Value of information in agro-food logistics management

A case of the Dutch floriculture supply chain network

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Quoc Viet Nguyen

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Chapter 1. Introduction

Logistics management is defined as "the part of supply chain management that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services and related information between the point of origin and the point of consumption in order to meet customers' requirements" (CSCMP, 2019). This definition by the Council of Supply Chain Management Professionals and earlier definitions, e.g., by Cooper et al. (1997), consistently emphasize the importance of integrating information flows in managerial decision-making on physical flows. Over the last two decades, practitioners and researchers have increasingly considered information as an essential logistics resource that leverages the existing resources (e.g., manpower, warehouse space, vehicle capacity) to subsequently improve logistics efficiency and effectiveness (Closs et al., 1997; Lee & Whang, 2001; Lumsden & Mirzabeiki, 2008; Jonsson & Myrelid, 2016).

This thesis contributes to the above-mentioned theme, i.e., utilizing information flows for better managing physical flows, and focuses on agro-food supply chains. In the following, Section 1.1 and Section 1.2 discuss the practical and scientific contexts, which motivate the research. Section 1.3 introduces the research objective, research framework, and the outline of the thesis.

1.1 Logistics challenges in the Dutch floriculture sector

The Dutch floriculture sector is a vivid sector with a long tradition and it is of great importance to the Dutch economy. The sector consists of approximately 6000 (inter)national suppliers (i.e., growers, importers) of cut flowers and potted plants, 2500 customers (i.e. wholesalers, exporter, retailers), 70 logistics service providers (LSPs), five auction sites, and several cross-docking distribution centers (RoyalFloraHolland, 2019). Among these actors, Royal Flora Holland (RFH) plays the key role. It is a primary cooperative owned by Dutch growers. Similarly to a generic food supply chain network, each organization in the Dutch sector belongs to the networked supply chains: at the same time, a supplier has multiple customers and a customer has multiple suppliers, and these connections change over time (Trienekens et al., 2014, p. 500).

Two major types of physical flows in the network can be distinguished: direct and auction flows. Direct flows refer to flows of products sold via direct trade between suppliers and buyers. Auction flows are for products sold via auction clocks. In the last five years, the volume of direct flows has been substantially increasing. In 2017, 57% of sale volume in the sector was of direct flows (RoyalFloraHolland, 2019). This thesis focuses on the logistics processes for the *direct flows*.

The logistics processes of direct flows concern mainly the transportation between supply chain stages and the internal processes at cross-docking distribution centres, as shown in Figure 1.1. The logistics processes from customers to further downstream firms are not included in this research. The internal processes, in stage order, include (i) break-bulking: trolleys that contain multiple orders from different customers are break-bulked after unloading, (ii) consolidating: small volumes of different products to be delivered to the same customer are consolidated in one trolley, and (iii) aggregating: multiple trolleys to be delivered to the same customer area are aggregated.

From the supply side, high uncertainty relating to product perishability, quantity, origin, and timing often leads to inefficiencies such as low truck utilizations in transportation (de Keizer et al., 2015). From the demand side, customer orders are increasingly characterized by (i) multiple order lines of small volumes ranging from only a few flower buckets or a few plant pots, (ii) high frequency, and (iii) short delivery lead-time (e.g., four hours) (Breijer, 2017). This trend brings difficulties in the transportation and internal logistics processes to maintain a high delivery service level at low cost. For example, frequent orders with short delivery lead-times results in an increasing number of daily less-than-truckload truck movements because limited time is allowed for load consolidation; a large number of small orders significantly increases processing times of internal logistics operations, especially at the break-bulking and consolidating. Last but not least, the difficulties are amplified by the fact that the logistics processes for direct flows involve a huge number of dissimilar small-, medium-, and large-sized suppliers and customers who are interdependent in the processes.

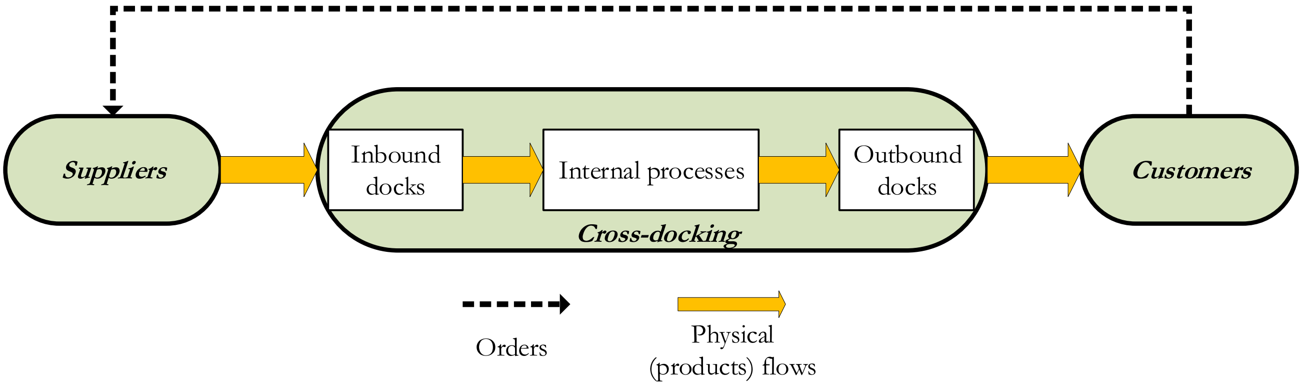

Figure 1.1 Logistics processes for direct flows in the Dutch floriculture sector

During the last five years, the Dutch sector has undergone a rapid virtualization enabled by the increasing use of tracking/sensing devices and ICTs (information and communication technologies) at growers, customers, and distribution sites (Verdouw et al., 2013). As a result, the Dutch floriculture supply chains have become information-rich environments (Verdouw et al., 2014b). New types of information from various sources such as real-time product location/condition information and real-time truck utilization information become available. The question is how to utilize the information to overcome the above-mentioned logistics challenges.

The Operations Research and Logistics group from Wageningen University participates in *DaVinc³i community* (2016-2019), *DaVinc³i* (2011-2015), and *iFlow* (2015-2019), which are the three research projects set up to strengthen the Dutch floriculture sector. Davinc³i community serves as a collaborative research forum focusing on innovative ideas and practices for floriculture logistics (Davinc3i, 2019). Within DaVinc³i, the PhD thesis by de Keizer (2015) investigates different concepts of logistics collaboration, coordination, and consolidation at the strategic level. This PhD thesis and the corresponding research are part of iFlow funded by the Topconsortium for Knowledge and Innovation in Horticulture (TKI Tuinbouw) and the focus is on the operational logistics processes of daily direct trade (direct flows).

1.2 Value of information in logistics management

Data-information-knowledge is a well-known concept (Zins, 2007). *Data* are patterns without meaning and data become *information* after being interpreted for decision-making purposes (van der Vorst et al., 2005). A collection of useful information in turn provides valuable *knowledge* (Bellinger et al., 2004).

Information and knowledge are used to support decision-makers in decision-making. In the rest of this thesis, information and knowledge are merged into a single construct as information.

The logistics and supply chain management literature defines the *value of information* (VOI) as the expected or realized benefits from using the information in specific decisions, where the benefits are described as improvements of key performance indicators (KPIs) influenced by the decisions (Ketzenberg et al., 2006; Davis et al., 2011; Ganesh et al., 2014b). Therefore, assessing the VOI requires making the connection from data and the information generated from data to supply chain decisions (Janssen et al., 2017). As further elaborated in Chapter 2, the previous literature presents numerous case studies on different information types, but mainly related to inventory decisions. The connections between data/information and decisions concerning other processes such as the integrated production and distribution processes have not been elaborately studied. Furthermore, conflicting results are found from studies on the same information type in the literature (as elaborated in Chapter 2). This requests the development of a comprehensive framework and guidance for better understanding the VOI in supporting logistics and supply chain decisions.

An important aspect to be stressed is that VOI is not only about information availability but also about its characteristics (Hazen et al., 2014). Major characteristics discussed in the literature are *availability* - whether information is existing, *timeliness* - how up to date the information is in a particular situation, *accuracy* - how accurate the information reflects the underlying reality, and *completeness* - level of detail of information (Cappiello et al., 2003; Hazen et al., 2014). Availability has been discussed the most in the literature. A limited number of studies examine how other information characteristics affect the VOI in logistics and supply chain decisions (see Chapter 2). In the past five years, *big data,* its 5Vs (volume, velocity, veracity, variety, and value), and its vast applications in logistics and supply chain management have attracted significant research attention (Sonka, 2014). Review articles published in this period report the exponential growth of data and information due to data/information sharing among supply chain organizations, diverse embedded tracking/sensing devices, and ubiquitous usage of smartphones and computer systems (Addo-Tenkorang & Helo, 2016; Wang et al., 2016b; Zhong et al., 2016). Data/information from various sources have different characteristics. Understanding how different characteristics can enhance decision-making to bring process improvements becomes critical to support big-data investment decisions.

Also relevant to the development from data to big data, the role of data in decision-making has shifted. From being used to estimate parameters of analytic models, (big) data is now increasingly utilized to discover valuable patterns and insights of logistics processes (Kuo & Kusiak, 2018). This shift consequently requires new analytic approaches to effectively evaluate the value of the information derived from data and big data. Delen & Demirkan (2013) categorize analytic models in three categories: (i) *descriptive* models investigating the past and the current state of physical and information flows; (ii) *predictive* models utilizing the output of descriptive models to project the future states; and (iii) *prescriptive* models using the outputs from descriptive and predictive models to determine the most appropriate decisions to improve the KPIs. The extant VOI literature is dominated by optimization models and analytical model based on complicated mathematical formulations, game theory, and probability theory (as reported in Chapter 2). As data increases to big data, it is essential to combine (big data) descriptive and predictive analytics with prescriptive analytics. Particularly with regards to decision-making at the operational level, simulation models (e.g., discrete-event simulation or multi-agent simulation) complemented by descriptive/predictive analytics (e.g., data mining) are promising to capture the dynamics in logistics processes.

1.3 Research objective and framework

The supply chain network structure of the Dutch floriculture sector resembles the common structure of agro-food supply chains. Moreover, the logistics challenges in the sector are also representative examples for the generic trend in the agro-food sector (van der Vorst et al., 2011; Fernie & Sparks, 2014). Using the Dutch floriculture supply chain network as the case study platform, the overall research objective is **to investigate the value of information to improve logistics management in agro-food supply chain networks**. To achieve this objective, four research questions are defined following the research framework depicted in Figure 1.2.

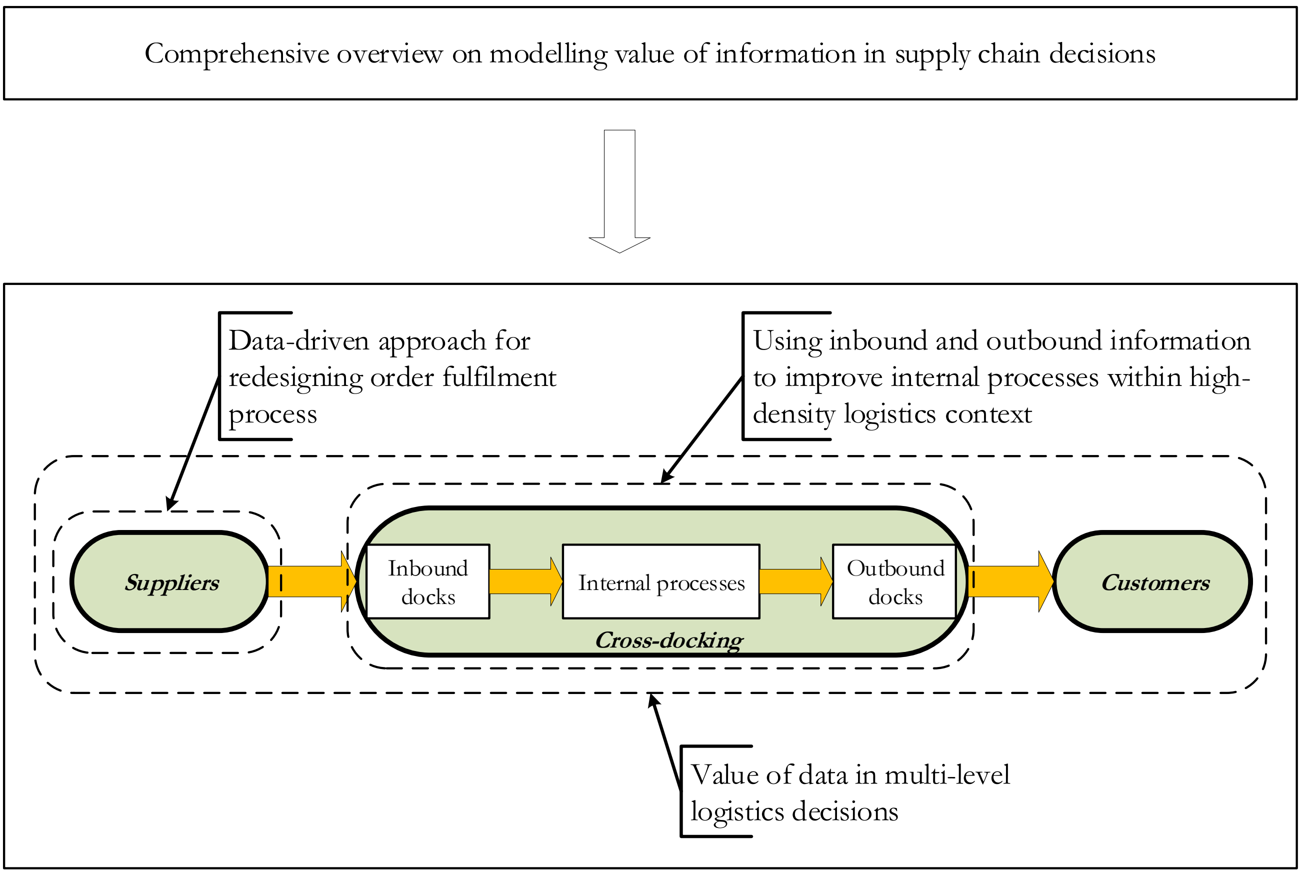

Figure 1.2 Research framework

Because the VOI topic is not new and there exists a considerable amount of research, a systematic literature review is conducted with a broad scope that covers primary supply chain decisions including facilities, inventory, transportation, sourcing, and pricing (Chopra & Meindl, 2013). The review connects fragmented studies on different information types to provide a comprehensive overview on VOI in order to answer the first research question:

RQ1. *How to model the value of information in decision-making and what are the influential factors on the value of information in supply chain decisions?* Chapter 2 presents the results of the review. A framework of four primary dimensions to model VOI in supply chain decisions is presented. These dimensions are *supply chain decisions*, *information*, *modelling approach*, and *supply chain context*.

Applying the four-dimension VOI framework to agro-food logistics, the next three research questions are positioned along the physical flows in the Dutch sector (Figure 1.1) from suppliers to cross-dockings and then to customers. The logistics processes from customers to further downstream firms (e.g., florists, supermarkets) are not included in the research scope. Each research question studies specific data/information types. Furthermore, depending on the characteristics of the logistics challenges, each research question focuses on different dimensions among the four dimensions of modelling VOI.

RQ2 and RQ3 explore the use of information in improving logistics processes at cross-dockings and at agro-food suppliers, correspondingly:

RQ2. *How to use information flows to improve internal logistics processes at agro-food cross-dockings?* Chapter 3 discusses RQ2. Cross-docking logistics aims at facilitating a seamless physical flow from inbound to outbound docks. The inbound-flow scheduling decision has been extensively investigated in the literature (Van Belle et al., 2012). Focusing on the outbound-flow scheduling decision, RQ2 examines the value of available information at cross-dockings including information on inbound and outbound flows, i.e. inbound information and outbound information. This chapter especially emphasizes the *supply chain context* dimension by assessing the VOI in different settings of the High-Density Logistics (HDL) context (formally defined in the chapter), which is caused by the increasing customer requirements mentioned in Section 1.1. The impact of information characteristics is also studied, particularly accuracy of the information on inbound flows provided by suppliers.

RQ3. *How to use information flows to improve order fulfilment processes at agro-food suppliers?* Chapter 4 addresses RQ3. Given the limited delivery time windows and frequent orders of small volumes, anticipatory shipping (AS) approach is explored. The concept of AS is patented by Amazon (Spiegel et al., 2011) and further studied by Lee (2017). Within the setting of AS in agro-food supply chains, products can be transported and temporarily stored at cross-docking distribution warehouses before actual customer orders are received. Applying the AS concept to agro-food supply chains is challenging because of the product perishability. Therefore, an effective data-driven approach is required. Chapter 3 focuses on the *modelling approach* dimension and presents a multi-method approach combining data mining and multi-agent simulation to support agro-food suppliers in AS decision-making. Considering different quality decay characteristics, the data mining mines the historical customer orders for products that fit the AS strategy. The multi-agent simulation effectively captures the dynamics in production and transportation planning including the complicated consolidation of less-than-truckload loads.

Whereas RQ2 and RQ3 focus on logistics processes at individual firms, RQ4 aims at utilizing information flows to improve logistics processes at supply chain level:

RQ4. *How to use information flows to improve agro-food logistics processes at supply chain level?* RQ4 is studied in Chapter 5. Hazen et al. (2016) report that big data and big data analytics can upgrade the efficiency and sustainability of interdependent supply chain processes. RQ4 explores the use of the booming data (big data) collected from direct-flow logistics processes in the Dutch supply chain network. Data collected from various sources have different characteristics. Analyzing the impact of data characteristics is essential in assessing the value of the data. This chapter highlights the *information* and *supply chain decisions* dimensions by showing how information is extracted from the data and how the extracted information is connected to different logistics decisions. Especially, it shows how big data's 4Vs (velocity, variety, volume, and veracity) affect the characteristics of the extracted information, which determines how the information can be used in logistics decisions at different levels. At the individual-firm level, the decisions at cross-dockings are studied. At the supply-chain level, the decisions concern the collaboration in transportation among suppliers, the coordination between suppliers and cross-dockings, and the coordination between cross-dockings and customers.

Chapter 6 integrates all the findings presented in Chapter 2 to 5 to address the overall research objective. This chapter further discusses the scientific and managerial contribution, and directions for future research.

Chapter 2. Value of information in supply chain decisions: A review of the literature and research agenda

This chapter is based on the published journal article:

Viet, N.Q., Behdani, B., and Bloemhof, J. (2018).

The value of information in supply chain decisions: a review of the literature and research agenda.

Computers and Industrial Engineering 120, 68-82.

DOI: https://doi.org/10.1016/j.cie.2018.04.034

Abstract

The purpose of this chapter is to provide a structured overview of the value of information in different supply chain decisions and to identify a research agenda based on the current state of research on the topic. The chapter uses the systematic literature review methodology to review journal articles published in the 12-year period from 2006 to 2017. Each selected study is analysed using a rigorous review framework of four primary dimensions, including "supply chain decisions", "information", "modelling approach", and "supply chain context". The review of articles shows that the current literature is rich in assessing the value of information in inventory decisions, yet insufficient in other supply chain areas such as facility, transportation, sourcing, and pricing. In addition, the value of information is subject to contextual supply chain parameters and varies in accordance with the characteristics of the information (such as accuracy, timeliness, and completeness). Furthermore, the focus of the existing literature is on "information availability" in supply chain decisions, and the impact of important information characteristics on the value of information has not been studied extensively. The research on information timeliness and its influence on supply chain performance is especially limited. Based on the discussion and results of our review, a research agenda is offered and sample research questions are discussed.

2.1 Introduction

Over the past two decades, information sharing and information and communication technology (ICT) have been widely discussed as the main enablers to improve supply chain performance and to prevent critical supply chain problems such as the bullwhip effect (Lee et al., 1997; Hofmann, 2017). However, access to more information in a supply chain can be challenging in practice. Information sharing requires a high level of trust between collaborating parties in the chain (Ebrahim - Khanjari et al., 2012; Tsanos & Zografos, 2016). In addition, access to information is not cost free and may require significant investments in ICT infrastructures to gather and share data (Lee et al., 2000; Zhong et al., 2016). Several recent studies show that despite substantial investments in ICT systems, many organizations have failed to gain the expected improvements in their supply chain performance (Fawcett et al., 2011). This might primarily imply that investment in gathering and sharing information per se does not guarantee enhanced supply chain performance (Wu et al., 2006). It is particularly important to clearly understand which information must be shared in a supply chain and how that information may contribute to an improved design and operation of a supply chain. Evaluating the "value of information" (VOI) before investing in an ICT infrastructure or participating in information sharing with other parties in the chain would be helpful to overcome these drawbacks.

VOI is defined from two different points of view in the literature. VOI can be defined as an estimate of the willingness to pay of a potential user of the information in order to have access to it (Lumsden & Mirzabeiki, 2008; Jonsson & Myrelid, 2016). Another definition, which is the more dominant view in the literature, defines the VOI based on the (expected or realized) benefits of using the information in decision making in a supply chain (Lumsden & Mirzabeiki, 2008). These benefits are described as improvement in one or several key performance indicators (KPIs) achieved through the use of the information compared with the base scenario in which the information is unavailable or unused (Ketzenberg et al., 2006; Davis et al., 2011; Ganesh et al., 2014b). In this chapter (and this thesis), we adopt the latter definition. This implies that we aim to make a connection between the information and the supply chain decisions. The availability of (further) information has no value unless it contributes (or is expected to contribute) to a better decision(s) in a supply chain.

VOI is a growing topic in supply chain management research (Shiau et al., 2015). However, a recent review of the literature on this topic is lacking. In addition, the existing literature does not provide a framework that supports a comprehensive assessment of VOI in supply chain decisions. We are aware of three previous literature reviews on VOI. The earliest was performed by Huang et al. (2003). They presented a review of studies on the impacts of sharing production information on supply chain dynamics up to 2003. As a reference framework, they categorized papers using seven dimensions: (i) supply chain structure, (ii) decision-making level, (iii) information types, (iv) information sharing modes, (v) performance indices, (vi) modelling of the supply chain or analytical methods, and (vii) impact analysis of supply chain parameters. Following the work of Huang et al. (2003), Li et al. (2005) carried out an in-depth review of 12 selected papers on the last two dimensions. They specifically focused on the value of information sharing and the factors that affect that value in a supply chain. As one important conclusion, they discussed that the value and the factors are dependent on the context and how the information is utilized in decision-making problems. Another review that focuses on the topic of VOI is presented by Ketzenberg et al. (2007). They investigated 27 papers up to 2005 and introduced a framework to explain how supply chain parameters influence the value of information sharing in "inventory replenishment decision". The five constructs in their framework are (i) the level of uncertainty in the supply chain, (ii) the sensitivity of the supply chain to uncertainty, (iii) the responsiveness of the supply chain, (iv) the available information in the supply chain and (v) the uses of information in supply chain decision making.

Our aim in this literature review is to complement and expand the previous works by reviewing and synthesizing the findings of relevant literature published in the 12-year period from 2006 to 2017. Moreover, while inventory decisions are the focus in the aforementioned reviews, this review broadens the scope by considering decisions in other supply chain areas, i.e. facility (location and design), transportation, sourcing and pricing. In addition, we emphasize the impact of information characteristics on VOI, a dimension that is not included in the above-mentioned frameworks. One party in a supply chain may continuously receive information from different sources (e.g. information from sensing/tracking/tracing devices, information from business transactions, and information shared by other parties in the chain). This information usually has heterogeneous characteristics that may highly influence the VOI in a supply chain (Sellitto et al., 2007; Hazen et al., 2014). For instance, although the availability of final consumer demand is important for inventory planning by a distributor, the "timeliness", i.e. the timing that the information becomes available for use, is also important to make decisions for optimal supply chain planning (Tsanos & Zografos, 2016). More discussion on the key information characteristics is presented in Sections 2.2 and 2.3.

The chapter is structured as follows. Section 2.2 introduces the review methodology. Important findings from the literature are discussed in Section 2.3. In Section 2.4, we present an agenda for future research based on the findings from the literature and propose a framework as a guidance tool to evaluate the VOI in supply chain decisions. Section 2.5 concludes our study.

2.2 Review methodology

The review process is based on the five-step guide for a structured literature review proposed by Denyer & Tranfield (2009). The steps are explained as follows.

i. Question formulation: establish a clear focus of the review
ii. Locating studies: define the method to locate as much as possible the studies relevant to the review questions
iii. Study selection and evaluation: assess if a study does actually address the review questions using a set of criteria
iv. Analysis and synthesis: decompose each study into parts and explain how the parts relate to each other, then make the connections between those parts and develop the knowledge that readers are unable to acquire from reading the individual studies in isolation
v. Reporting and using the results: report the results of the review

The introduction explained the motivation for and the context of this review. The research questions are formulated as "how the value of information has been modelled in supply chain decisions in the existing literature" and "what factors may influence the value of information in a supply chain decision". In this section, we first clarify how relevant studies are located and then selected (i.e. steps ii and iii). Then, we present the review framework, which includes the dimensions used in analysing the selected literature (i.e. step iv). The results from the review are discussed in Section 2.3 (i.e. step v).

2.2.1 Article selection and evaluation

As discussed in the introduction, the scope of this literature review is limited to journal articles published in the 12-year period from 2006 to 2017. Conference proceedings were excluded in our search. The literature search was performed on two databases – Scopus and Web of Science – within limited subject areas, i.e. business, management, decision science, economics. The focus was on articles whose objective was to assess the VOI in supply chain decisions.

To locate relevant studies from the databases, we used the following combination of terms associated with VOI and supply chain management research:

[("value of information" <u>and</u> (logistics <u>or</u> supply chain)) <u>in</u> (abstract, title, keywords)].

This search strategy resulted in 169 studies. In order to reach the articles that did not use the phrase "value of information", two additional searches were performed. The second search used keywords that are semantically close to "value" (i.e. profit, cost, benefit, saving, surplus) and "information" (i.e. data, knowledge), as follows:

[((information <u>or</u> data <u>or</u> knowledge) <u>and</u> (value <u>or</u> profit <u>or</u> cost <u>or</u> benefit <u>or</u> saving <u>or</u> surplus)) <u>in</u> (title)] <u>and</u> [(logistics <u>or</u> supply chain) <u>in</u> (abstract, title, keywords)].

We limited the second search to "title" because those keywords commonly appear in the "abstract" or "keywords" of a large amount of potentially irrelevant literature. The third additional search complemented the second search; we changed the search scope from "title" to "title, abstract, keywords", and included "logistics decision" and "supply chain decision" to exclude irrelevant articles. The search criteria was as follows:

[((information) <u>and</u> (value <u>or</u> profit <u>or</u> cost <u>or</u> benefit <u>or</u> saving <u>or</u> surplus)) <u>in</u> (abstract, title, keywords)] <u>and</u> [("logistics decision" <u>or</u> "supply chain decision") <u>in</u> (abstract, title, keywords)].

These two additional searches yielded 229 studies. We combined the results from the three searches, removed duplicate articles, and then read the article titles and abstracts. This process shortened the list to 95 journal articles.

A number of papers list "value of information", "big data" or "data mining" among their keywords. The potential association among these phrases was recognized. Because knowledge and techniques in the fields of big data analytics, particularly data mining, have been applied widely in various supply chain functions (Olson, 2015; Addo-Tenkorang & Helo, 2016; Wang et al., 2016b; Zhong et al., 2016; Kache & Seuring, 2017), a fourth search was performed similar to the first three searches with the following search criteria:

[("big data" <u>or</u> "data mining") <u>and</u> (logistics <u>or</u> supply chain) <u>and not</u> ("logistics regression")

<u>in</u> (abstract, title, keywords)],

which resulted in 158 articles. During the screening, we excluded a large number of articles whose objectives were on technical and algorithmic aspects of big data (e.g. algorithms and frameworks to prepare and extract information from big data) but not on the connection between the value of big data and supply chain decisions. In other words, we focus on the most important "V", i.e. value, among the 5Vs of big data, i.e. volume, variety, velocity, veracity, and value (Opresnik & Taisch, 2015; Addo-Tenkorang & Helo, 2016). Finally, we selected 22 articles that assessed the VOI extracted from big data in a specific supply chain decision(s). With regard to reviews on big data applications in supply chain management (i.e. the 5Vs of big data, where and how big data analytics has been applied in supply chain management), we refer to recent review papers by Addo-Tenkorang & Helo (2016), Zhong et al. (2016), Hofmann (2017), and Nguyen et al. (2018).

In total, 117 journal articles over the period 2006-2017 were selected for the analysis and synthesis steps in this review. Although Scopus and Web of Science can be trusted to hold the most relevant journal articles on supply chain management topics (Chicksand et al., 2012; Fahimnia et al., 2015), there might be relevant articles that not in these databases. Moreover, there could be a marginal chance that some relevant literature was missed with the key words and conditions of the literature search. However, the authors believe that the most relevant articles have been located by those searches and they can provide a comprehensive representation of the existing research on VOI in supply chain decisions. Among those 117 articles, 24 articles (including review papers) discuss the uses of different information in general supply chain contexts, 93 articles study the VOI in a specific supply chain decision-making process. Section 2.3 focuses on discussing the findings from reviewing these 93 articles. Figure 2.1 shows the timely distribution of the selected articles in this review. The number of VOI articles found under the big data and data mining search is limited up to 2013 but is now increasing.

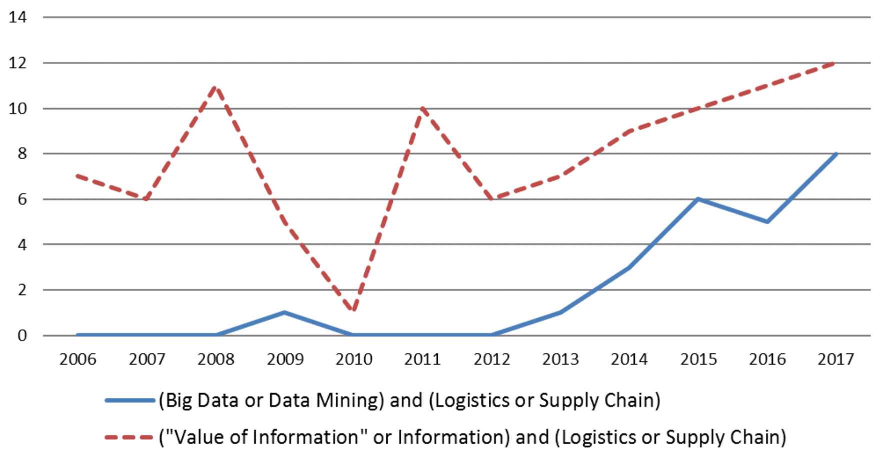

Figure 2.1. Time distribution of reviewed articles.

2.2.2 Review framework

As discussed in the introduction, Huang et al. (2003) used seven elements in the reference framework to review the literature on VOI: (i) decision-making level, (ii) performance indices, (iii) information types, (iv) information sharing modes, (v) modelling of the supply chain/analytical methods, (vi) supply chain structure, and (vii) impact analysis of supply chain parameters. With the aim of revealing the connection between "information" and "supply chain decisions", we integrated those seven elements into a comprehensive framework of four primary dimensions as shown in Figure 2.2. The *supply chain decisions* dimension covers the first two elements and is linked to the "why" question, i.e. why one evaluates the value of a piece of information. The *information* dimension covers the elements (iii) and (iv) and the information characteristics; this dimension addresses the nature of the information and it links to the "what" question, i.e. what information with what characteristics is to be evaluated. The *modelling approach* dimension covers element (v) and it answers the "how" question, i.e. how to evaluate the VOI. The *supply chain context* dimension covers the last two elements and it defines the supply chain environment in which the VOI is evaluated. These dimensions are explained in detail in the following.

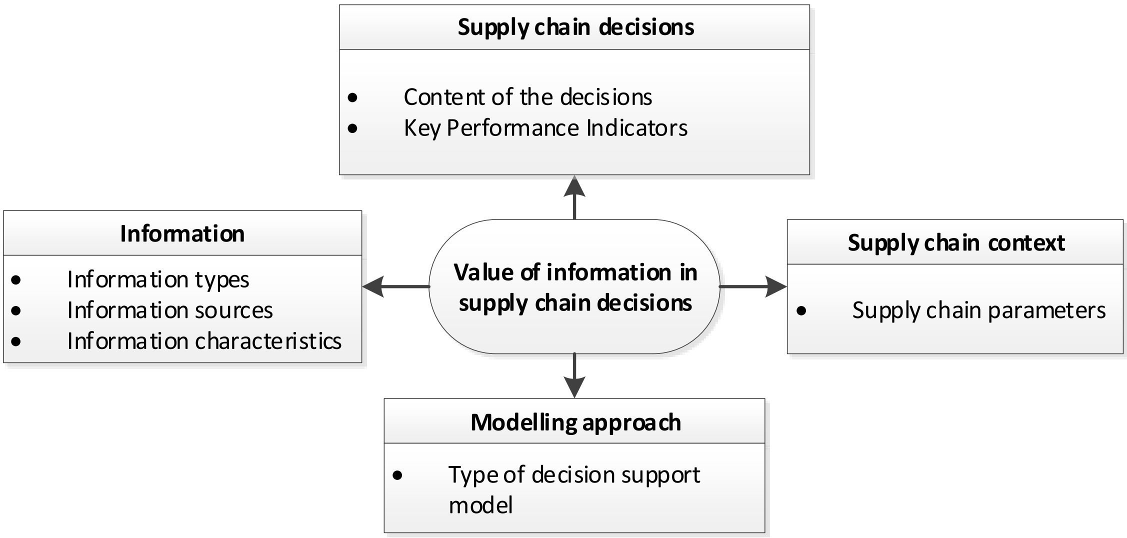

Figure 2.2. Review framework.

2.2.2.1 Supply chain decisions dimension

Supply chain decisions utilize information to improve the KPIs of the supply chain. The decision dimension defines the objective of evaluating the VOI, the content of the decision (i.e. what is decided?), and what KPIs are targeted in the decision. In this review, the taxonomy of supply chain decisions is grounded on five determinant drivers of supply chain performance introduced by Chopra & Meindl (2013), i.e. facilities, inventory, transportation, sourcing, and pricing.

- The facilities category includes the changes in the physical infrastructures (e.g. production and storage sites) of the chain. Example are changes in the role, location, capacity, and layout of the facilities.
- Inventory refers to raw materials, work in process and finished goods within the supply chain. Ketzenberg et al. (2007) classified the inventory decisions from the uses of information into three categories: (i) replenishment decisions concern inventory review policies, order quantity, and order timing; (ii) capacity allocation decisions refer to production planning at upstream members and the allocation of capacities to downstream members in situations of insufficient inventory to meet the total demand or when inventory imbalances arise; (iii) supply chain coordination decisions describe joint replenishment policies to improve the chain-wide efficiency, e.g. vendor managed inventory.

- Transportation decisions concern the movement of inventory from point to point in the supply chain. This category also includes decisions on internal transportation and distribution processes at warehouses.
- Sourcing decisions determine who will perform a particular supply chain activity in the short term or the long term. Example decisions are in-house/outsource production and supplier selection.
- Pricing decisions are about the strategies (e.g. differential pricing or discounting) used to define the price of products and services provided by the company.

2.2.2.2 Information dimension

The information dimension identifies the type of the information that is used in the decision making, the source of the information, and the characteristics of the information. Concerning information types, Huang et al. (2003) presented six categories of information: (i) product, (ii) process, (iii) inventory, (iv) resource, (v) order, and (vi) planning. We extend this categorization based on our review as discussed further in Section 2.3.

