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DOTTORATO DI RICERCA IN INGEGNERIA MECCATRONICA E DELL'INNOVAZIONE MECCANICA DEL PRODOTTO

INDIRIZZO DI IMPIANTI INDUSTRIALI E LOGISTICA

CICLO XXXI

Sustainable Operations Management for Perishable Products along Global Supply Chains

Progettazione di Operations Sostenibili per Prodotti Deperibili su Filiere Globali

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Coordinatore: Chiar.ma Prof.ssa Daria Battini

Supervisore: Chiar.mo Ing. Riccardo Accorsi, PhD.

Dottoranda: Giulia Baruffaldi

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ABSTRACT

In the last years, together with the proliferation of quality and safety standards, the global trade of perishable products has dealt with the increasing concern of costumers on credence attributes (e.g. quality, safety, sustainability, fair trade, etc.). Consequently, supply chain actors claim for a higher compliance with such standards, as well as, for a major information disclosure on the products' journey. From their side, researchers are called to develop sustainable solutions to handle products perishability, in order to support managers during the daily operations. Quality and safety of perishable products are affected both by the logistics operations and by the environmental conditions experienced along the supply chain. Due to the seasonality in the weather conditions, the realization of effective temperature-controlled storage and distribution operations is the most important driver to control the quality degradation and the safety decay of perishable products. However, the realization of cold chains is highly energy-intensive, negatively affecting the environmental impact of perishable products supply chains (PPSC). The new advance in IT and in traceability systems represent an opportunity for companies to implement effective cold chains, while addressing to the customer's demand for transparency. However, although the recognized importance of information sharing for the supply chain coordination and integration, the openness toward always more global markets and the distrust of companies to share strategic information limit the collaboration among supply chain actors. Moreover, always more often companies decide to entrust the transportation and storage processes to 3PL providers, which deal with several clients and a high variety of products.

Aim of this dissertation is proposing innovative methods, models and tools aided to improve the overall performance along the supply chains for perishables products. Beyond the efficiency of the supply chain operations, the definition of 'performance' assumes other three dimensions: quality, safety and sustainability. The research elaborates on two research questions that narrow down the set of potential approaches to the problem to the improvement of the overall performance of perishable products distribution network and of storage operations. The research activity is developed according to a research framework, where the research questions are addressed by research levers, that are explored according to research topics. Each topic requires a specific methodology, however the overarching methodological approach presented in this dissertation

includes four fundamental aspects: the minimization of the level of approximation of data in input, the use of case-study deriving from real-world instances, the use of simulation to study complex systems through their model and the role of data visualization.

Initially, this dissertation depicts the state-of-the-art of the current industrial practice in PPSC and identifies the main research trends over the last decade. The following two chapters illustrate the research activity. The first focus on the development of logistics solutions for the management of the flows of goods among the supply chain actors, and the second narrow down the research focus to the warehousing systems located within PPSC and particularly to the warehouse operations. The explored research topics lead to theoretical, methodological and practical contributions.

SOMMARIO

Negli ultimi anni, insieme alla diffusione di leggi e standard a tutela della qualità e sicurezza dei prodotti deperibili, il mercato si è confrontato con il crescente interessamento dei consumatori verso quelle caratteristiche dei prodotti come qualità, sicurezza e sostenibilità ambientale. Di conseguenza, mentre i diversi attori della filiera richiedono sempre maggiore visibilità sul viaggio dei prodotti, i ricercatori sono chiamati a sviluppare soluzioni logistiche per supportare i manager durante le attività giornaliere. La qualità e la sicurezza dei prodotti deperibili sono impattate sia dalle attività logistiche che dalle condizioni ambientali subite durante lo stoccaggio e il trasporto. L'implementazione della cold chain è il maggiore driver per tutelare tali aspetti, tuttavia la sua realizzazione è altamente impattante sia dal punto di vista energetico che ambientale. Le nuove tecnologie a supporto della tracciabilità rappresentano un'opportunità per le aziende al fine di implementare cold chain efficienti e allo stesso tempo rispondere alla maggiore domanda di informazioni da parte dei consumatori. Tuttavia, anche se la condivisione di informazioni tra gli attori supporta il raggiungimento di una maggiore integrazione e coordinamento nella filiera, l'apertura verso mercati sempre più globali e la diffidenza delle aziende a condividere informazioni strategiche con potenziali competitors, ostacola il flusso informativo lungo la supply chain. Inoltre, sempre più spesso le aziende scelgono di focalizzarsi sul loro core business e di affidare il trasporto e lo stoccaggio di prodotti ad aziende 3PL, che si trovano quindi a dover gestire numerosi clienti e una grande varietà di prodotti.

Obiettivo di questa tesi è proporre modelli, metodi e strumenti innovativi per migliorare le performance lungo le filiere di prodotti deperibili. In aggiunta ad una maggiore efficienza, in questa tesi la definizione di 'performance' assume altre tre dimensioni: qualità, sicurezza e sostenibilità ambientale. La ricerca presentata risponde a due principali research questions che focalizzano l'attenzione sul miglioramento delle performance agendo sul trasporto e sullo stoccaggio. Per rispondere a tali domande, la ricerca presentata approfondisce alcuni argomenti, esplorati rispetto ad alcune leve. Il quadro metodologico utilizzato in questa tesi include quattro principali aspetti: la riduzione del livello di approssimazione dei dati, l'utilizzo di casi di studio forniti da aziende, l'uso della simulazione per studiare sistemi complessi attraverso i loro modelli, ed infine, il ruolo chiave della visualizzazione dei dati e dei risultati.

All’inizio, la tesi dipinge lo stato dell’arte della pratica industriale corrente nell’ambito delle filiere di prodotti deperibili e identifica i principali trend nella ricerca lungo l’ultimo decennio. I successivi due capitoli illustrano l’attività di ricerca svolta. Il primo si focalizza su soluzioni logistiche per la gestione dei flussi di merce tra gli attori della filiera e il secondo si concentra sullo stoccaggio e in particolare sulle operations all’interno dei magazzini. I risultati ottenuti portano contributi alla ricerca, alla metodologia e supportano le aziende a livello tattico e strategico.

1 INTRODUCTION

Perishable products supply chains contribute for a large portion to the world economy (Siddh et al., 2015). Perishability, in its broadest sense, is defined as the set of phenomena, such as "decay, damage, spoilage, evaporation, obsolescence, pilferage, loss of utility or loss of marginal value of a commodity" (Amorim, et al., 2013), which generates a decrease of the usefulness of the original product. Based on this definition, examples of supply chains dealing with products perishability can be drawn from different industrial sectors. While in some industries perishability is introduced by the short product life cycle (e.g. in fast fashion industry), in others assumes a more "physical" meaning, being related to the safety decay and quality degradation of products. The most renown examples of supply chains dealing with perishability in this latter meaning are provided by the food sector. This is the first in in the European Communities for revenues, although the perishable food waste caused by damage and spoilage at grocery retailers still accounts for the 15% (Ferguson and Ketzenberg, 2006, Yang et al., 2017).

The quality and safety of perishable products are affected both by the logistics operations (e.g. by the duration of the transportation, warehousing and other processes) and by the environmental conditions experienced by products along the supply chain (De Keizer et al., 2017). The temperature and humidity, at which products are exposed over their life-cycle strongly affect the expected shelf life and other product properties (e.g. taste, flavor, freshness) (Hertog et al., 2014). Temperature, in particular, is touted as the most important driver to control the physicochemical changes of perishable products (Stoecker, 1998) that can be reduced by temperature-controlled storage and distribution (Meneghetti and Monti, 2014).

Therefore, regulators have concentrated efforts in the development of standards and quality and safety assurance systems to guide companies during the distribution operations in order to ensure proper storage conditions and preserve the safety of stocks. However, the implementation of "cold chains" requires a significant amount of energy, enhancing the environmental impacts of perishable products. According to the International Institute of Refrigeration, around the 15% of the worldwide electricity consumption is produced by the cold chain infrastructures, while the electricity use is responsible for the 80% of the global warming impact of refrigeration systems (IIR, 2015, Gallo, 2017). Although, the global market of refrigeration-dependent food, beverages and pharmaceuticals is continuously growing (Fikiin et al., 2017).

Moreover, in the last decades, together with the proliferation of laws and regulations, the trade of perishable products has dealt with the increasing consumers concern about the so-called credence attributes of products such as quality, safety, sustainability, organic, fair trade, etc. (Bernués, et al., 2003). Consequently, costumers highly demand for a major information disclosure on the products journey (Marshall et al., 2016).
In order to address the customer's request for transparency and ensure the respect of the quality and safety standards simultaneously, three main issues have caught the eye of companies: the implementation of always more accurate traceability systems, the strategic sharing of information along the supply chains, and the performance improvement of the logistics operations.

Traceability systems address to the need of performing a more effective and efficient control along supply chains, enabling the tracking and sharing of information about the chain-of-custody, from origin, ownership and exchange, as well as about products history (i.e. the environmental conditions experience during its journey). Thus plays a crucial role to prevent product counterfeiting, fraud and the distribution of products that could potentially threat to public health (Papert et al., 2016).

The key role of information sharing in the supply chain management is recognized by both practitioners and researchers (Burgess et al., 2006). However, often companies are not keen on enhancing the level of information exchange among supply chain actors (Yao et al., 2008) in order to protect their sales strategies by exploiting the information asymmetry between offer and demand (Afzal et al.,2009). Nevertheless, according to several authors, from a high level of information sharing derives higher coordination and process integration in the supply chain (Gimenez, 2006), which finally results in reducing the overall cost, smoothing the demand uncertainty, and enhancing the service level (Li and Lin, 2006, Klass-Wissing and Albers, 2010). The new advances in information and communication technologies (ICT) allow the implementation of shared ICT infrastructures that facilitate operative mechanisms that horizontally and vertically link the supply chain actors (Van Luxemburg et al., 2002, Pramatari and Doukidis, 2007). The diffusion of ICT enables the exchange of timely and accurate information among the actors and builds a strategic lever to optimize logistics operations and exploit economies of scale for both storage and distribution (Bartolacci et al., 2012, Zhu et al., 2018).

To maintain their competitive advantage in always more global markets, companies concentrate efforts on the continuous performance improvements. Especially, the improvement of the logistics operations plays a key role for Third Party Logistics (3PL). In the last decades, the trend to outsourcing has grown as well as the offer of value-added logistic services (Langley, 2015, Shi et al., 2016, Large et al., 2011). These services create new business opportunities for 3PL providers but require continuous review of the provided processes to meet the clients' requirements. Particularly in warehousing and distribution operations, enhancing efficiency and service level is increasingly challenging given the large inventory mix and the need to manage many clients contemporarily. Moreover, in perishable products supply chain logistics complexity increases due to the limited shelf life and the sensitivity of products to the external environment. Furthermore, due to the type of products (i.e. food products) these supply chains are usually affected by high seasonality in the demand.

Despite such crucial role of logistics operations performance along perishable products supply chains (Amorim et al, 2011), the existing literature reveals gaps in addressing some managers' concerns. As of today, a large body of the literature on perishable products supply chain focuses on the inventory management. However, some current trends reveal an increasing interest in the adoption of a more comprehensive perspective to enhance the overall performance improvement along the entire supply chain, aiming not only to the integration among single processes but also to the cooperation among SC actors.

To summarize the illustrated research background, Figure 1 locates the aforementioned key issues into three grey boxes, corresponding to different categories:

1. *External Issues* (1) include the customers' concerns about the credence attributes of products, the regulations in force on the matter of perishable products quality and safety, and the advances in IT, such as in the field of traceability systems;
2. *Supply Chain Issues* (2) involve the always more global markets, the increasing trend to outsourcing, the supply chain coordination, and the strategic sharing of information;
3. *Products Issues* (3) are products perishability and temperature-sensitivity, seasonality and products life cycle.

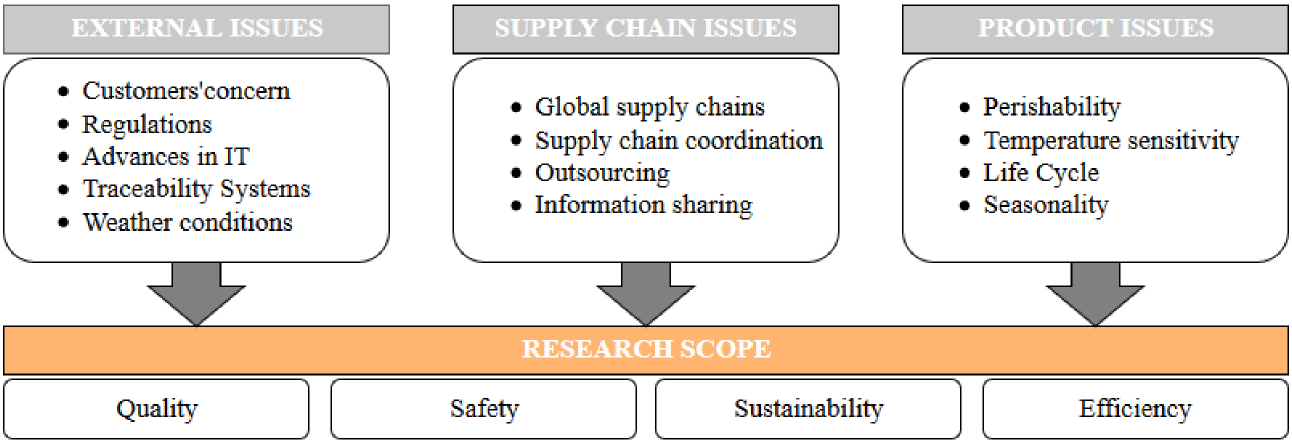

Figure 1: Research background framework

Given the three categories, the research project presented in this dissertation falls within the scope of creating sustainable and integrated perishable products supply chains in order to improve the overall performance. Particularly, the definition of 'performance' presents four dimensions, according to Akkerman et al. (2010), which, beyond the efficiency of the supply chain operations, identify three main pillars of perishable product management: quality, safety and sustainability. Similarly, Manzini and Accorsi (2013) propose a framework for the Food Supply Chain (FSC), where they claim that to improve the overall performance the simultaneous control of quality, safety, environmental sustainability and logistics efficiency of products and processes should be realized "from farm to fork".

Based on these statements, the research is motivated by a set of research questions that are discussed in detail in the next sub-chapter, followed by the research purpose and objectives. Then, the scope and demarcation behind this thesis are illustrated as well as a research framework and the methodology.

1.1 Research questions and objectives

This thesis is primarily motivated by the following overarching question.

RQ. 1: How to improve the overall performance of perishable products supply chains?

Such question is wide and can be approached by a variety of angles and standpoints. In addition, the definition of performance as a four-dimensional concept, increases the complexity of *RQ.1*. To narrow down the set of potential approaches to the problem, this question has been divided into two sub-questions.

RQ. 2: How to improve the overall performance of perishable products distribution network?

Underpinned by this research question, the first purpose of this thesis is to contribute to the further development of logistics solutions for the management of the flows of goods among the supply chain actors.

RQ.3: How to improve the storage operations performance under the constraint of products perishability?

The second research question narrow down the research focus to the warehousing systems located within perishable products supply chains and particularly to the warehouse operations.

As they are posed, the second and third research questions can encompass a wide range of related sub issues. For this reason, this thesis includes a set of research topics, that are underpinned by specific objectives. These will be explicated in the following chapters.

In addition, a transversal goal of this thesis is to provide knowledge to both scholars and practitioners on the criticalities affecting the management of the logistics operations in perishable products supply chain.

1.2 SCOPE AND DEMARCATIONS

The breadth of the research scope as it was previously introduced makes it important to delimit the research area by defining the demarcations. The research presented in this dissertation presents limitations both related to the geographic boundaries and to the set of selected topics.

Firstly, the research is geographically limited to Europe. Particularly, the research refers to the products quality and safety standards issued by the European Union. It is also worth underlining that the thesis includes a number of case studies provided by companies with corporate headquarters in Italy.

Secondly, with the aim of addressing the illustrated research questions, the set of research topics included in this dissertation gravitate towards two macro areas only. These are transportation and storage. Even the approach to investigate these macro areas reflects a specific standpoint. This thesis focuses on the study of logistics solutions to optimize the supply chains networks and the storage operations for perishable products.

The introduced demarcations both identify the research path and expose the limitations of this thesis. Further limitations deal with the specific methodologies implied to study the following research topics. Therefore, they are discussed within each specific chapter.

1.3 RESEARCH FRAMEWORK

The research presented in this dissertation has been developed following the framework illustrated in Figure 2, in which a number of research topics are identified for each research question.

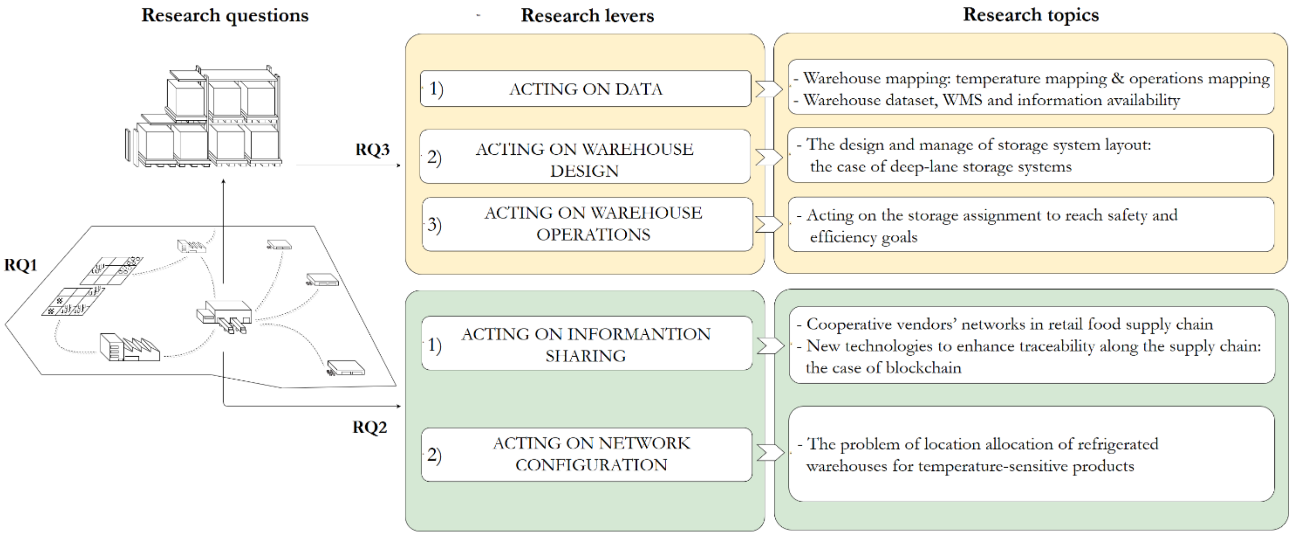

Figure 2: Research Framework

To address to *RQ.2* two research levers are proposed. The first explores the role of the information sharing along the supply chain. Given the breadth of such lever, it is explored according to two topics. The first focuses on the impact of a major information sharing among SC partners in order to improve the daily operations. The second explores the state-of-the-art of new emerging technology, i.e. the blockchain, and its potential role in supply chain traceability. The second strategic lever deals with the supply chain network configuration and faces the location allocation problem for perishable products warehouses.

To address to *RQ.3* three strategic levers are explored: acting on data, acting on the selection of the proper layout and storage mode and acting on the optimization of the warehousing operations. The first lever involves three research topics. These are: the mapping of the warehouse operations and of the environmental conditions, the study of the impact of the availability of information on the products characteristics (e.g. life cycle, labelled storage temperature conditions) on the overall warehouse performance, and the selection of the proper customization of the Warehouse Management System. The research topic underpinned by the second lever includes the design and manage of deep lane storage system layout. Such storage systems guarantee high storage density for end-of-line warehouses in product flow manufacturing systems, which are mostly diffused in food processing and beverage industry. Finally, the third lever focus on warehouse operations and particularly on the development of an innovative storage assignment policy that enhance the products safety and reduce the total travelling picking time simultaneously.

1.4 METHODOLOGY

The methodology utilized in this dissertation includes different approaches, models and research tools according to each specific presented research topic. These will be illustrated with a major level detail in the following. However, this chapter contains a general overview of the adopted methodological approach to the research. Four main pillars can be identified.

Firstly, the minimization of the level of approximation of data in input assumes a critical role in this thesis in order to enhance the reliability of the final results (1). Therefore, a great deal of attention focuses on the development of accurate approaches to the data collection, as well as, on the building of proper data architectures. Particularly, relational SQL databases represent a proper support to collect and manage data derived from supply chain operations.

In order to achieve (1), the use of case studies and proof-of-concept deriving from real-world instances is preferential to validate the proposed logistic solutions. This aspect constitutes the second pillar (2).

Third (3), given the reliability of the input data, this thesis supports the use of simulation to study complex systems through their model, whose parameters are varied to analyze the response of the system to multiple input scenario in an affordable way.

Fourth (4), data visualization is an important aspect of this thesis and particularly for its role in providing practitioners with user friendly, effective tools and methods supporting the decision-making.

Based on these four pillars, a number of research topics in this dissertation are explored according to a specific protocol that, therefore, deserves a special attention in this chapter. Such protocol is illustrated by the mean of a framework represented in Figure 3.

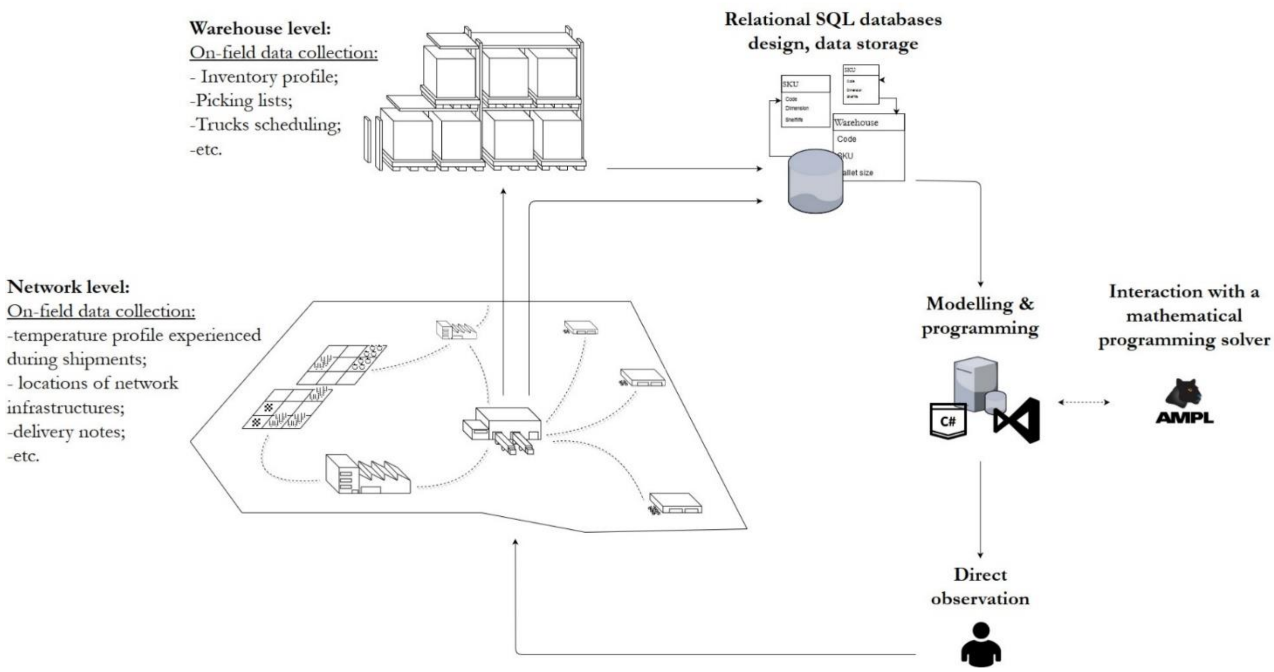

Figure 3: Methodology framework

As shown in the figure, a real-world complex system (e.g. a warehouse, a supply chain) produces a significant amount of data. The protocol suggests gathering and storing such data into properly developed relational SQL databases. Data, in this shape, can successively be investigated through models that explain or optimize the behavior of the observed system. The effectiveness of such models can also be assessed through the development of decision support systems (e.g. software realized through programming language) for the simulation, according to (3). In order to solve the model, the realized software can be also interfaced with a mathematical programming solver. Moreover, according to (4), the development of user-friendly graphic-user interfaces (GUIs) enables the users to easily interact with the model and the input data.

It is worth noting that the protocol is for a circular approach. It starts from the direct observation of the system in order to collect data and successively return to the system to verify the effectiveness of the proposed logistics solution.

1.5 RESEARCH ACTIVITY

The research activity performed with respect to the introduced research levers led to a set of outcomes, which are summarized in Figure 4. All these outcomes contribute to the research scope, in accordance with the two research sub-questions. However, they have been obtained through the adoption of different perspectives. According to an operational perspective, some outcomes aided to the performance improvement of the daily activities, while others support the strategic decision making on how to transform the daily activities in order to maintain and enhance the competitive advantage in the long-term (i.e. strategic perspective).

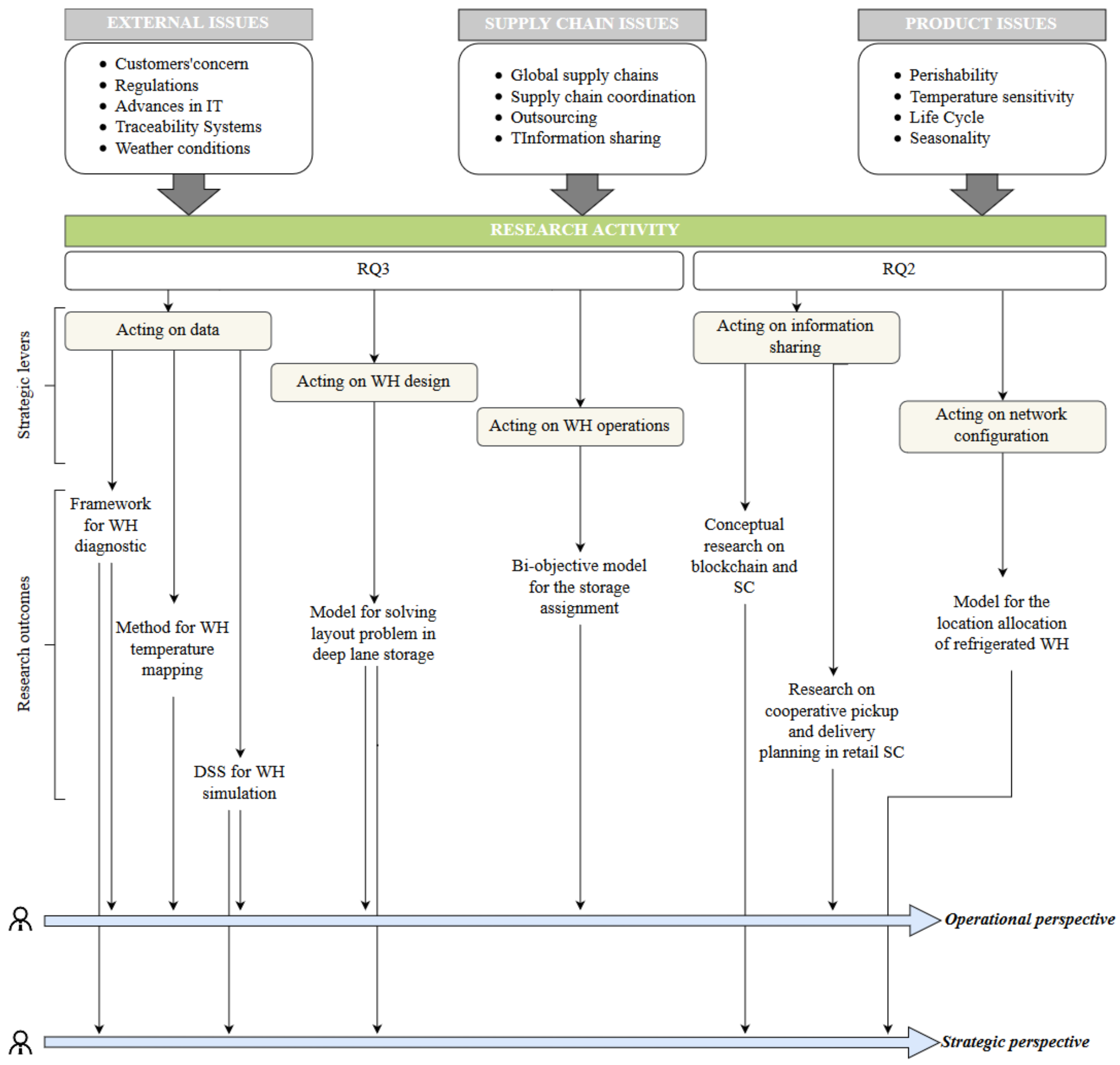

Figure 4: Outcomes of the research activity

The research outcomes generated with the aim of addressing to RQ2 include a study on the impact of a major information sharing among SC partners in order to improve the daily operations, a conceptual research on the potential role of the application of the blockchain technology along the supply chain, and a location-allocation model for refrigerated warehouses. As illustrated in the figure, while the first outcome is for an operational perspective, the others assumes a strategic perspective.

With respect to RQ3, the research lever 'acting on data' led to the development of a diagnostic-support framework for the planning and implementation of performance improvement projects, a decision-support tool that aids 3PL managers to decide on the proper Warehouse Management System customization and a method for the warehouse temperature mapping. The latter is for an operational perspective, while the other two research outcomes support the decision making both at the operational and at the strategic lever. Similarly, a model tailored for deep-lane storage system enable to manage existing block storage warehouses, and to aid the design of new block storage systems from green field. Finally, the a bi-objective model for the storage assignment support the daily put-away in warehouses handling temperature-sensitive products. These research outcomes will be discussed in detail in chapter 3 and chapter 4.

1.6 NOMENCLATURE

Acronym	**Definition**
3PL	Third Party Logistics
BC	Blockchain
BRT	British Retail Consortium
CFD	Computational Fluid Dynamics
DLT	Distributed Ledger Technology
DSC	Digital Supply Chains
DST	Decision Support System
E-R	Entity Relationship
ERP	Enterprise Resource Planning
GAP	Good Agricultural Practices
GUI	Graphic-user Interface
HACCP	Hazard Analysis of Critical Control Points
HVAC	Heating, Ventilation and Air Conditioning systems
ILP	Linear Programming Model
ISO	International Organisation for Standardisation
KPI	Key Performance Indicator
LCA	Life Cycle Assessment
OF	Objective Function
PMS	Performance management system
PPSC	Perishable Products Supply Chain
SC	Supply Chain

SCM Supply Chain Management

1.7 THESIS OUTLINE

This thesis has been developed in accordance with the research framework presented above. Research levers and research topics have been arranged in a sequence of chapters, as shown in Figure 5.

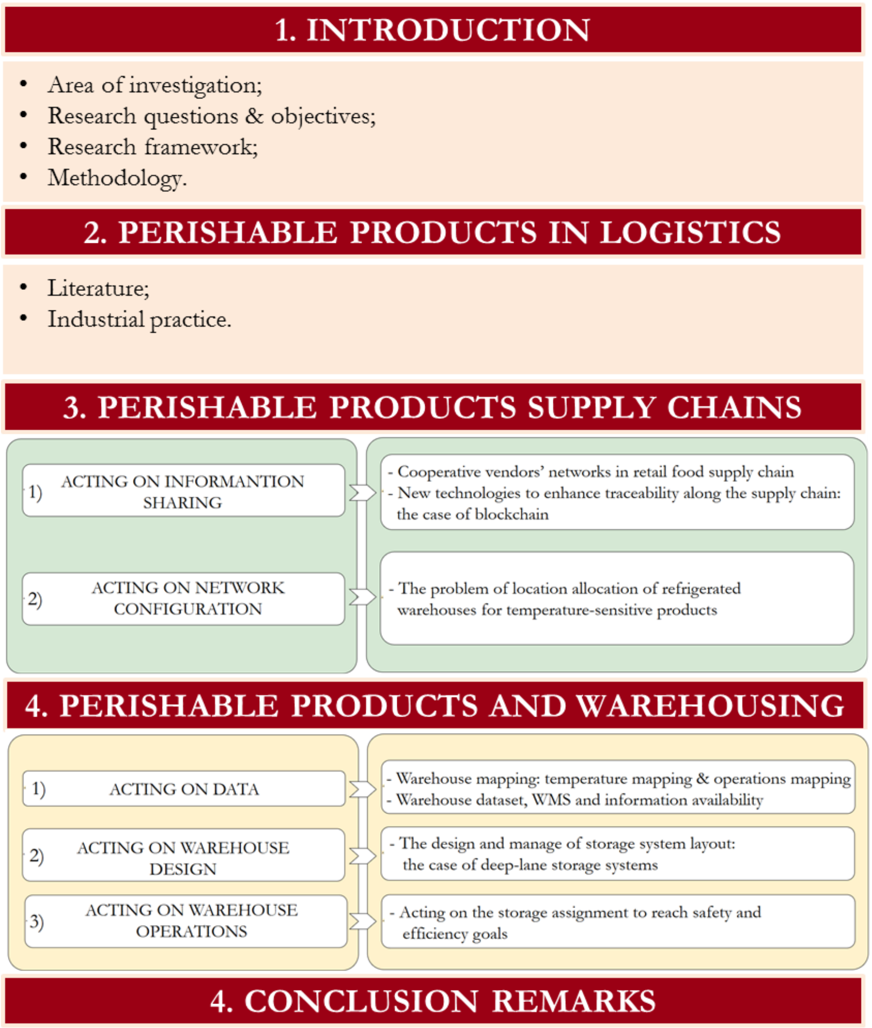

Figure 5: Thesis outline

Chapter 1 introduces this dissertation by outlining the area of investigation, the research questions and objectives, the research framework and the methodological approach.

Chapter 2 discusses the current industrial practice on the matter of perishable products supply chains, in order to introduce the reader to the reasons driving the choice of the research topics (see 2.1). Then, 2.2 explores the background on perishable products supply chains by illustrating a bibliometric analysis of the literature produced over the last decade. Finally, 2.3 lists the references. The results of the bibliometric analysis are exposed in [4] of the list of appended papers presented at the end of this dissertation.

Chapter 3 addresses to RQ2, by exploring the three research topics underpinned by two strategic levers, as illustrated by the figure. The first lever, acting on information sharing, is reported in sub-chapter 3.1, while the second, acting on network configuration, is in sub-chapter 3.2. 3.1.1 illustrates the research topic on the impact of the adoption of a cooperative approach in distribution, while 3.2.1 focus on new technologies supporting traceability along the supply chain, and specifically discusses the case of blockchain technology. 3.2 describes the problem of location allocation of refrigerated warehouses for perishable temperature-sensitive products. Then, 3.3 lists the references. The readers who are interested in deepening the introduced research topics are referred to [3], [7] and [8] of the list of appended papers.

Chapter 4 addresses to *RQ.3* by presenting the explored research topics gravitating towards the three strategic levers identified by the research framework. After an initial literature industrial practice analysis on warehousing, the sub-chapters 4.2 and 4.3 describes the three research topics addressing to the first strategic lever, 'acting on data'. Particularly, 4.2 focus on warehouse mapping. While 4.2.1. expands the aspect of operations mapping by proposing a tailored decision-support framework for the implementation of operations performance improvement projects, 4.2.2. focus on the key role of the temperature mapping for perishable products warehouses. 4.3 focus on the strategic role of the WMS in enabling and controlling the flow of information along the supply chain and discuss the aspect of WMS customization in presence of scarce information availability from the other SC actors. 4.4 describes the research topic underpinned by the second lever, which deals with the opportunity to act on warehouse layout and operations to improve the overall perishable products warehouse performance. Particularly, 4.4.1 reports the case of deep lane storage system proposing a model for designing and managing the deep lane storage system layout. Then, 4.4.2 focuses on warehouse operations and illustrates a storage assignment policy that enhance the products safety and reduce the total travelling picking time simultaneously. Since some of these research topics utilizes the case study methodology, sub-chapter 4.1.3 provide the reader with an overview of the most important characteristics of the main explored case studies. Finally, 4.5 reports the references. The presented research outcomes are presented in [1], [2], [5], and [6] of the list of appended papers.

Chapter 5 concludes the dissertation by illustrating the obtained results, the managerial insights and proposing potential future developments.

Finally, the readers who are interested in exploring some of the presented research topics are referred to the list of appended papers.

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2 PERISHABLE PRODUCTS IN LOGISTICS: LITERATURE & INDUSTRIAL PRACTICE

In the last decades, industrial and scientific interest on perishable products supply chain management has grown, together with the customers' concern about the product characteristics. The so-called credence attributes of products, such as quality, safety, sustainability, fair trade, etc., have become important drivers in the customer's purchasing choice with respect to the traditional factors such as price (Cimino and Macelloni, 2012). Critical events, e.g. food safety scandals, product counterfeiting and fraud, affects the customer's trust, entailing commercially devastating implications for companies, such as product recalls (Thirumalai and Sinha, 2011), reputational damage, and punitive liability damage (Hobbs, 2006). Customers increasingly demand for more transparency on the products journey, which unmasks unfair marketing tactics (e.g. greenwashing, companies present themselves as environmentally friendly when their practices are not sustainable) (Marshall et al., 2016) and proves the compliance of the products and processes with the regulations in force.

In the last years much legislation has been enforced on the matter of perishable products quality, safety and sustainability both at the international and national level (European Commission, 2013, Council Regulation, 2002). Such regulations strengthen the role of quality and safety control, of products traceability and of environmental issues.

Particularly, the perishable products sector saw the proliferation of quality assurance systems, enabling the verification that the quality and safety requirements are fulfilled. The most renowned quality assurance systems are the Good Agricultural Practices (GAPs), Hazard Analysis of Critical Control Points (HACCPs) and International Organisation for Standardisation (ISO). While the first two includes technological and management issues and are tailored for the agricultural and food sector, ISO focuses on management and is independent of any specific sector (Trienekens and Zuurbier, 2008). Specifically, the ISO 9000 series focusing on quality is the most used. In addition to these general quality assurance systems, many private food quality and safety standards have also been developed, such as the British Retail Consortium (BRT) for the inspection of suppliers of food products. With respect to sustainability, both mandatory and voluntarily standards have been developed to address both to the social, i.e. employers' safety, and environmental dimension of sustainability in the different industrial sectors (Akkerman et al., 2010, McKinnon et al., 2010). One of the most widespread voluntary standards for companies aiming to minimize their environmental impact is represented by the ISO 14000 series. Specifically, the ISO 14040: 2006 includes the Life Cycle Assessment (LCA) study for the quantification of the environmental impacts of products and services along their life cycles. The application of standards enhances the customer's trust by certifying that a certain level of quality, safety and sustainability is reached (Kotsanopoulos and Arvanitoyannis, 2017, Giacomarra et al, 2016), enabling the certified companies to enhance their competitive advantage.

Given the increasing customer's concern and the outlined regulatory framework, the goal of enhancing the quality, safety, sustainability and efficiency along the whole perishable products supply chain represents a challenging task for logistics, due to the characteristics of the perishable product market and the perishable nature of products.

The following two sub-chapters explore the perishable product supply chains from the point of views of the industry and research. The first illustrates the current industrial practice on the matter of perishable product supply chain management with a focus on transportation and storage, while the latter draws the landscape of the main research trends in the field.

2.1 INDUSTRIAL PRACTICE

A first important challenge that perishable products supply chains run into while trying to enhance the overall performance is that they act in always more global environment. This entails that companies purchase resources (i.e. raw materials, products and services) and sells their products in always more further markets. Therefore, in such wider networks often production companies decide to focus on their core processes and to entrust to Third Party Logistics (3PLs) providers the transportation and storage processes. As instance, most of the companies in the food industry rely on 3PL to perform the distribution of their products. This is the case of Italy, given the still successful market of the "made in Italy" products.

Particularly, 3PLs providers have come a long way since their dawning in 1980s. The types of services that companies entrusted to 3PL providers, at first, were limited to transport and storage operations. In the last decades, with the increasing trend to outsourcing, the offer of value-added logistic services has grown (Langley, 2015, Large et al., 2011). These services create new business opportunities for 3PL providers but require continuous review of the provided processes to meet the clients' requirements. Usually, 3PL warehouses and transport networks, have to manage multiple-company inventory, merging different items in size, turn over, and storage and transportation conditions requirements (Shi et al., 2016). Furthermore, customer satisfaction as well as quality and flexibility (Hamdan and Rogers, 2008) assume a critical importance in maintaining durable partnerships with customers.

With respect to warehouses, the fishbone analysis illustrated in Figure 6 provides an overview of such issues. The 3PL's managers often deal with a wide number of clients with specific requirements in terms of standards, service level, infrastructure (i.e., storage mode), and tasks (Tan, 2009). SKUs (stock keeping units) may differ for dimensions, storage conditions (e.g., temperature and humidity), economic value, ergonomics, etc. Furthermore, each product is characterized by a specific life cycle. Consequently, another issue to be handled, is the strong presence of seasonal demand and turnover of the whole inventory–mix, as well as the changing storage mix over an observed horizon. A slow-moving SKU in a selected period may rapidly change its turn-over, or new SKUs can enter the system pushed by increasing demand after a marketing campaign (Manzini et al., 2015, Mattsson 2010).

However, 3PLs often deal with partial information availability from the clients (Liu et al., 2008). This uncertainty refers to the SKUs characteristics and the future demand or the daily work flow. For example, warehouses may not know in advance which product (product code, lot code, quantity) will enter the system during the day (Giannikas, 2013). This lack of information increases the complexity in daily warehouse management planning and may affect the success of extensive improvement projects. This results in sub-optimal performance of 3PL warehouses, especially in terms of enhancement of costs and working times.

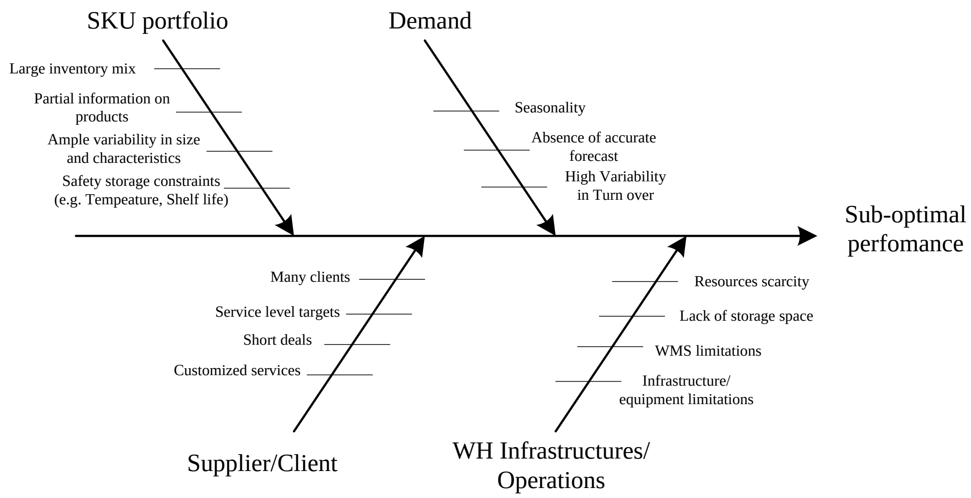

Figure 6: Cause effect analysis of sub-optimal performance of 3PL warehouses

3PLs also must face the unpredictable preferences of clients (Faber et al., 2013), which often result in short contract durations (Randall et al., 2011, Aktas et al., 2016). For this reason, extensive investments in storage infrastructures and services to satisfy the clients' requirements may not generate sufficient return. As instance, since huge investment in automation and storage infrastructures may be justified in vertically integrated supply chains in which the warehouses have full visibility on the product characteristics (i.e. volume, product life cycle, etc.), they cannot be as much as profitable in 3PL warehouses. Moreover, industrial evidence highlights how the urgent management of the aforementioned issues lead the managers away from the application of optimized and standardized procedures or best practices (Lam et al., 2015, Gallmann and Belvedere, 2011).

Similarly, the transportation management by 3PL providers is complicated by the partial information availability on the products and by the large clients' portfolio. Therefore, the daily management may result in low performance in terms of load saturation, level of service and routes planning. In order to have access to further resources to address to the clients' demand, 3PL providers are used to develop horizontal networks through the sub-contracting (Selviaridis and Spring, 2007), which further obstacle the information flow along the supply chain. The complexity further increases while dealing with perishable products. Just to mention a specific case, the distribution of biomedical and medical products to hospitals and nursing homes is usually realized during specific time slots during the day, highly complicating the decision making on the routes planning.

However, above all, one of the most relevant challenges along perishable products supply chains is represented by the correct management of the transportation and storage of temperature-sensitive products in order to avoid the breakup of the "cold chain" (Ndraha et al, 2018). Particularly in the food industry, the conservation temperature is the most important driver for the safety, quality, and even sustainability (i.e., refrigeration) of the processed and delivered products (Bakker et al., 2012). The realization of this task is affected by several issues, among them the elevated number of SC actors involved, the different climatic conditions experienced by products in geographically dispersed networks, and the different laws and regulations in force along the supply chain. Moreover, perishable products require different conservation temperature conditions (e.g. frozen, chilled, ambient) to control the quality degradation and shelf life reduction. All these issues prevent companies to provide consumers with full visibility on the environmental conditions experienced by the products along their journey and, therefore, on the compliance of the quality and safety standards. This goal is partially addressed by the implementation of traceability systems. Traceability systems are constituted from two core technologies: the so-called *identification technologies* (e.g. RFID, temperature sensors) that allow the data identification and measurement, and the *communication technologies*, which support the sharing of data among the actors of the supply chain (Brofman Epelbaum & Martinez, 2014). Although several advances have been done on the field of tracking and tracing technology and many large shippers have modern ERP-systems, with built in functionality for track and tracing and APIs for integration towards logistics service providers, their large-scale implementation along the supply chains require wide-reaching agreements within sectors, and specifically the establishment of trustworthy collaborations between companies (Fritz and Schiefer, 2009). In the transportation of perishable products, usually is difficult to trace the position of products once they are loaded into containers (Hsueh and Chang, 2010). Such described situation may not only prevent customers to have full visibility on the products they purchase but also producers may lose track on the environmental conditions experienced by products along the journey.

In support of this argument, Figure 7 reports some results of the monitoring of the temperature conditions experienced by a container for the transport of wine from the case of a renown Italian wine producer. The wine producer was concerned about the quality of its products at the table of their customers in Norway, since usually wine travels in non-refrigerated containers.

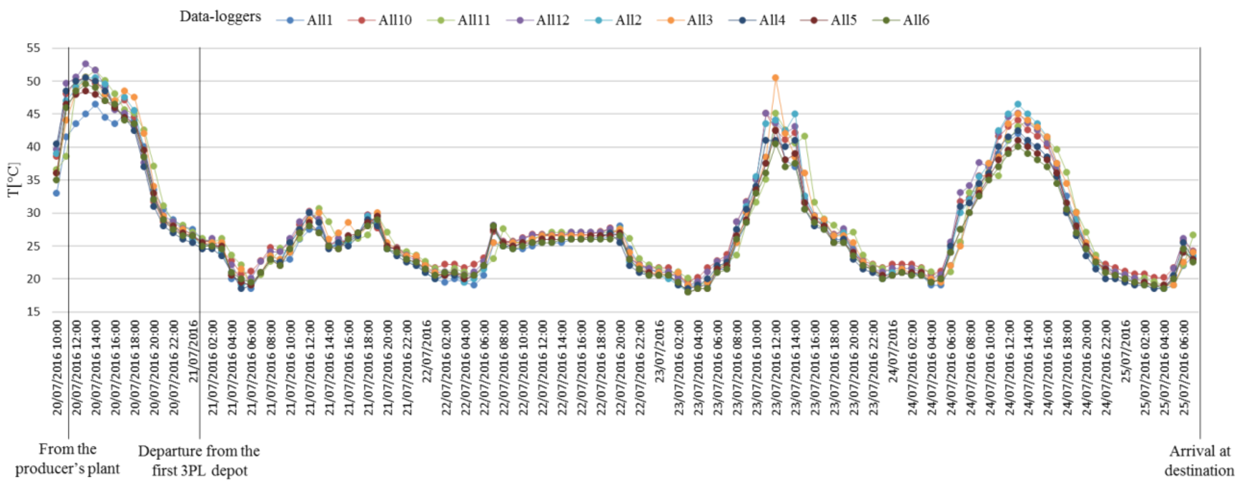

Figure 7: Temperature profile experienced during the shipment from Italy to Norway (from July, 2016, to August, 2017)

The monitored campaign was conducted during a shipment from the wine producer's facility, located in the North of Italy, to the retailer depot in Vestby, Norway. The container departed on July 20th and arrived in Vestby on July 25th, 2016. The container travels thought three different transport modes: roadway, railway and seaway, and the chain-of-custody saw the involvement of 3PL providers. The monitoring was realized using data-loggers, which measure temperature and relative humidity of the environment and record the results in an internal memory. The sample rate was set to 1 hour, while the resolution was 0.5°C. Results showed a critical temperature profile, with peaks of more than 50°C, despite the optimal conservation temperature should be until around 18°C.

2.2 RESEARCH TRENDS

In order to support companies and managers during the daily manufacturing, storage, packaging, and transport operations (Accorsi et al., 2017, Accorsi et al., 2018, Gallo et al., 2017), scholars are called to develop sustainable solutions to handle products perishability. To explore the scientific landscape on perishable products supply chain to provide the reader with an initial macroscopic overview of the literature on the topic, this chapter presents a bibliometric analysis. Particularly, a database containing all the papers on the topic published over the last decade was analysed through a pattern classification tool, allowing to outline the geographic distribution of publications, as well as, the set of publishing journals and the most important authors in the field. In addition, this study allowed to identify the main research trends over the last decade.

The dataset was retrieved from Web of Science on February 26th, 2018, which is one of the most widely used search engine among the scientific community. The search of "perishable products supply chain" in some of the most known search engines (i.e. Engineering Village, Scopus) was conducted and Web of Science revealed the highest number of publications. To explore the published papers over the last decade, the time span from 2008 to 2018 was selected. Among all types of publications, the study was limited to the articles and reviews, allowing to obtain a sample database of 263 works. Then, such database was exported and analysed both through the Web of Science functionalities and the freely available software VOSviewer, for the construction and visualization of bibliometric maps (Van Eck and Waltman, 2010). The software is able to draw bibliometric distance-based maps, paying a lot of attention to their graphical appearance and, therefore, facilitating the users' understanding.

The sample of 263 publications received in total 2,847 citations (i.e. 2,406 without considering the self-citation practice) according to the Web of Science Core Collection, with an average number of citations per item of 10.78. Particularly, Figure 8 shows the total number of citations received by the analysed set of papers per year, while assigning the papers to the year of publication.

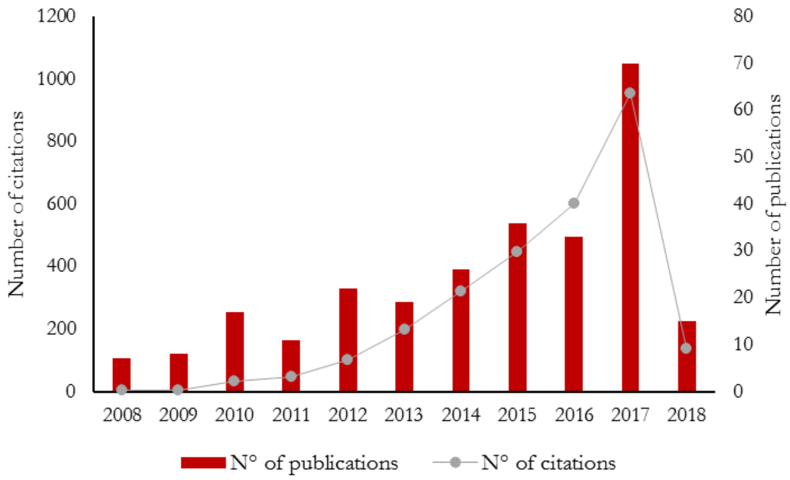

Figure 8: Total number of citations received per year

While the number of publications varies over the years, a general increasing trend can be recognized. Particularly, 2017 was the most prolific year. Therefore, we can hope to obtain similar results in 2018, considering that 15 papers have been published in January and February only. It is worth noting how the citations number assumes a more marked exponential trend over the last decade. According to the Web of Science data, the analysed papers contribute to several research areas. However, five of them result more explored: Engineering, Operations Research Management Science, Business

Economics, Computer Science, and Food Science Technology. Particularly, Engineering includes more than the half of the published papers. The following sub-sessions explore the research topics with a major level of details. However, firstly, analyses on the geographical distribution of papers, the set of publishing journals and the panel of main authors are presented. The specific methodology utilized for each of these analyses is discussed in the following.

2.2.1.1 Geographical distribution

The Web of Science dataset assign each publication to one of more countries according to the address of the organizations to which the authors belong. A VOSviewer functionalities to refine the study to those countries that produced a minimum number of publications of 5 was utilized. Moreover, only the papers that were cited at least once were considered. Under these constraints, 16 countries meet the threshold. Figure 9 shows the number of papers, represented by the orange bubbles, and the number of citations, represented by the red columns, per country. The figure was obtained with the Excel Power Map.

