decomposition scheme is developed to solve instances of realistic sizes in under one minute of CPU time to near-optimality. In addition, to verify whether our optimized solutions hold during the actual operation of the warehouse, a simulation study is also performed to mimic five different and observed warehouse layouts. The simulation results show that the average utilization of most stations is quite high since the model does not consider buffers. Our findings also show that the depot count significantly influences system efficiency, whereas the location of depots has only a minor impact on the overall performance of the LGT vehicle system. Chapter D has been published as Emde, S., Tahirov, N., Gendreau, M., Glock, C. H. (2021): Routing automated lane-guided transport vehicles in a warehouse handling returns. *European Journal of Operational Research* 292 (3), 1085–1098. The definitive publisher authenticated version is available online at https:// doi.org/10.1016/j.ejor.2020.11.038.

Chapter B. Manufacturer encroachment and channel conflicts: A systematic review of the literature*

Abstract: To reach more customers, many manufacturers utilize multiple distribution channels consisting of a direct and an indirect sales channel. In particular, the strong growth of internet sales (or e-commerce) has driven companies to redesign their distribution channels to take advantage of the opportunities e- commerce offers. Opening a direct sales channel, however, also leads to managerial challenges. The most significant one is channel conflicts that manufacturers encounter when adding a direct channel to an existing traditional channel. Manufacturers that engage in direct selling may compete with their extant independent retailers. Competition between manufacturers and retailers starts when the former intrude into the market (segment) that was traditionally served by the retailers via manufacturer-owned stores and online sales, which is commonly referred to as manufacturer or supplier encroachment. This paper aims to provide a systematic and exhaustive review of multi-channel distribution systems in a combined forward and reverse supply chain where the manufacturer competes with its

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independently-owned intermediaries (retailers or wholesalers). First, to organize our discussion, all works obtained during the literature search were classified and evaluated in accordance with a proposed conceptual framework. The paper then discusses the sampled works and evaluates possible research gaps. Finally, based on the analysis of the literature, managerial implications and promising future research directions are proposed.

B.1. Introduction

Due to developments in technology and the growth of the third-party logistics sector, many companies have started to modify their distribution strategy (e.g., Federal Express, United Parcel Services; see Tsay et al., 2004a, Matsui, 2016). In particular, the strong growth of internet sales (or e-commerce) has driven companies to redesign their distribution channels to take advantage of the opportunities e-commerce offers, such as reduced costs (especially in terms of overhead and operating costs), low cost/barriers for entering new market segments, and worldwide sharing of information (Webb, 2002). To reach more customers, many manufacturers utilize multiple distribution channels (the literature also refers to dual-channels, dual distribution channels, or concurrent channels) consisting of a direct and an indirect sales channel (Chung et al., 2012). In addition to that, the COVID-19 pandemic has also changed customer purchase behaviour, with customers starting to shop products online that had traditionally been purchased in brick-and-mortar stores (such as grocery). The increase in online sales the COVID-19 pandemic brought about induced many retailers and manufacturers to adopt online channels (He et al., 2021, Hong et al., 2021).

If a manufacturer markets its products through its website (online) or company-owned (brick-and-mortar) stores, a *direct sales channel* is used. In *indirect sales channels*, the manufacturer sells its products and provides services through intermediaries (e.g., retailers, e-tailers, wholesalers; see Rosenbloom, 2007, Coughlan et al., 2014). Take, for example, DELL, HP, Nike, and Apple, who sell their products directly via their webshops and through their exclusive physical stores, while many superstores also vend the same products (David et al., 2015). In the initial phase of e-commerce, companies often used direct channels to provide information about new products and additional services that complemented brick-and-mortar stores for customers that were retailer-loyal or hesitant to purchase over the internet. Direct sales have increased strongly over the last decades, however. According to a survey published in The New York Times (Tedeschi, 2000), about 42% of the leading US suppliers launched to sell over the internet. Direct sales have continued to increase over recent years (e.g., Cai, 2010, Tu et al., 2019). According to the U.S. Census Bureau, in 2018, e-commerce shipments of U.S.

manufacturers and e-commerce retail sales were $4,010.6 billion (up by 7.5 % from 2017) and $519.6 billion (up by 13.2 % from 2017), respectively (E-Stats 2018).

Both analytical and empirical studies show that the conventional motives for a manufacturer to add a direct sales channel are reaching new customers, increasing profit, and achieving price differentiation (Gabrielsson et al., 2002, Tsay et al., 2004b, Vinhas et al., 2005, Chen et al., 2011). In essence, selling both via independent retailers and through an online channel provides several advantages to a manufacturer, who is usually interested in leveraging both channels simultaneously. For instance, selling online benefits from shipping and handling (S&H) fees (i.e., for specific products, consumers may not evaluate shipping cost when sellers introduce aggressive pricing). Thus, sellers may collect profits from S&H operations, dynamic and/or personalized pricing, auctions (e.g., via platforms such as eBay), dynamic updating of product assortments, having a direct relationship with end-customers, collecting improved demand information (e.g., for forecasts), or tracking customers' preferences and behaviors (Tsay et al., 2004b). Furthermore, having independent retailers provides advantages to manufacturers in terms of sales effort activities implemented by the retailers (brand building, customer education, building product awareness, etc.; see Tsay et al., 2004a, Chen et al., 2008). Therefore, many manufacturers tend to employ direct and indirect sales channels simultaneously when formulating their distribution strategy.

Opening a direct sales channel, however, also leads to managerial challenges. The most significant one is channel conflicts that manufacturers encounter when adding a direct channel to an existing traditional channel (Webb, 2002). A channel conflict occurs “when one channel member’s actions prevent the channel from achieving its goals” (Coughlan et al., 2014, p. 24). In the case of manufacturer encroachment, retailers often perceive the manufacturer’s direct sales activities as a threat. The consequences of the rising competition as well as measures both the manufacturer and the retailers may adopt to mitigate problems are essential to be addressed. Other important managerial issues that need to be investigated in a multi-channel distribution context are operational decisions related to, for example, inventory control, order and delivery management, and return/refund management. Especially for online channels, the return policy plays an important role in the customers’ purchasing decisions. For the manufacturer, offering a customer-friendly return policy is a wise strategy to gain competitive advantages in the market (Li et al., 2017). To mitigate customer concerns on the quality and usability of products purchased online, many manufacturers offer a full return policy in coordination with retailers (Li et al., 2019).

This paper aims to provide a systematic and exhaustive review of multi-channel distribution systems from the perspective of a manufacturer. The literature on multi-channel distribution systems has been reviewed a couple of times in the recent past (see Verhoef et al., 2015, Agatz et al., 2008, Beck et al., 2015), but only from the retailers' point of view. These surveys review works in which the retailer is the main (and in many cases, the only) player and discuss various internal (e.g., store operations) and external (e.g., customer interaction) characteristics of multi-channel retailing. To the best of the authors' knowledge, the work at hand is the first systematic literature review that investigates a manufacturer's channel design strategies and coordination mechanisms in a multi-channel context. The distribution systems we are interested in are illustrated schematically in Figure B.1. Note that *multi-channel distribution systems*, in our point of view, involve at least two different types of channels. That is, manufacturers selling through multiple retailers do not qualify as multi-channel distribution systems in the context of this paper. The major contributions of the work at hand are as follows: 1) It develops a conceptual framework for analyzing scenarios where a manufacture encroaches into the retail market; 2) It investigates factors that induce the manufacturer to introduce a direct channel; 3) It explores possible strategies that the manufacturer may adopt to alleviate conflicts with its retailers; and 4) it investigates operational decision problems in a multi-channel distribution setting.

The remainder of this paper is structured as follows. Section B.2 describes the conceptual framework addressed in this paper. Section B.3 then introduces the literature search and selection strategy and descriptively evaluates the literature sample. Our main findings in response to the research questions are presented in Section B.4. Section B.5 summarizes major insights obtained and proposes opportunities for future research. Section B.6 concludes the paper.

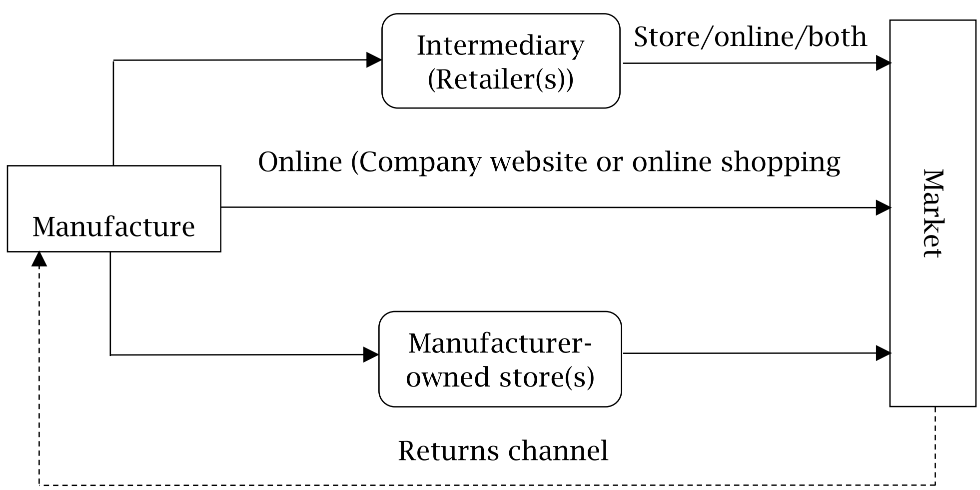


Figure B. 1. General network design of the multi-channel distribution systems discussed in this chapter.

B.2. Scope of this review and framework development

B.2.1. Conceptual framework

This section develops a framework for classifying studies on multi-channel distribution systems. Our focus is on a manufacturer that competes with its independent intermediaries by adding a wholly-owned direct sales channel. The literature refers to this kind of competition as *manufacturer* or *supplier encroachment* (Tannenbaum, 1995, Arya et al., 2007, Xiong et al., 2012). For the sake of simplicity, throughout the paper, a *manufacturer (he)* and *retailer (she)* are synonyms for *supplier* and i*ntermediary*, respectively. Furthermore, when we say online (internet, e-commerce) sales, we imply sales through the manufacturer's website or e-commerce platforms (such as Amazon or eBay). Note that our focus is on the distribution of tangible products and that we do not consider online channels that offer digital services or products. From our point of view, physical products are more difficult to deal with than digital ones, as they require inventory, distribution, and return logistics, which is not the case for virtual products. Therefore, operations management methods that aim on managing tangible products prevail in the literature and are therefore the focus of our research.

Earlier works related to our conceptual framework are those of Sibley et al. (1998), Chiang et al. (2003), and Tsay et al. (2004a), who modeled and analyzed similar scenarios using game-theoretic approaches. The traditional marketing literature that investigates distribution strategies or distribution intensity is beyond the scope of our research. This paper instead concentrates on works that studied strategic, tactical, and operational decisions from the manufacturer's perspective. In terms of the timeframe, we break the decision-making process down into two phases: *pre-adoption* and *post-adoption*. In the pre-adoption phase, the manufacturer develops strategies for the multi-channel distribution system, whereas in the post-adoption phase, he manages the systems (see Figure B.2). Our objective in this context is to explore "what" and "how" questions emerging in the pre-adoption and post-adoption phases, respectively.

B.2.1. Development of research questions and classification

In the pre-adoption phase, manufacturers need to evaluate their distribution strategy. Adding a direct (physical or online) distribution channel is a strategic decision that may affect the profitability of the entire distribution system. Before selecting a (new) channel, the manufacturer needs to evaluate all possible tradeoffs and consider all affected supply chain members (To et al., 2006). In particular, the retailers' perspectives have to be evaluated carefully, because a manufacturer that engages in direct selling may compete with his extant independent retailers, which may reduce their profit. Furthermore, overriding customer preferences or ignoring the market environment may lead to a failed channel adoption and extra costs. Therefore, in the pre-adoption phase, the manufacturers have to consider key factors that influence this kind of strategic channel selection decision. In this regard, we propose our first research question (*RQ 1*):

1. Which determinant factors induce the manufacturer to establish a direct sales channel?

In the post-adoption phase, the manufacturer has to manage the distribution system. Both *tactical* and *operational* decisions have to be made. *Tactical decisions* are related to the effective management of the manufacturer-retailer interaction. After a manufacturer's encroachment, the resulting competition may lead to channel conflicts, mainly because retailers perceive that the manufacturer is determined to become a vertically integrated giant by using the retailers' loyal customers – a loyalty that the retailers had to build up at their expenses – for his advantage. Earlier empirical studies (e.g., Osmonbekov et al., 2009, Chang et al., 2010) have shown that if a manufacturer adds a direct (online) channel, relationship conflicts emerge that decrease the retailer's economic performance, which in the long run reduces the performance of the entire supply chain (Coughlan et al., 2014: 24). Although the manufacturer may appear as a new competitor in the market, he tends to employ both channels simultaneously, rather than bypassing intermediaries (retailers). To mitigate channel conflicts, the manufacturer may apply various mechanisms such as directing customers to retailers, lowering wholesale prices, or product differentiation. IBM, for example, directed orders to its distributors, Random House sold more expensive than its retailers (see David et al., 2015), and Euroka Forbes Ltd., Dell, Toshiba, and Ralph Lauren all offered products in different qualities in each channel (Ha et al., 2016). In terms of *operational decisions*, managing multi-channel distribution systems introduces new and changes existing operational decision problems (e.g., with respect to inventory control, delivery management, or return/refund management) that have to be solved efficiently. For example, multi-channel distribution offers customers new purchasing and return options such as “buy online, return in-store” or “buy online, pick up in-store”, which necessitate making joint decisions in terms of inventory control and product returns (Xie et al., 2017). Hence, we propose our second research question (*RQ 2*):

2. How does the manufacturer manage multi-channel distribution systems?

We aim to review and classify all works obtained during the literature search in accordance with the proposed research questions that represent the core dimensions of our conceptual framework. The classification will facilitate summarizing the literature sample, interpreting research contributions, and identifying future research opportunities. This entails the identification of various problem dimensions to evaluate and organize the literature sample. Moreover, the problem dimensions will be used for comparing analytical studies to empirical ones and for showing how well theoretically discussed multi-channel systems match those that can be found in practice.

Figure B.2 summarizes the conceptual framework that guides our literature search and evaluation and that contains our classifiers for each of the two research questions. The conceptual framework was developed in a combined inductive/deductive way. Our literature search and evaluation started with an initial framework that was then gradually refined upon examining the identified literature until the framework reflected the sampled literature as good as possible.

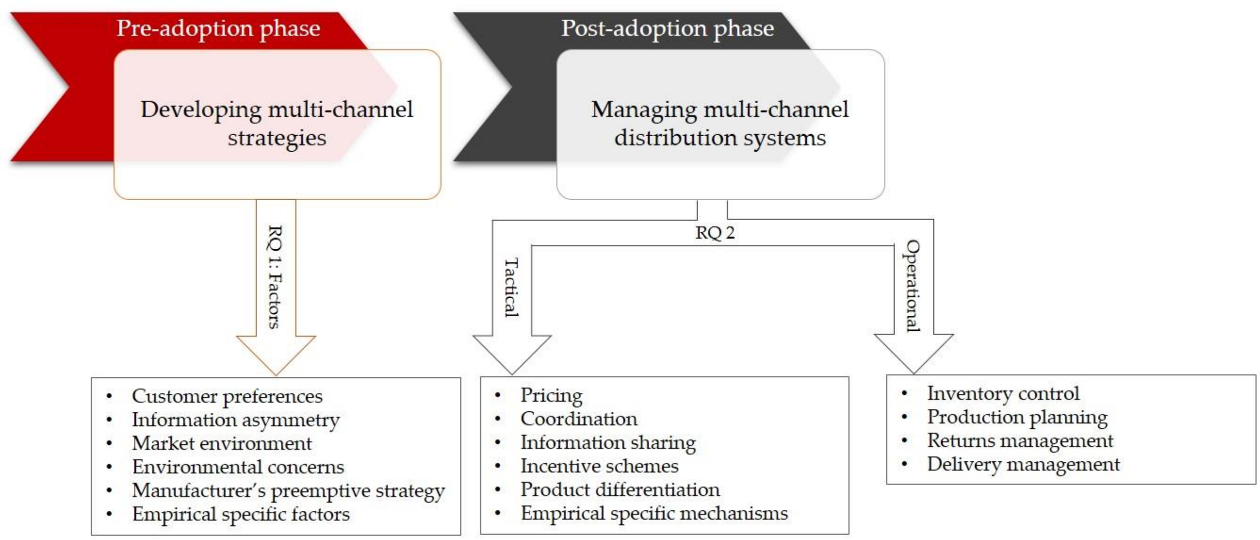


Figure B. 2. Conceptual framework and classification

B.3. Systematic literature review methodology

The literature differentiates between three common types of literature reviews, namely narrative reviews, systematic reviews, and meta-analyses (Hochrein et al., 2012). *Narrative reviews* examine literature published on a certain topic without following a specific literature search and selection methodology. Major weaknesses of *narrative reviews* are therefore that results are difficult to reproduce, that the literature search may be incomplete, and that the review is generally open to biases (Grant et al., 2009). *Meta-analyses* statistically analyze papers and synthesize them, eventually graphically with narrative commentary (Grant et al., 2009, Tranfield et al., 2003). In contrast to narrative reviews, *systematic literature reviews* follow a transparent and reproducible literature search and selection methodology, and they have increased in popularity over recent years. Since each discipline has idiosyncrasies in its research, the guidelines for conducting systematic literature reviews have to be adapted to each discipline (Durach et al., 2017). Systematic reviews enable researchers to define major scientific contributions and synthesize findings, also using statistical methods (Tranfield et al., 2003). This paper aims to provide a systematic overview of multi-channel distribution systems where the manufacturer adds a direct channel in addition to his existing independently-owned retailers. Following the guidelines for conducting systematic literature reviews described in Tranfield et al.

(2003) and Durach et al. (2017), we systematically searched for relevant works that fall into our scope. To facilitate the literature search, keywords were developed that were then integrated into a search string to survey the scholarly databases Scopus and Business Source Premier (via EBSCO Host). To generate the search string, two keyword groups were developed, and all keywords from those groups were combined (Table B.1). During the search process, the initial inclusion criterion for a paper was that it needs to contain at least one of the keyword combinations in its title, abstract, or list of keywords.

Table B. 1. Keyword groups used for generating the literature search string

Group A	Group B
Dual-channel (dual channel)	Supply chain
Multi-channel (multi channel)	Retailing
Multiple channels	Distribution
Concurrent channels	Supplier
Omni-channel (omnichannel)	Manufacturer
Internet channel	Factory
E-channel	
Cross-channel (cross channel)	
Hybrid channel	
Two-channel (two channels)	
E-commerce	
Encroachment	
Mobile channel	

The database search was enhanced by an additional search of all works cited in a paper that met the inclusion criteria (snowball search). Only works published in peer-reviewed academic journals were considered relevant. All papers had to be published in English during the years 2000-

2020[1]. We considered papers that study scenarios in which a manufacturer opens a direct channel and thus competes with his independently-owned retailers. Therefore, papers that focus on retailer competition, multi-channel retailing, or competition between physical (brick-and-mortar) retail channels and e-tailer (e-commerce retailer) channels were not considered relevant. For a first evaluation, all papers were screened based on their titles and abstracts. Those works that remained in the sample after the initial screening were read to evaluate their relevance based on the defined inclusion/exclusion criteria and to assess their content.

B.4. Review of multi-channel distribution systems

B.4.1. Descriptive results

Our literature search led to a total of 540 initial hits in the two databases. After eliminating duplicates from the list, our first-stage sample contained 300 papers. In the next step, we carefully read the paper's abstracts and excluded 75 papers that did not meet our selection criteria. The remaining 225 papers were completely read and an additional 71 irrelevant papers were excluded. Adding 26 papers obtained during the

[1] All works that were published until February 2020 were included in the sample, which is the date of the literature search.

snowball search led to a final sample consisting of 180 papers. The search steps are summarized in Table B.2.

Table B. 2. Procedure and results of the literature search

Steps	Description	Sample size
1	*Database search: 312 hits in Scopus, 228 hits in Business Source Premier.*	540
2	*Eliminating duplicates: 240 papers removed.*	300
3	*Screening of all papers' abstracts: 75 papers excluded.*	225
4	*Examination: All (225) papers were completely read, 71 papers excluded.*	154
5	*Snowball search: 26 papers added; final sample obtained.*	180

Figure B.3 shows the number of papers that addressed multi-channel distribution systems published per year[2]. It can be seen that the number of published papers followed an increasing trend over the years. Figure 4 shows in which peer-reviewed academic journals the sampled papers were published. From the 61 journals contained in our sample, only six journals, namely the *International Journal of Production Economics* (25), the *European Journal of Operational Research* (20), the *Journal of Cleaner Production* (12), the *International Journal of Production Research* (11), *Computers & Industrial Engineering* (9), and *Applied Mathematical Modelling* (7), account for more than 50 % of the sampled papers. To improve readability, journals (48) that published only one or two of the sampled papers are summarized in the category other. This category

[2] Note that the year 2020 was not included in Figure B.3 to avoid biasing the analysis, as only January and February 2020 were considered in the literature search.

includes, for example, *Management Science*, *Manufacturing & Service Operations Management*, and *Annals of Operations Research*.

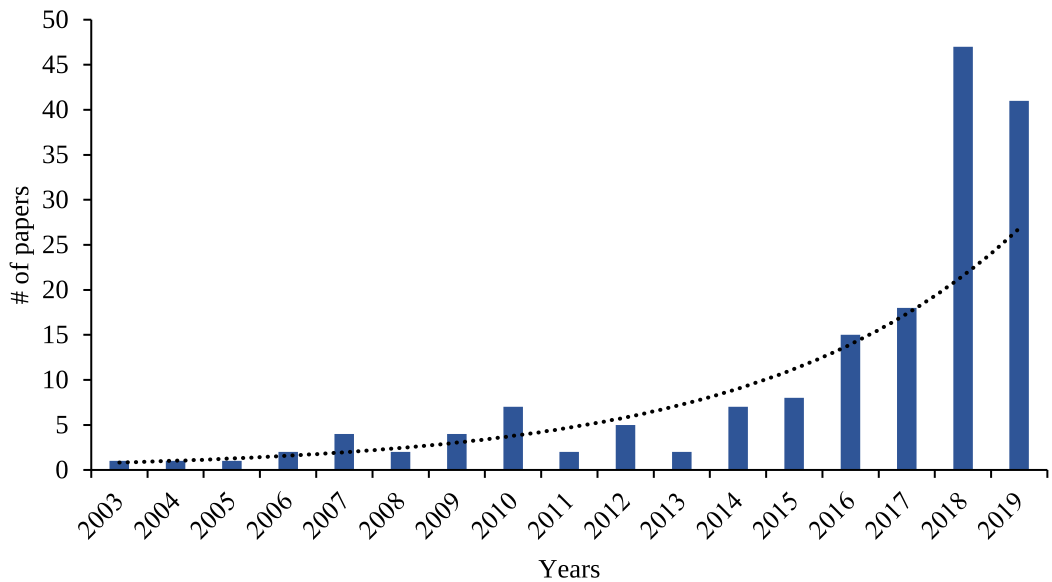
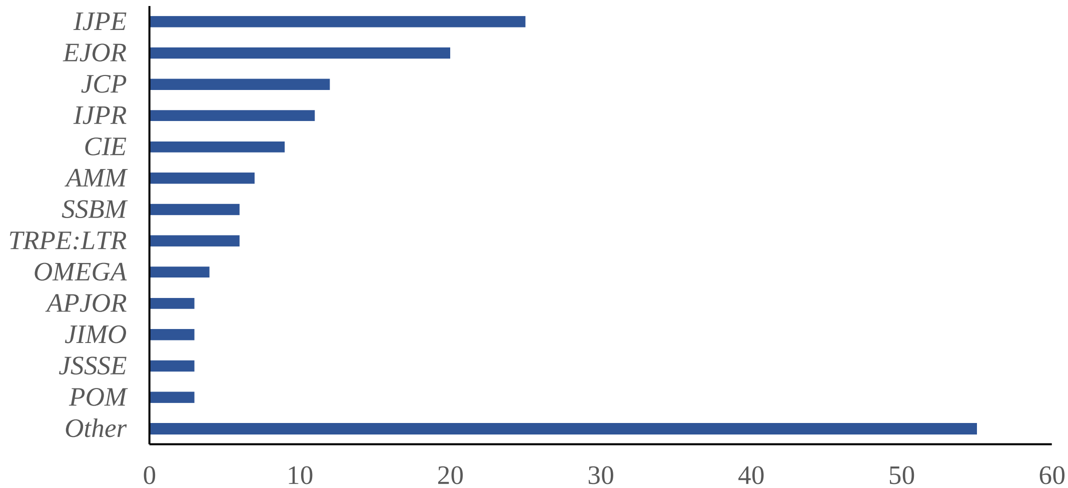


Figure B. 3. Number of sampled papers published per year



Notes: *IJPE- International Journal of Production Economics, EJOR - European Journal of Operational Research, JCP - Journal of Cleaner Production, IJPR - International Journal of Production Research, CIA - Computers & Industrial Engineering, AMM - Applied Mathematical Modelling, SSBM - Springer Science Business Media New York, APJOR - Asia-Pacific Journal of Operational Research, JIMO - Journal of Industrial and Management Optimization, JSSSE - Journal of Systems Science and Systems Engineering, POM - Production and Operations Management*

Figure B. 4. Journals that published the highest number of sampled papers

The following subsections discuss the literature sample and classify the sampled works in light of the proposed research questions. Note that to comply with the space restrictions imposed on this paper, only a selection of works that made, in the authors' opinion, the most important contributions to the research questions formulated above are discussed in the following sections. All sampled papers are considered in the descriptive statistics and the classification provided in the online Appendix (doi: 10.1016/j.ejor.2021.12.006), though.

B.4.2. Literature analysis

B.4.2.1. RQ 1: Which factors induce the manufacturer to establish a direct sales channel?

B.4.2.1.1. Customer preferences

The ultimate objective of a supply chain is to satisfy customer requests as good as possible. Therefore, customer channel preferences are one factor that a manufacturer should consider when opening a direct sales channel. Chiang et al. (2003) took account of this fact and studied the role of the customers' channel acceptance in the manufacturer's decision about the operation of a direct sales channel. Building on two empirical studies of Liang and Huang (1998) and Kacen et al. (2002), the authors incorporated a *customer acceptance index* θ for the direct sales channel (with $0 < \theta < 1$ implying low and $\theta > 1$ implying high customer acceptance) into the manufacturer's profit function. The authors focused on products that have a low acceptance for direct selling ($0 < \theta < 1$) and showed that the manufacturer can use the direct channel as a strategic tool: The fact that the direct channel could draw away customers from the retail channel induces the retailer to lower its price, which increases both the demand in the retail channel and the profit of the manufacturer. A second customer category may generally prefer online channels regardless of the product category. These customers are often referred to as *online-captive customers*, and they may be another reason for a manufacturer to open a direct channel. Chiang et al. (2005), for example, investigated the case where the manufacturer faces customers with a preference for an online channel. The authors incorporated a direct channel preference rate ($0 \leq \alpha \leq 1$) into their model and showed that the dual-channel dominates other channel options when α adopts a medium value. Chen et al. (2008) modeled service competition between a manufacturer and a retailer to examine channel structures (direct only, dual, and indirect only) the manufacturer could select. They assumed that product availability, delivery time, and shopping convenience influence customers' shopping behavior. The authors further assumed that there are two customer segments: time-sensitive and time-insensitive costumers who patronize retail and online channels, respectively. Depending on the customers' willingness to wait, the manufacturer determines the delivery lead time of the online channel. The study suggests that the manufacturer should sell all products through the direct channel if the cost of the direct channel is low and the manufacturer can implement a short delivery lead time. When the cost of the direct channel exceeds a certain threshold and the retailer inconvenience cost is high, the optimal strategy of the manufacturer is to employ both channels. Finally, when the direct channel is costly and the retailer's inconvenience cost is low, the manufacturer should still use the dual-channel, but share the profit with the retailer. To test their game-theoretic model, the authors conducted human-subject laboratory experiments. They verified the structural predictions of the model and showed that the model is capable to accurately predict the subjects' channel strategies in reaction to changes in the channel environment. Other researchers analyzed a hybrid customer segment in which customers are heterogeneous in their channel choice with some preferring a classical retail channel and others a direct sales channel. Khouja et al. (2010), for example, analyzed different combinations of distribution systems and assumed that consumers belong to one of two categories: *Retail-captive customers* prefer to buy from the retail channel only, and *hybrid segment consumers* may use either the retail or the direct channel. The authors showed that the number of consumers in the two segments, the consumers' channel preferences, and the unit product costs in the direct and retail channels are the major determinants of the channel selection decision. A similar model was proposed by Hsiao et al. (2013), who divided consumers into "*grocery*" and *"Internet"* shoppers according to the utility they obtain from the physical and the online channel. The authors used a channel preference parameter to calculate the gross utility of purchasing online, with the latter being the product of the channel preference parameter and the price the customer is willing to pay for a product. Depending on the gross utility of the consumers, the manufacturer either opens a direct channel or delegates the demand to the retailer. A case study by Du et al. (2018) also showed that customer channel preferences influence a manufacturer's decision to adopt a direct channel. The authors analyzed the Supor Group, a large Chinese manufacturing company, who had identified a potential price-sensitive customer segment patronizing over the Internet. The firm decided to serve these customers by offering products with a lower price and quality than those sold offline to these customers. Further related works are those of Yang et al. (2017) and Rodríguez and Aydın (2015), who developed models that consider customers that may switch between a retail and an online channel depending on the stock level of the channels. Both works investigated how consumer switching behavior influences the manufacturer's and the retailer's profits, and hence, channel choice, under optimal inventory and service level decisions. Chen (2015) argued that when the manufacturer invests in his brand, the demand of manufacturer (brand)-loyal customer's increases, which induces the manufacturer to sell items through his website especially if customers have a preference for the direct channel. The author showed that the direct channel outperforms the traditional retail channel in terms of profit, which increases as the brand loyal customers' preference parameter and the price elasticity of demand increase. Rofin and Mahanty (2018) compared the profits of three different dual-channel scenarios where a manufacturer either sells his brand products directly, through retailers or via e-tailers. The authors found that if the consumers' preference for an online channel is low, *company stores* combined with *e-tailers* are the best choice for the manufacturer, while in the case of a high online channel preference, traditional retail stores should be combined with a direct online channel. Finally, a few authors mentioned that some manufacturers offer low-carbon or remanufactured products through their direct channels to reach consumers with a preference for green distribution channels (Gan et al., 2017, Ji et al., 2016). Gan et al. (2017) investigated the case where the manufacturer transforms returned products into *"like-new"* products and vends them through his direct and a traditional retail channel. In determining the price of the product, the authors considered both the preference of the consumers for the direct channel and the remanufactured product's parameters. The results of the paper imply that introducing a direct channel improves the total profit of the supply chain.

B.4.2.1.2. Information asymmetry

In a supply chain, downstream members (retailers) usually have more information about demand than upstream members (manufacturers). From the manufacturer's perspective, incomplete information makes demand forecasting and capacity planning difficult (Xie et al., 2014). In the scenario studied by Zhao et al. (2018), the retailer has the option to share information on demand variability and forecast accuracy, but makes this dependent on the manufacturer's encroachment and three (i.e., zero, high and low) production cost scenarios. In case of no production cost, manufacturer encroachment makes the retailer better off, which induces her to share demand information with the manufacturer. Under high production cost and without manufacturer encroachment, sharing information hurts the retailer, whereas for low production cost, regardless of whether the manufacturer encroaches, sharing demand information always makes the retailer worse off.

To get direct access to customer demand information and to reduce the impact of demand variability on his profit, the manufacturer may open a direct channel. Cao et al. (2010) investigated the case where due to demand uncertainty for products with many design attributes, the manufacturer opens his own retail store to obtain direct information on the customers' product preferences. Several authors studied the influence of demand (market) uncertainty on opening a direct channel in the context of information asymmetry. Lei et al. (2014) addressed the manufacturer's channel choice strategy under horizontal (among the retailers) and vertical (with the manufacturer) information sharing of multiple retailers for the case of uncertain demand. The results of the study show that since vertical information sharing can lead to an increase in the wholesale price, the retailers have no incentive to share information unless being paid a fee by the manufacturer, who is always better off from vertical information sharing. Although horizontal information sharing benefits the retailers, the manufacturer's profit and channel choice decision are not affected regardless of whether the retailers share information among themselves. Furthermore, the authors showed that adopting a dual-channel strategy may pay off for the manufacturer even with uncertain demand if he can lower the direct sales price and if there is a favorable market condition. Similarly, Roy et al. (2016) studied the case where the manufacturer adds a direct channel to an incumbent retail channel to cope with market uncertainty. In a multi-channel distribution setting, the authors determined the optimal stock level, sales price, promotional effort, and service level for each channel. The results demonstrate that depending on the members' contribution to channel coordination (promotional effort and service level assurance), both may maximize their profits. Dumrongsiri et al. (2008) also argued that demand variability has a strong impact on the manufacturer's decision for opening an online channel. By considering consumer acceptance, demand variability, and channel service quality, the authors developed a game model to explore the manufacturer's dual-channel equilibrium. Their findings show that from the manufacturer's perspective, the dual-channel outperforms the single-channel when the retailer's marginal selling cost and service quality are high, and the wholesale price, consumer valuation of the product, and demand variability are low. In addition, the authors pointed out that adding a direct channel can increase the profit of the whole system when the channel members follow a centralized decision-maker and the consumers' service sensitivity is high. Further works that considered similar motives are those of Xie et al. (2014), Zhang et al. (2018), and Sun et al. (2019).

B.4.2.1.3. Market environment

Several authors pointed out that the market environment may also induce the manufacturer to open a direct sales channel in addition to an existing retail channel. The marketing literature addressed three main market environment characteristics in studies investigating distribution structures: *dynamism* (i.e., the volatility of a market), *complexity* (i.e., the number and diversity of the channel members, competitors, etc.), and *munificence* (i.e., the extent to which a company has access to available environmental resources) (Aldrich 1979, Achrol and Stern 1988). Kabadayi et al. (2007) investigated how multi-channel distribution systems influence the company's performance given alternative business strategies and market conditions. Evaluating data they had collected at 291 electronic component manufacturers, the authors showed that the firms benefit from adopting multi-channel systems if those structures are appropriately aligned both with the firm's business strategy and its environment. Firms following the cost leadership strategy use a single (or a few) and mostly indirect channels in uncertain environments. Firms following a differentiation strategy, in contrast, use a multi-channel strategy employing direct channels in highly uncertain environments. The work of Gabrielsson et al. (2002) also empirically examined alternative distribution channel strategies of four different PC companies (Fujitsu ICL, IBM, SNI, Compaq) that intended to increase their sales volumes in the Western European market. The results indicate that the companies adopted multiple channels in cases where the demand volatility and market diversity were high. Qiu-xiang et al. (2018) studied a dual-channel supply chain where the manufacturer aims at maximizing both his profit and market share, while the retailer is only interested in maximizing her profit. The authors investigated the stability region of the Nash equilibrium for alternative market sizes and customer loyalty values assuming that both actors are interested in a fair sharing of the overall profit. Li et al. (2019) found that to expand his market share and profit, the manufacturer may sell both online and through a retailer who vends a substitutable store brand in addition. Using a game-theoretic model, the authors analyzed three distribution scenarios of the manufacturer while considering the manufacturer's direct selling diseconomy and the retailer's store brand quality decisions: the case where only the retail channel is used (I), the case where only the direct channel is used (II), and the case where both channels are used (III). Their results reveal that in the first scenario, the manufacturer's national product may be removed from the market by the retailer as the store brand's quality increases. Furthermore, by opening a direct channel (scenario III), the manufacturer is better off if the direct selling diseconomy is low, whereas the retailer's profit decreases; this is the equilibrium strategy for both parties. Matsui (2016) showed that to expand the market share, distributing through a dual-channel may be promising for a manufacturer if the products are not substitutable. The author studied the case of two manufacturers with individual dual-channels who compete in distributing their products. The author developed a sequential price-setting game model and showed that in case of sufficient product differentiation, asymmetric distribution is the best response for the manufacturers, where one manufacturer uses only a direct channel, while the other employs a dual-channel. If product differentiation is low, both manufacturers may improve their profits if they only sell through retail channels and, hence, select a symmetric distribution strategy. Feng et al. (2019) investigated the case where the manufacturer implements a trade-in program (a used article is accepted by a retailer and the manufacturer in part-payment for a new one) through the online and the retail channel to stimulate market demand. Furthermore, to encourage the retailer to collect used products, the manufacturer can provide a subsidy to her. By considering old and new consumer segments, the authors analyzed optimal trade-in policies and pricing decisions in the dual-channel. The findings show that the trade-in program can reduce the double marginalization effect if the number of new consumers exceeds the old ones and the trade-in rebate offered by the retailer is less than the subsidy offered by the manufacturer.

B.4.2.1.4. Environmental concerns

Today's companies consider items returned from their customers more seriously, for example because of production's environmental impact, high prices of raw materials, or customer satisfaction. To improve responsiveness in terms of return/refund procedures, many manufacturers collect used products directly from end customers (Saha et al., 2016). In this respect, having a direct channel may lead to advantages as it facilitates directly collecting used items from customers. Therefore, some authors studied the manufacturer's direct channel decision in a closed-loop supply chain setting in the context of product returns. Saha et al. (2016), for example, analyzed three different reverse logistics scenarios (i.e., dual-channel closed-loop supply chain with third-party, retailer, and manufacturer collection) of a manufacturer who implements a reward-driven return policy to collect used products for remanufacturing. The authors explored how those collection options influence profits, product and transfer prices, and the reward value of used items. The results show that if the consumers are sensitive to the reward value paid by the manufacturer and the number of consumers preferring the direct channel is high, then collecting directly increases the manufacturer's profit and the remanufacturing rate. Similarly, Taleizadeh et al. (2018) developed a game-theoretic model for single-forward with dual-reverse (SD) and dual-forward with dual-reverse (DD) channel structures of a supply chain consisting of a manufacturer, a retailer, and a 3PL service provider. For these channel structures, the authors explored the optimal prices, quality levels, and sales and collection efforts, which are major drivers for introducing an online channel. The findings show that in a decentralized supply chain, the DD model benefits the manufacturer mostly, whereas, with coordination, all channel members can benefit from opening an online channel in a closed-loop supply chain. Batarfi et al. (2017) developed a mathematical model for a closed-loop supply chain where the manufacturer adopts an online channel for selling customized products and for collecting returns with different return policies. The main purpose of their study was to analyze how the pricing, returns, and inventory decisions affect the total profit before and after opening a dual-channel. The authors' findings show that adopting a more generous return policy (in terms of the proportion of the selling price refunded to a customer) increases the overall profit, such that the dual-channel strategy outperforms the single-channel strategy.

Other researchers pointed out further environmental aspects manufacturers of eco-friendly products have to consider when deciding on whether to sell them directly or via a retailer. Li et al. (2016), for example, proposed a game-theoretic model of a manufacturer producing a green product to compare the performance of a single-channel and a dual-channel in terms of profit. The authors showed that the total system profit increases as the greening cost declines and the sensitivity of the customer in the greenness of the product increases. The manufacturer was shown not to introduce a direct channel when the greening cost exceeds a certain threshold. Ji et al. (2016) explored the manufacturer's emission reduction in production and the retailer's promotion of low-carbon products for the case where cap-and-trade regulations exist and customers prefer low-carbon products. The authors found that if the low-carbon sensitivity coefficient of demand is high and a joint emission reduction strategy is implemented, both the manufacturer and the retailer may benefit from opening an online channel and from the cap-and-trade mechanism. Similar works are those of Yang et al. (2018a, 2018b), who investigated the manufacturer's channel selection and pricing strategy as well as optimal levels of carbon emission reduction under a cap-and-trade regulation. In the scenario considered by the authors, the manufacturer tends to sell non-perishable (low-emission) products online and perishable (high-emission) products through the retail channel. The authors showed that promoting products jointly and allowing larger carbon quotas (by the government) when the online channel preference of the customers is low can encourage the manufacturer to employ a dual-channel leading to an increase in profits of both parties. Barzinpour and Taki (2018) developed a network design model that aims to maximize the total supply chain profit by considering various transportation modes with different lead times, costs, and greenhouse gas emissions. The authors showed that the manufacturer has to consider a trade-off between costs and emissions for finding the optimal prices for the different channels to maximize total profit. The results reveal that opening a direct channel is profitable for both supply chain members. In the scenario studied by Cao et al. (2020), under remanufacturing subsidy and carbon tax policies promoted by the government, the manufacturer opens an online channel to sell only remanufactured products.

