Alma Mater Studiorum – Università di Bologna

DOTTORATO DI RICERCA IN

MECCANICA E SCIENZE AVANZATE DELL'INGEGNERIA

Ciclo XXXIII

Settore Concorsuale: 09/B2

Settore Scientifico Disciplinare: ING-IND/17 - Impianti Industriali Meccanici

Advanced decision-support methods for the design, control, and optimization of perishable products life cycle

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Esame finale anno 2021

Abstract

In the last decades, global food supply chains had to deal with the increasing awareness of the stakeholders and consumers. Their demand for safe, high-quality, and sustainable products posed new challenges for the food industry, requiring novel approaches to deal with perishable items. In order to address these new challenges for food supply chain systems, an integrated approach to design, control, manage, and optimize product life cycle is required.

Therefore, it is essential to introduce new models, methods, and decision-support platforms to design and manage efficient and sustainable logistic operations tailored to perishable products. The research trends on perishable products show a growing interest in the integration of industrial processes and product life cycle sustainability. However, there is a lack of decision-support methods providing integrated and interdisciplinary solutions to optimize the life cycle of perishable products. This thesis aims to fill this gap in the literature by providing novel practice-ready decision-support models and methods to optimize the logistics of food items.

Firstly, this dissertation proposes a comprehensive review of the main peculiarities of perishable products, their quality degradation process, and the primary environmental stresses accelerating this decay. The thesis then focuses on top-down strategies to guide practitioners and managers in optimizing the supply chain system from the strategical to the operational decision level.

The criticality of the environmental conditions (e.g., temperature and humidity) is assessed both for newly constituted and existing supply chains. The former case is analyzed through the classification of products' characteristics and supply chain characteristics. The latter is analyzed by introducing an innovative integrated traceability tool enhancing the control and monitoring of the product life cycle. Based on these criticalities, the dissertation evaluates the main long-term logistics investment strategies (i.e., packaging, containment, and refrigeration solutions) to preserve the quality of food products.

Several models and methods are proposed to optimize the strategical, tactical, and operational logistics decisions to enhance the sustainability of the supply chain system while guaranteeing adequate food preservation from adverse environmental conditions. The innovative models and methods proposed in this dissertation promote a novel approach, namely “climate-driven logistics”. This approach integrates climate conditions and their consequences on the quality decay of products in innovative methods supporting the storage, packaging, and distribution decisions. The results of this ex-ante approach to climate conditions is an enhancement of the sustainability of perishable product life cycle and the increase of safety and quality of the distributed products.

Given the uncertain nature of the environmental stresses affecting the product life cycle, an original stochastic model and solving method are proposed to support practitioners in controlling and optimizing the supply chain systems when facing uncertain scenarios.

The application of the proposed decision-support methods to real case studies proved their effectiveness in increasing the sustainability of the perishable product life cycle. The dissertation also presents an industry application of a global food supply chain system, further demonstrating how the proposed models and tools can be integrated to provide significant savings and sustainability improvements.

Sommario

Negli ultimi decenni, la globalizzazione delle filiere agroalimentari si è dovuta confrontare con una crescente consapevolezza degli stakeholder e dei consumatori. La domanda di prodotti sicuri, di elevata qualità e sostenibili ha posto nuove sfide per l'industria alimentare, che necessita perciò di nuovi strumenti per soddisfare le richieste di maggiore efficienza e sostenibilità. Questi strumenti dovranno fornire una risposta integrata alla progettazione, controllo, gestione e ottimizzazione del ciclo di vita dei prodotti deperibili.

Servono perciò nuovi modelli, metodi e piattaforme di support alle decisioni per guidare la progettazione e l'efficientamento di processi logistici sostenibili che siano pensati appositamente per i prodotti deperibili. L'analisi della letteratura su questi prodotti mostra un interesse crescente verso l'integrazione dei processi industriali e lo sviluppo di una logistica sostenibile. Tuttavia, si registra una mancanza di metodi di supporto alle decisioni integrati e interdisciplinari per l'ottimizzazione del ciclo di vita dei prodotti agroalimentari. Questa tesi si pone l'obiettivo di fornire nuovi metodi e strumenti e di guidarne l'applicazione pratica al fine di ottimizzare la logistica delle filiere agroalimentari.

La tesi propone dapprima un'analisi esaustiva delle principali caratteristiche intrinseche dei prodotti deperibili, del loro processo di decadimento qualitativo e dei principali stress ambientali che ne accelerano il deperimento. In seguito, la dissertazione si concentra sullo sviluppo di strategie top-down per supportare manager e professionisti del settore nell'ottimizzazione delle filiere dal livello strategico fino a quello operativo.

La criticità delle condizioni ambientali, come temperatura e umidità, viene valutata sia per nuove filiere che per quelle già esistenti. Per le prime, la tesi propone una valutazione basata sulla classificazione delle caratteristiche dei prodotti e della filiera. Per le seconde, invece, viene proposto una piattaforma innovativa per la tracciabilità integrata con l'obiettivo migliorare il controllo e il monitoraggio del ciclo di vita dei prodotti. Successivamente, sulla base del livello di criticità stimato, vengono valutate le principali decisioni di investimento a lungo termine per preservare la qualità dei prodotti deperibili: packaging e soluzioni per isolare il prodotto dall'ambiente esterno e sistemi di refrigerazione.

A seguire, vengono proposti diversi modelli e metodi per l'ottimizzazione strategica, tattica e operativa della logistica con l'obiettivo di incrementare la sostenibilità della filiera, garantendo al contempo la consegna di prodotti di elevata qualità. I modelli e algoritmi innovativi proposti in questa tesi incentivano l'adozione di un approccio innovativo: la logistica "climate-driven". Questo approccio

integra le condizioni ambientali e i loro effetti sul decadimento qualitativo dei prodotti all'interno di nuovi metodi di supporto alle decisioni di stoccaggio, packaging e distribuzione.

Data l'incertezza che caratterizza intrinsecamente queste fonti di stress ambientale per i prodotti deperibili, si introducono un modello e un metodo di risoluzione di natura stocastica. L'obiettivo di questi nuovi strumenti è aiutare i professionisti nel controllo ed ottimizzazione di sistemi logistici in contesti di elevata incertezza.

L'applicazione dei metodi proposti a casi applicativi provenienti da realtà industriali di filiere nazionali e internazionali dimostrano la loro efficacia nell'incrementare la sostenibilità dei prodotti deperibili in ogni fase del loro ciclo vita. La dissertazione introduce inoltre il caso di studio di una complessa filiera agroalimentare globale per dimostrare come i modelli e strumenti proposti possano essere integrati per gestire ogni aspetto della distribuzione di questi prodotti ed ottenere un risparmio e una riduzione degli impatti ambientali significativi.

Advanced decision-support methods for the design, control, and optimization of perishable products life cycle

by

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Anno 2021

Table of contents

Table of figures

Table of tables

1. Introduction

The design, management, control, and optimization of the Product Life Cycle (PLC) is an integrated approach to manage products, information, resources, and industrial processes, starting with the collection of data about products in all the stages of the Supply Chain System (SCS). Based on data, the SCS is classified and analyzed to support the development of integrated models, tools, and strategies to optimize the supply chain. The application of these methodologies is examined to monitor the outcomes of this improvement procedure. The reiteration of the analysis, optimization, and monitoring steps lead to continuous improvements in the management of PLC, as shown in figure 1.

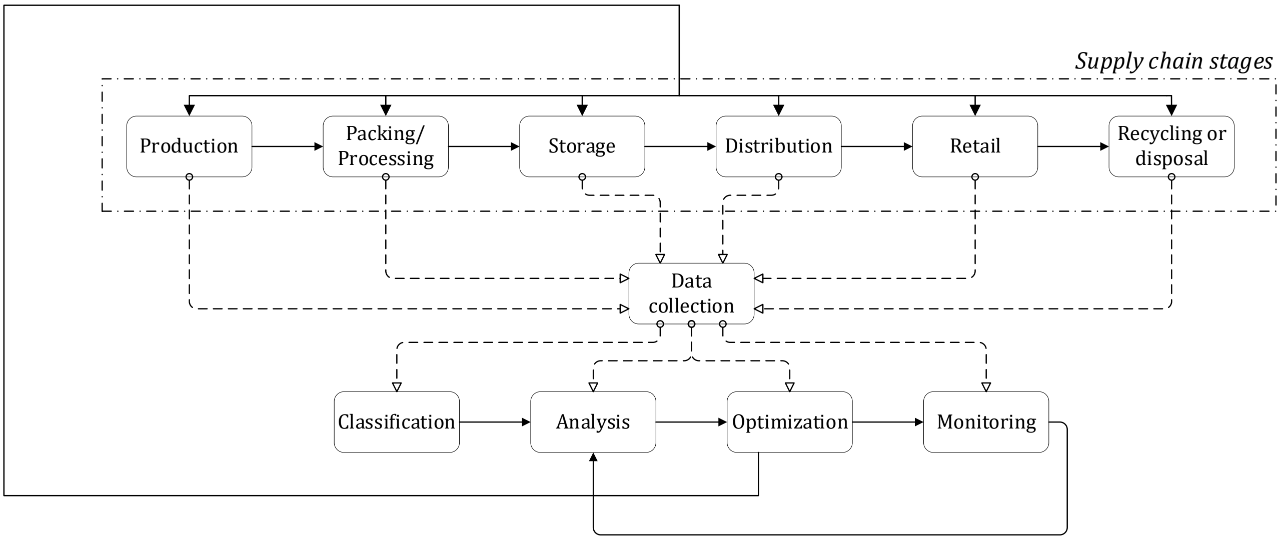

Figure 1. Framework for product life cycle management.

There are two essential prerequisites to be satisfied to manage PLC effectively.

The first prerequisite for PLC optimization is the cooperation between all the stakeholders of the supply chain. Stakeholders represent all the companies, entities, and people whose support permits the existence of the supply chain. These must share information to have a clear and complete view of the product at each stage of the network (Jiang, Xu & Cai, 2012). The availability of complete and updated information on the supply chain is a crucial enabler of an integrated life cycle approach (Burgess et al., 2006). It permits the adoption of a Supply Chain Management (SCM) approach. SCM aims to design, manage, and control integrated supply chains, making decisions with an integrated approach that considers the consequences of each choice on the different actors of the network. SCM leads to a win-

win approach where coordinated decisions increase the efficiency of the system, and the profits are shared among supply chain actors to encourage these cooperative approaches.

Nowadays, the lack of cooperation is still a frequent problem preventing the collection, sharing, and exploit of data and the development of integrated management strategy (Hsiao & Huang, 2016). Different actors belonging to the same supply chain are still reluctant to share information as they exploit information asymmetry to increase their bargaining power and their profit share (Afzal et al., 2008). However, several studies proved that cooperation is essential to develop and apply integrated management approaches that increase the efficiency of the supply chain and reduce the total cost and environmental impact (Abed et al., 2013; Li & Lin, 2006; Klaas-Wissing & Albers, 2010). Whenever different actors are reluctant to share information, cooperation can be achieved by fairly sharing the profits that the increased efficiency of the supply chain generates when information is shared (Stellingwerf et al., 2019; Pan, 2010).

Another key prerequisite for PLC optimization is the adoption of an interdisciplinary approach. The development of integrated solutions requires an in-depth knowledge of the product and the processes (e.g., manufacturing and logistics activities) transforming it. As the design, control, and optimization of PLC affect every aspect of the industrial processes, from production to recycling or disposal, it is essential to integrate different points of view on the decision-making process to evaluate the consequences of each decision on the whole PLC.

These prerequisites are vital for perishable products. Perishables experience a progressive decay of their utility or value. This decay is due to obsolescence or physical, biochemical, and physiological reactions affecting the product (Amorim et al., 2011). Some examples of perishable items are pharmaceuticals, chemicals, dairy products, or fashion.

Food products represent typical examples of perishable items. A short shelf life characterizes food due to the proliferation of microorganisms that progressively reduce their quality, causing spoilage (Stoecker, 1998). Food is the second-largest manufacturing sector in Europe with a value of € 175.6 billion in 2001, according to Eurostat (2004). As this sector is less vulnerable to economic fluctuations, it remains a crucial sector also during a crisis, although this also means it also experiences modest growth than other sectors.

The complexity of food life cycle management is due to several peculiarities of this sector. Indeed, the food sector is extremely fragmented, with hundreds of thousands of operating companies (Accorsi et al., 2018). Furthermore, in modern supply chains, the number of stages of the network and the actors involved in food processing and distribution are increasing and distributing globally. The distance between the actors of the same supply chain, the differences in their cultures and languages, the erosion of the profits due to the number of nodes involved, and the low margins of many food products make cooperation even harder in this sector (Hsiao & Huang, 2016).

Food Supply Chain System (FSCS) represents the supply chains of food products that are characterized by complex interactions among harvesters, producers, processors, packagers, distributors, and retailers of food products. This system is characterized by a myriad of small-sized companies, especially in some stages such as harvesting, retailers, cooperating with bigger enterprises to compete in global markets. Most FSCSs sell products with low margins that are considerably affected by the costs of logistics, which therefore represent a crucial aspect of increasing the value of the products. A typical example of these supply chains is the Ecuadorian banana sold in Europe through a global supply chain system with significant carbon emissions (Roibás et al., 2016).

Interdisciplinarity plays a vital role in managing the food life cycle. Along with the multiple aspects to be considered to optimize the PLC, from logistics to production, maintenance, information technology, and data analysis, food also requires some specific knowledge for the type of product to be processed. The reduction of food losses requires considering their characteristics, such as the seasonality and the ideal storage conditions. Therefore it is essential to also consider knowledge in other disciplines, such as food science and technology, to avoid that the best decision according to a partial understanding of the product can cause unexpected adverse effects determining a decrease in the value of the product itself.

1.1 The role of logistics in perishables life cycle

Data about losses prove the importance of novel integrated and interdisciplinary tools for Perishable Products Life Cycle Management (PPLCM). Currently, up to 30% of all produced food – corresponding to 1.3 billion tons of food per year – is lost throughout the supply chain before it reaches the consumers, implying substantial economic, environmental, and ethical issues (Kefalidou, 2016). Food loss happens when the quality of food decreases below a tolerance level, becoming unfit for human consumption due to loss of flavor and changes in textures and taste, or become even harmful for human health. An improper management strategy of perishables that do not consider the peculiarities of the specific product and its optimal storage conditions accelerate its quality decay and increases losses. Therefore, preservation of food requires analyzing and understanding the whole supply chain and developing an integrated approach considering growing, harvesting, processing, packaging, storage, and distribution and tailored on the specific properties and characteristics of the product (Rahman, 2007). The knowledge of the specific product and FSCS is essential as the properties that must be preserved depends on the particular application context. Indeed, consumers can appreciate a property when it belongs to one specific product but not to another one (e.g., consumers appreciate crust formation for breakfast cereal ingredients but not for fresh food). Furthermore, the same environmental condition can be favorable for one product and not for another (e.g., higher temperatures are favorable for exotic fruits but harmful for cherries).

Figure 2 shows the example of the quality decay of broccoli shipped along an Italian route from Naples to Perugia in August. Data characterizing the quality decay of broccolis refers to Jacobsson et al. (2004), while the distribution path refers to an existing supply chain distributing food and vegetables in Italy. Whether the vehicle is not refrigerated, broccolis experience about 50% of quality decay in just 8 hours, while with refrigeration, the quality decay for the same route is about 5%. This example shows the importance of proper storage conditions of products considering their intrinsic characteristics, such as their ideal storage conditions.

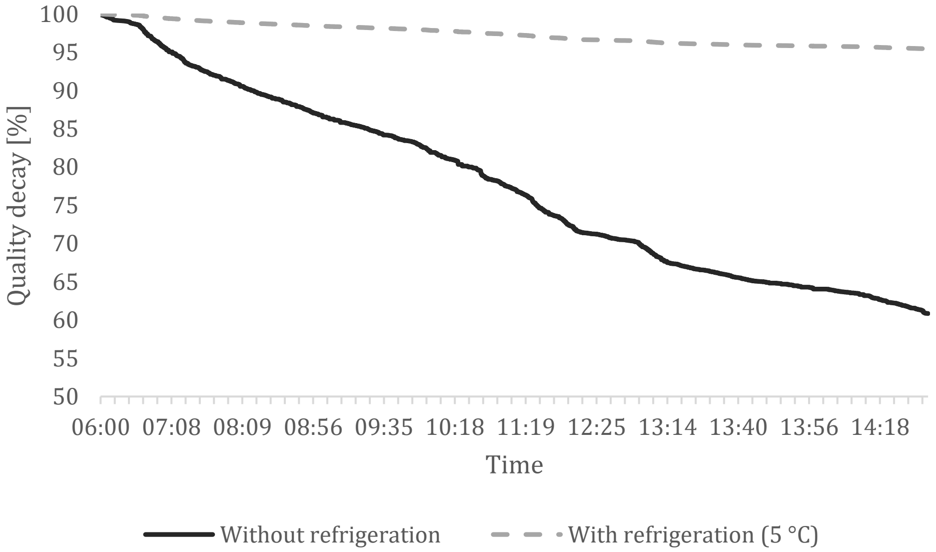

Figure 2. Product quality decay.

While every product has a typical life cycle with its own duration determined by the specific characteristics of the product itself, the example of figure 2 clearly shows how some external causes, namely stresses, can alter the life cycle. Stresses are environmental factors (e.g., temperature, humidity, vibrations) affecting the products throughout every stage of the supply chain and shortening its life cycle, with direct consequences on the product's quality and accelerating its end-of-life. These stresses are typical of the environment surrounding the item and affect it in every phase of the life cycle. Whilst stresses are unavoidable, an effective Product Life Cycle Management (PLM) strategy should mitigate the effects of harmful stresses by modifying the environmental conditions in the microenvironment surrounding the product or isolating the product with a proper packaging solution (Piergiovanni & Limbo, 2016).

When the desired conditions of the microenvironment are far from the optimal ones, the solutions to reduce the negative effect of adverse environmental conditions can be very expensive both economically and environmentally (e.g., for carbon emission to refrigerate the storage rooms). Therefore, it is necessary to evaluate the effect of such conditions on the product. The same stress can determine a completely different impact on the item. The intrinsic characteristics of the product and the ideal storage conditions should be known to find out the more sustainable solutions. For some mechanical items, the manufacturer can provide information on the ideal storage conditions of the product (e.g., an interval of temperatures maximizing the PLC). However, for food, the ideal conditions have been studied for a long time by food scientists who provided optimal ranges for several parameters, such as temperature, humidity, water activity, and so on (Rahman, 2007; Caccioni, 2005).

Logistics plays an essential role in preventing adverse conditions to accelerate PLC and causing losses (Thyberg & Tonjes, 2016). By managing the material and information flows within the supply chain, logistics managers can protect products from external stresses. To achieve this result, they need support-decision tools to assess alternatives to identify the solutions that best fit the specific product based on its characteristics and on the stresses it experiences, for example, by adopting the best package and choosing the best route and vehicle for deliveries.

Logistics is a critical component of the final cost of products as it constitutes a considerable share of the final cost that varies between 12% for electronics up to 31% for food in Italy (Ministero delle Politiche Agricole Alimentari e Forestali, 2014). Its importance increases along with the distances among nodes in global supply chains. Although logistics play such a crucial role in perishable product supply chains (Amorim et al., 2011), most of the approaches in literature do not consider the peculiarities of such products and the stresses they experience to provide tailored solutions to manage PLC. A large body of the literature on perishable products supply chain provides general-purpose tools and models, often focused only on inventory management or distribution, separately.

Most supply chain decisions are strictly interdependent. However, only a few approaches integrate problems and issues of different supply chain stages while considering the peculiarities of perishable products. This lack of integrated and interdisciplinary approaches characterizes both support decision framework for strategical decisions and integrated models and tools to manage operatively the PLC within an existing supply chain.

1.2 Aim of the thesis

This thesis aims to provide integrated and interdisciplinary approaches, models, and tools to support the design, control, and optimization of the perishable product life cycle. There are few attempts for PPLCM with an integrated approach. Usually, researchers focus on single stages of the supply chain. However, the sum of the optimization of single supply chain processes rarely conducts to the overall optimization of the system. Furthermore, literature often focuses on the analysis of FCSC from a single perspective (e.g., logistics, food science, information technology), rarely applying an interdisciplinary approach. Finally, many logistics models and tools are not tailored to the peculiarities of perishable products. Hence, their objective is to optimize variables that do not take into account the specific requirements of such products. For example, the minimization of the total costs that do not include the ones for product losses could increase the margin in the distribution or storage phase. Still, it could determine an unacceptable quality decay of the product, vanishing all the expected margins when trying to sell it to the clients.

As the knowledge of the application context is essential to create effective logistics tools for PLM, the first sections provide some classification methods for products and supply chain systems. Then, based on an analysis of supply chains, the next sections provide several models and tools to support decision-making with an integrated approach. As the stresses affecting the PLC and determining the optimal solutions for supply chain management are uncertain and cannot always be forecasted, some tools for stochastic management of products are provided, too. Finally, the proposed methods and tools are applied to a case study to prove the effectiveness in the real context of a food supply chain.

The provided methods and tools support practitioners and managers from the initial analysis of the AS-IS situation to the optimization and monitoring of the TO-BE solution. They aim to represent a practical handbook for managing the supply chain system with an integrated approach. Furthermore, these tools highlight the importance of a comprehensive and interdisciplinary approach for PLM for students and researchers, addressing some existing gaps in the literature and showing potential future developments.

An innovative logistics strategy, ‘climate-driven logistics’, is proposed as a new approach to the optimization of FSCS. Climate-driven logistics increases the sustainability of the supply chain by scheduling logistics operations, choosing packaging and vehicle alternatives, and finding the best distribution route also based on climate conditions. An optimization considering climate conditions guarantees the delivery of high-quality products reducing unnecessary preserving solutions (e.g., avoiding expensive packaging solutions and reducing the use of refrigeration) by exploiting the most favorable distribution routes and reducing the exposure to critical environmental stresses.

1.3 Thesis outline

This section presents an outline of the thesis. The following chapters follow a framework for PPLCM, shown in figure 3. This framework aims to provide practical guidelines to manage the supply chain with an integrated approach, either for already existing networks or for new ones. The proposed models, methods, and tools illustrated in the next sections have been applied to practical cases to show their effectiveness in the real world.

The thesis adopts a typical supply chain system with four stages. This configuration does not compromise the generalization of the proposed approaches as additional stages can be added in each of the proposed methods and treated similarly to the other stages.

The four stages of the supply chain are the following:

- Suppliers. These nodes provide the products to the following nodes of the network. The products supplied by such nodes can be either raw materials, semifinished or finished products.
- Processing nodes. They process food, prepare finished products or meals, and pack them for their distribution. For networks selling unprocessed materials, which is frequent for the distribution of fruits and vegetables, the processing nodes could only work as packing nodes. Sometimes, they also include storage rooms.
- Storage nodes. They collect, store, and consolidate products before selling. Such nodes can be either warehouses or cross-docks.

  Warehouses have racks where products are stored for medium or long terms and then collected either as unit loads or by pickers.

  Cross-docks are nodes intended for fast-moving items that do not need storage as the delivery towards clients occurs within 24 hours from their arrival at the node. This solution does not contain racks as products are stored for a short time, and racks would not be efficient for these nodes usually intended just for consolidation.
- Clients. They could be stores selling the products to the final clients or other companies belonging to other supply chains, further processing and distributing products until reaching the final consumer.

Among these different stages, there is the distribution phase that is also part of the processes studied in this thesis and included in the proposed models and tools.

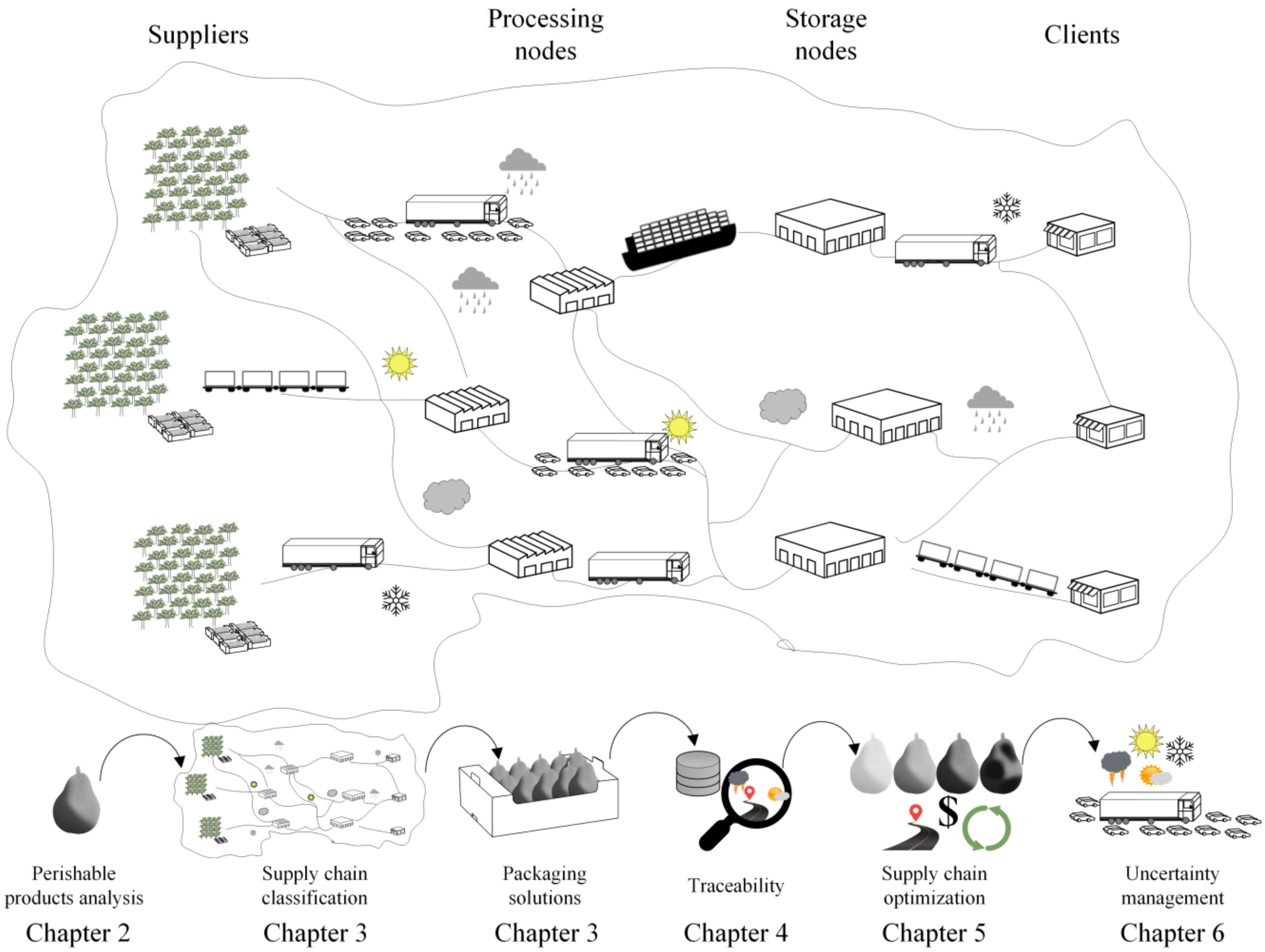

Figure 3. Thesis outline.

The remainder of this manuscript is organized in the following chapters, according to the framework presented in figure 3.

- Chapter 2 introduces some peculiarities of perishable products. It resumes the main intrinsic characteristics of these products that are useful to evaluate the effect of external stresses on the product life cycle. Indeed, each product has some ranges of ideal storage conditions to maximize its life cycle duration. Furthermore, different products experience different consequences when faced with adverse environmental conditions.

  Based on such characteristics, similar products are grouped as a starting point to classify products and supply chains and suggest the best strategy to optimize the life cycle. Based on these characteristics and response to stresses, the items can be associated with a criticality score that will guide practitioners in defining the best management strategy for them.

- Chapter 3 introduces a classification framework for supply chains that integrates the one based on products. These classifications aim to provide a two-dimensional criticality map to support practitioners and managers in evaluating how critical the stresses are for their products. The criticality score highlights the necessity to invest in infrastructures to avoid product losses and increase the sustainability of their supply chain.
  When the criticality is lower, logistics managers can reduce the investments in infrastructures, as a proper packaging solution can protect products adequately. Therefore, this chapter also analyses the choice of packaging alternatives. It introduces the main properties of packaging and the effects on food preservation. As packages create a protected microenvironment mitigating the negative impact of environmental stresses, this chapter also analyzes how the right package paired with a perishable product can lower its risk and avoid expensive investments in infrastructures while preserving product' quality.

- From chapter 4, the focus switches from new supply chains to the analysis and the development of methods and tools for existing supply chains. The aim of this chapter is the analysis of the AS-IS situation with the development of integrated tools for product traceability. A cooperative approach among supply chain actors in an SCM perspective is essential for this step of the analysis. However, this chapter also introduces new methods to enhance data integration even if the cooperation and current integration between the databases of the different actors is still not complete.
  Traceability of products throughout their life cycle allows practitioners to highlight the critical stages of an existing supply chain to mitigate the highest risks for the product. For an existing supply chain, there are not the same chances to design the best solutions in advance with a strategic perspective, as the previous chapters suggest. However, traceability can point out the exact steps in which the environmental stresses threaten PLC the most and take action to mitigate these risks.
  The same tools and methods proposed in this chapter to analyze the AS-IS situation also provides monitoring information for the TO-BE situation. The efficacy of the solutions applied to mitigate the risks in the most critical phases of the supply chain can be assessed with the same tools. Monitoring the implementation of PLC solutions also allows practitioners to continuously improve the supply chain system and enhance PLM according to the framework proposed in figure 1.

- Chapter 5 proposes several methods, models, and tools for the optimization of PLC. The previous chapters focused on the analysis of products and supply chains. In contrast, from this moment on, the dissertation will focus on practical tools to manage the network in the next steps. After taking major strategic decisions according to the identified criticalities of the supply chain system, these tools support making shorter-term decisions about the product life cycle.
  This chapter proposes some tools to evaluate where to locate new nodes of the network, how to manage flows of materials and allocate them to the available nodes, how to choose the best transportation mode and how to manage operatively an existing supply chain of perishable products.
  This chapter aims to provide logistics managers with a set of practical tools to manage their supply chain in an integrated manner. These tools follow the product in its whole life cycle to guarantee the delivery of high-quality goods to the clients and enhancing the sustainability of the supply chain at the same time.

- Chapter 6 introduces the topic of uncertainty. The environmental stresses affecting PLC are not deterministic. Temperature, for example, cannot always be forecasted accurately. This uncertainty has consequences on the decision-making process to manage the supply chain. It can modify the expected stresses that the product experience in its life cycle and can make it challenging to provide a schedule to manage the operative decision level for the supply chain. Therefore, this chapter presents methods, tools, and algorithms to manage the supply chain and mitigate the risks originating from stochastic processes affecting PLC.

- Chapter 7 illustrates a real case study of a global supply chain of perishable products. The methods, tools, and algorithms introduced in the previous sections have been applied to this case study to prove the effectiveness of the proposed methodology to design, control, and optimize PLC.
  Through the sequence of models and tools proposed in this dissertation, managers can optimize their PLC with an integrated approach from the strategic to the operational decisional level.

- Chapter 8 concludes the manuscript by highlighting the main steps of the proposed methodology, the models and tools for PLM, and the most important results achieved with the application of the proposed approach.
  The chapter illustrates the main benefit of the application of an integrated and interdisciplinary approach for PLM, resumes general tips and managerial insights for the

application of the proposed methodology, and highlights the actors that can benefit from the application of these tools in their decisional process.

1.4 Scope and demarcations

Managing the entire PLC requires making several decisions concerning all supply chain stages and several research areas.

These decisions are integrated into an SCM approach, as the activities in a single node of the network affect the optimal strategies in the other stages. For example, different harvesting decisions determine different varieties and quantity of products available, the entity of flows to be handled, purchases of missing products from an external market, the right package to adopt, the vehicles for distribution, and so on.

Whilst the breadth of decisions for PLM imposes some demarcations, these interdependencies among the decisions in different stages of the supply chain require an interdisciplinary and integrated approach also when focusing only on some of the supply chain stages.

In particular, this thesis has its main focus on logistics for perishable products. The tools illustrated in the next chapters will provide support for PLM from production, after the harvesting phase, to the final delivery to clients, without supporting the decision-making process within the stores.

According to their time horizons, the decisions supported by the tool provided in this dissertation are:

- Strategic decisions. These are long-term decisions with a time horizon going beyond the year. They will affect the future development of the supply chain, such as the design of the supply chain network. Some examples of strategic decisions are choosing the best location for a new warehouse, how to source raw materials, and the purchase of a fleet of vehicles.
- Tactical decisions have a medium-term horizon concerning several months and up to a year. Tactical decisions do not need to be continuously reviewed as they provide solutions for seasonal problems. Some examples of such decisions are: the allocation of material flows between the storage nodes, the definition of fixed delivery routes.
- Operational decisions are short-term, daily reviewed decisions. The level of detail of these decisions can concern a single product. Within the frame of the strategic and tactical decisions taken at a higher decisional level, the operational decisions determine how to handle each perishable item, and their effect on PLC is directly observable. Typical operational decisions

are: which node provides products to the next stages of the supply chain for a specific order, how to aggregate products in loads to be handled by a single vehicle, the optimal delivery route, the schedule of operators, and vehicles' daily activities.

Finally, it is important to remark on the geographical scope of this dissertation. Although many case studies included in this thesis come from Italian companies or at least are focused on their Italian distribution centers, many of them have global supply chains, with suppliers and clients distributed all over the world. It is worth noting that several approaches and tools proposed in this dissertation are particularly suitable for global supply chains, which currently represent an increasing share of the food supply chain throughout the globe. However, all the approaches presented in this thesis can also be applied to a local context, although some of the contributions included in models and tools could become negligible in local networks (e.g., temperature variations and product losses during distribution).

1.5 Methodology

The methodology utilized in this dissertation includes different approaches based on the specific research topic. The whole structure of this thesis is intended to follow a structural path guiding researchers, practitioners, and managers in PLC design and optimization from scratch, according to the framework illustrated in figure 3. Therefore, some methods and tools that will be presented subsequently in this dissertation can be identified. However, some of them will be adopted in more than one chapter throughout the thesis.

A critical pillar that will conduct the reader through all the following chapters is data collection. Data are the starting point of each of the proposed methods and tools. Data are collected at each stage of the supply chain system to reach the desired integration for PLM. Structured data architecture will be essential to gather and organize all the data to feed the analysis and tools proposed in this dissertation. In particular, relational SQL DBs are adopted to organize and collect input data, feed processing tools, and store the outcomes of the proposed approaches. This extensive data collection is the fundamental of a PLM approach. It will allow practitioners to assess the effectiveness of the proposed methodology and feed further analysis in a continuous improvement perspective.

The main software used for the data collection procedures in this thesis will be Microsoft Access and Microsoft SQL Server. Data collected and used in the following sections come from on-field activities whenever it is possible. They have been collected from several industries collaborating with the Department of Industrial Engineering of the University of Bologna during the development of research activities with real applications.

When the primary data is not available, the required information is extracted from published papers in literature and well-known public DBs (e.g., World bank data).

Another critical pillar used to process data and implement the proposed solutions is developing computer applications with the .NET C# programming language. Code written within the Microsoft Visual Studio programming environment has been developed to convert algorithms in practical, ready-to-use tools for practitioners to analyze, optimize, and monitor PLC.

Furthermore, data visualization plays a crucial role in the proposed framework as it is useful to provide practical insights for PLM, track and trace the product in every stage of the supply chain, monitor the application of the suggested strategies, and evaluate the outcomes of the proposed methodology. The supply chain operating conditions are analyzed with a combination of Graphic Users Interfaces (GUIs) coded in C# and data visualization techniques developed with Microsoft Excel, MATLAB, Power BI, and other existing tools. Charts and interfaces provide fast, user-friendly, and informative graphics to highlight criticalities, compare the AS-IS and TO-BE scenarios and evaluate the effectiveness of the proposed tools.

In the first chapters, the methodology involves the use of classifications for products and supply chains based on their characteristics. Data collected for this purpose are analyzed with clustering techniques to group together similar products that should be managed with the same approaches.

Once these techniques classified products and identified criticalities, several mathematical models have been implemented to support the decision-making process and provide the best solution to manage each of the modeled stages of the supply chain.

Several Mixed-Integer Linear Programming (MILP) models are introduced in chapter 5 to optimize PLC. The models have been implemented in the AMPL mathematical language and optimized with commercial solvers, such as Gurobi. These models have frequently been included in software application gathering the input data, allowing users to manipulate them to perform what-if analysis and storing and visualizing results with GUIs to facilitate the interpretation of their outcomes.

In Chapter 6, stochastic programming provides optimization methods for uncertain context. Uncertainty is typical of the unexpected stresses affecting the products, so traditional MILP models could not provide the desired outcomes as they require approximations of stochastic parameters with deterministic ones.

Finally, given the complexity of some of the proposed models, some heuristics and metaheuristics approaches are introduced to solve problems of greater sizes typical of real-world instances.

Figure 4 depicts the proposed framework for the design, control, and optimization of PLC and the methodology.

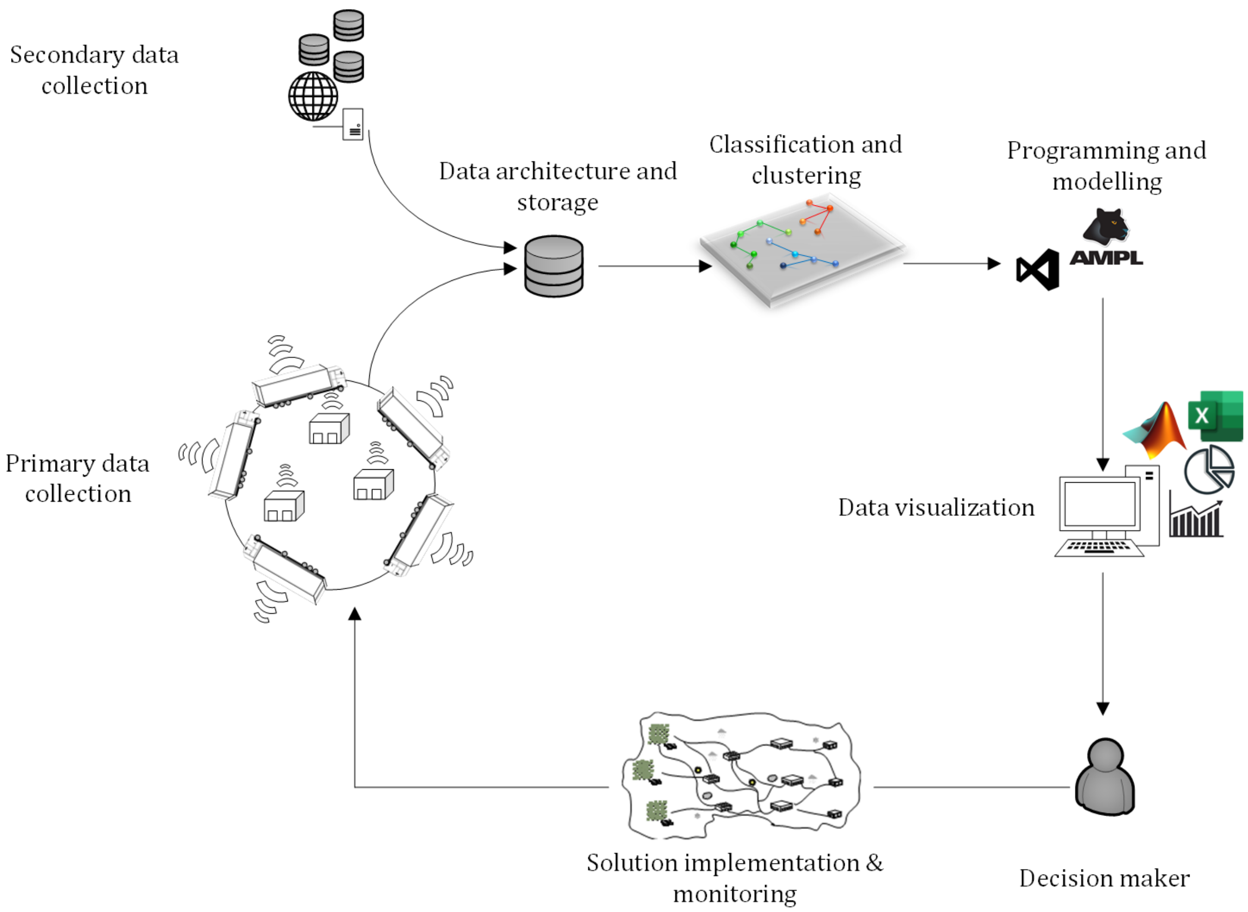

Figure 4. Methodology framework.

1.6 Pillars of assessment

This section introduces the main pillars of assessment that will be adopted in the following chapters as evaluation metrics to quantify the effectiveness of the proposed tools.

Choosing a metric to evaluate the entire PLC is a complicated task. It requires simple indicators able to resume in a nutshell several activities that are very different from each other. The chosen metrics should cumulate the effect of all the processes the product goes through, from the production to processing, packaging, storage, distribution, sale. These assessment pillars should consider the effort PLC requires to the supply chain system (machinery power, maintenance, vehicle fuel consumption, and so on).

The indicators adopted in the following chapters refer to the three dimensions of sustainability:

- Economic sustainability, such as costs, profits, energy consumption, fuel consumption.

- Environmental sustainability, such as CO_2 equivalent emissions, water consumption, plastic and carton wastes, number of vehicles' trips, traveled distance.
- Social sustainability, such as food losses, customers satisfaction.

Along with these indicators, it is also important to individuate some product-specific metrics referring to quality. As it could be tough to find a simple metric to measure the quality of perishable products, the following chapters will frequently adopt the remaining shelf life as a product-specific KPI. Shelf life measures the time interval for which the perishable item remains fit for consumption or saleable according to clients, which adopts a series of objective and subjective quality control to determine whether the product fits consumers' expectations or not.

1.7 Nomenclature

This section introduces the nomenclature adopted throughout the dissertation.

Acronym	**Definition**
3PL	Third-Party Logistics
DB	Database
DC	Distribution Center
DST	Decision Support System
E-R	Entity Relationship
ERP	Enterprise Resource Planning
FSCS	Food Supply Chain System
GHG	Greenhouse Gases
GIS	Geographic Information System
GUI	Graphic-user Interface
HACCP	Hazard Analysis of Critical Control Points
ILP	Integer Linear Programming Model
IoT	Internet of Things
ISO	International Organization for Standardization
KPI	Key Performance Indicator
LAP	Location-Allocation Problem
LCA	Life Cycle Assessment
MAP	Modified Atmosphere Packaging
MILP	Mixed-Integer Linear Programming Model

PLC	Product Life cycle
PP	Polypropylene
PP-PLC	Perishable Product Life Cycle
PPLCM	Perishable Product Life Cycle Management
RFID	Radio-Frequency Identification
SC	Supply Chain
SCM	Supply Chain Management
SCS	Supply Chain System
SL	Shelf life
SMILP	Stochastic Mixed-Integer Linear Programming
SGA-ST	Stochastic Genetic Algorithm implementing Scenario Tree
TW	Time window
VRP	Vehicle Routing Problem

1.8 Chapter's highlights

- The food sector is the second-largest manufacturing sector in Europe with a value-added of about € 200 billion per year.
- Food is a perishable item and experiences a decay of quality with time. Up to 30% of the whole produced food is wasted each year.
- Product life cycle optimization requires an integrated approach based on cooperation among the stakeholders of the supply chain system and an interdisciplinary approach.
- This thesis aims to fill some extant gaps in the literature by providing integrated and interdisciplinary tools tailored to perishable products. It also introduces a new logistic strategy, namely climate-driven logistics, to improve the sustainability of FSCSs.
- The optimization of the product life cycle can be achieved by preserving product quality from environmental stresses, such as temperature. As these stresses are uncertain, this thesis also provides stochastic tools to face such uncertainties.

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2. Perishable products classification

The content of this chapter is based on the research presented in the following paper:

Gallo, A., Accorsi, R., Baruffaldi, G., Ferrari, E., Manzini, R. (2018). ***A taxonomy framework to manage perishable products in cold chains****. XXIII Summer School "Francesco Turco", Palermo, Italy, 12 – 14 September 2018.*

Perishable products have a limited lifetime, after which they are considered unsuitable for consumption (Paam et al., 2016). The quality decay affecting such products is due to a combination of mechanical, physical, chemical, and biological processes happening during the life cycle of these products. Mostly, these reactions are due to the proliferation of bacteria, yeasts, molds, and viruses populating the environment around products (Stoecker, 1998).

2.1 The proliferation of microorganisms in food

The proliferation of these microorganisms affecting perishable products is strictly related to environmental conditions that enable their lives and foster their diffusion. The main cause accelerating the proliferation of microorganisms is temperature, but several other factors are also to be monitored to avoid losses. When the environmental conditions are favorable for these microorganisms, they start growing by following three typical phases.

The first is the lag phase, and its characterized by slow or no-growth. To avoid food losses and guarantee a good quality level of the delivered products, it is essential to extend this phase as long as possible. Indeed, during the lag phase, the product experiences neither severe quality decay nor visible or noticeable changes in the appearance or taste. During this period, microorganisms try to adapt to the environment, looking for favorable conditions allowing them to proliferate, so it is important to create a microenvironment around the product with adverse conditions for such pathogens so that they cannot adapt to the environment and cause damages to the product.

If the environmental conditions are favorable for microorganisms, then the lag phase is followed by exponential growth. In this phase, the pathogens can more than double their number at every hour, so this phase usually determines product losses. Unless this deterioration is rapidly noticed and handled, microorganisms lead to changes in taste, texture, slime production. If such deterioration continues, then the product reaches the death phase.

Although food loss and food waste are usually used interchangeably to indicate spoilage, there is an important difference between them. Food losses indicate the cases in which the death phase occurs before reaching the consumer. Poor management strategy, errors, and irregularities in the processes (i.e., in the production, harvesting, processing/manufacturing, storage, transportation, and sale phase) are responsible for food losses. Conversely, food wastes represent the cases when the death phase occurs when the consumer already owns the product (i.e., households or caterers). Therefore, it is due to its poor storage and inventory management (Bilska et al., 2016).

As the main focus of this dissertation is on industrial processes and the scope of this thesis includes up to the arrival at the final consumers, we will focus on the reduction of food losses, more than wastes.

Product losses affect all three dimensions of sustainability of the food supply chains. The missing profits for unsold products and the costs resulting from the losses (i.e., for harvesting, processing, packing, storage, and distribution phases already performed), as well as the costs for waste management (Kim et al., 2011), influence the economic sustainability of the supply chain (1). Furthermore, the energy consumption and the carbon emissions due to the refrigeration (Gallo et al., 2017) and the exploitation of land and resources for harvesting (Vandermeersch et al., 2014) impact on the environmental sustainability of the supply chain (2). Finally, social sustainability (3) is compromised by food shortage due also to product losses, especially in developing countries, and food waste, especially in developed countries (Kefalidou, 2016).

The proliferation of microorganisms causing the deterioration of perishable items represents the main difference between supply chains of perishable products and all the other supply chains. For perishables, a continuous and significant change in their quality characterizes products. This decay could determine a serious deterioration of their taste and appearance before products reach the points of consumption (Ahumada & Villalobos, 2009).

2.2 Quality decay formulations

Several researchers studied the kinetics of natural processes determining the proliferation of bacterias that causes the quality decay of perishable products. Many mathematical formulations describing how these processes evolve with time have been proposed. Among the others, Arrhenius provided a well-known equation to describe the kinetics of such deterioration processes. The Arrhenius equation (Eq. 2.1) is an empirical collision model that clearly states the non-linear relation existing between the environmental temperature in the product's microenvironment and the acceleration of its quality decay process (Cisse et al., 2009).

$$k = k_{\infty} e^{-\frac{E_a}{RT}} \tag{2.1}$$

where:

- k_{∞} is the pre-exponential factor expressed in $1/s$. It corresponds to the value of k at $T = \infty$.
- T is the temperature expressed in degrees Kelvin. This value depends on the microenvironmental conditions where the biochemical process is happening. Therefore, logistics decisions can alter this value and slow down the deterioration process.
- E_a is the activation energy of the biochemical process, expressed in J/mol. The value of this parameter depends on the specific reaction whose kinetic is analyzed.
- R is the ideal Boltzmann gas constant equal to $8.31 \frac{J}{mol\ K}$.

This equation clearly shows how the deterioration process of a perishable item depends on a combination of intrinsic characteristics of the product itself (i.e., the activation energy of the processes causing the quality decay of the specific product) and the environmental stresses it experience (i.e., the environmental temperature).

Feeding the input of the Arrhenius equation is sometimes a complex task due to the specificity of the quality decay processes affecting the product's quality. However, researchers proposed some alternative equations to overcome this issue. In particular, the pre-exponential factor is unknown for many biochemical processes. When practitioners can not estimate the value of this parameter, they can apply other equations based on the one provided by Arrhenius.

Connors et al. (1986) provided the following set of equations to overcome the problem of the unknown pre-exponential factor. This equation can be easily fed by experimentally estimate the shelf life of the analyzed product at a fixed micro-environmental temperature, which can be achieved by storing the product in a refrigerated environment.

$$Q_{10} = e^{\frac{E_a}{R}\left(\frac{10}{(T_0+10)T_0}\right)} \tag{2.2}$$

$$AAF = Q_{10}{}^{[(T-T_0)/10]} \tag{2.3}$$

$$AAT = \frac{RT_0}{AAF} \tag{2.4}$$

$$\Delta sl = \frac{100}{AAT} \tag{2.5}$$

where:

- RT_0 is the known shelf life of the product exposed at a constant temperature.
- T_0 is the controlled temperature at which the known shelf life has been measured.
- $Q_{10}$is the resulting aging factor.
- AAF is the accelerated aging factor.
- AAT is the accelerated aging time.
- Δsl is the percentage shelf life decay that determines the expected length of the product life cycle.

Another well-known equation for the kinetics of chemical reactions is the Eyring equation. The equation requires additional parameters to find out the value of k, as shown by Eq. 2.6.

$$k = \frac{k_B}{h} T \times e^{-\frac{\Delta H^* - T\Delta S^*}{RT}} \tag{2.6}$$

where:

- k_B is the Boltzmann constant, equal to 1.381×10^{-23} J/K.
- h is the Planck constant, equal to 6.626×10^{34} J s.
- ΔH^* is the activation enthalpy expressed in J/mol.
- ΔS^* activation entropy expressed in J/mol K.

The Arrhenius equation is one of the most known kinetic equations. It is still applied in many real applications due to the many contributions in literature providing useful values for the parameters of this equation. However, researchers made many attempts to propose alternative equations that are not based on the Arrhenius one (Chan & Dill, 1998; Peleg et al., 2002) to overcome some limits of this formulation. Indeed Arrhenius equations could not be precise whenever the analyzed process has an optimal temperature value, as occur for the deterioration of perishable products.

Other researchers revised equation 2.1 by proposing improvements to estimate the proliferation rate of bacterias better than with the canonical Arrhenius formulation (Knies & Kingsolver, 2010; Peleg et al., 2012). For example, (Valentas et al., 1997) proposed the following modified Arrhenius equation.

$$\ln(k) = \ln(k_{ref}) - (\frac{E_a}{R})[\frac{1}{T} - \frac{1}{T_{ref}}] \tag{2.7}$$

where k_{ref} is the constant growth rate at the reference temperature T_{ref}.