With regard to the source of information, we made a distinction between three sources of information in this chapter. (i) Company-internal refers to information available within the company, such as commercial information, customers' historical information, RFID (radiofrequency identification)-enabled warehousing information. (ii) Chain-internal relates to information sharing among actors in the chain. (iii) Chain-external includes information that originates from sources outside the chain, such as public or paid-subscription governmental data, real-time traffic data or real-time port data.

There are many information characteristics mentioned in the literature, such as relevance, timeliness, accuracy, completeness, consistency, format, security, etc. Information characteristics are also addressed under two other terms: information quality dimensions (Miller, 1996; Gustavsson & Wänström, 2009), information value attributes (Sellitto et al., 2007; Herrala et al., 2009; Leviäkangas, 2011). We consider these terms interchangeable in the perspective of how they affect the VOI. The focus of this review is on three intrinsic characteristics: accuracy, timeliness, and completeness (Cappiello et al., 2003; Hazen et al., 2014) (Table 2.1). We argue that these characteristics are innate and objective to information, whereas other characteristics can be controlled by the information systems and the information-sharing agreement (Nelson et al., 2005).

Table 2.1. Definition of intrinsic characteristics of information

Characteristics	**Definition**
Accuracy	Accuracy defines how the available information reflects the underlying reality
Timeliness	Timeliness indicates how up to date the information is and how well it meets the demand for information in a particular time and space
Completeness	Completeness refers to different levels of detail of the information

2.2.2.3 Supply chain context dimension

The supply chain context dimension describes the supply chain factors that affect the VOI. Within the area of inventory decisions, Li et al. (2005) list the trends of impact (i.e. increase or decrease) of six factors on the VOI: demand variance, capacity, order batch size, service level, inventory costs and lead time. Ketzenberg et al. (2007) organize these factors and introduces new factors (i.e. supply chain structure and the number of facilities in the supply chain, inventory review policies, product perishability) into their framework as mentioned in the introduction. For instance, demand variance is an indicator of the uncertainty level in the supply chain; capacity is relevant to the responsiveness of the supply chain.

2.2.2.4 Modelling approach dimension

As mentioned in the introduction, analysing VOI in a supply chain decision is equivalent to studying how the information is used to improve the decision making in the chain. Delen & Demirkan (2013) and Wang et al. (2016b) categorize the decision models into three categories. (i) Descriptive models build the past and the current state of information in the supply chain. (ii) Predictive models utilize the output of descriptive models to project the future state of information in the supply chain. (iii) Prescriptive models use the outputs from descriptive and predictive models to determine the most appropriate decisions to improve the supply chain performance. Particularly in the field of VOI, predictive modelling techniques include data mining and forecasting, and prescriptive modelling techniques include optimization, simulation, and multi-criteria decision making.

2.3 Findings

The results from studying the selected articles are presented based on the aforementioned review framework. We discuss the findings on the information dimension, the context dimension, and the modelling approach dimension in Sections 2.3.1, 2.3.2, and 2.3.3. Section 2.3.4 gives an overview of the supply chain decisions. Each sub-section of Section 2.3.4 is dedicated to reviewing the decisions in a specific supply chain area, the information types used in those decisions, and the information characteristics that affect the VOI.

2.3.1 Information dimension

2.3.1.1 Information types

Because this review covers a broader scope of supply chain decisions, the six-category information model presented by Huang et al. (2003) was extended to include nine information categories: demand, inventory, planning, product, manufacturing process, transportation process, return product, supply, public information (Figure 2.3). Demand (i.e. consumer demand) and inventory (i.e. inventory level, point of sale [POS]) categories are the most analysed information types because they are very relevant to inventory decisions, which are studied in a large number of articles. Research on other information categories is limited. The planning information category includes planned orders, order policy, and demand forecast. The product category includes information on product location, product condition, and product cost. The manufacturing process category includes production-related information, i.e. capacity, yield, shopfloor operations, resource constraints. The transportation process category includes shipment content, delivery lead time, and advance load information. The return-product category is the information on quantity, timing, and condition of return product. The value of return-product information has received growing attention with the recent development of reverse supply chains (Karaer & Lee, 2007; Flapper et al., 2012;

Panagiotidou et al., 2017). The supply category includes information on supplier characteristics and supply quantity. Public information includes information outside the supply chain such as weather forecast information, information from social media, real-time traffic condition.

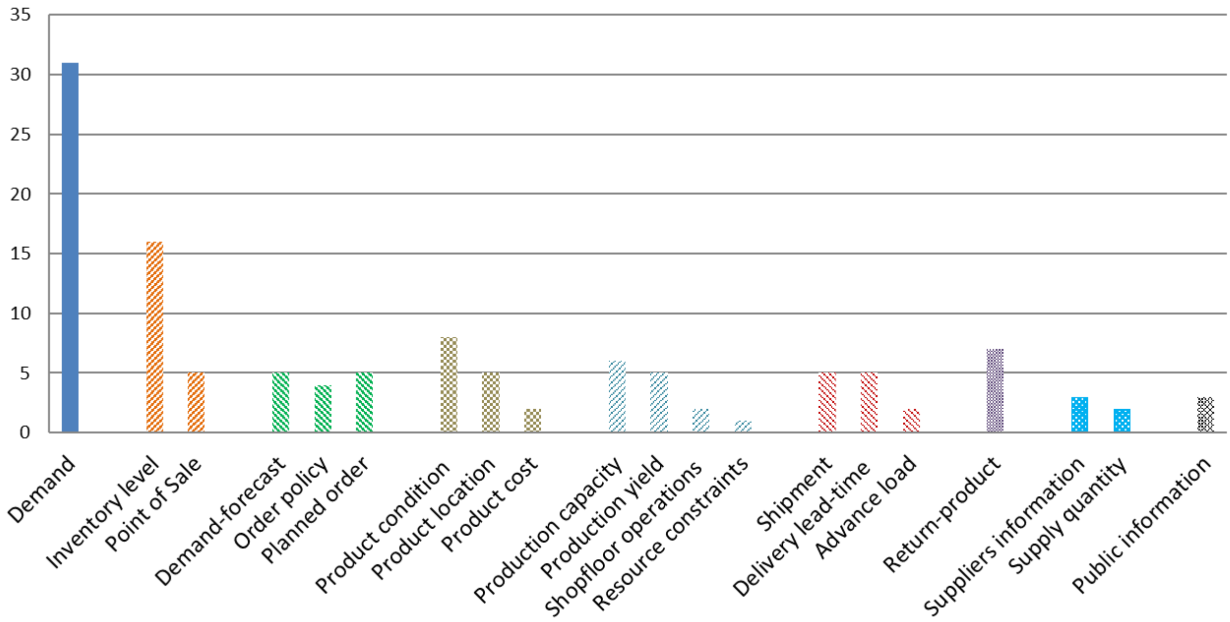

Figure 2.3. Number of articles per information type.

2.3.1.2 Information sources

In terms of information sources, chain-internal information sharing has been the focal point of the literature (covering about 69% of the reviewed articles). Information can be shared from downstream to upstream in the chain, such as demand information (Viswanathan et al., 2007), or reversely, such as manufacturer's production capacity information shared to retailers (Bakal et al., 2011), or between actors of two different chains at the same stage such as sharing load information among shippers (Zolfagharinia & Haughton, 2014). In chain-internal information sharing, sharing raw data (e.g. demand forecast, inventory level) is very common (Rached et al., 2015). The data receivers need to process the data to extract the desired information; for an example of information processing, see Jonsson & Mattsson (2013). Most company-internal information (28% of the reviewed articles) is generated from sensing, tracking, and tracing technologies. Examples are RFID data in warehouses and shopfloor (Zhong et al., 2015), shipment data (Flamini et al., 2011), product location (Bryan & Srinivasan, 2014), and condition data (Ketzenberg et al., 2015; Li & Wang, 2017; Salinas Segura & Thiesse, 2017). We found three articles (3% of the reviewed articles) discussing the VOI from chain-external information sources: the value of weather information in warehouse workforce planning by Steinker et al. (2017), the VOI extracted from social media in operations management by Cui et al. (2017), and the value of real-time traffic information in vehicle routing by Flamini et al. (2017).

2.3.1.3 Information characteristics

The characteristics of information are not explicitly discussed in most of the reviewed articles. Most existing papers investigate the VOI based only on "information availability" (Figure 2.4). In other words, these studies consider two scenarios of decision making, with and without a specific piece of information. Despite a long list of information characteristics as mentioned, this review found that indeed the three intrinsic characteristics, i.e. completeness, accuracy, timeliness, are expressly deliberated upon the most. These characteristics have been modelled differently in the literature (Table 2.2). Timeliness is modelled by parameters that indicate the timing of obtaining the information in advance of decision making. Inaccuracy is incorporated by adding information errors, which usually follow statistical distributions, to the actual base values. Information inaccuracy can occur as a result of both human factors, e.g. overstating demand forecast (Yan & Pei, 2012), and system factors, e.g. tracking system measurement errors (Flamini et al., 2011). Completeness is studied through multiple scenarios: no information, partial information, and complete information. Overall, information completeness and accuracy are often explored but research on information timeliness is still very limited, as also suggested more than a decade ago by Huang et al. (2003).

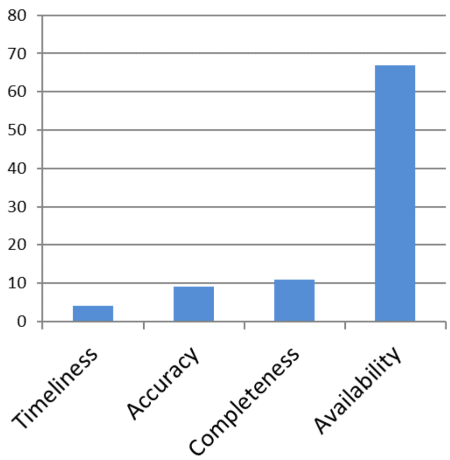

Figure 2.4. Number of articles per information characteristic.

2.3.2 Supply chain context dimension

The value of an information type can be affected by many supply chain factors. For example, the value of demand information is influenced by production capacity, product substitution, product lifetime, order batch size, lead time, etc. In Table 2.3, we summarize the factors and their influences on the VOI discussed in the 24 reviewed articles that go beyond a numerical sensitivity test and deliberately investigate the effect of supply chain factors on the VOI by performing scenario analyses.

The results are consistent in most articles. Still, there are some contradictory findings in the literature. The effect of demand uncertainty is an example. A common finding in the literature is that the VOI increases as demand uncertainty increases, as concluded on the value of product condition information in Ferguson & Ketzenberg (2006), i.e. model A. Yet Ketzenberg et al. (2015) found a contradictory result which implies that the value of product condition information decreases as demand uncertainty increases, i.e. model B. In order to understand the contradictory findings, it is essential to analyse how the factor is related to the changes in KPIs achieved from using the information in decision making. In model A, the supplier shares the information to the retailer in this period before the retailer places the order. It eliminates the product outdating uncertainty when the retailer realizes the demand in the next period. Thus, the retailer total cost (as KPI) depends primarily on the lost-sale cost due to the demand uncertainty. In model B, the retailer places the order in this period and learns about the product condition via RFID tags in the next period after the products arrive. Therefore, the information only helps in optimizing issuing policy (first expired first out) to mitigate the product outdating. In this case, the retailer total cost is not only dependent on the demand uncertainty but also on the product outdating uncertainty.

2.3.3 Modelling approach dimension

Table 2.4 summarizes the types of decision support models used for assessment of VOI in the reviewed articles. Approximately 11% of the articles use predictive models, including forecasting methods (de Brito & van der Laan, 2009; Scott, 2015; Steinker et al., 2017), data mining (Lin et al., 2009; Yi, 2014; Lee, 2017), and big data analytics (Zhong et al., 2015; Kaur & Singh, 2017). Fifty percent of the articles use prescriptive analytical models, which are complex mathematical models, game theory, and probability theory. For example, with game theory, actors' quantitative decisions (e.g. order quantity, pricing) are adjusted corresponding to the information received from other actors. Optimization models (including heuristics, dynamic, integer, stochastic, and mixed-integer programming) are also used in 26% of reviewed articles. A limited literature (13%) applied simulation (mostly discrete-event simulation) in their studies.

In a study on the use of POS and order data in demand forecasting, Williams & Waller (2011) conclude that the modelling approach (i.e. bottom-up and top-down forecasting) should be selected according to the availability of the information. In addition, the choice of a modelling approach may have an impact on the assessment of the VOI. In a study by de Brito & van der Laan (2009), the value of demand information is examined with four different forecasting models, which have different requirements on information completeness. The most informed model (i.e. the model that requires the most detailed information) does not necessarily lead to the highest VOI.

Table 2.2. Modelling timeliness, accuracy, and completeness in the existing literature.

Characteristic	**Article**	**Types of information**	**Modelling**	
Timeliness	(Liu et al., 2009)	Product location (tracking)	q-period lagged information (q = 0, 1, 2, …; q = 0: real-time information)	
	(Tjokroamidjojo et al., 2006)	Advance load information	Number of days in advance that the information is shared	
	(Zolfagharinia & Haughton, 2014)			
	(Banerjee & Golhar, 2017)	Product specifications	Two moments of sharing the information by the retailer: before or after the supplier starts the base unit production	
Accuracy	(Ketzenberg, 2009)	Demand, yield, capacity	A probability p (0, 0.05, 0.25, 0.5) that inaccuracy occurs in randomizing the information (p = 0: accurate information)	
	(Flamini et al., 2011)	Product location	Randomizing measurement errors (follow a uniform distribution)	
	(Kaman et al., 2013)	Shopfloor operations	Randomizing errors between actual and observed states (follow a uniform distribution)	
	(Cannella et al., 2015)	Inventory level	Adding error as a percentage of the record	
	(Cui et al., 2015)	POS, replenishment policy	Adding decision deviations (follow a normal distribution) to the order quantity, which is based on the replenishment policy	
	(Kwak & Gavirneni, 2015)	Demand	Adding information errors (follow a normal distribution) to the actual values	
	(Ketzenberg et al., 2015)	Product condition		
	(Rached et al., 2015)	Demand, delivery lead time		
	(Lu et al., 2017)	Demand		
Completeness			***Partial information***	***Complete information***
	(Ketzenberg et al., 2006)	Demand, return quantity, recovery rate	A limited number of information signals to limit the range of the variables	Infinite number of information signals
	(Bakal & Akcali, 2006)	Yield rate	Different support for uniform distribution, e.g. (0, 1), (0.4, 0.6)	Uniform distribution with very small interval
	(Chen et al., 2007)	Inventory, demand, capacity	Sharing 1 or 2 types of information	Sharing 3 types of information
	(Larbi et al., 2011)	Content of inbound trucks in a sequence	A small number of inbound trucks	A very large number
	(Liu & Kumar, 2011)	Inventory level	Weekly and mix of weekly/daily	Daily sharing
	(Bryan et al., 2016)	Shipment location	Tracking devices installed at a number of transportation stages	Tracking devices installed at all the transportation stages
	(Karaer & Lee, 2007)	Inventory level	The information only includes mean and variance of the distributions	Detailed values
	(Mukhopadhyay et al., 2008)	Product cost		
	(de Brito & van der Laan, 2009)	Demand, product return		
	(Cheong & Song, 2013)	Yield		
	(Wagner, 2015)	Demand		

Table 2.3. Effect of supply chain factors.

Article	Studied information type	Influencing factor	VOI increase		VOI decrease	
			as factor increases	as factor decreases	as factor increases	as factor decreases
(Byrne & Heavey, 2006)	Demand	Production capacity			x	
(Ferguson & Ketzenberg, 2006)	Product condition	Demand uncertainty	x			
(Chiang & Feng, 2007)	Inventory level	Holding cost	x			
(Karaer & Lee, 2007)	Return-product location and quantity	Lead time of reverse channel	x			
(Choudhury et al., 2008)	Inventory level	Demand uncertainty	x			
		Network size (number of retailers)			x	
		Production capacity	x			
(Ferguson & Ketzenberg, 2008)	Demand and inventory level	Product lifetime		x		
(Ganesh et al., 2008)	Demand	Product substitution			x	
(Bakal et al., 2011)	Production capacity (supplier)	Production capacity	x			
(Davis et al., 2011)	Inventory level	Capacity			x	
		Penalty cost				x
		Demand uncertainty			x	
(Hussain & Drake, 2011)	Demand	Order batch size		x		
(Flapper et al., 2012)	Advance return	Return time	x			
(Bendre & Nielsen, 2013)	Lead time	Lost-sale cost	x			
(Kaman et al., 2013)	Shopfloor operations	Holding cost	x			
(Ketzenberg et al., 2013)	Unattended POS (vending machine)	Demand uncertainty	x			
(Ganesh et al., 2014b)	Demand	Product substitution			x	
(Ruiz-Benítez et al., 2014)	Return-product quantity	Shipping cost			x	
		Decay rate of product	x			
(Zolfagharinia & Haughton, 2014)	Advance load	Service radius and trip length	x			
(Ketzenberg et al., 2015)	Product condition	Demand uncertainty			x	
(Rached et al., 2015)	Demand and delivery lead time	Holding cost	x			
(Yan & Pei, 2015)	Demand	Product differentiation			x	
(Shang et al., 2010)	Demand	Logistics system	VOI is significant when the logistics systems is flexible to enable flexible ordering			
(Xue et al., 2011)	Supply quantity	Review policy	VOI depends on the inventory review policy			
(Cho & Lee, 2013)	Demand	Lead time	VOI is significant when lead time is shorter than the seasonal period			
(Babai et al., 2016)	Demand	Autoregressive demand parameter	VOI is significant when the parameter is less than 0.7			

Table 2.4. Employed decision support models in the reviewed articles

Type of decision support model	Articles
Analytical	(Bakal & Akcali, 2006), (Hsiao & Shieh, 2006), (Ketzenberg et al., 2006), (Lin & Tsao, 2006), (Chiang & Feng, 2007), (Karaer & Lee, 2007), (Ganesh et al., 2008), (Ha & Tong, 2008), (Wu & Edwin Cheng, 2008), (Yao & Dresner, 2008), (Chen & Lee, 2009), (Liu et al., 2009), (Shang et al., 2010), (Bakal et al., 2011), (Jakšič et al., 2011), (Xue et al., 2011), (Axsäter & Viswanathan, 2012), (Chen et al., 2012), (Yang et al., 2012), (Cho & Lee, 2013), (Ganesh et al., 2014a), (Ganesh et al., 2014b), (Giloni et al., 2014), (Lee & Cho, 2014), (Ruiz-Benítez et al., 2014), (Salzarulo & Jacobs, 2014), (Cannella et al., 2015), (Cui et al., 2015), (Kwak & Gavirneni, 2015), (Rached et al., 2015), (Wagner, 2015), (Babai et al., 2016), (Bian et al., 2016), (Bryan et al., 2016), (Sabitha et al., 2016), (Banerjee & Golhar, 2017), (Huang & Wang, 2017), (Li & Wang, 2017), (Lu et al., 2017), (Panagiotidou et al., 2017)
Game theory	(Mukhopadhyay et al., 2008), (Wu et al., 2011), (Yan & Pei, 2012, 2015), (Ma et al., 2017), (Zhang et al., 2017)
Dynamic programming	(Ferguson & Ketzenberg, 2008), (Ketzenberg, 2009), (Davis et al., 2011), (Flapper et al., 2012), (Bendre & Nielsen, 2013), (Kaman et al., 2013), (Ketzenberg et al., 2013), (Ketzenberg et al., 2015), (Yang et al., 2016), (Flamini et al., 2017), (Gaukler et al., 2017)
Integer programming	(Tjokroamidjojo et al., 2006), (Chen et al., 2007), (Krikke et al., 2008), (Thomas et al., 2015b)
Stochastic programming	(Cheong & Song, 2013), (Bryan & Srinivasan, 2014), (Rijpkema et al., 2016)
Mixed-integer programming	(Zolfagharinia & Haughton, 2014), (Kaur & Singh, 2017)
Heuristics	(Ferguson & Ketzenberg, 2006), (Viswanathan et al., 2007), (Flamini et al., 2011), (Larbi et al., 2011), (Dettenbach & Thonemann, 2015)
Data mining	(Lin et al., 2009), (Yi, 2014), (Lee, 2017), (Tsai & Huang, 2017), (Cui et al., 2017)
Big data analytics	(Zhong et al., 2015)
Forecasting	(de Brito & van der Laan, 2009), (Williams & Waller, 2011), (Scott, 2015), (Steinker et al., 2017)
Monte Carlo simulation	(Sohn & Lim, 2008), (Salinas Segura & Thiesse, 2017)
System dynamics	(Hussain & Drake, 2011), (Li et al., 2016)
Discrete-event simulation	(Byrne & Heavey, 2006), (Choudhury et al., 2008), (Kim et al., 2008), (Schmidt, 2009), (Liu & Kumar, 2011), (Rijpkema et al., 2012), (Jonsson & Mattsson, 2013), (Rached et al., 2016)

Table 2.5. The uses of different information types in supply chain decisions

		Articles	Major types of information used in the decision
Inventory decision			
Replenishment	Inventory review policy	(Xue et al., 2011), (Babai et al., 2016)	Demand, supply quantity
	Reorder point	(Schmidt, 2009), (Shang et al., 2010), (Liu & Kumar, 2011), (Salzarulo & Jacobs, 2014), (Cui et al., 2017), (Salinas Segura & Thiesse, 2017)	Demand, inventory level
	Safety stock	(Schmidt, 2009)	Demand
	Order frequency/timing	(Lin & Tsao, 2006), (Viswanathan et al., 2007), (Yao & Dresner, 2008), (Axsäter & Viswanathan, 2012), (Ketzenberg et al., 2013), (Bryan & Srinivasan, 2014), (Ketzenberg et al., 2015), (Gaukler et al., 2017)	Demand, inventory level, POS, planned order from downstream, location of product, production lot freezing and plan
	Order quantity	(Ferguson & Ketzenberg, 2006), (Hsiao & Shieh, 2006), (Ketzenberg et al., 2006), (Chen et al., 2007), (Chiang & Feng, 2007), (Ferguson & Ketzenberg, 2008), (Bakal et al., 2011), (Hussain & Drake, 2011), (Jakšič et al., 2011), (Williams & Waller, 2011), (Bendre & Nielsen, 2013), (Cheong & Song, 2013), (Jonsson & Mattsson, 2013), (Cannella et al., 2015), (Cui et al., 2015), (Rached et al., 2015), (Dettenbach & Thonemann, 2015), (Ketzenberg et al., 2015), (Bryan et al., 2016), (Li et al., 2016), (Rached et al., 2016), (Yang et al., 2016), (Banerjee & Golhar, 2017), (Panagiotidou et al., 2017)	Demand, inventory level, POS, demand forecast, planned order, supply lead time, supply quantity, shipment position, yield distribution, production capacity, product location, product condition
	Order-up-to level	(Choudhury et al., 2008), (Ganesh et al., 2008), (Wu & Edwin Cheng, 2008), (Chen & Lee, 2009), (de Brito & van der Laan, 2009), (Liu et al., 2009), (Davis et al., 2011), (Cho & Lee, 2013), (Ganesh et al., 2014a), (Ganesh et al., 2014b), (Giloni et al., 2014), (Kwak & Gavirneni, 2015), (Sabitha et al., 2016), (Lu et al., 2017)	Demand, inventory level, planned order, return product probability, product location, shipment position
Capacity allocation		(Byrne & Heavey, 2006), (Ketzenberg et al., 2006), (Karaer & Lee, 2007), (Sohn & Lim, 2008), (Ketzenberg, 2009), (Flapper et al., 2012), (Rijpkema et al., 2012), (Kaman et al., 2013), (Salzarulo & Jacobs, 2014), (Thomas et al., 2015b), (Rijpkema et al., 2016)	Demand, inventory level, POS, advance return, return product visibility, recovery yield, production capacity, resource constraints in production, shopfloor operations, product condition
SC coordination		(Chen et al., 2007), (Viswanathan et al., 2007), (Choudhury et al., 2008), (Ferguson & Ketzenberg, 2008), (Yao & Dresner, 2008), (Thomas et al., 2015b)	Demand, inventory level, planned order, production capacity, resource constraints in production

Transportation decision		
Service network design	(Shang et al., 2010)	Demand
Design and scheduling of services	(Tjokroamidjojo et al., 2006), (Flamini et al., 2011), (Larbi et al., 2011), (Ruiz-Benítez et al., 2014), (Lee, 2017), (Steinker et al., 2017), (Tsai & Huang, 2017)	Inventory level, return-product quantity, shipment (products types and quantities, sequences), product location, advance load
Vehicle routing	(Krikke et al., 2008), (Flamini et al., 2011), (Yi, 2014), (Zolfagharinia & Haughton, 2014), (Zhong et al., 2015), (Flamini et al., 2017)	Product location, advance load, inventory level, shopfloor operations
Empty vehicle repositioning	(Kim et al., 2008)	Product location (RFID)
Sourcing decision		
Selecting key suppliers	(Lin et al., 2009), (Wu et al., 2011), (Yang et al., 2012), (Kaur & Singh, 2017)	Suppliers' reliability, supplier's production cost, product quality
Modifying sourcing contract terms	(Ha & Tong, 2008), (Lee & Cho, 2014), (Wagner, 2015)	Demand, inventory level
Pricing decision		
Determining wholesale price	(Mukhopadhyay et al., 2008), (Bian et al., 2016), (Huang & Wang, 2017), (Ma et al., 2017), (Zhang et al., 2017)	Product cost
Postponing pricing decision	(Bakal & Akcali, 2006)	Yield rate
Determining real-time/dynamic price	(Scott, 2015), (Li & Wang, 2017)	Real-time demand (load)
Determining prices in competing retailers	(Chen et al., 2012), (Yan & Pei, 2012, 2015)	Demand, demand forecast

2.3.4 Supply chain decisions dimension

Information is traditionally known as a substitute for inventory (and capacity) in the literature (Tan et al., 2002; Borgman & Rachan, 2007). Therefore, it is not surprising that a large number of articles study the VOI in inventory decisions (Figure 2.5). Transportation is the second major area. There is a limited literature on sourcing and pricing decisions. Our search of the literature found no works on VOI in facilities decisions. The reason may be that facilities decisions require an enormous volume of historic data on uncertain supply chain parameters such as demand and supply, which are often not available to researchers. Most of the literature on supply chain network design and facilities decisions focuses on decision-making environments in which no information or limited information (i.e. probability distribution) on supply chain parameters is available (Govindan et al., 2017). Table 2.5 summarizes the supply chain decisions from the uses of information in each supply chain area. In the following sub-sections, the existing literature for each decision area is discussed separately in detail.

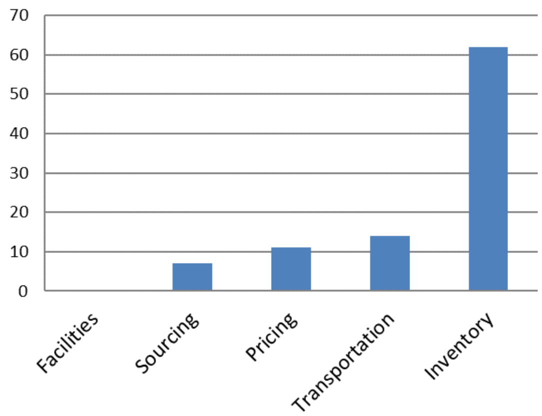

Figure 2.5. Number of articles per supply chain area.

2.3.4.1 Inventory decisions

Inventory decisions are categorized into replenishment, capacity allocation, and supply chain coordination. In terms of information type, the major focus is on the value of demand, inventory, planning, and manufacturing process information categories (Table 2.5). There has also been increasing interest in evaluating the value of product information, transportation process information and return-product information. For instance, product condition information captured by sensing devices improves order-quantity decisions in perishable supply chains by reducing product spoilage uncertainty (Ketzenberg et al., 2015; Salinas Segura & Thiesse, 2017). Product location information from tracking devices is also valuable because it diminishes the uncertainty about replenishment arrival time, especially when products have to be transported through multiple facilities before reaching the retailers (Bryan & Srinivasan, 2014). Delivery lead-time information also reduces the uncertainty of replenishment arrival time and subsequently contributes to better decisions on order quantity (Rached et al., 2015, 2016). Return-product quantity information is also useful in making decisions on production plans for new products (Karaer & Lee, 2007).

Regarding information accuracy, inaccurate inventory records are prevalent, especially at retailers (Kang & Gershwin, 2005). The existence of errors considerably reduces the VOI, yet it is important to pinpoint the range of errors in which the VOI remains appreciable. Kwak & Gavirneni (2015) show that as the variance of errors exceeds the variance of demand, inaccurate inventory-level information shared by retailers has no more value to the supplier. In other studies, Cannella et al. (2015) and Lu et al. (2017) show that inaccurate inventory records may eradicate the bullwhip effect avoidance features resulting from collaborative sharing of inventory level information. Ketzenberg et al. (2015) indicate that product travel time and temperature information is useful in inventory issuing policy when the errors are less than 14% of the actual values. Note that these figures are subject to supply chain context and case-specific parametric settings.

Concerning information completeness, the existing literature shows that in some cases partial information can perform almost as well as complete information. In a study of demand, return-product quantity and recovery rate information by Ketzenberg et al. (2006), the value of more than five information signals (partial information) converges quickly to within 1% difference from the value of infinite information signals (complete information). As concluded by Cheong & Song (2013), partial supplier yield rate information (i.e. when only mean and variance are known) can be sufficient in determining the newsvendor's regular ordering quantity; however, partial information cannot replace complete information in a strategic decision to select reliable suppliers because an improvement in the mean and variance of the yield rate cannot guarantee a monotonic profit improvement.

Information timeliness in inventory decisions is studied only by Liu et al. (2009) and Banerjee & Golhar (2017). Banerjee & Golhar (2017) study the timing of sharing the product specification information from the retailer to the manufacturer (i.e. before or after the manufacturer starts the base unit production). Using a trade-off model between the supply chain costs and the benefits resulting from the retailer's behaviour of intentionally delaying information sharing, the authors indicate the importance of timely information sharing among supply chain partners. Liu et al. (2009) show that real-time tracking information of product location allows a cost-effective policy on order quantity and timing, whereas delayed information in the long run will entail an increase in holding and shortage costs.

Regarding KPIs in inventory decisions, the combination of holding and shortage costs is the most considered performance measure. A few articles studying perishable products also consider the outdating cost (Ferguson & Ketzenberg, 2006, 2008; Ketzenberg et al., 2015). Moreover, a common practice is to include transportation costs in the inventory costs model. As a result, the impact of an information type and its value in reducing transportation or inventory cost cannot be seen separately. The impact of information on KPI's may look inconsistent in some cases. For instance, in evaluating the VOI in reducing inventory costs, Rached et al. (2015) conclude that the gains from sharing demand information and warehouse-retailer lead-time information simultaneously are not cumulative; whereas Ketzenberg et al. (2006) suggest that investing in an additional type of information (between two types: demand and return product) results in an additional payoff. The difference between these findings lies in how the information helps to reduce the costs. In Rached et al. (2015), both demand and lead time play the same role in order-quantity decisions to reduce the retailer's holding cost. As a result, either piece of information is sufficient for the decision. In Ketzenberg et al. (2006), demand and return complement each other in the order-quantity decision. Thus, the additional information type will result in additional holding cost reduction for retailers.

2.3.4.2 Transportation decisions

The value of different information is studied in different transportation and distribution decisions including strategic decisions (e.g. service network design), tactical decisions (e.g. service design and scheduling of services), and operational decisions (e.g. vehicle routing and empty vehicle repositioning). Lumsden & Mirzabeiki (2008) indicate that product location information as a critical information type for all supply chain members. For instance, it is used to optimize vehicle routing (Flamini et al., 2011; Yi, 2014). Kim et al. (2008) also discuss the value of product location information enabled by RFID in decisions on repositioning empty vehicles. Larbi et al. (2011) utilize the shipment information of inbound trucks in optimizing cross-docking outbound scheduling. Besides supporting inventory decisions, inventory-level information also helps to coordinate the transportation (i.e. routing and scheduling of services) (Krikke et al., 2008; Ruiz-Benítez et al., 2014).

The effect of information timeliness in transportation decisions is discussed in two articles. Tjokroamidjojo et al. (2006) and Zolfagharinia & Haughton (2014) answer the question of how much time in advance the load information should be provided by shippers to carriers so that it brings a positive value to the decision making. Tjokroamidjojo et al. (2006) show that 3-day and 5-day advanced load information (ALI) have close values. Zolfagharinia & Haughton (2014) suggest that it is not practical to have more than 3-day ALI in the trucking industry, and show that the value of 3-day ALI is only slightly higher than the value of 2-day ALI. In other words, significant cost improvement can be achieved with 2-day ALI, which considerably eases the information-sharing effort for shippers.

Examining information completeness in the case of scheduling cross-docking operations, Larbi et al. (2011) indicate that knowing the content of the next 14 inbound trucks is as good as knowing the content of all the trucks in the sequence. This number can be even lower if the number of destinations decreases. Nevertheless, the VOI in this case needs to be tested against important supply chain factors such as the cross-docking capacity to act corresponding to the level of information obtained.

Flamini et al. (2011) quantify the VOI on location and condition of transported goods in optimizing vehicle routing of the distribution process. Information inaccuracy due to measurement errors of tracking systems is reported to cause performance deterioration; however, the levels of deterioration are in accordance with the routing algorithms used.

2.3.4.3 Sourcing decisions

In sourcing decisions, information is used in selecting suppliers or modifying sourcing contract terms. Concerning supplier selection, Lin et al. (2009) propose a data-mining-based framework that gathers the big data of suppliers' characteristics and shipment records to cluster potential suppliers into primary and secondary supplier groups. On more tactical decisions on short-term sourcing, Wu et al. (2011) study the benefits to a buyer when suppliers share their product quality information; based on the information, the order quantities are adjusted. By having the supplier's reliability and product cost information, a buyer can switch between single-sourcing (winner-take-all) and dual-sourcing (diversification) strategies (Yang et al., 2012).

Modifying terms in contracts under information sharing is studied by Wagner (2015), Lee & Cho (2014), and Ha & Tong (2008). From a retailer's perspective, Lee & Cho (2014) suggest that the value of stock-out quantity information may be significant because the retailer can specify the penalty cost to the supplier in the contract under deterministic and stochastic demand situations. From a supplier's perspective, shared demand information in a two-echelon supply chain allows the supplier to switch contract types, such as from linear price-based contracts to quantity-based contracts (Ha & Tong, 2008). The value of demand information is also examined by Wagner (2015) in a two-echelon supply chain. Two levels of information are modelled in this study: complete information refers to knowing the demand's full distribution function, and incomplete information equals knowing only the mean and variance of the demand distribution. The analytics show that with complete information, the supplier can adjust the wholesale price in such a way that benefits both firms only if the supplier correctly assesses the level of information known by the retailer.

2.3.4.4 Pricing decisions

A limited literature addresses the VOI in pricing decisions. Bakal & Akcali (2006) study the value of perfect yield rate information in making pricing decisions in the automotive parts remanufacturing industry. Because perfect yield information is difficult to attain, the authors suggest a strategy of postponing pricing decisions to deal with the random yield. In the study by Mukhopadhyay et al. (2008) about wholesale price, a traditional retailer shares with the manufacturer its cost of adding an extra value to the products. Accordingly, the manufacturer decides the wholesale price to the retailer and the direct price for their own online channel. The value of sharing the cost information is positive to the retailer only when the value-added cost is lower than a threshold value; beyond this value, sharing the information is no longer beneficial to the retailer. Ma et al. (2017) report a similar finding that the manufacturer's profit always increases when using the shared cost information by retailers in wholesale price decisions, whereas the benefit of sharing information to retailers is uncertain. Also in the context of manufacturer-retailer information sharing, Bian et al. (2016) and Huang & Wang (2017) conclude that sharing demand-forecast information benefits the manufacturer and hurts the retailer in the short term; however, because the value of information sharing is positive to the entire supply chain, the manufacturer can motivate the retailer to share information using the compensation policy suggested in the paper. Scott (2015) proposes an analytical method that utilizes the value of load information shared by shippers to carriers to estimate real-time truckload market prices; the study indicates that the more in advance the information is shared, the better price the shippers can receive.