B.4.2.1.5. Manufacturer's preemptive strategy

The opening of a direct channel can also be a response of the manufacturer to activities of his competitors (e.g., the introduction of a new store brand or the forming of a retailer alliance against the manufacturer). Note that competitors may both be others manufacturers or independent retailers. Chen et al. (2018), for example, investigated the case where the retailer may launch a discount store to sell off-price products supplied by a different manufacturer. Depending on the channel setup cost, the manufacturer may open a direct channel to prevent the retailer from opening a discount store. The authors investigated how the opening of the direct channel and the discount store affects both parties' profits. They found that it can be beneficial to the manufacturer to introduce an online channel even at high costs, as this may accelerate competition, which prevents the retailer from selling off-price products at a reasonable price. In this case, launching a discount store will be too costly for the retailer, who thus decides against opening it. Several authors, such as Xu et al. (2014), Li et al. (2017), or Li et al. (2016b), accounted for risk behavior in their models. Li et al. (2016b) considered a manufacturer that is interested in opening an online channel and who faces a risk-averse retailer selling perishable products in an uncertain market environment. The authors found that when the retailer is more risk-averse, the retailer's sales price decreases, and the manufacturer's initial stock increases. Further, the results demonstrate that the retailer's risk aversion always makes both parties worse off and decreases channel efficiency. The manufacturer can, however, coordinate the dual-channel with the help of a risk-sharing contract. Zhang et al. (2018) proposed a sequential game model for a manufacturer who has the potential to encroach and a retailer who is dominant in the supply chain. In the retailer-led supply chain, the manufacturer is able to open a direct channel under sharing of both full and partial direct selling cost information with the retailer. The retailer, in turn, may implement a service improvement strategy to increase demand as an anti-encroachment strategy. The authors analyzed equilibrium results under different strategies (such as retail or no retail service with or without encroachment) to investigate the impact of the service investment strategy, information sharing, and encroachment on the manufacturer's consumer utility and the profit of the supply chain. The findings reveal that the retailer is always worse off when the manufacturer opens the direct channel, whereas the manufacturer benefits from encroachment if there is no retail service investment and the fixed setup cost for the online channel is not considered. Further, encroachment is expected to reduce the retail service level; the manufacturer, therefore, needs to evaluate the tradeoff between a loss in the retail service level and the competitive advantage gained from opening the direct channel. From the retailer's perspective, investing in retail services is an effective anti-encroachment strategy. Matsui (2016) considered two parallel manufacturers that introduce a direct online channel depending on the respective other's channel selection decision. Each manufacturer has three distribution policies: only retail (R), only direct (D), and dual-channel (RD). In the RD policy, two manufacturers sell differentiated products through both retail and direct channels, and both manufacturer-retailer chains compete with each other; this is referred to as inter-brand competition. Further, the manufacturers also compete with the retailers, referred to as intra-brand competition. By employing a Stackelberg duopoly and sequential price-setting game model, the author explored the equilibria for this competition. The results show that the optimal distribution strategy is an asymmetric distribution policy, where one manufacturer adopts a dual-channel and where the other one uses only a direct channel. As a major practical implication, the author proposed that the manufacturer should not implement the dual-channel strategy if his competitor has implemented such a channel already when products are not differentiated; instead, the manufacturer should use a direct channel only in this case. Otherwise, the symmetric distribution policy can intensify inter-brand competition leading to channel conflicts. Wang et al. (2016) investigated the case where two manufacturers sell complementary products through a common retail channel. Under consistent (direct online channel price is the same as the retailer's price) and inconsistent pricing, one simultaneous (Bertrand) and two sequential (Stackelberg) game models were developed to find optimal decisions for all parties. Depending on the pricing decision of the second manufacturer and the retail service on complementary products, the first manufacturer decides whether to open a direct channel or not. The authors pointed out that under a low retail service level, opening a direct online channel increases the profit of manufacturer 1 moderately under inconsistent pricing, but due to the emergence of a channel conflict, his demand decreases in the retail channel leading to a reduction in his profit. Further, the retailer should not increase the service level, which incurs additional service costs and entails a demand reduction.

B.4.2.1.6. Factors only addressed in empirical works

Our systematic literature search identified a set of empirical studies that could not be assigned to one of the dimensions discussed in Sections 4.2.1.1 to 4.2.1.5. These works are briefly discussed in this subsection.

To et al. (2006) developed a prediction model for the adoption of a direct online channel using the applied logistic regression technique. They hypothesized that both external (e.g., competitive pressure) and internal (e.g., technical resources) factors affect a manufacturer's decision to open a direct online channel. To test the model, they utilized a dataset obtained from the database of the Hong Kong government's Census and Statistics Department. The findings showed that *relative advantage* (i.e., a characteristic of innovation influencing its adoption, Rogers 1983) affects the adoption of the online channel positively. Since companies generally react to the actions taken by their competitors, the more *competitive pressure* a manufacturer faces in a market, the higher the probability of adding an online channel. The authors also reported that *technical resource* competence positively affects the likelihood of selecting an online channel. Grandon et al. (2004) explored the link between the strategic value of a direct channel and the adoption of the channel. The authors determined three independent variables as sources of strategic values, namely *operational support* (cost reduction, improving customer service level, etc.), *managerial productivity* (to facilitate the decision-making process, to unify information and improve access to information, etc.), and *strategic decision aids* (supporting of cooperative partnerships, information provision for strategic decisions, etc.). The adoption variables (dependent) include *organization readiness* (financial and technological resources), *external pressure*, *compatibility*, *perceived ease of use,* and *usefulness*. To collect data, the authors conducted an internet survey among managers/owners working at 100 small and medium enterprises in the US. The strategic factors, namely *perceived usefulness*, *perceived ease of use*, *compatibility,* and *external pressure* were statistically significant as determinants of online sales channel adoption. In particular, the *compatibility* of the company's culture, values, and preferred work practices with e-commerce was shown as an influential factor in the adoption of e-commerce. Gabrielsson et al. (2002) showed that the *manufacturer's dominance* and the *stage of the product life cycle* have an impact on the manufacturers' channel selection strategy. By examining four companies' channel design approaches, the authors suggested that when the manufacturer has relative power or is dominant in the chain, a dual-channel should be selected, and potential channel conflicts will likely be reduced. The authors claimed that at the *growth* and *maturity* stages of the product life cycle, manufacturers use dual-channels to reach all customer groups, whereas, in the *decline* stage, they use a hybrid or a direct channel because a low-cost channel is preferable during this stage. Note that in a hybrid sales channel, the marketing efforts are shared between the manufacturer and an intermediary, where the former's responsibilities are mainly promotion and gaining new customers, and the latter is responsible for selling and distribution activities.

B.4.2.2. RQ 2: How does the manufacturer manage multi-channel distribution systems?

B.4.2.2.1. Tactical level decisions

Channel conflicts play an important role in multi-channel distribution systems. They primarily emerge because of differences between the channel members' objectives (goal conflict), disagreements over the responsibilities in the channel (domain conflict), and differences in perceptions of the marketplace (perceptual conflict) (Coughlan et al., 2014). Conflicts that arise as a consequence of a manufacturer opening direct sales channels have been referred to as *multi-channel conflicts* in the literature (e.g., Du et al., 2018). Conflict management is an important instrument for the manufacturer to maintain the retailers' willingness to sell the manufacturer's products. The literature has proposed various coordination mechanisms the manufacturer can adopt to manage channel conflicts and to ensure coherence and consistency in the interaction with the retailer(s) (Osmonbekov et al, 2009). This section, therefore, explores possible measures the manufacturer could adopt to impede (or at least to soften) conflicts with the retailers.

B.4.2.2.1.1. Pricing

In a situation where the manufacturer encroaches, an inefficient pricing strategy may trigger conflicts between the parties. In many cases, researchers assumed that the manufacturer is the chain leader who sets the direct sales price before the retailer and who also has the power to determine the wholesale price. The major purpose of game models developed in this research stream is then to find an equilibrium between the manufacturer's and the retailer's pricing decisions. Note that most studies in this area assumed that the demand is a function of the product's price.

The work of Chiang et al. (2003) investigated a monopolist manufacturer and either a single or two (oligopolistic) retailers. The manufacturer was assumed the Stackelberg leader who sets the wholesale price and the direct market price. In the second phase of the game, the retailers define their optimal pricing strategy by taking into account the piecewise-linear demand that depends on the price and the customer acceptance rate. The authors argued that under certain conditions, an equilibrium can be reached where the manufacturer uses a direct channel to threaten the retailer that he may cannibalize the retailer's customers and to increase his profit indirectly. The strategic use of the direct channel stimulates the retailer to lower her price and boost sales. The findings further showed that when the customer acceptance of the direct channel is smaller than a cannibalistic threshold, adding a direct channel is not detrimental to the retailer. In the scenario investigated by Tsay and Agrawal (2004a), the retail channel and the direct channel demands depend on the sales efforts made by the manufacturer and the retailer. The manufacturer acts as the Stackelberg leader and sets both the wholesale price as well as the sales effort to maximize his profit. The retailer, in turn, maximizes her profit considering the given wholesale price and sales effort. The authors examined three different distribution strategies: retail channel only, direct channel only, and both. In contrast to conventional expectation, introducing a direct channel alongside a retail channel is not necessarily a threat for the retailer. Because the manufacturer reduces the wholesale price to preserve some of the retailer's selling efforts, this can lead to a win-win situation in some cases. Moreover, a reduction of the wholesale price can also prevent double marginalization and hence improve overall system efficiency. Cattani et al. (2006) investigated three pricing strategies that aimed to mitigate channel conflicts between a manufacturer (Stackelberg leader) and a retailer (follower). In contrast to the two works discussed above, the authors modeled the customer utility (that is a function of the price and purchase effort of the product) for the two channels separately and independently. After determining optimal wholesale and retail prices as a base case for a single channel, the authors examined three strategies for the dual-channel: In Strategy 1, the manufacturer keeps the wholesale price unchanged (compared to the base case), while the retailer can increase her price for customers closer to the retailer. If the cost of the direct (web) channel is low, then the manufacturer is better off with this strategy, while the retailer worsens her position. If Strategy 2 is selected, the retailer keeps the price stable and the manufacturer agrees to reduce the wholesale price. If the purchase effort of the web channel is high, then the manufacturer increases his profit in this scenario. Finally, if Strategy 3 is adopted, then the manufacturer optimizes his profit by adjusting the wholesale price. The manufacturer would, however, still ensure not to undercut the retail price. The findings of this study show that Strategy 3 outperforms the other two strategies. A similar model was proposed by Arya et al. (2007), in which the manufacturer establishes the wholesale price as the first mover. Afterwards, the retailer defines the optimal ordering quantity that maximizes her profit. The authors pointed out that the manufacturer can make both the retailer and the consumers better off if he reduces the wholesale price by a significant amount, and if the retailer provides retail services efficiently. Dumrongsiri et al. (2008) investigated the case where the optimal prices and quantities for both channels are determined in a Nash game. In this case, the manufacturer sets wholesale and direct prices while the retailer decides on both the price and stocking levels. Assuming stochastic demand, the authors showed that the manufacturer is better off with a dual-channel if the retailer's marginal cost is high and the wholesale price, consumer valuation, and demand variability are low. To explore equilibria for manufacturer-retailer competition, Cai et al. (2009) analyzed pricing strategies from manufacturer-Stackelberg, retailer-Stackelberg, and Nash game perspectives. By considering consumer channel preference parameters, the authors compared these models under consistent (i.e., the direct price equals the retail price) and inconsistent pricing scenarios and showed that with consistent pricing and a high consumer preference value, the supplier Stackelberg game outperforms the other two games. Hua et al. (2010) studied the manufacturer's pricing decision under a centralized and decentralized supply chain framework. In the centralized supply chain, the manufacturer determines the retail price, the direct sales price, and the lead time, while in a decentralized setting, the parties make optimal pricing decisions individually to maximize their own profits in a Stackelberg game. The authors further examined the influence of lead time and customer acceptance of the direct channel on optimal pricing decisions in both settings. They found that lead time has a strong impact on both parties' pricing policies and profits, and concluded that in both centralized and decentralized settings, the optimal lead time and prices (retailer, direct sale, and wholesale) converge as the customer acceptance of the direct channel increases. Huang et al. (2012) optimized pricing and production quantity decisions for both centralized and decentralized supply chain scenarios. The authors showed that in a centralized supply chain, the total profit is jointly concave in the direct sales price and in the retail price. Note that in a centralized dual-channel supply chain, the retailer and the manufacturer are vertically integrated, and the prices are determined by the central decision-maker. In a decentralized supply chain, the manufacturer is the Stackelberg leader and pricing depends on the customers' channel preference. In contrast to the above models, Xiong et al. (2012) introduced a two-period dual-channel model for a manufacturer selling durable products through an independent retailer and his own internet channel. The manufacturer enters the market in period 1 and the retailer withdraws from the retail channel in period

2. The authors employed a Stackelberg game where the manufacturer, as the leader, determines the wholesale price and where the retailer, as the follower, determines optimal sales and leasing values, depending on the direct channel selling cost. Finally, the manufacturer establishes the quantity of products to be sold via the direct channel. Their results showed that the direct selling cost is a key factor in determining the optimal strategy for both members. More specifically, when the direct selling cost decreases, the quantities sold in the direct channel increase, whereas the quantities sold over the retail channel decrease. Furthermore, consistent with Arya et al. (2007), the authors concluded that the manufacturer's encroachment can make both players better off. The work of Chiang et al. (2003) was later extended by Xu et al. (2012), who investigated the influence of the lead time on the manufacturer's pricing strategies. The authors investigated a scenario where the manufacturer reduces his direct prices if the customers are willing to accept late deliveries. To avoid that the retailer purchases via the direct channel as well, the manufacturer also reduces the wholesale price. To prevent cannibalization and to increase sales volumes, the retailer also lowers her price. In the equilibrium, both parties earn positive profits. Zhang et al. (2019) studied how the manufacturer's wholesale pricing decision and information sharing (i.e., one- and two-sided information sharing) affect the equilibria. The authors assumed that the manufacturer can set two types of wholesale prices: exogenous (i.e., the price is determined based on information about products in the same category and is therefore an input parameter) or endogenous (i.e., the price is set strategically and is hence a decision variable). The authors assumed that the manufacturer can invest into

product quality to increase the demand in both channels, but that the retailer cannot observe the investment. The results of numerical examples show that under a one-sided information sharing scenario, the manufacturer prefers not to set the price strategically when the exogenous price adopts moderate values. His preference increases with his information accuracy under one-sided information sharing, and it decreases under two-sided information sharing. The authors further pointed out that if the manufacturer has the power to set the wholesale price, he shares his information regardless of whether or not the retailer shares her information.

B.4.2.2.1.2. Coordination

To mitigate channel conflicts and to maintain sustainable manufacturer-retailer relationships, the supply chain members can utilize various contracts (Arshinder et al. 2008). The contracts mainly aim to improve overall supply chain performance in terms of a reduction of overstocking and understocking costs, increasing the total profit, and sharing risks among supply chain members (Tsay, 1999). For more information about supply chain coordination mechanisms, the reader is referred to Arshinder et al. (2008). Papers that proposed different contracts to facilitate coordination between the manufacturer and the retailer are discussed in this section. Xu et al. (2014), for example, proposed a *two-way revenue sharing* contract for a decentralized dual-channel supply chain where the objectives of both the manufacturer and the retailer are to increase their profits individually. This novel contract, where the manufacturer gets a fraction of the retailer's revenue and vice versa, consists of a traditional revenue sharing contract and a reverse revenue sharing contract.

Under a Stackelberg game model, the authors compared a *price-only* contract with the new *two-way revenue sharing* contract and found that the proposed contract led to a higher supply chain performance. Cao (2014) introduced an *improved revenue sharing* contract to coordinate manufacturer-retailer competition in a market with disrupted demand. Under demand disruptions and for the case where disruption does not occur, the author analyzed optimal pricing and quantity decisions of the supply chain members and showed that the proposed contract makes both the manufacturer and the retailer better off. Another *revenue sharing* contract was proposed by Xie et al. (2017, 2018) to coordinate manufacturer-retailer competition. Both works investigated the impact of the revenue sharing ratio on the direct, retail, and wholesale prices and the recycling rate in a closed-loop supply chain. The authors also employed *reverse revenue sharing*, where the manufacturer shares cost savings from remanufacturing with the retailer, which encourages the retailer to engage in remanufacturing, increasing supply chain profit. Chen et al. (2012) investigated three coordination methods in a decentralized supply chain where a manufacturer competes with a retailer. By means of a game-theoretic (Stackelberg) approach, the authors compared the optimal profits of the parties under the proposed contracts. The authors showed that a contract including *wholesale price* and *direct channel price* can coordinate a dual-channel supply chain, but that it generates an advantage only for the retailer. Moreover, also complementary contracts using a *two-part tariff* and a *negotiated profit sharing mechanism* were proposed. The findings show that both the manufacturer and the retailer are better off when the lump sum fee paid by the retailer (*two-part* *tariff*) and the retailer's shared profit (*negotiated profit sharing*) are within predetermined (lower and upper) ranges. Similarly, to manage conflicts between the manufacturer and the retailer, a t*wo-part tariff* contract was addressed by Zheng et al. (2017) and Zhang et al. (2018). In the case of Zheng et al. (2017), by including a *channel substitution rate* into the Stackelberg game model, the authors examined optimal decisions for a manufacturer-led, a retailer-led, and a collector-led dual-channel closed-loop supply chain. The results of the study show that depending on the *channel substitution rate*, the channel power structure has a strong impact on supply chain efficiency. The authors argued that in the decentralized model, the competition between the forward channels affects the entire supply chain negatively. Therefore, for different channel power structures, they implemented a *two-part tariff* to coordinate the channel in light of economic, social, and environmental objectives. In the scenario studied by Zhang et al. (2018), coordination was investigated under a dynamic pricing strategy for decentralized decisions. The authors also considered the service value offered by the retailer while finding equilibrium outcomes for the members. The results show that a higher service value does not always bring benefits to the retailer and the manufacturer in a decentralized situation. To achieve coordination, the authors proposed a *two-part tariff* which includes a fixed fee paid by the retailer to the manufacturer. The findings show that the fixed fee increases for a while as the service value increases, and then it declines. The optimal fixed fee can maximize both the manufacturer's and the retailer's profit. Shang et al. (2015) studied a *profit sharing* contract in a three-stage dual-channel supply chain consisting of a manufacturer, a distributor, and a retailer and assumed that the actors have different risk preferences and negotiation powers. The proposed *profit sharing* contract determines that the retailer pays a certain percentage of her profit to the distributor and that the distributor transfers a certain percentage of its own profit and the amount obtained from the retailer to the manufacturer. Under various risk preference scenarios (such as risk-averse retailer, risk-averse manufacturer, or risk-neutral distributor) and for different values of the negotiation power, the authors examined the selection of optimal profit sharing parameters. The results show that a member can obtain a higher portion of the extra profit and a higher compensation fee if he/she has a higher negotiation power. Furthermore, the channel members can increase their profit share by raising their risk-aversion degree. Jabarzare et al. (2019) investigated a non-cooperative and two cooperative game structures involving a manufacturer and a retailer. The retailer's investment in product quality was assumed to induce competition with the manufacturer. To coordinate the supply chain, the authors employed a *revenue* and a *profit sharing* contract and analyzed their effect on the profits of the parties. The results demonstrate that under the *revenue sharing* contract, the non-cooperative game can be beneficial if the customers are price-sensitive. For quality-seeking customers, in turn, cooperation between the manufacturer and the retailer makes all supply chain members better off if a *profit sharing* contract is employed. Chen et al. (2008) showed in a human-subject experiment in which they induced service competition between a manufacturer and a retailer that under certain conditions, *profit sharing* contracts make the manufacturer better off if he decides to use a dual-channel. The authors found that when the direct channel is too costly and the retailer's inconvenience cost is low, the manufacturer should use the dual-channel and share his profit with the retailer. Other authors studied *cost sharing* contracts for coordination. Zhou et al. (2018), for example, investigated a *cost sharing* contract in a dual-channel supply chain under different pricing and service strategies. In their case, the retailer offers pre-sale services to customers, leading to a situation where the manufacturer's online channel benefits from the retailer's efforts as well. The proposed contract ensures that the manufacturer takes over a share of the retailer's sales effort cost. The results show that under both differential and non-differential pricing strategies, the *cost sharing* contract encourages the retailer to improve her service level, and it may prevent price competition between the two channels. Raza et al. (2019) studied coordination between a manufacturer and a retailer where the manufacturer sells regular and green products through a direct and a retail channel. The authors developed a *cost sharing* contract where the retailer takes over a certain portion of the cost incurred by the manufacturer for producing the green product. Considering demand cannibalization (leakage), the authors examined the total profit of the supply chain for the case where both the manufacturer and the retailer are risk-averse. The results show that the demand leakage parameter has a negative impact on pricing, greening effort, and overall supply chain profitability. The findings further reveal that coordinating the supply chain with a *cost sharing* contract always outperforms decentralized decision-making where the supply chain members aim to maximize their profits independently. Y. Zhou et al. (2018) explored equilibrium strategies in a centralized and a decentralized dual-channel supply chain where customer demand is sensitive in emissions. In the decentralized supply chain, considering the consumers' brand and low-carbon preference, the manufacturer determines an optimal emission reduction effort as well as wholesale and direct sales prices, and then the retailer decides on his optimal advertisement effort and retail price. To achieve coordination, the authors simultaneously employed two contracts: a *cooperative advertising* and an *emission reduction cost sharing* contract. In the *cooperative advertising* contract, the manufacturer shares a part of the advertisement cost with the retailer, which helps to mitigate channel conflicts somewhat. The results of the study show that under high low-carbon and brand preference of consumers, implementing both contracts simultaneously is more efficient (e.g., the whole supply chain can achieve a Pareto optimum) than using the *cooperative advertising* contract alone. Another contract type studied by a few authors is a *quantity discount* contract. David and Adida (2015), for example, proposed this contract to coordinate the competition incurred among one manufacturer and multiple retailers. To determine the equilibrium solution for the decentralized case, the authors proposed a Stackelberg game model in which the manufacturer first sets the total wholesale quantity and the direct channel quantity, and then all retailers choose their quantities. The authors showed that increasing the number of retailers intensifies the competition between direct and indirect channels, which decreases the profit of each retailer. The authors proposed a *linear quantity discount* contract in which the discount per unit is a linear function of the order quantity of a retailer. By comparing the proposed contract with *revenue sharing* and *linear price discount* contracts, the authors pointed out that the *linear* *quantity discount* contract can perfectly coordinate the supply chain and that it increases the total supply chain profit; the retailers' profits, however, are lower than in the decentralized case without a contract. Considering that limitation of the contract, the authors suggested that the manufacturer can pay a fixed fee to the retailers to ensure that they continue operating, which makes all firms better off. A similar contract was examined by Modak et al. (2018), who intended to coordinate a decentralized dual-channel supply chain in which the stochastic demand depends on the selling prices (both for the online and offline channel) and online delivery time. To reduce double marginalization and to motivate the retailer, the manufacturer provides an all-unit *quantity discount* to the retailer and gets a *franchise fee* from the retailer. To this end, the authors derived the optimal discount and defined upper and lower bounds for the *franchise fee.* The results show that the supply chain benefits from the proposed hybrid mechanism as long as the expected profits of the channel members are at least as high as their expected profits in the decentralized setting. To alleviate channel conflicts between a manufacturer and a retailer, some works used *price discount* contracts. Cai et al. (2009), for example, introduced this contract to coordinate a dual-channel supply chain consisting of one manufacturer and one retailer. The authors developed three different game models (i.e., manufacturer-led Stackelberg, retailer-led Stackelberg, and Nash game) under consistent and inconsistent pricing. The results show that under consistent pricing, a member can obtain higher profits if he/she is the Stackelberg leader. Furthermore, in this case, the manufacturer-retailer competition was compared with and without a *price discount* contract in terms of profit. The authors pointed out that a simple *price discount* contract can coordinate the channel, increasing the manufacturer's and the retailer's performance. Saha et al. (2016) investigated a *price discount* contract to coordinate a multi-channel closed-loop supply chain consisting of a manufacturer, a retailer, and a third-party collector. First, for the case without cooperation, the authors analyzed the profit of each member under three different collection modes (i.e., direct collection, collection through the retailer, and collection via the third party collector). The findings indicate that the manufacturer and the retailer obtain maximum profits under their own collection mode. In contrast to that, collecting through the retailer maximizes the customer's utility compared with the other three collection modes. To coordinate the channel, the authors implemented a three-way *price discount* contract in which the manufacturer gives a discount on the wholesale price to stimulate the retailer to give a discount to the customer. To increase sales in the direct channel, the manufacturer provides a discount on the price of the direct channel as well. Finally, the manufacturer also gives a discount to the third party to enable it to pay a reward to the customer for product returns. The results of the study show that the proposed mechanism can coordinate the system perfectly and that all channel members benefit from the contract.

B.4.2.2.1.3. Information sharing

Effective communication among the channel members is another powerful tool to manage channel conflicts. Apart from improving the supply chain's performance (for example in terms of responsiveness), information sharing also facilitates coordination between the manufacturer and the retailer, in particular when the manufacturer owns a direct channel and thus competes with the retailer. Papers that studied various *information sharing* mechanisms are discussed in this section.

Yue et al. (2006), for example, investigated the effect of sharing demand forecast information on the performance of both channel members and the whole supply chain. In a Stackelberg game model, the manufacturer, as the game leader, sets the wholesale price, the direct sales price, and the production quantity, and the retailer responds to these decisions by setting the retail price. Note that both the manufacturer and the retailer use a demand forecast for their pricing decisions. Under two different production scenarios (*make to order-MTO* and *make to stock-MTS*), the authors analyzed the profits of the parties in case of *no information sharing* (in this case, by using their own forecasts, they make decisions individually to maximize their own profits) and *information sharing* (here, before making decisions, the parties share their forecasts). The authors found that under MTO, the manufacturer always benefits from information sharing, while the retailer and the whole supply chain are better off only if the manufacturer overestimates demand. In the MTS scenario, the manufacturer provides incentives to induce the retailer to share forecast information. The authors showed that information sharing can lead to a win-win situation in case of low and high forecast accuracy of the retailer and the manufacturer. M. Liu et al. (2016) proposed a game-theoretic model for a dual-channel supply chain with a risk-averse manufacturer and a risk-averse retailer. The manufacturer was assumed not to be informed about the retailer's degree of risk-aversion. If the retailer hides her information, the manufacturer may overestimate her degree of risk aversion, which enables the retailer to increase the retail price leading to a higher profit. If the manufacturer underestimates the retailer's degree of risk aversion instead, the retailer agrees to share her information with the manufacturer to avoid a reduction in her expected profit. The authors also showed that under a complete information scenario, the expected profits of the manufacturer and the entire supply chain are higher than in the case of asymmetric information. In the scenario studied by Yan et al. (2016), the retailer is the leader of the supply chain that consists of two manufacturers; only one manufacturer also has a direct channel in addition to the retail channel. First, the authors investigated the optimal pricing strategy utilizing a Stackelberg game in which the retailer initially sets the retail price markup, and then the manufacturers decide on the wholesale and the direct sales prices. The authors thereby assumed that the supply chain members have asymmetric information about the production cost. Hence, each manufacturer may correctly or incorrectly report his cost information. For various scenarios (e.g., manufacturer 1 correctly reports his cost, while manufacturer 2 exaggerates his cost, both exaggerate their costs, etc.), the authors examined the profits of the supply chain members. The results show that under *superior information* (i.e., the retailer cannot detect if the manufacturer misreports cost information) case, although the manufacturers benefit from exaggerating their costs (this increases the wholesale price), the retailer and the whole supply chain suffer from that strategy. Zhang et al. (2018) proposed a game model to find optimal decisions for members of a supply chain in which the manufacturer produces a product at a certain quality level and sells it both through a retailer and a direct channel. The authors explored the effects of various information structures on the profits of the supply chain members and product quality. The equilibria were investigated under *asymmetric information* (only the retailer knows the demand information and the manufacturer forecasts the market size according to the retailer's order quantity), *full information* (both have the information), and *no information* cases. The results reveal that setting a lower quality, *asymmetric information* enables the manufacturer to better offset the quality investment cost and the revenue obtained from the retail channel. Further, without considering the quality decision, the manufacturer is always better off in the *full information* case. The findings also show that both the manufacturer and the retailer can achieve win-win outcomes with information sharing if the manufacturer's direct sales cost is either very small or above a certain threshold value.

B.4.2.2.1.4. Other incentive schemes

From the manufacturer's perspective, introducing a direct channel does not necessarily aim to undermine his traditional retail channel. In some cases, the manufacturer accepts orders over his website, but the retailer fulfills the orders. Thus, both members of the chain benefit. This section investigates papers that study the manufacturer's initiatives to lower channel conflicts by diverting orders to the retailer and promoting/advertising products.

Tsay et al. (2004a) proposed the *referral to direct* and the *referral to reseller* mechanisms that direct the consumers to one of the channels to fulfill demand. In the first case, by displaying sample products, the retailer provides a showroom and supports customers ordering directly at the manufacturer. In return for her sales effort, the retailer receives a certain fraction of the selling price from the manufacturer. In the *referral to reseller* case, the retailer fulfills the entire demand, and the direct channel only provides sales activities such as information, advertisement, and other pre-sales services. The authors further examined the equilibrium for each scheme and showed that by implementing the proposed methods, both members are better off. Mechanisms as those theoretically investigated by Tsay et al. (2004a) can also be observed in practice. The Chinese manufacturing company Haier, for example, encountered conflicts with its retailers in the initial phase of selling directly (Du et al., 2018), as the retailers expected to lose their customers after some time. The manufacturer then agreed with the retailers that retail stores would also provide delivery and installation services for products sold online. A former third-party logistics provider was also replaced by the stores that now also take care of last-mile deliveries. Chen (2015) studied the effect of cooperative advertising on a dual-channel supply chain where the manufacturer sells a branded product both through a retail and a direct channel. The advertising mechanisms investigated by the author are *local advertising* and *national brand advertising* promoted by the retailer and the manufacturer, respectively. The author assumed that apart from increasing market share, the promotional activities may mitigate channel conflicts. Therefore, in the developed Stackelberg game model, the manufacturer aims to find optimal investments for promoting his brand, while the retailer's objective is to determine the optimal investment in local advertising of the brand product. Numerical studies showed that the profits of both members are sensitive to the level of local advertising, i.e., the national brand investment. Moreover, higher investments in advertising can increase the market share and profits of each member. Zhang et al. (2018) investigated the manufacturer's encroachment decision by presenting two advertising techniques; *informative* and *persuasive.* For both techniques, the authors analyzed three advertisement strategies by means of a game-theoretic approach, namely *manufacturer advertising (MA), retailer advertising (RA),* and *cooperative advertising (CA*), intending to maximize the individual profits of the channel members. The authors showed that in case the MA or CA strategies are implemented, both the manufacturer and the retailer benefit, while the manufacturer is worse off and the retailer is better off when only the retailer advertises (RA). Furthermore, the authors emphasized that under an effective advertisement strategy, retailers do not always suffer from manufacturer encroachment, specifically for industries where advertising is a vital tool to attract customers. Xie et al. (2017) studied cooperative advertising in a dual-channel closed-loop supply chain that uses a double revenue sharing contract. In this case, the manufacturer can remanufacture end-of-life products at a lower cost than producing new products; thus, he encourages the retailer to engage in recycling by sharing the remanufacturing cost savings. The advertisement investment is carried out by both the manufacturer and the retailer, and it aims on promoting the manufacturer's sales, in particular, to lay the ground for recycling in the future. The authors pointed out that cooperative advertising can contribute to reducing channel conflicts by increasing the total profit of the supply chain.

B.4.2.2.1.5. Product differentiation

Product differentiation and an associated brand strategy can also help to alleviate channel conflicts and support retailers in increasing their profits (Yan, 2011). The manufacturer can earn additional profits if he can sell products with different product characteristics, for example in terms of quality, environmental characteristics, or product complementarity, to different groups of customers. One of the first works on this topic is the one of Ha et al. (2016), who investigated the role of product quality in the manufacturer's encroachment decision. By considering two performance drivers, namely the manufacturer's cost for improving the quality of a product and the selling cost disadvantage of the online channel compared to the indirect channel, the authors analyzed the case of no encroachment, encroachment with the same product quality in both channels, and encroachment with quality differentiation. The authors showed that introducing a direct channel is beneficial to the manufacturer when the selling cost disadvantage of the online channel or the quality improvement cost is low. The retailer is always worse off if the manufacturer opens a direct sales channel, however. Jabarzare et al. (2019) also investigated the channel choice under product differentiation for the case of price- and quality-dependent demand and assumed that the manufacturer sells low-quality products directly and high-quality products via an independent retailer. The authors used competition-cooperation models to analyze the channel selection decision and showed that when the demand is quality-sensitive, then using a profit-sharing contract improves the position of both parties. Raza et al. (2019) modeled a situation where a manufacturer sells green products through retailers and nongreen products through an online channel at different prices. The authors proposed a model that supports the manufacturer in finding optimal wholesale, direct channel, and retail channel prices as well as an optimal investment for greening the product both for the case of a decentralized and centralized supply chain setting. The results demonstrate that offering products at different prices reduces demand leakage from one channel to another and increases revenues. To offer large assortments for certain products, an online channel can be an optimal choice for build-to-order manufacturers. For example, before purchasing, a customer can configure a Dell computer directly on the manufacturer's website (Rodríguez, et al. 2015). In this context, Batarfi et al. (2016) considered a manufacturer that can produce standard (make-to-stock) and customized (build-to-order) products. The authors developed an inventory control model for this scenario and assumed that the manufacturer offers customized products over the internet to meet the customers' individual preferences, and standard products via retail stores. The authors compared the performance of two-channel setups (single channel vs. dual-channel) by maximizing the total profit of the supply chain for both setups in the markup margin, the production/order quantity, and the number of shipments. In the scenario studied by Cao et al. (2010), two manufacturers have to decide about whether or not to open their own retail stores in addition to an independent retailer's channel, considering product substitution across channels, demand uncertainty, and the manufacturers' market shares. The results imply that for standard products with high substitution (e.g., food), the manufacturer benefits from selling through the indirect channel, also because these products have a low demand uncertainty. Products with more design attributes that cannot be substituted well (e.g., apparel goods), in contrast, should better be sold via a dual-channel. The authors argued that products with more design attributes may be subject to higher demand uncertainty which the manufacturer can better control if he has the chance to interact with customers (i.e., to understand their requests) directly through department stores. Another paper that falls into this category is the one of Li et al. (2018), who assumed that the manufacturer offers his national brand product both via a direct and a retail channel. In the retail channel, the retailer may sell store brands in addition to the manufacturer's brand. The authors considered different levels of online channel acceptance and different utilities the customers draw from the store brand product and developed a game-theoretic model to analyze the introduction of the direct channel and the store brand product. The results show that the manufacturer's channel selection strategy depends on the retailer's brand strategy and the degree of direct channel acceptance. That is, if the retailer does not introduce store brands and the channel acceptance rate is low, then there is no incentive for the manufacturer to open a direct channel; otherwise, he should introduce the direct online channel. Vinhas et al. (2005) analyzed go-to-market practices for 115 products produced by 11 eminent manufacturers. The authors found that *product differentiation* is a suitable instrument to mitigate destructive competition between a manufacturer and a retailer and to avoid customer losses and free riding. This is especially the case when a manufacturer sells over both an own and an independent channel in the same location than retailers and when he offers the same products. Du et al. (2018) empirically analyzed a situation where the similarity of online and offline products led to channel conflicts and a price war between manufacturers and retailers. Haier, a Chinese company producing white appliances, followed a differentiation strategy by offering customized products through its online channel and standard products through the offline (retail) channel. The implemented strategy made both the manufacturer and the stores better off and the revenue of the stores increased.

B.4.2.2.1.6. Mechanisms only addressed in empirical works

Similar to the case of RQ 1, a set of empirical studies could not be assigned to one of the mechanisms discussed in the above sections. These works are shortly discussed in this subsection.

As a conflict mitigation tool, Chen et al. (2011) proposed *label licensing*. In this case, stores or original equipment manufacturers (OEMs) permit contract manufacturers (CMs) to produce their brands by charging a license fee. The authors assumed that CMs may have difficulties entering the market and competing with well-known brands, even if they produce those brands for OEMs or large retailers. The authors analyzed the CMC Group, a worldwide optical storage media manufacturer based in Taiwan. As a contract manufacturer, CMC produces various types of products for both well-known retailers (Walmart, Staples) and original equipment manufacturers (HP, Philips) with their brands. To satisfy the unmet demand of a certain customer segment, CMC decided to develop an own brand and to sell both over retailers and directly. However, CMC encountered difficulties competing with eminent store brands in the same marketplace. The authors argued that if CMs have a low capability in marketing, it may be risky for them to develop an international brand and compete with dominant retailers. Instead, stronger collaboration with intermediaries enables the CMs to concentrate on their manufacturing competencies and gradually improve their branding experience via a label licensing strategy. Chung et al. (2012) explored factors that affect the relation of manufacturer-intermediary dyad after the manufacturer's encroachment. They analyzed the manufacturer's relational governance from transactional and functional reliance perspectives. The former indicates to which extent the manufacturer's revenues depend on the intermediary, whereas the latter one refers to how much the manufacturer depends on the intermediary's business performance, e.g. in terms of order processing or collecting customer feedback. The authors' findings show that a manufacturer's investment in intangible assets (e.g., training or operational coordination) of the intermediaries and well-developed end-customer relationships established by intermediaries increase the manufacturer's reliance on intermediaries. Furthermore, there is a positive relationship between the manufacturer's web transaction facility (online payment, order processing, and tracking) and transactional reliance on intermediaries; that is, the more robust the manufacturers' own web transaction facility, the more he relies on his intermediaries. In addition, as the manufacturer's market penetration and sales increase, he needs more complementary sales efforts (for example, pre-sales and post-sales services) of intermediaries.

B.4.2.2.2. Operational level decisions

From the manufacturer's perspective, managing multi-channel distribution systems introduces new and changes existing operational decision problems that have to be solved efficiently. The following subsections explore studies that discuss operations management issues in a multi-channel distribution setting.

B.4.2.2.2.1. Inventory control

Inventory control aims to manage stock in a way that ensures high customer service at a minimal cost. In multi-channel systems, inventory management is especially challenging as stock levels have to be coordinated between the different actors and channels involved, because demand information is often not available and has to be forecasted, and because product return rates are often high in multi-channel systems (especially for Internet channels). In this sub-section, we discuss studies that considered the optimization of inventory control decisions in multi-channel distribution settings.

Chiang et al. (2005), for instance, investigated a dual-channel inventory model in which stock is kept both at the manufacturer's warehouse and in the retailer's store to satisfy both direct (online) and regular retail demand. The authors assumed that the customers' arrival at the retail store and orders placed via the direct channel follow a Poisson distribution with constant intensity and that the replenishment lead times for both warehouses are independent exponential random variables. The authors also incorporated a so-called *retail-customer search rate* and a *direct-customer search rate* into the model to account for the fact that some retail/direct customers are willing to search for and purchase the product in the respective other channels when the product in the retail/direct store is out of stock. By developing a *Markov* model, the authors analyzed the channel performance in terms of long-term holding and lost sales costs. The results show that the dual-channel strategy reduces costs, especially when the number of customers of both channels is close to each other and the customer search rates (channel substitution) are low. Moreover, the findings suggest that increasing the customers' search rates does not always improve channel performance, but that it can increase the total inventory costs. Chiang et al.'s (2005) work was extended by Takahashi et al. (2011), who considered production and delivery setup costs in the proposed inventory control model in addition. In contrast to the *one-for-one inventory* policy studied, e.g., by Chiang et al. (2005), the proposed inventory policy does not release replenishment orders one by one, but instead always orders multiple units and continues with replenishments as the inventory reaches the maximum level. The authors pointed out that the proposed policy can decrease the total cost (consisting of holding, lost sales, production, and delivery setup costs) and reduce the number of setups at the expense of a small increase in the stocks at the warehouse and the retailer's store. Boyaci (2005) studied a multi-channel distribution system where stocking decisions are made according to base-stock policies at both the manufacturer and the retailer. The author investigated both vertical (in the form of double marginalization) and horizontal (in the form of product substitutability) competition between the two parties and determined equilibrium stocking levels. The results imply that both types of competition affect profits negatively. Further, higher substitution rates induce both channels to overstock, while higher double marginalization leads to overstocking in the manufacturer's direct channel and to understocking in the traditional retail channel. A number of studies addressed the joint optimization of inventory and pricing decisions in a multi-channel distribution setting. Roy et al. (2016), for example, developed a model that aims on finding optimal values for the order quantity, the sales prices of both channels, promotional effort, and the guaranteed service level (with the latter three affecting customer demand). The authors examined the profits of the channel members for three-channel configurations, namely a traditional retail channel, a direct online (or e-tail) channel, and a dual-channel. Numerical studies showed that joint optimization of promotional effort and service level, with the remaining variables being individually optimized, maximizes the dual-channel's profit. Further works that discussed inventory control decisions in the context of dual-channel supply chains are those of Hsieh et al. (2014), Jafari et al. (2016), and Batarfi et al. (2019).

B.4.2.2.2.2. Production planning

A number of scholars optimized the manufacturer's production decisions in the context of a dual-channel supply chain. Liu et al. (2010), for example, investigated the manufacturer's optimal production quantity and selling prices for both channels under stochastic demand and information asymmetry. The authors formulated the expected profits for the supply chain members for both centralized and decentralized systems. To coordinate the decentralized system, the authors proposed two contracts, namely a *single* and a *menu of contracts*. Employing a *principle agent* approach, the authors compared the decentralized system with the contracts to the centralized system and showed that from the manufacturer's perspective, the centralized system does not always outperform the decentralized system with a possible contract when the selling cost of the traditional retail channel is smaller than those of the centralized system. The results show that the manufacturer should implement a *menu of contracts* especially when the information uncertainty about demand in the traditional channel is high. Huang et al. (2012) developed a two-period pricing and production planning model for a dual-channel supply chain where the demand is disrupted during the planning period. In the first period, before demand occurs, the manufacturer determines the production quantity and sales prices. In the second period, after realizing the market demand, both production quantity and prices are adjusted to maximize the profit. The results show that in both centralized and decentralized settings, the optimal production plan is quite robust in terms of demand disruptions. That is, only when the demand disruption exceeds a certain threshold, the manufacturer changes the original production plan. Furthermore, if the manufacturer acts as a central decision-maker, it is always beneficial to adjust prices in response to a demand disruption. The authors also emphasized that in a decentralized system, the customers' preference for the direct channel and the scale of demand disruption influence the optimal pricing strategies of both chain members. In the scenario studied by Xie et al. (2014), the manufacturer has to plan his production capacity and allocate it to the channels in a multi-channel distribution system. To handle demand uncertainty, the authors proposed a two-stage solution procedure: In the first stage, the production capacity is optimized based on a contract menu provided by the manufacturer (that contains the capacity allocation and the payment for capacity reservation) and the retailer's shared demand information. In the second stage, the manufacturer employs a capacity reservation contract in which the manufacturer either charges or compensates the retailer for additional capacity requested or capacity shortages. The findings show that under decentralized decision making, the manufacturer can always improve both his own and the entire chain's profit with a capacity reservation contract.

B.4.2.2.2.3. Returns management

Both to achieve competitive advantages in the marketplace and to satisfy legal requirements, manufacturers offer return services to their customers. Especially manufacturers selling online encounter high return rates today (Abdulla et al., 2019). Handling returns, therefore, has become a key operational aspect for manufacturers. This section discusses studies that considered returns management in a multi-channel distribution setting.