The knowledge of the concentration of the spoilage limit (log N_l) and the initial load (log N_0) of the proliferation of the analyzed bacterias (both expressed in $\log\frac{CFU}{g}$) allows estimating the residual shelf-life (expressed in hours) of the perishable product by applying the following equation.

$$SL = \frac{\log N_l - \log N_0}{k_{ref} - \exp\left[\left(\frac{-E_a}{R}\right)\left(\frac{1}{T} - \frac{1}{T_{ref}}\right)\right]} \quad (2.8)$$

2.3 Environmental stresses

Atanda et al. (2011) and Rahman (2007) reviewed the main environmental stresses affecting perishable products. Among the other environmental factors, the temperature is undoubtedly the primary stressor for perishable products. Generally, temperature increases foster the proliferation of microorganisms and accelerate the reactions determining quality decay and product losses, causing changes in the product's appearance and other effects, such as the reduction of water content. Also, exposure to solar radiation contributes to the increase of temperature on the product surface, so a good management practice is to avoid direct sunlight exposure.

Humidity is another important stressor for perishable products. Products exchange water with the environment as vapor. The more is the water within a product, the more it will give up moisture to the air. Conversely, whether the water content of the food is low, it will absorb moisture from the environment. For such reason, dry foods must be stored in an environment with low humidity and vice versa to avoid compromising product quality.

The composition of the atmosphere represents another potential stressor for perishable products. This issue fostered the adoption of Modified Atmosphere Packaging (MAP). Altering the composition of the atmosphere can shorten or extend product shelf life based on the quantity of certain gases in its microenvironment (e.g., carbon dioxide) and the characteristics of the product. Therefore, MAP recreates a favorable atmosphere for the perishable item to lengthen product life cycle.

The pressure is another stressor for perishable products as it can damage their texture and accelerate the quality decay process.

Furthermore, there is another key factor in decreasing the shelf life of perishable products. As the definition itself of perishable products refers to a limited life cycle of such products as they lose their value with time, the time itself represents an important stressor for such products. The time required to deliver products to the clients is highly dependent on SCM strategies, cooperation, and supply chain efficiency. Shortening product travel time during distribution and storage time is essential to deliver high-quality products to the final consumers.

Most of these stresses are highly dependent on climate and weather conditions (Salin, 1998). This increases the complexity of PPLCM due to the high uncertainty associated with such phenomena. Therefore, the management strategies for the product life cycle should also consider the risks due to unpredictable environmental conditions to reduce product losses.

2.4 Product intrinsic characteristics

Whilst the stresses affecting perishable products are usually attributable to the causes listed before, regardless of the specific product, the effects on products' quality depend on some intrinsic characteristics of products. The type of perishable item, its biochemical structure, the production area, the harvesting season, and many other factors define the product's intrinsic characteristics that determine their response to specific environmental stresses. The peculiarities of perishable products reflect on the ideal storage conditions analyzed by food scientists. They define the optimal microenvironment for such products.

The main parameters evaluated to determine the optimal storage conditions of perishable products are:

- Safe temperature. It represents the optimal temperature in the microenvironment surrounding the perishable product. For most of the products, it is a range of temperatures determining the maximum duration of product shelf life.
- Safe humidity. Similarly to temperatures, an interval of optimal values where the product shelf life is maximized also exists for humidity.
- Ethylene. It is a natural ripening hormone of plants that affects the growth, the development, and storage life of many fruits and vegetables (Keller et al., 2013). Crops itself produce ethylene, so there is a double aspect to be considered. On one side, perishable items produce ethylene themselves. From another side, that same ethylene accelerates the life cycle of other perishable products by softening and ripening them and causing a fast deterioration during storage and shipping phases.

  Its effect on perishable products can be disruptive, as it is estimated to cause significant product losses (from 10% up to 80% based on the type of product). Therefore it must be removed from the storage and distribution environment.

- Frost damages. The primary stressor for perishable products is considered high temperatures. However, some products experience permanent damages when exposed to frost. For most fruits and vegetables, freezing occurs a few degrees below the freezing temperature of water due to the substantial water content constituting them. Frost seriously damages many perishable products, changing their appearance, texture, and color and make them unfit for sale and consumption.

  Frost damages depend on several factors: the minimum temperature reached, the rate of drop in temperature (i.e., the faster is the decrease in temperature, the more are the damages), the duration of exposure to low temperatures, and product sensitivity to frost (Kays, 1999).

- Water content. Water is the predominant constituent in most foods, and the water content significantly influences the thermophysical properties of foods. For fruits and vegetables, water content varies with the maturity of the harvested product, growing conditions, and the moisture lost after harvest (Rao & Rizvi, 1986).

2.5 Food losses and quality standards

Nowadays, perishable product losses constitute a real plague on society. The Food and Agriculture Organization of the United Nations (FAO) estimates that roughly one-third of the total food intended for human consumption and produced throughout the globe is currently lost or wasted, which amounts to about 1.3 billion tons per year (Buzby & Hyman, 2012). According to Gustavsson et al. (2011), the industrialized world wastes much more food than developing countries. Indeed, the per capita food waste by consumers in Europe and North America amounts to 95-115 kg/year. In comparison, in sub-Saharan Africa and South/Southeast Asia, it is equal to 6-11 kg/year.

With the global population expected to be between 8.3 and 10.9 billion people by 2050 (Prosekov & Ivanova, 2018), food shortage will happen much more frequently. Furthermore, as land available for cultivation has already been destined for current crops or replaced by factories and cities, it represents a scarce resource. This reason further proves the importance of reducing product losses and wastes as the costs and the environmental impact of loss reduction is much lower than devoting new land to crop. Furthermore, also the social dimension of sustainability would benefit from the decrease in food losses by contributing to an increase in the availability of food all over the globe, including developing countries.

Product losses are becoming an increasing issue, also due to dietary transitions. People worldwide are diversifying their diets due to growth in household incomes and the higher quality standards of life in modern countries. These increases in food varieties eaten by populations around the globe are pushing the development of the global food market and the consumption of shorter shelf life items, which is associated with increases in food losses and consumption of land and other resources (Lundqvist et al., 2008). The increasing traveling distances due to global supply chains, where nodes are distributed worldwide, also increases the time to reach the retailers. Global supply chains extend the distribution, which is the most critical phase of the perishable product life cycle, where the product is more exposed to potential environmental stresses due to the changes in its environment as it travels to the next stage of the supply chain.

Indeed, distribution is a critical phase in the perishable product supply chain system. During distribution, it is more frequent to face adverse environmental conditions, and the control of supply chain actors on the products they sell is lower. Furthermore, the control of perishable products during distribution is frequently more challenging due to outsourcing this phase to third parties. Third-Party Logistics (3PL) providers, for example, are third-party companies operating the distribution and other logistics phase on behalf of the supply chain actors. These operators increase the efficiency of the distribution phase as they are specialized in such operations but decrease the control of the supply chain on their product compared to the use of proprietary vehicles that can share data continuously with the DB of supply chain actors.

The diffusion of global supply chains and the increasing variety of products coming from abroad foster the perception of lower control on perishable products not only by companies operating in the supply chains but also by consumers. The industrialization and globalization of the food supply chain have increased consumers' skepticism about the quality and safety of the food they eat (Toler et al., 2009). The bacterial outbreaks and food safety scandals happened in the past years threatened consumer confidence in food safety (Yeung & Morris, 2001; Thirumalai & Sinha, 2011). In order to increase product safety and restore consumers' trust, regulators adopted many standards on food quality and preservation and introduced new laws and regulations (Regattieri et al., 2007; Abad et al., 2009; Council Regulation, 2002). Such regulations strengthen rules on quality and safety control and product traceability. For example, regulators determine the temperature ranges within some perishable products must be stored to be considered fit for consumption. Whether products are exposed to temperature stresses going beyond the preset threshold, they can not be sold and must be discarded to avoid risks for consumers' health. Other regulations impose stricter traceability information on product origins and impose to correctly inform consumers about the production and processing sites of the product and its nutritional values.

In order to increase consumers' safety and avoid risks for their health, regulators adopted new rules and standards about quality assurance systems. Such systems aim to guarantee the quality level of products to consumers, giving them more information and control over the products they buy. Some of these quality assurance systems are the Good Agricultural Practices (GAPs), Hazard Analysis of Critical Control Points (HACCP), and International Organisation for Standardisation (ISO). GAP and HACCP include technological and management issues and are intended explicitly for the food sector, ISO focuses on management practices, and it is independent of any specific industry (Trienekens & Zuurbier, 2008).

Furthermore, new regulations to be considered when managing perishable product supply chains also concern environmental aspects. As environmental issues and global warming concerns are increasing throughout the globe, rules about the emission of perishable product supply chains are spreading. As concern on carbon emissions reduction increases, many international and national authorities are introducing new regulations to reduce the emissions (Bai et al., 2017).

Among the other systems, cap-and-trade is one of the most adopted approaches for reducing carbon emissions. Based on some objective criteria, the authorities allocate a maximum amount of carbon emissions to each company. Whether the company's carbon emissions exceed this limit, then the company should buy the right to emit such exceeding quantity in a carbon trading market from more companies emitting less than their allowed amount. This system incentives companies to acquire new and efficient assets emitting less carbon and therefore reducing their impact on the environment. An important example of such cap-and-trade initiatives at an international level is the European Emissions Trading System (EU-ETS), the first and largest carbon market globally, covering approximately 45% of carbon dioxide emissions in the European Union (European Commission, 2013).

The increasing interest in carbon emissions reduction initiatives is also due to the economic benefits of reducing carbon emissions. Air pollution is becoming a significant problem in big cities, and the emissions of supply chains are an important cause of this issue. For example, air pollution caused 1.23 million deaths in China, 103,027 in the United States, and 23,036 in the United Kingdom in a single year, which amounts respectively to 9.7–13.2%, 3.2–4.6%, and 4.6–7.1% GDP of such countries (Shi et al., 2020). As a result, governments and factories are under growing pressure to limit their carbon emission quantity.

2.6 Logistics solutions

Logistics plays a crucial role in ensuring the respect of these regulations about perishable products and guaranteeing the delivery of high-quality products. As the most critical phases for PPLCM are storage and distribution, effective logistics decisions are essential to meet quality standards and to increase the level of service provided to the clients.

Some of the most important logistics decisions for PPLCM to increase the sustainability of these supply chains, also represented in figure 5, are:

- **Packaging**. By protecting products from external stresses, packaging conducts a primary role in preserving the quality of perishable products. Packaging isolates perishable products from the external environment and creates a microenvironment with favorable conditions for the perishable items. It attenuates the fluctuations of the temperature of the external environment, protects the product from humidity and mechanical stresses (i.e., vibrations and impacts), and can recreate a microenvironment with its own atmosphere to extend product shelf life (Modified Atmosphere Packaging). In the last decades, the interest in packaging has increased a lot due to their fundamental role in protecting products, facilitate handling operations, and marketing reasons.

- **Vehicle type**. Distribution is the most critical phase of product shelf life. During distribution, the product could face continuously face environmental stresses and unstable weather conditions. Throughout the journey from one node to the next one, the product travels across different geographical areas with different climatic conditions. It experiences temperature and humidity fluctuations and vibrations depending on the type of vehicle used and the infrastructure (e.g., roads). Furthermore, different types of vehicles have different costs and environmental emissions. For example, vessels emit few carbon emissions if compared with trucks. However, vehicle alternatives also entail changes in travel times. For this reason, although the vessel is economically and environmentally convenient, sometimes it is not viable not only due to the lack of infrastructures and routes but also due to much longer travel times that could increase product losses and reduce the level of service provided to the clients.

- **Storage time**. As the quality of perishable products decays fast, it is essential to reduce the storage time to the minimum necessary time. Perishable products are usually fast-moving items that reach storage nodes just for consolidation and are stored in the warehouse while waiting for the other products to be ready for shipments to complete clients' orders. As the storage of perishable products must be limited to reduce losses, these products prompt the adoption of new logistics solutions such as cross-docking to verify, label, weight, and consolidate products and ship them to their destination within a single working day.

- **Refrigeration**. Reducing the storage time and choosing the best type of vehicle could not be enough to preserve product quality. Critical environmental conditions could compromise product quality and safety also during short time intervals. For this reason, refrigeration is essential to avoid product losses. Refrigeration, along with a proper package, represents an effective solution to recreate an ideal micro-environment for perishable products. It is the best solution to reduce the negative effect of high environmental temperatures, especially for foods that perish in a few days when not stored at their ideal conditions (e.g., cherries). However, refrigeration is highly energy consumptive and therefore threatens the economic and environmental sustainability of the supply chain. Intensive use of refrigeration should be avoided when possible to reduce the carbon emissions of food supply chains.

- **Flows allocation**. Whilst all product lots in the same supply chain go through the same supply chain stages, the choice of allocating them to a specific node of each stage is an important logistics decision. An effective allocation balances the network, avoids oversaturation of some processing or storage nodes, and meets clients' demands while optimizing the sustainability of the supply chain. The allocation of flows is a typical problem that can be optimized by mathematical decision support models.

- **Distribution route**. The choice of the best distribution route for each delivery is another critical aspect to increase the sustainability of supply chains of perishable products and to avoid the exposure of perishables to critical stresses that may cause product losses. The best distribution route is the one that aims to reduce the travel time to limit the reduction of shelf life of the product, and it should also avoid the geographical areas with a higher risk of critical environmental conditions that could compromise product quality.

- **Traceability**. Traceability is an essential tool to control the product throughout its life cycle and monitor its stresses to guarantee compliance to regulations and quality standards and increase consumers' trust by giving them detailed information on the product's origin, processing area, and safety. A well-structured traceability system allowing to follow the product in every stage of the supply chain requires a complete integration of information systems and cooperation and information sharing among all the supply chain actors.

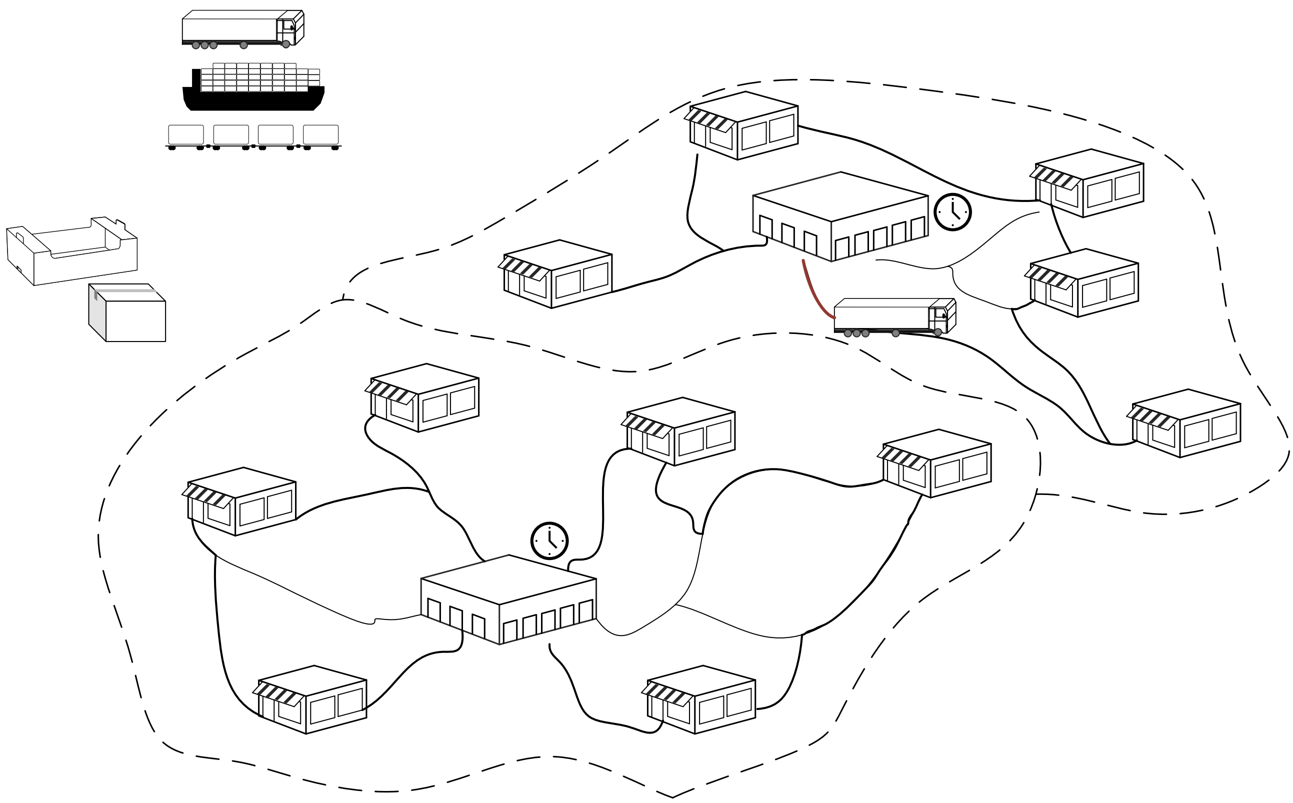

Figure 5. Main logistics decisions for food preservation.

2.7 Research trends

This section introduces a literature review to assess the current developments of research trends about perishable products and the most studied logistics solutions to handle these products. A bibliometric study has been conducted to highlight the research trends about the supply chains of perishable products.

2.7.1 Map of keywords

The bibliometric analysis involves a sample of 500 papers collected on Web of Science on August 16, 2020, and contains papers published within a time interval between 2000 and 2020. The papers were extracted from the Engineering Village search engine and analyzed through the software VOSviewer. VOSviewer collects information from papers to create and visualize bibliometric maps and networks (Van Eck & Waltman, 2009). This software gathers bibliometric and text data from published papers, extracts the main keywords, and highlights trends and connection among research trends.

Figure 6 shows the map of keywords extracted from the analyzed papers. Each circle represented in the graph corresponds to a keyword, as indicated in the text within the circle. The dimension of the circle corresponds to the number of papers containing the keyword. Each link connecting two keywords represents a connection between them. The graph creates connections when in at least one paper, there is the co-occurrence of the two keywords. A strength value characterizes each link, represented by the thickness of the link. The strength of a link corresponds to the number of papers with co-occurrences between the two keywords. Therefore, a couple of keywords that are not connected by links represents nonrelated items and could also suggest future research to evaluate new connections between topics. Figure 6 also shows clusters of keywords, represented by circles of the same color. Clusters are created based on the co-occurrence of groups of keywords.

As shown in the figure, the most cited keyword is model, as its circle is the greatest in the network. Most of the research about perishable products focuses on developing models to study perishable products, their characteristics, and quality decay and to optimize their management. The keyword "model" is strictly related to other keywords, better specifying what kind of models are proposed in the literature. Indeed, the most relevant keywords in the green cluster refer to inventory management, optimal order quantity, and optimal pricing problems. Furthermore, other keywords in the cluster suggest some of the most important features considered in the models. Among them, the satisfaction of clients' demand is the most relevant keyword. Other important features are:

- Product lifetime and expiration date.
- Quality deterioration models.
- The assessment of product freshness.
- Product shortage.
- Discounts.

The red cluster instead contains keywords focusing on transportations models and studies. The main keywords related to "model" refers to routing problems. Some of the most important features included in this cluster refer to:

- Vehicles and transport.
- Transportation cost.
- Delivery, routes, and distribution.
- Time windows.
- Risk and uncertainty.
- Temperature and quality loss.

Other essential keywords included in the network refer to the various stages of the supply chain considered in these studies and the importance of coordination among them, wastes and their relationship with uncertainty, and the relevance of policies on perishable products. Other keywords could refer to the aim of these studies, such as the objective function of the proposed models and algorithms:

- Cost minimization.
- The maximization of the profit and value.
- The reduction of processing times.
- The maximization of the shelf life.

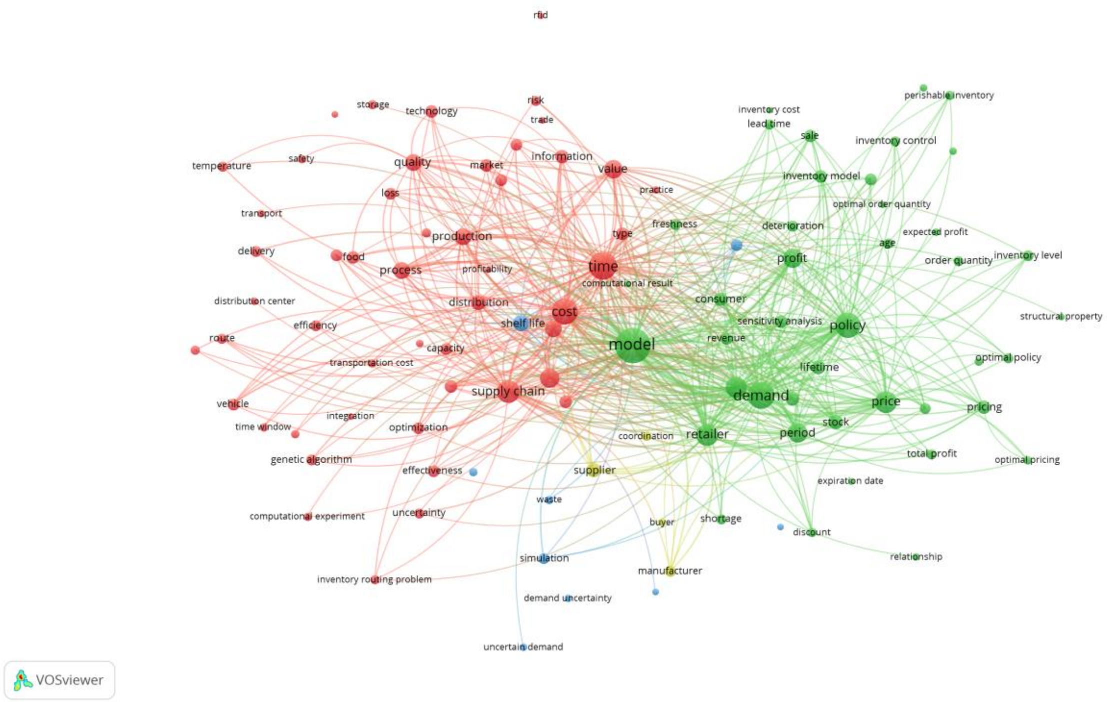

Figure 6. Map of interconnections among keywords.

2.7.2 Evolution of research trends

Figure 7 identifies the main research trends over the years. VOSviewer allows users also to perform temporal analysis and analyze how the trends distribute chronologically by coloring the keywords not based on the average publication year rather than based on clusters of related words.

In this analysis, the keywords in purple and blue are cited more around the years 2000 than in the last years, while those in green and yellow are cited more in recent years. The first research trends focused on the single phases of production and distribution but also on the coordination between supply chain actors, on order quantity models to determine the order quantity of perishable products. The first objective functions focused on the maximization of revenues. Researchers also focused on traceability systems to obtain more information on the product. The use of RFID technology was assessed to track perishable products during their life cycle.

Then, researchers focused on cost minimization and the definition of the product price. In these years, policies on perishable products attracted the interest of researchers along with the reduction of processing times and the maximization of the value provided to clients. The models focused on inventory management.

More recently, papers focused on processes. The focus on consumer increased models focused on optimal pricing and in lead times reduction to maximize the shelf life of the products. The interest in storage models reduced in favor of distribution models supporting the choice of the best vehicles and vehicle routing with time windows. The focus on quality deterioration and the role of temperature on quality decay increased. Furthermore, new sub-optimal approaches were applied to manage perishable products, such as genetic algorithms.

In the last years, researchers focused more on integrated models managing both inventory and routing. The interest moved from costs and pricing to product quality and loss and waste reduction. Several papers also focus on determining the expiration date of perishables. The aim is to provide high-quality products to clients, with a high level of freshness and by maximizing product shelf life. Furthermore, models started to consider also uncertainty and focused on how to handle risks.

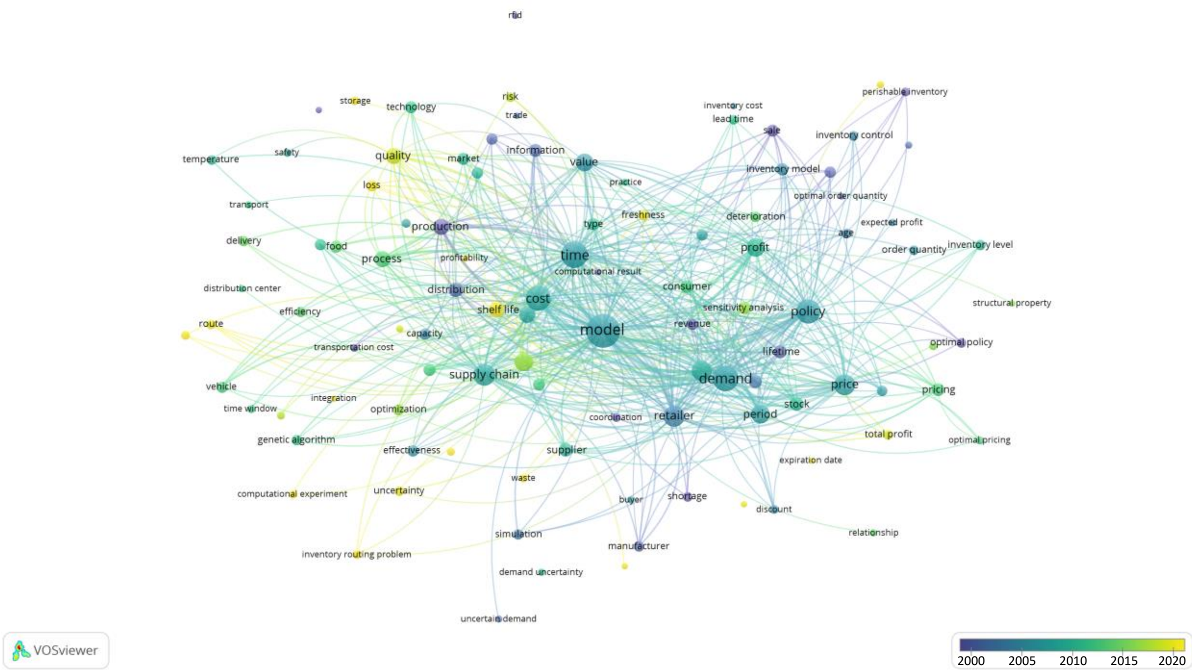

Figure 7. Map of keywords with the year of publication.

2.7.3 Publishing journals

The leading scientific journals publishing the analyzed sample of papers were individuated to assess the main disciplines covering the research on perishable products. Figure 8 shows the results of this analysis by ordering journals according to the number of published papers. The figure only included journals with the highest number of published papers (i.e., more than five papers published among the 500 analyzed papers).

The International Journal of Production Economics is the journal publishing more papers on perishable products, with 42 papers published out of the 500 analyzed ones. The next journals with more publications within the proposed sample are the European Journal of Operational Research, Computers & Industrial Engineering, Computers & Operations Research, International Journal of Production Research, and Operations Research. So the main research areas focusing on perishable products concern the engineering and management field, the operation research, and the support to the decision-making process aided by computer applications. The journals included in the figure cover about 30% of the papers in the sample. Many other contributions were published in other journals containing only a few of the papers in the sample or international conferences proceedings.

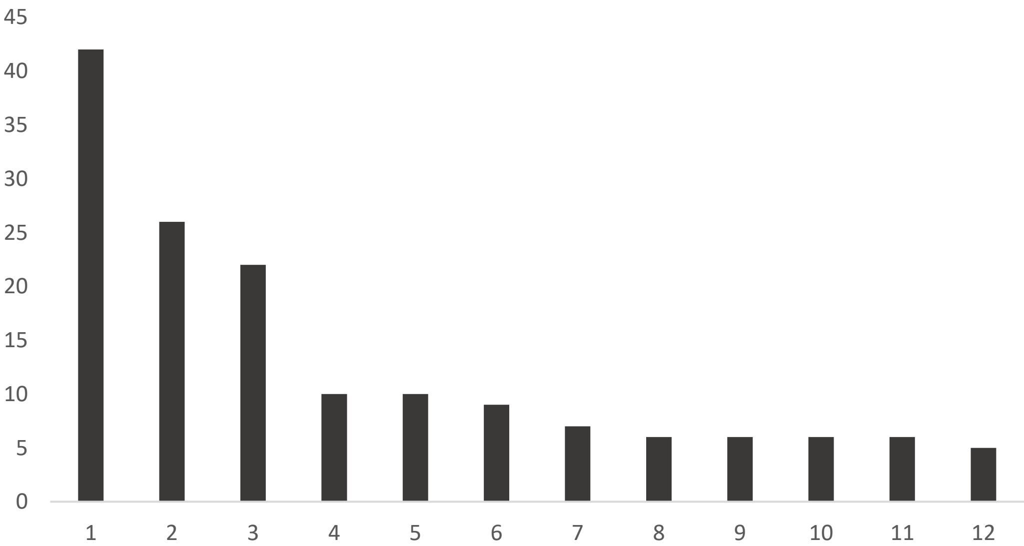

Figure 8. Number of publications per journal.

2.7.4 Chronological analysis

Figure 9 shows the number of papers in the sample for each publishing year. This figure aims to understand if there is a recognizable trend in the number of published papers. The figure shows an increasing trend of papers, implying a growing interest in perishable products. Indeed, despite some fluctuations, the number of papers published per year continue increasing, with the current maximum of 57 papers in 2019. Furthermore, with 40 papers published within August 2020, the current year will probably go beyond the results of the previous year, indicating that there is still lots of research to be conducted on perishable products.

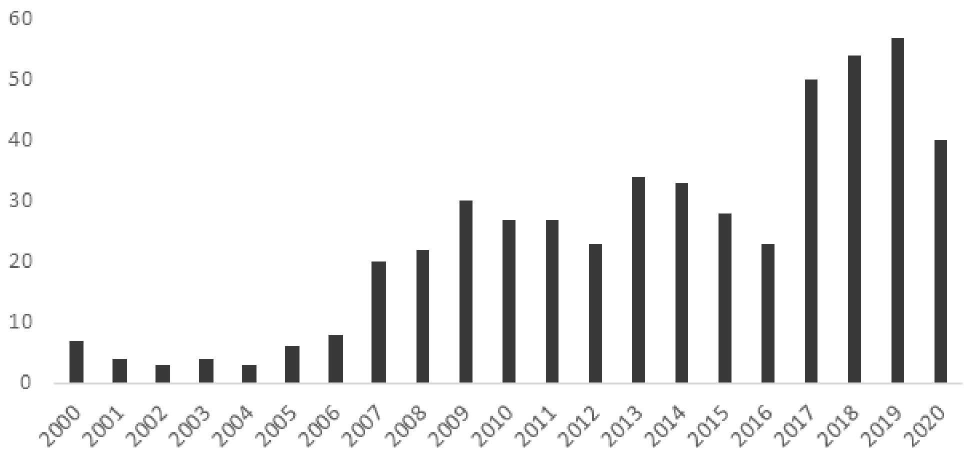

Figure 9. Number of publications per year.

2.8 Products classification

The previous sections introduced the main peculiarities of perishable products determining the extension of their life cycle. They then described the main environmental stresses affecting the products based on their intrinsic characteristics. These stresses reduce products' quality and cause losses and risks for consumers' safety. Therefore, new standards and regulations were introduced to safeguard consumers. After reviewing the main logistics decisions that can help to reduce losses and quality decay and the main research trends about perishable products, this section introduces a product classification framework. This classification aims to guide practitioners to identify how to handle their specific products at a strategic decisional level. For this decision-support framework, this thesis pair the proposed product classification with a supply chain classification introduced in the next chapter.

2.8.1 Classification levers

This classification considers the main intrinsic characteristics of food products introduced in section 2.3:

- Ideal temperature (in degrees Celsius).
- Ideal relative humidity (as a percent value).

- The production of ethylene on a scale from 0 (i.e., the product does not produce ethylene) to 3 (i.e., the product produces a high quantity of ethylene).
- The sensitivity to ethylene on a scale from 0 (i.e., no sensitivity to ethylene) to 3 (i.e., high sensitivity to ethylene).
- Frost damages on a scale from 0 (i.e., no sensitivity due to frost) to 3 (i.e., high sensitivity to frost).
- The initial freezing points (in degrees Celsius).
- The water content (as a percent value).

These characteristics are peculiarities of the products themselves. Hence they are independent of the environmental conditions that these products experience or the specific supply chain producing them. Based on these characteristics, this section proposes an original classification framework. It classifies some fruits and vegetables, but the same framework also applies to any other perishable product. If the type of item is different from the products analyzed in this section, other intrinsic characteristics representing peculiarities of the specific item to be classified can be added to the proposed ones to extend this classification.

The following example classifies 41 products. The secondary data used to quantify the five proposed characteristics have been collected from Mayer (1997), Rao & Rizvi (1986), and Caccioni (2005) and are shown in the following table.

Table 1. Intrinsic characteristics of fruits and vegetables.

Product	Ideal temperature [°C]		Ideal relative humidity [%]		Production of ethylene	Sensitivity to ethylene	Frost damages	Initial freezing point [°C]	Water content [%]
	Min	Max	Min	Max					
Fuji apples	1	1	90	92	3	1	1	-1.1	85.4
Gala apples	1	1	90	92	3	1	1	-1.1	85.4
Golden delicious apples	1	1	90	92	3	1	1	-1.1	85.4
Granny smith apples	1	1	90	92	3	1	1	-1.1	85.4
Red delicious apples	1	1	90	92	3	1	1	-1.1	85.4
Apricots	0	0	90	95	3	0	0	-1.1	85.4
Asparagus	0	0	90	95	0	1	0	-0.6	92.6
Bananas	12	14	90	95	2	3	3	-0.8	75.1
Brussels sprouts	-1	-1	90	95	1	3	0	-0.8	84.3
Cabbages	0	0	90	95	1	2	0	-0.9	89.7
Cantaloupes	5	5	85	90	2	1	2	-1.2	92.1
Carrots	0	0	90	95	1	2	0	-1.4	89.8

Celery	0	0	90	95	1	3	0	-0.5	95.1
Cherries	0	0	90	95	0	0	0	-1.8	82.2
Cucumbers	13	13	90	95	1	3	3	-0.5	95.4
Grapefruits	10	15	85	90	1	0	2	-1.1	89.0
Grapes	0	0	90	95	0	0	0	-2.1	81.8
Lemons	11	15	85	90	1	0	2	-1.4	86.3
Lettuce	0	0	90	95	1	2	0	-0.2	95.1
Mushrooms	0	0	90	95	2	1	0	-0.9	92.6
Nectarines	0	0	90	95	3	1	2	-0.4	88.9
Onions	-2	-2	75	80	1	1	0	-0.9	89.0
Oranges	0	5	85	90	1	0	2	-0.8	86.1
Peaches	0	0	90	95	3	1	2	-0.9	88.9
Abate pears	0	0	90	95	2	1	0	-1.6	83.8
Conference pears	0	0	90	95	2	1	0	-1.6	83.8
“Decana” pears	0	0	90	95	2	1	0	-1.6	83.8
“Decana del comizio” pears	0	0	90	95	2	1	0	-1.6	83.8
Guyot pears	0	0	90	95	2	1	0	-1.6	83.8
Kaiser pears	0	0	90	95	2	1	0	-1.6	83.8
William pears	0	0	90	95	2	1	0	-1.6	83.8
Pineapples	10	10	90	95	1	0	3	-1.0	86.5
Plums	0	0	90	95	2	0	1	-0.8	83.9
Potatoes	4	6	95	98	1	1	2	-0.6	79.0
Pumpkins	7	10	75	75	1	1	2	-0.8	95.0
Radish	0	0	90	95	0	1	0	-0.7	95.4
Raspberries	0	0	90	95	2	0	0	-0.6	87.0
Spinach	0	0	90	95	0	0	0	-0.3	90.2
Strawberries	0	0	90	95	1	0	0	-0.8	89.5
Red tomatoes	2	8	85	90	2	2	3	-0.5	93.1
Green tomatoes	10	12	85	90	2	2	3	-0.6	93.1

2.8.2 Products clusterization

Based on the characteristics in table 1, a clustering algorithm groups the products into homogeneous clusters. Clusters identify similar products requiring the same storage conditions and experiencing similar quality decay when exposed to similar environmental stresses. Therefore, the products in the same cluster require the same optimization strategies.

The clustering algorithm applied to group the products is the *k*-means algorithm. This algorithm partitions the perishable products in *k* clusters based on the characteristics shortlisted in table 1.

Firstly, the algorithm initializes a matrix representing the elements' set. Each row of the matrix represents a product. The matrix columns define the classification parameters (e.g., ideal temperature, ideal relative humidity). An iterative procedure made of four steps group together the items by calculating the centroids of each cluster and by using these to assign each element to a new cluster. The steps of the proposed algorithm are the following:

Step 1. The k-means algorithm starts with *k* random "means" value.

Step 2. Each element is associated with one of the *k* clusters by calculating the nearest of the *k* means.

Step 3. The means are adjusted by calculating the centroids of the clusters generated in Step 2.

Step 4. Steps 2 and 3 are repeated until there is a convergence in the clustering results.

At the convergency, the *k*-means algorithm generates *k* subsets, each of them containing similar perishable products. The *k*-means algorithm requires the desired number of clusters as an input parameter. The proposed classification creates a set of six clusters. Table 2 resumes the characteristics of the centroids of the clusters, representing the average values of the characteristics of all the products assigned to them. Table 3 presents the detailed association of each product to the six clusters.

The obtained clusters roughly cover typical food sub-categories. For instance, cluster 1 groups together onions and pumpkins, while cluster 4 contains the exotic fruits and other products with the highest ideal temperature values. Cluster 6 includes cherries and grapes that have low ideal temperature values, and they neither produce ethylene nor are sensitive to it. These products are highly susceptible to high temperatures. Still, they have the lowest freezing point and the lowest water content. Cluster 5 is the biggest one. It contains thirteen products that produce lots of ethylene, such as apples, apricots, and peaches. Similarly to cluster 6, cluster 3 includes products with low ideal temperature, freezing point, and water content. However, these products produce ethylene, and they are sensitive to this ripening hormone.

Table 2. Centroids of the *k*-means algorithm.

Cluster	Ideal temperature [°C]		Ideal relative humidity [%]		Production of ethylene	Sensitivity to ethylene	Frost damages	Initial freezing point [°C]	Water content [%]
	Min	Max	Min	Max					
Cluster 1 (2 products)	2,5	4	75	77,5	1	1	1	-0,85	92
Cluster 2 (8 products)	0	0	90	95	0,75	1,25	0	-0,61	92,53
Cluster 3 (9 products)	-0,11	-0,11	90	95	1,78	1,33	0	-1,49	84,52
Cluster 4 (7 products)	10	12,14	88,57	93,29	1,29	1,29	2,57	-0,86	86,34
Cluster 5 (13 products)	0,92	1,77	88,85	92,69	2,54	0,77	1,31	-0,91	87,11
Cluster 6 (2 products)	0	0	90	95	0	0	0	-1,95	82

Table 3. Association of products to the six clusters.

Product	Cluster
Fuji apples	5
Gala apples	5
Golden delicious apples	5
Granny smith apples	5
Red delicious apples	5
Apricots	5
Asparagus	2
Bananas	4
Brussels sprouts	3
Cabbages	2
Cantaloupes	5
Carrots	3
Celery	2
Cherries	6
Cucumbers	4
Grapefruits	4
Grapes	6
Lemons	4
Lettuce	2
Mushrooms	2
Nectarines	5
Onions	1
Oranges	5
Peaches	5
Abate pears	3
Conference pears	3
“Decana” pears	3

“Decana del comizio” pears	3
Guyot pears	3
Kaiser pears	3
William pears	3
Pineapples	4
Plums	5
Potatoes	4
Pumpkins	1
Radish	2
Raspberries	5
Spinach	2
Strawberries	2
Red tomatoes	5
Green tomatoes	4

The perishable product classification proposed in this chapter is the first step of a wider classification framework for FSCS, also requiring a supply chain classification introduced in the next chapter. By comparing its characteristics with the ones of the centroids of the clusters depicted in table 2, researchers and practitioners can assign a new product to the corresponding cluster. This assignment procedure suggests managing the perishable item according to the other ones belonging to the same cluster whenever they face similar environmental conditions.

The classification of supply chains proposed in the next chapters supports the identification of the best logistic strategy to optimize PLC for the products belonging to the same cluster.

2.9 Chapter’s highlights

- Perishable products experience a progressive deterioration of their quality due to chemical, biological and mechanical processes.
- This decay depends on the intrinsic characteristics of the product and is accelerated by adverse environmental conditions.
- In order to safeguard consumers' safety, regulators introduced rules and standards to guarantee the delivery of high-quality products to consumers.
- The number of publications trying to provide solutions to food supply chain optimization is increasing. The interest shifted from the cost of this product and the optimization of single supply chain stages to a coordinated approach to increase product quality and reduce losses.
- This chapter introduces a novel classification framework for perishable products to identify similar items based on their intrinsic characteristics. A clustering algorithm group similar products together, suggesting the same logistics management strategy to optimize their life cycle.

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3. Supply chains classification

The content of this chapter is based on the research presented in the following paper:

Gallo, A., Accorsi, R., Baruffaldi, G., Ferrari, E., Manzini, R. (2018). ***A taxonomy framework to manage perishable products in cold chains****. XXIII Summer School "Francesco Turco", Palermo, Italy, 12 – 14 September 2018.*

Gallo, A., Accors, R., Ferrar, E., Manzin, R. (2017). ***Climate conditions and transportation: A hidden connection in cold chain management****. 22nd International Symposium on Logistics (ISL 2017) - Data Driven Supply Chains, Ljubljana, Slovenia, 9 – 12th July 2017.*

Perishable products experience a progressive decay of their quality due to some natural processes that determine the length of their life cycle. The previous chapter focused on the ideal storage conditions that extend the shelf life of perishable products to a maximum. If practitioners could always recreate a microenvironment with all the characteristics lying into the optimal intervals, then the product quality would be maximized along with customer satisfaction. The adoption of some logistics solutions, such as the refrigeration of storage rooms and vehicles, modified atmosphere packaging (MAP), and insulated covers for transportations permits to obtain environmental conditions close to the optimal ones. However, the adoption of innovative solutions and the alteration of the environment is expensive, both economically and environmentally. This chapter aims to introduce a classification of supply chain systems that, paired with the one for products introduced in the previous chapter, support identifying the best investment strategy for the design of logistics solutions preserving product quality. The proposed classification framework reduces the adoption of unnecessary expensive solutions threatening the sustainability of the FSCS while guaranteeing high-quality products.

3.1 Geographical areas and climate conditions

The mitigation of the stresses affecting PLC requires strict control of the environmental conditions to maintain an adequate level of freshness of food. For food products, customer satisfaction increases with the level of freshness of the product at the client's site (Wang et al., 2016). The level of freshness reduces with time and when the product experiences adverse environmental conditions, for example, due to high temperature. These factors influence the appearance of the product, its texture, flavor, and ripening, making it undesirable for the final consumers.

Logistics must preserve the product from stresses to reduce losses or wastes, and avoid threats to consumers' health. The perishable products must be stored at their optimal storage conditions (see table 1) in every stage of their life cycle. As climate conditions represent the main stressor for perishables, their criticality represents the most crucial factor when classifying supply chains. For example, temperature accelerates the physical, chemical, and biological processes affecting PLC more than linearly, as clearly stated by the Arrhenius equation (see section 2.2), which describes a non-linear connection between temperature and the reaction rate that induces the shelf-life decay.

This exponential relation between climate conditions and the reaction rate of quality decay pushed the practitioners to adopt new preserving solutions to protect the PLC from adverse environmental conditions within storage nodes and vehicles adopted for transportation and increase the level of service for clients (James et al., 2006; Smith et al., 1990).

The importance of investments in infrastructure and innovative preserving solution for FSCS increases when the supply chain is located in geographical areas experiencing critical conditions frequently (e.g., tropical, desertic, and icy regions). Therefore, the criticality of climate conditions represents the most critical factor in the sustainability of FSCSs.

Some contributions in literature tried to propose solutions to mitigate the effect of adverse climate conditions on the FSCSs. For example, Zanoni & Zavanella (2012) modeled the effect of temperature both on the food quality degradation, the energy requirements, and the sustainability of the cold chain. Although their model focuses on the contributions for the storage rooms, the criticality of climate conditions mainly arises during transportation. As the climate conditions within a geographical area are uncertain, Hsu et al. (2007) proposed a stochastic vehicle routing problem with time-windows that considers different deterioration rates for perishable items depending on temperature. Gwanpua et al. (2015) proposed a software to optimize the trade-off between food quality, calculated via kinetic models, energy consumption, and global warming impact of the cold chains. Jedermann et al. (2014) provided some managerial insight for cold chains to reduce product losses. They estimate the rate of product losses using the Arrhenius equation and propose using smart packaging or other containment solutions to minimize food losses.

These contributions aim to measure the impact of environmental stresses on products and to suggest management strategies to reduce quality degradation without compromising the sustainability of the FSCS. However, there are not contributions in literature yet that use climate conditions in the geographical area of an FSCS for supply chain classification and propose investments in logistics solutions coherently. The development of a classification framework based on such characteristics would support managers in evaluating long-term logistics strategies rather than focusing on the efficient utilization of the available equipment, further increasing the sustainability of the FSCS.

3.2 Food preservation solutions in developing countries

The adoption of new technologies progressively contributed to the reduction of food losses in developed countries. Nevertheless, the substantial investments to acquire these technologies, the expertise required for their production, use, and maintenance often prevent their adoption in developing countries (Kefalidou, 2016).

This expensiveness led to a clear difference between developing and developed countries (Paam et al., 2016). Food losses, which occur before the product reaches the consumers' household, happen more frequently in developing countries due to unbearable costs for the poorest countries. On the other hand, food wastes, which occurs in the final phases of the food chain pertaining to retailers' and consumers' behavior, happen more frequently in developed countries. Mostly, food loss and food waste occur in developing and developed countries, respectively.

A lack of investments in infrastructures, food production, and preservation technologies, and poor knowledge of food utilization and logistics strategies lead to food losses. At the same time, the unawareness of consumers and poor storage conditions at stores and households lead to food wastes. Table 4 shows the rate of food wastes and losses in developing countries and compares it with the ones occurring in the European Union, China, and India, according to the FAO Food Balance Sheets (FAO, 2017).

Table 4. Cumulative food losses and wastes rate in different geographical areas.

Time intervals	China	European Union	India	Developing Countries
1984-1988	7.38%	6.09%	12.63%	11.97%
1989-1993	6.83%	6.20%	13.00%	11.13%
1994-1998	7.22%	6.39%	13.29%	9.53%
1999-2003	6.91%	6.61%	13.54%	9.53%
2004-2008	7.34%	6.45%	13.99%	9.92%
2009-2013	8.57%	5. 84%	14.15%	9.45%

As shown by the data in table 4, in developing countries, the adoption of food preservation technology could not be feasible (i.e., because of a lack of adequate access to electricity) or not affordable due to the high installation and maintenance costs. Even if refrigeration decelerates the chemical and biological processes of food quality degradation, extending the shelf life of the products (Stoecker, 1998), it is energy-intensive. Indeed, Coulomb (2008) states that refrigeration consumes about 15% of the overall electricity consumption worldwide.

Still, the role of refrigeration in reducing food losses is undoubted. For example, in China, the cold chain adoption rate is 5% for fruit and vegetables, 15% for meat, and 20% for aquatic products, while the food losses for these categories are respectively 20-30%, 12%, and 15% (Wang et al., 2013). As stated by Parfitt et al. (2010), post-harvest losses are partly a function of the technology available in a country, as well as the extent to which markets have developed for agricultural produce.

Therefore, logistics managers should be able to find an effective trade-off between energy consumption by the refrigeration system and the shelf life decay (Vanek & Sun, 2008) to reduce product losses without compromising the economic and environmental sustainability of the FSCS.

3.3 Emissions and carbon pricing

In the last decades, the environmental sustainability of the food supply chain system is becoming a crucial factor for its stakeholders. As the actual carbon emissions are not sustainable in the long term for our planet, there is a growing consensus among governments and businesses to impose rules and carbon pricing initiatives. These initiatives aim to mitigate the Greenhouse Gases (GHGs) due to citizens and the supply chains (Rausch et al., 2011). FSCSs have a significant impact on GHGs emissions. Agriculture is responsible for almost a third of the total human emission of GHGs (Ledo et al., 2018). Therefore, it is vital to regulate the emissions also within this sector.

By raising the costs of carbon-intensive products and therefore raising their price, the carbon pricing initiatives push consumers towards more sustainable products. These initiatives include carbon taxes and cap-and-trade systems. Carbon taxes correspond to the payment of taxes based on the total amount of emissions produced by the supply chain. Conversely, the cap-and-trade system is a system of tradable emission allowances, where most emitting companies must acquire emission shares from low-emitting companies (Goulder & Schein, 2013). These systems aim to incentivize supply chain systems to be more environmentally friendly by reducing their carbon emissions. Therefore, in geographical areas where the government imposes carbon pricing initiatives or where the carbon emissions are higher, a sustainable supply chain system should reduce the utilization of refrigeration systems.

The carbon pricing initiatives are currently spreading throughout the globe and cover Europe, most of America, the East of Asia, and Australia, while most of Africa and Asia do not apply carbon pricing initiatives (World Bank, 2020). Figure 10 shows the carbon pricing initiatives currently implemented around the globe. The color associated with each country represents the year of implementation of the carbon pricing initiative. It clearly states how the interest in the reduction of carbon emissions is increasing in recent years.

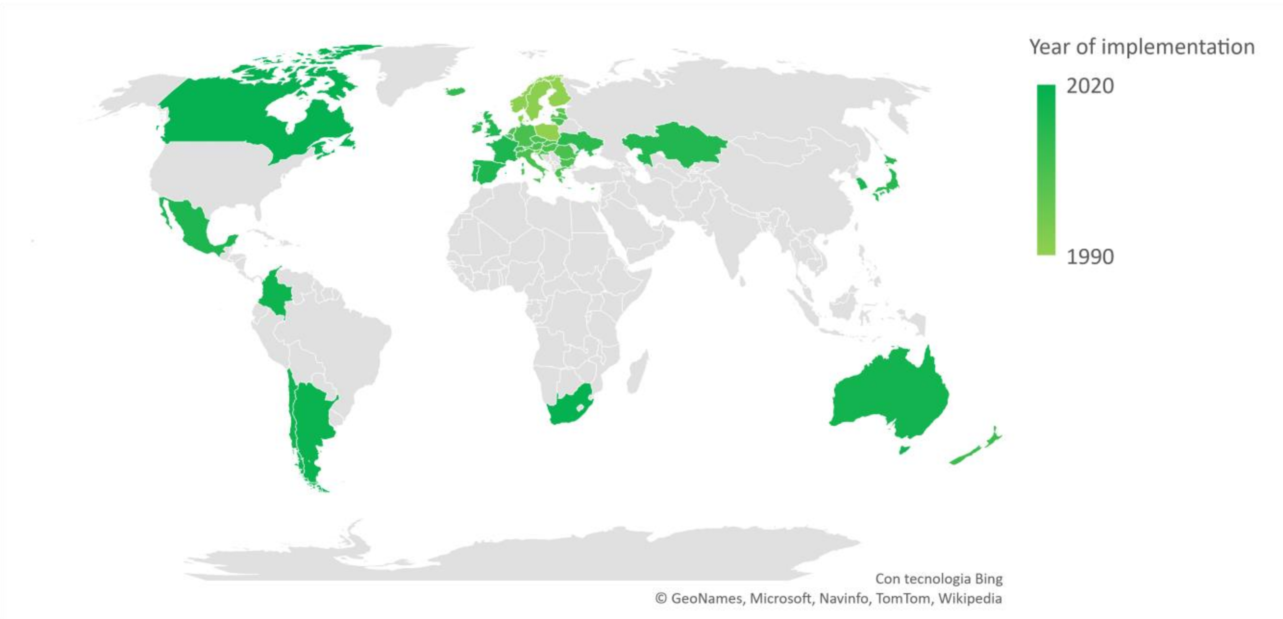


Figure 10. Carbon pricing initiatives by year of implementation.