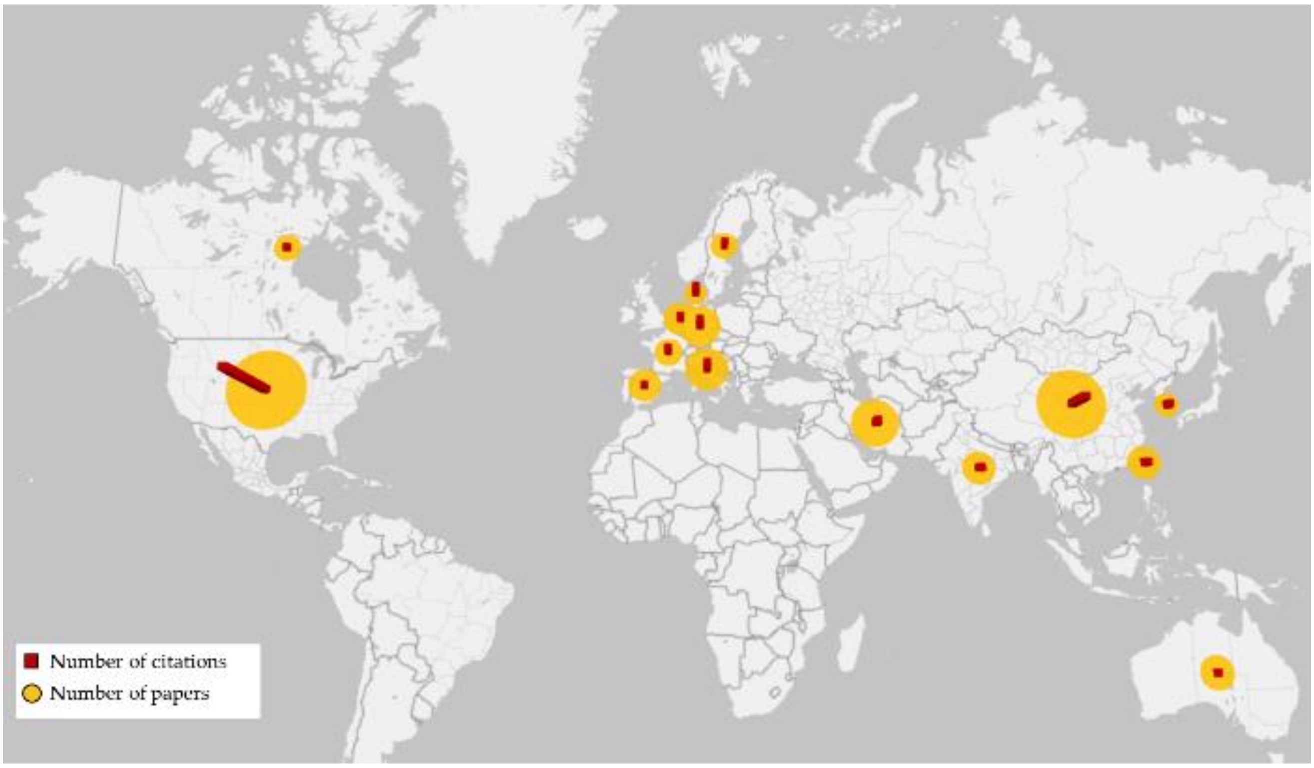

Figure 9: Geographic landscape

Particularly, USA and People's Republic of China are the most prolific countries, followed by Iran and England. However, considering the average number of citation per publication, Denmark, France, and Sweden produced the most cited papers, followed by Germany and Italy.

2.2.1.2 *The journals*

Figure 10 shows the landscape of journals included in the sample database through the item density visualization VOSviewer functionality.

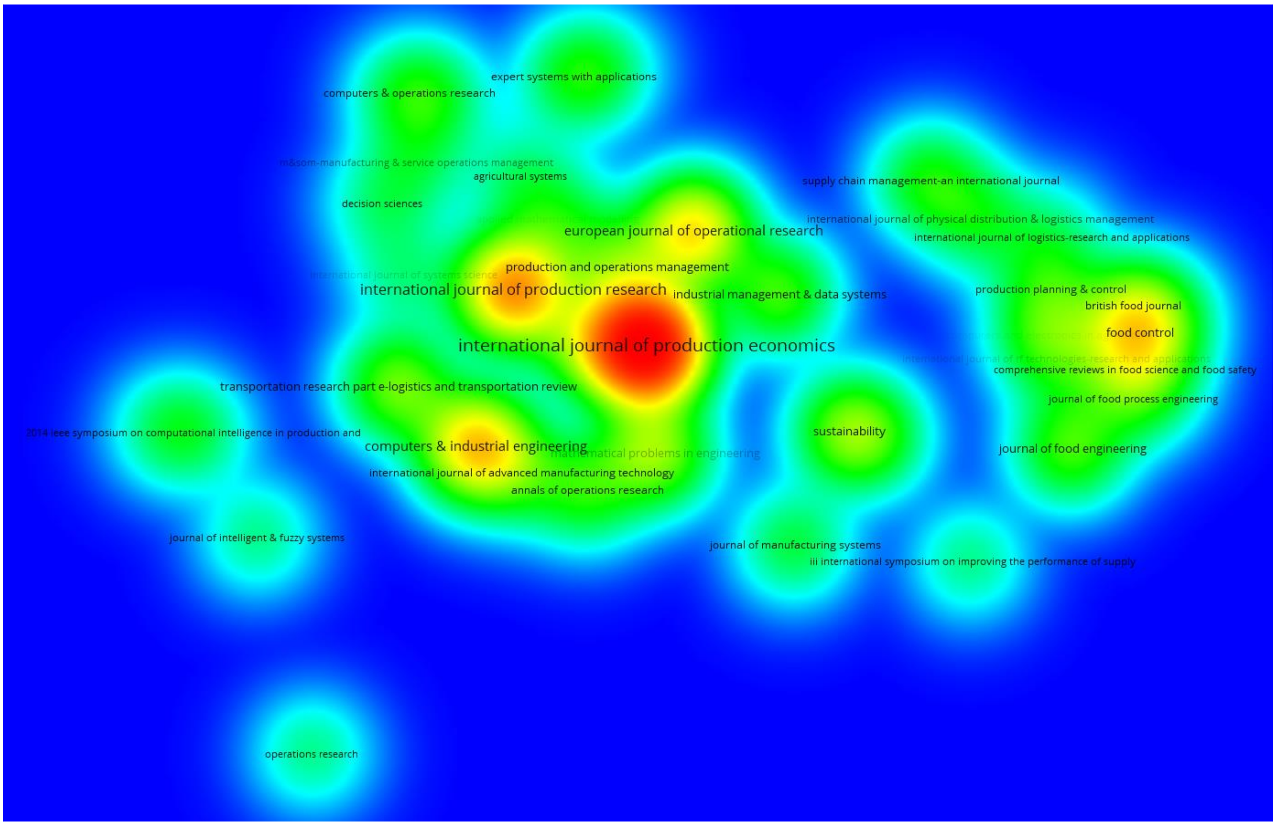

Figure 10: Journals density visualization

This map was obtained through a bibliographic coupling analysis, where the relatedness of items, i.e. journals, is determined based on the number of references they share. Then the fractional counting was used to calculate the weight of a link between two items, which means that the weight value is fractionalized according to the number of references they share with other journals. The map includes only those journals that produced a minimum number of 2 papers that have been cited at least once. The resulted number of journals is 41. Each point in the item density visualization has a color that indicates the density of items at that point. The density is calculated considering both the number of neighboring items and the distance among these items. The more the color tends to red, the higher the item density is. Particularly, the color scale in the figure represents the number of publications. As instance, the International Journal of Production Economics, with its 31 published papers, is located in the central highest density zone in the map. On the contrary, the Operations Research is in a lower density zone and presents weak links with other journals. All other settings have given by default. Among the journals landscape, five revealed the highest number of publications: International Journal of Production Economics (impact factor 3.493), International Journal of Production Research (2.325), Computer & Industrial Engineering (2.623), European Journal of Operational Research (3.297), and Mathematical Problems in Engineering (0.802). Figure 11 represents the publication trend of these journals on the topic over the last decade.

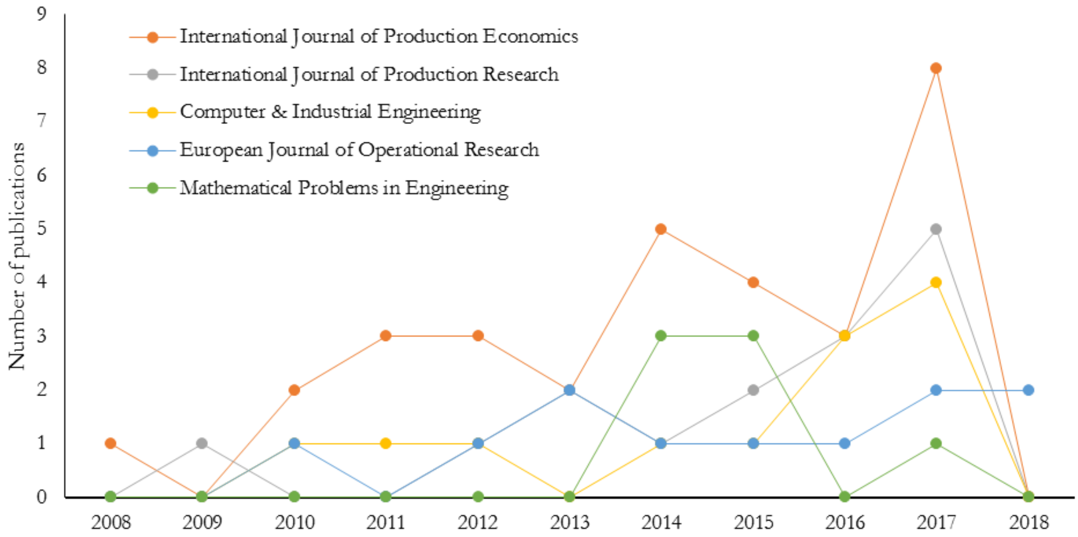

Figure 11: Main journals trend

2.2.1.3 The authors

Aim of this analysis is the identification of the most important authors in the field. To explore the authors landscape, a citation analysis was conducted, given the widespread assumption that the number of citations reflects the publication's notoriety and, therefore, the influence of an author's work (Van Nunen et al., 2017). In this type of analysis, the relatedness of items is determined by the number of times they cite each other. Consequently, in Figure 12 the weight of the bubble representing an author reflects the number of his/her publications, while the bubble colour showcases the average number of citations the publication received by the other authors in the map. The colour red corresponds to an average number of citations of more then 40, while the colour blue corresponds to a number inferior to 10. Moreover, the distance between two authors reflect the tendency of these authors to cite each other. Lines connecting items represent links. VOSviewer, by default, shows the 500 strongest links between items only. All other settings have given by default.

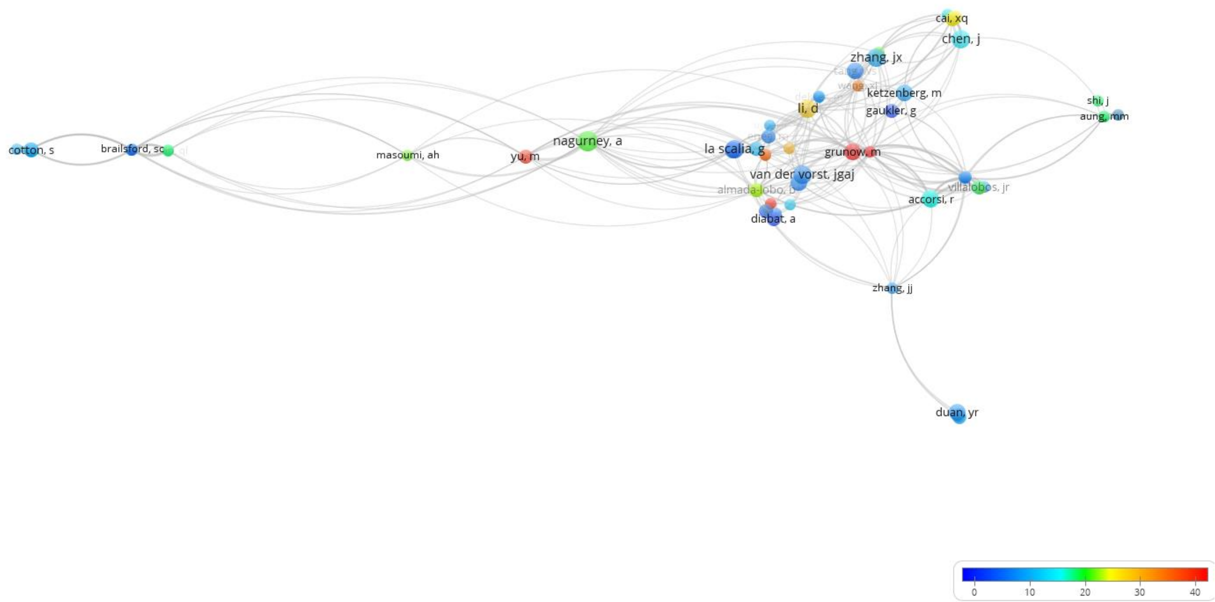

Figure 12: Authors map

Based on these assumptions, the most influential contributions belong to six authors: Grunov, M., Akkerman, R., Govindan, K., and Yu, M., followed by Wang, X.J., and O' Brien, C. It is worth noting how Grunov, M., shares links with all the other authors, Akkerman, R., with four other authors, Govindan, K., and Wang, X.J., with three authors, and the remaining with two other authors. Particularly, Yu, M., is in the most distant position with respect to the others. Table 1 reports the nine most relevant contributions from these authors, according to the number of citations. The table also indicates the research areas, which are: Engineering (E), Operations Research Management Science (ORMS), Business Economics (BE), and Transportation (T).

Table 1: Main References

References	Citations	Research areas
(Rong et al., 2011)	130	ORMS, E
(Govindan et al., 2014)	80	ORMS, E
(Yu and Nagurney, 2013)	71	BE, ORMS
(Wang and Li, 2012)	65	BE, ORMS
(Masoumi et al., 2012)	43	BE, ORMS, T
(Wang et al, 2009)[a]	42	ORMS, E
(Piramuthu et al., 2013)	30	BE, ORMS
(Grunow and Piramuthu, 2013)	28	ORMS, E
(Wang et al., 2009)[b]	26	ORMS, E

(Rong et al., 2011) acquired a huge success in the scientific landscape, because their innovative methodology to model food quality degradation have been exploited by several other scholars in the development of a mixed-integer linear programming models used for production and distribution planning; among these, (Grunow and Piramuthu, 2013) and (Yu and Nagurney, 2013). The first focus on the role of sensor-enabled RFID-generated item-level information in a highly perishable food supply chain, assuming the perspective of retailers, distributors, and customers. The latter develop a network-based fresh food supply chain model for the determination of the optimal product flow throughout the supply chain, under the constraints of oligopolistic competition and perishability. Similarly, (Masoumi et al., 2012) face the challenges of oligopolistic competition among the producers of pharmaceuticals, proposing a supply chain network model. (Wang et al., 2009)[a] and (Piramuthu et al., 2013) explore the topic of traceability to control the products quality. (Wang et al., 2009)[a] propose an optimisation model that integrate traceability initiatives with operation factors to achieve the desired product quality while reducing the phenomenon of product recall. (Piramuthu et al., 2013) study the recall dynamics generated by products contamination in a perishable food supply network through three different visibility levels, such as at supplier level, manufacturer level, and retailer level. The topic of traceability is also discussed by (Wang & Li, 2012), who propose a pricing approach based on the dynamic identification of the food shelf life, with the aim of enhancing the retailer's profit while reducing food spoilage. (Wang et al., 2009)[b] focus on production planning, presenting a model for the determination of the optimal batch size and dispersion to improve traceability and manufacturing performance. Finally, (Govindan et al., 2014) present a multi-objective optimization model that integrates the topic of sustainability in the decision-making process on distribution in a perishable food supply chain network.

2.2.1.4 Research trends

To identify the main research trends over the last decade, a co-occurrence analysis of all the keywords in the database was conducted. Results are shown in a map (see Figure 13), where the relatedness of pairs of items is calculated with respect to number of documents in which they occur together. Since the focus was not to count the total number of occurrences of a keyword but, to identify all the documents in which each keyword occurs at least ones, the fractional counting approach was implemented. A threshold to 8 as the minimum number of occurrences was set and the study was limited the set to the most connected keywords. A total number of 62 keywords was obtained. However, some terms in the map result duplicated. Particularly, VOSviewer does not distinguish among singular and plural. Therefore, to overcome this problem, nine of these keywords that correspond to the ones with a lower weight were removed. All other settings have been given by default. The distance among items was calculated based on the association strength (Van Eck and Waltman, 2009), representing the ratio between the number of co-occurrences of term i and term j and the total number of occurrences of i multiplied for the total number of occurrences of j. The higher the association strength between two nodes of the network, the shorter their distance is. The color scale refers to the average year of publications. Therefore, Figure 13 provide an overview of the most cited keywords over the years, enabling to guess the most debated research topics. A preliminary analysis showcases how the highest color variation is limited to the time span between 2013 and 2016, therefore the color scale was re-set to this period. This phenomenon is partly influenced by the selected threshold of occurrences and to the publication trend (see Figure 8). However, it is worth noting how, reducing the minimum number of occurrences to 3, a similar phenomenon is obtained. Therefore, it is possible to assume an initial phase of *warmup* of the literature on perishable products supply chain (i.e. from 2008 to 2013) characterized by exploratory studies on different themes. Then, from 2013 scholars have focused on some relevant topics, making the research trends more visible. Particularly the years 2014 and 2015 see the majority of the total keywords, while 2017 include only two keywords.

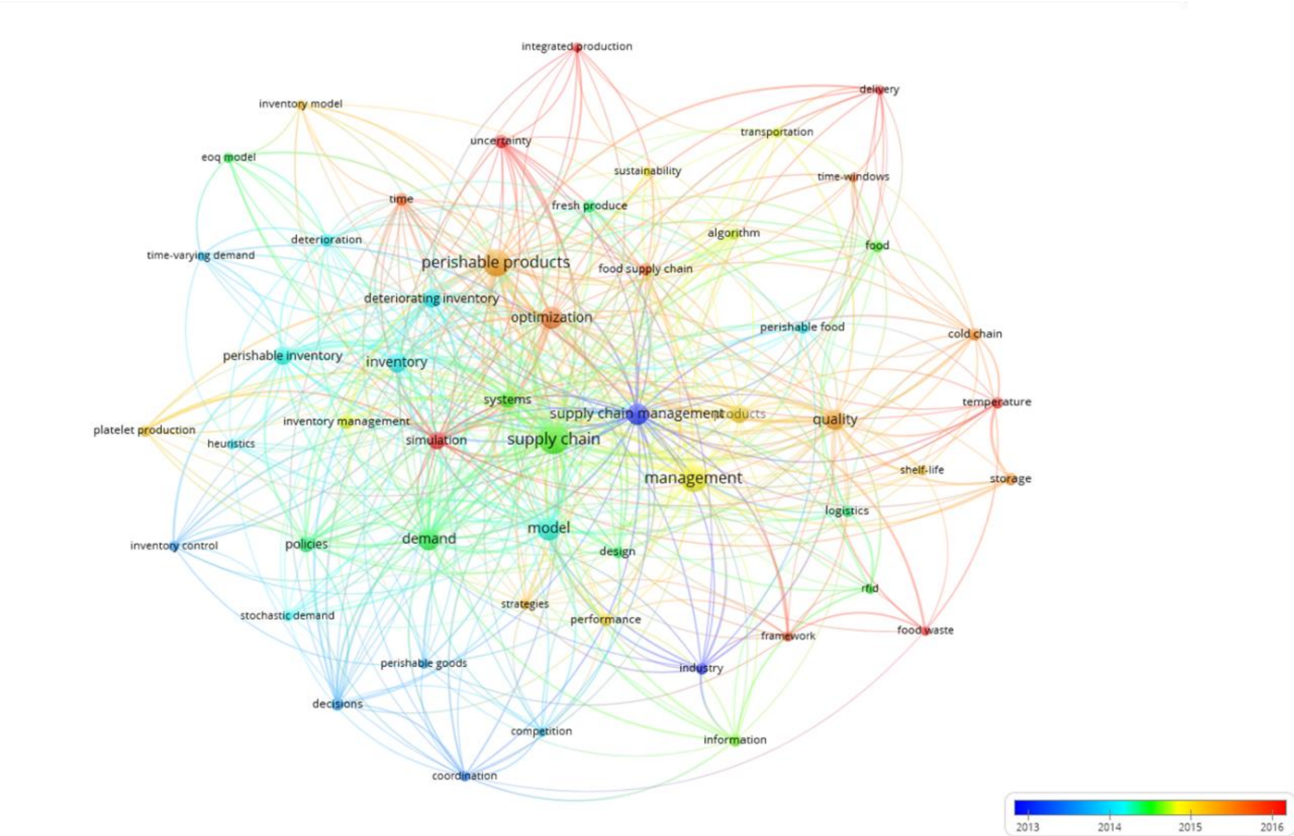

Figure 13: Map of keywords

Based on the map of keywords, the identified research trends result the following:

Table 2: Research trends

Year	**Research trend**
(2013)	The impact of the adoption of a *competitive* approach vs. a *cooperative* approach among supply chain actors
(2013-2014)	The *inventory* management in presence of *perishable* products
(2013-2014)	The handling of the *variability* in the products *demand*
(2014)	The implementation of *traceability systems* (i.e. RFID) for the tracking and tracing of *information* along the products journey
(2014)	*Sustainability* of products and processes
(2014)	*Transportation*
(2014)	*Food products* and *fresh produce*
(2014)	The *Platelet production*
(2014-2015)	The handling of *shelf life* of products
(2015)	The management of the *cold chain*
(2015)	The *quality* of products
(2015)	The management of the *Food Supply Chain*
(2015)	The handling of *time-windows* for the deliveries
(2016)	The monitoring and the control *temperature*
(2016)	*Integrated production* processes
(2017)	The *deliveries* planning
(2017)	The *food waste* reduction

Despite the limitations related to use of very specific search keys to build the database, the obtained results provide the reader with a macroscopic overview of the extant literature on the topic. Moreover, not only Figure 13 allows to visualize the past research trends, but also could support researchers in the identification of potential gaps in the literature. Particularly, the distance among nodes in the map could show unexplored links among research topics, while the bubble size could indicate a still little debated topic.

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3 PERISHABLE PRODUCTS SUPPLY CHAINS

3.1 INFORMATION SHARING AND PERISHABLE PRODUCTS DISTRIBUTION NETWORKS

The practice of supply chains to share information in order to enhance the knowledge of SC actors on the flow of materials within the supply chain is identified with the name of "Supply Chain Disclosure (SCD)" (Marshall et al., 2016). Information sharing is touted as one of the key driver to supply chain management (SCM) (Burgess et al., 2006). Particularly, two dimensions characterize information sharing in SCM: the extent to which information is communicated among SC partners, i.e. quantity (or level) of information sharing, and the combination of accuracy, adequacy, timeliness, and credibility of information exchange, together defining the quality of information sharing (Li et al., 2006, Byrne and Heavey, 2006). The extant literature widely discusses the benefit of information sharing on SC coordination and processes integration, revealing a positive effect on performance improvement, cost reduction, time to market shortening and service level enhancement (Li and Lin, 2006, Kembro et al., 2014). Moreover, in addition to internal governance, supply chains receive some external pressures to information disclosure from the market. These include, for instance, the increasing interest of costumers on credence attributes of products and the regulations in force on the matter of products safety and quality. Critical events, such as food safety scandals, can highly damage brand reputation and enhance the level of information demanded by customers. As instance, Bernués et al, (2003) report that the red meat industry has experience a long crisis that is partly due to a lack of communication between the industry and consumers. Furthermore, the new communication technologies and the massive advent of social media facilitate the rapidly exposure of potential lacks in the execution of correct supply chain practices by companies.

According to the literature (Holmberg, 2000), four basic questions should drive companies in the selection of the proper strategy to handle with supply chain information disclosure in order to maximize the SC performance: (1) what to share?, (2)Whom to share it with?, (3) When to share?, and (4) How to share it?. The choice on the type of information to share (1) relies on the adopted perspective, whether operational or strategic (Moberg et al., 2009). The first involves short-term quantitative information on the daily operations management and affect the order cycle times and in inventory levels, as well as the customer service improvement (Sezen, 2008). The strategic perspective deals with the exchange of long-term, qualitative and sensitive information aided to strengthen the collaboration among SC partners and to improve the marketing, logistics and other business strategies. The four categories of supply chain information disclosure to public identified by Marshall et al. (2016) fall in this latter perspective. They distinguish among information on SC membership, i.e. corporate responsibility information, on provenance of products and raw materials, on environmental impact and on social aspects, e.g. human rights and labour rights respect. The disclosure of information from all categories may strengthen the brand reputation but also can contribute to reduce poor supply chain practices. Moreover, chain traceability address to the need of performing a more effective and efficient control of processes along supply chains. However, the effectiveness of the decision on (1) highly relies on the choice on (2). The information exchange can incur among different internal functions in a firm, with suppliers and with customers (Huo et al., 2014). However, when a company evaluates to disclose information outside its internal functions deals with the current vertical direction tendency of the information exchange along SC (Yao et al., 2008). Furthermore, not only companies are not keen on sharing information with their competitors but also, are aware that they can benefit from the information asymmetry (Afzal et al, 2008) toward their transacting parties (Akerlof, 1970). Even though, it is common belief that the sharing of accurate and timely information with partner and suppliers can increase the responsiveness to variations in the SC and in the customers demand (Li et al., 2006), while communicating information to customers in a timely manner may enhance their satisfaction and loyalty (Li and Lin, 2006). For these reasons, increasingly, industries see the capability of capturing and sharing real-time information as a key to improve SC performance (Cachon and Fisher, 2000). Therefore, several efforts are devoted to solve (4). Thus is demonstrated by the broad adoption of information systems along the SC, such as Enterprise Resource Planning (ERP) or warehouse management systems (WMS), as well as to the increasing interests for the application of Auto-ID technologies (e.g. RFID, WNSs).

However, due to the introduced limitations in the decision process on (2), information disclosure is perceived as a loss of power by many organizations that fear to pave the way to potential rivals (Li and Lin, 2006). Particularly, as previously mentioned, with increasing recourse to logistics outsourcing and the increasing competition within the logistics service market (Langley, 2015), always more often Third Party Logistic providers (3PL) deals with the unpredictable preferences of clients (Faber et al., 2013). The difficulty of organizations in setting up trustworthy partnership and in agreeing on common strategies in order to improve the whole SC performance highly affects the adoption and the development of shared technological platform for the information exchange. The uncertainty on the results and the numerous actors of various types are involved in a typical supply chain may discourage companies to extensively invest in shared infrastructures. In addition, such investments may not generate sufficient return if they aim to satisfy the requirements of just one of a few of their clients or suppliers.

Based on these statements, the remainder of this chapter illustrates two research topics, which approach to the problem of supply chain information disclosure considering the operational and strategic perspective of (1) indicated by (Holmberg, 2000), as indicated in Figure 14.

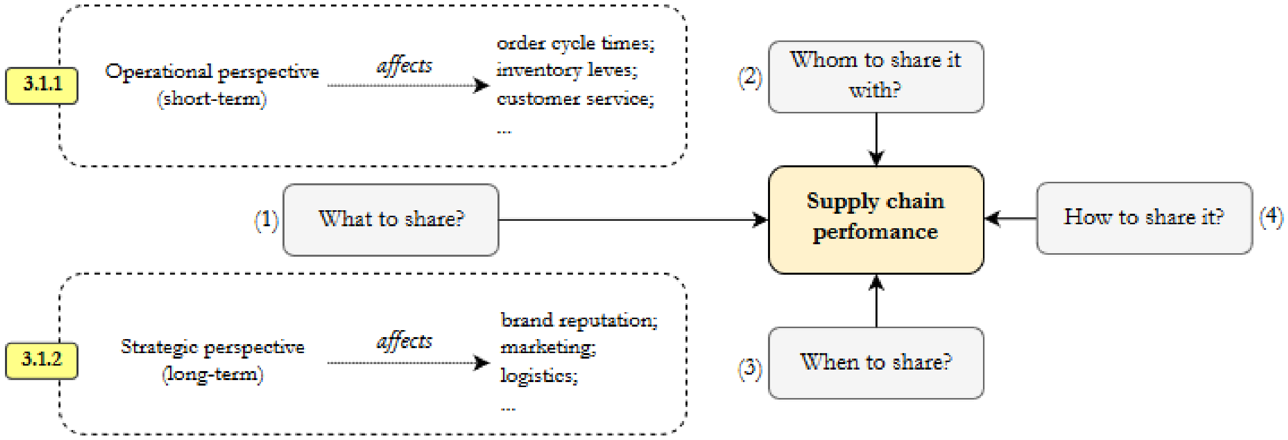


Figure 14: Four questions driving supply chain information disclosure (Holmberg, 2000)

The first (see 3.1.1) studies the impact of a major information sharing among SC partners in order to improve the daily operations, addressing to (2) and (3). The second (see 3.1.2) assumes a strategic perspective by exploring the state-of-the-art of new emerging technology, i.e. the blockchain, and its potential role in supply chain traceability, focusing on (4).

3.1.1 Cooperative vendors' networks in retail food supply chain

New patterns in consumer habits, the increasing relevance of marketing and logistics levers to enhance competitiveness and exploit the distribution channels, the rapid growth of private labels, and the huge concentration of the market share by retailers are progressively changing the balance of power in supply chains. The abuse of retailer buy power is routinely played against suppliers (Nicholson and Young, 2012) and results not only in supplier fleecing but also in less effective supply operations. The imbalance of bargaining power is acute in agro-food supply chains due to the fact that in the national EU markets, a small circle of retailers is positioned between thousands of suppliers. Particularly, in fresh fruit and vegetable supply chains the fragmentation of the supply is further affected by the unavoidable fluctuations in product volume and quality during the growing season. As a consequence, because suppliers have access to few alternative buyers, they suffer the threat of de-listing, late payments, low-prices, uncertainty in demand volume and frequencies, as well as other types of abuses (Vlachos et al., 2008, Van der Stichele and Young, 2009). Conversely, the retailer wants a limited cluster of suppliers with sufficient processing and distribution resources and capabilities and who are responsible for collecting products from the growers and farmers, managing the inventory and serving the retailers with a just-in-time (JIT) approach (Morgan et al., 2007, Vander Stichele and Young, 2009). Examples of this practice include the Dutch and Nordic supermarkets and Italian retailers, where large volumes of product pass through a minimal number of depots, thus enabling the tight control of product specifications and packaging standardization (Shaw and Gibbs, 1995, Caputo and Mininno, 1998). As a consequence, such imbalance of bargaining power may impact on the level of information exchange among supply chain actors. Moreover, it limits the diffusion of IT, which enables the exchange of timely and accurate information among the actors and builds a strategic lever to optimize logistics operations and exploit economies of scale for both storage and distribution.

Specifically, logistics and distribution play a crucial role in the retail agro-food market. Such role is further enforced by the product perishability and the limited shelf life (James et al., 2006). Therefore, the effective management of the buyer-supplier relationship is important as firms must rely on suppliers for outsourced logistics activities. To strengthen this connection, firms tend to elicit the cooperation of suppliers to ensure effective and quality supply processes (Lay, 2009). The adoption of a cooperative approach among the actors may facilitate the exchange of strategic information (i.e. the daily orders) to optimize the products distribution, reducing the whole transportation costs. The extant literature on the field underlines that the supply chain actors are reluctant in strengthening the relationships and sharing information (i.e., with whom, what and how) (Kembro et al., 2014), because the characteristics of the environment where cooperation is built-up significantly affects the benefits resulting from the partnership (Yigitbasioglu, 2010).

Whereas contingency factors incorporate several aspects, such as economic, governance and relational (Lay, 2009), this chapter focuses on logistics as a key lever to gain the advantages deriving from a cooperative approach between the actors of food retail supply chains. Particularly, where in the agro-food market a subset of vendors fulfils the daily demand from the retailer depots, the proper management of deliveries with respect to time-window constraints and fleet availability becomes critical. Moreover, whereas target-oriented depots (Kumar, 2008) close to the markets positively enhance the front-end service level, they also result in multiple drop offs for suppliers and less-saturated truck loads. A higher level of cooperation among partners, customers, distributors, suppliers, 3PL providers and even competitors may facilitate the information sharing among actors which would enable to optimize the routes, to better consolidate the loads, to enhance the vehicle utilization and reduce the total transport costs.

Despite the common wisdom of the beneficial effect of cooperation in supply chains (Angulo et al., 2004, Sandberg, 2007, Limoubpratum et al., 2015), retailers are reluctant to nurture a cooperative approach between suppliers because they fear to lose their bargaining power but also for the cost driver. The implementation of shared IT systems, the re-organization of communication procedures to favour cooperation requires indeed infrastructural investments and generates transaction cost. Often, the unforeseeable benefits of cooperation in comparison with such costs discourages the supply chain actors.

This chapter explores the design of cooperative networks between actors of the food retail supply chain and focuses on the logistic lever to quantify the costs and benefits (i.e., transport costs and service level), resulting from a cooperative pick-up and deliveries planning between the vendors and the retailer. In order to compare a priori the impact on the logistics operations of the competitive and the cooperative scenarios, an integer linear programming (ILP) model is adopted to solve the vehicle routing problem and provide comparable lower bounds of the total transport costs objective function. The model has been incorporated into an original support-decision tool which allows geography-depended and customized multi-scenario what-if analyses.

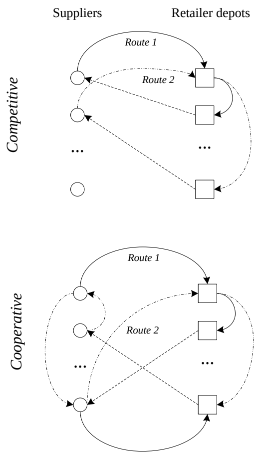
Rather than focusing on the vehicle routing formulation of food products deliveries, this chapter contributes to provide quantitative proofs on the impact that a cooperative approach in the retail supply chain has on the overall logistics costs and inefficiencies. The managerial implication associated to the obtained results might support the practitioners that operate in the logistics services as well as the retailer. Although the importance of supply chain cooperation and integration has been widely verified (van der Vaart and van Donk, 2008, de Keizer et al., 2014), the extant relationships between suppliers and customers and the conditions that contribute to positive collaboration have yet to be fully investigated. Moreover, few papers use simulation techniques to analyse such relationships (Lyu et al., 2010).

The model is built upon some re-known VR problem formulations proposed by the extant literature (Cruijssen et al., 2007), and then tailored to optimize a food vendors' network that serves the retailer depots. It is then used to analyse and assess the effects of adopting a cooperative approach among the actors of the network on the transport cost and service levels experienced by the vendors, the carriers, and the retailer. According to what stated in Boyer et al. (2009), three independent factors affecting the delivery costs and service levels are considered, namely, network density (1), order distribution within time-windows (2), and truck availability per time-window (3).

Assuming a set of suppliers and a set of retailer depots that shape the observed regional network, a maximum number of vehicles (e.g., trucks) is available to serve the network by carrying the order from the vendors to the retailers within required time-windows. The working day is split into eight homogeneous time-windows, called periods in the model (i.e. from 1 to 8), that discretize the emission period of the order o, i.e., od_o. Then, each order o has a due period, i.e., dd_o, that represents the time limit within the goods must be delivered. Each order o requires at least a pallet p of a product, which is less than the unit loaded. The cost of transport for vehicle m is fixed, i.e., cf_m, and associated with the truck booking, while the cost per kilometer, i.e., cv_m, is variable and associated with the travel routes. The complete list of sets, indices, and parameters are presented in Table 3.

Table 3: List of sets, indices and parameters

Index ∈ Set	***Description***	***Notation***	***Description***
$o \in O$	*Orders*	$od_{(o)}$	*Order period for order o (period)*
$p \in P$	*Pallets*	$dd_{(o)}$	*Due period for order o (period)*
$m \in M$	*Vehicles*	$d_{(o)}$	*Demanded quantity (weight) by order o (kg)*
$i,j \in N$	*Nodes*	$dn_{(o)}$	*Requiring node per order o*
$pkg, ret \subset N$	*Node subsets*	$pr_{(o)}$	*Required product by order o*
$t \in \{0, \dots, 8\}$	*Periods*	$sd_{(m)}$	*Starting period for vehicle m* $\in \{0, \dots, 8\}$
		$on_{(m)}$	*Origin node for vehicle m*
		$C_{(m)}$	*Weight capacity of vehicle m*
		$cf_{(m)}$	*Fixed service cost for truck m (€/vehicle)*
		$cv_{(m)}$	*Cost per kilometer of truck m (€/km)*
		$\delta^{t}_{(m,i)}$	*Availability of truck m at node i per period t* $\in \{0,1\}$
		$w_{(p)}$	*Weight of pallet p(kg)*
		$on_{(p)}$	*Origin node for pallet p*
		$dn_{(p)}$	*Destination node for pallet p*
		$pd_{(p)}$	*Production date for pallet p*
		$cs_{(p)}$	*Storage cost of pallet p(€/pallet period)*
		$pr_{(p)}$	*Product of pallet p*
		$Cp_{(j,t)}$	*Production capacity of node j in period t*
		$d_{(i,j)}$	*Road distance of the arc between ij (km)*



The decision variables are defined as follows:

$y_{(m,i,j,t)}$: $\begin{cases}1\\0\end{cases}$ where 1 if vehicle m is travelling in period t from i to j; 0 otherwise.

$y_{(p,m,i,j,t)}$: $\begin{cases}1\\0\end{cases}$ where 1 if pallet p is loaded on vehicle m and is travelling in period t from i to j; 0 otherwise.

The following equation represents the objective function (*OF*) of the problem and quantifies the overall fixed and variable transport costs associated with the pick-up and delivery routes. The definition of the *OF* is limited by the set of constraints as described in Equation (1) to Equation (15).

$$min \sum_m \sum_j y_{(m,on_m,j,\, sd_m)} \cdot cf_{(m)} + \sum_m \sum_{i\ j:i\neq j} \sum_t y_{(m,i,j,t)} \cdot d_{(i,j)} \cdot cv_{(m)}$$

Equation (1) links the decision variables and imposes that the loading capacity of the generic vehicle m is not exceeded.

$$\sum_p w_{(p)} \cdot y_{(p,m,i,j,t)} \leq C_{(m)} \cdot y_{(m,i,j,t)} \qquad \forall\ m,i,j,t \qquad (1)$$

To avoid retailer stockouts (Ehrenthal and Stolzle, 2013), Equation (2) imposes that each order o is completely fulfilled on time.

$$\sum_{pr_p = pr_o} \sum_m \sum_i \sum_{j=dn_p} \sum_{t \leq dd_o} w_{(p)} \cdot y_{(p,m,i,j,t)} \geq d_{(o)} \qquad \forall\ o \qquad (2)$$

Equation (3) enables the loading process of a generic vehicle m from its departing node on_m, thereby avoiding the opportunity to share vehicle m among suppliers and collect loads from different vendors. This constraint depicts the scenario where the retailer exploits its bargaining power with a limited subset of potential vendors by avoiding information sharing, which results in independent deliveries. Conversely, when the constraint (3) is relaxed, each truck m is allowed to retrieve loads of products from different vendors, thereby reducing the number of travelled routes.

$$\sum_t y_{(p,m,i,j,t)} = 0 \qquad \forall\ p,m: on_{(m)} \neq on_{(p)}, i,j: i = j \tag{3}$$

Equation (4) disregards the fact that generic vehicle m departs before its departing time, while Equation (5) links the route of vehicle m to the vendor node on_p where pallet p is produced.

$$\sum_p \sum_i \sum_j y_{(p,m,i,j,t)} = 0 \qquad \forall\, m,t: t \leq sd_{(m)} - 1 \tag{4}$$
$$y_{pmijt} \leq \sum_j \sum_t y_{(p,m,on_n,j,t)} \qquad \forall\, p,m,i,j,t \tag{5}$$

The constraints (6) avoid exceeding truck availability at each departing node on_m for period t.

$$\sum_j y_{(m,on_m,j,sd_m)} \leq \delta^t{}_{(m,on_m)} \qquad \forall\, m,t,on_{(m)} \tag{6}$$

Equations (7) and (8) control for vehicle routing by ignoring that vehicle m departs and arrives, respectively, at the same node many times, while Equation (9) disregards that vehicle m travels along multiple arcs during the same period.

$$\sum_i \sum_t y_{(m,i,j,t)} \leq \sum_i y_{(m,on_m,i,sd_m)} \qquad \forall\ m,j \tag{7}$$
$$\sum_j \sum_t y_{(m,i,j,t)} \leq \sum_j y_{(m,on_m,j,sd_m)} \qquad \forall\ m,i \tag{8}$$
$$\sum_i \sum_j y_{(m,i,j,t)} \leq \sum_j y_{(m,on_{m,},j,sd_m)} \qquad \forall\ m,t \tag{9}$$

The following constraints from Equation (10) to Equation (13) aim to control flow incongruences, as, respectively, the arrival of vehicle m to its origin node (10), the conservation of the flow between nodes and arcs (11), and the link between a pallet and the order with which it is associated.

$$\sum_j y_{(p,m,j,i,t-1)} = 0 \qquad \forall\ p,m,i = on_{(p)}, t \geq 2 \tag{10}$$
$$\sum_j y_{(p,m,i,j,t)} = \sum_j y_{(p,m,j,i,t-1)} \qquad \forall\ p,m,i \neq on_{(p)}, t \geq 2 \tag{11}$$
$$\sum_j y_{(m,j,i,t-1)} \geq \sum_j y_{(m,i,j,t)} \qquad \forall\ m,t,i \neq on_{(m)} \tag{12}$$
$$\sum_{j \neq on_n} \sum_m \sum_{t \geq sd_{(m)} \wedge t \geq od_o} y_{(p,m,on_n,j,t)} = 1 \qquad \forall\ p,o: pr_{(o)} = pr_{(p)} \tag{13}$$

Equation (14) completes deliveries within the required timeframe, and equation (15) limits the product weight loaded at generic node i to its production capacity.

$$sd_{(m)} + \sum_j \sum_t y_{(p,m,on_p,j_t)} + \sum_{i,j} \sum_{t \geq sd_m} y_{pmij_t} \leq dd_o \qquad \forall\ o, m, p: pr_o = pr_p \tag{14}$$

$$\sum_p \sum_m \sum_{j \neq on_n} w_p \cdot y_{pmijt} \leq Cp_{it} \qquad \forall\ i \in pkg, t \tag{15}$$

The description of the model and the support-decision tool are out of the scope of this chapter. The readers who are interested in learning about them are referred to (Accorsi et al., 2018[a]). The chapter, instead, focus on the application of the proposed methodology to study the supply chain for fresh fruit and vegetable products of an Italian large-scale retailer in the Emilia-Romagna region.

A multi-scenario sensitivity analysis is presented, in order to assess how the benefits from the logistic cooperation are affected by the density of the connectivity of the network (i.e., how the nodes are spanned and mutually connected), as well as by the variability in the order releasing and in the fleet availability.

3.1.1.1 *How cooperative vendors' networks affects logistics: a case study of a regional retailer supply chain*

The proposed methodology is applied to study the supply chain for fresh fruit and vegetable products of an Italian large-scale retailer in the Emilia-Romagna region. The regional firms lead the Italian agro-food sector, and accounts in Europe for 3% the number of companies and for 5% the total sector revenue in 2015. About 14% the regional agricultural area is devoted to fruit and vegetables crops, ranking as third in surface among the other Italian regions (Intesa Sanpaolo, 2016). The region Emilia-Romagna presents a quite developed and capillary food retail sector with an average grocery's surface of 270 sqm per 1000 inhabitants, with picks in the provinces of Ferrara and Piacenza (Fanfani and Pieri, 2015).

Over pure logistics and infrastructural aspects, the Emilia-Romagna region presents about 40% the overall roadways in the North-East of Italy (Regione Emilia Romagna, 2016). The province of Piacenza offers the highest density of road infrastructures, followed by Parma and Forlì-Cesena (Uniontrasporti, 2011). The main transport way crosses diagonally the region, connecting along a line Bologna, Rimini, Modena, Parma, Reggio nell'Emilia and Piacenza. Three main secondary axes are developed traversally to the secondary highways, in a typical fish-bone shape. This configuration favours the location of the logistics nodes along the main highways. Together, these characteristics make the observed geography a valid testbed for the application of the proposed approach.

The observed network encompasses twelve nodes, five retailer depots and seven vendor facilities that supply different varieties of peaches, plums, pears, tomatoes and potatoes. In order to validate the proposed approach, 96 alternative system configurations are analysed and compared. The characteristics of each configuration differ on the distribution of the order release during the day (1), the fleet availability during the day (2), the network density and its geography (3), as well as on the organizative strategy adopted between the vendors (i.e., the As-Is vs. a coopertive approach) (4). With respect to (1), an instance demand profile comprised of 48 orders per day is considered. The characteristics of each order are expressed in terms of size and release time (i.e., time of emission). The distribution of the order size and the time of emission may be impacted by seasonality, by advertising campaigns promoted by the retailer, and by product turnover at the grocery shelves.

The plots in Figure 15 illustrate the profile of the orders that are to be filled daily by the vendors. To include the uncertainty factor of retailer demand, four potential order profiles defined by the value of discrete probability $p(od_o = t)$ of the order o emitted in time-window t are evaluated. These profiles distribute the order differently within the time-windows, approximating roughly the shape of well-known continuous probability density functions, specifically, uniform, normal, and lognormal distributions, as presented in Figure 15. Thus, the profiles are named using their reference distribution throughout the remainder of this paper. Another profile refers to as parabolic to indicate an order profile mainly concentrated in the first and the last time-windows.

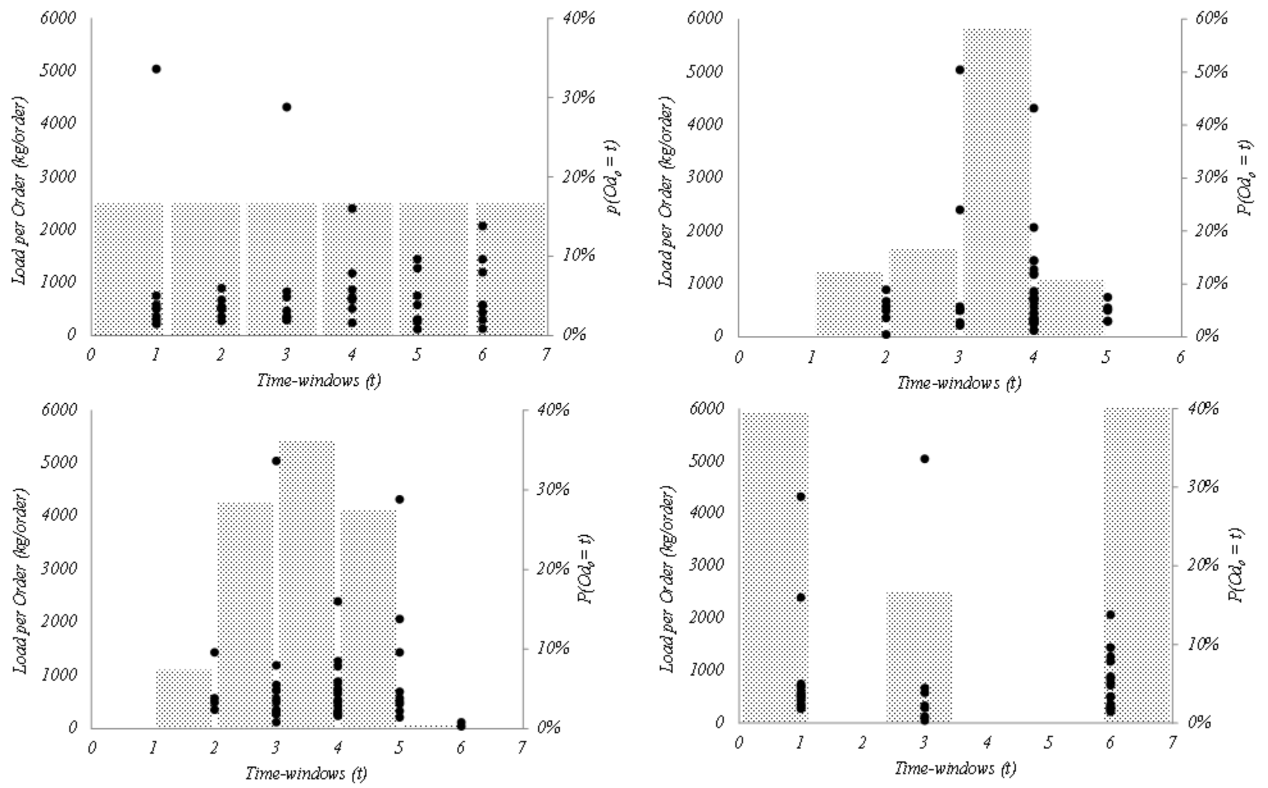


Figure 15: Dot plots of the daily distribution of the orders classified by the time-window of emission and by the load size (1); Bar graphs of the discrete probability density $p(od_o = t)$ (2).

Given the alternative order profiles to be fulfilled, the availability of the trucks used for deliveries (2) significantly constrain the problem. The truck fleet is not usually owned by either the supplier or the retailer, but instead belongs to one or many 3PL carriers, and its availability throughout the day is affected by a host of unpredictable factors. Therefore, the number of available trucks per time-window t and supplier i, i.e., ${\delta^t}_{mi}$, is not constant but rather is assumed variable according to four profiles of truck availability. The parameter $\sum_m {\delta^t}_{mi}$ indicates the number of available trucks at supplier facility i in time-window t. The first profile, the uniform profile, allocates one truck per time-window and supplier, resulting in a fleet of eight trucks. The other profiles distribute the truck fleet according to different discrete distributions, as illustrated in Figure 16, that approximate the aforementioned probability density for the order profiles. These distributions identify four alternative scenarios that address the aforementioned four order profiles in a multi-scenario what-if analysis.

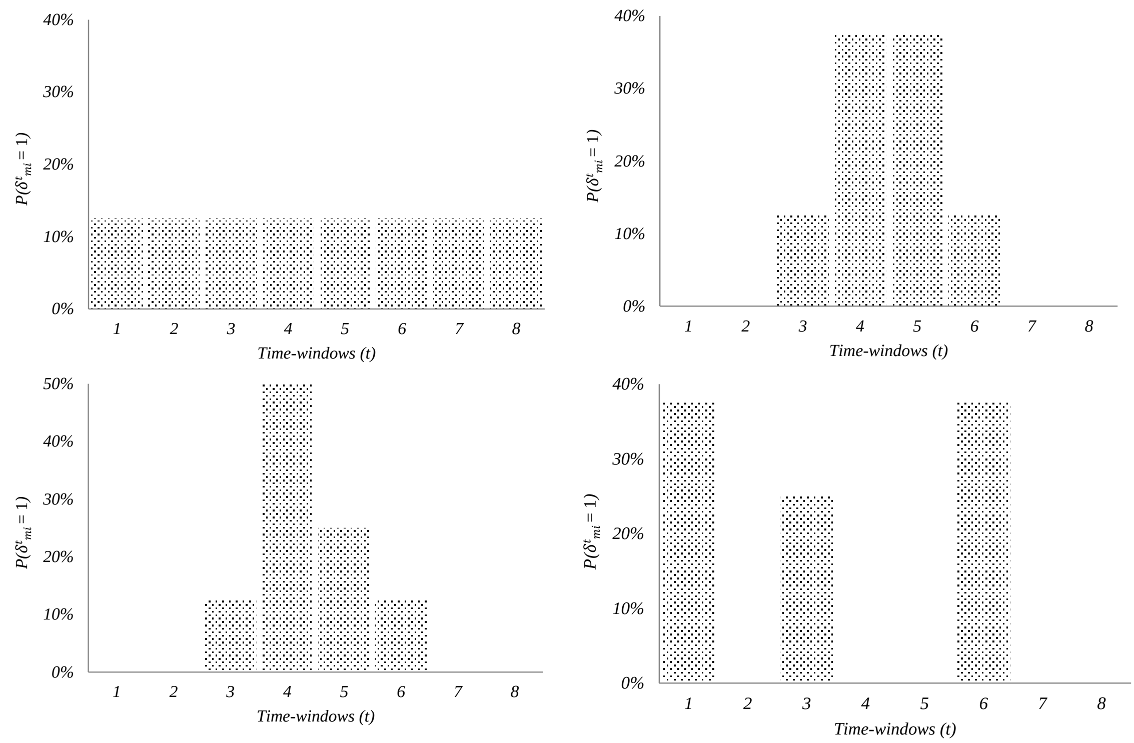
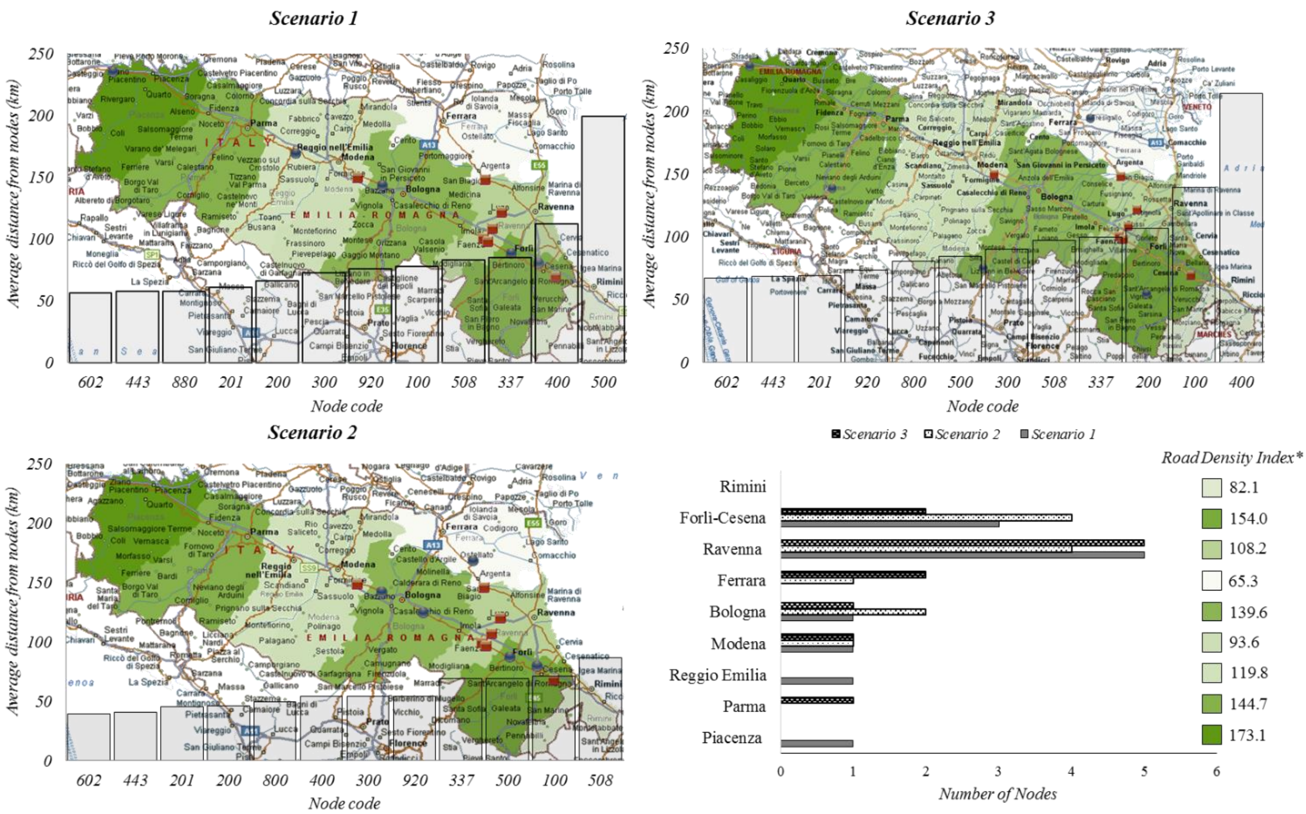


Figure 16: Bar graphs of the discrete probability density $p(\delta^t{}_{mi} = 1)$ per truck m.