Batarfi et al. (2017) examined how various return policies (with a full refund, partial refund, or no refund) affect a dual-channel supply chain. In their proposed framework, the manufacturer sells customized and refurbished (i.e., both standard and customized items sold at a lower price) products via his online channel, while the retailer only offers standard products. Used products are collected and refurbished by a 3PL service provider. The authors developed a profit maximization model in which customers are sensitive to prices and the return policy of the products. The results show that the dual-channel always outperforms the single-channel in terms of the total supply chain profit. The results also suggest that a more generous return policy and more repairable items returned increase both the manufacturer's and the system's profit. In a similar vein, Li et al. (2017) explored the strategic effect of different return policies (i.e., *full refund* in the direct channel-*D*, *full refund* in the retail channel-*I*, *full refund* in both channels-*B*, and *no refund* in both channels-*N*) on a dual-channel supply chain. By building two-stage Stackelberg game models, they analyzed the optimal pricing decisions and equilibrium profits of the members, and further discussed the return strategies from both the manufacturer's and the retailer's perspective. The results show that the manufacturer should utilize strategy *B* when the return rate is low and that otherwise, he should prefer policy *N*. From the retailer's perspective, for low return rates, the retailer benefits from the strategy *I*, and otherwise, she prefers strategy *D.* Gan et al. (2017) investigated a closed-loop multi-channel supply chain consisting of a manufacturer, a retailer, and a collector. In their case, the manufacturer sells a remanufactured product and the retailer a new product. Using a Stackelberg game, the authors compared a single-channel approach to a multi-channel approach considering two factors: the *customer's interest in remanufactured products* and the *customer's preference for buying the remanufactured product via a direct channel.* The results show that the multi-channel distribution strategy outperforms the single-channel strategy in terms of total supply chain profit. In particular, the supply chain can realize the highest profit when customers of expensive products are inclined to switch from new to remanufactured products. The findings also indicate that the lower the *acceptance of remanufactured products*, the higher the retail price, which lowers new product demand in the retail channel and the manufacturer's profit. A decline in *direct channel preference*, in turn, decreases the profit of both the manufacturer and the collector. Given these results, the authors suggested that the manufacturer should give customers incentives to return products and purchase remanufactured products through the direct channel to increase his profit.

B.4.2.2.2.4. Delivery management

An excellent distribution performance requires adequate delivery management. Empirical studies have shown that *delivery service quality* has a strong influence on the consumer's acceptance of the direct channel (Deveraj et al, 2002, Rohm and Swaminathan, 2004). A key measure of service quality is delivery lead time that has a notable effect on the customers' channel choice, demand, and loyalty (Hua et al., 2010). It is therefore not surprising that researchers also investigated the role of transportation cost and service in the context of multi-channel distribution operations. Hua et al. (2010), for example, analyzed the impact of delivery lead time and customer acceptance of the direct channel on the manufacturer's and retailer's pricing decisions in a dual-channel distribution system. By including a so-called *demand transfer ratio* that measures demand loss in the direct channel due to an increase in lead time or direct sales price, the authors developed a two-stage optimization technique and a Stackelberg game to find the optimal delivery lead time and prices. The results imply that in a centralized scenario, the manufacturer should increase the direct sales price if he shortens the quoted lead time, whereas the retailer should decrease the price only if customers are transferred to the retail channel. If customers are not transferred, the retailer should keep constant or increase the retail price. In a decentralized setting, if the manufacturer reduces the lead time, at the same he should increase the direct sales price, while the retailer should lower the retail price. Further, the authors discussed that the customer acceptance of the direct channel and product type have a strong impact on the lead time and pricing decision. They suggested that the customers' acceptance of the direct channel is usually low for products that necessitate extensive investigation (e.g., clothes, digital products). In this case, the manufacturer should equalize the wholesale and direct sales prices and substantially shorten the lead time, while the retailer should set the retail price higher or equal to the direct sales price. Products that can easily be inspected (e.g., CDs, books) usually have high customer acceptance of the direct channel. In this case, the retailer should undercut the retail price, while the manufacturer should increase the direct and wholesale prices as well as the lead time considerably. Xu et al. (2012) investigated the manufacturer's channel configuration strategy considering the *delivery standard of the direct channel* and the *customers' channel preference.* Using a two-stage Stackelberg game model, the authors determined the optimal *delivery lead time* for the direct channel and *prices* for both channel members. In the decentralized dual-channel, the *delivery lead time* should be shorter than in the centralized case. Similarly, Modak et al. (2018) studied the joint optimization of delivery lead time and prices in a dual-channel supply chain where the stochastic demand depends on the prices of both channels and the lead time of the online channel. The findings show that in the centralized case, the online sales price decreases if the online channel *lead time* increases. If the customers' online *lead time sensitivity* increases, longer online lead times push customers to the retail channel, which leverages the retailer's demand; the centralized system benefits from a higher turnover in the retail channel in this case. In the decentralized case, the retailer increases her price if the online delivery lead time increases, as the longer lead time pushes customers to the retail channel (and vice versa).

B.5. Discussion

B.5.1. Data analysis

This section descriptively evaluates the literature sample in light of the two research questions formulated earlier. To gain a better understanding of the existing literature on multi-channel distribution systems, we present an overview of the number of papers that investigated the different concepts and channel structures discussed in Section B.4. Based on these evaluations and our discussion of the sample, we present managerial implications and research opportunities in Sections B.5.1 and B.5.2, respectively.

Figure B.5 presents an overview of the number of papers classified in light of *RQ 1.* As can be seen, most of the sampled papers (49) considered *customer preferences* as a reason for introducing a direct channel, followed by *environmental concerns* (26) and *information asymmetry* (22). The drivers, *manufacturer's preemptive strategy* and *market environment* were considered as major factors in 14 and 12 works, respectively. Four empirical studies proposed further factors that did not match the identified dimension and therefore were discussed under *empirically specific factors.*

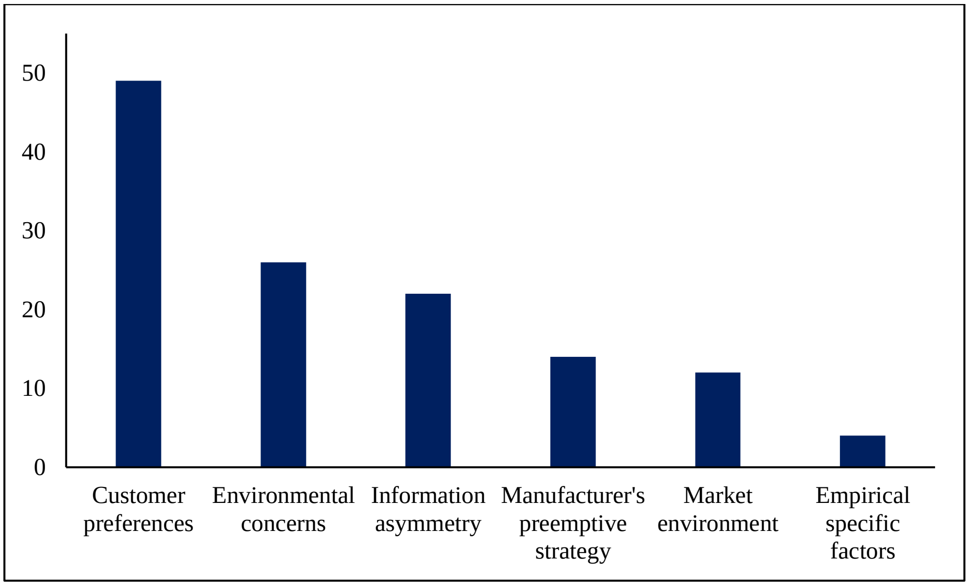


Figure B. 5. Number of papers per RQ 1 classification

Figure B.6 gives an overview of the mechanisms that were used to handle channel conflicts between the manufacturer and the retailer. To coordinate the dual-channel supply chain, researchers mainly studied *pricing* (99), *coordination with contracts* (58), *information sharing* (18), *incentive schemes* (14), and *empirically specific* (3) mechanisms. A number of studies (32) suggested *product differentiation* to avoid channel conflicts while the manufacturer encroaches into the retail market. In terms of contracts, most of the sampled papers studied *revenue sharing contracts* (16), followed by *cost sharing* (8), *price discount* (8), *profit sharing* (8), and *two-part tariff* (5) contracts. Other contract types, namely *franchise fee* (3), *quantity discount* (2), *buy-back* (2), *capacity reservation* (1), and *risk sharing* (1), have received limited attention so far.

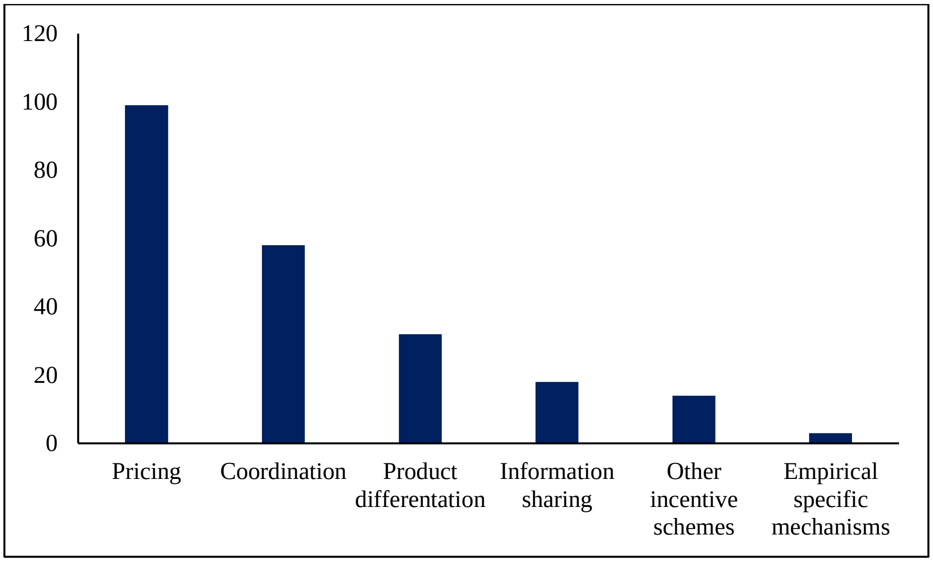


Figure B. 6. Numbers of papers per method of conflict management

Figure B.7 summarizes the operations management decisions considered in the literature sample. Altogether, the data presented here provides evidence that operations management issues have largely been overlooked in the literature on dual-channel supply chains so far. Most sampled papers investigated *returns management* (16), followed by *inventory management* (15) and *production planning* (13). *Delivery management* (7), *assortment management* (1), *order fulfillment* (1), and *location problems* (1) have received only a little attention so far.

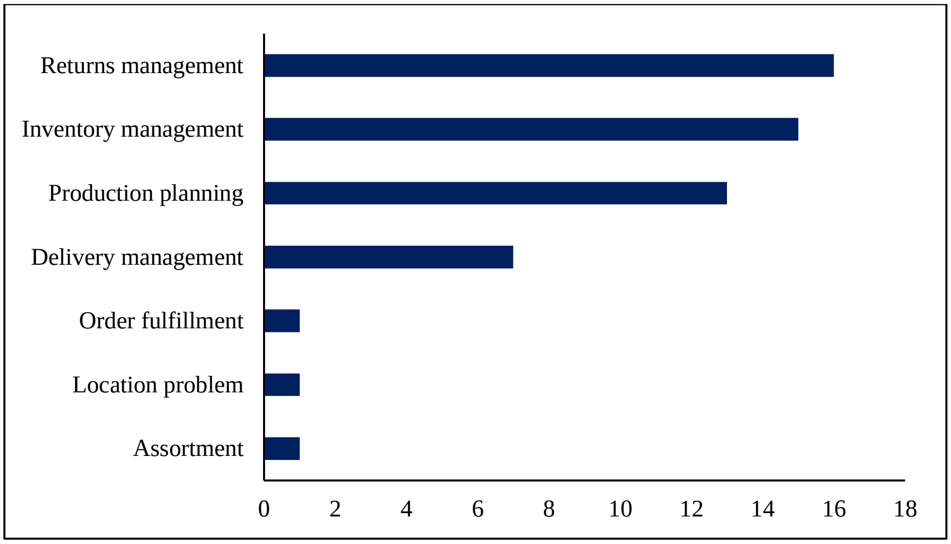


Figure B. 7. Number of papers per operational decisions

Note that our literature sample primarily (93 %) consists of analytical research that formulates models of manufacturer-retailer competition, where the manufacturer is often the dominant party. Only twelve empirical studies fall into our area of interest. As mentioned in Section 2, the dimensions also facilitate comparing analytical studies to empirical ones and evaluating how well theoretically discussed multi-channels decisions match those that can be found in practice. In this respect, Table B.3 introduces the extent to which analytical and empirical research integrate.

Table B. 3. Integration of empirical and analytical research

	Classifiers | Papers	Chen et al., 2011	Vinhas et al., 2005	Gabrielsson et al., 2002	To et al., 2006	Chung et al., 2012	Rosenzweig, 2009	Kabadayi et al., 2007	Grandon et al., 2004	Dubelaar et al., 2005	Du et al., 2018	Chen et al., 2008	Yu et al., 2018
RQ 1	*Customer preferences*		x							x	x	x	
	Information asymmetry												
	Market environment		x	x			x	x					x
	Environmental concerns												
	Manufacturer's preemptive strategy												
RQ 2	*Pricing*											x	
	Coordination						x				x	x	
	Information sharing	x					x						
	Incentive schemes		x								x		
	Product differentiation	x	x								x		
	Inventory control												
	Production planning												
	Returns management												
	Delivery management										x		

In terms of *RQ 1*, we note that analytical and empirical research are consistent with respect to two factors, namely *customer preferences* and *market environment.* The remaining three factors (i.e., *information asymmetry, environmental concerns, and manufacturer's preemptive strategy*) were only considered in analytical research. Mitigation tactics for channel conflict are the same both in analytical and empirical papers. With regard to operational level decisions, only *delivery management* was investigated in both research streams.

We also investigated the network configurations studied in the sampled papers. We found that the vast majority of studies (144) examined *two-tier* multi-channel distribution systems. This category was further divided into four sub-types (see Figure 8 in the online Appendix). While a considerable number of studies (122) focused on the *MD-R* (i.e., a single manufacturer distributing products directly (online, store or both) and through a retail channel) network design, less attention has been paid to the *MD-Rs* (10; a single manufacturer distributing products through direct (online, store or both) and multiple retail channels), *MsD-R* (10; multiple manufacturers selling products directly and through a common retailer) and *MsD-Rs* (3; multiple manufacturers distributing products both directly and through multiple retail channels) configurations. There are only six works that investigated multi-channel distribution systems with a *three-tier* network design. The closed-loop multi-channel distribution system (23) can be divided into four different designs. In most of the sampled papers, the manufacturer collects the returned items directly (9; *MD-R-M*), followed by works where the retailer (8; *MD-R-R*) or a third party is responsible for collecting the products (4; *MD-R-3PL*). Few attempts have been made to investigate dual-channel reverse logistics where the manufacturer handles the returns directly and through 3PL simultaneously (2; *MD-R-3PL&M*).

Descriptions of all related configurations and the papers investigating them are presented in the following figures (Figures B.8, B.9, and B.10).

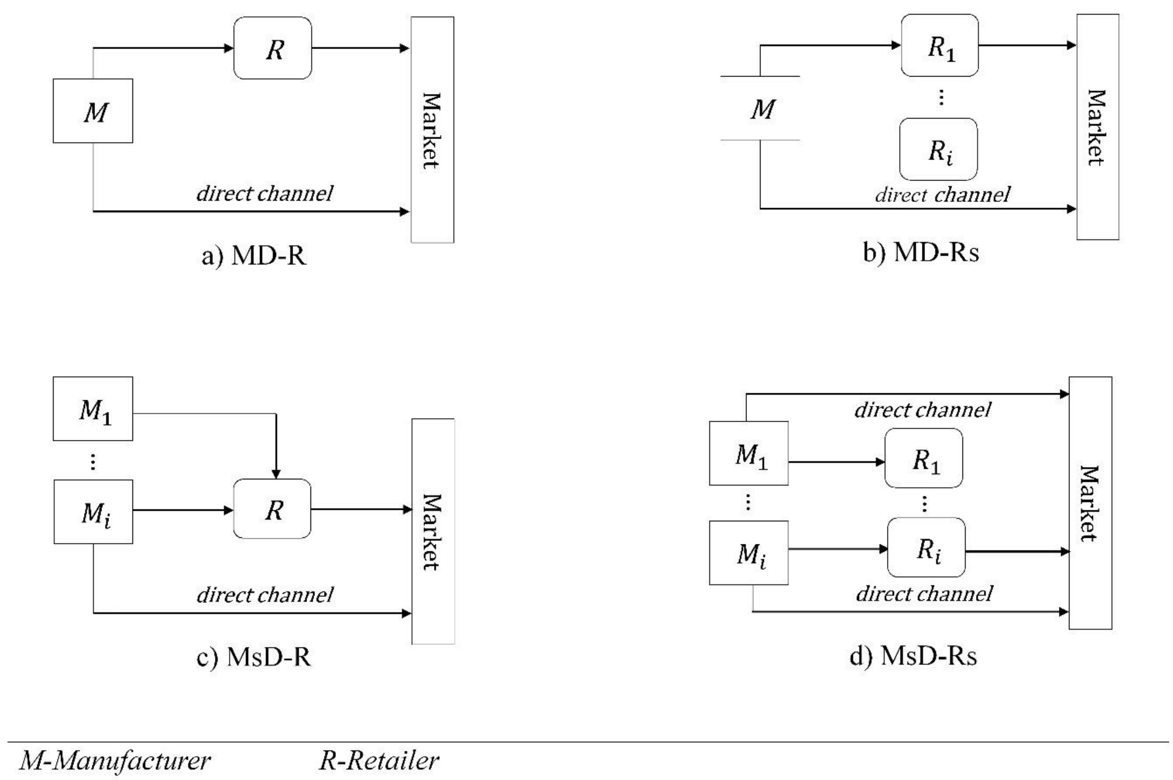
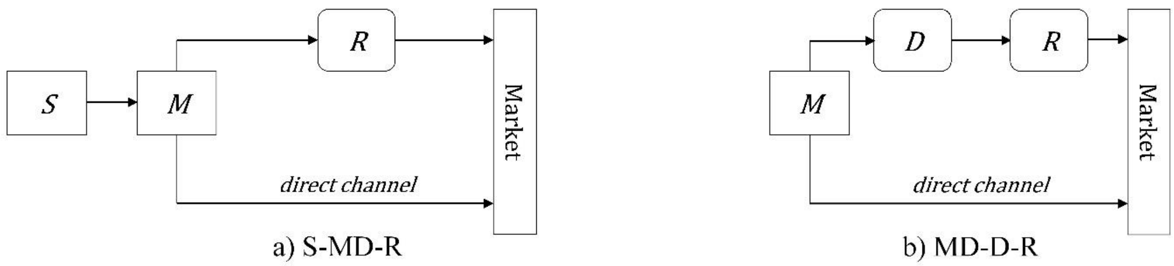
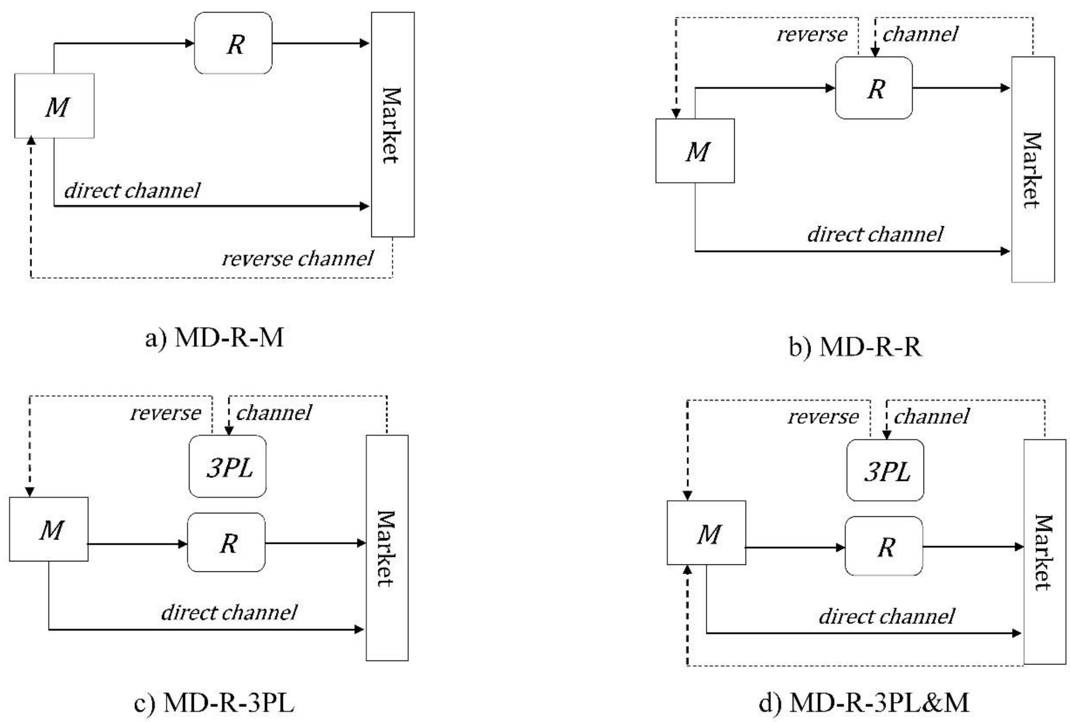


Figure B. 8. Configurations of two-tier multi-channel distribution systems



S- Supplier *M-Manufacturer* *R-Retailer* *D-Distributor*

Figure B. 9. Configurations of three-tier multi-channel distribution systems



M-Manufacturer *R-Retailer* *3PL- Third-party logistics provider*

Figure B. 10. Configurations of closed-loop multi-channel distribution system

Finally, to gain insights into the methods employed in the literature sample, we analyzed analytical and empirical works separately. The analytical works primarily utilized *game-theoretic models, mathematical programming,* and *heuristics.* Note that the vast majority (88 %) of the employed models were deterministic, while only few models were formulated under a stochastic environment. *Game-theoretic models* enjoyed the highest popularity in the sampled works (87 % of the sampled papers). Most authors used the *Stackelberg* (110) model, followed by *Nash equilibrium* (39) game models. These game-theoretic models vastly focused on pricing decisions, which is a critical factor for demand management and customer satisfaction both from the manufacturer's and the retailer's point of view. Apart from this, in a situation where the manufacturer encroaches, an inefficient pricing strategy may trigger conflicts between parties. In many cases, researchers assumed that the manufacturer is the chain leader who sets the direct sales price before the retailer and who also has the power to determine the wholesale price. Thus, the major purpose of the game models is to find an equilibrium between the manufacturer's and the retailer's pricing decision. In terms of *mathematical programming* models, non-linear programming (*NLP*) was used by ten studies; other modeling techniques received much less attention. Only eight authors used various *heuristics* (e.g., genetic, ant colony, etc.) to solve their proposed model. In many cases, the demand was expressed as a function of the product's price associated with own- and cross-price sensitivity parameters. Note that the demand function assumed in the sampled works is a key component of the objective function, and for this reason, we classified papers according to ten ($F1 \ldots F10$) different types of demand functions that were most frequently used in our literature sample. A table summarizing the modelling approaches used and the most important assumptions made about demand in the sampled works is provided in the Appendix B (Table B.7). In the empirical studies, data was collected in *case studies* (5), *surveys* (5), or *lab experiments* (1), or *secondary data* was collected and analyzed (1). For the case studies and surveys, mainly qualitative research methods (e.g., multiple levels of analysis (Yin 2009), theory building (Eisenhardt 1989a, p.533), a structured–pragmatic–situational (SPS) approach (Pan & Tan 2011)) and prediction models (e.g., regression, structural equation modeling, partial least squares, confirmatory factor analysis) were employed.

B.5.2. Managerial implications

The results of our study give guidance to manufacturers to improve channel design and operation in case they intend to add a direct channel to an extant retail channel. Our review outlined possible implications of opening a direct channel in light of our proposed conceptual framework.

Adding a direct sales channel requires strategic considerations, and it is, therefore, crucial for practitioners to understand the determinants of the channel selection decision as well as possible consequences. Our findings suggest that in the *pre-adoption* phase, managers should especially consider *customer preferences* and the *market environment*. The first factor refers to the extent to which customers prefer to purchase directly from a manufacturer. Especially when opening an online channel, manufacturers should incorporate the customer acceptance rate into the demand function along with the product's price (Chiang et al., 2003). In this regard, segmenting current and future potential customers could be of help to understand customer preferences and to adjust the channel design accordingly. A segmentation analyses could be conducted based on channel types (e.g., retail-captive vs. online-focused vs. hybrid segment customers), price (e.g., price-sensitive vs. quality-sensitive customers), or customer loyalty, for example. The second factor relates to dynamics of the market such as demand volatility, uncertainty, or potential market growth. Empirical evidence shows that manufacturers adopt multiple channels especially when market diversity and growth are high (Gabrielsson et al., 2002, Vinhas et al., 2005). A firm's business strategy and the market environment also play an important role in the channel design decision: firms following a cost leadership strategy should use a single and, in most cases, an indirect channel if the market environment is uncertain (Kabadayi et al., 2007); firms following a differentiation strategy should use a dual-channel if the products are not substitutable and the market has a potential growth (Matsui, 2016). Furthermore, managers should consider product-related factors if they are planning to offer over the internet. Product compatibility for online sales, for example, plays a critical role in the adoption of the direct channel. In fact, an efficient web-based sales channel predominantly depends on the offered product type (Dubelaar et al., 2005). Furthermore, with respect to the product life cycle, research has shown that companies should employ a dual-channel, especially during the growth stage to reach all customer segments. During the decline stage, they should switch from a dual- to a (low-cost) single or hybrid channel. The reason is that in this stage, prices decrease continuously, which makes it necessary to use a low-cost channel. Also, the manufacturer type is important when deciding whether or not to open a direct sales channel. Contract manufacturers, in particular, may have trouble entering the market with own brands and competing with well-known brands, even if this manufacturer produces brand products for OEMs or eminent retailers (Chen et al., 2011). From the perspective of the customer, multiple channels are usually better due to more options to choose from and due to a broader market coverage of the manufacturer (Vinhas et al., 2005). Customer-oriented manufacturers and those suffering from *information asymmetry* can use an online channel as a cost-effective communication tool and facilitator (To et al., 2006). Apart from this, manufacturers can draw additional advantages from a direct online channel, such as cost reductions, synchronization with an existing physical store, image improvement, customization, or improved operational efficiency.

Despite the various advantages we discussed above, adding a direct channel also causes managerial challenges which mainly result from the higher complexity of such distribution systems. In the *post-adoption* phase, managers need to develop new or modify existing decision support mechanisms to address these challenges. First, manufacturers should be aware that encroaching into the retail market increases competition and may reduce the retailer's trust in the manufacturer. In the long run, both could negatively affect the relationship between the manufacturer and the retailer and lead to channel conflicts. Conflicts become especially pressing when the manufacturer offers similar products similar or lower prices in the same market over the direct channel. Yet, channel intermediaries may preserve their importance because they enable manufacturers to reach out and serve end customers; manufacturers, therefore, often intend to continue working together with retailers instead of bypassing them. Furthermore, manufacturers may not want to lose an existing retailer if this retailer accounts for a huge share of his sales. Home Depot is an example in this context, which informed its manufacturers to terminate selling their goods online, as it would otherwise end the partnership (Greenberg, 2000).

The big question is how manufacturers can balance a direct and a conventional retail channel. Our findings suggest that the manufacturer can coordinate both channels using an appropriate *pricing* system or a *contract* (e.g., profit sharing, two-part tariff, or wholesale discount), which can increase the profits of both players. Another feasible conflict mitigation tactic is the *product differentiation* strategy. In this case, a manufacturer can either offer a different (e.g., customized) product or a similar product with lower quality and price via the direct channel. Various *incentive schemes* also facilitate ceasing channel conflicts. In an e-collaboration scenario, for example, the manufacturer may provide a system that clarifies order ownership (i.e., the manufacturer may define a rule, for example, that orders only from business customers will be processed through the direct channel. This signals a fair treatment to the retailer, who is still responsible for regular customers). Another example is the collaboration between Procter & Gamble and Walmart, who utilize an internet-supported technology to facilitate joint planning, for example with respect to inventory tracking, synchronization of demand planning, or order management. Manufacturers can refer customers to retailers or assign additional responsibilities to the retailers, such as installation or last-mile delivery, which may motivate the retailers due to additional sources of income. Other managerial challenges are related to operational level decisions. Today's competition forces manufacturers to become more responsive and to increase the value of services offered to their customers. As a result, new purchasing options such as "buy online, return in-store" or "buy online, pick up in-store", emerge. To achieve better operational efficiency, manufacturers have to make decisions in terms of inventory control or the collection of returns jointly with their retailers. A sound explanation of this could be that manufacturers are usually far away from the market, which means that they can communicate with customers via retailers. Last but not least, by investing, the manufacturers should improve IT infrastructures including bar code technologies, automatic inventory replenishment, electronic fund transfer systems, and the main competence of employees who can easily adapt to those kinds of transformations.

B.5.3. Research opportunities

The analyses in Sections B.4 and B.5.1 showed that a considerable body of research investigated multi-channel distribution systems. Although this topic has been explored widely, there still remain several opportunities for future research that we summarize in the following.

1. Considering new factors that influence customers' channel preference.

Starting with the work of Chiang et al. (2003), the sampled works assumed that the customers' channel preference, in particular their preference for the online channel, varies by product category. Obviously, the customer assesses some products as being more compatible for online shopping than others, and for such products, the customer's acceptance of the direct channel is high. We see, however, that other factors, such as *customer demographics (age, gender, education, etc.), learning and forgetting,* or *culture* can influence online buying behavior as well (Akman et al., 2014, Rahman et al., 2018), and therefore such aspects could be taken into account in future research as well.

2. Designing complex supply chain network flows.

The vast majority of the sampled papers investigated multi-channel distribution systems with two stages comprising one manufacturer and one retailer; only six papers studied a *three-tier* configuration. Considering the still increasing complexity of global supply chains, future work could study the performance of multi-channel supply chains consisting of a supplier, one or multiple manufacturers, one or multiple distributors, and multiple retailers. Today, some companies switch their distribution systems from multi-channel to omni-channel or hybrid channel systems (Verhoef et al., 2015). In contrast to dual-channels or concurrent channels, the omni-channel is often described as a cooperative channel strategy. Omni-channel distribution systems have, however, so far been investigated only from a retailer's perspective (Verhoef et al., 2015, He et al., 2019, Wei et al., 2020, Cui et al., 2021 and also see a commentary- *"Omni-channel from a manufacturer's perspective"* by Ailawadi, 2021). Therefore, further research is needed to gain insights into how omni-channel distribution systems affect the position of the manufacturer. Furthermore, a configuration in which the manufacturer vends products both through an online channel and brick-and-mortar stores directly has only infrequently been addressed, which may point towards research opportunities in this area. Our findings also show that reverse logistics has received little attention, and therefore multi-channel distribution systems with one or multiple return channels could be further explored in the future as well. More specifically, no study considered the simultaneous collection of returned items by a retailer and directly by the manufacturer or the simultaneous collection via a retailer and a 3PL service provider. Furthermore, apart from works that studied product differentiation, most of the sampled papers considered only a single product. In particular, the planning of product assortments (Rodríguez et al., 2015) and the distribution of customized products (Batarfi et al., 2016, 2019) have received only little attention. Therefore, future research should investigate how the production and distribution of multiple product types affect the performance of multi-channel distribution systems.

3. *Investigating new coordination mechanisms.*

To prevent channel conflicts and to balance the objectives of the different supply chain actors, a number of studies proposed different supply chain contracts. The types of contracts that have been investigated in the context of multi-channel distribution systems are quite limited, however, and do not reflect the plethora of contracts that have been discussed in the supply chain management literature. Therefore, future research could evaluate other contract types in multi-channel distribution systems, such as *transshipment, percentage markup pricing, subsidy,* or *two-part compensation commission* contracts. To improve coordination, joint decision making (i.e., joint planning, joint product development, joint product promotion, etc.) and the use of information technology for this purpose (e.g., EDI, RFID, ERP) could be addressed in future research.

4. *Analyzing new operational decisions in multi-channel distribution systems.*

Only a relatively small number of sampled works investigated operational decision problems in multi-channel distribution settings. In particular, *product assortment* (Rodríguez et al. 2015), *order fulfillment* (Nekoiemehr et al. 2019), and *location problems* (Gan et al. 2015) have received only limited attention (*1 paper each*). Surprisingly, no paper has studied *sourcing, warehouse operations, workforce management, production scheduling,* or *demand forecasting* functions in a multi-channel distribution context, which warrants further research in this area.

5. Need for more empirical research in this area.

Most of the sampled works (93 %) are analytical papers that formulate mathematical models mainly employing game-theoretic approaches. For single-channel settings, several papers empirically investigated manufacturer-retailer relationships (Kadiyali et al., 2000, Sharma et al., 2020) or the manufacturer's pricing strategy (Sudhir, 2001, Draganska et al., 2010), among others. Multi-channel settings have only infrequently been analyzed empirically so far, however. Future research could therefore conduct field experiments involving retailers and manufacturers to gain insights into the behaviors of both parties and to examine how well equilibria obtained from game-theoretic models reflect real-world retailer-manufacturer partnerships. Theoretically, manufacturers employing a dual-channel should not sell products online at lower prices than the manufacturer's retailers to avoid channel conflicts. It is, however, still to be examined whether or not these results hold in practice.

6. Investigating multi-channel distribution systems in a global supply chain environment.

Globalization and dynamic market environments have forced companies to adapt their business model to global market requirements. Most of the sampled works did not consider the specifics of global supply chains in their investigation of multi-channel distribution. Since most supply chains are global today, it is important to consider globalization factors in the design of distribution systems. For example, due to challenges in international transportation, companies are more vulnerable to disruptions if they source/deliver over great distances (Sheffi 2015). In addition, planning coordinating operations in a global context (e.g. in terms of forward and backward logistics issues or sales and operations planning) becomes more complex in a global supply chain setting. Therefore, future research should investigate how globalization affects the performance of companies in a multi-channel distribution context.

7. Investigating virtual products in a multi-channel context

This review focused on works that study the distribution of tangible products under various multi-channel supply chain configurations. Tangible products are still dominant in online buying (kindly refer to *E-commerce statistics for individuals (2020), Eurostat, online data code: isoc_ec_ibuy*), and a very substantial share of both the retail and the manufacturing industry focuses on tangible products (*E-Stats 2019:*

https://www.census.gov/programs-surveys/e-stats.html). In research on multi-channel distribution, the vast majority of studies investigates operations management methods for tangible products. However, the market for virtual products (e.g., informative content, mobile apps, music, etc.,) is growing rapidly and in practice, companies use different channels for vending such products. From a pure operational standpoint, the vending of virtual products and services in a multi-channel distribution system is easier, as, e.g., inventory control, the transportation of goods, and product return and refund issues do not play a role or are easier to manage. In contrast to this, the distribution of virtual products also has challenges, e.g., in terms of intellectual property rights, return and refund issues etc., that may also influence the channel design decision. Future research should therefore investigate how the distribution of virtual products affect the design and performance of multi-channel distribution systems.

8. Using more realistic modelling principles

Most problems formulated in the sampled papers were based on game-theoretic approaches, and here especially Stackelberg and Nash equilibrium models. In most of these models, a deterministic demand function was assumed that depends on a static price associated with own-price and cross-price sensitivity. The objective often was to investigate equilibria for single-period and single-product scenarios. Future research could investigate equilibria for the case of stochastic demand, dynamic prices and multiple periods to arrive at more realistic outcomes. For examining complex channel structures, simulation models could also be an interesting technique to ensure that modelling efforts remain tractable.

B.6. Conclusion

This study presented the results of a systematic literature review on multi-channel distribution systems. The distribution systems we addressed comprise one or multiple manufacturers who may operate direct physical and direct online distribution channels in addition to selling products via retailers.

All works (180) obtained during the literature search were evaluated in light of two research questions. The first research question (*RQ 1*) focused on factors that induce a manufacturer to open a direct channel and to compete with his independently-owned retailers. *RQ 1* addressed factors such as customer preferences, information asymmetry, environmental concerns, market environment, or preemption. The second research question (*RQ 2*) evaluated possible mechanisms that the manufacturer could adopt to cease emerging conflicts with the retailers and methods to handle operational decision problems.

The results of the review show that customer preferences for direct or online channels may vary by product category and purchasing attitude (i.e., there may be online- or retail-captive customers), and that customer preferences have a strong impact on the manufacturer's channel selection strategy. Most works in our literature sample studied two-tier supply chains in which a manufacturer distributes the products both directly and via a retailer; these structures are usually referred to as *dual-channel* supply chains. Our findings also showed that research on multi-channel distribution systems had a strong focus on developing and evaluating contracts to resolve channel conflicts; operational problems that occur in multi-channel distribution systems have received much less attention. Most works in our literature sample also developed game-theoretic models to find equilibria for the manufacturer and the retailer, especially in terms of prices, for various scenarios (e.g., considering product compatibility, customer preferences, or risk aversion). We identified several research gaps future research could try to close, namely 1) considering new factors that influence customers' channel preference, 2) designing more complex supply chain networks, 3) investigating new coordination mechanisms, 4) analyzing new operational decisions in multi-channel distribution systems, 5) conducting new empirical studies, 6) investigating multi-channel distribution systems in a global supply chain environment, 7) investigating virtual products in a multi-channel context, and 8) using more realistic modelling principles.

This review could help the academic community to better understand the state-of-research on multi-channel distribution systems, and it is supposed to stimulate further research in this area. Our work also aims to give insights to practitioners in terms of strategic and operational decision-making in multi-channel distribution systems.

The work at hand has some limitations. Since we used the scholarly databases Business Source Premier (via EBSCO Host) and Scopus for searching for relevant literature, we may have missed works that are not registered in these databases. Moreover, the review was limited to articles published in English and in peer-reviewed journals. Other sources, such as books or conference proceedings, could contain relevant works as well. Future research could address these limitations to extend the scope of this review.

Appendix B

Table B. 4 Papers classified according to RQ 1

Classification	Articles
Customer preferences (49)	Aslani et al. (2019), B. Li et al. (2016a)*, B. Li et al. (2016b)*, Barzinpour et al. (2018)*, Batarfi et al. (2016), Bernstein et al. (2009), C. Liu et al. (2019), Chiang et al. (2003), Chiang et al. (2005), Dai et al. (2019), Dan et al. (2012), Fakhrzad et al. (2018), Feng et al. (2019)*, Gan et al. (2017), H. Xu et al. (2012), Hsiao et al. (2014), Hua et al. (2010), Huang et al. (2012), J. Chen et al. (2012), J. Xu et al. (2018), J. Zhao et al. (2017), J.Q. Yang et al. (2017), Ji et al. (2017)*, Khouja et al. (2010), Kumar et al. (2006), L. Xu et al. (2018)*, L. Yang et al. (2018b)*, Modak et al. (2019), Perlman et al. (2019), Pu et al. (2017), Q. Li et al. (2019)*, Q. Zhao et al. (2017), Rahmani et al. (2019), Rodríguez et al. (2015), Rofin et al. (2018), S. Zhang et al. (2018)*, Saha et al. (2016)*, Takahashi et al. (2011), Taleizadeh (2018), T-H. Chen (2015), W. Wang et al. (2016), W-G. Zhang et al. (2017), X. Chen et al. (2017), X. Wang et al. (2018)*, Zhou et al. (2018), Vinhas et al. (2005), Dubelaar et al. (2005), Du et al. (2018), Chen et al. (2008)
Environmental concern (26)	L. Xu et al. (2018)*, Z. Zhang et al. (2019), Saha et al. (2016)*, Zheng et al. (2017), Giri et al. (2017), Barzinpour et al. (2018)*, Feng et al. (2019)*, Ji et al. (2017)*, Xie et al. (2017), Batarfi et al. (2017), Taleizadeh et al. (2018), Xie et al. (2018), Javadi et al. (2019), L. Feng et al. (2019), Karimabadi et al. (2019), Qi et al. (2018), Ji et al. (2018), B. Li et al. (2016a)*, L. Yang et al. (2018c), L. Yang et al. (2018b)*, G. Li et al. (2019a), Q. Li et al. (2019)*, B. Li et al. (2019), R. Zhang et al. (2019), C. Yu et al. (2019), X. Wang et al. (2018)*
Information asymmetry (22)	R. Yan et al. (2010), Y. Zhang et al. (2018), Yue et al. (2006), Dumrongsiri et al. (2008), Cao et al. (2013), Lei et al. (2014), Li et al. (2017)*, Roy et al. (2016), Cao et al. (2010), Xie et al. (2014), Huang et al. (2018), Qiu et al. (2018), Fang et al. (2019), Sun et al. (2019), Zhao et al. (2018), B.Yan et al. (2016), B. Li et al. (2016b)*, P. Chen et al. (2017)*, Bin Liu et al. (2010), Q. Zhang et al. (2019), H. Liu et al. (2014), J.X. Zhang et al. (2019)

Manufacturer's preemptive strategy (14)	B. Li et al. (2016b)*, B. Li et al. (2019), Chai et al. (2019), G. Xu et al. (2014), J. Chen et al. (2018), L. Wang et al. (2016), Li et al. (2017)*, Matsui (2016)*, P. Chen et al. (2017)*, Raza et al. (2019), S. Yang et al. (2015), S. Zhang et al. (2018)*, Tu et al. (2019), Z. Liu et al. (2018)
Market environment (12)	C. Wang et al. (2018), Matsui (2016)*, Jafari et al. (2016), L. Feng et al. (2019), Lee et al. (2019), Qiu-Xiang et al. (2018), G. Li et al. (2019b), Vinhas et al. (2005), Gabrielsson et al. (2002), Rosenzweig (2009), Kabadayi et al. (2007), Yu et al. (2018)

Note: *Papers that fall into more than one category were highlighted with an asterisk.*

Table B. 5. Papers classified by RQ 2

Conflict mitigation tactics		Articles
Coordination with contracts (58)	Revenue sharing (16)	Cai (2010)*, Cao (2014), Chai et al. (2019)*, G. Xu et al. (2014)*, Gamchi et al. (2018), Geng et al. (2007), Kundu (2018), L. Xu et al. (2018), Moon et al. (2018), P. Chen et al. (2017), Raza et al. (2019)*, Ryan et al. (2013)*, Tang et al. (2018b), T-H. Chen (2015), Xie et al. (2017), Xie et al. (2018), Rosenzweig (2009), Du et al. (2018)
	Cost sharing (8)	C. Yu et al. (2019), Fakhrzad et al. (2018), Kundu (2018), Pu et al. (2017), Raza et al. (2019)*, Xie et al. (2018), Y-W. Zhou et al. (2018), Zhou et al. (2018)
	Price discount (8)	Cai et al. (2008)*, Hsieh et al. (2014)*, J. Xu et al. (2018), Qi et al. (2018), Saha et al. (2016), Saha et al. (2018)*, Xie et al. (2014),Y. Zhang et al. (2018)
	Profit sharing (8)	Feng et al. (2019), J. Chen et al. (2012), Jabarzare et al. (2019), R. Yan (2008), Ranjan et al. (2019), Shang et al. (2015), Yan (2011), Chen et al. (2008)
	Two-part tariff (5)	B. Li et al. (2019), F. Zhang et al. (2018)*, J. Chen et al. (2012), Taleizadeh (2018), Zheng et al. (2017)
	Franchise fee (3)	Geng et al. (2007), Modak et al. (2019)*, Y. Yan et al. (2018)
	Quantity discount (2)	David et al. (2014), Modak et al. (2019)*
	Reverse revenue sharing (2)	Cai (2010)*, Geng et al. (2007)
	Buy-back (2)	Hsieh et al. (2014)*, Ji et al. (2018)
	Capacity reservation (1)	Xie et al. (2014)
	Risk sharing (1)	B. Li et al. (2016b)*
		Amrouche et al. (2020), Chen et al. (2008), Chiang et al. (2003), Dumrongsiri et al. (2008), Cai et al. (2008)*, Cattani et al. (2006), H. Xu et al. (2012), Huang et al. (2012), Ryan et al. (2013)*, G. Xu et al. (2014)*, Matsui (2016), B.Yan et al. (2016), Roy et al. (2016)*, Soleimani at al. (2016), Xiao et al. (2016), Jafari et al.