Through the application of an analytical model, Zakeri et al. (2015) showed that the implementation of carbon pricing initiatives fosters the environmental sustainability of supply chains, reduces costs, and increases the service level. Indeed, the reduction of the emissions of the production systems promotes the adoption of modern and more efficient machinery to process and pack products, also improving the economic sustainability of the supply chain.

Garnett (2011) analyzed the GHGs emissions of food supply chains both at the global and regional level and highlighted the most GHGs intensives stages of the supply chain and food types. Their analysis indicates that the less environmentally sustainable stage is the agricultural one, while the GHGs emissions are higher for meat and dairy products. Similar results have also been highlighted by comparing LCAs studies about food products presented by Clune et al. (2017). Their research highlighted that supply chain systems producing grain, fruit, and vegetable are responsible for fewer carbon emissions than the other foods.

Many models have been proposed to reduce the carbon emissions of FSCS. Guo et al. (2017) proposed a forward/reverse logistic model to optimize the supply chain under low-carbon emissions. Hua et al. (2016) focused on inventory management by presenting a model to maximize the freshness of the delivery products under carbon emissions constraints both by carbon emission tax and cap-and-trade mechanism. Adekomaya et al. (2016) proposed a redesign of food transportation systems to reduce energy consumption and improve the sustainability of the FSCS. They focused on alternatives energy sources to fossil fuel to reduce the global impact of food supply chains. Gallo et al. (2017) proposed an integrated model to optimize the energy consumption in FSCSs that considers the impact of the logistic decisions and the impact of wastes and refrigeration.

3.4 Global supply chains and traveling distances

Another crucial aspect of identifying the best long-term logistics solution for the design of an FSCS is the distance between the nodes of the supply chain. In the last decade, the traveling distance in the supply chains increased with the proliferation of global supply chains.

Even the definition of product shelf life and the length of the product life cycle are based on a time interval. The increasing distance among the nodes of a supply chain network implies an increased time to reach the nodes of the chain. Therefore, global supply chains represent both an opportunity to reach global markets with many potential clients and business opportunities and a threat to product quality and safety.

The distribution represents the most critical phase of the perishable product life cycle. Lengthening this phase means exposing the product to environmental stresses for a prolonged interval, accelerating the quality decay, and increasing the uncertainties intrinsically present in the environmental stresses (e.g., temperature fluctuations, risks of mechanical collisions, and vibrations, traffic conditions). For such reasons, global supply chains have been considered a threat to sustainable food supply chains, compared to a local alternative (Coley et al., 2009).

As the exposure to the environmental conditions in global supply chains is higher, it requires refrigerated systems and more insulating packages to guarantee the delivery of high-quality products to the clients. Furthermore, choosing the right vehicle and the best distribution route is much more essential in global supply chains in order to have a sustainable FSCS.

Although the distances between the nodes of a supply chain system are typical of the specific network, two crucial factors could suggest if a new supply chain located in a geographical area would likely become global or not. Whether the knowledge of the specific supply chain and the strategy of its stakeholders is the best predictor of the future geographical extension of the supply chain, product import and export in the operating sector could be a good predictor too.

Indeed, if the importation of products from abroad is high in a specific country, it is likely that the production of raw materials in that country is not sufficient to produce all the products within its borders. Therefore, many suppliers of the new supply chain could be located abroad, and the traveled distance to source products increases. Similarly, whether the exportation of products of the same sector from the operating country is high, it is likely that the internal demand for products is already satisfied by the current production, and a new supply chain could also export part of its production. Therefore, many clients could be located in different geographical areas, with an increase in distance and time for distribution.

3.5 Long-term logistics strategies for PLC

According to the literature and the typical industrial practice, logistic managers exploit two main long-term levers to strategically reduce losses of perishable products.

(1) The first lever is the adoption of refrigeration systems, which represents the best lever to minimize losses if the focus is not on the overall sustainability of the supply chain system. The adoption of refrigeration systems allows maintaining an adequate temperature and humidity set-points for perishable products at every stage of the supply chain: after harvesting and during processing, storage, distribution, and sale. By maintaining the ideal storage conditions for the products, refrigeration slows down the chemical and biological reactions causing the proliferation of bacterias (Stoecker, 1998).

    However, when the objective is not just the reduction of food losses but the overall sustainability of the supply chain, unnecessary use of cooling systems is discouraged by its consequences on energy consumption, which increases the total costs and the carbon emissions of the supply chain system (Fikiin et al., 2017). Indeed, refrigeration is an energy-intensive system, and its installation, utilization, and maintenance costs may be prohibitive, especially for developing countries.

(2) The second lever deals with packaging and other containment solutions. The use of adequate packaging solutions, along with the choice of insulating materials for storage rooms, facilities, and containers, contributes to the reduction of energy consumption. Innovative packaging solutions, such as modified atmosphere packaging and edible coatings (Ghidelli & Pérez-Gago, 2017), can insulate products from the external environment and mitigate the stresses that could compromise product quality (Manzini et al., 2017).

    The cost of packaging solutions is usually lower and could be more accessible also in developing countries. It also lowers the carbon emissions significantly as the environmental impact of packages is usually due to production and reuse, while the utilization does not constitute a carbon-intensive activity. However, packaging and containment solutions can only protect perishable products when the criticality of the environmental conditions is not too high. Indeed, packages aim to preserve a favorable atmosphere within their microenvironment more than actively modify the existing conditions.

3.5.1 Climate-driven logistics

Currently, logistics managers adopt only the two aforementioned strategies to optimize PPLCM. This thesis introduces a third strategy lowering the current criticalities of the supply chain. This strategy, the climate-driven logistics, concerns the management of the FSCS and deals with the planning of conservation and distribution operations along the perishable supply chain according to climate conditions (Accorsi et al., 2017). The climate-driven logistics aims to reduce energy consumption due to refrigeration and increase the effectiveness of packaging and containment solutions by integrating these two traditional levers.

Specifically, it exploits the knowledge of climate conditions and weather forecasts to aid the following decisions:

- Schedule the deliveries of perishable products according to weather conditions, avoiding the time of the day when the environmental conditions are more critical (such as the afternoon in hot regions);
- Select the best route toward the customers to encounter more favorable climate conditions. The chosen route should avoid passing through regions with critical environmental conditions while avoiding longer routes to preserve product quality. Choosing the best route option does not guarantee significant increases in products' quality in local supply chains but proved to be a critical aspect in global supply chains and even within a single country (see chapter 5);
- Choose the proper facility where to storage products according to climate conditions. Climate-driven logistics could also suggest the best option to locate a new storage node or other facilities. As the perishable item spent a long portion of its life cycle stored within these nodes, considering climate conditions when choosing the location of a new node could save a significant amount of money and reduce the carbon emissions to refrigerate the storage rooms;
- Assign the proper best location to each product within a storage node. The environmental stresses experienced by perishable products could even change within the same facility (Accorsi et al., 2018).

A climate-driven approach, along with proper packaging solutions, could prevent the use of refrigeration without compromising the quality of the perishable products. The effectiveness of a climate-driven approach increases both with products' sensitivity to the environmental stresses and for geographical areas experiencing critical climate conditions. As this strategy is of managerial nature, its implementation costs are organizational, and they are meager compared to the other two levers.

3.5.2 Criteria for choosing the best strategy

Figure 11 schematizes the three proposed strategies.

Each strategy aims to optimize the shelf-life of perishable products by reducing the stresses due to adverse environmental conditions. However, different implementation costs and different levels of effectiveness characterize the three strategies. Therefore, the final choice of the strategy (or strategies) to adopt depends on the specific environmental conditions the product experience throughout its life cycle.

In order to have a reasonable comparison among the strategies and with the aid of some charts, the figure exemplifies the expected cost trend for each unit of the volume of distributed products when the production increases. Each line represents the expected trend of the costs of a given product in agreement with the selected strategy. Each chart illustrates two illustrative cost trends (i.e., a continuous curve and a dashed curve) to highlight the differences due to the specific solution adopted based on the specific characteristics of products. Indeed, each strategy entails similar cost trends regardless of the peculiarities of the product, but the actual cost may differ. Some examples of factor determining a different cost with the same strategy are:

- the materials adopted for the packaging solutions,
- the size of the refrigeration system,
- products' intrinsic characteristics (e.g., fresh cherries need refrigeration more than plums, so the unit cost of cherries is higher even if they present a similar trend).

A couple of illustrative products are shown along with each chart. They represent products that are most likely to require the approach illustrated in the chart. For example, cherries are fast perishable items that require refrigeration to be stored at their ideal environmental conditions as their quality decay is very fast at high temperatures. Indeed, the shelf life of cherries reduces from a few days to hours when the storage temperature passes from 6 to 18°C (Yaman & Bayoındırlı, 2002).

Conversely, apples and pears, which belong to clusters 5 and 3, respectively, are less affected by adverse environmental conditions, although also their shelf life is maximized at low temperatures (around 0°C). Therefore, they can be preserved at a high-quality level without using refrigeration if they are provided with an appropriate package.

For products with a lower shelf life, such as tomatoes and apricots, but still less susceptible to adverse environmental conditions than critical products like cherries, a climate-driven logistics strategy can instead reduce spoilage risks without compromising the sustainability of the FSCS.

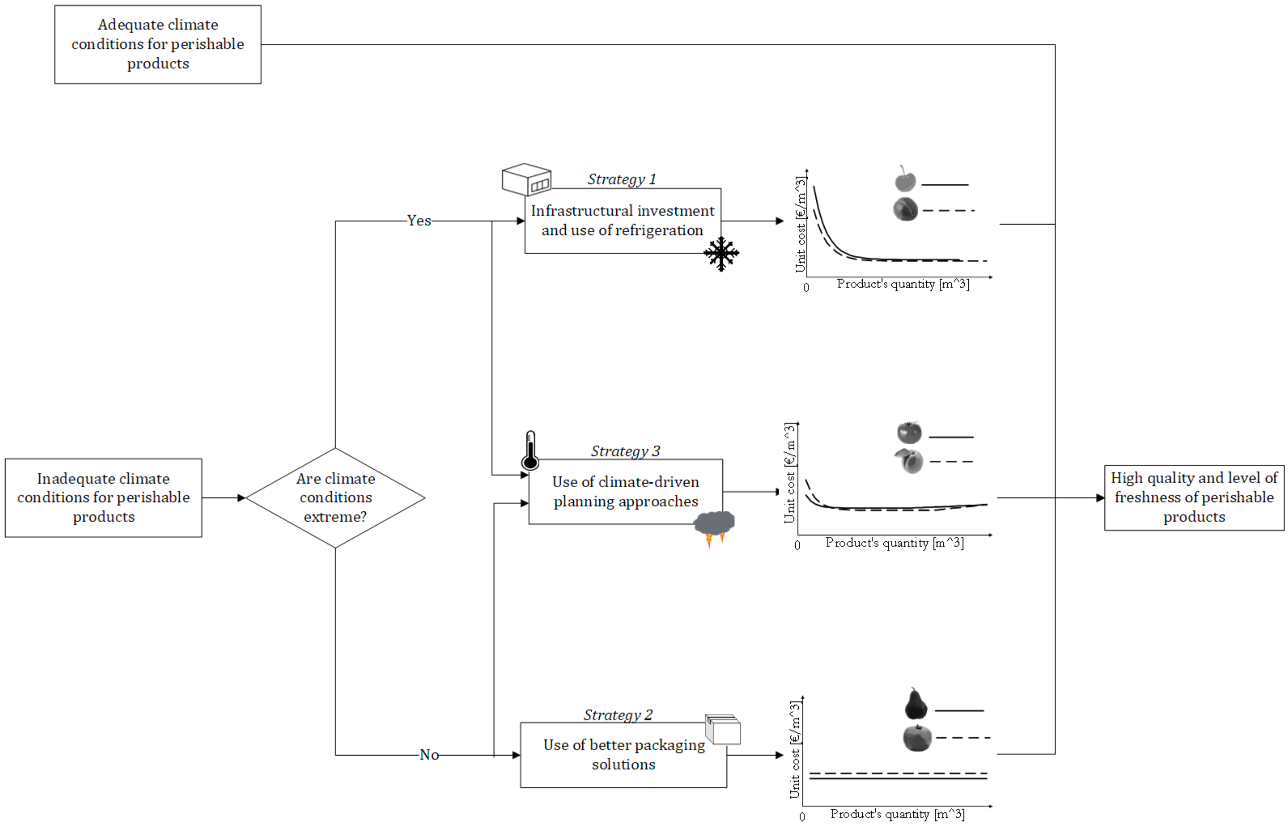


Figure 11. Long-term logistics strategies for PPLCM (Gallo et al., 2018).

Strategy 1 (i.e., investments in infrastructures) guarantees the ideal storage conditions for perishable products even in the presence of a critical external environment through climate-controlled chambers. Refrigeration systems regulate the set-point of temperature and humidity according to the product stored within the storage room and protect products during storage and transportation (i.e., refrigerated containers). However, strategy 1 is less convenient in terms of costs and carbon emissions. Therefore, logistic managers should avoid refrigeration, especially when the same achievements can be obtained with packaging solutions or by lowering risks through a climate-driven planning approach. As shown in figure 11, this strategy compels the higher fixed costs than the others to install the technology in all the plants and vehicles. Nevertheless, the resulting unit costs exponentially decrease when the flow of distributed perishable products increases.

Strategy 2 experiences constant costs per volume of the distributed product since the cost of packaging grows linearly with the flow of products. Different packaging solutions have different constant unit costs. However, the cost of packaging is smaller than the investments needed for the infrastructure. However, packaging can guarantee the effective insulation of the products and avoid losses only if the environmental stresses are not critical as it can not alter the conditions within its microenvironment actively.

Finally, strategy 3 does not present direct costs for either infrastructure or packaging materials. The costs represented in figure 11 refer to indirect costs associated with organizational aspects of the supply chain operations. This strategy entails applying an innovative paradigm in PPLCM, where products are processed and distributed according to climate conditions (Accorsi et al., 2017). The climate-driven approach suggests the proper batch of the day (e.g., at the end of the day or early in the morning) when the logistics activities should be performed and suggest the nodes the product should visit and the distribution route.

For these reasons, this framework requires skills, information systems, and management costs for its implementation. These costs decrease when allocated to a more massive flow. However, when the quantity of perishable products increases, the complexity of the management strategy rises, and the organizational costs increase too. The climate-driven approach reduces the need for refrigeration, looking for favorable weather conditions. Therefore, it represents a cheap alternative to design and optimize an FSCS. This strategy is appropriate both for critical environmental conditions and for moderately adverse conditions. The aim of climate-driven logistics is not to replace the other two approaches. Conversely, it should be integrated with them to contribute to the increase in the sustainability of the FSCS.

3.6 Classification of supply chains

The previous sections introduced some characteristics of the supply chain systems that differentiate them in terms of consequences on the perishable product life cycle:

- The climate conditions within a geographic area have a direct and critical impact on the product life cycle. The product must be protected by environmental stresses by insulating materials and refrigeration systems to avoid food losses.
- Some developing countries could not afford new, expensive technology to mitigate the consequences of adverse environmental conditions. Furthermore, the cost of refrigeration technologies is not only due to their installation but also to their utilization and maintenance and require continuous access to the energy grid.
- Creating a microenvironment with the ideal storage conditions for perishable products could be expensive and emit much carbon. The increased awareness of environmental sustainability, climate change, and carbon pricing initiatives could prevent the intensive use of refrigeration systems. However, the reduction of food losses due to such systems is undoubted. Therefore, more environmentally sustainable alternatives must substitute them.
- The increased traveling distance and time erode the shelf life of perishable products and threaten their safety for consumers. In order to reduce product losses without giving away

the potential of global markets, the FSCSs must adopt insulating systems to preserve the perishable item.

This section aims to introduce a classification framework for supply chains that classifies them according to the aforementioned characteristics. The combination of this classification and the one for products proposed in the previous chapter will allow logistics managers to make long-term investment decisions for a new supply chain, preserving product quality without compromising the sustainability of the FSCS.

This geographical-based classification includes those aspects that deal with the localization of the nodes of the supply chain. The geography is the area where the supply chain operations (i.e., packaging, storage, distribution) take place. Figure 12 shows some maps illustrating how to assess the criticality of the characteristics presented in the previous sections. These characteristics are not exhaustive, but they represent a starting point to show how to apply a comprehensive classification framework for supply chains of perishable products. The World Bank (2017) provided the data for these parameters, also showing the evolution of these values with time.

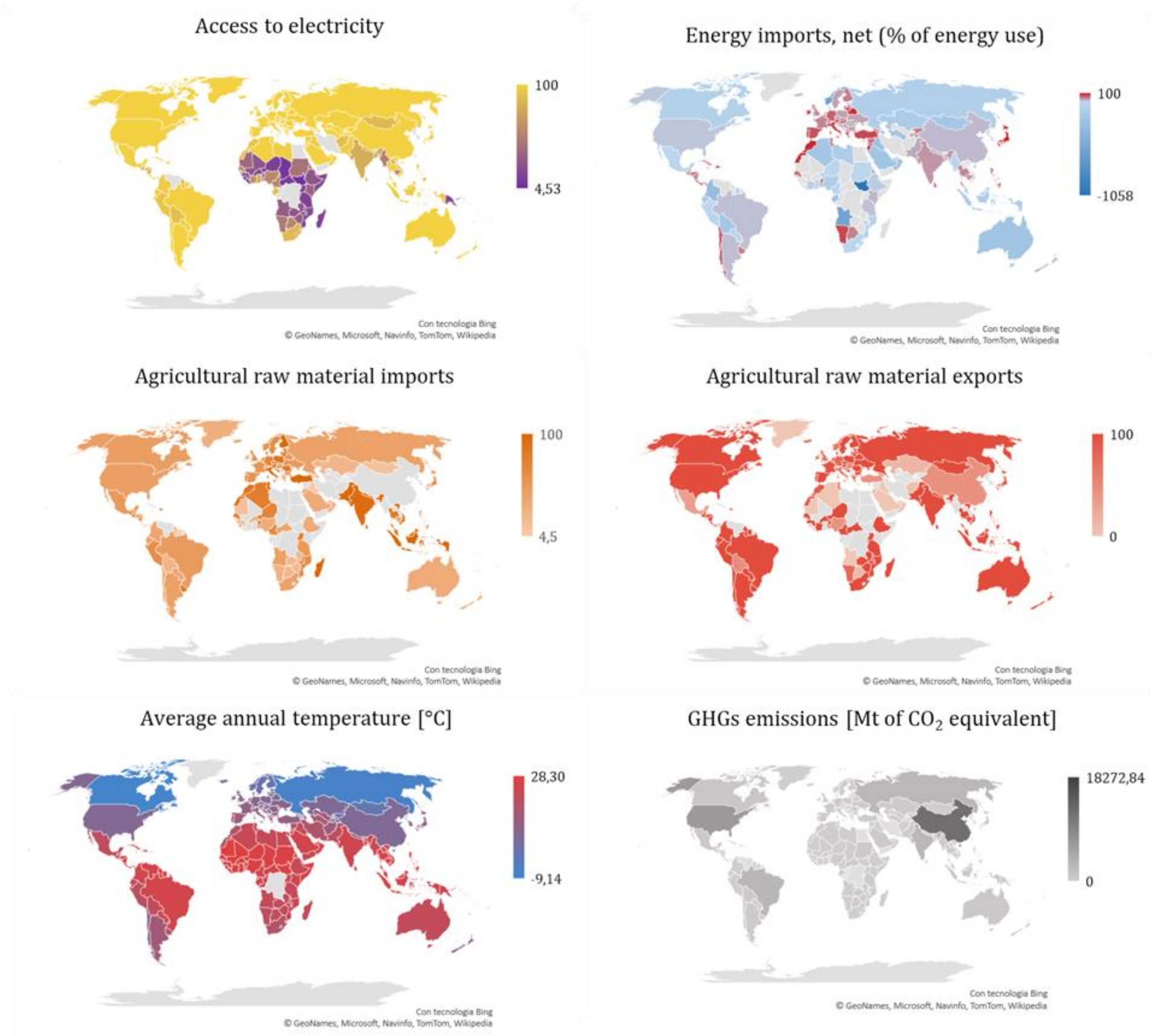


Figure 12. Geographical parameters for supply chain classification (as a percentage value, if not specified) (Gallo et al., 2017).

Once that data on geographical characteristics are collected, a Boolean algebra approach classifies sets of similar geographical areas, suggesting the most appropriate strategy for them. The detailed list of the involved parameters is the following:

- Access to electricity. Let AE be the countries with high access to electricity and $\overline{AE}$ be the countries with low access to electricity;
- Energy imports net. Let EI be the countries with high energy imports net value and $\overline{EI}$ be the countries with low energy imports net value;
- Agricultural raw materials exports. Let AME be the countries with high agricultural raw materials exports value and $\overline{AME}$ be the countries with low agricultural raw materials exports value;

- Agricultural raw materials imports. Let AMI be the countries with high agricultural raw materials imports value and $\overline{AMI}$ be the countries with low agricultural raw materials imports value;

- Temperature. Let ET be the countries with extreme temperature values, both very high values or very low values, and $\overline{ET}$ be the countries without extreme temperature values;

- Total greenhouse gas emissions. Let GHG be the countries with high greenhouse gas emissions values and $\overline{GHG}$ be the countries with low greenhouse gas emissions values;

Using the union and intersection operators between the sets, we classify the countries according to these parameters to provide a taxonomy of the geographic areas. For example:

- the presence of extreme climate conditions
- the poor availability of energy and its high costs (e.g., due to energy import)
- the high flow of long-ray container shipment (i.e., connected to the import/export balance of agro-food products)
- The high GHGs emissions and the high price of carbon emissions due to carbon pricing initiatives

make a geographic area potentially interested in reducing the use of refrigeration and implementing a climate-driven logistics approach to mitigate the adverse effect of critical temperatures. The intersection of these sets highlight and point out such areas.

$ET \cap (\overline{AE} \cup EI) \cap GHG$ = climate-based solutions;

$ET \cap (AE \cup \overline{EI}) \cap (\overline{AME} \cup \overline{AMI}) \cap \overline{GHG}$ = refrigeration-based solutions;

$\overline{ET} \cap (\overline{AE} \cup EI) \cap (\overline{AME} \cup \overline{AMI})$ = packaging-based solutions;

$\overline{ET} \cap (\overline{AE} \cup EI) \cap (AME \cup AMI)$= containment-based solutions for vehicles;

Figure 13 puts together all the geographic characteristics illustrated in this section to provide a guideline for the best long-term strategy to apply in each country according to the Boolean algebra-based formulations introduced above.

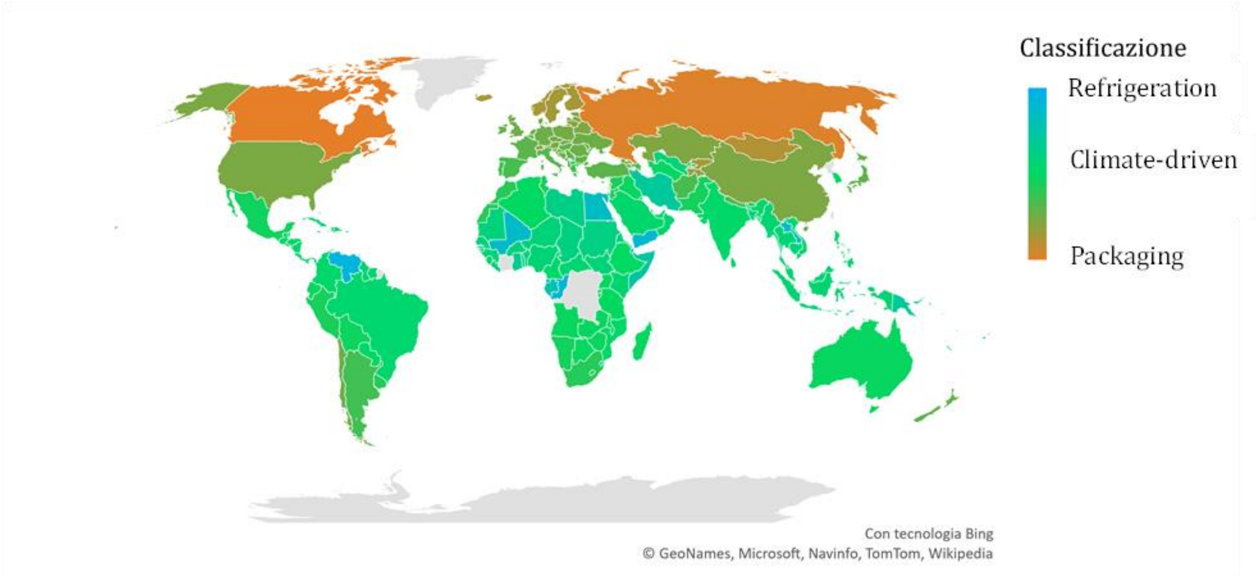


Figure 13. Classification of countries based on their characteristics.

3.7 Identification of the best long-term strategy

After classifying the supply chain based on geographic characteristics and introducing the three main logistics strategies, this section presents an approach to deduce the best strategy for a specific FSCS.

The products and supply chain classification framework proposed in the previous and this chapter is mainly conceived for newly constituted FSCS because it also involves investments to establish new nodes of the network and fleets of vehicles. For example, whether the best strategy is the investment in infrastructure, the nodes of the network and the vehicle should be equipped with a refrigeration system. Similarly, if climate-driven logistics is the best option to optimize the supply chain system, the nodes of the network should be located accordingly to climate conditions in the geographical area of the supply chain.

As previously introduced, Figure 11 shows that if the geographical area does not experience critical environmental conditions, proper packaging solutions combined with a climate-driven planning approach can avoid using refrigeration without affecting the products' shelf-life.

3.7.1 Seasonality of perishable products

The main drivers guiding the decision-making process for the long-term strategy to optimize product life cycle are the sensitivity of the products to the environmental stresses introduced in the previous chapter and the criticality of climate conditions in the geographic area of the FSCS. There is a strong relationship between the two drivers, as a high product sensitivity emphasizes the criticality of environmental stresses.

Therefore, the peculiarities of a specific product determine the actual criticality of climate conditions. However, the stresses are not the same throughout the year as the climate conditions change according to seasons. Furthermore, the products are not always available within a geographic region, as the harvesting and selling processes for many food products occur within a precise time interval related to the season. The seasonality of the perishable products complicates the evaluation of the criticality of climate conditions. The criticality assessment should not consider just an average temperature value for the whole year, but the actual environmental stresses during the season of production and commercialization of the product.

For this reason, this section identifies the ten top producing countries for each of the products classified in table 1 (chapter 2). For each of these countries, an online historical climate database (Weather Underground, 2018) provided the weekly average temperature and relative humidity data. Then, the seasonality data for each product were gathered from FAO databases based on harvesting seasons. Based on this information, the ideal storage conditions of the classified fruits and vegetables (i.e., temperature and relative humidity) have been compared with the actual climate conditions only during the production seasons. As the proposed products are 41, and this section considers ten producing countries each, the total number of combinations is 410.

3.7.2 Map of criticality

The classification framework proposed in this thesis calculates two criticality scores for each couple of products and geographic areas: one for temperature and one for relative humidity (RH). The procedure to estimate the criticality scores is illustrated in table 5.

Table 5. Criticality scores estimation.

$\lvert Ideal\ temperature - actual\ temperature \rvert$	Temperature criticality score
$x > 20$	4
$15 < x < 20$	3
$10 < x < 15$	2
$5 < x < 10$	1
$0 < x < 5$	0

$\lvert Ideal\ RH - actual\ RH \rvert$	RH criticality score
$y > 20$	4
$15 < y < 20$	3
$10 < y < 15$	2
$5 < y < 10$	1
$0 < y < 5$	0

After estimating these two criticalities scores for each product in table 3 in each of its ten top producing countries, the framework calculates two average criticality scores for each cluster of products introduced in chapter 2 in each geographic region. Figure 14 shows the results of this analysis for temperature (a) and relative humidity (b). The height of the bars represents the criticality of the environmental conditions for a specific supply chain system of a perishable product belonging to one of the clusters. The higher the bar, the more critical the environmental conditions experienced by the cluster's products will be. The map also highlights the countries are the most important producers for each cluster (countries that are not the top producers of the products in a cluster do not have the bar associated with that cluster).

(a)

(b)

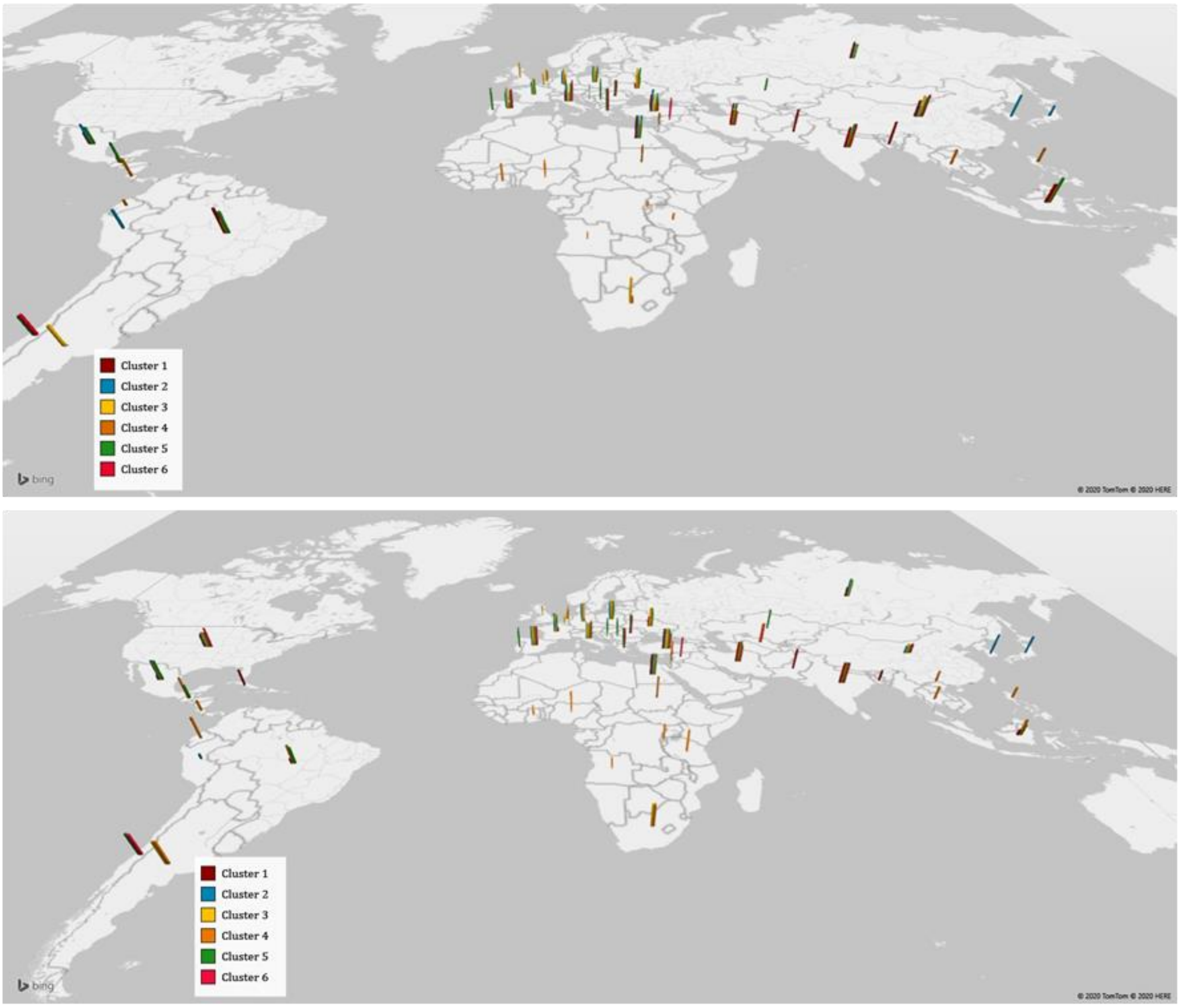


Figure 14. Criticality of temperature (a) and relative humidity (b) for each cluster of products in each region.

The clusters resulting from the *k*-means algorithm, related to the climate profiles of the production regions as shown in figure 14, provide managerial insights and guidelines toward the identification of the most effective strategy to adopt, according to figure 11. The higher the bar representing the criticality of the environmental stresses, the more this framework suggests investing in infrastructures altering the climate conditions within nodes and vehicles of the FSCS. For example, the strawberries and the cherries experience critical conditions in most of their producing countries and require refrigeration systems to avoid losses. Other products, such as apricots in Italy and raspberries in Portugal, experience critical conditions only in a few producing countries. Conversely, some products do not experience critical conditions in most producing countries, such as lemons and bananas.

In general, products in cluster 5 and cluster 6 are more frequently exposed to critical conditions (e.g., apricots, raspberries, plums, nectarines, and cherries). At the same time, high criticalities do not threaten products in cluster 4 in their top producing countries (e.g., lemons, potatoes, tropical fruits), and proper packaging solutions can replace the use of refrigeration.

The map in figure 14 also highlights clusters of products harvested throughout the globe or within a single continent, which are the case respectively of cluster 4 and cluster 6.

3.7.3 Criticality matrix and strategy identification

The previous subsections estimated two criticality scores based on the values in table 5. This criticality only depends on (1) the characteristics of the perishable products introduced in the previous chapter and (2) their comparison with the weekly average climate conditions in the geographic areas according to the seasonality of the food items.

The result of this comparison is a map of criticality that shows how critical the climate conditions are for each cluster of products in different geographical areas. Figure 15 transpose these results in a criticality matrix. The matrix has two dimensions: the product's sensitivity to climate conditions on the abscissa and the criticality of climate conditions on the ordinate.

When the sensitivity and the criticality of climate conditions are low, then containment solutions are more appropriate to optimize the PLC in the long-term. Conversely, when the sensitivity and criticality of climate conditions are high, then investments in infrastructures should be preferred.

Climate-driven logistics lower the criticality of climate conditions by exploiting the more favorable conditions during the day and choosing the nodes and the routes in geographical areas with a climate that is similar to the ideal one.

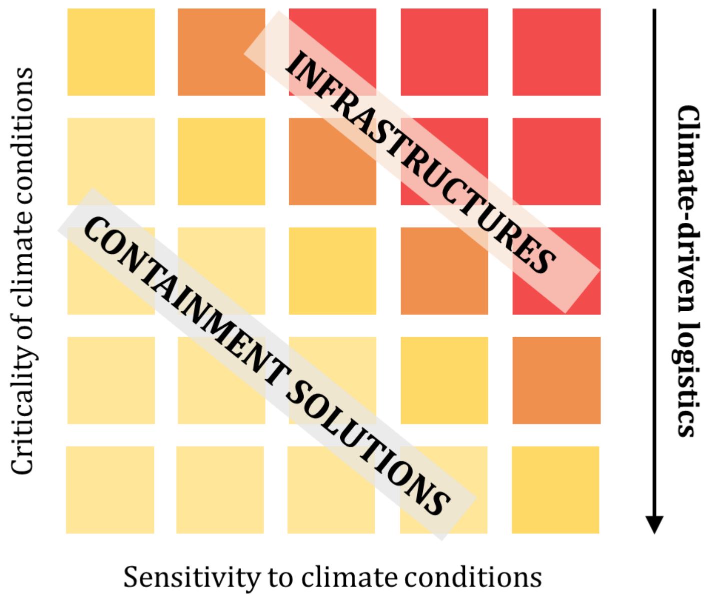


Figure 15. Criticality matrix.

The criticality matrix does not take into account the other characteristics classified in the previous sections. However, other factors influence the final decisions, primarily by determining the feasibility of investments in refrigeration systems in the most critical supply chains.

- The access to electricity and the energy import determine if there is electricity enough for refrigeration systems and if the cost of this solution is not too high. Indeed, refrigeration should be discouraged in countries where access to electricity could reduce the effectiveness of refrigeration systems or higher impacts on sustainability than the food losses resulting from adverse environmental conditions.

- At the same time, in a country with high GHGs emissions and implementing carbon pricing initiatives, the carbon emissions due to refrigeration could not be acceptable. Therefore, if the combination of climate-driven strategies and packaging solutions can avoid refrigeration, they should be preferred.

- Conversely, high imports and exports of food items could suggest that the new supply chain will be global. Therefore, the traveled distance to supply raw materials and to distribute the finished products to the clients increases, implying that the products will be exposed to environmental stresses for a longer time. In such cases, the refrigeration systems often represent an effective solution to reduce food losses that could become otherwise unavoidable.

Finally, other essential optimization suggestions come from the other product's characteristics introduced in chapter 2. Frost damages increase the criticality of cold climates on the perishable items. When products are characterized by high water content, they usually have an initial freezing point close to the freezing point of water (0 °C). Therefore, a cold climate could easily damage the item determining its loss. Furthermore, it is vital to isolate products with high sensitivity to ethylene from products producing lots of this hormone to avoid product perishment.

3.8 Application of the proposed classification framework

This section summarizes the classification framework introduced in this chapter and the previous one to guide practitioners and decision-makers in investing in long-term logistics solutions to preserve the product's quality.

The most effective strategy to manage perishable products differs based on their characteristics and those of the supply chain. Perishable products require proper environmental conditions throughout their life cycle to preserve their quality. Therefore, refrigeration represents the best strategy to minimize food losses. However, when considering all the three dimensions of sustainability (i.e., economic, environmental, social), the intensive use of refrigeration often is counter-productive. Refrigeration systems and the investments in infrastructure for new nodes and vehicles with temperature-controlled environments require high installation, utilization, and maintenance costs. Moreover, refrigeration is energy-intensive, and carbon emissions associated with this preserving solution threaten sustainability more than increasing the performance of the FSCS.

However, refrigeration does not represent the only investment solution to preserve product quality from adverse environmental conditions. Packaging and containment solutions represent a cheaper alternative that insulates the microenvironment containing the product from the external conditions. Some of these solutions also entail the recreation of a controlled atmosphere within the package itself that could be sufficient to protect the perishable item until it reaches the clients' site. However, packaging and containment solutions could not be enough to preserve the product in critical environments, where the environmental conditions are significantly different from the optimal ones, and in global supply chains, when the product travel for a significant part of its shelf life.

The proposed framework classifies products and supply chains based on their properties and suggests the best long-term logistics strategy for food preservation for new FSCS, as shown in figure 16. Firstly, the type of product the FSCS will produce should be identified. Practitioners should collect all the information about this product, as illustrated in table 1 for agricultural products. Whether the type of perishable product differs from the 41 products introduced in the previous chapter, then other characteristics could be identified to classify the product.

For other agricultural products, practitioners can identify the most representative cluster for them by applying the k-means clustering algorithm. The association of products and their clusters allows approximating the characteristic of the product with those of clusters' centroids. The comparison between the ideal storage conditions of the centroid and the climate conditions in the geographic area of the supply chain determines the resulting criticality of the environmental stresses for the product. Practitioners should compare these values only during the weeks of production of the product (i.e., according to its seasonality). If the resulting criticality of the supply chain is high, then logistics managers should consider investments in infrastructures and refrigeration systems. Otherwise, packaging and containment solutions, along with applying a climate-driven logistics strategy, would be sufficient to prevent quality decays.

Given a supply chain of a perishable product, practitioners can address the following questions through this framework:

1. What is the cluster the product belongs to?
2. What kind of characteristics has the geographical area of the FSCS?
3. Are climate conditions critical for product preservation?
4. If the conditions are critical, is refrigeration a feasible solution?

The application of a climate-driven planning approach represents a cheap and effective strategy to reduce the criticality of the environmental conditions, thus reducing the use of refrigeration also for critical stresses.

Table 6 highlights the benefits of the application of the proposed classification framework for the different actors. It presents the benefits for the production nodes, storage nodes, policymakers, and distributors.

Table 6. Benefits of the application of the framework (Gallo et al., 2018).

Actor	How to apply the taxonomy framework	Outcomes
Production nodes	Concentrate the harvesting and processing of products in the most favorable geographic areas	Reduce food losses
Storage nodes	Choose the warehouse with the best position to stock products; Find the best strategy to manage perishable products	Reduce the total energy consumption and costs for refrigeration
Policymakers	Foster the development of regional supply chains of products with more favorable climatic conditions	Enhance the sustainability of the supply chains
Distributors	Distribute perishable products through the best routes according to the climate-driven framework	Reduce the use of refrigeration during transportation

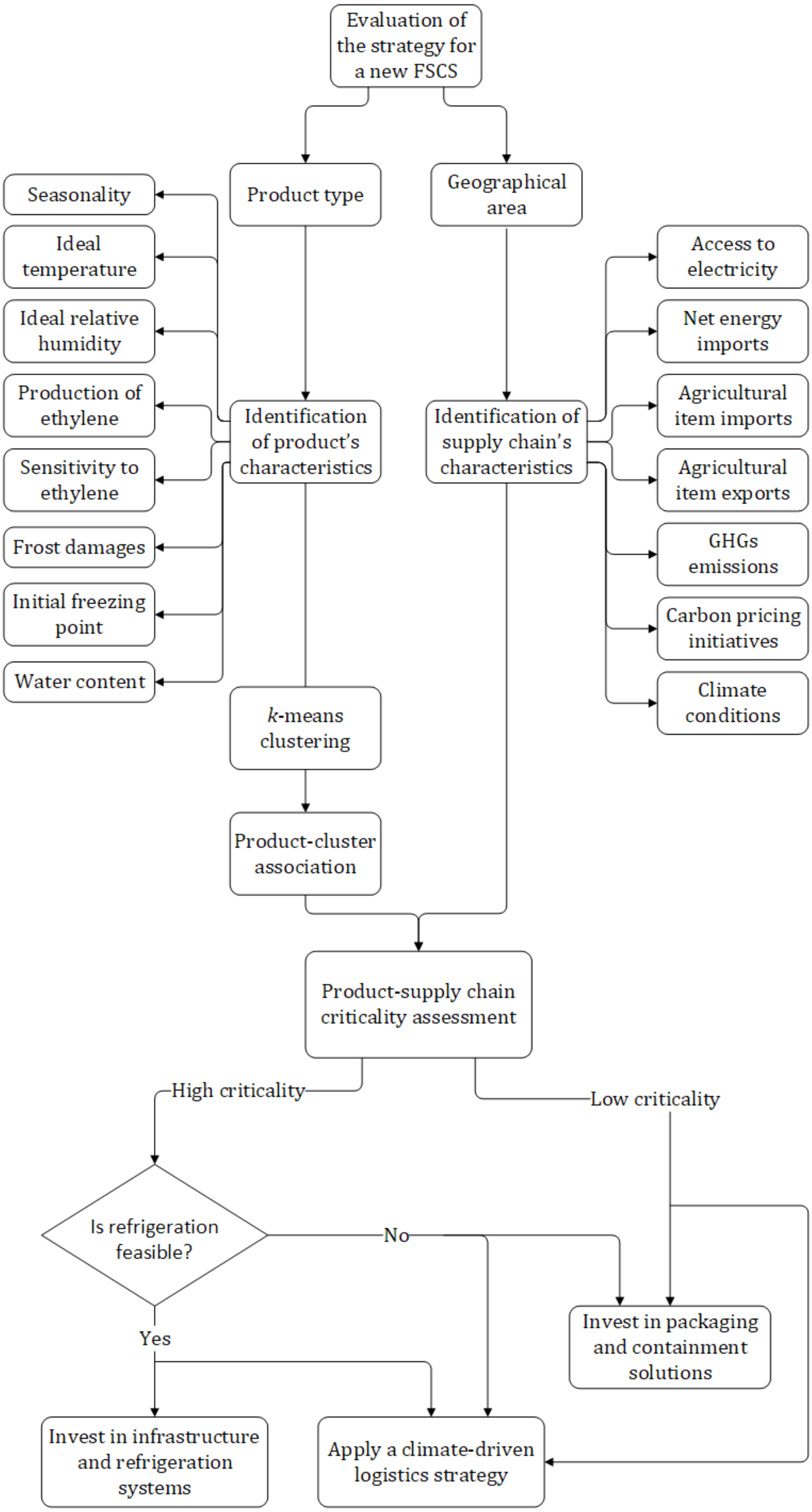


Figure 16. Classification framework for new food supply chain systems.

3.9 Case study of the distribution of fresh lettuce

This section illustrates the application of the classification framework and the identification of the best long-term preservation strategy for an FSCS of fresh lettuce located in India. The classification framework introduced in this and the previous chapter provides general guidelines for the decision-making process of logistic managers. When considering a specific FSCS, however, other data can integrate the proposed classification and provide more precise identification of the best logistics strategy.

The first step of the classification framework consists of the identification of products' intrinsic characteristics that do not depends on external factors. Lettuce is a product with very high water content (95.1%). Therefore, its freezing point is very close to 0°C (-0.2°C). It should be stored very close to this temperature. Indeed, the ideal storage temperature of this product is equal to 0°C, while the ideal relative humidity is comprised between 90% and 95%. Fresh lettuce produces a low quantity of ethylene while it is quite sensitive to this hormone. Conversely, it is not subjected to frost damages at low temperatures. Based on such characteristics, the *k*-means clustering algorithm assigned lettuce to cluster 2, as shown in table 3. The cluster includes other seven products that must be stored at low temperatures and high relative humidity and are characterized by high water content.

The second step in the application of the proposed framework is the classification of the geographical area of the supply chain. India is the third main producer of lettuce and chicory, after China and the United States of America (FAO, 2017). According to the data provided by the World Bank, and illustrated by maps in figure 12, India is characterized by:

- 79.17% of access to electricity.
- 34% of energy imports.
- 1.89% of agricultural raw material imports
- 1.57% of agricultural raw materials exports.
- The average annual temperature is 23.95°C.
- India is characterized by high GHGs emissions (2,828 million tons of greenhouse gas emissions), although it does not implement carbon pricing initiatives.

The critical environmental conditions in this country would suggest the adoption of refrigerated systems to reduce the losses. However, access to electricity, the high energy import combined with the high GHGs emission in this country suggest avoiding an intensive use of refrigeration for FSCS in this country. Therefore climate-driven logistics could generally represent a better strategy for FSCS located in India.

The assessment of the criticality of environmental conditions for lettuce in this specific country could suggest a different strategy for this specific product. However, the comparison between the environmental conditions in India and product seasonality showed an average of 22.55 °C during the week of production, which is very far from the ideal conditions of this product, confirming the need for preserving solutions to reduce the environmental stresses affecting the product in this region. Climate-driven logistics could represent an effective strategy to handle the logistics of this FSCS, as also illustrated in figure 13.

The criticality of environmental stresses for an FSCS of lettuce in India is also confirmed by the application of the equations introduced in section 2.2. According to Tsironi et al. (2017), the following data can be used to evaluate the kinetic reactions of lettuce at 2.5 °C:

- $E_a = 66.9 \frac{kJ}{mol}$.
- $k = 0.251 \frac{1}{days}$.
- Shelf life: 14 days.

Therefore, by the application of equations (2.2) to (2.5), the shelf life of this product, considering its seasonality and the average climate conditions in India, reduces to just a few hours. The introduction of climate-driven logistics could exploit more favorable conditions, either in the location of the nodes of the supply chain or in the timing of distribution activities. Indeed, weather data about temperatures in 2019 in India showed that the exploitation of the most favorable temperature conditions during distribution could lower the experienced temperature between 5°C and 10°C. If the FSCS adopts refrigerated rooms in the storage nodes in combination with a climate-driven distribution strategy, the shelf life of the fresh lettuce could be extended between 6 and 11 days (Tsironi et al., 2017).

3.10 Product refrigeration

Refrigeration systems extend the shelf life of perishable products for several days. By actively modifying the environmental conditions within the storage room, refrigeration slows down the reactions determining the proliferation of bacterias in food, extending the lag phase introduced in 2.1

(Stoecker, 1998). For some products, refrigeration could even extend the shelf life for months by freezing and storing them at subfreezing temperatures (i.e., usually between -18 and -35°C). However, this shelf life extension at low temperatures is not generalizable as some products (e.g., bananas) experience some chilling injuries when exposed to low temperatures. Finally, it is worth noting that not all foods require refrigeration. As shown in the description of products' characteristics, the ideal storage conditions are not the same for all the products. Some products, such as dry foods, can be stored at the environmental temperature without experiencing a severe quality decay.

3.10.1 Cooling phases of food

Although, in general, cold chains prevent products' spoilage, different products require different storage conditions and different management strategies in the supply chain operations (Akkerman & Donk, 2008; Vaclavik & Christian, 2003). For example, highly perishable products, such as fruit and vegetables, can be stored at 4–8°C to avoid alterations in colors and flavors and preserving safety threats for the consumers at the same time.

Furthermore, fresh fruits and vegetables are live products, characterized by a respiration rate. Indeed, these products consume oxygen and emit heat during their life cycle. Therefore, this heat of respiration increases the refrigeration load that should be removed from the environment to reach the desired temperature set-point. It further complicates the refrigeration of such products and increases the required energy consumption. Additionally, as a high water content characterizes these products, they usually experience a loss of moisture known as dehydration or transpiration. The transpiration rate represents the moisture loss of fruits and vegetables per unit of their mass and unit time. This phenomenon can be controlled at low temperatures and with the right relative humidity within the storage room.

Three phases characterize the freezing of food (Stoecker, 1998):

- Cooling up to the freezing point, which removes the sensible heat.
- Freezing, which removes the latent heat.
- Further cooling to reach the desired temperature set-point, which removes the sensible heat of the frozen product.

If the desired set-point is not below the freezing point, the cooling contribution will focus on the first phase, only removing the sensible heat to cool down the product.

Water content has a vital role in cooling perishable products. Indeed, the specific heat and latent heat of food are estimated quite accurately based only on the water content of the food item (Siebel, 1918), as in the following equations

$$h_{specific} = 3.35a + 0.48 \tag{3.1}$$

$$h_{latent} = 1.26a + 0.84 \tag{3.2}$$

both expressed in $\frac{kJ}{kg \cdot °C}$, where a represents the fraction of the water content of the food.

3.10.2 Refrigeration loads for storage nodes and vehicles

The refrigeration of the products' microenvironment consists of the subtraction of heat, causing a variance between the conditions within the controlled environment and the external conditions. This section does not focus on the size of refrigeration systems as it aims to calculate the total energy load to estimate the sustainability of this food preservation solution.

The refrigeration load is the total amount of heat that exceeds the desired conditions within the storage environment and must be subtracted to reach the ideal storage conditions. The refrigeration load comprises three contributions:

- The transmission load is the heat introduced within the temperature-controlled environment by walls, floor, and ceiling.
- The infiltration load is due to the warm air introduced within the microenvironment by doors, windows, and fissures.
- The product load represents the heat subtracted from the food itself as it is introduced in the temperature-controlled environment from the external one.
- The internal load is the contribution coming from all the heat sources within the temperature-controlled environment. It comprises the contributions due to lights, production systems, machinery, and operators.
- The refrigeration equipment load is generated from the refrigeration system itself during its normal functioning (e.g., reheating and defrosting).

Figure 17 schematizes the various contributions of the refrigeration loads within a refrigerated node. A similar schematization can be adopted for refrigerated vehicles.