2.4 An agenda for future research

In this chapter, we review the VOI literature in the 12-year period from 2006 to 2017. Each selected article has been studied based on four dimensions of the review framework, i.e. supply chain decisions, information, modelling approach, and context. Based on the literature and the findings from the previous section, opportunities for future research in each dimension of the review framework are discussed in this section. Furthermore, based on the literature studied, a step-wise approach to evaluate the VOI in the supply chain domain is presented at the end of this section.

2.4.1 Key areas and questions for future research

Based on our review and analysis of the literature in this chapter, we propose the following directions and scientific questions for future research on VOI in the supply chain domain.

- *Supply chain decisions: expanding the research beyond inventory decisions and looking into interdependencies of different decisions*

  As mentioned in the previous section, the main focus in the current VOI literature is on assessing the VOI in inventory decisions, yet other areas of supply chain management such as facilities, transportation, sourcing, and pricing are not adequately explored in the literature. With the evolution towards virtual supply chains enhanced by the Internet of Things, the increasing use of advanced ICTs, and inter-organizational information exchange, the availability of information in the supply chain has been improved (Kache & Seuring, 2017; Nguyen et al., 2018). Decision makers have access to more and new information types, i.e. the increasing (big) data variety in supply chains (Hofmann, 2017). Thus, there is a need for further research on how to make the utmost use of different existing and new information types in strategic, tactical, and specially operational planning decisions (Verdouw et al., 2013; Buijs & Wortmann, 2014). Furthermore, much more information is available in real time across the supply chain. As a result, we need to focus further on using real-time information to improve the supply chain processes at the operational level (especially in handling unexpected events). In addition, the existing literature on VOI has not fully captured the interdependence among chain processes. VOI has been primarily studied in different single decisions. The VOI in decisions that involve interdependent processes and the VOI in managing the interdependence among supply chain processes are therefore promising research areas to study. The following general questions need further attention in each specific supply chain area:

(1) *What is the value of existing and new information types in supply chain operational decision making?*
Example of new information types are real-time chain products (location and condition) and real-time chain resources based on virtual objects in virtual supply chains (Verdouw et al., 2015). Moreover, the use of chain-external information such as information extracted from social media networks using big data and predictive analytics and real-time public information need more investigation from supply chain researchers and practitioners (Chavez et al., 2017; Flamini et al., 2017).

(2) *What is the value of supply chain information in coordinating interdependent supply chain processes?*
Concerning two core and interdependent processes in supply chains, i.e. production and distribution, the problem of coordinating and integrating production and distribution planning at tactical and operational levels has been studied extensively (Bilgen & Ozkarahan, 2004; Fahimnia et al., 2013). Recent studies on this problem have compounded operations research models with emerging ICTs following the research agenda suggested by Bilgen & Ozkarahan (2004). However, necessary information (e.g. order information, warehouse operations information, traffic conditions) is assumed to be available (and accurate, complete, and timely) in most of the proposed models (Moons et al., 2017). In

real life, this information is often unknown, particularly the timing characteristic of order information.

- *Information: attention to information characteristics in the assessment of VOI in the supply chain domain*

The main focus of the literature has been on the availability of information, and the importance and implications of information characteristics in determining the VOI is generally lacking. Particularly timeliness is an information characteristic that is not adequately addressed. Because more accurate/complete/timely information is costly and requires a high level of effort, a better understanding of what degree of accuracy/completeness/timeliness is needed in each decision process can be promising from a practical point of view (Hazen et al., 2014). We suggest the following question for future research:

(3) *What is the value of information in supply chain decision making resulting from different characteristics of the information?*
This question is indeed a general question and can be applied to all categories of supply chain decisions as mentioned in the previous sub-sections. For instance, in information sharing within collaborative transportation, we need to study how the VOI varies in the time dimension, the accuracy dimension, and the completeness dimension. Such an analysis can lead to an effective and efficient information-sharing agreement among supply chain actors or a more viable investment in developing the infrastructure for information gathering and processing.

- *Supply chain context: looking into the dynamic and multi-actor characteristic of VOI*

Although the VOI literature has explored the effects of different supply chain factors in some specific cases, social aspects of VOI are generally overlooked (Montoya-Torres & Ortiz-Vargas, 2014). Information characteristics are subject to supply chain actors' behaviours and interests. Having dissimilar goals and capabilities for information gathering, sharing, and processing, their information-sharing approaches are diverse about which information to share, when and how much to share, and how accurate it will be, etc. As a result, the VOI in a multi-actor context can be very dynamic. Therefore, considering the multi-actor nature of VOI, the following question is worth investigating:

(4) *What are the dynamic values of information in a supply chain multi-actor context?*
Continuing with the example about collaborative transportation, answering the above question can help a chain actor to form a feasible and beneficial collaboration with a group of suitable actors. Similarly, as suggested by Fahimnia et al. (2013), VOI in information-sharing models to solve the integrated production-distribution problem needs to be considered in a multi-actor context with different patterns of supply chain actors' ownership and power positions. Based on actor-network theory and resource-dependence theory, Hazen et al. (2016) also discuss future research topics, including how one actor's capability and adoption of big data analytics affect the sustainability performance of another actor in the supply chain. This research direction can be linked with research on how to increase the dynamic VOI generated from big data in such a multi-actor context.

- *Modelling approach: more diverse and complementary methods in evaluating VOI*

Prescriptive analytical modelling and optimization are the dominant modelling approaches in evaluating VOI in the literature. However, simulation methods are appropriate, especially to evaluate VOI in real cases, due to their capability to capture the high complexity and uncertainty in supply chains (Chatfield et al., 2007; Govindan et al., 2017). The use of simulation models are therefore suggested because VOI is subject to different supply chain factors. Besides discrete-event simulation, multi-agent simulation (MAS) particularly suits multi-actor contexts in which agents (i.e. actors in the chain) interact with each other in a co-operative manner to accomplish a common goal (Behdani, 2012). Nevertheless, a specific challenge for MAS is to define decision rules and model the heterogeneous characteristics of agents. Here is where the simulation can benefit from predictive analytics such as data mining. This enhances the simulation due to clustering, patterns and relations discovery from historic (big) data (Zhong et al., 2016). This also implies further research towards multi-method frameworks for evaluating VOI in the supply chain domain (Nguyen et al., 2018). Therefore, we suggest the following question:

(5) *How complementary multi-method modelling approaches (especially, using predictive and prescriptive models) can be developed to assess the value of information in supply chain decisions?*
For instance, to evaluate the VOI in information-sharing models for facilitating collaborative transportation, MAS allows the modelling of uncertain parameters at each collaborating actor's facilities, such as unloading and loading time, travel time, etc. In addition, frequent order patterns and frequent trajectory patterns can be extracted from historic transportation orders by data mining (Zhong et al., 2015). These patterns can be integrated in the simulation to define the environment and actor behaviour settings in the collaboration.

2.4.2 A step-wise research approach to study VOI in the supply chain domain

In addition to the aforementioned gaps, a well-defined step-wise approach to assess the VOI is also lacking in the literature. Therefore, based on the reviewed articles, such an approach is presented in Figure 2.6. Combining the review framework and this step-wise approach helps future researchers identify the necessary elements and steps in their studies. To evaluate the value of an information type (i.e. additional information), we need to compare the base scenario, which is defined based on the existing information in the supply chain process (i.e. base information), with information scenarios, which are developed considering different intrinsic characteristics of the additional information. Tables 2.2 and 2.5 work as general guidelines in defining different information scenarios. Table 2.2 supports modelling different information characteristics, and Table 2.5 is a reference for selecting the relevant information type for different decisions. One piece of information might be utilized in more than one decision in the supply chain. For instance, the inventory level information of a retailer can be used for material ordering and also for arranging the distribution route from a central warehouse. In that case, the VOI would be the cumulative VOI for different decisions.

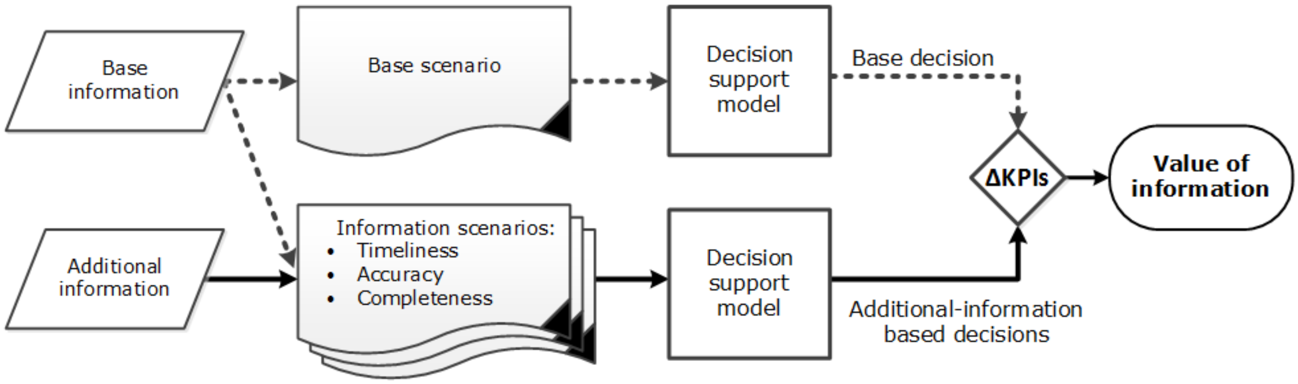

Figure 2.6. Step-wise approach to assess the VOI in supply chain decisions.

2.5 Conclusion

The purpose of this chapter was to provide an overview of existing research on VOI in supply chain decisions. We focused on how the values of different information types have been studied in different supply chain decisions, which modelling approaches are used, and what are the influential factors on the VOI in each case. In total, 93 articles published in peer-reviewed journals from 2006 to 2017 were analysed using a rigorous review framework. The findings indicate that the current literature on VOI is rich in inventory decisions, yet insufficient in other supply chain areas, and research on the VOI in integrating and coordinating interdependent supply chain processes is still limited. In addition, the impact of information characteristics such as accuracy, completeness, and especially timeliness has not been examined extensively. Based on the insights from our literature analysis, we have also provided an agenda for future research. We especially suggest further research on the impact of information characteristics on the VOI, on analysing the dynamic VOI in supply chain multi-actor settings, and on developing multi-method modelling approaches, particularly combining data mining and simulation, to better evaluate the value of (big) data in real industrial cases. We hope that this review encourages further reconceptualization and model building as well as new studies in the merging domain of data-driven decision making in supply chains. Data-driven decision making has increasingly become a determinant of competitive advantage for each company and each supply chain. Particularly in the big data context, evaluating the value of big data is a challenge (Zhong et al., 2016). We notice that many research papers cover the problems of collecting and analysing big data, yet do not map and examine the value of the extracted information from big data to specific supply chain decisions. Identifying the decisions helps to identify the right data and information with the right characteristics and the right big data analytics method to use. Evaluating the value of the information is useful to adjust the costs of collecting and analysing against the benefits resulting from improved supply chain processes and operations.

Chapter 3. Value of information to improve daily operations in high-density logistics

This chapter is based on the published journal article:

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Value of information to improve daily operations in high-density logistics.

International Journal on Food System Dynamics 9, 1-20.

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Abstract

Agro-food logistics is increasingly challenged to ensure that a wide variety of high-quality products are always available at retail stores. This chapter discusses high-density logistics issues caused by more frequent and smaller orders from retailers. Through a case study of the distribution process in a Dutch floricultural supply chain, we demonstrate that using inbound and outbound information flows to plan daily warehouse operations improves the logistics performance. A discrete-event simulation and a simulation-based scheduling algorithm are used as decision-support models to assess the value of information. The results indicate that the higher the density of logistics process, the higher the value of the information. Future research will investigate different uses of information as more types of information become available in the agro-food sector supply chains.

3.1 Introduction

Nowadays consumers increasingly expect daily fresh agro-food products to be always available at retail stores (van der Vorst et al., 2011). However, because of the perishability of agro-food products, most retailers prefer to hold only small amounts of inventory to reduce holding costs, which involve costly temperature and humidity controlled storage processes (Trienekens et al., 2014), and spoilage costs, which occur because of continuous decay of product quality (Akkerman et al., 2010). In the last two decades, the assortments of products have increased significantly for most retailers, e.g., US grocery retailers had 50% more products in 2010 compared with 2003 (FMI, 2010). Therefore, a common policy in retail inventory management is to order small quantities of many different products frequently (Fernie & Sparks, 2014). A consequence of this phenomena is increased complexity of logistics operations and distribution of perishable products. Retailers' orders have become smaller, more frequent, and with shorter lead times required to meet the consumers' requirements (Romsdal et al., 2014; Verdouw et al., 2014b). This trend leads to a high-density logistics context in the distribution process of agro-food supply chains in which small quantities of a wide product assortment have to be distributed more frequently within short timeframes.

The term "high-density logistics" (HDL) has been used in the literature without being formally defined (e.g., Lee and Whang, 2001, p. 59). We start with a clear definition of this concept and its constituents in Section 3.2. An important factor in managing the complexity of the logistics and distribution process in an HDL context is accessing and utilizing information. We further investigate the value of information (VOI) in HDL through an illustrative case study of the distribution process in a Dutch flower supply chain. Section 3.3 provides a concise theoretical background on VOI in the supply chain and logistics and discusses a stepwise framework to assess the VOI in improving logistics performance. Section 3.4 introduces the case study. The results of the case study are reported in Section 3.5. The last section concludes with our findings, discusses the implications of this study for agro-food supply chains, and suggests directions for future research.

3.2 Defining High-Density Logistics

The Council of Supply Chain Management Professionals defines logistics management as "the part of supply chain management that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services and related information between the point of origin and the point of consumption in order to meet customers' requirements" (CSCMP, 2019). This definition emphasizes four aspects of logistics: (i) efficiency and effectiveness, (ii) physical flows, (iii) customer requirements, and (iv) information flows. In defining HDL, we connect the first three aspects to the three dimensions that characterize an HDL context. Then we propose the use of the fourth aspect, information flows, as a mean to tackle the logistics challenges caused by HDL. The dimensions in defining the HDL environment are shown in Figure 3.1 and elaborated in the following.

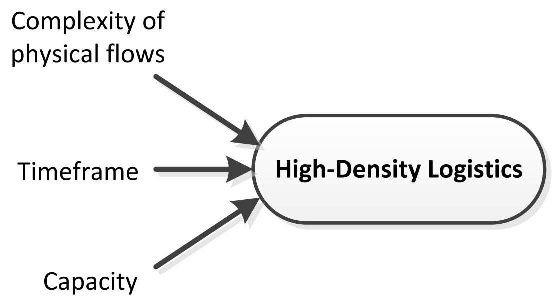

Figure 3.1. Three dimensions in defining high-density logistics

- *Complexity of physical flows in the logistics process*: a physical flow involves moving products between two points in the supply chain, which can be within a facility or between facilities. The complexity of physical flows in a logistics process can be influenced by the number of items that need to be handled throughout the logistics process (i.e. the number of physical flows) or by the number of material handling activities (i.e. the number of stages) in the process. For example, in the distribution process between a manufacturer and a retailer in the case studies by Liu et al. (2009) and Bryan and Srinivasan (2014) , the flow complexity is influenced by the fact that a large number of shipments have to pass multiple facilities and stages before arriving at the retailer. Another example is the order-picking process in a distribution center in which the daily total number of orders, the number of order lines and stock keeping units (which are located in different picking zones) per order will affect the complexity of the process (Le-Duc, 2005). In these examples, increasing customer requirements on product variety (with small orders) is the main cause of increased complexity.
- *Timeframe of the logistics process*: this is defined by the time required to perform logistics activities, e.g. the timeframe of the distribution process is the required delivery lead time of an order. Time is one of the most important aspects in fast-moving consumer product chains and agro-food value chains (Brandenburg & Seuring, 2011). As these chains have become more demand-driven (Trienekens et al., 2003), customer requirements have also become stricter on delivery lead times to improve the chains' competitive advantage (Morash et al., 1996).
- *Capacity*: the capacity of logistics resources utilized in a logistics process such as human resource, truck fleet size, and travelling space in the warehouses. Because the resources are limited and shared among different supply chain actors or different logistics processes (Arshinder et al., 2011), an efficient and effective capacity allocation is a determinant factor in the success of the logistics activities (Perona & Miragliotta, 2004).

Given a fixed capacity, a logistics process develops towards a high-density context if the timeframe becomes shorter or the complexity of physical flows becomes higher.

An example of an HDL context is city logistics distribution operations. Recently, many western European cities have applied strict regulations that force the distribution activities of retail chain to take place within a specific time period (Quak & de Koster, 2007). These regulations make the distribution schedule from distribution centers to retail outlets more difficult because of the shorter time available for order processing and delivery, and increasing congestion because there are more trucks moving on city roads within the same time windows (Stathopoulos et al., 2012). At the same time, the size of retail order is decreasing, and subsequently, the number of handling and the physical flows in order processing (e.g., receiving, sorting, transferring, picking) at the distribution warehouse are increased (Quak & de Koster, 2009). In this example, HDL is caused by both a shorter timeframe and a higher complexity of physical flow.

The second example of HDL is the distribution in the Dutch floricultural sector. The supply chain network of the sector consists of approximately 5000 national and international growers; 1200 buyers, including wholesalers, exporters, importers; 70 logistics service providers; 6 auction sites and many market places. The consumers of flowers and ornamental plants have not only become more demanding with regard to product variety and availability at shops but also on product shelf life (van der Vorst et al., 2012; Verdouw et al., 2013). As a result, buyers place more small orders for a large variety of products every day (de Keizer et al., 2015). The average order size has dropped from full flower trolleys to less than a trolley (e.g. a number of buckets). From the point of view of auctions and distribution, this implies that a full flower trolley has to be split over several buyers; thus the number of handling operations and the complexity of logistics processes have increased significantly. Moreover, because the buyers demand products with a longer shelf life, shorter delivery lead times (i.e. between 2 and 4 hours) have become the "new normal" (Wallace & Xia, 2014). In this example, both dimensions have become more restricted (i.e. a shorter timeframe and a higher complexity of logistics and distribution processes), which makes the daily distribution in the Dutch sector very challenging. In Section 3.4, we specifically discuss the logistics challenges caused by HDL at the distribution warehouse for a Dutch flower supply chain.

Integrating information flows in decision-making can leverage the existing logistics resources to achieve the distribution challenge (Lee & Whang, 2001; Lumsden & Mirzabeiki, 2008). The Dutch floricultural sector is active in improving information sharing and information availability throughout the supply chain network (Verdouw et al., 2014a). Taking advantage of the rising momentum of information availability, we propose that the daily distribution process in the case study can be improved by using outbound and inbound information flows in operational planning. Outbound information includes order information such as required lead times, quantity, and destination for each consignment. Inbound information basically includes the contents of the inbound trucks. In addition, the growers can also share information on the arrival time of the inbound trucks with the warehouse operator. In the case study, we examine the value of both outbound and inbound information. Before introducing the case study and the use of inbound and outbound information in decision making, we provide the theoretical background on the VOI in supply chain and logistics decision making in the following section.

3.3. Value of information in the supply chain and logistics

We first provide an overview of the literature on the VOI in decision making to improve logistics performance. Thereafter, we discuss a stepwise framework to evaluate the value of inbound and outbound information in the case study.

3.3.1 Value of information in supply chain and logistics decisions

VOI can be seen from two angles. The first associates VOI with the willingness of the information users to pay to gain access to the information (King & Griffiths, 1986). The second defines VOI as the resulting (or expected) benefits from using the information in making a specific decision (Lumsden & Mirzabeiki, 2008). The benefits are determined as improvements in one or several key performance indicators (KPIs) that are achieved through the use of the information in decision making compared with the base scenario in which the information does not exist (Ketzenberg et al., 2006; Ganesh et al., 2014b). Therefore, a piece of information can have different values when it is used in different supply chain and logistics decisions. Here, we adopt the second approach, which is also the dominant view in the literature.

The largest part of the VOI literature is about the value of information sharing in inventory decisions such as decisions on order quantity, order frequency, safety stock, etc. The general conclusion from these studies is that the VOI is positive, yet numerically sensitive to logistics process parameters such as capacity, inventory costs, and lead time (Li et al., 2005). We refer to Ketzenberg et al. (2007) and Giard and Sali (2013) for extensive reviews on the value of information sharing in inventory decisions. The second largest area of the literature concerns the VOI in transportation decisions. In collaborative transporation, advanced load information from shippers enables carriers to better plan vehicle routing, and the pickup and delivery schedule (Tjokroamidjojo et al., 2006; Zolfagharinia & Haughton, 2014). Product location information enabled by tracking and tracing technologies is a highly demanded information type by supply chain members (Lumsden & Mirzabeiki, 2008). This type of information is frequently used in optimizing transportation decisions, including vehicle routing and repositioning of empty vehicles (Kim et al., 2008; Flamini et al., 2011).

The literature focusing on the VOI to improve distribution and warehousing decisions is limited. The use of outbound information (i.e. order information) has been considered extensively in the order-picking literature (de Koster et al., 2007), whereas the literature on the value of inbound information, especially information on truck-arrival time, is rather scant. The reason is that most of the literature assumes that the truck contents and arrival time information are always available for solving distribution warehouse problems, such as inbound and outbound truck scheduling (Ladier & Alpan, 2016). In one of the few studies on this domain, Larbi et al. (2011) studied the VOI on inbound truck contents and arrival time to improve the scheduling of outbound trucks. In their study, three scenarios were explored: full information (i.e. every detail about inbound truck content and arrival time is known), partial information (i.e. contents and arrival times of a number of inbound trucks are known), and no information (i.e. no inbound information is available). The authors concluded that knowing the contents and arrival times of the next 14 inbound trucks is as valuable as knowing the arrival times of all the next trucks to arrive. However, their approaches use exact truck arrival time, which is hard to obtain; in reality, many factors such as traffic congestion can affect the truck arrival time. In addition to Larbi et al. (2011), who explicitly discuss the value of inbound information in managing warehouse operations, other studies have emphasized the importance of considering the uncertainty of truck-arrival time in solving the truck scheduling problem; see for example the study by Konur & Golias (2013).

An important factor in determining the VOI in logistics is the characteristics of the information. Most of the literature considers only the availability aspect of information. In other words, these studies compare two scenarios: decision making with- and without information. However, in many cases, not only the availability of information but also other information characteristics such as timeliness, accuracy, completeness, consistency, and security may influence the VOI. Information characteristics have also been addressed under two different terms: information quality dimension (Miller, 1996; Gustavsson & Wänström, 2009), or information value attributes (Sellitto et al., 2007; Leviäkangas, 2011). These terms are interchangeable from the perspective of their impact on the VOI. A recent extensive literature review on the VOI by Viet et al. (2018a) reveals that the three intrinsic characteristics of information - accuracy, timeliness and completeness – have been studied the most. The definition of these characteristics is provided in Table 3.1. In the case study, we also focus on these three characteristics in the assessment of the VOI because they are objective to the information (Hazen et al., 2014).

Table 3.1. Definitions of three intrinsic information characteristics

Characteristic	**Definition**
Accuracy	Accuracy defines how the available information reflects the underlying reality
Timeliness	Timeliness indicates how up to date the information is and how well it meets the demand for information in a particular time and space.
Completeness	Completeness refers to different levels of detail of the information.

3.3.2 Stepwise framework to assess the VOI

We follow the stepwise framework on assessing the VOI in supply chain and logistics decisions as proposed by Viet et al. (2018a). As depicted in Figure 3.2, the VOI is assessed by comparing the KPIs resulting from two decision-making scenarios:

- In the base scenario, base information is used. Base information is a given set of information (with some specific information characteristics) that is available originally to the decision maker. Accordingly, the base decision is the output from the decision-support model using this base information. In some cases, no information is used in the base scenario.
- In the information scenario, additional information is added to the base information. The additional information is expected to contribute to an improvement in the logistics performance. The decision maker aims to assess the value of this additional information. Given the additional and the base information as input, the decision-support model generates the decision based on the additional information as output. The difference between performance measures in this case and the base scenario determines the VOI. Furthermore, multiple information sub-scenarios can be defined by considering different options for different information characteristics. Studying these sub-scenarios will provide insight into the impact of the information characteristics on the VOI. The results of this analysis can be used to determine the requirements for information characteristics in information sharing between different actors in the chain.

In the framework, different decision-support models can be used in the base and information scenarios. For instance, in the study by Larbi et al. (2011), a polynomial algorithm is developed for full information scenarios and two heuristics are used for the partial and no information scenarios. In the next section we apply this framework to the case study.

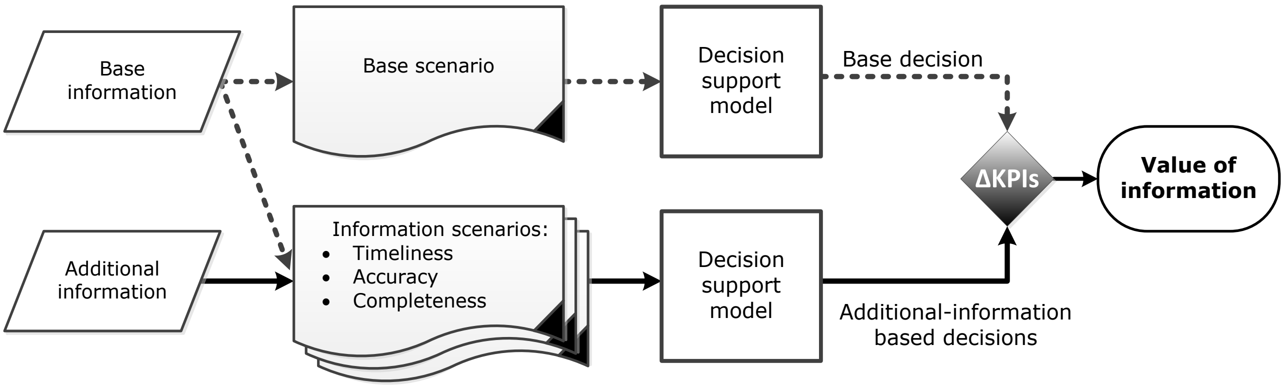

Figure 3.2. Stepwise framework to assess the VOI in improving the logistics performance

3.4. A case study on a Dutch flower supply chain

In this section, we elaborate on the current HDL situation at the distribution warehouse of a Dutch flower supply chain and the scope of this study. Subsequently, we discuss how the value of inbound and outbound information can be assessed by mapping each concept in the research framework to the case study.

3.4.1 Case description

The distribution warehouse in this case study is part of a Dutch flower supply chain. The flower growers send the flower orders by trucks to the warehouse, and the warehouse is responsible for distributing the right flowers to the right buyers in the right quantities. The buyers' facilities are in the neighborhood surrounding the warehouse. Figure 3.3 shows the information flows and the physical flows in the supply chain.

3.4.1.1 Information flows

After processing the orders from the buyers received in a day, growers send online forms to the distribution warehouse indicating the destination of each flower bucket in the flower trolleys that will be transported by trucks to the warehouse. Regularly, the warehouse receives the forms the night before the flower trolleys arrive. Urgent orders, which require lead times of around two hours, are not considered in this study because the growers often send flowers for urgent orders directly to the buyers' facilities. In addition, currently information on the truck arrival time is not included in the online forms. We design multiple scenarios about the availability of truck arrival time information in the experiment section.

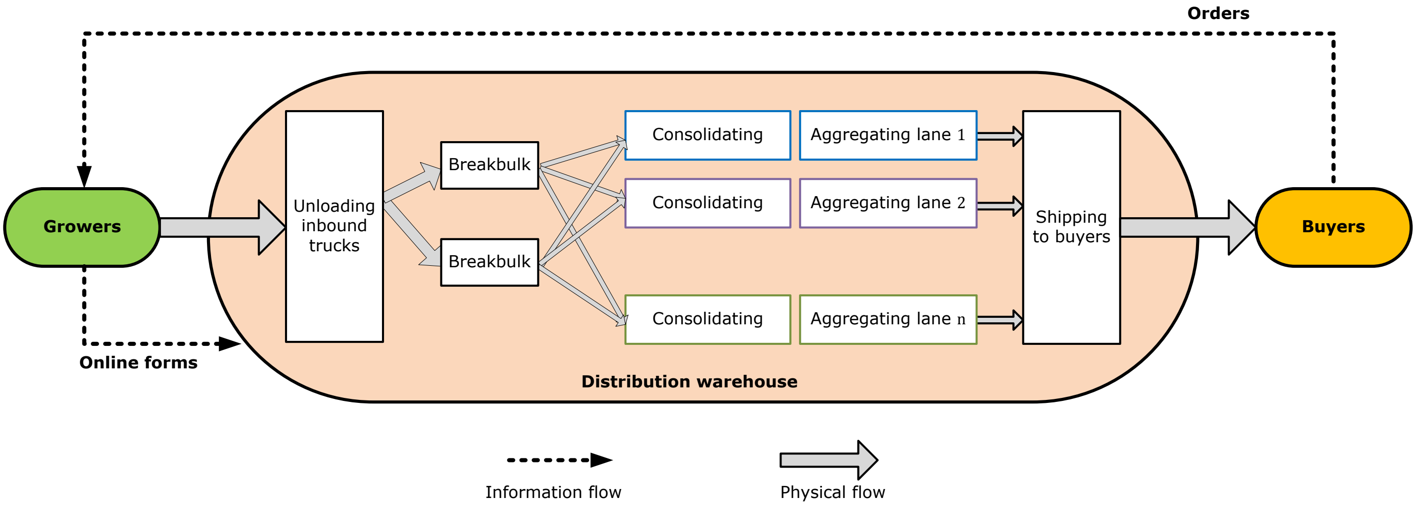

Figure 3.3. Information flows and physical flows in the Dutch flower supply chain

3.4.1.2 Physical flows

At the grower sites, many buckets of the same type flower are consolidated to make full trolleys. Each trolley can contain a maximum of 30 buckets. The inbound trucks transporting the trolleys usually arrive at the warehouse from 9:00 hours in the morning. The trucks are unloaded on a first-come first-serve policy. As shown in Figure 3.3, the internal process at the warehouse between unloading and shipping consists of three stages: breakbulk, consolidating, and aggregating. All unloaded flower trolleys are queued at the breakbulk area, with a first-in first-out policy. Next to the breakbulk area are multiple parallel consolidating and aggregating lanes. Each lane is reserved for a buyer, or a group of buyers whose facilities are closely located to each other. Empty trolleys are prepared at the lanes to receive flower buckets from the breakbulk area.

From the breakbulk area, flower trolleys are distributed to the consolidating and aggregating lanes following the "put system" order-picking (de Koster et al., 2007), which is a popular method for floricultural products and for distribution systems with a large number of orders and a short time window for picking. A worker can carry a trolley directly to a consolidating and aggregating lane if all the buckets in the trolley are to be distributed to the same destination. This happens when the order quantity is large enough. Otherwise, the workers have to drive the trolley to multiple consolidating and aggregating lanes and place the correct number of (ordered) buckets in the trolleys waiting at the lanes. Currently, on average, 60% of inbound trolleys are split among multiple buyers' lanes due to the high number of small order quantities and the high number of flower varieties. As a consequence, the average time for processing an inbound trolley has increased. The number and complexity of the physical flows has also increased because the worker has to move a trolley multiple times. As a result, congestion often occurs in the travelling space between the breakbulk and the consolidating and aggregating areas. Here we define the variable β as "the percentage of inbound trolleys that are not split at breakbulk stage"; so in the base case, β is equal to 40%. Later this variable will be varied to model different levels of high-density in the distribution process. The lower β is, the higher the complexity of the physical flows, and thus the higher the density level.

At each consolidating and aggregating lane, flower buckets are merged into full trolleys again. Full trolleys are aggregated and physically connected before they are shipped to the buyers. Currently one worker is in charge of a number of lanes. The worker waits until an aggregating lane reaches 12 trolleys, which is the maximum size, and then ships the set of aggregated trolleys to their destination. It takes a worker on average 15 minutes to drive the aggregated set to the buyers' facilities. Larger aggregating sizes require longer shipping time.

At the buyers' facilities, trolleys are then re-processed for deliveries to their next customers. The buyers place high value on deliveries within a 4-hour time window from 9:00 to 13:00 hours which provides sufficient time for their internal logistics activities. We specify this "time window" as T (hours). In the experimental design, T is varied to demonstrate different levels of density. The lower T is, the higher the density level.

3.4.1.3 Scope of this study

In the current situation, the warehouse distributes flowers to a large number of buyers. In the case study, we simplify the current warehouse situation by modelling only three consolidating and aggregating lanes (three groups of buyers). This simplification is justified because we aim for an illustrative case to study the HDL context and the VOI. Therefore, the VOI could be higher in the real situation with the entire distribution system. In addition, we assume a fixed time period for unloading each inbound truck. Our focus is on the complexity of the operations in the three internal stages: breakbulk, consolidating, and aggregating. Two workers work at the breakbulk, consolidating, and aggregating areas. One worker waits at the three aggregating lanes. The day shift of the workers ends when all the inbound trolleys have been processed and delivered.

3.4.2 Applying the VOI assessment framework to the case study

In this case study, we aim to evaluate the value of inbound and outbound information in improving the logistics performance at the warehouse. Specifically, inbound information is the truck-arrival time information, and outbound information is the order information. Ketzenberg et al. (2007) conclude that the value of additional information depends on the base information in the base scenario. The more information types used in the current decision-making, the lower the value of the additional information can be. Currently, outbound information is available at the warehouse but unused. To understand the value of the outbound and inbound information, we consider three scenarios:

(i) Base scenario: no information is used in decision-making as in the current situation;
(ii) Outbound information scenario: only outbound information is used; and
(iii) Total information scenario: both outbound and inbound information is used.

In the following, we first define the logistics KPI and the planning decision. Subsequently, we discuss the mapping of each concept in the VOI framework to the case study in each scenario.

- *KPIs*: The first indicator KPI_1 is defined as the number of full trolleys that are distributed to the buyers before the time window T. The travelling cost at the shipping stage is mainly associated with the utilization of the shipping workers, which is insignificant in this case. The second indicator KPI_2 is the completion time to deliver all the inbound trolleys to the buyers. To quantify the VOI, we used the total improvement in these KPIs where the KPIs are equally important:

$$VOI = \sum_{i=1}^{2} \frac{KPI_i\, information\ scenario - KPI_i\, base\ scenario}{KPI_i\, base\ scenario} \times 100\% \quad (1)$$

- *The decision*: Truck-arrival time information is used to schedule outbound trucks in Larbi et al. (2011) and Amini et al. (2014). In this case study, we scheduled the outbound shipping trips by dynamically changing the aggregating sizes at each aggregating lane because the aggregating sizes directly affect both KPIs. Dynamically updating the aggregating sizes every hour can reduce a worker's productivity. In this case study, we aim to locate the aggregating sizes of the lanes before and after the time window T for future practical implementation.