Pricing (100)	(2016), B. Li et al. (2016a), B. Li et al. (2016b)*, Jamali et al. (2018)*, J.X. Chen et al. (2017), Giri et al. (2017), H. Liu et al. (2017), Barzinpour et al. (2018), Rofin et al. (2018), Feng et al. (2019)*, L. Yang et al. (2018c), Saha et al. (2018)*, Modak et al. (2019)*, G. Li et al. (2019), L. Wang et al. (2019), Rahmani et al. (2019), Khouja et al. (2010), Bin Liu et al. (2010), Hua et al. (2010), Hsieh et al. (2014)*, T-H. Chen (2015), Rodríguez et al. (2015), W. Wang et al. (2016), Q-H. Li et al. (2016), Ding et al. (2016), M. Liu et al. (2016), Ji et al. (2017), L. Wang et al. (2017), Gan et al. (2017), J. Zhao et al. (2017), Matsui (2017), Q. Zhao et al. (2017), J. Xu et al. (2018), F. Zhang et al. (2018)*, Heydari et al. (2018), Liang et al. (2018), Y-W. Zhou et al. (2018), Taleizadeh et al. (2018), C. Wang et al. (2018), J. Chen et al. (2018), Kundu (2018), Z. Liu et al. (2018), Javadi et al. (2019), G. Li et al. (2019a), Tu et al. (2019), Q. Zhang et al. (2019), Q. Li et al. (2019), Aslani et al. (2019), Ranjan et al. (2019), B. Li et al. (2019), Z. Li et al. (2019), Limin Wang et al. (2019), Jabarzare et al. (2019), Cao et al. (2019), Dai et al. (2019), Qin et al. (2019), C. Liu et al. (2019), Karimabadi et al. (2019), Chai et al. (2019)*, Raza et al. (2019)*, Perlman et al. (2019), C. Yu et al. (2019), Ke et al. (2018), Qi et al. (2018), Ji et al. (2018), X. Wang et al. (2018), Qiu-Xiang et al. (2018), Y. Zhou et al. (2018), Ma et al. (2018), T. Zhang et al. (2018), H. Liu et al. (2014), Bernstein et al. (2009), W-G. Zhang et al. (2017), Y. Yan et al. (2018), Glock et al. (2015), R. Yan et al. (2010), Tsay et al. (2004), Shi (2019), Xiong et al. (2012), B. Liu et al. (2019), Arya et al. (2007), Hsiao et al. (2014), Kumar et al. (2006), Y. Wang et al. (2009), Huang et al. (2009), Cai (2010)*
Product differentiation (32)	Albert et al. (2016), Barzinpour et al. (2018), Batarfi et al. (2016), Batarfi et al. (2019), C. Liu et al. (2019), Cao et al. (2010), Cao et al. (2019), Feng et al. (2019)*, Gan et al. (2017), H. Li et al. (2018), Heydari et al. (2018), Hsieh et al. (2014)*, J. Zhao et al. (2017), J.X. Chen et al. (2017), J.X. Chen et al. (2018), Jabarzare et al. (2019), Jamali et al. (2018)*, L. Wang et al. (2019), Liang et al. (2018), Limin Wang et al. (2019), R. Zhang et al. (2019), Ranjan et al. (2019), Raza et al. (2019)*, Rodríguez et al. (2015), Shi (2019), Tang et al. (2018a), Tu et al. (2019), W. Wang et al. (2016), Yan (2011), Chen et al. (2011), Vinhas et al. (2005), Du et al. (2018)
Information sharing (18)	B.Yan et al. (2016), Bin Liu et al. (2010), Cao et al. (2013), Zhao et al. (2018), Fang et al. (2019), Huang et al. (2018), J.X. Zhang et al. (2019), Lei et al. (2014), M. Liu et al. (2016), P. Chen et al. (2017), Q. Zhang et al. (2019), Qiu et al. (2018),

	R. Yan et al. (2010), S. Zhang et al. (2019), Sun et al. (2019), Yue et al. (2006), Chen et al. (2011), Rosenzweig (2009)
Incentive schemes (14)	A. Roy et al. (2016)*, Aslani, A et al. (2019), J. Xie et al. (2017), J. Zhang et al. (2018), L. Yang et al. (2018), L.Yang et al. (2018), S.Kundu. (2018), T-H. Chen (2015), Tsay and Agrawal (2004), Y. Zhou et al. (2018), Yu, C et al. (2019), Z. Liu et al. (2018)
Operational decisions	
Inventory control (15)	Batarfi et al. 2017*, Batarfi et al. 2019, Boyaci 2005, Chiang et al. 2005, Geng et al. 2007, Glock et al. 2015, Hsieh et al. 2014, J.Q. Yang et al. 2017, J.Q. Yang, et al. 2019, Jafari et al. 2016, Modak et al. 2019, Rodríguez et al. 2015, Roy et al. 2016, Takahashi et al. 2011, Z. Zhang et al. 2019
Production planning (13)	Batarfi et al. 2016, Batarfi et al. 2019*, Bin Liu et al. 2010, Cao et al. 2019, Yu et al. 2015, Huang et al. 2012, J.Q. Yang, et al. 2019, Liu et al. 2007, Rodríguez et al. 2015, Soleimani at al. 2016, Sun et al. 2019, Takahashi et al. 2011, Xie et al. 2014
Returns management (16)	Batarfi et al. 2017*, G. Li et al. 2019a, Gan et al. 2017, Giri et al. 2017, Javadi et al. 2019, Ji et al. 2018, Karimabadi et al. 2019, L. Yang et al. 2018c, Liang et al. 2018, Saha et al. 2016, Taleizadeh 2018, Taleizadeh et al. 2018, Xie et al. 2017, Xie et al. 2018, Z. Zhang et al. 2019, Zheng et al. 2017
Delivery management (7)	Barzinpour et al. 2018, H. Xu et al. 2012, Hua et al. 2010, J.Q. Yang et al. 2017, Modak et al. 2019, Nekoiemehr et al. 2019, Chen et al. (2018)

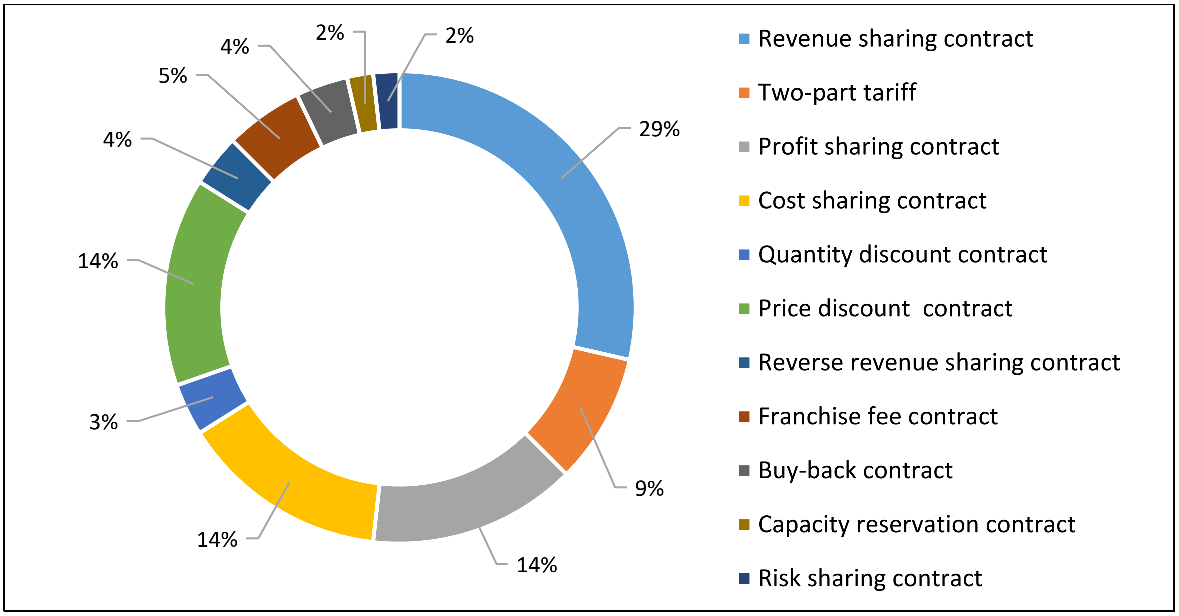


Figure B. 11. Percentage of works per contract types agreed between the manufacturer and the retailer

Table B. 6. Papers classified according to network configurations

Network configurations		**Articles**
Two-tier multi-channel supply chain	MD-R (122)	Amrouche et al. (2020), Albert et al. (2016), Arya et al. (2007), Aslani et al. (2019), B. Li et al. (2016a), B. Li et al. (2016b), B. Li et al. (2019), B. Liu et al. (2019), Barzinpour et al. (2018), Batarfi et al. (2016), Batarfi et al. (2019), Bernstein et al. (2009), Bin Liu et al. (2010) Bo et al. (2018), Boyaci (2005), C. Liu et al. (2019), C. Wang et al. (2018), C. Yu et al. (2019), Cai (2010), Cai et al. (2008), Cao (2014), Cao et al. (2013), Cao et al. (2019), Chiang (2010), Chiang et al. (2003), Chiang et al. (2005), Dai et al. (2019), Dan et al. (2018), Danetal (2012), Zhao et al. (2018), Ding et al. (2016), Dumrongsiri et al. (2008), F. Zhang et al. (2018), Fakhrzad et al. (2018), Fang et al. (2019), Feng et al. (2019), Feng et al. (2019), G. Li et al. (2019), G. Xu et al. (2014), Gamchi et al. (2018), Geng et al. (2007), H. Li et al. (2018), H. Liu et al. (2014), H. Xu et al. (2012), Hsiao et al. (2014), Hua et al. (2010), Huang et al. (2009), Huang et al. (2012), Huang et al. (2018), J. Chen et al. (2012), J. Xu et al. (2018), J.Q. Yang et al. (2017), J.Q. Yang, et al. (2019), J.Q. Zhang et al. (2018), J.X. Chen et al. (2017), J.X. Zhang et al. (2019), Jabarzare et al. (2019), Jafari et al. (2016), Ji et al. (2017), Ke et al. (2018), Khouja et al. (2010), Kumar et al. (2006), Kundu (2018), L. Xu et al. (2018), L. Yang et al. (2018a), L. Yang et al. (2018b), Lee et al. (2019), Li et al. (2017), Limin Wang et al. (2019), Liu et al. (2007), M. Liu et al. (2016), Matsui (2017), Modak et al. (2019), Moon et al. (2018), Nekoiemehr et al. (2019), P. Chen et al. (2017), Pu et al. (2017), Q. Li et al. (2018), Q. Li et al. (2019), Q. Zhang et

		al. (2019), Q. Zhao et al. (2017), Q-H. Li et al. (2016), Qi et al. (2018), Qin et al. (2019), Qiu et al. (2018), Qiu-Xiang et al. (2018), R. Yan (2008), R. Yan et al. (2010), R. Zhang et al. (2019), Rahmani et al. (2019), Ranjan et al. (2019), Raza et al. (2019)[*], Rodríguez et al. (2015), Rofin et al. (2018), Roy et al. (2016), Ryan et al. (2013), S. Zhang et al. (2019), Shi (2019), Soleimani at al. (2016), Sun et al. (2019), Takahashi et al. (2011), Tang et al. (2018a), Tang et al. (2018b), T-H. Chen (2015), Tsay et al. (2004), Tu et al. (2019), W. Wang et al. (2016), W. Yan et al. (2018), X. Chen et al. (2017), X. Wang et al. (2018), X. Yu et al. (2019), Xiao et al. (2016), Xiong et al. (2012), Y. Yan et al. (2018), Y. Zhou et al. (2018), Yan (2011), Yue et al. (2006), Y-W. Zhou et al. (2018), Z. Li et al. (2019), Zhou et al. (2018)
	MD-Rs (10)	Cao et al. (2010), David et al. (2014), Glock et al. (2015), H. Liu et al. (2017), Lei et al. (2014), Ma et al. (2018), W-G. Zhang et al. (2017), Y. Wang et al. (2009), Y. Zhang et al. (2018), Chiang et al. (2003)
	MsD-R (10)	B.Yan et al. (2016), Chai et al. (2019), G. Li et al. (2019b), Hsieh et al. (2014), J. Chen et al. (2018), J. Zhao et al. (2017), L. Wang et al. (2017), L. Wang et al. (2019), Perlman et al. (2019), T. Zhang et al. (2018)
	MsD-Rs (3)	Jamali et al. (2018), Matsui (2016), S. Yang et al. (2015)
Three-tier multi-channel supply chain	MD-D-R (5)	Yu et al. (2018), Heydari et al. (2018), J.X. Chen et al. (2018), Saha et al. (2018), Shang et al. (2015)
	S-MD-R (1)	F. Zhao et al. (2015)
Closed-loop multi-channel supply chain	MD-R-M (9)	G. Li et al. (2019a)[*], Javadi et al. (2019)[*], Ji et al. (2018), Karimabadi et al. (2019), L. Yang et al. (2018c), Liang et al. (2018), Saha et al. (2016)[*], Taleizadeh (2018)[*], Z. Zhang et al. (2019)
	MD-R-R (8)	Batarfi et al. (2017), G. Li et al. (2019a)[*], Javadi et al. (2019)[*], Ji et al. (2018), Liang et al. (2018), Saha et al. (2016)[*], Xie et al. (2017), Xie et al. (2018)
	MD-R-3PL (4)	Batarfi et al. (2017), Gan et al. (2017), Saha et al. (2016)[*], Zheng et al. (2017)

MD-R-3PL&M (2)	Giri et al. (2017), Taleizadeh et al. (2018)*

Note: *Papers that fall into more than one category were highlighted with an asterisk.*

Table B. 7. Analytical papers classified according to modelling methods

Methods					
Game theory		Mathematical programming		Heuristics	
Types					*# of papers*
Stackelberg game	110	Nonlinear programming	10	Problem-specific algorithm	6
Nash Equilibrium	39	Simulation	3	Genetic algorithm	2
Cooperative game	12	Queuing models	2	Multi-ant colony algorithm	1
Bertrand competition	4	Linear programming	1		
Bayesian Nash Equilibrium	3	Mixed integer linear programming	1		
Cournot competition	3	Multi-objective possiblistic LP	1		
Dynamic game	2				
Signaling game	2				
Collusion game	1				

Major decision variables					
Decision variables					*# of papers*
$\{p_r, p_d, w\}$	95	$\{I_r, I_m\}$	3	$\{p_r, p_d, w, q\}$	2
$\{p_r, p_d\}$	10	$\{p_r, p_d, w, e\}$	3	$\{O_r, O_d, w\}$	2
$\{p_r, p_d, O_r, O_d,\}$	9	$\{p_r, p_d, w, \tau\}$	2	$\{p_r, p_d, w, t\}$	2
$\{O_r, O_d\}$	5	$\{p_r, p_d, O_r, O_d, w, t\}$	2	$\{p_r, p_d, e, s_e\}$	1
$\{p_r, p_d, w, g\}$	5	$\{p_r, p_d, w, s_e\}$	2	$\{O_r, O_d, w, t\}$	1
$\{p_r, p_d, f, s_e\}$	4	$\{O_r, O_d, n\}$	2		
$\{p_r, p_d, O_r, O_d, w\}$	4	$\{p_r, p_d, O_r, O_d, n\}$	4		

Major assumptions on demand		
Demand function types for direct and retail channel	*Demand types (Deterministic vs. Stochastic)*	*Articles*
$\boldsymbol{F1}\ (\boldsymbol{A}, \boldsymbol{\alpha}, \boldsymbol{p}, \boldsymbol{b}, \boldsymbol{s})$ **(43)**	*Deterministic*	Yue et al. (2006), Cai et al. (2008),J. Chen

$D_d = \alpha A - b_d p_d + s_d p_r$ $D_r = (1-\alpha)A - b_r p_r + s_r p_d$		et al. (2012),Huang et al. (2012), Cao et al. (2013), Ryan et al. (2013), F. Zhao et al. (2015), Lei et al. (2014), Matsui (2016), Saha et al. (2016), Soleimani at al. (2016), B. Li et al. (2016b), Giri et al. (2017), P. Chen et al. (2017), Barzinpour et al. (2018), Tang et al. (2018a), Rofin et al. (2018), Feng et al. (2018), L. Yang et al. (2018c), Saha et al. (2018), L. Wang et al. (2019), Hua et al. (2010), S. Yang et al. (2015), W. Wang et al. (2016), Batarfi et al. (2016), Xie et al. (2017), L. Wang et al. (2017), Gan et al. (2017), J. Zhao et al. (2017), X. Chen et al. (2017), F. Zhang et al. (2018), J. Chen et al. (2018), Y. Zhang et al. (2018), Fang et al. (2019), Z. Li et al. (2019), Jabarzare et al. (2019), Cao et al. (2019), Arya et al. (2007), Kumar et al. (2006), Y. Wang et al. (2009), Huang et al. (2009), Cai (2010), Amrouche et al. (2020)
$\boldsymbol{F2\ (A, p, b, s)}$ **(21)** $D_d = \begin{cases} A_d - b_d p_d + s_d p_r, if\ p_r \geq \dfrac{b_d p_d - A_d}{s_d} \\ 0 \quad otherwise \end{cases}$ $D_r = \begin{cases} A_r - b_r p_r + s_r p_d, if\ p_r \leq \dfrac{A_r + s_r p_d}{b_d} \\ 0 \quad otherwise \end{cases}$	$Deterministic$	G. Xu et al. (2014), David et al. (2014), Shang et al. (2015), Li et al. (2017), Yu et al. (2018), B.Yan et al. (2016), Jafari et al. (2016), H. Liu et al. (2017), Bin Liu et al. (2010), Hsieh et al. (2014), Ding et al. (2016), M. Liu et al. (2016), Bo et al. (2018), J. Xu et al. (2018), Qiu et al. (2018), Z. Liu et al. (2018), L. Yang et al. (2018a), Feng et al.

		(2019), Glock et al. (2015), Xiong et al. (2012), Matsui (2017)
$\boldsymbol{F3}\ (\boldsymbol{p}, \boldsymbol{\theta})$ **(20)** $D_d = \begin{cases} \frac{\theta p_r - p_d}{\theta(1-0)}, if\ \frac{p_d}{\theta} \leq p_r \\ 0 \quad otherwise \end{cases}$ $D_r = \begin{cases} 1 - \frac{p_r - p_d}{1-\theta}, if\ \frac{p_d}{\theta} \leq p_r \\ 1 - p_r \quad otherwise \end{cases}$	$Deterministic$	Chiang et al. (2003), R. Yan (2008), H. Xu et al. (2012), Cao (2014), Xiao et al. (2016), Geng et al. (2007), W. Yan et al. (2018), C. Wang et al. (2018), Y. Yan et al. (2018), Yan (2011), J.X. Chen et al. (2018), J.Q. Zhang et al. (2018), B. Liu et al. (2019), G. Li et al. (2019b), H. Li et al. (2018), S. Zhang et al. (2019), Ke et al. (2018), Qi et al. (2018), Ji et al. (2018), X. Wang et al. (2018)
$\boldsymbol{F4}\ (\boldsymbol{A}, \boldsymbol{p}, \boldsymbol{s}, \boldsymbol{\beta}, \boldsymbol{SL})$ **(18)** $D_d = A_d - p_d + s_d p_r + \beta SL$ $D_r = A_r - p_r + s_r p_d + (1-\beta)SL$	$Deterministic$	Y-W.Zhou et al.(2018), Taleizadeh et al. (2018), Tu et al. (2019), Q. Zhang et al. (2019), Shi (2019), Albert et al. (2016), Zhao et al. (2018), Q-H. Li et al. (2016), Q. Li et al. (2019), X. Yu et al. (2019), Dai et al. (2019), Qiu-Xiang et al. (2018), Moon et al. (2018), Y. Zhou et al. (2018), Ma et al. (2018)
$\boldsymbol{F5}\ (\boldsymbol{\alpha}, \boldsymbol{p}, \boldsymbol{\varphi})$ **(10)** $D_d = \alpha A - \frac{1}{1-\varphi} p_d + \frac{\varphi}{1-\varphi} p_r$ $D_d = (1-\alpha)A - \frac{1}{1-\varphi} p_r + \frac{\varphi}{1-\varphi} p_d$	$Deterministic$	B. Li et al. (2016a), Zheng et al. (2017), Tang et al. (2018b), Cao et al. (2010), Q. Zhao et al. (2017), Zhou et al. (2018), Liang et al. (2018), B. Li et al. (2019), Liming Wang et al. (2019), Hsiao et al. (2014)
$\boldsymbol{F6}\ (\boldsymbol{A}, \boldsymbol{\alpha}, \boldsymbol{p}, \boldsymbol{b}, \boldsymbol{s}, \boldsymbol{\gamma}, \boldsymbol{GL})$ **(10)** $D_d = (1-\alpha)A - b_d p_d + s_d p_r + \gamma_d GL$	$Deterministic$	Jamali et al. (2018), Rahmani et al. (2019), Ji et al. (2017), Heydari et al. (2018), Xie et al. (2018), Aslani et al. (2019),

$D_r = \alpha A - b_r p_r + s_r p_d + \gamma_r GL$		Ranjan et al. (2019), Q. Li et al. (2018) T. Zhang et al. (2018), H. Liu et al. (2014)
$\boldsymbol{F7\ (b, \rho, SE)}$ **(8)** $D_d = \rho(b_r SE_r + b_d SE_d)$ $D_r = (1-\rho)(b_r SE_r + b_d SE_d)$	$Deterministic$	Dumrongsiri et al. (2008), Dan et al. (2012), J.X. Chen et al. (2017), Taleizadeh (2018), Kundu (2018), Gamchi et al. (2018) R. Yan et al. (2010), Tsay et al. (2004)
$\boldsymbol{F8\ (A, \alpha, p, b, s, \pi, DT, \varepsilon)}$ **(8)** $D_d = (1-\alpha)A - b_d p_d + s_d p_r - \pi_d DT + \varepsilon_d$ $D_r = \alpha A - b_r p_r + s_r p_d + \pi_r DT + \varepsilon_r$	$Stochastic$	Modak et al. (2019), Khouja et al. (2010), J.Q. Yang et al. (2017), Chen et al. (2008), Qin et al. (2019), C. Liu et al. (2019), Lee et al. (2019), Karimabadi et al. (2019)
$\boldsymbol{F9\ (A, \alpha, p, s, \rho, SE)}$ **(7)** $D_d = \alpha A - p_d + s_d p_r + \rho SE_d$ $D_d = (1-\alpha)A - p_r + s_d p_d + \rho SE_r$	$Deterministic$	Roy et al. (2016), Dan et al. (2018), G. Li et al. (2019), T-H. Chen (2015), Bernstein et al. (2009), Liu et al. (2007), W-G. Zhang et al. (2017)
$\boldsymbol{F10\ (Demand\ functions\ is\ characterized\ by\ Normal\ and\ Poisson\ distribution)}$ **(14)**	$Stochastic$	Chiang et al. (2005), Chiang (2010), Takahashi et al. (2011), Z. Zhang et al. (2019), Xie et al. (2014), Rodríguez et al. (2015), Huang et al. (2018), Nekoiemehr et al. (2019), J.Q. Yang, et al. (2019), Sun et al. (2019), J.X. Zhang et al. (2019), R. Zhang et al. (2019), Chai et al. (2019), Raza et al. (2019)
Notations		
$\{d, r, m\}$	Denotes direct (manufacturer owned channel), retail channels and a manufacturer, respectively.	
p_d, p_r	Price of channels	

w	Manufacturer's wholesale price
D_d, D_r	Demand of channels
O_d, O_r	Order quantity of channels
n	Number of shipments
f	Free riding rate
g	The green degree of the product decided by the manufacturer
τ	Collection/return rate
s_e	Level of sales effort
I_r, I_m	Base stock level
t	Lead time
e	Carbon emission level
b_d, b_r	Own-price sensitivity (elasticity)
s_d, s_r	Cross-price sensitivity
A	Market base demand
α	The proportion of the base demand
θ	Channel preference of the customers
π	Delivery time-sensitivity parameter of the demand in the online channel
φ	The degree of substitution among products
β	Service/quality sensitivity
ε	Exogenous random variable
GL	Parameter of the green/low carbon emission level
DT	Parameter of delivery time
SE	Parameter of service effort

Chapter C. Configuration of Last-Mile Distribution Networks for an Encroaching Manufacturer*

Abstract: In some supply chains for consumer goods, e.g., athletic footwear and high-tech consumer products, manufacturers encroach on traditional retail channels by establishing an alternative direct-order channel offering consumers home-delivery of customized products. Advancements in information technology and rising customer expectations have popularized the transition from multi- to omni-channel distribution. However, this transition did not mean excluding brick-and-mortar stores from the omni-channel retail strategy. Thus, there is a need to explicitly consider customer channel preferences and delivery services in addition to strategic, tactical, and operational decisions to help manufacturers realize a cost-effective supply chain. To this end, we investigate single-, multi-, and omni-channel distribution strategies for the case of a manufacturer selling both standard and customized products to different customer segments with varying preferences. We develop an integrated optimization model that includes a location-routing problem for designing a combined two-echelon supply chain for an omni-channel distribution system with fragmented customer demand

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being met over multiple shopping and delivery options. Owing to the complexity of the problem, we propose a decomposition metaheuristic for performing a computational study on large realistic instances. Our findings suggest that an omni-channel distribution system is a feasible strategy that can reach more customer segments at low logistics costs. Finally, we quantify the effect of in-store pick-up as opposed to home-delivery on total logistics costs.

C.1. Introduction

E-commerce is rapidly gaining importance today. Global e-commerce sales have reached \$ 4.89 trillion in 2021 and are expected to reach \$ 6.39 trillion by 2024 (Statista 2021). In the early years of e-commerce, companies used their websites to only inform customers about their products (e.g., Daimler–Chrysler, Nikon, and Rubbermaid), whereas today, they use websites and platforms to actively sell products (Chung et al. 2012). Besides retailers (e.g., Walmart and Tesco), manufacturers (e.g., Polo Ralph Lauren, Apple, and Macmillan) have also revamped their sales strategies because of the developments in information technology and changing consumer buying behavior (Cattani et al. 2006; Ryan et al. 2013; Abhishek et al. 2015).

These changes in the selling activities of manufacturers have led to different types of distribution channels: from single channels, which were common in the past, to multi- and omni-channels that are now gaining popularity. In multi-channel settings, the manufacturer adopts an entirely owned direct sales channel (i.e., a physical or online channel) in addition to its existing independently owned retailers. This allows the manufacturer to compete with the retailer by adding a direct channel. In the literature, this practice is referred to as manufacturer encroachment (Arya et al. 2007; Tahirov & Glock 2022). Meanwhile, omni-channel (OC) systems include the synergetic management of multiple available channels and customer touchpoints to provide a flexible shopping experience to customers (Verhoef et al. 2015). In multi-channel distribution systems, the firms perform physical store replenishments and e-commerce shipments through separate warehouses and distribution systems, whereas they integrate all facilities in omni-channel systems (Millstein et al. 2018). In addition, OC systems focus on improving the customer-shopping experience. An example of an OC system is a scenario wherein a customer can buy a product online and receive it either via home delivery or by picking it up from an automated parcel locker or in-store, with the option of using the same channels for returns (Hübner et al., 2016; Paul et al., 2019). Studies indicate that both multi-channel and OC distribution systems allow manufacturers to expand their market share, extend customer reach, increase sales, and improve functional complementarity (Cattani et al. 2006; Arya et al. 2007; Chopra 2018; Gao et al. 2020).

A transition from the single- to multi-channel or from multi-channel to OC distribution systems poses new strategic, tactical, and operational challenges to manufacturers (Hübner et al. 2016; Ailawadi & Farris 2017). Starting a new distribution channel or a fulfilment center involves a location decision and is therefore a strategic decision; in contrast, the effective management of the emerging channel conflicts between a manufacturer and a retailer (after encroachment) is a tactical decision (Coughlan et al. 2014). Operational issues are related to ordering, fulfilment, inventory, and logistics decisions, and they need to be handled efficiently. For example, last-mile delivery services such as parcel and grocery deliveries, can introduce routing complexity and extra costs for companies (Janjevic et al., 2020). Therefore, considering these decisions, manufacturers need to carefully evaluate tradeoffs (e.g., minimize total logistics costs or maximize customer service level) while switching from one type of distribution channel to another. Using a well-configured supply chain, it is possible to increase cost efficiency, realize a high customer service level, and create good manufacturer-retailer relationships (Chopra 2016; Arshinder et al. 2008). For example, manufacturers can utilize physical stores of the retailers as dark stores instead of bypassing independent retailers completely (i.e., a retailer's stores are used as warehouses for fulfilment/pickup of online orders) or they can attempt to reach different customer segments and reduce potential price wars between channels by selling different products (Ailawadi 2021). In this context, also the city logistics concept becomes relevant (Boccia et al., 2011): Companies need to minimize the negative effects of freight distribution (pollution, congestion, etc.) along with logistics costs to reach urban customers and improve sustainability, mobility, and quality of life in cities. Thus, firms can establish intermediate facilities (e.g., distribution centers or dark stores) to improve vehicle management, freight consolidation, and coordination by considering city infrastructure. In today's new era of commerce, OC marketing and commerce have increased the importance of retailers' physical stores, and therefore, manufacturers and retailers conduct business in close collaboration for mutual benefit. Manufacturers can leverage retailers' physical stores to provide quicker delivery and convenient pickup options for online orders; this, in turn, can increase foot traffic to retail stores (Ailawadi & Farris 2017; Jindal et al. 2021). As an OC trailblazer, Nike (besides its SNKRS app and Nike Plus Loyalty Program) expanded its OC initiatives across independent retail partners (Ailawadi 2021). In brief, beside location and routing decisions, possible channel conflicts, granular features of customer demand, and delivery services must be considered to achieve a well-configured distribution network and meet rising customer expectations.

In the operations research literature, location and routing decisions are jointly investigated in the location-routing problem (LRP). In this research field, the three types of decisions mentioned above are not investigated simultaneously in the context of channel transitions. For the scenario studied here, the manufacturer aims to evaluate three different distribution systems (i.e., single channel, multi-channel, and OC) wherein strategic (e.g., adding a direct channel and opening dark stores at a retailer's stores), tactical (e.g., the manufacturer sells only customized products over its direct channel and standard products through the retailer's channel to mitigate channel conflicts), and operational (e.g., routing) decisions are made. Furthermore, in the related literature, only a few studies (e.g., Aksen et al. 2008; Janjevic et al. 2020) report on the granularity of customer demand (i.e., segmented customers and their preferences for various product types) and OC distribution systems (i.e., multiple shopping and pickup options), which leads to several opportunities in this research stream. In addition, OCs are often interpreted as a retail concept and have been investigated from a retailer's perspective; however, they still need to be analyzed from a manufacturer's perspective (Ailawadi 2021). Given the paucity of existing literature, we propose an integrated optimization model that includes a

LRP for the design of a combined two-echelon supply chain for an OC distribution system with fragmented customer demand met over multiple shopping and delivery options. The work in hand contributes to the literature by

- Analyzing the manufacturer's three (single channel, multi-channel, and OC) distribution network design choices through the lens of the attendant location and routing decisions.
- Exploring the effect of the number of open dark stores and in-store pickup options on channel decisions.
- Developing a decomposition solution method for the omni-channel LRP to solve large-scale instances efficiently.

The remainder of this paper is organized as follows. Section 2 discusses the related literature and defines the research gap addressed in this study. Section 3 outlines the formal problem description, and Section 4 presents the model formulations. In Section 5, we present the computational complexity of the proposed model and solution methods. The computational study is described in section 6. Finally, Section 7 concludes the paper.

C.2. Background and literature

We draw on and contribute to two research streams to establish our study: I) manufacturer encroachment and channel strategy, and II) multi-echelon LRPs.

C.2.1. Manufacturer encroachment and channel strategy

Manufacturers vend their products through intermediaries such as wholesalers and retailers; however, in practice, many manufacturers (e.g., Apple and Nike) also act as retailers and sell products directly to end customers through their physical stores (outlets) or online channels. Developments in information technology have triggered manufacturers to adopt wholly owned direct sales (online) channels in addition to their existing conventional (offline) channels. This channel selection decision can lead to competition between manufacturers and retailers; this type of competition is referred to as manufacturer encroachment (Arya et al., 2007).

A recent systematic review of manufacturer encroachment by Tahirov and Glock (2022) reported that the manufacturer's channel selection process comprises two phases: (I) developing multi-channel strategies and (II) managing the (multiple) channels. For the first phase, the authors outline the major determinant factors (e.g., customer preference, information asymmetry, and market environment) that force the manufacturer to adopt a direct sales channel; customer preference is identified as the most important factor that plays a significant role in the channel design of our work. With respect to the second phase, the authors present major tactical (e.g., pricing, coordination and product differentiation) and operational decisions (e.g., inventory, delivery, and assortment) made by the manufacturer while managing multi-channel distribution systems. Within the literature on manufacturer encroachment, a large body of research addresses tactical issues under the “dual-channel supply chain” topic, wherein the studies primarily investigate either an efficient pricing strategy, a coordination mechanism, or both, using game-theoretic models. Sibley et al. (1998), Chiang et al. (2003), Tsay et al. (2004), Chiang et al. (2005), and Arya et al. (2007) analyzed the manufacturer’s dual-channel strategy using game-theoretic approaches to determine the equilibrium between the pricing decisions of the manufacturers and retailers. For example, Chiang et al. (2003) studied a scenario in which the manufacturer is the Stackelberg leader and sets wholesale and direct channel prices by considering a customer acceptance (preference) parameter for the direct channel. The authors showed that a desired equilibrium for both parties can be reached, for a given customer acceptance parameter where the manufacturer uses the direct channel as a strategic tool for threatening the retailer with cannibalization. This strategy encourages the retailer to reduce its price, which leads to a sales uplift at the retailer, and the manufacturer’s profit can increase indirectly. Tsay et al. (2004) suggested that adding a direct channel can improve the overall efficiency of a dual-channel distribution system when the manufacturer adjusts the wholesale price as a game leader. The authors proposed two mechanisms: *referral to direct* (i.e., the retailer functions as a showroom and receives commission for diverting) and *referral to reseller* (i.e., the retailer fulfills the entire demand) that decrease the operational costs for both parties. Arya et al. (2007) investigated a model in which the wholesale price is first established by the manufacturer, and then, the retailer decides on the optimal order quantity. The authors suggest that manufacturer encroachment can help both parties if the manufacturer decreases the wholesale price significantly, and if the retailer provides high-level retail services.

Besides the pricing strategy, product differentiation is another powerful mechanism to handle channel conflicts between manufacturers and retailers, and it has been investigated both analytically (Cao et al., 2010; Ha et al., 2016; Li et al., 2018; Raza et al., 2019) and empirically (Vinhas et al., 2005; Du et al., 2018). A manufacturer can increase its profit if it can sell products with different characteristics, e.g., in terms of quality, functionality, or product complementarity, to different customer segments. For example, Dell offers its consumers the ability to configure a computer (i.e., customized product) on the company website before ordering (Rodríguez et al., 2015). This was another motivation for considering multiple products in our study. Cao et al. (2010) studied a scenario in which two competing manufacturers open their own retail stores in addition to those of existing independent retailers by considering demand uncertainty, product substitution, and market share.

Their findings indicated that the manufacturers' profits increase if they use a dual-channel configuration with higher demand uncertainty and low product substitutability (which occurs for products with many design attributes). The authors also suggested that manufacturers tend to distribute staple products over an indirect channel because they are highly substitutable and have a low level of demand uncertainty. Based on the case reported by Raza et al. (2019), a single manufacturer can sell a standard product over a direct channel and a green product through a retail channel at various prices. Their proposed model aims to find the optimal values of selling and product differentiation price, greening effort (investment), and inventory level while assuming that the manufacturer and retailer are risk averse. The findings indicate that selling products at different prices diminishes demand cannibalization between channels and leads to revenue growth for the two parties. Du et al. (2018) supported analytical research by conducting an empirical study (at Haier, a Chinese appliance company) wherein selling identical products through both online and offline channels causes channel conflicts and a price war between manufacturers and retailers. The company follows a differentiation strategy and sells customized products through an online channel and standard products through retail stores to ensure that both parties are better off.

C.2.2. Multi-echelon location-routing problem

The LRP was conceptualized in the 1960s (e.g., Von Boventer 1961; Maranzana 1965) and further developed in the late 1970s (e.g., Harrison 1979) and the early 1980s (e.g., Laporte and Nobert 1981) because of the emergence of the integrated logistics concept and expansion of international trade (Min et al., 1998). The synthetic expression $\lambda/M_1\ .../M_{\lambda-1}$ for an LRP was first introduced by Laporte (1988) and then enhanced by Boccia et al. (2011). Based on this expression, λ denotes the number of layers and $M_1/\ .../M_{\lambda-1}$ represents the type of routes linking the layers. In addition, R is used for dedicated routes to differentiate the routes, and T is used for multiple node routes. The overline on letters R and T specifies where location decisions are made. For example, $(3/R/\overline{T})$ refers to an LRP comprising three layers: R routes between the first and second layers, T routes between the second and third layers, and location decisions for secondary (i.e., starting points of routes are referred to as primary facilities) facilities (Boccia et al. 2011).

The existing literature is abundant with many variants of the LRP. They have been classified in accordance with the number and types of locations, types of fleets, characteristics of demand (i.e., deterministic or stochastic), number of network layers, and solution methods, and so on (Nagy et al. 2007). We refer interested readers to reviews on the LRP to gain a comprehensive overview (Min et al. 1998; Nagy et al. 2007; Prodhon et al. 2014; Cuda et al. 2015; Schneider et al. 2017) on the LRP. We aim to discuss only selected studies on multi-echelon LRPs ($ME-LRP$) that pertain to our work in terms of modelling and our proposed conceptual framework (i.e., last-mile distribution networks for the OC setting).

Ambrosino et al. (2005) investigated a four-layer distribution network design problem that involves facility, warehousing, transportation, and inventory decisions under both static and dynamic scenarios. The authors formulated two types of mathematical programs: the first is based on the warehouse LRP introduced by Perl et al. (1985), and the second is based on flow variables and constraints. For Aksen et al. (2008), the retailer makes location (brick-and-mortar stores) and routing decisions to satisfy the demand for both walk-in (i.e., who visit the nearest stores in person) and online customers. In the developed model, the authors assume that the roles of walk-in and online customers could be exchanged. That is, online customers buy online; however, they prefer picking up the item at the nearest store, whereas a walk-in customer may purchase a bulky good in the store, but prefer to receive home delivery. Boccia et al. (2011) proposed three different mixed-integer programming formulations for a two-echelon capacitated LRP ($2E-CLRP$) wherein location decisions are made for both primary and secondary facilities along with two different routing decisions. Lee et al. (2010), Contardo et al. (2012), and Zhao et al. (2017) studied the $2E-CLRP$ by proposing exact and heuristic solution methods. The computational results of these studies indicate that the developed heuristics can find good solutions in a reasonable time and outperform extant heuristics. Lin et al. (2009) investigated three-echelon distribution systems that comprise location and two-level routing decisions with two types of clients (big and small). The developed model was implemented in a national finished goods distribution system for label-stock manufacturers. Their analysis suggests that the inclusion of big clients in first-level routing reduces the total logistics cost. Within the context of urban logistics services (ULS), Winkenbach et al. (2016) proposed a large-scale deterministic MILP model to solve the $2E-CLRP$ with transportation mode choice. Further, they developed an optimal routing cost estimation formula and an optimization heuristic that enabled them to achieve their goal within a reasonable time with a small optimality gap to solve the large-scale MILP real case instances. Govindan et al. (2014) formulated an LRP with time-window constraints by considering greenhouse gas emissions in perishable goods freight. Their work aimed to optimize two objectives: total operational costs and environmental effects. The authors also introduced a hybrid metaheuristic algorithm based on multi-objective particle swarm optimization and an adapted multi-objective variable neighborhood search to solve the developed multi-objective model. Their developed solutions outperformed existing benchmark algorithms based on a *genetic algorithm* method. Hamidi et al. (2012) developed a four-layer multiproduct LRP that considers location, allocation, routing, and transshipment decisions. They solved a small-sized problem using a numerical solver and obtained the exact solutions for the developed model. Later, Hamidi et al. (2014) proposed a heuristic method to solve the same model. Their results indicate that the proposed method (i.e., based on the greedy randomized adaptive search procedure and tabu search) solves the problem efficiently. Based on a case study of last-mile distribution reported by an e-commerce platform, Janjevic et al. (2019) investigated a last-mile distribution network in which the location of both satellite facilities (SFs) and collection-and-delivery points (CDPs, i.e., as an additional fulfilment option), allocation of client segments to active SFs, and vehicle size and routing decisions were optimized.