Figure 17 shows three alternative configurations of the network which vary by node density and geographical distribution both the retailer depots and the vendor's facilities (3). The bar chart quantifies the travelling distance to achieve a generic node from the others for the vendors (i.e., square points) and the retailer (i.e., circle points). The horizontal bar chart illustrates how the nodes are located in the nine provinces of Emilia Romagna. Furthermore, the road density index is reported and illustrated in the map over a green colour scale. The darker the green, the higher road density in that province is. Reasonably, the nodes located in those provinces coloured in light green would be less accessible in comparison with the others.



* As defined by (Uniontrasporti, 2011)

Figure 17: Network density and node-to-node route road distance.

As a consequence, 48 alternative system configurations are identified by the combination of (1), (2) and (3). Then, such scenarios fuelled the model to investigate the impacts of the two distribution regimes: the regime where cooperative approach are not allowed (i.e., named As-Is in the following), and the vendors operate independently to serve the retailer; and a regime that implements a cooperative approach between vendors in the planning of the deliveries to the retailers (i.e., named To-Be in the following). The results from the optimization, reported in Table 4 and Table 5, are reported in terms of the total transport costs (i.e., the objective function) and the number of vehicles required to fulfil demand.

Table 4: Results by the simulation: Transport Costs.

Scenario 1		*Order profile*			
As-is	Transport Costs (€)	Uniform	Normal	Lognormal	Parabolic
	Uniform	*4574*	*4461*	*4630*	*4574*
Truck Availability	Normal	*infeasable*	*infeasable*	*4630*	*infeasable*
	Lognormal	*infeasable*	*4461*	*4630*	*4574*
	Parabolic	*infeasable*	*4601*	*4718*	*infeasable*

Scenario 2		*Order profile*			
As-is	Transport Costs (€)	Uniform	Normal	Lognormal	Parabolic
	Uniform	*infeasable*	*infeasable*	*3410*	*3410*
Truck Availability	Normal	*infeasable*	*infeasable*	*3333*	*infeasable*
	Lognormal	*infeasable*	*infeasable*	*3333*	*3410*
	Parabolic	*infeasable*	*infeasable*	*3410*	*3410*

Scenario 3		*Order profile*			
As-is	Transport Costs (€)	Uniform	Normal	Lognormal	Parabolic
	Uniform	*infeasable*	*infeasable*	*5808*	*6203*
Truck Availability	Normal	*infeasable*	*infeasable*	*5901*	*6203*
	Lognormal	*infeasable*	*infeasable*	*5901*	*6203*
	Parabolic	*infeasable*	*infeasable*	*5885*	*infeasable*

Scenario 1		*Order profile*			
Cooperative	Transport Costs (€)	Uniform	Normal	Lognormal	Parabolic
	Uniform	*2755*	*2809*	*2369*	*3279*
Truck Availability	Normal	*3036*	*3427*	*2669*	*3345*
	Lognormal	*3240*	*2381*	*2669*	*3423*
	Parabolic	*3322*	*2303*	*2372*	*3932*

Scenario 2		*Order profile*			
Cooperative	Transport Costs (€)	Uniform	Normal	Lognormal	Parabolic
	Uniform	*2676*	*2090*	*2329*	*2691*
Truck Availability	Normal	*2905*	*2258*	*2096*	*infeasable*
	Lognormal	*2458*	*2287*	*2027*	*2697*
	Parabolic	*3013*	*2159*	*2898*	*3182*

Scenario 3		*Order profile*			
Cooperative	Transport Costs (€)	Uniform	Normal	Lognormal	Parabolic
	Uniform	*2975*	*infeasable*	*2060*	*2691*
Truck Availability	Normal	*2905*	*2174*	*2075*	*2811*
	Lognormal	*2838*	*2461*	*2096*	*2697*
	Parabolic	*3001*	*2231*	*2078*	*infeasable*

Table 5: Results by the simulation: Required Trucks.

Scenario 1		*Order profile*			
As-is	Required Trucks	Uniform	Normal	Lognormal	Parabolic
	Uniform	*7*	*6*	*6*	*7*
Truck Availability	Normal	*infeasable*	*infeasable*	*6*	*infeasable*
	Lognormal	*infeasable*	*6*	*6*	*7*
	Parabolic	*infeasable*	*7*	*7*	*infeasable*

Scenario 2		*Order profile*			
As-is	Required Trucks	Uniform	Normal	Lognormal	Parabolic
	Uniform	*infeasable*	*infeasable*	*6*	*7*
Truck Availability	Normal	*infeasable*	*infeasable*	*6*	*infeasable*
	Lognormal	*infeasable*	*infeasable*	*6*	*7*
	Parabolic	*infeasable*	*infeasable*	*7*	*7*

Scenario 3		*Order profile*			
As-is	Required Trucks	Uniform	Normal	Lognormal	Parabolic
	Uniform	*infeasable*	*infeasable*	*6*	*7*
Truck Availability	Normal	*infeasable*	*infeasable*	*6*	*7*
	Lognormal	*infeasable*	*infeasable*	*6*	*7*
	Parabolic	*infeasable*	*infeasable*	*7*	*infeasable*

Scenario 1		*Order profile*			
Cooperative	Required Trucks	Uniform	Normal	Lognormal	Parabolic
	Uniform	*5*	*5*	*4*	*6*
Truck Availability	Normal	*6*	*5*	*4*	*6*
	Lognormal	*6*	*4*	*4*	*6*
	Parabolic	*5*	*4*	*4*	*7*

Scenario 2		*Order profile*			
Cooperative	Required Trucks	Uniform	Normal	Lognormal	Parabolic
	Uniform	*6*	*4*	*5*	*6*
Truck Availability	Normal	*5*	*4*	*4*	*infeasable*
	Lognormal	*5*	*5*	*4*	*6*
	Parabolic	*5*	*4*	*6*	*7*

Scenario 3		*Order profile*			
Cooperative	Required Trucks	Uniform	Normal	Lognormal	Parabolic
	Uniform	*7*	*infeasable*	*5*	*6*
Truck Availability	Normal	*5*	*4*	*4*	*6*
	Lognormal	*6*	*5*	*4*	*6*
	Parabolic	*5*	*4*	*4*	*infeasable*

Table 4 identifies the combination of the order profiles and truck availability scenarios and their performance in terms of transport costs and service level (i.e., feasible vs. unfeasible). By considering the As-Is regime, the number of trucks used to satisfy retailer demand varies between six and seven, while the adoption of the cooperative approach reduces the number of trucks between four and seven. Table 5 displays the savings achieved using a cooperative approach in term of number of used trucks. The cooperation among the vendors allows the carriers to collect products from different facilities and select the optimal picking-delivery routes. The infeasible scenarios in the As-Is regime are solved with the To-Be regime. This indeed widens the opportunities for the vendors, the retailers, and the carriers that seek to optimize the transport costs. The benefits in terms of the required number of trucks are remarkable. As instance, in the scenario 1 the To-Be regime accounts for transport cost savings that range from 30% (i.e., decentralized orders with uniform trucks) to 50%

(i.e., normal and lognormal order distribution with concentrated availability of trucks) of the As-Is benchmark.

3.1.1.2 Outcomes from the case study and managerial implications

The obtained results and the associated managerial insights are summarized and discussed in the following sub-sections, which are organized by metric of performance accounted by the delivery process.

Travelled distance and distribution of the deliveries

Figure 18 and Figure 19 show the travelled distance per time-window given the distribution of the orders and the availability of the fleet in the *As-Is* and the *To-Be* regimes. In Figure 18, although the three scenarios obtain different performances, most of the deliveries is concentrated in the last time-windows as a result of the intent to increase the average saturation of the trucks. In all the scenarios, the lognormal orders distribution allows for decreasing the time needed to complete some routes and concentrating the deliveries in the centre time-windows of the day. Focusing on the Scenario 1, the uniform distribution of the trucks availability and the lognormal distribution of orders significantly relax the problem, as both contribute to fulfil the retailer demand in all of the alternative system configuration. Specifically, when the orders are uniformly distributed, only a uniform trucks fleet can effectively satisfy demand. Although this scenario showcases a critical supply condition for arranging delivery tours, it is not unusual. While the demand from the retailer, if not properly scheduled or fixed with agreements, can be arbitrarily distributed along the daily time-windows, the presence of trucks for deliveries is affected by a wide set of factors, such as traffic, delays and queues in loading operations, and the aim of keeping the fleet balanced is difficult to accomplish if the fleet is owned by the supplier or by 3PL carriers. The lognormal order profile meets all of the distributions of truck availability and is thereby preferred by the retailer because it allows for the highest service level. Conversely, the suppliers do not prefer the lognormal order profile because it can result in higher transport costs. The different geographic distribution of the network nodes in both scenario 2 and 3, makes the fulfilment of normal distributed orders unfeasible for all the fleet availability profiles, despite the average distance from nodes is different. However, the scenario that matches the normal distribution of the order with the normal availability of the trucks is not feasible in all the scenarios. Moreover, the three scenarios show different performances when matched with the parabolic distribution of the order release. These conclusions enforce the premise (Gevaers et al.,

2014) that the density of the network nodes is not only negatively correlated with the transport costs but also constrain significantly the routing problem in the presence of narrow delivery windows. Figure 19 cumulates the distances travelled per time-window and highlights how the *To-Be* regime use the last periods to complete most of the retrieving and delivery routes. While in the Scenario 1 all the configurations are solved, in the scenarios 2 and 3, those configurations characterised by the parabolic distribution of the order release remain infeasible.

The managerial insight of these results should discourage the retailer from releasing the orders in the first and last time-windows of the day, in order to avoid the raise of the transport costs (i.e., compare the value of the objective function in Table 4) and to avoid stock-out or unfulfilled demand.

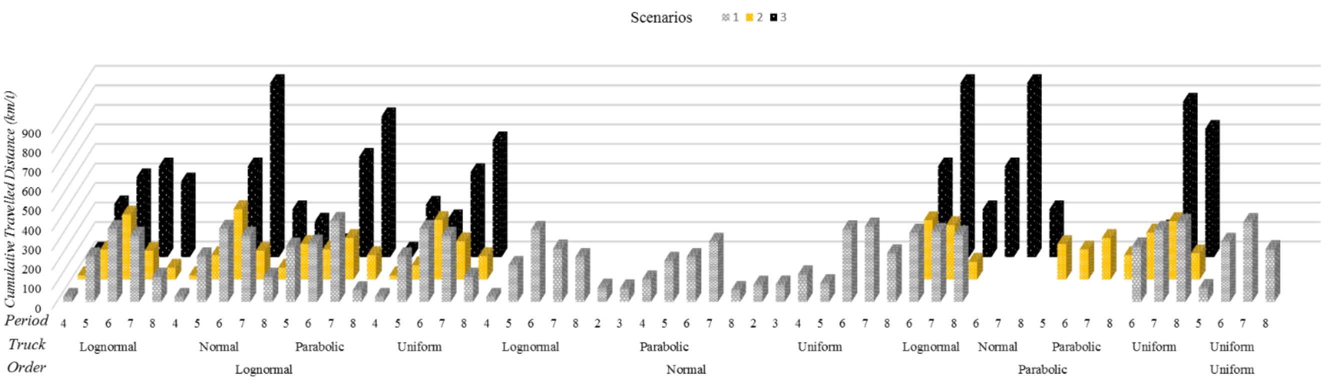


Figure 18: Results by the As-is regime.

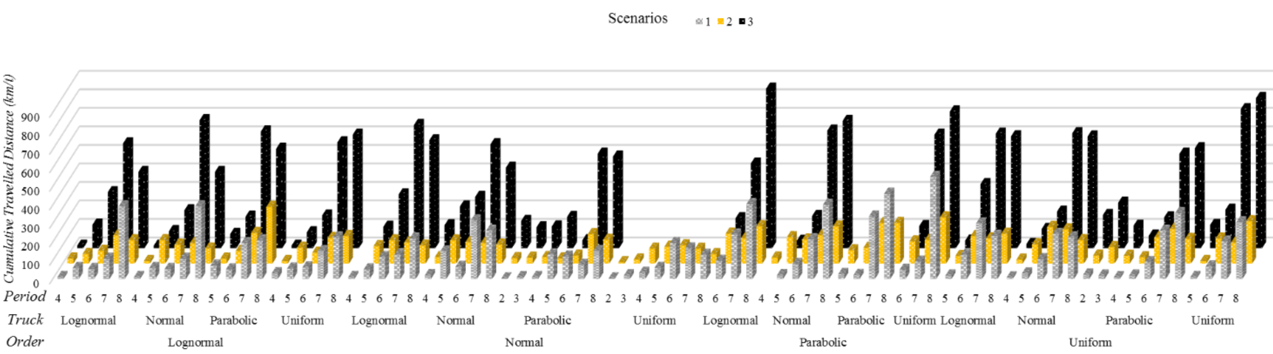


Figure 19: Results by the To-be regime.

Level of service and truck utilization

To explore how the *As-Is* and the *To-be regimes* differ in the resulting performances, the statistics regarding the service level and truck utilization are reported. With a weighted average lateness of -

1.68 periods, -1.62 periods, 1.58 periods per order for the scenario 1, 2, and 3 respectively, the *As-Is* regime guarantees to fulfil the retailer approximately 16%, 13.6%, and 10.1% in advance than with the *To-Be* regime. It is worth noting that, given a geography where the retailer's depots are located far from the main highway, the Scenario 3 account for the lowest saving in lateness (i.e., 10.1%). Given a time window of one hour and thirty minutes, as used in the proposed case study, the 16% advance is an equivalent of approximately 15 minutes in time and is therefore considered negligible. However, further assessments would be necessary in the presence of larger time windows. Conversely, considering the vehicle utilization, Figure 20 indicates how the loads are distributed among the trucks and how the *To-Be* regime results in a higher average saturation, i.e., 38% vs. 25% for the *As-Is*. Specifically, Figure 20 relates to the aforementioned vendor approach of uniform truck profiles and lognormal orders distribution, where the performances in terms of truck saturation are quite representative of the whole data set.

The cooperative approach implemented among vendors obviously provide advantages to the carrier, which increases the number of stops per route thereby reducing its unit cost. However, the benefits for the carrier are affected by multiple factors and mainly by the distribution of the order release.

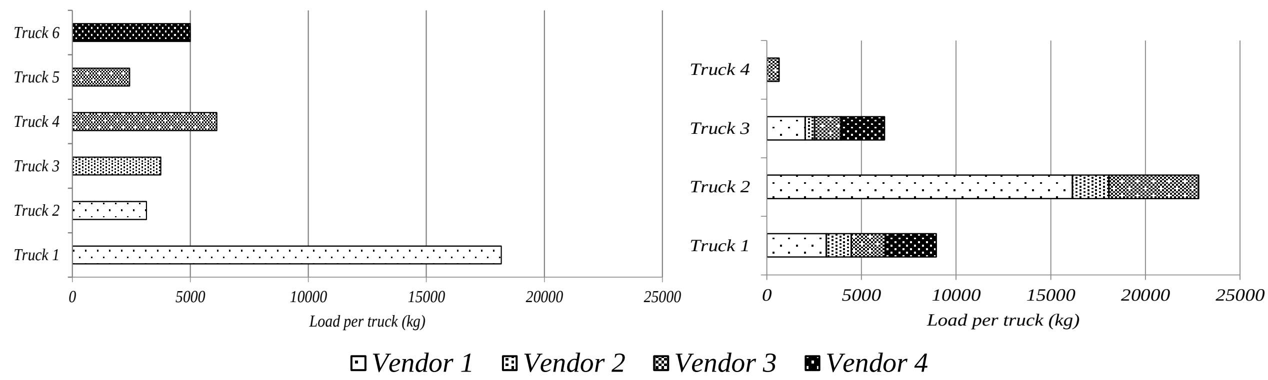


Figure 20: Truck utilization in As-is vs. To-be regime

Density-of-connectivity

The following analysis highlights the dependency between the network density, the average distance travelled and the transport costs. Particularly, Figure 21 quantifies the average distance travelled by a truck to achieve each retailer node (top bar graph) and the average travelling cost incurred to serve a given depot (bottom bar graph). This cost is calculated as the fixed loading cost to rent a truck load (e.g., 200 Euro per truck) plus the variable travelling costs in terms of Euro per kilometre multiplied by the kilometres necessary to serve the given retailer from the previous node. The travelling costs are significantly affected by the density of the suppliers in the presence of the *To-Be* regime but are primarily influenced by the density of the other delivery nodes in the presence of the *As-Is* regime.

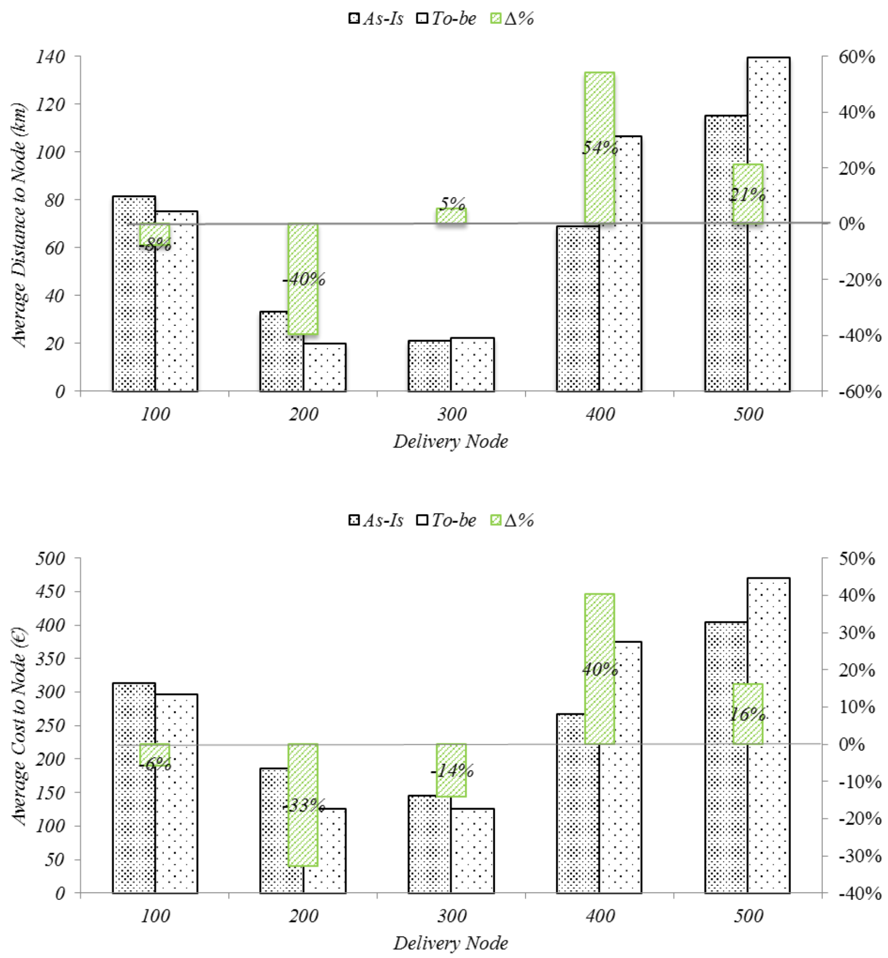


Figure 21: Average travelled distance to node

Figure 21 summarizes the results obtained from the optimization of the deliveries in both regimes, and assess which node gains the most with a cooperative approach. The average savings allocated to each retailer depot depend on the number of deliveries per route, and on how each arc contributes to the total route travelling.

In order to provide practitioners with managerial insights of when a cooperative approach among vendors should be implemented, Figure 22 assesses and compares the retailer depot node over a density-of-connectivity perspective. The curves above present the percent of nodes achievable from a given depot within a value of cumulative routing distance, which is defined as the sum of the distances to achieve all the nodes of the network. The cumulative routing distance represents the upper bound of the transport costs function, corresponding to the case where each depot behaves as a hub in a so-called *hub-and-spoke* network. For instance, in the Scenario 1, retailer Node 200 is linked with an approximate 55° percentile of the nodes within a 20° percentile of the cumulative routing distance.

The bottom curves in Figure 22 graph the percentile of the routing distance to achieve the other nodes. These allow to investigate the differences between the arc of the network.

The Scenario 1 is indeed characterized by a high variability in the arcs' routing length. In such a scenario, the depots 200 and 300 connect with approximately 60% of the network nodes within 20% of the routing distance, while the depot 500 accounts for the 70% of the routing distance. The Scenario 2 showcases a different behaviour of the curves which reflect the poor variability of the arcs illustrated in Figure 17. Lastly, the Scenario 3 has an intermediate behaviour between the others.

It is worth noting that, while Figure 21 summarizes the results obtained for the optimization of the delivery process, Figure 22 is built just on the network geography of the observed instance. Thus, this might behave as a user-friendly abacus that allow foreseeing the benefits and costs resulting by a cooperative approach between vendors and the retailer in the delivery process. In the view of this, we exemplify the behaviour of the Scenario 1. For the depots 200 and 300, the high concentration of suppliers within the 20° route distance results in evident transport cost savings when implementing a cooperative approach. Conversely, as in the case of depot 500, the convenience of cooperative delivery clusters is less evident, particularly in the last part of the curve, which is drawn by supplier nodes.

While the bottom curves of Figure 22 are sufficiently representative of the density-of-connectivity of the network, the graph above contributes to the discussion regarding the role of curve convexity as an abacus to choose the proper approach to adopt when serving the retailer, and who among the depots should invest in building-up the cooperative regime (e.g., depot 200 vs. depot 500).

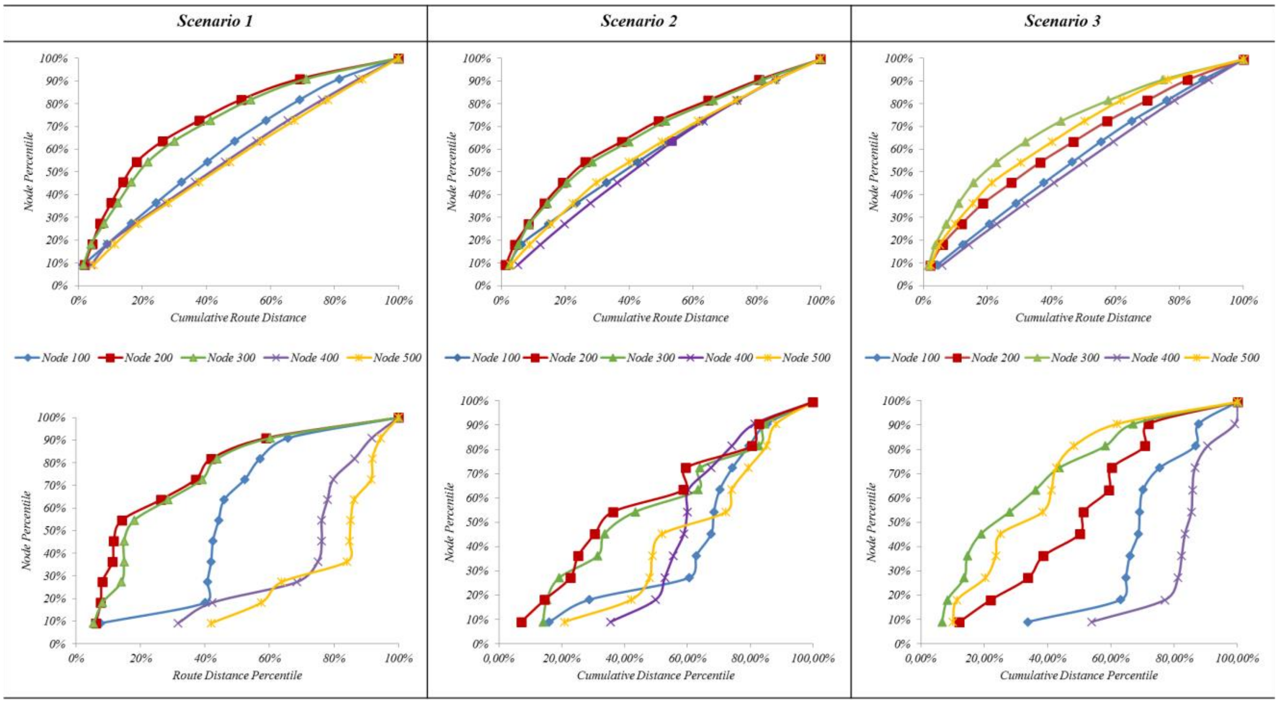


Figure 22: Density-of-connectivity

The adoption of the cooperative approach results in multiple stops per route to complete both retrieving and delivery missions. In the Scenario 1, the longer-ray deliveries include the routes from the suppliers from Eastern nodes to depot 500 (i.e., Piacenza). The longer-ray routes collect from a small number of close vendors and then carry out inexpensive stops to depot 100 (i.e., Bologna) and depot 400 (i.e., Reggio nell'Emilia) before serving depot 500. The shorter-ray routes leave room for collecting products from different suppliers, thereby operating the loading and delivery activities within the same tour. Furthermore, among the short-ray routes the delivery cluster is no longer identified by the farthest node but depends on the farthest visited vendor such that more opportunities to optimize routing occur. The potential return from implementing a cooperative approach is thereby affected by the distance of the depots to be served, which are classified in Table 6.

The travelling for cooperation metric, i.e., $T(n)^{coop}{}_{d}$ (i.e., km) defines the difference between the longest route travelled to achieve the generic node *n* and the distance between node *n* and the supplier cluster barycentre. Given a generic *As-Is* route to achieve node *n*, travelling for cooperation roughly quantifies the room to shift toward the *To-Be* regime and grows with the density of vendor and delivery nodes. The higher this density, the higher the marginal convenience of visiting that node with a cooperative approach. Furthermore, by identifying homogeneous type of deliveries based on the average travelled distance, the suppliers can customize alternative delivery strategies by choosing the *As-Is* rather than the cooperative approach. In Table 6, we compare the routes travelled to serve depots 100 and 200, respectively, with a percentage value of $T(n)^{coop}{}_d$ equal to 73% and 100%. Depot 200 is located within a cluster of suppliers, and the travel path to serve the retailer is comparable to that travelled in the loading tour. Conversely, depot 100 is far from the vendors, and thus the travelling distance to achieve it limits the room for more efficient loading tours. The greater the distance between a demand node and a generic supplier cluster, the less effectiveness a cooperative approach and shared transport services between vendors will be.

Table 6: Retailer depots classification over the Scenario 1

		Input			*Output: Cooperative approach*			
Delivery node	*Province*	*Distance from closest vendor (km)*	*Distance from farthest vendor (km)*	*Distance from vendors baricenter (km)*	*Distance from closest previous node*	*Distance from farthest previous node*	*Average $T(n)^{coop}{}_d$*	*Average (%) $T(n)^{coop}{}_d$*
Node 100	Bologna	13	114	65	71	92	179	73%
Node 200	Forlì	18	101	0	15	29	120	100%
Node 300	Cesena	14	110	30	20	36	78	72%
Node 400	Reggio nell'Emilia	53	168	129	53	130	144	53%
Node 500	Piacenza	155	270	224	115	233	49	18%

3.1.1.3 *Final remarks*

In the view of the obtained results, the adoption of a cooperative approach contributes to gain mutual benefits for the vendors, the retailer and even for the carriers. According to the vendor's perspective, despite a slightly growth of the average delivery lateness, the wider feasibility in meeting and fulfilling different order release profiles is a clear benefit that paves the way for further opportunities to reduce the total transport cost. Whether the retailer tolerated a short delay in the arrivals, it would take advantage from higher resilience of the delivery service able to couple with multiple order release and fleet availability profiles.

According to the carrier perspective, the reduction of the needed trucks to complete the delivery service in the cooperative regime, results in increasing the average truck load utilization, and enhancing his profit. The carrier is indeed encouraged to strengthen the relationship with the vendors and the retailer, which can obtain both a better price of his logistics services. Notwithstanding with these mutual advantages, the illustrated case study should elicit a carefully assessment of the network geography before choosing for the adoption of a cooperative approach.

When evaluating cooperation costs and opportunities, the methodology introduced in this paper suggests the involvement of only those nodes with the highest benefits, rather than extending the cooperative regime to all vendors. By quantifying the economic benefits resulting from cooperation through the proposed tool, the retailer and the 3P carrier, rather than the vendors, can benchmark and payback for the implementation of an ICT infrastructure, thus enabling the management and sharing of retailer orders and tracking vendor loading capacities. The evaluation of the costs associated with transport and delivery activities is crucial when deciding whether to implement cooperative networks (Bo and Hammervoll, 2010, Somapa et al., 2012). Common prescriptions for improving the performance of retailers consider key suppliers and leverages their resources and capabilities to implement effective category management that will reduce retailer costs and provide a basis for service differentiation (Morgan et al., 2007). The provided methodology also addresses the identification of those suppliers who are able to cooperate and provide improved delivery services to the retailer. Accordingly, to exploit the benefits of a cooperative regime, the implementation of source-oriented depots is recommended (Juga et al, 2008).

Findings from the analysis highlight the powerful position of the retailer in creating the conditions for more efficient supply chains, properly balanced delivery networks, and sustainable food retailing (Jones et al., 2008) either by concentrating the orders or by sustaining alliances and cooperation among vendors.

The obtained results highlight the benefits provided by involving the vendors in the delivery planning. These also confirm the expectations that node density is correlated with the benefits of sharing pick and delivery tours among vendors. Although the three observed geography of the network provide different performances, the cooperative regime not only results in optimizing the total delivery transport costs, but it also enhances the delivery service levels and improves the capabilities of vendors to meet uncertain retailer demands.

A necessary development of the proposed methodology is that it provides and embeds an alternative algorithm, such as simulated annealing (Min and Melachrinoudis, 2016), which permits scaling-up the instance and solving large-scale problems within a reasonable time. Opportunities for cooperation at up-stream (growers-suppliers) and down-stream (retailer depots-retailer shops) echelons of the supply chain need yet to be explored by scaling-up the problem and improving the solving method.

The description of how the proposed model might shift to an inventory-routing problem with shelf-life and product expiration constraints will be the focus of further research. Specifically, the throughput of the processing or packaging lines, rather than the picking efficiency at the vendor's facility, further constrain the supply system and make the cooperative scenario even more preferable given the stated uncertainty in the order distribution within the time-windows and the given availability of trucks.

3.1.2 New technologies to enhance traceability along the supply chains: the case of blockchain technology

Few information technologies are gaining as much as attention as blockchains (BC). Though the main application of the blockchain technology is the Bitcoin currency (Moody's Investors Service, 2016), thousands of start-ups are innovating on novel blockchain applications in various industries, such as healthcare (Tierion.,2016) and insurance (McKinsey&Company,2016).Several initiatives are in mainstream media (Wheeler, 2017), riding on the trend of the increasing pressure to disclose supply chain information (Marshall, 2016). Several experts and industry speakers outline blockchains as a disruptive technology (Brennan et al, 2016, Swan, 2015, Walport, 2016). This chapter focuses on blockchain as a potential answer to the aforementioned question: *how to share information along the supply chain?* And particularly, on its role in the realization of a full end-to-end traceability along supply chains, enabling the timely information disclosure of the chain-of-custody of products to supply chain partners and customers. Particularly, blockchain technology might put into practice a "product centric" approach (Mattila et al., 2016), acting as a "data collector" in the SC in order to share complete information on products over their entire life-cycle between all the organizations. Nevertheless, in addition to the current technological limitations (Tschorsch and Scheuermann, 2016), the implementation of the blockchain to SC face some barriers. Some of them are inherited by the current debate on the implementation of shared technological platform by the SC while others are blockchain specific. The nature of this research is conceptual, as there, by the time of the investigation, did not exist any actual supply chain implementation of blockchain technology. Therefore, this chapter aims to draw the state-of-the-art of the current application of blockchain to the supply chain and of the literature and to offer some food for thought. This work was realized in collaboration with the Department of Packaging Logistics of Lund University in 2017 and involves the study of the existing literature on the topic and the collection of information on the current industry initiatives.

3.1.2.1 *The birth of blockchain technology*

Firstly, an anonymous creator with the pseudonym of Satoshi Nakamoto with Bitcoin (Nakamoto, 2008) introduced the shared ledger paradigm. Nakamoto was able to solve the cryptographic researchers' Byzantine General Problem (Lamport, 1989), proposing an original system for electronic transactions which overcomes the need to rely on trusted authorities to ensure the 'honesty' of participants at the transaction through a decentralized consensus based on proof-of-work. However, the first use of the term "shared ledger" to indicate any database, ledger, and application that is shared by an industry, a private consortium, or that is open to the public is claimed by Richard Brown, Chief Technology Officer of the Distributed Ledger Group (De Meijer, 2016). As stated in (Hull et al., 2016), shared ledger technologies provide an original framework that has the potential to radically change business collaboration across several sectors, among them: finance, healthcare, and supply chain.

The activities and applications of blockchain are classified by Swan (Swan, 2015) in three broad categories: (1) Blockchain 1.0 embeds all the aspects related to currency and digital payment systems, e.g. Bitcoin, (2) Blockchain 2.0 includes economic, market, and financial applications that extend Blockchain 1.0, e.g. smart contracts, (3) Blockchain 3.0 is all applications beyond (1) and (2), e.g. government, art, and health. In illustrating (3), Swan hypes the extensibility of blockchain as the potential deployment of the blockchain core technology concepts in every field. In particular, the author claims how blockchain introduces a new conceptual paradigm in computing (Swan, 2016), which involves the distributed ledger and the decentralized consensus. As of today, there is no unified terminology and many sources use the terms 'block chain', 'blockchain', 'distributed ledger' and 'shared ledger' interchangeably (Walport, 2016).

According to the Report of Credit Suisse (Brennan et al., 2016), three main properties or levels of a ledger of digital records or transactions exist: the number of copies, the reader, and write access. A unique centralized copy of a ledger characterizes the traditional systems, (e.g. in government, in the current banking system and in large corporations), while a distributed ledger is an asset database that is shared across the nodes of a network, the peers (Hull et al., 2014). All participants, who are connected to the peers (through a one-by-one connection) and are executing on behalf of the business they are working for, have their own identical copy of the ledger. Any changes are sent to all the copies (in a time step between a few seconds to a few minutes) making the ledger auditable.

Moreover, distributed ledgers are decentralized in order to eliminate the need of a unique trusted authority and enhance robustness (Raval, 2016). The reader access distinguishes between public ledgers, i.e. all participants can view the ledger, and a version of the ledger with a more restricted access, i.e. private. Private ledgers can be decentralized but not distributed. The last level corresponds to the authorization of the node to take part of the consensus mechanism. If all the nodes of the network can join the consensus mechanism the ledger results unpermissioned, otherwise is permissioned. In the latter case, the Report's authors compare the network with a hub and spoke model (Arnäs et al, 2013). Bitcoin blockchain is one type of unpermissioned public ledger.

Vitalik Buterin classifies the Bitcoin blockchain as "public blockchain" to indicate an unpermissioned public ledger, distributed and characterized by low efficiency (due to a resource consuming mining process) and immutable stored transactions (Buterin, 2017). To perform the validation of transactions the Bitcoin blockchain relies on a decentralized consensus mechanism among the nodes of the network. In other words, once approved by the network transactions can be updated on the blockchain where it cannot be tampered with. Thus, ensures the reliability and the security of data. Two other types of blockchains are increasingly used in proof of concepts and startups: consortium and private blockchains. Consortium blockchains are partially decentralized permissioned ledgers where the reader access can be both public and restricted to a group of participants. In private blockchains the consensus process is restricted to only one organization (Xu et al., 2016). Due to the fact that private blockchains can no longer be decentralized (Zheng et al, 2016), some blockchain experts do not consider it as a "proper blockchain", but still, as a type of distributed ledger technology (DLT) (O'Connell, 2017).

3.1.2.2 Blockchain and supply chains: the literature

Peters et al. (2015) assess the use of blockchain as a ledger to record all the ownership details of physical assets (e.g. Everledger). Consequently, as a public ledger, blockchain could enhance the information transparency on products and processes along the whole supply chain (SC) (Badzar, 2016). Furthermore, the prerogative of blockchain of creating a trustless environment could impact business processes integration (Weber et al., 2016) and, consequently, on operational and business performance (Flynn et al., 2010). In 2017, Korpela et al. (2017) proposed to use blockchain to accelerate the transition to digital supply chains (DSC), favouring the strategic sharing of information between all SC actors, improving coordination, communication, and processes integration. Yuan and Wang (2016) are the first to discuss the potential advantages of blockchain in transportation research. They hype blockchain as the proper infrastructure to store and manage data from the physical space by integrating such technology into the IoT architecture to support the digitalization of the physical entities (e.g. roadside devices, vehicles, assets). Key IoT technologies, such as RFID and sensors, can provide a considerable amount of data that has to be managed in order to ensure data security and, importantly, confidence in the data quality. Thus, the trustless environment paradigm and the use of smart contracts seem to provide a charming solution (Huckle et al, 2016). In their work, Mattila et al. (2016) explored the opportunities of using blockchain to support product-centric information management in order to provide an effective architecture to collect data on products over their entire life-cycle. The combined use of RFID and blockchain is also explored by Tian to enable track and tracing of products in the Chinese agri-food market in order to enhance food safety and quality while reducing food waste (Tian, 2016). Abayratne and Monfared (2016) discuss the potential benefits of the application of blockchain to a manufacturing supply chain for cardboard boxes. The authors point out the mutual advantages achieved by customers, who can easily access a great deal of data on products from the forestry to the waste recycler, and organizations, which can improve the control of processes and the security of transactions through the usage of smart contracts. Encouraged by the fact that a broader accepted key-driver for successful Supply Chain Finance (SFC) programs is the development of technological solutions favoring the collaboration among businesses and the speed-up of cash flows, Hofmann et al (2018) explore the potential benefits of the introduction of blockchain-based solutions to SCF. While agreeing in claiming that BC would not scatter the rules of SCF, the authors underline how BC technology could enable SFC to speed up processes, make leaner structures and offer less-costly services. Particularly, they estimate blockchain would simplify the onboarding of suppliers onto SCF platforms, favouring the inclusion of the long-tail supplier-base. Moreover, BC based platform allowing the issuance of trade related documents could affect SFC improving the ability to track the goods flows and leading to faster payments.

3.1.2.3 Blockchain and supply chains: Industry initiatives

The Gartner's 2017 hype curve places blockchain near the peak of the slope. However, it is worth noting that its position is still sliding downward on that slope (Columbus, 2017), i.e., moving away from the expectations of being “a universal” technology. Despite the acknowledged immaturity of this technology (Wang et al., 2016), by the time of the research, the current landscape of blockchain-based startups accounts for more than 1200 (Blockchain Ecosystem Database, 2016). According to Friedlmaier et al. (2016), by the time of publication the 32% of the total number of startups have headquarters in the US, while European startups accounts for the 26 %. The authors show how the 42% of startups offers products and services for the Financial and Insurance sector, which also receives the 97% of venture capital investments. However, both scholars, practitioners and governmental institutions show an increasing interest for the deployment of blockchain characteristics, among which decentralization, persistency and auditability of data, as well as, integrability with other technologies in several potential fields (e.g. healthcare, energy, transportation and storage).

Some new-born startups that exploit blockchain for product traceability (Moe, 1998) are achieving a lot of visibility. This is the case of Provenance, which in July 2016 started to work with the UK's retailer Co-op in order to track fresh food, such as fish, eggs, and dairy, through its supply chain (Wheeler, 2017). Co-op customers are able to access information on the product journey through an app on their smartphones. Through deploying blockchain technology while collaborating with external certifiers and auditors, i.e. non-governmental organizations certifying socially sustainable fishing, Provenance meets the increasing interest of customers for proven attributes of products (e.g. safety, local, fair trade, environmentally sustainable) (Brofman Epelbaum, and Martinez, 2014).

In October 2016, the large retail organization Wal-Mart, IBM, and Tsinghua University signed an agreement aided to explore the opportunities of blockchain in food authentication and supply chain tracking (IBM, 2017)[a], Walmart becoming one of the 400 IBM clients testing blockchain technology (March 2017). That same month, the New York Times announced that Maersk was up to use the IBM version of blockchain to track avocados, flowers, and machine parts on its cargo ships. In addition to realizing an effective traceability system, another aim of Maersk was reducing the paperwork (e.g. documents, approvals, stamps, etc.) related to each container which previously required the involvement of as many as 30 people (Popper and Lohr, 2017). Furthermore, IBM, which has around 650 employees dedicated to the application of blockchain technology, has recently included new features in its IBM Watson IoT Platform that enable IoT devices to send data to private blockchain ledgers. Use cases include data recording (position, arrival times, and status of shipping containers) and environmental condition (i.e. temperature and humidity) monitoring during freight transportation, component tracking, and compliance, and log operational maintenance data (IBM, 2017)[b]. Another example is the startup company Modum.IO (pilot project launched in June 2016), whose purpose is the monitoring of temperature and humidity values experienced by medical products during shipments that do not require refrigeration (Campbell, 2016). Upon the arrival at the depot of destination data is transferred to the Ethereum blockchain, where specific smart contracts monitor the temperature compliance with the extant regulations (European Commission,2013). However, the current investigation of the effective benefits generated by the application of blockchain to the logistic field is still at an explorative stage. Furthermore, Reyes reports how DLT are currently under many regulatory discussions (Reyes, 2016). The lack of effective regulations affects the spread of new uses of DLT, for instance, with the application of unfitting payment laws. In January 2016, Mark Walport, as the UK's Government's Chief Scientific Officer, point outs the need for a regulatory framework for DLT, which should result from the joint work of academia, industry, and governmental institutions. Such framework should be able to follow the rapid evolvement in the use of this technology (Walport, 2016).

3.1.2.4 Research outcomes and research agenda

Literature and existing trials confirm the large potential and interest in the adoption of blockchain technology in supply chains, but given the current knowledge, some factors speak against a potential disruptive effect.

- The logic of blockchains in supply chains demands for a mechanism to establish physical trust, such as a reputation system or a central authority creating trust.
- Industrial experience reveal that the integration of logistics activities and adoption of supply chain technology may not be straightforward.
- Companies and individuals need to have clear incentives to implement and use blockchain technology. While some potential benefits are present, as of today, it is not apparent how they will be realized.

Therefore, this research findings confirm the paper by Mattila et al (2016), also questioning supply chain disruption by blockchain technology. Supply chain management represents a significant area for information technology innovation (Cachon and Fisher, 2000), due to the key role of information exchange among SC actors on the overall supply chain performance (Burgess et al., 2006). However, industrial experience reveals that the integration of logistics activities and adoption of supply chain technology may not be straightforward. The extant literature has already identified a plethora of factors that influence organizations in the decision process on adopting a particular technology (Kwon and Zmud, 1987). Particularly, in their work Patterson et al. (2003) explore organizational and environmental factors, providing a framework to classify the antecedents of technology adoption by supply chains (i.e. firm size, organizational structure, integration of supply chain strategy with overall corporate strategy, past financial performance, supply chain partner pressure, transaction climate and environmental uncertainty). The current debate on the adoption of blockchain technology by supply chain assesses several of the statements from Patterson et al. Although, some variations are identified. Firstly, the authors claim that large organizations are more willing to adopt supply chain technology. However, some blockchain experts (Piscini, 2017) believe that to increase the chances of success at larger scale, at first blockchain should be adopted by a few number of players representing a selected sample of key functions and sharing a common goal, i.e. a so-called minimal viable ecosystem. Thus is in accordance with the statement introduced by Glaser (2017) claiming "the higher the closedness of the ecosystem, the more suitable is a blockchain infrastructure". A second variation relates to the environmental uncertainty. If in one hand, many organizations facing high environmental uncertainty are keener on adopt supply chain technologies, on the other hand the lack of knowledge on blockchain long-term effects on supply chain makes a stable environment more suitable for its adoption. For example, a highly competitive environment determining frequent changing of SC actors may affect the decision process on how to allocate the blockchain costs along the supply chain (Vaughan, 2016), especially considering the blockchain characteristic of data persistency. Moreover, the trustless paradigm introduced by blockchain scatters the role of the transaction climate among SC actors as well as the debate about decentralization in technologies adoption. As the public blockchain is unlikely to attract business interest, companies going forward with distributed ledger technologies are likely to resort to consortium and private blockchains (Buterin, 2017).

In addition to the aforementioned need for regulations and standards, future research can expand the domain of the connection of the physical and digital. Moreover, the temperature monitoring protocol developed through the blockchain, as implied by Modum.Io, deserves special attention by actors of perishable products supply chain. Further developments should deal with the management of distributed ledger/blockchain platform by multi-actor supply chains. Particularly, more efforts should be devoted to the management of the ownership of data (Mattila et al, 2016) and the sharing of responsibility for the platform. Potential future studies can also expand the lynchpin of blockchain success in the financial sector, which is its role in discarding the need for central authority (Hofmann et al, 2018). The use of smart contracts in certifications might provide large value to supply chain finance.

3.2 THE STRATEGIC LEVER OF NETWORK CONFIGURATION IN PERISHABLE PRODUCTS DISTRIBUTION

As of today, refrigeration is recognized as the most efficient preserving technology in extending the product shelf life while maintaining the initial physicochemical properties of products. Among the different perishable products requiring preservation, food products represent around one third. Refrigeration plays therefore an important role in reducing the global post-harvest losses, which account for roughly the 25% of the food production worldwide (IIR,2009). Together with the population growth, the climate change and the increasing consumption of refrigeration-dependant foods (Garnett 2011), the impact of refrigeration on the world energy consumption per year is rising, accounting for more than the 15% (Coulomb, 2008).

Researchers and industry alike agree that improving the energy efficiency plays a pivotal role in reducing both energy costs and the environmental impacts, aiming at realizing more sustainable supply chains (Meneghetti and Monti, 2014). In the past, the availability of low-cost energy sustained the design of less efficient cold chains mostly powered by fossil fuels. For this reason, supply chains such as food supply chains are often built as inefficient transformation systems, which consume more energy than they provide (e.g., as nutritional value). Transportation and storage of perishable temperature-sensitive products highly contribute to the global energy consumption, requiring refrigeration equipment in order to maintain the products at the labelled conservation temperature without interrupting the cold chain. In the last years, an increasing number of papers have been provided on the energy efficiency along the supply chain. Two viable perspectives can be found in the literature.

The first deals with the improvement of the energy efficiency of refrigeration systems for buildings and means of transport. As instance, researchers are currently investigating the use of alternative refrigerants (Li, 2017) and of different transport modes (Rai and Tassou, 2007), as well as of innovative technologies to enhance the energy efficiency of the building envelope (Mazzeo et al, 2017).

The second focuses on the improvement of the energy efficiency through more sustainable SC operations, such as product design, manufacturing process, warehousing, distribution etc. The increasing awareness of the environmental impacts associated with the perishable products industry pushed researchers belonging to different disciplines (e.g., agriculture, economics, engineering) to study and formulate models, methods, tools, and technical pathways able to enhance the economic and environmental sustainability of the perishable products supply chains as a whole. Focusing on the food industry, the combination of environmental care strategies and the SCM practices in the lead to the development of models that include the environmental issue in the planning objectives. As instance, Validi et al. [27] propose a multi objective model for the minimization of both the GHG emissions and cost associated with food distribution in an Irish supply chain. Yang et al. [28] explore quantitative green supply chain management methods and associated marketing strategies based on the temperature control of the distribution operations for perishable products. Accorsi et al. [29] develop a decision-support model to design carbon balanced agro-food supply chains through the optimal location of network nodes, carbon plantings, and renewable energy power systems. Savino et al. [30] illustrate a framework to evaluate sustainability improvements and the resulting economic impacts through a value chain approach. Gwanpua et al. [31] design a tool for the optimization of the trade-off between food quality, energy use, and global warming impacts associated with a retail cold chain. This tool assesses the impact of alternative technologies, plants, and cold rooms on the overall energy costs and the quality of the supplied perishable products. Vanek and Sun [32] introduce an optimization model to explore the trade-off between the energy consumption for food distribution activities and the loss of energy in terms of nutritional values resulting from food spoilage. Their model is used to compare and assess the adoption of faster or slower transport modes from a twofold perspective, which looks at the energy efficiency and the food losses. De Keizer et al. [35] formulate a MILP model for the distribution of fresh food under quality and perishability constraints, which is aimed at determining the optimal positioning of stocks and the order decoupling point throughout the supply chain. Ene et al. (2016) deal with the application of the green principles in warehouses, proposing a genetic algorithm for the decision on order picking routes, in order to minimize the energy consumption during the picking, which is touted as the most time and energy consuming operation.

According to the literature, a recognized strategic decision for the minimization of the travelled distance within the supply chain and, consequently, of the cost of transport, of the energy consumption and of the total GHG emission, is where to locate the facilities (e.g. manufacturing plants, warehouses, etc.) within the supply chain network. Despite traditional literature on facility location problem (Owen and Darkins, 1998, Farahani and Hekmatfar, 2009) aims to pursue only the minimum network cost, new studies have started to include the minimization of the carbon emission and the energy consumption. Some examples are provided by Jing and Zhongqin (2016) and by Saif and Elhedhli [36], which provide and solve a bi-objective inventory-location model aimed at identifying the trade-off between the distribution and inventory costs and the GHG emissions caused by the refrigerants in a cold chain.

This chapter focuses on the problem of locate refrigerated warehouses within a supply chain network for perishable products with the goal of minimizing the energy consumption and the total cost. Particularly, a model is proposed for the resolution of the location problem, which further determines the best strategy for the allocation of the products to the refrigerated warehouses, therefore, belonging to the class of the so-called location allocation problems (Cooper, 1963). Given the specificity of the supply chain of perishable products and particularly of food products, characterized with variable and seasonal demand over time, the proposed model is time dependant (i.e. “dynamic model”). Particularly, according to the classification proposed by Arabani and Farahani (2012), this model is an “implicitly dynamic model”, which allow to open a warehouse that remains open throughout the planning horizon.

Based on this background, the novel contribution of this model lies in the fact that combines the objective of minimizing the total economic and energy cost within a supply chain network with the problem of stocking and transporting perishable products that are temperature-sensitive. Given its time-dependant nature, the model handles not only seasonality in products demand but also, seasonality in the external temperature (for further discussion on this topic see 4.4.2.1). Moreover, the model considers multiple products, varying for labelled conservation temperature and shelf life extension. It is worth underlining how these two aspects are indicted as potential future development of the location-inventory-routing problem for perishable products proposed by Hiassat et al. (2017). In addition, the proposed model further extends the idea of (Accorsi et al., 2017) to incorporate a climate-driven perspective in the strategic planning of the production, storage and distribution operations of perishable products, considering the interactions with the external weather conditions.

The decision on the most suitable location for a refrigerated warehouse is therefore pursued by the model considering, in addition to transportation and establishment costs, the variation in the energy consumption of facilities through a planning horizon, accounted trough the total thermal load, which vary location by location and from time unit to time unit according to the global irradiance and the external temperature.