  From the scheduling problem perspective, the problem in this case study falls into the category of a single batch-process machine with dynamic job arrivals. Full trolleys at the aggregating lanes that need to be shipped can be seen as jobs, the single machine is the worker, the batch service time is the shipping time of the set of aggregated trolleys, and the decision variable is the batch size, i.e. the aggregating size. This type of scheduling problem has been studied extensively in the literature (Ikura & Gimple, 1986; Lee & Uzsoy, 1999). The classic problem formulation is "given n jobs J_i with release times r_i ($i = 1, 2, \ldots, n$) and batch service time μ independent of batch size, minimize the completion time". In this case study, the problem setting is slightly different because in addition to the completion time KPI_2, the number of full trolleys distributed to the buyers before the time window T (KPI_1) must also be considered. Moreover, the batch service time depends on the batch size. Therefore, we formulate the problem as "given n jobs J_i with release times r_i ($i = 1, 2, \ldots, n$) and batch service time μ_s (which depends on batch size s), maximize Q_T and minimize the completion time; where Q_T is the number of jobs finished before time T". Moreover, the release time r_i, i.e., the time when a trolley at the aggregating lane is ready for shipping, is unknown. We explain the method to estimate the release time r_i using the information in each information scenario.

3.4.2.1 Base scenario

- *Base information*: in the base scenario, which represents the current situation, no information is used in the decision making. The shipping worker waits until an aggregating lane reaches 12 trolleys. In this case, the aggregating size combination is (12, 12, 12) for three lanes.
- *Decision-support model* is not needed in this base scenario.

3.4.2.2 Outbound information scenario

- *Additional information*: order information
- *Decision-support model – a scheduling algorithm*: we developed a polynomial time scheduling algorithm based on the order information. Without the truck arrival time, the objective of the algorithm is solely to improve KPI_2, the completion time. Two main inputs for the algorithm are (i) the total trolley quantity ordered for each aggregating lane and (ii) the estimated time interval for a trolley to be fully filled with flower buckets at the aggregating lanes (i.e. the inter-arrival of the release time r_i). The total trolley quantity ordered can be easily calculated from the order information. The second input is estimated based on the average deterministic flow time at the breakbulk and consolidating stages, similar to the common practice of modelling warehouse handling in the literature (Boysen et al., 2010; Konur & Golias, 2013). With the two inputs, the algorithm can calculate the completion time for each aggregating size combination. The algorithm loops exhaustively through all the combinations of the aggregating sizes and selects the one with the shortest completion time. The pseudo-code is provided in Appendix 3.A.
- *Information characteristics*: we assume that the order information is accurate, complete and available at the moment of decision-making.

3.4.2.3 Total information scenario

- *Additional information*: both the truck-arrival time information and the order information
- *Decision-support model – a simulation-based scheduling algorithm*: knowing the truck arrival time information, the time that the inbound trolleys enter the internal process is known. The dynamic operations at the breakbulk and consolidating stages cannot be modelled by queueing systems. To estimate the release time r_i, we built a discrete-event simulation model that includes only the breakbulk and consolidating stages (i.e. a partial simulation model) using the Enterprise Dynamics 9 software package (EnterpriseDynamics, 2018). Discrete-event simulation is widely used for modelling logistics operation processes (Tako & Robinson, 2012). Given the truck arrival time information and order information, the partial simulation model records the release time r_i of each full trolley at each aggregating lane. Because the simulation model uses stochastic cycle times of worker operations at the breakbulk and consolidating stages (Appendix 3.B), the recorded release time r_i are different for different simulation runs. However, the recorded release time r_i from a single run is an acceptable estimation because we do not need the exact release time of each job arrival, but the estimated release time of an s-sized batch of jobs; i.e. the time that a s-sized set of aggregated trolleys is ready for shipping.

  Using the recorded release time r_i as input, we developed a similar scheduling algorithm to the one in the outbound information scenario. The algorithm loops exhaustively for the entire set of aggregating size combinations. Before the time window T, the algorithm selects the combination with the highest KPI_1, the number of trolleys delivered within the time window T. After the time window T, it selects the combination with the shortest KPI_2, completion time of the remained trolleys. The pseudo-code is provided in Appendix 3.C.

- *Information characteristics*: each information characteristic needs specific interpretation according to the specific logistics context. In this case study, we interpreted the characteristics as follows and explain why the focus is on information accuracy.
  - Information accuracy: the inbound information is inaccurate if the trucks actually arrive earlier or later than the arrival time provided.
  - Information completeness: with regard to the level of detail for inbound truck arrival information, it is common in practice that, instead of an exact time, a time window in quarter hours is provided for each truck (Konur & Golias, 2013). In other words, the lower and upper bounds of a truck's arrival time are known. For example, the information states that truck A will arrive in one-quarter time window between 9:00 and 9:15 hours, and truck B will arrive in a two-quarter time window between 9:00 and 9:30 hours. In these cases, the warehouse operator can use the mid-arrival time windows in his scheduling as suggested by Konur & Golias (2013): truck A is expected to arrive at 9:07:30 hours, and 9:15:00 hours for truck B. Therefore, we associate the impact of information completeness with the impact of information accuracy by investigating the impact of information accuracy in different ranges of inaccuracy.
  - Information timeliness: from the time dimension, the information is considered timely if it arrives before the warehouse operator makes the schedule. Because this case study does not include the urgent orders, we assume that the growers will have sufficient time to provide the truck arrival information on the online forms.

3.4.2.4 Summary of decision-making flows in the three scenarios

For a fair comparison of the KPIs in all three scenarios, the output aggregating size combinations in these scenarios need to be examined by the same tool and in a stochastic environment to reflect the dynamic nature of warehouse operations. The partial discrete-event simulation was extended to include the complete distribution process i.e. full simulation model. Figure 3.4 summarizes the decision-making flows in the three scenarios.

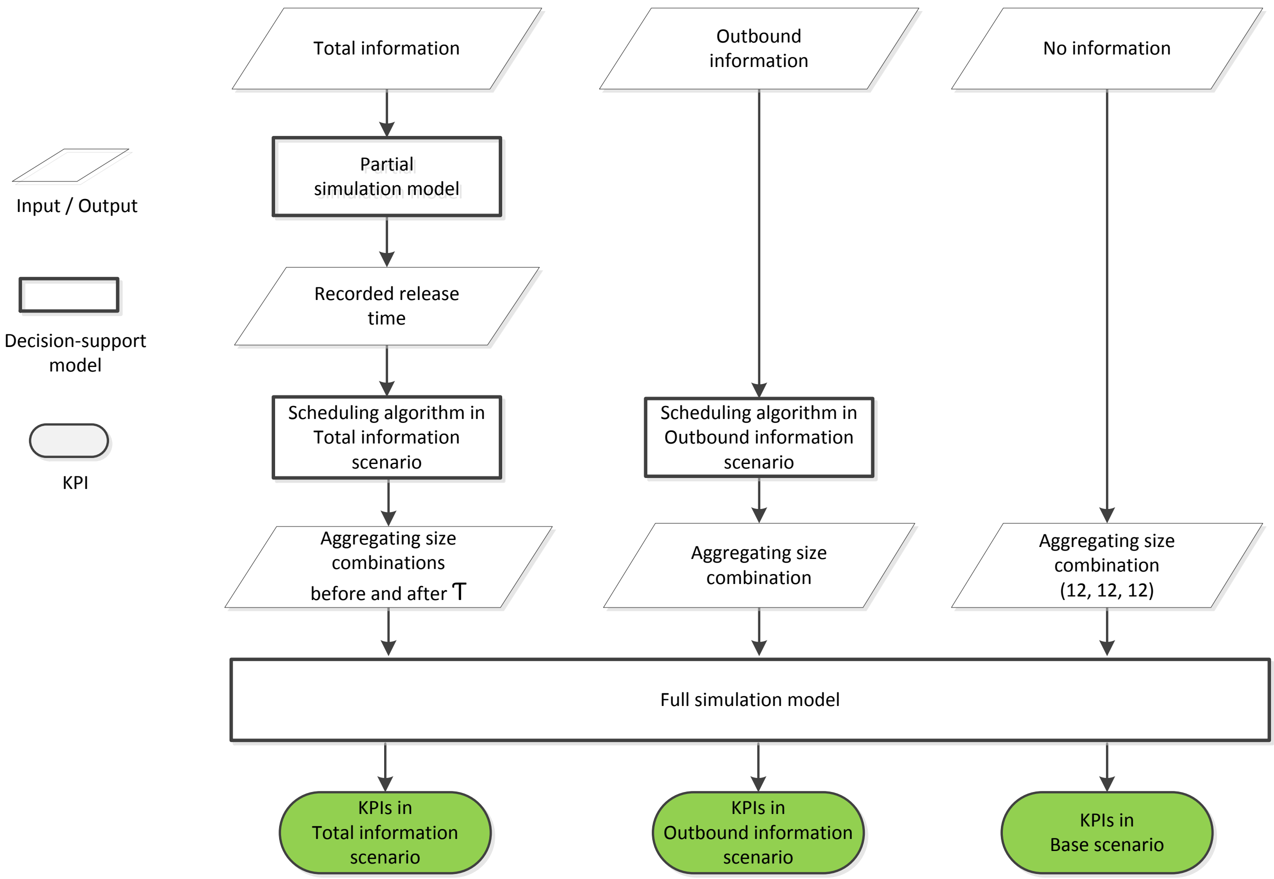

Figure 3.4. Decision-making flows in the three scenarios

3.4.3 Experimental design and results

We designed different sets of experiments to test the VOI in different parameter settings, in different density levels, and in different scenarios of information accuracy. In each set of experiments, one parameter is varied while the others are fixed at the values in the current situation. Because of the stochastic nature of the parameters in the simulation model, it is incorrect to measure the VOI based on the KPIs observed from a single run. Therefore, we executed 50 separate runs for each parametric setting to achieve narrow intervals with a 95% confidence level. In this way, the mean KPIs obtained from the 50 runs could be used to calculate the VOI. The experiments and the results are elaborated in the following.

3.4.3.1 Value of accurate information

We investigate the VOI assuming that accurate order information and accurate and exact arrival times of all the trucks are provided. The VOI is subject to logistics process parameters (Li et al., 2005). To carry out the sensitivity experiments, we generated five different datasets based on five different means of the inbound truck inter-arrival time, as shown in Table 3.2. The bold values indicate the current situation. The current literature has not considered truck inter-arrival time when assessing the value of truck-arrival time information in truck scheduling. We aim to test if the truck inter-arrival time can be an influential factor on the internal handling operations and the value of order and truck-arrival time information.

Table 3.2. Parameter setting in experiments on the inter-arrival time of inbound trucks

Parameter	Value
Inter-arrival time of trucks	Exponential distribution with mean: 6, 8, **10**, 12, 15 minutes
β	**40%**
Time window T	**4** hours

In the five sensitivity experiments, the inter-arrival times of 30 trucks were randomly generated using exponential distribution with different means when the trucks' contents, i.e. β, and time window T were unchanged. Each truck carries between 8 and 12 full trolleys. For each full trolley, the allocation of flower buckets to three buyer destinations was randomized using uniform distribution, yet the sum of the quantities was always 30. Currently 40% of the inbound trolleys are fully ordered by one buyer destination (β = 40%); in this case, the possible quantity combinations are (30, 0, 0) or (0, 30, 0) or (0, 0, 30). Details of the other parameters, such as the cycle times at breakbulk, consolidating, and aggregating stages are provided in Appendix 3.B.

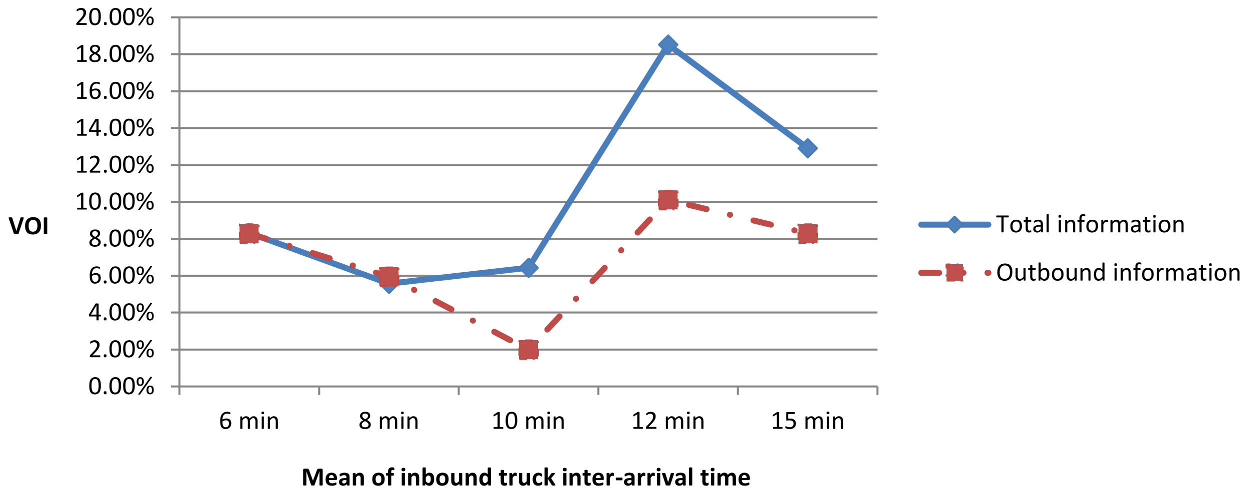

Figure 3.5. VOI with different means of truck inter-arrival time

The value of outbound information ($VOI_{outbound}$) and the value of total information (VOI_{total}) are positive as shown in Figure 3.5. The VOI is the percentage improvement in KPIs compared with the base scenario, as presented in Equation 1. The numerical values vary between 1.99% and 10.11% for $VOI_{outbound}$, and between 5.57% and 18.52% for VOI_{total}. We observe that the VOI_{total} is generally higher than the $VOI_{outbound}$. This result supports the conclusion by Ketzenberg et al. (2007) and Ketzenberg et al. (2006): using an additional information type results in additional benefits. In this case, inbound information adds additional value on top of the outbound information. However, this conclusion is not always true. Interested readers are referred to the results of the case study by Rached et al. (2015) and the analysis on this issue by (Viet et al., 2018a).

Furthermore, we observed no clear relationship between the $VOI_{outbound}$ and the truck inter-arrival time means, which is intuitive. However, the gap between VOI_{total} and $VOI_{outbound}$ increases as the mean inter-arrival time becomes larger. This gap can be interpreted as the additional value from the truck arrival time information, inbound information. We define $VOI_{inbound}$ as the additional value of the inbound truck arrival time information, given that the order information is already in use in decision making. We measured $VOI_{inbound}$ in Equation 2 by comparing the KPIs in the total information scenario with those in the outbound information scenario. In other words, the outbound information scenario serves as the base scenario in assessing the $VOI_{inbound}$.

$$VOI_{inbound} = \sum_{i=1}^{2} \frac{KPI_i\,Total\,information - KPI_i\,Outbound\,information}{KPI_i\,Outbound\,information} \times 100\% \qquad (2)$$

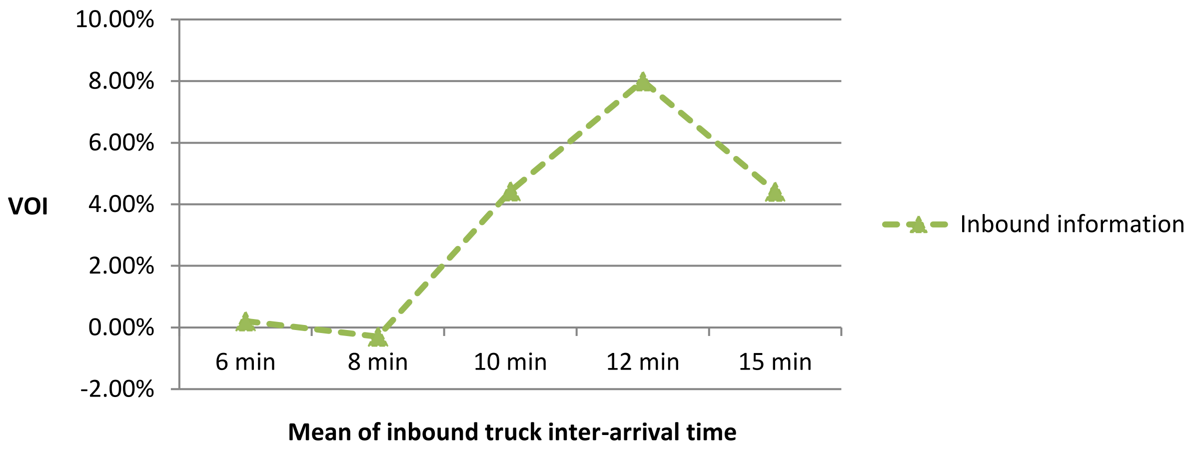

Figure 3.6. $VOI_{inbound}$ with different means of truck inter-arrival time

Figure 3.6 reports the numerical values of $VOI_{inbound}$ in the five experiments on inbound truck inter-arrival times. In the cases of 6 minutes and 8 minutes, the $VOI_{inbound}$ is close to zero (0.20% and 0.30%, respectively). The $VOI_{inbound}$ is higher when the inter-arrival time mean is larger. This observation implies that the additional information does not always result in additional value in some specific contexts (in this case, for the small value of the mean truck inter-arrival time). We suggest that the $VOI_{inbound}$ is small with the small mean inter-arrival times because the observed deterministic flow time of the breakbulk and consolidating stages in the outbound information scenario performs well with small inter-arrival time. As a result, the difference between the KPIs in total information scenario and outbound information scenario is small, thus $VOI_{inbound}$ is small. As the mean inter-arrival time becomes larger, the flow time, especially at the consolidating stage, fluctuates more widely. Therefore, the deterministic value cannot be representative for the dynamic flow time of products through the stages.

3.4.3.2 Value of accurate information for different density levels

We measured the VOI at different levels of density by changing the value of the time window T and the value of β.

3.4.3.2.1 Time window T: timeframe of the logistics process

By varying T, the timeframe of the logistics process is changed. The smaller T is, the higher the density level. In the experiments on T, the truck-arrival times and the truck contents were unchanged, as shown in Table 3.3.

Table 3.3. Parameter setting in experiments on time window T

Parameter	**Value**
Inter-arrival time of trucks	Exponential distribution with mean of **10** minutes
β	**40%**
Time window T	5, **4**, 3, 2 hours

Figure 3.7 illustrates the results. On the timeframe dimension, the $\mathrm{VOI}_{\mathrm{outbound}}$ (and thus $\mathrm{VOI}_{\mathrm{total}}$ also) increases as the density level increases. Also, one can see that as the timeframe of the process is long enough, these two VOIs converge to zero (at 5 hours) because the combination of maximum aggregating sizes (12, 12, 12) for the base scenario performs well with long timeframes as suggested by Ikura and Gimple (1986). Contradictorily, the $\mathrm{VOI}_{\mathrm{inbound}}$ peaks at T = 4 hours and then decreases as the density level increases; at T = 2 hours, the $\mathrm{VOI}_{\mathrm{inbound}}$ is approximately equal to zero.

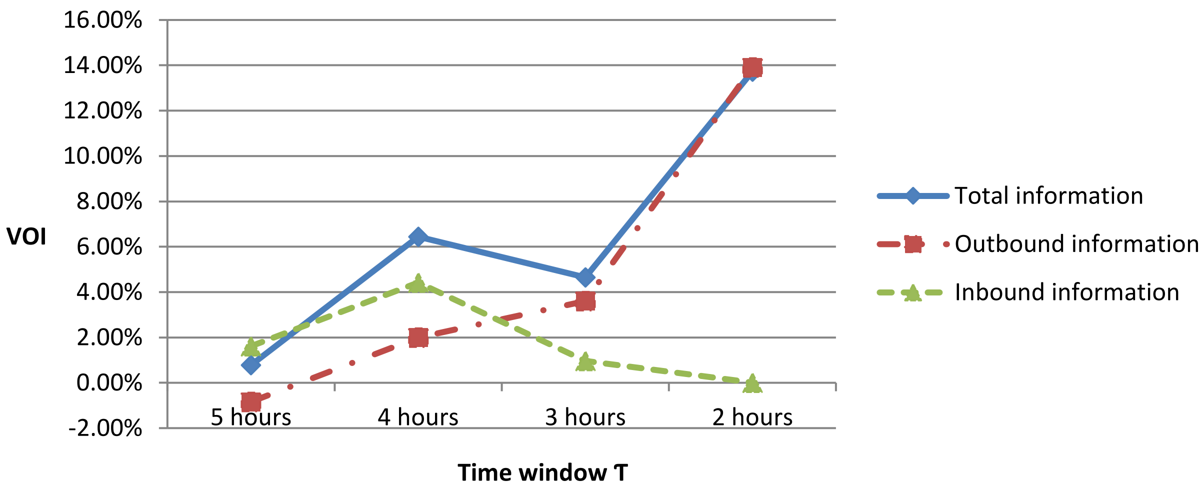

Figure 3.7. VOI with different settings for time window T

3.4.3.2.2 β: the complexity of physical flow

By varying β, the complexity of the physical flow is altered. The lower β is (i.e. the more trolleys are split over multiple buyer destinations), the higher the complexity, and thus the higher the density level. In the experiments on β, the truck arrival times and the time window T were unchanged, whereas the allocation of flower bucket quantities to each buyer destinations was done according to different values of β, as shown in Table 3.4.

Table 3.4. Parameter setting in experiments on β

Parameter	Value
Inter-arrival time of trucks	Exponential distribution with mean of **10** minutes
β	60%, **40%**, 20%, 0%
Time window T	**4** hours

Figure 3.8 shows the results. On the complexity of the physical flows dimension, the $VOI_{inbound}$ increases as the density level increases, whereas the $VOI_{outbound}$ does not have a clear relationship with the density level. As a result of increasing $VOI_{inbound}$, the VOI_{total} also increases.

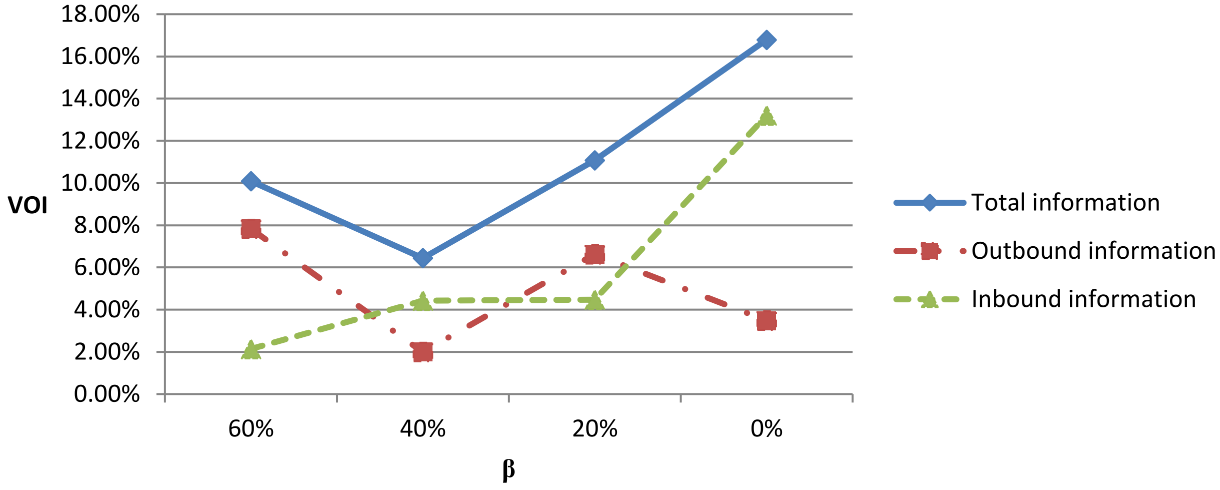

Figure 3.8. VOI with different settings for β

3.4.3.3 Summary on the value of accurate information

The impact of process parameters on the values for inbound, outbound, and total information are summarized in Table 3.5. Overall, the results of the experiments point to (i) a positive correlation between the $VOI_{inbound}$ and the mean inbound truck inter-arrival time, (ii) a positive correlation between the $VOI_{inbound}/VOI_{total}$ and the density level on the physical flow complexity dimension, and (iii) a positive correlation between the $VOI_{outbound}/VOI_{total}$ and the density level on the timeframe dimension. Understanding the impact of the parameters on VOI, especially the parameters that affect the dimensions of HDL, improves the decision about which information to collect and use in different characteristics of the HDL processes.

Table 3.5. Summary on value of accurate information

VOI	Impact of process parameter		
	Mean truck inter-arrival time	*Density level on timeframe dimension*	*Density level on physical flow complexity dimension*
Outbound information	Non-monotonic	Positively correlated	Non-monotonic
Inbound information	Positively correlated	Non-monotonic	Positively correlated
Total information	Non-monotonic	Positively correlated	Positively correlated

3.4.3.4 Impact of inaccurate information

In the previous experiments, we assumed that the information was accurate. Now, we consider inaccurate truck-arrival time information and examine how information accuracy influences the $VOI_{inbound}$. Three scenarios of information accuracy were established by adding random errors to the exact truck arrival times. The mean of truck inter-arrival time was kept at 10 minutes as in the current situation. In detail, suppose t_i (i = 1, 2, ..., 30) are the accurate truck-arrival times, the inaccurate truck-arrival times are $t_i + \varepsilon_i$ (i = 1, 2, …, 30) where ε_i are the randomized integers following uniform distributions with three different intervals: (-7,7) minutes, (-15,15) minutes, and (-30,30) minutes. These three intervals link to three inbound trucks' arrival time windows of one-, two-, and four quarters of an hour, respectively (Konur & Golias, 2013). With each error interval, we randomized two different data sets. In each scenario, we input the full simulation model with the inaccurate truck-arrival times, yet with the same aggregating size combinations obtained from the decision making based on the accurate information scenario. The purpose is to examine how the decisions based on the accurate truck-arrival time information perform in the case of inaccurate truck arrival times.

The results of experiments on inaccurate information are shown in Table 3.6. Intuitively we would expect that inaccurate information would reduce the VOI. The results support the expectation, yet it is not clear if there is a relationship between the magnitude of reduction and the error interval. Generally, the $VOI_{inbound}$ remains positive in most of the experiments except one case in the error interval of (-15, 15).

Table 3.6. Results of the experiments on inaccurate information

Error interval (minutes)	Truck-arrival information	$VOI_{inbound}$
0	Accurate information	4.42%
(-7,7)	Inaccurate information dataset 1	2.10%
(-7,7)	Inaccurate information dataset 2	1.80%
(-15,15)	Inaccurate information dataset 1	-2.08%
(-15,15)	Inaccurate information dataset 2	3.46%
(-30,30)	Inaccurate information dataset 1	3.31%
(-30,30)	Inaccurate information dataset 2	4.16%

3.5 Conclusion and discussion

This chapter discusses the HDL context in agro-food supply chains in which the distribution process is confronted with more frequent small orders and short lead times. The capacity of logistics resources, the expected timeframe of logistics activities, and the complexity of physical flows in a logistics process are the main factors that shape HDL. The concept is further elaborated through a case study on the distribution warehouse of a Dutch floricultural supply chain. We further discuss the value of inbound and outbound information to improve the logistics performance in the HDL context. We find that as the density of the logistics context increases, the VOI increases. We also discuss the impact of information characteristics on the VOI; we particularly examine information accuracy and find that inaccurate truck-arrival information diminishes its value.

This research contributes to agro-food logistics by explicitly characterizing the HDL in agro-food supply chains, which is mainly caused by the increasing development from supply-driven towards demand-driven requirements. As proposed, effective uses of information flows are the key to overcome the logistics challenges. Extensive research is available on tackling technical challenges of virtual supply chains and smart systems of tracking, tracing, and sensing devices (Verdouw et al., 2013; Verdouw et al., 2016; Wolfert et al., 2017). However, effective real-time uses of different information types enabled by such systems and virtualization in supply chain and logistics decisions remains a promising research area. For example, under regulations on food traceability, the availability of product location and condition information has been improved in the agro-food sector (Heyder et al., 2010; Bosona & Gebresenbet, 2013). Besides direct uses in relation to food safety, quality and food waste, this information can be useful in handling and distribution planning.

Decision-support models developed in the case study can be applied in operations planning at cross-docking distribution warehouses for fresh agricultural products. Particularly, the simulation-based scheduling approach in the total information scenario is suitable to capture dynamics and complex operations in the distribution process. For future research, we suggest two directions to extend the models. Firstly, we only discussed the use of inbound and outbound information in the outbound shipping scheduling decision. This information could have additional value if used in other decisions such as dynamic work force scheduling. We can model the dynamic work shifts of workers by varying the cycle time at each stage in the simulation. Another interesting direction is to include urgent orders in the scheduling process. Entering of flower trolleys linked to urgent orders into the internal distribution process can immediately trigger outbound shipping regardless of the current number of trolleys at the aggregating lanes; thus, it can affect the KPIs and the original shipping planning. Furthermore, the distribution network could be redesigned to be able to handle the distributions of different order types with different required lead times. In that case, we anticipate that the inbound information flows will play a more crucial role in efficient process coordination and resources allocation across the entire network.

Appendix 3.A

Pseudo-code for the scheduling algorithm in the outbound information scenario

```
initialization
        S = all combinations of aggregating sizes at lanes A, B, C
        T = buyer time window
        Completion_time = a big number
        Output = (0,0,0)
        "α is the estimated inter-arrival time that a trolley becomes full at the aggregating lanes.
        It is calculated based on the average flow time at Breakbulk and Consolidating"

for (sA, sB, sC) in S:
        lA = ( tuples (r_sA , sA , μ_sA) )
        lB = ( tuples (r_sB , sB , μ_sB) )
        lC = ( tuples (r_sC , sC , μ_sC) )
        "r_s is the release time of the s-sized aggregated set of trolleys at the aggregating lane r_s =
        s * α."
        "μ_s is the shipping time for the s-sized aggregated set of trolleys"
        L = sorted ( lA ∩ lB ∩ lC ) by the ascending order of  r_s
        time = 0
        for all tuples in L:
            time = max(time, r_s) + μ_s
        endfor
        if  (time < Completion_time)
        then
             Completion_time = time
             Output = (sA, sB, sC)
endfor

return Output
```

Appendix 3.B

Parameter in the simulation model	Value	Unit
Number of trucks	30	Truck
Number of trolleys per truck	Uniform(8,12)	Trolley
Size of a full trolley	30	Bucket
Percentage of full trolleys ordered by only one buyer	40%	
Worker's walking time between breakbulk area and consolidating areas	Normal distribution (30,5)	Second
Time to sort, scan, and place a bucket on the trolleys at consolidating	Normal distribution (6,0.5)	Second
Shipping time to different buyers destinations (larger size of aggregating requires longer time)	Normal distribution (15,1) * max(1, size/9)	Minute

Appendix 3.C

Pseudo-code for the scheduling algorithm in the total information scenario

```
initialization
        S = all combinations of aggregating sizes at lanes A, B, C
        T = buyer time window
        KPI1 = 0
        Completion_time = a big number
        Output1 = (0,0,0)  "aggregating sizes before T"
        Output2 = (0,0,0)  "aggregating sizes after T"

for (sA, sB, sC) in S:
        lA = ( tuples (r_sA , sA , μ_sA) )
        lB = ( tuples (r_sB , sB , μ_sB) )
        lC = ( tuples (r_sC , sC , μ_sC) )
        "r_s is the appearing time of the s-sized aggregated set of trolleys at the aggregating lane
        based on the recorded release time r_i of each trolley"
        "μ_s is the shipping time for the s-sized aggregated set of trolleys"
        L = sorted ( lA ∩ lB ∩ lC ) by the ascending order of  r_s
        time = 0
        kpi1 = 0
        while (time < T):
            time = max(time, r_s) + μ_s
            kpi1 = kpi1 + s
        endwhile
        if (kpi1 > KPI1)
        then
            KPI1 = kpi1
            Output1 = (sA, sB, sC)
endfor

Identify the remained trolleys after the time T for each destination

for (sA, sB, sC) in S:
        reA = ( tuples (r_sA , sA , μ_sA) )
        reB = ( tuples (r_sB , sB , μ_sB) )
        reC = ( tuples (r_sC , sC , μ_sC) )

        "reA, reB, reC are the sets of the remained trolleys after the time window T"
        reL = sorted ( reA  ∩ reB ∩ reC ) by the ascending order of  r_s
        time = 0
        for all tuples in reL:
            time = max(time, r_s) + μ_s
        endfor
        if    (time < Completion_time):
        then
            Completion_time = time
            Output2 = (sA, sB, sC)
endfor

return Output1 and Output2
```

Chapter 4. Data-driven process redesign: Anticipatory shipping in agro-food supply chains

This chapter is based on the published journal article:

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Data-driven process redesign: anticipatory shipping in agro-food supply chains.

International Journal of Production Research.

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Abstract

Anticipatory shipping uses historical order and customer data to predict future orders and accordingly ship products to the nearest distribution centers before customers actually place the orders. It is a method to meet the increasing customer requirements on delivery service and simultaneously to reduce operational costs. This chapter presents a case of anticipatory shipping in the context of agro-food supply chains. The challenge in these chains is the product perishability that leads to product obsolescence in the case of un-balanced supply and demand. This study introduces a data-driven approach that integrates product quality characteristics in data analytics to identify suitable products for anticipatory shipping at the strategic level. It also proposes process redesigns concerning production and transportation at the operational level to realize anticipatory shipping. Finally, using historical data from a Dutch floriculture supplier as input for a multi-agent simulation, the proposed approach and process redesigns are verified. The simulation output shows that anticipatory shipping could increase delivery service level up to 35.3% and reduce associated costs up to 9.3%.

4.1 Introduction

In agro-food supply chains, highly frequent orders of small volumes, high product variety, and short customer delivery windows increase the challenges in logistics management to maintain a high service level at low cost (Trienekens et al., 2014; Fredriksson & Liljestrand, 2015). Effective real-time process coordination and supply chain collaboration with information sharing are among the potential solutions to overcome these challenges (Thomas et al., 2015a). Supply chain process redesign such as reorganizing the roles and processes performed by supply chain firms is also a promising approach (Van Der Vorst et al., 2009). Particularly, data-driven process redesigns to improve logistics performance have recently received increasing research attention because of the rapid growth of data generation and collection in the supply chains (Kuo & Kusiak, 2018). Useful information and patterns extracted from data and big data enables various strategic and operational process redesigns across supply chain functions (Wang et al., 2016b; Nguyen et al., 2018; Viet et al., 2018a).

Anticipatory approaches, which refer to using historical data to make a current decision in anticipation of what may happen in the near future, are investigated in different decisions, e.g., freight selection in long-haul round-trips by Pérez Rivera & Mes (2017). This chapter addresses *anticipatory shipping* (AS), a data-driven redesign strategy regarding shipping decisions to expedite delivery service and reduce operational costs. The AS concept was patented by Amazon in 2011 (Spiegel et al., 2011). It is about shipping a product, which is at the moment of shipment not linked to a specified delivery address, to the nearest distribution center from where the product can be eventually delivered to its actual customer in the future. Unordered products can be re-shipped to other distribution centers in the next period of AS planning. The existing literature on AS is rather limited. As one of few studies, Lee (2017) presents a model to support AS in omni-channel retails. The author first divides demand points into different clusters, and then employs Apriori-based association rule mining to predict future orders within each cluster, and finally applies a genetic algorithm to minimize the transportation cost and travelling time for anticipatory shipping in the distribution network. The model was applied for AS at a garment retail.