They formulated an extended routing cost approximation approach to estimate the near-optimal route length for deliveries to CDPs and individual customers. The authors further developed a problem-specific heuristic that enables them to solve those problems in a reasonable time to make large-scale problem instances more tractable. Their results suggest that the integration of CDPs into a network can significantly reduce the cost of a company. In an OC environment, Janjevic et al. (2020) studied a last-mile LRP with multiple time-differentiated delivery services, transportation modes, and product-exchange options. From the literature, the authors extended existing closed-form continuum approximations of the optimal routing cost and utilized these approximations in the developed three-echelon capacitated LRP by considering location decisions, delivery service offerings, transportation mode choices, and product-exchange alternatives. Their results suggested that an integrated optimization approach leads to better network design performance and a reduction in total logistics cost.

C.2.3. Literature gap

Our review showed that the network design and channel strategy of the manufacturer are yet to be comprehensively investigated in the literature. The vast majority of studies on manufacturer encroachment and manufacturer channel strategy investigate a single echelon supply chain network configuration that comprises single manufacturers distributing products directly (online, store, or both) and through a retail channel (Tahirov and Glock, 2022). Today, many firms switch their distribution systems from multi-channel to OC settings (Verhoef et al., 2015). However, OC is primarily interpreted as a retail concept because the related literature (Cui et al. 2021; He et al. 2019, Verhoef et al. 2015; Wei et al. 2020) has exclusively addressed this phenomenon from the perspective of a retailer (Jindal et al. 2021). In practice, however, it is common for a manufacturer to vend products to end consumers through its direct channel in addition to existing intermediaries such as retailers or wholesalers (Ailawadi 2020). In this case, manufacturers can either use the extant (or prospective) nearby stores as a fulfilment center or as pickup points (i.e., buy online pick-up in-store, BOPIS), which are key elements in the omni-channel distribution system as they both offer flexibility to customers and boost store sales (Paul et al., 2019, Ailawadi 2020). To the best of our knowledge, no study has examined omni-channel distribution systems from the perspective of the manufacturer (Ailawadi, 2020; Tahirov and Glock, 2022).

Switching from a single channel to a multi-channel or from a multi-channel to an OC brings new strategic, tactical, and operational challenges. In the manufacturer encroachment and LRP literature, these three types of decisions are yet to be investigated simultaneously. Further, in the manufacturer encroachment literature, only a relatively small number of studies have investigated operational decision problems (*product assortment*- Rodríguez et al. 2015, *order fulfilment*-Nekoiemehr et al. 2019*, allocation*-Yu et al. 2018) in multi-channel distribution settings (Tahirov and Glock, 2022). There is limited literature on LRP considering the granular characteristics of customer demand and OC distribution systems. In this respect, only a few studies have considered OC settings (Aksen et al., 2008; Janjevic et al., 2020) and multiple products (Hamidi et al. 2012).

We present the major model attributes of the existing research and our study in Table C.1 to differentiate our work from the most closely related studies. Furthermore, we note that none of the contributions in the current literature propose a strategic network design model that simultaneously considers (1) the manufacturer channel selection strategy; (2) customer preferences for various shopping/pick-up options and products that form heterogeneous demand zones ; (3) location decisions that utilize retailers' physical stores as fulfilment and pick-up points; and (4) incorporation of a service level parameter that affects the manufacturer's channel selection strategy considerably. Therefore, this study aims to fill a significant gap and contribute to the related literature.

Table C. 1. Benchmark of selected studies on manufacturer encroachment and multi-echelon location-routing problem

References	Strategic decisions			Tactical decision		Operational decision		Granularity of OC		
	Location	Adding a new channel	Service level	Product differentiation	Other (e.g., pricing, contract)	Diverse routing (2+)	Other (e.g., inventory, assortment)	Segmented customer	Diverse purchase & pickup options	Diverse transportation modes
Manufacturer encroachment										
Chiang et al. (2003)		x			x					
Tsay et al. (2004)		x			x					
Arya et al. (2007)		x			x					
Cao et al. (2010)		x								
Ha et al. (2016)		x		x						
Rodríguez et al. (2015)		x		x			x			
Yu et al. (2018)		x					x			
Raza et al. (2019)		x		x						
ME-LRP										
Ambrosino et al. (2005)	x					x		x		
Aksen et al. (2008)	x							x	x	
Boccia et al. (2011)	x									x
Lee et al. (2010)	x					x				x
Contardo et al. (2012)	x									x
Winkenbach et al. (2016)	x									
Hamidi et al. (2012)	x			x		x				
Janjevic et al. (2019)	x							x	x	x
Janjevic et al. (2020)	x					x		x	x	x
Our study	x	x	x	x		x		x	x	x

C.3. Problem description

We address a strategic distribution network design problem for parcel-sized, imperishable, non-food products sold by a manufacturing company. To lend decision support from the manufacturer's perspective, we analyze various distribution network designs, which include single-channel (*Scenario 1*), multi-channel (*Scenario 2*), and OC (*Scenario 3*) designs. We also explore how customer composition, in terms of shopping and product preferences, affects the efficiency of the planned network design. We distinguish the following customer segments (Gauri et al. 2021):

- **Segment – T** prefers shopping for standard products in brick-and-mortar stores (i.e., retail stores).
- **Segment – C** prefers buying customized products and getting items via a last-mile delivery service, which is realized directly by the manufacturer's warehouse.
- **Segment – S** prefers buying standard products and getting items via a last-mile delivery service, which is fulfilled through dark stores (DS) located at a retail store (R).
- **Segment – BOPIS** prefers shopping online and picking products up in a dark store

These customer segments constitute various demand zones, which must be met with low logistics costs and high service levels. Thus, we consider the following scenarios:

Scenario 1: The manufacturer adopts a single-channel configuration in which only the demand for the standard product of the in-store captive customers (T) are satisfied through physical stores replenished via heavy trucks (i.e., vehicle type = *heavy truck*) by the manufacturer (Figure C.1-a).

Scenario 2: In the multi-channel scenario, the manufacturer considers online captive customers who prefer customized products and fulfil their orders via a small/light vehicle (i.e., vehicle type = *urban van*) directly from their warehouse (Figure C.1-b). In this case, the manufacturer implements a product differentiation strategy that can prevent channel conflicts between the manufacturer and retailers.

Scenario 3: The manufacturer adopts an omni-channel distribution network design, which aims to satisfy all customer segments. In this case, in addition to the multi-channel distribution system (Scenario 2), the orders of the last-mile delivery customer zone (S) for the standard product are delivered through dark stores located near retail stores. In addition, dark stores are utilized to serve BOPIS customers who buy customized and standard products online and pick them up from a nearby dark store located at a retail store (Figure C.1 - c).

The objective from the manufacturer’s perspective is to optimize the number of possible locations (DS), vehicles, and routing decisions while evaluating the three scenarios in the distribution network configuration. The intended configuration for each scenario is described in Figure C.1.

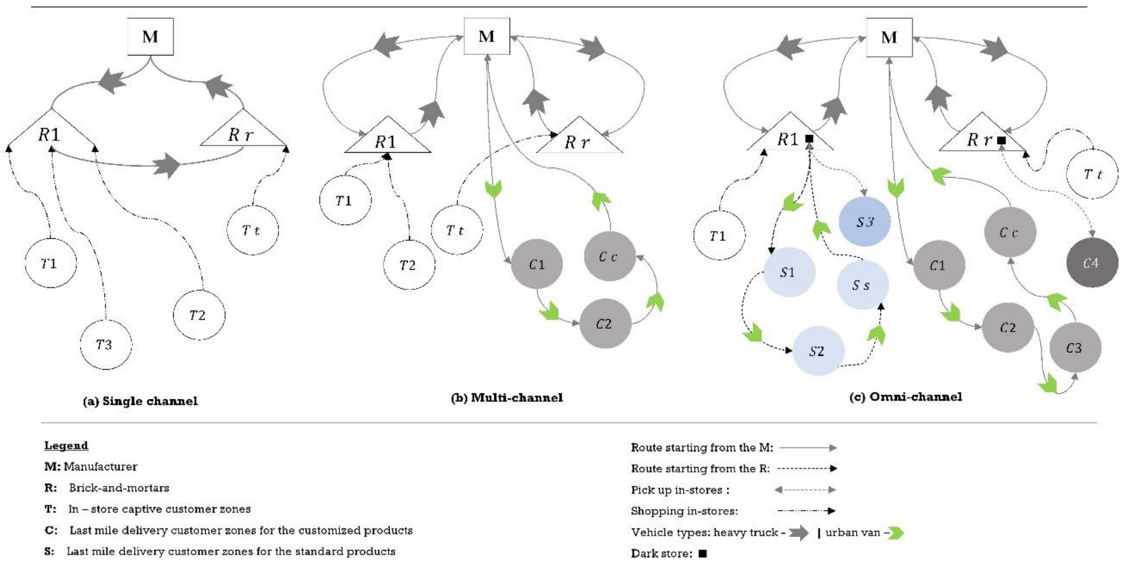


Figure C. 1. Illustration of distribution network configuration scenarios

The investigated distribution network comprises the following:

- Manufacturer (M): The manufacturer ships both types of products to retailer stores via heavy trucks. In addition, the manufacturer delivers customized products to *Segment – C* customer zones using urban vans. The production capacity of the manufacturer is assumed to be infinite.
- Brick-and-mortar stores (R): Brick-and-mortar stores belong to independent retail companies. They are located near customers; the

functions of these stores are twofold: in-store sales and dark store sales. In-store sales are the conventional in-person shopping type. The dark stores (DS) are used as fulfilment centers for online orders of standard products delivered by urban vans, and they also serve as pickup points for both types of products purchased online by BOPIS customers.

- In-store captive customer zones (T): These zones patronize conventional (offline) channels.
- Last-mile delivery customer zones for customized products (C): These zones include customers shopping for customized products online and receive orders delivered from the manufacturer's warehouse.
- Last-mile delivery customer zones for standard products (S): These zones contain customers shopping for standard products online and receive their orders shipped via dark stores.
- BOPIS customers (i.e., proper subset of segment S and C; dark green and blue nodes in Figure C.1-c) if they are located near (i.e., $\leq \phi$ given distance range) to an opened dark store; otherwise, they are served via last-mile delivery through the manufacturer's depot and open dark store, respectively.

C.4. Model development

The notations used in this study are summarized in Table C.2, and all models are developed based on the following assumptions:

- We consider two product types (standard and customized); these items are produced by the manufacturer and are in unlimited supply.
- The demand of each customer zone for a product type is deterministic, and demand splitting is not allowed; that is, either the entire demand of a customer is satisfied or none at all. Since we are proposing a model for strategic decision support, in practice, the demand of a customer zone may be a forecast or an estimate depending on the demographics and population density of the respective area.
- The total demand and weight of the set of traditional customers T is equivalent to the total demand and weight of the set of retail stores R such that the total demand and weight of T customers is distributed equally among the retail stores. The demand of traditional customers is satisfied directly in retail stores where customers purchase and pick up products. No shipments are made from retail stores to traditional customers.

- Demand nodes $(T, S, \& C)$ represent various customer zones comprising multiple neighboring customers that may or may not overlap geographically.
- Dark stores are located in the retailer's physical stores and have identical capacities; the set of potential dark stores DS is equivalent to the set of retail stores R.
- We consider two types of vehicles with different capacities. All vehicles of the same type have an identical capacity.
- Each customer zone $s \in S$ and $c \in C$ must be served by a single open dark store and the manufacturer, respectively. Customer zones $(S \cup C)$ located near (i.e., $\leq \phi$ – within a given distance range) a retailer are defined as BOPIS customers and can be assigned to an open dark store to pick up their order. In that case, they do not need to be visited by a delivery truck.
- All distances between nodes are measured via the Euclidean metric.

Table C. 2. Parameters and decision variables of the MILP models.

Sets	
P	Set of products (either standard or customized), index $p \in P$
R	Set of brick-and-mortar stores, index $r \in R$
DS	Set of dark stores, index $k \in DS$, such that $DS \subseteq R$
T	Set of in-store captive customer zones, index $t \in T$
C	Set of last-mile delivery customer zones for the customized products, index $c \in C$
S	Set of last-mile delivery customer zones for the standard products, index $s \in S$
D	Set of all demand points, index $d \in D \equiv T \cup S \cup C$
H	Set of heavy trucks, index $h \in H$
U	Set of urban vans, index $u \in U$
N^1	Set of nodes for the combination of the first and second layer, $M \cup R$

N^2	Set of nodes for the combination of the first and third layer, $M \cup C$
N^3	Set of nodes for the combination of the second and third layer, $R \cup S$

Parameters

K	Dark store capacity
Q_v	Vehicle capacity, $v \in H \cup U$
F	Fixed opening cost for a dark store at a retail store
G_v	Fixed cost of using the vehicle type $v \in H \cup U$
D_{jp}	Demand of demand point j for the product p, $j \in D$, $p \in P$
w_i	Weight that denotes the number of clients/people existing in each customer zone i, $i \in R(T) \cup S \cup C$
α	Percentage of the total number of clients that must be served
d_{ij}	Distance (km) between nodes i and $j, i, j \in N^1, N^2$ and N^3, respectively
$\vec{d}_{bk}$	Distance (km) from the customer zone b to the possible opening dark store k at the retail store, $b \in S \cup C, k \in DS$
ρ_{bk}	$\{0,1\}, b \in S \cup C, k \in DS$: 1 if the customer zone is located near (i.e., $\leq \phi -$ given distance range) to the opening dark store; 0 otherwise
t_v	Transportation cost per kilometer per vehicle type, $v \in H \cup U$
$N1, N2, N3$	Number of nodes $\lvert N^1 \rvert$,$\lvert N^2 \rvert$, and $\lvert N^3 \rvert$ in the corresponding sets

Variables

y_k	Binary variable: $\{0,1\}$, $k \in DS$: 1, if the dark store k is opened at a retail store; 0 otherwise.
a_{ik}	Binary variable: $\{0,1\}$, $i \in S \cup C, k \in DS$: 1 if a client i at the second layer is assigned to the opened dark store k, be it as a BOPIS customers (customers in set C or S) or as last-mile home-delivery customers (in set S); 0, otherwise.
g_i	Binary variable: $\{0,1\}$, $i \in R \cup S \cup C$: 1 if a customer zone i or retail store r is served; 0 otherwise.
f_v	Binary variable: $\{0,1\}, v \in H \cup U$: 1 if a type of v vehicle is used ; 0 otherwise.
x_{ijh}	Binary variable: $\{0,1\}$, $i, j \in \{0\} \cup R, h \in H$: 1 if i precedes j at the first layer route performed by vehicle h; 0 otherwise. Note that $i = 0$ and $j = 0$ refers to the manufacturer.
x'_{iju}	Binary variable: $\{0,1\}$, $i, j \in \{0\} \cup C, u \in U$: 1 if i precedes j at the combined layer route performed by vehicle u; 0 otherwise. Note that $i = 0$ and $j = 0$ refers to the manufacturer.
r_{iju}	Binary variable: $\{0,1\}$, $i, j \in R \cup S, u \in U$: 1 if i precedes j at the second layer route performed by vehicle u; 0 otherwise.
q_{rhp}	Continuous variable: $\{\geq 0\}$, $m \in \{0\}, r \in R, h \in H, p \in P$: the flow of product p from the manufacturer to the store r on vehicle h.
L_{iv}	Continuous variable: $\{\geq 0\}$, $i \in \{0\} \cup R \cup S \cup C, v \in H \cup U$: auxiliary variable for subtour elimination constraint.

C.4.1. Single-channel distribution scenario (Model S)

The first scenario aims to optimize the transportation and fixed costs of using heavy trucks to supply the retail stores. The problem is identical to the single depot capacitated vehicle routing problem (CVRP) with a homogenous fleet (e.g., Kulkarni & Bhave, 1985; Laporte, 1992; Salhi et al. 2014, etc.), multiple products, and service-level constraints. Appendix C provides the formal model. Note that there is no optimization problem to solve in the second layer, because customers have no choice but to shop in-store, the only channel available in this scenario. Customers who want a home delivery cannot be served.

C.4.2. Multi-channel distribution scenario (Model M)

In this scenario, the manufacturer adopts the multi-channel distribution system in which the manufacturer ships customized goods to last-mile delivery customer zones via urban vans in addition to replenishing physical stores with standard products. The objective of this model is to minimize the transportation and fixed costs of using each vehicle type. Similar to Model S, this problem can be modeled as two separate CVRP, one for the replenishment of the retailers from the manufacturer using heavy trucks, and one for the delivery of customized products from the manufacturer to the home-delivery customers using urban vans. A combined formal model is presented in Appendix C.

C.4.3. Omni-channel distribution scenario (Model O)

The manufacturer makes both strategic (i.e., opening a dark store at a retailer's store) and operational (i.e., routing) decisions. This problem was defined as a combined two-echelon LRP. Our problem type matches that of the $3/T/T$ setting. In our case, the first T contains two different multiple-node routes from the manufacturer to the retailer's stores (i.e., between the first and second levels) and from the manufacturer to the last-mile customer zones for the customized products (i.e., between the first and third levels). The proposed model differs from the classical warehouse LRP (Perl and Daskin, 1985) and aims to solve a more complex problem, which includes three different routing decisions: multiple products, multiple vehicles, and various shopping and pick-up options for different types of customer zones. The mathematical programming formulation of this model is inspired by models proposed by Ambrosino et al. (2005) and Boccia et al. (2011), which incorporate multiple products, various purchase and pickup options, and level of service for segmented customer zones. The objective of the developed model is minimizing the total cost, which includes the facility fixed opening cost, fixed cost of using a vehicle, and routing costs. The proposed model is formulated as

Minimize

$$\sum_{k\in DS} y_k \cdot F + \sum_{v\in H\cup U} f_v \cdot G_v + \sum_{h\in H}\sum_{i\in\{0\}\cup R}\sum_{j\in\{0\}\cup R} x_{ijh}\cdot t_h \cdot d_{ij}$$

$$+\sum_{u\in U}\sum_{i\in\{0\}\cup C}\sum_{j\in\{0\}\cup C} x'_{iju}\cdot t_u \cdot d_{ij}$$

$$+\sum_{u\in U}\sum_{i\in R\cup S}\sum_{j\in R\cup S} r_{iju}\cdot t_u$$

$$\cdot\, d_{ij} \qquad (O1)$$

Subject to

$$\sum_{i\in R\cup S\cup C} g_i \cdot w_i \geq \alpha \cdot \sum_{i\in R\cup S\cup C} w_i \qquad (O2)$$

$$\sum_{h\in H}\sum_{j\in\{0\}\cup R} x_{rjh} = g_r \qquad \forall r\in R \qquad (O3)$$

$$\sum_{u\in U}\sum_{j\in\{0\}\cup C} x'_{cju} + \sum_{k\in DS} a_{ck}\cdot \rho_{ck} = g_c \qquad \forall c\in C \qquad (O4)$$

$$\sum_{u\in U}\sum_{j\in R\cup S} r_{sju} + \sum_{k\in DS} a_{sk}\cdot \rho_{sk} = g_s \qquad \forall s\in S \qquad (O5)$$

$$\sum_{i\in\{0\}\cup R} x_{ijh} - \sum_{i\in\{0\}\cup R} x_{jih} = 0 \qquad \forall j\in\{0\}\cup R, h\in H \qquad (O6)$$

$$\sum_{i\in\{0\}\cup C} x'_{iju} - \sum_{i\in\{0\}\cup C} x'_{jiu} = 0 \qquad \forall j\in\{0\}\cup C, u\in U \qquad (O7)$$

$$\sum_{i\in R\cup S} r_{iju} - \sum_{i\in R\cup S} r_{jiu} = 0 \qquad \forall j\in R\cup S, u\in U \qquad (O8)$$

$$\sum_{i\in\{0\}\cup R} x_{i0h} \leq 1 \qquad \forall h\in H \qquad (O9)$$

$$\sum_{i \in \{0\} \cup C} x'_{i0u} \leq 1 \qquad \forall u \in U \qquad (O10)$$

$$\sum_{i \in R \cup S} \sum_{l \in R} r_{ilu} \leq 1 \qquad \forall u \in U \qquad (O11)$$

$$\sum_{r \in R} \sum_{p \in P} q_{rhp} \leq Q_h \cdot f_h \qquad \forall h \in H \qquad (O12)$$

$$\sum_{c \in C} \sum_{p \in P} D_{cp} \sum_{j \in \{0\} \cup C} x'_{lju} \leq Q_u \cdot f_u \qquad \forall u \in U \qquad (O13)$$

$$\sum_{s \in S} \sum_{p \in P} D_{sp} \sum_{j \in R \cup S} r_{sju} \leq Q_u \cdot f_u \qquad \forall u \in U \qquad (O14)$$

$$\sum_{i \in S \cup C} \sum_{p \in P} D_{ip} \cdot a_{ik} \ \leq \ K \cdot y_k \qquad \forall k \in DS \qquad (O15)$$

$$\sum_{h \in H} q_{khp} - \sum_{i \in S \cup C} D_{ip} \cdot a_{ik} \quad = 0 \qquad \forall k \in DS, \forall p \in P \qquad (O16)$$

$$Q_h \cdot \sum_{z \in \{0\} \cup R} x_{rzh} - q_{rhp} \geq 0 \qquad \forall h \in H, \forall r \in R, \forall p \in P \qquad (O17)$$

$$Q_h \cdot \sum_{z \in \{0\} \cup R} x_{0zh} - q_{rhp} \geq 0 \qquad \forall h \in H, \forall r \in R, \forall p \in P \qquad (O18)$$

$$\sum_{j \in R \cup S} r_{sju} + \sum_{j \in R \cup S} r_{kju} - a_{sk} \leq 1 \qquad \forall s \in S, \forall k \in DS, \forall u \in U \qquad (O19)$$

$$\sum_{k \in DS} a_{sk} = \ g_s \qquad \forall \ s \in S \qquad (O20)$$

$$L_{ih} - L_{jh} + N1 \cdot x_{ijh} \leq N1 - 1 \qquad \forall \ i \in R, j \in R, h \in H \qquad (021)$$

$$L_{iu} - L_{ju} + N2 \cdot x'_{iju} \leq N2 - 1 \qquad \forall\, i \in C, j \in C, u \in U \qquad (O22)$$

$$L_{iu} - L_{ju} + N3 \cdot r_{iju} \leq N3 - 1 \qquad \forall\, i \in S, j \in S, u \in U \qquad (O23)$$

$$y_k = \{0,1\} \qquad \forall\, k \in DS \qquad (O24)$$

$$a_{ik} = \{0,1\} \qquad \forall\, i \in S \cup C, k \in DS$$

$$g_i = \{0,1\} \qquad \forall\, i \in R \cup S \cup C$$

$$f_v = \{0,1\} \qquad \forall\, v \in H \cup U$$

$$x_{ijh} = \{0,1\} \qquad \forall\, i,j \in \{0\} \cup R, h \in H$$

$$x'_{iju} = \{0,1\} \qquad \forall\, i,j \in \{0\} \cup C, u \in U$$

$$r_{iju} = \{0,1\} \qquad \forall\, i,j \in R \cup S, u \in U$$

$$q_{rhp} \geq 0 \qquad \forall\, r \in R, h \in H, p \in P$$

$$L_{iv} \geq 0 \qquad \forall\, i \in \{0\} \cup R \cup S \cup C, \forall\, v \in H \cup U$$

The objective function (O1) comprises five cost elements: fixed opening cost for dark store locations, fixed usage cost for each vehicle type and transportation cost for three routes. The constraints are summarized as follows: Constraint (O2) imposes that at least α percent of all customer nodes must be served according to their preferences, i.e., it is the service level constraint. Constraint (O3) ensures that if a client on a first-type route $(r, r \in R)$ is served, it must be visited by exactly one heavy truck

($h, h \in H$). Constraints (O4) and (O5) ensure that if a client on the second- ($c, c \in C$) and third-type route ($s, s \in S$) are served without being assigned to an opened dark store as a BOPIS customer, then it must be visited by exactly one urban van ($u, u \in U$). Those constraints also enforce that BOPIS customers (i.e., located within the given maximum allowable coverage distance) must be assigned either to a dark store or be served by a route originating from the dark store and the manufacturer, but not both. The next three constraints (O6), (O7), and (O8) for each route guarantee that for each vehicle type, the number of entering arcs in a node is equal to the number of leaving ones. Constraints (O9), (O10), and (O11) impose that each vehicle can be used a maximum of once on a tour. For each vehicle, constraints (O12), (O13) and (O14) ensure that the quantity of each product type shipped by a vehicle cannot exceed its capacity if that vehicle is used. Constraint (O15) ensures that an opened dark store can satisfy the demand of customer zones S and the near customers ($S \cup C$) assigned as BOPIS customers, up to its capacity. For each product type, constraint (O16) guarantees that the total flow from the manufacturer must be equal to the total demand of the customers including S and BOPIS ($S \cup C$). Constraints (O17) and (O18) guarantee that the flow of products ($p \in P$) between the manufacturer and the retailer's stores is positive only if they are both visited by the same vehicle. Constraint (O19) links the routing and assignment variables. More exactly, a client $s, s \in S$, can only be assigned to a location $r, r \in R$, if the dark store at that store is active and a route from that location through that client exists. In the literature, this is also referred to as a chain barring constraint. Constraint (O20) ensures that each customer $s, s \in S$, either as a last-mile delivery or BOPIS customer, must be assigned to one opened dark store $k, k \in DS$, if it is served.. Constraints (O21), (O22), and (O23) are constraints that eliminate subtours on each route. The last set of constraints (O24) express integrality and non-negativity constraints.

C.6. Solution methods

The LRP comprises two NP-hard problems: facility location and vehicle routing. LRPs are therefore NP-hard problems that are solved using various heuristic methods (Tuzun et al. 1999, Ambrosino et al. 2009). Thus, we propose a heuristic method based on a decomposition of the proposed model into sub-problems, that is, location and capacitated vehicle routing problems, to solve practical-size problems within a reasonable solution time. We employ a tabu search mechanism (Glover 1990) to decide on the number of dark stores to open, and we solve an assignment problem sequentially to assign the first S customers to the nearest opened dark stores. The reason for prioritizing customer S is that they can be served only through dark stores. In addition, the manufacturer aims to minimize the number of open dark stores because of fixed costs and additional operations. Then, we assign the nearest C

customers (i.e., BOPIS) to open dark stores if they have available capacity (*Phase 1*). We use a solver based on the famous Lin–Kernighan heuristic (Lin and Kernighan, 1973) (*Phase 2*) to solve the routing problems. Finally, we calculate the total cost (*Phase 3*). Figure C.2 summarizes the general structure of the proposed solution method. In a nutshell, the bold notations describe best found values of the decision variables and objective function (i.e., $\boldsymbol{y}$ –opened DS; $\boldsymbol{z}$ – assignment of customer zones ($S \cup C$) to the opened DS; $\boldsymbol{x}, \boldsymbol{x}'$& $\boldsymbol{r}$ – routes; $\boldsymbol{f}$ – number of vehicle per type, $\boldsymbol{\Phi}$ – objective value of ACSP model) and the remaining ones are major input parameters (i.e., Loc –location coordinates; D – demand of demand points). Note that $\{S', BS\}$ and $\{C', BC\}$ are the proper subset of the S and C sets and denote home delivery and BOPIS customer zones, respectively. Considering the major assumptions presented in Subsection 3.1, we outline the detailed procedures of the proposed sequential heuristic as explained below.

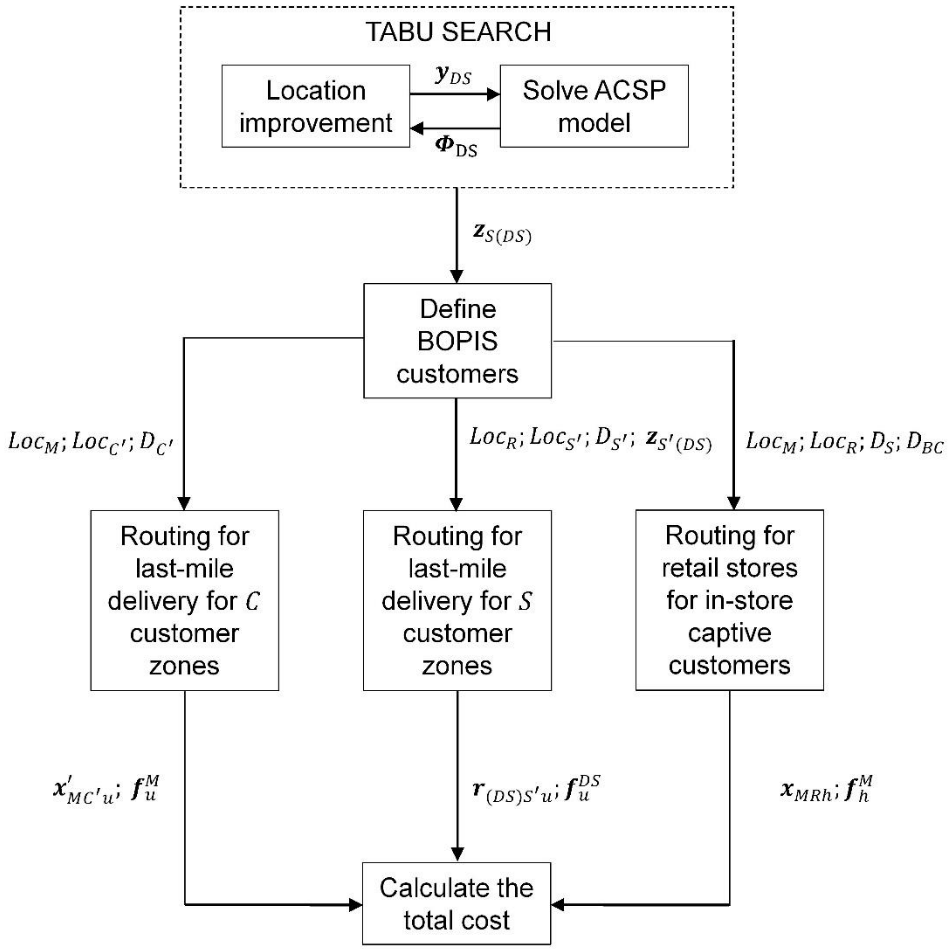


Figure C. 2. Flowchart of the solution method

Phase 1: First off, we open all dark stores and solve the allocation problem using a default solver (i.e., Gurobi 9.1.2) that assigns customer zone $s, s \in S$, to the nearest locations (ACSP - allocation of customer zones for standard products). The output of this solution allows us to obtain the initial objective value and maximum number of open dark stores (N_{max}) to which at least one client is assigned. Then, we calculate the minimum number of required dark stores (i.e., $N_{min} = \lceil \sum_{s \in S} D_s / K \rceil$, where

D_s and K denote the demand of $s, s \in S$, customer zones, and dark store capacity, respectively), which are considered as input (fixed locations) parameters in the following allocation problem.

ACSP Model

Minimize

$$\Phi = \tau \cdot \sum_{s\in S} \sum_{k\in \mathrm{DS}} z_{sk} \cdot c_{sk} + \sum_{k} y_k \cdot F \quad (1)$$

Subject to

$$\sum_{s\in S} z_{sk} \cdot D_s \leq K \cdot y_k \qquad \forall\, k \in DS \quad (2)$$

$$\sum_{k\in DS} z_{sk} = \eta_s \qquad \forall\, s \in S \quad (3)$$

$$\sum_{s\in S} \eta_s \cdot w_s \geq \alpha \cdot \sum_{s\in S} w_s \quad (4)$$

$$y_k = y_k^{TS} \quad (5)$$

$$z_{sk} = \{0,1\} \qquad \forall\, s \in S, \forall\, k \in DS$$

$$\eta_s = \{0,1\} \qquad \forall\, s \in S \quad (6)$$

In the above formulation, z_{sk} and η_s represent binary decision variables. The former denotes the assignment of customer zone $s, s \in S$ to the opened dark store $k, k \in DS$, whereas the latter represents whether a customer zone s is served. The remaining notations indicate the input parameters, i.e., c_{sk}, τ, D_s, K, w_s, α, y_k^{TS}, and F represent distance, symbolic transportation cost equal to 1, demand, dark store capacity, number of clients/people existing in each customer zone s, percentage of the total number of clients that must be served, indicates the opened dark stores obtained from TS algorithm, and fixed opening cost for a dark store, respectively. Note that the distance c_{sk} between DS and customers is a surrogate for the actual routing cost to reduce computational complexity.

We employ a tabu search (TS) procedure to make location (i.e., dark store) decisions. We employ two types of moves (swap and insert) to obtain a good configuration of dark stores. Once the N_{min} number of dark stores is selected randomly, the incumbent solution is evaluated based on the objective value (1) of the sequentially solved model (1)-(6). Our overall best solution includes three elements: number of dark stores (N), list of the best locations, and objective value (1). Subsequently, swap moves are performed by keeping N constant. To this end, we employ a function (i.e., *getNeighbors (bestLocation)*) that swaps open and closed facilities. That is, one entry among the opened dark stores is randomly selected and it is changed to be closed; another entry among the closed ones is selected and set to be opened. The swap moves are performed to evaluate all closed dark stores within the internal termination condition (i.e., 300 CPU s.). Then, an insert move is performed by increasing the number of open dark stores by one. This process continues until the number of dark stores reaches N_{max}.

The locations in a neighbor solution that improves the incumbent solution are declared tabu and kept in the tabu list until the tabu list size reaches $\xi = \lceil |DS|/4 \rceil$ (Tsubakitani and Evans, 1998). We follow a "*first in, first out*" rule to update the tabu list; this means that after a number of entries in the tabu list, the first element of the tabu list is deleted once its size (row) equals ξ. This procedure is outlined in Algorithm 1.

Algorithm 1: Tabu search algorithm for the location and allocation problem

```
N ← N_min
allBestSolution = [ ]
allBestAllocation = [ ]
overallBestSolution ← [N, [ ], +∞ ]
overallBestAllocation = [ ]
while (N ≤ N_max ):
    initialLocation ← randomly chosen N locations
    bestLocation ← initialLocation
    bestObjective, bestAllocation ← solve ACSP (bestLocation)
    tabuList.append([bestLocation; bestObjective)
    flagDiversification ← False
    while (not termination condition):
        if flagDiversification is False:
            currentNeighborhood ← getNeighbors(bestLocation)
        else:
            newLocation ← randomly chosen N location
            currentNeighborhood ← getNeighbors(newLocation)
            flagDiversification ← False
        for candidate in currentNeighborhood:
            if candidate in tabuList:
                flagDiversification ← True
                break
            else:
                currentObjective, currentAllocation ← solve ACSP (candidate)
                if currentObjective < bestObjective:
                    bestLocation ← candidate
                    bestObjective ← currentObjective
                    tabuList.append([bestLocation; bestObjective])
```

```
            if tabuList size = ξ:
                delete tabuList[0]
        if bestObjective < overallBestSolution[2]:
            overallBestSolution = [N, bestLocation, bestObjective]
            overAllBestAllocation =bestAllocation
        allBestSolution.append([N, bestLocation, bestObjective])
        allBestAllocation.append(bestAllocation)
    N ← N + 1
```

Based on the obtained outputs (i.e., number, location and unused capacity of the opened dark stores) and given parameters (i.e., distance from $c, c \in C$ to the opened dark store $k, k \in DS$ and manufacturer), we assign customer zones $c, c \in C$ to the opened dark stores. Here, three constraints must be ensured: a customer zone c must be located within distance ϕ from the opened dark store, the dark store must have an available capacity and the desired percentage (α) of the total number of clients that must be served. If there are more customer zones c that fulfill these criteria than can be served given the limited capacity of the opened dark stores, we prioritize those zones c that are the farthest from the manufacturer plant. Finally, along with the assigned $c, c \in C$, customers, customers $s, s \in S$, (assigned by solving model ACSP) located within the distance ϕ from the opened dark store are determined as BOPIS customers and removed from the $\{0\} \cup C$ and $R \cup S$ nodes, respectively, while solving the routing problems in Phase 2.

Phase 2: In this phase, the following steps are performed to solve the routing problems:

- *Step 1:* Solve the CVRP from the manufacturer to the last-mile delivery customer zones for the customized product via urban van by considering updated $M \cup C$ nodes.
- *Step 2:* Solve the CVRP from the manufacturer to the retailer via a heavy truck. The retailers' demands (i.e., for standard products) were updated by considering the assigned S and C customers' demand for standard and customized products, respectively.
- *Step 3:* Solve CVRPs from each opened dark store to the last-mile delivery customer zones for standard products via an urban van considering updated $R \cup S$ nodes.
- *Step 4:* Calculate the cost of the solution.

Note that in Step 1 and Step 2, more customers may be served than is necessary to satisfy the service level constraints ($O2$). Therefore, the most expensive tours are removed until the desired percentage (α) of the total weighted number of clients that must be served is reached. For Step 3, this constraint has already been considered during the allocation problem Π (Constraint (4)).

We used the Lin–Kernighan–Helsgaun (LKH) heuristic solver, which is an efficient implementation of the Lin–Kernighan heuristic (Lin and Kernighan, 1973) in terms of solution performance and quality (Helsgaun, 2009; Taillard & Helsgaun, 2019). The focal concept in the Lin–Kernighan algorithm is the definition of allowable moves that facilitates the subset of r-opt moves to be considered while transforming a tour into a shorter tour (Helsgaun, 2000). Specifically, we use the LKH-3 (downloaded from http://akira.ruc.dk/~keld/research/LKH-3/, LKH 3.0.7, May 2022) version, which is an extension of LKH-2 (which primarily solves TSPs) and can solve vehicle routing problems with capacity effectively. LKH-3 transforms the problem into standard symmetric traveling salesman problems and utilizes penalty functions to manipulate constraints (Helsgaun, 2017).

Phase 3: Finally, we add the number of opened dark stores (Phase 1) multiplied by the fixed opening cost and logistics costs obtained from Phase 2 (*Step 4*) to calculate the total cost, that is, the objective function ($O1$).

C.6. Computational study

This section presents the numerical experiments conducted to explore the performance of the proposed solution methods and outlines the managerial implications of the channel transition of an encroaching manufacturer. In the following subsections, we first describe the instance data and computational environment, followed by computational results and the analysis of the proposed model.

C.6.1. Instances and computational environment

Two sets of instances were used in the computational study. The first set is adapted from the famous "Barreto set" (Barreto et al. 2007) of LRP instances, composed of 18 instances with the number of customers n ranging from 12 to 318, number of capacitated locations (corresponding to retailers / potential dark stores) k ranging from 2 to 15, and various capacitated vehicles. We use the given capacity for $u, u \in U$, urban delivery van type vehicles because the "Barreto set" contains only one type of vehicle, for each instance; however, the given capacities are increased by 4 for $h, h \in H$, heavy truck type capacities. The "Barreto set" is interpreted as small and medium size instances that can be solved via a numerical solver; therefore, they are included for benchmarking.

Moreover, we generate new instances. Set L involves 20 large instances with $n = 1000$ customer zones. These instances are generated closely to the real-world case based on data from a fashion company operating in Berlin, Germany. Our proposed model (OC) captures the company's distribution network configuration where standard and customized athletic footwear are vended through retail stores and the company's website, respectively. Recently, offering customized products (i.e., usually via online channels) has become more popular among footwear companies along with standard products (e.g., https://www.nike.com/nike-by-you). We obtain the number and location of retail stores and factory (i.e., the central warehouse of the factory) within the Berlin metropolitan area using publicly available information. We use ArcGIS 10.3 and Google Earth Pro software to retrieve the exact two-dimensional (x, y) coordinates (i.e., from the Universal Transverse Mercator (UTM) 39 WGS 84) of locations (i.e., retail stores and factory warehouse) and corners of the rectangular area, whose area is roughly equivalent to the Berlin metropolitan area (Figure C.3). First, we converted coordinates from meters to kilometers, and then, within the rectangle's boundary, we generate x_i, i.e., between the interval (370, 416) and y_i, i.e., between the interval (5800, 5837) coordinates for each customer zone $i, i \in S \cup C$. For L instances, the demand of each customer zone per product type $(D_{jp}, j \in T \cup S \cup C, p \in P)$ and the capacity of dark stores (K) are generated uniformly in the range of [1,100] and [5000, 10000], respectively. The vehicle capacity for each type was considered $Q_u = 1000$ and $Q_h = 10000$. The fixed opening cost of a dark store is a linear function of the capacity values and calculated as $\lceil 0.25\ €/unit \cdot K \rceil$.

For each set of instances, we split the total customer zones among the three types of customer segments $j, j \in T \cup S \cup\ C$, randomly. To this end, we generated a uniformly distributed random number $q_j \in [1,10]$. Then, we set the customer counts n_j for each segment j such that the ratio of customer counts $n_1 : n_2 : n_3$ corresponds to the random ratios $q_1 : q_2 : q_3$. Afterwards, we round each n_j to either the next largest or smallest integer, where the sum total must be equal to the total number of customer zones (e.g., for the L instances, the total customer zones–1000 may be split into $6:5:3$ ratios, and this implies that the number of customers per segment $T, S, \& \ C$ is 429, 357, and 214, respectively). The weight $(w_j, j \in T \cup S \cup C)$ for each customer zone is a uniformly distributed random number ranging from $[1, D_j]$. The fixed cost of using a vehicle (G_h, G_u) and transportation cost (t_h, t_u) per vehicle type are considered (15, 6) and (8, 3), respectively. Finally, the distance range ϕ for BOPIS customers is considered less than $3\ km$. Dataset for L instances can be downloaded via this DOI: https://doi.org/10.5281/zenodo.7049674.