Finally, the model selects the most suitable temperature set point for each opened refrigerated warehouse in accordance with the inventory mix and quantifies the potential products losses generated by a wrong conservation temperature.

The remainder of this chapter is organized as follows. Sub-chapter 3.2.1 illustrates the model characteristics, 3.2.2 introduce a case study from an Italian network and 3.2.3 discusses the application of the model to the case study. Finally, 3.2.4 concludes the chapter and proposes potential future developments.

3.2.1 A location allocation model for refrigerated warehouse

Problem statements and parameters

The model is formulated as follows. The modelled network is composed by a set of producers P, a set of retailers C and a set of potential geographical locations for the warehouses L. The set P represents both vegetables and fruit growers while the set C consists of retailer depots and retailer shops. The producers supply the retailers with a set of products I, whose demand vary over a time horizon D. Aim of the model is identify, within the list of potential locations for refrigerated warehouses, the optimal subset that minimize the objective function along D. Furthermore, each identified warehouse assumes a specific temperature of set point within a pre-defined set T.

In this model, the product demand is represented by the parameter $off_{i,p,c,d}$, indicating the amount of product i, i.e. the lot size, ordered by the retailer c to the grower p in d. Once this lot enters the network, incurs in three consecutive stages, 1) the transport from the producer's facility to the warehouse l located at a distance $d_{p,l}$, 2) the storage in l, 3) the transport from the warehouse to the retailer depot/shop, located at a distance $d_{l,c}$. The transport phase is performed during a single unit of time d and generates costs proportional to travelled distance with respect to a unit cost of transport *kmc,* including the cost of energy. In addition, the flows of goods in the network during 1) and 3), the so-called upstream flows and downstream flows, may vary for trucks capacity (i.e. c^{up}, c^{down}).

Under normal circumstances, the storage phase for each product i lasts for a pre-defined turn-over Δt_i. However, this parameter is affected by the temperature set-point of the warehouse where the product is stocked. Particularly, at a specific t the product may incur in physicochemical changes that contribute to reduce the product shelf life. Whether the reduced shelf life is shorter than the turn-over, the lot is disposed and exit the network as waste. This case is triggered by a positive value of the parameter $\Delta tdecay_{it}$, which represents the time span to subtract to the turn-over if the product i is stocked at the temperature t. Moreover, the parameter $cwaste_i$ quantifies the cost of disposal of the product i. The opening of a new warehouse generates some cost items. The first is represented by the cost of establishment f_l and includes the amortization. The others quantify the thermal load of the warehouse over the time horizon D, divided in its different contributions, and in accordance with the cost of energy in the location l, e_l. These are the following:

- $Q^{tr}_{l,d,t}$: the transmission load represents the heat conducted into the warehouse through the walls, floor and ceiling;
- $Q^{inf}_{l,d,t}$: the infiltration load quantifies the effect of the warm air entering the refrigerated space through the open windows, doors and cracks;
- $Q^{sol}_{l,d,t}$: the contribution to the total thermal load generated by the irradiation on the warehouse floors and ceiling;
- The internal load account for the heat generated by the lights ($Q^{int,lux}_{l,d,t}$), the personnel ($Q^{int,pers}_{l,d,t}$) and the electric motors ($Q^{int,mach}_{l,d,t}$) inside the refrigerated warehouse;
- The product load (Q^{prod}) represents the heat removed/added from/to the products as they are cooled/heated to the temperature set point. This contribution is related to the specific heat of each product, the difference between the temperature of the incoming product and the temperature set point. Therefore, in the model the parameter $qp_{l,d,t,i}$ represents the heat generated to bring the temperature of the product i to the temperature set point t of l. Furthermore, the product load further account for the heat generated by the respiration of the stocked products ($qresp_{i,t}$), which is affected by the temperature set point.

The impact of the introduced contributions on the total thermal load varies in case of refrigeration and heating. Particularly, each contribution may require more energy or less energy to maintain the temperature set point. This aspect is represented by a positive or a negative value of each contribution in accordance with the following equations quantifying the energy balance of the warehouse.

Refrigeration:

$$Q^{tot} = \left(Q_{l,d,t}^{tr} + Q_{l.d.t}^{inf} \right) - \mu \left(Q_{l,d,t}^{int,lux} + Q_{l,d,t}^{int,pers} + Q_{l,d,t}^{int,mach} + Q_{l,d,t}^{sol}\right) - Q^{prod} \quad (1)$$

Heating:

$$Q^{tot} = \left(Q_{l,d,t}^{int,lux} + Q_{l,d,t}^{int,pers} + Q_{l,d,t}^{int,mach} + Q_{l,d,t}^{sol}\right) - \mu\left(Q_{l,d,t}^{tr} + Q_{l.d.t}^{inf}\right) + Q^{prod} \quad (2)$$

Where μ is the performance of the refrigeration/heating system.

In addition to the introduced parameters, $load_{t,l,d}$ indicates if the temperature set point *t* inside *l* is higher of the external temperature in quantifying the heat of respiration of products. It is worth noting that the model does not include a parameter indicating the load generated by the refrigeration equipment. According to the literature, this contribution usually represents the 15% of the total thermal load, as can be seen in the objective function illustrated in the following.

To facilitate the readers understanding, Table 7 summarizes the list of parameters.

Table 7: List of parameters

Sets	*Description*
$i \in I$	Products
$d = 1, .., D$	Unit of time
$l \in L$	Potential location for the warehouses
$c \in C$	Retailers
$p \in P$	Producers
$t \in T$	Set-point temperature of the warehouse
Indices	*Description*
$d_{p,l}$	Distance between producers and potential locations [km]
$d_{l,c}$	Distance between potential locations and retailers [km]
kmc	Cost of transport [€/km]
f_l	Cost of establishment of a new warehouse in *l* [€]
e_l	Cost of energy in location *l* [€/kWh]
$cwaste_i$	Cost of disposal of *i* [€/ Tons]
c^{up}	Capacity of the trucks along the upstream flows (i.e. from producers to potential locations) [Tons]
c^{down}	Capacity of the trucks along the downstream flows (i.e. from potential locations to retailers) [Tons]
c_l^{WH}	Capacity of the warehouses [Tons]
$off_{i,p,c,d}$	Order of a lot of product *i* from the producer *p* to the retailer *c* generated during the unit time *t* [Tons]
Δt_i	Average turn-over of product *i,* i.e. average time span of stocking of the product *i* inside the warehouse [units of time]
$\Delta tdecay_{it}$	Time span to subtract to Δt_i due to the shelf life reduction generated by the stocking of the product *i* at the temperature set point *t* [units of time]
$load_{t,l,d}$	Parameter that indicates if the temperature set point *t* inside *l* is higher of the external temperature [bool]
$Q_{l,d,t}^{tr}$	Transmission load [kWh/unit load]
$Q_{l,d,t}^{inf}$	Infiltration load [kWh/unit load]
$Q_{l,d,t}^{sol}$	Irradiation load [kWh/unit load]
$Q_{l,d,t}^{int,lux}$	Internal load generated by lights [kWh/unit load]
$Q_{l,d,t}^{int,pers}$	Internal load generated by people [kWh/unit load]
$Q_{l,d,t}^{int,mach}$	Internal load generated by electric motors [kWh/unit load]
$qresp_{i,t}$	Heat of respiration of product *i* stocked at temperature *t* [kWh/kg]
$qp_{l,d,t,i}$	Heat generated to bring the temperature of the product *i* to the temperature set point *t* of *l* [kWh/kg]

Variables

The variables of this model belong to three sets. The first set includes binary variables representing decisions, while the second set is for quantification of the flows of goods within the network. Finally, the third set is for auxiliary variables. Table 8 lists and describes theses variables.

Table 8: List of variables

Variables	*Description*
Decision variables	
$y_l = \begin{cases} 1 \\ 0 \end{cases}$	If a warehouse is open in the location *l* Otherwise
$T_{l,t} = \begin{cases} 1 \\ 0 \end{cases}$	If the warehouse opened in the location l has the temperature set point t Otherwise
Network variables	
$x_{i,p,l,d} = \begin{cases} 1 \\ 0 \end{cases}$	If the lot of product *i*, arriving from *p* in *d* is stocked in the warehouse in the location *l* Otherwise
$x_{i,l,c,d} = \begin{cases} 1 \\ 0 \end{cases}$	If the lot of product *i*, stocked in the warehouse in the location *l*, is shipped to the retailer *c* in *d* Otherwise
$v_{p,l,t} \in Z^+$	The vehicles that travel in *d* from the producer *p* to the warehouse located in *l*
$v_{l,c,t} \in Z^+$	The number of vehicles that travels in *d* from the warehouse located in *l* to the retailer *c*
$stock_{i,l,d,t} \in R^+$	The amount of product *i* stocked in the warehouse in *l* at the temperature *t* in *d*
$waste_{i,p,l,d,t} \in R^+$	The amount of product *i* arrived from *p* and stocked in the warehouse in *l* at the temperature *t* disposed in *d*
$w_{i,p,l,d,t} = \begin{cases} 1 \\ 0 \end{cases}$	If the product *i* arrived from *p* and stocked in the warehouse in *l* at temperature *t* must be disposed in *d* Otherwise
Auxiliary variables	
$z_{i,p,l,d,t} = \begin{cases} 1 \\ 0 \end{cases}$	If the product *i* arrived from *p* is stocked in the warehouse in *l* at temperature *t* in *d* Otherwise

Objective function

The model consists of an economic objective, which is the result of four cost items. Equation (1) introduces such objective.

$$\text{Min } \theta = \quad \sum_l^L y_l f_l + \qquad \text{a)}$$

$$\sum_l^L \sum_p^P \sum_d^D (v_{p,l,d} * d_{p,l} * kmc) + \sum_l^L \sum_c^C \sum_d^D (v_{l,c,d} * d_{l,c} * kmc) + \qquad \text{b)}$$

$$(\sum_{Tset} \sum_l^L \sum_d^D (Q_{l,d,T}^{tr} + Q_{l,d,T}^{inf}) * T_{l,t} * 1.15 * e_l + \qquad \text{c)}$$

$$\sum_{Tset} \sum_l^L \sum_d^D (Q_{l,d,t}^{sol} + Q_{l,d,t}^{int,lux} + Q_{l,d,t}^{int,pers} + Q_{l,d,t}^{int,mach}) * T_{l,t_l} * 1.15 * e_l + \qquad \text{d)}$$

$$\sum_l^L \sum_d^D \sum_i^I \sum_{Tset} stock_{i,l,d,T} * qresp_{i,t} * load_{t,l,d} 1.15 * e_l + \qquad \text{f)}$$

$$\sum_c^C \sum_p^P \sum_i^I \sum_l^L \sum_d^D \sum_{Tset} off_{i,p,d,c} * z_{i,p,l,d,t} * qp_{ldti} * 1.15 * e_l + \qquad \text{g)}$$

$$\sum_p^P \sum_l^L \sum_{Tset} \sum_i^I \sum_d^D waste_{i,l,d,T} * cwaste_i \qquad \text{h)}$$

The first cost item a) represents the cost of establishing a new warehouse in the location l, while the second b) quantifies the cost of transport within the network. The combination of c), d), e), f), and g) represents the third cost item and account for the total cost of energy required to balance the cumulated thermal load of all the established warehouses along the time horizon. Lastly, h) represents the cost of wasted products.

Constraints

The constraints of this model can be classified in five sets. The first set controls the stock of each warehouse:

$$\sum_{Tset} stock_{i,l,d,T} = \sum_c^C \sum_p^P (off_{i,p,d,c} * x_{i,p,l,d}) \qquad \forall l, d = 1, i \qquad (2)$$

$$\sum_{Tset} stock_{i,l,d,T} = \sum_{Tset} stock_{i,l,(d-1),T} + \sum_c^C \sum_p^P (off_{i,p,d,c} * x_{i,p,l,d}) - \sum_c^C \sum_p^P (off_{i,p,d-\Delta t_i,c} * x_{i,l,c,d}) - \sum_p^P \sum_{Tset} waste_{i,p,l,d,T} \qquad \forall l, d > \Delta t_i and\ d > 1, i \qquad (3)$$

$$\sum_{Tset} stock_{i,l,d,T} = \sum_{Tset} stock_{i,l,(d-1),T} + \sum_c^C \sum_p^P \left(off_{i,p,d,c} * x_{i,p,l,d}\right) - \sum_p^P \sum_{Tset} waste_{i,p,l,d,T} \qquad \forall l, d \leq \Delta t_i \; and \; d > 1, i \qquad (4)$$

$$\sum_i^I stock_{i,l,d,T} \leq cap_l^{WH} * T_{l,t} \qquad \forall l, d, t \qquad (5)$$

Constraint (2), (3), and (4) control the value of the variables $stock_{i,l,d,T}$ in each unit of time d. Since the warehouses are opened in d=1, the stock is initially represented only by the incoming products lots in d=1. In the following units of time, the amount of the stock for each product also varies in accordance with the lots that are shipped to the retailers and the ones that are send to disposal. Then, Constraint (5) ensures that the stock capacity of the warehouse never exceeds in each unit of time d.

The second set of constraints controls on the flows of goods within the network.

$$\sum_c^C \sum_l^L x_{i,p,l,d} * off_{i,p,d,c} = \sum_c^C off_{i,p,d,c} \qquad \forall i, p, d \qquad (6)$$

$$\sum_l^L x_{i,p,l,d} \geq min\{1, \sum_c^C off_{i,p,d,c}\} \qquad \forall i, p, d \qquad (7)$$

$$\sum_c^C off_{i,p,c,(d-\Delta t_i)} * x_{i,l,p,(d-\Delta t_i)} = \sum_c^C off_{i,p,c,(d-\Delta t_i)} * x_{i,l,c,d} + \sum_{Tset} waste_{i,p,l,\left(d-\Delta tdecay_{i,T}\right),T} \qquad \forall i, l, p, d > \Delta t_i \qquad (8)$$

$$\frac{\sum_c^C \sum_i^I off_{i,p,c,d} * x_{i,p,l,d}}{c^{up}} \leq v_{p,l,t} < 1 + \frac{\sum_c^C \sum_i^I off_{i,p,c,d} * x_{i,p,l,d}}{c^{up}} \qquad \forall l, d, p \qquad (9)$$

$$\frac{\sum_p^P \sum_i^I off_{i,p,c,d-\Delta t_i} * x_{i,l,c,d}}{c^{dw}} \leq v_{l,c,d} < 1 + \frac{\sum_p^P \sum_i^I off_{i,p,c,d-\Delta t_i} * x_{i,l,c,d}}{c^{dw}} \qquad \forall l, d - \Delta t_i \geq 1, c \qquad (10)$$

Constraint (6) ensures that each lot of product i shipped by p in d is stocked in one warehouse in l only. Constraint (7) states that each incoming lot in d must be stocked in a warehouse in the same d. Constraint (8) imposes that each lot of product i, stocked in a warehouse in the location l can exit the system as shipped to c or as waste. Constraints (9) and (10) regulate the number of vehicle within the upstream and downstream flows.

The third set of constraints is on the handling of the temperature set point in each warehouse and includes two constraints.

$$\sum_{d}^{D}\sum_{Tset} T_{l,d,T} = D * y_l \qquad \forall l \qquad (11)$$

$$\sum_{T \in Tset} T_{l,T} \leq y_l \qquad \forall l, d \qquad (12)$$

Constraint (11) imposes that each established warehouse has a single temperature set point, while Constraint (12) states that if a warehouse is not open in *l*, it cannot have a set point.

The fourth set of constraints controls the waste generation within the network.

$$waste_{i,p,l,d,t} = \sum_{c}^{C} off_{i,p,c,\left(d-(\Delta t_i - \Delta tdecay_{i,T})\right)*w_{i,p,l,d,T}} \qquad \forall l,p,i,t,d > \Delta t_i - \Delta tdecay_{i,T} \qquad (13)$$

$$waste_{i,l,d,T} = 0 \qquad \forall l,p,i,t,d \leq \Delta t_i - \Delta tdecay_{i,T} \qquad (14)$$

$$x_{i,p,l(d-\left(\Delta t_i - \Delta tdecay_{i,T}\right))} \geq w_{i,p,l,d,T} \qquad \forall l,i,p,t,d > \Delta t_i - \Delta tdecay_{i,T} \qquad (15)$$

$$w_{i,p,l,d,T} * (\Delta t_i - 1) \geq \Delta tdecay_{i,T} * T_{l,T} \qquad \forall l,i,t,d,p \qquad (16)$$

$$w_{i,p,l,d,t} \leq \Delta tdecay_{i,T} * T_{l,T} \qquad \forall l,i,d,t \qquad (17)$$

Constraints (13) and (14) defines the amount of waste in *l* of product *i* arrived from *p* for each unit of time *d* as related to the binary variable $w_{i,p,l,d,t}$. Constraints (15), (16), and (17) set the value of $w_{i,p,l,d,t}$, which assumes a positive value if $\Delta tdecay_{i,T}$ is higher than 0 and if in the time unit $d - (\Delta t_i - \Delta tdecay_{i,T})$ a lot of product *i* is stocked in a warehouse in *l*.

Finally, two auxiliary constraints control the value of the variable $z_{i,p,l,d,t}$.

$$\sum_{Tset} z_{i,p,l,d,t} = x_{i,p,l,d} \qquad \forall i,p,l,d \qquad (18)$$

$$z_{i,p,l,d,t} \leq T_{l,t} \qquad \forall t,l,d,i \qquad (19)$$

3.2.2 A case study from an Italian network

This model is applied to the case of a network of 4 fruits and vegetables growers and 17 retailers' depots located in the North of Italy. While the location of growers' and retailers' nodes reflects real-world instances (Accorsi et al., 2018[b], ISTAT, 2010), in order to validate the model, 16 potential warehouse locations are assumed (see Figure 23).

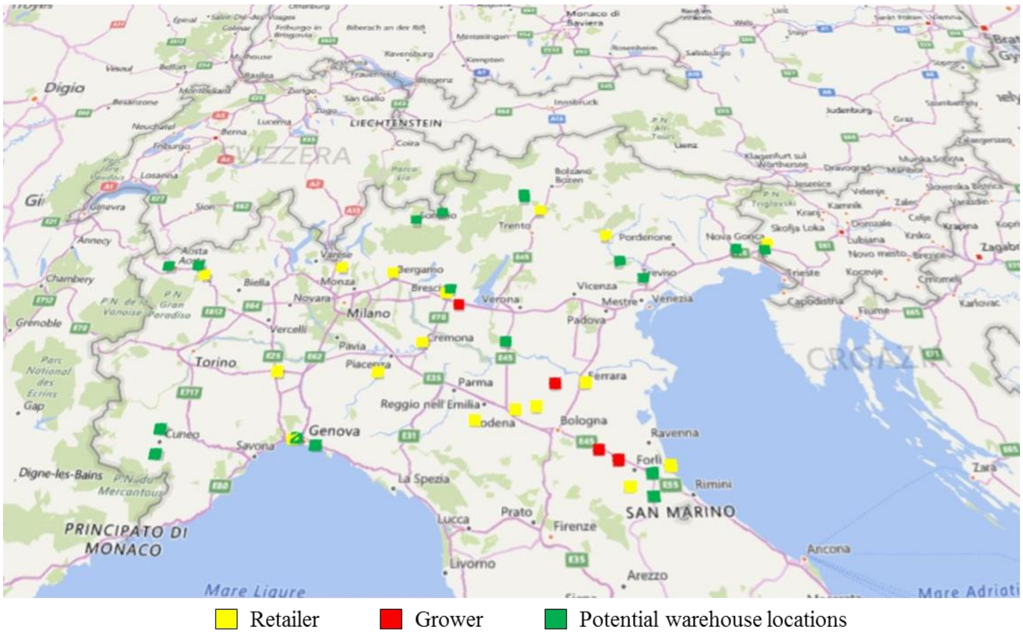


Figure 23: Potential Network

For each of the 8 Italian regions belonging to the observed network (Aosta Valley, Piedmont, Lombardy, Liguria, Emilia-Romagna, Trentino South-Tyrol, Veneto, Friuli Venezia Giulia), two locations are proposed: one located in a zone characterized by low concentration of contours, i.e. a sunny area, and one located where the contours are dense, i.e. shaded area. As shown in the Figure 24, in the second case the mountains and hills protect the location from the sun.

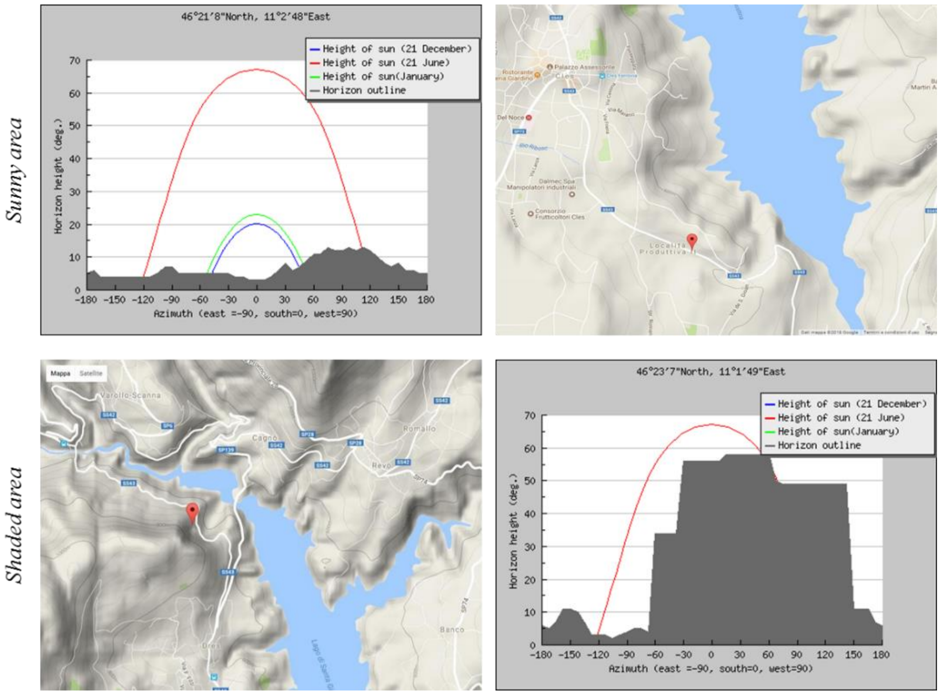


Figure 24: Shaded areas and sunny areas

The observed time horizon is set to 1 year while the single unit of time is set to a week. Each week, the growers supply the retailers with four products (i.e. apples, mandarins, grapes, and kiwi), whose demand vary with the seasonality. Moreover, each product has specific characteristics (i.e. turn-over, specific heat, heat of respiration, cost of waste) and differs from quality degradation curve (Rong et al., 2011). A single type of warehouse facility is assumed (i.e. for dimension, orientation, building materials, capacity, and establishing cost), while the cost of energy for each of these regions (e_l) results the same. Particularly, the warehouse capacity is set to 20,000 tons and the facility dimensions are set to 130x67x9 m^3. Three potential temperature set points for each warehouse are assumed: 0°,8°, and 15°C. The first represents the suitable conservation temperature for each of the four products, while the others affect the quality of the stock, generating waste. Figure 25 summarizes the introduced products characteristics and showcases the profile of the parameter $off_{i,p,d,c}$ for the kiwi along the time horizon.

Products	Temperature [°C]	cwaste [€/t]	Δt [weeks]	Δtdecay [weeks]	heat of respiration [mW/kg]	specific heat [kJ/(kg*K)]
	0			0	8,3	
Kiwi	8	4740	10	2	32	3,9
	15			6	48	
	0			0	9,2	
Mandarins	8	2280	9	1	30	3,9
	15			4	62,1	
	0			0	9,7	
Apples	8	2170	14	1	32	3,81
	15			8	53,6	
	0			0	8,2	
Grapes	8	2550	3	1	22	3,71
	15			2	47	

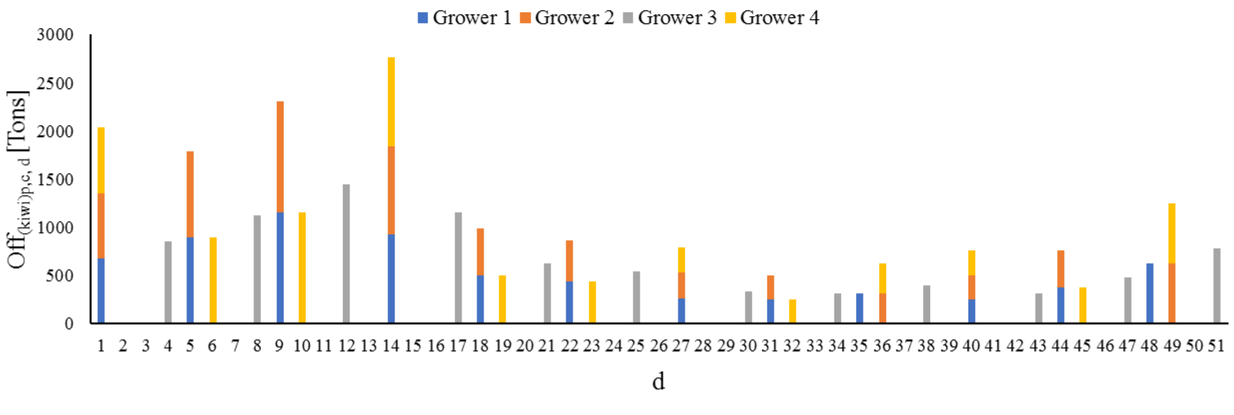


Figure 25: Products characteristics

As previously introduced, the calculation of Q^{prod} is affected by the products characteristics. Given the short travelled distance, the food products are assumed to travel through non-refrigerated trucks. With respect to the other contributions of the total thermal load, further assumptions have been made, in accordance with (Stoecker, 1998).

$Q^{tr}_{l,d,t}$ is calculated through Equation (20):

$$Q^{tr}_{l,d,t} = \sum_{s}^{S} U * A * \Delta temp \tag{20}$$

Where S indicates the sections of the facility (i.e. walls, floor, and ceiling), U is the overall heat transfer coefficient, A is the outside surface area of the section and $\Delta temp$ is the difference between the internal and external temperature.

$Q^{inf}_{l,d,t}$ is calculated trough Equation (21):

$$Q^{inf}_{l,d,t} = 6 * V_{air} * \mathrm{A}_{leak} * \mathrm{Cp}_{air} * \Delta temp * \rho_{cold} * \mathrm{D}_{time} \tag{21}$$

Where V_{air} is the average wind velocity, A_{leak} is the smaller of the inflow or outflow opening area, Cp_{air} is the specific heat of air, ρ_{cold} is the density of the refrigerated air, and D_{time} is the density open time factor.

With respect to the internal load, $Q^{int,mach}_{l,d,t}$ is assumed equal to 0, $Q^{int,pers}_{l,d,t}$ is calculated considering 10 operators working over one shift of 8 hour per day, and $Q^{int,lux}_{l,d,t}$ quantifies the total heat produced by the lightning of the facility according to average power installed for m^2 of 10 W.

The input data for the calculation of $Q^{sol}_{l,d,t}$ have been retrieved from the website PVGIS (PVGIS, 2018), instead of utilizing the existing standards (e.g. UNI 10349: 1994), allowing to obtain a more accurate estimation of the weekly global irradiance for each potential location l. As instance, Figure 26 provides an overview of the cumulated value of $Q^{sol}_{l,d,t}$ for each potential location over the time horizon, with respect to the ones located in sunny areas and in shaded areas. As expected, the figure shows how the blue columns (i.e. locations in shaded areas) are always smaller than their corresponding orange column (i.e. locations in sunny areas) of the region. Specifically, Piedmont and Trentino South-Tyroll reveal the higher difference between shaded and sunny areas.

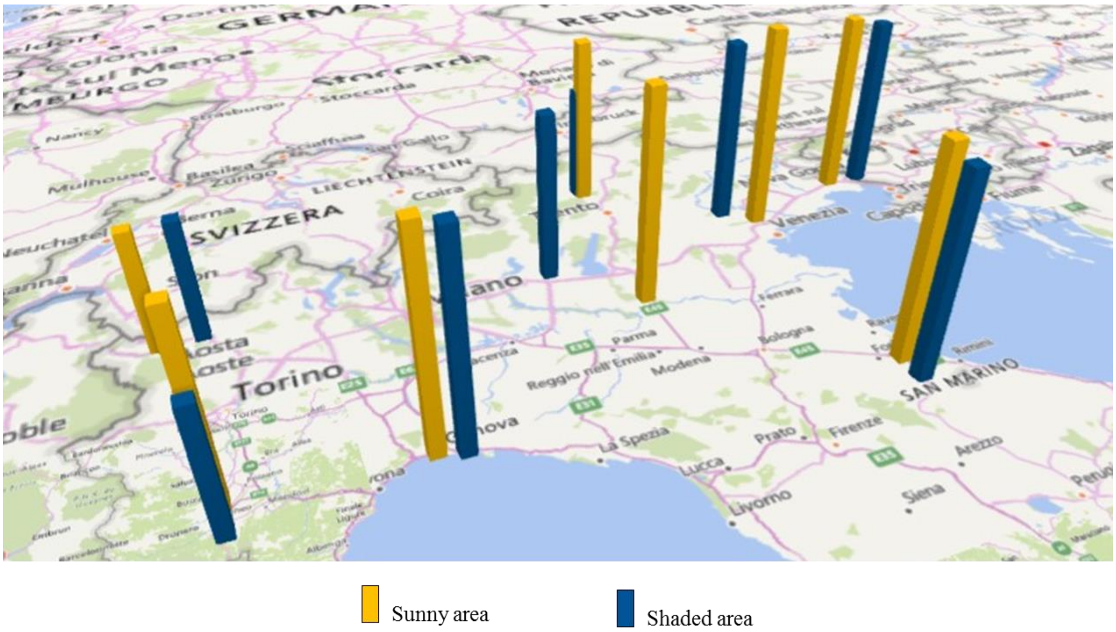


Figure 26: Cumulated value of $Q^{sol}_{i,d,t}$

The proposed model is written using AMPL and solved via a commercial linear programming solver, i.e. Gurobi, using a generic branch-and-cut algorithm. Computation time for the resolution of this case study is around 10 minutes.

The illustrated case study was used as a testbed for the proposed model. The model lead to the opening of five warehouses located in Emilia-Romagna, Lombardy and Veneto. Three of these are in shaded areas (WH_BRESCIA_o, WH_CESENA_o, WH_TREVISO_o) while the others are located in sunny areas (WH_MANTOVA_s, WH_CESENA_s). To further explore these results, Figure 27 provides an overview of the different cost items composing the objective function θ for each of the five warehouses.

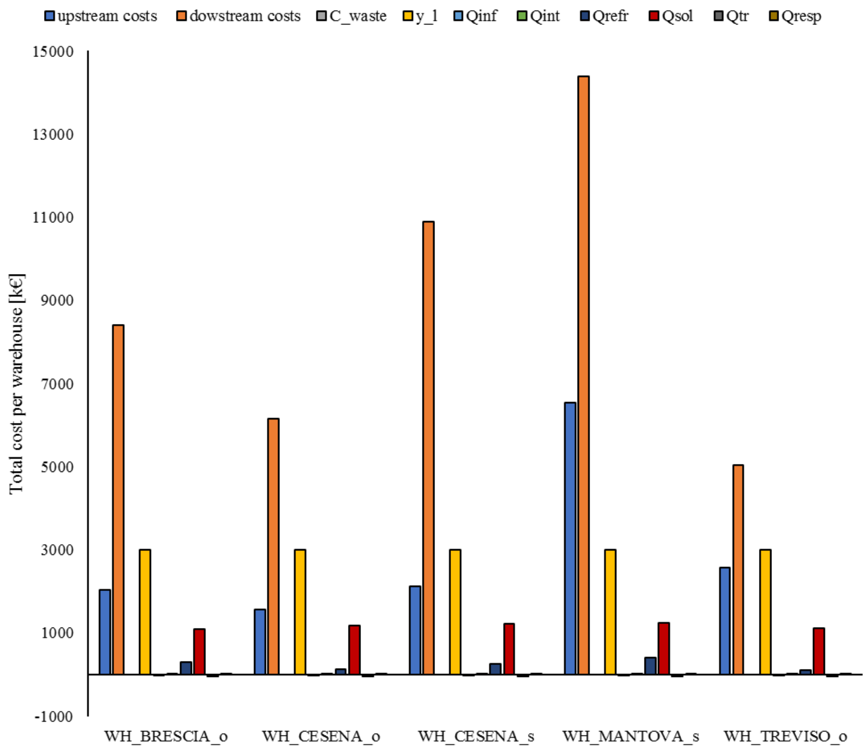


Figure 27: Cost items

Firstly, the figure showcases how the most impactful cost items are generated by the transport, by the establishment of a new warehouse, by $Q^{sol}_{l,d,t}$ and by $Q^{inf}_{l,d,t}$, while the others can be considered as negligible. Particularly, the cost generated by $Q^{sol}_{l,d,t}$ and the cost of the upstream flows is similar in four of these warehouses. The cost of the downstream flows is the highest in all cases, in particular in WH_MANTOVA_s and WH_CESENA_s. The cost of establishing a new warehouse is the same according to the input data, while $Q^{sol}_{l,d,t}$ also present a very similar profile. The different values of $Q^{inf}_{l,d,t}$ reflect the different average speed velocity of each location. A special attention deserves the cost of waste, since the model chose to set the temperature of each warehouse at 0°C, preventing from the waste production.

3.2.3 Discussion

The outcomes of the previous section reveal how the transport costs seems to drive the selection of the location of the warehouses. Therefore, Figure 28 and Figure 29 investigate the geographical configuration of the obtained network. Firstly, Figure 28 locates the new warehouses in the map and represents the upstream and downstream flows as a blue line. The thicker the line, the higher the number of the trips is. The figure reveals the pivotal role of WH_MANTOVA_s, which is in the midpoint of the network and serves all the retailers.

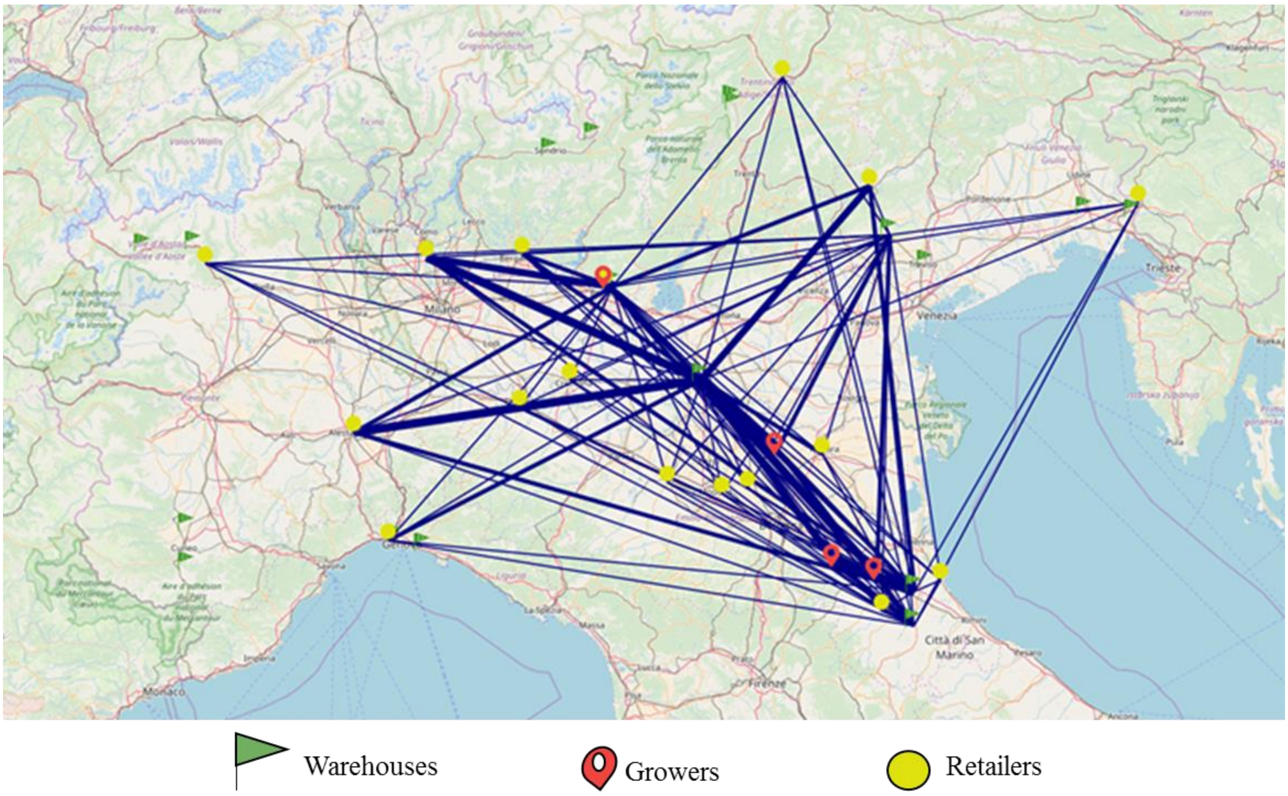


Figure 28: Upstream and downstream flows

To further explore the thickest blue lines, Figure 29 shows the cumulated demand from the retailers over the time horizon (yellow columns).

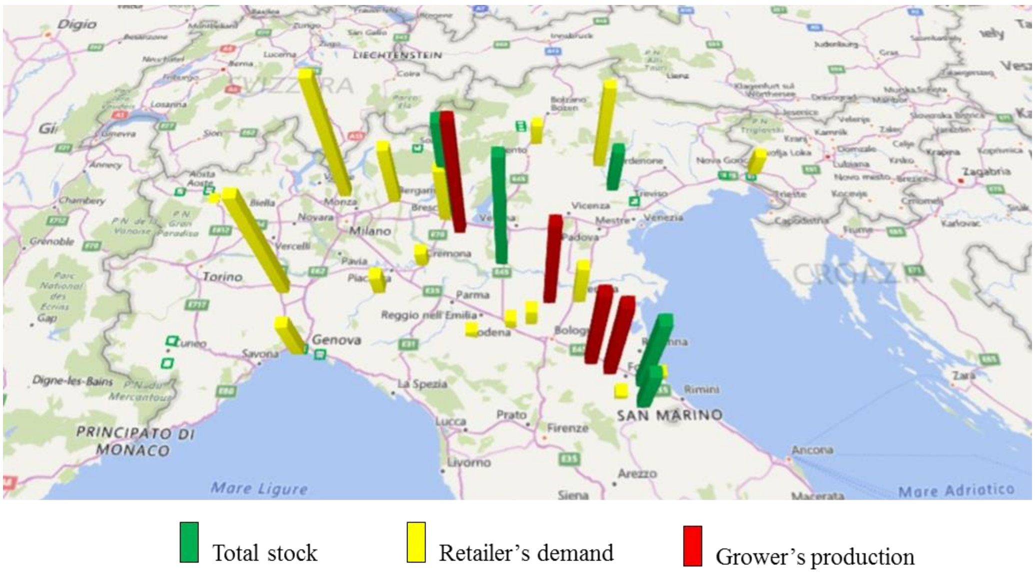


Figure 29: Cumulated stock, retailer's demand and grower's production along the time horizon

As expected, to higher yellow columns correspond a higher number of trips (i.e. higher downstream flows). The figure also shows the cumulated value of the goods produced by the growers along the time horizon and the cumulated value of the stock for each warehouse. It is worth noting how the model chose to locate the warehouses that cumulate the higher stock near the growers' plants. Specifically, these four warehouses and the growers draws an imaginary line connecting the city of Cesena and the city of Brescia. The two warehouses that cumulates the major value of the stock are WH_MANTOVA_s and WH_CESENA_s, as can be shown in Figure 30 that showcases through a size and colored scale the weekly value of the stock for each warehouse.

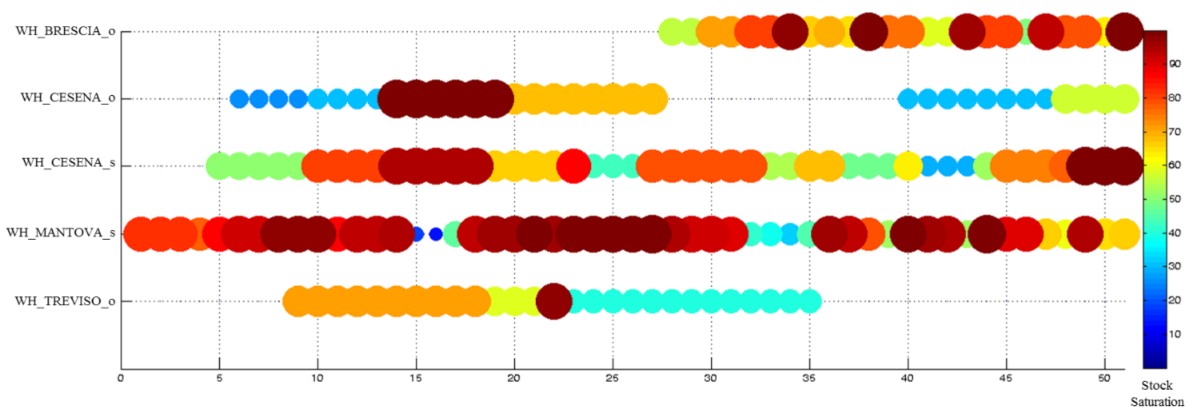


Figure 30: Stock profile for each time unit

The application of the model to this case study arise some consideration. First, the model tends to open warehouses in shaded areas, where the value of $Q_{l,d,t}^{sol}$ is lower. However, whether the geographical location is nearer to the midpoint of the network or to the growers' plants the minimization of $Q_{l,d,t}^{sol}$ takes second place to the minimization of the transport costs.

3.2.4 Concluding remarks

The proposed model aims to solve a location-allocation problem for refrigerated warehouses tailored for perishable temperature-sensitive products. Despite the single case study methodology and the small-scale network analysed, results highlight the pivotal role of the transport in the decision making, although, whether possible, the model choose locations with lower value of the thermal load and particularly of $Q_{l,d,t}^{sol}$. Future developments of this research involve the exploration of the model response in case of wider networks and with multiple inventory characterized by very different degradation curves.

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4 PERISHABLE PRODUCTS AND WAREHOUSING

4.1 WAREHOUSING SYSTEMS AND PERISHABLE PRODUCTS: AN INITIAL OVERVIEW

4.1.1 On warehousing operations: literature and industrial practice

Warehouses play a crucial role in logistics because they contribute to address to a multitude of missions for companies (De Koster et al., 2006, Lambert et al., 1998). Notwithstanding the recent trends in operations management supporting the implementation of lean supply chains and the just-in-time approach to minimize the inventory, the lack of accurate demand forecasting, as well as, the rapid changes in the customers' demand strengthen the crucial role of warehouses along the supply chain. Warehouses provide a buffer location for transshipments enabling not only to merge products and reduce the cost of the transports but also to consolidate a mix of products in the same customer order. Moreover, warehouses aid to achieve production economies and to take advantage of quantity purchase discounts. They constitute a buffer between the production schedule of producers and the receiving capacity of the client, supporting the customer service policies of the firms. To summarize, warehouses contribute to reduce the total cost of logistics, including reverse logistics while providing a temporary storage for materials that must be disposed or recycled.

Although several types of warehouses exist (e.g. holding warehouses, distribution warehouses, cross-dock warehouses, transship warehouses, work-in-process warehouses, etc.) and several levels of automation can be implemented, scholars have identified some operations that are common to all warehouses. These are: receiving, put-away, storage, picking, sorting, packing, and shipping (Bartholdi and Hackman, 2013, Gu et al., 2007). Receiving includes all the activities related to the arrival of unit-loads, such as unloading, acceptance check, temporal storage in a buffer. The put-away process refers to the positioning of unit-loads to storage locations and the choice of how assign the incoming unit-loads is given by the selected storage assignment policy. Warehouses are often provided with a reserve area and a forward or fast-peak area. The latter is usually located near the I/O docks in order to shorten the picking retrieving tour for the operators and, usually, stocks the fast-moving SKUs. Once the locations in the fast-peak area remain empty, they are replenished with new SKUs from the reserve area. The picking process is triggered by the receipt of customers' orders and the successive elaboration of the picklists, according to the item retrieval policy in force (e.g.

FIFO, FEFO, LIFO). Then, the picked items are staged for shipping. This activity usually involves the order accumulation, the sortation and the packaging.
In order to control the execution of these operations, a relevant role is played by the Warehouse Management System (WMS). This is a management information system that controls the physical and informative flows within the warehouse, involving both inbound and outbound processes (Shiau and Lee, 2010). A WMS gathers, stores and provides information on products, resources and processes, recording the transactions and transferring it to the other modules of the company's ERP and the transportation management systems (Verwijmeren, 2004). Some technologies as Auto-ID Data Capturing, or Radio-frequency identification may be integrated to support the data collection (Ramaa et al., 2012). Faber and de Koster, 2002, list the advantages from the introduction of a WMS: better space utilization, more accurate inventory, productivity increase and enhancement of the number and quality of services offered to clients. They even distinguish between *Basic* WMS and *Complex* WMS, which manages a network of warehouses, implementing integrated inventory management and picking policies. Furthermore, a *Complex* WMS offers value-added functionalities as data-driven planning, traceability, dock allocation, automated process supervision and control (automated guided vehicles or automated storage and retrieval system) (Roodbergen and Vis, 2009). Both practitioners and researchers recognize the role of the WMS in improving the warehouse performances (Faber et al, 2013, Lam et al, 2010, Staudt et al., 2015).
The commercial offer of WMSs includes a wide variety of solutions. Harris, 2016, overviews the WMS's features proposed by the top vendors and software houses. He classifies these features into seven *modules* according to their purpose and function. Figure 31 shows the relationship between each module and the physical flows of products throughout a warehouse (extendedly referenced in Bartholdi and Hackman, 2013, Gu et al., 2007), while Table 9 provides a brief description of the WMS functionalities and the main operations.

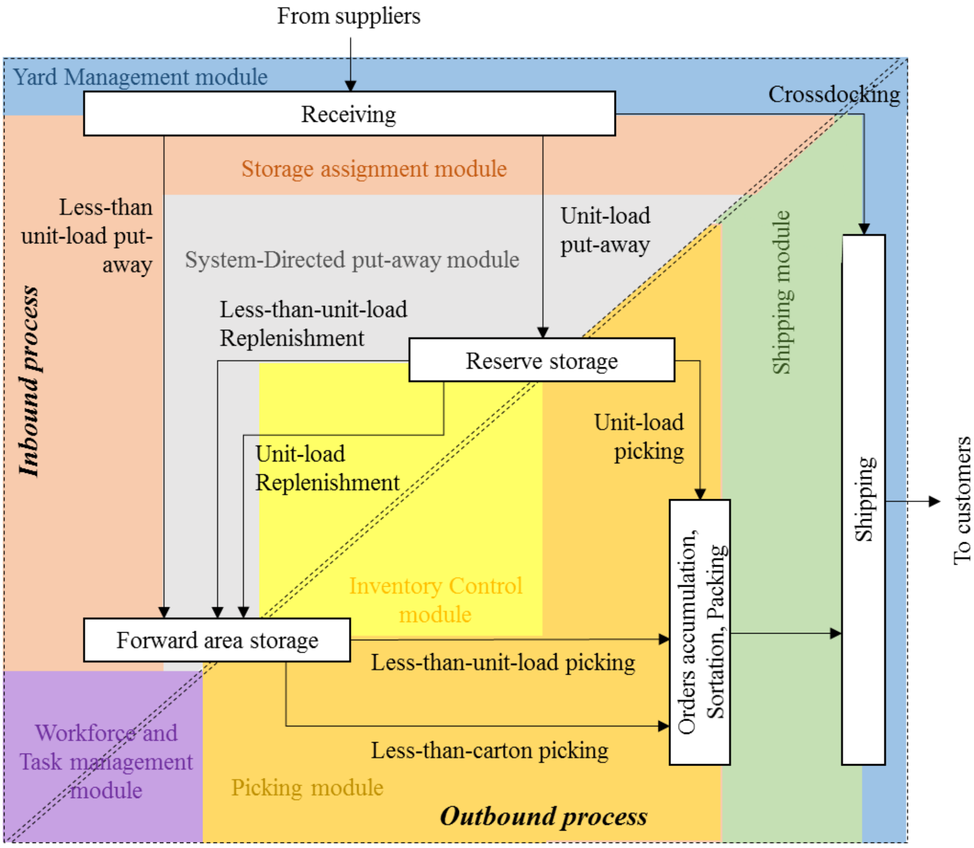


Figure 31: The warehouse operations and the associated WMS management modules

Table 9: Warehouse operations description

Operation	Description	WMS module
Receiving	The incoming loads (i.e., pallets) are unloaded, checked, tracked in the system and prepared for put-away activities.	- Barcode reading/printing - Yard management: doors allocation, arrival scheduling.
Put-away	The loads are stored into the racks or assigned to a physical location within the storage system. The loads can be stored into the reserve area or direclty to the forward (picking) area. A careful put-away reduces significantly the travelling during the retrieving activities (i.e., 55% of total warehouse costs).	- Storage assignment: how to assign loads to the empty locations. - Replenishing policy: how to re-fill the forward area from the reserve.
Picking	In response to the customer orders, picking lists are generated and devoted to the operators to perform the retrieving activities.	- Picking tour optimization (Picking list management) - Inventory control - Retrieving policy management: FIFO, LIFO, FEFO, FMFO (first-empty-first-out).
Sorting Packing Shipping	These include the loads preparation and the checkout activities. These activites are extremely labour-intensive since requires accurate control to avoid claims or back-orders.	- Shipping documentation printing. - Aided packing and cartonization: loading sequence suggestion. - Labor management

Given this overarching description of the warehouse operations, a specific topic is widely explored in this dissertation and therefore deserve a greater deal of attention: *the storage assignment problem*, i.e., how to assign the SKUs according to the storage locations (Petersen and Aese, 2004, Chuang et al., 2012 and 2016, Horta et al., 2016), as a strategic lever to reduce the total travelling picking costs.

4.1.1.1 The strategic role of the storage assignment

As already mentioned, the picking activity account for the 55% of the total warehouse costs (Bartholdi and Hackman, 2013). Therefore, the literature widely looks at the storage assignment problem as a key driver of efficiency and as a mean to enhance the overall warehouse performance. Yingde et al. (2012) distinguish two types of assignment problems according to the characteristic of the demand profile that a warehouse experiences. In presence of static demand, the inbound and outbound flows of SKUs are relatively stationary in the planning horizon. Conversely, in the presence of dynamic demand profiles, the inventory mix, i.e., the set of SKUs in the inventory, changes periodically because of the seasonality item life-cycle or item turn-over. Seasonality and other exogenous phenomena such as supply chain disturbances, stock-out, customer marketing campaigns and bull-whip effects influence warehouse performance. To address the dynamics of the storage system, the assigned locations should be periodically re-organized to maintain the efficient warehouse operation, which often results in the so-called *re-warehousing* (Sadiq, 1993). Re-warehousing is a notably labor-intensive activity, but the literature about this process is poorly extended. Housseman et al. (2009) arguments that the lack of interest on re-warehousing is because of the manual nature of this activity, which is rarely supported by algorithms and decision support tools. Some consequences of unhandled storage assignment of food products in warehouses are discussed by Hui et al. (2015). The lack of experience of the decision makers and the scarce information availability may result in sub-optimal decisions, which may generate waste of warehouse resources (i.e., space and time), product damages and economic and reputational decline. A dynamic approach to re-warehousing, which is named dynamic stock location assignment (D-SLAA), is introduced by Sadiq (1993) and improved and deepened by Sadiq et al. (1995), Landers et al. (1994) and Garfinkel (2005). The D-SLAA heuristics is based on a periodically run algorithm to revise the assignments of storage locations in accordance with the varying inventory mix. The goal of the algorithm is to minimize the total order-processing time as the sum of the time to pick and re-warehouse. First, the D-SLAA considers the future demand, product characteristics and relationships among the items to perform a capacity analysis (global phase). In the local phase, a hybrid clustering approach is introduced to arrange products into clusters and select the candidate locations for each cluster. The final assignment solution is obtained through progressive adjustments. First, the algorithm considers interchanges among clusters and within clusters. The interchanges are evaluated with respect to the history of usage of SKUs and ergonomics objectives. Kofler et al. (2010) present a bi-objective approach to support managers during re-warehousing. They identify the optimal warehouse assignment scenario according to two drivers: fast-moving SKUs should be located near the I/O docks, and products with high affinity should be located in close positions. These researchers' approach is validated through a simulation of picking and handling processes. An insight of re-warehousing is reducing the capacity of the pickers to memorize the locations of the demanded SKUs, which affects the experience curves that the workers use (Grosse et al., 2013). Thus, instead of re-warehousing, constant healing and adaptive assignment procedures are favored. Few but frequent re-assignment tasks help maintaining the storage system well balanced over seasonality (Kofler et al., 2010). Chiang et al. (2011) further extended this topic by presenting an adaptive approach called the data-mining-based storage assignment approach to find the optimal storage assignment for new products. Tsamis et al. (2015) proposed an adaptive strategy for storage location assignment to aid warehouse adaptation according to frequent changes in customer demand. They embedded the product intelligence paradigm (Giannikas et al., 2013) into the warehouse management system (WMS) to find the proper location for each incoming SKU based on the status of the inventory at the time of receiving. Further recent contributions to storage assignment and storage slotting problems in dynamic demand systems are presented by Kim and Smith (2012), Li et al. (2015), Zhang et al. (2014) and Manzini et al. (2015). Specifically, the latter used a class-based storage assignment policy based on popularity to handle the inventory life cycle to aid storage class sizing and design. They proposed a rolling measure of popularity. The *popularity rolling index* in t quantifies the number of picks that the generic SKU w accounts in the last Δt units of time (e.g., 15 days) as follows:

$$Pop^{roll}{}_{i,\Delta t}(t) = \sum_{t-\Delta t}^{t-1} Pop_i(t) \qquad (1)$$

where i is the SKU

Δt is the step (e.g. a week, a month expressed in term of periods).