In the context of agro-food supply chains, the inherent *product perishability* is a main criterion in logistics processes and distribution network design (Hasani et al., 2012; Van Kampen & Van Donk, 2014; Dolgui et al., 2018). AS may shorten delivery time and reduce transportation costs. Yet, when considering the product perishability, which causes quality decay, obsolescence/spoilage, and constraints on reshipping products in case of mismatching between anticipatory and actual orders, practitioners can question the possibility and benefit of AS for agro-food supply chains. In fact, the Apriori-based association rule mining used in the study of Lee (2017) stresses only order frequency of products in frequent itemset mining. The time relationship between orders, i.e., inter-arrival time of orders, is not considered. This approach is not effective for perishable products with limited shelf-life because the products may already fall to an unacceptable quality level before its orders arrive.

This study contributes to the agro-food supply chain literature by exploring AS in agro-food supply chains with a focus on products with a short shelf-life. It aims to answer two AS-relevant questions: (i) which products with which quantity and to which distribution centers should be considered in AS, and (ii) how the current production and transportation processes should be redesigned to effectively and efficiently facilitate the AS strategy.

The rest of this study is organized as follows. Section 4.2 discusses the agro-food supply chain context and decision-making regarding AS. Section 4.3 first proposes a data-driven approach that integrates product perishability in the time-based association rule mining to select strategic products for AS. Next, it introduces two redesign options in the operational production and transportation processes to realize the AS strategy. Section 4.4 applies the proposed approach and redesign options for a real-world company in the Dutch floriculture sector. A multi-agent simulation model is developed to assess the company's performance in the current situation and in the AS scenarios. Section 4.5 describes the experiment designs and results. Finally, Section 4.6 concludes this study and discusses future research directions.

4.2 Exploring anticipatory shipping in agro-food supply chains

This section first describes the supply chain context in which the AS strategy is explored. It then discusses the relevant decisions and necessary process redesigns to enable AS.

4.2.1 Supply chain network structure and processes

Figure 4.1 displays the fresh agro-food supply chain network for exploring AS. The network consists of several suppliers (e.g., fresh vegetables/fruits/flowers growers) and a few regional cross-dockings that serve a number of customers (e.g., exporters, retailers). The cross-docking distribution method is widely employed for fresh agro-food products to limit the quality decay during transportation and distribution and costly conditioned storage (Agustina et al., 2014).

The order fulfillment process is usually as follows. Customers place orders via online trading platforms or suppliers' web shops. The common characteristics of orders for fresh agro-food products are multiple order lines of small volumes, high frequency, and short delivery lead-time required to meet increasing consumer demand on product availability and quality (Viet et al., 2018b). After receiving the orders from customers, suppliers carry out necessary production and transportation activities to send the ordered products to the cross-docking indicated in the orders. At the cross-docking, unloaded products are immediately distributed to customers' facilities. For the transportation process, load consolidation is commonly employed to improve vehicle utilization and reduce travelling distance/time (Nguyen et al., 2014). Load consolidation decisions concern determining the time, quantity, or both to wait for the next load before dispatching vehicles. In practice, for agro-food chains, it is challenging to effectively implement consolidation due to short (and different) delivery time windows of orders (Baykasoglu & Kaplanoglu, 2011; Yilmaz & Savasaneril, 2012).

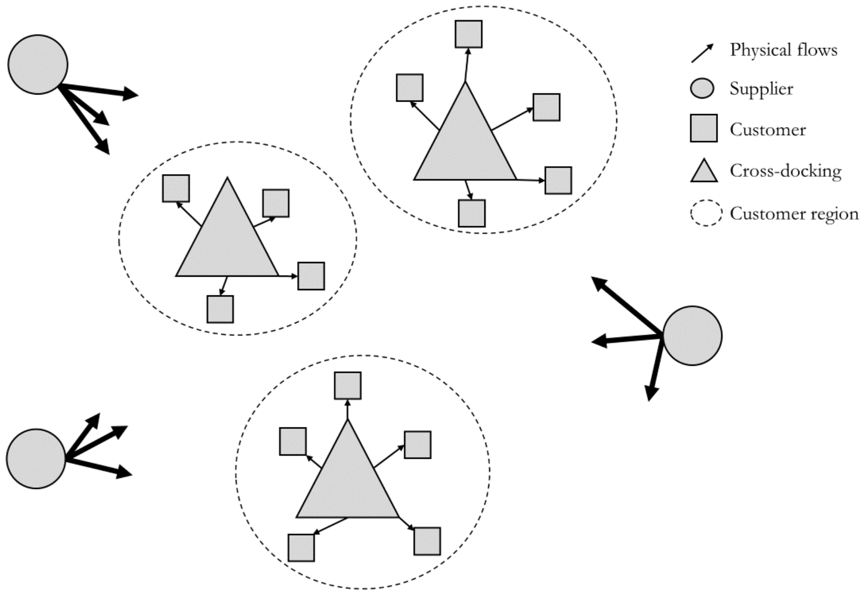

Figure 4.1. The agro-food supply chain network

4.2.2 Supply chain process redesigns and decision-making for anticipatory shipping

In an AS setting, the role of the cross-docking is extended as shown in Figure 4.2. Besides the cross-docking distribution service, the cross-docking additionally serves as the second customer-order decoupling point by providing a temporary storage for AS products and order-picking service when actual customer orders are received. Value-added activities such as labelling can also be performed at the cross-docking.

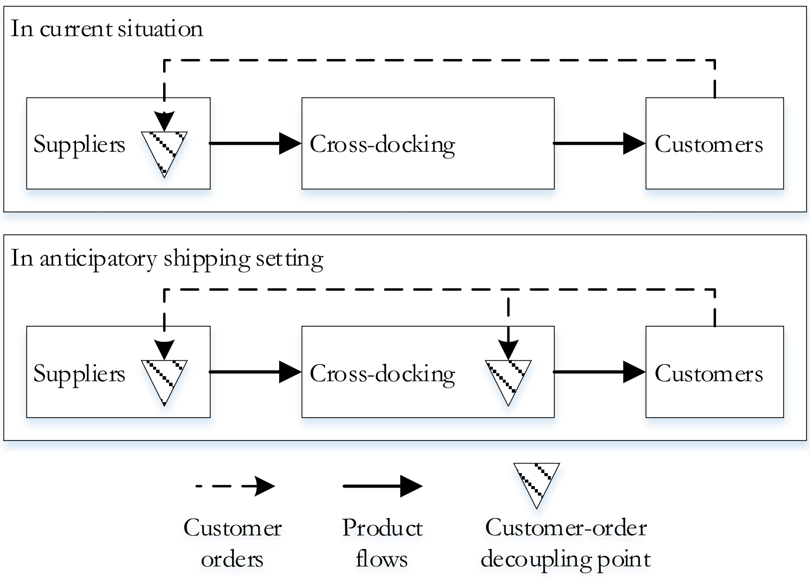

Figure 4.2. Customer-order decoupling points in anticipatory shipping setting

From the supplier side, selected AS products will be periodically (e.g., daily) transported to cross-docking warehouses before their associated orders arrive. Actual orders from customers will be directly fulfilled from temporarily stored products at the cross-docking if the inventory is sufficient (Figure 4.2). Otherwise, the orders will be processed by the suppliers following the original order fulfilment processes. AS products held at cross-docking will become obsolete after a given time period, which depends on the quality decay characteristics of the products. Focusing on the supplier's perspective, the relevant decisions for this redesign are as follows:

- At the strategic level, the decision is on "*which products with which volumes should be considered in AS and to which cross-docking these products should be sent* ". Selecting the wrong products and the wrong cross-docking destinations result in additional production and transportation costs, and especially costly product obsolescence. Section 4.3.1 presents a data-driven approach to support this decision.
- At the operational level, the decision is on "*how the production and transportation processes should be redesigned to effectively realize AS*". Producing and transporting AS volumes of the selected products can put further pressure on the original supply chain processes. Section 4.3.2 discusses two promising redesign options for this decision.

4.3 A data-driven approach to support anticipatory shipping in agro-food distribution networks

This section presents the data-driven approach to support agro-food suppliers with two decisions defined in the previous section.

4.3.1 Association rule mining to select strategic products for anticipatory shipping

A well-known application of association rule mining is the "market basket analysis". The market basket represents the set of products purchased by a consumer in every store visit. For example, if product A, B, and C are frequently purchased together, the association rule among them is generated as "if the consumer buys A and B, the consumer will buy C as well" with some statistics on support and confidence.

Association rule mining has been widely applied to support logistics and supply chain decisions such as product configurations (Song & Kusiak, 2009), supplier selection and order quantity allocation (Kuo et al., 2015), and anticipatory shipping (Lee, 2017). In all these applications, frequent sets are mined from historical data, and accordingly the association rules among set items are generated based on the sets' frequencies.

The purpose of the association rule mining in this study is to identify potential products and their volumes for AS to appropriate cross-docking destinations. It considers not only the frequency element but also the time element to address the product perishability. Moreover, instead of looking for the relationships among different products, the approach focuses on each single product to assess its suitability for AS. The following sub-sections describe the mining procedure in details.

4.3.1.1 Input

Input of the association rule mining includes a set of m products P_i $(i = 1, 2, \dots, m)$ and for each product P_i, its n sets of historical orders O_{ij} $(j = 1, 2, \dots, n)$ from customers of n cross-docking centers CD_j within the examined period T (e.g., 6 months).

4.3.1.2 Time-based association rule mining

The time relationship between orders is crucial in determining the potential of an agro-food product for AS. The association rule concerns the inter-arrival time of two consecutive orders of the same product P_i supplied to the same CD_j. An order O_{ij}^k $(k = 1, 2, \dots, |O_{ij}| - 1)$ satisfies the association rule if its consecutive order O_{ij}^{k+1} arrives within a time threshold τ_i, which is defined based on the product P_i's perishable characteristics. The time threshold in the association rule mining helps in integrating the product perishability in the data mining. It represents the potential to anticipatorily ship a future order knowing that it will arrive within an expected time interval. A small value of τ_i should be used for products that have fast rates of quality decay. Fresh agro-food products such as vegetables, fruits, and flowers may require small thresholds, e.g., 24 or 48 hours.

The confidence level of product P_i to be considered for AS to CD_j is calculated as $c_{ij} = \frac{|O_{ij}^*|}{|O_{ij}| - 1}$, where O_{ij}^* is the set of all the orders O_{ij}^k $(k = 1, 2, \dots, |O_{ij}| - 1)$ in O_{ij} that satisfy the association rule.

Assume that AS products will be transported to the cross-dockings every day, then v_{ij} denotes the daily target AS volume of product P_i to cross-docking CD_j. The volume v_{ij} can be forecasted based on the historical daily aggregate volumes of product P_i supplied to cross-docking CD_j using simple methods such as moving average over a number of past days or more sophisticated methods such as autoregressive integrated moving average (Steinker et al., 2017). Depending on the characteristics of customer orders at agro-food suppliers, different forecasting methods can be used to calculate the volume v_{ij}. There exists a rich literature on demand forecasting methods for perishable products, for example Gutierrez-Alcoba et al. (2017), Dellino et al. (2018), and Sillanpää & Liesiö (2018). A method that generates higher accuracy brings less obsolescence in the AS strategy. Because the focus of this study is not on introducing a forecasting model for v_{ij}, the basic moving average over the past D days is adopted as

$$v_{ij} = \frac{\left(\sum_{d=1}^{D} v_{ij}^d \right)}{D}$$

where v_{ij}^d is the aggregate demand volume on day d $(1, 2, \dots, D)$ of product P_i to cross-docking CD_j.

4.3.1.3 Output

The time-based association rule mining generates $m * n$ tuples $(P_i, c_{ij}, |O_{ij}|, v_{ij})$ for $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$. A product P_i is considered for AS to cross-docking CD_j if

$$c_{ij} \geq \varepsilon_T \text{ and } |O_{ij}| \geq size_T \text{ and } v_{ij} \geq v_T,$$

where ε_T, $size_T$, and υ_T are the predefined lower bounds of confidence level (e.g., 60%), size of order set (e.g., 60 orders in 3 months), and daily volume (e.g., half a truckload) for the examined time period T. In fact, ε_T, υ_T, and $size_T$ can also be defined at product level. A high confidence level indicates a high potential for AS. The minimum order size $size_T$ is required to rule out products which are not frequently ordered. The minimum daily volume υ_T is needed to select products with considerable daily aggregate volumes.

4.3.2 Process redesigns to support operational decisions

Within an AS setting, *AS orders* are defined as the orders of the selected products for AS. The primary difference between AS orders and actual orders is the timing of order processing, i.e., producing and transporting. Actual orders are linked to specific delivery time windows required by customers. Therefore, the time windows to process the actual orders are fixed whereas the supplier can determine when to produce and transport an AS order to the cross-docking facilities. To support this decision, two approaches are proposed in this section. These approaches are based on the nature of the production and transportation processes at the supplier.

4.3.2.1 One-Time AS

With a One-Time AS option, the process of the AS orders (either production process or transportation process) is executed either at the beginning of the working day before the actual orders arrive, or at the end of the working day after processing all the actual orders. In both cases, an increased worker hour rate (labor cost) should be accounted for when quantifying the benefit of this One-Time AS strategy.

This strategy suits the contexts in which the considered process (production or transportation) has a *natural end*, which means the workers start at a fixed time in the morning and stop in the afternoon or evening after processing all the received orders. In reality, it is not uncommon that workers of the production department end their shifts much earlier (due to shorter operating time) than truck drivers of the transportation department, who often work overnight. However, in case where the suppliers use Logistics Service Providers (LSPs) for transportation, the workers of the transportation department (e.g., for making transportation plans and preparing products at the supplier dock) can also have earlier end times.

4.3.2.2 Distributed AS

With a Distributed AS option, the supplier integrates the processing of the AS orders into the processing of actual orders. For the production process, it means that the AS orders are inserted into the production scheduling of actual orders. For the transportation process, it means that the AS orders can be transported in the same truck with actual orders. For example, if three actual orders with the aggregate volume of half a truckload are ready to be loaded, the half-truckload volume of AS orders can be produced, consolidated, and then transported with these orders if time and destination are appropriate. This approach does not require extra truck movements to transport the AS orders and potentially improves transportation costs.

This strategy fits the supplier context in which the considered process (production or transportation) is planned and executed continuously *throughout the day*, which leaves limited time to implement the One-Time AS.

4.4 A multi-agent simulation to assess the benefit of anticipatory shipping for a Dutch horticulture supplier

This section applies the proposed approach to a Dutch ornamental potted plant supplier. This real-world case study demonstrates the performance of the association rule mining in selecting suitable products for AS. Furthermore, the performance of the process redesign options are investigated using a multi-agent simulation.

Multi-agent simulation is an effective simulation method to model dynamic load consolidation in real-time transportation planning (Baykasoglu & Kaplanoglu, 2015). A multi-agent simulation model is developed to assess the performance of the AS approach for the Dutch supplier. The model is implemented in Python using the MESA package (Masad & Kazil, 2015). MESA provides a comprehensive platform for multi-agent simulations with an effective combination of data analytics on large datasets in the association rule mining.

4.4.1 Case description

Blue Plant (not an actual name) is a large-sized Dutch company located in Aalsmeer. The company supplies more than 190 sorts of ornamental potted plants to numerous international and national customers. The orders are placed via an online platform for direct trades between suppliers and customers provided by Royal Flora Holland (RFH) (RoyalFloraHolland, 2019). The ordered products are transported to three RFH cross-dockings from where the products are distributed to the customers' facilities.

Blue Plant receives customer orders from 06.00 to 16.00 on weekdays. On average, around 500 orders are processed every working day. The company promises five-hour lead times for orders to RFH Aalsmeer and six-hour for orders lead times to RFH Naaldwijk and Bleiswijk.

The production process at Blue Plant includes picking plant pots from the supply rooms and placing plant pots in trolleys for transportation. For several customers, labelling is also included. The production department starts at 06.00 and finishes around 18.00 after producing all the received orders.

Blue Plant carries out the transportation using its own fleet of 21 trucks. The company aims to consolidate multiple small orders to improve vehicle utilization. However, due to the short delivery time window, the average truck utilization was approximately 41% in 2017. The truck drivers start at 06.00 and the latest shift ends around 22.00 after transporting all the orders.

4.4.2 Simulation model structure

The simulation model includes a worker agent and a number of truck agents. The worker agent is responsible for receiving orders, scheduling and executing the production process, and planning the transportation process. The truck agents execute the transportation.

Sub-section 4.4.2.1 presents the structure of customer orders and transportation plans, which are modelled as Python class objects. Next, Sub-section 4.4.2.2 describes in details the order processing flow performed by the agents.

4.4.2.1 Customer orders and transportation plans

A customer order O_k is modelled as a tuple

$(P_k, V_k, Des_k, T_k^{arr},\ T_k^{del}, Pro_k^{sta}, Pro_k^{end}, T_k^{ear}, T_k^{lat}, Ser_k)$, where

- *Basic order information.* P_k is the product, V_k is the volume, Des_k is the cross-docking destination, T_k^{arr} is the order's arrival time, and T_k^{del} is the required delivery time.
- *Planning information.* Pro_k^{sta} and Pro_k^{end} is the start and end time of the production time window allocated to the order. T_k^{ear} is the earliest time for loading. T_k^{lat} is the latest time for loading to meet the required delivery time.
- *Performance information.* Ser_k is used to record whether the order is delivered on time or not.

The transportation is planned following the time-quantity load consolidation policy (Baykasoglu & Kaplanoglu, 2011; Zhou et al., 2011). Multiple orders of small volumes can be consolidated into one transportation plan. A transportation plan $Plan_p$ is modelled as a tuple $(Ord_p, V_p, Des_p, T_p^{ear}, T_p^{lat}, Final?_p\ )$, where

- Ord_p is a list of orders to the same destination Des_p contained in the transportation plan. V_p is the aggregate volume of all the orders.
- T_p^{ear} and T_p^{lat} are the earliest and latest time to load all the orders for truck departure. $T_p^{ear} = Max(T_k^{ear})$ and $T_p^{lat} = Min(T_k^{lat})$ for all orders O_k in the list Ord_p.
- $Final?_p$ has values of True or False. True means the plan has met the loading condition and is finalized. False means the plan is available for further load consolidation.

As in the time-quantity load consolidation policy, the loading condition is either the time reaching the latest loading time T_p^{lat} or the aggregate volume V_p reaching a predefined consolidation level, e.g., 50% of a truckload.

4.4.2.2 Order processing flow

This sub-section describes how the production and transportation processes are planned and executed in the current situation and in the two AS scenarios.

4.4.2.2.1 The current situation

The order processing flow starts from order receipt to production planning, to transportation planning, and to transportation executing, as summarized in Figure 4.3.

In every time step of the simulation, the worker agent carries out the following actions: (i) checking for new arriving orders, (ii) processing the received orders, i.e. production and transportation planning in steps 1.1 and 1.2, and (iii) finalizing transportation plans that reach the loading condition in step 2.1. Also in every time step, the truck agents are either executing the transportation plans assigned to them (i.e., step 2.2 and 2.3) or waiting to receive the next finalized transportation plans.

The worker agent processes orders following first-in-first-out policy. For an order O_k, the worker agent determines the production time window as follows:

- Production start time Pro_k^{sta}: if the production line is available at the current time step t , then $Pro_k^{sta} = t$. If the production line is processing another order, for example O_c, then $Pro_k^{sta} = (Pro_c^{end}$ + 1), which is the time step after the order O_c is ready.

- Production end time Pro_k^{end} : Pro_k^{end} is set as $(Pro_k^{sta} + production\, rate * V_k)$, where V_k is the volume of the order O_k. A stochastic production rate (time per truckload) is used.

The production executing step is not explicitly modelled, yet the total production time is recorded. Using the start and end time of production, the worker agent can plan the transportation for the order O_k as follows:

- Earliest loading time T_k^{ear} is calculated as the sum of Pro_k^{end} and a small extra time amount to make sure that the ordered product are ready by T_k^{ear}.

- Latest loading time T_k^{lat} is calculated considering durations of loading, driving, docking, and buffer time (accounts for unexpected delays in production and transportation process):

$$T_k^{lat} = Max\begin{pmatrix} T_k^{ear}\ ,\ (T_k^{del} - Loading\ time - Driving\ time\ to\ Des_k \\ -Docking\ time - Buffer\ time) \end{pmatrix}$$

Figure 4.4 elaborates step 1.2.3 in Figure 4.3, which involves making transportation plans with load consolidation. Following the decision tree and the load consolidation conditions in Figure

4.4, the worker agent determines if the order O_k will be consolidated into an existing transportation plan or if a new transportation plan will be created for it.

In step 2.1, the worker agent finalizes the existing transportation plans that reach the loading condition (time or quantity) described in the end of Section 4.4.2.1. The finalized transportation plans are assigned to available trucks for executing.

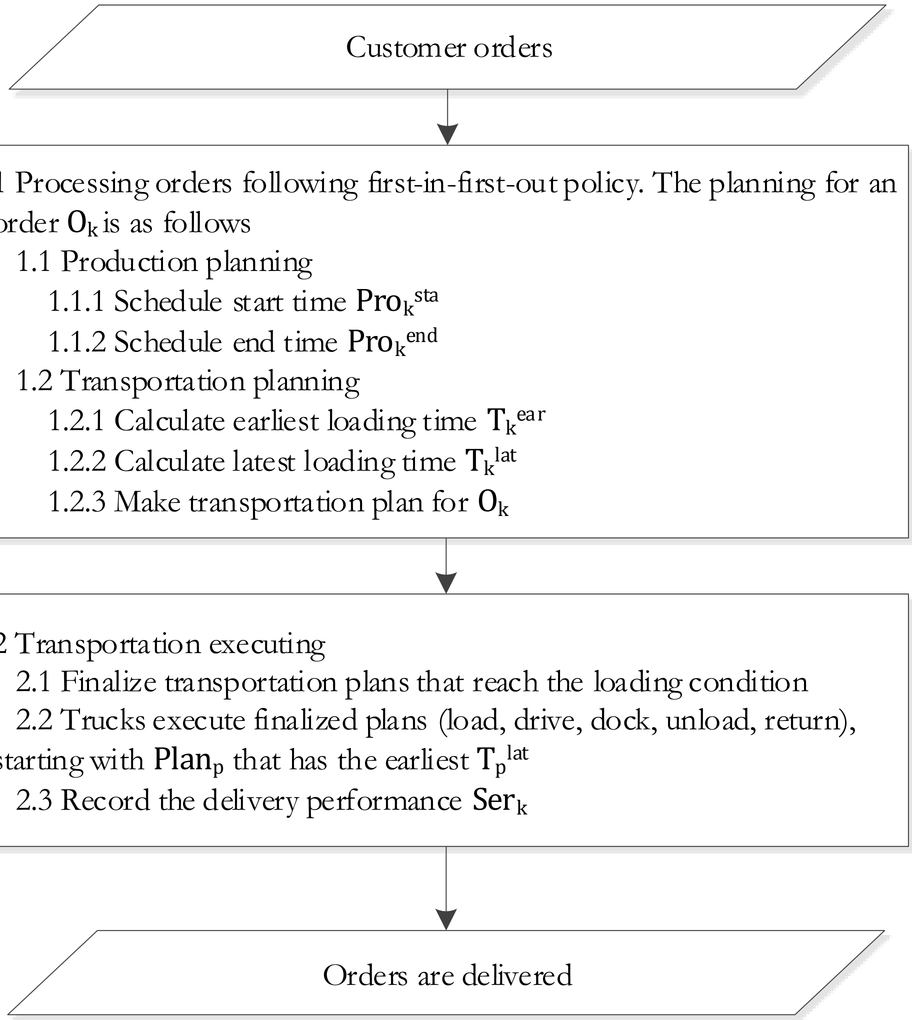

Figure 4.3. Order processing flow in the current situation

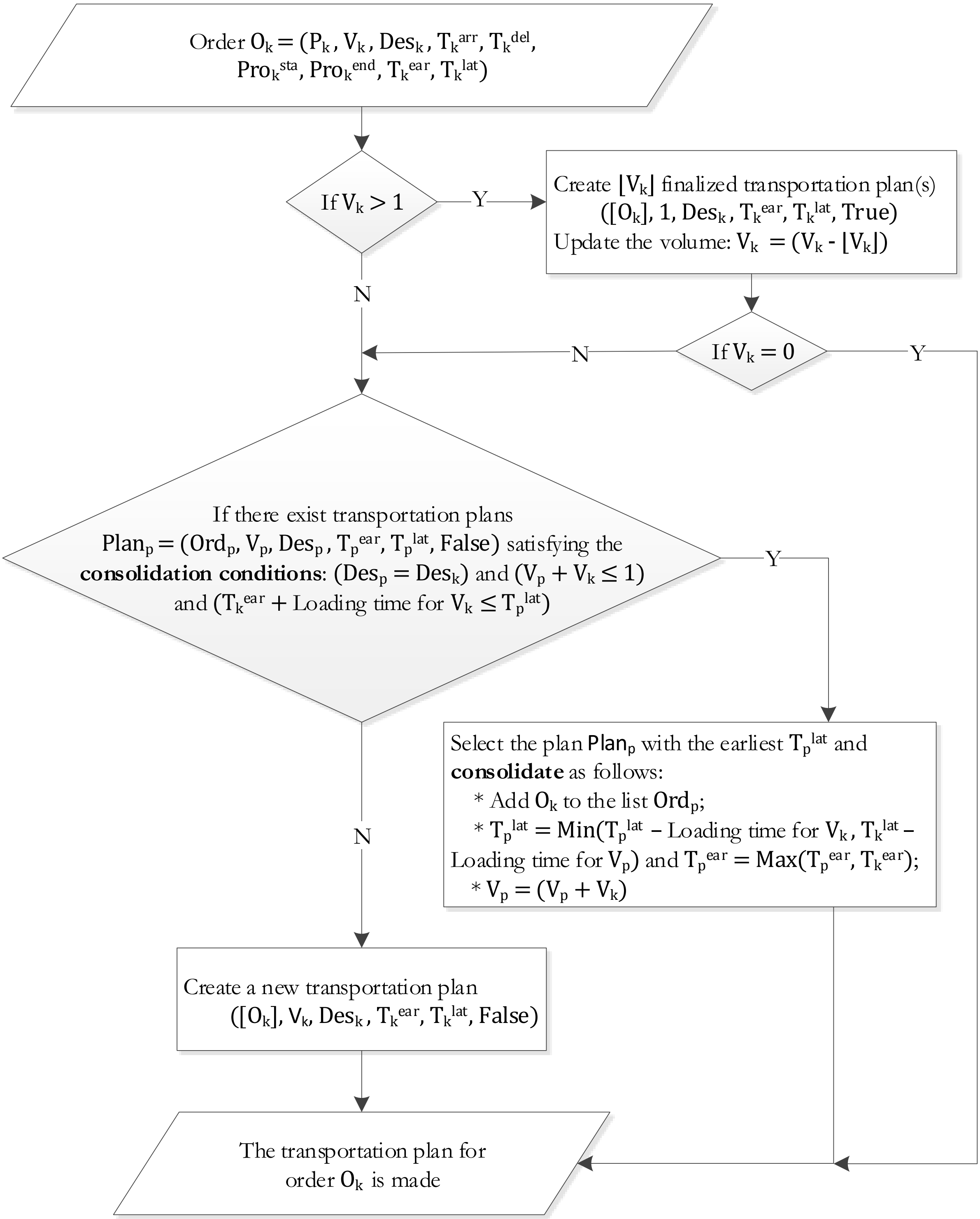

Figure 4.4. Making transportation plan for an order

4.4.2.2.2 Two anticipatory shipping scenarios

Because Blue Plant receives no orders in the weekend and less orders on Friday compared to other weekdays, the AS strategy is implemented from Monday to Thursday. The following paragraphs explain how the production and transportation processes are planned in the AS scenarios.

Production process. In both AS scenarios, the production of AS orders are carried out in the early morning and finished before the official start time (i.e. 06.00). In the One-Time AS scenario, at the beginning of order processing, the worker agent checks if the AS inventory at the corresponding cross-docking can fulfil the orders and accordingly determine the necessary volume for production to fulfil the orders. In the Distributed AS scenario, besides the AS inventory at the cross-dockings, the supplier can also use the produced AS volumes that are not yet transported to the cross-dockings.

Transportation process. In the One-Time AS scenario, the AS volumes are consolidated and transported to the cross-dockings by 06.00. In the Distributed AS scenario, the produced AS orders are gradually consolidated with the not-finalized transportation plans that contain actual orders. The same consolidation condition described in Figure 4.4 is used.

Figure 4.5a and Figure 4.5b extend Figure 4.3 to integrate the production and transportation for AS orders into the processes for actual orders.

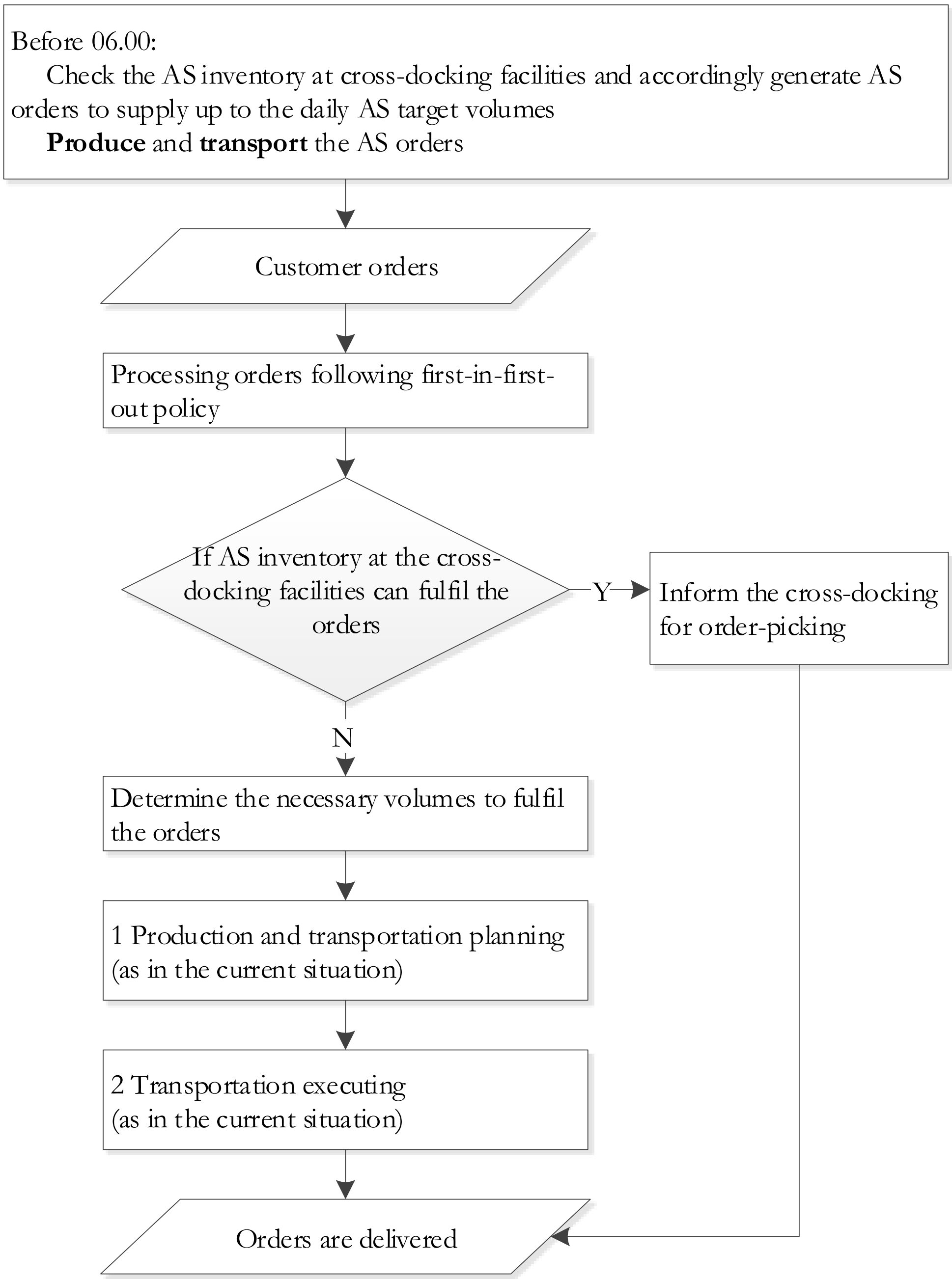

Figure 4.5a. Order processing flow in One-Time AS scenario

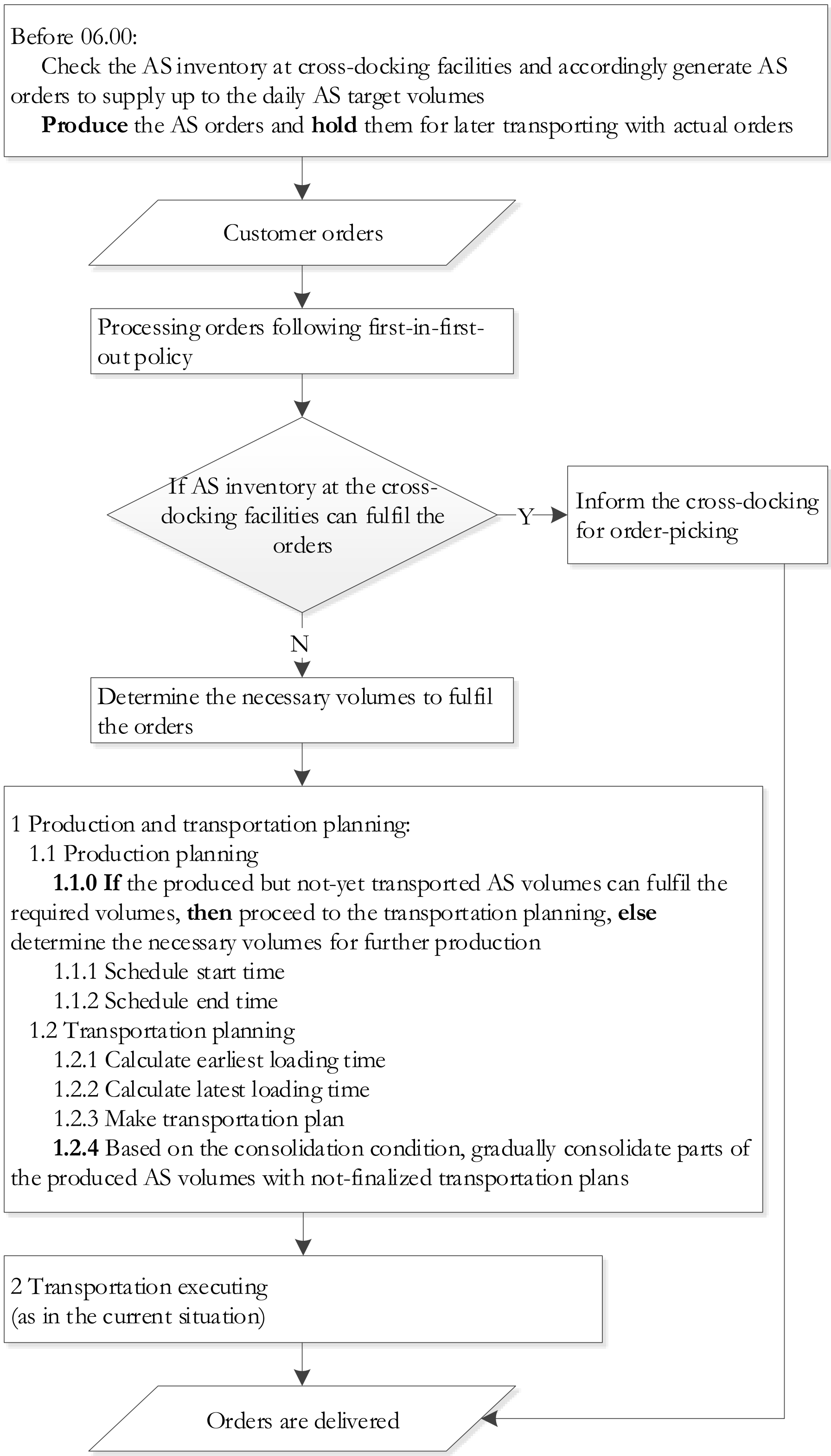

Figure 4.5b. Order processing flow in Distributed AS scenario

4.4.3 Key Performance Indicators

The Key Performance Indicators (KPIs) are defined as follows. Delivery service level represents the delivery performance and the other KPIs are used to measure the operational costs.