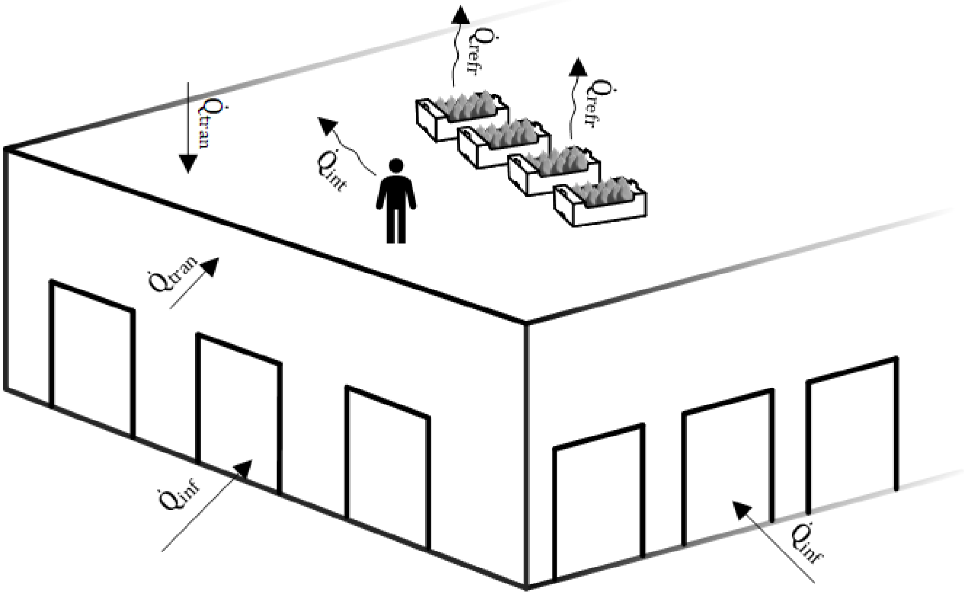


Figure 17. Schematization of the refrigeration load contributions.

The transmission load depends on the materials covering the temperature-controlled environment. Its contribution can be estimated with the following:

$$\dot{Q}tran = \frac{1}{\frac{1}{\mathrm{h}_{inner_{v,T}}}+\sum\frac{L_v}{k_v}+\frac{1}{\mathrm{h}_{outer_{v,T}}}}\mathrm{A}_{\mathrm{outer}_v}\left|\mathrm{T}^{\mathrm{env}}{}_{\mathrm{n,m,t}} - T\right| \tag{3.3}$$

where:

$\mathrm{h}_{inner_{v,T}}$	Heat transfer coefficient at the inner surface of vehicle *v* at temperature *T*, $\left[\frac{\mathrm{kW}}{\mathrm{m^2 °C}}\right]$.
$\mathrm{h}_{outer_{v,T}}$	Heat transfer coefficient at the outer surface of vehicle *v* at temperature *T*, $\left[\frac{\mathrm{kW}}{\mathrm{m^2 °C}}\right]$.
L_v	Width of the surface of vehicle *v*, [m].
k_v	Thermal conductivity of vehicle *v*, $\left[\frac{\mathrm{kW}}{\mathrm{m °C}}\right]$.
$\mathrm{A}_{\mathrm{outer}_v}$	Exchange surface of vehicle *v*, [m^2].
$T^{env}{}_{n,m,t}$	External temperature in the route between node *n* and node *m* during period *t*, [°C]
T	Temperature set-point inside the vehicle or the node, [°C].

The infiltration load considers the heat load due to the warm air entering the refrigerated rooms. This value changes with time. The determination of the size of the refrigeration system should consider the maximum infiltration load in time. As this section aims to estimate the total energy consumption to estimate the economic and environmental sustainability of refrigeration systems, the average value provides the best estimation. This load is not only due to the presence of wind introducing the airflow in the temperature-controlled environment but also to the different density of air between the cold environment and the warm one (ASHRAE, 2002). The estimation of the infiltration load is given by the following:

$$\dot{Q}inf = \frac{sv_n}{sv_{dryair,n}} ACH_n \left(\left(h^{env}{}_{n,t} - \mathrm{h}_{n,T} \right) + (\omega^{env}{}_{n,t} - \omega_{n,T}) h_{fg} \right) \quad (3.4)$$

where:

sv_n	Storage capacity of node n, [m^3].
$sv_{dryair,n}$	Volume of dry air in the storage room of node n, $\left[\frac{\mathrm{m}^3}{\mathrm{kg}}\right]$.
ACH_n	Number of air exchange in node n, [1/s].
$h^{env}{}_{n,t}$	Enthalpy of external air in node n during period t, $\left[\frac{\mathrm{kJ}}{\mathrm{kg}}\right]$.
$\mathrm{h}_{n,T}$	Enthalpy of air in the storage room, $\left[\frac{\mathrm{kJ}}{\mathrm{kg}}\right]$.
$\omega^{env}{}_{n,t}$	Relative humidity of external air in node n during period t.
$\omega_{n,T}$	Relative humidity inside the node in node n with at temperature T.
h_{fg}	Heat of vaporization of water, $\left[\frac{\mathrm{kJ}}{\mathrm{kg}}\right]$.

Two contributions constitute the product load. The first component is the heat that must be subtracted from the product to reach the desired temperature set-point. The other contribution is the heat due to the respiration of fruits and vegetables that must be removed from the environment to keep the desired temperature. As introduced in the previous subsection, the product load is made up of the sensible heat of the fresh product, the latent heat for freezing, and the sensible heat of the frozen product. Therefore, the product load is estimated by the following three contributions:

$$\dot{Q}refr = m \left(c_{p,fresh} (T_1 - T_{freeze}) + h_{latent} + c_{p,frozen} (T_{freeze} - T_2) \right) \quad (3.5)$$

where:

m	Mass of food item [kg].
$c_{p,fresh}$	Specific heat of the product before freezing, $\left[\frac{\mathrm{kJ}}{\mathrm{kg}\ {}^\circ\mathrm{C}}\right]$.
$c_{p,frozen}$	Specific heat of the product after freezing, $\left[\frac{\mathrm{kJ}}{\mathrm{kg}\ {}^\circ\mathrm{C}}\right]$.
h_{latent}	Latent heat of fusion of the product, $\left[\frac{\mathrm{kJ}}{\mathrm{kg}}\right]$.
T_1	Environmental temperature, $[{}^\circ C]$.
T_2	Desired temperature set-point, $[{}^\circ C]$.
T_{freeze}	Freezing temperature of the product, $[{}^\circ C]$.

When the refrigeration process aims to cool down the temperature within the room without freezing food, the product load is determined only by the first contribution of specific heat before freezing.

The internal load is generated by the people, lights, and all the dissipating equipment in the temperature-controlled room. The contribution of heat due to an average person is the following:

$$\dot{Q}int_{people} = 270 - 6\,T \tag{3.6}$$

expressed in $\frac{W}{person}$ where T is the temperature within the temperature-controlled environment. Therefore, the lower the storage room temperature, the more the additional load to be subtracted.

The estimation of the contribution due to the dissipating equipment can be derived from the information provided by the producer (e.g., the wattage of the light bulb and the power of the motor indicated by the supplier).

Finally, as the refrigeration load equipment is part of the normal functioning of the refrigeration systems, and it can also be due to the reheating process, which is not an undesired load, it will be neglected in the next chapters. However, this contribution is usually estimated through a safety factor of 10% that covers unexpected situations (Stoecker, 1998).

3.10.3 Reduction of energy consumption and emissions due to refrigeration

In the last decades, the research on refrigeration systems for FSCS focused on improving refrigeration technology and reducing the associated GHGs emissions. Hoang et al. (2016) propose using superchilling technologies that lower temperature 1-2°C below the initial freezing point of the product through a blast freezer. This solution reduces the environmental impacts of about 18% compared to the chilling technologies. Cascini et al. (2016) assessed the environmental footprint of commercial walk-in refrigeration systems through a comparative Carbon Footprint Assessment of two commercial refrigeration systems composed of refrigerant and refrigeration units. Bagheri et al. (2017) proposed a mathematical model to evaluate the thermal characteristics of refrigerated trailers and their performances. Bermejo-Prada et al. (2017) assessed the industrial viability of hyperbaric storage at room temperature (HS-RT) to preserve food safety and quality. This solution could lower energy consumption, eliminate refrigerants, and reduce GHGs emissions. Tassou et al. (2009) evaluated the use of air cycle technologies and direct power generation from the engine's heat to power refrigeration systems. Both represent promising technologies to reduce the emissions for food refrigeration for future applications.

Furthermore, some researchers proposed Computational Fluid Dynamics (CFD) models to improve the efficiency of refrigeration solutions. Smale et al. (2006) reviewed several CFD models to support the design of storage and transport solutions to reduce the variability around the temperature set-point, protecting the food quality, and reducing energy consumption. Getahun et al. (2017) proposed a CFD model of airflow for a fully loaded refrigerated shipping container to estimate the actual airflow within the refrigerated environment accurately.

Other studies focused on the reduction of the environmental impact of refrigeration systems within the retailers' nodes. Ge and Tassou (2009) focused on medium temperature retail food refrigeration systems. They proposed system models and the assessment of thermodynamic cycles to identify optimal control strategies in the food retail. Gullo et al. (2017) assessed the performance of pure CO_2 refrigeration based on the transcritical R744 refrigeration systems for food retail.

3.11 Packaging solutions for food

Packaging and containment solutions generally provide a cheaper alternative to preserve product quality from adverse environmental conditions. Packages aim to insulate the product from the external conditions by creating a microenvironment that mitigates the stresses due to climate conditions and mechanical damages (e.g., vibrations during distribution) and reduce the risks of contamination. The packaging is essential for logistics, not only for food preservation. It facilitates materials handling by making it much more efficient, and it represents the primary tool for modern consumer marketing. According to Robertson (2013), the packaging sector represents about 2% of the gross national product in developed countries, and nearly half of this packaging is devoted to food preservation.

A package completely isolates the food product when it is inert, opaque, impervious, and closed to the external environment (Piergiovanni & Limbo, 2010). Whether the package has all these properties, then the quality decay of the product depends only on the biochemical processes causing the proliferation of bacterias, without accelerating this reaction caused by the environmental stresses. In such a case, the quality decay of the product can be modeled as it is only dependent on product characteristics. Otherwise, the attributes of the package and the environmental conditions affect the product's quality decay. In order to furtherly slow down the quality decay of fresh produce, modified atmosphere packaging (MAP) changes the concentration of some gases within the package, for example, the oxygen level and the CO_2 quantity, that in their atmospheric concentration causes a faster decay of product quality (Phillips, 1996).

When the package does not completely insulate the product from the external environment, then the quality decay of the product is influenced by the permeability of the packaging solution. The following equation assesses the variation of the quantity of gas or vapor permeating the microenvironment within the package with time:

$$\frac{dW}{dt} = \frac{KP}{l} A(P_{out} - P_{in}) \tag{3.6}$$

Where:

- KP is the permeability rate.
- l is the thickness of the package.

- A is the surface of the package.
- P_{out} is the partial pressure of the considered gas or vapor from the external environment.
- P_{in} is the partial pressure of the considered gas or vapor from within the package.

In the last decade, researchers proposed several models and evaluation metrics to assess the performance of food packaging solutions. Defraeye et al. (2015) proposed an integrated performance evaluation of packaging for fresh products. González-Buesa et al. (2009) proposed a mathematical model relating the micro-perforation film area with the transmission rate for the packaging of fresh-cut fruits and vegetables. Belay et al. (2016) reviewed the mathematical models to design and evaluate the performances of MAP systems for fresh products. Guerrero et al. (2015) assessed the effects of an active coating based on soy protein to extend the shelf-life of beef patties.

Investments in better containment solutions for transportation also contribute to the product's quality preservation. Adekomaya et al. (2016) suggested a re-design of the food transport system to minimize the energy consumption in diesel engine driven vapor compression systems. Ahmed et al. (2010) proposed the use of phase change materials (PCMs) for the insulation of the refrigerated truck trailer. These materials reduce the peaks of heat transfer rates. Manzini and Accorsi (2013) investigated the effects of logistics decisions on transport and packaging solutions to increase the quality of perishable food. Michel et al. (2017) presented a design approach for a multi-layer insulation wall for refrigerated vehicles containing a composite layer of PU-PCM foam.

The concerns about the environmental impacts of logistics also focused on packaging and containment solutions. Chiellini (2008) assessed the adoption of alternative packages with bio-based, biodegradable, and recycled materials. These innovative packages employ materials having a lower environmental impact, such as hydrogels (Farris et al., 2009), renewable fibers, biopolymers, and bioplastics (Johansson et al., 2012).

3.11.1 Packaging solutions for fresh fruits and vegetables

Plastic and carton containers are the top choices as packaging solutions for fruits and vegetables in retail and food service industries (Singh et al., 2006). These packages protect the product from mechanical impacts but do not insulate the product from environmental conditions. They do not recreate a distinct microenvironment from the external conditions. Therefore, products distributed within these packages are exposed to adverse environmental conditions, and the mathematical formulation of their quality decay process is just product-dependent and does not take into account the mitigation effect of packaging. However, these packaging solutions are essential to facilitate the material handling of fresh produce, and their utilization in such industries is a standard de-facto for many fruits and vegetables.

In the last decades, Reusable Plastic Crates (RPCs) replaced disposable crates due to environmental concerns. The introduction of a closed-loop supply chain complicates the logistics flows of such packages. Still, it has clear vantages on the sustainability of the supply chain, as this plastic material can be recycled many times to produce new RPCs. According to Singh et al. (2006), RPCs require 39% less energy, generates 29% less total GHGs emissions, and the waste resulting from their adoption is 95% less than corrugated containers. Accorsi et al. (2014) provide a Life Cycle Assessment (LCA) comparison between disposable containers (cardboard boxes, plastic crates, wooden boxes) and RPCs. Their results show that the environmental impact of RPCs is highly dependent on the configuration of the supply chain network, as the closed-loop supply chain requires new logistics flows to manage the return of the crates.

3.12 Case study of RPCs to substitute disposable containers in an FSCS

This section presents the assessment of the substitution of disposable containers, both plastics and carton containers, with RPCs. This study aims to evaluate the impact of the adoption of RPCs on the sustainability of a supply chain distributing fresh fruits and vegetables to schools, canteens, hospitals, and restaurants in Italy. This analysis will focus on the storage node located in Bologna and serving nodes, mainly located in the Emilia-Romagna region.

The storage node receives fresh products from 290 suppliers. Most of the suppliers are located in Italy, while 16% are located in other countries in Europe, America, and Africa (mainly France, The Netherlands, Poland, and Spain). Figure 18 shows a density map of the flows of fresh products supplied by the producers distributed in Europe to the storage node located in Bologna. Each supplier provides only some of the products according to their production area and the seasonality of the product. Therefore, the same food item can be supplied from a geographic region for some weeks and from a different country during other weeks due to seasonality issues.

Local suppliers are preferred whenever available due to the short shelf-life characterizing most of the fruits and vegetables and the low value of these products. Supplying fresh produce from abroad entails high logistics costs that sometimes constitute the main share of the total costs of these items.

Figure 18. Yearly entity of products flows supplied from the producers to the storage node.

These suppliers provided about 21 million kilograms of fresh products, contained in about 3.7 million packages per year in the AS-IS situation. All these packages are disposable in the AS-IS scenario. The products that reach the storage nodes are weighted, labeled, consolidated, and put onto pallets or roll containers for distribution towards the clients. The type of food items distributed by this supply chain is about 14,500, where each item can be present in several types due to its provenience or species. The preliminary analysis conducted during this study involved about 2,000 nodes out of 5,800 clients served by the warehouse located in Bologna. However, these nodes require most of the products distributed from the storage node. Indeed, the total quantity distributed to these nodes is about 19 million kilograms per year, contained in about 4.3 million packages. Data about products, packages, nodes, and logistic flows were stored in a Microsoft Access database counting ten tables and about 1.3 million records.

Figure 19 illustrates the location of all the clients involved in the analysis, mostly located in the Emilia-Romagna region and close to Bologna, as the company has several other warehouses distributed in Italy serving other clients in all the country.

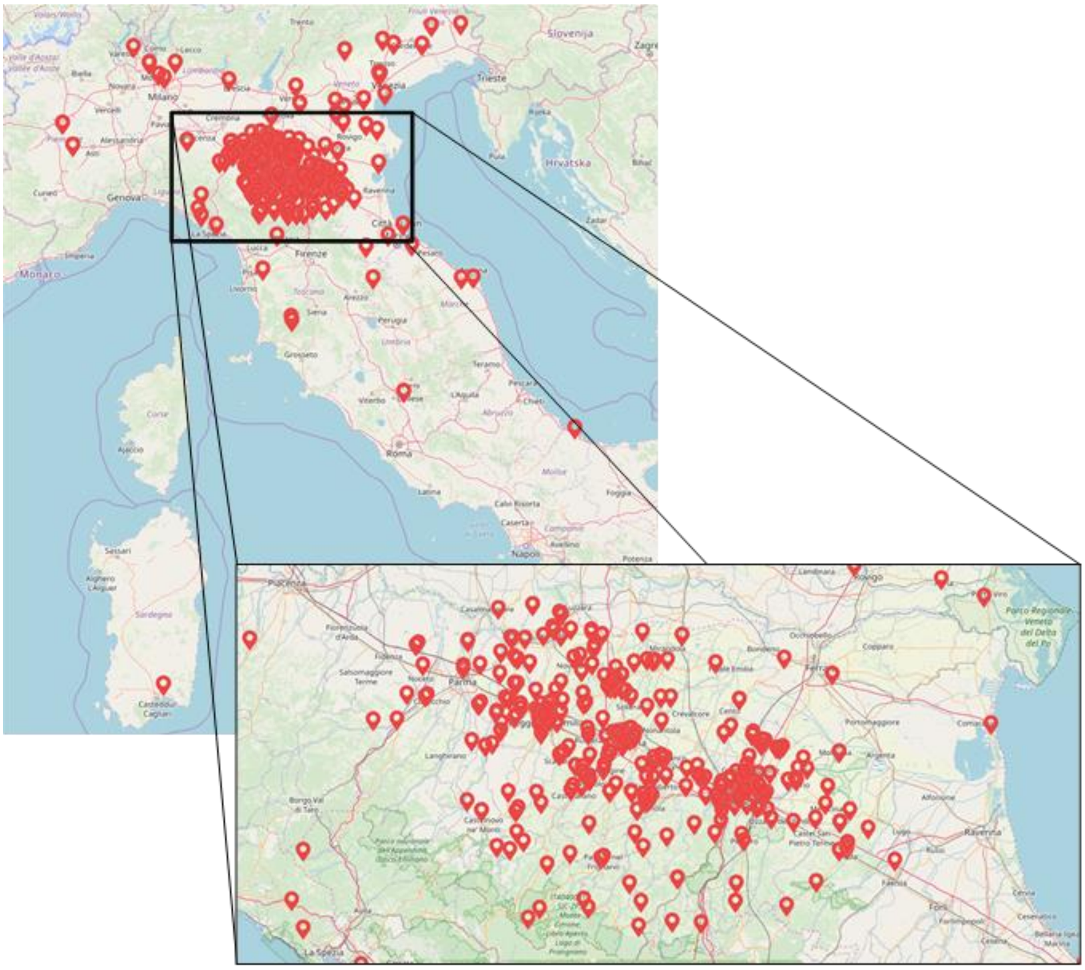
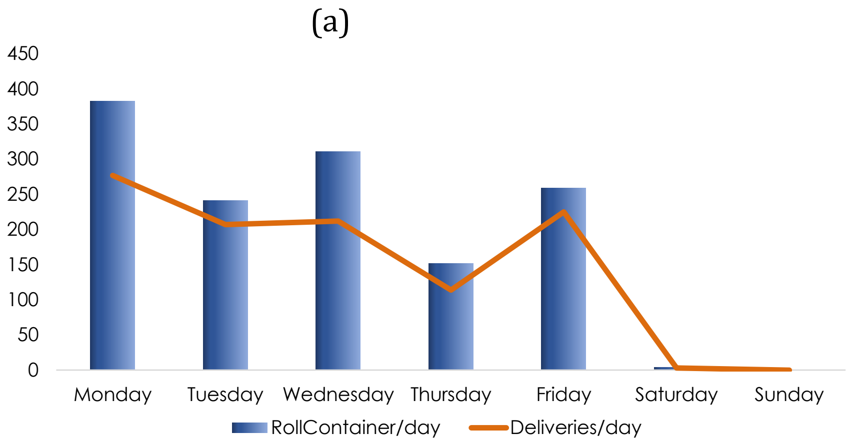


Figure 19. Location of the about 2,000 nodes served by the warehouse located in Bologna.

Figure 20 shows some statistics about the daily and weekly outbound flows from the warehouse located in Bologna through the nodes illustrated in Figure 19. As the products are perishable and can be stored only for few days, and the main flows are directed through nodes located in schools, hospitals, and canteens with a little storage space, most of the nodes receive two or three deliveries during the week. These deliveries are usually sent at the beginning, in the middle, and at the end of the working week. The highest number of deliveries is reached on Monday and Friday as most of the nodes require only two deliveries, while on Wednesday the number of deliveries is lower although the quantity delivered is high. Indeed, most of the nodes requiring deliveries on Wednesday are clients with a higher demand serving lots of points of consumption that need more frequent delivery of fresh products.

The monthly analysis of the roll containers distributed to clients shows that the flow of products is usually constant, except for summer and holidays, like in December (Christmas) and April (Easter).



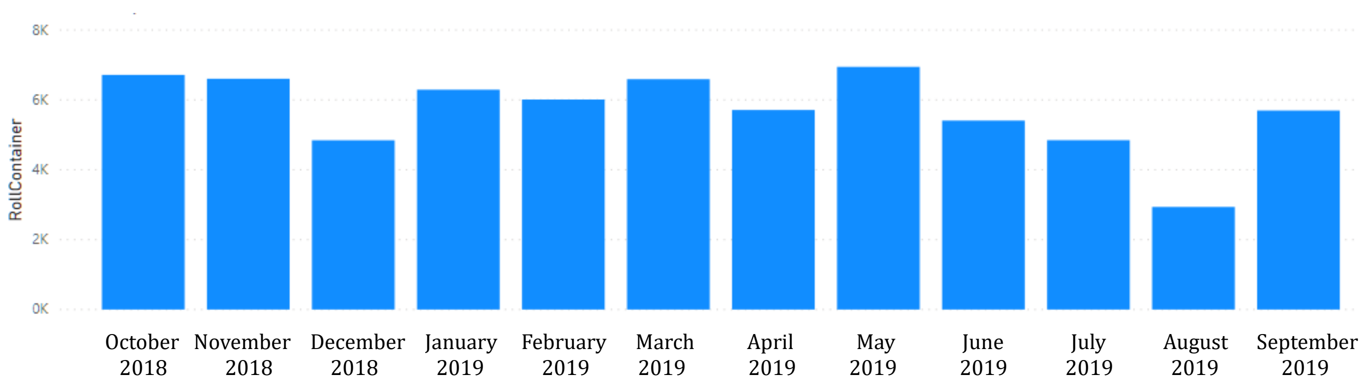


Figure 20. Daily (a) and weekly (b) statistics on outbound flows from the Bologna warehouse.

Table 7 resumes the main product categories and provides some statistics about the annual quantity distributed by the storage node located in Bologna. The table provides information about the total number of Stock Keeping Units (SKUs), the net tons of each category distributed during 2019, and the number of handling units carrying such products.

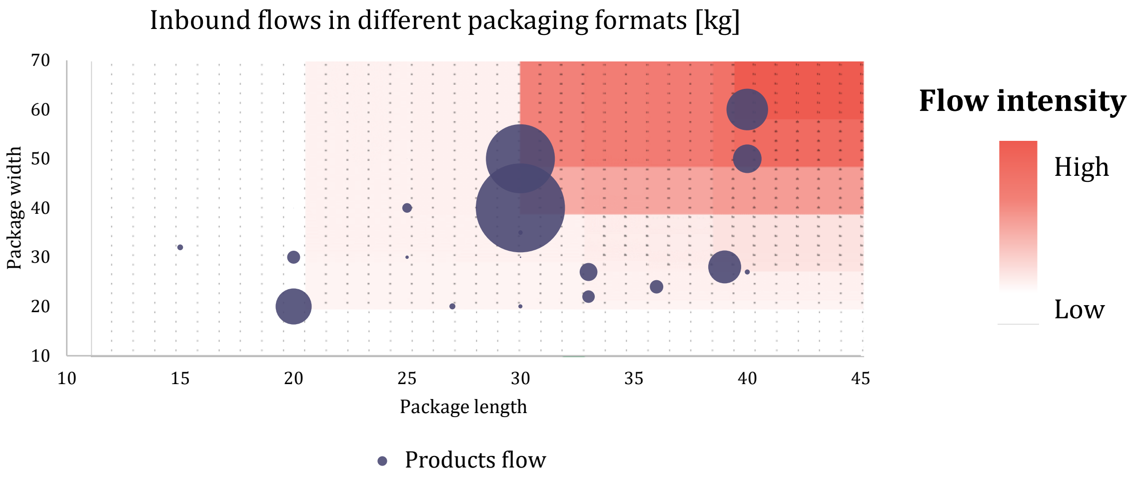
Table 7. Product categories.

Product category	SKUs	Handling units	Net tons distributed
Vinegar	1	98	0,91
Garlics	21	44483	10,28
Apricots	32	29311	199,05
Pineapples	53	267526	542,81
Peanuts	5	5935	29,64
Oranges	120	201445	1857,35
Asparagus	14	385	1,62
Bananas	40	183301	1686,8
Chards	24	7229	44,94
Artichokes	20	267	1,33
Cardoons	2	9	0,06
Carrots	78	185955	1167,19
Chestnuts	13	140	0,56

Cabbages	111	46195	301,56
Cucumbers	22	9270	41,66
Chicory	61	45515	195,45
Onions	95	59489	419,47
Tangerines	83	79855	720,31
Watermelons	35	24952	193,78
Jams	4	152	0,28
Cherries	15	1127	4,63
Green beans	3	28	0,12
Figs	14	82	0,26
Fennels	40	104466	347,25
Strawberries	54	66643	81,7
Candied fruits	8	70	0,24
Exotic fruits	79	170812	263,83
Fresh fruits	123	558273	782,62
Dryed fruits	56	2575	14,63
Mushrooms	30	14517	31,69
Endives	29	17629	67,57
Persimmons	21	6587	26,61
Kiwi	69	95950	462,23
Lettuce	86	216322	698,06
Fresh beans	17	1443	1,04
Dryed beans	88	3439	19,83
Lemons	43	49707	287,95
Pomegranades	13	16669	15,34
Eggplants	32	27928	154,86
Apples	251	309055	2243,89
Melons	80	119001	346,14
Honey	1	2	0,05
Loquats	1	1	0,01
Walnuts	20	285	0,83
Mixed vegetables	11	8248	15,64
Potatoes	103	335415	2458,2
Peppers	88	30594	131,17
Pears	156	137783	815,47
Peaches	80	62280	352,66
Tomatoes	141	289778	1641,86
Grapefruits	9	6329	35,96
Leeks	22	7039	37,09
Roots	32	2605	9,31
Radish	11	3423	6,09
Celery	31	25562	114,84
Snacks	2	7425	4,8
Plums	49	33375	257,78
Grapes	65	32944	195
Courgettes	86	70750	464,14

In the AS-IS situation, the storage node handled 52 different formats of disposable crates, with a remarkable complexity in the material handling due to the high number of formats put onto pallets and roll containers that reduce the total saturation of these tertiary packages. This analysis aims to compare these 52 formats with just 6 RPC formats. The proposed RPCs are modular, so the six formats can be mixed easily onto the tertiary roll without compromising the saturation.

Firstly, an analysis of the entity of flows transported with each of the AS-IS packaging formats has been conducted. This analysis aims to identify the base dimensions of the package carrying most of the products' flows in order to assess what TO-BE formats would be adequate to contain the future flows of materials. Figure 21 shows the result of this analysis, highlighting that most of the flow requires crates with base dimensions of 30 cm x 40 cm, 30 cm x 50 cm, or 40 cm x 60 cm.



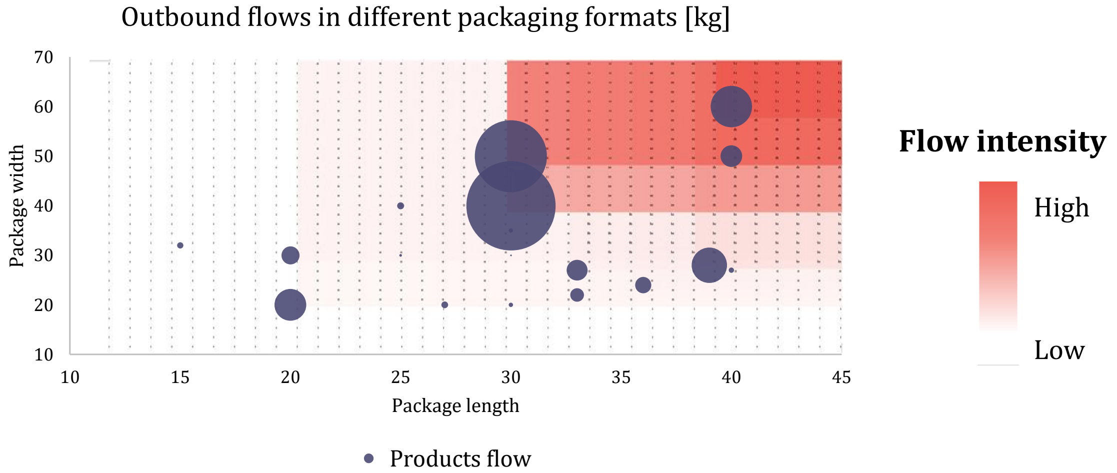


Figure 21. Intensity of inbound and outbound products flow in different packaging formats.

The RPCs producer provides six formats for the TO-BE solutions having two different base dimensions (i.e., 60 cm x 40 cm and 30 cm x 40 cm) at different heights, as listed in the following:

- Package 1: $60x40x20$ $[cm^3]$

- Package 2: $60x40x16$ $[cm^3]$
- Package 3: $60x40x13$ $[cm^3]$
- Package 4: $60x40x10$ $[cm^3]$
- Package 5: $30x40x16$ $[cm^3]$
- Package 6: $30x40x10$ $[cm^3]$

Figure 22 shows some examples of products in the disposable package adopted in the AS-IS scenario and in the RPCs that will replace them in the TO-BE scenario.

Figure 22. Disposable packages (on the left) and RPCs (on the right) for fruits and vegetables.

The association of each product with the new packaging formats has been performed with a clustering approach. This step aims to associate each product with the packaging format with the most similar dimensions with the AS-IS package adopted. This procedure guarantees the adoption of a package containing the items also when their actual dimensions are not known. A k-means algorithm has been applied to associate each product to its new package, resulting in the distribution of products in the six new formats presented in figure 23.

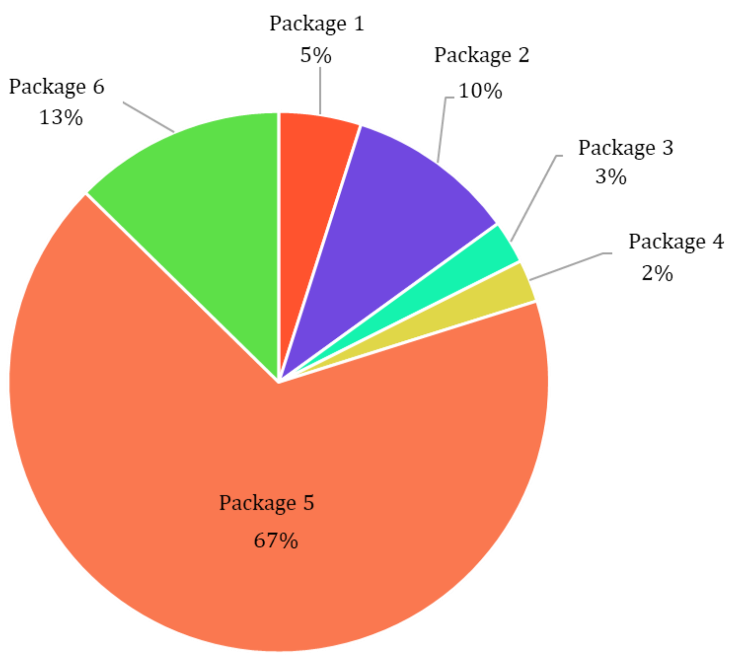


Figure 23. Allocation of products to new packaging formats.

The $30x40x16$ $[cm^3]$ format resulted in the most appropriate package for most of the products. The rationalization of the 52 AS-IS disposable packaging with just six TO-BE packages facilitated the material handling of fresh products in the TO-BE solution. The use of modular packages increases the stability of the tertiary packaging, allowing to stake a higher number of crates onto the same pallet. Indeed, looking at the inbound flows in a typical working day at the storage node, the average height of the incoming pallets increased significantly in the TO-BE solution, as shown in figure 24.

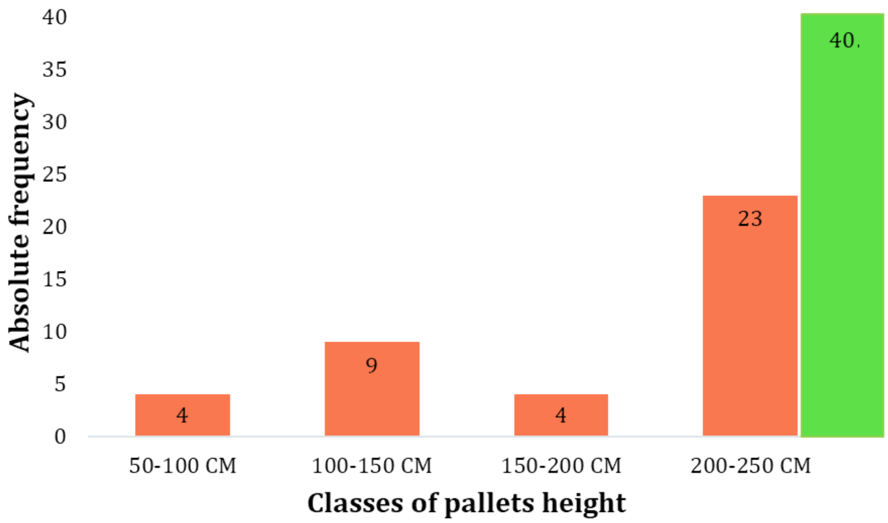


Figure 24. Frequency analysis of pallets heights.

Figure 25 shows that the adoption of the RPCs to replace part of the total products distributed by the storage node provided significant improvements also in the saturation of all the storage areas of the warehouse. The figure represents the dynamical saturation of the areas during a typical working day. The green bars represent the saturation of the area throughout the day in the TO-BE scenario. In contrast, each other color represents a different storage area in the AS-IS scenario.

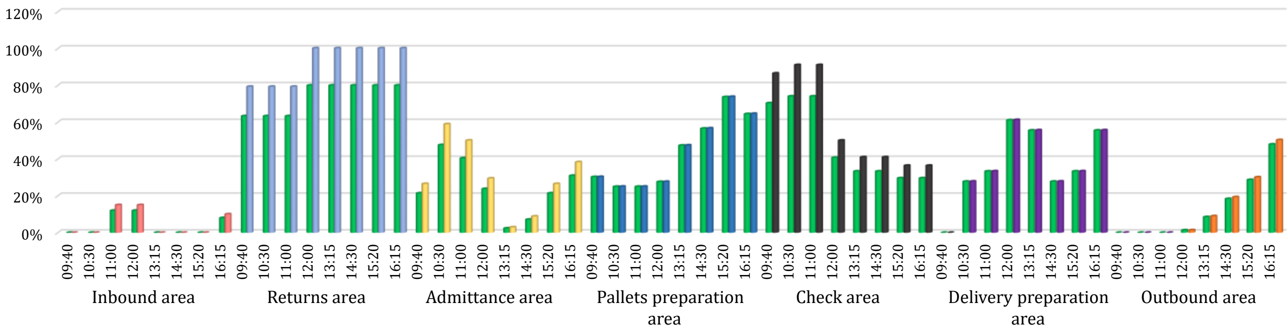


Figure 25. Dynamic saturation of the areas of the storage node.

Figure 26 shows the maximum saturation of each area included in the analysis in figure 25:

- The inbound area represents the unloading area for the inbound truck.
- The returns area is the waiting area for products to be returned to suppliers.
- The admittance area is the area where products are weighed, labeled, and scanned at their arrival in the storage node.
- The pallet storage area is the area where the deliveries on pallets are prepared and wait for transportations.
- The check area is where products are stored when they are not accepted after the first checks on weights and scans. These products can be accepted after further checks.
- The delivery preparation area is the area where roll containers are prepared for deliveries.
- The outbound area is the area where products are loading onto trucks for their delivery.

The grey circle within each area in Figure 26 represents the maximum saturation of that area with the AS-IS disposable packages, while the green circle represents the maximum saturation in the TO-BE solution with RPCs. The size of the circle represents the saturation, the more it occupies the storage area, the more is the saturation.

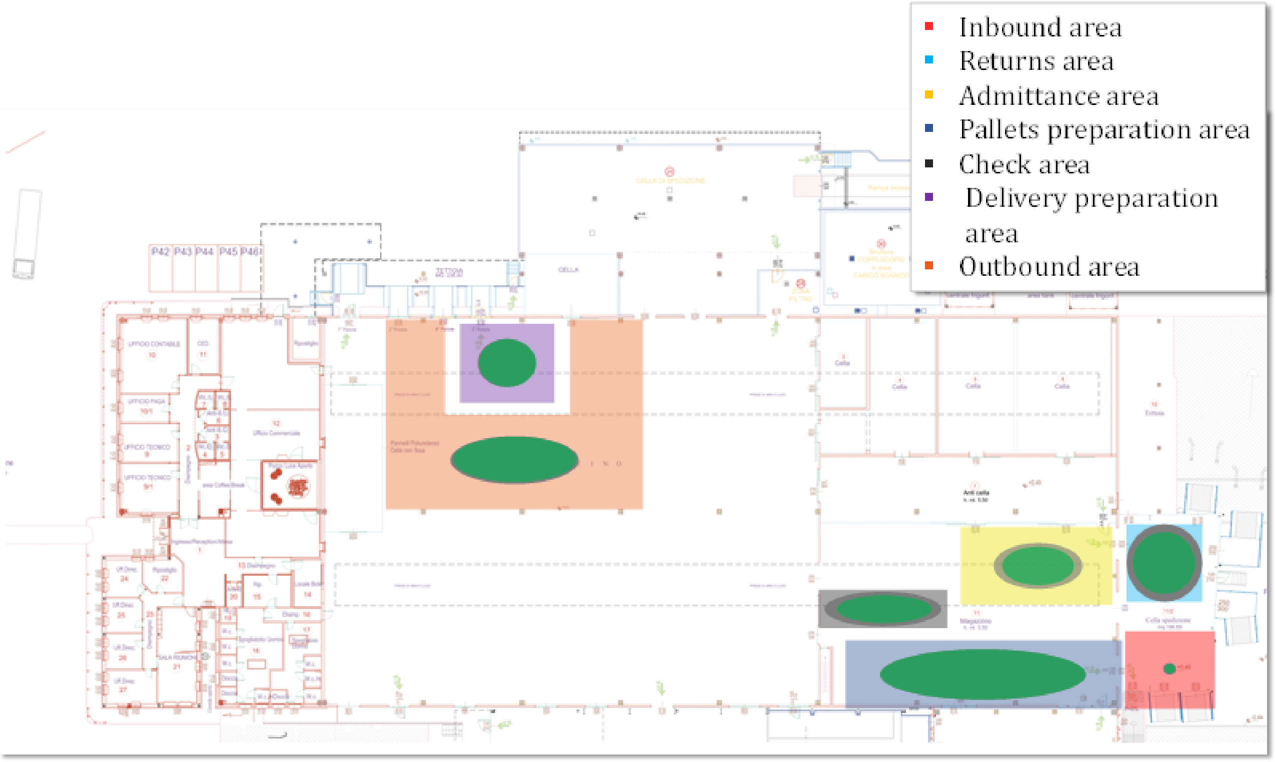


Figure 26. Maximum saturation of each area of the storage node.

Furthermore, the analysis of the TO-BE scenario proves that the adoption of RPCs to substitute disposable crates for fresh fruits and vegetables leads to a 3% reduction of the total number of crates needed. During a working week, the number of crates decreased by about 800 crates, and tertiary packages for distribution decreased by 13 units. Reusable containers reduced the quantity of packaging wastes of about 180 kg a week.

These reductions of secondary and tertiary packages lead to a 1.5% decrease in transportation costs and a 30% decrease in disposal costs. According to Singh et al. (2006), the adoption of RPCs to replace the disposable container will also decrease by 29% the GHGs emissions of the FSCS.

3.13 Chapter’s highlights

- The quality decay of perishable products is determined by the interaction of their intrinsic characteristics and the environmental stresses they experience throughout their life cycle.
- The environmental conditions (e.g., temperature, humidity) in the geographical area of the supply chain determines the level of criticality of the specific FSCS.
- The level of criticality of the FSCS suggests investing in long-term logistics solutions to preserve product quality and increase the overall sustainability. If the environmental stresses can determine severe damages to product quality, then the logistics manager should invest in infrastructure and refrigeration systems. A low criticality level suggests investing in packaging and containment solutions.
- An innovative logistics strategy, climate-driven logistics, is introduced in order to mitigate the environmental stresses affecting the product without requiring expensive investments. By exploiting the geographical areas and the time of the day (e.g., nights, first hours in the morning) with more favorable climate conditions, it allows to significantly reduce the quality decay and improve the economic and environmental sustainability at the same time.
- Once the best logistics strategy based on the expected environmental stresses has been identified, other supply chain characteristics (e.g., access to electricity, imports, and exports) could change the optimal decision. For example, some solutions could not be, or other factors affecting product quality could foster the adoption of refrigeration.
- The last sections focus on the sustainability of refrigeration and packaging solutions, providing some mathematical formulation to estimate the energy consumption of refrigeration systems and the insulating properties of packages. Finally, the analysis of the sustainability of reusable plastic crates for fresh fruits and vegetables compared to disposable plastic or carton crates provide some insights on the impact of packaging on the overall sustainability of an FSCS.

3.14 References

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4. Traceability and monitoring solutions

The content of this chapter is based on the research presented in the following paper and book chapters:

Gallo, A., Accorsi, R., Manzini, R., Santi, D., Tufano, A. (2018). ***Improving integration in supply chain traceability systems for perishable products****. FoodOPS, in: I3M 2018, Budapest, Hungary, 17 – 19 September 2018.*

Manzini, R., Accorsi, R., Bortolini, M., Gallo, A. (2019). ***Quality assessment of temperature-sensitive high-value food products: An application to Italian fine chocolate distribution****. In: Accorsi, R., Manzini, R., 2019. Sustainable Food Supply Chains. Planning, Design, and Control through Interdisciplinary Methodologies, chapter 14. Elsevier.*

The classification framework proposed in the previous chapters supports the identification of critical environmental conditions for new supply chains. In such cases, there are no primary data available on the FSCS as it is not operating yet. However, the identification of criticalities is much easier and precise when there is the chance to collect traceability data on-field. However, once the nodes of the supply chain are established, changing their position, investing in refrigeration systems, and other long-term solutions is much more challenging and not always feasible. Still, the identification of criticalities can support the decision-making process by suggesting the adoption of logistics solutions to preserve the products in the most critical stages of their life cycle or suggesting the phases or the transportation route where the access to alternative solutions can increase the sustainability of the FSCS.

The development of an integrated traceability tool gathering and storing product data during its entire life cycle is an effective approach to (1) identify risks for products' safety and quality, (2) individuate the less sustainable phases in the product's life cycle and support the identification of improvement solutions, and (3) monitor the outcomes of the application of these improvements. The reiteration of this process can point out other risks for the sustainability of the FSCS in a continuous improvement approach (Figure 27).

The identification of potential risks for the product's safety and quality should be followed by the analysis of logistics alternatives to preserve the product and increase the performances of the FSCS. An example is the adoption of alternative packages and the selection of the distribution route or the temperature set-point of a refrigerated room.

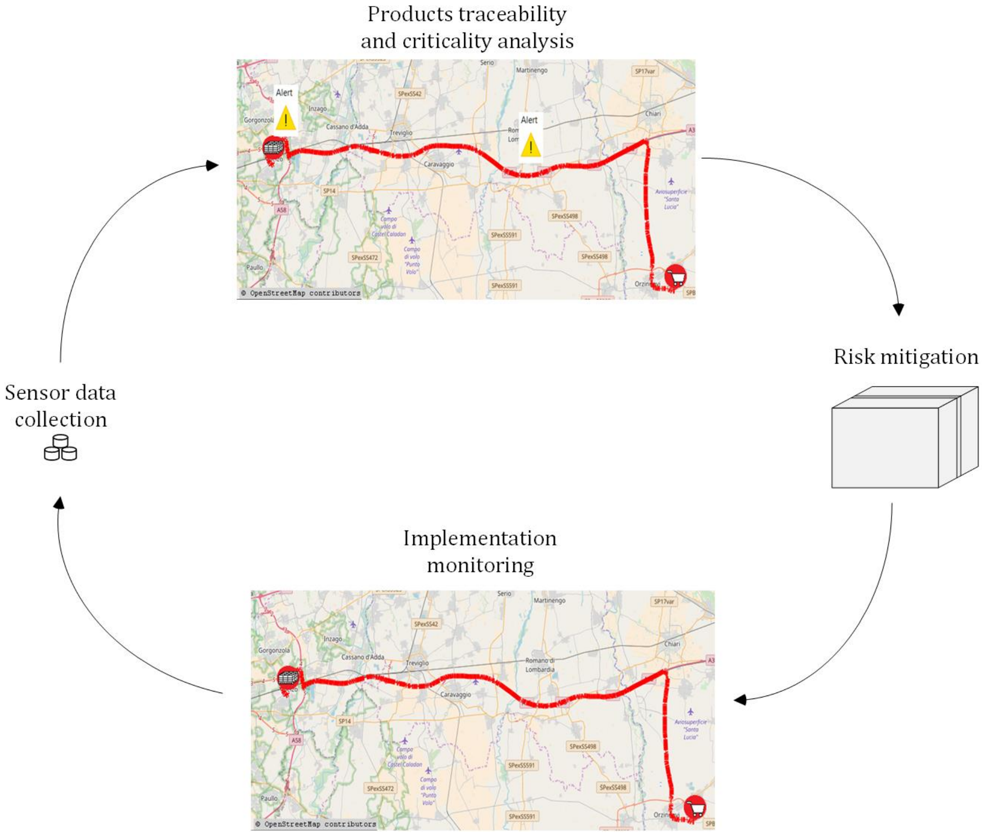

Figure 27. Traceability system to mitigate safety risks.

4.1 The role of traceability in FSCSs

Traceability represents a major concern in FSCSs for several reasons. According to the International Organization for Standardization, traceability is "*the ability to trace and follow a food, feed, food producing animal or ingredients, through all stages of production and distribution*" (ISO standard 8402:1994).

Firstly, traceability is essential to assure the quality and safety of products by mitigating potential risks of contamination for the consumers (Beulens et al., 2005; Jones et al., 2004; Qi et al., 2014). Indeed, as FSCSs become global and travel distances increase, food quality and safety gain the attention of final consumers (Matzembacher et al., 2018) at the place of consumption (Manzini & Accorsi, 2013).

The distance and time to consumer increase with the risks of experiencing environmental stresses and spoilage due to the proliferation of bacteria. In the last decades, policymakers introduced strict regulations to ensure product safety and quality to safeguard citizens' health (Regattieri et al., 2007; Abad et al., 2009). These regulations followed severe outbreaks due to a lack of hygiene and preservation rules that threaten consumers' trust in FSCS. The use of sensors tracking products during all the phases of their life cycle and databases to stock these data can prove the compliance to regulations and standards (Shanahan et al., 2009). Therefore, logistics providers adopted traceability systems to guarantee the quality of their products and comply with the HACCP method and ISO 9001:2000 protocol (Hajnar et al., 2004), as introduced in chapter 2.

Secondly, traceability represents a value-added activity for consumers. The increased awareness of food safety issues intensified customers' concern about the provenience of the items they bought and on the countries where they are processed (Storøy et al., 2013; Zhang & Wang, 2009).

Finally, traceability enables the continuous control of perishable products and the current performances of the supply chain effectively. It enables tracking and tracing the products throughout the FSCS (Salomie et al., 2008). Tracking products means controlling the supply chain and knowing where products are stored and shipped. Tracing, instead, concerns monitoring products' quality and other characteristics backward and forward along the FSCS. Product tracing allows highlighting the criticalities at every stage of the product life cycle.

The use of barcodes (Galimberti et al., 2013), temperature and humidity sensors, and RFID tags (Bibi et al., 2017) are widespread in the food industry. Furthermore, recent developments in traceability systems enable complex and integrated monitoring systems based on IoT, continuous monitoring, and real-time alerting (Accorsi et al., 2017). New traceability systems integrate wireless sensor networks, blockchain, and smart contracts to continuously transmit their data to the control and alerting systems (Li et al., 2015; Xiao et al., 2016; Kim et al., 2018). This innovation enables the integrated analysis of the product, comparing the stresses it experiences throughout its life cycle:

- The internal traceability allows practitioners to follow the products within the infrastructures (e.g., ports, multimodal hubs) and nodes (e.g., manufacturer, suppliers, customers) of the FSCS.
- The external traceability allows the analysis of environmental conditions and the product's location during the distribution phases.

However, the adoption rate of these innovations is not fast enough. The traceability systems require expensive equipment to be settled-up (Sun et al., 2017) and robust digital infrastructures for data collection. The prohibitive costs and the complexity of the infrastructures frequently incite companies to adopt inadequate solutions (Hardt et al., 2017). The use of inappropriate technology and the lack of standardization between different monitoring systems often cause missing data during storage and transportation. The extreme fragmentation of the food sector, counting hundreds of thousands of companies (Accorsi et al., 2018), reduces the level of control on FSCS. Furthermore, companies often outsource several logistics activities to 3PL companies. As commercial software for traceability does not follow standardized protocols, the output of these tools cannot be merged easily (Bosona &

Gebresenbet, 2013) and complicates the data integration process that enables PPLCM approaches. Additionally, companies are reluctant to exchange traceability data between different stages of the supply chain to integrate them into a unique database.

The lack of integrated software and cooperation results in heterogeneous and not aligned monitoring systems throughout the supply chain system (Muljarto et al., 2017) and prevent creating a seamless cold chain (Li et al., 2015), as shown in figure 28. The consequences of not aligned monitoring systems can threaten products' safety and quality, weakening the trust between producers and consumers.

Table 8 reviews the main issues preventing the adoption of integrated traceability systems in FSCS, according to the literature. The lack of standardization and the high costs to install and maintain the technological infrastructure are recognized as the main issues slowing down the adoption of innovative traceability solutions.

Table 8. Classification of issues preventing the collection of integrated traceability profiles.