All instances are solved on a PC with an Intel Core-i7-6700 CPU, 3.40 GHz, and 8 GB RAM using Windows 10 Pro x64. To solve these instances, the solution methods (Section 5) are implemented in Python 3.8.8. For benchmarking and for solving the allocation subproblem, Gurobi 9.1.2 is employed as the default solver.

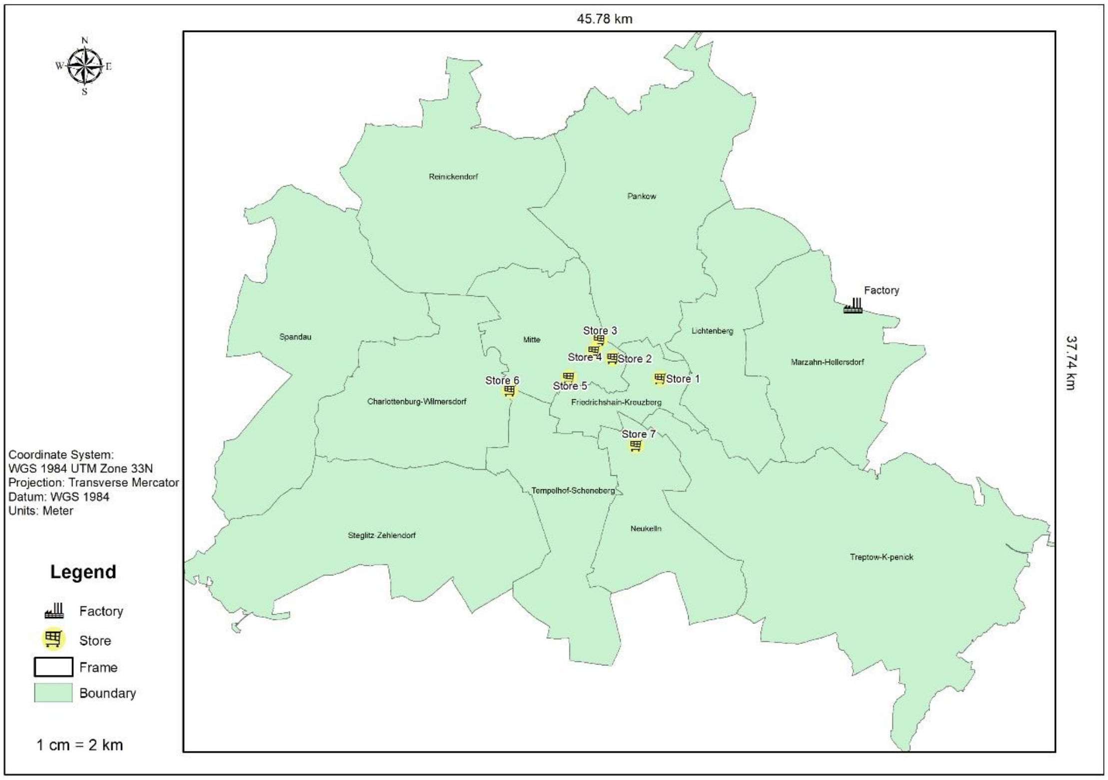


Figure C. 3. Location of retail stores and factory warehouse in the Berlin metropolitan area

C.6.2. Computational results

The computational study has two objectives. We study the computational performance of the proposed decomposition metaheuristic technique, and we perform several analyses to provide managerial implications for a manufacturer designing its supply chain network using this technique on the *L* instances.

C.6.2.1. Computational performance

Recall that we used the "Barreto set" for benchmark purposes. Thus, 18 instances were solved using the Gurobi solver and our proposed solution methods. Because Gurobi was not capable to solve even some small- and medium-sized instances within a reasonable time interval with a 0 % optimality gap, we set the solution time limit to 36000 CPU seconds for all runs. We recorded the best objective (upper bound-UB, i.e., the best feasible solution), the best bound (lower bound-LB), and the optimality gap (Gap_{Gurobi}). The optimality gap was obtained as follows: $Gap_{Gurobi} = \frac{UB-LB}{UB} \cdot 100$. Furthermore, to compare the solution quality and time of our proposed solution methods, we also recorded the best objective and solution time (*CPU sec.*) for each instance, solved using our decomposition metaheuristic. The objective values of the Gurobi (UB) and the decomposition heuristic were compared by employing the gap ($Gap = \frac{UB_{Gurobi} - Best\ Obj._{decomposition\ metaheuristic}}{UB_{Gurobi}} \cdot 100$). Table C.3 presents the benchmark results.

Table C. 3. Algorithmic performance for the “Barreto set” instances

No	Instance	Gurobi				Decomposition metaheuristic		Gap %
		Best Obj. (UB)	Best bound (LB)	Gap_{Gurobi} (%)	CPU time (s)	Best Obj.	CPU time (s)	
1	Christofides69-50 × 5	4906	4097	16.49	36000	4294	16.15	−12.47
2	Christofides69-75 × 10	14516	11968	17.55	36000	12299	21.09	−15.27
3	Christofides69-100 × 10	3478	2844	18.23	36000	2941	23.57	−15.44
4	Daskin95-88 × 8	17473.60	3694	78.86	36000	6094.79	18.34	−65.12
5	Daskin95-150 × 10	-	235897	-	36000	319270	25.27	-

6	Gaskell67-21 × 5	12175	9329	23.38	36000	9980	8.78	−18.03
7	Gaskell67-22 × 5	15248	9895	35.11	36000	10420	9.05	−31.66
8	Gaskell67-29 × 5	19308	14581	24.48	36000	14747	12.03	−23.62
9	Gaskell67-32 × 5	24601	18020	26.75	36000	18362	14.16	−25.36
10	Gaskell67-36 × 5	3653	3056	16.33	36000	3185	15.88	−12.81
11	Min92-27 × 5	177067	146328	17.36	36000	151155	11.28	−14.63
12	Min92-134 × 8	345084	200701	41.84	36000	219341	22.45	−36.44
13	Or76-117 × 14	187385.20	86296.30	53.95	36000	115968.20	39.90	−38.11
14	Perl83-12 × 2	1086	1086	0.00	5.92	1086	5.11	0.00
15	Perl83-55 × 15	16306	9591	41.18	36000	10022	43.07	−38.54
16	Perl83-85 × 7	6788	4734	30.26	36000	4843	19.65	−28.65
17	Perl83-318 × 4	-	-	-	36000	8564600	14.20	-
18	Srivastava86-8 × 2	6176	6176	0.00	1.19	6176	3.62	0.00
Avg.							17.98	−23.51

Table C.3 indicates that Gurobi can obtain optimal (i.e., with 0 % gap) solutions for only two unrealistically small instances (14th and 18th) in a few CPU seconds. However, optimal solutions could not be obtained for the remaining instances within the time limit; instead, the UB and LB were determined. The 17th instance could not be loaded into memory during the pre-solve phase, and therefore, the best bound of the instance could not be obtained. For our proposed solution method, the results indicate that it obtains the same objective values as Gurobi for two small instances (14th and 18th). In general, the results clearly indicate that our problem-specific decomposition metaheuristic outperforms Gurobi in terms of solution quality, which a −23.51% gap and 17.98 CPU s solution time.

We solve the L instances and report the results in terms of the best objective values and solution times to pose more of a computational challenge to our decomposition metaheuristic (see Table C.4). The average solution time is 81.03 CPU s, which is a reasonable solution time interval for such large instances, given the strategic nature of the problem.

Table C. 4. Algorithmic performance for the large instances (n = 1000)

Instance	Decomposition metaheuristic	
	Best Obj.	CPU time (s)
L1	10870	86.68
L2	12610	80.54
L3	12950	90.57
L4	9749	79.31
L5	11397	82.36
L6	9226	69.31
L7	11153	79.20
L8	12395	106.38
L9	11680	87.26
L10	12904	70.28
L11	11178	90.29
L12	9079	50.17
L13	10702	61.23
L14	9103	54.31
L15	12384	100.32
L16	12658	93.27
L17	10706	78.32
L18	11922	95.25
L19	11686	78.27
L20	9432	87.16
Avg.		81.02

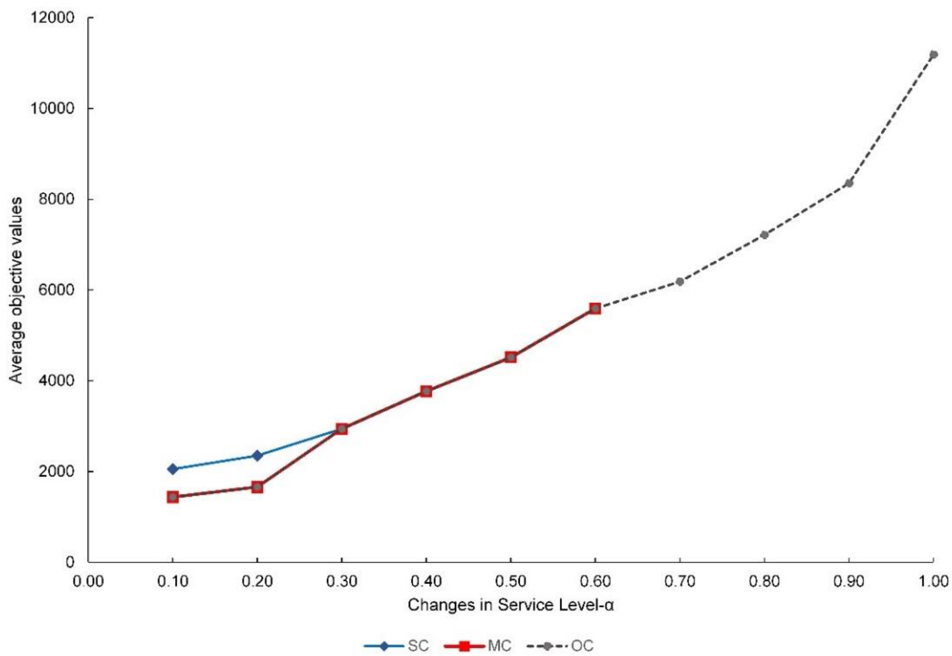
C.6.2.2. Managerial implications

Apart from the algorithmic performance, we investigate the managerial implications crucial for practitioners aiming to optimize their supply chain network design. For this purpose, we reuse the set L instances solved by our proposed heuristic.

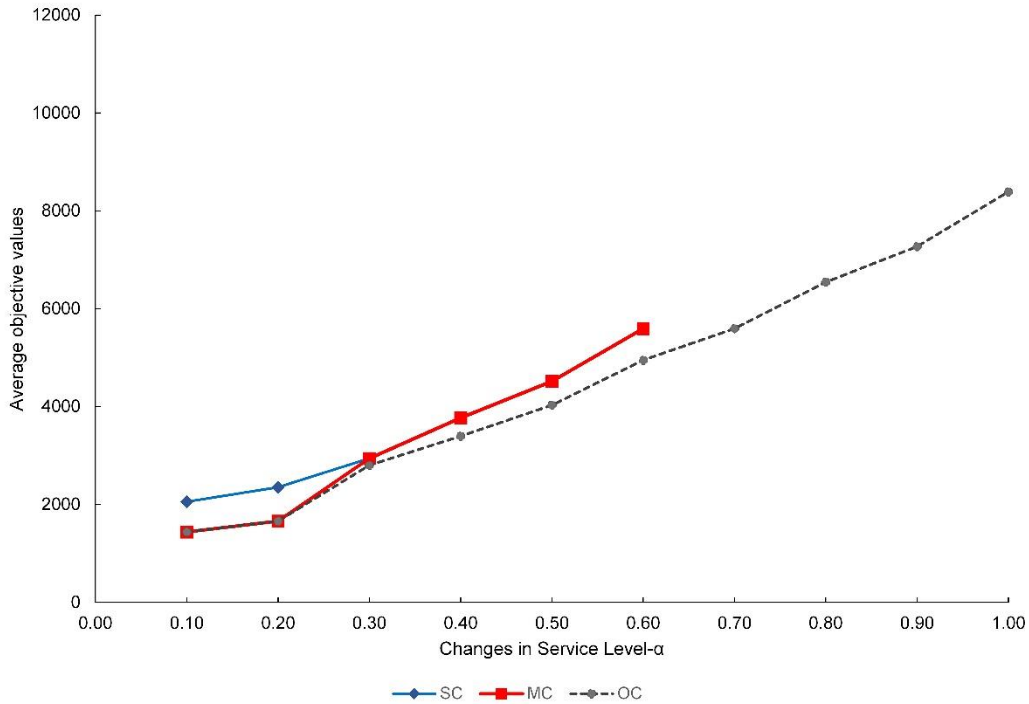
C.6.2.2.1. Comparison of three network configurations

We address a manufacturing company planning to expand its market penetration and reach various customer segments. The company wants to analyze three distribution network designs: single-channel, multi-channel, and OC. For such strategic decisions, the company must make a trade-off between the total logistics cost and customer service level (SL). For example, shipping customized products directly from the factory to consumers is certainly more expensive from a logistics perspective than only selling standard products through mass-market retail stores. However, adding another shipping channel opens up completely new markets, allowing selling customized products with presumably higher margins. This is expressed in our models through the service level α. For the three developed models (SC, MC, and OC), tuning the α parameter (in the S2 and O2 constraints, respectively) enabled us to observe changes in the logistics cost per channel type with changes in α. The SC distribution system can only serve the T segment, the MC distribution system can serve T & C segments, and only the OC distribution system can serve all three ($T, C, \& S$) segments. Consequently, only the OC system can achieve a service level of 100%, provided that there are any customers at who are interested in receiving standard products via home delivery. The initial value of the α parameter is considered 0.10 (or 10 % service level) and increased by 0.10 up to 1 (or 100 % SL). The average objective value (total logistics cost) of all L instances is calculated for each α value. Figure C.4-a shows the observed changes. The chart reports that, between 10 and 20 %, the SC distribution system is costlier than MC and OC distribution systems, which incur the same amount of logistics cost. The reason is that the MC and OC distribution systems are more flexible and are capable to serve certain number of last-mile delivery customer zones for customized product via urban van which is cheaper than heavy truck.

The costs of all three channel configurations become equal when the service level reaches 30 %. The company can serve only 30 % of total customers via SC, because only the customers satisfied with shopping for standard products in-shop can be reached. A further increase in the service level (i.e., starting from 30%) is possible via MC and OC distribution systems; however, MC cannot serve more than 60 % SL, because it does not allow home-delivery of standard products from a dark store. The company can serve all customer segments only via the OC distribution system; however, the total logistics cost increases gradually. Further, it is insightful to observe that there is a steep rise in logistics costs when SL exceeds 90 %. This may be the threshold for the company during decision making. As can be seen, in the range of [0.10, 0.60] of the α value, MC and OC incur the same logistics cost, however, OC is more flexible than MC and can lead to a lower cost at a certain SL. That is, OC is capable to serve last-mile delivery customers for standard products (S) over a dark store while serving physical stores. But, the fixed opening cost for a dark store enforces that OC behaves in the way MC does. Hence, it can be interesting to observe the logistics cost of the three distribution systems by discarding the fixed opening cost of dark stores. From the manufacturer's perspective, in practice, this can be realized by either using its outlets (i.e., 0 cost for opening a DS) or stores of an independent retailer in exchange for various incentive schemes (i.e., considerably low cost for opening a DS). Figure C.4-b illustrates the observed changes wherein in the range [0.3, 0.6] of the α value, OC outperforms MC in terms of logistics cost. Further, the logistics cost of OC also has a gentle rise when the SL increases. In summary, it is crucial to make effective decisions on supply chain network design to define the company policy for the customer service level. In this context, our investigation suggests that MC and OC outperform SC distribution system in terms of logistics cost. Moreover, our analysis shows that OC is an economically viable distribution system for achieving a cost-effective supply chain (i.e., if fixed opening cost of the dark store is discarded or significantly decreased) and meeting the expectations of various customer segments in terms of shopping and product preferences.



(a) With presence of dark store fixed opening cost



(b) With absence of dark store fixed opening cost

Figure C. 4. Average total costs for different changes in service level (α) per a channel type

C.6.2.2.2. Effect of the number of dark stores

In the OC model, dark stores play a crucial role in consolidating last-mile delivery and in-store pick-up services. Naturally, minimizing the number of opened dark stores is a major objective of the proposed model because opening a dark store incurs additional costs. Meanwhile, the transportation costs decrease as the number of dark stores rises, because the average distance for last-mile deliveries is less and more customers have the BOPIS option. In addition, a higher number of BOPIS customers reduces the complexity of last-mile routing operations as well. In this respect, we investigate how the number of DS affects the transportation costs. In our numerical study of the L instances, two dark stores were established in most cases (85 %). Therefore, we run those instances (i.e., by setting α to 100 %) for various dark store counts, i.e., from N_{min} to N_{max} inclusively, as Algorithm 1 enables us to retrieve the best locations, allocation and objective value for each N between N_{min} and N_{max}. Figure C.5 depicts the results. The transportations costs drop gradually with an increase in the number of dark stores. The results suggest that opening the third dark store decreases the transportation costs by 16 % ,whereas opening the 4th dark store decreases the preceding (i.e., corresponding to opening 3 dark stores) transportation costs by 16 %, followed by 23 % (from 4 to 5). As can be seen, opening five dark stores has a more positive impact on reducing transportation costs, whereas opening the next two dark stores (6th and 7th) does not affect the transportation costs. On average, opening one more dark store leads to a decrease in transportation cost by 19 %; this can provide sound insights for a company during decision making regarding channel design. If a company wants to gain competitive advantages, offering multiple pickups or return points to customers can be a wise strategy in terms of customer satisfaction. Moreover, as mentioned above, if a manufacturer can significantly reduce (or completely avoid) the fixed cost of opening a dark store, in this case opening a feasible number of dark stores (i.e., in our case 5) can reduce the transportation costs. Therefore, understanding the effect of opening additional dark stores can facilitate an effective decision-making process.

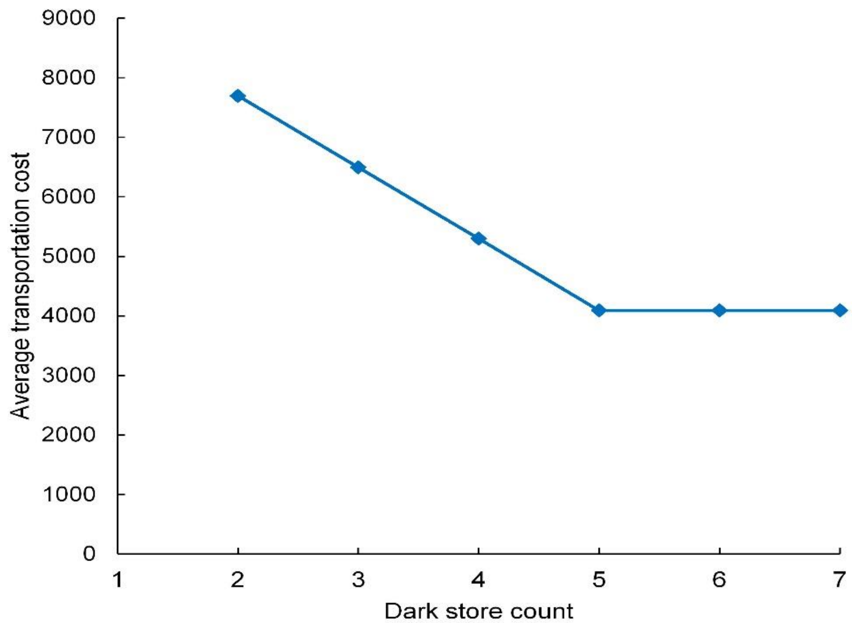


Figure C. 5. Effect of the number of dark stores

C.6.2.2.3. Effect of in-store pickup

In the proposed OC model, customers (i.e., $S \cup C$) located within a defined distance range are assigned to an open dark store as BOPIS customers. The in-store pickup concept is a significant element of the OC distribution system and offers a flexible shopping experience to customers. Thus, we investigate the effect of BOPIS customers on total logistics costs. Further, we performed this analysis on the set of L instances where $\alpha = 100\%$. For all instances, the average BOPIS customers are roughly equal to 5 % (i.e., 4.82 %) of the total home delivery customers (both S and C). We assume this value to be a baseline scenario. Then, we turn home-delivery customers into BOPIS customers by increasing 5 % for a new scenario. To this end, for S customers, a randomly selected node is removed from its route and assigned as a BOPIS customer to the corresponding DS from which the route originated. For C customers, a randomly selected node is assigned to the nearest opened DS and removed from the route. The procedure repeats until achieving the required percentage. Afterwards, we record the average objective value for each instance. Figure C.6 illustrates the results.

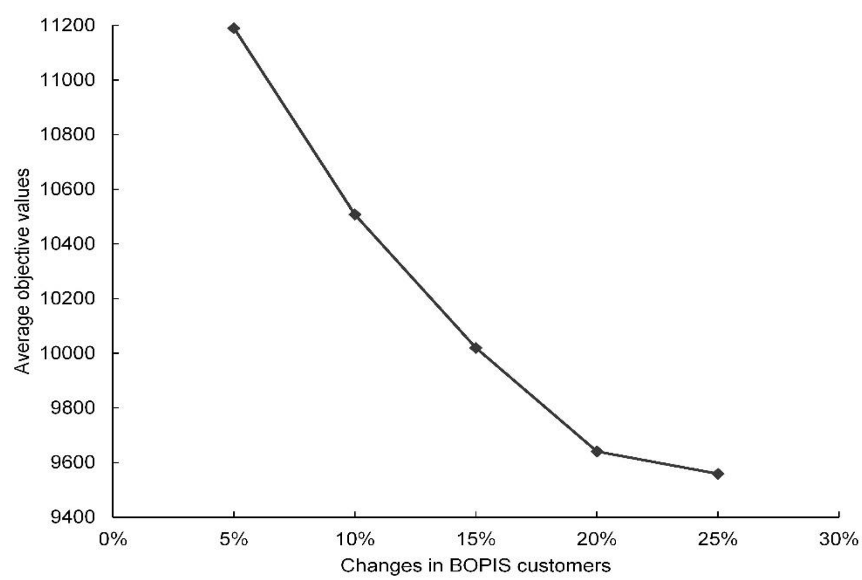


Figure C. 6. Effect of in-store pickup

In general, the logistics cost declines as we increase BOPIS customers. The logistics costs drop dramatically between 5 and 20%; subsequently, they decline more slowly. This investigation shows that an increase in BOPIS customers leads to a reduction in the total logistics costs. Companies can leverage this and invest some effort in motivating online shoppers to pick up in-store (e.g., by offering special discounts or redeeming bonus points). Moreover, having data on costs saved enables the company to determine the investment budget for promotional activities. Besides cost savings, this initiative can give rise to making the complicated last-mile delivery operations easy within city limits and achieving sustainability.

C.7. Conclusion

We investigated three distribution network design scenarios: single channel, multi-channel, and OC for a manufacturer selling standard and customized products. We addressed the proposed model from the manufacturer's perspective and analyzed its channel-selection strategy under customer service-level constraints. For each scenario, a mathematical model was developed; the proposed model was the OC model, and this contributes to the related research stream. The proposed model is an integrated optimization model that includes an LRP for designing a combined two-echelon supply chain network for an OC distribution system with fragmented customer demands met over multiple shopping and delivery options.

We developed a problem-specific decomposition metaheuristic to solve large-scale instances, and this outperforms a default solver on the instances adapted from the "Barreto set," in terms of solution quality.

In the computational study, we explored methods to achieve a cost-effective supply chain and meet the expectations of various customer segments in terms of shopping and product preferences. We discovered the effect of the number of dark stores on large-scale instances and reported a percentage increase in the total logistics cost while opening a new dark store. Further, we investigated the effect of in-store pickup on the total logistics cost.

Our findings indicate that logistics costs decrease substantially with an increase in the number of BOPIS customers. This suggests that it may well be worthwhile from the supply chain manager's perspective to invest some effort into motivating customers to forego home deliveries in favor of in-store pickups, maybe by offering reduced shipping fees and opening convenient pickup locations. Moreover, our results show that to reach various customer segments, OC is a feasible distribution system for almost every value of service level. To gain competitive advantages and increase customer satisfaction, utilizing retailers' physical stores as a DS could be a wise strategy, albeit they incur additional fixed costs. Furthermore, we show that an increased number of DS significantly reduces transportation costs. Therefore, understanding the effect of opening additional dark stores can be paramount for effective decision-making.

Future research should focus on developing powerful exact solution methods to solve realistic instances because default solvers cannot solve large instances. Customer returns can be included in OC LRPs to reflect real-world OC operations. In this context, the effect of “buy online, return in-store (BORIS)” customers can be investigated. Further, our proposed model can be investigated under stochastic or multiperiod settings.

Appendix C

Mathematical formulations of single channel and multichannel scenarios

Single channel distribution scenario model (S)

Minimize

$$\sum_{h\in H} G_h \cdot f_h + \sum_{h\in H} \sum_{i\in\{0\}\cup R} \sum_{j\in\{0\}\cup R} x_{ijh} \cdot t_h \cdot d_{ij} \qquad (S1)$$

Subject to

$$\sum_{i\in R\cup S\cup C} g_i \cdot w_i \geq \alpha \cdot \sum_{i\in R\cup S\cup C} w_i \qquad (S2)$$

$$\sum_{h\in H} \sum_{j\in\{0\}\cup R} x_{rjh} = g_r \qquad \forall r \in R \qquad (S3)$$

$$\sum_{i\in R\cup S\cup C} g_i = \sum_{j\in\{0\}\cup R} \sum_{r\in R} \sum_{h\in H} x_{rjh} \qquad (S4)$$

$$\sum_{i\in\{0\}\cup R} x_{ijh} - \sum_{i\in\{0\}\cup R} x_{jih} = 0 \qquad \forall j \in \{0\} \cup R, h \in H \qquad (S5)$$

$$\sum_{i\in\{0\}\cup R} x_{i0h} \leq 1 \qquad \forall h \in H \qquad (S6)$$

$$\sum_{p\in P} \sum_{r\in R} D_{rp} \sum_{j\in\{0\}\cup R} x_{r0h} \leq Q_h \cdot f_h \qquad \forall h \in H \qquad (S7)$$

$$L_{ih} - L_{jh} + N1 \cdot x_{ijh} \leq N1 - 1 \qquad \forall\, i \in R, j \in R, h \in H \qquad (S8)$$

In this formulation, the objective function (S1) minimizes the total logistics cost including the fixed cost of using a vehicle per route and transportation cost. Constraint (S2) imposes that at least α percentage of all customer nodes must be served according to their preferences. Constraint (S3) ensures that if a client on the first route $(r, r \in R)$ is served, it must be visited by exactly one heavy truck $(h, h \in H)$. Constraint (S4) guarantees that a customer zone can be served if and only if it is visited by one heavy truck. The constraint (S5) ensures that for each vehicle $(h, h \in H)$ the number of routes entering and leaving the node is equal. The sixth set of constraints (S6) ensures that vehicle type $h, h \in H$, can be used a maximum of once on a tour. Constraint (S7) ensures that the demand for the standard product $p, p \in P$, realized by a heavy truck $h, h \in H$, must be less than equal to the capacity of a heavy truck if it is used. Finally, constraint (S8) is a subtour elimination constraint.

Multichannel distribution scenario model (M)

Minimize

$$\sum_{h \in H} G_h \cdot f_h + \sum_{u \in U} G_u \cdot f_u + \sum_{h \in H} \sum_{i \in \{0\} \cup R} \sum_{j \in \{0\} \cup R} x_{ijh} \cdot t_h \cdot d_{ij}$$
$$+ \sum_{u \in U} \sum_{i \in \{0\} \cup C} \sum_{j \in \{0\} \cup C} x'_{iju} \cdot t_u \cdot d_{ij} \qquad (M1)$$

Subject to

In addition, the same six constraint sets presented in the single-channel scenario (i.e., S2, S3, S5, S6, S7 and S8);

$$\sum_{u \in U} \sum_{j \in M \cup C} x'_{cju} = g_c \qquad \forall c \in C \qquad (M2)$$

$$\sum_{i \in R \cup S \cup C} g_i = \sum_{j \in \{0\} \cup R} \sum_{r \in R} \sum_{h \in H} x_{rjh} + \sum_{j \in \{0\} \cup C} \sum_{c \in C} \sum_{u \in U} x_{cju} \qquad (M3)$$

$$\sum_{i \in \{0\} \cup C} x'_{iju} - \sum_{i \in \{0\} \cup C} x'_{jiu} = 0 \qquad \forall j \in \{0\} \cup C, u \in U \qquad (M4)$$

$$\sum_{i \in \{0\} \cup C} x'_{i0u} \leq 1 \qquad \forall u \in U \qquad (M5)$$

$$\sum_{p \in P} \sum_{c \in C} D_{cp} \sum_{j \in \{0\} \cup C} x'_{cju} \leq Q_u \cdot f_u \qquad \forall u \in U \qquad (M6)$$

$$L_{iu} - L_{ju} + N2 \cdot x'_{iju} \leq N2 - 1 \qquad \forall\, i \in C, j \in C, u \in U \qquad (M7)$$

The objective function (M1) minimizes the fixed costs of using each vehicle type (heavy trucks and urban vans) and transportation costs from the manufacturer to the retailer's stores (R) and last-mile delivery customer zones (C) by shipping standard and customized products, respectively. The constraint sets impose the same conditions (i.e., M2-all demand must be satisfied if they are served; M3- a customer node is served if and only if it is visited; M4-flow constraints; M5 & M6- vehicle use and capacity constraints; M7- subtour elimination constraints), as the constraint sets of the first model impose.

Chapter D. Routing Automated Lane-Guided Transport Vehicles in a Warehouse Handling Return*

Abstract: Faced with high return rates, many e-commerce retailers are considering novel technical solutions to expedite the processing of returned items in their warehouses. One such solution consists of lane-guided transport (LGT) vehicles. These small, electric vehicles follow optical markers on the floor, picking up boxes of returned items at a depot and dropping them off at workstations, releasing the logistics workers to focus on the productive task of actually processing the items instead of carrying them through the warehouse. These types of systems are simple to set up from a technical perspective; however, the routes on the warehouse floor still need to be carefully planned. This gives rise to the following routing problem. Given a set of stations to be served from multiple depots by a fleet of LGT vehicles, which stations doing what type of work should be visited on what route? Only one route per depot is allowed, but multiple vehicles may use the same route. Moreover, since routes cannot be changed on short notice, we consider an infinite planning horizon where the demand rate of the stations depends on the type of work they are assigned to do (e.g., handling defective items or

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refurbishing). We develop a decomposition heuristic, which solves instances derived from industry data to near-optimality in less than a minute. We also show that the depot location is rather unimportant for the overall system performance, but that the depot count can have a significant influence.

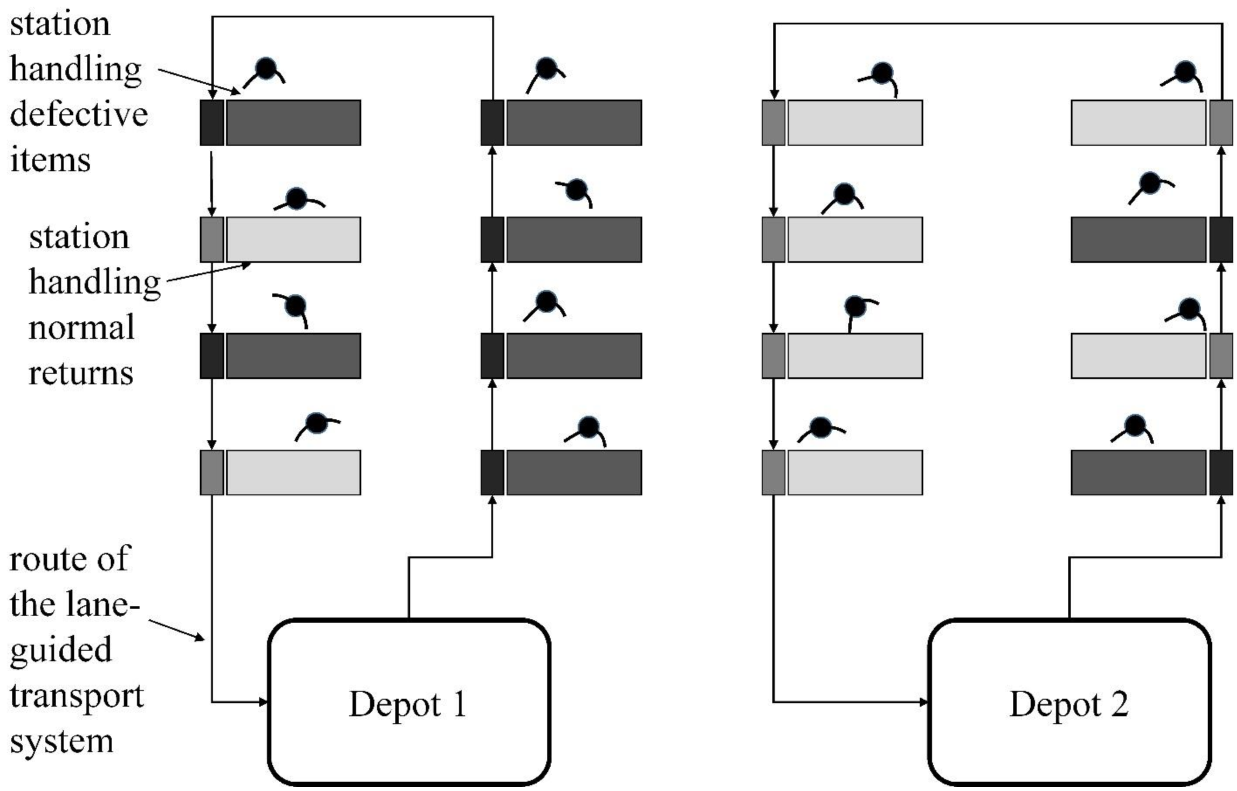
D.1. Introduction

Warehousing is a central part of essentially any supply chain handling physical goods and usually accounts for a sizeable share of all logistics costs (De Koster, Le-Duc, & Roodbergen, 2007). Among the processes associated with warehousing operations, manual order handling is by far the most labor intensive (Petersen & Aase, 2004). Especially modern e-commerce retailers face enormous pressure to organize their warehousing processes in an efficient manner, as they deal with broad assortments, large, very diverse order volumes, and tight schedules to ensure customer satisfaction (Boysen, de Koster, & Weidinger, 2019). Despite these pressures, a recent white paper by Trottmann and Zhang (2017) finds that only "over 10% of warehouses in the U.S. were using sophisticated automation technologies in 2016", but that the number of robots in warehouses is projected to grow "15 times by the end of 2021".

While order picking in the forward supply chain has received a substantial amount of attention both from academia as well as technical innovators (see, e.g., surveys by Boysen et al., 2019; Gu, Goetschalckx, & McGinnis, 2010; Van Den Berg, 1999), return flows are less often considered, although they account for a significant share of warehousing activity. In online retailing, e.g., re- turns are reported to be in excess of 30% in many product categories (Dennis, 2018). In this context, we consider the following case we encountered at a major European e-commerce company selling mainly apparel.

D.1.1. Lane-guided vehicles in a returns warehouse: practical case and problem description

Given the high return rates in online fashion retailing, the company realized that the traditional manual processes for handling returns are inadequate. While human interaction is unavoidable when actually inspecting individual items, workers should at least not waste time carrying items around the warehouse. In consequence, it was decided to install a lane-guided transport (LGT) system in a newly erected warehouse, which is exclusively used to handle returns. The entire process flow is as follows. When trucks carrying returned items arrive at the warehouse, they are unloaded by logistics workers and the individual items are pre-sorted into two categories: items that are clearly defective and need to be either shipped back to the manufacturer or recycled, and items that may be resold once checked, refurbished and / or repackaged. Standard-size bins filled homogeneously either with items to be recycled or items to be resold are then deposited at a depot on the main warehouse floor. From the depot, bins are picked up one after another by LGT vehicles, which automatically carry them to an available station. At the station, a human operator sifts through the items in the bin and processes them appropriately (either recycling or refurbishing, depending on the station). When all items in a bin have been processed, the bin with the processed items is added to a queue to be picked up by a passing LGT vehicle to be taken back to the depot, where they are either sent to the main warehouse for resale, or loaded onto outgoing trucks for recycling / return to the manufacturer. Since refurbishing and recycling are fundamentally different activities, each station is only equipped to do either the one or the other. Moreover, handling a bin of defective items takes substantially longer than preparing a bin of items for resale; at the retailer we visited, the former takes almost twice as long as the latter on average. The warehouse floor is schematically depicted in Figure D.1-a.



(a) Example warehouse floor with 16 stations served by two depots.

(b) Lane-guided transport vehicles[1]

Figure D. 1. An example Problem

The LGT system consists of guide strips attached to the floor and a fleet of automated guided vehicles, which mindlessly follow the guide strips non-stop at the same constant speed. When they pick up a bin, be it at the depot or at one of the stations, a bar code on the bin tells them where to take the bin, while bar codes on the floor designate the individual stations. Bins are automatically deposited on top of the vehicles and automatically dropped off at their destinations by simply passing through a mechanical pilot device. The vehicles never need to stop or slow down. The bar codes on the floor and the bins determine whether a bin is

[1] The picture belongs to SSI Schäfer. SSI Schäfer permitted the usage in the context of this paper.

dropped off or simply passes through. If a vehicle passes by a point-of-use that has bins waiting for transport and the vehicle is not currently carrying a bin, the bin is picked up. Note that the type of station (recycling or refurbishing) does not matter because the bins are standardized such that any vehicle can carry any bin. The whole system relies entirely on optical guidance and does not require sophisticated sensors or control logic. Vehicles are battery- operated, but a single charge usually lasts for an entire shift. Optical guide strips can be rerouted relatively easily during off-hours. LGT vehicles are depicted in Figure D.1-b.

Concerning the station types, it is known from historical data how many stations of each type are required (e.g., the total number of stations must be split into 30% stations handling defective items and 70% stations handling for-resale items). Since the processing time per bin depends on the type, demand rates vary de- pending on the assigned station type (refurbishing is faster than recycling, hence refurbishing stations have a higher handling capacity / transport demand per time unit).

In this paper, we address the following optimization problem, the *lane-guided transport system routing problem* (LTSRP). Given a set of stations that have a certain transport demand per time unit depending on what class they are assigned, and given a set of de- pots, how many vehicles should be assigned to each depot, what routes should these vehicles take, and what type should each station be assigned? The total number of stations of each type is given. Since the guide lanes cannot be changed on short notice, each depot can only serve exactly one route. Consequently, since vehicles move at a given constant speed and the stations require a certain number of bins per time unit, the throughput of each vehicle per time unit depends on the length of the assigned route. If a route is longer, more vehicles are necessary to meet the same transport demand. The primary objective is to minimize the total number of vehicles.

D.1.2. Contribution and paper structure

The contribution of this paper consists of modelling the novel problem of routing LGT vehicles in a returns warehouse, where stations can be assigned different roles. This problem is fundamentally different from classic (multi-depot) routing problems because multiple vehicles serve the same route, stations can be assigned different roles (e.g., handling defective or to-be-refurbished items), and the longer the route, the more vehicles are needed to serve the demand. We propose a decomposition heuristic based on tabu search to solve this problem, and show in a computational study that this procedure performs well on instances of realistic size. Finally, we derive some managerial insight into the connection be- tween depot count and location and vehicle fleet size.

The remainder of this paper is structured as follows. In Section D.2 we review the literature. Section D.3 formally introduces the problem and a mixed-integer programming formulation. In Section D.4, we analyze the computational complexity of the problem and some important special cases. Solution methods are presented in Section D.5 and tested in Section D.6. Finally, the conclusions follow in Section D.7.

D.2. Literature review

Routing pickers or automated devices in warehouses has great relevance in practice, since item picking and stocking are among the most labor-intensive activities in a warehouse (De Koster et al., 2007). As such, it is not surprising that it has received a lot of attention from academia as well. Surveys on warehousing optimization problems in general can be found in Petersen and Aase (2004), Gu et al. (2010) and Boysen et al. (2019).

Often, returned items are processed separately from normal receipts from suppliers, occasionally even in separate warehouses. Classically, returned items are transported manually (i.e., by a logistics worker pushing a cart, e.g., De Brito, De Koster, & van de Vendel, 2002) or by some rigid automated transport system, like a conveyor (De Brito & De Koster, 2004). Moving returned items manually, however, is clearly not very efficient as this is a non- value-adding activity. On the other hand, rigid conveyor belts may lack flexibility and cannot easily be redeployed if the warehouse layout changes. LGT vehicles are supposed to combine the advantages of both systems: on the one hand, paid workers need not waste their time carrying items around the warehouse; on the other hand, LGT systems scale well and are quite flexible since they rely only on optical markers that can be rearranged easily.

Recently, many novel (semi-)automated warehousing technologies have been developed (surveyed by Azadeh, De Koster, & Roy, 2019). Although most of these systems are discussed in the context of forward operations, there is no reason why some of them could not also be used to handle returns. Lane-guided transport vehicles have, to the best of our knowledge, not yet been discussed in this context in the academic literature.

In general, literature on optimizing return flows in a warehouse is relatively scarce (Boysen et al., 2019). Among the few exceptions are Schrotenboer, Wruck, Roodbergen, Veenstra, and Dijkstra (2017); Wruck, Vis, and Boter (2013) and Schrotenboer, Wruck, Vis, and Roodbergen (2019), who integrate return flows into the batching and routing decisions of an otherwise classic manual warehouse.