The implications of the adoption of this metric will be further explored in the remainder of this chapter.

4.1.2 Storing perishable products

Handling the temperature conditions experienced by the inventory is fundamental in warehouses and any other points along the supply chain where products pause for long periods. Despite the continuous advances in climate conditioning, temperature monitoring and control, and insulating technologies for storage facilities, the indoor air temperature is not uniformly distributed and varies significantly among different locations on different days and seasons. The phenomenon of air stratification in the storage area (Bouzinaoui et al., 2005) and the structural characteristics of the facility (e.g., insulating materials, exposition to solar beams, layout) limit the ability of storage areas in ensuring safe conditions for the stock-keeping units (SKUs).

The heating, ventilating, and air conditioning (HVAC) systems can partially address this issue but require huge investments and increase operative costs because of their energy consumption. The changing profile of the inventory mix, which results in turn-over and different safe storage temperatures for different SKUs, also reduces the convenience of using climate-conditioning plants. The presence of dynamic demand, product seasonality and other exogenous supply chain disturbances results in periodical changes in the inventory mix, which increases the overall complexity of maintaining safe storage conditions for the entire set of SKUs.

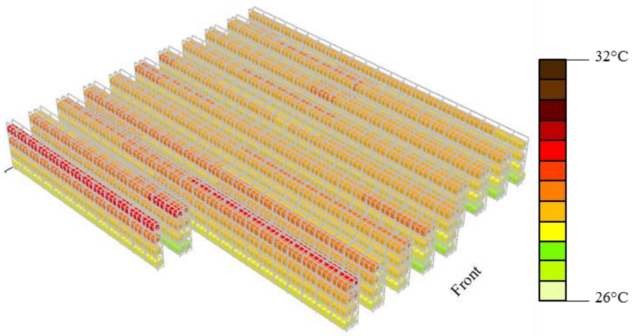
Uncontrolled storage temperature may produce physicochemical changes and loss of quality (Park et al., 2012, Hertog et al., 2014), which affect the capacity of complying with regulations and consumer expectations. In the food item storage, high temperature, high relative humidity and the air motion conditions enhance the rate of growth of microorganisms, which are responsible for off-flavoring, slime production, changes in the texture and appearance, and product spoilage (Vaikousi et al., 2008). Undesired product changes are avoided by containing in temperature-controlled storage and transport, which require properly equipped facilities (or vehicles) that are continuously powered. Up to 15% of the world energy consumption per year is accounted by product refrigeration (James and James, 2010). The refrigeration cost can be reduced using technological advances and through efficient use of the existing equipment and revision of storage operations (Twinn, 2007). Exemplifying this, Broekmeulen (1998) developed a storage assignment for fruit and vegetable storage according to different measured temperatures in the warehouse to reduce quality losses. The distribution of indoor temperature in warehouses was recently studied by Porras-Amores et al. (2014), who monitored and analyzed the vertical gradients of indoor temperature in four Spanish warehouses with passive air conditioning and a warehouse with air conditioning equipment for over 1 year. They underlined the effects of the air stratification issue (Armstrong et al., 2009). In addition, Ho et al. (2010) studied the air velocity and temperature distribution with a particular focus on refrigerated warehouses. They noted warehousing best-practice such as storing products as close as possible to the cooling units in compliance with the limitation imposed by safety operators. Moreover, evidences from the food industry reveal how the indoor environmental conditions are strictly affecting to the health of workers and productivity (Rohdin & Moshfegh, 2011).

4.1.3 The explored Case Studies

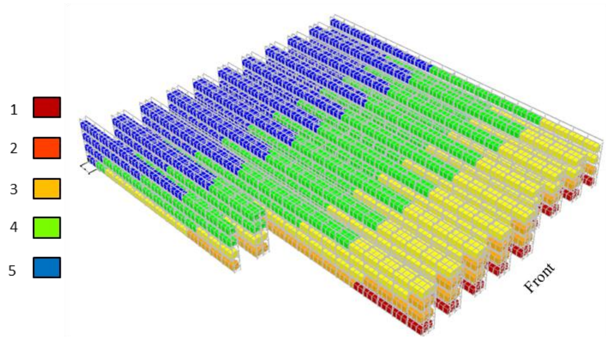
4.1.3.1 Case I: A 3PL warehouse for biomedical products

Case I presents a manual 3PL warehouse for biomedical products and equipment. The whole storage capacity is approximately 6,000 pallets, and the storage system is four levels high, twelve aisles wide, with on average twenty-four bays per aisle. About 900 pallet locations (i.e. four shelves) are devoted to the storage of coffee, while the remainder stocks products and equipment for dialysis. Case I focuses on the latter part and the most influential characteristics (Bartholdi and Hackman, 2013, Thomas and Meller, 2015) are summarized in Figure 32. Specifically, the observed warehouse holds 5,088 pallet locations in ten-aisle selective racks. The warehouse experiences high turn-over and presents a wide variety of products, and most are perishable and characterized by very different life cycles. More than 700 SKUs are stored yearly in the selective racks with an average turn-over index of about 60 days. Despite the long-term partnership with the client, the provider has scarce information visibility on the variation of inventory mix. This complicates the planning of the warehousing activities and affects the fulfillment of the high standards of efficiency and service level required. With respect to the picking policy, SKUs are picked according to the FEFO policy at each rack level trough the means of counterbalance lift trucks and no reserve area is utilized. The as-is put-away process is randomly performed by the workers who assign the incoming pallets to the first empty location they find. The random assignment policy does not require specific information about the SKUs and their behavior and avoids the costs for implementing dedicated WMS's functionalities. The facility is located in north-central Italy, where a mix of continental and Mediterranean climates results in highly wet and warm summers but cold winters. Despite an air-forced ventilating system, the facility is not climate-controlled, and the air temperature varies in the layout and with the seasons. Given the complexity in managing such inventory, the company seeks to find new solutions to improve the overall warehouse performance.

Parameter	Value
Pallet racking	Single - deep
Number of pallet locations	5088
Levels of pallet rack	4
Number of aisle	10
Number of base modules	848
Pallet opening height	2,06 m
Pallet opening width	0,9 m
Horizontal travel speed	2,5 m/s
Vertical travel speed	0,45 m/s



Thermal mapping
Temperature Distribution: 3/08/2015, 12:00 a.m.



Class of Distance: 5

Operations data	Value	
Time horizon	27/03/2015-15/01/2016	
Current storage assignement policy	Random	
Types of SKUs	704	
Number of picks	61554	
Incoming pallets	19870	
Avg saturation	80%	
Avg Rotation Index	60 days	
	4-30°C	75% of SKUs
Labelled temperature range of SKUs	4-25°C	15% of SKUs
	-19-70°C	10% of SKUs

Figure 32: Characteristics of the wareshouse from Case I

4.1.3.2 *Case II: A 3PL warehouse for the storage of wine, spirits, and alcoholic items*

The warehouse is five levels high and includes nine shelves and five aisles. Over a surface of 2400 m², a total number of 4000 locations is completely devoted to the storage of beverage products, such as water, beer, spirits, alcoholic drinks and fine wine. The ground level is entirely dedicated to the picking tasks (i.e. cases from pallets and even bottles), which represent the 98% of the retrieving, while the other levels belongs to the reserve area where unit loads are storage according to a random assignment policy. Two or three operators per shifts perform the picking activity over 12 hours a day. The implemented picking policy is the FEFO policy. Figure 33 represents the 3D map of the observed warehouse.

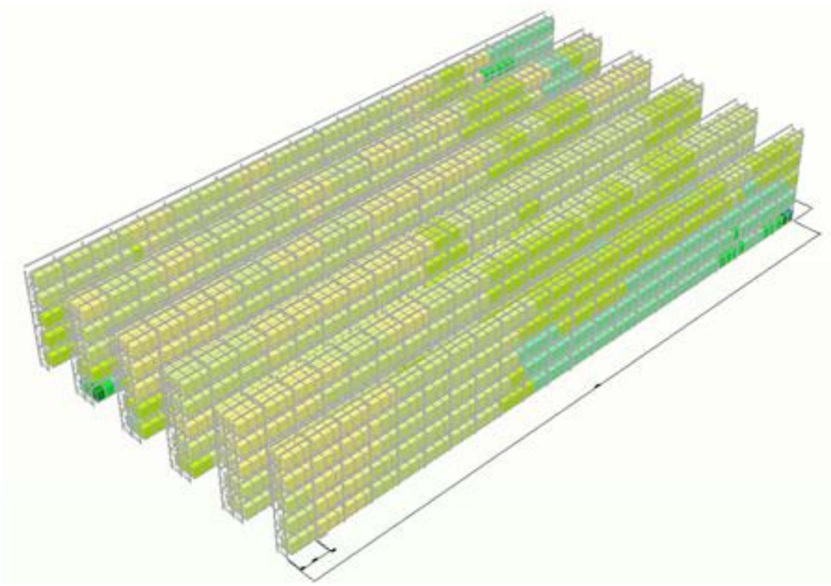


Figure 33: 3D map of the warehouse of Case II

4.2 WAREHOUSE MAPPING

4.2.1 Operations mapping

The design and management of warehousing systems find still room in the current research debate. The existing literature reveals an increasing interest in the field of warehouse performance evaluation (Wu and Dong, 2007), providing managers with the proper panel of performance indicators that measure warehouse operations. The identification of the most appropriate set of key performance indicators (KPIs) and their continuous monitoring is instrumental for detecting possible inefficiencies and identifying potential levers of improvement (Keebler and Plank, 2009). However, according to Davarzani and Normann (2015), the literature reveals a gap in addressing some managers' concerns. Existing performance evaluation tools are mainly devoted to measuring the output of specific operations. These authors suggest including in the future agenda for warehousing research a focus on the analysis of the relationships among outputs of different processes and operations. This approach will facilitate the development of plans to improve the overall warehouse performance instead of focusing on a single process from the beginning. This new approach is particularly relevant in highly complex contexts, such as 3PL warehouses. According to Nilsson and Darley (2009), the belief of linearity and perfect rationality of logistic operations must not drive the development of models and algorithms that help to explain and manage systems such complex systems. Thus, an elevated level of knowledge about the processes and stored products is fundamental to control a complex warehouse (Faber et al., 2013). Based on these statements, the operations mapping as the identification of the current procedures and practices of a warehouse is sine-qua-non to identify possible improvement levers. Moreover, since managers often delegates specific tasks to the employees, the operations mapping allow them to reach a general comprehension of the complexity of the system in its whole. Notwithstanding such important role of operations mapping for the identification of potential improvement levers, the literature reveals a gap in providing managers with structured approaches and guidelines to lead them throughout the operations mapping, the identification of possible inefficiencies, and the planning and implementation of improvement projects.

4.2.1.1 *From the operations mapping to the implementation of improvement projects. A diagnostic-support framework for 3PL warehouses*

In order to fulfill the identified research gap, a practice-ready diagnostic-support framework focused on the planning and implementation of performance improvement projects in warehousing systems is proposed. The framework is devoted to the warehousing systems that manage different clients, products categories, storage requirements, and demand patterns. Specifically, 3PL warehouses match this profile. Instead of assessing the enabling conditions for the economic sustainability of different 3PL services (Ballou, 2006, Kari and Finne, 2012), or focusing solely on the measurement of the impact of storage modes and operations on the holding costs (Azzi et al., 2014), this sub-chapter explores the whole phases of decision-making on the implementation of performance improvement projects in a systemic manner. In addition, this framework is generalizable as it can be applied to guide step-by-step 3PL managers from different industrial realities. However, the framework presents some limitations, which deal with the fact that its application results highly time and resource intensive and requires the set-up of collaborations between the 3PL and its clients. The framework consists of five phases (Phase I-V) (see Figure 34). The first (Phase I) takes an exhaustive picture of the as-is configuration of the system, exploring both the physical infrastructures and the operations. Phase II starts with data collection and calculates a set of high-, low-level metrics and statistics that provide a quantitative diagnosis of the observed warehouse. These phases support the practitioners to identify the most critical operations and/or infrastructural features that deserve improvement. The third phase configures a PMS (performance management system) and benchmarks or upgrades it through a survey of the literature. Once the PMS is finalized, the first task of Phase IV realizes a focused analysis of the literature on existing methods and models (and eventually case studies) addressing to those KPIs. The aim of Phase IV is the design of an effective improvement scenario through the prototyping, testing and comparison with other alternative scenarios. Phase V concludes the framework with the implementation of the improvement scenario.

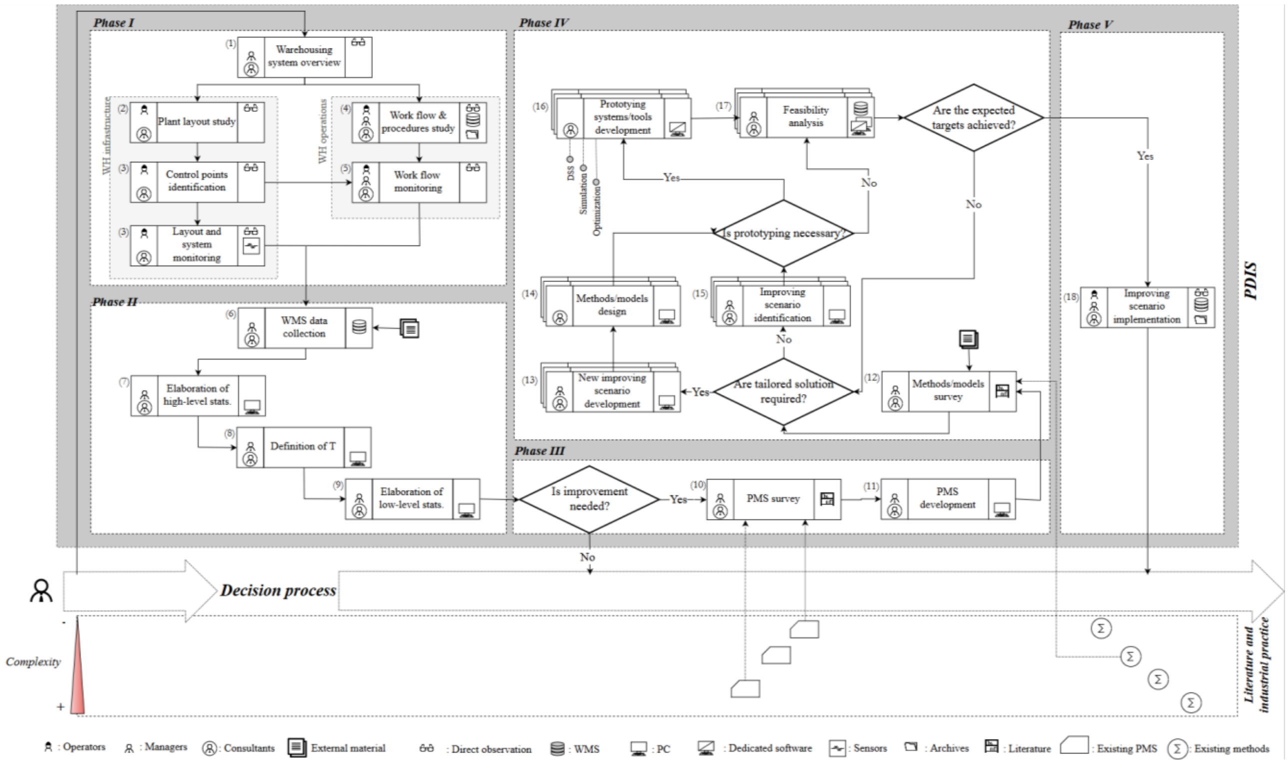


Figure 34: Diagnostic-support Framework

The implementation of the framework requires the involvement of different actors, such as the warehouse managers, the warehouse operators and the consultants. The latter can be external consultants, e.g. scholars, or a company's working team. As shown in the figure, each of the five phases is composed by tasks, which can involve different actors. Moreover, each task can be performed by means of the company WMS, i.e. the WMS data collection, or using common spreadsheets and data manipulation software, i.e. the elaboration of statistics. Some of these tasks do not require any informatic support, i.e. performed through direct observation, while others require the use of dedicated software. Tasks are clustered into the phases with respect to the temporal sequence, the physical place where the tasks are performed, and the tasks' priority tree. Particularly, a new phase will not start until all the previous set of tasks are completed. It is worth noting, that the framework is iterative and leads the practitioners to continuously examine the sources of inefficiency and fix them with focused improvement projects.

The five phases are illustrated as in the following.

Phase I: Study of the layout and the warehouse processes.

The undertaken assumption of the framework is that better understanding the current warehouse configuration is sine-qua-non to identify improvement levers. Therefore, Phase I is conducted entirely inside the warehouse. First, Task 1 entails an initial inspection of the warehouse, involving both managers and consultants, to provide a general overview of the storage system. Such overview includes the kind of products to be stored (e.g., perishable, hazardous, fragile, heavy), the number of clients, the available storage resources (i.e., both vehicles and workers), and the current storage policies (e.g., storage-assignment, picking, and routing policies). Then, Phase I has a twofold focus: the warehouse infrastructures and the operations. Tasks oriented to the mapping of warehouse infrastructures deal with the study of the plant layout (Task 2), the identification of a set of control points (CPs), that localize where the SKUs pause, are handled and stored (e.g. the packaging and weighing departments and the I/O docks), and the monitoring of the system's features (e.g. locations, aisles, CPs and racks) (Task 3). Example of this task are the temperature mapping of the storage locations by the means of a thermo-camera and sensors, or the frequency of access to a specific aisle. This deserves a special attention for those warehouses that stock perishable products. The temperature mapping activity will be discussed in further detail in chapter 4.2.2. Tasks oriented to the operations mapping include the study of the flows of freight and personnel through the storage zones and among the CPs, the study of work-flow and procedures (e.g. drawing of flow charts and spaghetti charts) (Task 4), and the monitoring of daily activities (Task 5). Task 4 determines who is responsible for each activity, where goods and personnel are located throughout the work-flow, and how the activities are performed. Task 5 requires some campaigns of on-field observation of the workflow, in order to account for the impact of each task on the total working time. To this purpose, the sampling batch of monitoring (e.g., a day, a week) is determined in accordance with the personnel availability.

Phase II: Micro and macro statistics elaboration.

As the flows of goods and personnel across the warehouse are identified at Phase I, aim of the second phase is to quantify such flows over a significant time horizon (e.g., six months, one year, five years). Therefore, the tasks belonging to Phase II involve the collection, the storage and the study of the associated data and records from the company data infrastructures (e.g., WMS, ERP). This phase can be conducted entirely outside the warehouse whether the consultants are provided with an online access to the WMS. In case of missing data, the company can evaluate at this point, the transaction costs of involving the clients in data collection.

Data gathering is focused on the fulfilment of a set of tables illustrated in Figure 35. This process includes an Outbound list (i.e., the picking order list), Inbound list (i.e., the incoming SKUs list), Items list (i.e., the SKU master file) and Inventory, which collects the daily inventory snapshots.

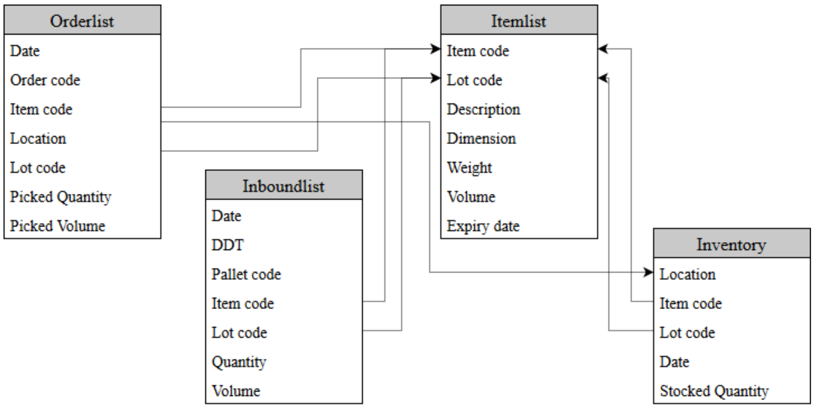


Figure 35. Data collection tables.

The tables and data fields showed in Figure 35 take inspiration from Baruffaldi et al. (2018). Further information on the main fields composing the data tables can be found at 4.3.1.3. Given the complexity of the collected data, its analysis and manipulation are organized into two separate tasks. First, a set of high-level metrics are calculated to better comprehend the characteristics and behaviour of the system (Dallari et al., 2008). These metrics aim to obtain average or synthetic metrics (e.g., average level of inventory, the cumulated number of stored SKUs, the average SKUs popularity). This task leads to identify the proper horizon of analysis in view of eventual seasonality and other time-driven behavior. Then, the dataset is examined in detail by matching records from different tables and quantifying low-level metrics, which enable to study the trend of a metric through the selected time horizon T. These metrics may involve frequency analysis and percentile cumulative curves, or bird's eye views of the warehouse layout accounting for specific indicators such as popularity, COI index and the turn over index (Bartholdi and Hackman, 2011)

Phase III: PMS development

Phase III is triggered by the identification of room for performance improvement. In such case, Task 10 entails the study of the literature and existing PMSs. Task 11 starts from the findings of the previous tasks and looks at the sources of inefficiency (e.g., the presence of redundant activities, time and space waste) to establish a panel of KPIs to control, as a leverage to increase the overall warehouse performance. Then, the deliverable of this phase is a development of a tailored PMS for the observed warehouse.

Phase IV: Improvement scenario design

Aim of Phase IV is the design of the improvement scenario to address to the panel of KPIs included in the established PMS. Firstly, Task 12 is to explore the literature in order to find the existing approaches, methods and models to cope with such indicators. Furthermore, in order to support the practitioners in the improving scenario design, Figure 36 is proposed. This table is inspired by the work of Gu et al. (2007), who classify warehouse design and operations planning problem areas. Each potential area of intervention is described by the adopted perspective in managing the KPIs (i.e., long-term, mid-term and short-term) and the company's willingness in dedicating resources, involving workers, customers, external consultants, investing in different technologies and infrastructures, changing procedures and layout. The issues/criticalities illustrated in 2.1 may affect the "company willingness" and discourage the implementation of improvement scenarios. For instance, an improvement scenario that involves extensive re-arrangements of the warehouse layout does not meet a short-term perspective. Another example is when the design of new receiving procedures requires the involvement of the client that is responsible to provide timely information about the incoming shipments.

				Goal	Company willingness											
						To involve			To invest					To change		
				Perspective	To dedicate resources (*i.e.* time, people)	Warehouse employees	Customers	External consultant	In equipments	In automation	In WMS customization	In SC technology	In training	Operations procedure	Layout	To innovate
Warehouse	**Design**	Overall structure		*Long term*	X				X	X			X		X	
		Sizing and dimensioning		*Long term*	X				X	X					X	
		Department layout		*Long term*	X										X	
		Equipment selection		*Mid term*	X	X			X	X			X		X	
		Operations strategy		*Mid term*	X	X					X			X		
	Operations	Receiving and shipping		*Mid term*	X	X	X	X				X	X	X	X	X
		Storage	Zoning	*Mid term*	X	X								X		
			SKU-department assignement	*Short term*		X	X				X			X	X	
			Storage locations assignment	*Short term*		X	X				X			X		
		Order picking	Batching	*Short term*		X	X				X			X		
			Routing and sequencing	*Short term*		X					X			X		
			Sorting	*Short term*		X	X			X				X		

Figure 36: Supporting table to Task 12.

The collateral benefit of Task 12 is to bridge industrial practice and research, highlighting potential gaps in the literature in fulfilling the managers' concerns. The decision-maker can at this point decide to design new methods/models/approaches or to implement existing models. Both paths are performed through an iterative approach, which enable to design (Task 14), prototype (Task 16), and test (Task 17) different scenarios to choose the one that achieve the expected targets. Specifically, Task 14 is to design new methods/models to address to a new improvement scenario. Then, Task 17 conducts a technical-economic feasibility analysis that requires a strict collaboration between managers and consultants. It is worth noting that the type of improvement scenarios and the metrics of the PMS drive the selection of the proper methodology, as well as the models and the tools (e.g., simulation, optimization, decision-support tools) to use for the feasibility analysis. As example, the simulation provides valuable support for the assessment and the quantification of the mid and long-term impacts resulting from different scenarios. The development of such tools are usually devoted to the WMS software provider, rather than to external consultants (e.g., scholars).

Phase V: Improvement scenario implementation

Lastly, Phase V includes all the activities needed for the implementation of the best improvement scenario, such as the customization of the WMS or the coding of new procedures, and, therefore, the framework encourages the joint efforts of all the actors.

4.2.1.2 *Experiences from a real world-warehouse. The implementation of the diagnostic-support framework on Case I.*

In order to validate the presented framework, the five phases have been tested trough Case I. Particularly, to perform Phase I, a series of inspections of the workflow and interviews with the personnel and managers has been conducted. Figure 37 reports some of the results of the different tasks. Particularly, the figure provides a 3D representation of the warehouse layout and reports the main structural and operative characteristics.

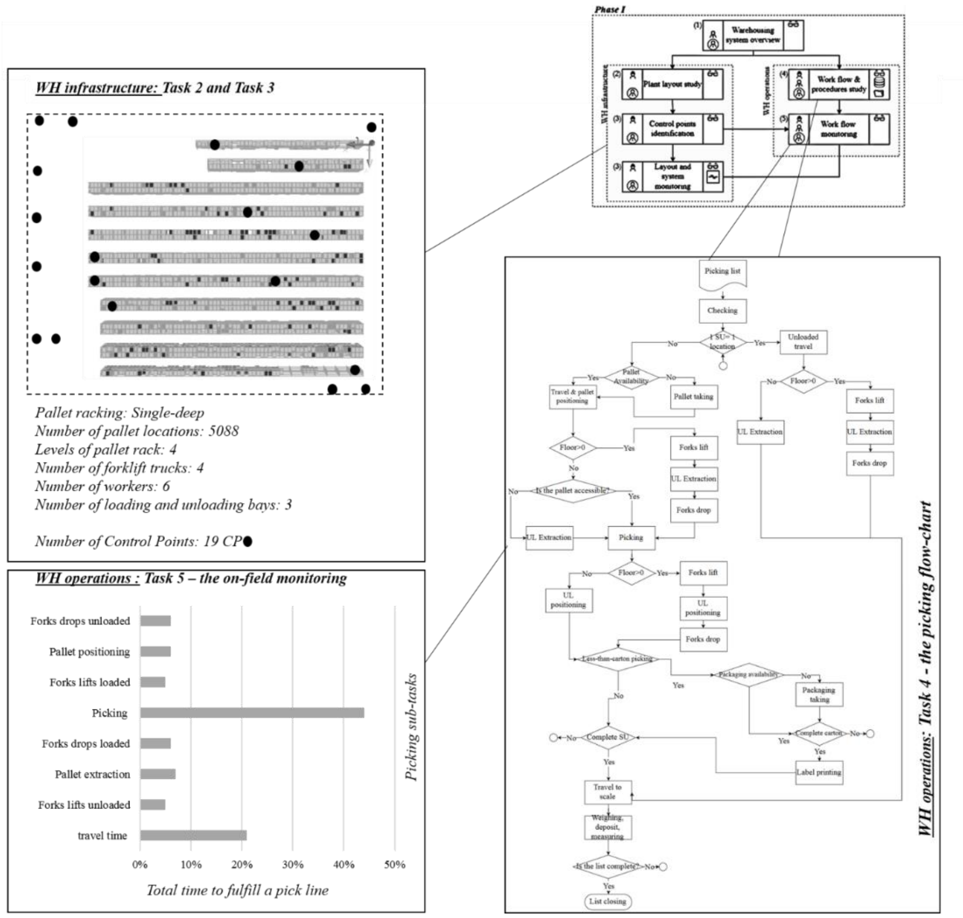


Figure 37: Outcomes from Phase I

With respect to Task 3, 19 CPs are set on the plant layout. Dealing with the outbound flow, Figure 37 illustrates the picking process with a flowchart developed during Task 4. Each order is fulfilled by a single operator and neither batch-picking nor zone-picking are implemented. The picking list is printed by the WMS according to the FEFO (First-expired-first-out) policy and the pick lines are ranked according to the shortest routing path. In contrast, no procedures for the put-away are defined. Therefore, the operators adopt a random assignment policy, and store the incoming loads to the nearest empty locations. The monitored activities (reported in Figure 37– Task 5) regard the whole picking process which accounts for an average travelling time per pick line of 37 seconds, while the picking/grabbing task is 44% of the total time to complete a line. In addition to the operations mapping, a warehouse temperature tracking campaign was conducted. The outcomes of this activity will be discussed in chapter 4.2.2.

With respect to Phase II, the observation period T for the retrieving of data from the WMS was set of about 10 months, from March 27th, 2015, to January 15th, 2016. Several macro and micro statistics were developed. Among these, Figure 38 represents the popularity distribution among the SKU locations during the 2nd of February, 2015.

3D rapresentation of the Popularity distribution inside the warehouse: February 2nd, 2015

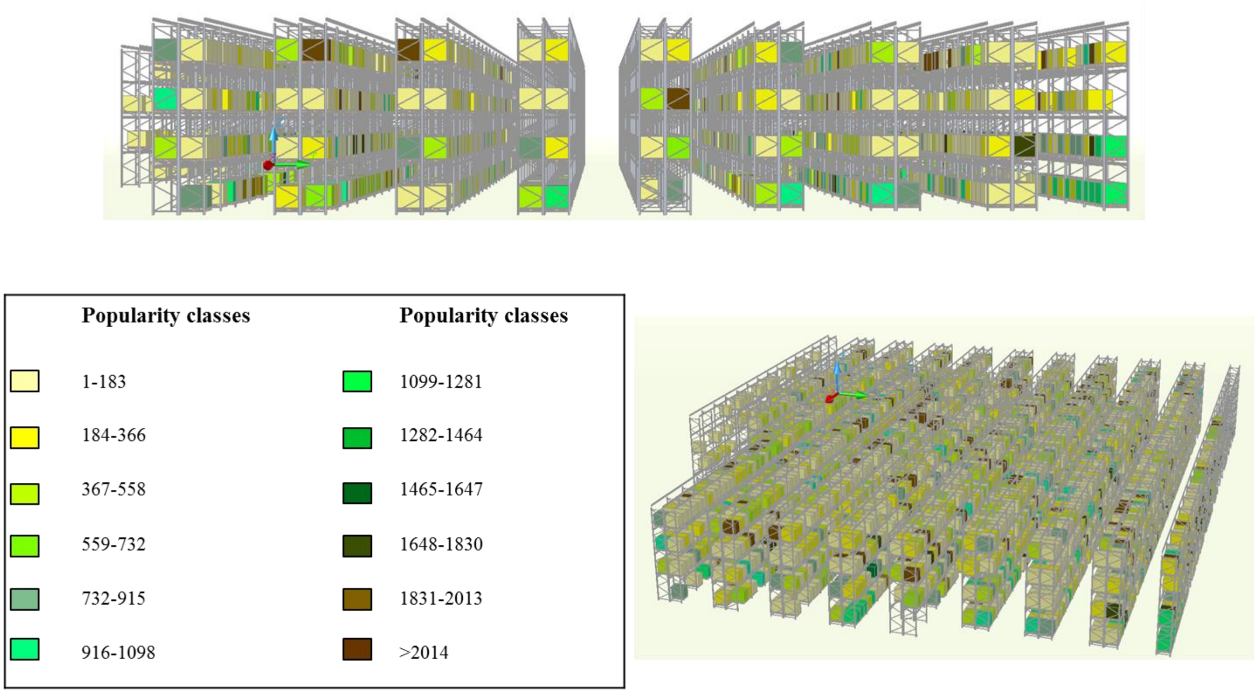


Figure 38: Popularity analysis.

The reported storage layout gives a 3D representation of the warehouse, where the value of popularity of each SKU is expressed with a green-colored pallet filling its storage location. The

darker the pallet, the higher the value of its popularity. According to the proposed figure, storage areas (i.e., clusters of locations in the racking system) characterized by homogenously colored pallets (i.e., same value of popularity) are hard to be identified.
The findings of the previous phases (especially from Task 5) highlight how the picking process was the most time-intensive operation, in agreement with the literature evidences that demonstrate that, typically, the cost of picking accounts for more than 55% of the total warehouse costs (Bartholdi and Hackman, 2011), and most is due to travelling. Figure 37 showcases how along the whole picking mission, the activities of picking/grabbing and the horizontal travelling result the most time-consuming. However, as the picking/grabbing task cannot be improved without the adoption of new technologies and equipment (e.g. voice picking), the travelling time presents the most significant room for improvement. For such reason, the company decided to focus the improvement scenario on this single metric (e.g. daily picking travelling time) assumed as leading KPI of the PMS.

The framework implementation results in proposing a new storage assignment policy for picking task improvements and in developing a C#.NET tool that embeds the proposed policy, simulates the inbound and outbound streams, and quantifies the performances. The proposed policy and the feasibility analysis will be illustrated in detail in chapter 4.4.2, while the characteristics of the developed tool can be found in 4.3.1.2.

4.2.1.3 Outcomes from this research

Outcomes from Case I give rise to some general considerations on the application of the proposed framework. Firstly, the high level of detail and the rigor in the results elaboration justify the key role of the data collection activity. However, gathering the information needed by the framework is time intensive and, for this reason, its application to handle short-term improvement project cannot be profitable. Conversely, whether adopting a mid- or long-term perspective, in addition to the main aims of the framework, some further advantages can be achieved, as the enhancement in the awareness of managers of their warehousing system. Dealing with the number of mastered processes, managers claim to be more aware of the whole flow of goods through the system after the framework application. Further evidences from the case study showcase benefits derived from a higher involvement of personnel in the improvement process. Since the data collection phase entails the collaboration of a great deal of operators and managers, a collateral advantage consists on a higher people engagement in achieving the projects goals. Furthermore, to a higher level, this phase contributes to set a up a major data sharing among the 3PL warehouse and its clients. As previously introduced, the operational environment of 3PL companies often lack integrated ICT systems and architectures able to link and connect the client and vendor orders and delivery data or the client's physical distribution activities connected with 3PL services (Giannikas et al., 2013). Since logistics operations are frequently outsourced, information is neither stored with nor sent to the service provider, who is often unaware of the whole process he is called upon to manage. The lacking and unbalanced information in the client-3PL relationship increases the complexity of finding and implementing procedures with mutual beneficial impacts on both actors.

Lastly, the experience gained by different case studies contributes to enrich and improve the framework itself.

4.2.2 Temperature mapping

The mapping of temperatures and the indoor environmental conditions plays a key role for those companies that deal with the storage of temperature-sensitive products, such as pharmaceutical products, and fresh food like fruit and vegetables, frozen foods, and meat and dairy products. The temperature mapping process involves the tracking of the temperature profile variation in storage areas, as temperature-controlled chambers, industrial fridges and warehouses over a horizon of time. Aim of such process is to verify whether the environmental conditions experienced by the stored products are in accordance with their labelled conservation conditions. The temperature mapping allows identifying how the temperatures fluctuate due to architectural features, or the properties of the observed facility and workers operations. Climate, weather seasonality and infrastructural characteristics and the layout of the warehouse, such as the side of docks, proximity to fans and skylights, may affect the uniformity of the temperature within the storage facility, despite the presence of Heating, Ventilation and Air Conditioning (HVAC) systems. The results obtained by the temperature mapping are applied to set the proper location where to install monitoring systems, and thus verifying the compliancy of the temperature values with the quality conservation standards. Mapping is also used to identify potential improvement action to reduce the so-called hot and cold spots within a storage area (WHO, 2014).

For these reasons, quality managers are often asked to schedule temperature mapping activities of the facilities to record data on the temperature fluctuation over the time. Despite temperature mapping is a common practice in warehousing, there is not a unique sharing protocol guiding managers trough the mapping process. Both regulatory agencies and private organizations provide several nonbinding guidance documents. On the contrary, the literature reveals a lack of contributions about tools and methods for the temperature mapping activity of warehouses.

4.2.2.1 On the temperature distribution in warehouses: Literature and industrial practice

The development of strategies to measure and control the indoor temperatures in warehouses have caught the eye of both researchers and practitioners to prevent the products quality and safety loss caused by inadequate storage conditions. The technology progress has led to design more efficient HVAC systems. Nevertheless, the problem of deciding where to locate those systems within the storage layout is widely explored by architects and engineers due to the non-homogeneous temperature distribution inside buildings. Particularly, the so-called phenomenon of air stratification (Armstrong et al., 2009) generates distinct air temperature values at different heights of the facility. Such phenomenon is caused by different density between hot and cold air, so that warmer air rises while cooler air falls. Without other airflow ventilation mechanisms, the stratification of air remains stable over time. Buildings characterized by high ceiling, such as warehouses, which are the most affected by the air stratification (Li, 2016). In addition, during the winter months, high temperature beneath the roof leads to a significant reduction of the heating energy efficiency (Aynsley, 2005, Accorsi et al., 2017). Porras-Amores et al., 2014, provide a detailed investigation on the air stratification phenomenon in five different type of warehouses in Spain. Given the vertical temperature variation, products stored in a warehouse for a quite large horizon of time may experience different thermal stresses according to the given height they are stored at. In addition, the structural characteristics of the facility, such as the position of docks, doors and windows that generate air infiltration (Brinks et al., 2015), as well as the operational practices (e.g. the ventilation, the position of the control points, and workers operations) also affects the temperature distribution among the locations at the same height Figure 39 summarizes the main issues affecting the temperature distribution inside warehouses.

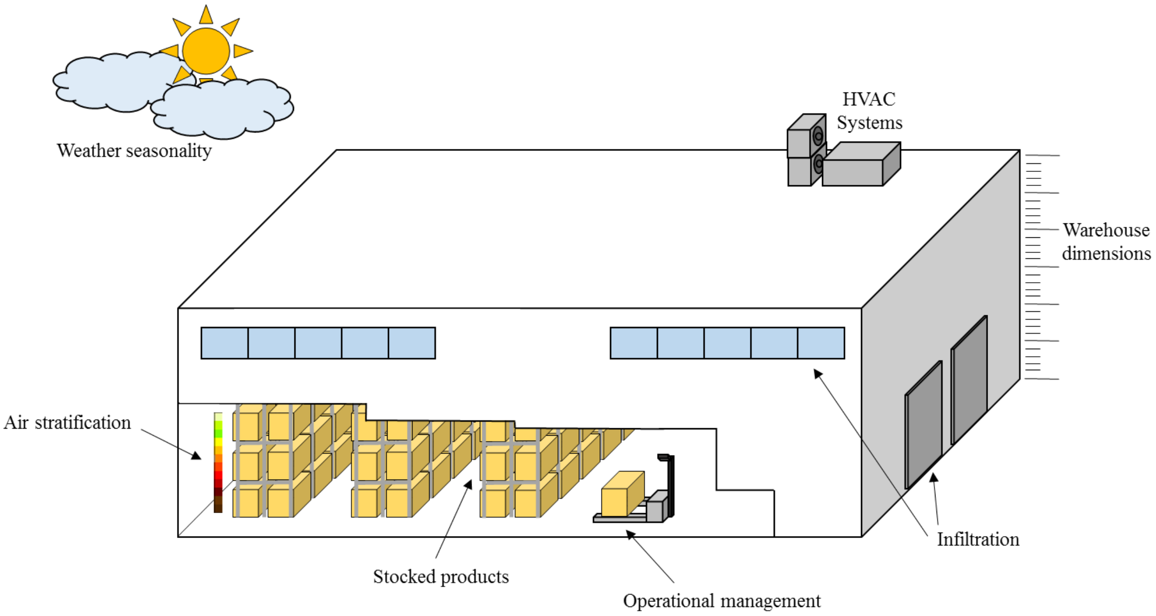


Figure 39: Outline of the main issues affecting the temperature distribution in warehouses.

The extant literature highlights how an accurate design of the layout of the cooling units may increase the uniformity of air temperature. Particularly, some techniques and systems, such as air circulation and mechanical air ventilation devices, contribute to reduce the air stratification phenomenon. The set of these induced mechanisms can be defined as thermal de-stratification process. Despite several studies explore the calculation of the air stratification effects and investigate the setting of thermal destratification mechanisms in warehouses, the industrial practitioners usually adopt rough and approximated design approaches (Wang and Li, 2017). Few studies suggest the effective adoption of computational fluid dynamics (CFD) techniques. Ho, Rosario, & Rahman, 2010, use the CFD to analyze the temperature distribution in a large refrigerated warehouse with several products stacks and cooling units. This study demonstrates that numerical modeling can be used to predict the air temperature distribution in refrigerated warehouses but the presence of an elevated number of design parameters and their interactions extensively increase the complexity of computation, enhancing the costs and time to perform the analysis and the inaccuracy of the results. As a consequence, the on-field monitoring of the temperature conditions experienced by the storage locations is still the most adopted strategy when analyzing the temperature distribution within a storage area (Zhu and Wang, 2013). The regulatory framework concerning the temperature mapping of warehouses suggests that the extension of the time horizon to monitor relies on the type of stoked products and the behavior of the locations to experience temperature fluctuations. Especially in those warehouses without HVAC systems, the temperature fluctuation is particularly affected by weather seasonality, which becomes increasingly critical due to the climate change (Chapman, 2007).

4.2.2.2 *Temperature mapping protocols: the state-of-the-art*

Among the aforementioned bunch of guidelines based on Good Manufacturing Practices (GMP), the company Vaisala (Vaisala, 2017) proposes a nine-step protocol for the warehouse temperature mapping, that well summarizes the most important activities that should be conducted. It is worth noting that, similarly to the other existing guidelines, the development of detailed documentation about the performed activities is fundamental in order to validate the obtained results. Therefore, the first step (Step 1) involves the creation of a validation plan, with the aim to establish the company's goal and the adopted approach. The Step 2 is to identify the areas of potential risks within the facility, as those locations where unacceptable temperatures and humidity values are expected given to architectural characteristics of the facility. A fair practice is to realize a preliminary thermal inspection of the storage system in order to identify cold and hot spots.

In addition to the validation plan, in the third step (Step 3) a protocol for the mapping test that define the data format, the number and the layout of the sensors, the calibration process description and the acceptable range of temperature is developed. The sensor distribution is defined during Step 4. Currently, there are no specific formulas to determine the adequate sensor distribution, which is usually decided according to good practice. Reasonably, a higher number of sensors leads to a more accurate data collection. With respect to the humidity monitoring, it should be driven by the sensitivity of the products to the effects of moisture. The selection of the best fitting tracking technology (Step 5) is important to validate the temperature mapping, and a phase involving control, calibration, set up and validation of the tracking equipment is recommended (Step 6). Step 7 involves the phase of testing and data gathering. Results from this last phase are then used to propose possible adjustments, i.e. to the HVAC systems, or to decide on the location of particular products (Step 8). Finally, Step 9 involves the final temperature mapping documentation and dissemination.
Given this overarching protocol, no more detailed indications are provided in order to lead managers though each step. Particularly, the activity of temperature mapping documentation and dissemination should deserve a great deal of attention not only for its role in disseminating the results of the temperature mapping (see Step 9) but in supporting the decision-maker (i.e. the

managers) during Step 8. How data is presented, in addition to data analysis, plays a crucial role in this latter step and, therefore, the topic of data visualization should be anticipated at Step 7.

4.2.2.3 *Warehouse temperature data analysis & visualization. Experience from real-world warehouses.*

The warehouse temperature mapping activity could lead to different outcomes, such as the validation of the temperature control protocol in force or the identification of potential lacks in the current management. Particularly in the latter case, an exhaustive analysis on the monitored data is fundamental to guide managers during the decision-making in Step 8. Particularly, the obtained results can be used, at first, to identify potential solutions (1) and, then, to assess such solutions through a feasibility analysis (2). Thus, the way the results are visualized acquires an important role to facilitate the managers in both (1) and (2). To showcase to the reader the benefits generated by the use of an accurate data visualization, this section presents two testbeds from two different supply chains. Both cases illustrate the application of the temperature mapping in a real-world warehouse. The first warehouse stores biomedical products, i.e. products and devices for dialysis, (see Case I) the second stores beverage items, such as wine, spirits and other alcoholic drinks (see Case II). The first warehouse belongs to a 3PL company that mostly deals with the storage and distribution of biomedical products. Due to the regulations in force on the good distribution practices for pharmaceutical products for humans (European Commission, 2013) and the standards imposed by the clients, the main performance driver the 3PL managers are measured for is the product safety. On the contrary, due to the type of stored products, the second warehouse is not requested to apply severe procedures on the matter of temperature monitoring. However, whether uncontrolled storage temperature conditions slightly affect the product safety, the perception of quality of some product, i.e. wine, for the final user is influenced by the temperature variations experienced by the products during storage. Consequently, the involved 3PL adopts a quality driven approach in the storage operations in order to guarantee a high level of service to its clients. Therefore, the warehouse mapping activity represents a strategic lever to enhance its competitive advantage. Both warehouses are located in the North of Italy where weather conditions are usually characterized by a continental climate, with humidity and high temperature in summer and cold in winter. Since the warehouses are not dedicated to the aforementioned products categories only, they are not climate-controlled, and the weather seasonality highly affects the temperature conditions experienced by products. The analyses illustrated in the following focuses on temperature since the packaging in use preserves the inventory from the effects of indoor moisture.

The protocol proposed by Vaisala was applied to both warehouses. At first, Step 2 allows to identify the cold and hot spots. As instance, Figure 40 presents two pictures obtained by a thermal camera in Case I. The thermal inspection was conducted in July. Figure 40(a) shows a view of an aisle between two racks while in Figure 40(b) a gate in the inbound area is shown. It is worth noting how the temperatures within the truck achieve value up to 50 °C, and this is the stress the load is expected to suffer. The brighter the color of the locations in the thermal pictures, the higher the intensity of the emitted infrared radiations will be.

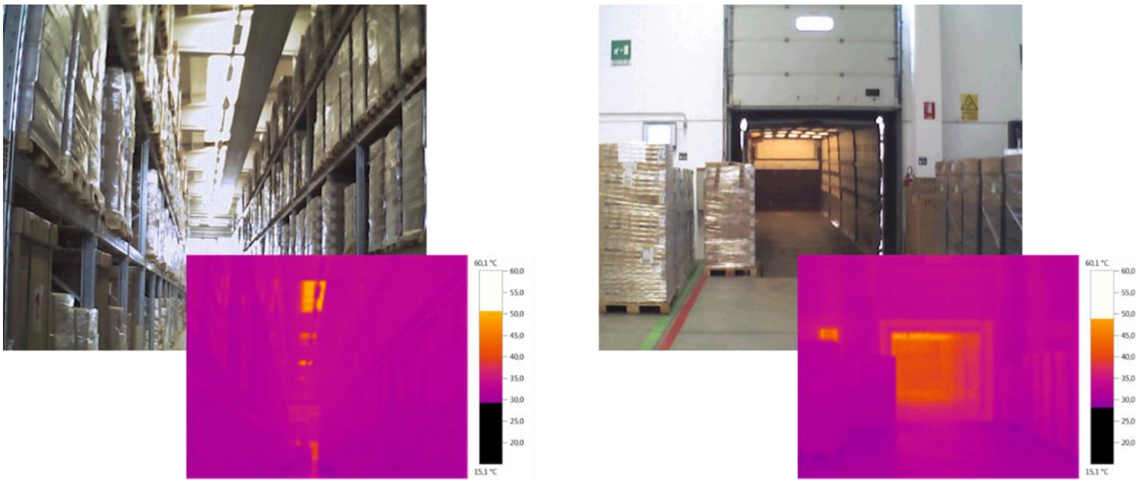


Figure 40: (a) thermal photo of a warehouse corridor, (b) thermal photo of an I/O dock.

To study the distribution of the air temperature, a set of temperature loggers was installed, and a tracking campaign was conducted. Furthermore, one sensor per side of the facility was installed on the external walls. The loggers are self-sufficient digital thermometers and hygrometers that provide temperature and humidity measurements with 8-bit resolution (±0.5 °C), respectively. The tracking campaign lasted for approximately 12 months in both warehouses and a sample rate of 1 hour was adopted. The identification of the proper number of loggers was driven by the trade-off between the desired level of accuracy and the economic lever. Therefore, while in Case I, 80 loggers out of 5000 locations were installed, Case II saw 41 loggers out of 4000 locations. The choice on the distribution of the loggers inside the warehouses was motivated by the position of the cold and hot spot primarily, and by the aim of uniformly mapping the entire facilities secondly. During the data analysis, having to deal with the great number of non-monitored locations, a calculation algorithm was developed. This aims to determine the temperature and humidity values expected at each of these locations based on the historical dataset. Since the calculation algorithm is the same for temperature and humidity, the following reports the exemplification for just the temperature values. Figure 41 displays the 3D representation of a rack, where the pallet represents the physical location of the data loggers. Let assume to calculate the temperature experienced by a generic location A (i.e., not tracked) during a day d at time t. Given the sample rate of the sensors, this calculation is performed for each sample (e.g. at t= 13:00, t = 14:00, t=15:00) over the horizon of monitoring.

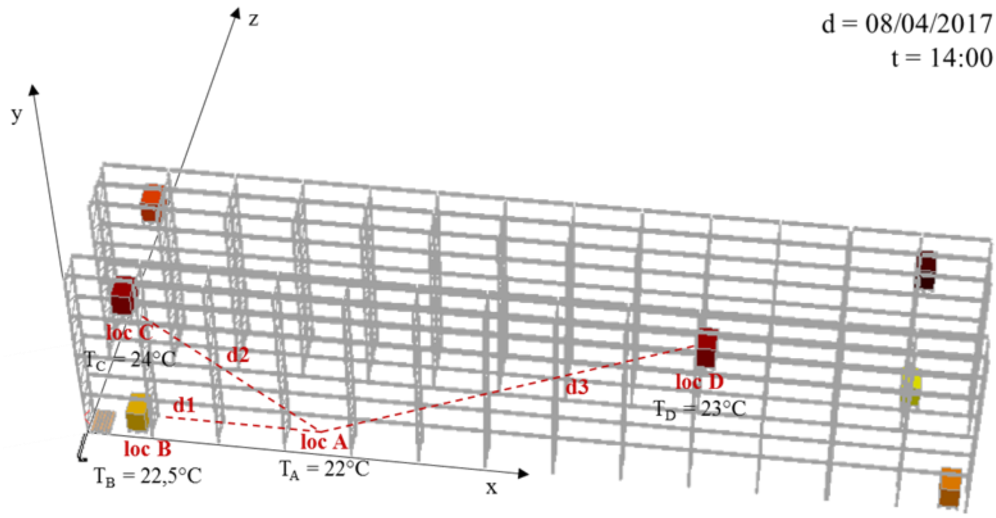


Figure 41: 3D representation of a rack

The calculation of the temperature expected at location A requires the identification of the three nearest locations to A through the 3-Dimensional Euclidean distances. Let the locations B, C, and D the nearest available as illustrated in Figure 41. As example, the distance between A and B (i.e. d1) is calculated according to Equation (1) as follows:

$$d1 = \sqrt{(B_x - A_x)^2 + (B_y - A_y)^2 + (B_z - A_z)^2} \quad (1)$$

where Bx, By, and Bz are the coordinates of location B and Ax, Ay, and Az are the coordinates of location A.

Then, the temperature expected at location A (i.e. TA) is calculated through the Equation (2) as follows:

$$T_A = \frac{\frac{T_B}{d1} + \frac{T_C}{d2} + \frac{T_D}{d3}}{\frac{1}{d1} + \frac{1}{d2} + \frac{1}{d3}} \quad (2)$$

Where TB, TC, and TD are the temperature values respectively of B, C, and D while d1, d2, and d3 are the Euclidean distance of B, C, and D from A.

The application of this calculation algorithm generates a great amount of data. It will suffice to consider that a single day of mapping generates 24 values of temperature for each storage location. The obtained dataset was used to feed several analyses concerning the study of the temperature and humidity profile of locations over the observed time horizon. As instance, Figure 42 represents the temperature profile recorded in Case I between the 3rd of August 2015, and the 9th of August 2015. It is worth noting how the daily average temperature value increases over the period. This can be easily seen in the four histograms representing successive daily inventory snapshots taken at 6:00 p.m. They graph a frequency analysis where the total number of locations is split into twelve temperature range according to the temperature experienced by each location in that moment.