- *Delivery service level*. The order sizes vary greatly from less than a quarter of a truckload to more than five truckloads. Measuring the service level by the number of on-time delivered orders would accidentally treat small and large orders equally. Therefore, the percentage of the total on-time delivered volume among the total delivered volume is used to measure the delivery service level.
- *Production time and driving time*. The cost in the production process is the labor cost, which is measured by the production time and the labor hour rate. The cost in the transportation process includes the drivers cost and other variable costs (e.g., fuel), which can be measured by the driving time.
- *Obsolete volume*. Compared to other floriculture products such as cut-flower, ornamental potted plants of Blue Plant have a slow rate of quality decay (de Keizer et al., 2015, p. 64). However, this study imposes a stricter rule on quality decay as AS products that are not ordered after 48 hours become unfit for direct trades, i.e., obsolete. They will be then registered for auction channel organized by RFH with lower expected price (compared to the expected price in direct trades) (Truong et al., 2017). The use of this stricter rule allows to verify if the approach is applicable to general agro-food products with faster quality decay.
- *Holding volume*. To measure the registration and holding cost for AS volumes, the total daily average volumes stored at RFH cross-docking are used, i.e., the average of the daily target AS volume and the volume at the end of a day. This cost exists only in the two AS scenarios.

4.5 Experiment designs and results

Actual orders data from January to June were provided. The five-month orders from January to May serve as the dataset for the time-based association rule mining. Three week orders in June (the weeks that contain national holidays were excluded) serve as input data for the experiment. In this way, the over-fitting issue is avoided in assessing the performance of the association rule mining. The detailed designs and results concerning the time-based association rule mining and the operational processes are discussed in Section 4.5.1 and Section 4.5.2 correspondingly.

4.5.1 Selected products for anticipatory shipping

The lower bound of confidence level ε_T represents the time association between customer orders. It is thus necessary to study the effect of the confidence level on the KPIs. In the time-based association rule mining, ε_T was varied as 60%, 70%, and 80% for all 194 products. The fixed parameters in the association rule mining are as follows.

- $m = 194$ products
- $n = 3$ RFH cross-dockings, i.e., Aalsmeer, Naaldwijk, and Bleiswijk
- $T = 5$ months
- $\tau_i = 24$ hours for all products
- $v_T = 0.5$ of truckload for all products
- $size_T = 100$ orders
- $D = 5$ days as the number of past days in moving average
- Increased rate of labor cost to process AS orders in the early morning: 137%

Table 4.1 shows the aggregate results of the mining output. A higher lower bound of confidence level results in smaller numbers of selected products, which is intuitive. An example of detailed output is shown in Table 4.2.

Taking the confidence level of 80% for example, the maximum total AS volume in three weeks is 37.4 * 4 days * 3 weeks = 448.8 truckloads, which is 45.5% of the total ordered volume during the three weeks. This number indicates that the selected type of products are the major products at Blue Plants and they are ordered frequently.

Table 4.1. The aggregate output of the association rule mining

Lower bound of confidence level	*Number of product types*	*Number of (product, cross-docking) pairs*	*Total daily AS volume (truckloads)*
60%	28	43	64.5
70%	24	37	56.8
80%	15	23	37.4

Table 4.2. Selected products and cross-dockings with confidence level of 80%

Product	*Destination*	*Confidence level*	*Daily AS volume (truckloads)*
Bromelia Cupcake mix	Aalsmeer	89%	3.42
	Bleiswijk	87%	1.24
	Naaldwijk	88%	1.71
Bromelia gemengd	Aalsmeer	87%	4.10
	Naaldwijk	88%	2.93
Guzmania Cupcake mix	Aalsmeer	86%	0.62
	Naaldwijk	87%	1.13
Guzmania Tempo	Aalsmeer	88%	2.17
	Naaldwijk	87%	1.45
Multiflower Astrid	Aalsmeer	82%	1.71
	Naaldwijk	83%	1.02
Tillandsia Anita	Aalsmeer	87%	2.11
	Naaldwijk	86%	1.24
Vriesea Cupcake mix	Aalsmeer	88%	2.00
	Naaldwijk	89%	2.33
Bromelia op hout	Naaldwijk	87%	0.52
Coupe Lisa	Bleiswijk	81%	0.87
Coupe Quito 16cm	Aalsmeer	81%	1.27
Gzumania hope	Aalsmeer	81%	0.98
Multiflower Shannon	Aalsmeer	84%	0.90
Tillandsia Josee	Aalsmeer	81%	0.57
Vriesea Era	Aalsmeer	83%	0.82
Vriesea Style	Naaldwijk	84%	2.28
		Total daily AS volume	37.40

4.5.2 Operational processes in the current situation and the AS scenarios

In the simulation, a time step represents one minute. The production time and the driving time are modelled stochastically. Per each value of confidence level, 100 replicate runs were carried out to obtain narrow confidence intervals. In this way, the average KPIs can be used to report the experiment outcome. Details of parametric settings in the simulation model are shown in Table 4.3.

Table 4.3. Parameter settings in the simulation model

Parameter	*Value*	*Unit*
Consolidation level	50%	truckload
Number of trolleys per truckload	22	trolley
Number of trucks	21	truck
Loading and unloading time per truckload	15	minute
Docking time	10	minute
Extra time in production	5	minute
Buffer time for unexpected delays	30	minute
Production time per truckload	Uniform distribution (10,15)	minute
Driving time to RFH Aalsmeer	Uniform distribution (6,20)	minute
Driving time to RFH Naaldwijk	Uniform distribution (30,70)	minute
Driving time to RFH Bleiswijk	Uniform distribution (30,70)	minute

4.5.2.1 Delivery service level

The total delivered volume during the three weeks is 985.3 truckloads. As shown in Figure 4.6, the delivery service level in the current situation is 61.6%. It is significantly improved in the AS scenarios. The One-Time AS redesign increases the delivery service level by 27.6% (from 61.6% to 89.2%) and up to 35.3% (from 61.6% to 96.9%). With the Distributed AS redesign, the improvement ranges from 19.0% to 23.9%. In both the AS scenarios, the delivery service level decreases as the confidence level rises because a higher confidence level leads to smaller daily AS volumes supplied to the cross-dockings, thus less AS inventory available for direct order fulfilments.

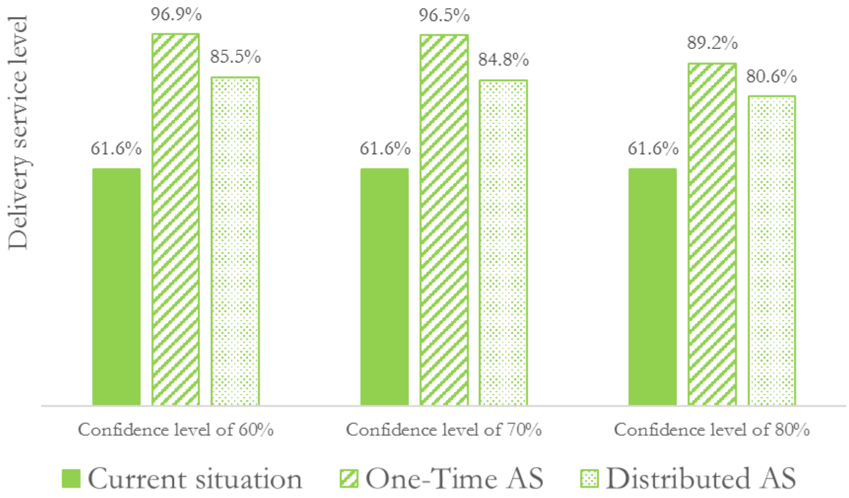

Figure 4.6. Delivery service level in the AS scenarios in comparison with the current situation

4.5.2.2 Production time and driving time

Figure 4.7 displays the time-related KPIs in the current situation and the two AS scenarios. In the two AS scenarios, the production time is inconsiderably different. Compared with the current situation, the AS production times increase slightly by 13.5 hours and up to 32.6 hours. This is due to the extra production for AS orders and the increased rate of labor costs in the early morning.

There are considerable reductions in the driving time. The One-time AS option cuts the driving time by 214.3 hours and up to 254.3 hours. The Distributed AS option leads to larger reductions, i.e., between 378.7 and 453.5 hours, because the AS orders are consolidated with the actual orders in the Distributed AS redesign.

Similarly to the case of delivery service level, as the confidence service level is set higher, the production time and the driving time decreases because smaller AS volumes are produced and transported daily.

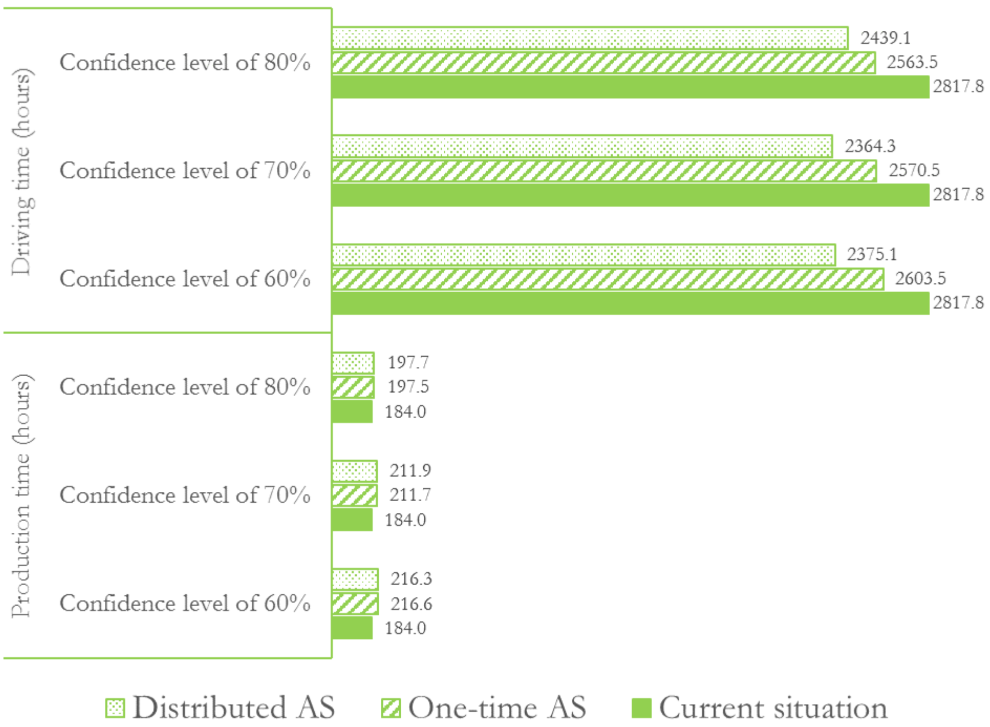

Figure 4.7. Production time and driving time in the AS scenarios in comparison with the current situation

4.5.2.3 Holding and obsolete volumes

In the current situation (non-AS strategy), no holding cost as cross-dockings and no obsolete cost occur. Figure 4.8 shows the holding volume and obsolete volumes in the AS scenarios. In general, because the daily AS volumes become smaller as the confidence level rises, the AS holding and obsolete volumes decrease accordingly. Particularly, the obsolete volume especially falls largely when the confidence level increases from 70% to 80%. This indicates that the inter-arrival time based association is effective to limit the obsolescence in anticipatory shipping for agro-food products. These effects are consistent in both the AS scenarios.

With the confidence level of 80%, the One-Time AS obsolete volume is 4.4 truckloads, approximately 1.16% of the total 379.2 truckloads AS-shipped. In the Distributed AS scenario, the obsolete volume is 13.1 truckloads, approximately 3.74% of the total 350.1 truckloads AS-shipped. These numbers are low even though the simulation model adopted a faster rate of quality decay (Section 4.4.3).

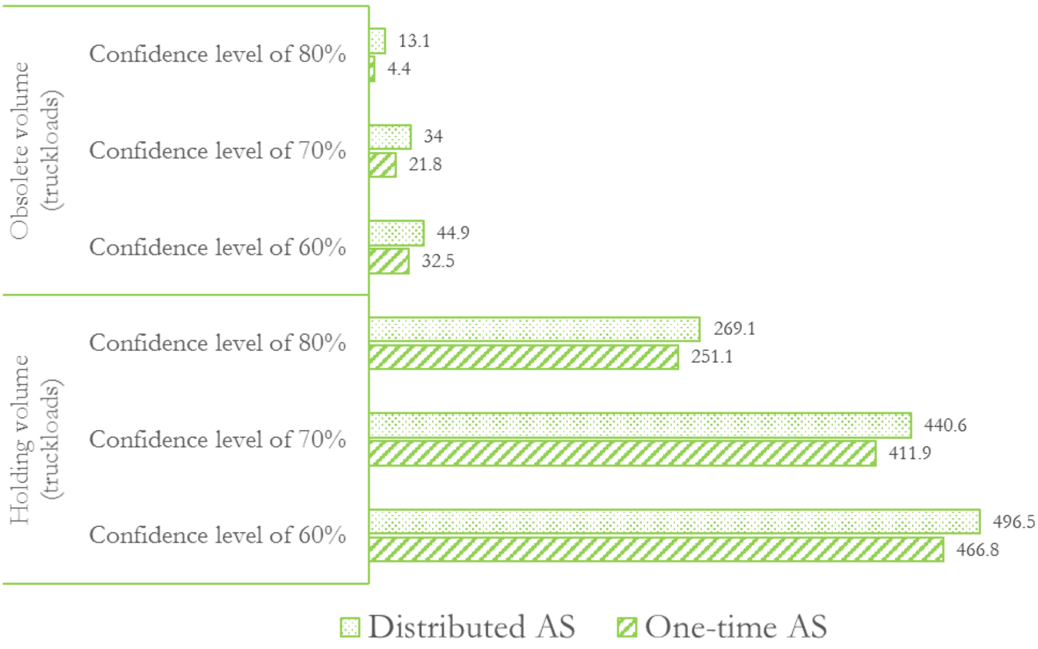

Figure 4.8. Holding and obsolete volumes in the One-time AS and Distributed AS scenarios

4.5.2.4 The effect of confidence level

As discussed throughout the previous sub-sections, the effects of the confidence level on the KPIs point to the trade-off between the delivery service level and other KPIs as summarized in Table 4.4.

Table 4.4. The effect of confidence level on the KPIs and the resulting influences to Blue Plant

KPIs	*As confidence level increases*	*Impact to Blue Plant*
Delivery service level	Decreases	Negative
Production time	Decreases	Positive
Driving time	Decreases	Positive
Holding volume	Decreases	Positive
Obsolete volume	Decreases	Positive

To locate an appropriate lower bound of confidence level in association rule mining, a cost estimation, as a single KPI, for the AS strategy is necessary. For this purpose, the cost structure in Table 4.5 is used. An improved delivery service level in fact can bring unquantifiable benefits such as enhanced relationships with customers. In this case study, the delivery service level is estimated in monetary value using the cost of re-registration and re-distribution for the late delivered trolleys (to fulfil other orders). The cost of obsolete volume is represented by the cost to register and distribute the obsolete volumes in the auction channel. The total cost in the current situation includes late-delivery cost, labor cost in production and transportation process, and variable costs of truck driving. The AS holding cost and obsolete cost are added in the two AS scenarios.

As reported in Table 4.6, the One-Time AS strategy increases the total cost in the current situation by 1.0% at the confidence level of 60%. However, if the confidence level is set to at least

70%, the total cost can be reduced from 3.4% and up to 9.3% at the confidence level of 80% (due to lower production and driving time and lower obsolete volumes). With the Distributed AS option, to obtain a cost reduction of 5.3%, the confidence level must be from 80%. At all parameter combinations, the One-Time AS option outperforms the Distributed AS strategy. What can be concluded here is that the One-Time AS option is more suitable to the current production and transportation processes (and the cost structure) at Blue Plant.

Table 4.5. Cost structure based on consultation with RFH managers

Type of cost	*Value*
Late-delivery cost per trolley	€ 4.33
Obsolete cost per trolley	€ 2.65
Registration and holding cost per trolley per day at cross-docking	€ 3.83
Variable costs per truckload per hour of driving	€ 8.75
Labor hour rate	€ 27.00

Table 4.6. Estimated 3-week cost in the current situation and the two AS scenarios

Confidence level	*Current situation*	*One-Time AS*	*Distributed AS*
60%	€ 141,728	€ 143,081	€ 148,788
70%	€ 141,728	€ 136,894	€ 143,615
80%	€ 141,728	€ 128,530	€ 134,185

4.6 Conclusion and discussion

This study explores the concept of anticipatory shipping (AS) for fresh agro-food products with limited shelf-life and quality decay during supply chain processes. It proposes a data-driven approach to support agro-food suppliers strategically select the right products for an AS setting. To address the product perishability, the approach imposes a time constraint on the inter-arrival time between consecutive orders in the association rule mining. Further, two process redesign options, i.e. One-Time AS or Distributed AS, are discussed to support operational decisions on how to combine the process for AS into the original production and transportation processes.

The association rule mining and the redesigns are applied to a case study of a Dutch ornamental potted plant supplier. Out of 194 products, 15 products are selected for AS at the confidence level of 80% (with the aggregate volume of approximately 45% of the total supply volume by the supplier). The performance of the One-Time AS and Distributed AS redesign options are assessed using a multi-agent simulation, which is developed to capture the dynamic planning of the production and transportation processes for less-than-truckload orders. The simulation output shows a trade-off between the delivery service level and other KPIs related to operational cost such as driving time, holding and obsolete volumes. To the Dutch supplier in the case study, the One-Time AS outperforms the Distributed-AS and provides a potential improvement up to 35.3% for the delivery service level and up to 9.3% for the cost reduction.

This study can be extended with the following aspects. First, only 1PL suppliers were considered in the agro-food supply chain network. In case the suppliers use LSPs for transportation, the same redesign options are applicable, yet several adaptions are necessary. For example, instead of using the delivery time windows, the promised pickup time window by the LSPs should be used to determine the time and consolidation level in the load consolidation policy. Second, each demand point is assumed to be supplied from only one cross-docking center in the region, which is in principle because of the characteristics of the case described in this study. However, for a more generic distribution network, a clustering step is necessary to assign demand points to different distribution centers.

This chapter considers only the process redesigns for AS at agro-food suppliers. Future research can address the process redesigns at the cross-docking to facilitate an effective and efficient service for AS from the network perspective. Aggregate demand on the network level for AS storage and distribution needs to be investigated using the historical order and logistics data. Frequent-patterns based association rule mining can be useful to design the storage policy of AS product from different suppliers. Additionally, because the delivery time windows are expanded for the orders that can be fulfilled by the AS inventory at the cross-docking, the order-picking policy (e.g., picking priority, time, and frequency) can be redesigned to save labor cost and travelling distance. Another interesting research question is how AS can enhance the opportunity for horizontal collaboration in transportation among the suppliers. Small delivery time windows bring a restriction on vehicles' dispatching time in vehicle capacity-sharing based horizontal collaboration. For the transportation of AS orders, the time restriction is no longer applied, thus may it improve the performance of the collaboration. The multi-agent simulation in Section 4.4 can be extended for such the study.

Chapter 5. Value of data in multi-level supply chain decisions: A case of booming data in the Dutch floriculture sector

This chapter is based on a paper submitted to an international journal.

Viet, N.Q., Behdani, B., Bloemhof, J., and Hoberg, K. (2019).

Value of data in multi-level supply chain decisions: A case of booming data in the Dutch floriculture sector.

Abstract

Firms have always collected and used relevant data in supply chain decision-making. Over the last decade, as data significantly increases to big data, firms struggle with decisions on big-data investments because assessing the benefits in return is challenging. To help firms understand the value of data and big data in supply chain decision-making, this chapter presents a multi-level framework that shows how data and the information derived from the data are linked to supply chain decisions at different levels. It highlights the connections within data characteristics, big data's 4Vs (volume, variety, velocity, veracity), information characteristics (timeliness, accuracy, completeness), and decision characteristics. As data increases in one or more Vs dimensions, firms must identify which information characteristics are improved by the increasing data and accordingly reassess the opportunities offered by the information in supporting current and further decisions.

The framework is applied to explore the potential value of the booming data in the Dutch floriculture sector. This case study discusses how the increasing data enhances information characteristics that enables multi-level decisions to overcome logistics challenges. Four analytics applications are introduced to demonstrate how the data is used in four logistics decisions at different time horizons (short- or long-term) and at different supply-chain-level horizons (individual-firm level or supply-chain level). It is observed that each of the big data's Vs is required by different decisions according to the decisions' characteristics. Based on the findings, promising directions for future research are discussed.

5.1 Introduction

For many decades, various types of data collected from supply-chain processes have been used in decision-making. Kuo & Kusiak (2018) conducted an extensive review on how the usage and role of data have evolved from 1961 to 2013. The authors indicate that between 1961 and 1999, data were mainly used to estimate parameters of analytical models, whereas from 2000, the role has shifted toward the discovery of meaningful patterns to support data-driven decision-making. Especially during the last decade, the boom in social media, e-commercial transactions, and advances in data collection technologies such as tracking and sensing devices have significantly changed the shape and role of data in supply chain practice and research (Arunachalam et al., 2018). Data flow in the supply chains has increased sharply not only in volume, i.e., amounts of data being collected and processed, but also in velocity, i.e., the speed of data generation and streaming, and variety, i.e., data types and sources (Govindan et al., 2018; Lim et al., 2018). This phenomenon has resulted in the widely discussed term big data. Veracity and value are the other two Vs mentioned in the literature that link big data to decision-making in supply chains (Assunção et al., 2015; Zhong et al., 2016). Veracity refers to the accuracy and reliability of big data and value concerns the process of realizing the benefits from using the information extracted from big data in specific supply chain decisions (Addo-Tenkorang & Helo, 2016; Nguyen et al., 2018).

Scholars and practitioners seem to agree on the vast opportunities offered by big data for improvements in supply chain processes (Mikalef et al., 2017; Samuel et al., 2018). The eagerness around big data has encouraged firms to move forward with big data strategies or risk lagging behind in the competition with rival firms (Frizzo-Barker et al., 2016; Richey et al., 2016). However, these often involve substantial investments in infrastructures that capture, store, and stream the big data and/or on human resource (analytics) capacity to manage and make use of big data (Schoenherr & Speier-Pero, 2015; Liu & Yi, 2017). As a result, it is not uncommon to see firms of all sizes struggling with these investment decisions because examining the expected benefits in return, i.e., the value of big data, is complicated. Zhong et al. (2016) argue that the value of reports, statistics, and decisions obtained from big data is hard to measure due to large influences at micro and macro levels. In fact, many big data projects generated disappointing returns on investment according to a survey by Gartner in 2016 (Grover et al., 2018). Therefore, structured methods to assess the expected value of big data are essential to help firms understand the value of big data and rethink their big-data investment decisions.

The extant literature provides several frameworks based on different perspectives to assess the value of big data in supply chain decisions. Sanders (2016) presents a systematic framework to determine the business value of big data along the four primary processes in supply chains: sourcing, making, moving, and selling. Brinch (2018) conducts a content-analysis-based literature review of 72 articles. From a business process perspective, a conceptual big data supply chain management framework is then proposed following three dimensions of value discovery, value creation, and value capture. The author suggests that the value creation of big data depends on the ability to utilize the information generated from the big data for strategic or operational decision-making. Grover et al. (2018) reason that the value of big data is created through the combination of insight generation and its actual use in specific business decisions. The authors introduce a framework of strategic value creation by big data analytics that links big data analytics to six value creation mechanisms, i.e., transparency and access, discovery and experimentation, prediction and optimization, customization and targeting, learning and crowdsourcing, and continuous monitoring and proactive adaptation. Readers are referred to these articles for an overview on value creation of data.

From supply chain process improvement perspective, this study aligns with the above-mentioned frameworks that big data creates value through supporting supply chain decisions, which are turned into actions for impact. To complement these frameworks, the objective of this study is to reveal in which way data and big data are actually linked to strategic and operational supply chain decisions. Furthermore, it aims to show how the approach to utilize big data in decision-making should be adapted from that of (small) traditional data. For these purposes, this study presents a multi-level framework based on a data-information-decision perspective. The framework stresses the underlying connections within data characteristics, information characteristics, and multi-level decision characteristics. Each element of the framework is examined first in the traditional data context and then in the big data context. This way discloses how big data and its Vs can improve the framework's elements, especially the characteristics of the information derived from the data, to create further value in supporting supply chain decisions. Accordingly, firms can identify essential elements to improve so that firms can avoid missing business opportunities and unnecessary investments in inessential elements in the transition from data to big data.

The framework is illustrated by a case of the booming data (to big data) in the Dutch floriculture sector. This case study focuses on decision making to overcome logistics challenges in the sector. Four analytics applications are presented to demonstrate how the data is transformed and used in four logistics decisions at different levels. The decisions improve logistics performance not only of individual firms but also of the supply chains and sector through supply chain collaboration and coordination. Understanding the multi-level value of the data reinforces the commitment of bottom-up timely and accurate data contribution from firms in the supply chains.

The rest of this chapter is organized as follows. Section 5.2 introduces the multi-level framework. Section 5.3 describes the case study and how the framework is applied to connect the booming data to the decisions. Section 5.4 presents in details the analytics applications. Section 5.5 concludes our study and discusses future research directions.

5.2 The value of data and big data in supply chain decisions

This section relies on the existing studies in the literature on the value of (big) data to introduce the multi-level framework. Relevant (not exhaustive) studies are referred in the discussions on each element of the framework. First, the framework is elaborated in the context of traditional data. The section continues with how the elements of the framework are affected as data increases to big data with the influences of big data's 4Vs, i.e., volume, variety, velocity, and veracity.

5.2.1 The data-information-decision multi-level framework

Data-information-knowledge is a well-known concept in the field of information science (Zins, 2007). Data are patterns without meaning and data become information after being interpreted for a decision-making purpose; a collection of useful information, in turn, makes valuable knowledge for decision makers in the supply chains (Lumsden & Mirzabeiki, 2008). Here, information and knowledge are merged into one single construct, i.e., *information*. Through decision-making, actionable information is turned into actions to improve supply chain processes (Grover et al., 2018). Accordingly, assessing the value of data requires making the connection within the data, the information derived from the data, and supply chain decisions (Hofmann, 2017; Janssen et al., 2017). Information is extracted from the data using descriptive and predictive models; information becomes the input of prescriptive models (e.g., simulation, optimization) in the decision-making process that outputs decision(s) (Delen & Demirkan, 2013).

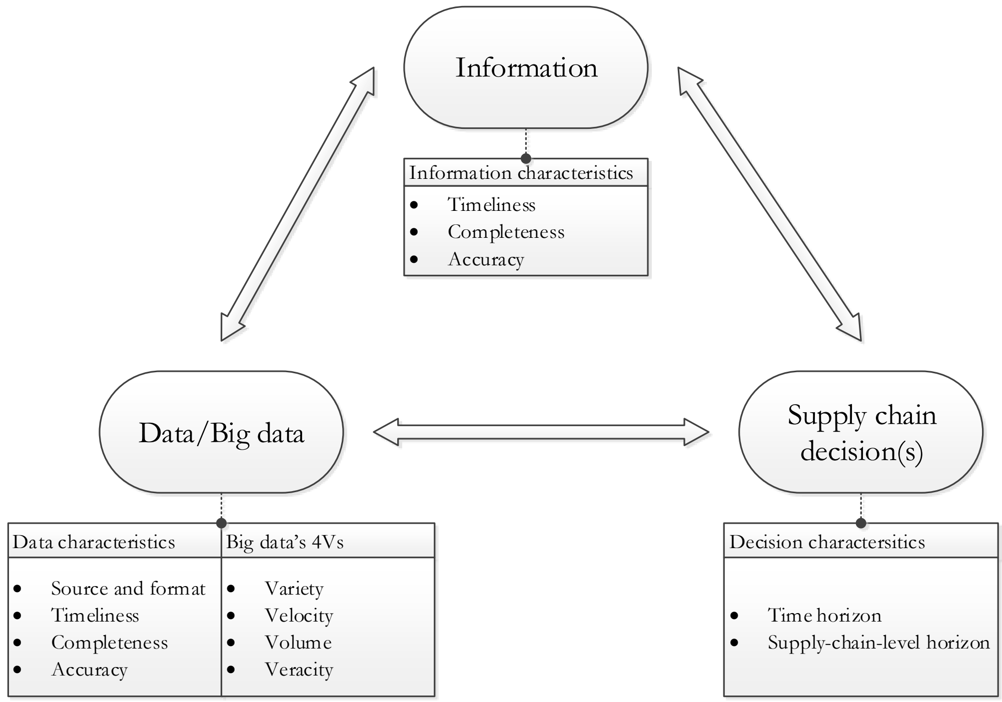

Figure 5.1. The multi-level framework based on data-information-decision

As shown in Figure 5.1, the underlying connections within data, information, and decisions are determined by the association among data characteristics, information characteristics, and decision characteristics. Decision makers iteratively look for data/information and decisions that match in characteristics because a decision with specific decision characteristics requires data/information with specific data/information characteristics (Jonsson & Myrelid, 2016; Viet et al., 2018a). The following paragraphs elaborate on the decision characteristics and data/information characteristics.

The supply chain literature commonly defines decisions on the strategic, tactical, and operational time horizon. To show different characteristics of supply chain decisions, decisions are structured on a time horizon and a supply-chain-level horizon (Figure 5.2). Concerning the time horizon, for simplicity, two groups are specified for long-term (i.e., strategic and tactical) and short-term (i.e., operational and real-time) following Wang et al. (2016b). The supply-chain-level horizon includes an individual-firm level and a supply-chain level. Decisions at the supply-chain level involve multiple firms and concern the coordination and collaboration in supply chain processes (Hazen et al., 2016).

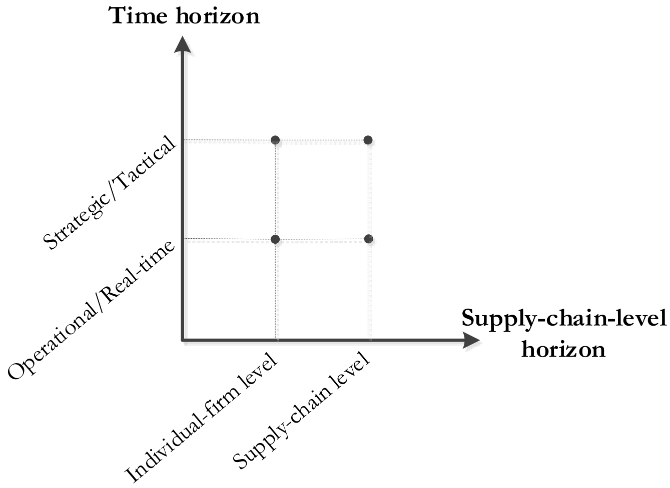

Figure 5.2. Supply chain decisions based on time and supply-chain-level horizons

As information is the output of data processing, information characteristics are linked to data characteristics. Following Hazen et al. (2014), the essential data characteristics in decision-making are referred to as data timeliness, data completeness, and data accuracy. These three intrinsic data characteristics directly affect the three intrinsic characteristics of information, i.e., information timeliness, information completeness, and information accuracy, which together determine the relevance and value of the information to a specific decision. Timeliness indicates how well the information meets its user's demands in a particular time and space. Completeness refers to the breadth and depth levels of the information granularity. Accuracy defines how the information reflects the underlying reality. Readers are referred to Viet et al. (2018a) for an extensive review on the impact of information characteristics on the value of information.

5.2.2 From data to big data

As data increases to big data, the data characteristics in Figure 5.1 are commonly perceived as big data's 4Vs, i.e., volume, variety, velocity, and veracity (Govindan et al., 2018). The following paragraphs address how other elements of the framework, especially the information and decision characteristics, are enhanced in the transition from data to big data.

In many cases, descriptive, predictive, and prescriptive models may need to be extended to their big data versions to handle large datasets from heterogeneous sources, and in a real-time manner (Choi et al., 2018). For example, a study by Wang et al. (2016a) reported the challenges in distribution network design when the volume of data flowing between the network nodes increases tremendously at a fast rate. The authors introduced a robust big data network design (prescriptive) model that uses both the historical and the most up-to-date operational and behavioral data from the network nodes. Furthermore, the roles of descriptive and predictive models in the case of big data have been expanded from supporting parameter setting for prescriptive models to pattern discovery, classification, and clustering (Choi et al., 2018).

Fosso Wamba et al. (2018) report that the characteristics of the information extracted from big data are directly influenced by the big data's 4Vs. Regarding information timeliness, big data are captured from various supply chain processes in real-time in many cases (Singh et al., 2016; Kaur & Singh, 2017; Kim et al., 2017). This enables the generation of information for smaller intervals and at higher frequency. In the case of demand forecasting, it is necessary to consider different time horizons of the forecasts with big data because the forecast information can become available from daily to hourly and real-time (Hofmann & Rutschmann, 2018). A new concept, "nowcast", is proposed by See-To & Ngai (2016) as real-time forecasting based on real-time big data streaming. Nowcast is useful to supply chain managers as most of their decisions are concerned with day to day business processes and hour to hour operations. Nevertheless, real-time big data availability must be accompanied by suitable big data analytics models that process and analyze the data within a reasonable computational time (Wolfert et al., 2017).

With regard to information completeness, big data can improve the depth (i.e., more granular) and broaden the breadth of the information (i.e., from intra-organizational to inter-organizational). For instance, tracking and tracing systems can be implemented at a smaller unit level (e.g., truck level to batch level) and for a wider scope covering more participating supply chain firms (Dai et al., 2015). The same trend applies to inventory and resources tracking on a manufacturing shop floor and warehouses and significantly improves the level of information detail (Zhong et al., 2017). Another example relates to information from consumers. Online clickstreams data and consumers' reviews and sentiments from social media and online sales provide additional information (besides order information) that provides firms with more insights about the customers (Huang & Van Mieghem, 2014; Chong et al., 2016).

Concerning information accuracy, data capture by tracking and sensing devices can offer a higher level of data and information accuracy. Many types of data that were previously inaccessible or inaccurate due to economic or technical reasons become available and reliable. Examples include massive data on traffic conditions from sensors (Li et al., 2015), massive data on speed in urban areas (Ehmke et al., 2016), and networked sensor data (Li & Wang, 2017). Big data descriptive and predictive analytics also contributes to identifying noise/abnormal data and higher forecasting accuracy (Lamba & Singh, 2017).