Lane-guided transport vehicles are a simple kind of automated guided vehicle (AGV). AGVs have a long tradition in many areas such as manufacturing (e.g., Umar, Ariffin, Ismail, & Tang, 2015), container terminals (e.g., Jeon, Kim, & Kopfer, 2011), and warehouses (e.g., Ferrara, Gebennini, & Grassi, 2014). The literature on designing and controlling AGVs is surveyed by Vis (2006). The survey articles by Qiu, Hsu, Huang, and Wang (2002), Fazlollahtabar and Saidi-Mehrabad (2015), and

Vivaldini, Rocha, Becker, and Moreira (2015) specifically review routing and scheduling techniques for AGVs.

Most models and techniques from the AGV routing literature are not directly applicable to LGT routing, however, because they usually assume that the AGVs have to process a set of tasks with given origins and destinations. AGV routing then consists of finding a suitable route for each AGV from their assigned origin to destination, possibly considering the given marked driving lanes and current traffic situation. For this reason, AGV dispatching / scheduling (i.e., assigning tasks to specific vehicles) and routing (i.e., finding paths between pairs of coordinates for each vehicle) are often solved conjointly (e.g., Miyamoto & Inoue, 2016; Vivaldini, Rocha, Martarelli, Becker, & Moreira, 2016). LTSRP is different in that all transport requests either originate or terminate at a depot and are not explicitly given when the routes are planned. Instead, only demand rates for the individual station types are known. Deciding specific loads and timetables for the vehicles is therefore impossible, and planning paths between individual origin/destination pairs is pointless. Indeed, this relative simplicity (and low cost) of LGT system is one of the reasons why our industry partner considers them so attractive.

Given that all LGT vehicles go around in circles covering all stations assigned to them on a fixed round-trip route, LTSRP bears some similarity to a *single-loop AGV flow path layout* (Vis, 2006). LTSRP is somewhat more complex, however, because a warehouse may have more than one depot (and hence more than one loop), and the primary goal is not the minimization of total travel distance or response time but the number of required vehicles. Single-loop flow paths are typically used to facilitate the flow of materials through a facility given predicted from-to charts, indicating the expected material flow between stations (Asef-Vaziri & Laporte, 2005). LTSRP, on the other hand, is based on predicted demand rates at the stations.

From a modeling perspective, routing a set of vehicles to visit a set of stations (or customers) is reminiscent of the classic multiple travelling salesman problem (surveyed by Bektas, 2006) and vehicle routing problem (surveyed by Toth & Vigo, 2014). These problems are different, however, in that they do not consider demand rates, multiple vehicles per route, or station assignments. Vaidyanathan, Matson, Miller, and Matson (1999) and Emde and Schneider (2018) introduce just-in-time vehicle routing (JITVRP), where routes are determined for a fleet of vehicles supplying customers with given demand rates. Consequently, similar to LGT routing, the total transport demand depends on the duration of the routes. Unlike vehicle routing, we can assign a route to multiple vehicles, each of which has unit capacity, and consider demand rates over an infinite planning horizon, instead of given absolute demands. These characteristics are similar to the family of cyclic inventory routing problems (CIRP, recent contributions by Raa, 2015; Raa & Dullaert, 2017; Zenker, Emde, & Boysen, 2016). CIRP also deal with the basic problem of planning routes for a fleet of vehicles, given demand rates at the customers over an infinite planning horizon. CIRP, however, are mostly concerned with minimizing transport and inventory cost while observing limited vehicle and customer capacities, which are only of low significance for routing lane-guided vehicles.

D.3. Problem description

To model the problem concisely, we make the following assumptions.

- For the distance matrix, the triangle inequality holds.
- All vehicles are homogeneous and move at the same constant speed.
- LTSRP is a medium-term problem, because changing guide lanes takes some time and cannot be done on short notice. Therefore, we also do not consider operational issues like battery swaps etc., the time for which can simply be taken into account when calculating the average speed of the vehicles.
- We assume that the system is perfectly balanced, in the sense that whenever a bin is delivered to a specific station, a bin is also collected to go back to the depot. Note that, on aver- age, this must be the case, since every bin that goes out must come back at some point. Moreover, note that we ignore start- up effects, which may

play a role, as it may take a while for all stations to be supplied with their first bins. However, in the case company we visited, stations have an input buffer, i.e., each station tends to have a few bins waiting to be processed. If this buffer is filled before the shift starts or still contains some items from the previous shift, start-up effects may be mitigated.

- All parameters are known and deterministic, and stations of the same type operate at the same speed. This is a simplification of reality because some stations might be faster than others (e.g., because they are manned with a more experienced employee), and there are stochastic influences (some bins may be processed faster than others, even though they are of the same type). However, the exact content of the bins and personnel available in each shift are usually not known when the routes are planned, and can hence not be accounted for explicitly. We investigate the impact of a stochastic environment in a simulation study in Section D.6.3.
- Route crossings are allowed. We assume that the LGT vehicles have some kind of collision avoidance system.

D.3.1. Formal problem description

Let $S = \{1, \dots, n\}$ be the set of stations, and let $D = \{1, \dots, m\}$ be the set of depots from which vehicles set out. Note that this implies that there are m different routes to be determined because every depot is associated with only one guiding lane / route. Going from depot $i \in D$ to station $s \in S$ takes $t_{is}^{\rightarrow}$ time units, going from station s to depot i takes $t_{si}^{\leftarrow}$, and going from station s to station s' takes $t_{ss'}$ time units. Let C be the set of classes that can be assigned to each station (e.g., some station may be designated for handling refurbishments, another for handling defective items). The total required number n_c of stations of each class is given, $\forall\, c \in C$, based on historic data and demand predictions. We assume that $\sum_{c \in C} n_c = n$. Depending on the assigned class, a station has a certain transportation demand of d_c bins per time unit. Each vehicle has a transport capacity of 1.

A solution to LTSRP is defined by the following.

- The vehicle count $v_i \in \mathbb{N}$, $\forall\, i \in D$, i.e., the size of the vehicle fleet at depot i,
- an m - partition $\{\gamma_1, \ldots, \gamma_m\}$ of the set S and permutations π_i of sets γ_i , $\forall\, i = 1, \ldots, m$, denoting in which order the stations in set γ_i are visited by the vehicles setting off from depot i, and
- a mapping $\rho: S \rightarrow C$, indicating that station $s \in S$ is assigned to class $\rho(s) \in C$.

We say that a solution is feasible if and only if it satisfies the following conditions. First, there are exactly as many stations of each class as are required, i.e., for all $c \in C$, it must hold that $|\{ s \in S : \rho(s) = c\}| = n_c$.

Second, there is a sufficiently large number of vehicles at each depot to meet the total demand of its route, i.e., for all $i \in D$, it must hold that

$$\sum_{s\in\gamma_i} d_{\rho(s)} \cdot \left(t^{\rightarrow}_{i,\pi_i(1)} + \sum_{j=1}^{|\gamma_i|-1} t_{\pi_i(j),\pi_i(j+1)} + t^{\leftarrow}_{\pi_i(|\gamma_i|),i} \right) \leq v_i,$$

where $\pi_i(j) \in S$ denotes the jth station to be visited on the route departing from depot i. Note that since stations have a class- dependent demand rate, the longer the route, the higher the demand that accumulates in the meantime, and the more vehicles are necessary to satisfy the demand.

Investment and operating cost is mostly associated with the vehicles themselves, once the depots and system as a whole have been set up. Consequently, our primary goal is to minimize the total vehicle fleet. As a secondary objective, we minimize the total duration of the routes because this is likely to reduce the energy consumption and increase service frequencies for a given vehicle fleet. Consequently, we minimize

$$\sum_{i\in D} (M \cdot v_i + t^{\rightarrow}_{i,\pi_i(1)} + \sum_{j=1}^{|\gamma_i|-1} t_{\pi_i(j),\pi_i(j+1)} + t^{\leftarrow}_{\pi_i(|\gamma_i|),i}), \qquad (1)$$

where M is a sufficiently large number to enforce a lexicographic ordering of objectives, e.g., $M = n \cdot \max_{s\in S, i\in D} \{\max\{t^{\leftarrow}_{si}, t^{\rightarrow}_{is}\}\}$.

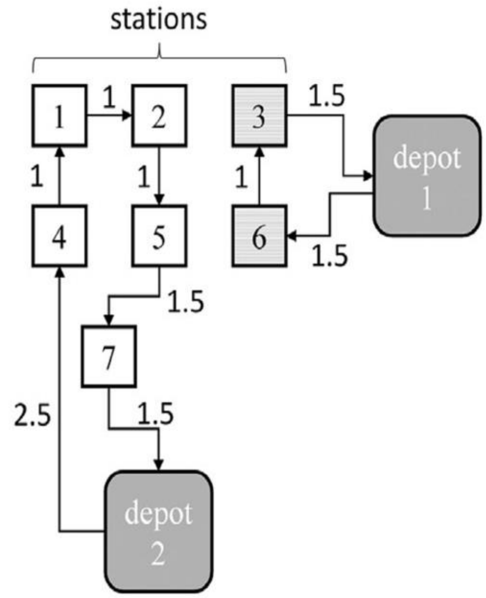
D.3.2. Example of an LTSRP solution

Consider an example LTSRP problem with $n = 7$ stations to be supplied from $m = 2$ depots. There are two types of stations ($C = \{1, 2\}$), where stations of type 1 have a transport demand of $d_1 = 0.1$ bins per time unit, and stations of type 2 have a transport demand of $d_2 = 0.4$ bins per time unit. A total of $n_1 = 5$ stations of type 1 are required, while $n_2 = 2$ stations of type 2 must be designated. In this example, the stations and depots are on a Cartesian plane with Manhattan distances. The travel times from / to the depots and between stations are given as a table in Figure D.2-a, and an optimal solution is depicted in Figure D.2-b. This solution corresponds $\pi_1 = \langle 6,3 \rangle$ and $\pi_2 = \langle 4, 1, 2, 5, 7 \rangle$.

The total duration of route 1 is 1.5 + 1 + 1.5 = 4 time units, and of route 2 is 2.5 + 1 + 1 + 1 + 1.5 + 1.5 = 8.5 time units. Route 1 consists of two stations of type 2, yielding a total demand per time unit of 2 · 0.4 = 0.8; for route 2, the total demand per time unit is analogously 5 · 0.1 = 0.5. Consequently, it takes $\lceil 4 \cdot 0.8 \rceil = 4$ vehicles to serve route 1, and $\lceil 8.5 \cdot 0.5 \rceil = 5$ vehicles to serve route 2. The objective value is hence $M \cdot (4 + 5) + 12.5$.

$t_{ss'}$	1	2	3	4	5	6	7	$t^{\leftarrow}_{s,1}$	$t^{\leftarrow}_{s,2}$
1	0	1	2	1	1.5	2.5	2.5	3.5	3.5
2	1	0	1	1.5	1	1.5	2.5	2.5	3.5
3	2	1	0	2.5	1.5	1	3	1.5	3.5
4	1	1.5	2.5	0	1	2	1.5	3.5	2.5
5	1.5	1	1.5	1	0	1	1.5	2.5	2.5
6	2.5	1.5	1	2	1	0	2	1.5	2.5
7	2.5	2.5	3	1.5	1.5	2	0	3	1.5
$t^{\rightarrow}_{1,s'}$	3.5	2.5	1.5	3.5	2.5	1.5	3		
$t^{\rightarrow}_{2,s'}$	3.5	3.5	3.5	2.5	2.5	2.5	1.5		

(a) Example problem data.



(b) Optimal solution in the example; stations with white background are of type $c = 1$, stations with shaded background are of type $c = 2$.

Figure D. 2. An example problem

D.3.3. MIP model

To enable the use of default solvers, we formulate LTSRP as a mixed-integer linear programming model as follows. We introduce binary variables $x_{ss'i}$ to encode the routing decision and binary variables y_{sc} to denote the assignment of stations to classes. Auxiliary continuous variables $\tau^{\rightarrow}_s$ and $\tau^{\leftarrow}_s$ stand for the total route duration from the depot up until station s and from station s back to the depot, respectively. Finally, variables $\boldsymbol{v}$ and $\boldsymbol{w}$ encode the transport capacity demand. The notation is summarized in Table D.1.

Table D. 1. Parameters and decision variables of the MILP model.

Sets	
S	set of stations, indices $s, s' \in S \cup \{0\}$, where 0 denotes a depot
C	set of station types, index $c \in C$
D	set of depots, index $i \in D$
parameters	
M	large integer, e.g., $M = n \cdot \max\{1, \max_{c \in C}\{d\ c\}\} \cdot \max_{s \in S, i \in D}\{t^{\leftarrow}_{si}, t^{\rightarrow}_{is}\}\}$
$t_{ss'}$	travel time from station s to station s'
$t^{\rightarrow}_{is}$	travel time from depot i to station s
$t^{\leftarrow}_{si}$	travel time from station s to depot i
d_c	demand rate of a station of type $c \in C$ (number of bins per time unit)
variables	
w_s	continuous variable: total demand up to station s
v_i	integer variable: number of vehicles stationed at depot i
$\tau^{\rightarrow}_s$	continuous variable: duration of the route serving station s on arrival at station s
$\tau^{\leftarrow}_s$	continuous variable: duration of the route serving station s from the visit of station s until the return to the depot
$x_{ss'i}$	binary variable: 1, if station s' is the immediate successor of station s on a route departing from depot i ; 0, otherwise
y_{sc}	binary variable: 1, if station s of type c; 0, otherwise

Minimize $F\,(\boldsymbol{x}, \boldsymbol{v}, \boldsymbol{\tau}^{\rightarrow}, \boldsymbol{\tau}^{\leftarrow}, \boldsymbol{w}, \boldsymbol{y}) =$

$$\sum_{i \in D}(M * v_i + \sum_{s \in S}(x_{0si} * t^{\rightarrow}_{is} + x_{s0i} * t^{\leftarrow}_{si} + \sum_{s' \in S: s' \neq s} x_{ss'i} * t_{ss'})) \qquad (2)$$

Subject to

$$1 = \sum_{\substack{s' \in S \cup \{0\}: \\ s \neq s'}} \sum_{i \in D} x_{ss'i} \qquad \forall s \in S \qquad (3)$$

$$1 = \sum_{\substack{s' \in S \cup \{0\}: \\ s \neq s'}} \sum_{i \in D} x_{ss'i} \qquad \forall s' \in S \qquad (4)$$

$$\tau_s^{\rightarrow} \geq \sum_{i \in D} x_{0si} * t_{is}^{\rightarrow} \qquad \forall s \in S \qquad (5)$$

$$\tau_s^{\leftarrow} \geq \sum_{i \in D} x_{s0i} * t_{is}^{\leftarrow} \qquad \forall s \in S \qquad (6)$$

$$\tau_{s'}^{\rightarrow} \geq \tau_s^{\rightarrow} + \sum_{i \in D} t_{ss'} * x_{ss'i} - \mathrm{M} \cdot (1 - \sum_{i \in D} x_{ss'i}) \qquad \forall s, s' \in S, s \neq s' \qquad (7)$$

$$\tau_s^{\leftarrow} \geq \tau_{s'}^{\rightarrow} + \sum_{i \in D} t_{ss'} * -\mathrm{M} * (1 - \sum_{i \in D} x_{ss'i}) \qquad \forall s, s' \in S, s \neq s' \qquad (8)$$

$$0 \leq w_{s'} \leq w_s - (\tau_s^{\rightarrow} + \tau_s^{\leftarrow}) \cdot d_c + \mathrm{M} * (2 - x_{ss'i} - y_{sc}) \qquad \forall s \in S, s' \in S \cup \{0\}\ s \neq s', c \in C, i \in D \qquad (9)$$

$$v_i \geq w_s - M \cdot (1 - \sum_{\substack{s' \in S \cup \{0\}: \\ s \neq s'}} x_{ss'i}) \qquad \forall s \in S, i \in D \qquad (10)$$

$$n_c = \sum_{s \in S} y_{sc} \qquad \forall c \in C \qquad (11)$$

$$1 = \sum_{s' \in S} x_{0s'i} \qquad \forall i \in D \qquad (12)$$

$$1 = \sum_{s \in S} x_{s0i} \qquad \forall i \in D \qquad (13)$$

$$0 = \sum_{\substack{s' \in S \cup \{0\}: \\ s \neq s'}} \sum_{i \in D} (i * x_{s'si} - i * x_{ss'i}) \qquad \forall s \in S \qquad (14)$$

$$1 = \sum_{c \in C} y_{sc} \qquad \forall s \in S \qquad (15)$$

$$x_{ss'i} = \{0; 1\} \qquad \forall s, s' \in S \cup \{0\}; s \neq s'; i \in D \qquad (16)$$

$$v_i \in \mathbb{N} \qquad \forall\, i \in D \qquad (17)$$

$$y_{sc} \in \{0; 1\} \qquad \forall\, s \in S, \forall\, c \in C \qquad (18)$$

Objective function (2) minimizes, foremost, the total number of vehicles and, secondly, the total travel duration. Constraints (3) and (4) ensure that each station has exactly one predecessor and one successor on the route that serves it. Inequalities (5) through (8) set the trip duration $\tau_s^{\rightarrow}$ up to station s and the trip duration $\tau_s^{\leftarrow}$ from station s back to the depot. These values are used in Con- straints (9) to determine the total demand w_s of the route serving station s up to station s. Note that the demand at some station s equals the demand rate d_c times the route duration $\tau_s^{\rightarrow} + \tau_s^{\leftarrow}$, which is only relevant if stations s and s' are actually direct suc- cessors on the same route, i.e., $x_{ss'i} = 1$. (10) sets the number of vehicles needed at depot i to the total demand at the last station on the route departing from depot i. Since each vehicle has a capacity of 1 (carrying unit loads), the total demand, rounded up to the next integer, equals the required number of vehicles. Con- straints (11) make sure that the correct number of station types are assigned. Constraints (12) and (13) enforce that each depot has exactly one route, and (14) ensure that a route starting at some depot i also ends at the same depot i. Due to Constraints (15) , each station is assigned exactly one class. Finally, there are the integral- ity constraints (16) through (18).

D.4. Time complexity

The LTSRP is clearly NP-hard as, for a given number of vehicles, it essentially comes down to a classic routing problem, which are generally NP-hard even if there is only one depot and one vehicle, i.e., the classic travelling salesman problem (TSP). It is, however, not immediately obvious that the complexity status of TSP transfers to LTSRP if we only regard the primary objective (minimizing the vehicle count) because, in general, finding the shortest route is not necessary for finding an LTSRP solution with the minimum number of vehicles. However, NP-hardness holds even in this case, as we demonstrate in the following.

Proposition D.4.1. *Given an LTSRP instance, minimizing the number of vehicles is NP-hard in the strong sense even if there is only one depot ($m = 1$) and one station class ($|C| = 1$).*

Proof. We show that LTSRP with only the vehicle count objective is NP-hard by reduction from TRAVELLING SALESMAN, which is well known to be NP-hard in the strong sense (Garey & Johnson, 1979).

TRAVELLING SALESMAN: Given a complete weighted digraph $G(V, E, w)$, where $V = \{1, \dots, \bar{n}\}$ is the vertex set, $E = \{(i, j) | \, i, j \in V, i \neq j\}$ is the edge set, and $w: W \to \mathbb{N}$ is the weight function, and and integer B, is there a Hamiltonian cycle $\langle \sigma_1, \dots, \sigma_{\bar{n}+1} \rangle$ such that $\sum_{i=1}^{\bar{n}} w(\sigma_i, \sigma_{i+1}) \leq B$?

We transform an instance I of TRAVELLING SALESMAN to an instance I' of LTSRP in polynomial time by adding a station for each vertex but one, i.e., $S = V \setminus \{1\}$, and declaring the left-out vertex the depo, i.e., $D = \{1\}$. The travel times between station is given as $t_{ss'} = w(s, s')$, $s, s' \in S$, and between depot and stations as $t_{1s}^{\rightarrow} = w(1, s), s \in S$; analogous for $t_{s1}^{\leftarrow}$. There is only one station type, whose demand is $d_1 = 1/(B \cdot (\bar{n} - 1))$ and which need to be set up $n_1 = \bar{n} - 1$ times. Is there a solution to I' with no more than one vehicle?

Since there is only one depot and all stations have the same demand, it is clear that a TSP solution no longer than B for instance I is also an LTSRP solution with no more than one vehicle for instance I'. The same also holds true in the opposite direction: a solution to the transformed LTSRP instance with one vehicle also necessarily corresponds to a TSP tour no longer than B. The total demand per time unit of all $\bar{n} - 1$ stations sums up to exactly $1/B$. Therefore, the only way to achieve a vehicle count of no more than 1 is to have a closed path that visits all stations with a total duration of no more than B. It is not only the routing that makes LTSRP hard, however. Even if we assume that routes are given, merely assigning station classes to the given routes is hard.

Proposition D.4.2. *Given an LTSRP instance and routes $\pi_1, \ldots, \pi_m$, minimizing the number of vehicles is NP-hard in the strong sense.*

Proof. We reduce LTSRP with given routes from 3-PARTITION, which is well-known to be strongly NP-hard (Garey & Johnson, 1979).

3-PARTITION: Given $3q$ integers a_j, $j = 1, \dots, 3q$, and and integer Q, where $Q/4 < a_j < Q/2$ and $\sum_{j=1}^{3q} a_j = qQ$, is there a partition of the set $\{1, \dots, 3q\}$ into q sets $A_1, \dots, A_q$, each containing three elements, such that $\sum_{j \in A_i} a_j = Q,\ \forall i = 1, \dots, q$?

We transform a 3-PARTITION instance I to an LTSRP instance I' consisting of $n = 3q$ stations, q depots ($D = \{1, \dots, q\}$), and $3q$ station classes ($C = \{1, \dots, 3q\}$). Each station class $c \in C$ corresponds to one integer in the 3-PARTITION instance I, such that the demand of a class c is $d_c = a_c/Q$ and only $n_c = 1$ station of each type is needed, $\forall c \in C$. We introduce q routes $\pi_1, \dots, \pi_q$ (one per depot), each consisting of three stations, i.e., $\pi_i(j) = 3 \cdot (i-1) + j, \forall i = 1, \dots, q, j = 1, 2, 3$. The driving time $t^{\rightarrow}_{i,\pi_i(3\cdot(i-1)+1)}$ from depot i to the first station on the connected route, the driving times $t_{\pi_i(3\cdot(i-1)+1),\pi_i(3\cdot(i-1)+2)}$ and $t_{\pi_i(3\cdot(i-1)+2),\pi_i(3\cdot(i-1)+3)}$ from station to station on the route, and the driving time back to the depot $t^{\leftarrow}_{\pi_i(3\cdot(i-1)+3),i}$ can assume arbitrary values as long as they add up to $t^{\rightarrow}_{i,\pi_i(3\cdot(i-1)+1)} + t_{\pi_i(3\cdot(i-1)+1),\pi_i(3\cdot(i-1)+2)} + t_{\pi_i(3\cdot(i-1)+2),\pi_i(3\cdot(i-1)+3)} + t^{\leftarrow}_{\pi_i(3\cdot(i-1)+3),i} = 1$.

Instance I is a YES-instance if and only if instance I' permits a solution with no more than q vehicles, i.e., $\sum_{i \in D} v_i = q$.

Each route visits exactly three stations. Since there can be no station with 0 demand (because $a_j > Q/4$) , each route needs at least one vehicle to meet the demand. Given that there are q routes in total, no route may use more than one vehicle in order for the total to not exceed q. The total demand rate of all station classes equals $\sum_{c \in C} d_c = \sum_{c \in C} \frac{a_c}{Q} = q$. Since each route has the same du- ration of 1 time unit, the total demand does not depend on what station the classes are assigned to. However, if the total demand rate on some route sums up to less than 1, another route must necessarily pick up the slack and have a total demand rate of more than 1. Consequently, the only assignment of classes to stations that ensures that every route uses exactly one vehicle is such that the three stations on each route have a total demand rate of 1. This is possible if and only if the corresponding 3-PARTITION integers sum up to Q. The correspondence between the solutions to I and I' is hence obvious.

D.5. Solution methods

By Propositions D.4.1 and D.4.2, LTSRP combines two problems that are already NP-hard individually, namely routing the vehicles and assigning classes to the stations. Our own computational experiments show that default solvers take an unacceptably long time to solve realistic instances. While problem-tailored exact solution procedures may fare better, short solution times are quite important in practice to allow quickly evaluating different warehouse layouts. We therefore propose a decomposition heuristic, the parts of which we describe in more detail in the following. On the top level, we assign stations to depots via a tabu search approach (Section D.5.1). Consequently, we determine the route for each depot (Section D.5.2). Finally, we assign a class to each station (Section D.5.3).

D.5.1. Assigning stations to depots

In the first step, we determine which stations are served by which depot, i.e., we seek a partition $\{\gamma_1, \ldots, \gamma_m\}$ of the set S. To find an initial assignment, we propose the constructive heuristic outlined in Algorithm 1. Starting from depot $i = 1$, we associate with each station that has not yet been assigned (initially all stations) a regret value if it were assigned to another depot, i.e., the difference between the distance between that station and the current depot i and the distance to the closest depot i'. Stations are assigned according to these regret values in descending order (ties are broken randomly) until $\left\lceil \frac{i \cdot n}{m} \right\rceil$ stations are assigned. Then the steps are repeated for the next depot $i + 1$. This way, every depot is assigned about the same number of stations.

Algorithm 1: Opening heuristic to find an initial station-depot assignment for

Input: instance of LTSRP

$\bar{S} := S$;

$\bar{D} = D$;

foreach $i \in D$ **do**

  $\gamma_i := \emptyset$;

  $\bar{D} := \bar{D} \backslash \{i\}$;

  for $j := \left\lceil \frac{(i-1)\cdot n}{m} \right\rceil + 1$ to $\left\lceil \frac{i \cdot n}{m} \right\rceil$ **do**

    $s' := argmax_{s \in S} \left\{ min_{i' \in D} \{ t^{\rightarrow}_{i's} + t^{\leftarrow}_{si'} - t^{\rightarrow}_{is} - t^{\leftarrow}_{si} \} \right\}$;

    $\gamma_i := \gamma_i \cup \{s'\}$;

    $\bar{S} := \bar{S} / \{s'\}$;

Output: partition $\gamma_i, \ldots, \gamma_m\}$

The purpose of Algorithm 1 is to generate a feasible solution quickly. However, this solution is likely to be quite poor, given that the algorithm only considers travel times as a criterion when constructing routes. To improve this solution further via neighborhood search, we employ a tabu search scheme (Glover, 1989; 1990).

A solution is encoded as a partition $\{\gamma 1, \ldots, \gamma m\}$. Starting from the initial solution output by Algorithm 1 , a neighbor is reached by either a swap move, where some station $s \in \gamma_i$ is exchanged with another station $s' \in \gamma_{i'}$, or by a push move, where some station $s \in \gamma_i$ is moved to another set $\gamma_{i'}$, $i, i' \in D, i \neq i'$. Each neighbor is evaluated by following the steps outlined in the following Sections D.5.2 and D.5.3, constructing a complete solution from the partition by first determining the (near-)optimal route for each depot and then assigning classes to stations. Note that for each neighbor, only the depots whose assignment has actually changed from the incumbent solution need to be rerouted. Subsequently, the objective function (1) can be evaluated. Of all neighbors, the non-tabu neighbor with the best objective value becomes the new incumbent, and the next iteration starts.

When a neighbor S' is accepted, the original assignments of the stations that were swapped or moved are made tabu for $\xi = \lceil n/4 \rceil$ iterations, i.e., if accepted neighbor S' was reached by pushing some station $s \in \gamma_i$ to a different depot $i \neq i'$, then station s must not be reassigned to depot i for the next $n/4$ iterations. Whenever a move is performed, we update a counter of how often a station has been assigned to a given depot. If no new best solution has been found for 300 iterations, the search is restarted by forcing the 25% assignments that have occurred the least frequently (tie breaker: random). TS terminates after a total of 7000 iterations. The procedure is outlined in Algorithm 2.

Algorithm 2: Tabu search for LTSRP.

input: an instance of LTSRP

$\Theta^{\max} := 300$;// max number of iterations before diversification

$\Theta := 0$; // number of iterations since new best solution has been found

$i := 1$; // iteration counter

$\Gamma := \Gamma^* := \{\gamma_i, \ldots, \gamma_m\}$ // station-depot assignment obtained via Algorithm 1;

while $i \leq 7000$ **do**

  foreach *non-tabu neighbor of* Γ **do**

    Find short routes $\Pi := \{\pi_1, \ldots, \pi_m\}$ via LKH (Section D.5.2);

    Determine station-to-class mapping ρ and vehicle counts $V := \{v_1, \ldots v_m\}$ by solving a transportation problem (Section

    Calculate objective value for complete solution as per Eq. (1);

  $\Gamma :=$ best non-tabu neighbor of Γ;

  Update tabu list;

  if *objective value of* Γ *is better than objective value of* Γ^* **then**

    $\Theta := 0$;

    $\Gamma^* := \Gamma$;

    $\Pi^*, \rho^*, V^* :=$ routes, mapping, and vehicle counts for Γ^*;

  else

    $\Theta := \Theta + 1$;

  if $\Theta \geq \Theta^{max}$ **then**

    $\Gamma :=$ force the 25% least-used station-depot assignments in Γ;

    reset tabu list;

    $\Theta := 0$;

  $i := i + 1$;

return *best found LTSRP solution* Γ^* *with routes* Π^*, *mapping* ρ^* *and vehicle counts*

D.5.2. Routing vehicles

Given an assignment γ_i of stations to depot i, $\forall\, i \in D$, we determine a good route π_i for each depot in this step. Our goal is to minimize the total number v_i of vehicles, which depends on the total demand rate of the stations served and the route length. We do not assign station classes in this step, hence the demand rate cannot be influenced; however, for a given set of stations, the shortest route is obviously optimal with regard to fleet size. Regardless of the station types assigned, for a given depot i and sta- tion assignment γ_i, it cannot make sense to prefer a route with a longer duration to one with a shorter one. Note, however, that finding the very shortest route may not be necessary for optimality with regard to vehicle count because additional duration does not automatically imply the need for additional vehicles.

Given this, finding the best route for each depot decomposes into a series of m TSP. Since, at least for the vehicle count, an optimal solution is not strictly required, a heuristic TSP solver seems appropriate. LKH, based on the famous Lin-Kernighan heuristic (Lin & Kernighan, 1973), is generally considered to be one of the best heuristic TSP solvers, balancing speed and solution quality (Helsgaun, 20 0 0; 20 09; Taillard & Helsgaun, 2019). In a nutshell, the core of the Lin-Kernighan heuristic is a generalization of $k - opt$ local search, where edges from a tour are iteratively removed and reinserted in order to find better tours in the neighborhood. For our tests, we use the implementation downloaded from http: //akira.ruc.dk/~keld/research/LKH/ (LKH 2.0.9, July 2018).

LKH outputs short routes π_i for each depot $i \in D$. In the last step, we assign specific classes to each station.

D.5.3. Assigning classes to stations

By Proposition 4.2, assigning a class to each station is NP-hard even if the routes are already given. We solve this problem heuristically as a transportation problem. At this stage, we are given fixed routes π_i, $i \in D$, and their respective durations, which we designate as

$$\tau(\pi_i = t^{\rightarrow}_{i,\pi_i(1)} + \sum_{j=1}^{|\gamma_i|-1} t_{\pi_i(j),\pi_i(j+1)} + t^{\leftarrow}_{\pi_i(|\gamma_i|),i}.$$

Let $G(V,A)$ be a directed network consisting of vertices V and arcs A. Every arc $(e,e') \in A$ is associated with a cost $c_{ee'}$. Each vertex $e \in V$ is associated with a supply or demand g_e, depending on whether g_e is positive or negative, respectively.

The network has $|C|$ source nodes, $e_c, c \in C$, and m sink nodes $\bar{e}_i$, $i = 1, \dots, m$, such that $V = \bigcup_{c \in C}\{e_c\} \cup \bigcup_{i \in D}\{\bar{e}_i\}$. Every source node e_c stands for one station type $c \in C$; the total supply is $g_{e_c} = n_c, \forall c \in C$. Each sink node $\bar{e}_i$ represents one route/depot; its demand corresponds to the number of stations assigned to the respective depot, i.e., $g_{\bar{e}_i} = -|\gamma_i|$, $\forall i \in D$. Each source node e_c is connected to each sink node $\bar{e}_i$ by an arc $(e_c, \bar{e}_i), \forall\, c \in C, i \in D$. The cost per unit of flow is $c_{e_c,\bar{e}_i} = \tau(\pi_i) \cdot d_c$.

Determining the minimum cost flow in this network is equivalent to solving a Hitchcock transportation problem, which can be solved efficiently (Schrijver, 2003). Let $f(e_c, \bar{e}_i) \in \mathbb{N}^0$ be the optimal flow on arc $(e_c, \bar{e}_i)$, and let $\tilde{c}(e_c, \bar{e}_i) = f(e_c, \bar{e}_i) \cdot c_{e_c, \bar{e}_i}$ be the cost associated with this flow. We can derive the assignment of classes to stations from the flow on each arc: for each $c \in C$ and $i \in D$, exactly $f(e_c, \bar{e}_i)$ stations of type c must be assigned to depot i. Note that it does not matter which stations from given set γ_i are assigned to class c as long as the total numbers add up to the given flows; the exact positions of the stations on the route are not important for the assignment of classes. Also note that this assignment is al- ways feasible due to the way the network is set up: in total, $|\gamma_i|$ station types are assigned to depot i (i.e., one for each station on the route), and a total of n_c station types are assigned per class c. The required number $\tilde{v}_i$ of vehicles can then be easily derived as $\tilde{v}_i = \lceil \tau(\pi_i) \cdot \sum_{c \in C} d_c \cdot f(e_c, \bar{e}_i) \rceil, \forall\, i \in D$.

Proposition 5.1. *Given routes π_i, $\forall\, i \in D$, the total number of vehicles $\sum_{i \in D} \tilde{v}_i$ as derived above is at most m greater than optimal.*

Proof. Given a minimum cost flow, the total cost of the flow $lb \coloneqq \sum_{c \in C} \sum_{i \in D} \tilde{c}\,(e_c, \bar{e}_i)$ constitutes a lower bound on the optimal number of vehicles given routes π_i, because the minimum cost flow matches the "supply" n_c with the "demand" $|\gamma_i|$ in the cheapest way, and neither n_c nor $|\gamma_i|$ nor the cost $c_{e_c, \bar{e}_i}$ can be changed if the routes are given. It follows that

$$\sum_{i\in D} \tilde{v}_i = \sum_{i\in D} \left\lceil \tau(\pi_i) \cdot \sum_{c\in C} d_c \cdot f(e_c, \bar{e}_i) \right\rceil \leq \sum_{i\in D} \sum_{c\in C} f(e_c, \bar{e}_i) \cdot c_{e_c,\bar{e}_i} + m$$

$$= \sum_{c\in C} \sum_{i\in D} \tilde{c}(e_c, \bar{e}_i) + m = lb + m.$$

Example (cont.): Consider the example from Section D.3.2. Given two tours $\pi_1 = \langle 6, 3\rangle$ and $\pi_2 = \langle 4, 1, 2, 5, 7\rangle$, the corresponding flow network is in Figure D.3. The optimal flow is bold in the figure. The corresponding solution is depicted in Figure D.2b.

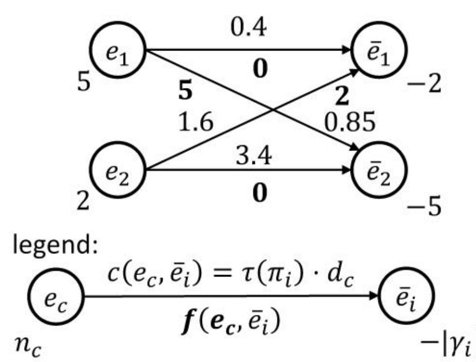


Figure D. 3. Minimum cost flow network in the example.

D.6. Computational study

This section reports on the numerical experiments con- ducted to investigate the performance of the proposed heuristic (Section D.6.2.2) and derive insights into the optimal design of a warehouse supplied by lane-guided transport vehicles (Section D.6.2.3). Since we are, to the best of our knowledge, the first to discuss lane-guided transport systems from an OR perspective, we first describe the instance data we use in Section D.6.1.

D.6.1. Benchmark instances and computational environment

We have access to a real-world data set from a major European e-commerce retailer. Since the data is proprietary, however, we cannot immediately use it. Instead, we generate three different instance sets that correspond proportionally to the real industry case. Instance set S contains small instances with $n = 9$ stations. While these instances are unrealistically small, they are just about the largest size that a default solver can still handle; we there- fore include them for benchmarking purposes. Set M contains the medium size instances with $n = 60$ stations. These instances correspond most closely to the real-world case. Finally, we consider set L with $n = 150$ stations to pose more of a computational challenge to our solution methods. The number of depots is $m = 3$ in all cases. Each set contains 20 instances, i.e., there are 60 instances in total.

First off, we convert all distance-related parameters to time-related by dividing distances by the average movement speed of the lane-guided vehicles. Since these vehicles move by design at the same constant speed without ever slowing down (except for maintenance or recharging breaks), we set this speed to 1 m/s. For sets S and , we draw two-dimensional coordinates (x_i, y_i) for each station, where x_i and y_i are randomly drawn numbers from the interval (1 , 15) (for the small instances in set S) or (1 ,

100) (for the large instances from set L). Distances between stations (and depots) are then measured via the Euclidean metric. Depot $i = 1, \ldots, m$ is placed in location $(2.5 + (i-1) \cdot 5, 0)$ (S) and $(16.67 + (i-1) \cdot 33.33, 0)$ (L), respectively; i.e., the depots are positioned equidistantly at the “bottom”of the square warehouse. For the real-world M instances, we reuse the data from our industry partner, randomly fudging the numbers such that they are proportionally correct. The general layouts of the M instances can be observed in Figures D.7 and D.8 in Appendix D.

In the industry case, there are two station classes (handling to-be-refurbished and defective items, respectively), i.e., $C = \{1, 2\}$. The split between these classes is about 7: 3, which we use for the S and M instances by setting the station count to $n_1 = 6$ and $n_2 = 3$ (S) and $n_1 = 42$ and $n_2 = 18$ (M). The demand rate is set as $d_1 = 0.1$ bins per time unit and $d_2 = 0.4$ bins per time unit (S), and $d_1 = 0.001$ bins per time unit and $d_2 = 0.003$ (M), where one time unit corresponds to one second of real time.

To pose more of a computational challenge, for set L, we consider $|C| = 4$ classes. For each class $c \in C$, we generate a uniformly distributed random number $r_c \in [1, 10]$. Then we set the station counts n_c for each class c such that the ratio of station counts $n_1 : n_2 : n_3 : n_4$ corresponds to the random ratios $r_1 : r_2 : r_3 : r_4$. Finally, we round each n_c to either the next largest or smallest integer such that the sum total equals $n = 150$.

The demand rate d_c for each station class is a uniformly distributed random number from the interval $[0.0001, 0.001]$.

All instances are solved on a PC with an Intel Core i7-6700 CPU, 3.40 GHz, and 8 GB RAM under Windows 10 Pro x64. For solving the instances, the solution methods discussed in Section D.5 are implemented in Java (SE 9). As a benchmark, we also employ Gurobi 8.1.1 to solve our MIP model. Our instance data can be downloaded via this DOI: https://doi.org/10.17632/bhnx77wx94.1

D.6.2. Computational results

Our computational study is split into two parts. In Section D.6.2.2, we investigate the computational performance of our proposed solution methods. We then use these methods in Section D.6.2.3 to gain insights into the optimal design and layout of a warehouse served by lane-guided transport vehicles.

D.6.2.1. Parameter tuning

To set the number of iterations for our tabu search heuristic, we vary the number of iterations in the range of 3000–10000 and document the best objective found by our procedure. We run the test on the real-world instance set M for layout type 1. Note that the results are similar for the other instance types; we therefore refrain from printing all of them. The average objective value of the best solution obtained for the different numbers of iterations is shown in Figure D.4. As the figure indicates that the best objective value is almost always found after about 7000 iterations, we set this value for the rest of our computational study. Note that the other parameter values we use (e.g., for the tabu tenure) are in the usual ranges often used in the literature. We therefore do not conduct further tuning.

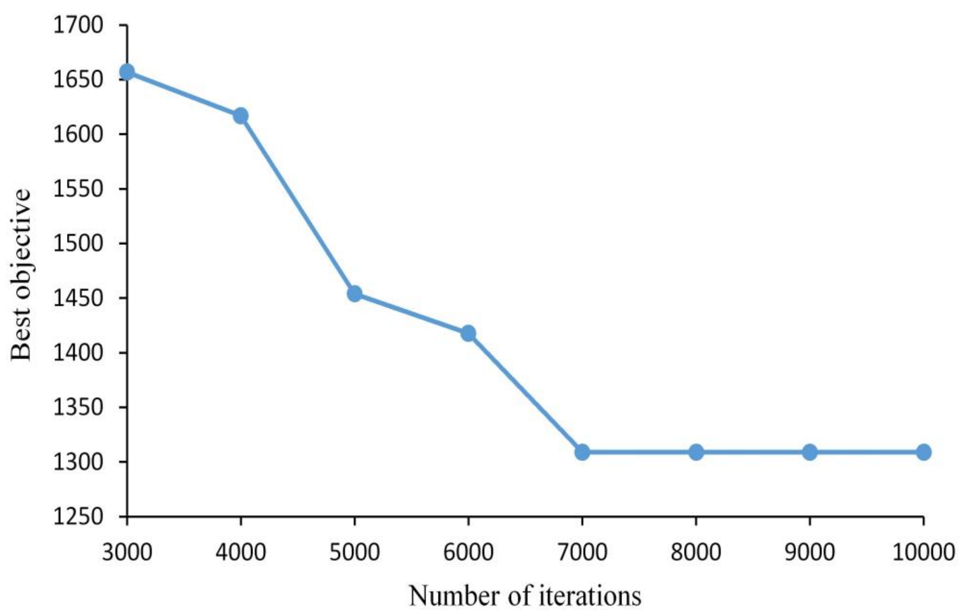


Figure D. 4. Performance of the tabu search heuristic depending on the number of iterations, averaged over the M instances.