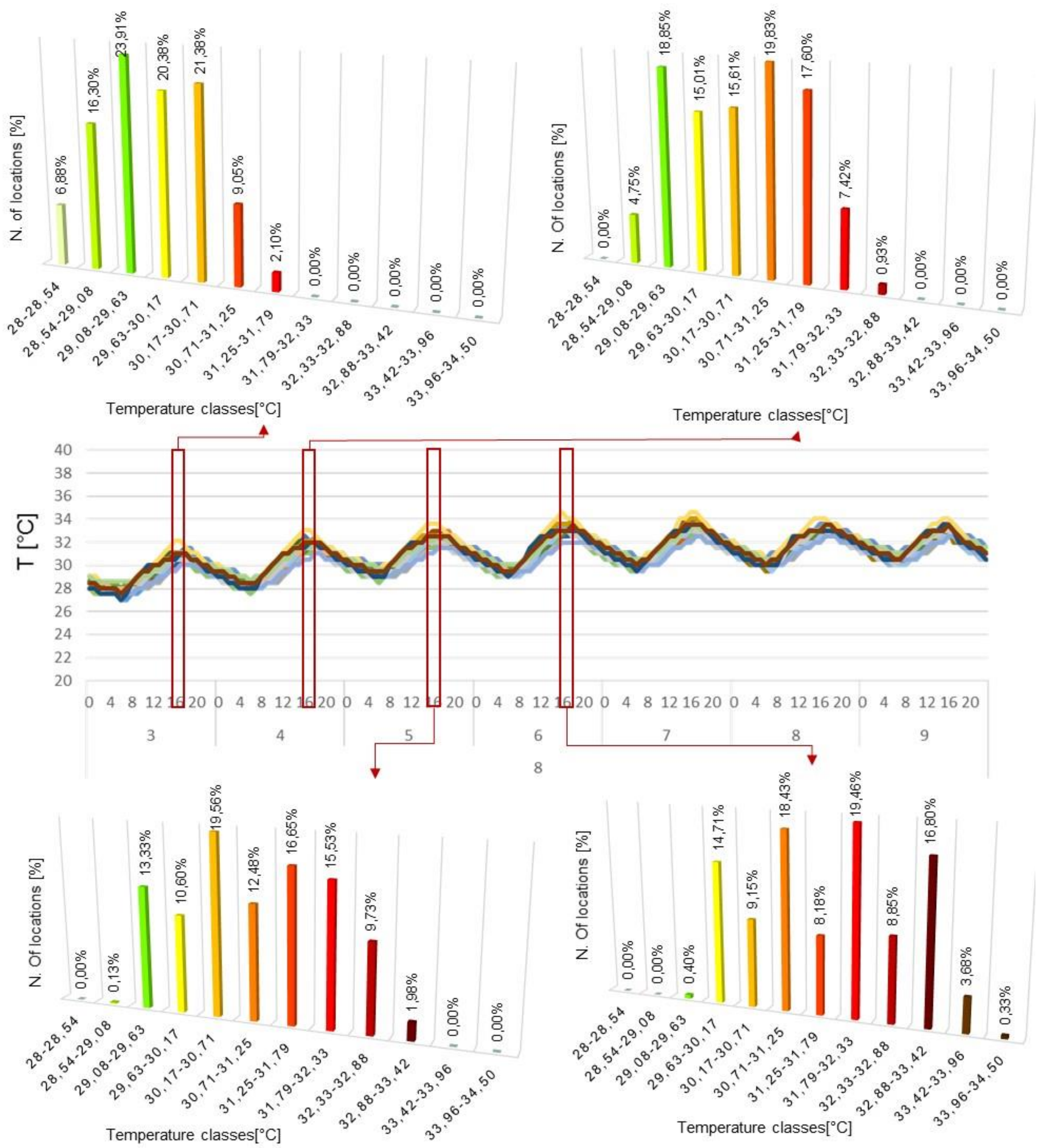


Figure 42:Temperature mapping activity: weekly profile

Focusing on the daily temperature variation, Figure 43 showcases four inventory snapshots representing the observed warehouse obtained by the mean of tool developed inside the Department of Industrial Engineering of the University of Bologna. The tool, named Layout Designer, aids the 3D visualization of warehouses. Through a developed add-on, the tool was able to import the dataset and color the storage locations according to a proper colored scale based on temperature. These snapshots represent four moment *t* of the 8th August 2015, such as 6:00 a.m., 12:00 a.m., 6:00 p.m., and 12:00 p.m. It is worth noting how the temperature profile varies significantly over the day.

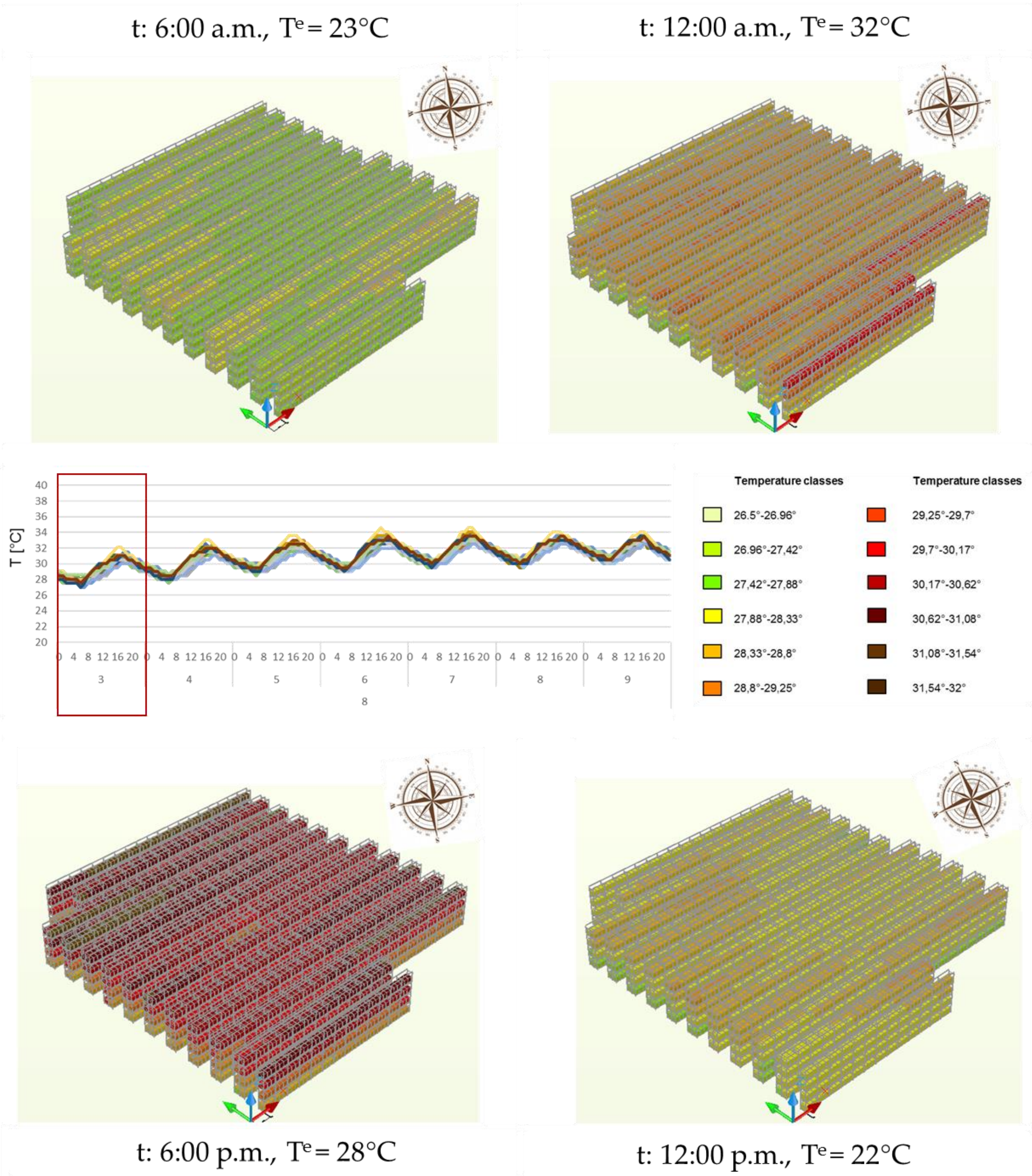


Figure 43: Temperature mapping activity: daily profile

4.2.2.3.1 Case I.

According to the safety driven approach, during the temperature mapping a high level of accuracy is required in order to guarantee the respect of the imposed standard. The inventory presents five different required conservation temperature ranges, but the most belong to the range of 4-30°C. According to the preliminary thermometric inspection, the most critical locations resulted those at the highest levels or near to the skylights. Each aisle presents the same sensors distribution: six sensors distributed respectively in the front, in the center and in the back of the rack. The same bay contains two sensors on the ground level and on fourth level respectively. The tracking campaign lasts from March 2015 to February 2016.

The overall temperature profile shows a maximum variation of about 20°C from summer to winter. It is worth remembering how the weather conditions were particularly severe in summer 2015. This period resulted indeed the most critical with respect to the compliancy with the safety standards. As instance, Figure 44 shows some 3Dimensional views of the warehouse on 4th of August 2015 at 6 p.m. The storage locations are colored according to a temperature scale (from 26°C to 32°C). It is worth noting how the temperature values vary significantly all over the warehouse. Particularly, Figure 44 reveals the impact of the phenomenon of air stratification, showing a maximum difference of 4 degrees between the ground and the fourth rack level.

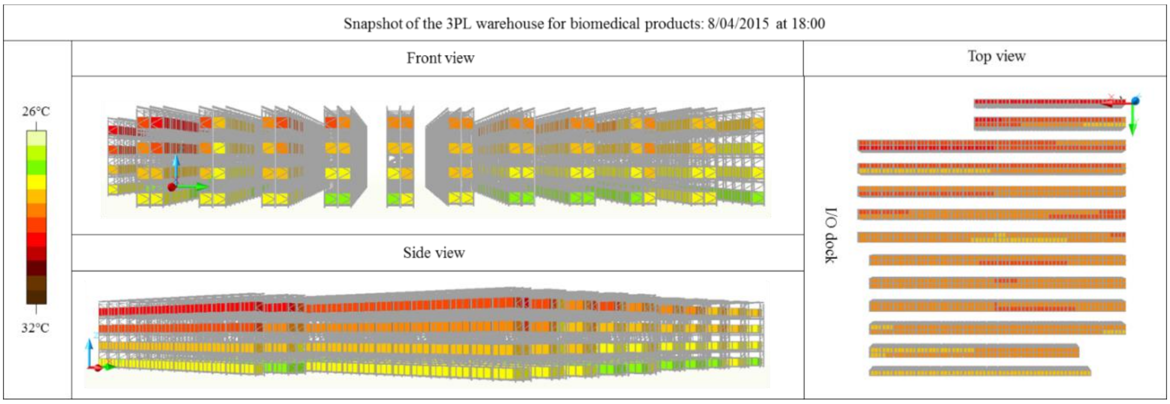


Figure 44: Snapshots of the 3PL warehouse for biomedical products: 8/04/2018

4.2.2.3.2 Case II.

For its chemical characteristics, the most temperature-sensitive product over the inventory-mix results to be wine. Particularly, the safe storage temperature conditions vary from 6°C and 12.5°C for white wine (i.e. sparkling, light bodied, and full bodied white wine) and from 10°C and 18°C for red wine (i.e. light bodied, medium bodied, and full bodied red wine). Two temperature tracking campaign of three months respectively were conducted. The winter monitoring lasted from December 2016 to February 2017 while the summer monitoring took place from July 2016 to September 2016. Since the warehouse is developed along its length, in addition to the vertical air temperature distribution warehouse managers were particularly interested to identify the temperature variation among the same rack given the inbound doors placed over the front. The tool highlights how the temperature varies significantly from the front to the back of the rack for the ground level, while the upper levels present values that are more similar. This is evident in Figure 45, which represents some warehouse view on the 10th of January 2015.

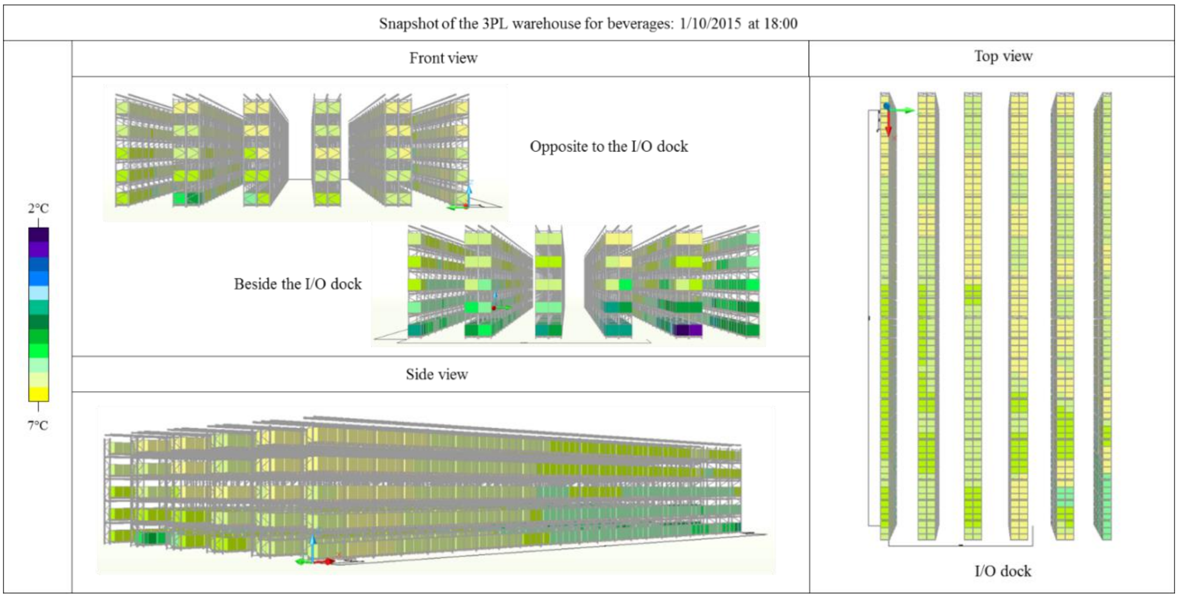


Figure 45: Snapshots of the 3PL warehouse for beverages: 1/10/2016

4.3 WAREHOUSE DATASET, WAREHOUSE MANAGEMENT SYSTEMS AND INFORMATION AVAILABILITY

A strategic role to enable and control the flow of information along the supply chain is played at the warehouse level by the Warehouse Managements System. This ERP module controls the flows of goods and information as well as the personnel tasks, supervising the operations within a warehouse (Ramaa et al, 2012). The introduction of WMSs at the different levels of a supply chain facilitates the creation of information infrastructures that the enterprises exploit even in procurement, production, storage and distribution activities (Tan, 2009). As instance, in view of this, an increasing number of 3PL providers are investing in WMSs. The 19th annual report on the logistics outsourcing (Langley, 2015) shows that the 58% of the companies have already purchased a WMS and the 33% have invested in WMS customization (e.g. functionalities for the labor management, analytics). The WMS provides knowledge and enables the improvement of the performances of the warehousing operations but requires input data, whose collection is constrained by several exogenous factors and is at least expensive. Particularly, in warehouses hold by 3PLs one of this factor deals with the scarce information availability along the supply chain (Selviaridis and Spring, 2007), which affects the visibility on the operations to be managed. Although the crucial role of the information in operations management is unanimously stated (Cantor and Mcdonald, 2009, Ruel et al., 2017, Mandal and Bagchi, 2016), the 3PL providers usually make decisions with partial visibility on the client's processes, especially during the tender of new clients. The competition among 3PL providers and consequently the high turn-over in their clients' portfolio reduce the opportunity for long-standing and trustworthy partnerships and discourage the data and information sharing. The schedule of the incoming trucks, the loads of these trucks, the variation of the turnover, the changes in the inventory mix, and the order forecasts are examples of this unknown information (Accorsi, 2017).

This limits the implementation of the so-called *product intelligence paradigm* in 3PL warehousing operations (McFarlane et al., 2013, Lu et al., 2013). This paradigm exploits the interdependency between a physical entity (e.g., a product) and its informative content (Meyer et al., 2009). For example, the use of some metrics such as the COI defined by Haskett, 1963, to classify an item and organize the put-away activities accordingly that contributes to reduce the travelling for picking (Chan and Chan, 2011), but needs a set of information provided by the client, as the unit volume of the products and the number of orders (De Koster et al., 2007).

4.3.1 WMS customization and information availability: A decision-support tool

Among the jungle bid of WMSs that sees hundreds of standardized solutions, the choice of the proper tool and the customizations that better perform with each business can be challenging. The 3PL operations manager should consider carefully the adoption of a WMS and its customization in the view of the achievable benefits. Three main issues affect such decision:

1) Costs of information technologies (IT). Both the scientific literature and the practice highlight the positive effects of IT on the 3PL provider's performances (Evangelista et al., 2012). Nevertheless, four cost drivers should be taken into account (Chen and Tsou, 2007): the IT infrastructure, the alignment between the IT and the business strategies, the re-organization of the organigram and the communication procedures (e.g., activities coordination, communication rules, procedures) to meet the IT capabilities, the workers training.

2) Partial information availability. The lack of visibility on the characteristics of the inventory (e.g., weight, volume, safe conservation conditions per each stock-keeping-unit SKU) or the clients targets (e.g., demand forecast, products life cycle) limits the benefits resulting by a WMS.

3) Uncertainty on the benefits. The long-term benefits resulting from the implementation of a WMS feature are hard to be predicted for the level of the achievable customization and the unexpected changes in the business operational conditions. This often discourages the 3PL providers to invest in WMS's features.

Based on these statements, an original decision-support tool that aids 3PL managers to decide on the proper Warehouse Management System (WMS) customization is proposed. Aim of the proposed tool, named Store Simulator, is to support 3PL managers in designing the proper WMS customization, which is increasingly challenging given the large inventory mix and the variable clients portfolio that 3PL have to manage. The tool is intended to address the Issue 3. Particularly, it is able to assess the long-term impacts resulting by implementing a WMS feature on a set of economic and logistics KPIs. Moreover, it can be used to study and compare the effects of a higher information availability on the warehouse performances (Issue 2). For these reasons, Store Simulator could provide a valuable support to the investments assessment in the WMS design and customization (Issue 1).

However, two main limitations have to be claimed. First, the tool bases on a specific data architecture that need to be fueled by precise data. The more precise the dataset, the more reliable the decisions resulting from the analysis will be. As a consequence, in order to obtain robust WMS assessments, the 3PL company has to involve their clients on an overall and long-term project of data gathering and sharing. Second, a logistic specialist is required in designing and proposing the alternative WMS's features to be tested as well as for the interpretation of the results.

4.3.1.1 Literature background

The purpose of selecting the set of features of a WMS has been already debated by Giannikas et al., 2013, which identify two decision drivers: the flexibility, i.e. reacting quickly to changes in customers demand and the adaptability, i.e. maintaining high service levels when customers' requirements change. They also argue that the partial visibility on the processes bounds the level of reachable performances in the warehouse operations. Kearns and Lederer, 2003, show the role of data sharing in strengthening and improving the operations between companies in the supply chain. Others accounts the related impacts on the bullwhip effect (Lee et al, 1997, Cantor and Mcdonald, 2009) and state how the updating of ERPs and WMSs make companies more responsive to the changes of the customer' demand (Sambamurthy et al., 2003, Comuzzi and Parhizkar, 2017). The proposed tool addresses a still uncovered gap of the warehousing literature exploiting optimization and simulation techniques to quantify the impacts of the information availability on the performances of the warehousing operations and aiding the decision-making on the WMS features and customization to implement. Since this tool overviews the dynamic behavior of a storage system and the implemented WMS along an observation horizon, it extends the limitation of the one illustrated by Accorsi et al., 2014, which was intended to aid the design and management of effective storage systems from green field and investigated how to combine storage allocation and assignment policies in an existing facility with dedicated storage locations. Dedicated storage is indeed not suitable in 3PL warehouses since the inventory mix changes continuously in accordance with demand seasonality and the clients' portfolio. Simulation allows to study complex systems through their model, whose parameters are varied to analyze the response of the system to multiple input scenario in an affordable way (Manzini et al., 2005). Chan and Chan, 2010, indicate simulation as suitable to study the impact of the information sharing on the entire supply chains and Dorigatti et al., 2016, propose a framework based on simulation to study the benefits from collaboration and information visibility. Fleisch and Tellkamp, 2005, use simulation to study the level of visibility on the inventory along the entire supply chain, while Ramanathan, 2014, tests the impacts of supply chain collaborations. The challenging task of developing a tool that reproduces the behavior of real-world non-automated warehouses is widely recognized in the literature (Cagliano et al., 2011), and few are the contributions on this topic. Table 10 shortlists some of these over the past two decades. It is worth noting how some scholars have started to explore this research topic quite early, while in the recent years it has been overlooked by literature. The table classifies the works with respect to the involved processes, the set of decision levers, the type of storage system (i.e. OPS or unit-load warehouse), the tool scopes (i.e. the warehouse design or operations management), the set of outcoming performance metrics, the approach used in what-if multi-scenario analyses, the use of real input data and, lastly, the use of object-oriented programming languages. The check states if the contribution presents the specific characteristics, while the acronym 'NS' indicates whether it is not specified in the text.

Table 10: Literature overview

Contributions		This work	(Accorsi et al., 2014)	(Gagliardi et al., 2007)	(Galè et al., 2002)	(Lam et al., 2011)	(Longo, 2011)	(Macro and Salmi, 2002)
Processes	Receiving	✓	✓		✓		✓	
	Put-away	✓	✓	✓	✓		✓	✓
	Storage	✓		✓				✓
	Picking	✓	✓	✓	✓	✓	✓	✓
	Sorting						✓	
	Packing						✓	
	Shipping				✓		✓	✓
Decision levers	Storage assignment	✓	✓	✓	✓			✓
	Picking Policy	✓	✓			✓		✓
	Order batching		✓					
	Routing Policy		✓					
	Emptying policy	✓						
	Allocation strategy		✓	✓				
	Layout configuration	variable	variable	variable	fixed	variable	fixed	variable
	Put-away policy	✓						
Type of storage system	Unit-load warehouse	✓	✓	NS	NS		✓	
	OPS	✓	✓	NS	NS	✓		✓
Objective	Design		✓					✓
	Operations management	✓		✓	✓	✓	✓	✓
Performance metrics	Single							
	Multiple	✓	✓	✓	✓	✓	✓	✓
Multi-scenario analysis	Setting-based	✓	✓	✓	✓	✓	✓	✓
	Time-based	✓						
Real Input data	Arrivals	✓	✓			✓		✓
	Demand	✓	✓			✓		✓
Object-oriented language		✓	✓				✓	

With respect to the other contributions, this paper focuses on the impact of information visibility on the warehousing operations. The proposed tool quantifies multiple KPIs related to the receiving, the put-away, the storage, the picking processes, instead a single metric of a single process (Chen et al., 2010), and involves the interdependencies between the storage and picking policies within a multiple-level order-picking system. In addition, a great deal of attention is devoted to the data collection process to enhance the robustness of the results in accordance with the real-world instance. However, the main contribution presented by our DST regards the opportunity to quantify the evolution of the overall warehouse performance over a given time horizon, behaving as a digital twin of the company's WMS. The building of the multi-scenario analysis is, therefore, obtained as a result of a combination of specific logistic choices (i.e. setting-based multi-scenario analysis), whose impact can be evaluated day-by-day (time-based multi-scenario analysis). Finally, it is worth noting how the proposed tool includes the opportunity to choose the put-away policy to implement. Moreover, the user can set the capacity of a buffer where to stock the incoming unit loads before the put-away activity.

4.3.1.2 Decision-support-tool overview

This tool manipulates an historical dataset representing the available knowledge on the warehousing operations and simulates the behavior of the storage system over a given horizon (e.g. a year) according to the alternative WMS features and capabilities. These features control and influence the behavior of the warehouse. A set of features results in a specific release of the WMS (i.e., a management scenario). Thus, different sets correspond to multiple to-be scenarios. The to-be scenarios are compared with the benchmark (i.e., the as-is or current scenario) over a panel of performance indicators (i.e., travelling for picking, utilization of locations) which enables to identify the most performing management scenario. The implemented WMS's features include the management of both put-away and picking operations (see Table 10), which together account for the 70% of the total operating costs (Bartholdi and Hackman, 2013).

Figure 46 shows the conceptual framework of the proposed tool, where the main functions are outlined through the use of pseudocode.

Framework of the progressive-adapting methodology implemented in the DST

a) **Import settings:**
Buffer capacity: b
Step: m
Period (a day): t
Replenishing time: t_r where j is the last t_r in t
Simulation Periods: T
Assignment policy: k
Retrieving policy: n
Inventory snapshot: $s_{tr,\,t}$
Unit load = u
Orders = o
Picklines = pl

b) **Import Data:** import data from the database
c) **Simulation**

while (t<=T){

Set $s_{tr=1,t} = s_{tr=j,t-1}$
Set $L^{unitload}_{t}$ as the list of incoming unit loads u in t
Calculate $pop^{roll}_{u,t,m}$ for each u in t according to m

Set $L^{orders}_{t}{}^{imp}$ as the imported list of orders o in t
Set $L^{pickline}_{o,pl}{}^{imp}$ as the imported list of pickline pl in o

for each t_r {

Perform the picking process according to n
Produce $s_{tr,\,t}$
Produce $L^{orders}_{t,tr}{}^{sim}$ as the simulated list of orders in t in (t_{r-1}, t_r)
}

Set $L^{orders}_{t}{}^{sim}$ as the simulated list of orders o in t

Solve the assignment problem according to k
Perform the put-away process
Update $s_{tr,t}$
}
}
d) **Print results in the database**

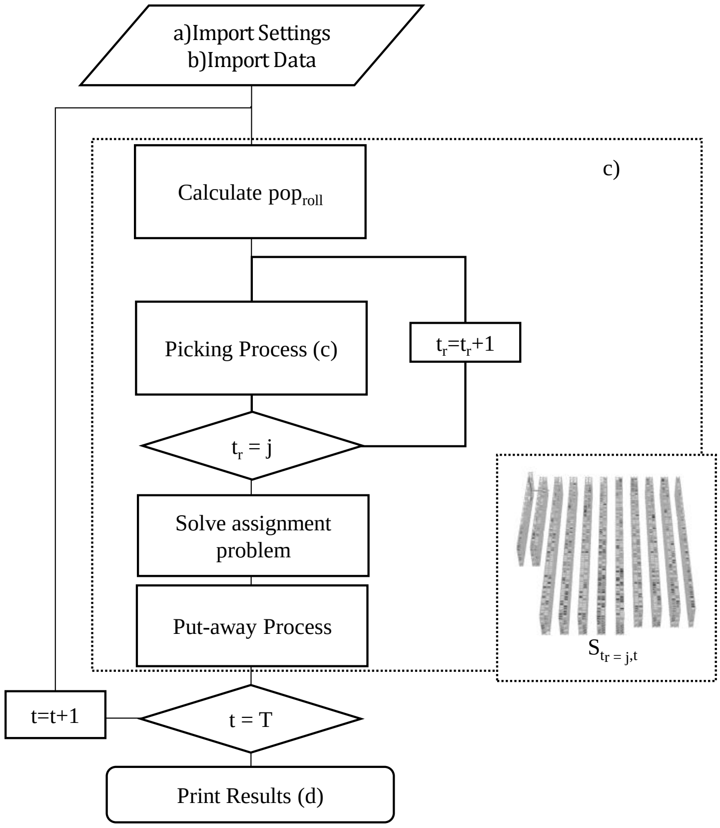


Figure 46: Conceptual framework of the DSS

The proposed tool implements two key patterns: the aforementioned *adaptive storage assignment,* explored at 4.1.1.1, and the *progressive adaptation.* The latter entails that, starting from an initial inventory collecting the stored volume per each SKU, the tool progressively adapts to the introduction of a new WMS management feature. Thus, the configuration of the storage system evolves during the day (i.e., within time batches called replenishing time), and along a time horizon according to inbound lines (i.e., incoming loads), the available empty locations, and the chosen management policy (i.e., that is the object of analysis). The replenishing time t_r is a batch within the day (e.g., 12:00-18:00-20:00) that decouples put-away from picking activities and represents the instant when the inventory configuration is updated in the WMS. As a consequence, the inventory configuration at t_r is a combination of original frames (i.e., locations and held SKUs not yet visited) and adapted frames made by the storage locations visited at least once according to the selected management scenario (i.e., WMS's features).

Furthermore, the tool framework is built upon three basic assumptions. First, the flow of loads is one-directional, from inbound to outbound. Re-locating flows (i.e., SKUs moved among locations) are not allowed. Second, each storage location is single SKU and all the locations are devoted to picking (i.e., multi-level picking). Once a pallet of a generic SKU i is assigned to an empty location l, this remains occupied until the whole stock is retrieved. Third, the pallet received at day t is stored in day t and retrieving is allowed from day $t+1$.

According to Power and Sharda, 2007, the proposed decision-support tool (DST) is classified as a model-driven decision support system. Its architecture is made of multiple patterns for the simulation of the warehousing operations. The DST implements and solves even optimization problems for the storage assignment. Particularly, it can be interfaced with a generic commercial solver (e.g., Gurobi) for linear or multi-objective models that are written in AMPL. Store Simulator is written in C#. NET, using LINQ libraries, and is connected to a relational SQL database, which is described in the following sub-section. The DST is intended for users with poor informatics skills, as 3PL managers that have to decide about the WMS customization. Thus, two user-friendly graphical user interfaces (GUIs) are developed. The proposed tool is highly customizable and can quickly incorporate new management scenario (i.e., WMS's features) to be tested and assessed.

4.3.1.3 A Dataset to map the warehouse operations

The tool embeds a properly developed database, inspired to the typical WMS's data architecture, that tracks the warehouse's inbound and the outbound operations within a given horizon (Accorsi et al. 2014). The tables include required and auxiliary ones. The first set tracks the essential information that draw the storage system, the inbound flows, the demand orders. The auxiliary tables are involved case by case depending on the WMS's feature to be assessed. Table 11 further describes the characteristics of each table.

Table 11: The database tables

Input Tables	**Data**
Mandatory	
SKU	The SKUs' characteristics (e.g. SKU code, description, volume, weight, labelled temperature standard)
OrderList	The historical demand orders and the associated picking tours: date and time of the pick, SKU code and lot code, order code and picked quantity.
Inventory	The initial inventory snapshot that reports per each SKU the cartons stored per location.
InboundList	The historical records of the incoming unit loads, including the list of SKUs per pallet, the arrival time and the truck code.
Location	The characteristics of the storage locations (e.g. distance from the I/O dock)
WH	Information on the warehouse, e.g. location, sizes and the number of aisles and bays.
Auxiliary	
Temperature	Indoor temperature per unit time (e.g. hour, minute) within a selected period of time (e.g. a month, a year)
Weather	Outdoor temperature values (maximum, minimum) and humidity recorded during each day of the simulation.
Output Tables	**Data**
Mandatory	
SimulationOrderList	The picks list resulting from the simulation. This table has the same structure of ORDERLIST.
SimulationSettings	Summarizes the user choices and the simulation settings.
SimulationInventory	Inventory snapshot taken during each day of the simulation.
SimulationStockBuffer	The list of pallets queued in the pre-storage buffer (i.e., inbound docks)
Auxiliary	
SimulationResults	Value of the objective functions used in the optimization of the assignment process.
SimulationSolver	Results of the algorithm for the selection of the trade-off solution of the multi-objective optimization problem.

Both required and auxiliary tables are organized in the entity-relational diagram of Figure 47, which underlines the connection between input and output tables.

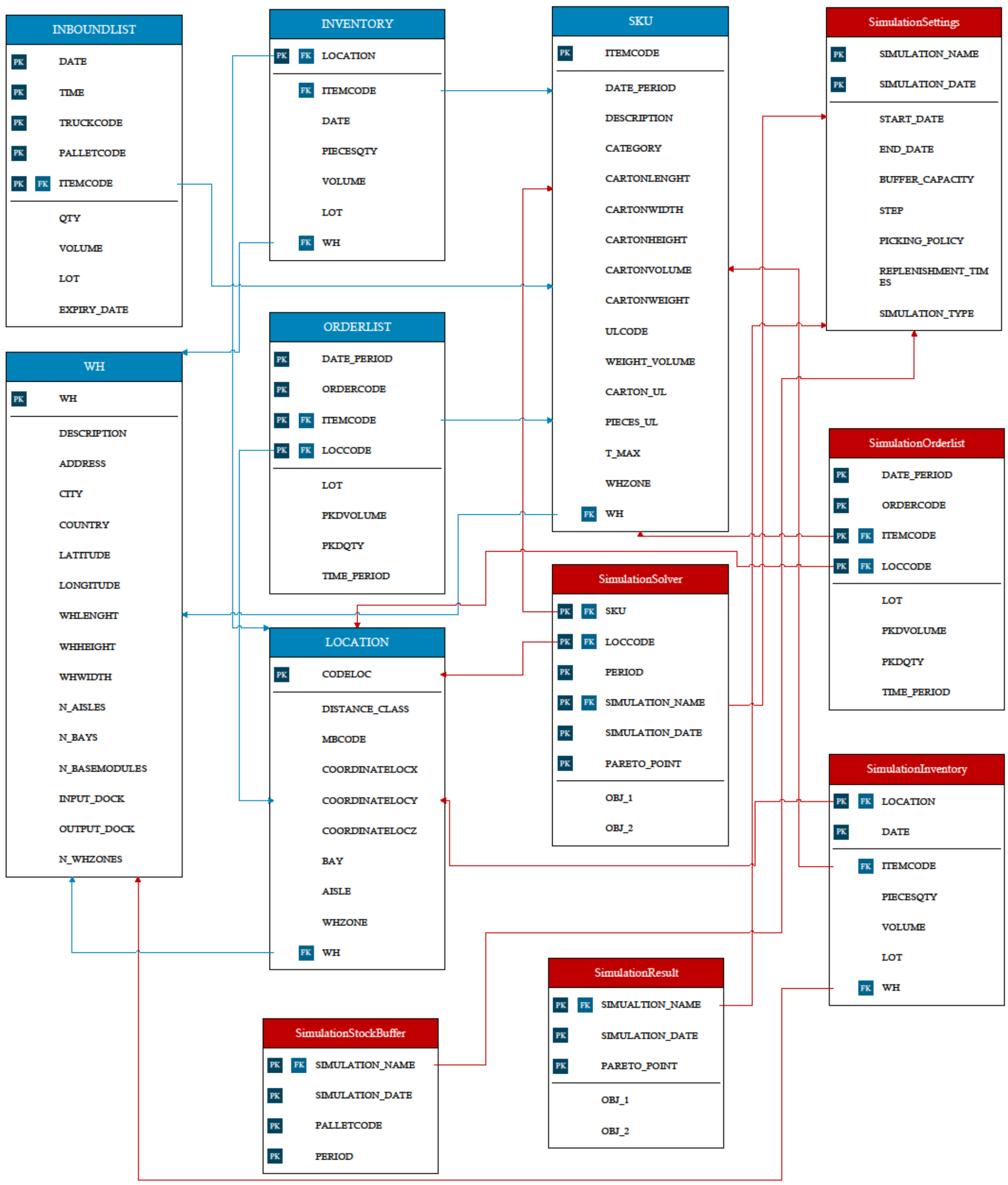


Figure 47: Entity Relationship (E-R) Diagram

4.3.1.4 *Simulation Settings and Graphic User Interfaces*

Two GUIs enable setting the simulation parameters and the visualizing the KPIs resulting by simulating each management scenario. Figure 48 summarizes the *levers* of analysis manageable through the GUIs and provides an exemplifying set of settings.

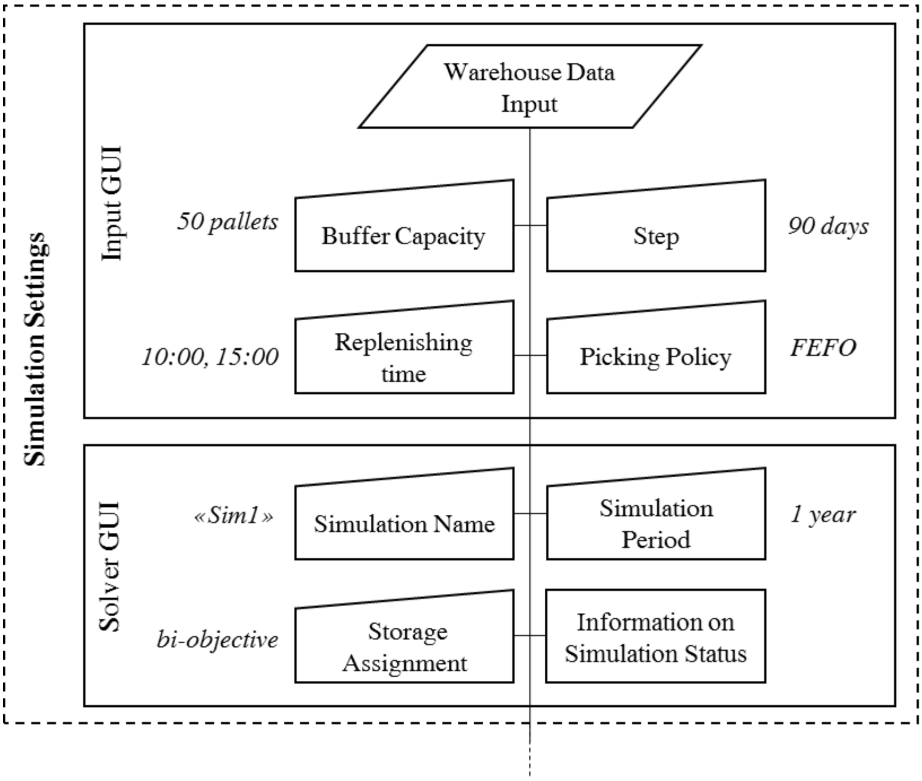


Figure 48: Graphic user interfaces (GUIs) functionalities

The first lever is the aforementioned *replenishing time* t_r. This reflects the typical work flow of the warehouse, as the working shifts, or the distribution of the truck arrivals over the day. High-frequency replenishing requires at least one (in small warehouse) operator entirely devoted to put-away activities. Low frequency replenishing concentrates the put-away activities in a specific, generally longer, time batch.

The capacity of the inbound buffer b is another lever of analysis. When, at time t_r, the empty locations are less than the incoming pallets the DST temporarily assigns the remaining loads to the buffer. The buffer is indeed the floor storage area placed at the inbound dock where the trucks are unloaded, and the pallets wait for put-away. The larger the buffer capacity b, the less the storage volume utilization will be. Nevertheless, a larger buffer enables holding the incoming SKUs until adequate storage locations are again available. In view of this, the manager should carefully handle the relationship between the replenishing time and the buffer capacity. The *step* Δt, measured in periods (e.g., days), is a key driver of analysis. It represents the time batch used to quantify the dynamic behavior of a SKU and organize the storage assignment policy accordingly (see chapter 4.1.1.1). Usually, the average turnover of a warehouse is a fair value to quantify this *step*. High values of *step* compared to the inventory turnover (e.g., 1 or 2 months) flatten the differences among the SKUs and smooth the seasonality. Conversely, short values (e.g., 1 day) may not reflect the real behavior of a SKU.

The storage assignment policy k is the rule to assign an incoming pallet to a storage location. The DST incorporates a wide set of assignment policies to be tested with different 3PL companies and business. These base either on a sorting algorithm (i.e., ranking heuristics) (see for details Accorsi et al., 2012), or on optimization techniques. The former, generally implemented through SQL scripts, are quicker easier to be implemented, and require usually cheaper WMS's customization. The latter are generally more performant, but require a commercial linear solver, whose annual fee is expensive for low-margin business as 3PL, as well as advanced mathematical and informatics skills, and lastly generate higher software maintenance costs.

The user can also decide for the picking policy to pursued. The fulfillment of the customers' orders requires the punctual analysis of the inventory configuration, in order to figure out where each SKU is located. Different picking policies generate different picking lists and consequently different configuration of the inventory and the empty locations. As example, a policy can favor the minimization of the travelling for the picking tour (i.e., retrieving a SKU from the locations closer to the docks), another can favor the emptying of the storage locations (i.e., retrieving a SKU from the locations with least residual stock), which particularly fits with 3PL companies that sell pallets locations to their clients. The two developed GUIs are shown in Figure 49.

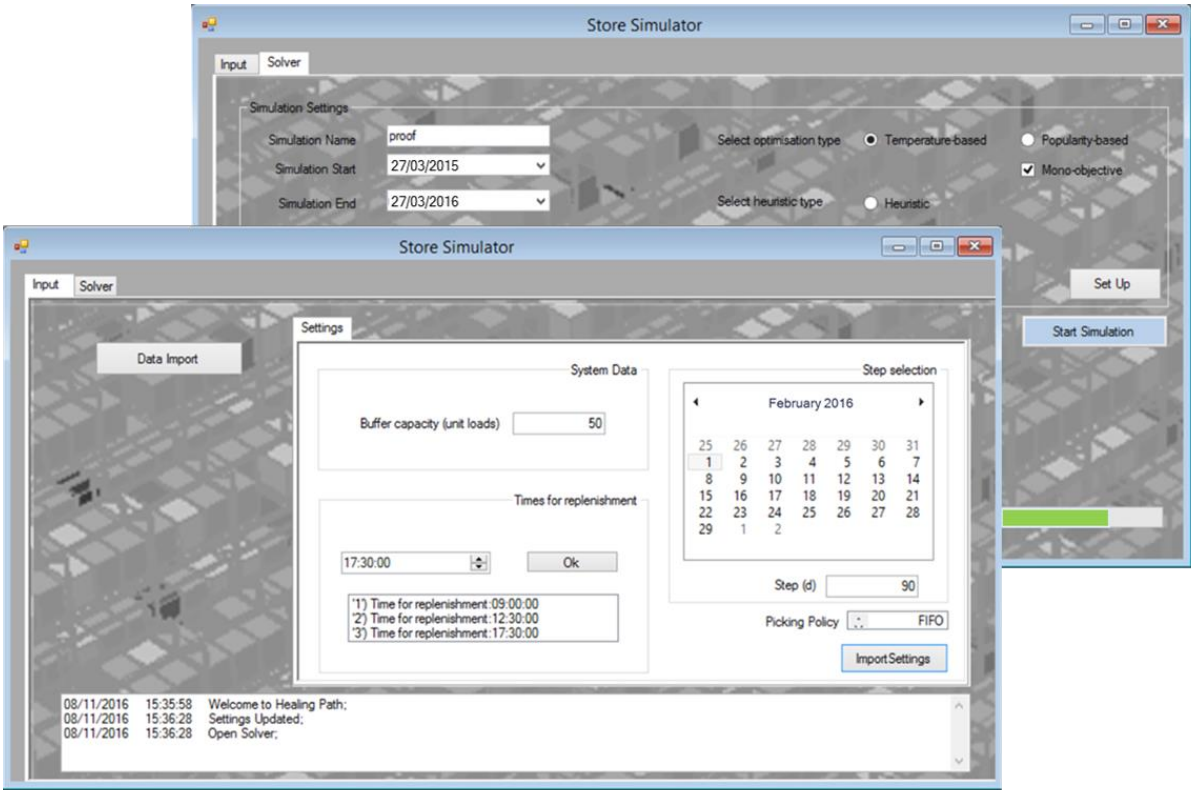


Figure 49: Graphic Users Interfaces (GUIs)

4.3.1.5 *Example of application*

In order to describe the DST functionalities and to validate their effectiveness, this sub-chapter illustrates the application of the tool to support the WMS customization of Case I. Due to its ample inventory mix and the reluctance of its clients to share strategic information on products, this warehouse represents a valid testbed for the DST. Seven alternative management scenarios, likewise replicating different WMS features, have been simulated and compared to the as-is upon the performance of the picking activities (i.e., travelling time). The multi-scenario analysis aims to identify the best management scenario and to aid the managers in assessing and quantifying the economic return from the WMS customization in accordance with higher information visibility. It is worth noting that, among the wide set of warehousing KPIs, it is assumed the travelling time for picking as metric of performance. Each management scenario differs from the others further for the level of the information availability as indicated in Table 12.

Table 12: Required information for each simulation

Simulation Code	Simulation Settings: common	Simulation Settings: specific	Required Information
1	Buffer Capacity: 150 pallets Step: 90 days Times for Replenishment: 11:00, 15:00, 21:00 Simulation Period: 27 March-23 December	Storage Assignement technique: Heuristic Item Retrieval Policy: FIFO Dimensional Constraint: None	
2		Storage Assignement technique: Opt. Mono-objective Item Retrieval Policy: FIFO Dimensional Constraint: None	
3		Storage Assignement technique: Opt. Bi-objective Item Retrieval Policy: FIFO Dimensional Constraint: None	Information on products characteristics (i.e. labelled temperature conditions);
4		Storage Assignement technique: Heuristic Item Retrieval Policy: FEFO Dimensional Constraint: None	Information on products characteristics (i.e. expiry date);
5		Storage Assignement technique: Opt. Mono-objective Item Retrieval Policy: FEFO Dimensional Constraint: None	Information on products characteristics (i.e. expiry date);
6		Storage Assignement technique: Opt. Bi-objective Item Retrieval Policy: FEFO Dimensional Constraint: None	Information on products characteristics (i.e. labelled temperature conditions, expiry date);
7		Storage Assignement technique: Heuristic Item Retrieval Policy: FEFO Dimensional Constraint: Weight	Information on products characteristics (i.e. expiry date, weight);

The what-if simulation analysis is conducted in agreement with a basic assumption: the demand orders and the trucks arrival are known at the beginning of each period (day) t. All the tested management scenarios share the settings of the buffer capacity (i.e. 150 pallets), of the *step* (i.e., 90 days), and of the replenishing times t_r (i.e., three per day at 11:00 am, 12:00 am, and 9:00 pm). They differ for the adopted storage assignment policy and the picking policy. For the first, three storage assignment policies based on the popularity index (Gu et al., 2007) are thereby investigated. These are as follows: (*k*=1) a popularity-based ranking rule, named in the following *heuristic*, (*k*=2) a class-based optimization model based on the popularity parameter, and (*k*=3) a bi-objective optimization model based on popularity and conservation temperature parameters, that aims at minimizing the temperature stresses during storage for the most sensitive SKUs.

For the second lever, two solutions are compared: the first-in-first-out (FIFO) and first-expiring-first-out (FEFO) policies that are commonly recommended to control the shelf-life of perishable products (Hertog et al., 2014).

Per each period t, and replenishing time t_r, the tool calculates the rolling popularity $Pop^{roll}{}_{u_i,t,\Delta t}$ for the set of incoming SKUs $L^{ul}{}_{t_r,\,t}$ and implements the three alternative storage assignment policies (*k:* 1, 2, 3) as schematized in Figure 50.

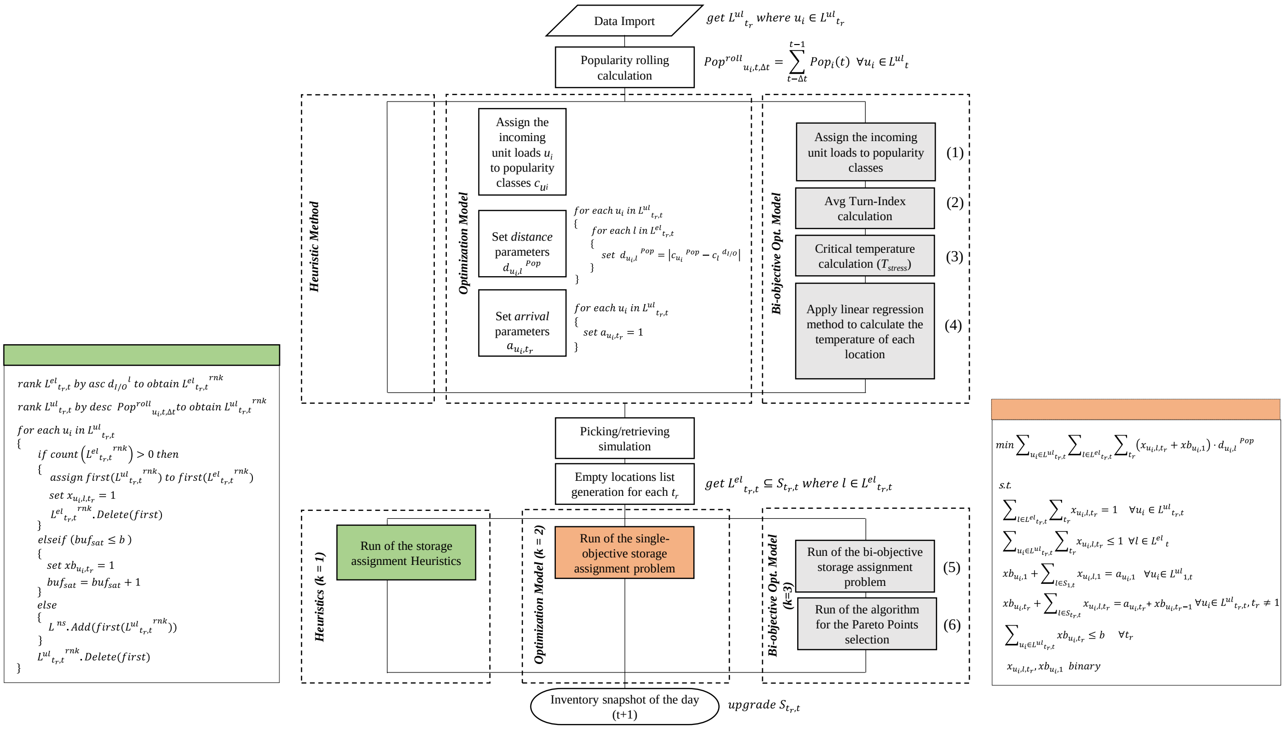


Figure 50: Tool functionalities

The heuristic ranks the list of incoming SKUs (${L^{ul}_{t_r,\,t}}^{rnk}$) by the popularity rolling value and assigns them to the empty locations (${L^{el}_{t_r,\,t}}^{rnk}$) sorted by their distance from the I/O dock ${d_{I/O}}^{l}$. At each replenishing time t_r, the SKUs and the location sorted lists are matched, and the locations filled accordingly (i.e., SKUs with higher popularity rolling in the closer locations). The sorting process can be constrained by some parameters as the weight or the volume of the pallet, and the available location filtered accordingly. In this case, the tool implements also a *weight* constrained-heuristic.

Two optimization models for the assignment problem are formulated and solved. The first linear integer model assigns a generic SKU of popularity class $c_{u_i}^{Pop}$ to a generic location of storage class $c_l^{d_{I/O}}$ (i.e., built upon the distance from I/O dock $d_{I/O}$) with the objective of minimizing the number of pallets stored out-of-their-class. As result, a unit load u_i of generic SKU i belonging to the first popularity class ($c_{u_i}^{Pop} = 1$) is assigned (i.e., $x_{u_i,\,l,t_r} = 1$) to an empty location l belonging to the first storage class ($c_l^{d_{I/O}} = 1$) whether available at time t_r.

The second assignment problem is formulated through a bi-objective policy that will be illustrated in detail in chapter 4.4.2.1.

The computation time to assess each scenario varies with the assignment policy and the observed time horizon. Obviously, this time is higher for the optimization techniques than for the heuristics. Each run of the solver (i.e., one per replenishing time t_r and period t and more in case of the bi-objective problem) takes few seconds (between 1 and 5 seconds). This time is the same that the WMS feature would require in a real application and allows understanding the feature responsiveness to the operational tasks.

The what-if simulation analysis quantifies a set of KPIs that allows the assessment of each management scenario. This panel includes the overall travelling distance for picking, the average warehouse utilization percentage, the buffer utilization, the average pick lines per day, and whether or not the temperature stresses have been involved in the management scenario. Specifically, all the to-be scenarios reduce the travelling time for picking compared to the as-is (see Figure 51).

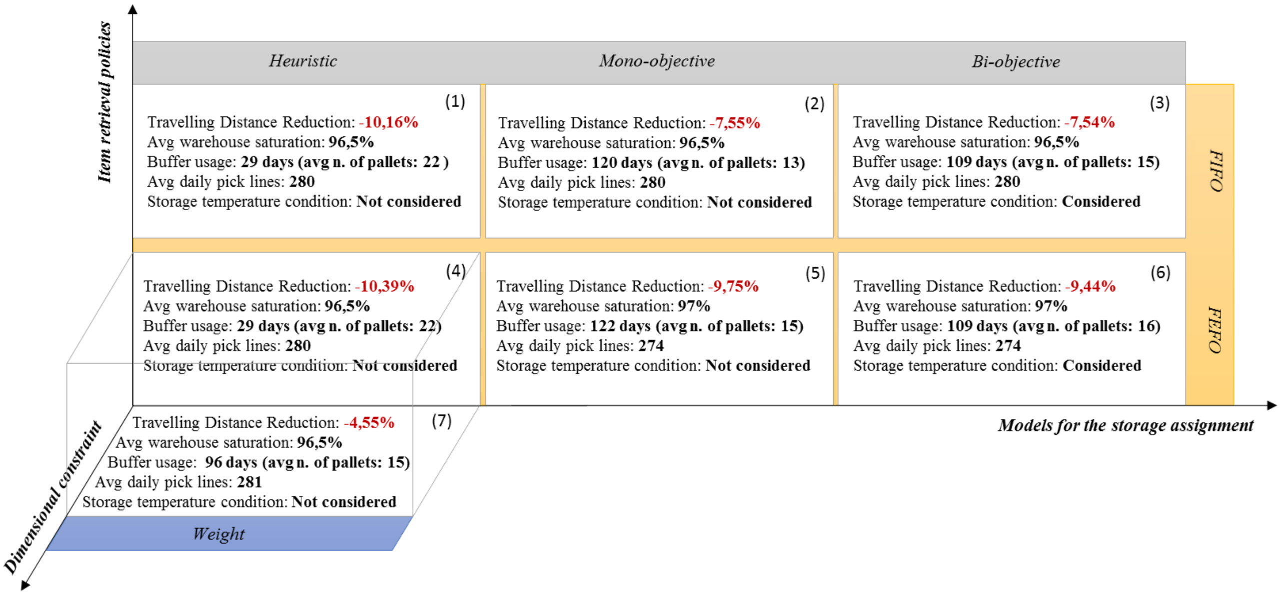


Figure 51: Simulations results

The scenarios characterized by the FEFO picking policy (i.e., scenarios 4, 5 and 6) better perform in term of travelling reduction than those ruled by the FIFO picking policy (i.e., scenarios 1, 2 and 3). The scenario 4 implements the heuristic-driven storage assignment, obtaining the highest travelling saving. Nevertheless, the FEFO-based scenarios require additional details from the client, which should track the expiration date of each pallet. On the contrary, the FIFO-based scenarios guarantee good performances and needs just the records of truck's arrival to manage the picking policy accordingly. Notwithstanding with the convenience for the 3PL provider, the picking policy is often negotiated with the client and is influenced by the sector, the demand seasonality, the products' turnover, the characteristics of the inventory mix and the information availability.