With regard to decision characteristics, the current literature reports many big-data enabled decisions that address short-term process improvements with the aim of long-term values in the future (Richey et al., 2016; Kuo & Kusiak, 2018). With regard to the time horizon, improved information timeliness and completeness support short-term decisions, and enhanced information completeness and accuracy allow long-term decisions. With regard to the supply-chain-level horizon, the current literature has focused on exploiting the value of big data to improve processes only within individual chain firms (Barbosa et al., 2017). However, with improved information characteristics, especially information completeness, decision makers are able to consider decisions that involve multiple firms in either vertical or horizontal relationships. Based on well-established theories, such as actor network theory and resource dependence theory, Hazen et al. (2016) suggest that big data can upgrade interconnected supply chain processes toward higher efficiency, effectiveness, and sustainability. Consequently, the value of big data at both individual-firm level and supply-chain level should be investigated.

Overall, the characteristics of the information derived from big data determines the link between the big data and supply chain decisions. Big data's 4Vs enhance information characteristics, which make the information relevant and useful to broader supply chain decisions (that are not considered before). In practice, big data discussions often start with the question if a body of data is qualified as big data considering the conditions on volume, variety, velocity, and veracity (Roden et al., 2017; Brinch et al., 2018). More important than determining the terminology, the message based on the framework is that when data increases in one or more Vs direction, supply chain firms must identify the enhanced information characteristics. This helps to realize how the current decisions can be better made or to consider further decisions that can be supported by the enhanced information.

5.3 Exploring the value of big data in the Dutch floriculture sector

This section demonstrates the data-information-decision multi-level framework. It first describes the logistics processes and challenges and the big data in the Dutch floriculture sector. Subsequently, the framework is applied to assess the potential value of the data.

5.3.1 Case description

The Dutch floriculture sector is a vibrant sector with a long tradition. It consists of approximately 6000 (inter)national small, medium, and large suppliers (i.e., growers), 2500 customers (i.e., wholesalers, exporter, retailers), 70 logistics service providers (LSPs), and five auction and distribution sites (RoyalFloraHolland, 2019). Among these actors, Royal FloraHolland (RFH) plays a key role in the auction and logistics processes.

There are two major types of physical flows in the network. Auction flows are for products sold via auction clocks. Direct flows refer to products sold via direct transactions between suppliers and customers. The volume of direct flows has increased substantially in the last 5 years to approximately 57% of sales volume in 2017 (RoyalFloraHolland, 2019). The case study in this study is about the logistics processes of direct flows. RFH has five cross-docking facilities located in different supplier regions and offers cross-docking distribution for direct flows. Figure 5.3 depicts the logistics processes.

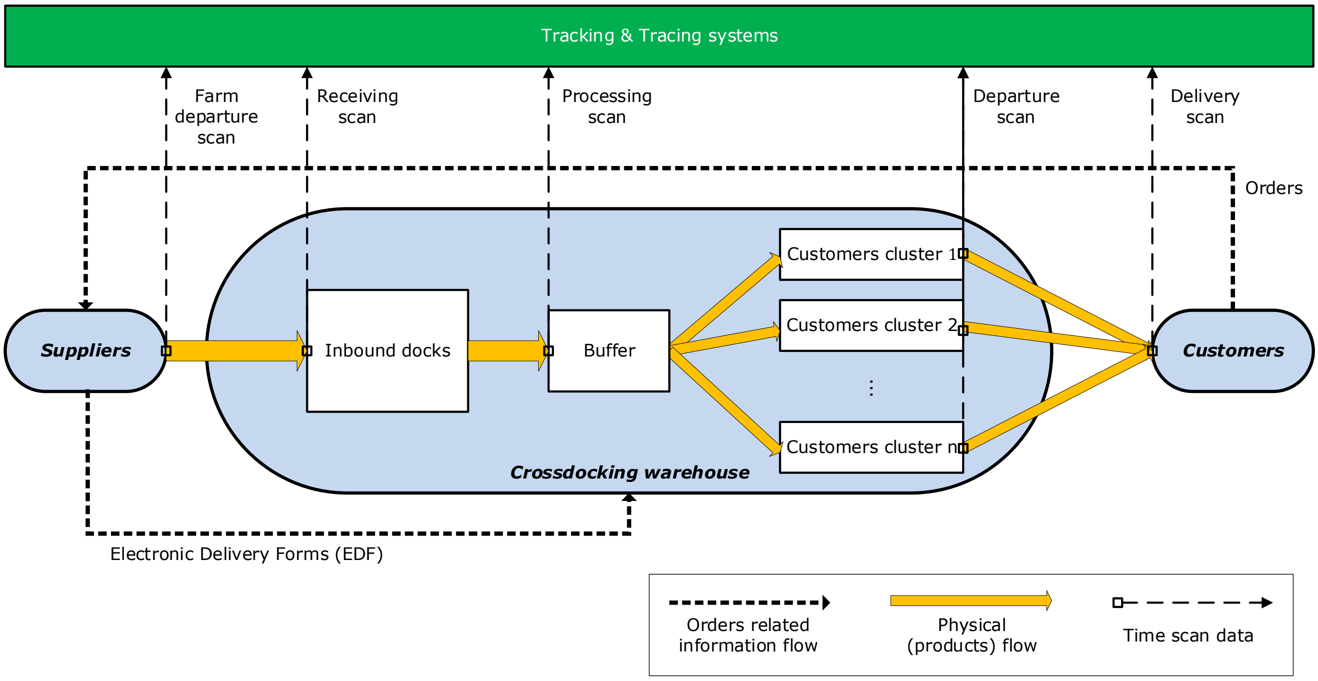

Figure 5.3. Physical and information flows in the logistics processes of direct flows.

5.3.1.1 Data flows

5.3.1.1.1 Orders and electronic delivery forms

Customers send orders to suppliers via an online trading platform. Suppliers send ordered products in trolleys to RFH cross-docking. To facilitate the cross-docking service, information flows must move ahead of physical flows (Buijs et al., 2016). Suppliers are required to send an electronic delivery form (EDF) for each order, in advance to trolley arrivals, stating supplier information, product quantity, and delivery destination.

5.3.1.1.2 Tracking and tracing systems

As a step toward supply chain virtualization (Verdouw et al., 2013), radiofrequency identification (RFID)-enabled tracking and tracing systems have been implemented since 2016. Suppliers and customers have access to the systems to trace product location at the trolley level. Trolley scans are made at the following points: departing from suppliers (farm departure scan), arriving at inbound docks (receiving scan), processing at the buffer (processing scan), departing from customer clusters (departure scan), arriving at customer boxes (delivery scan). The farm departure scan began in November 2017 as a pilot project, and data from that are currently limited.

5.3.1.1.3 Data to big data

The data in this case study concerns the data of direct flows including (i) historic and real-time EDF data of direct flows and (ii) the scan data captured at all stages in the supply chain network. The direct-flows data increases rapidly with regard to volume, variety, and velocity dimensions due to the increasing number of daily transactions among a huge number of suppliers and customers, and also due to the broader implementation of tracking and tracing across the sector. Section 5.3.3 assesses the potential value of this big data.

5.3.1.2 Physical flows

Suppliers send ordered products by trucks to RFH. The transport is executed by LSPs or by the suppliers themselves as first-/second-party logistics (1PL/2PL). Around 30% of Dutch suppliers are 1PLs. RFH is responsible for distributing the trolleys to customers within 1 hour from the receiving point at inbound docks. Trolleys arriving at RFH at the weekend or outside 04.00–16.00 hours on weekdays are not bound to the time constraint. The case study concerns only the trolleys with a 1-hour limitation. Different from traditional cross-docking where products are brought from inbound to outbound trucks, in this case unloaded trolleys are moved to a processing buffer. From the buffer, trolleys are moved to different customer clusters. From the clusters, tractor drivers transport the trolleys to the customer boxes (5–10 minutes driving).

5.3.2 Logistics challenges

The following sections describe the major logistics challenges for suppliers and RFH where the potential decisions enabled by the big data can be made to create business value.

5.3.2.1 Suppliers

Customers in general agro-food supply chains increasingly order small quantities of diverse products and even with small required lead times (Viet et al., 2018b). In the Dutch sector, less-than-full trolley orders and 4-hour order lead times have become a new normal. To meet the short delivery time, the Dutch 1PL/2PL suppliers have to load and dispatch their trucks as soon as the products are ready. Therefore, they do not have enough time to effectively consolidate multiple less-than-truckload orders. Similarly, time-related difficulties also arise for the LSPs in scheduling trucks to pick up multiple less-than-truckload loads. This leads to low truck utilization and a high number of truck movements in the areas around the Dutch floricultural greenhouses (de Keizer et al., 2015). In-time delivery and higher truck utilization (thus lower transportation cost) are the challenges for suppliers.

5.3.2.2 Cross-docking operators

To assure 1-hour delivery, cross-docking operators must schedule an appropriate number of workers at each distribution stage per time period. Ladier & Alpan (2016) show that workforce scheduling is actually the most significant problem for cross-docking managers. Uncertainty about the volume and timing of inbound arrivals and a broad range of operating hours complicate workforce scheduling. Cross-docking terminals often require suppliers to provide information on estimated product arrival time to proactively schedule the necessary workforce (van der Spoel et al., 2017). However, Van Belle et al. (2012) indicate that in real-life situations, there are serious deviations between the estimated and actual information. Thus, predictive models play a crucial role in cross-docking workforce scheduling. In the Dutch sector, the estimated arrival time of trucks is not even available in the EDFs. This causes high uncertainty about the inbound flows and makes workforce scheduling a big challenge.

5.3.3 The potential value of big data to overcome logistics challenges

Using the framework, the big data is mapped to potential decisions that can help Dutch firms to overcome their logistics challenges. The focus is on how these decisions become possible with the increasing data. The decisions are organized following the two-dimensional decision structure in Figure 5.2. Sub-sections 5.3.3.1 and 5.3.3.2 discuss the decisions at the individual-firm level and supply-chain level correspondingly. Both short-term and long-term decisions are addressed for each level.

5.3.3.1 Individual-firm level

The increase in data at individual suppliers is limited compared with the amount of aggregate data at cross-docking. This sub-section focuses on the RFH cross-docking.

5.3.3.1.1 Short-term: decision 1

The current challenge for cross-docking is workforce scheduling. The literature provides workforce scheduling models that address strategic/tactical scheduling (Bard, 2004; Defraeye & Van Nieuwenhuyse, 2016) and daily scheduling with fluctuations in demand volume and arrival time (Lusa et al., 2008; Steinker et al., 2017). For these levels of demand aggregate, the added value of big data is not clear because traditional approaches are still applicable. The major contribution of big data, as discussed by See-To & Ngai (2016), is the capability to enable "nowcast" with acceptable accuracy to support real-time workforce adjustment decisions. According to two recent literature review articles on cross-docking logistics (Ladier & Alpan (2016); Van Belle et al. (2012)), real-time big data predictive applications for cross-docking decisions are limited but highly necessary to support regular real-time decision-making. Section 5.4.1 presents a big-data predictive model using historical time scan data, and historical/real-time EDF data to forecast the inbound volume at a smaller time horizon, i.e. hourly, to support real-time workforce adjustment decisions. In the application, the big data's variety, velocity, and veracity (i.e., reliable historical time scan data, real-time and historical EDF data from all suppliers) help to improve the timeliness and accuracy of forecast information.

5.3.3.1.2 Long-term: decision 2

Big data improve the insights into business activities in the sector. Accumulated EDF data allows RFH to rethink their role in the sector and provide new services. A new service concerning the temporary storage and fulfilment by cross-docking is introduced as follows.

Short order lead times and frequent small orders lead to low truck utilization, limited delivery time windows, and high daily truck movements. In addition, buyers often order the same products every day or even at two different periods in the same day. A potential strategy for suppliers is to pre-ship their products to temporary storage facilities at RFH cross-docking, from where near-future orders can be fulfilled directly. The pre-ship strategy is also known as anticipatory shipping in the literature (Lee, 2017).

RFH needs to decide on storage design/space and logistics processes to facilitate the pre-ship strategy. The historical data can support this strategic decision. Having detailed EDF data at the product level from thousands of suppliers, RFH can use the data to estimate the storage and fulfilment demands for each supplier and the aggregate demand for the whole supply chain network. In this decision, the volume and variety of the data improve the completeness of the information on potential suppliers for the new service. Section 5.4.2 presents the analytics to support this strategic decision.

5.3.3.2 Supply-chain level

At the supply-chain level, the value of the big data is linked to decisions that facilitates the coordination and collaboration among the Dutch firms.

5.3.3.2.1 Short-term: decision 3

At the operational/real-time decision-making level, the value of the data is created through better supply chain visibility, which enables effective and efficient process coordination. Two specific coordination issues are identified.

First is the coordination between suppliers and the cross-docking with regard to inbound scheduling (i.e., truck scheduling/sequencing and truck-to-door assignment). When the farm departure scan is implemented network-wide, dynamic inbound scheduling becomes more efficient with real-time updated truck departure times and real-time estimated truck arrival times. The important big data characteristics in this coordination are velocity, i.e., real-time time scan data. The data velocity is able to enhance the timeliness of information on the inbound flows. This type of operational decision has been studied in the literature, see for examples studies by Maknoon et al. (2017), and Ladier & Alpan (2018).

Second is the coordination between cross-docking and customers. Cross-docking aims to distribute all inbound trolleys within 1 hour. However, in many circumstances, customers do not have enough capacity (e.g., conditioned storage, workers) to hold and process a high volume of products arriving in a short time, which results in long trolley queue in front of the boxes and then quality decay occurs. Cross-docking can postpone the delivery when the customer boxes are fully occupied. This not only helps to avoid quality decay of the product but also provides more time to distribute other trolleys, which can improve the service level of the distribution processes. This type of coordination can be facilitated by timely communication between numerous customers and cross-docking operators, and real-time trolley scan data at inbound docks. The key characteristics here are data velocity, information timeliness, and information completeness. Section 5.4.3 describes a coordination system based on tracking and tracing and a simulation to demonstrate the benefit resulting from coordination.

5.3.3.2.2 Long-term: decision 4

At the strategic decision-making level, the data can support the horizontal collaboration in transportation among the Dutch suppliers.

Horizontal collaboration in transportation is a promising method to improve truck utilization, reduce transportation costs, and increase service level (Cruijssen et al., 2007). At the network level, collaboration reduces the workload at the consecutive supply chain stage (i.e., truck docking at cross-docking), reduces truck movements and road congestion, and improves the sustainability of the sector. Many unsuccessful attempts by the Dutch 1PL/2PL suppliers were made to collaborate horizontally on sharing truck capacities, i.e., on the way to RFH, supplier A picks up the products of supplier B if the truck is not full. In 2017, RFH conducted interviews with the suppliers to gain insights into the factors that hindered the collaboration. Time limitations and limited information on potential parties to collaborate were identified as the two determinant factors.

The missing information on potential parties with strategic fit for collaboration and the time limitation can be tempered using historical tracking data. To answer the question "with whom to collaborate", several dimensions can be used to measure the fitness, including company characteristics, companies' internal processes, external parameters, geographic and cultural similarities (Naesens et al., 2009). In this case study, the time dimension is crucial. Due to the short delivery time window, suppliers need to know who the specific suppliers are whose products frequently share the same delivery time windows as their products to establish an effective and efficient collaborating protocol. Section 5.4.4 introduces a descriptive analytics using historical tracking data to discover sets of strategic-fit suppliers who can potentially collaborate with each other. It is important to have data on numerous suppliers in the analytics. In this application, the volume and variety of the big data help to improve the information completeness.

5.3.3.3 Summary of the decisions

Table 5.1 summarizes the four decisions. In all the decisions investigated, the data variety (i.e., data sources, data types) seems to play the most important role in improving the information characteristics. In the decisions involving multiple supply chain actors (i.e., decision 2, 3, and 4), information completeness, i.e., the coverage of the information, becomes critical. Another observation is that not all big data's 4Vs are necessarily required in every decision. Specific decisions appreciate specific big data characteristics. The next section presents the analytics models that support the four decisions.

Table 5.1. Characteristics of the decisions and their connections with big data characteristics and information characteristics

	Decision 1. Real-time workforce adjustment at cross-docking	**Decision 2.** Strategic design of storage and fulfilment service at cross-docking	**Decision 3.** Delivery postponement in real-time process coordination	**Decision 4.** Strategic partner selection in horizontal collaboration
Decision characteristics				
Strategic/tactical		X		X
Operational/real-time	X		X	
Individual-firm level	X	X		
Supply-chain level			X	X
Information characteristics				
Timeliness	X		X	
Completeness		X	X	X
Accuracy	X			
Big data characteristics				
Volume		X		X
Variety	X	X	X	X
Velocity	X		X	
Veracity	X			

5.4 Four analytics applications to support logistics decisions in the Dutch floriculture sector

This section includes four parts that describe the analytics models to support the four decisions summarized in Table 5.1. All the analytics work was implemented in Python using CORE i5 computer. Through each part, readers can see how the data are transformed and used in the descriptive, predictive, and prescriptive models, and especially how and which data and information characteristics are linked to the decision characteristics.

5.4.1 Real-time workforce adjustment at cross-docking

The major challenge in daily workforce planning is to schedule the right number of employees at the peak hours. The historical data (Figure 5.4, units: trolleys) reveals four frequent peaks at 07.00, 10.00, 11.00, and 14.00 hours. However, the inbound volumes at these peaks vary widely, which causes difficulty in determining the required workforce. Taking the peak at 14.00 hours for example, it is usually the highest and the most fluctuating with a mean of 158 trolleys and standard deviation of 55 trolleys. This deviation can result in the difference of ± 3 workers. The operator needs a timely forecast with acceptable errors, i.e., information timeliness and accuracy, on how many trolleys will arrive between 14.00 and 15.00 hours. For demonstration purpose, the modeling aim is formulated specifically for the peak at 14.00–15.00 hours as "to forecast the arrival volume between 14.00 and 15.00 hours given the forecasting moment at 13.00 hours, assumed that 1 hour is enough to request additional employees (e.g., from the auction department)".

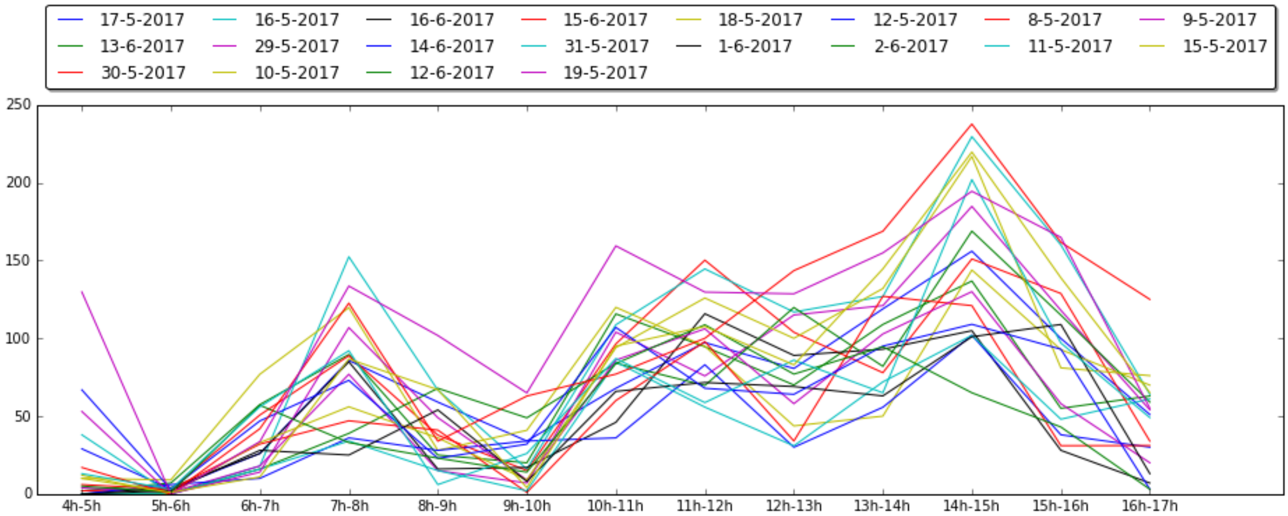

Figure 5.4. Inbound volume per hour in high season.

5.4.1.1 *k*NN-based forecasting model

The *k* nearest neighbors (*k*NN) algorithm is selected because it is intuitive and easy to communicate model parameters and output. The algorithm searches in historical databases for *k* dates that share the highest similarity with the target date and use those dates as references for calculating the forecast (Wu et al., 2008). The following explains the most important features of the *k*NN model.

5.4.1.1.1 Similarity function

The historical time scan data helps to trace backward the EDF registration time of trolleys arriving between 14.00 and 15.00 hours. It is observed that most of the 14.00-15.00 trolleys have been registered in the EDF database within 7 hours before their arrivals. As the decision-making moment is at 13.00 hours, the total registered volume per hour in the EDF database from 06.00 to 13.00 hours are selected to model the similarity function, denoted as $x_1, x_2, \ldots, x_7$. A non-weighted Euclidian-distance-based similarity function $S(D^a, D^b)$ between two dates D^a and D^b is defined as $S(D^a, D^b) = \sum_{i=1}^{7} \sqrt{(x_i^a - x_i^b)^2}$. The smaller $S(D^a, D^b)$ is, the more similar two dates D^a and D^b are. The model selects the k most similar dates to the target date D^*, denoted as $D^1, D^2, \dots, D^k$.

5.4.1.1.2 Model training

The value of k impacts the forecast accuracy. Moreover, similarly to overfitting issue in regression models, using a fixed k is not effective due to the seasonality and trends in floriculture supply chains. Therefore, for each specific target date D^*, a specific value of k is used. The process of looking for the best parameter k is called "model training". A training set is required for this purpose. The arrival volume per hour (Figure 5.4) depends on the week day, especially Monday and Friday. As a result, the selection of d days for the training set follows the approach below:

- If D^* is a Monday or a Friday, d previous Mondays or d previous Fridays are selected.
- Otherwise, d previous days among Tuesdays, Wednesdays, and Thursdays are selected.

Given a training set, possible values of k are tested. The value that generates the highest forecast accuracy, i.e., the lowest mean of absolute errors (MAE), is selected.

5.4.1.1.3 Target dimension calculation

The target dimension of the target date $D^*$is estimated as a ratio $r^*$of the total volume registered via EDF from 06.00 to 13.00 hours as $T(D^*) = r^* \times (\sum_{i=1}^{7} x_i^*)$. The ratio r^* is estimated as the average of the k ratios of the k selected dates $D^1, D^2, \dots, D^k$, as $r^* = \frac{1}{k} \sum_{n=1}^{k} \frac{T(D^n)}{\sum_{i=1}^{7} x_i^n}$. Detailed steps of the forecast model is described in Algorithm 5.1.

5.4.1.2 Results and discussion

The model is tested for two months of May and June. This period includes weeks of both high, shoulder, and low season. Regarding computational time, less than 2 seconds was required to generate the forecasts for the whole period with different sizes of training sets. Table 5.2 presents the MAE measured in number of trolleys, ranging from 16.1 to 20.1 trolleys. Because the employee productivity is around 25-30 trolleys per hour, the MAEs are translated to the exact number or ± 1 different from the actual required workers. These small forecast errors helps to reduce the labor costs and maintain the service level.

Table 5.2. Forecasting results by MAE (number of trolleys)

Set K of potential values for k	Size of training set (days)		
	$d = 2$	$d = 3$	$d = 4$
$K_1 = \{1, 2, 3, 4\}$	18.7	19.1	19.4
$K_2 = \{5, 6, 7, 8\}$	19.8	20.1	19.9
$K_3 = \{1, 2,3,4,5,6,7, 8\}$	*16.1*	*16.7*	*17.4*

The best model (in italic) uses K_3. This set includes both small and high values of k, which improves the flexibility of the model in choosing the parameter for capturing trends and seasonality. Additionally, it is observed that the most immediate dates, i.e., $d = 2$, represent better the target date. Other heuristic approaches can also be used to calculate the similarity function and target dimension. Data mining algorithms such as support vector machines or neural networks may improve forecast accuracy. However, these algorithms are constrained by interpretability of the model output. Given the intuitiveness, the forecast accuracy, and the fast computation, the *k*NN model is able to support the real-time workforce adjustment decision.

As seen in the modelling process, the timeliness and accuracy of the forecast information rely on the real-time and historic EDF data from all the suppliers, i.e., data velocity and variety, and the reliable historic time scan data, i.e., data veracity. These data conditions are usually satisfied in most of today's cross-docking warehouses.

Algorithm 5.1. *k*NN forecasting model

Input
- A target date D^*
- Historical EDF data of the previous 8 weeks from D^*
- Real-time EDF data from 06.00 to 13.00 hours on D^*
- A set K of values for k

Step 1. Model training
- Make training set of d days: $trainset = (t^1, t^2, \dots, t^d)$
- **for** each k^i in K:
  - **for** each day t^j in $trainset$:
    - Find k^i most similar dates to t^j
    - Calculate the target dimension $T(t^j)$
    - Calculate the absolute error between the actual value and $T(t^j)$
  - **end for**
  - Calculate the MAE resulting from using k^i
- **end for**
- Select the k^* with the smallest MAE

Step 2. Generate the forecast using k^*
- Find k^*most similar dates to D^*
- Calculate the target dimension $T(D^*)$

Output
- $T(D^*)$ as the forecast for D^*

5.4.2 Strategic design of storage and fulfilment services at cross-docking

Using the historical EDF data, RFH can identify potential suppliers for the pre-ship strategy and accordingly estimate the aggregate demand for storage and fulfilment services. In detail, RFH needs to perform a descriptive analysis for each supplier. The aim is to identify a list of products that are frequently ordered (i.e., every day) by customers located from the same cross-docking destination. This can be done using the time-base association rule analysis.

5.4.2.1 Time-based association rule analysis

The EDF does not include the detailed timing but the product, customer, and date of the order. A EDF data point can then represent a customer order. The association rule among the orders is defined as "if an order of product X to a cross-docking Y is received on date D, the consecutive order of X to Y is received by date $(D + \tau)$". By using τ, the rule imposes a limitation on the inter-arrival time of orders, which is required to reduce the potential spoilage in perishable supply chains. Depending on the quality decay characteristics of products, different values of τ can be used, e.g., 1 or 2 days.

The aim of the analysis is to locate the product X that satisfies the rule with a predetermined threshold of confidence. Details of the analysis for a supplier is shown in Algorithm 5.2.

A relevant question for the pre-ship strategy is "what to do if the pre-shipped products are not ordered after, for example, one day?". In the setting of the Dutch sector, pre-shipped products can be registered for auction channel after a predefined time period. Nevertheless, selecting a high confidence level helps to temper this undesirable outcome. Especially for potted ornamental plants with slow quality decay rate, τ can be extended to 2 or 3 days instead of 1 day and the corresponding confidence levels can be set higher.

Algorithm 5.2. Time-based association rule mining (for data of a supplier)

Input

m products X_i $(i = 1, 2, \dots, m)$ and n cross-docking destination Y_j $(j = 1, 2, \dots, n)$

$m \times n$ sets of historical EDF data E_{ij} of product X_i supplied to cross-docking Y_j

τ is the predetermined limitation on inter-arrival time of orders

ω is the predetermined threshold on order size to filter products that are not frequently ordered

Analysis

for each E_{ij}:

s is the size of E_{ij}

if $s < \omega$ **then break for**

Sort E_{ij} by time ascending

$count = 0$

for k from 1 to $(s - 1)$:

if (inter-arrival time of orders k and $k + 1$) $\leq \tau$ **then** $count \mathrel{+}= 1$

end for

$c_{ij} = \frac{count}{s-1}$ as the confidence of product X_i to be considered for pre-shipping to cross-docking Y_j

end for

Output

A list of (X_i, Y_j) pairs with c_{ij} satisfying the predetermined confidence threshold

5.4.2.2 Numerical example

For demonstration to RFH, the analysis of the historical EDF data is performed for a large-size supplier A. The same analysis is applicable to other suppliers. Supplier A supplies 194 different types of products to two RFH cross-docking centers, CD1 and CD2, from January to June 2017. The time limitation τ was set at 1 day. The confidence level for all six 1-month periods was set at 80%. Instead of one 6-month period, six 1-month periods are adopted to provide further insights into the robust suitability over time of products for pre-shipping strategy and also the seasonal effects.

Tables 5.3 shows the results. 12 product types meet the rule and confidence conditions for CD1 and their volume accounts for 39% of the total ordered volume (received by supplier A) for CD1. 12 product types do so for CD2 and their volume accounts for 49% of the total ordered volume. Moreover, 9 types satisfy the rule and the predetermined confidence for both cross-docking destinations. The high volumes of these products indicate a high potential for these products to be included in the pre-shipping strategy. These numerical results suggest that supplier A is a promising client for the new storage and fulfilment service by RFH.

The information obtained from the association rule analysis can serve as hard proof in communication with suppliers about the strategic new service of storage and fulfilment. Because RFH needs to perform the analysis to extract the information for each supplier, i.e., information completeness, RFH is required to use the historical EDF data of all the suppliers for a long time period, i.e., data volume and variety.

Table 5.3. Confidences in % for selected products supplied to CD1 and CD2

Product	CD1						CD2					
	Jan	Feb	Mar	Apr	May	Jun	Jan	Feb	Mar	Apr	May	Jun
Bromelia cupcake	94	94	93	90	91	93	95	92	93	92	90	92
Bromelia gemend	95	93	89	91	93	93	95	93	91	91	92	93
Guzmania cupcake	92	89	89	87	86	88	92	90	90	86	87	89
Guzmania tempo	91	92	92	88	87	85	91	91	91	87	84	88
Multiflower astrid	93	86	89	87	85	89	93	89	81	86	83	89
Multiflower shannon	93	89	88	86	88	87	92	89	81	84	86	85
Tillandisa anita	93	92	83	92	88	91	93	90	82	88	90	93
Vriesea cupcake	92	93	91	91	89	90	94	91	93	88	90	93
Coupe quito	84	88	81	84	84	86	88	84	81	81	88	82
Guzmania deseo	92	91	83	82	84	86						
Guzmania hope	84	86	82	90	85	88						
Vriesea era	89	89	83	81	82	83						
Bromelia mix							91	89	89	85	86	89
Tillandisa josee							92	81	84	83	83	83
Bromelia op hout							91	90	91	88	92	91

5.4.3 Delivery postponement in real-time processes coordination

An effective coordination requires effective real-time data and information sharing between the involved actors (Thomas et al., 2015a). In this case study, a coordination system for data streaming and information sharing between customers and cross-docking is presented and the coordination's benefit is assessed using a discrete-event simulation model.

5.4.3.1 A coordination system based on tracking and tracing

A real-time coordination system based on tracking and tracing systems is used to coordinate the delivery processes from cross-docking to the customer boxes.

The tracking and tracing systems, based on real-time receiving and processing scan data, provide customers with real-time information on the arrival timing and quantity of trolleys in their orders. Using this timely information, customers can estimate the time and volume of trolleys arriving at their boxes. In case of expected insufficient capacity, customers can directly send signals to postpone the delivery to the cross-docking operator. Accordingly, the corresponding trolleys can be marked as postponed delivery at the corresponding customer clusters (Figure 5.4) and (if necessary) moved to the postponed delivery buffer. As soon as signals to resume delivery are received from customers, cross-docking workers can resume the delivery of these trolleys.

5.4.3.2 A discrete-event simulation to assess the benefit of coordination

Using the coordination system, customers can actively smooth out the trolley arrival process at their boxes. Consequently, it is easy to see that product quality can be maintained and congestion at boxes can be avoided. Moreover, coordination can potentially improve the internal distribution processes within cross-docking. Postponing a delivery means more time is available to expedite another delivery. A discrete-event simulation model was built using Enterprise Dynamics 9 (EnterpriseDynamics, 2018) to examine the potential improvement. The model is described in the following.

5.4.3.2.1 Conceptual model

The entire distribution system is modeled at the aggregate level. The inbound volume is divided into two streams. The first stream goes to Customer Cluster 1, whose box has sufficient capacity. The second stream goes to Customer Cluster 2, whose box has limited capacity. Customer Cluster 2 is the actor involved in the coordination system. The delivery to Customer Cluster 2 is postponed when the box's status is marked full, and the delivery is resumed when the box becomes less than full. Thus, trolleys do not have to queue outside the box of Customer Cluster 2.

5.4.3.2.2 Key performance indicator

Because the simulation aims to examine the effect of the coordination system on the internal distribution process, the key performance indicate (KPI) is defined as the percentage of inbound trolleys for Customer Cluster 1 that are delivered within 1 hour.

5.4.3.2.3 Input data and experimental design

The actual trolley arrival times of a selected day in the peak season May-June 2017 was used as input data. On this day, the KPI is only 86%. Among 216 customer boxes observed in 2017 with capacity of 120 trolleys on average and ranging from 10 to 2000 trolleys, 59% of the boxes were often over full. Therefore, to model the current situation, the volume for Customer Cluster 2 of the total inbound volume was set at 59% and the average box size was set at 120. In the experimental design, the volume of Customer Cluster 2 and the average capacity of customer boxes were varied. For each parametric setting, 200 separate runs were executed to achieve narrow intervals of the lower and upper bounds of the 95% confidence level.

5.4.3.2.4 Results and discussion

The simulation results are displayed in Figure 5.5. With the current situation (the solid line at a box size of 120), the improvement in the KPI is 4% (from 86% to 90%). This improvement is positively correlated with the volume for Customer Cluster 2 and negatively correlated with the average box size. These are intuitive because either increasing the volume or decreasing the average box size of Customer Cluster 2 causes more frequent postponement signals, which saves more time for processing the trolleys of Customer Cluster 1.

As the volume for Customer Cluster 2 falls under 55%, the improvement in the KPI is no longer significant. Therefore, timely postponement signals from a large number of customers to the cross-docking operator, i.e., information timeliness and completeness, is crucial to gain more benefit from the coordination. Moreover, improvement in the KPI enabled by the real-time coordination system can lead to a reduction in the workforce. It is then promising to integrate the real-time coordination system with the real-time predictive model for workforce adjustment to leverage the use of the big data. This is possible by combining real-time big data analytics and tracking and tracing systems.

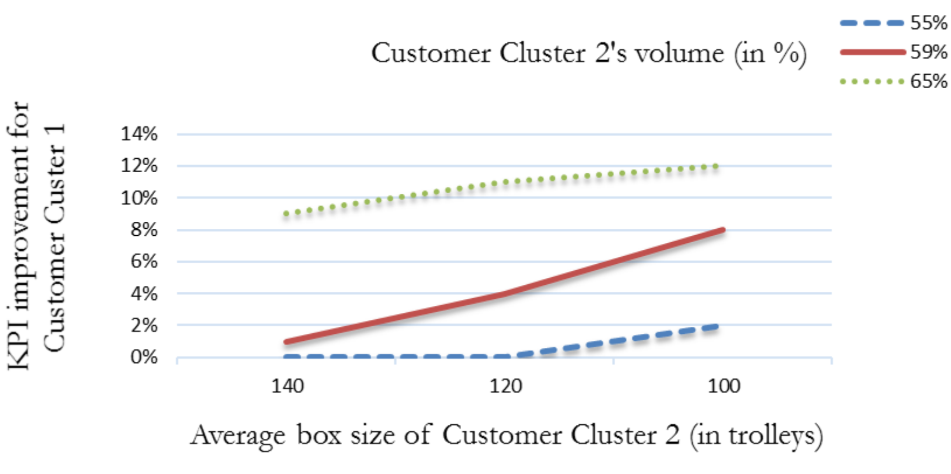

Figure 5.5. The improvement in KPI resulting from real-time coordination.