D.6.2.2. Algorithmic performance

Table D.2 shows the results for the S instances. For these instances, optimal solutions are available as reported by Gurobi. The table reports these optimal results (opt) and the time it takes to obtain them ($CPU\ sec.$). The optimality gap is listed for our tabu search scheme (TS) for both objectives, number of vehicles (absolute gap) and total route duration (relative gap).

Table D. 2. Algorithmic performance for the small instances ($n = 9$).

No	CPU sec.		number of vehicles		route duration	
	TS	Gurobi	opt	TS additional	opt	TS gap
S1	2.3	15552.54	29	0	52	0.00%
S2	1.38	16991.95	24	0	41	0.00%
S3	1.9	10542.84	25	0	49	0.00%
S4	1.43	7631.71	21	0	36	0.00%
S5	1.44	10370.32	25	0	45	0.00%
S6	1.52	8244.57	22	0	38	0.00%
S7	1.41	6911.29	22	0	38	2.56%
S8	1.34	15384.76	17	0	36	0.00%
S9	2.41	11904.84	24	0	36	0.00%
S10	1.43	9306.74	24	+1	45	-9.76%
S11	1.28	18751.62	29	0	52	1.89%
S12	1.73	11216.77	23	0	40	0.00%
S13	1.83	12104.89	30	0	54	0.00%
S14	1.43	19160.34	33	0	52	0.00%
S15	1.38	15210.22	27	0	48	0.00%
S16	1.66	6629.84	13	0	20	0.00%

S17	1.33	2833.24	15	0	26	0.00%
S18	1.29	12808.99	19	0	32	0.00%
S19	1.66	12615.63	31	0	56	0.00%
S20	1.32	18468.18	36	0	64	0.00%
avg.	1.57	12132.06	24.45	0	43	-0.27%

Recall that we use a lexicographic ordering of objectives, hence a solution is considered optimal if it employs the minimum number of vehicles and, for this number of vehicles, the shortest route duration. This explains why in instance $S10$, the route duration gap is negative: TS failed to find a solution with the minimum number of vehicles; employing an extra vehicle allowed reducing the route duration by 9.76%. Overall, TS found a solution with the minimal vehicle count in all cases but one. Among these instances where the vehicle fleet is minimal, the route duration is above the optimum twice, with a gap of about 2.6% and 1.9%. Gurobi takes more than 3 hours on average to find the optimal solution, while TS terminates within less than 3 seconds in every instance. For the larger instance sets M and L, Gurobi is unable to obtain optimal solutions or even useful bounds in acceptable time. To nonetheless have a benchmark, we use the following nearest neighbor heuristic (NN), which is similar to how routes are assigned in practice. Starting from depot $i = 1$, assign the unassigned station closest to it as the first station on the route. Then add as-yet unassigned stations one-by-one to the emerging route such that each station is the closest station to the last station added, until the route contains n/m stations. In this case, go to the next depot $i := i + 1$, and repeat the process until all stations are assigned. Finally, the station classes are determined by solving the transportation problem described in Section D.5.3.

The results are in Table D.3. On average, TS saves about 0.75 vehicles and 7.53% in route duration versus the NN solution. These results are obtained in less than 10 seconds in all instances, which should be sufficiently fast for practical deployment.

Table D. 3. Algorithmic performance for the medium instances ($n = 60$).

No	Layout	CPU sec.	number of vehicles		route duration	
			NN	TS	NN	TS gap
M1	Type 1	7.73	9	0	228	0.00%
M2	Type 1	6.78	10	0	294	0.00%
M3	Type 1	7.01	9	0	258	0.00%
M4	Type 1	7.03	13	0	354	0.00%
M5	Type 2	6.86	10	-1	280	-14.75%
M6	Type 2	6.98	12	-2	323	-10.24%
M7	Type 2	6.64	10	-1	282	-13.71%
M8	Type 2	6.78	12	-1	343	-12.83%
M9	Type 3	7.33	11	0	331	-4.42%
M10	Type 3	7.31	13	-1	386	-2.93%
M11	Type 3	7.12	14	-1	424	-4.18%
M12	Type 3	8.55	14	0	432	-3.10%
M13	Type 4	7.77	10	-1	277	-11.69%
M14	Type 4	7.61	12	0	343	-7.86%
M15	Type 4	7.92	14	-1	392	-6.52%

M16	Type 4	7.67	13	-1	362	-9.04%
M17	Type 5	7.72	10	-1	275	-13.17%
M18	Type 5	7.36	12	-2	330	-10.00%
M19	Type 5	7.64	10	0	292	-14.96%
M20	Type 5	8.32	12	-2	340	-11.11%
avg.		7.41	11.5	-0.75	327.3	-7.53%

Table D.4 lists the same data for the *L* instances. For these in- stances, using TS saves an average of 1.55 vehicles and 2.86% route duration. In other words, despite using more vehicles, the NN solution still requires longer routes. The runtimes of TS are well below one minute in all cases, indicating that the procedure scales well.

Table D. 4. Algorithmic performance for the large instances ($n = 150$).

No	CPU sec.	number of vehicles		route duration	
		NN	TS	NN	TS gap
L1	55.66	21	-1	987	-3.79%
L2	56.67	25	-1	1000	-2.46%
L3	59.36	28	-2	1038	-5.38%
L4	55.93	34	-1	981	-2.19%
L5	53.12	30	-2	985	-3.68%
L6	53.63	29	-2	982	-3.81%
L7	54.05	32	-1	1005	-0.90%
L8	48.24	32	-1	966	-1.68%
L9	54.35	28	-1	985	-1.76%
L10	45.02	32	-4	990	-2.59%
L11	44.00	28	-2	1023	-2.51%

L12	51.71	22	-1	975	-3.39%
L13	48.26	36	-1	1006	-3.07%
L14	42.19	32	0	999	-1.11%
L15	45.52	20	-1	953	-2.14%
L16	51.30	32	-2	994	-1.64%
L17	50.35	26	-1	972	-1.89%
L18	48.40	29	-3	1022	-5.80%
L19	52.72	30	-3	1026	-4.37%
L20	51.03	20	-1	939	-2.96%
avg.	51.07	28.30	-1.55	991.40	-2.86%

Finally, as another benchmark, we compare our TS heuristic with the LKH heuristic for the multiple travelling salesman problem (mTSP). As we pointed out in Section D.2, the LTSRP bears some resemblance to the mTSP in that we are looking for m short loops originating at the depots. Presumably, an mTSP heuristic may therefore also work well on the LTSRP. We benchmark our proposed TS method against the LKH- 3 solver (code downloaded from http://webhotel4.ruc.dk/ ~keld/ research/LKH-3, version 3.0.6), which is a state-of-the-art heuristic for the mTSP (Helsgaun, 2017). We proceed as follows while employing the LKH-3 solver on the medium size instance set. First, we use the LKH-3 solver to obtain near-optimal routes. Because LKH-3 assumes only a single depot, we assign each route to the nearest depot. Finally, the station classes are determined by solving the transportation problem described in Section D.4.3. The results are given in Table D.5.

The data clearly indicate our problem-specific TS heuristic outperforms a generic routing heuristic in terms of solution quality. This is because looking for shortest routes is just a subproblem of LTSRP. Since the transportation demands increase the longer a route, assigning stations to depots is a critical first step. An optimal mTSP solution may contain quite long individual routes if this minimizes the total travel distance over all routes. However, this leads to a large number of vehicles required for this long route. TS does not fall into this trap as it assigns stations to depots in a separate step (see Section D.5.1).

Table D. 5. TS vs. LKH-3 (n = 60).

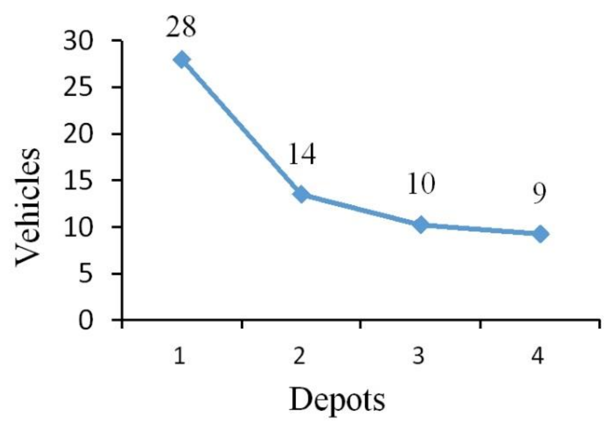
No	Layout type	CPU sec.		number of vehicles		route duration	
		TS	LKH-3	LKH-3	TS additional	LKH-3	TS gap
M1	Type 1	7.73	0.09	25	-16	268	-18%
M2	Type 1	6.78	0.02	30	-20	320	-9%
M3	Type 1	7.01	0.09	25	-16	264	-2%
M4	Type 1	7.03	0.01	36	-23	388	-10%
M5	Type 2	6.86	0.02	25	-16	273	-12%
M6	Type 2	6.98	0.03	28	-18	305	-4%
M7	Type 2	6.64	0.02	25	-16	276	-11%
M8	Type 2	6.78	0.03	15	-4	304	0%
M9	Type 3	7.33	0.05	25	-14	278	12%
M10	Type 3	7.31	0.04	30	-18	332	11%
M11	Type 3	7.12	0.08	26	-13	283	30%

M12	Type 3	8.55	0.06	31	-17	322	23%
M13	Type 4	7.77	0.04	12	-3	284	-15%
M14	Type 4	7.61	0.05	14	-2	343	-8%
M15	Type 4	7.92	0.04	27	-14	384	-4%
M16	Type 4	7.67	0.06	14	-2	365	-10%
M17	Type 5	7.72	0.06	15	-6	287	-18%
M18	Type 5	7.36	0.05	31	-21	346	-15%
M19	Type 5	7.64	0.08	28	-18	310	-22%
M20	Type 5	8.32	0.03	17	-7	357	-17%

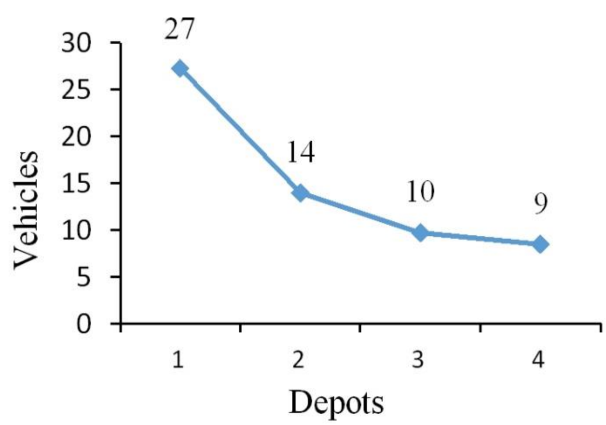
D.6.2.3. Investigation of the layout of the warehouse

In this section, we explore the dependency of the lane-guided transport vehicle system's performance on the arrangement of the depots on the warehouse floor. The warehouse at our industry partner exhibits a type 1 layout as per Figure D.7 in Appendix D; however, this need not be ideal. It is in many cases possible to site the depots in different locations and / or increase or decrease their number. While having only one depot (or a few depots) maximizes space utilization and lowers investment and operating cost for the depots, increasing the number almost certainly lowers the necessary vehicle fleet size because the depots may be closer to the stations.

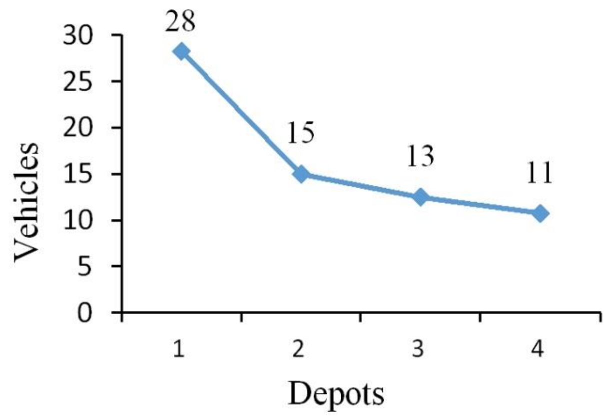
To investigate this tradeoff, we test five different layout types (see Figure D.7 in Appendix D) on the real-world instance set M. Type 1 represents the "classic" layout we encountered in practice, the others are hypothetical. The best found vehicle count for each of the layout types under different numbers m of depots as reported by TS is depicted in Figure D.5.



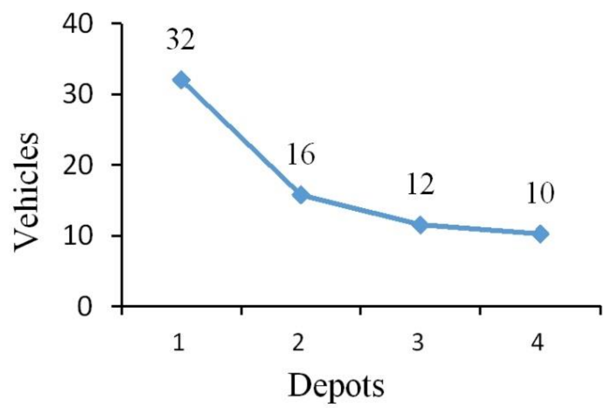
(a) Warehouse layout, type 1.



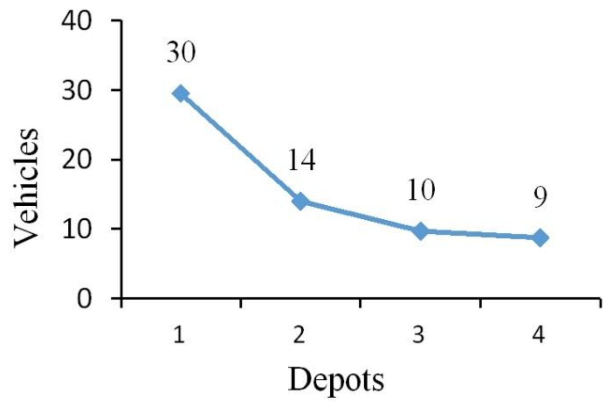
(b) Warehouse layout, type 2.



(c) Warehouse layout, type 3.



(d) Warehouse layout, type 4.



(e) Warehouse layout, type 5.

Figure D. 5. Number of vehicles vs. number of depots for five different warehouse layouts.

In terms of layouts, type 2 dominates all others, albeit not by a large margin. This suggests, at the very least, that spreading out the depots is a good idea. Layout types 4 and 5 perform surprisingly poorly, probably because it is harder to assign sensible recti- linear routes in a warehouse where the rows of stations are broken up by depots. This may be for the best, however, because it may be more difficult to supply depots in the center of the warehouse by truck. With regard to the number of depots, increasing the number from one to two just about halves the number of required vehicles. This is a substantial reduction that may well be worthwhile in most scenarios, seeing that the depots may even be relatively close to each other, on the same side of the warehouse, in order to reap these benefits (e.g., layout type 1). Increasing the depot count further, however, has a significantly weaker effect. Having more than three depots is almost pointless. This suggests that, at least in the industry case studied with $n = 60$ stations, maintaining two or three depots is advisable. Less than this, and the vehicle fleet explodes. More than this, and space and money is wasted on depots without any significant operational benefit.

D.6.3. Simulation study

Our objective of minimizing the fleet size is a surrogate objective, since we do not know the actual demand at the stations ahead of time, only the demand rates. To test whether our optimized solutions hold up during actual operation of the warehouse, we propose the following simulation study.

We implement a simulation study that imitates the warehouse of the case company using the commercial software Tecnomatix Plant Simulation 15 by Siemens. A simulation model is developed for each warehouse layout type introduced above, and warehouse operations are simulated for one working day consisting of an eight-hour shift. The scenario we consider is as follows: After a bin has been loaded onto a vehicle, it starts travelling on the track and carries the bin to the relevant station. Sensors placed on the track and barcodes on the bin enable the vehicle to drop off the bin if the station is not occupied. If the vehicle passes by a point-of-use that has bins waiting for transportation and if the vehicle is empty, the bin is picked up. In the AGV literature, this dispatch policy is sometimes referred to as *first encountered, first served* (Vis, 2006). The outputs that are obtained from our proposed heuristic, such as route duration (length), number of vehicles, and station assignments, are used as input parameters in the simulation model. We assume that each station starts with a full box of items to work on at the beginning of the planning horizon and that the stations do not have a buffer at the inbound side, i.e., a new bin can only be taken to a station once the old one is completed. The parameters assumed in the simulation are summarized in Table D.6. Note that we also experimented with different probability distributions for the demand events, specifically a Poisson distribution and a constant (non-random) rate. However, the outcomes were not substantially different, and therefore we only present the results for the parameters in the table.

Table D. 6. Parameters for the simulation study.

Parameter	Parameters
vehicle speed	1 meter/second
vehicle capacity	1 bin
drop off/pick up time	3 seconds
loading and unloading time	4 seconds
demand rate per bin of station type 1	$\mathcal{N}$ (1000, 50) seconds/bin
demand rate per bin of station type 2	$\mathcal{N}$ (333, 16) seconds/bin

The major purpose of the simulation study is to explore to what extent our findings from the MIP model, in particular the number of vehicles, are optimal for real-world operations. For this purpose, we evaluate the utilization (or occupancy rate) of the stations in a simulation model that mimics the real-world operations. We de- fine the utilization rate as the percentage of the eight-hour shift that a station spends doing productive work as opposed to wait- ing for a bin to be dropped off. Ideally, the utilization should be 100%, i.e., the station never starves for material. During the simulation, we analyze five different warehouse layouts and obtain the working percentage of each station. The results are summarized in Figure D.6.

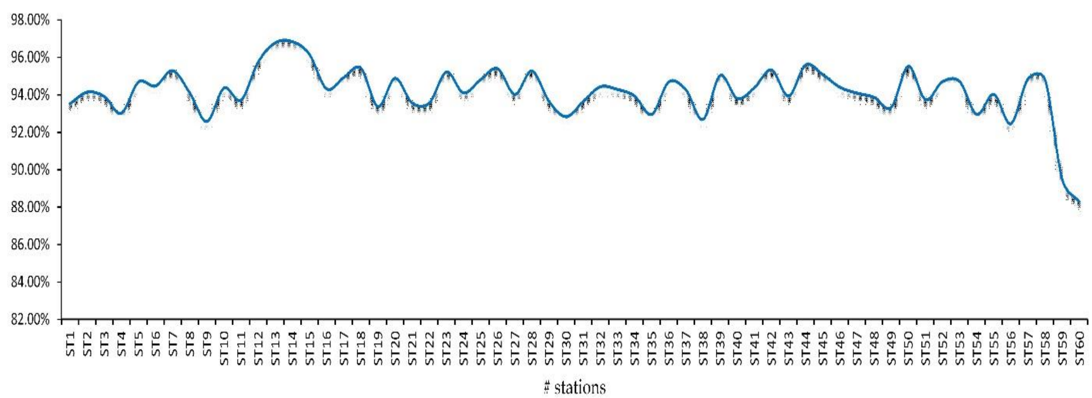


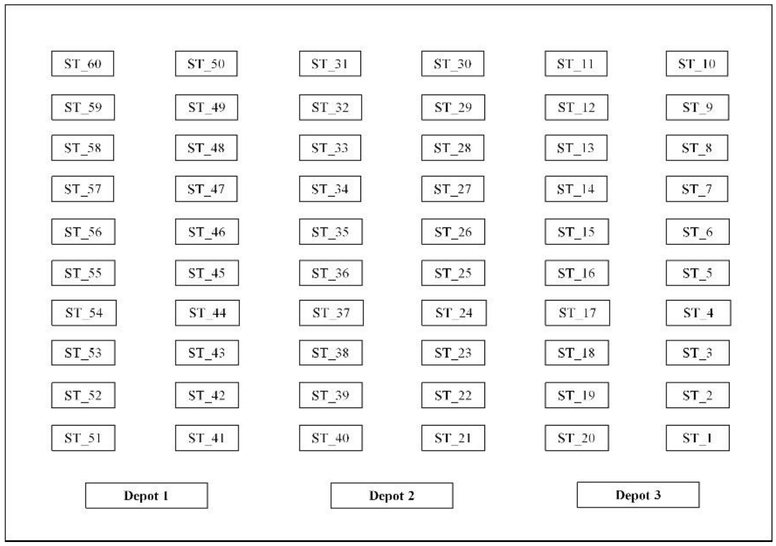
Figure D. 6. Utilization of the stations, averaged across the five different warehouse layouts.

As can be seen, the average utilization of most stations is around 94%, which is quite high given that we do not consider buffers. The utilization would probably be even closer to 100% if bins could be dropped off into a waiting line ahead of time. Note that the utilization, while high on average, is not evenly distributed. The vast majority of stations has an occupancy rate in excess of 90%; however, for a few stations it can be as low as 85%. These stations tend to be at the end of their respective routes, i.e., farthest from the depot on the loop. While these occupancy rates are still high, this is certainly something to keep in mind when considering installing LGT systems. To check whether the optimized vehicle counts returned by our heuristic might be too large, we reduce the vehicle fleet on each route by one. Rerunning the simulation, the average utilization drops to about 75.6%, indicating that the vehicle fleet size returned by our heuristic is indeed close to minimal if a utilization close to 100% is desired.

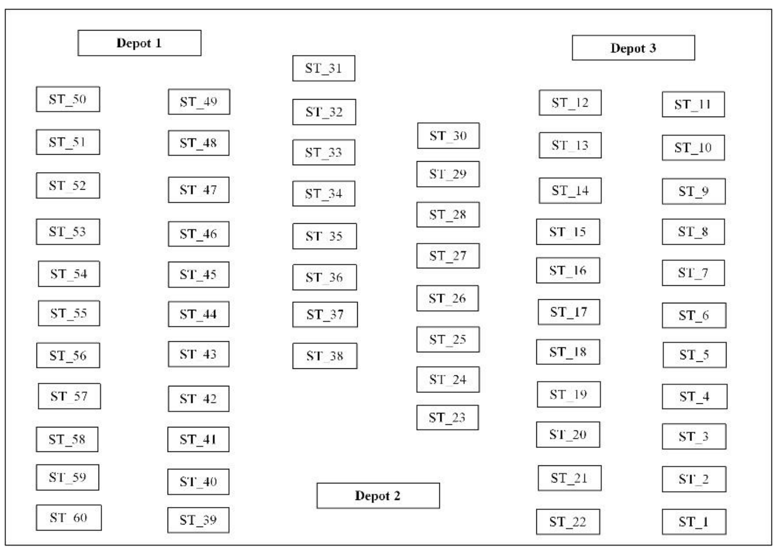
D.7. Conclusion

We investigate the problem of optimizing the use of lane- guided transport vehicles in a returns warehouse. This includes deciding on the optimal number of vehicles, their routes, and the assignment of types to the stations that are visited. We present a three-stage heuristic decomposition scheme, which is shown to solve instances of realistic size in under one minute of CPU time to near-optimality. In a computational study, we also discover that the location of the depots has little influence on the overall performance of the LGT vehicle system. It may therefore be most expedient to site depots such that they are easily accessible for delivery trucks. The number of depots, on the other hand, significantly influences the system efficiency. The total number of required vehicles can be halved in many cases if two depots instead of one are used. Further reductions are possible by installing a third depot, but at this point the marginal utility of additional depots is diminishing. Finally, our simulation study shows that the utilization of the individual stations may vary depending on where they are on a route. Since LGT vehicles do not have any sophisticated control logic, stations at the beginning of a route tend to be a little better served than stations at the end of a route. Overall, however, the average utilization is close to 100%; we expect that small fluctuations can most probably be smoothened by using buffer inventories at the stations. Future research should focus on developing powerful exact procedures, as default solvers do not seem adequate to solve realistic instances. On a more strategic level, it can be interesting to com- pare the performance and throughput of a lane-guided transport system with alternative transportation (or manual) systems, e.g., by way of simulation or queuing theory models. Finally, some of our assumptions may be relaxed; e.g., only non-crossing routes might be allowed if the vehicles cannot otherwise avoid collisions.

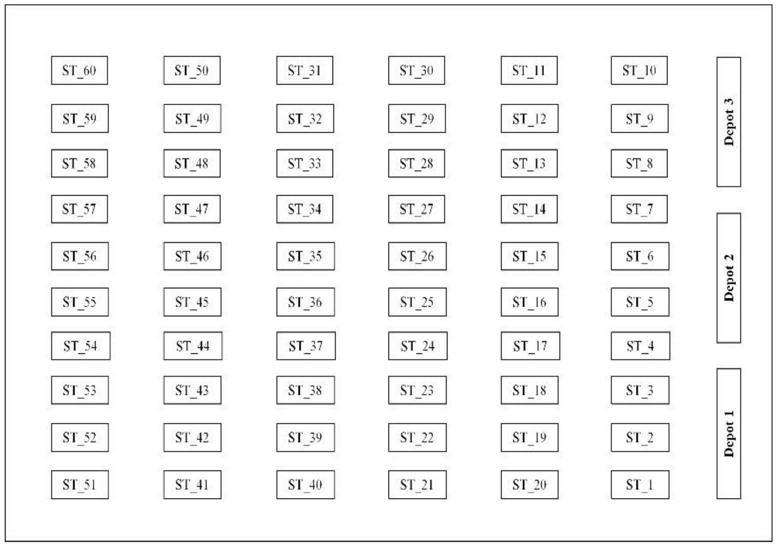
Appendix D



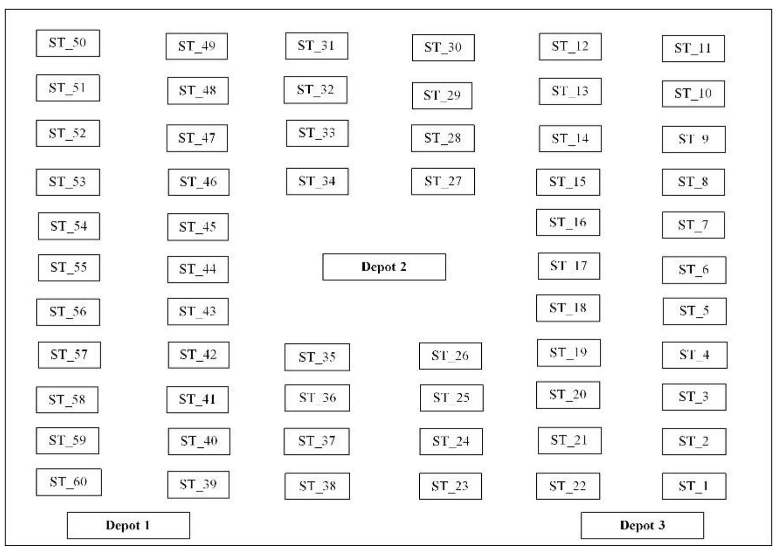
(a) Warehouse layout, type 1



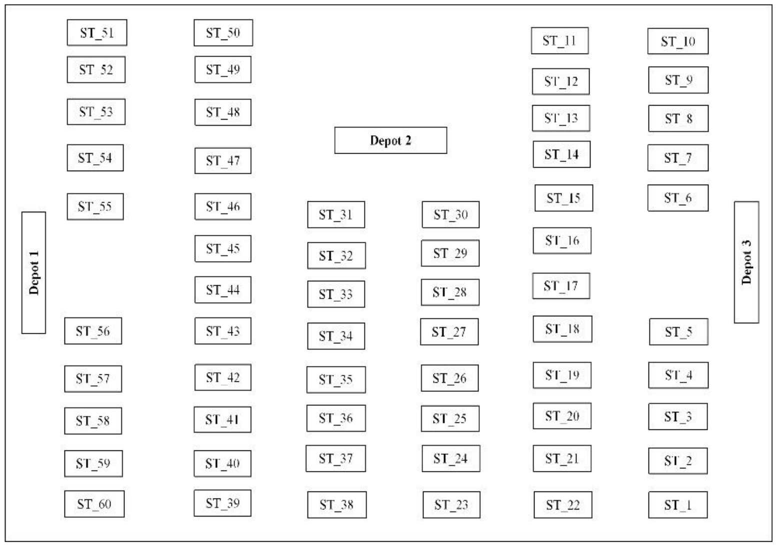
(b) Warehouse layout, type 2



(c) Warehouse layout, type 3

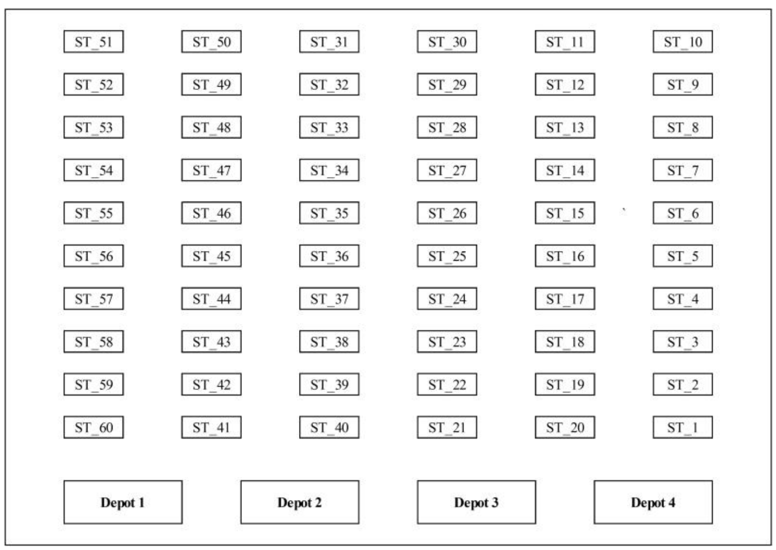


(d) Warehouse layout, type 4

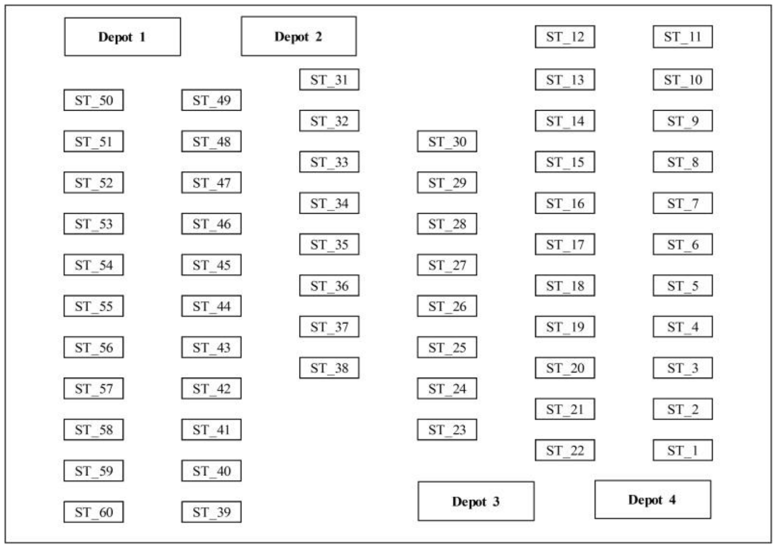


(e) Warehouse layout, type 5

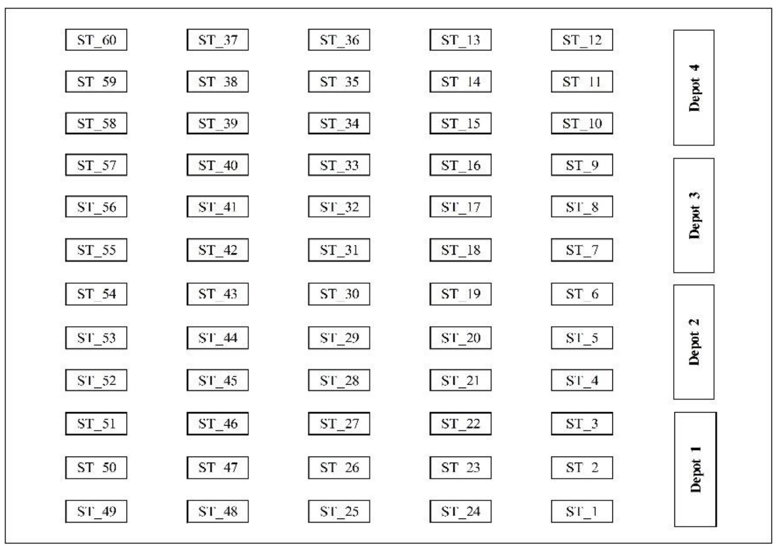
Figure D. 7. Different layout types with three depots.



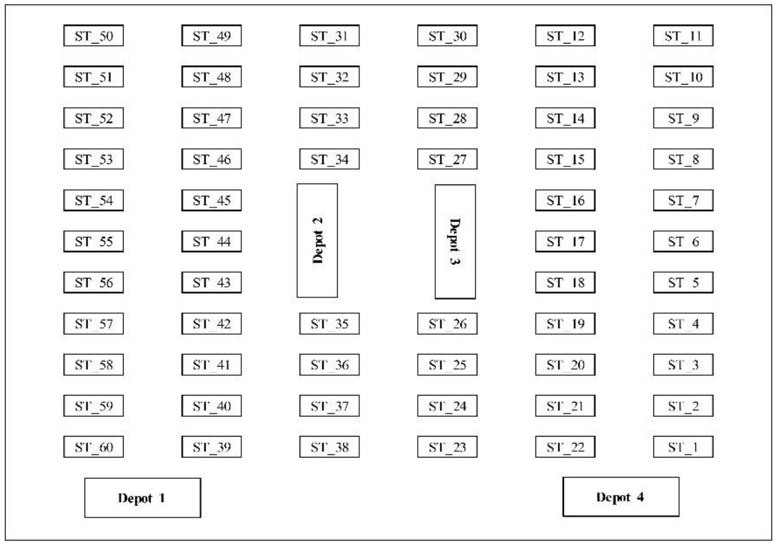
(a) Warehouse layout, type 1



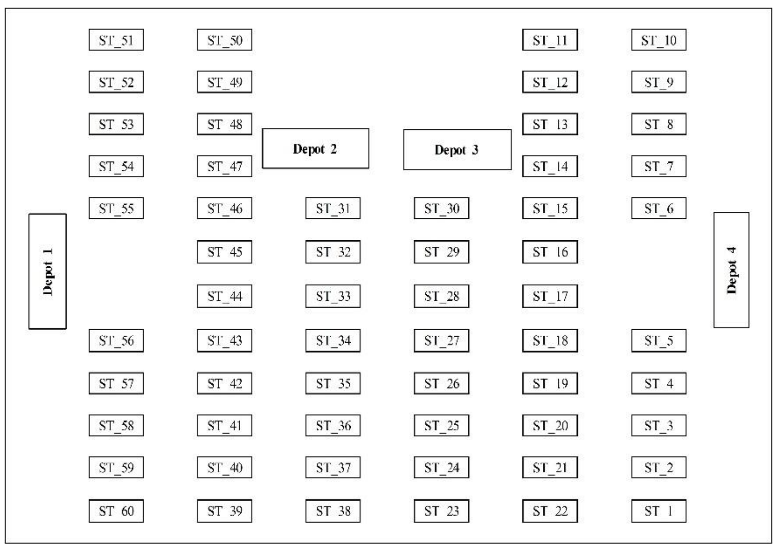
(b) Warehouse layout, type 2



(c) Warehouse layout, type 3



(d) Warehouse layout, type 4



(e) Warehouse layout, type 5

Figure D. 8. Different layout types with four depots.

Chapter E. Conclusion

This thesis investigated the design and management of distribution systems in a multi-channel context. There is a substantial amount of literature on multi-channel distribution systems available, but prior research had a strong focus on the retailer's perspective. Moreover, existing studies considered strategic, tactical, and operational decisions either separately or no more than two of them jointly. The novelty of this thesis is the investigation of multi-channel distribution systems from the perspective of a manufacturer and an evaluation of how strategic, tactical, and operational decisions can be considered simultaneously, i.e., in a holistic decision-making approach that helps manufacturers realize a well-configured supply chain. We addressed this topic from various aspects and laid it out clearly in three chapters.

Chapter B provided a systematic literature review on multi-channel distribution systems in which manufacturers introduce a direct sales channel in addition to vending products via independent intermediaries (i.e., retailers or wholesalers). We evaluated all works in light of the developed conceptual framework; our main research objective was to understand what factors induce manufacturers to adopt a direct sales channel and how manufacturers manage emerging channel conflicts with the retailers and handle operational decision problems.

We conclude that manufacturers should especially consider *customer preferences* and the *market environment* while developing channel strategies. The first factor refers to the extent to which customers prefer to purchase directly from a manufacturer. Especially when opening an online channel, manufacturers should incorporate the customer acceptance rate into the demand function along with the product's price. The second factor pertains to the dynamics of the market (e.g., potential market growth, uncertainty). The sampled works with an empirical focus show that manufacturers adopt multiple channels especially when market diversity and growth are high. Another important factor is *information asymmetry* which stimulates especially customer-oriented manufacturers to use an online channel as a cost-effective communication tool and facilitator as they suffer from a lack of information of end customers.

Albeit adding a direct channel has advantages (e.g., increasing profit, reaching more customers), it gives rise to managerial challenges which mainly result from the higher complexity of such distribution systems. First, manufacturers should be aware that encroaching into the retail market increases competition and may lead to channel conflicts. Channel conflicts may become especially fierce when the manufacturer offers similar products at similar or lower prices in the same market via the direct channel. Our findings point out that manufacturers can balance a direct and a conventional retail channel and coordinate both channels using an appropriate *pricing* system or *contract* (e.g., profit sharing, two-part tariff, or wholesale discount), which can make both members better off. Other feasible conflict mitigation mechanisms are *product differentiation* strategies and various *incentive schemes* (e.g., *referral to retailers*: Manufacturers can refer customers to retailers or assign additional responsibilities to the retailers, such as installation or last-mile delivery, which may motivate the retailers due to additional sources of income).

Other managerial challenges relate to *operational-level decisions.* Today's competition and increasing customer expectations force manufacturers to configure more responsive supply chain systems. To achieve better operational efficiency, manufacturers have to make decisions in terms of order fulfilment, inventory control, product delivery, or the collection of returns jointly with their retailers.

Further, we identified the following research gaps for future research directions: 1) considering additional factors that influence customers' channel preference, 2) designing more complex supply chain networks, 3) investigating new coordination mechanisms, 4) analyzing new operational decisions in multi-channel distribution systems, 5) conducting new empirical studies, 6) investigating multi-channel distribution systems in a global supply chain environment, 7) investigating virtual products in a multi-channel context, and 8) using more realistic modelling principles.

Chapter C investigated a channel transition scenario i.e., from single- to multi-channel and from multi-to omni-channel, for a manufacturer selling standard and customized products. For each distribution network scenario, we developed a mathematical model by considering customer service-level constraints. The core of the chapter is the formulated omni-channel scenario model that contributes to the related literature. Thus, the proposed model is an integrated optimization model that includes a location-routing problem for designing a combined two-echelon supply chain network for an OC distribution system with fragmented customer demands met over multiple shopping and delivery options. Further, we incorporated two granular features, i.e., customer segmentation based on shopping/picking preference and customer service level, into the model which help to adjust the channel design accordingly.

Since the developed model is an NP-hard problem, we proposed a problem-specific decomposition metaheuristic to solve large-scale instances, and this enabled us to solve large realistic instances effectively in terms of solution quality and time.

The findings showed that to reach more customer segments, the OC is a feasible distribution system. We also suggest that manufacturers should invest some effort into motivating customers to make use of the "buy online pick-up in-store" shopping style, as more BOPIS customers can decrease logistics costs substantially. We also showed that retailers still play significant roles for manufacturers. Manufacturers, for example, can utilize the retailers' physical stores for fulfilment and picking locations (i.e., as dark stores), which enable the manufacturer to gain competitive advantages and increase customer satisfaction. Manufacturers have to keep in mind that they incur additional fixed costs, though. Moreover, the results indicated that an increased number of dark stores substantially reduces transportation costs and the routing complexity of last-mile delivery operations. Therefore, understanding the effect of opening additional dark stores can consolidate decision-making on channel design.

Finally, Chapter D investigated a case in which an apparel company plans to improve the processing of returned items in its warehouse. To expedite the process (i.e., refurbish and recycle), the case company considers implementing fully automated lane-guided transport vehicles. In this respect, we investigated an internal logistics problem by optimizing the use of lane-guided transport vehicles in a warehouse handling returns. The developed model aims to find the optimal values for the following decision variables: the number of vehicles, routes, and assignment of roles (recycling and refurbishing) to the stations that are visited. Our primary objective was optimizing the number of LGT vehicles and total duration of routes to reduce investment (i.e., procurement of LGT vehicles) and operation (i.e., energy consumption and increased service frequencies of a vehicle) costs, respectively. Further, we developed a decomposition heuristic which enabled us to solve realistically sized instances in under one minute of CPU time to near-optimality.

In a computational study, we analyzed the impact of the number of depots and depot locations (i.e., for various warehouse layout types) on the overall performance of the LGT vehicle system. The results showed that the number of depots has a significant influence on the system efficiency, while the locations have a minor effect on the overall performance of the LGT vehicle system. In addition, the average utilization of stations found in the simulation study indicates that the number of vehicles obtained from our proposed model can be optimal for real-world operations.

Although this dissertation widely explores development and management issues in manufacturer distribution systems, there still remain several opportunities for future research. For example, besides product category and shopping experience, new factors (e.g., customer demographics, learning and forgetting effects), that affect customers' channel preference could be considered in future studies. In a multi-channel context, to improve coordination between manufacturers and retailers, joint decision-making (i.e., joint planning, joint product development, joint product promotion, etc.) and the growing power of information technology for this purpose could also be addressed in future research. Furthermore, multi-channel distribution systems from the manufacturer's perspective have only infrequently been analyzed empirically so far. Future research could therefore conduct field experiments involving retailers and manufacturers to gain insights into the behaviours of both parties and to examine how well equilibria obtained from game-theoretic models reflect real-world retailer-manufacturer partnerships. Since most manufacturers' supply chains are global today, those companies may encounter disruptions during sourcing or delivery. Therefore, it would be interesting to investigate how globalization affects the performance of manufacturers in a multi- or omni-channel distribution context. In addition, to reflect real-world omni-channel operations, customer returns can be included in an omni-channel distribution system of a manufacturer and in this context, the effect of "buy online, return in-store (BORIS)" customers can be investigated. Further, the proposed models in this dissertation can be investigated under stochastic and multiperiod settings.

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