Dealing with the comparison between the storage assignment policies, the savings in the picking travelling distance decrease from the heuristic to the bi-objective assignment, while the buffer utilization increases. Indeed, the scenarios 2, 3, 5, and 6 utilize the buffer for more days than the scenarios 1 and 4. This leads to two considerations. First, the optimization technique exploits the buffer to organize (and eventually postpone) the put-away activities with the purpose to assign each SKU to its proper storage class. Second, the capacity of the buffer (i.e., the floor storage area besides the docks) should be accurately designed, since it affects the storage assignment process and the resulting storage configurations. In response to the input dataset and the simulated inbound and outbound profiles, the optimization policy is not convenient as expected, and its implementation as WMS's feature is not justified. Although the scenarios 3 and 6 account for higher travelling distance, the bi-objective assignment policy better complies with the safe storage temperature requirements. Nevertheless, the adoption of this WMS feature compels the visibility of the provider on the temperature ranges for safe conservation of each SKU. Lastly, the scenario 7 represents the worst case in term of travelling minimization. Nevertheless, it allows to comply with the work safety standards that recommend storing the heavy loads at the bottom (i.e., low levels) of the racks.

Further outcomes can be obtained by the study of the monthly trend of the average travelling time per pick line for the tested alternative scenarios. The average time for pick line is a well-known metric of performance for 3PL providers, since the clients commonly pay the storage service in terms of fulfilled lines. It is worth noting that a significant difference between the worst and the best scenarios is quantified. This changes month by month and achieves four seconds and half per line at Month 7. Such a saving is multiplied for the monthly number of lines and results in about 6-7% reduction in the required labor time per month. The obtained result aids the 3PL managers in quantifying the return on investment of each management scenario in comparison with the as-is and evaluating the payback of the associated WMS's feature implementation.

Some last considerations arise by observing Figure 52, which illustrates the multi-scenario comparison of the storage layout bird's views, as appear at the last period t of the time horizon (i.e., 10 months). The three-dimensional layouts have been obtained through a script written in AutoLISP and a developed interface with the AutoCAD® Software that is incorporated in the proposed tool. This comparison highlights how the most performing scenarios (i.e., 1 and 4) in terms of picking travelling reduction tend to assign the fast-moving SKUs (i.e., the darkest unit loads) to the low levels and close to the I/O docks. The heuristics performs better than both the optimization policies, while the constrained-heuristics is affected by the weight of the incoming unit load and is the worst performing. This result can be influenced by the distribution of the truck arrivals at each day and along the day, and the number of incoming unit loads u_i (i.e., their popularity class $c_{u_i}^{Pop}$) received by each truck.

Furthermore, the comparison underlines the insight complexity for a manager in understanding and foreseeing the dynamic behavior of a combination of storage and picking policies over a long time horizon. After ten months different daily management scenarios result in extremely difference storage configurations, and this reflects the uncertainty by the managers on deciding for the implementation of a specific WMS's feature.

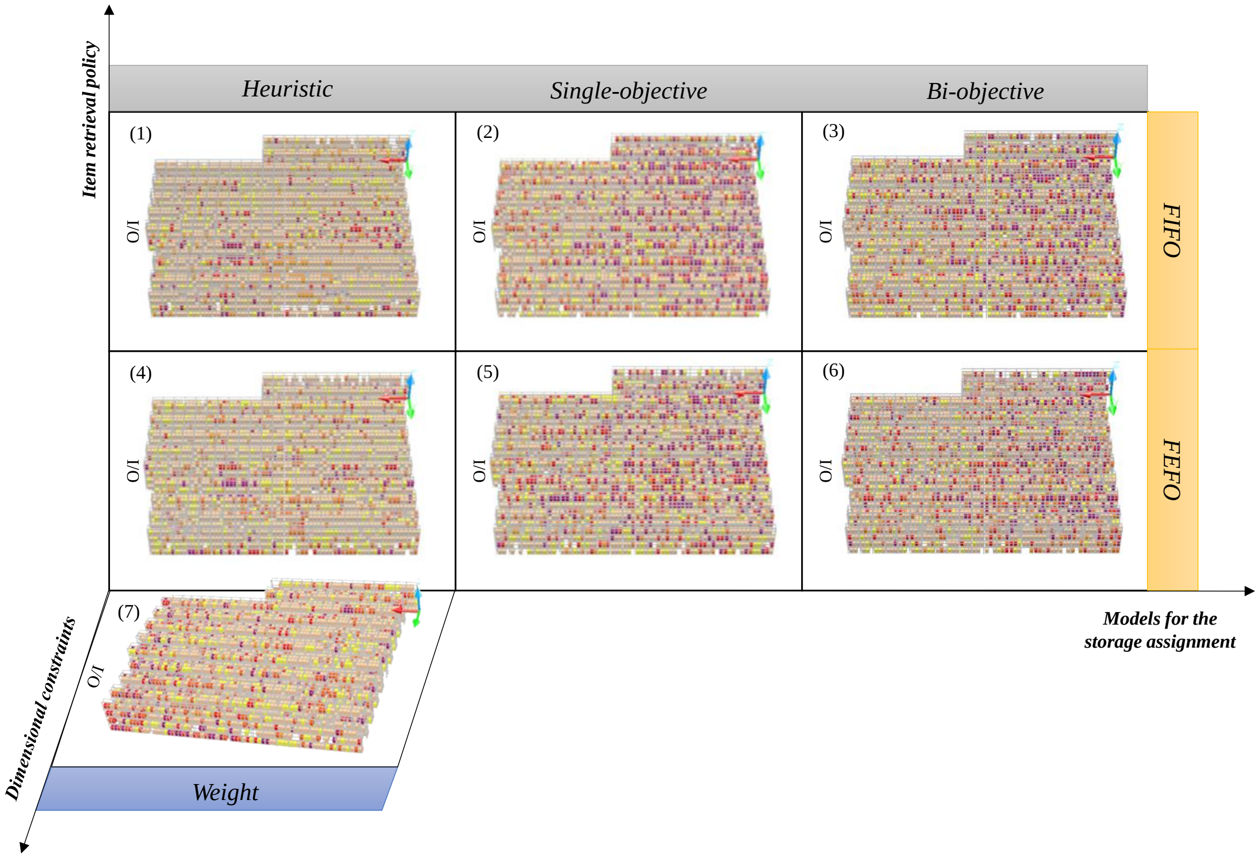


Figure 52: Multi-scenario comparison of the layout bird's views.

4.4 ACTING ON WAREHOUSE DESIGN AND ON WAREHOUSE OPERATIONS TO HANDLE PRODUCTS PERISHABILITY

The structure of this chapter takes inspiration by the work of Gu et al. (2010), who propose two potential macro areas of intervention in storage systems, warehouse design (1) and warehouse operations (2). This classification has been already discussed in 4.2.1.1, where a table is proposed to guide managers through the decision-making in the identification of possible alternative *to-be* scenarios with the aim of improving the warehouse performance (i.e. Phase IV of the proposed diagnostic-support framework).

This chapter explores both (1) and (2), by introducing two research topics with the sharing goal of improving the overall warehouse performance. Despite the different area of intervention, two common threads bind these research topics. The first is the implementation of the progressive adaptation approach (see 4.1.1.1). As previously defined, such approach entails that the adaptation of a storage system to a given desired configuration is pursued progressively, at a ratio that depends by the average inventory's turnover and the distribution of the replenishing times (see 4.3.1.2), as showcase in Figure 53.

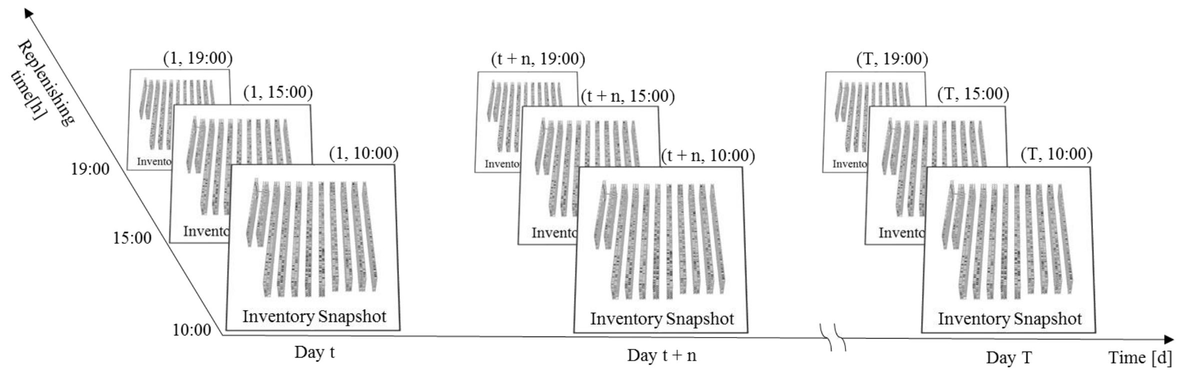


Figure 53: The progressive adaptation approach

The second is the focus on storage assignment as a strategic lever to control the overall warehouse costs (see 4.1.1.1).

With respect to (1), the progressive adaptation approach is implemented through an iterative-decision support model for designing and managing deep lane storage system layout, which are mostly diffused in perishable product supply chains (i.e. food processing and beverage industry). The model both implements the lane assignment policy of an existing warehouse to maximize the daily performance and utilized the lane assignment to aid the design of a new warehouse from green field according to a specific inventory mix and the expected demand profile.

Dealing with (2), progressive adaptation approach is applied by proposing an original adaptive storage assignment policy leading the warehouse to an optimal configuration that ensure both the minimization of the picking costs and the safety of the perishable stock.

4.4.1 Acting on warehouse design to handle products perishability

The research presented in this sub-chapter contributes to the extant literature on layout problems in block storage systems, by proposing an integer linear programming model (ILP) to manage existing block storage warehouses, and to aid the design of new block storage systems from green field. The management of a warehouse (1) deals with the assignment of the incoming product lots to the optimal lane depth, storage mode, and zone in a constrained and capacitated storage environment. The design of a warehouse from green field (2) is aided by identifying the optimal configuration of lane depths and storage modes that minimizes the infrastructural costs.

Block stacking storage guarantees high storage density for end-of-line warehouses in product flow manufacturing, which are mostly diffused in processing industry (e.g., food, beverage, tissue). In these warehouses, the incoming lots are stored into deep lanes of homogeneous products and block stacks (i.e., floor storage) are created to enhance the volume utilization. When the pallets are too heavy, fragile, or irregular, the height stacks is limited to ensure the operators safety and avoid products damaging. Otherwise, the lots are moved into other storage modes suitable for deep lane storage as drive-in, drive-through, or pallet-flow racks.

The set of available lanes or the adopted storage infrastructures influence significantly the warehouse performances in terms of space and time efficiencies. The space efficiency is measured by two metrics named accessibility and honey combing (Bartholdi and Hackman, 2013). The accessibility space is the part of the aisle required to access to a lane, both on the floor or in the rack, whilst the honey combing space is made by the unoccupied pallet positions within a lane, that might not be filled by other lots until the lane is completely emptied, in order to avoid double-handling. A produced lot can be stored in deep or short lanes. Deep lanes result in lower accessibility costs but higher honey combing, and vice versa. The time efficiency is measured by the travelling and the handling time for pallet put-away and retrieving operations. While the travelling time is determined by the place of a lane on the layout (i.e., its storage zone), the handling time is the time to store (to retrieve) a pallet into (from) a location and is affected by the type of the storage mode i.e., floor, drive-in rack, flow-rack. As example, flow-racks save time for both put-away and retrieving compared to drive-in racks, but costs more.

As a consequence, both space and time inefficiencies generate costs accounted by infrastructure mortgage and labor. To minimize these costs the best setting of the lane depths, the types of storage mode, and the layout of the storage zones, should be identified.

The determination of the proper lane depth for a product has ancient tradition in the scientific literature since the nineteen seventies (Kind, 1975, White et al.,1981). Many provided analytical models calculate the optimal lane depth for single or multiple products (Goetschalckx, 2003.) that minimize the space loss in block storage systems, assuming constant demand and production profiles. Specifically, Table 13 reports some of these contributions from the literature.

Table 13: Existing lane depth models

	Reference	**Model**	
q_i: incoming batch size of SKU i q: incoming batch size for generic SKUs z_i: stackability of SKU i k_i: lane depth of SKU i I_i: inventory of SKU i k: lane depth for generic SKUs l: pallet length of SKU i a: aisle width i: $1,..,n$ SKUs j: $1,..,m$ lanes	Kind (1975)	$k_i = \sqrt{\frac{q_i a}{l z_i}} - \frac{a}{2l}$	(1)
	Mason and White (1981)	$k_i = \sqrt{\frac{(q_i + 2I_i)a}{l z_i}}$	(2)
	Goetschalckx and Ratliff (1991)	$k_j = \frac{ja}{2l}$	(3)
	Kay (2009)	$k = \left\lfloor \sqrt{\frac{a[2max(q_i)] - n)}{2nlz}} + \frac{1}{2} \right\rfloor$	(4)
	De Koster (2010)	$k = \sqrt{\frac{a}{ln}\sum_{i=1}^{n} q_i}$	(5)
	Bartholdi and Hackman (2013)	$k_i = \sqrt{\frac{a}{2}\frac{q_i}{z_i}}$	(6)

The presented formulations assume that a generic SKU i experiences a constant demand and are produced in the same lot quantity in a given time horizon. However, these assumptions are strong and limit the applicability of these models in practice to real-world warehousing systems, that often experience demand seasonality.

4.4.1.1 A decision support model to manage and design deep lane storage system layout

The proposed integer linear programming (ILP) model minimizes the accessibility, honey combing, travelling and handling costs by choosing the lane depth, the storage mode and the layout zone to allocate the incoming product lots. This model is formulated to manage the daily assignment of the produced lots in existing block storage warehouses (1). The management of a warehouse deals with the allocation of the incoming lots to the optimal lane depth, storage mode, and zone in a given constrained and capacitated storage environment. According to this purpose (1), the available lanes per depth, storage mode, and layout zone are known at each day t as result of the assignment at day *t-1*.

Furthermore, a second purpose (2) is also addressed. This model, indeed, aids the design of new block storage systems from green field. The design of a warehouse from green field (2) is aided by identifying the optimal configuration of lane depths and storage modes that minimizes the infrastructural costs. To address this second purpose, the model is run over an historical profile of inbound and outbound tasks (i.e., provided by existing and benchmark facilities) to study how the resulting daily optimal storage configuration evolves within a horizon of time due to seasonality. The collection of the optimal layout configuration at generic day t for all t in the observed horizon, provides a set of guidelines to the designer, and highlights how and when (i.e., which t periods) to face to particular storage space requirements.

The model assigns the incoming produced lots to the optimal lane depth, storage mode, and storage zone, by minimizing the costs resulting from space and time inefficiencies. Space losses are generated by accessibility and honey combing, whilst time losses are due to travelling and handling activities. Multiple criteria contribute to the lane assignment. Short or deep lanes influence the space losses, the storage modes affect the handling time and the infrastructural costs, while the storage zones result in different travelling time. Furthermore, the quantity and the frequency of the incoming lots varies day by day in accordance with the SKUs seasonality. The model formulation bases on the following notations.

$i: 1,..,I$ SKUs

$k: 1, .., K$	Lane depths
$n: 1, .., N$	Layout zones
$y \in Y$: {*floor* storage, *drive-in*, *flow-rack*}	Storage modes
$t: 1, .., T$	Day t within a given horizon T
q_{it}	Quantity of pallets of the incoming lot of SKU i for produced at day t
D_{it}	Expected pallet daily demand of SKU i around day t
$H_{it}=\left\lfloor \frac{q_{it}}{D_{it}} \right\rfloor$	Expected integer number of inventory cycles of SKU i at day t
$c_{it}: 0, .., H_{it}$	Cycle of inventory of the lot of SKU i produced at day t
z_{iy}	Stackability of SKU i in the storage mode y
l_{kynt}	Number of available lanes of depth k, storage mode y and zone n at day t
$lt_{kynt} = \begin{cases} 1 \\ 0 \end{cases}$	1 if $l_{kynt} > 0$; 0 Otherwise
a_y	*Accessibility* space required by each lane for storage mode y
cs_y	Cost per pallet position in storage mode y (€/sqm)
ca	Cost for floor space loss (€/sqm)
d_n	Average *travelling time* to storage (retrieve) a pallet to (from) a lane in zone n (min)
ct	Unit cost of travelling task (€/min)
th_y	Average *handling time* per pallet in (from) a lane of storage mode y
ch	Unit cost of handling task (€/min)

The model is solved at each day t of a given time horizon T. Given an existing warehouse, the type, the number, and the zone of the available lanes at period *t*, vary according to the assignment policy and the retrieving operations performed until the day *t-1*. This parameter, l_{kynt}, is deduced by the solution of the model and the associated inventory snapshot at day *t-1*.

Equation (7) quantifies the integer number of lanes of depth k, storage mode y and zone n to be allocated at the lot of SKU i produced at the inventory cycle c_{it}.

$$al_{ikync_{it}} = \left\lceil \frac{q_{it} - c_{it}\, D_{it}}{z_{iy} k} \right\rceil lt_{kynt} \tag{7}$$

Equation (8) and equation (9) determine respectively the *honey combing* and the *accessibility* space losses due for the assignment of the lot of SKU i to $al_{ikync_{it}}$ lanes of depth *k*, in storage mode *y*, and zone n. These losses are cumulated during all the inventory cycles from c_{it}= 0 to H_{it} resulting by ratio between the lot quantity q_{it} and the expected daily demand D_{it} of SKU i at period t. The term H_{it} represents the expected number of days spent by the lot of SKU i produced at period t in inventory until its last pallet is retrieved. As a consequence, according to the SKU seasonality, two generic lots of SKU i produced respectively at day t and t': $t \neq t'$ cumulate more (or less) space losses if the expected demand at period t, D_{it}, is lower (or higher) than $D_{it'}$.

$$\sum_{c_{it=0}}^{H_{it}} (al_{ikync_{it}} z_{iy} k - (q_{it} - \; c_{it} D_{it})) \tag{8}$$

$$\sum_{c_{it=0}}^{H_{it}} (al_{ikync_{it}} a_y) \tag{9}$$

Given these notations, sets, and parameters the ILP model is defined in the following.

Decision variables

$x_{ikynt} = \begin{cases} 1 \\ 0 \end{cases}$ *If the incoming lot of SKU i at day t is assigned to depth k, in storage mode y and zone n* / *Otherwise*

ol_{ikynt} *Integer number of k-deep lanes of storage mode y in zone n assigned to lot of SKU i produced at day t*

Objective function

$$\begin{aligned}
min \sum_{n=1}^{N} \sum\nolimits_{y \in Y} \sum_{i=1}^{I} \sum_{k}^{K} \sum_{c_{it=0}}^{H_{it}} (al_{ikync_{it}} z_{iy} k - (q_{it} - \; c_{it} D_{it}))\, x_{ikynt} cs_y & \quad \textit{Honey combing costs} \\
+ \sum_{n=1}^{N} \sum\nolimits_{y \in Y} \sum_{i=1}^{I} \sum_{k}^{K} \sum_{c_{it=0}}^{H_{it}} (al_{ikync_{it}} a_y)\, x_{ikynt} ca & \quad \textit{Accessibility costs} \\
+ \sum_{n=1}^{N} \sum\nolimits_{y \in Y} \sum_{i=1}^{I} \sum_{k}^{K} q_{it}\, x_{ikynt} d_n ct & \quad \textit{Travelling costs} \\
+ \sum_{n=1}^{N} \sum\nolimits_{y \in Y} \sum_{i=1}^{I} \sum_{k}^{K} q_{it}\, x_{ikynt} th_y ch & \quad \textit{Handling Costs}
\end{aligned} \tag{10}$$

Equation (10) quantifies the total *honey combing*, *accessibility*, *travelling* and *handling* costs resulting by the assignment of the produced lots to the available storage configuration at day t. The problem objective is to minimise Equation (10) in accordance with the following set of constraints.

Constraints

$$\sum_{k}^{K}\sum_{y}^{Y}\sum_{n}^{N}x_{ikynt}=1 \qquad \forall\, i,t \qquad (11)$$

$$\sum_{i}^{I}ol_{ikynt}\leq l_{kynt} \qquad \forall\, k,y,n,t \qquad (12)$$

$$\frac{q_{it}x_{ikynt}-c_{it}\,D_{it}}{z_{iy}k}\cdot lt_{kynt}\leq ol_{ikynt} \qquad \forall\, i,k,y,n,t,lt_{kynt}=1,c_{it}=0 \qquad (13)$$

$$ol_{ikynt}=\ al_{ikync_{it}}\cdot x_{ikynt} \qquad \forall\, i,k,y,n,t,c_{it}=0 \qquad (14)$$

$$x_{ikynt}\in\{0,1\} \qquad \forall\, i,k,y,n,t \qquad (15)$$

$$ol_{ikynt}\in Z^{+} \qquad \forall\, i,k,y,n,t \qquad (16)$$

Equation (11) ensures that the lot of SKU i produced at day t is assigned exclusively to one lane depth, storage mode and zone. This avoids to split the lot in different storage areas and facilitates first-in-first-out (FIFO) policy. Equation (12) implements the *capacity constraint* and assumes that ol_{ikyt}, i.e., the number of lanes occupied by the incoming SKUs at the day t, is not higher than the number of available empty lanes in t. Constraints (13) and (14) links together the variable ol_{ikyt} and x_{ikyt} and quantifies the number of the occupied lanes of depth k, storage mode y, and zone n, as the lanes allocated to the SKU i at day t.

The model is developed through an iterative procedure illustrated in Figure 54. The model (1) implements the lane assignment policy of an existing *warehouse*, (i.e., *warehouse mode)*, or (2) aids the design of a new warehouse from *green field*, (i.e., *green field mode*). Both goals are addressed by the flow-chart of Figure 54.

Procedure flow chart	Step 1: Goal and Data Settings

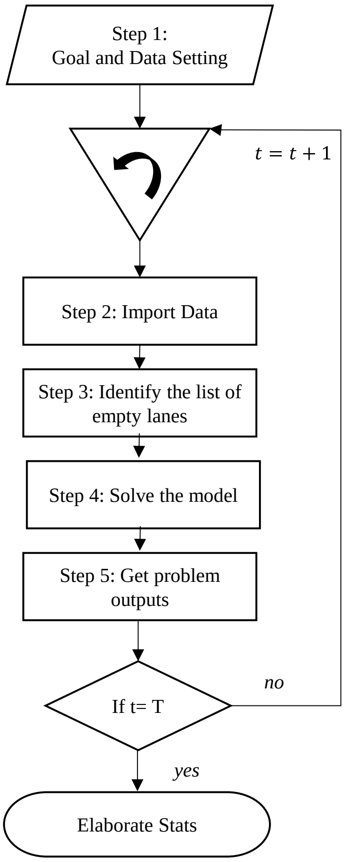
Set
Layout $l_{kynt>0}$, $lt_{kynt=1}$
SKU i: $1,..,I$
Day t: $1,..,T$
Goal *Green Field, Warehouse*

For each day t

Get
Inventory snapshot of (t-1)
Demand D_{it}

Set
Layout capacity l_{kynt}, lt_{kynt}

Get
Variables x_{ikyt}, ol_{ikyt}



Goal Setting

(1) Warehouse mode: implements the lane assignment policy of an existing warehouse in order to maximize its daily performance.

(2) Green field mode: aids the design of a new warehouse from green field according to the specific inventory mix and the expected demand profile (D_{it}).

Data Setting

Data	Warehouse mode	Green Field mode
cs_y	$\frac{1}{\text{Ammortization charge}}$	Cost of rack per pallet position (*)
Warehouse capacity	Limited	Unlimited
Layout	Defined	Undefined
Number of zones	Defined	Defined (1 zone)

(*) see Sisko [28] for costs estimates

Figure 54: Procedure flowchart

The first step requires the setting of the problem parameters on the bases of the chosen scope of analysis. Historical demand profiles are used to calculate the expected demand D_{it} of SKU i at each period t included in the horizon T. The methods used to calculate D_{it} refer to the extant literature and are not discussed in this paper. In *warehouse* mode, these include the set of SKUs I, of the observed horizon T, the set of lane-depths K, the set of storage mode Y, the set of zone N, and the initial number of available lanes l_{kyn0} per each k, y, n at day t = 0. The unit costs cs_y are set as the cost of an empty pallet position (i.e., unutilised space) assuming not amortized storage infrastructures of an existing warehouse. As example, since *flow-rack* cost more than *floor storage*, leaving empty a floor location is expected to be more convenient than a flow-rack one.

In green field mode, the sets I, T, K, Y are defined, but since the layout does not still exist, only a virtual zone, with no specified dimensions and coordinates, is considered (i.e., N=1). For this reason, the number of available lanes l_{kynt} per each k, y, n, and t is unlimited and the constraints (12) and (13) are therefore relaxed.

In this case, the model enables the assessment of the proper number of lanes required to respond to the given production and demand profiles over an observed horizon in order to minimize the total infrastructural and operational costs. In the green field case, the unit costs cs_y are for new storage infrastructure, so that less-expensive storage modes are preferred (e.g., floor storage) to minimize the capital cost. Furthermore, given the virtual zone the travelling costs ct are neither considered. The model is solved at each day t. In *warehouse* mode, the model solves the lane assignment problem in the given capacitated warehouse by minimizing the overall costs resulting from *space* and *time* inefficiencies. The obtained solution identifies daily the optimal lane assignment configuration and quantifies the *space* and *time* costs accounted by a generic SKU i, lane k, storage mode y, and zone n, and how are distributed among these. The model also provides the level of daily saturation of the storage zones or the lane types, aiding the identification of which are *critical* or *redundant*.

In *green field* mode, the model defines the optimal *layout configuration* that meets the production profile at day t. After a representative time horizon *T (e.g., 6 months)*, the daily optimal *layout configuration* can be analysed to identify a cost-effective compromise that responds to the storage needs of the specific flow manufacturing system.

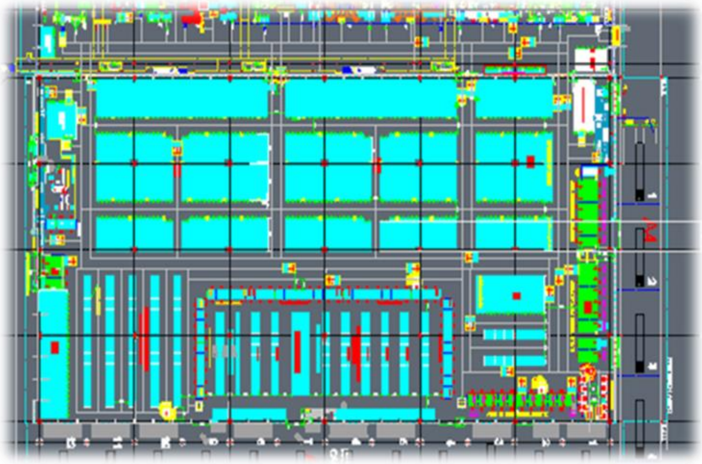
4.4.1.2 A case study from a perishable products supply chain: A beverage industry

This model is validated with a real-world end-of-line block storage system of a renowned brand of the beverage industry. Firstly, the iterative procedure is applied, by the so-called warehouse mode, to study the impact of the proposed lane assignment policy on the total costs resulting by space and time inefficiencies. The overall characteristics of the warehouse necessary to quantify the model parameters are summarized in Figure 55. The SKUs set includes 92 products, which are not concurrently present in the inventory mix due to seasonality. The storage layout is made by seven zones, each reporting the initial number of available lanes l_{kyn0} of depth k and storage mode y. The average travelling time d_n to achieve a generic lane in zone n is calculated as the single-command time to store/retrieve a pallet assuming rectangular distances, but more sophisticated patterns (Hamzheei et al., 2014) can quickly replace this parameter.

Warehouse characteristics

Industry: Beverage
Initial warehouse capacity:
l_{kyn0} on the layout

SKUs I: 92
Horizon T: 01/16 – 05/16
Days T: 124
Storage mode Y: *Floor-storage(fs), Drive-in(di), Flow-rack(fr)*
Zone N: 7
Incoming lots: 1904
Produced/Shipped pallets: 78,618
Stackability: up to 4 levels
Aisle width: 5000 mm
Pallet gap: 100 mm
Pallet size: 1100x1000 mm



	cs_y(€)	th_y(min)	a_y (m)
fs	1	0.043	2.5
di	0.16	0.36	2.5
fr	0.05	0.27	1.25

ca= 7.4 €/sqm
ct = 0.6 €/min
ch = 0.6 €/min

Zone 1 $l_{10,fr,1,0} = 50$ $d_{1} = 1.13$ min	**Zone 6** $l_{5,di,6,0} = 30$ $d_{6} = 1.13$ min		**Zone 4** $l_{7,di,4,0} = 10$ $d_{4} = 1.9$ min
Zone 2 $l_{5,fs,2,0} = 15$ $d_{2} = 1.7$ min			**Zone 7** $l_{3,fs,7,0} = 10$ $d_{7} = 2.4$ min
	Layout.	**Zone 3** $l_{10,fs,3,0} = 10$ $d_{3} = 2.2$ min	**Zone 5** $l_{7,fr,5,0} = 40$ $d_{5} = 2.9$ min

Figure 55: Characteristics of the beverage warehouse: parameters *and* layout.

The iterative procedure solved the model for each day t within the horizon T. Figure 56 shows the value of the objective function split into its four contributions (i.e., honey combing, accessibility, travelling, and handling) and for each zone n. The trends of saturation over T of the zone n, corresponding to a lane depth k and storage mode y, illustrated in Figure 56, measure when and which as-is storage resources critical or redundant. As example, values of saturation close to 100%, indicates the preferable lane types (i.e., depth, mode and zone) to minimize the total storage cost. Conversely, low saturation (under 50%) indicate that the observed lane types are redundant and oversized for the given production and demand profiles. The different requirements of Zone 1 and Zone 7 (i.e., never chosen by the model) or Zone 2 reflect also the different labour need of each zone and provide a guideline to the warehouse managers in planning resources (i.e., operators and vehicles) re-allocation.

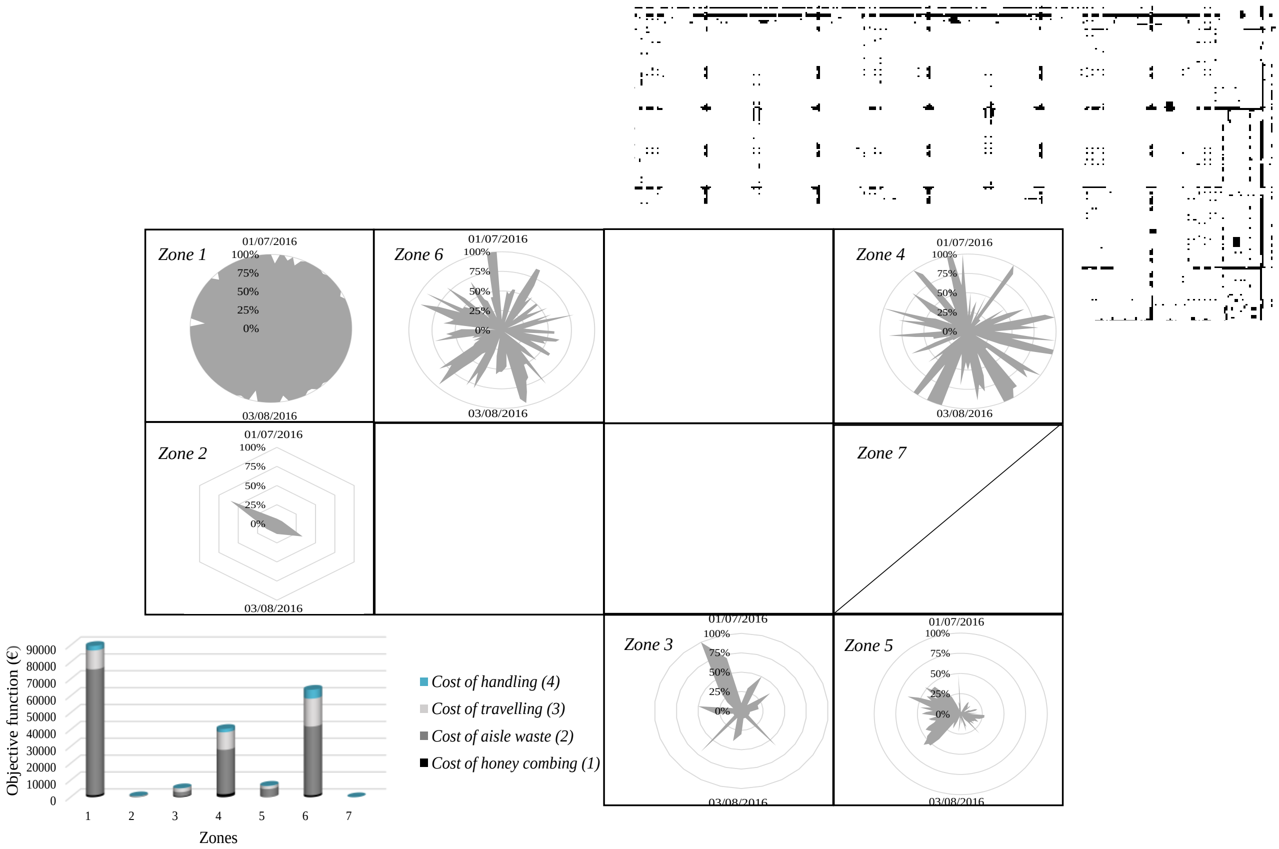


Figure 56: Saturation (i.e., ratio of occupied lanes to total lanes) of the zone n and cumulated objective function per zone n during the horizon T.

In order to validate how the model can support the design of a new warehouse from green field, the production and demand profiles assumed as historical data collected from others and similar manufacturing plants of the beverage company was used. Then, the iterative model for the horizon T was implemented, with the capacity constraints (12) and (13) relaxed. Figure 57 quantifies the number of lanes of depth k and storage mode y assigned daily to the incoming product lots in order to minimise the costs from space and time inefficiencies.

Case Greenfield: Results

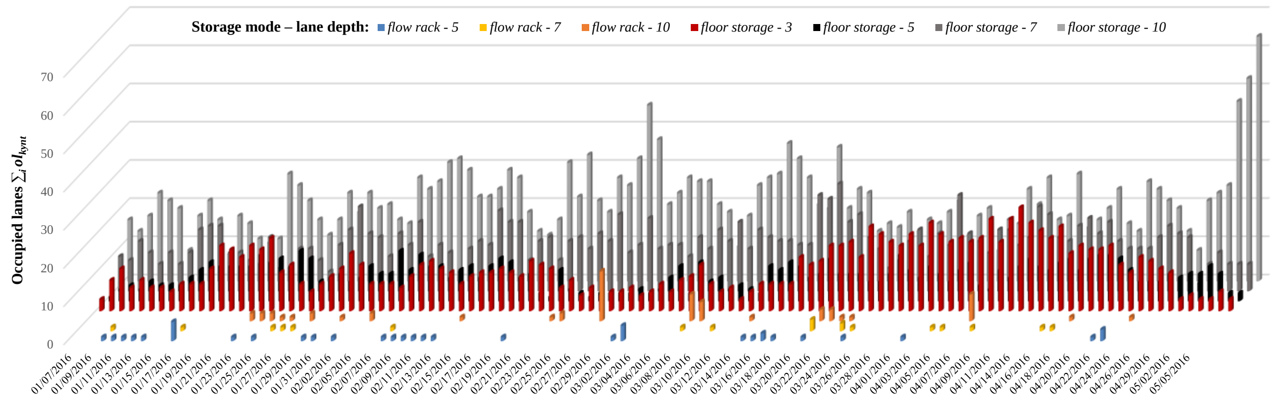


Figure 57: Green field case: lanes of k depth and storage mode y assigned daily to minimize the overall storage costs.

This obtained result enables to assess the requirements of lanes and storage modes that meets the production and demand profiles. The layout of the new warehouse can be defined by identifying the recurrent storage configurations in terms of lane depth k, storage mode y, and of number of occupied lanes ol_{ikyt}. As expected, the floor storage mode is the most preferred because of its low investment cost. The chosen daily lane depths reflect both lot quantity q_{it} and demand D_{it} and results in favouring long lanes of seven and ten depths. Even though the flow-rack is the most expensive storage mode, it guarantees low accessibility costs, and it is thereby preferred to the drive-in mode, as showed by the orange and light blue bars of Figure 57.

4.4.1.3 *Discussion and concluding remarks*

The results obtained from the case study showcase how using the ILP model for an existing warehouse enables understanding how the space and time inefficiencies (and the related costs) are accounted for a given lane depth, a storage mode or a layout zone within a horizon of time. By adopting this model, the warehouse operations' manager can even properly schedule and optimize the put-away tasks according to the daily storage space availability. To this purpose, the model might be embedded as a customized functionality of a warehouse management system (WMS) in a block-storage system. Nevertheless, the applicability of this model requires the awareness of the behaviour of the incoming SKUs. At least the i^{th} SKU's code, the number of pallets of each lot q_{it} and the expected demand D_{it} should be known. Whereas the expected demand is not known day by day, the average pallet consumption per each SKU (i.e., obtained from historical demand profiles) corrected by seasonality can be used to fuel the model. Therefore, the application of the proposed

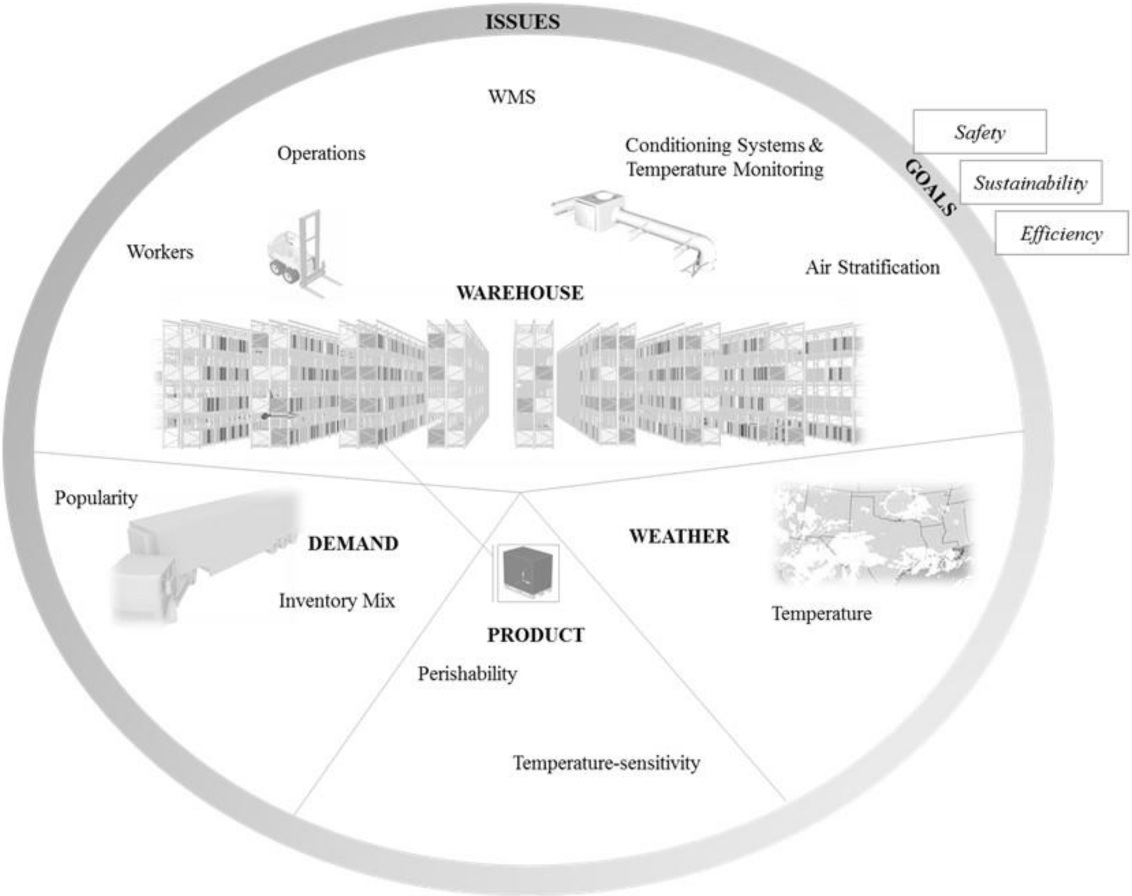
ILP model is limited to those block-storage environments with good visibility on the production process and on the incoming pallet flows at each working shift. This visibility is addressed by the majority of the block-storage warehouses, and particularly by those that implement automated storage/handling architectures (e.g., laser guided vehicles LGVs) (Manzini et al., 2016).
The second analysis is to demonstrate how this model aids the design of new block-storage warehouse from green field. The results, obtained by relaxing the capacity constraints (i.e., Eq. 12 and 13), identify a sub-set of recurrent storage configurations (i.e., made by the combination of a lane depth and a storage mode) that meet the daily requirements of storage space. Therefore, the designer might understand in advance the optimal requirements for the storage configuration and manage consequently the design from brown field, i.e., the stage that involves the physical and structural constraints of the building. In this case, the inputs to fuel the models (i.e., average production and demand per SKU) derive from the WMS of comparable plants that are used as benchmark, or from forecasting analysis. The level of reliability of the results strongly depends by the accuracy of the input data and their fitness with the real world.

While the model provides support to managers in layout planning and re-design, the selection of a unique optimal layout configuration over the time horizon T is far from its scope but will be certainly the input for future research developments. The faced storage layout problem might also be extended and integrated with the design of the layout of the overall manufacturing facility (Ferrari et al., 2003). Furthermore, multi-scenario what-if analysis might explore the relation between the production-demand profiles and the resulting space and time inefficiency to identify integrated production-scheduling and storage management best practices.

4.4.2 Acting on warehouse operations to handle products perishability

The research topic explored in this chapter contributes to the literature field on the storage assignment problem, proposing an original adaptive storage assignment policy for perishable temperature-sensitive products, which enables one to mutually manage both efficiency and stock safety goals. Dynamically implemented with the daily inbound flows, the proposed adaptive policy avoids the re-warehousing activity, which would require periodical expensive and labor-intensive re-location of the entire inventory. The proposed storage assignment policy is particularly suitable for environments that handle a high variety of inventory mix with high turn-over, such as 3PL provider warehouses. This policy autonomously balances the management of the inventory between the efficiency and stock safety levers. The proposed methodology is also a tool to assess how the existing storage infrastructure (i.e., layout, HVAC system, insulation, facility site and solar exposition) responds to incurring stressing temperatures, which are the associated costs in term of efficiency, and how or when infrastructural investment may be returned.

With the existing wide literature on warehousing theories and problems, Figure 58 illustrates a framework to summarize and highlight the interdependencies among warehouse issues, entities and goals. The framework provides a view of the topics of interest in the literature and shows how they mutually contribute to addressing the safety, efficiency and sustainability goals. The figure is organized with four main pillars: the warehouse (1), demand profile (2), product (3), and climate conditions (4). The warehouse includes the pattern related to operation planning, labor management, design of computer-aided warehouse control systems (i.e., WMS), infrastructural features and devices for air conditioning and indoor-temperature control. The demand issue addresses the management of order profiles, demand seasonality and changing inventory mix. The product involves the characteristics of the handled items in terms of perishability and thermal stress sensitivity. Finally, the climate considers the effects of external environmental stresses on supply chain operations.



Topic	References
Workers	Grosse et al., 2013, Hui et al., 2015
Operations	Bartholdi and Hackman, 2011, Gu et al.,2007, Koster et al., 2007, Petersen and Aase, 2004, Thomas and Meller, 2015.
WMS	Tan, 2009, Ketikidis et al.,2008, Harris, 2015, Giannikas et al., 2013.
Conditioning Systems & Temperature Monitoring	Badia-melis et al.,2015, Ho et al., 2010.
Air Stratification	Armstrong et al., 2009, Aynsley, 2005, Bouzinaoui et al., 2005, Porras-Amores et al., 2014.
Temperature	James and James, 2010, Jedermann et al., 2014.
Perishability	Akkerman et al., 2010, Amorim et al., 2013, Goyal and Giri, 2000.
Temperature-sensitivity	Hertog et al., 2014, Bakker et al., 2001, Park et al., 2012, Vaikousi et al., 2008.
Popularity	Gu et al., 2007, Bartholdi et al., Hackman, 2011.
Inventory Mix	Yingde and Smith, 2012, Manzini et al., 2015.
Goals	Manzini et al., 2013, Akkerman et al., 2010.

Figure 58: Literature overview

4.4.2.1 A bi-objective storage assignment policy to handle temperature-sensitive products

The proposed policy has the twofold objectives of optimizing the warehouse efficiency and of minimizing the temperature stress to the stored products. As previously introduced in 4.2.1.2, the application of the diagnostic-support framework to Case I paves the way for the development of this policy. Particularly, the policy assigns the incoming perishable items (e.g., biomedical and pharmaceutical, food and beverage) to the available storage locations in order to reduce the total travel for picking and to maintain the safe storage temperature conditions simultaneously. The policy is suitable for those contexts characterized by dynamic demand, in which two types of seasonality exist (see Figure 59).

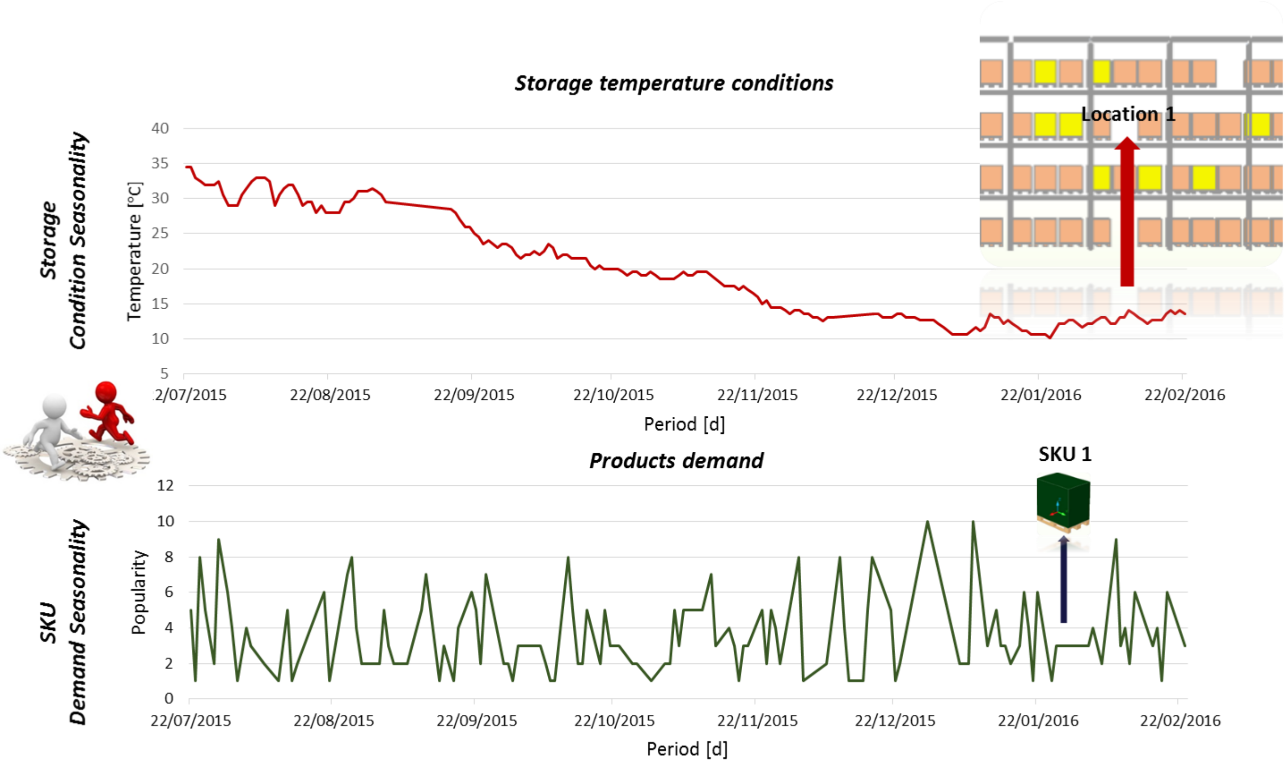


Figure 59: the two types of seasonality

While seasonality in products demand (e.g. fluctuations in demand and stock mix) pushes practitioners and warehouse managers to periodically revise the storage configuration, the seasonality in temperature conditions, caused by seasons and climate, may incur thermal stresses to the inventory. The latter is particularly evident in climate-uncontrolled or passive air-forced environments. Therefore, an adaptive storage assignment policy that simultaneously manages the seasonality in weather and demand is proposed. The policy favors a warehouse configuration that address both aspects. The incoming SKUs are located according to two metrics: the demand, which

pushes the fast-moving SKUs toward the most-convenient locations, and the air temperature measured at different storage locations, which may alter the safe conservation conditions. Because the *optimal* storage configuration periodically changes because of the inventory mix, demand and weather seasonality, its *static* definition is misleading and therefore replaced by a *dynamic* definition. The dynamic optimal storage configuration evolves day-by-day and the aim of this methodology is minimizing its difference from the *as-is* storage configuration, which represents the actual storage configuration by the start of the daily activities. Therefore, the policy proposes to run a two step approach before the daily warehouse operations, when arrivals and deliveries are known. Firstly, a bi-objective integer programming model for the storage assignment is launched and the resulting Pareto curve is calculated trought the ε-constrained method (1). Then, an algorithm to select the trade-off solution on this curve is solved (2). Consequently, it can be argued that the method dynamically adapts to the daily inventory, demand, and whether conditions.
This approach is illustrated in the following sub-sections.

4.4.2.2 The model

Problem statement

The model is formulated as follows. The model considers a set of storage locations J and a set of SKUs W. Furthermore, it considers I as the set of unit loads i of SKU w. To incorporate the temporal dimension into the model, T (e.g. a year) as the set of considered periods (e.g. days) is introduced. The model assumes that, during each period t, the workers perform the put-away tasks during a set of time-windows T_r (e.g. shift). In addition, a buffer S, which is necessary for cross-docking activities, is also used to manage the put-away tasks. The solution defines the set of put-away tasks to assign the incoming unit-load i of SKU w to location j during each time window (t_r) in period t. The model optimizes the overall *convenience* that results from the daily assignment of the incoming loads to the available storage locations. The definition of *convenience* is twofold, and two objective functions are therefore introduced. The *efficiency* objective (Equation 4) is to minimize the total travel for picking and is based on the popularity index, which is defined as the pick lines cumulated by a generic SKU in a time horizon (Gu et al., 2007) and widely diffuses in both practice and class-based storage systems (Koster et al., 2007). Both theory and industrial experiences agree that locating the most popular SKUs, i.e. the most requested SKUs, to the nearest locations significantly reduces the travel for picking. Given the dynamic dimension of the policy, the time-dependent variation of the product demand is considered through a rolling measure of popularity (Manzini et al., 2015) (see 4.1.1.1). As previously introduced, the *popularity rolling index* in t quantifies the number of picks that the generic SKU w accounts in the last Δt units of time (e.g., 15 days) as follows:

$$Pop^{roll}{}_{w,\Delta t}(t) = \sum_{t-\Delta t}^{t-1} Pop_w(t) \tag{1}$$

where $Pop_w(t)$ is the popularity of SKU w in period t, and Δt is the rolling time step.

The duration of the rolling time step should be carefully set. A too short rolling step roughly accounts the same value of popularity for all SKUs, whereas a too long step tends to reduce the effectiveness of a dynamically adaptive policy. Although the proper setting of this value could be central in further studies, this policy considers Δt as equal to the average warehouse turnover as a good approximation in this study. The *efficiency* objective implements a class based formulation. For this reason, each location j belongs to a specific class c_j, built on the single command travelling time to achieve the location j from the I/O dock. Conversely, each unit load i_w belongs to a class c_{i_w}according to the percentile of the popularity rolling index.