5.4.4 Strategic partner selection in horizontal collaboration

The historical time scan data provide details on arrival times at cross-docking for products from all the suppliers, i.e., data volume and variety. Using the data, the following descriptive model aims to answer the question "who should collaborate with whom" by revealing sets of suppliers whose products frequently arrived at RFH in the same time window. The aim is translated to frequent patterns mining. Frequent patterns are patterns (e.g., set of items in an order, set of sequences in logistics trajectories) that appear frequently in a dataset (Han et al., 2004). Apriori is a well-established and well-developed patterns mining algorithm. Details of the algorithm are referred to Wu et al. (2008). The following presents important concepts of the Apriori algorithm.

5.4.4.1 Pattern and frequency

A pattern in this case is a set of suppliers whose product arrives at RFH inbound docks in the same time window. The patterns are created from a historical time scan database by dissecting the data into 24 time windows of 60 minutes, i.e., 00.00–01.00, 01.00–02.00, ..., 23.00–24.00.

The minimum support (i.e., the minimum frequency of a pattern appearing in the dataset to be considered as frequent) affects the computational time. A smaller minimum support results in a larger set of frequent patterns, thus a longer computational time. In this case, the minimum support is set at 100 times (approximately 38% of 260 working days in 2017), which resulted in about 20 minutes (implemented in Python, core i5 CPU) given the dataset of around 1,200,000 data points.

5.4.4.2 Results of frequent patterns mining

The model is run for the 2017 data from two RFH cross-docking warehouses. RFH cross-docking 1 has greater inbound volumes than RFH cross-docking 2. The results are shown in Table 5.4. In general, the high numbers of sets indicate a huge potential for reducing truck movements and increasing truck utilization in the sector.

Table 5.4. Number of frequent supplier sets

	RFH cross-docking 1			RFH cross-docking 2		
	Frequency 100–200	Frequency 200–300	Frequency >300	Frequency 100–200	Frequency 200–300	Frequency >300
Two-supplier sets	453	53	21	120	11	2
Three-supplier sets	84	1	0	11	1	0

Many suppliers belong to multiple two or three different supplier sets. These suppliers can have more options to collaborate with one or more suppliers. An example is displayed in Figure 5.6. Three suppliers 1, 2, and 3 are located less than a 3-minute drive from each other. Their production sizes are quite similar. From the geographic dimension, supplier 1 can collaborate with either supplier 2 or supplier 3. However, according to the model output, supplier 1 shares significantly more frequent product arrival time windows with supplier 2 (i.e., 371 times to CD1 and 415 times to CD2) than with the supplier 3 (i.e., 164 times to CD1 and 115 times to CD2). This indicates that it is more beneficial for supplier 1 to collaborate with supplier 2.

The descriptive model output provides the essential information to initiate communication among the Dutch suppliers. The 1PL/2PL suppliers that belong to the same sets can immediately discuss how the collaboration could be arranged. For example, a static optimal routing among the suppliers locations is needed. Moreover, information-sharing aspects, such as which information (e.g., truck capacity requests or offers) and when to share information, are important issues that need to be addressed. For suppliers who use LSPs, a collective arrangement with LSPs is promising (Yilmaz & Savasaneril, 2012).

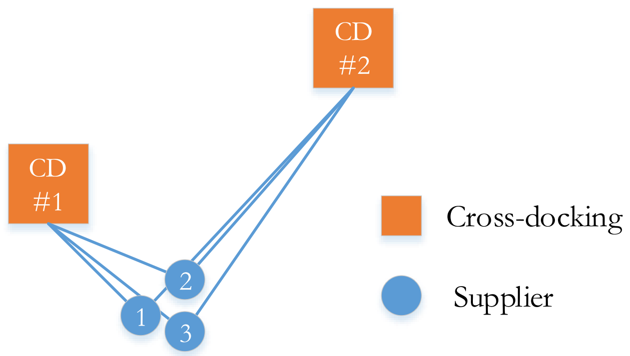

Figure 5.6. Example on selecting potential partner.

5.5 Conclusion and discussion

This chapter discusses a data-information-decision multi-level framework to show how data and big data are linked to multi-level supply chain decisions for process improvement. The framework explicitly addresses the underlying connections within data (data characteristics), information (information characteristics), and supply chain decisions (decisions characteristics). It shows that the value of data and big data lies in how the data characteristics enhance the characteristics of the information generated from the data. In the transition from data to big data, firms are suggested to examine how the big data's 4Vs contribute to improving the information characteristics, i.e., timeliness, accuracy, and completeness, because these determine the relevance and usefulness of the information to different supply chain decisions.

The framework is applied to study the potential value of the big data to support multi-level decisions on the logistics processes in the Dutch floriculture sector. Following a two-dimensional matrix of decision characteristics, the value of the data are connected to four different logistics decisions. At the individual-firm level, the data is used in a *k*NN forecasting for real-time workforce adjustment and a time-based association rule mining for strategic design of a new storage and fulfilment service. At the supply-chain level, the data enables a real-time coordination in the distribution process from cross-docking to customers and an Apriori application to support the suppliers select strategic partners in horizontal collaboration. The analytics work reveals that decisions with different characteristics benefit from different big data's Vs and information characteristics. Due to the limited data provided for this research, only parts of the available EDF and time scan data were used for demonstration in the applications for long-term decisions, i.e., association rule mining and Apriori. However, the proposed approaches are applicable to larger datasets as the computational time remains polynomial.

The following directions are suggested for future studies. First, recent literature reviews on big data analytics by Wang et al. (2016b) and Nguyen et al. (2018) indicate that the value of big data has been linked mainly to predictive power (e.g., forecasting). The descriptive models in the case study have shown that big data descriptive analytics can help firms to uncover hidden patterns, correlations, and insights that allow them to incrementally or radically change their processes. The value of big data from big data descriptive analytics should receive further research attention. Second, the big data in the case study supports co-creation of values among firms through supply chain coordination and collaboration. This points to the necessity of investigating big data applications from the perspective of the supply network and sector. Potentially with greater scope, big data applications for cross-industry supply chain processes in the circular economy are worth exploring (Tseng et al., 2018).

The presented framework does not address organizational aspects such as data-driven culture in upstream and downstream supply chain firms and data governance (Arunachalam et al., 2018; Grover et al., 2018). Dynamic behaviors in the multi-actor setting of supply chains can result in a highly dynamic environment for data capture and sharing, which directly affect the data characteristics and thus the value of the data. Readers are recommended to combine our framework with the aforementioned frameworks in the literature for a multi-aspect understanding.

Chapter 6. Conclusions and general discussions

6.1 Conclusions

This thesis aims to investigate the value of information (VOI) to improve agro-food logistics management. In line with this research objective, the following four research questions have been studied using the Dutch floriculture supply chain network as the case study platform:

- RQ1. How to model the VOI in decision-making and what are the influential factors on the VOI in supply chain decisions?

- RQ2. How to use information flows to improve internal logistics processes at agro-food cross-dockings?

- RQ3. How to use information flows to improve order fulfilment processes at agro-food suppliers?

- RQ4. How to use information flows to improve agro-food logistics processes at supply chain level?

In answering **RQ1**, Chapter 2 presents a generic four-dimension framework to model the VOI in supply chain decisions, i.e. the VOI framework (Figure 6.1). The influential factors are addressed along these dimensions as follows.

- The *supply chain decisions* dimension concerns the content of decisions and corresponding KPIs that are influenced by these decisions. The VOI is subject to the decision in which it is used. An information type can be valuable to various supply chain decisions. For example, inventory level information is used not only in inventory decisions (e.g., replenishment order quantity and frequency), but also in transportation decisions (e.g., vehicle routing). In that case, the VOI will be the cumulative KPI improvements resulting from different decisions.

- The *information* dimension refers to which information to be assessed and its characteristics. The levels of information timeliness, accuracy, and completeness determine the usefulness of information in a specific decision, thus determining the VOI. More timely/accurate/complete information results in higher costs. Therefore, identifying the degree of timeliness/accuracy/completeness required by supply chain decisions helps to adjust costs (of acquiring the information with desired characteristics) to the expected benefits (VOI).

- The *modelling approach* dimension addresses how the considered information is integrated in decision support models. Different modelling approaches have dissimilar requirements on the level of information timeliness/accuracy/completeness. However, the literature review shows that the most informed approach (e.g., the approach that requires detailed data rather than statistics of the data such as mean and variance) does not necessarily lead to the highest VOI. Additionally, in the context of big data, multi-method modelling approaches (e.g., combined data mining and simulation) are promising to exploit the value of big data.

- The *supply chain context* dimension concerns the supply chain environment (defined by multiple supply chain factors) in which the VOI is assessed. The value of an information type can be affected by many supply chain factors. For example, several studies indicate that the value of demand information depends on production capacity, delivery lead time, and flexibility of logistics systems to respond to the changes in demand. Consequently, the VOI needs be assessed in multiple scenarios of supply chain factors to reveal the relationships between the VOI and these factors.

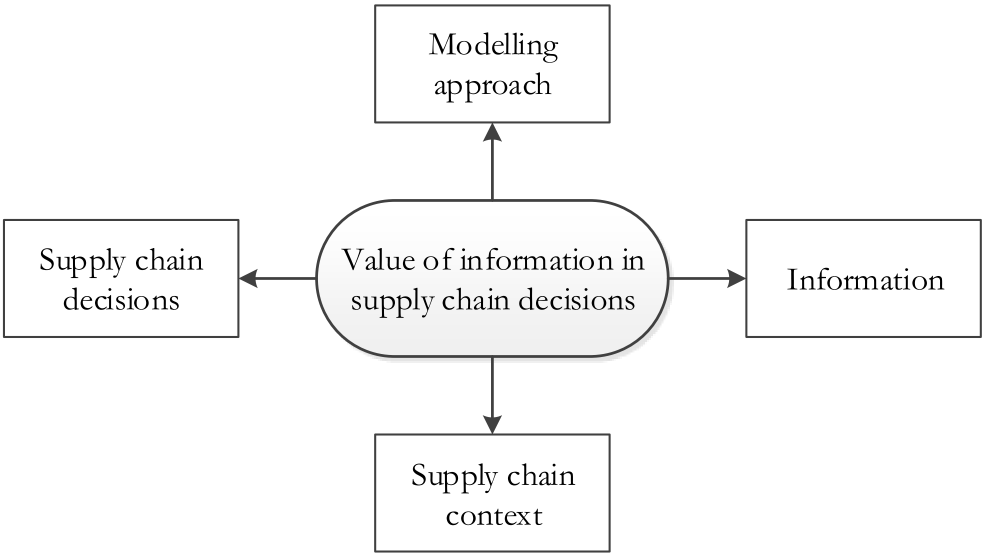

Figure 6.1. Four-dimension of the VOI framework (based on Figure 2.2)

Applying the generic VOI framework to logistics processes in agro-food supply chains, three representative case studies were conducted to address the other three research questions. In each case study, specific dimensions of the VOI framework are emphasized. RQ2 and RQ3 investigate the use of information to improve logistics processes at cross-dockings and suppliers, correspondingly. RQ4 examines the use of information with a multi-level perspective, which concerns not only processes at individual firms but processes at supply-chain level as well. Table 6.1 structurally summarizes how the VOI was modelled in different logistics decisions within the case studies.

Table 6.1. Four dimensions of modelling VOI in the case studies

	Logistics decision	*Information*	*Modelling approach*	*Supply chain context*
Internal logistics processes at agro-food cross-dockings	Dynamic aggregating sizes in outbound-flow scheduling	Inbound information (content and arrival time of inbound trucks) and outbound information (customer orders) Information accuracy: deviations of actual truck arrival time and provided arrival time	Discrete-event simulation and simulation-based scheduling algorithm	Multiple scenarios on density levels of logistics process (based on timeframe and flow complexity)
	Real-time workforce adjustment	Real-time forecast information of inbound volume at peak hours (with acceptable accuracy level) generated from real-time and historical tracking data and electronic delivery form data	*k*NN based forecasting	
	Strategic design of storage and fulfilment service for anticipatory shipping (AS)	Information on potential suppliers for AS extracted from the massive historical electronic delivery form data	Time-based association rule mining	
Order fulfilment process at agro-food suppliers	Production and transportation planning in AS	Information on suitable products for AS extracted from historical order data Confidence level of information (information accuracy): the level that determines if a product is suitable for AS or not	A multi-method approach combining data mining (time-based association rule mining) and multi-agent simulation	One-time AS or Distributed AS scenarios based on the nature of production and transportation processes
Logistics processes at supply chain level	Delivery postponement in real-time coordination between cross-dockings and customers	Real-time estimated inventory level information at customers based on real-time tracking data	Discrete-event simulation	
	Strategic partner selection in horizontal collaboration in transportation among agro-food suppliers	Information on potential partners extracted from massive historical tracking data	Apriori based frequent pattern mining	

Chapter 3 addresses **RQ2** by examining two common information types at cross-docking: (i) inbound information of truck content and arrival time provided by suppliers, and (ii) outbound information of customer orders. In general, using these types of information in the outbound scheduling decision improves the delivery service level and reduces the completion time. Inaccuracy is found diminishing the value of truck arrival time information. The relationship between the error interval and the magnitude of VOI diminution could not be clearly formulized, yet the VOI remains positive in most of the examined error intervals.

Additionally, the effect of supply chain context on the VOI is further explored. Chapter 2 defines the high-density logistics context (HDL) based on three main dimensions of logistics processes: (i) timeframe, (ii) the complexity of physical flows, and (iii) capacity. Given a fixed capacity, a logistics process moves towards HDL if the timeframe becomes shorter or the complexity is increased. In the Dutch floriculture and general agro-food supply chains, the HDL context is caused by highly frequent orders of small volumes and high product variety (i.e. high physical flow complexity), and short customer delivery time windows (i.e. short timeframe). By varying the parameter settings regarding the timeframe and the complexity of inbound flow of the cross-docking, it is found that the VOI increases as the density level is increased. However, each information type reacts dissimilarly to the causes of the increased density level (i.e. shortened timeframe or increased physical flow complexity). The value of inbound information is positively correlated with the density level on the physical flow complexity, whereas the value of outbound information is positively correlated with the density level on the timeframe. Identifying the causes of HDL helps cross-docking operators determine which information to collect and use in decision-making.

Chapter 4 answers **RQ3** by focusing on the use of customer order information, which is a primary information type at agro-food suppliers. Using the customer order information, anticipatory shipping (AS) is explored. Concerning the HDL dimensions, the AS strategy provides agro-food suppliers with more time for order processing (timeframe) and less number of orders to be processed (flow complexity) because part of the received orders can be directly fulfilled by products stored at cross-dockings.

A multi-method modelling approach combining data mining and multi-agent simulation is introduced to study AS in agro-food supply chains. The data mining (i.e. time-based association rule mining) selects suitable products for AS by imposing a time constraint on customer order inter-arrival time. The time constraint is to integrate the quality decay characteristic of agro-food products. Two operational redesigns regarding how the AS products are processed (produced and transported) are also proposed to effectively realize the AS strategy. The redesign is based on the nature of the existing production and transportation processes at suppliers. The multi-agent simulation model is developed to assess the outcome of the data mining and the performance of the redesigns. In the case of a Dutch potted plant supplier, it is shown that AS could increase delivery service level up to 35.3% and reduce associated costs up to 9.3%.

In the data mining, a confidence level is used to determine if a product is suitable for AS or not. From the information dimension of the VOI framework, the confidence level can be associated with information accuracy. The simulation shows that a higher confidence level causes a trade-off: it leads to a lower obsolescence and lower operational costs (e.g., holding, labor), yet at the same time it also leads to a lower delivery service level. Depending on the cost structure in the supply chains, agro-food suppliers can choose an appropriate confidence level to employ.

Chapter 5 approaches **RQ4** from the perspective of big data collected from logistics processes throughout the supply chains. A multi-level framework (Figure 6.2) is introduced to address the links among data, information extracted from data (i.e. information dimension of the VOI framework), and multi-level decisions (i.e. supply chain decisions dimension of the VOI framework). The framework points to the need to repetitively select the data/information of which the characteristics match the requirements by the decisions at different levels.

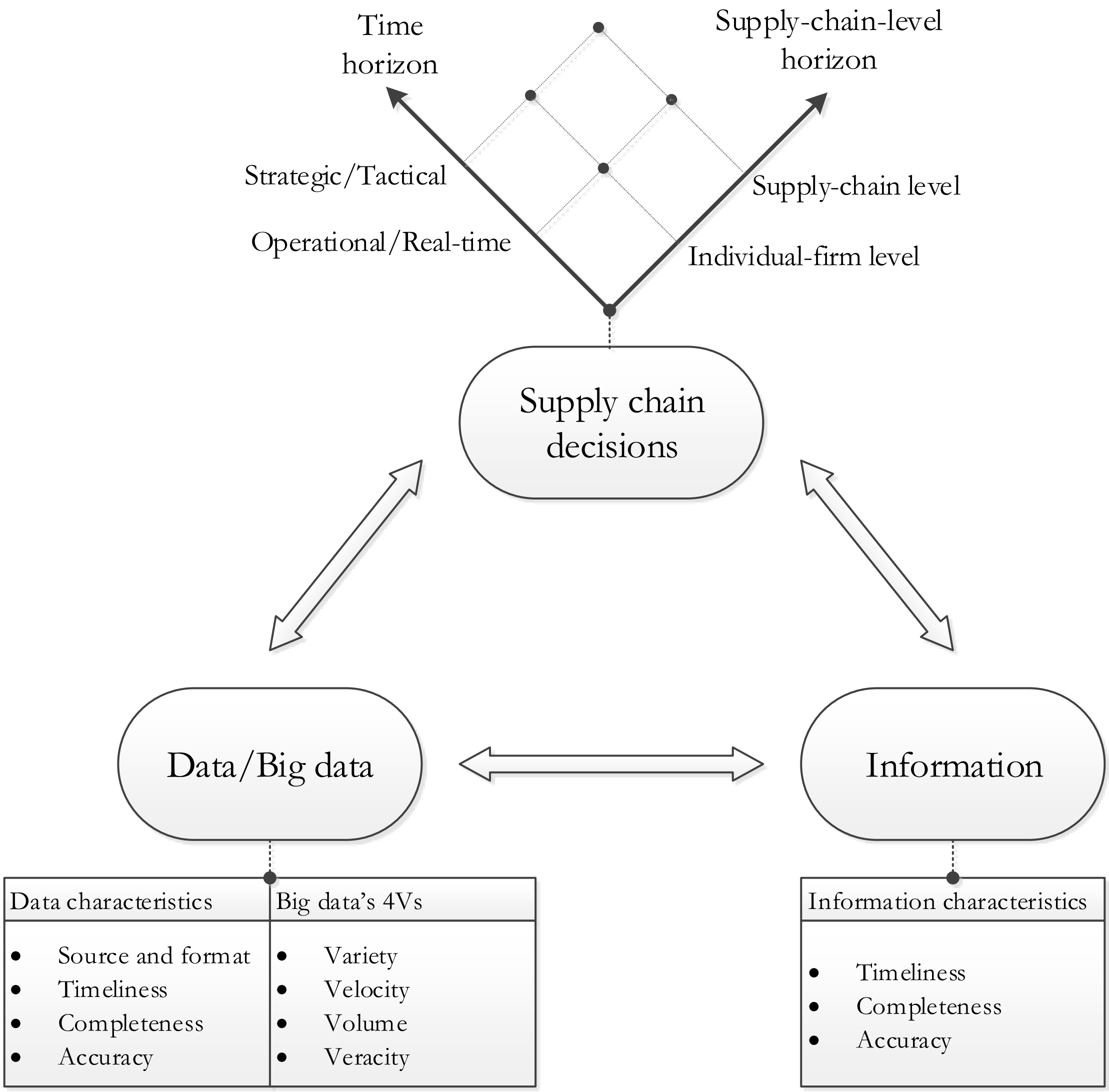

Figure 6.2. The multi-level framework (based on Figures 5.1 and 5.2)

The multi-level framework is applied to examine the value of the booming data in the Dutch floriculture sector. The data concern logistics processes of direct flows and include: (i) time scan data from tracking and tracing systems, and (ii) electronic delivery form data (EDF) provided to cross-dockings by suppliers. Four analytics applications are developed for demonstrating the multi-level value of the data. Two applications support decision-making at cross-dockings:

- Real-time forecasts of inbound volume at peak hours are enabled by a *k*NN forecasting model using historical and real-time trolleys' time scan data and EDF data. The forecast information is shown to be within an acceptable accuracy level and timely to support real-time workforce adjustment decision.

- Strategic decisions on the design of temporary storage at cross-dockings to facilitate AS can be supported using historical EDF data. Because EDFs can represent customer orders, cross-dockings can estimate the aggregate demand for AS storage by applying the time-based association rule mining on the massive historical EDF data from all suppliers.

The other two applications concern the collaboration and coordination in the supply chain network:

- Using real-time time scan data from the tracking and tracing systems to estimate trolleys' arrival time, customers can share the estimated real-time inventory information to cross-dockings. This information enables delivery-postpone decision to reduce the complexity of outbound flows at cross-dockings and the complexity of inbound flows at customers.

- Applying Apriori frequent-pattern mining on the historical time scan data results in information on groups of suppliers whose products frequently arrived at cross-dockings in the same time windows. Using this information, Dutch suppliers can identify potential partners for sharing truck-capacity in horizontal collaboration. In the HDL context, the collaboration improves the capacity dimension at suppliers and also reduces the complexity of the inbound flows at cross-dockings.

In each application, it is shown how the data's volume, variety, velocity, and veracity (4Vs) enhance information accuracy, timeliness, and completeness. The enhanced information characteristics in turn determine how the information can be utilized in the current decisions and further decisions that are not considered before. Especially for the decisions at the supply-chain level, information completeness (i.e., coverage of the information) is critical. Additionally, not all the 4Vs are necessarily required. Decisions of different characteristics require specific information characteristics that are enhanced by different Vs among the 4Vs.

Integrating the findings from all the research questions helps to attain the **overall research objective**. Firstly, from a generic supply chain context, the VOI framework was introduced with four important dimensions, i.e., supply chain decisions, information, modelling approach, supply chain context. Investigating the influences of these dimensions is crucial in assessing the value of an information type in a specific logistics problem. Secondly, employing the VOI framework for agro-food logistics, the uses of common information types available at suppliers, cross-docking distribution warehouses, and the supply chain network were demonstrated. The effects of the dimensions of the VOI framework were also addressed while studying these information types. Particularly, considering the networked structure of agro-food supply chains, the research revealed the multi-level perspective of VOI in supporting the strategic/operational logistics decision-making at individual firms and the collaboration/coordination in the supply chain network. The next sections (6.2 and 6.3) discuss in detail how the findings of this thesis can be used in research and practice.

6.2 Scientific contribution

The presented work contributes to the literature on information management in logistics management. The findings from this thesis can be used in future research in two ways.

First, the thesis supports studies on VOI in the conceptual design step. The four-dimension VOI framework informs researchers of important elements to consider. It also helps to compare relevant studies in the literature for combining complementary results or for comprehending conflicting results. Whereas the VOI framework focuses on information and decisions, the multi-level framework suggests to expand the focus to include data/big data in the research design. This is necessary due to the fast increase from data to big data in supply chains. The literature review finds that many papers on big data analytics cover only the data analysis to extract information (e.g., to generate forecast information from historical data), but do not map the extracted information to specific decisions. The multi-level framework proposes to conduct a thorough decision analysis (decision-information-data) prior to the data analysis (data-information-decision). With this decision analysis, potential multi-level decisions and their characteristics are first identified. This enables researchers to determine the right information with the right characteristics to obtain (e.g., level of forecast accuracy), which in turn helps to focus on the right Vs of big data and select the right data analytics methods.

Second, the demonstrative analytic models (Table 6.1) developed for the case studies can be extended to generic agro-food distribution systems, especially ones that consist of cross-dockings. Particularly in the context of data-rich supply chains, the multi-method approach combining data mining and multi-agent simulation demonstrates the positive effect resulting from the synergy between operations research and data mining in particular and data science in general. To improve order fulfilment processes, a traditional operations research approach would mostly use customer order data as input for a prescriptive model, e.g., simulation or optimization, to locate optimal settings of essential process parameters. Using methods in data science, insights and patterns obtained from the data can enrich the solution space with promising scenarios, of which anticipatory shipping is one example.

6.3 Managerial contribution

In this information-rich economy, firms in supply chains always seek to harness the booming information flows for business values. This thesis provides firms a better understanding of these values.

Just as the value of food depends on its quality, the value of information is subject to information characteristics. Firms need to determine the desired information characteristics before making investments in ICTs to obtain the information. In this way, the desired characteristics can be continuously improved by the right investments and investing in unnecessary information characteristics can be avoided. For instance, concerning the time scan data in tracking and tracing systems in agro-food supply chains, relevant questions include how to assure that the scans are made by employees with a timely and accurate manner (information timeliness and accuracy), and if it is necessary to further expand the tracking systems from batch level to items level (information completeness). Similarly, collaborating firms should set up requirements for information sharing. Considering truck-capacity sharing within horizontal collaboration, it is essential to agree on when the information should be shared (timeliness), e.g., real-time or at a number of fixed moments during working hours. On the one hand, it ensures the effectiveness of the information sharing, i.e., information at the right time. On the other hand, it increases the efficiency by reducing efforts in executing the sharing and processing received information.

Assuming that firms obtain information with the desired characteristics, the expected outcome may not be achieved because the value of information is very case-specific. The same piece of information can bring different values due to the influences of supply chain factors. As a result, investments in ICT need to be accompanied by appropriate investments in other factors (e.g., production capacity, workforce) so that the information-based decisions can be effectively implemented. Taking the real-time workforce adjustment decision as an example (Chapter 5), real-time and accurate forecast information enables the decision, yet the effectiveness of the decision largely depends on the flexibility of the workforce to meet the adjustment.

Also, the value of information is accumulative. Supply chain information can be used in many different decisions. In the context of agro-food supply chains, many types of information collected from tracking and sensing devices are originally available to meet regulations on product traceability and safety. Besides this direct use, the four analytic models (Chapter 5) demonstrate multiple uses of these information types in strategic and operational logistics decision-making. In addition, intra-organizational information flows can generate considerable values. Customer orders from the sales department can help to strategically redesign logistics processes for improving delivery service and operational costs (Chapter 4). Thus, data and information collected internally by different departments should be inter-exchanged for a more effective exploitation.

Last, the multi-level perspective of value of information should be considered. The increasing information flows help firms better manage not only their own logistics processes but also the logistics collaboration and coordination at the supply-chain level. The analytic applications using data from tracking and tracing systems are demonstrative cases that show the opportunities offered by the data (Chapter 5). In fact, perceived business values at the supply-chain level reinforce the commitment of bottom-up timely and accurate data contribution from all firms in the supply chain network.

6.4 Directions for future research

Based on the findings from the thesis, this section discusses a number of directions for future research linked to the dimensions of the VOI framework. Especially, the last paragraph reflects on the overall approach employed by this thesis to assess the VOI.

- *Supply chain decisions*. An information type can be useful to many decisions. The thesis has investigated the use of inbound and outbound information in the outbound-flow scheduling decision at cross-docking. A comprehensive evaluation of these types of information should adopt a holistic approach that considers also the immediate cross-docking decisions including inbound scheduling (e.g., truck-to-door assignment) and internal processes planning (e.g., workforce planning).

The HDL context has been defined on three dimensions: the complexity of physical flows, the timeframe, and the capacity of logistics processes. The presented approaches in this thesis support different logistics decisions associated with one or more dimensions of the HDL context. In fact, these approaches can be combined. For instance, integrating anticipatory shipping in horizontal collaboration is a promising approach as discussed at the end of Chapter 4. Future studies can further explore different data-driven process optimizations and redesigns that focus on each single HDL dimension and accordingly investigate the synergic effect of implementing these solutions simultaneously.

- *Information*. Considering the multi-actor context in the supply chains, the dependence on information flows needs to be addressed. For example, in case the transportation is outsourced, essential information types such as expected truck-arrival time at cross-dockings and load pick-up time windows depend on the LSPs, who perform the tasks. Consequently, factors such as the capability for data/information gathering, processing, and sharing at LSPs directly affect the characteristics (e.g., accuracy and timeliness) of the information. Therefore, assessing the VOI in such cases needs to consider not only the focal actor but also the characteristics, interests, and behaviours of other involved actors in the supply chains. For this purpose, agent-based simulation may be helpful for modelling actors' diverse characteristics, dissimilar interests, and dynamic behaviours.

- *Supply chain context*. In all the case studies, customer requirements on physical flows were fixed. In other words, one type of customer order was modelled in the logistics processes. Unexpected circumstances such as urgent orders (e.g., with one- or two-hour lead-time) often occur in reality. It is interesting to explore the impact of these events on the VOI. Data mining methods could be applied to historical data to gain insights of these events, i.e., discovering customers' behaviours. Modelling customer behaviour reflects the complexity in supply chain processes, and therefore contributes to a better assessment of the VOI.

The literature offers two approaches to measure VOI. The first defines VOI as the estimate of willingness-to-pay by a potential user to have access to the information (King & Griffiths, 1986). The second, which is the dominant one in the literature and adopted by this thesis, defines VOI based on the benefits (savings) of using the information in decision making. By choosing the latter, the functional values (i.e. performance improvement such as cost/time reduction) were emphasized and the VOI was measured by KPI improvements in this research. Symbolic values, which relates more to the first approach, were not discussed in the dimensions of modelling the VOI. Grover et al. (2018) indicate the need to consider inter-organizational aspects such as signalling (i.e. firms gain substantial reputation via the signals made through gathering and using data/information) and herding (i.e. firms seek to acquire information/information technologies from observing prior acquisitions by other firms). Top management usually consider these values in strategic investment decisions regarding ICTs for data-driven decision-making. Further extending the introduced VOI framework to integrate the symbolic values is certainly a challenge for future research.

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Summary

The logistics management literature has defined the *value of information* (VOI) as the expected benefits from using the information in specific decisions, where the benefits are assessed as improvements of key performance indicators influenced by these decisions. In the past ten years, data and information flows in agro-food supply chains have exponentially increased due to diverse embedded tracking/sensing devices, ubiquitous usage of computer systems, and increasing information sharing among firms. This promises a huge potential value when the data is gathered and turned into information/knowledge that can be used to make better informed decisions. With a focus on *agro-food logistics management*, the overall objective of this PhD thesis is *to investigate the VOI to improve logistics processes*. Using the Dutch floriculture supply chain network as the case study platform, the research particularly deals with logistics challenges caused by the trend of customer orders in the agro-food sector: high frequency, numerous order lines of small volumes, and short required delivery lead-times.

Chapter 2 aims to provide a comprehensive overview on the VOI and to subsequently propose a framework to model the VOI in supply chain decisions. A systematic literature review is conducted for this purpose. Studying 117 selected journal articles published from 2006 to 2017 results in a VOI framework of four dimensions, which are "supply chain decisions", "information", "modelling approach", and "supply chain context". The review also shows that the current literature is rich in assessing the VOI in inventory decisions, yet not in other areas such as facility, transportation, sourcing, and pricing. Furthermore, the focus of the existing literature is on information availability; the impact of important information characteristics such as timeliness, accuracy, and completeness on the VOI has not been studied extensively. Based on the synthesized findings, a structured research agenda is offered and sample research questions are discussed.

Applying the VOI framework to agro-food logistics, Chapters 3 and 4 study the VOI to improve logistics processes at agro-food cross-dockings and agro-food suppliers, respectively. Expanding the scope from processes within individual firms, Chapter 5 addresses the VOI to improve logistics processes at supply chain level (i.e. coordination and collaboration).

Chapter 3 first discusses the high-density logistics context caused by the above-mentioned characteristics of customer orders. It then demonstrates that using the inbound and outbound information flows to plan daily operations improves the logistics performance at agro-food cross-dockings. A discrete-event simulation and a simulation-based scheduling algorithm are employed as analytic approaches to assess the VOI. It is found that the higher the density of logistics processes, the higher the value of the information.

Chapter 4 examines the value of customer order information. To improve the order fulfilment process at agro-food suppliers, the anticipatory shipping (AS) concept is explored. A multi-method approach combining data mining and multi-agent simulation is proposed to support AS decision-making. This is the first attempt in the literature to integrate product quality decay in data mining to select suitable products for AS. Additionally, two process redesigns at the operational level are proposed to effectively realize AS. Using historical data from a Dutch potted-plant supplier as input for a multi-agent simulation, the proposed approach and process redesigns are verified. The simulation output shows that AS could increase delivery service level up to 35.5% and reduce associated costs up to 9.3%.

Chapter 5 first presents a multi-level framework to show how (big) data and information derived from data are connected to supply chain decisions at different levels, i.e. short/long term and individual-firm/supply-chain level. The multi-level framework is then applied to examine the value of the booming data in the Dutch floriculture sector. Four analytics applications are developed to demonstrate the multi-level values of the data. (i) At the individual-firm level, two applications support cross-docking logistics: a kNN forecasting model for real-time workforce adjustment and an association-rule mining application for strategic redesign of storage and fulfilment service. (ii) At the supply-chain level: a discrete-event simulation model for real-time coordination between cross-docking and customers, and an Apriori frequent-pattern mining application for selecting strategic partners in horizontal collaboration among agro-food suppliers. The modelling processes explicitly show how raw data are transformed and analysed, and how big data's 4Vs (volume, variety, velocity, veracity) and information characteristics are required by each logistics decision.

The research presented in this thesis contributes to the literature on information management in logistics management. The VOI framework and the multi-level framework help practitioners and researchers gain a better understanding of the VOI and influential factors in assessing the VOI. The demonstrative models show how different types of supply chain data and information can be utilized in data-driven logistics decisions, not only to improve processes within individual firms, but also to upgrade interconnected processes at the supply-chain level toward higher effectiveness and efficiency.

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Wageningen,
September 2019.

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Completed Training and Supervision Plan

Quoc Viet Nguyen

Wageningen School of Social Sciences (WASS)

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
Writing research proposal	WUR	2016	6
Data Analysis and Logistics	Beta-TRAIL	2015	3
LNMB Integer Programming	LNMB	2015-2016	4
Decision Science II ORL-30306	WUR	2016	6
European Logistics Association PhD workshop	ELA, Wroclaw, Poland	2017	3
"*Value of information in improving daily operations in high-density logistics*"	IGLS conference (peer-reviewed)	2017	1
Scientific Writing	Wageningen in'to Language	2017	1.8
Facility Logistics Management	Beta-TRAIL	2017	1
PhD Workshop on Business Analytics	Kuehne Logistics University	2017	0.5
"*The value of big data in supply chain decisions: a multi-level perspective*"	EURO conference	2018	1
Visiting Kuehne Logistics University under WASS Junior Researcher Grant	Kuehne Logistics University	2018	-
"*Data-driven process redesign: anticipatory shipping in agro-food supply chains*"	CORS conference	2019	0.5
"*The impact of information sharing on the performance of horizontal logistics collaboration: A simulation study in an agri-food supply chain*"	IFAC conference MIM (peer-reviewed)	2019	1
B) General research related competences			
WGS Competence Assessment	WGS	2015	0.3
WASS PhD introduction course	WASS	2015	1
WGS Information Literacy	WGS	2015	0.6
Reviewing a scientific paper	WGS	2016	0.1
C) Career related competences/personal development			
Social Dutch I & II	Wageningen in'to Language	2016	4.8

WPC Symposium organization (convening a session)	WGS	2016	1
WASS PhD Council member	WASS	2015-2017	4
Teaching assistant: - Decision Science II - Advanced Supply Chain Management - Sustainable Food Chains	ORL, WUR	2016-2019	2
Supervising MSc theses	ORL, WUR	2016-2018	2
Total			**44.6**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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Additional information

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