	High infrastructure cost	Lack of standardization	Lack of cooperation	Missing traceability data
Abad et al. (2009)	✗	✓	✗	✗
Alfian et al. (2017)	✗	✗	✗	✓
Bibi et al. (2017)	✓	✓	✗	✗
Galimberti et al. (2013)	✗	✓	✗	✗
Hardt et al. (2017)	✗	✓	✓	✗
Jones et al. (2004)	✓	✓	✗	✗
Li et al. (2015)	✗	✓	✗	✗
Qi et al. (2014)	✓	✗	✗	✗
Regattieri et al. (2007)	✓	✓	✗	✓
Shanahan et al. (2009)	✗	✗	✓	✗
Storøy et al. (2013)	✗	✓	✓	✗
Sun et al. (2017)	✓	✗	✓	✗
Zhang and Wang (2009)	✗	✓	✓	✗
Hsiao and Huang (2016)	✗	✗	✓	✗
Badia-Melis et al. (2015)	✓	✓	✗	✓
Kim et al. (2018)	✓	✓	✓	✗

In such a scenario, whether distribution actors are not able to guarantee the continuity of the cold chain from the producer to clients, potential product contaminations become a concrete threat to consumers' health or at least might compromise product quality (Stoecker, 1998). Indeed, foodborne and waterborne diseases still kill millions of people per year worldwide (Aung & Chang, 2014). Traceability is an essential tool to individuate food incidents and ensure food safety and quality promptly.

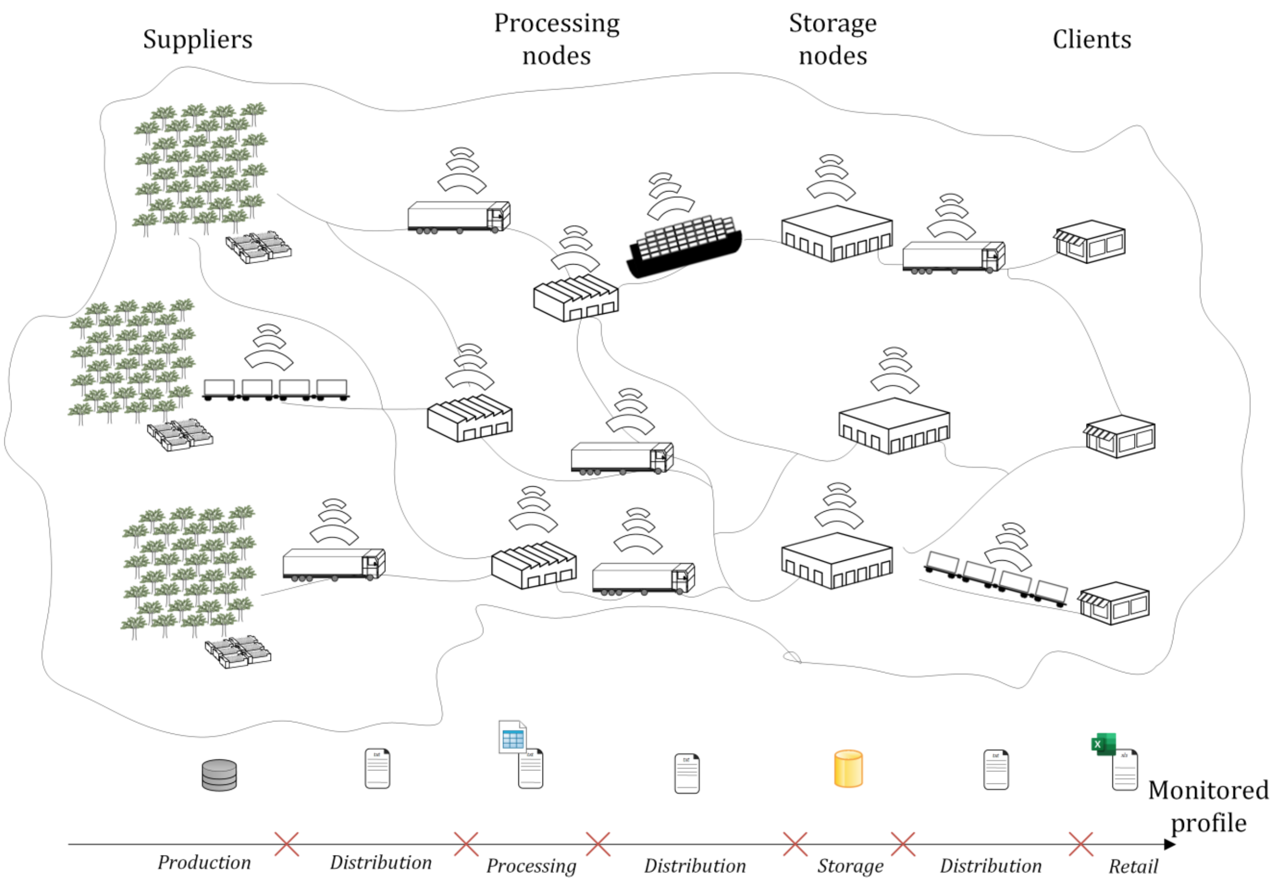

Figure 28. Lack of data integration in current FSCSs.

4.2 A novel framework for integration of traceability data for FSCSs

A data integration tool represents a practical solution to improve the integration of the traceability of perishable products throughout the supply chain system. It merges data from different, independent (i.e., belonging to a single company and based on its need only) and heterogeneous data sources (i.e., with a different data structure) into a unique, comprehensive, and robust database. Once a seamless traceability profile of the product is reconstructed, a comparative analysis of the product in each stage of its life cycle can support the identification of critical steps and allows to mitigate safety and quality issues promptly.

This chapter introduces a novel framework to integrate partial traceability data from heterogeneous data sources (Figure 29). This framework gathers data from several supply chain actors unwilling to introduce a unique traceability system and enable a complete monitoring profile of perishable products. Furthermore, it enriches traceability data with a data estimation process and integrating on-field data with those coming from climatic databases.

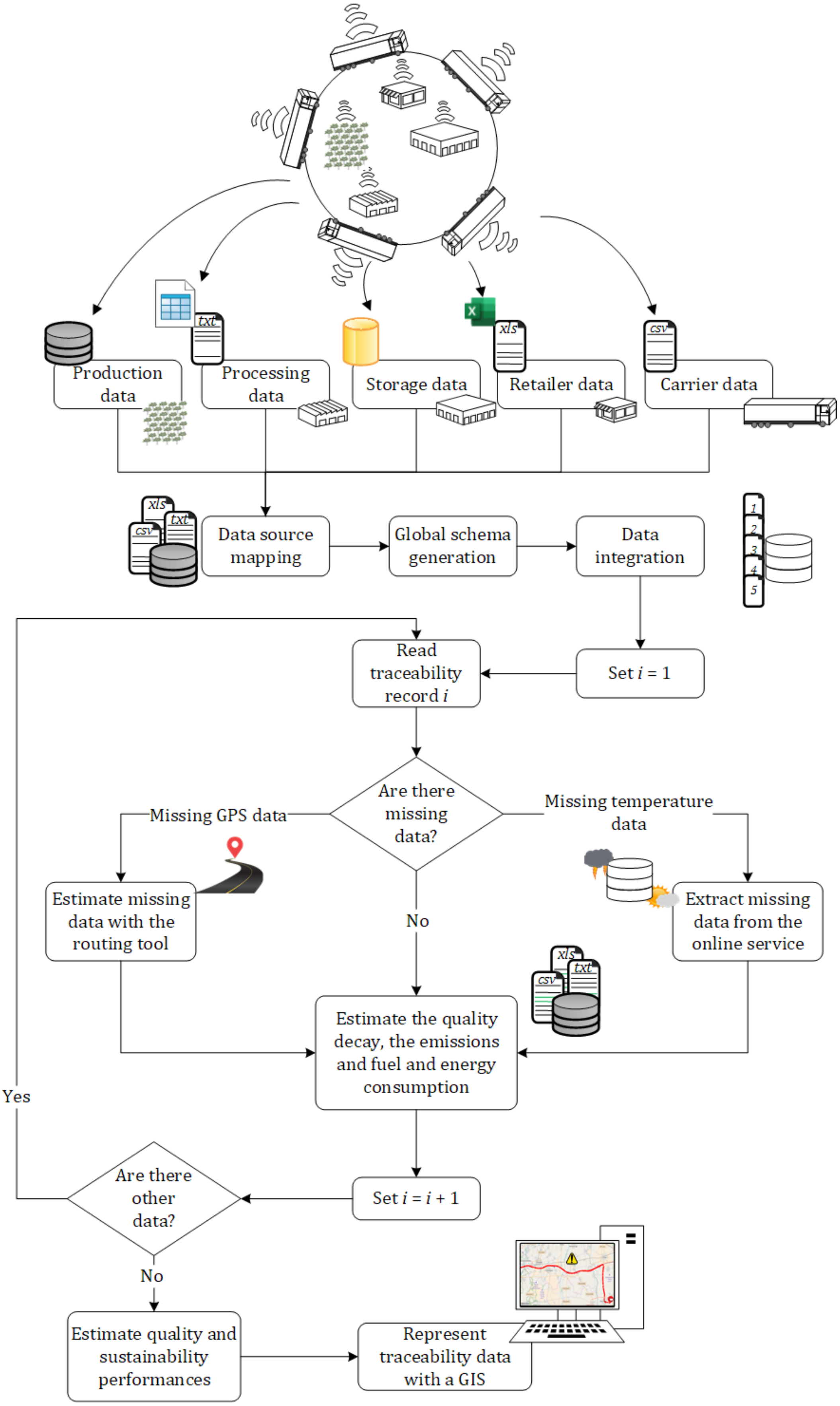

Figure 29. Framework for the development of an integrated traceability tool.

The novel framework proposed in this thesis has been applied to create a decision support tool developed in the C# .NET language. This application aims to aid practitioners to track and trace the perishable products at each stage of the FSCS. This system reads and merges data from different monitoring systems sources. The application gathers some essential data from the different commercial traceability tools used in the FSCS. Indeed, each monitoring system contains a minimum set of information (i.e., date, time, and a set of monitored parameters, such as position or temperature). As these data come from different tools with different formats and structures, they are unified in a unique data structure that monitors products from production to the retail stores.

The tool allows final users to monitor the position and the environmental stresses the products experience during their whole life cycle from a unique data source. The tool tries to automatically associate the essential attributes of all the data formats by analyzing their titles. Then, users can manually configure the remaining associations to complete the integrated data schema.

Besides, the tool provides a procedure to fill missing data. Missing data can be due to errors during the writing process of sensors, communication errors, or sensors running out of power or memory. Furthermore, different traceability sensors can provide monitoring data at different sampling intervals. The filling process infers automatically missing data from a routing tool and weather forecasts services. It also integrates rules about usual distribution patterns followed by carriers and estimates missing values to normalize data with different sampling intervals. Data are uniformed to the minimum available sampling interval to maximize the amount of information provided to the final users.

The users can monitor the route followed by the fleet of vehicles during distribution Geographic Information System (GIS) based on OpenStreetMap. The tool provides a reconstruction of the seamless profile of the monitored parameters (e.g., temperature and relative humidity) during the entire products' life-cycle. This visualization aids users by highlighting criticalities during storage and distribution. An integrated and easy-to-use traceability profile supports practitioners in perceiving the need for better storage and distribution solutions (e.g., using better insulating materials during the distribution, change the temperature set-point in warehouses).

The output of the tool is a unique database containing all the traceability data about the product. It includes both internal and external traceability data. These data can help to assure the product's safety, estimate its quality, and can improve consumer's confidence resulting in a more transparent system. Furthermore, the accurate estimation of product quality and other parameters allowing a better assessment of the exact variable costs associated with every product enables the adoption of dynamic pricing and smart labels. Dynamic pricing associates a different price to each item according to its quality and appearance at the point of sale (Adenso-Díaz et al., 2017). It requires an in-depth knowledge of the product and all the processes it went through in order to determine the resulting cost associated with its life cycle. Furthermore, it can foster the consumption of products with a lower, but acceptable, quality level by attributing the right price to them and encourage their consumption. It can be coupled with smart labeling initiatives to inform consumers on the condition of the perishable item they are buying (Kuswandi et al., 2012), and show them the actual provenience of the food and to guarantee that it was stored accordingly to regulations and quality standards.

Currently, there are not similar approaches in the literature to merge different traceability data into a continuous monitoring system managing missing data with the integration of climate databases and a GIS. However, there are some attempts to improve traceability systems in a supply chain by applying individually some of the functionalities presented in this data integration tool. Xiao-dong and Jian-zhen (2009) propose a data schema and an Object-Oriented Model to create a virtualized data integration system to integrate heterogeneous data sources. As the data sources are not physically integrated into a unique database, their solution breaks down the queries into sub-queries for each independent data source. Then, it integrates the results into a unique answer to the user. Alfian et al. (2017) present a traceability system using RFID and wireless sensors network, including data mining techniques to predict the missing data. The data mining techniques estimate missing temperature and humidity values from sensors using a neural network. It provides an estimation of the environmental stresses without recurring to weather forecasts or historical data. It does not predict the location of the products during transportation. Wang et al. (2017) included in their traceability system a quality evaluation method based upon fuzzy classification and neural network. Their system classifies the quality level of the products along with standard traceability data for food supply chains.

4.3 Data integration

The lack of a standardized data structure for traceability data causes a proliferation of data formats and schemas, one for each supply chain actor. Their integration in a unique database is not a simple task. The monitored dataset of each step of the FSCS is stored in different files. These files contain information, formats, schemas, sampling intervals, and time horizons that differ from each other. Besides, the physical locations of the servers containing these files coincide with the position of the nodes of the supply chain system, and they usually do not exchange such data.

Therefore, practitioners can easily visualize traceability information of a single step of the whole process from production to distribution. The existing tools for traceability systems allow them to monitor the position and the environmental stresses experienced by perishable products. They usually implement a warning system that alerts users whenever a criticality arises (i.e., the environmental conditions are far from the optimal storage conditions, causing potential safety issues), activating corrective actions to ensure consumers' safety. However, users can track and trace their products only for the single stage of the supply chain in which they operate. The lack of visibility of the whole process can assure compliance with the standards and the quality of products only for a little portion of its life cycle. In order to overcome this issue, users should have access to distributed data sources and manually uniform the data structure and integrate data whenever they want to monitor the whole life cycle of a single product.

The data integration process aims to integrate data from independent data sources and store them into a unique materialized data structure. A materialized data structure consists of a physical data source containing all the integrated data and locally stored into a server. The server stores the integrated data source that does not need to be recreated every time it is accessed. Users can query the database to monitor a single product in each stage of the supply chain, from the production to the client node. As traceability information concerns many actors, from producers to distributors, retailers, and final consumers, a materialized data structure is preferred to manage the high number of queries coming from distributed computers. As the server physically stores the information, it is unnecessary to access the distributed data sources continuously. Furthermore, with a materialized data structure, the queries require neither to be subdivided into subqueries directed to the single data sources nor to be aggregated to set up the final result.

Figure 30 illustrates the data integration process. It presents a simplified supply chain system and represents traceability data for a single product. The traceability systems collect data about the perishable item starting from the production stage. After harvesting and packing, the product is shipped to a storage node and stocked in a storage room. Then, the product is distributed to the clients according to their demand, waiting for a consumer. The traceability data gathered in each stage of the supply chain contains a similar set of data with the monitored profiles, hereafter called relevant data (i.e., date, time, coordinates of the location, temperature, relative humidity), and additional data (e.g., data about sensors functioning, additional notes). The data types and formats are different, as there is not a standard format. Some of them are stored in a database, while others could be directly saved into single files (e.g., Excel spreadsheets, CSV, text files).

Firstly, it is necessary to map the different schemas of the data sources. The additional data are filtered out, and the tool only retains the relevant data from the distributed data sources. The different data schemas are analyzed, and potential differences in the units of measurement and the data format are solved with the aid of users. This normalization results in a unique data structure constituting the global schema generated to create an integrated data source. After defining the global schema, the tool extracts data from their sources and adds them to the integrated data source according to the defined schema.

This phase consists of the ex-post reconstruction of the monitored profiles for a single product. The tools order data chronologically. In order to reconstruct the seamless profile of each product, this phase associate with the item only the data referring to the time in which it was present in the considered node of the FSCS (i.e., it associates to the product the data from a warehouse only when during the period the item was into it).

Traceability data from nodes (i.e., production, storage, and client nodes) usually do not provide useful information to identify when the product enters or leaves the node. For this reason, the tool identifies relevant data starting from the ones of the transportation stages, which usually includes details allowing the reconstruction of the products distributed for each trip. It is possible to realize when the product is loaded on the vehicle from the previous node of the supply chain and when it is unloaded in the next node by analyzing the time and the GPS monitoring values of the transportation stage.

The repetition of this step for each transportation stage leads to identifying the time in which the product enters and leaves from each node. Then, knowing when the product enters and leaves the system (i.e., the timestamp associated with production and deliveries), it is possible to retrieve the traceability data for the product covering the entire life cycle.

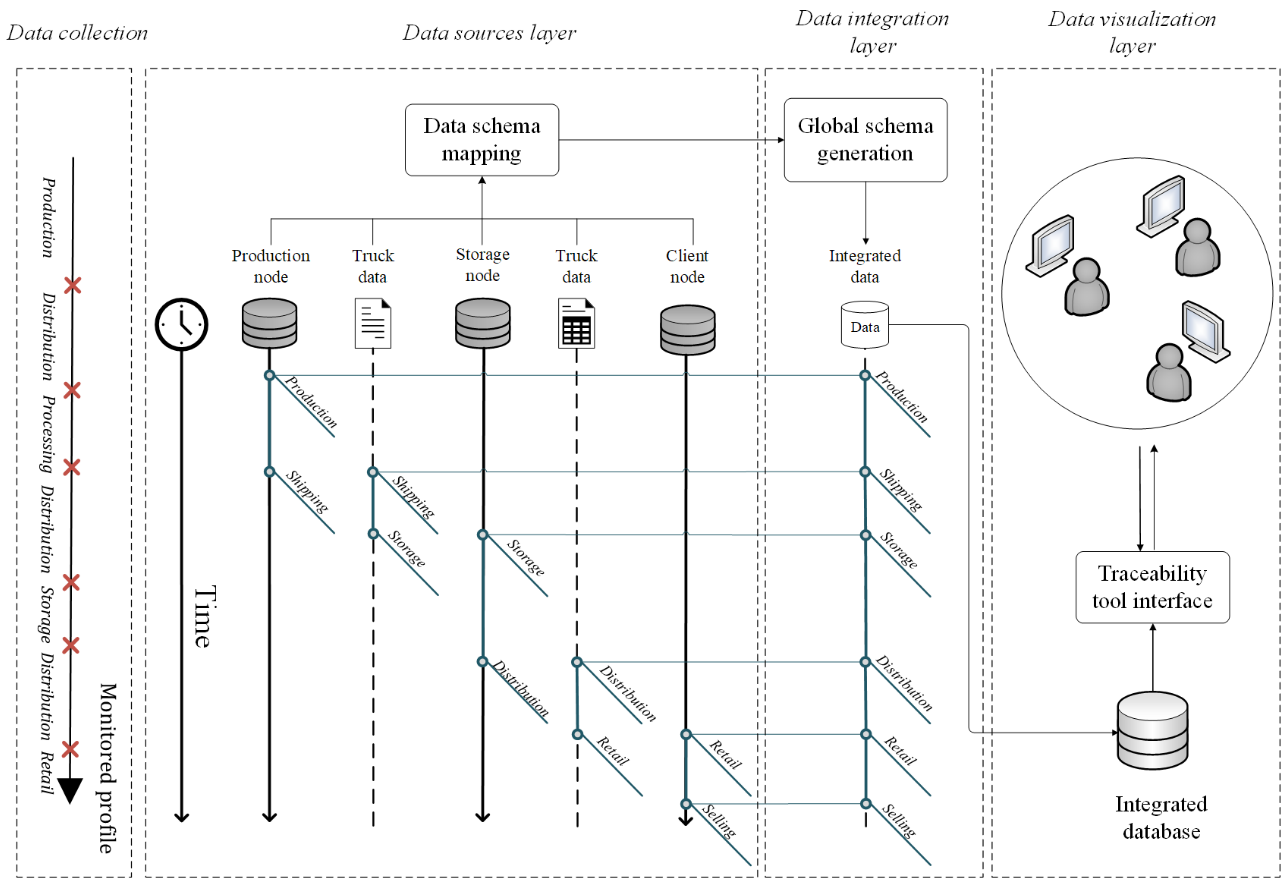

Figure 30. Data integration process (Gallo et al., 2018).

This process is repeated for each product sold to create a single data source containing all the traceability data. The aforementioned procedure represents an ETL (Extract, Transform, and Load) process that realizes the materialized data structure. The tables of the integrated database are represented in Figure 31.

The output of this process is an integrated database that can be easily accessed by users to retrieve complete traceability data for a single product in order to know the place of its origin, where it has been processed and packed, stored, and the location visited during transportation. Users can also monitor the environmental stresses experienced by products and can be alerted whether safety issues have occurred. Furthermore, the integrated database represents the input data for the data visualization module of the traceability tool.

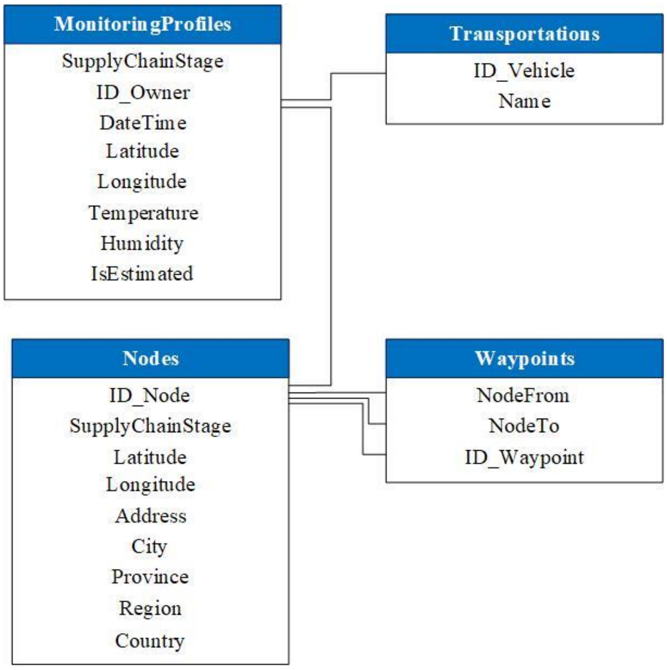

Figure 31. Representation of the integrated database (Gallo et al., 2018).

4.4 Data estimation for a complete PLC traceability

The data integration process described in the previous section has chronologically reconstructed the monitoring sequence creating a seamless profile of the movements and the environmental stresses affecting the product. However, differences in the data sources persist. The sampling intervals of different sensors could not correspond, and missing values can cause a lack of traceability data preventing the assurance of compliance with regulations and standards.

The so-called "data estimation process" aims to solve these issues by creating normalized traceability profiles. A normalized profile is characterized by the same sampling interval from the production to the client nodes, without missing values. It certifies the respect of standards and regulations for the entire product's life cycle and allows the representation of an inclusive monitoring profile providing insights to practitioners from every stage of the supply chain.

The data estimation process fills the missing location and climatic (e.g., temperature, humidity) data. Firstly, the tool solves differences in the sampling intervals of sensors with the adoption of the minimum sampling interval to guarantee the maximum detail of the output data and avoid data losses. Intermediate values for sensors with higher sampling intervals are estimated with the same procedure as the other missing data, presented in figure 32.

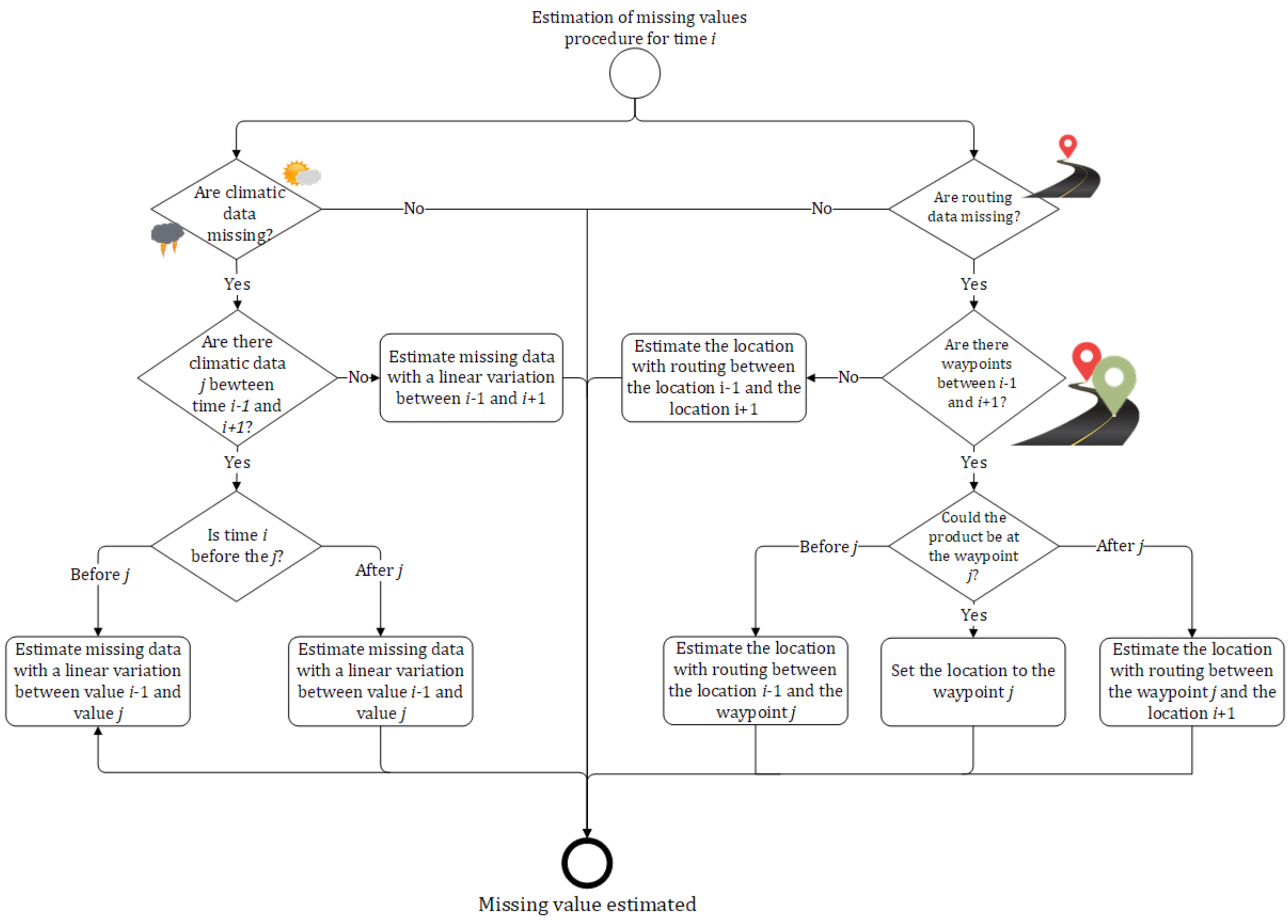

Figure 32. Data estimation process (Gallo et al., 2018).

4.4.1 Estimating location data

This procedure fills missing location data based upon the combination of the experience on the commonly adopted routes and the application of a routing module calculating the optimal route. The routing module is based upon the open-source maps provided by OpenStreetMap and the open-source route planner Itinero.

The analysis of past distribution patterns makes it possible to fill missing values by identifying whether the transportation between the departing and the arrival node usually entails the visit of an intermediate point (e.g., a secondary distribution center of the supply chain), known as a waypoint. This is an effective strategy as the distribution routes are usually seasonal, and they tend to be the same every week. Furthermore, waypoints are not just a mere transit point as the trucks can also wait in the waypoint for some time, therefore facilitating the identification of the position of the product.

With the analysis of the location of the previously monitored location value, the location of the next value, and the intervals of the missing values, it is possible to estimate whether the product could be at a waypoint in the route from the starting point to the waypoint or after in the route between the waypoint and the endpoint. Whether the product could be at the waypoint, then the location of the waypoint is used to fill the missing value. Based on the estimation, if the product has not reached the waypoint yet, the missing value is estimated by applying the routing function between the previous monitored value and the location of the waypoint. Conversely, whether the truck has already gone beyond the waypoint, the missing value is estimated by applying the routing module between the waypoint and the next monitored value. Finally, if there is not a waypoint between the two monitored values, the missing value is estimated through the routing module applied to the locations of the previous and the next monitored values.

As the routing module can calculate the best route between two locations and the time associated, it is possible to estimate each missing value without other approximations.

4.4.2 Estimating climatic data

The filling procedure for missing climate data is based upon the data of online weather forecasts services. These services offer weather forecasts for the next days and a database containing historical weather data to retrieve climate data from the past. The presented traceability tool uses the World Weather Online's historical weather data. This service provides data about temperature, relative humidity, and many other climatic parameters. As the change in the temperature and relative humidity values is not so relevant within a single hour, the climate data estimation procedure adopts a linear variation of the values as follows:

- if there are not climate data available in the online weather service between the previous monitored value and the next monitored value, then a linear variation between these two values is considered for the estimation;
- If the time of the missing value is included between the previous monitored value and the historical climatic data, then the missing value is filled with a linear variation between these values;
- Conversely, if the time of the missing values is included between the historical climate data and the next monitored value, then a linear variation between these two values is used.

As the climate estimation module needs the location to retrieve climate data, if both the position and the environmental stresses are unknown, the tool estimates the position before filling climate data.

4.4.3 Estimation of sustainability data and performance evaluation

Based on the data provided by the integration and missing data estimation processes, the tool estimates other useful traceability parameters to enhance the control of the supply chain system during the distribution phase. Each record in the database is enriched with additional information coming from the routing tool.

Given the type of vehicle used in the distribution phase, its saturation is estimated based on the type of product and the quantity it carries. The road network data associates every road in the network with its type (e.g., tertiary, secondary, motorway). Given a GPS record, the tool individuates the closest route to the vehicle and extracts the road type.

The information about the vehicle, its saturation, and the type of road allow the tool to estimate the equivalent carbon dioxide (CO_2 equivalent) emissions, the fuel, and the energy consumption based on the online Finnish database's unit values LIPASTO (2020).

Finally, the tool estimates also the quality degradation of the products as a percentage value, where 100% is equal to a product with the maximum quality level. The quality decay of perishable products requires some input parameters that can be extracted from the data sources or can be provided manually by the users. The equations used to assess the quality level of products are the ones introduced in chapter 2 (Eq. 2.5 and Eq. 2.8).

Pseudomonas spp. was used as the specific spoilage indicator, as it is one of the most critical spoilage microorganisms that can affect fruit products (Raposo et al., 2017). Microbial growth curve fitting of inputs (i.e., initial bacteria concentration, pH, Aw) (Serradilla et al., 2013; Buyukunal, 2015) was performed at the temperature range of 0°C to 25 °C.

In order to find out quantitative metrics to evaluate the impact of adopting the proposed tool, this subsection introduces some Key Performance Indicators (KPIs). As the tool aims to provide integration of heterogeneous data sources and increase the control of products and supply chains, the metrics evaluate the increased knowledge delivered by this tool.

Table 9. KPIs to evaluate the performance of the traceability tool.

KPI	Notation
Number of records tracked	r_t
Number of records estimated	r_e
Maximum sensors' sampling interval [min]	$maxSI$
Minimum sensors' sampling interval [s]	$minSI$
Uniformed sampling interval [s]	uSI
Number of data sources integrated	$n_{sources}$
Number of safety alerts raised	n_{alerts}

4.5 Integrated traceability and monitoring tool

An effective traceability tool should track the products throughout their life cycle, from production to the final consumer, and trace all the essential characteristics assuring the compliance to regulations and standards and increase consumers' trust. Practitioners should be able to use the tool to have a quick and clear view of the status of all nodes and the fleet of vehicles of their supply chain. This fosters identifying potential safety issues as soon as they arise, urging corrective actions or recalls, and preventing consumers' health risks.

In order to provide an effective tool for practitioners, the proposed software combines an easy-to-read interface with an integrated database showing traceability data according to chronological order. The user interface includes an interactive Geographic Information System (GIS) based on OpenStreetMap showing in real-time the status of each entity (i.e., node and vehicle) combined with several charts that show the real-time traceability data. The interface displays the clock of the system that is refreshed at each sampling interval. Every time the clock is refreshed, the tool updates the position of each vehicle and the charts with the following monitored values. All the charts automatically change based on the data they plot, adapting the axis, and adding new data points at each iteration.

The data plotted are:

- The position of each node and vehicle;
- The temperature value in Celsius degrees;

- The quality degradation of each batch of product as a percentage of their initial quality level;

For transportations only, the following additional data are calculated and shown:

- The distance traveled;
- The grams of CO_{2e} emitted;
- Energy consumption;
- Fuel consumption for each vehicle.

Furthermore, in the input phase, users can provide other columns from the database to plot additional data and have more in-depth real-time insight into PPLC. The traceability system automatically connects the additional data to the entities of the network (i.e., supply chain nodes, single products, vehicles) based on the input provided by the end-user. An interactive map displays the real-time position of the product and their provenience, reconstructing the flow of materials from production to the retail.

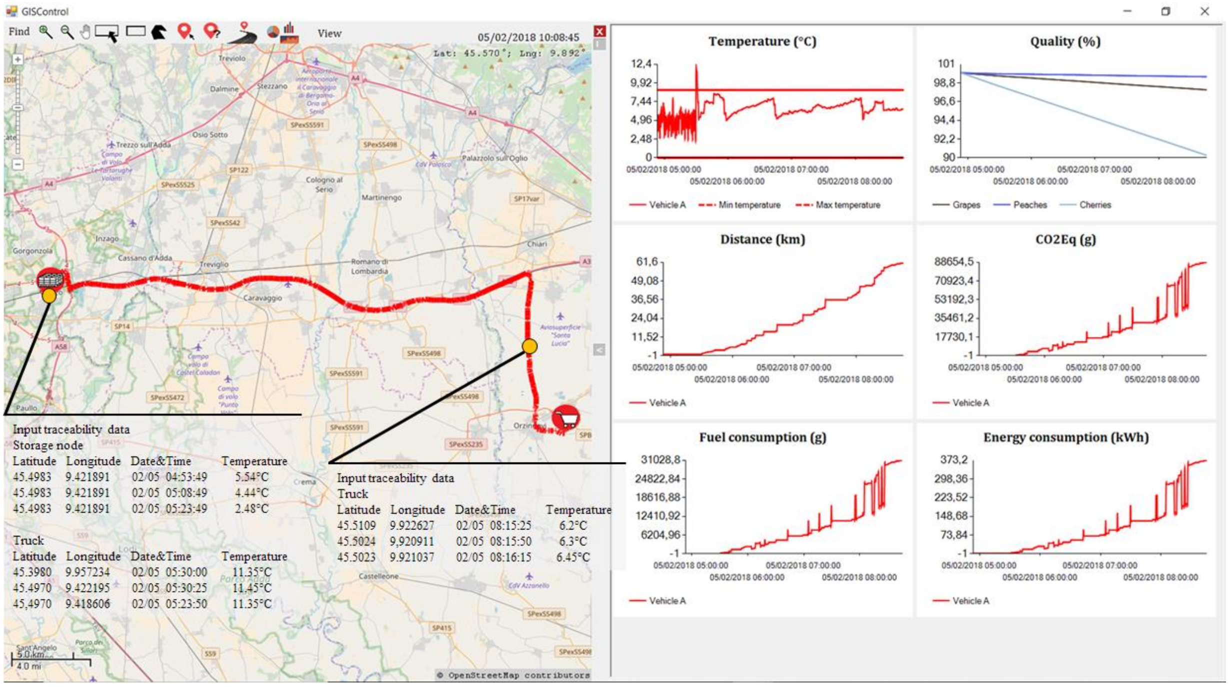

Figure 33. Main interface of the traceability tools.

4.6 Numerical example of fresh fruit FSCS

A numerical example from a real case of a 3PL has been used to test the original tool proposed in this chapter. The example shown in Figure 3 concerns the distribution of three batches of products (i.e., cherries, peaches, and grapes) from a warehouse to the client. The client demands the delivery of products within 09:00 AM at the destination node. Both the storage and the client nodes are in Lombardy, Italy.

As the most crucial goal of a traceability system is to avoid any safety issues for consumers, the traceability tool takes as an input a desired temperature interval. This interval can be regulated to coincide with the compulsory temperature values to comply with all the regulations but could also be stricter (e.g., according to the service level the company aims to guarantee). The temperature chart shows the current temperature value within each node or vehicle, and two lines representing the minimum and maximum acceptable temperature value.

Whether the integrated database is filled with real-time data (e.g., using wireless sensors network), the tool can immediately show the monitored value. Whenever the monitored values overstep the acceptable range, an alert is prompted by the traceability tool to signal the risk of safety issues. Then, corrective actions can be performed to quickly bring the temperature again within the acceptable interval, avoiding spoilage (figure 34). Conversely, whether the tool is used to show historical data, the deviation from the acceptable temperature interval can be used to identify possible safety risks to recall products that were not stored correctly during their life cycle.

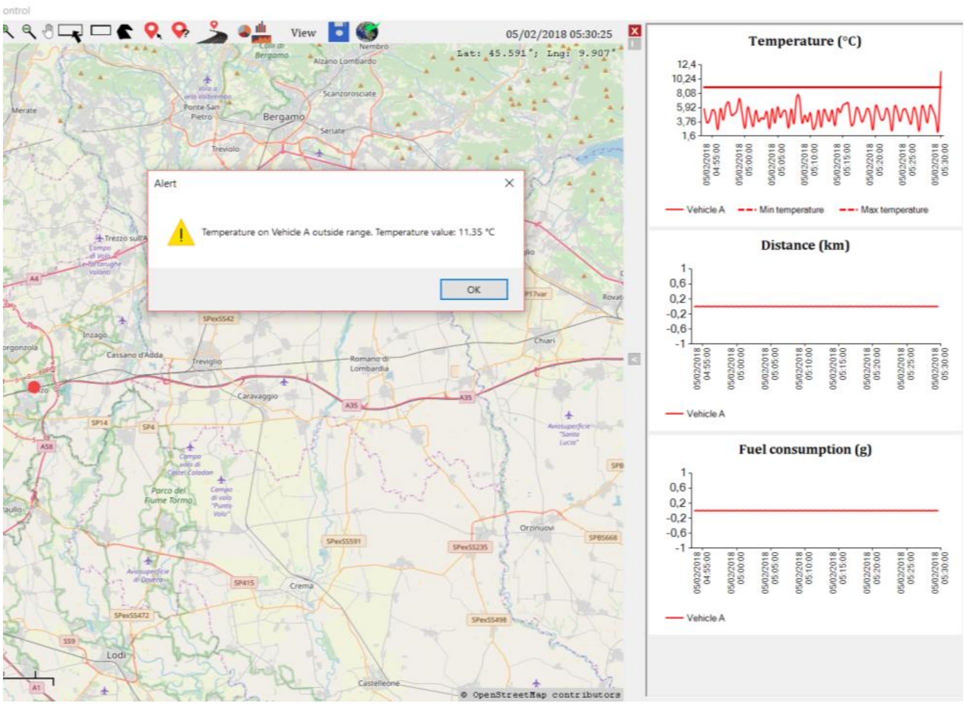

Figure 34. Alert window for the violation of the temperature interval.

Table 10 summarizes input and output parameters for the growth rates of *Pseudomonas* spp at different temperature values. The generated growth rates of *Pseudomonas* spp. in all tested products increased significantly with storage temperatures ($p < 0.05$). The parameters of the Arrhenius model for the growth of *Pseudomonas* spp. and the estimated shelf-life of all tested products are illustrated in Table 11.

Table 10. Input and output parameters for the microbial growth rates.

	Isothermal temperature conditions				
	0 °C	5 °C	10 °C	15 °C	20 °C
Cherries					
N_0 (log CFU/g)	1.42	1.42	1.42	1.42	1.42
N_{max} (log CFU/g)	8.26	8.26	8.26	8.26	8.26
k (h^{-1})	0.012[a]	0.024[b]	0.044[c]	0.074[d]	0.116[e]
λ (h)	15.35	24.06	40.47	74.19	148.38
Peaches					
N_0 (log CFU/g)	3.35	3.35	3.35	3.35	3.35
N_{max} (log CFU/g)	8.26	8.26	8.26	8.26	8.26
k (h^{-1})	0.017[a]	0.034[b]	0.061[c]	0.106[d]	0.161[e]
λ (h)	107.74	53.37	29.19	16.8	11.06
Grapes					
N_0 (log CFU/g)	3.35	3.35	3.35	3.35	3.35
N_{max} (log CFU/g)	8.26	8.26	8.26	8.26	8.26
k (h^{-1})	0.012[a]	0.024[b]	0.044[c]	0.074[d]	0.116[e]
λ (h)	148.38	74.19	40.47	24.06	15.35

[a-e]Different superscripts in the same row indicate significant differences ($p < 0.05$).

* N_0= initial microbial concentration, N_{max} = maximum microbial concentration, k = growth rate, λ = lag phase.

Table 11. Input paramters for Arrhenius equation.

	k_{ref} (T_{ref} = 0 °C) (h^{-1})	E_a (kJ/mol)	R^2	Temperature (°C)	Estimated shelf-life (h)
Cherries	0.012	71.20	0.9974	15	90.9
Peaches	0.017	70.81	0.9965	5	122.6
Grapes	0.012	71.20	0.9891	1	271.3

Finally, table 12 summarizes the outcomes of the tool based on the KPI provided in the previous section.

Table 12. Performances of the traceability tool.

KPI	Value
r_t	199
r_e	357
$maxSI$	15
$minSI$	25
uSI	25
$n_{sources}$	2
n_{alerts}	1

Decision-makers can use the proposed tool to control their supply chain, certify the compliance to food regulations, and evaluate the level of service they provide to their clients. They can monitor the time elapsing from the production to the distribution of their products, their quality, estimate the costs for their transportation fleet based on the energy and fuel consumption and evaluate the environmental sustainability of their supply chain. Furthermore, practitioners can control the potential risk of contamination of their product. The system urges the adoption of corrective actions whenever the temperature goes beyond an acceptable value. It also supports the recalls effectively by easily individuating the position of spoiled products and reconstructing their flows from the production stage.

4.7 Reconstruction and simulation of complex monitoring profiles

4.7.1 The case of the simulation of traceability profiles during different seasons

The proposed tool can simulate the quality decay rate of perishables distributed through different routes or at different times and temperatures in a what-if environment, including different scenarios.

For example, figure 35 shows the temperature and quality decay of two products, namely broccoli and tomatoes, transported along the same route in each month of the year 2019. The analysis was conducted for these two products as they are produced throughout the year, according to their seasonality. For each month, a representative day has been chosen. The weather forecast service provided daily temperatures from those days, assuming that the vehicle was not refrigerated. The production, storage, and client's nodes come from a real case of a vendor of fruits and vegetables located in Bologna. Broccolis are produced in the Apulia region, while tomatoes come from Campania, two southern Italian regions. The carrier brings these products to the same warehouse in Bologna. The storage rooms at the warehouse node are refrigerated. The temperature within the node is equal to 2°C. The products received at the storage node are prepared for delivery and sent to the client's node the next day, early in the morning. Broccolis are delivered in Perugia, while tomatoes in Venice.

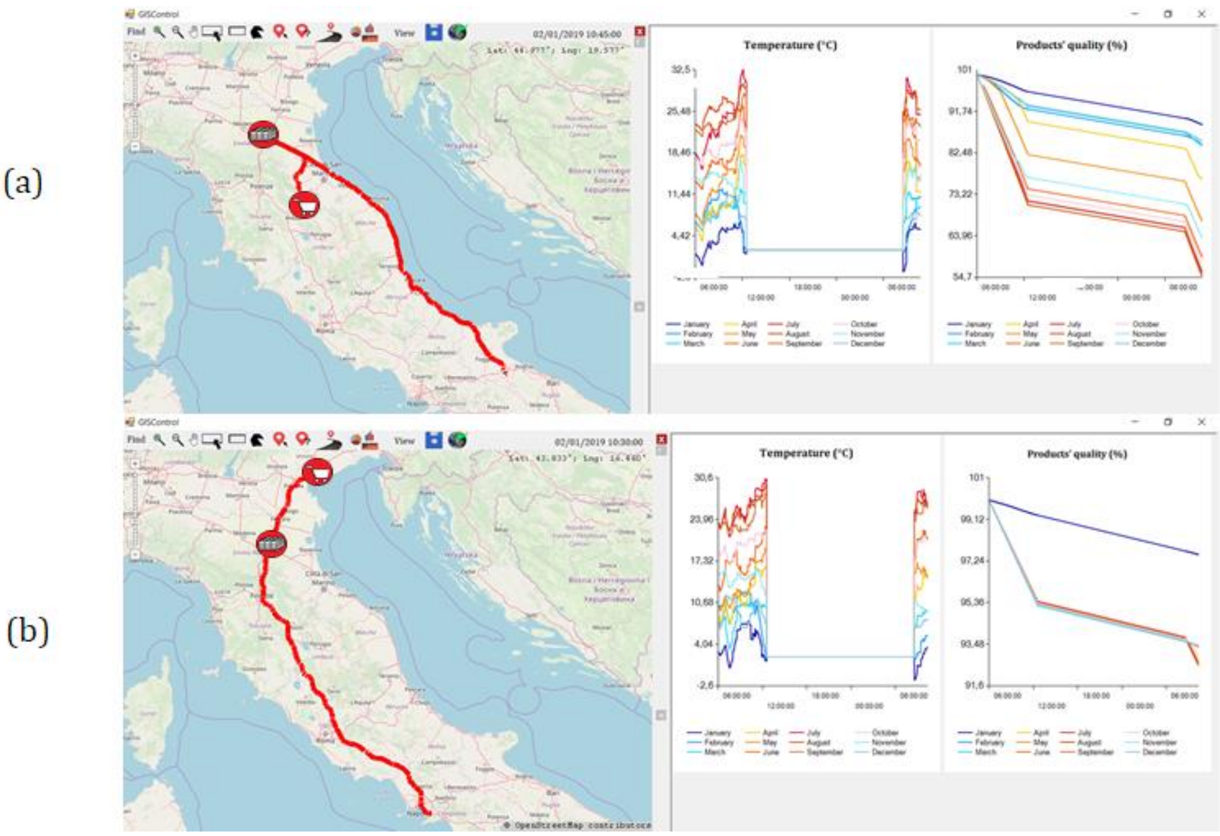

Figure 35. Delivery of broccoli (a) and tomatoes (b) with different climate conditions.

The figure represents the environmental temperature experienced by the products during transportation and storage according to their position and the simulated days. Based on this data, quality decay is estimated and represented, resulting in twelve different quality decay trends for every product throughout the year. These simulations enable the use of the tool to support and validate the decision-making process. By estimating the temperature and quality decay, it can prevent quality issues, suggesting the use of refrigerated vehicles or the change of distribution routes or their schedule in different periods of the year, according to the environmental conditions and the climate-driven logistics. This could avoid food losses and reduce costs for unnecessary use of refrigeration when it is less likely to harm food severely.

This simulation can be paired with decision-support models to minimize the distribution costs according to climate conditions and then simulate the real routes in a realistic environment to preempt criticalities.

As a result, this tool supports practitioners to monitor their supply chain thoroughly, allowing companies to certify the quality of their products and compliance with regulations. Furthermore, it allows estimating the consequences of the variation in the distribution route or schedule. Additionally, as the traceability system reconstructs the information flow for the whole product life cycle, it provides useful data that can be shared with the consumers. For example, the company can provide data about the geographical origin of the product, the nodes it visited along the supply chain, its quality, and the sustainability of the PLC. A resume of the traceability data contained in the database could be accessible online and accessible through the application of a QR code on products' packages (Tarjan et al., 2014). Consumers could then gain more trust in the products they eat and the companies producing, processing, storing, and delivering them.

The tool proposed in this section allows for the identification of potential safety issues quickly. Based on the charts showing the stresses experienced by the product, its quality and the phases where the decay is accelerated, and the sustainability of the distribution process, the tool provides insights to identify critical stages in the FSCS. Whenever a criticality is identified, logistics managers can implement additional preserving solutions for products' safety (e.g., change the package, use refrigerated vehicles).

4.7.2 The case of a multimodal distribution in a global FSCS

The tool can also analyze the performances of the FSCS and monitor the implementation of the solutions in TO-BE scenarios. Through the integration of sensors' data gathered at every stage of the supply chain and by different actors, it allows monitoring also complex supply chains that exploit multimodal transportation systems. Furthermore, it can also integrate other attributes, such as the vibrations. As vibrations are measured in a very short time interval (i.e., billions of values per second), the best solution for these data is to disable the normalization of the time intervals for all the monitored parameters. Indeed, there is no valuable information in storing billions of temperature data for each second, and it will also require a huge available memory to store this information.

Figure 36 shows an example of a complex transportation phase in a global FSCS based in Italy and distributing wine. This example concerns the distribution of wine to Vestby, Norway. The tool monitored the vibration data for this delivery in order to point out the most critical vehicle among trucks, trains, and vessels. Furthermore, it also collected temperature data.

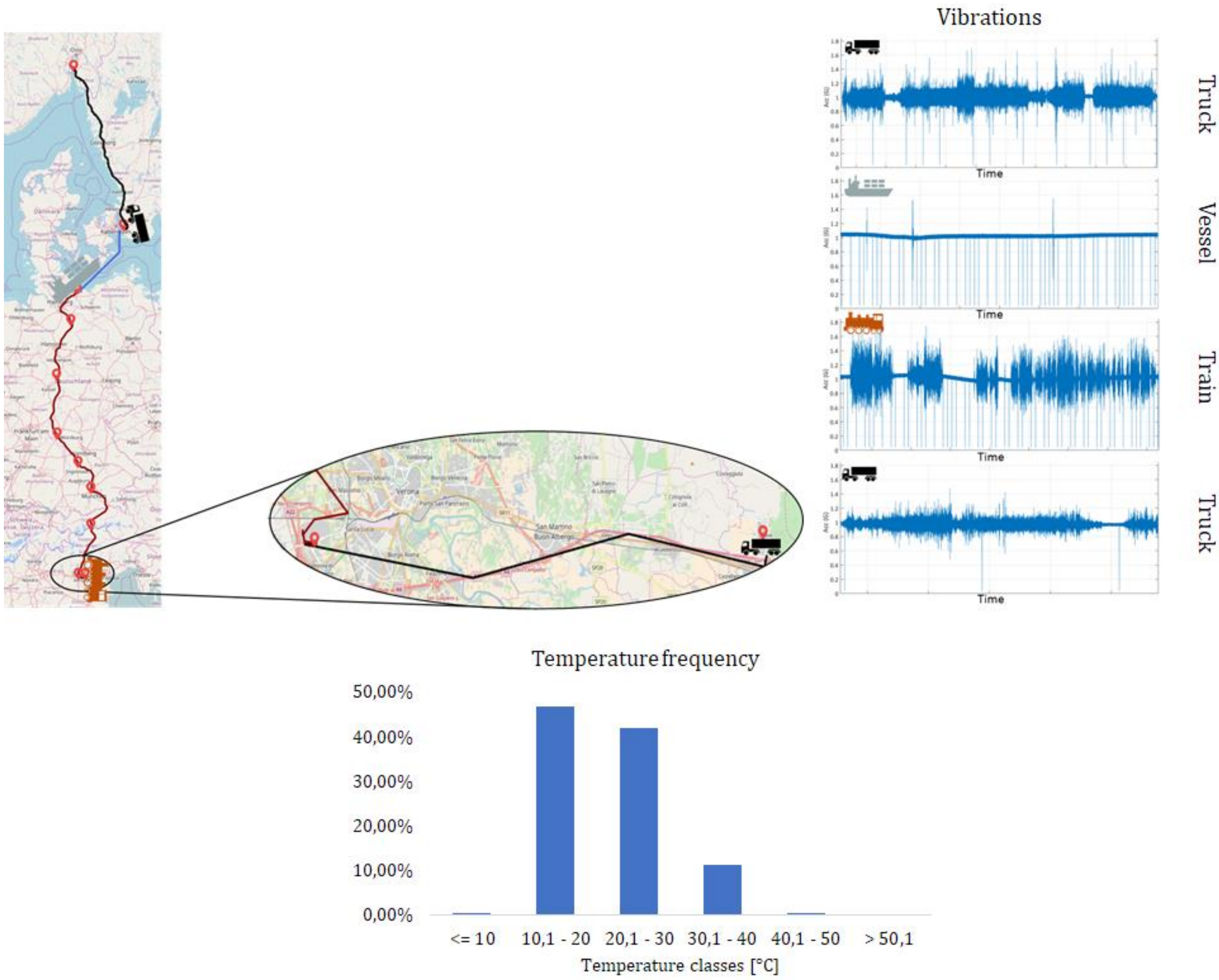

Figure 36. Example of monitored profile in a global FSCS.