The safety objective (Equation 5) maximizes the convenience of assigning the incoming unit-load i_w of SKU w to location j in time window t_r according to the highest expected temperature stress that is measured at that location along a horizon from t to $t + \Delta s$. The term Δs is the average horizon that a pallet is stored, which is calculated in the last $t - \Delta t$ periods. Assuming a location that is occupied till the load is completely retrieved, Δs represents the periods within the average inventory turnover and is therefore the horizon within which a load may experience stresses or critical temperature that affect its safe conservation. In order to calculate this highest stress temperature during Δs measured per load i_w and location j Equation (2) is formulated.

$$T^{stress}{}_{i_w,j,\Delta s}(t^*) = \begin{cases} max\{T_j(t): t^* < t \le t^* + \Delta s\} & \text{If } \left|max\{T_j(t): t^* < t \le t^* + \Delta s\} - T^{safe+}{}_{i_w}\right| \ge \left|min\{T_j(t): t^* < t \le t^* + \Delta s\} - T^{safe-}{}_{i_w}\right| \\ min\{T_j(t): t^* < t \le t^* + \Delta s\} & \text{Otherwise} \end{cases} \tag{2}$$

where $T_j(t)$ is the temperature measured at location j in period t.

Given the labelled temperature range of safe conservation for the unit load i_w located in j during t, defined as $[\, T^{safe-}{}_{i_w}, T^{safe+}{}_{i_w} \,]$, $T^{stress}{}_{i_w,j,\Delta s}(t^*)$ represents that value of temperature experienced by the products in Δs that is more distant from $[\, T^{safe-}{}_{i_w}, T^{safe+}{}_{i_w} \,]$. A smaller difference (i.e., degrees) between this temperature $T^{stress}{}_{i_w,j,\Delta s}(t^*)$ and the temperature range of safe conservation for load i_w [$T^{safe-}{}_{i_w}$, $T^{safe+}{}_{i_w}$] corresponds a smaller difference from the optimal storage configuration. Furthermore, given $T^{stress}{}_{i_w,j,\Delta s}(t^*)$, $T^{safe}{}_{i_w}$ is defined as:

$$T^{safe}{}_{i_w} = \begin{cases} T^{safe+}{}_{i_w} & \text{If } \left|T^{stress}{}_{i_w,j,\Delta s}(t^*) - T^{safe-}{}_{i_w}\right| \geq \left|T^{stress}{}_{i_w,j,\Delta s}(t^*) - T^{safe+}{}_{i_w}\right| \\ T^{safe-}{}_{i_w} & \text{Otherwise} \end{cases} \quad (3)$$

In order to facilitate the readers understanding, Figure 60 represents Δs and Δt according to the temporal dimension.

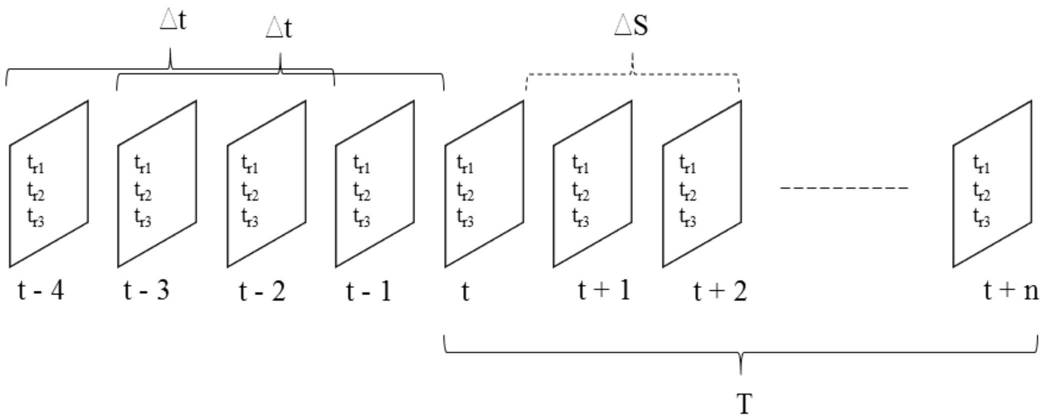


Figure 60: Representation of the time-related indices.

The list of the entities of the model are shown in Figure 61, while the parameters and the main model assumptions are listed in the following.

Assumptions

- The number and type of incoming pallets are known daily.
- The time-windows for the put-away and picking operations are known and decoupled.
- The incoming unit load i_w is assigned to a location j at the end of the daily operations.
- The unit load i_w assigned to location j on day t is available for picking on the following day.
- The list of empty locations available at each time window t_r is known.
- The unit loads are single SKU.
- Each storage location holds one unit load.
- The unit loads have standard sizes and can fill every storage location.

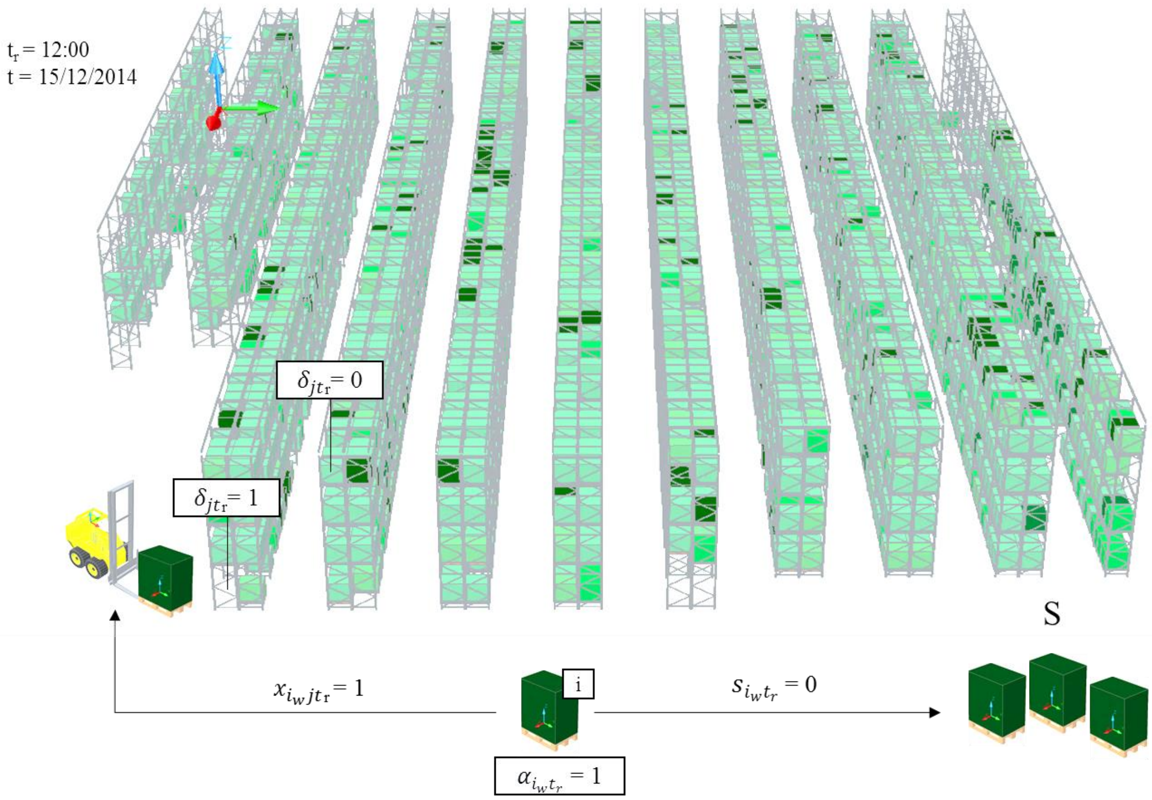


Figure 61: Schematic view of the main variable and parameters.

Parameters

S Integer buffer storage capacity (i.e., unit loads)

$\delta_{jt_r} = \begin{cases} 1 & \text{If the location j is empty during the time window } t_r \\ 0 & \text{Otherwise} \end{cases}$

$\alpha_{i_w t_r} = \begin{cases} 1 & \text{If the unit load } i_w \text{ arrives between the periods } (t_r\text{ -1}) \text{ and } t_r \\ 0 & \text{Otherwise} \end{cases}$

$d^T_{i_w j} = \left|T^{safe}{}_{i_w} - T^{stress}{}_{i_w,j,\Delta s}(t_r)\right|$ Distance between the location j and the optimal location for load i_w according to the safe temperature $T^{safe}{}_{i_w}$

$d^P_{i_w j} = \left|c_{i_w} - c_j\right|$ Distance between the class c of location j and the optimal class for load i_w according to its popularity-class c_{i_w}

$b^T_{i_w} = \left|T^{safe}{}_{i_w} - T^{stress}{}_{i_w,b,\Delta s}(t)\right|$ Distance between the buffer b and the optimal location for load i_w according to the safe temperature $T^{safe}{}_{i_w}$

$b^P_{i_w} = \left|c_{i_w} - c_b\right|$ Distance between the optimal class of load i_w and the distance-class of buffer b

Decision variables

Two binary decision variables, which indicate selection decisions about the assignment of the incoming unit load i_w to a location j or to the buffer in t_r are considered.

$$x_{i_w jt_r} = \begin{cases} 1 & \text{If the unit load } i_w \text{ is assigned to the location j during the time-window } t_r \\ 0 & \text{Otherwise} \end{cases}$$

$$s_{i_w t_r} = \begin{cases} 1 & \text{If the unit load } i_w \text{ is assigned to the buffer during the time-window } t_r \\ 0 & \text{Otherwise} \end{cases}$$

Objective functions

$$min\,\theta_1 = \sum_{i_w \in I} \sum_{j \in J} \sum_{t_r \in T_r} (x_{i_w j t_r}\, d^P_{i_w j}) + \sum_{i_w \in I} \sum_{t_r \in T_r} (s_{i_w t_r}\, b^P_{i_w}) \tag{4}$$
$$min\,\theta_2 = \sum_{i_w \in I} \sum_{j \in J} \sum_{t_r \in T_r} (x_{i_w j t_r}\, d^T_{i_w j}) + \sum_{i_w \in I} \sum_{t_r \in T_r} (s_{i_w t_r}\, b^T_{i_w}) \tag{5}$$

Equations (4) and (5), which are defined as the *efficiency* and *safety objective*, minimize the differences between the *as-is* and the optimal storage configurations. By including the parameters $d^P_{i_w j}$ and $b^P_{i_w}$, the efficiency objective implements the class-based formulation.

The definition of the class of popularity c_{i_w} of load i_w, which arrives at time window t_r of day t, is as follows: (1) all SKUs are ranked by decreasing value of popularity rolling; (2) the minimum and maximum values of popularity rolling are used to scale the percentile range; (3) each SKU matches with its percentile; (4) m popularity classes are identified over the percentile range, and each load i_w is assigned to its class c_{i_w} accordingly. Similarly, the storage locations are divided into m distance classes based on the travel time for a single command task. Given these definitions, the distance $d^P_{i_w j}$ of assigning load i_w to location j is the difference between the popularity class c_{i_w} and the distance class c_j.

The second term of Equation (4) accounts for the difference from the optimal storage configuration that results from the use of the buffer. The incoming load may wait in the buffer until the proper location is available. The convenience of storing load i_w in the buffer depends on the warehouse layout. To favor the put-away tasks and facilitate cross-docking operations, the buffer should be as close as possible to the I/O dock (i.e., $c_b = 1$).

Similarly, the safety objective quantifies the difference between the *as-is* and the storage configuration that minimizes the temperature stress to the stored products, which is calculated as the cumulated difference between the highest stress temperature during Δs experienced by each load i_w and ${T^{safe}}_{i_w}$. The first term in Equation (5) accounts for the loads that are stored in the rack, whereas the second is for the loads that queue in the buffer.

Constraints

$$\sum_{j \in J} \sum_{t_r \in T_r} x_{i_w j t_r} = 1 \qquad \forall\, i_w \in I \tag{6}$$
$$\sum_{i_w \in I} \sum_{t_r \in T_r} x_{i_w j t_r} \le 1 \qquad \forall\, j \in J \tag{7}$$
$$s_{i_w t_r} + \sum_{j \in J} x_{i_w j t_r} = \alpha_{i_w t_r} \qquad \forall\, i_w \in I, t_r = 1 \tag{8}$$
$$s_{i_w t_r} + \sum_{j \in J} x_{i_w j t_r} = \alpha_{i_w t_r} + s_{i_w, t_r - 1} \qquad \forall\, i_w \in I, t_r > 1 \tag{9}$$
$$\sum_{i_w \in I} s_{i_w t_r} \le S \qquad \forall\, t_r \in T_r \tag{10}$$
$$\sum_{i_w \in I} x_{i_w j t_r} \le \delta_{j t_r} \qquad \forall\, j \in J, t_r \in T_r \tag{11}$$
$$x_{i_w j t_r}, s_{i_w t_r} \in \{0,1\} \qquad \forall\, i_w \in I, j \in J, t_r \in T_r \tag{12}$$

Constraint (6) imposes the assignment of load i_w to a single storage location at a single time window t_r in period t. Constraint (7) ensures that each storage location j is filled by a single load at each time window $t_r \epsilon T_r$. Constraint (8) imposes the assignment of an incoming load directly to one storage location or temporarily to the buffer.

Constraint (9) imposes that each load i_w that is stored in the buffer at time window t_r can be assigned to a storage location in $t_r + 1$ instead of remaining in the buffer.

Constraint (10) ensures that the stock capacity of the buffer never exceeds in each time window $t_r \epsilon T_r$. Constraint (11) assigns unit load i_w to location j in period t_r only if j is empty in t_r. Constraint (12) denotes the binary nature of the decision variables.

4.4.2.3 *Pareto frontier and solution approach*

In multi-objective programming, the objectives are often mutually conflicting, and the proper "trade-off" between solutions must be identified (Fontana et al., 2014). These problems do not provide a single optimal solution, but a set of so-called Pareto optimal solutions. Each solution is Pareto-optimal whether is not improvable in one objective without influencing its performance in another one (Varsei and Polyakovskiy, 2017). In the literature, different approaches are used to solve multi-objective models. In this study the bi-objective model is solved using the augmented ε-constrained method (Khalili-Damghani et al., 2012, Mavrotas, 2009), and an algorithm to decide among the non-dominated solutions is introduced. Through the augmented ε-constrained method an approximation of the Pareto front which allows the assessment of the trade-offs between one objective and another is obtained.

The key assumption of the proposed algorithm is the variability of the "weight" of two objective functions along a horizon of time. The weight of the *efficiency objective* (θ_1) is usually constant throughout the year (but can be influenced by the demand seasonality), whereas the weight of the *safety objective* (θ_2) varies monthly and is higher during the seasonal temperature picks (e.g., August and January). The efficiency objective is thus considered the objective of higher priority. The weight of θ_2 should increase during the seasons that are characterized by highly stressing temperature, whereas the weight of θ_1 is not weather-dependent and always assumed to be as high as possible.

Figure 62 illustrates the steps of the proposed algorithm. The definition of the proper ε value (1) is the preliminary step to generate a set of Pareto-optimal (2) which together shape the Pareto front (3). These first three steps are common in the generic application of the ε-constrained method, but the following introduced steps are problem-oriented and specific of this model.

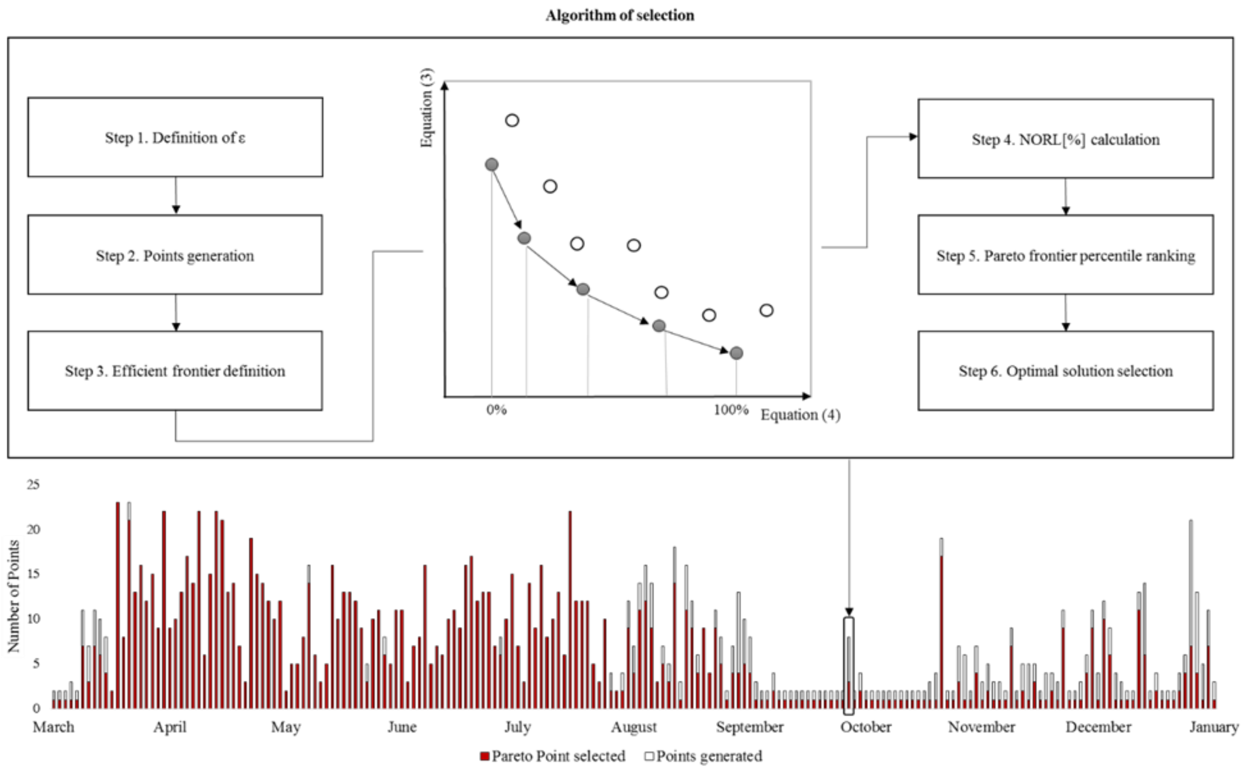


Figure 62: Construction of the Pareto curve and selection algorithm; Results from its application to the case study

We define parameter γ_{i_wjt} to indicate the class of load stored at each location j in period t. This parameter is a model output and enables an overview of the storage system at a generic period t in terms of compliance with the safe conservation conditions. Equation (13) quantifies the number of locations (4) that are filled by a load outside its safe temperature class in the horizon from t to $t+\Delta s$, and this index is named the Number Out-of-temperature-Range Location (NORL). The *NORL* index is assumed as a measure of weight of the *safety objective*, so that a higher NORL corresponds to higher importance of minimizing θ_2.

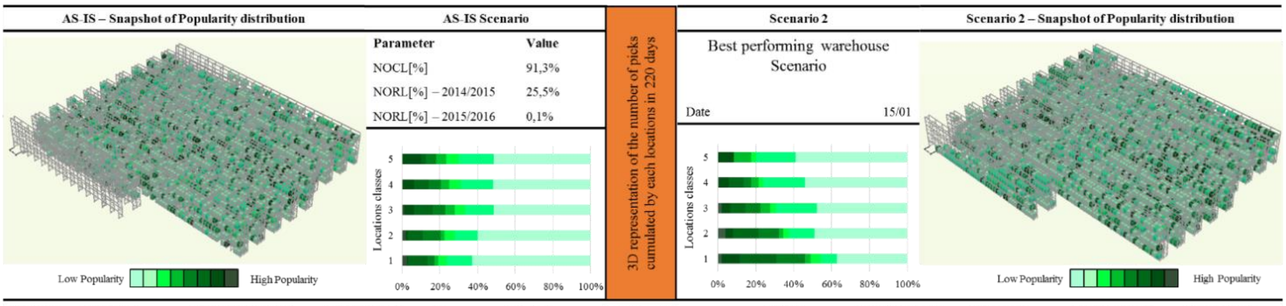
$$NORL(t) = \frac{\sum_{j,i_w} \gamma_{i_wjt} : (d^T_{i_wj} > 0)}{j - \sum_j \delta_{jt}} \tag{13}$$

The set of p non-dominated solutions between two anchor points is scaled into percentile classes (5), as illustrated in Figure 62, each of which is characterized by a minimum value of *NORL(t)*. The number of non-dominated points p generated in each period t is also a measure of the effect of weather conditions on the inventory safety, as further explored in the Discussion Section. Starting from the anchor point that results from θ_1, the selected solution in period t is the first in the same percentile class of *NORL* at period *t-1* (6). Therefore, starting from a period t characterized by an *NORL(t)* value close to 0 (e.g., March, October), the algorithm favors the *efficiency function*, unless the stressing temperature picks occur; otherwise, the algorithm autonomously tends to favor the *safety function*.

4.4.2.4 Model validation

This methodology was applied to Case I as a validating case study. As previously introduced, 3PL warehouses commonly suffer of rapid changes of the inventory mix, and the ability to address this issue is a strategic competitive lever. The 3PL providers must also respect the quality and safety standards particularly for perishable products, although long-term investments in infrastructures (e.g., HVAC systems) are discouraged by short-term deals with the clients (Li and Ma, 2014). Thus, Case I is a representative case to validate the methodology. Inputs for the feasibility analysis were collected throught the temperature tracking campagn illustrated in 4.2.2.3.1 and the operations mapping described in 4.2.1.2.

Successively, a multi-scenario what-if analysis was conducted to explore the response of the methodology to different inputs and compare the resulting benefits with the benchmark. The scenarios involve two main levers: the objective function and the time horizon. The objective function of the model varies among the bi-objective formulation (i.e., our proposal), single efficiency function (i.e., business-as-usual), and single safety function (i.e., consumer-expected). The time horizon lever considers ten months of warehousing operations (i.e., from March, 27th to January, 15th) that matched with the daily weather conditions in the last year (Horizon 1) and previous year (Horizon 2). By combining these levers, the benefits and limitations of the proposed methodology and its responsiveness to different business goals or weather conditions are explored. The models are written in AMPL and run through the DST in 4.3.1.2. A period t (i.e. a day) is considered with three shifts t_r per period. For each day t and scenario, the model generated one assignment solution for the efficiency and one for the safety function, or a set of non-dominated solutions with the bi-objective formulation. In the latter scenario, if an ε value is equal to the thermometer resolution (i.e., 0.5°C), the number of Pareto points depends on the weather conditions, and the solution on day *t* is selected according to the proposed algorithm. In any scenario, the solution in period *t* is used as input to iterate the methodology in period *t+1*. By simulating the effect of the known load arrival and retrieval on the daily inventory, the performance of each scenario is accounted for each period and compared in the final period with the real as-is storage state.



Scenario	Technique	Objective Function	Picking Policy	Δt	Routing Policy	Time Horizon	Buffer Capacity	Replenishment Times (t_r)	Total travel Time Reduction	Final value of NOCL index	Final value of NORL index
1	Optimisation	Mono-objective: Popularity	FEFO	90 days	Nearest Neighbour	27/03/2014-15/01/2015	150	11:00, 15:00, 21:00	10,48%	80,92%	17,99%
2		Bi-objective				27/03/2014-15/01/2015			11,61%	80,48%	15,84%
3		Mono-objective: Temperature				27/03/2014-15/01/2015			11,82%	89,35%	15,04%
4		Mono-objective: Popularity				27/03/2015-15/01/2016			10,48%	80,92%	15,15%
5		Bi-objective				27/03/2015-15/01/2016			11,92%	81,11%	12,95%
6		Mono-objective: Temperature				27/03/2015-15/01/2016			7,2%	89,41%	12,16%

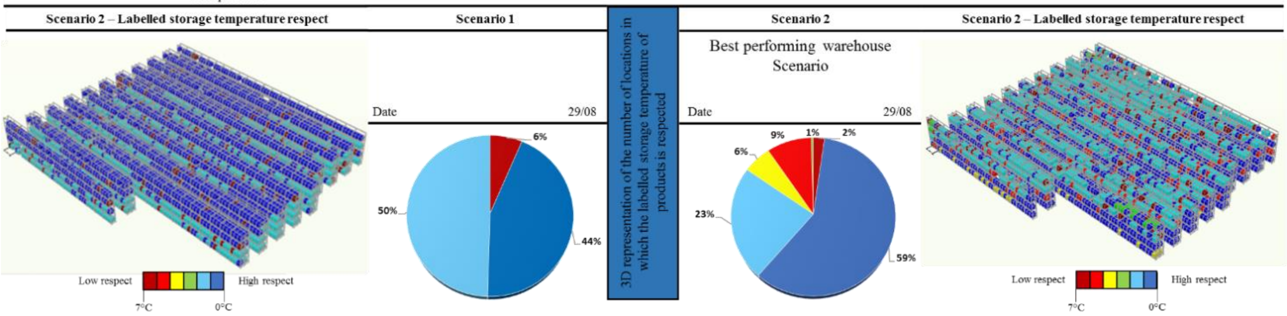


Figure 63: Multi-scenario analysis results

We consider the travel for picking the main metric of efficiency. The multi-scenario analysis shows improvements compared to the as-is policy. The proposed bi-objective policy saves 11,92% in Time Horizon 1 and 11,61% in Time Horizon 2. The bar charts on top of Figure 63 cumulate the total picking lines per distance class of storage location during the entire planning horizon (i.e., T:1,..,220). The 3D snapshots on the top of Figure 63 confirms that the bi-objective scenario tends to more often assign the fast-moving SKU to the locations in the warehouse front than the as-is.

To address the level of stock safety, a period t* (August, 29th, 2014) is selected to exemplify the benefit of the methodology. This day was considered for the extremely stressing temperature outside and inside the warehouse. Then, the NORL(t*,c) per class c of compliance with the safe temperature ranges is calculated as follows:

$$\mathrm{NORL}(t^*, c) = \frac{\sum_{j,i_w} \gamma_{i_w j t} : \left(d^T_{i_w j} \leq c\right)}{j - \sum_j \delta_{jt}} \; \forall c \epsilon C: \{0,1.5,3,4.5,5.5,7\} \tag{14}$$

Equation (14) classifies the inventory into 6 classes of storage locations: from those filled by loads that highly respect their safe temperature range to those filled by loads that do not respect this range. The pie charts at the bottom of Figure 63 compare $\mathrm{NORL}(t^*, c)$ between the business-as-usual and the proposed bi-objective scenario. The latter performs better: the high-respect locations increased from 44% to 59%, and the low-respect locations decreased from 6% to 2%.

To further explore the effect of the proposed bi-objective policy, the dynamics of the inventory must be observed. Similarly to the NORL index (Equation 13), the NOCL(t) index is introduced to account for the number of locations in period t that are filled by a load outside its popularity class (i.e., where $d^P_{i_w j} > 0$). A lower NOCL(t) value corresponds to a smaller difference between the storage configuration in t and the optimal configuration.

Figure 64 illustrates the dynamics of NOCL(t) and NORL(t) indices per *t* along the Time Horizon 2 for Scenarios 1, 2 and 3 of Figure 63.

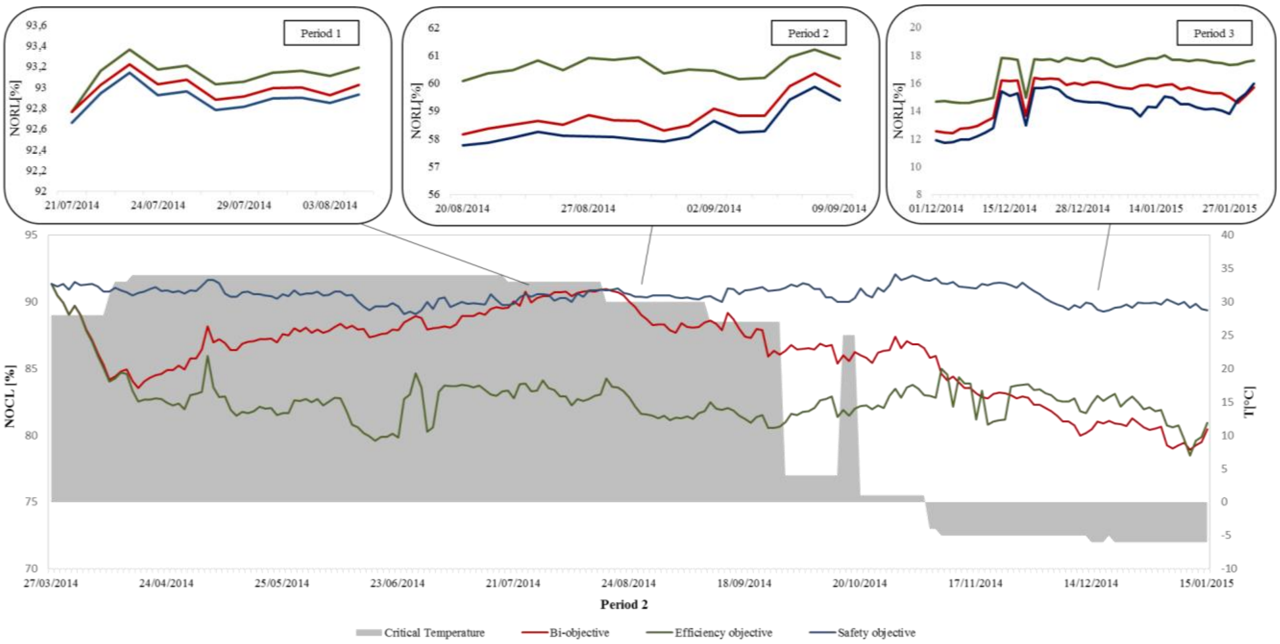


Figure 64: NOCL index profile: green line for Scenario 1, red for Scenario 2, and blue for Scenario 3; the grey area represents the highest stressing temperature measured inside the storage system.

In Figure 64, the bi-objective policy meets the blue line (i.e., safety function) when stressing temperatures (i.e., 30-35°C) occur and autonomously returns close to the green line (i.e., efficiency function) elsewhere. The algorithm at period *t* selects among the Pareto points the assignment solution that maintains a minimum difference between NORL(t-1) and NORL(t). As a consequence, to respond to the expected stressing temperatures in the horizon from *t* to *Δs+t*, the algorithm unbalances the storage assignment according to the safety function and prefers the efficiency function elsewhere.

In both Scenarios 1 and 2, NOCL(t) decreases during the observed horizon from the initial 91% to 80%, which is beneficial compared to the as-is, and there is potential for further improvements.

The NORL(t) value is illustrated for three periods (i.e., Period 1: t*, 2: t**, 3: t***) that correspond to three generic inventory behaviors.

In Period 1 (t*), the bi-objective line converges to the safety line to respond to the increase in inside temperature to 35°C. The lack of an adequate HVAC system does not prevent the acquisition of such critical temperatures, whereas 90% of the inventory mix has safe temperature ranges of 4÷30 °C. As a consequence, the reduction of NORL(t*) is not feasible regardless of the adopted policy (see the three parallel lines in Figure 64).

We call this over-constrained condition the suffering inventory status. The behavior of the algorithm in this status is showcased in the bar chart at the bottom of Figure 62 between May and July. The white bar accounts for the non-dominated solutions that were generated in each period t, whereas the dark bar below is the percentile of the selected solution. Where the dark bar completely covers the light one, the safety anchor point is selected. Thus, during the suffering inventory status, NORL(t) is high, although the policy is completely unbalanced toward the safety function.

In Period 2 (t**), the NORL(t) value is affected by the adopted policy. As expected, Scenario 3 performs better than the others, but the bi-objective policy is notably close to it. In this case, the loss of efficiency reflected by high NOCL(t) values is compensated by an increase in safety reflected by the NORL(t) index.

In Period 3 (t***), the bi-objective policy benefits from a mutual decrease in NOCL(t) and NORL(t). Far from the evidence, the bi-objective policy performs even better than the efficiency function in reducing NOCL(t) and perfectly combines the advantages of both single-objective policies. To avoid the stressing temperatures at the top locations during the warm season (Porras-Amores et al., 2014), the bi-objective policy progressively stores the loads at low levels and mutually reduces the number of time-intensive vertical movements in picking operations. Consequently, the total travel time for picking decreases as shown in Figure 65.

Figure 65 shows the saving of travel time for picking in the three scenarios compared to the as-is scenario. After a run-up period, the bi-objective policy confirms the result in Period 3: the travel time was reduced by approximately 12%, which is more than the efficiency policy, which stops at 10.5% saving.

This behavior paves the way for further considerations. The mutual effect of efficiency and safety on the inventory configuration should be addressed through a well-designed storage system (Accorsi et al., 2014), where the most convenient locations provide both efficiency and safety benefits. In this term, our methodology assesses how the warehouse infrastructure can respond to the demand and weather seasonality in accordance with the efficiency and safety requirements.

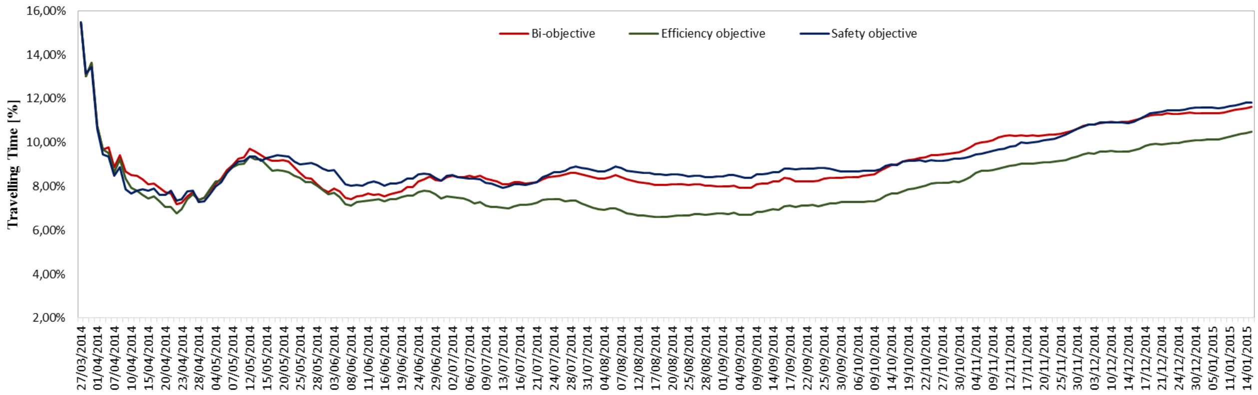


Figure 65: Saving in travelling time for picking compared to the as-is scenario.

The above findings demonstrate the effectiveness of the proposed bi-objective policy in the observed case study. Despite the aforementioned extensive phase of data collection led to the decision of using a single-case study methodology to validate the policy, results from the presented multi-scenario analysis make positive towards its adaptiveness in other contexts. Nevertheless, the limit to the policy application is the suffering inventory status condition (see Figure 64), where the potential benefits are reduced and an adequate HVAC system should be mandatory.

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5 CONCLUDING REMARKS

The main purpose of this dissertation is to propose innovative methods, models and tools aided to improve the overall performance along the supply chains for perishables products. Beyond the efficiency of the supply chain operations, the definition of 'performance' assumes other three dimensions: quality, safety and sustainability. The realization of this objective represents a challenging task for logistics given some external, supply chain and product issues. First of all, the regulatory framework and the increasing customers'concern about the credence attributes of products push companies to invest in performance improvement project. The new advance in IT and in traceability systems represent an opportunity for companies to address to the customer's demand for transparency. However, although the information sharing among supply chain actors is touted as a strategic lever to increase the supply chain coordination and integration, the openness toward always more global markets and the distrust of companies to share strategic information obstacle the information flow along the supply chain. Moreover, always more often companies decide to focus on their core processes and to entrust to 3PL providers the transportation and storage processes. Consequently, 3PLs have to deal with multiple company inventory and a high variety of products characterized by different demand and requiring specific conservation temperatures. Given the seasonality in the weather conditions, the realization of effective temperature-controlled storage and distribution operations is the most important driver to control the quality degradation and the safety decay of perishable products. However, the realization of cold chains is highly energy-intensive, negatively affecting the environmental impact of perishable products supply chains.

Based on these statements, the research presented in this dissertation elaborates on two research questions that narrow down the set of potential approaches to the problem to the improvement of the overall performance of perishable products distribution network and of storage operations.

The research activity is developed according to the research framework in Figure 2, where the research questions are addressed by research levers, that are explored according to research topics. Each topic is explored according to a specific methodology, however the overarching methodological approach to the research presented in this dissertation includes four fundamental aspects: the minimization of the level of approximation of data in input, the use of case-study deriving from real-world instances, the use of simulation to study complex systems through their model and the role of data visualization.

The outline of this dissertation is organized as follows. After a first introductive chapter, the second chapter of this thesis draws the state-of-the-art of the current industrial practice on perishable products supply chain, introducing the most important challenges for logistics and illustrating the background of this thesis. Moreover, the scientific landscape on perishable products supply chains is explored by the mean of a bibliometric analysis on the literature over the last decade.

The following two chapters illustrates the research activity. Chapter 3 addresses to *RQ.2*, by acting on two research levers: acting on information sharing and acting on network configuration. The first focuses on the impact of a major information sharing among SC partners in order to improve the daily operations and explores the state-of-the-art of the blockchain, and its potential role in supply chain traceability. The second results in a location-allocation model for refrigerated warehouses.

Chapter 4 addresses to *RQ.3* by exploring three strategic levers: acting on data, acting on the selection of the proper layout and storage mode and acting on the optimization of the warehousing operations which are illustrated in 4.2 and 4.3, in 4.4.1 and in 4.4.2 respectively. The first lever includes the mapping of the warehouse operations and of the environmental conditions, the study of the impact of the availability of information on the products characteristics on the overall warehouse performance, and the selection of the proper customization of the Warehouse Management System. The second includes the design and manage of deep lane storage system layout. The third lever focus on warehouse operations and particularly on the development of an innovative storage assignment policy tailored for temperature-sensitive products.

Underpinned by the research questions, the explored research topics lead to the development of innovative models, methods and tools, that are applied on different case studies, from which some general conclusion can be drawn. Figure 66 summarizes these research outcomes, highlighting the interdependences between the different works by the means of red lines. As instance, the development and the validation of the bi-objective model for the storage assignment presented in 4.4.2 was supported by the application of the framework for the warehouse diagnostic and the DSS for the warehouse simulation.

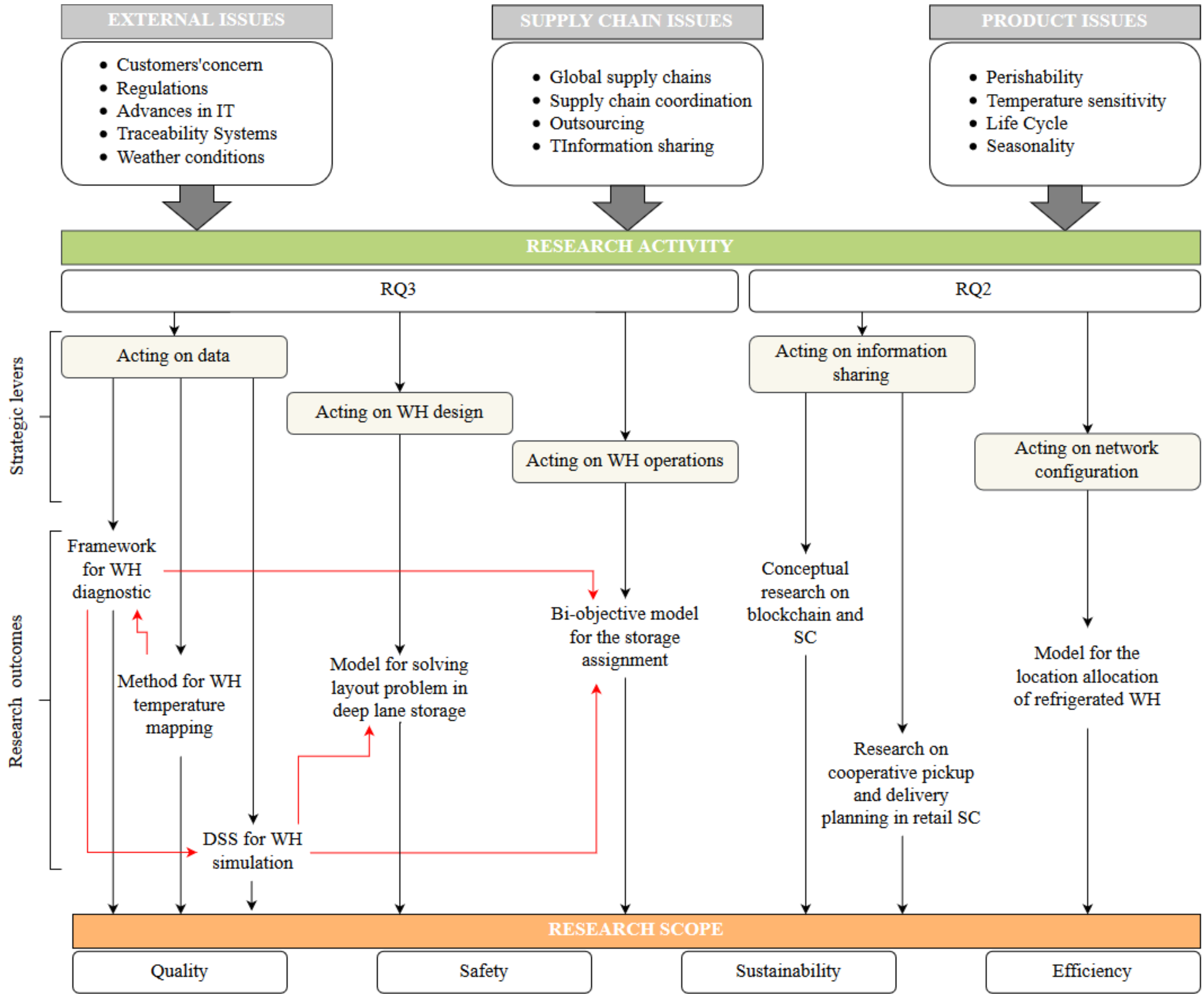

Figure 66: Framework of the main contributions presented in this dissertation

The following sub-chapters illustrate the theoretical, methodological and practical contributions of the research outcomes and the potential research developments.

5.1 Practical, theoretical and methodological contributions

The initial bibliographic analysis included in the second chapter highlights the increasing adoption of a more comprehensive perspective by researchers in approaching the problem of performance improvement along the supply chains for perishable products. This analysis also draws the landscape of the current literature with the aim of identifying the main research trends over the last decade, providing both scholars and practitioners with a detailed snapshot of the state-of-the-art. The most important contribution of the analysis concerns the methodology since the map of keywords proposed at Figure 13 constitutes a tool to explore the most debated research topics in the field enabling researchers to identify potential gaps in the literature. The outcomes of the bibliographic analysis introduce and justify the choice of some of the research topics discussed along this dissertation.

Among the research trends from the map of keywords discussed in 2.2.1.4, the impact of the adoption of a cooperative approach vs. a competitive approach among supply chain actors is further discussed in 3.1.1. Although the map shows how this research topic was still explored in 2013, its link with the strategic lever of information sharing make it more relevant than ever, specifically in the case of retail food supply chain. The presented research confirms the benefits generated by a cooperative pickup and delivery planning for vendors, retailers and even for carriers by the mean of quantitative results. Then this research provides managerial insights for practitioners to enhance the effectiveness of a cooperative approach. Firstly, a carefully assessment of the network geography before choosing for the adoption of a cooperative approach results fundamental. An initial evaluation of cooperation costs and opportunities may lead to the involvement of only those nodes with the highest benefits, rather than extending the cooperative regime to all vendors. The evaluation of the costs associated with transport and delivery activities is indeed crucial as well as the identification of those key suppliers who can cooperate and provide improved delivery services to the retailer. Findings from the analysis highlight the powerful position of the retailer in creating the conditions for more efficient supply chains, properly balanced delivery networks, and sustainable food retailing either by concentrating the orders or by sustaining alliances and cooperation among vendors. However, the obtained results highlight the benefits provided by involving the vendors in the delivery planning. These also confirm the expectations that node density is correlated with the benefits of sharing pick and delivery tours among vendors.

The conceptual research proposed in 3.1.2 depicts the state-of-the-art of the current application of the blockchain technology to the supply chain by the time of the research. This work contributes to enhance the level of knowledge on this topic with respect to industrial initiatives and the research. Moreover, it compares the specific characteristics of the blockchain with the common factors that influence organizations in the decision process on adopting a particular technology. The current debate on the adoption of blockchain technology by supply chain assesses several of these factors Although, some variations are identified. Firstly, it is a shared belief that large organizations are more willing to adopt supply chain technology. However, some blockchain experts believe that to increase the chances of success at larger scale, at first blockchain should be adopted by a few number of players representing a selected sample of key functions and sharing a common goal, i.e. a so-called minimal viable ecosystem. A second variation relates to the environmental uncertainty. If in one hand, many organizations facing high environmental uncertainty are keener on adopt supply chain technologies, on the other hand the lack of knowledge on blockchain long-term effects on supply chain makes a stable environment more suitable for its adoption. For example, a highly competitive environment determining frequent changing of SC actors may affect the decision process on how to allocate the blockchain costs along the supply chain, especially considering the blockchain characteristic of data persistency. Moreover, the trustless paradigm introduced by blockchain scatters the role of the transaction climate among SC actors as well as the debate about decentralization in technologies adoption. Finally, a brief research agenda on the topic is proposed.

The research on the strategic lever of network configuration in 3.2 results in a model for the location allocation problem for refrigerated warehouses. With respect to theory, the novel contribution lies in the fact that the model combines the objective of minimizing the total economic and energy cost within a supply chain network with the problem of stocking and transporting perishable products that are temperature-sensitive and vary for labelled conservation temperature and shelf life extension. The decision on the most suitable location for a refrigerated warehouse is therefore pursued by the model considering, in addition to transportation and establishment costs, the variation in the energy consumption of facilities through a planning horizon, accounted through the total thermal load, which vary location by location and from time unit to time unit according to the global irradiance and the external temperature. Finally, the model selects the most suitable temperature set point for each opened refrigerated warehouse in accordance with the inventory mix and quantifies the potential waste generated by a wrong conservation temperature. The model may support practitioners during the decision making on the location allocation problem of their warehouses. Despite the single case study methodology and the small-scale network analysed, results highlight the pivotal role of the transport in the decision making, although, whether possible, the model choose locations with lower value of the thermal load and particularly of $Q_{i,d,t}^{sol}$. However, since the model results highly rely on the input data, to achieve more general conclusions further case studies should be analyzed.

Chapter 4, which explores the macro area of warehousing for perishable products, includes four research topics that generates specific contributions that are listed in the following. However, it is worth underlining how the obtained results has been achieved by the mean of the initial application of the diagnostic-support framework proposed in 4.2.1.1, which constitutes the main methodological contribution of this chapter. The framework, tailored for complex environment such as 3PL warehouses, not only supports practitioners in the implementation of performance improvement projects but also contributes to setting up bridges between industrial practice and research, enabling the detection of potential gaps in the literature in fulfilling the managers' concerns. Framework phases and tasks are arranged in order to enhance the reliability of proposed logistic solutions by minimizing the level of approximation of data in input. The same approach can be found in the methodological protocol described in 1.4.

The application of the framework phases leads to development of models, tools and methods to support single or multiple tasks. Particularly, 4.2.2 is on task 3 of Phase I, "layout and system monitoring", by exploring the research topic of the temperature mapping. Despite its recognized importance, the literature reveals a lack of contributions about tools and methods for the temperature mapping activity of warehouses. Outcomes of this research lead to a method for the temperature warehouse mapping that highly focuses on data analysis and visualization as strategic tools to supports managers in the decision making on the implementation of possible adjustments, i.e. to the HVAC systems, or to decide on the location of products. Moreover, this research provides two case studies deriving from different real-world instances that highlights how safety is no more the only driver motivating the implementation of an effective temperature mapping activity, but also the products quality.

The research presented in 4.3 derives from the application of the framework task 14, "Prototyping systems/tools development" and results in an original decision-support tool, named Store Simulator, which aids a 3PL manager to decide on the WMS's feature to design in order to meet the client's requirements. This tool implements the adaptive storage assignment and the progressive adaptation and utilizes heuristics, optimization, and simulation techniques to perform the behavior of a specific storage or picking policy and assesses the short and mid-term impacts resulting by the implementation of the associated WMS' features. Fueled by a relational SQL database, inspired to the typical WMS's data architecture, that tracks the main storage data over an observation horizon, the tool provides a couple of GUIs that lead the manager through a data-driven what-if multi-scenario analysis. The tool provides practical contributions in addressing three critical issues affecting the design and customization of WMS in 3PL warehouses. First, it quantifies the short and mid-term impacts resulting by the implementation of a new WMS's feature, leading the manager to identify the proper management scenario that mostly enhances the efficiency, reduces the storage and picking costs, and has the shortest pay-back. Lastly, the DST aids the 3PL in establishing trustworthy added-value relationships with their clients based on increased awareness on the storage processes and higher visibility in the era of Industry 4.0.

4.4 explores the two potential macro areas of intervention in storage systems, warehouse design and warehouse operations, as introduced in Phase IV of the framework. The research presented in 4.4.1 results from task 14, "methods/model design", and leads to a decision-support model to face with layout problems in deep lanes storage. This model builds upon the extant literature by integrating the lane assignment problem, in presence of demand seasonality, with layout issues. The proposed ILP model manages an existing storage system, by implementing an optimal lane assignment policy in a capacitated layout and aids the design from green field according to the storage requirements of the manufacturing system by minimizing the storage space and time inefficiencies. By adopting this model, the warehouse operations' manager can properly schedule and optimize the put-away tasks according to the daily storage space availability. The green field mode identifies a sub-set of recurrent storage configurations (i.e., made by the combination of a lane depth and a storage mode) that meet the daily requirements of storage space. Therefore, the designer might understand in advance the optimal requirements for the storage configuration and manage consequently the design from brown field, i.e., the stage that involves the physical and structural constraints of the building.

The last explored research topic leads to a new policy (see framework task 14) for the storage assignment for temperature-sensitive products, which enables to mutually manage both efficiency and stock safety goals. This policy is based on a bi-objective integer programming model and an original solving algorithm. The policy is tailored for warehouses that handle temperature-sensitive products in presence of high demand and weather seasonality and strong inventory mix turn-over. With respect to theory, this is the first attempt to integrate the attention to product quality and safety, the optimization of the warehouse efficiency, and the management of seasonality in weather and demand in a storage assignment policy. This policy autonomously balances the management of the inventory between the efficiency and stock safety levers. The proposed methodology is also a tool to assess how the existing storage infrastructure (i.e., layout, HVAC system, insulation, facility site and solar exposition) responds to incurring stressing temperatures, which are the associated costs in term of efficiency, and how or when infrastructural investment may be returned.

5.2 FUTURE DEVELOPMENTS

The findings of this dissertation prove that still many challenges exist in the field of the management of the perishable products supply chains. Ample opportunities exist both for further research on the presented research topics and for unexplored research paths.

Focusing on the research topics included in this dissertation, the initial bibliometric analysis (see 2.2) could be further expanded including the comparison of the results obtained through other search engines (such as Scopus), to provide an overarching analysis of the existing literature.

The research on cooperative pickup and delivery planning in retail SC in 3.1.1 could require the development of the proposed methodology according to alternative algorithms, which permits scaling-up the instance and solving large-scale problems within a reasonable time. Moreover, further research could focus on the description of how the proposed model might shift to an inventory-routing problem with shelf-life and product expiration constraints.

According to the conceptual research on blockchain technology in 3.1.2, in addition to the need for regulations and standards, future research can expand the domain of the connection of the physical and digital. Moreover, the temperature monitoring protocol developed through the blockchain, deserves special attention by actors of perishable products supply chain. Furthermore, potential developments should deal with the management of distributed ledger/blockchain platform by multi-actor supply chains and with use of smart contracts in certifications that might provide large value to supply chain finance.

Despite the small-scale case study, the location allocation model for refrigerated warehouses in 3.2.1 gives rise to some initial considerations. However, future developments of this research should necessarily involve the exploration of the model response in case of wider networks and with multiple inventory characterized by very different degradation curves.

Many opportunities exist for the development of tailored phases of the diagnostic support framework proposed in 4.2.1.1 to handle specific categories of products. Specifically, the methodology for the temperature mapping presented in 4.2.2 could be embedded in a framework tailored for perishable products. The framework could be further extended by including the analysis of the links between storage and transportation operations with both procedural and information perspectives.

Future developments of the DST proposed in 4.3.1.2 could focus on extending the boundaries of analysis, and design new tools aimed to assess the impact of higher information availability and visibility on the economic and environmental performance of transport and distribution operations throughout the whole supply chain according to the Internet-of-Things paradigm.

Further research developments are expected for the model in 4.4.1. on the design of a deep lane storage system from brown field, where the facility has already been established, and physical constraints (e.g., walls, facility height) need to be involved. The faced storage layout problem might also be extended and integrated with the design of the layout of the overall manufacturing facility. Furthermore, multi-scenario what-if analysis might explore the relation between the production-demand profiles and the resulting space and time inefficiency to identify integrated production-scheduling and storage management best practices.

Further research developments on the matter of the bi-objective model for the storage assignment in 4.4.2.1 could explore the effect of some key parameters (e.g., inventory turn-over, environment temperature) on the policy and resulting benefits through a sensitivity analysis. Furthermore, the obtained results encourage the validation of this policy with different products and demand profiles and at different latitudes of the warehouse site.

Both the model proposed in 4.4.1. and in 4.4.2 might be embedded as a customized functionality of a warehouse management system (WMS) in order to support practitioners in the daily operations.

In addition to the further exploration of each research topic, ample opportunities exist for future research in the development of integrated model, tools and methods for the simultaneous control of storage and transportation for perishable products supply chains. Moreover, the initial bibliometric analysis that allows visualizing the past research trends, could even support researchers in the identification of potential gaps in the literature. As instance, future research could involve the deepening of the topic of the impact of the information transparency along the supply chain to prevent waste production.

LIST OF APPENDED PAPERS

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