The monitored profile shows that the vessel significantly reduces the vibrations. Instead, trucks and trains have higher picks in their vibration data that also change with the state of the road infrastructure and the chosen route. Significant vibrations can also have a negative effect on the products as they can cause unpleasant lesions causing changes in the appearance of the product due to the impact with the surface of the vehicle or other objects. Furthermore, these collisions can accelerate the quality decay of perishable products, as illustrated, for example, by La Scalia et al. (2015) for the strawberries.

Further developments of the proposed tool will include applying data mining techniques to estimate missing climatic data when the time interval is lower than the one of the available climate web service to improve the estimation of those values. Other improvements could entail using mathematical models to better estimate the environmental stresses of a single product within a monitored environment (e.g., warehouse, truck). Indeed, the temperature and relative humidity are not uniform within a storage node, and the sensors cannot cover every single position within the monitored environment. Therefore, considering the whole storage node at the same temperature value is an approximation that can be better estimated.

4.8 Case study of an Italian fine chocolate supply chain

This section presents an application of a monitoring approach and reconstruction of environmental stresses to the fine chocolate FSCS. The aim of this study is to determine the effect of environmental stresses on the product's quality, which may be affected by the type of packaging, the loading method, the vehicles, the storage time, and refrigeration systems. Chocolate is a temperature-sensitive product that demonstrates low melting resistance in tropical regions or during summer when the environmental temperatures reach their maximum peak.

As the high temperatures not only affect product quality and safety but also affect product appearance and taste significantly, it is essential to ensure that the storage and transportation conditions are close to the optimal ones to avoid a depreciation of the product.

In order to assess the effect of adverse environmental conditions on product value, this section proposes a closed-loop control system to simulate the environmental stresses monitored during the transportation and storage phase. Two steps constitute this system: the monitoring step and the simulation step. The monitoring step aims to measure the shipment conditions, collecting data on-field using the traceability framework introduced in this chapter. The monitored data concern temperature and relative humidity values, aiming to assess how these stresses affect product safety, and quality, taste, and appearance during the life cycle. Conversely, the simulation step reconstructs in a laboratory the stresses affecting the product to experimentally assess their impacts on the product features during the life cycle.

Temperature and humidity sensors inserted in the products' package collected data about the environmental stresses throughout the storage and distribution activities. Then, data are gathered together and analyzed to monitor the environmental stresses and reconstruct monitoring profiles. A detailed ex-post analysis of the collected data identifies the most critical steps of the FSCS to support operative decisions for food preservation (e.g., packaging improvements, containment decisions, etc.) to improve the control of food safety and quality. The simulation step supports the decision-maker in comparing the performance of different supply chain configurations in a what-if multi-scenario environment. It evaluates a selection of key performance indicators (KPIs) based on a chemical and sensory analysis conducted on simulated logistics processes.

The simulation step is conducted with a climate-chamber located in the Food Supply Chain Center of the University of Bologna, which also designed the chamber. The climate chamber is made of a 1800_1800_2000(h) mm steel climate chamber (see figure 37). The chamber can measure and control the temperature and relative humidity through the following actuators and components:

- heater, made of a 2kW power electric resistor;
- cooler, made of a 0.9kW vapor compression refrigeration cycle using R404A refrigerant fluid;
- ultrasonic humidifier with a capacity of 1.2 L/h and an electric power of 0.08W;
- deliquescence dehumidifier with calcium chloride salts devoted to reducing the humidity significantly within the chamber in a few minutes;
- electric dehumidifier, 0.2kW and capacity to reduce humidity equal to 10L in 24h;
- a tank of distilled water.

All devices are controllable both in on/off mode and by modulating their rated voltage through external power controllers. The climate chamber is shown in figure 37, along with its power system and the control panel.

Figure 37. Climate chamber of the Food Supply Chain Center (Manzini et al., 2019).

The temperature and relative humidity measurements are conducted through a commercial integrated sensor, including a PT100 resistance transducer with $\pm0.3°C$ accuracy and a capacitive humidity sensor with $\pm2\%$ accuracy.

In order to simulate a generic profile of temperature and humidity in agreement with the previously illustrated closed-loop approach, a customized LabView virtual instrument (VI) has been designed and implemented. This tool allows the user to import the temperature and relative humidity profiles to track and to physically control the sensors and actuators installed into the climate chamber.

The selected fine chocolate products are the well-known Gianduiotto and Cremino (see figure 38A and B, respectively) and a special product named Scorza (see figure 38C). This third selection comes from the wrinkled and irregular design of chocolate, similar to tree bark. The first recipe dates back to 1832 when chocolate was known only as a drink. The careful selection and mixing of the finest cocoa powders give this product a unique crumbly mouthfeel and vintage aroma. For this reason, the Scorza has been selected for this simulation process.

(A) (B) (C)

Figure 38. (A) Gianduiotto, (B) Cremino, (C) Scorza (Manzini et al., 2019).

A campaign of monitoring regional and international shipments executed in different seasons from the Italian production plant to different clients has been conducted. Two critical shipments from a large sample of monitored orders were selected. They were executed in September and October from the North of Italy towards the South. These two shipments involve some criticalities, as in this period the transportation already involves a nonrefrigerated truck. This choice is motivated because in the North temperatures are already lower during these months compared to summer. However, the climate was extremely and unexpectedly hot in the selected period of time, especially in the South of Italy. Figure 39(a) (shipment from Bologna to Messina) and Figure 39(b) (shipment from Bologna to Trapani) report the trend of the monitored temperature inside the truck containers.

(a)

(b)

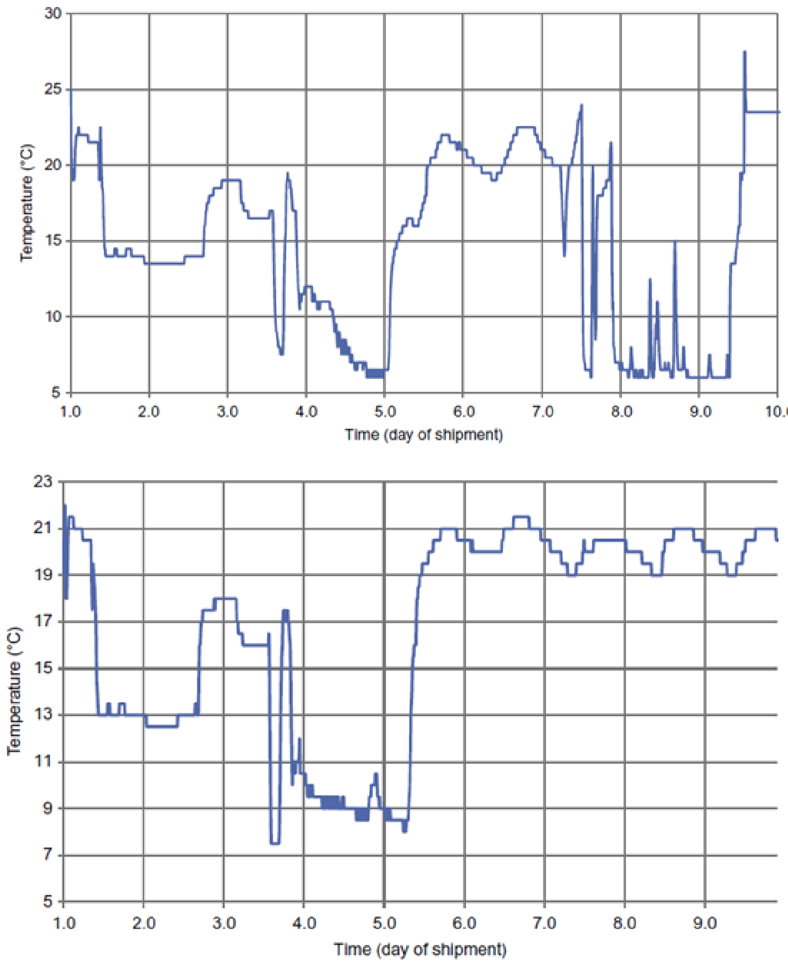

Figure 39. Monitored temperatures of the shipments (a) Bologna-Messina and (b) Bologna-Trapani (Manzini et al., 2019).

A panel of human experts assessed the effect of the stresses on the fine chocolates through several drivers grouped according to the five senses: sight, smell, taste, touch, and hearing. The generic summary score is the weighted mean quantified on different "basic sensations" (e.g., acidity, bitterness, crunchiness, sweetness, primary sensations). The global score is calculated as a weighted mean quantified on the five summary scores (assuming taste weight 73%, smell 20%, sight 4%, touch 1%, hearing 1%) and the final sensation score (assuming weight 1%). Given a generic score, the higher the value, the higher is the perceived level of quality.

The previously selected shipments have been simulated in the climate chamber. Given the selected chocolate products, three identical samples were compared: one subject to the stress run "simulation 1", i.e., the Bologna-Messina shipment; one subject to the stress run "simulation 2", i.e., the Bologna-Trapani shipment; and finally, one representing the so-called time-zero sample, corresponding to a constant temperature of 14°C and relative humidity of 60%.

The microbiological analysis conducted on the time-zero sample and the simulated samples does not reveal any significant effects in terms of safety. The experts involved in the analysis (21, 32, 43, 58, and 64 experts) did not know anything about the nature of the samples and the stresses they experienced.

The comparative what-if analysis conducted involved four main factors: Product, Analysis, Expert, and Sample. Each factor counts multiple options:

- Expert, i.e., different combinations of experts;
- Product, i.e., different chocolate products (Cremino, Gianduiotto, and Scorza);
- Sample, i.e., different shipments (Shipment 1, Shipment 2, and time-zero);
- Analysis, i.e., different times of analysis execution (1, 2, and 3).

The results are the following:

- There are no significant variations between Analysis 1 and Analysis 2 in terms of taste and smell. Consequently, the expert behavior is coherent in the first and the second analyses;
- The taste of Cremino and Scorza varies between the second to the third analysis, i.e., there is an effect due to the so-called "passing-time." In particular, the quality of the Scorza improves, while the quality of Cremino is reduced in terms of taste.
- Considering the smell test, both Cremino and Gianduiotto reduce their level of quality after 6 months. A not significant effect is observed in the Scorza product.
- Temperature stresses significantly affect the smell but not the taste.
- Time-zero analysis performs better for all products in terms of smell.
- The largest part of the group of experts (except for 45) found the time-zero samples better. In other words, they identified the samples not subjected to temperature stresses.

Figure 40 shows the results of the what-if analysis for (a) taste evaluation and (b) smell evaluation conducted with the statistical software Minitab.

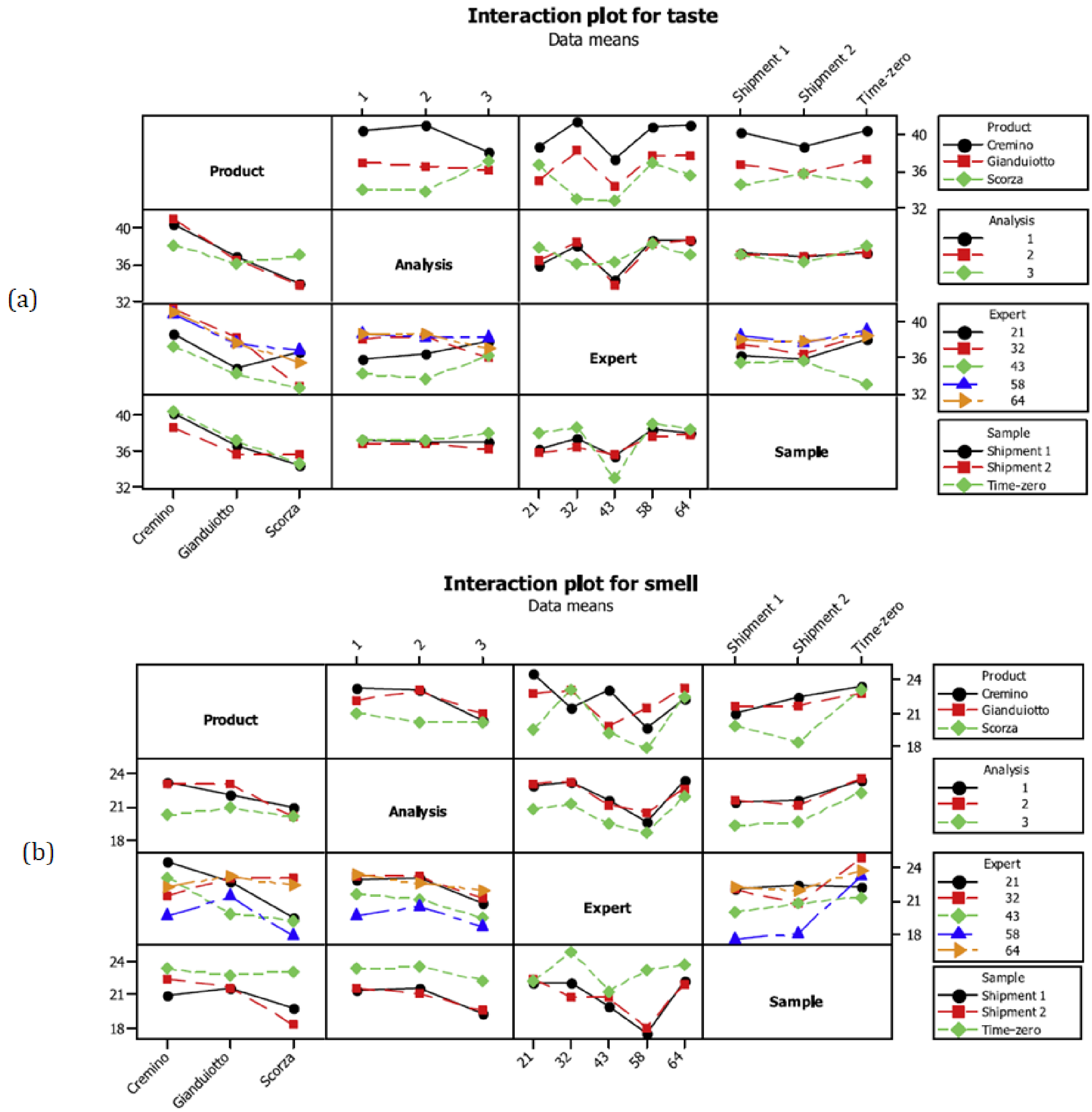

Figure 40. Results of the what-if analysis on (a) taste and (b) smell (Manzini et al., 2019).

The ability to monitor FSCS activities and their effect on the product with the traceability framework introduced in this chapter and the simulation of product performances in a what-if analysis aid the decision-maker in predicting the result of adopting new packages or using refrigeration systems to follow a specific target temperature profile.

The analysis conducted on the fine chocolate demonstrates that even if the two shipments did not cause safety issues for consumers, the quality could be altered by the environmental conditions compromising how the final consumer perceives the product. Therefore, the uncertainty of the climate conditions can be responsible for uncertainty regarding the quality of the product at the place of consumption, which is undesirable for the FSCS stakeholders.

4.9 Chapter's highlights

- Traceability supports the identification of criticalities for product quality and safety. It is the best solution to assess the criticality level in an existing FSCS.
- The collection of integrated traceability data on-field gives a clear and thorough view of the product during its life cycle. A complete monitoring profile provides data to track the provenience of the products and facilitates recalls whenever safety issues arise.
- Furthermore, tracing product quality, the temperature it experiences, and the sustainability performances of the supply chain aids to guarantee compliance to regulations and standards and establish trust with the consumers when data are shared with them.
- Recently, lots of innovative traceability solutions have been proposed. However, their costs and the lack of cooperation and data standards slow down their adoption in current FSCS.
- This chapter proposes an innovative, integrated traceability and monitoring tool. The tool reconstructs a seamless profile from heterogeneous and distributed data sources collected by separated, not standardized, traceability tools. It fosters cooperation also among supply chain actors reluctant to have a unique and shared traceability system.
- The tool also fills missing values with the integration of a routing module and by analyzing past delivery routes and by querying online climate databases.
- The proposed tool supports the monitoring of the FSCS and the simulation of a what-if analysis by analyzing the stresses experienced by a perishable product in different routes or seasons, providing insights to support the decision-making process.

4.10 References

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5. Models and methods for the optimization of perishable supply chain systems

The content of this chapter is based on the research presented in the following papers and book chapters:

Accorsi, R., Gallo, A., Manzini, R. (2017). ***A climate driven decision-support model for the distribution of perishable products****. Journal of Cleaner Production, 165, 917–929. doi:10.1016/j.jclepro.2017.07.170.*

Gallo, A., Accorsi, R., Baruffaldi, G., Manzini, R. (2017). ***Designing Sustainable Cold Chains for Long-Range Food Distribution: Energy-Effective Corridors on the Silk Road Belt****. Sustainability, 9, 2044.*

Accorsi, R., Bortolini, M., Gallo, G. (2019). ***Modeling by-products and waste management in the meat industry****. In: Accorsi, R., Manzini, R., 2019. Sustainable Food Supply Chains. Planning, Design, and Control through Interdisciplinary Methodologies, chapter 23. Elsevier.*

The previous chapters provided frameworks and methods to identify long-term preserving strategies for newly constituted FSCS. Then, an innovative traceability system was introduced to identify potential safety and quality issues in an existing supply chain and to monitor the FSCS performance.

This chapter will focus on proposing innovative, integrated, and interdisciplinary models and tools to support the decision-making process for an existing FSCS. These tools aim to follow the product throughout its life cycle, supporting the practitioners and managers in making the main logistics decisions affecting the sustainability performances of an FSCS. The proposed models and methods are tailored to perishable products, especially for the operational decisions affecting the resulting quality of the single product. For these decisions, the chapter will propose innovative models integrating a climate-driven logistics planning of the main operative processes of the FSCS.

A framework for the application of the proposed models and algorithms is shown in figure 41. This framework aims to support practitioners and logistic managers in the application of the proposed methods to optimize the FSCSs in all the decision levels and to identify the right model and solution method to address a specific issue of their supply chain systems.

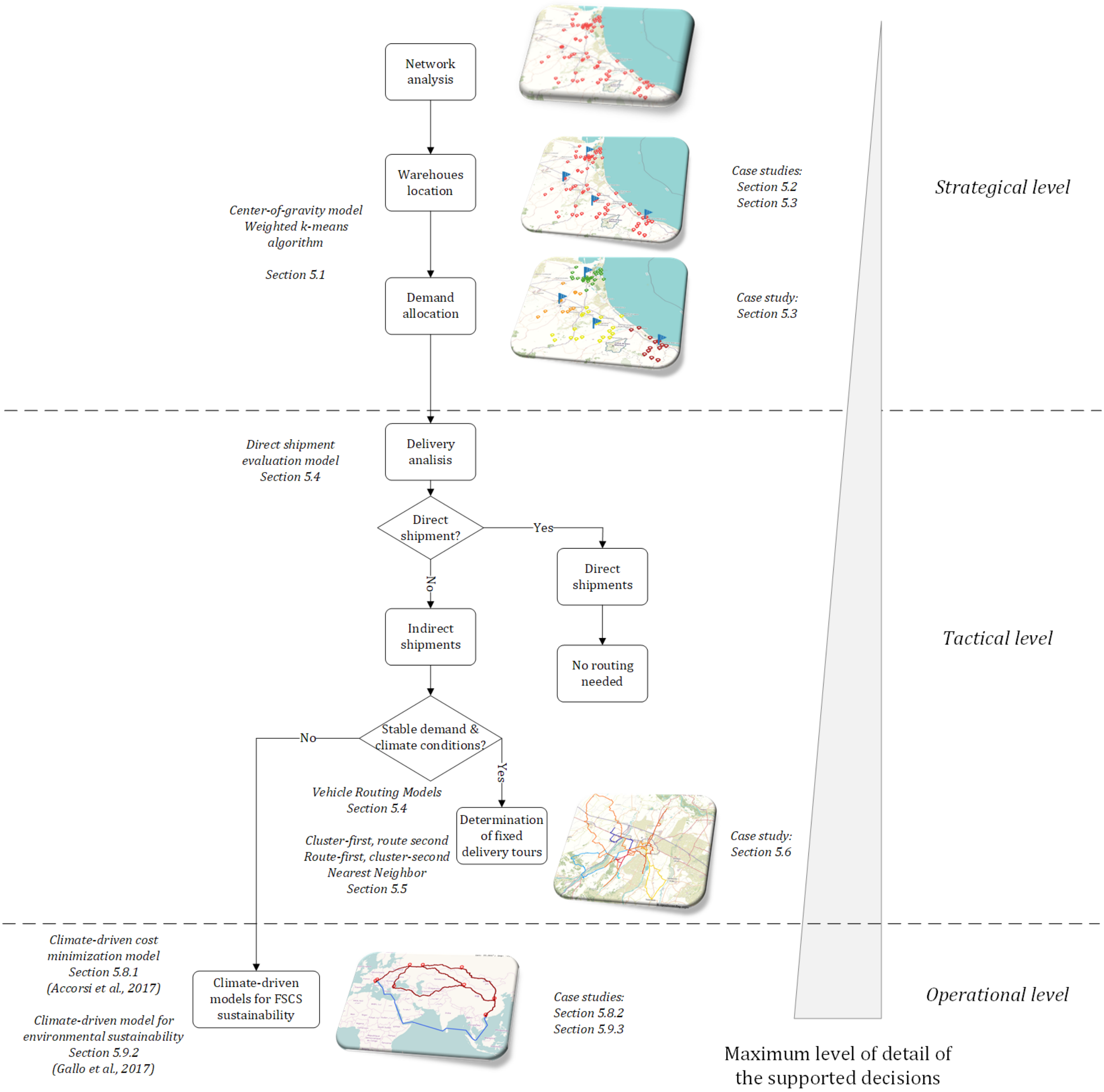


Figure 41. Framework for the application of the proposed models and methods.

5.1 Optimal location of storage nodes and demand allocation

This section introduces models and algorithms to address the strategic logistic decisions illustrated in figure 41. The logistics of perishable products is driven by reducing product waiting time, which leads to a progressive decay of the product's quality and value, as introduced in chapter 2. Time is the main factor affecting the product life cycle as the definition of the shelf life itself refers to the maximum time the product can wait on shelves before becoming unsuitable for selling and consumption.

Therefore, the determination of the optimal location of a new storage node (e.g., hub, distribution center) and the allocation of clients to storage nodes is usually conducted through the minimization of the distance between the nodes of the supply chain system. A typical mathematical modeling approach adopted for this choice is the center-of-gravity problem (Lukardi & Hamsal, 2020). This model determines the optimal location of a new warehouse by calculating the centroid of a set of spatially distributed clients. The centroid of these nodes indicates the spatial point that minimizes the traveling distances for distributing products to the clients. Therefore, as the traveling distances are minimized, also travel time is minimized when road conditions and the type of vehicle are constant. Furthermore, when the same conditions apply, this method minimizes also the transportation costs and carbon emissions due to the reduced traveled distances (Esnaf & Küçükdeniz, 2009).

The center-of-gravity problem requires the coordinates of clients as an input. Then, the distances determining the optimal location of the new storage node are usually determined as rectilinear or Euclidean distances (Lukardi & Hamsal, 2020), as in the following:

$$d_c = (|x_c - lat|^p + |y_c - lon|^p)^{\frac{1}{p}} \tag{5.1}$$

where:

- x_c is the latitude of the client's node c.
- y_c is the longitude of the client's node c.
- lat is the latitude of the new warehouse.
- lon is the longitude of the new warehouse.
- $p = 1$ when the distances are rectangular, $p = 2$ when they are Euclidean.

The center-of-gravity problem can be formulated (Liao & Guo, 2008) as in the following to determine the optimal location of D storage nodes and to assign clients to them at the same time:

Sets:

C Set of clients.

D Set of storage nodes.

Parameters:

dem_c Demand of client c.

x_c Latitude of client c.

y_c Longitude of client c.

Decision variables:

w_{cd} Binary variable: 1 if client c is assigned to storage node d, 0 otherwise.

lat_d Latitude of storage node d.

lon_d Longitude of storage node d.

d_{cd} Distance between client c and storage node d, calculated by Eq. (5.1).

Objective function:

$$\min \sum_{c \in C} \sum_{d \in D} w_{cd} d_{cd} dem_c \tag{5.2}$$

Subject to:

$$\sum_{d \in D} w_{cd} = 1 \, , \; \forall \, c \in C \tag{5.3}$$

$$d_{cd} = \sqrt{(x_c - lat_d)^2 + (y_c - lon_d)^2} \, , \forall \, c \in C, d \in D \tag{5.4}$$

$$w_{cd} \in \{0,1\}; lat_d, lon_d \in \mathbb{R}; d_{cd} \in \mathbb{R}^+; , \forall \, c \in C, d \in D \tag{5.5}$$

The objective function (5.2) minimizes the total traveling distances between the clients and their assigned storage node. Constraints (5.3) assign each customer to only one storage node. Constraints (5.4) assess the distance between the storage node and the client. This formulation adopts the Euclidean distance as defined by eq. (5.1). Finally, constraints (5.5) define the domain of the decision variables.

This formulation further minimizes the actual traveling distances of an existing supply chain by weighting the distances between clients and the warehouse based on the demand (the entity of the physical flow between the nodes). For new supply chains, when an accurate estimation of the demand of the clients is unknown, the same model can be applied without the parameter dem_c, providing a less accurate position for the new warehouses but still supporting the decision-making process.

The proposed mathematical modeling formulation is not linear. Therefore, the solution to this problem could be very hard to find out with commercial solvers. However, You et al. (2019) provide a linearization of this model that computes the optimal location with an acceptable approximation of the non-linear problem.

A frequent solving method for center-of-gravity problems is the k-means clustering algorithm (You et al., 2019; Blömer et al., 2016), where k represents the number of storage nodes. The traditional k-means formulation (introduced in 2.8.2) can be slightly modified to introduce also weights (Chen et al., 2009) associated with clients, as with the introduction of the demand in eq. (5.2). Liao and Guo (2008) provide an example of the adoption of a weighted k-means algorithm for a Capacitated Facility Location Problem.

The weighted k-means algorithm can be formulated as in the following (Mam et al., 2017):

Step 1. The k-means algorithm starts with k random "means" value.

Step 2. Each element is associated with one of the k clusters by calculating the nearest of the k means.

Step 3. The means are adjusted by calculating the weighted centroids of the clusters generated in Step 2:

$$\mu_d = \left(\frac{\sum_{c \in C} w_{cd} \cdot x_c \cdot dem_c}{\sum_{c \in C} w_{cd} \cdot dem_c}, \frac{\sum_{c \in C} w_{cd} \cdot y_c \cdot dem_c}{\sum_{c \in C} w_{cd} \cdot dem_c} \right) \quad (5.6)$$

Step 4. Steps 2 and 3 are repeated until there is a convergence in the clustering results.

Equation (5.1) provided the formulation of two types of distances: the rectangular and the Euclidean distances. Researchers also proposed other types of distances to determine the kilometers traveled by vehicles during product distribution, such as the Great Circle distance (Porcu et al., 2016). However, the driving distance represents the most appropriate distance for this storage node location problem as it considers the actual road traveled by the drivers during distribution. Indeed, driving distance provides a much more accurate estimation of the actual traveled distance. For example, the driving distances between the major United States cities are about 18% greater than straight-line distances (Shih, 2015). Therefore, providing driving distances as input both for the mathematical model and for the weighted k-means can provide far better results in minimizing the actual traveled distances of the FSCS. However, providing the driving distance to the mathematical model would require a mathematical formulation to estimate this distance as in constraint (5.4).

A practical solution for this issue is to individuate the best location for a new storage node that minimizes driving distance could entail the estimation of the best position with the Euclidean distance. The optimal point could not be a feasible location for a storage node as it frequently results in a location already occupied by existing activities or not exploitable for commercial reasons or without any connection to roads. Therefore, practitioners can assess locations close to the optimal ones and identify a set of possible locations for the new node. Then, the minimum total driving distance between each potential location in this set, and every clients can be estimated to find out the best location, as shown in figure 42.

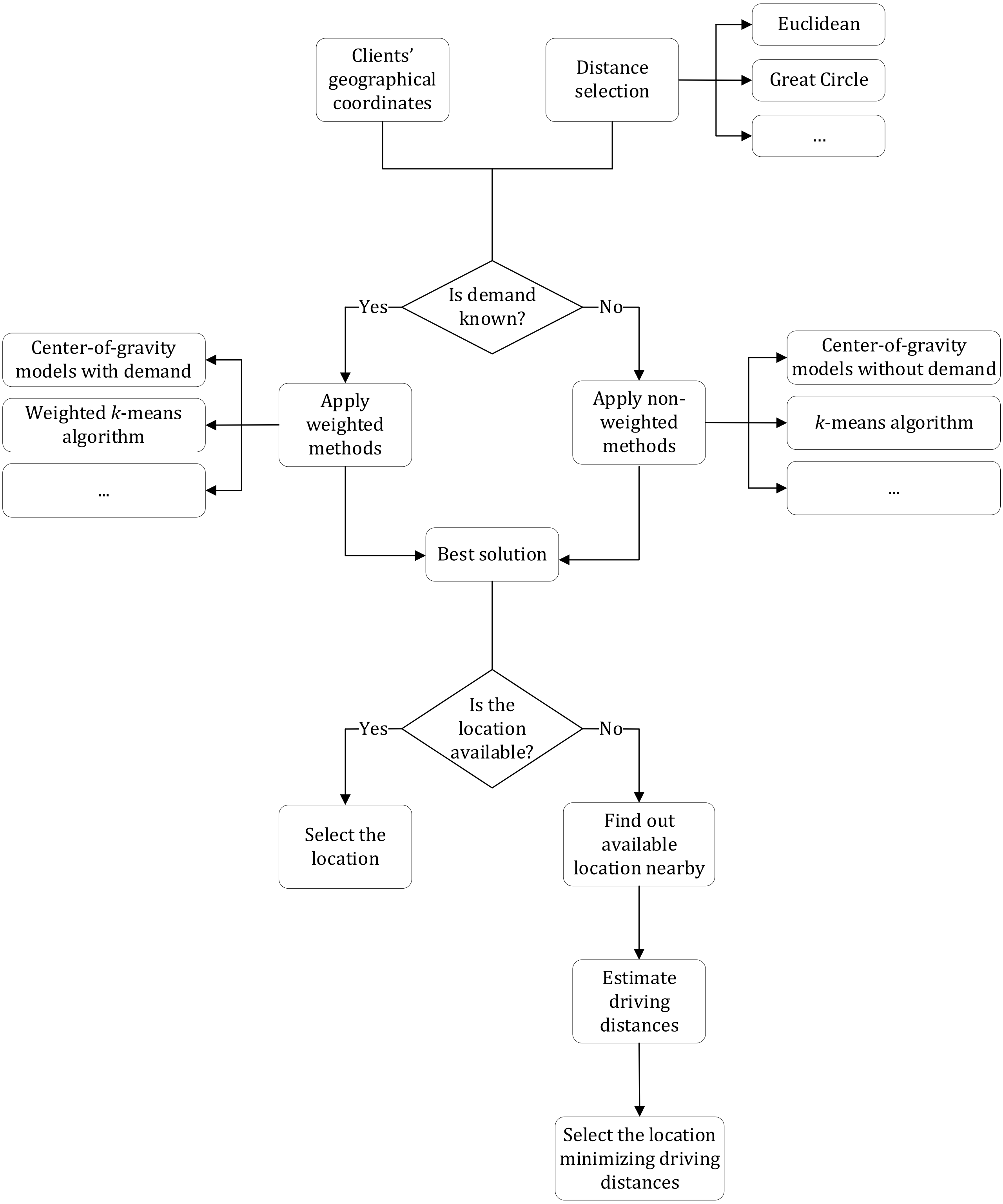


Figure 42. Estimation of the best location for a new storage node.

5.2 Determination of the optimal location of a new warehouse in the food catering industry

The food catering industry is an FSCS preparing and distributing ready-to-eat meals to schools, hospitals, and canteens (Fusi et al., 2016). Food catering systems are characterized by many clients with different demand volumes and distributed in sparse geographical areas, each with low sales volumes (Accorsi et al., 2014[a]). Therefore, these FSCS usually have a high number of nodes where meals are prepared, packed, and stored. Each of these nodes serves several clients located in a restricted geographical area, as their number and the daily demand of products require opening many facilities close to the points of consumption. Indeed, as this industry prepares ready-to-eat meals, the deliveries must usually be daily, while some nodes even require two deliveries per day (lunch and dinner).

Furthermore, the food catering system must adopt adequate cooking technology and packaging solutions to keep meals outside the "dangerous temperature range" (i.e., 10–65°C) in order to avoid safety risks for consumers (European Parliament, 2004). The meal preparation and delivery should then follow one of the following three main temperature profiles (Accorsi et al., 2019):

- Cook-warm: Meals are cooked and maintained hot (above 65°C) after production until the delivery to the final consumer.
- Cook-chill: Meals are cooked and swiftly blast-chilled, dropping them to a temperature lower than 10°C (within a maximum of 3h). Meals are rewarmed just before being served at the point of consumption.
- Cook-freeze: Meals are treated as in the case of cook-chill, but they are frozen (at a temperature lower than -18°C) instead of being blast-chilled.

Therefore, it is essential to reduce the time interval between meal preparation and consumption in order to ensure respecting these temperature intervals.

This section presents an application of the storage node location problems introduced in the previous section to the food catering industry. The food catering company considered in this study prepares meals for private companies, schools, universities, hospitals, and nursing homes. The FSCS is constituted by more than 800 storage nodes and clients distributed in most Italian regions in the North and in the Center, as shown in figure 43. The red pins in the map represent the clients, while the blue flags represent the nodes of the food catering company.

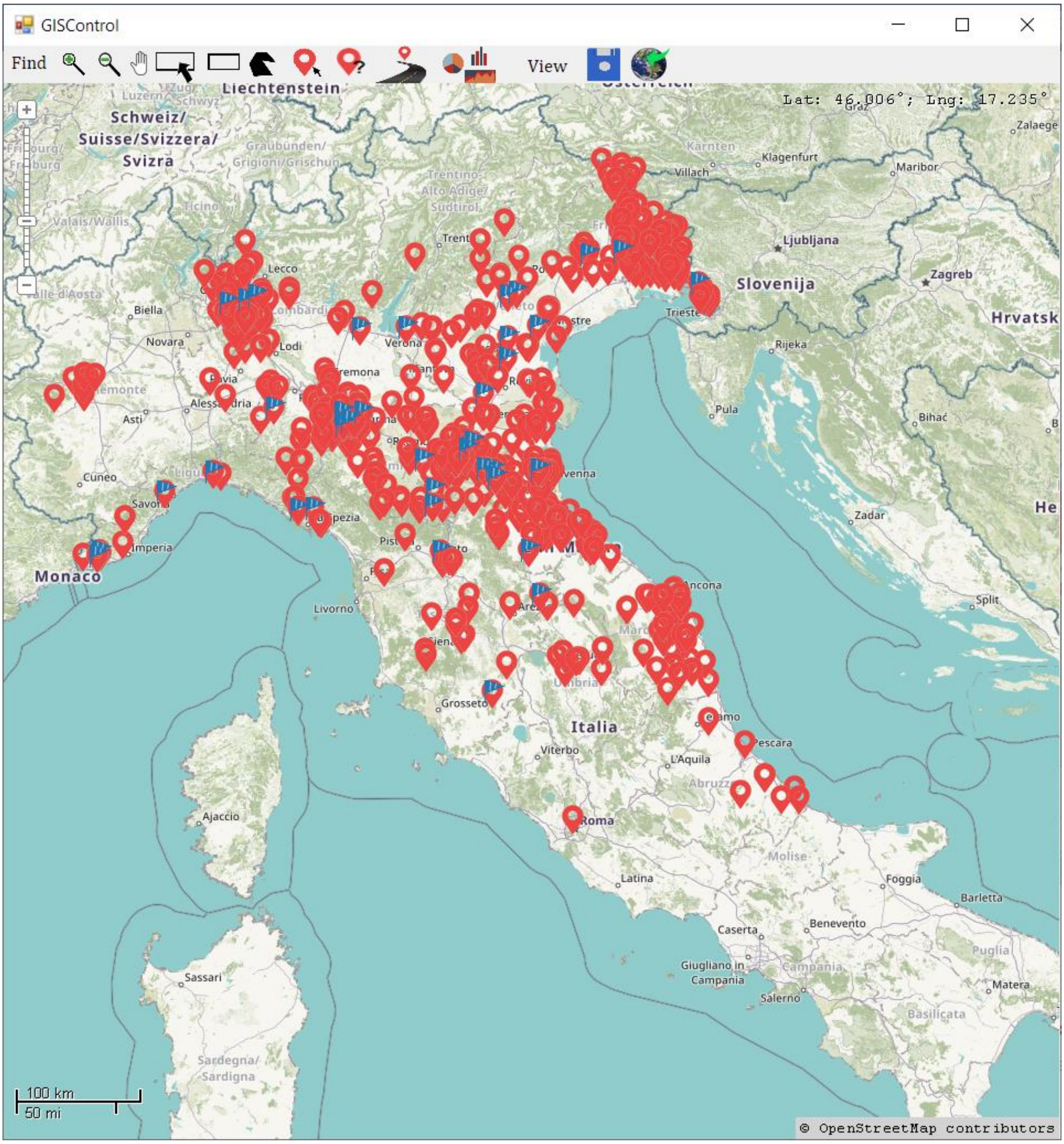


Figure 43. Geographic distribution of clients.

The proposed case study concerns creating a new facility for meal preparation, packing, and storage within the Emilia-Romagna region. The new facility, namely a Centralised Kitchen (CeKi), should replace the actual CeKi located in Collecchio, in the province of Parma. The CeKi serves 177 nodes located in the same province, except for one node located in the near province of Mantua. The 177 nodes are represented in figure 44 with a red pin, while the current CeKi is represented with a blue flag.

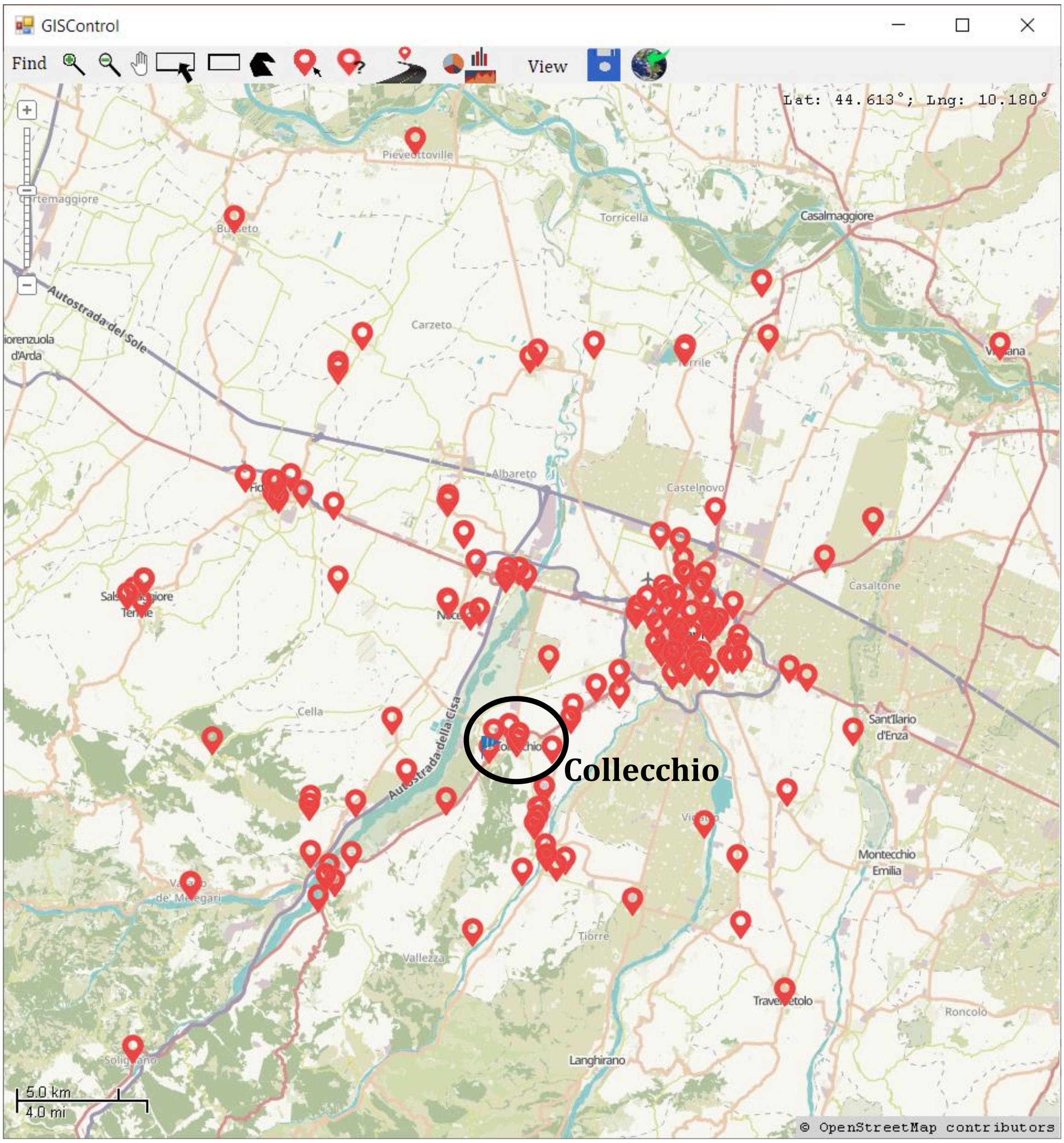


Figure 44. Geographic distribution of the nodes involved in the case study.

In order to find out the best location for the new CeKi, a comparison between the linearized mathematical model for the center-of-gravity problem and the weighted *k*-means algorithm, both based on the minimization of Euclidean distances, is proposed. The mathematical model requires the maximum error allowed in the linearization of Euclidean distances as an input, which was set to 0.01%.

The results of the two methods for estimating the best location for the new node are shown in figure 42. The green triangle in the map represents the optimal location suggested by the mathematical model, while the yellow triangle represents the solution provided by the weighted *k*-means algorithm. However, the two locations were not suitable for the construction of the new CeKi. Indeed, both of the locations were already devoted to other activities, or they were not directly connected to the road infrastructure. The food catering company individuated two available locations for the new CeKi close to the suggested solutions, which are shown in figure 45. The green square represents the location chosen on the basis of the results provided by the mathematical model, while the yellow square represents the location close to the solution of the weighted *k*-means algorithm.

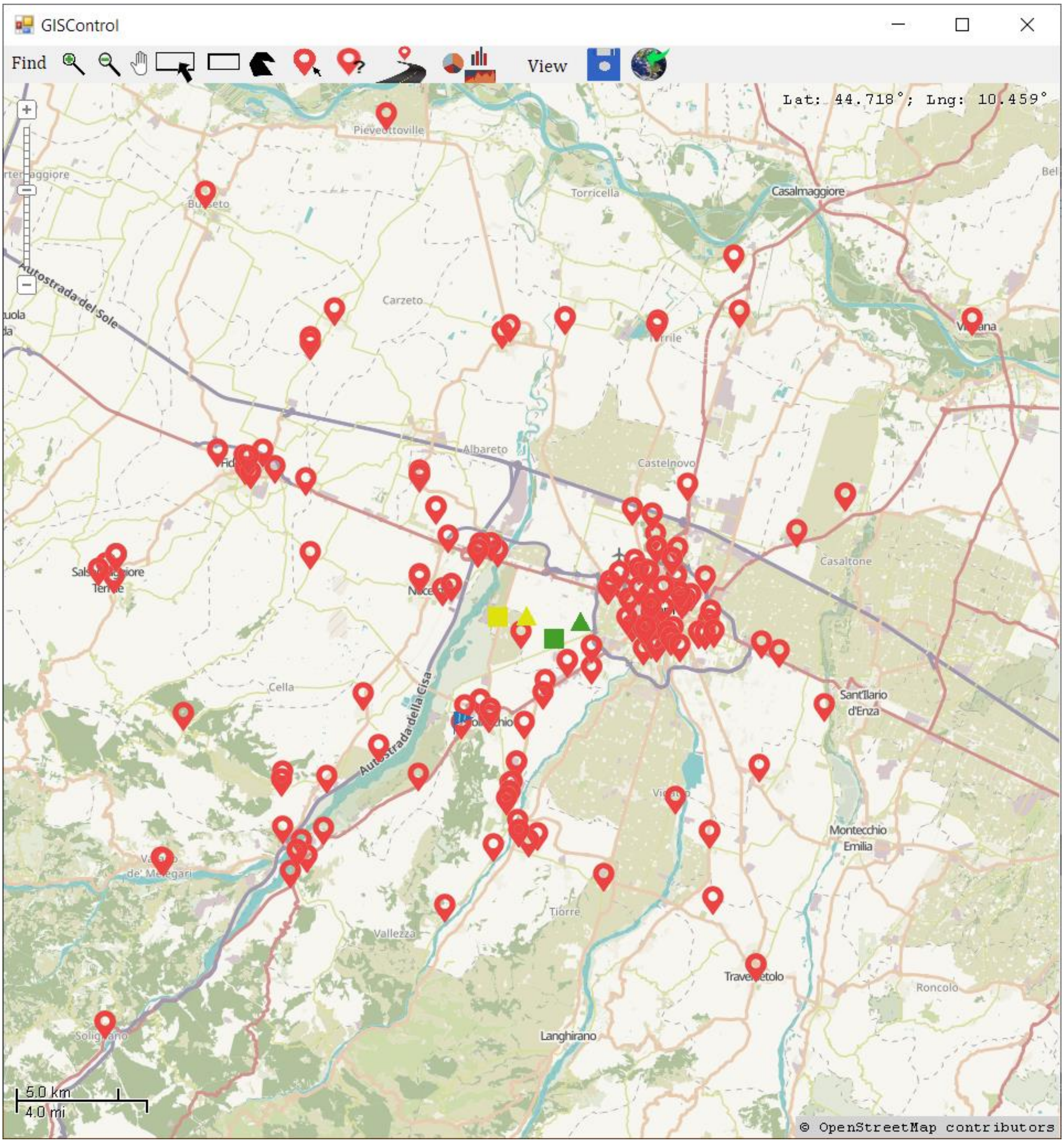


Figure 45. Results of the optimization model (green) and weighted k-means (yellow).

The comparison between these solutions was conducted by the estimated yearly driving distance, calculated by multiplying the driving distance between the storage node and the clients by the number of yearly deliveries given by the past demand. The driving distances are obtained with a routing tool based on the open-source software Itinero, as described in chapter 4. The results of this comparison are provided in table 13, which shows that the new locations reduce the yearly traveled distance by about 20%. The cumulated yearly distance is calculated as the total distance between the proposed locations for the CeKi and every client multiplied by the number of deliveries demanded per year. Given the further reduction of the total traveling distances provided by the mathematical model, the company decided to create the new CeKi in the available location 2. Therefore, the company moved the CeKi from the previous location in Collecchio to the new one in Vicofertile.

The results in table 13 do not consider any optimization of the delivery tours that could significantly reduce the resulting yearly distance when the clients demand a less-than-truckload delivery. The comparison between the driving distances has been made on the AS-IS tour without applying Vehicle Routing Problems (VRPs) to optimize the TO-BE solution. Indeed, the optimization of the tours does not concern the strategic optimization problem illustrated in this section, but it will be discussed in the next sections devoted to tactical decisions about delivery tours. The final comparison shown in table 13 has been conducted with the driving distances rather than the Euclidean distances of Eq. (5.2) to better estimate the traveled distances in the real application.

Table 13. Comparison of the total yearly distance for the proposed locations.

CeKi location	Latitude	Longitude	Yearly driving distance
AS-IS (blue flag)	44.747	10.202	634,944 km
Mathematical model solution (green triangle)	44.783	10.257	500,730 km
Weighted *k*-means solution (yellow triangle)	44.793	10.222	532,892 km
Available location 1 (green square)	44,791	10,274	504,598 km
Available location 2 (yellow square)	44.793	10.240	551,217 km

5.3 Storage nodes location-allocation problem in the food catering industry

The previous section presented the case of the food catering industry and applied the center-of-gravity problem and the weighted *k*-means algorithm to determine the best location of a single node. However, the model and the weighted *k*-means can determine the best location of multiple storage nodes at the same time. Therefore, this section integrates the previous one by showing the results of the application of the same methods to a more complex problem: revising the entire warehouse network within the Emilia-Romagna Italian region. This section aims to show the results of the methods presented in section 5.1 to handle the problem of multiple storage locations and the clients' allocation problem. Let's consider the same food catering FSCS introduced in the previous section. Almost half of the nodes of this FSCS (398 out of 784) are located in the Emilia-Romagna region. Therefore, the companies chose to locate in this region 15 of the 39 CeKis of the supply chain network.

Figure 46 shows the map of the Emilia-Romagna region with the clients in this region highlighted with a red pin, while the storage nodes currently used by the food catering company are shown with a blue flag.

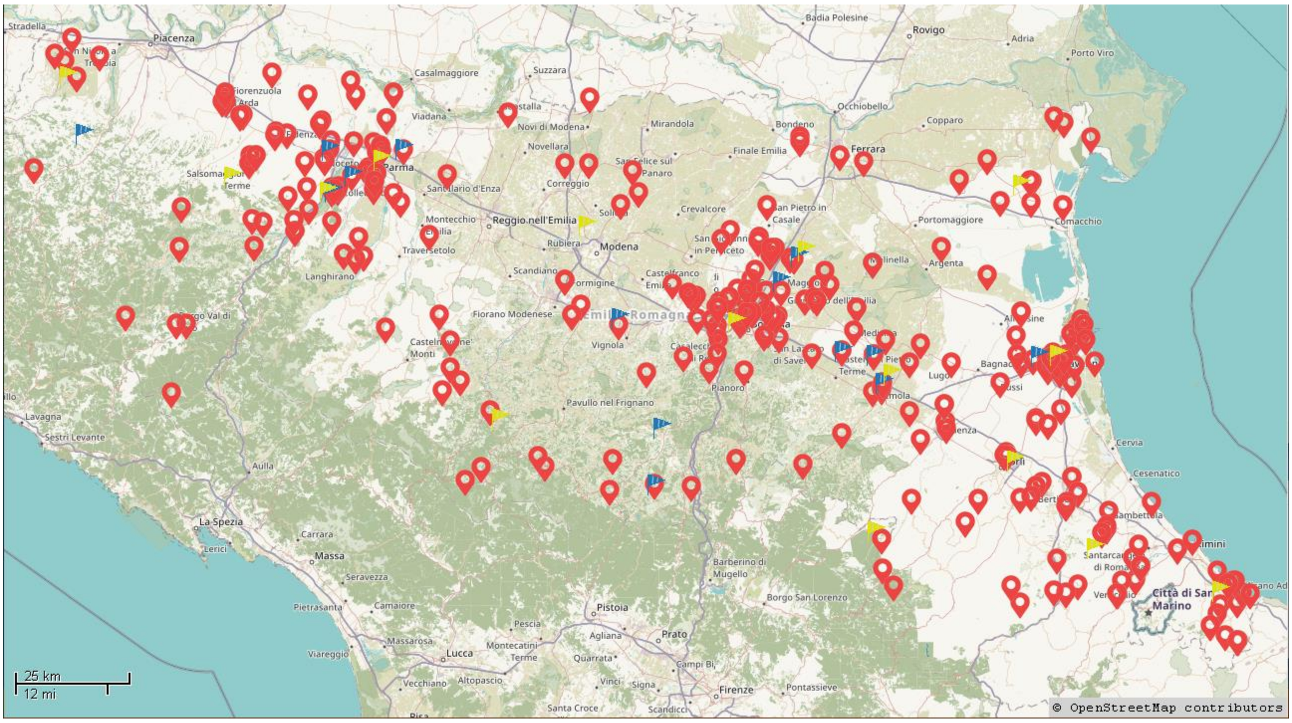


Figure 46. Map of the current locations of CeKis (in blue) and suggested locations according to the *k*-means (in yellow)

The mathematical model introduced in section 5.3 could not return an optimal solution in a reasonable time. Therefore, the weighted *k*-means algorithm has been applied to solve this problem. The number of centroids, *k*, is equal to the current number of storage nodes as this section aims to show the savings in traveled distance given by the relocation of the storage nodes of the FSCS.

The results of the application of the algorithm are shown in figure 46 with yellow flags. As the aim of this section is to show the application of the methods introduced in section 5.1 for multiple storage nodes location and for clients' application, the optimal locations proposed by the *k*-means algorithm are assumed as available locations for the realization of new storage nodes. Refer to the previous section for the procedure to choose an available location close to the optimal one.

Once the algorithm determined the optimal location for the storage nodes and the allocation of clients to them, the driving distances between each client and the associated storage node were estimated. The solution proposed by the weighted *k*-means algorithm better distributes clients to the storage node. The maximum number of clients associated with the same storage node decreased from 96 in the AS-IS to 76 in the TO-BE. Furthermore, the driving distances between clients and the associated storage nodes decreased by 42%. The average distance decreased from 23.63 km to 13.67 km.

5.4 Mathematical models to determine fixed delivery tours

Once the nodes of the FSCS have been established, one of the main tactical decisions concerning the logistics of perishable items is the definition of the distribution strategy and delivery tours (figure 41). When production and demand are stable enough over time, it is usually convenient for companies to define fixed delivery tours for distribution. These fixed tours are then periodically revised, according to seasonal fluctuations of the logistic flows.

Firstly, it is essential to assess if it is more convenient to recur to the storage node or direct shipments. Direct shipment models have been largely studied in the literature. Musa et al. (2010) provided a mathematical model to address the direct shipment problem in cross-docking. They proposed an Ant Colony Optimization algorithm to solve this problem for big size problems. Azizi and Hu (2020) integrated the location problem for new storage nodes with the vehicle routing problem with the direct shipment. They also proposed a benders decomposition algorithm to solve their model. A mathematical model to address the direct shipment problem can be formulated as (Mokhtarinejad et al., 2015):

Sets:

S	Set of suppliers
C	Set of clients.

Parameters:

$cost_{sc}$	Cost of direct delivery between supplier s and client c.
$cost_s$	Cost of shipment between supplier s and the storage node.
$cost_c$	Cost of shipment between supplier c and the storage node.
$cost_{st_s}$	Cost for processing inbound loads from supplier s at the storage node.
cap	Capacity of the vehicles.
dem_{sc}	Demand of products from the supplier s requested by client c.

Decision variables:

x_{sc}	Binary variable: 1 if there is direct shipment between the supplier s and client c, 0 otherwise.
y_s	Number of travels between the supplier s and the storage node.

z_c Number of travels between the storage node and the client c.

Objective function:

$$\min \sum_{c\in C} \sum_{s\in S} cost_{sc} \cdot x_{sc} + \sum_{s\in S} \left(cost_s + cost_{st_s}\right) \cdot y_s + \sum_{c\in C} cost_c \cdot z_c \quad (5.7)$$

Subject to:

$$\sum_{c\in C} dem_{sc}(1 - x_{sc}) \leq cap \cdot y_s \text{ , } \forall\, s \in S \quad (5.8)$$

$$\sum_{s\in S} dem_{sc}(1 - x_{sc}) \leq cap \cdot z_c \text{ , } \forall\, c \in C \quad (5.9)$$

$$x_{sc} \in \{0,1\}; y_s, z_c \in \mathbb{N}; \forall\, c \in C, s \in S \quad (5.10)$$

The objective function (5.7) minimizes the total costs for direct and indirect shipments. The cost of direct shipment only entails the costs for the delivery from the supplier to the client, without storage. As direct shipments avoid consolidation in the storage node, they usually entail higher variable costs due to less-than-truckload shipments. Conversely, the costs for indirect shipments include costs for transportation from the supplier to the storage node and from the storage node to the client. In addition, indirect shipment also involves a cost to process the load at the storage node (e.g., unloading, storing, handling, and loading the products).

Constraints (5.8) and (5.9) compute the number of vehicles required for indirect shipments as the demand of clients divided by vehicles' capacity. Finally, constraints (5.10) define the domain of the decision variables.

Direct deliveries are handled with a shipment between the supplier and the client. Conversely, indirect shipments flow into the storage node where they are consolidated. Here, multiple indirect shipments are loaded into a vehicle for consolidation in order to reduce transportation costs. This consolidation of shipments to foster Full Truck Loads imply the necessity of other mathematical models and algorithms to determine how to allocate deliveries to the available fleet of vehicle and what is the optimal routing to deliver products to clients while maximizing the sustainability of the FSCS.

The Vehicle Routing Problem (VRP) is widely studied in the literature. Several models have been proposed in the last decades to address this problem. It entails finding the optimal solution to serve multiple nodes with the available fleet of vehicles departing from one or multiple nodes of the supply chain network, called depots (e.g., the storage node). In the following, a simple formulation for the Capacitated Vehicle Routing Problem (CVRP) is introduced (Toth & Vigo, 2002; Labadie et al., 2016).

The CVRP determines the optimal routing strategy, guaranteeing that the vehicles' loads do not exceed their capacity. The following problem is defined on a directed graph $G = (N, A)$. The depot is represented by two nodes, 0 and $n+1$, in order to provide a simple formulation to avoid subtours. Subtours are cycles connecting the node of the network not including the depot, and should therefore be forbidden.

Sets:

N	Set of nodes.
V	Set of vehicles.
A	Set of arcs representing the shortest path between node *i* and node *j*.

Parameters:

cap^k	Capacity of the vehicle *k*.
dem_i	Demand of node *i*.
$time_{ij}$	Travel time for the route connecting node *i* and node *j*.
u_{cost}^k	Unit cost of vehicle *k*.
s_i	Service time to unload the delivery at node *i*.
M	Big positive constant.

Decision variables:

x_{ij}^k	Binary variable: 1 if vehicle *k* connects node *i* and node *j*, 0 otherwise.
t_i^k	Arrival time of vehicle *k* at node *i*.

Objective function:

$$\min \sum_{k \in K} \sum_{(i,j) \in A} time_{ij} \cdot u_{cost}^k \cdot x_{ij}^k \tag{5.11}$$

Subject to:

$$\sum_{j \in N \setminus \{i\}} \sum_{k \in K} x_{ij}^k = 1\ , \ \forall\ i \in N \setminus \{0, n+1\} \tag{5.12}$$

$$\sum_{j \in N \setminus \{0\}} x_{0j}^k = 1\ , \ \forall\ k \in K \tag{5.13}$$

$$\sum_{j \in N \setminus \{i\}} x_{ji}^k = \sum_{j \in N \setminus \{i\}} x_{ij}^k\ , \ \forall\ i \in N \setminus \{0, n+1\}, k \in K \tag{5.14}$$

$$\sum_{i \in N \setminus \{n+1\}} x_{i,n+1}^k = 1\ , \ \forall\ k \in K \tag{5.15}$$

$$\sum_{i \in N \setminus \{0,n+1\}} \sum_{j \in N \setminus \{i\}} dem_i x_{ij}^k \le cap^k \text{ , } \forall\, k \in K \tag{5.16}$$

$$t_i^k + s_i + time_{ij} \le t_j^k + M\left(1 - x_{ij}^k\right) \text{ , } \forall\, (i,j) \in A, k \in K \tag{5.17}$$

$$t_i^k \le \sum_{j \in N \setminus \{i\}} x_{ij}^k \cdot M \text{ , } \forall\, i \in N, k \in K \tag{5.18}$$

$$x_{ij}^k \in \{0,1\}; t_i^k \ge 0;\ \forall\, (i,j) \in A, k \in K \tag{5.19}$$

Eq. (5.11) minimizes the variable costs for transportation by computing the total time of the chosen routes and multiplying it for the unit cost of vehicles. Each client is visited by one vehicle (5.12). Each vehicle must depart from the depot (5.13), leave every node after visiting it (5.14), and return to the depot (5.15). Constraints (5.16) guarantee that the capacity of the vehicles is respected. Constraints (5.17) eliminate the subtours: if the vehicle visit node *j* after node *i*, then $x_{ij}^k = 1$ and the vehicle must visit *j* after serving client *i*. Otherwise, the constraint is always true. Constraints (5.18) force $t_i^k = 0$ when the customer *i* is not visited by vehicle *k*.

5.5 Solution methods to optimize fixed delivery tours

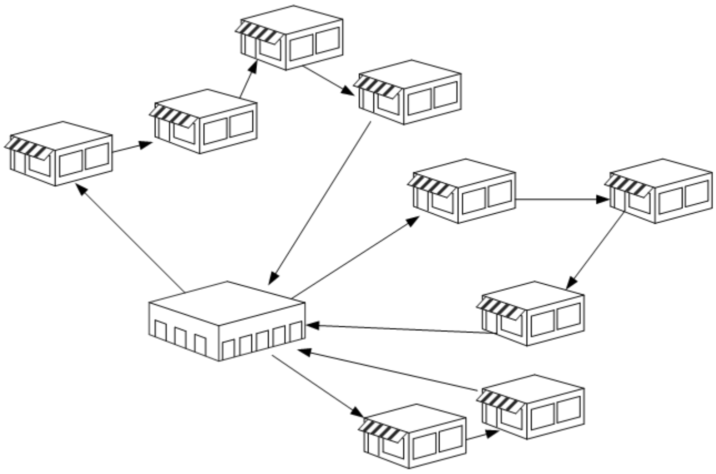
Although the CVRP introduced in the previous section is very simple, it is still an NP-hard model that could not be solved in a reasonable time for large-sized instances. In the last decades, lots of efforts have been devoted to solving VRP problems in a reasonable time. This section introduces some methods to solve the problem introduced in the previous section to solve a real instance that will be presented in section 5.6.

One of the simplest possibilities to solve the CVRP problem in a reasonable time is a constructive heuristic based on the nearest neighbor (Labadie et al., 2016). The constructive heuristics for this problem can be subdivided into:

- *Sequential route building*. These heuristics construct a route at a time by moving from the current node to the closest one. This procedure is repeated until the capacity of the vehicle is met. Then another vehicle is added until all clients have been associated with a truck. This method requires a smaller number of vehicles with better utilization of their capacity. However, the routes are not balanced. Indeed, the last route is usually much smaller than the other, as shown in figure 47 (a).
- *Parallel route building*. This method constructs *k* route at a time. At every step of the algorithm, each of the *k* vehicles moves to its closes client. The procedure is repeated until

each client is served. If all the k vehicles run out of capacity, a new vehicle is added. This procedure creates more routes, but they are more balanced, as shown in figure 47 (b).

(a)



(b)

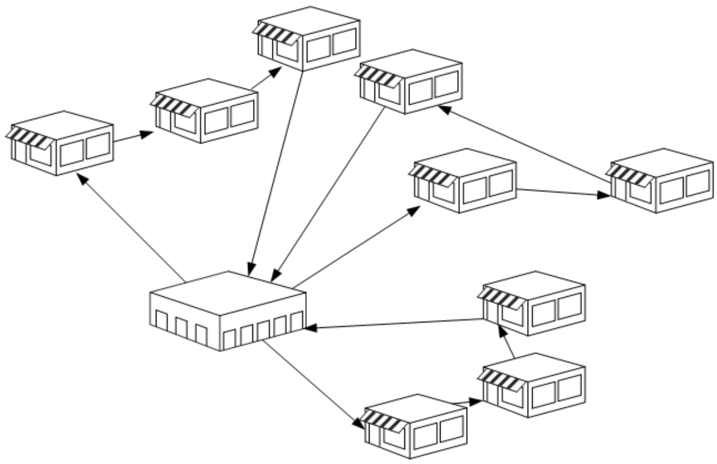


Figure 47. (a) Sequential and (b) Parallel route building for CVRP.

Another possible approach to solve larger instances of CVRP is the two-phase method, which consists of reconducting the CVRP to a simpler Traveling Salesman Problem (TSP). The two-phase methods can be subdivided into:

- *Cluster-first, route-second* consists of creating K clusters of clients with respect of vehicle capacity and then solve a TSP for each of them.

- *Route-first, cluster-second* consists of relaxing vehicle capacity and solving a TSP visiting all the clients. Then, a clustering algorithm is applied to split the TSP into K routes that respect the capacity of vehicles.

The phases of these methods can be solved with any clustering algorithm and any solving method for the TSP.

5.6 Determining the best delivery tours in the food catering industry

This section applies the CVRP model and some of the solution methods introduced in the previous section to determine the best delivery tours for the new CeKi located in Vicofertile, in the province of Parma as illustrated in section 5.2. Figure 48 illustrates the tours adopted in the AS-IS solution with the old CeKi located in Collecchio. In the AS-IS scenario, the food catering company performs 12 fixed daily routes from Monday to Friday, which visit 73 nodes.

As the food catering company is moving the CeKi from the current location in Collecchio to the location in Vicofertile as introduced in section 5.2, it needs to revise the delivery routes accordingly. These twelve fixed delivery routes entail 3,219 traveled kilometers every week.

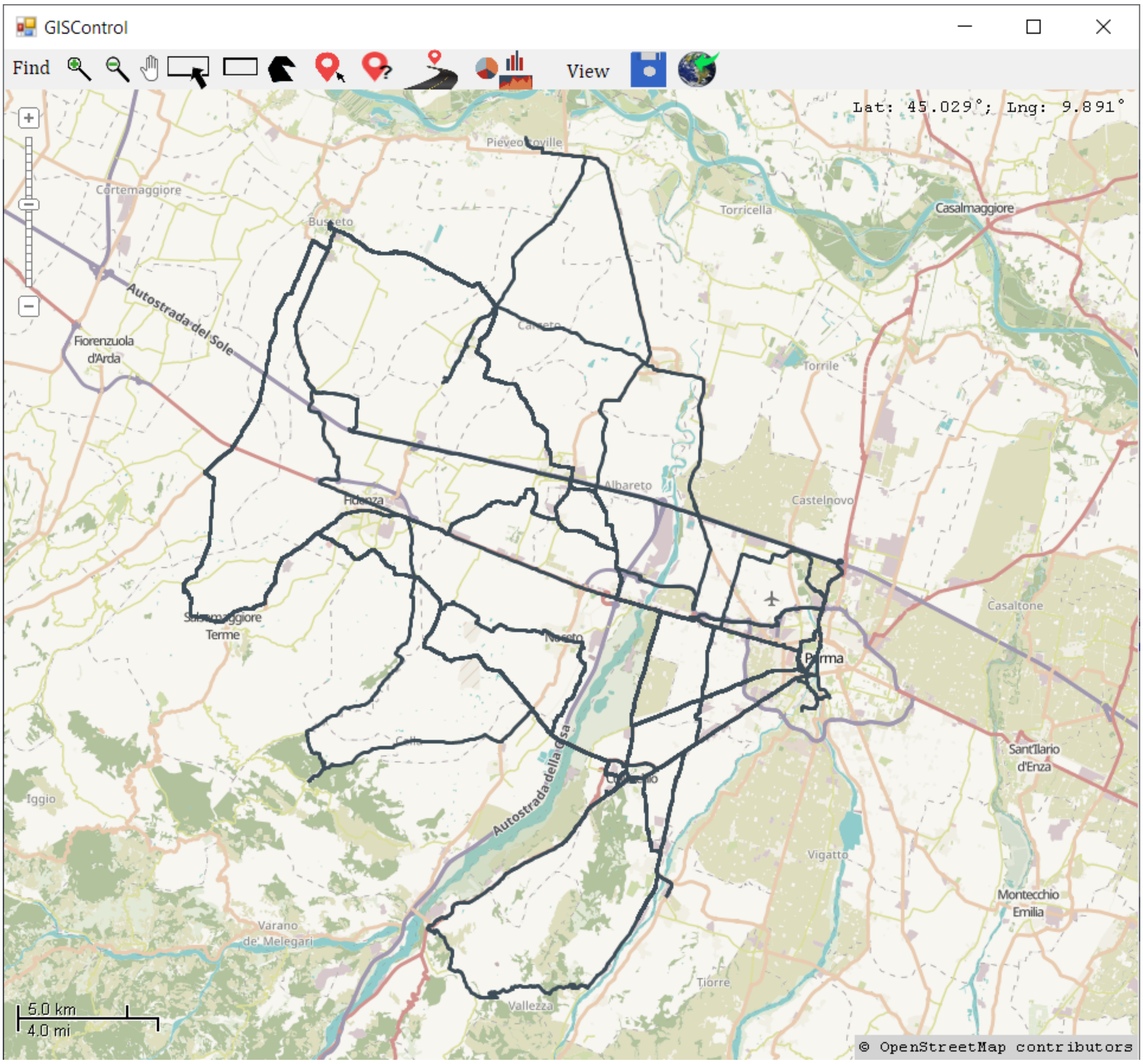


Figure 48. Routes of the old CeKi in Collecchio.

In order to improve the performances of the distribution operations, the methods illustrated in sections 5.4 and 5.5 have been applied to optimize the delivery tours for the new location of the CeKi. The vehicles used to distribute the products to the clients are trucks with a maximum capacity $cap_k = 33, \forall\ k \in V$. This section compares four different solutions for the TO-BE scenario:

- *Method 1*: performing the same delivery routes applied in the AS-IS scenario also for the new location of the CeKi.
- *Method 2*: apply a cluster-first route-second approach with the same number of clusters (i.e., vehicles) used in the AS-IS solution.
- *Method 3*: apply a cluster-first route-second approach that maximizes the saturation of the vehicles to reduce the total number of routes.
- *Method 4*: apply the Nearest Neighbor approach to determine the new routes.

Given the complexity due to the high number of nodes involved, the CVRP method has not been applied to the whole instance that would have required an unacceptable solving time, but in the cluster-first, route-second procedure.

As the distance between the current location of the CeKi and the next location is just 7 kilometers, a possible solution could be keeping the AS-IS routes as a potential solution also for the TO-BE scenario. Although the AS-IS delivery tours are not optimized for the new location of the CeKi, the estimated total travel distance for this solution is equal to 3,173 km/week. Therefore, this solution reduces the traveled distances of 46 km/week, further demonstrating that the new location in Vicofertile reduces distribution costs compared to the AS-IS location.

While the first method simply applies the same route in the TO-BE scenario, the other three approaches aim to find the best solution given the new location of the CeKi.

The clustering phase of the cluster-first route-second approach has been conducted with a k-means algorithm, as illustrated in Section 2.8.2. The second method proposed in this section creates 12 clusters (i.e., $k = 12$). This approach determines the centroids of the twelve clusters and assigns nodes to the clusters until the truck capacity is met. Once a cluster contains nodes with a total demand that meet the capacity of the truck (33 pallets), then other nodes can not be added to the cluster.

Once that the k-means algorithm grouped the nodes served by the same vehicle, the mathematical model introduced in section 5.4 optimizes the route-second phase. The model provides the best visiting order for the truck in order to satisfy the demand of every node with the minimum traveled distance. A from-to matrix of driving distances between all the nodes of each cluster has been produced with the routing tool introduced in the previous chapter. The unit cost of vehicles (u^k_{cost}) and the service time s_i has been set to 0 as the aim of this analysis is the minimization of the total driving distance.

Method 3 applies the same model and algorithm as method 2, but before applying the route-second step, it reduces the number of clusters in order to minimize the number of vehicles needed. This step is performed by calculating the minimum number of vehicles (i.e., clusters) needed to serve all the nodes:

$$k_1 = \left\lceil \frac{\sum_{i \in N} dem_i}{cap} \right\rceil \tag{5.20}$$

All the nodes in the clusters with a low number of nodes are then reassigned to the closest cluster among the k_1 biggest clusters. This procedure reduced the total number of vehicles for the fixed delivery tours from 12 to 8. Then the routing-second step is performed to optimize the distribution operations for each vehicle.

Finally, method 4 applies the Nearest Neighbor approach to construct clusters sequentially. In the first step, the algorithm assigns the closest node to the CeKi to the first vehicle. Then, the closest node to the last added one is assigned to the vehicle until the capacity is met. When another vehicle is needed, the algorithm finds out the closest node to the CeKi among the remaining ones and continues with the same procedure until all the nodes have been assigned to a vehicle.

The results of these four methods and the comparison with the AS-IS is provided in table 14. The reduction of the number of vehicles significantly reduces the traveled distances for this food catering problem. This is mainly due to routes in the AS-IS solution serving a low number of nodes as the previous location of the CeKi discouraged the assignment of the most isolated clients to vehicles traveling towards different directions. The new location of the CeKi, instead, allowed the reduction of vehicles and the aggregation of small clusters while reducing the traveled distances.

The best solution provided by the four methods is illustrated in figure 49. It is worth noting that in the solutions of method 1, illustrated in figure 49 (a), and method 2, illustrated in figure 49 (b), tend to be extended in single directions due to the higher number of vehicles involved and to the clustering method (the k-means algorithm without clusters reduction). Conversely, methods 3 and 4 tend to create closed loops as the lower number of clusters entail the aggregation of groups of nodes in different directions. Finally, the Nearest Neighbor fosters the creation of routes extending in more directions, with shapes similar to circles. This penalizes the last routes that usually aggregate nodes very far from the CeKi.

Table 14. KPIs of the proposed solutions for the vehicle routing problem.

KPI	AS-IS	Method 1	Method 2	Method 3	Method 4
Traveled distance [km/week]	3,219	3,173	2,585	2,140	2,049
Number of vehicles	12	12	12	8	8
Min. nodes assigned to a vehicle	2	2	1	5	5
Average vehicle saturation	61.9%	61.9%	61.9%	92.8%	92.8%

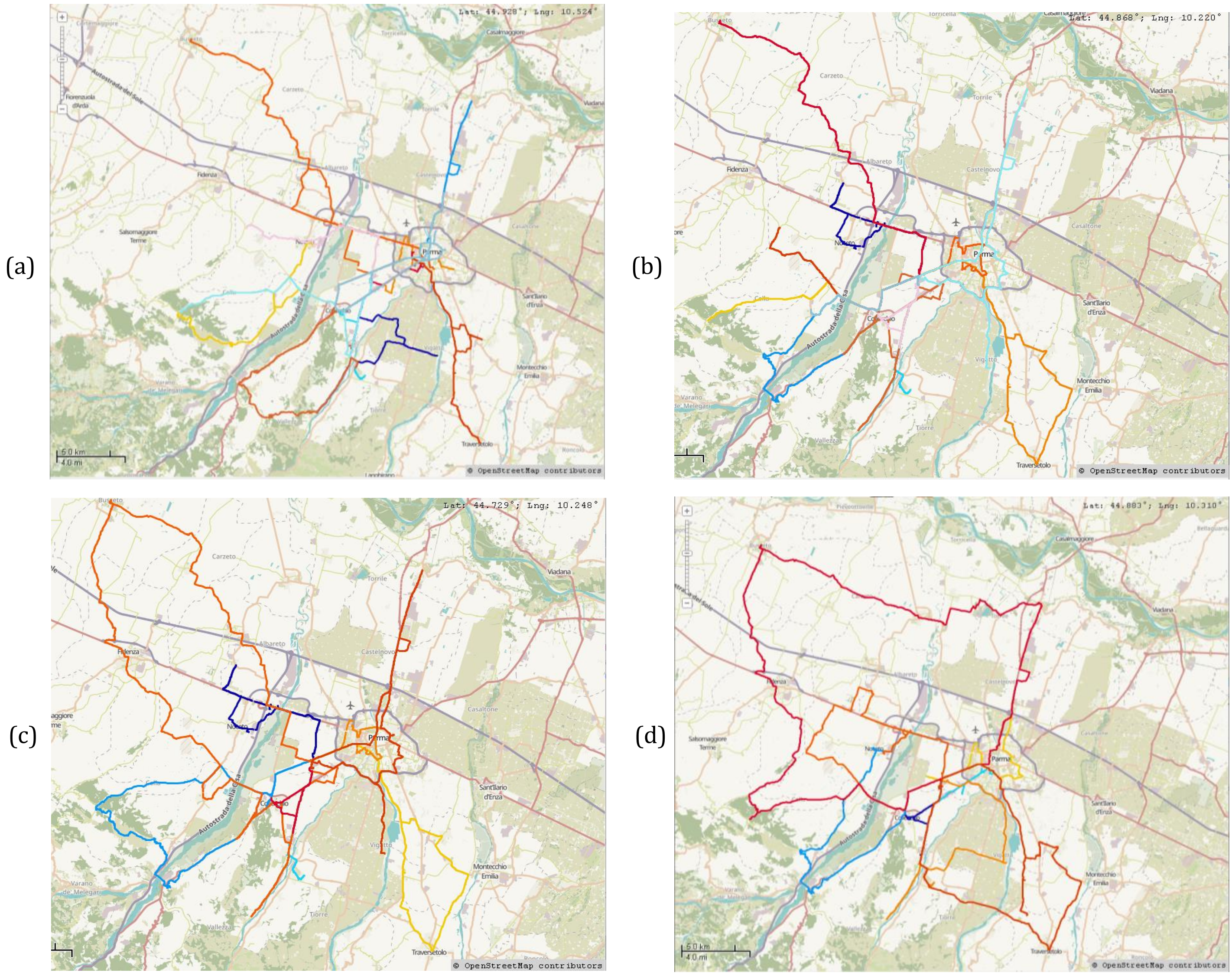


Figure 49. Best solutions for the four proposed methods.

5.7 Climate-driven approach for operational decisions in the FSCSs

Fixed delivery tours are usually adopted when the demand and the supply of the products are stable enough. However, with fixed delivery tours, the distribution is performed with the same solution regardless of the environmental conditions experienced affecting the vehicle routing. For example, the temperature and the relative humidity can vary significantly from one day to the next one. The quality degradation processes introduced in chapter 2 show that different environmental conditions can accelerate the decay of perishable products' quality. Furthermore, variations in the traffic conditions can change the travel time of the fixed routes and require changes in the schedule and in the solution to the vehicle routing problem.

Therefore, it is essential to introduce integrated and interdisciplinary climate-driven operational models to optimize the distribution in FSCSs (figure 41). These models are particularly suitable to determine the best distribution strategy when the demand and supply of products are not stable, and when products are sensitive to climate conditions. In the following, two innovative mathematical models are introduced to support the decision-making process for the distribution of perishable products.

The distribution of perishable products, particularly for fast perishable items like fruits and vegetables, is complicated by the effect of adverse environmental stresses on the products. Therefore, it is vital to make the right decisions to maintain favorable conditions in storage and transportation facilities to mitigate the acceleration of shelf life and quality decay (Smith & Sparks, 2004). Cold chains represent an effective solution to keep temperature-sensitive products at their ideal storage conditions to preserve their quality. However, as discussed in chapter 3, cold chains are highly energy-intensive, and their costs, carbon emissions, and performances are influenced by the climate.

Therefore, the perishability of products and the uncertainty of environmental conditions experienced throughout PLC characterize FSCS and make them more complex to manage than other supply chain systems (Soto-Silva et al., 2016), thus requiring tailored mathematical models. Although the effects of environmental stresses on perishable products are well-known, up to 30% of all produced food is still lost throughout the supply chain before it reaches the consumers (Kefalidou, 2016). Some of the possible causes of these losses are (Winkworth-Smith et al., 2015):

- wrong or insufficient packaging;
- storage of products with different decay rates and ideal storage conditions in the same storage room or container;
- storage of products producing ethylene and sensitive to it within the same microenvironment;
- Breaks and lack of good practice for operators in the cold chain (e.g., open doors vanishing the effect of refrigerators);
- Lack of refrigeration infrastructures;
- Last-mile deliveries carried out with inappropriate vehicles.

A set of strategies can be pursued to address these issues. As introduced in chapter 3, food losses can be reduced by adopting better packaging solutions (e.g., modified atmosphere, edible coating or insulation) (Chalco-Sandoval et al., 2017), investing in cold chain processes and infrastructures (e.g., pre-cooling facilities, refrigerated vehicles), or improving the management of cold chain operations. The use of cold chain infrastructures significantly decreased food losses in developed countries (Paam et al., 2016), where the main issue has become the preservation of food at consumers' households.

Therefore, cold chains could provide a significant reduction in food losses, also in developing countries (Hodges et al., 2010). However, since 40% of food deliveries would require refrigeration (James et al., 2006), the growth of global food demand and the routes traveled in global cold chains will enormously increase the energy request and the associated carbon emissions (Glouannec et al., 2014). Indeed, the supply of food throughout retail chains currently accounts for approximately one-third of the UK's GHGs emissions, with transport estimated to account for 1.8% of the total emissions (Tassou et al., 2009). Hence, a new systemic approach for sustainable cold chain design integrating climate-driven planning is essential.

As the need for refrigeration and its impact on the sustainability of FSCS is mainly dependent on how far the climate conditions are from the ideal storage conditions, the exploitation of more favorable climate conditions could significantly increase the performance of the FSCS. However, most of the solutions currently adopted aim to insulate the microenvironment containing the product from the external environment. Therefore, they represent *ex-post* solutions to mitigate the effect of a given climate. This has been fostered by the availability of low-cost energy leading to the design of less efficient cold chains. Therefore, FSCSs are often built as inefficient transformation systems, which consume more energy than they provide (e.g., as nutritional value).

These solutions are no more sustainable in the current world. Hence, the innovative solutions proposed in this chapter aim to plan the logistics decisions *ex-ante* in order to avoid the most critical environmental conditions. The ex-ante solutions aim to minimize the exposure to stresses (e.g., changing the route for deliveries to the customers, reducing the storage time in the storage node), and enhance the three dimensions of sustainability. Some attempts have been made to improve the ex-ante management of the FSCS. Hsu et al. (2007) proposed a stochastic vehicle routing problem with time-windows (SVRPTW) for optimal delivery routes, loads, fleet dispatching, and departure times for delivering perishable food from a distribution center to the retailers. Amorim and Almada-Lobo (2014) formulated a multi-objective VRPTW to minimize the distribution costs while maximizing the freshness state of the perishable products. Gwanpua et al. (2015) designed a tool for optimizing the trade-off between food quality, energy use, and the global warming impact of a given cold chain. Song and Ko (2016) provided a formulation of the VRP that involves both refrigerated and standard vehicles and maximize the level of freshness of the delivered food.

While this research demonstrates how to reduce the impact of cold chains, the minimization of costs and carbon emissions for refrigeration can be achieved not only by shortening the routes or by using different refrigerants but also by simply reducing the difference between the environmental and the ideal temperature. Although avoiding refrigeration of storage nodes and vehicles is unfeasible, a climate-driven approach supported by weather forecasts could be much more effective, as introduced in section 3.5.1.

As for harvesting (Ahumada & Villalobos, 2009; Ahumada & Villalobos, 2011), also the storage and transportation of food are significantly affected by environmental stresses. Indeed, the interaction between climate and the quality of perishable products affect the sustainability of FSCSs and can not be ignored (James and James, 2010; Zanoni and Zavanella, 2012, Accorsi et al., 2014[b]). Therefore, a climate-driven approach collecting weather data in real-time and exploiting favorable climate conditions could significantly improve FSCS sustainability (Accorsi et al., 2016). The application of a climate-driven logistics approach requires strong cooperation between the stakeholders of the FSCS. The exploitation of favorable climate conditions may entail changing the distribution routes or storing the products in different nodes based on the current weather, thus requiring a perfect synchronization of operations.

In the last decade, some attempts have been made to investigate how climate influences traveling behavior and passengers' mobility. Saneinejad et al. (2012) assessed how the weather influences people's traveling choices during their home-to-work trips in urban environments. Böcker et al. (2015) studied how weather affects the decision-making of urban travels from an environmental-psychological perspective. However, a mathematical model to optimize operational logistics decisions in FSCS with a climate-driven approach has never been formulated before. In order to fill this gap in the literature, two innovative integrated climate-driven models are proposed in the next sections.

When the decision-maker does not consider the climate in the strategic decisions and operational processes, perishable products could experience environmental conditions far from their ideal one during distribution. Maintaining the product at environmental conditions far from the ideal ones causes an acceleration in the quality decay. Currently, the environmental conditions during distribution are mostly suffered ex-post. The solution to mitigate the stresses and extend the life cycle of perishable products in such cases is the *adapting strategy*. The product is insulated from the external environment through packages and containment solutions, and the microenvironmental conditions are altered from the external ones with refrigeration systems. An ex-ante evaluation of climate conditions with a climate-driven logistics approach enables a second strategy, the *eluding strategy*. This strategy avoids the most critical distribution routes and schedules the deliveries according to clients' demand but also to climate conditions. Figure 50 illustrates the two strategies, which are not mutually exclusives as the load can adapt to the external environment with insulating packages and still avoid the most critical routes.

Given the uncertainty and dynamism of weather, finding the best decision between an adapting and an eluding strategy is not an easy task. For example, the cost of effective packaging and insulating solutions to avoid a fast quality decay should be compared to the cost resulting from the shipment postponement or the cost of a longer route with favorable climate conditions (Nguyen et al., 2014).

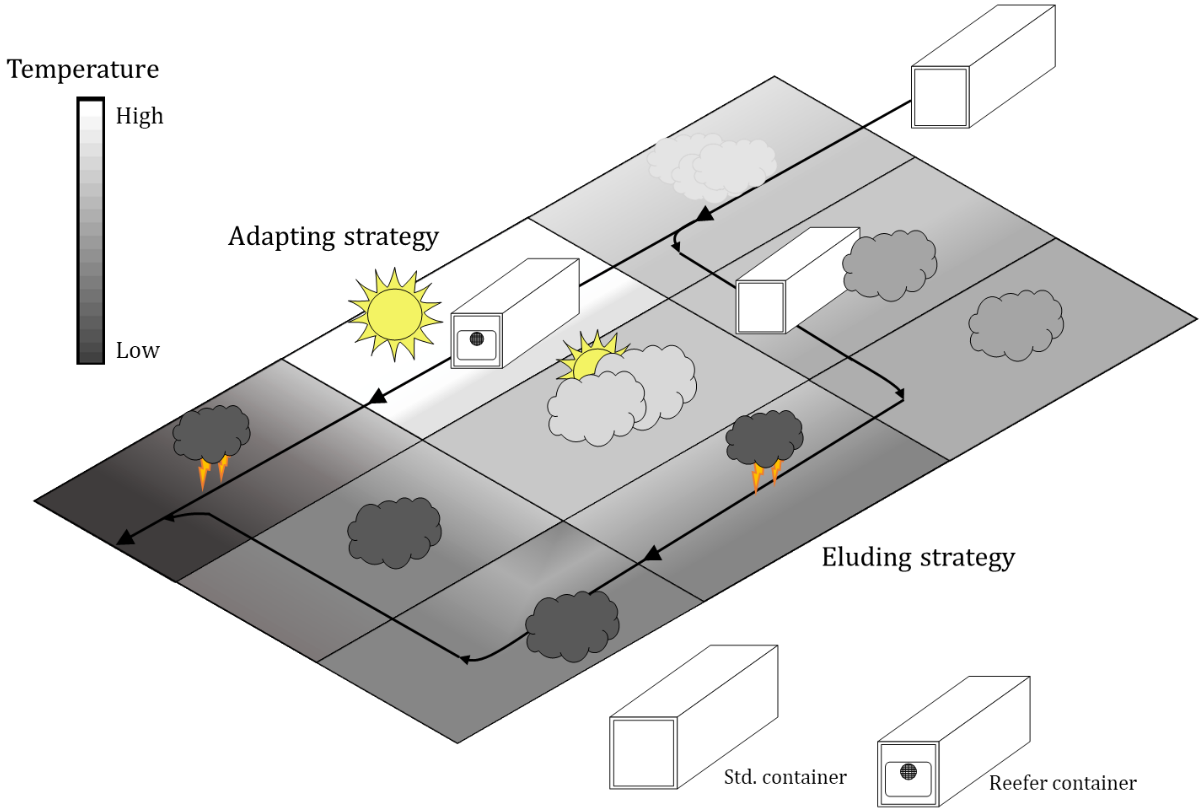


Figure 50. Adapting and eluding strategy in climate-driven distribution *(Accorsi et al., 2017[a]).*

5.8 A climate-driven cost minimization model for FSCS

5.8.1 Model formulation

In order to address the climate-driven logistics problem, this section introduces a novel MILP model illustrated by Accorsi et al. (2017). The model decides on perishable product storage and distribution operations by minimizing the overall costs for product packaging, refrigerated storage and delivery, and those resulting from product spoilage. This model incorporates the climate-driven logistics framework into a production scheduling-routing problem (PS-VRP) for perishable products. The proposed model optimizes production-storage-delivery operations, including the effects of climate conditions, which significantly influence food quality and the energy consumption of the cold chain.

The food quality decay is formulated through the equations (2.2) to (2.5), introduced in chapter 2. The heat transfer mechanisms for products in refrigerated storage rooms and vehicles are formulated through the thermodynamics models introduced in section 3.10.

Sets:

P	Set of products
N	Set of nodes
T	Set of time periods
W	Set of temperatures
Pkg	Set of packages
V	Set of vehicles
Q	Set of shelf-life values

Parameters:

$dem_{p,n,t}$	Demand of product *p* by node *n* at time *t*.
$pc_{p,n,t,q}$	Production capacity of product *p* in node *n* at time *t* with shelf life *q*.
hr_p	Heat of respiration of product *p*.
m_p	Mass of product *p*.
v_{pkg}	Volume of package *p*.
$\dot{Q}^{\mathrm{inf}}_{n,m,v,t,w}$	Infiltration load of cargo shipped between nodes *n* and *m* at time *t* and temperature *w*.
$\dot{Q}^{int}_{v}$	Internal load of cargo shipped with vehicle *v* due to engines.
$\dot{Q}^{tran}_{n,m,v,t,w}$	Transmission load of cargo shipped between nodes *n* and *m* at time *t* and temperature *w*.
$\dot{Q}^{refr}_{p,n,m,t,w}$	Thermal load of product *w* shipped between nodes *n* and *m* at time *t* and temperature *w*. It includes the load for freezing/refrigeration of product *i* and the load of product respiration.
$\dot{Q}^{pack}_{n,m,pkg,t,w}$	Thermal load of package p shipped between nodes *n* and *m* at time *t* and temperature *w*. This is the load required to keep the package at the temperature *T*.
$\dot{Q}^{inf}_{n,t,w}$	Infiltration load at node *n* at time *t* and temperature *w*.
$\dot{Q}^{int}_{n,w}$	Internal load of node *n* at temperature *w* due to engines, lights and workers.
$\dot{Q}^{tran}_{n,t,w}$	Transmission load of node *n* at time *t* and temperature *w*. It includes the load for freezing/refrigeration of products and the load of products respiration.
$\dot{Q}^{refr}_{p,n,t,w}$	Thermal load of product *p* in node *n* at time *t* and temperature *w*. It includes the load for freezing/refrigeration of products and the load of products respiration.
$\dot{Q}^{pack}_{n,pkg,t,w}$	Refrigeration load of package *p* in node *n* at time *t*. This is the load for keeping package at temperature *w* in node *n*.
$\Delta t_{n,m}$	Time needed to reach node *m* from node *n*.
$d_{n,m}$	Distance between node *n* and node *m*.

$\mathrm{T}_{\mathrm{n,m,t}}^{env}$	Average or critical environmental temperature experienced by load shipped during period *t* between node *n* and node *m*.
$\mathrm{T}_{\mathrm{n,t}}^{env}$	Average or critical environmental temperature at the node *n* during period *t*.
c_n^{kW}	Cost of energy in node *n* (i.e., geography dependent).
c_v^{kW}	Cost of energy for vehicle *v* (i.e., vehicle dependent).
c_v^{ship}	Shipping cost for vehicle *v.*
c_n^{stock}	Storage cost at node *n*.
$c_{p,n}^{disp}$	Disposal cost of product *p* in node *n*.
M	Very high constant.
sv_n	Storage capacity of node *n*.
sv_v	Load capacity of vehicle *v*.
$\Delta sl_{p,w}$	Percentage shelf life decay of product *p* stored at temperature *w*.

Decision variables:

$x_{p,n,m,pkg,v,t}^{w,q}$	Flow of product *p* shipped between nodes *n* and *m* with package *pkg* and vehicle *v* at period *t* at starting temperature *w*, with residual shelf life *q*.
$y_{n,m,v,t}^{w}$	Number of cargos shipped with vehicle *v* at period *t* from node *n* to *m* at temperature *w*, cargos (integer).
$z_{p,n,pkg,t}^{w,q}$	Stock of product *p* at node *n* with package *pkg* in period *t* at temperature *w* with residual shelf life *q.*
$T_{n,t,w}^{stock}$	Binary variable; 1 if storage temperature in node *n* at period *t* is *w*; 0 otherwise.
$disp_{p,n,t}$	Disposal flow of product *p* expired at node *n* in period *t*

Objective function:

$$\text{Min} \sum_{n\in N}\sum_{m\in N}\sum_{v\in V}\sum_{t\in t}\sum_{w\in W} y_{n,m,v,t}^{w}\left(\dot{Q}_{n,m,v,t,w}^{inf}+\dot{Q}_{v}^{int}+\dot{Q}_{n,m,v,t,w}^{tran}\right)\Delta t_{n,m}\cdot c_v^{kW}$$

$$+\sum_{p\in P}\sum_{n\in N}\sum_{m\in N}\sum_{pkg\in Pkg}\sum_{v\in V}\sum_{t\in T}\sum_{w\in W}\sum_{q\in Q} x_{p,n,m,pkg,v,t}^{w,q}\left[\mathrm{m}_p\left(\dot{Q}_{p,n,m,t,w}^{refr}+\mathrm{hr_p}\Delta t_{m,n}\right)+\dot{Q}_{n,m,pkg,t,w}^{pack}\right]c_v^{kW}$$

$$+\sum_{n\in N}\sum_{m\in N}\sum_{v\in V}\sum_{t\in T}\sum_{w\in W} y_{n,m,v,t}^{w}\cdot \mathrm{d}_{n,m}\cdot c_v^{ship}$$

$$+\sum_{p\in P}\sum_{n\in N}\sum_{m\in N}\sum_{pkg\in Pkg}\sum_{v\in V}\sum_{t\in T}\sum_{w\in W}\sum_{q\in Q} x_{p,n,m,pkg,v,t-\Delta t_{n,m}}^{w,q+\Delta \mathrm{sl}_{p,w}\cdot\Delta t_{n,m}}\left(\mathrm{m}_p\dot{Q}_{p,m,t,T}^{refr}+\dot{Q}_{m,pkg,t,w}^{pack}\right)\cdot c_m^{kW}$$

$$+\sum_{n\in N}\sum_{t\in T}\sum_{w\in W}\left(\dot{Q}_{n,t,w}^{inf}+\dot{Q}_{n,w}^{int}+\dot{Q}_{n,t,w}^{tran}\right)c_n^{kW}T_{n,t,w}^{stock}$$

$$+\sum_{p\in P}\sum_{n\in N}\sum_{pkg\in Pkg}\sum_{t\in T}\sum_{w\in W}\sum_{q\in Q} z_{p,n,pkg,t}^{w,q}\,\mathrm{m}_p\,hr_p c_n^{kW}$$

$$+\sum_{p\in P}\sum_{n\in N}\sum_{pkg\in Pkg}\sum_{t\in T}\sum_{w\in W}\sum_{q\in Q} z_{p,n,pkg,t}^{w,q}\, v_p\, c_n^{stock}$$

$$+\sum_{p\in P}\sum_{n\in N}\sum_{t\in T} disp_{p,n,t} c_{p,n}^{disp} \qquad (5.20)$$

Subjected to

$$\sum_{pkg\in Pkg}\sum_{w\in W}\sum_{q\in Q} z_{p,n,pkg,t}^{w,q} \geq \mathrm{dem_{p,n,t}} \quad \forall\, p\in P, n\in N, t\in T \qquad (5.21)$$

$$\sum_{w\in W} T_{n,t,w}^{stock} = 1 \quad \forall\, n\in N, t\in T \qquad (5.22)$$

$$\sum_{p\in P}\sum_{pkg\in Pkg}\sum_{q\in Q} z_{p,n,pkg,t}^{w,q} \leq MT_{n,t,w}^{stock} \quad \forall\, n\in N, t\in T, w\in W \qquad (5.23)$$

$$\sum_{n\in N}\sum_{m\in N}\sum_{v\in V}\sum_{w\in W} x_{p,n,m,pkg,v,t}^{w,q} \leq \sum_{w\in W} z_{p,n,pkg,t-1}^{w,q+\Delta\mathrm{sl}_{p,w}} + \sum_{m\in N}\sum_{v\in V}\sum_{w\in W} x_{p,n,m,pkg,v,t-\Delta t_{n,m}}^{w,q+\Delta\mathrm{sl}_{p,w}\cdot\Delta t_{n,m}} + pc_{p,n,t,q} - dem_{p,n,t-1} \quad \forall\, p\in P, n\in N, pkg\in Pkg, t\in T, q\in Q \qquad (5.24)$$

$$\sum_{w\in W} z_{p,n,pkg,t}^{w,q} \leq \sum_{w\in W} z_{p,n,pkg,t-1}^{w,q+\Delta\mathrm{sl}_{p,w}} + \sum_{n\in N}\sum_{m\in N}\sum_{v\in V}\sum_{w\in W}\left(x_{p,n,m,pkg,v,t-\Delta t_{n,m}}^{w,q+\Delta\mathrm{sl}_{p,w}\cdot\Delta t_{n,m}} - x_{p,n,m,pkg,v,t}^{w,q}\right) + pc_{p,n,t,q} - dem_{p,n,t-1} \quad \forall\, p\in P, n\in N, pkg\in Pkg, t\in T, q\in Q \qquad (5.25)$$

$$\sum_{w\in W} z_{p,n,pkg,t}^{w,q} \geq \sum_{w\in W} z_{p,n,pkg,t-1}^{w,q+\Delta\mathrm{sl}_{p,w}} + \sum_{n\in N}\sum_{m\in N}\sum_{v\in V}\sum_{w\in W} x_{p,n,m,pkg,v,t-\Delta t_{n,m}}^{w,q+\Delta\mathrm{sl}_{p,w}\cdot\Delta t_{n,m}} - \sum_{n\in N}\sum_{m\in N}\sum_{v\in V}\sum_{w\in W} x_{p,n,m,pkg,v,t}^{w,q} - dem_{p,n,t-1} \quad \forall\, p\in P, n\in N, pkg\in Pkg, t\in T, q\in Q \qquad (5.26)$$

$$\sum_{p\in P}\sum_{pkg\in Pkg}\sum_{w\in W}\sum_{q\in Q} z_{p,n,pkg,t}^{w,q} v_p - sv_n \leq 0 \quad \forall\, n\in N, t\in T \qquad (5.27)$$

$$y_{n,m,v,t}^{w}\mathrm{ven}_{n,m,v} \geq \sum_{p\in P}\sum_{pkg\in Pkg}\sum_{q\in Q} \frac{x_{p,n,m,pkg,v,t}^{w,q} v_p}{sv_v} \quad \forall\, n\in N, m\in N, v\in V, t\in T, w\in W, n\neq m \qquad (5.28)$$

$$disp_{p,n,t} = \sum_{pkg\in Pkg}\sum_{w\in W}\sum_{q\in Q:\mathrm{q}-\Delta\mathrm{sl}_{p,w}\leq 0} z_{p,n,pkg,t-1}^{w,q} + \sum_{n\in N}\sum_{m\in N}\sum_{pkg\in Pkg}\sum_{v\in V}\sum_{w\in W}\sum_{q\in Q:\mathrm{q}-\Delta\mathrm{sl}_{p,w}\Delta t_{m,n}\leq 0} x_{p,n,m,pkg,v,t-\Delta t_{m,n}}^{w,q} \quad \forall\, p\in P, n\in N, t\in T \qquad (5.29)$$

$$x_{p,n,m,pkg,v,t}^{w,q} \geq 0 \qquad \forall\, p\in P, n\in N, m\in N, pkg\in Pkg, v\in V, t\in T, w\in W, q\in Q \qquad (5.30)$$

$$y_{n,m,v,t}^{w} \in Z^{+} \qquad \forall\, n\in N, m\in N, v1\in V, t\in T, w\in W \qquad (5.31)$$

$$z_{p,n,pkg,t}^{w,q} \geq 0 \qquad \forall\, p\in P, n\in N, pkg\in Pkg, t\in T, w\in W, q\in Q \qquad (5.32)$$

$$T_{n,t,w}^{stock} \in \{0,1\} \qquad \forall\, n\in N, t\in T, w\in W \qquad (5.33)$$

$$disp_{p,n,t} \geq 0 \qquad \forall\, p\in P, n\in N, t\in T \qquad (5.34)$$

The objective function (5.20) minimizes the total operating cost for the storage and distribution operations of perishable products in response to customer demand. These costs include the following contributions, respectively:

- Transportations costs:
  - Fixed cargo power costs;
  - Variable cargo power costs;
  - Fixed cargo costs;

- Storage costs:
    - Storage refrigeration power costs;
    - Fixed storage power costs;
    - Variable storage power costs;
    - Variable storage costs;
- Disposal costs.

Constraints (5.21) enforce that the demand of product *p* at the generic node *n* must be satisfied within the due period *t*. Constraints (5.22) fix a single set-point temperature at node *n* during period *t*. Constraints (5.23) impose that the temperature of the inventory in node *n* at period *t* is equal to the temperature set-point defined by the set of constraints (5.22). Constraints (5.24) guarantee the flow conservation at the generic node *n*. According to (5.24), the volume of product *p* departing from node *n* with packaging *pkg* at period *t* and residual shelf life *q* should be lower than the sum of stock of product *p* at period *t*-1, the flow of *p* received at period *t*, the products produced in node *n*, minus those demanded by node *n* at period *t*-1.

Constraints (5.25) and (5.26) balance the inventory of product *p* stored at node *n* with packaging *pkg* and shelf life *q* at period *t*. Constraints (5.27) ensure that the total volume occupied by the inventory at node *n* and period *t* does not exceed its capacity. Constraints (5.28) impose that the volume of the products shipped from node *n* to *m* at period *t* does not exceed the cargo's capacity. Constraints (5.29) enforce that the flows of product *p* received at a generic node *n* with a residual shelf life of 0% are immediately disposed and quantified as losses. The remaining constraints (5.30)-(5.34) are a mix of non-negativity, integer, or binary restrictions on the decision variables.

The most important input data required by the model and the output it provides are summarized in Table 15.

Table 15. Main input and output of the proposed model (Accorsi et al., 2017 [a]).

INPUT
Products' characteristics
Vehicles available
Nodes (warehouses, plants, points of demand)
Packaging alternatives
Climatic data
OUTPUT
Storage temperature for each climate chamber and refrigerated container at each period
Production scheduling

Departure time and optimal route for each vehicle based on climate conditions and distance
Packaging solution for each product
Vehicle solution for each delivery

The proposed MILP model supports logistics and transport managers to enhance the economic and social sustainability of the FSCS. It integrates physical, energetic, and logistic parameters and requires a comprehensive knowledge of the supply chain system and cooperation among all the stakeholders.

The implementation of the climate-driven logistics framework requires weather forecast data, such as the expected temperature and relative humidity within the planning horizon. Consequently, the solution to the distribution problem changes according to the demand and FSCS geography (as commonly do), but even with the climate conditions experienced by the products.

5.8.2 The case of the distribution of cherries

The proposed innovative model is applied to a case study inspired by an Italian supply chain of fresh cherries. Cherries are high perishable items whose price and quality are highly affected by logistics decisions. The FSCS, illustrated in figure 51, is made of four production nodes devoted to the processing (i.e., calibrating, leaves cut) and packing phases, and three storage nodes, leading to a two-stage FSCS. Storage nodes demand products from the processing nodes. However, the number of stages of the FSCS included in the proposed MILP model could vary according to the input dataset.

The planning horizon T is one working day (May, 16th 2016), and the periods $t \in T$ are the clock hours in between 7:00 am and 2:00 pm. The short-term (i.e., daily) boundaries of the problem setting highlight the influence of the weather conditions on the scheduling of the shipments, but it can be quickly scaled to a mid-term (i.e., weekly, monthly) tactical planning. As the aim of this application is to illustrate how climate-driven logistics can increase the performances of the FSCS, it will focus on the *eluding* strategy. As a result, the lever of packaging choice is not considered, and just a 0.5 kg plastic case shipped via reefer container (i.e., TEU) is allowed. The main instance parameters are reported in table 16 and illustrated in figure 51.

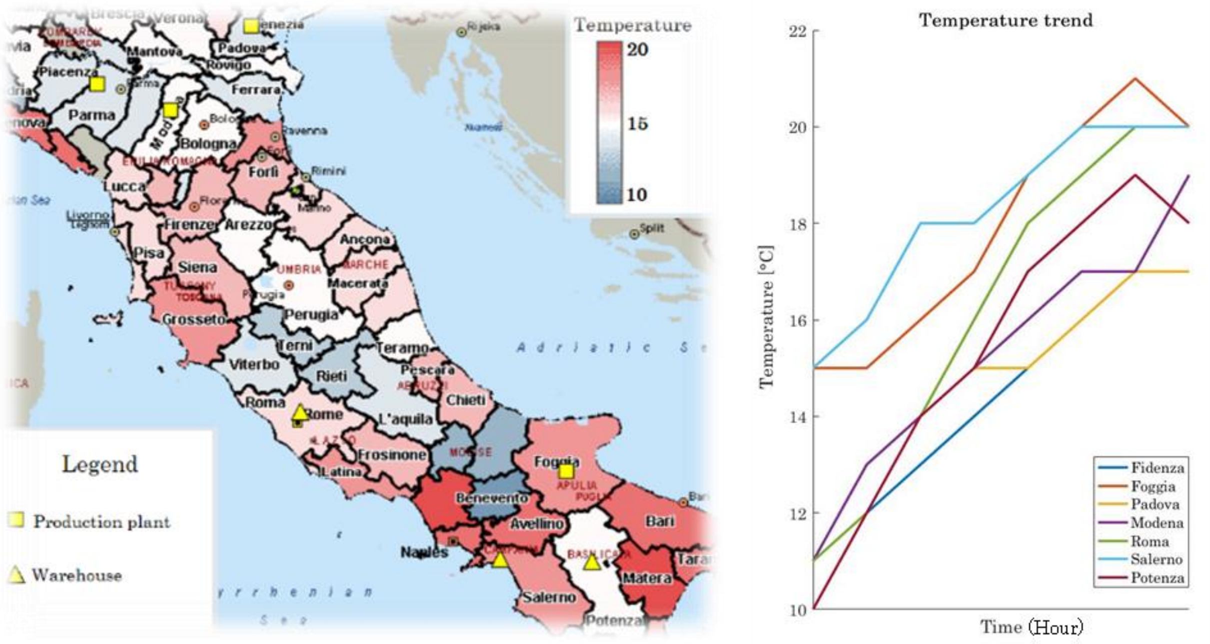


Figure 51. The geographic and climatic characteristics of the FSCS (Accorsi et al., 2017 [a]).

Table 16. Input parameters of the case study (Accorsi et al., 2017 [a]).

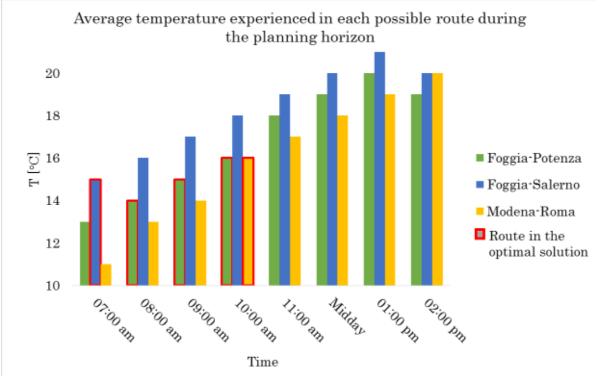
Processing Node	Processing Throughput (Cases/hour)	Warehouse	Demand (Cases)
Fidenza	2000	Roma	16,000
Foggia	4000	Salerno	1000
Padova	8000	Potenza	12,000
Modena	4000		
Product	Cherries		
Packaging Type *(II,III,IV)*	*Plastic Case*	*Pallet*	*Reefer TEU Container*
Packaging Weight	0.5 kg		
Packaging Material	Polyphrophilene		
Heat of respiration	0.0604 kJ/kg		

The model has been implemented in AMPL and solved with the Gurobi Optimization solver on a 2.4 GHz Quad Core processor, with 8 GB RAM. The testbed instance resulted in 37,694 variables (112 binary variables) and a few thousand constraints (i.e., 8665). The solutions have been obtained in an acceptable time, which is negligible for decision support in industrial practice.

According to the optimal solution, the shipments from the processing node to the distribution center tend to be performed at lower temperatures and to be concentrated within the earlier and fresher hours of the day (as illustrated in the histogram of Table 17).

Table 17. Optimal solution of the MILP model (Accorsi et al., 2017 [a]).

Optimal Solution	
Total cost	€ 22,060.60
Costs for Transportations	€ 4,069.36
Costs for Storage	€ 17,991.22
Number of Shipments	5



The obtained solution is the optimal trade-off between the supply chain constraints (i.e., characterized by the facilities' throughputs and capacities), the perishability constraints (i.e., built upon the quality degradation models introduced in chapter 2), and the savings of energy consumption for both storage and distribution operations. The route Modena-Roma is the most sensitive to the temperature's variation among the working hours. Hence, the vehicle on this route should depart as soon as possible. However, it is scheduled at 10:00 am to comply with the throughput of the processing node in Modena.

Such a trade-off is hard to be identified with the extant routing problem formulations. To highlight the gap between our proposal and the resulting benefits, we run the model according to three sets of constraints:

1) Supply chain and perishability constraints;

2) Perishability constraints;

3) Supply chain constraints.

The first, the so-called climate-driven, involves the whole set of constraints. The second, the so-called quality-driven, relaxes the throughput capacity constraints (5.24) and (5.25), so the model does not need setup time. It corresponds to the availability of inventory at every production node at each period. According to this scenario, the shipments tend to travel at the lowest external temperatures (i.e., in the morning) because the products to be shipped are always available when needed. The third, the business-as-usual, ignores the impact of the environmental conditions on the perishable products and the resulting hidden cooling costs in the production-distribution planning problem. This scenario facilitates the optimization of the supply chain activities: products are packed and delivered just-in-time in response to the customers' orders.

In figure 52, we compare these scenarios on the value of the objective function. It clearly shows that the quality-driven scenario (2) represents the lower bound of the problem, not generally feasible in practice due to technology constraints (the processing capacity of nodes). The transport costs are much lower due to the shipments performed during the colder hours of the day. However, this entails higher storage costs for cooling, experienced by the storage nodes that store the cherries for a longer time as they are received earlier.

When ignoring the impact of the climate conditions on the cooling costs, as happens in the business-as-usual scenario (3), the hidden costs for refrigeration increase both for vehicles and at the storage nodes and account for 90% of the total scenario's costs. In this scenario, the effect of the climate conditions on the cold chain costs does not influence the solution as it is accounted when the solution is already obtained. We calculated the refrigeration costs by applying to the objective function of the main model the values of the variables calculated with this alternative formulation that does not consider refrigeration costs in the optimization process.

Compared to the business-as-usual, the climate-driven scenario leads to a more accurate assessment of the energy costs generated by the cold chain operations and provides a decision-support for their minimization.

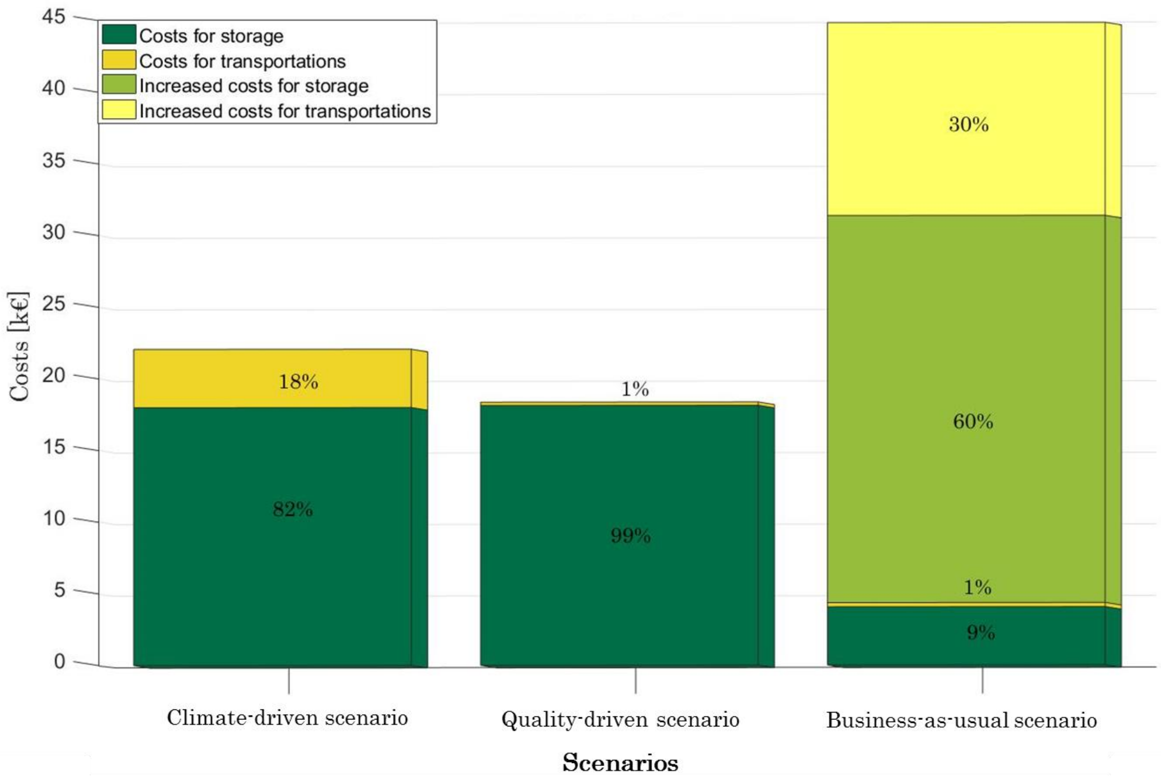


Figure 52. Comparison of the three different formulations (Accorsi et al., 2017 [a]).

Figure 53 further discusses the obtained solution by showing the unit transport costs (i.e., generated by cooling and routing) experienced by each pair of feasible routes and periods respectively for scenarios 2 (a) and 1 (b). The piece-wise linear functions represent the feasible region, while the circles is, per each destination, the optimal departing node and time obtained by solving the climate-driven logistic model. Obviously, the relaxed scenario (a) searches for the optimum in a wider feasible region and would results in more efficient solutions. However, figure 53 clearly shows that the presence of capacity constraints in the industrial practice compels the adoption of integrated decision-support tools that not only look at the shelf life decay, but are able to optimize the energy consumption of the cold chain while ensuring the quality of the delivered products and the respect of supply chain's limitations.

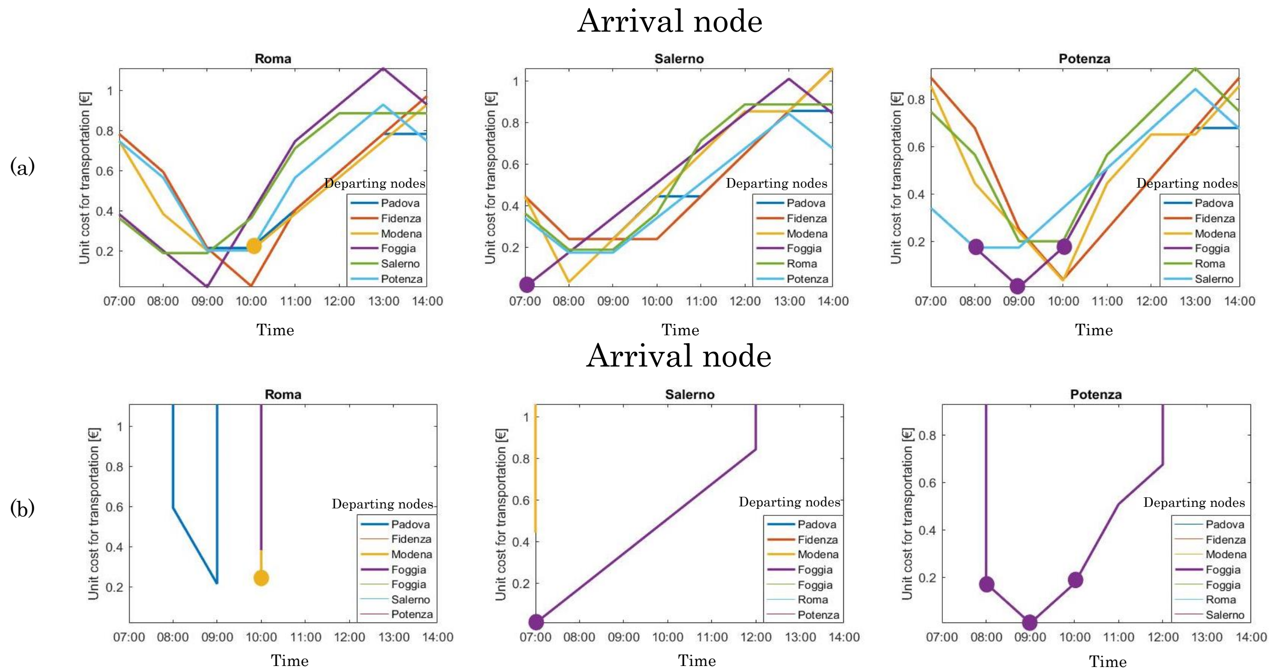


Figure 53. Unit cost for transportation: lower bound (a) vs. climate-driven logistics (b) (Accorsi et al., 2017 [a]).

The energy costs for transportation and storage depend on numerous factors, such as the departing hour, the route, and even the environmental temperature. In order to highlight the benefits of the proposed model, a sensitivity analysis was conducted on the weather conditions (i.e., temperature, humidity, and enthalpy of the external air). Ten different planning horizons have been optimized, one in the morning and one in the afternoon of each day from May, 16th 2016 to May, 20th 2016, as illustrated in Table 18.

Table 18. Sensitivity analysis on different working days (Accorsi et al., 2017 [a]).

Scenario	Day	Hour	Min Temperature [°C]	Max Temperature [°C]	Average Temperature [°C]
Scenario 1	1 (i.e., 5/16/2016)	7:00 am-2:00 pm	10	21	16.04
Scenario 2	1	2:00 pm-9:00 pm	14	21	17.84
Scenario 3	2	7:00 am-2:00 pm	11	20	15.79
Scenario 4	2	2:00 pm-9:00 pm	11	21	17.05
Scenario 5	3	7:00 am-2:00 pm	16	28	21.43
Scenario 6	3	2:00 pm-9:00 pm	18	28	22.89
Scenario 7	4	7:00 am-2:00 pm	16	26	21.11
Scenario 8	4	2:00 pm-9:00 pm	19	27	22.77
Scenario 9	5 (i.e., 5/20/2016)	7:00 am-2:00 pm	11	24	16.96
Scenario 10	5	2:00 pm-9:00 pm	12	24	17.00

This sensitivity analysis aims to assess the response of the model to different climate conditions and planning horizons. Figure 54 illustrates the results of the comparison between the three scenarios (climate-driven, quality-driven, and business-as-usual). It shows that even small variations of the external temperature cause a significant increase in refrigeration costs due to the fast perishability of cherries.

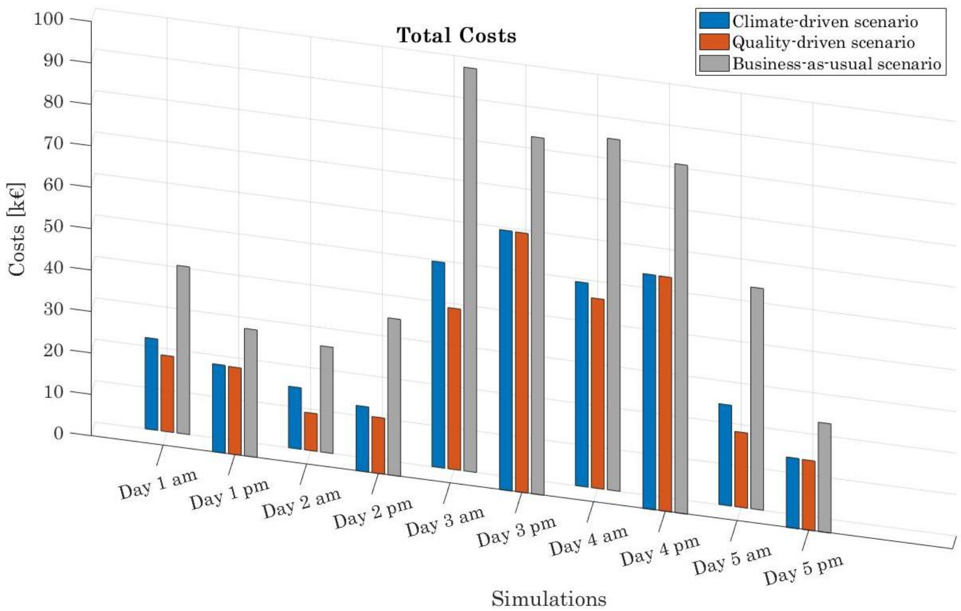


Figure 54. Results of the sensitivity analysis (Accorsi et al., 2017 [a]).

In the morning, the shipments are performed during the first hours, when the temperature is still low, as soon as the order is processed and packed. In the afternoon, the shipments depart just-in-time to achieve the destination within the due time because the first hours are the warmest. This behavior explains why, in the latter, the climate-driven is truly close to the quality-driven scenario, thereby leading to the following generalization. The proposed climate-driven model schedules the transport operations according to the external conditions to minimize the cold chain's overall refrigeration costs while respecting the shelf-life requirements.

Figure 55 deepens the discussion on the obtained solutions with a comparative frequency analysis of the periods (i.e., hours) used for the transport operations by each scenario. The business-as-usual case is not considered because it ignores the effects of climate on the decision-making, and it is therefore incomparable with the others. The right figure in figure 55 represents the quality-driven scenario. As this scenario does not consider setup time, we could have available inventory at the start of the simulations. This allows us to schedule deliveries in the first hours in the morning that are colder. For this reason, the right figure shows that transportations experience lower temperatures, so the bars at the highest temperature values are shorter than in the left figure.

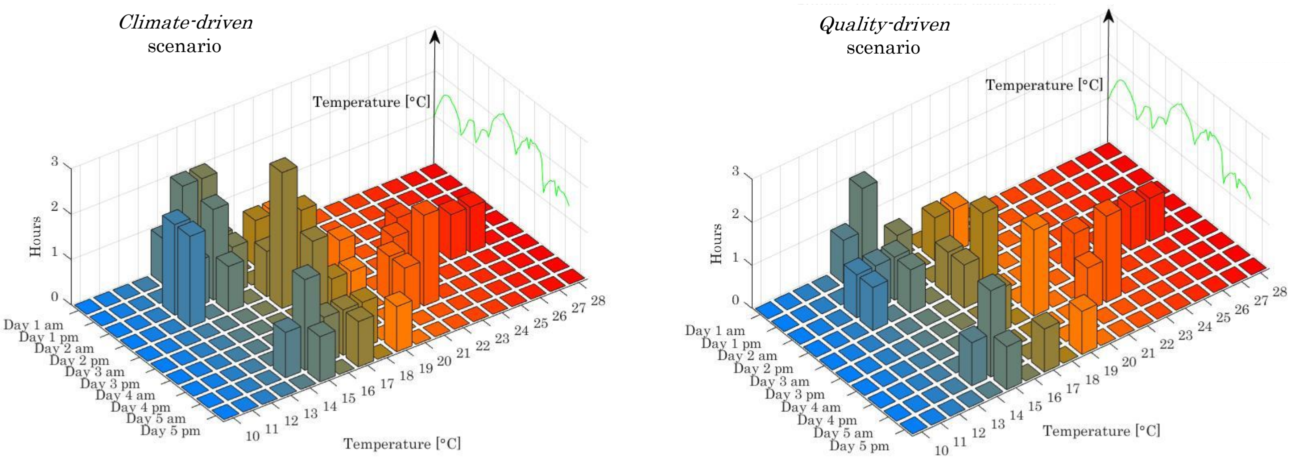


Figure 55. Comparative frequency analysis of transport periods and external temperatures (Accorsi et al., 2017 [a]).

Higher temperatures are more frequently measured in Scenarios 5-8 when the average external temperatures achieve their pick (as shown by the green line). For these scenarios, the feasible region where production-distribution solutions can be optimized is smaller, resulting in higher costs.

These exemplifying results legitimate the need for the integration of climate considerations into the production-distribution planning of cold chains.

5.9 A climate-driven model to enhance the environmental sustainability of the FSCS

5.9.1 Environmental sustainability assessment

The innovative model presented in this section extends the one introduced in section 5.8 by providing an operational MILP model presented by Gallo et al. (2017) to optimize the energy consumption incurred during the production, storage, and distribution stages of a cold chain. The proposed model incorporates the climate conditions experienced along each route and by each transport vehicle to increase the energy efficiency of the whole FSCS and, consequently, its environmental sustainability.

Compared to Rong et al. (2011) and de Keizer et al. (2017), who formulated the decrease in quality as influenced by the lead time at a certain conservation temperature, this model incorporates the climate conditions experienced on each route and quantifies the product quality decay accordingly. Compared to the model introduced in section 5.8, it includes the agriculture-farming stage in the designed food value chain; (2) optimizes an energy-based function; and (3) addresses a different research question, that is, how to distribute different fresh products throughout a long-ray cold chain sustainably.

According to Conforti and Giampietro (1997), in terms of energy, a food supply chain is sustainable when it does not consume more energy than it supplies as the nutritional value of the delivered food products. Because of this, we assume the ratio between the energy supplied and the energy consumed for the production and distribution of a food product throughout the cold chain as a performance indicator of its environmental sustainability. This metric is also known as the index of sustainability (IS), which is defined as follows:

$$IS = \frac{E_{consumed}}{E_{supplied}} \tag{5.35}$$

Where $E_{consumed}$ accounts for the overall energy consumed from the food growth to its consumption and $E_{supplied}$ represents its energy content. The food energy value represents the supplied energy, generally expressed in kcal/gr. Conversely, the energy required to power the growing and harvesting phases, processing and transformation, packaging, storage, and distribution represents the energy consumed. While the decisions about cold chain operations do not influence the food energy value, they significantly affect the energy consumed from farm to table.

The proposed model involves four supply chain stages (figure 56):

- The suppliers that supply raw food ready for transformation;
- The processing nodes, which represent the plants where the raw products are transformed and packed, making them ready for distribution;

- The storage nodes, where products are conserved, stored, and consolidated before and during distribution;
- The clients' nodes, where the food products meet the consumers. These include grocery shops, retail depots, wholesalers, or canteens.

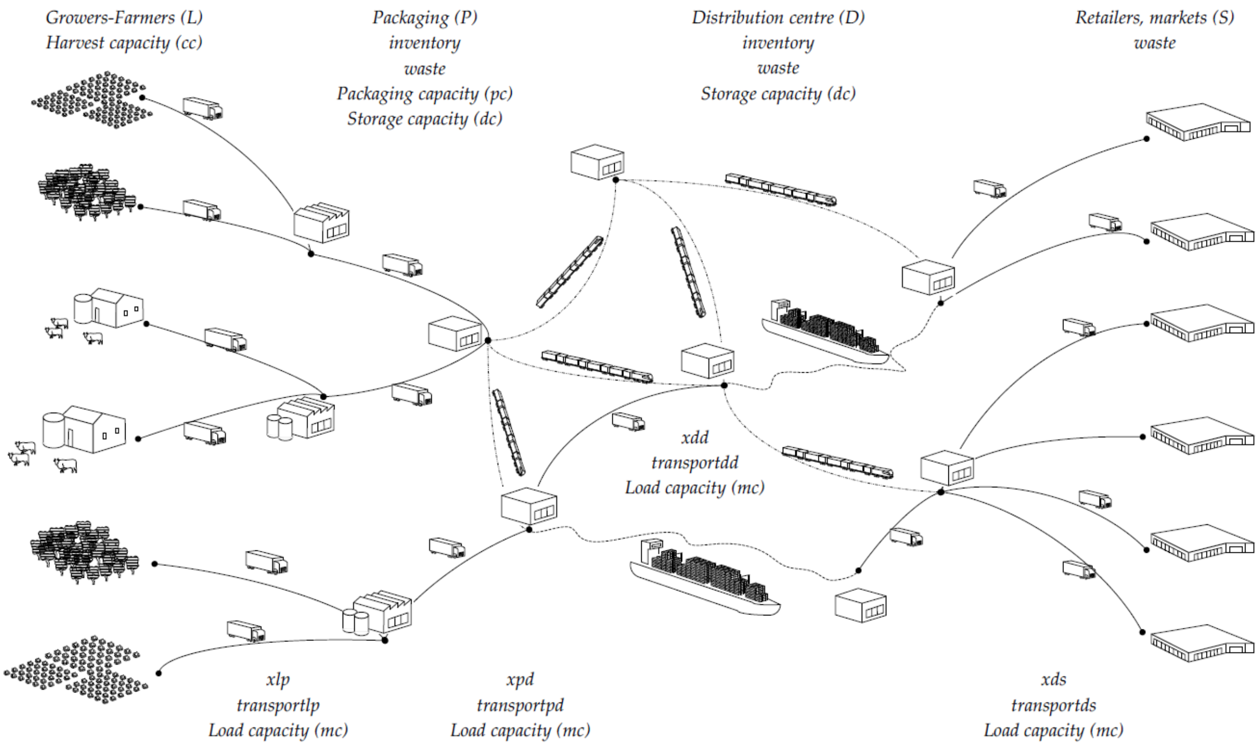


Figure 56. Network configuration (Gallo et al., 2017).

5.9.2 Model formulation

The definitions of the parameters, sets of indices, and decision variables included in the following objective function and constraints are given as follows:

Sets:

P	Set of products
L	Set of suppliers
N	Set processing nodes
D	Set of storage nodes
C	Set of clients' nodes
T	Set of time periods
W	Set of temperatures
V	Set of vehicles
Q	Set of shelf-life values

$NDC = N \cup D \cup C$	Union of processing, storage, and demand nodes
$ND = N \cup D$	Union of processing and storage nodes

Parameters:

$dem_{p,c,t}$	Demand of product *p* by client *c* at period *t*.
$cc_{p,l,t}$	Supply of product *p* from the supplier *l* at period *t*.
$pc_{p,n,t}$	Processing capacity of product *p* in processing node *n* at time *t*.
dc_{nd}	Storage capacity at processing and storage node *nd*.
mc_v	Transport capacity of vehicle *v*.
m_p	Mass of product *p.*
$ce_{p,l}$	Energy consumption to supply one unit of product *p* at supplier *l*.
$pe_{p,n}$	Energy consumption to process one unit of product *p* at processing node *n*.
$se_{p,nd}$	Energy consumption to store one unit of product *p* at packaging or storage node *nd*.
me_v	Energy consumption for each km traveled by vehicle *v*.
$q_{min_{p,ndc}}$	Minimum quality level for product *p* at packaging, storage, or client *ndc*.
we_p	Energy losses for the perishment of product *p*.
$coolevln_{w,v,l,n}$	Energy requirements to set vehicle *v* at temperature *w* to move from the supplier *l* to the processing node *n*.
$coolevnd_{w,v,n,d}$	Energy requirements to set vehicle *v* at temperature *w* to move from the processing node *n* to the storage node *d*.
$coolevdd_{w,v,d,d'}$	Energy requirements to set vehicle *v* at temperature *w* to move from the storage node *d* to the storage node *d'*.
$coolevdc_{w,v,d,c}$	Energy requirements to set vehicle *v* at temperature *w* to move from the storage node *d* to the client *c*.
$coolend_{w,nd}$	Energy requirements to set the facility temperature at *w* within the packaging or storage node *nd*.
$tln_{v,l,n}$	Lead time to move products from the supplier *l* to the processing node *n* with vehicle *v*.
$tnd_{v,n,d}$	Lead time to move products from the processing node *n* to the storage node *d* with vehicle *v*.
$tdd_{v,d,d'}$	Lead time to move products from the storage node *d* to the storage node *d'* with vehicle *v*.
$tdc_{v,d,c}$	Lead time to move products from the storage node *d* to client *c* with vehicle *v*.
$dln_{l,n}$	Travelling distance from the supplier *l* to the processing node *p*.

$dnd_{n,d}$	Travelling distance from the processing node *p* to the storage node *d*.
$ddd_{d,d'}$	Travelling distance from the storage node *d* to the storage node *d'*.
$ddc_{d,c}$	Travelling distance from the storage node *d* to the client *c*.
$\Delta slnd_{p,w,nd}$	Quality decay of product *p* stored at processing or storage node *nd* at temperature *w*.
$\Delta slvln_{p,w,v,l,n}$	Quality decay of product *p* transported by vehicle *v* from the supplier *l* to the processing node *n* at temperature *w*.
$\Delta slvnd_{p,w,v,n,d}$	Quality decay of product *p* transported by vehicle *v* from the processing node *n* to the storage node *d* at temperature *w*.
$\Delta slvdd_{p,w,v,d,d'}$	Quality decay of product *p* transported by vehicle *v* from the storage node *d* to the storage node *d'* at temperature *w*.
$\Delta slvdc_{p,w,v,d,c}$	Quality decay of product *p* transported by vehicle *v* from the storage node *d* to client *c* at temperature *w*.
M	Very high constant.

Decision variables:

$inv_{p,q,w}^{nd,t}$	Stock of product *p* stored within processing or storage node *nd* at temperature *w* and quality level *q* at period *t*.
$trln_{w,v,l,n,t}$	Number of vehicles *v* at temperature *w* moving products from the supplier *l* to the processing node *n* at period *t*.
$trnd_{w,v,n,d,t}$	Number of vehicles *v* at temperature *w* moving products from the processing node *n* to the storage node *d* at period *t*.
$trdd_{w,v,d,d',t}$	Number of vehicles *v* at temperature *w* moving products from the storage node *d* to the storage node *d'* at period *t*.
$trdc_{w,v,d,c,t}$	Number of vehicles *v* at temperature *w* moving products from the storage node *d* to client *c* at period *t*.
$xln_{p,q,w}^{v,l,n,t}$	Flow of product *p* transported by vehicles *v* from the supplier *l* to the processing node *n* at quality *q* and temperature *w* at period *t*.
$xnd_{p,q,w}^{v,n,d,t}$	Flow of product *p* transported by vehicles *v* from the processing node *n* to the storage node *d* at quality *q* and temperature *w* at period *t*.
$xdd_{p,q,w}^{v,d,d',t}$	Flow of product *p* transported by vehicles *v* from the storage node *d* to the storage node *d'* at quality *q* and temperature *w* at period *t*.
$xdc_{p,q,w}^{v,d,s,t}$	Flow of product *p* transported by vehicles *v* from the storage node *d* to the client *c* at quality *q* and temperature *w* at period *t*.
$z_{w,nd,t}$	Binary variable;1 if the processing or storage node *nd* are set at temperature *k* during period *t;* 0 otherwise.
$disp_{p,ndc,t}$	Disposal flow of product *p* expired at processing, storage or client node *ndc* in period *t*

Objective function:

$$min \sum_{w \in W} \sum_{v \in V} \sum_{l \in L} \sum_{n \in N} \sum_{t \in T} \left(me_v dln_{l,n} + coolevln_{w,v,l,n} tln_{v,l,n} \right) trln_{w,v,l,n,t}$$

$$+ \sum_{w\in W}\sum_{v\in V}\sum_{n\in N}\sum_{d\in D}\sum_{t\in T}\left(me_v dnd_{n,d} + coolevnd_{w,v,n,d} tnd_{v,n,d}\right) trnd_{w,v,n,d,t}$$

$$+ \sum_{w\in W}\sum_{v\in V}\sum_{d\in D}\sum_{d'\in D}\sum_{t\in T}\left(me_v ddd_{d,d'} + coolevdd_{w,v,d,d'} tdd_{v,d,d'}\right)\ trdd_{w,v,d,d',t}$$

$$+ \sum_{w\in W}\sum_{v\in V}\sum_{d\in D}\sum_{c\in C}\sum_{t\in T}\left(me_v ddc_{d,c} + coolevdc_{w,v,d,c} tdc_{v,d,c}\right) trdc_{w,v,d,c,t}$$

$$+ \sum_{p\in P}\sum_{q\in Q}\sum_{w\in W}\sum_{v\in V}\sum_{l\in L}\sum_{n\in N}\sum_{t\in T} ce_{p,l}\ xln_{p,q,w}^{v,l,n,t}$$

$$+ \sum_{p\in P}\sum_{q\in Q}\sum_{w\in W}\sum_{v\in V}\sum_{n\in N}\sum_{d\in D}\sum_{t\in T} pe_{p,n}\ xpd_{p,q,w}^{v,n,d,t}$$

$$+ \sum_{p\in P}\sum_{q\in Q}\sum_{w\in W}\sum_{nd\in ND}\sum_{t\in T} inv_{p,q,w}^{nd,t}\ se_{p,nd}$$

$$+ \sum_{w\in W}\sum_{nd\in ND}\sum_{t\in T} coolend_{w,nd}\ z_{w,nd,t}$$

$$+ \sum_{p\in P}\sum_{ndc\in NDC}\sum_{t\in T} disp_{p,ndc,t}\ \ we_p \qquad (5.36)$$

Subjected to

$$\sum_{w\in W} inv_{p,q,w}^{n,t} = \sum_{w\in W} inv_{p,q+\Delta slnd_{p,w,n},w}^{n,t-1} + \sum_w\sum_v\sum_l xln_{p,q+\Delta slvln_{p,w,v,l,n},w}^{v,l,n,t-tln_{v,l,n}} - \sum_w\sum_v\sum_d xnd_{p,q,w}^{v,n,d,t}$$
$$\forall p\in P, n\in N, q\geq q_{min_{p,n}}\in Q, t\in T \qquad (5.37)$$

$$\sum_{w\in W} inv_{p,q,w}^{d,t} = \sum_{w\in W} inv_{p,q+\Delta slnd_{p,w,d},w}^{n,t-1} + \sum_{w\in W}\sum_{v\in V}\sum_{n\in N} xnd_{p,q+\Delta slvnd_{p,w,v,n,d},w}^{v,n,d,t-tnd_{v,n,d}} +$$
$$\sum_{w\in W}\sum_{v\in V}\sum_{d'\in D} xdd_{p,q+\Delta slvdd_{p,w,v,d',d},w}^{v,d,d',t-tdd_{v,d',d}} - \sum_{w\in W}\sum_{v\in V}\sum_{c\in C} xdc_{p,q,w}^{v,d,c,t} - \qquad (5.38)$$
$$\sum_{w\in W}\sum_{v\in V}\sum_{d'\in D} xdd_{p,q,w}^{v,d,d',t}\quad \forall p\in P, d\in D, q\geq q_{min_{p,\mathrm{d}}}\in Q, t\in T$$

$$\sum_{q\geq q_{min_{p,c}}\in Q}\sum_{w\in W}\sum_{v\in V}\sum_{d\in D} xdc_{p,q,w}^{v,d,c,t-tdc_{v,d,c}} \geq dem_{p,c,t}\quad \forall p\in P, c\in C, t\in T \qquad (5.39)$$

$$\sum_{q\in Q}\sum_{w\in W}\sum_{v\in V}\sum_{n\in N} xln_{p,q,w}^{v,l,n,t} \leq cc_{p,l,t}\ \forall p\in P, l\in L, t\in T \qquad (5.40)$$

$$\sum_{q\in Q}\sum_{w\in W}\sum_{v\in V}\sum_{d\in D} xnd_{p,q,w}^{v,n,d,t} \leq pc_{p,n,t}\ \forall p\in P, n\in N, t\in T \qquad (5.41)$$

$$\sum_{p\in P}\sum_{q\in Q}\sum_{w\in W}\sum_{v\in V}\sum_{l\in L} xln_{p,q,w}^{v,l,n,t-tln_{v,l,n}} m_p \leq dc_n - \sum_{p\in P}\sum_q\sum_{w\in W}\sum_{v\in V}\sum_{d\in D}\left(inv_{p,q,w}^{n,t-1} -\right.$$
$$\left. xnd_{p,q,w}^{v,n,d,t}\right) m_p\ \ \forall\ n\in N, t\in T \qquad (5.42)$$

$$\sum_{p\in P}\sum_q\sum_{w\in W}\sum_{v\in V}\sum_{n\in N} xnd_{p,q,w}^{v,n,d,t-tnd_{v,n,d}} m_p + \sum_{p\in P}\sum_{q\in Q}\sum_{w\in W}\sum_{v\in V}\sum_{d'\in D} xdd_{p,q,w}^{v,d,d',t-tdd_{v,d',d}} m_p \leq$$
$$dc_d - \sum_{p\in P}\sum_{q\in Q}\sum_{w\in W}\sum_{v\in V}\sum_{d'\in D}\sum_{c\in C}\left(inv_{p,q,w}^{d,t-1} - xdd_{p,q,w}^{v,d,d',t} - xdc_{p,q,w}^{v,d,c,t}\right) m_p\quad \forall\ d\in D, t\in T \qquad (5.43)$$

$$\sum_{w\in W}\sum_{v\in V}\sum_{d\in D} xnd_{p,q,w}^{v,n,d,t} \leq \sum_{w\in W} inv_{p,q+\Delta slnd_{p,w,n},w}^{n,t-1} + \sum_{w\in W}\sum_{l\in L}\sum_{v\in V} xln_{p,q+\Delta slvln_{p,w,v,l,n},w}^{v,l,n,t-tln_{v,l,n}} \quad \forall p \in P, q \geq q_{min_{p,n\ in\ N}} \in Q, n \in N, t \in T \tag{5.44}$$

$$\sum_{w\in W}\sum_{v\in V}\sum_{c\in C} xdc_{p,q,w}^{v,d,c,t} \leq \sum_{w\in W} inv_{p,q+\Delta slnd_{p,w,d},w}^{d,t-1} + \sum_{w\in W}\sum_{n\in N}\sum_{v\in V} xnd_{p,q+\Delta slvnd_{p,w,v,n,d},w}^{v,n,d,t-tnd_{v,n,d}} + \sum_{w\in W}\sum_{d'\in D}\sum_{v\in V} xdd_{p,q+\Delta slvdd_{p,w,v,d,d'},w}^{v,d,d',t-tdd_{v,d',d}} - \sum_{w\in W}\sum_{v\in V}\sum_{d'\in D} xdd_{p,q,w}^{v,d,d',t} \tag{5.45}$$

$$\forall p \in P, q \geq q_{min_{p,d}} \in Q, d \in D, t \in T$$

$$disp_{p,nd,t} = \sum_{w\in W}\sum_{q<q_{min_{p,nd}+\Delta slnd_{p,w,nd}}\in Q} inv_{p,q,w}^{nd,t-1} \quad \forall p \in P, nd \in ND, t \in T \tag{5.46}$$

$$disp_{p,c,t} = \sum_{w\in W}\sum_{q<q_{min_{p,c}+\Delta slvdc_{p,w,v,d,c}}}\sum_{v\in V}\sum_{d\in D} xdc_{p,q,w}^{v,d,c,t} \quad \forall p \in P, c \in C, t \in T \tag{5.47}$$

$$trln_{w,v,l,n,t} \geq \sum_{p\in P}\sum_{q\in Q}\frac{xln_{p,q,w}^{v,l,n,t} m_p}{mc_v} \quad \forall\, w \in W, v \in V, l \in L, n \in N, t \in T \tag{5.48}$$

$$trnd_{w,v,n,d,t} \geq \sum_{p\in P}\sum_{q\in Q}\frac{xnd_{p,q,w}^{v,n,d,t} m_p}{mc_v} \quad \forall\, w \in W, v \in V, n \in N, d \in D, t \in T \tag{5.49}$$

$$trdd_{w,v,d,d',t} \geq \sum_{p\in P}\sum_{q\in Q}\frac{xdd_{p,q,w}^{v,d,d',t} m_p}{mc_v} \quad \forall\, w \in W, v \in V, d \in D, d' \in D, t \in T \tag{5.50}$$

$$trdc_{w,v,d,c,t} \geq \sum_{p\in P}\sum_{q\in Q}\frac{xdc_{p,q,w}^{v,d,c,t} m_p}{mc_v} \quad \forall\, w \in W, v \in V, d \in D, c \in C, t \in T \tag{5.51}$$

$$\sum_{p\in P}\sum_{q\in Q} inv_{p,q,w}^{nd,t} \leq M\, z_{k,nd,t} \;\forall\, w \in W, nd \in ND, t \in T \tag{5.52}$$

$$\sum_{w\in W} z_{w,nd,t} = 1 \;\forall\, nd \in ND, t \in T \tag{5.53}$$

$$inv_{p,q,w}^{nd,t} \geq 0 \qquad \forall\, p \in P, q \in Q, w \in W, nd \in ND, t \in T \tag{5.54}$$

$$trln_{w,v,l,n,t} \in Z^{+} \qquad \forall\, w \in W, v \in V, l \in L, n \in N, t \in T \tag{5.55}$$

$$trnd_{w,v,n,d,t} \in Z^{+} \qquad \forall\, w \in W, v \in V, n \in N, d \in D, t \in T \tag{5.56}$$

$$trdd_{w,v,d,d',t} \in Z^{+} \qquad \forall\, w \in W, v \in V, d \in D, d' \in D, d \neq d', t \in T \tag{5.57}$$

$$trdc_{w,v,d,c,t} \in Z^{+} \qquad \forall\, w \in W, v \in V, d \in D, c \in C,\ t \in T \tag{5.58}$$

$$xln_{p,q,w}^{v,l,n,t} \geq 0 \qquad \forall\, p \in P, q \in Q, w \in W, v \in V, l \in L, n \in N,\ t \in T \tag{5.59}$$

$$xnd_{p,q,w}^{v,n,d,t} \geq 0 \qquad \forall\, p \in P, q \in Q, w \in W, v \in V, n \in N, d \in D,\ t \in T \tag{5.60}$$

$$xdd_{p,q,w}^{v,d,d',t} \geq 0 \qquad \forall\, p \in P, q \in Q, w \in W, v \in V, d \in D, d' \in D, d \neq d',\ t \in T \tag{5.61}$$

$$xdc_{p,q,w}^{v,d,c,t} \geq 0 \qquad \forall\, p \in P, q \in Q, w \in W, v \in V, d \in D, c \in C,\ t \in T \tag{5.62}$$

$$z_{w,nd,t} \in \{0,1\} \qquad \forall\, w \in W,\ nd \in ND,\ t \in T \tag{5.63}$$

$$disp_{p,ndc,t} \geq 0 \qquad \forall\, p \in P, ndc \in NDC, t \in T \tag{5.64}$$

The objective function (5.36) minimizes the overall energy consumed across the cold chain from the suppliers to the consumers. It includes the following contributions:

- The energy to move products throughout the logistic network. This depends on the traveling distance, the transportation mode, and the type of the vehicle. Transport inter-modality is allowed in the model. The considered flows are illustrated in Figure 56;
- The energy to maintain vehicles and warehouses at the chosen temperature set-point. The closer the set-point is to the external temperature, the lower the energy consumption for refrigeration will be. However, the temperature set-point should respect the safe temperature range of the food products to avoid spoilage and quality decay;
- The energy required by crops and farms to process and package the products and to handle the products at the storage nodes (which is often negligible);
- The energy associated with food losses, which occur when a product's quality decay is below the acceptance threshold. The quality decay of a product depends on the amount of time spent in the cold chain and the experienced environmental stresses (e.g., temperature rise). The minimum level of quality accepted at each stage determines the resulting flow of losses (i.e., those products that expire and are not accepted).

Constraints (5.37) and (5.38) balance the stock of product p at quality level q stored in the processing nodes n and in the storage nodes d with temperature w and period t. Constraints (5.39) enforce that the demand of product p at the client c must be satisfied within the due period t. Constraints (5.40)–(5.43) guarantee the observation of, respectively, the supplier capacity, the processing and storage capacities at processing nodes, and the storage capacity at storage nodes. Constraints (5.44) and (5.45) ensure that the flows are balanced across the supply chain stages. Constraints (5.46) and (5.47) calculate the disposals of product p at period t when the quality falls behind the minimum acceptable level across the supply chain. Constraints (5.48)–(5.51) account for the minimum integer number of vehicles necessary to ship products throughout the FSCS. Constraints (5.52) fixes the temperature in the processing node n and storage node d at period t, which is equal to the set-point defined by constraint (5.53).

Lastly, constraints (5.54)–(5.64) define the domain of the decision variables.

5.9.3 The case of the New Silk Road Belt

The proposed MILP model is validated through a case study of a long-range cold chain inspired by the initiative of the Chinese Government to foster the creation of the New Silk Road. This project, presented in 2013, aims to build a network of transport infrastructures to promote economic development along the ancient Silk Road. It also aims to increase maritime routes connecting Far East countries with Europe (McBride, 2015).

This initiative will reduce traveling distances and time for freight transportation, enabling faster and safer routes between Europe and Asia, crossing 65 countries and touching about 63% of the world's population. The new Silk Road will be built along new railways, roadways, and maritime transport corridors. This logistics network requires the establishment of multi-modality transport infrastructures (Wang & Li, 2016) and associated transit and consolidation depots sustaining the development of new cities and urban areas. Furthermore, the availability of primary resources as water and energy to power this network should be guaranteed, as they affect the design of new transport and storage infrastructures.

The proposed model might be used to analyze the energy requirements of FSCS built the new corridors connecting Europe with China, to obtain the most effective freight route from an energy perspective. To this purpose, the illustrated case study focuses on the assessment of the energy requirements of new potential cold corridors for the trade of food and perishable products throughout the new Silk Road Belt. Among the evaluated corridors (figure 57), three (i.e., the northern, central, and southern corridors) are traveled by train, and the fourth is mainly maritime.

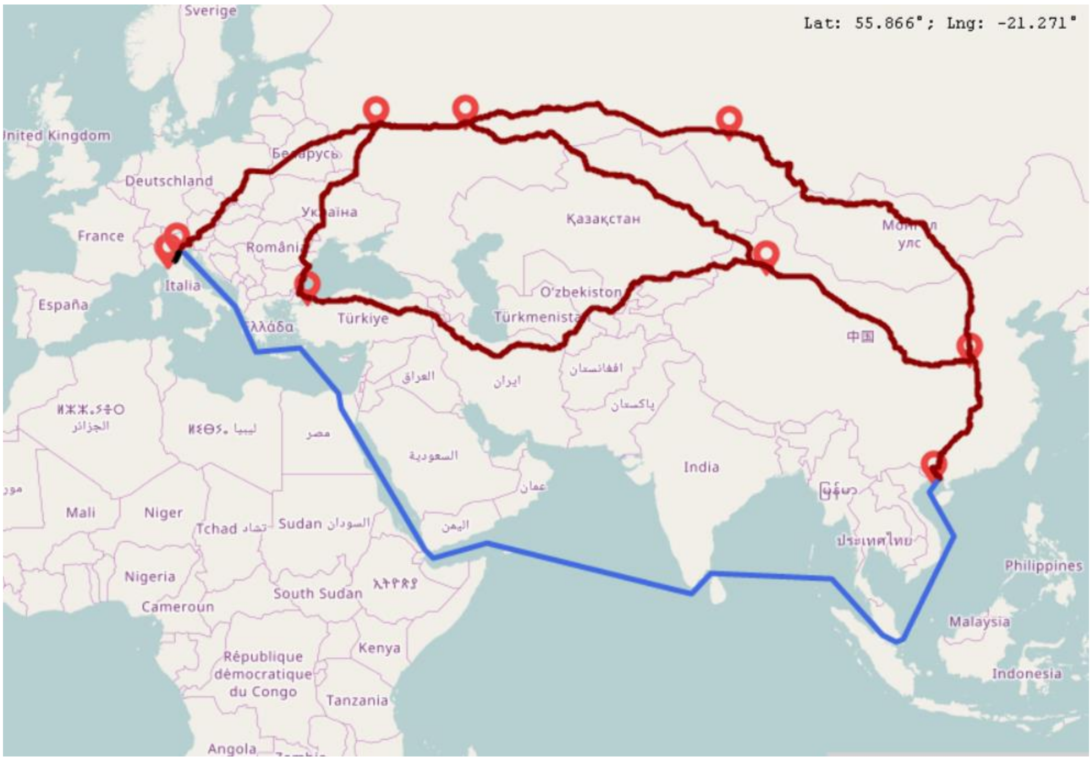


Figure 57. Alternative corridors along the Silk Road Belt (Gallo et al., 2017).

The case study is based on an FSCS built on ten logistics nodes distributing two perishable products, apples and ice-cream, from a Northern Italian city to the Chinese market located in Zhengzhou. The selected network draws some potential routes and connections between the main cities along the Silk Road Belt. These cover not yet existing transport infrastructures that are planned to be realized within the 'Belt and Road Initiative'. Other nodes might be considered in order to widen the set of potential connections available for distribution planning. This might be useful to identify the optimal connections to establish a strategic perspective on an energy effective cold chain. Nevertheless, given the planning horizon and the high granularity of the time periods chosen for this case study (i.e., each period is a day), the problem's complexity increases significantly, even with few nodes.

The case study focuses on two products with different characteristics in terms of energy value, shelf life, and optimal conservation temperature to stress how these factors influence the selection of the energy effective route. Thirty-five tons of products are processed and packed in Italy to be delivered to the Chinese retail market within 40 days. The proposed model is used to identify an effective energy corridor for each product and the most sustainable transport mode and to assess its sustainability performances in terms of the IS metric (eq. 5.35). Table 19 summarizes the input dataset in terms of the network's nodes and products' characteristics. The selected planning horizon, i.e., 40 days, involves the summer season, between July and August, when the external temperatures rise, and the refrigeration system is stressed. Given the high perishability of ice creams, their ideal temperature and the resulting shelf life are key drivers for the specific route and transport mode to adopt.

Table 19. Nodes of the FSCS and distributed products (Gallo et al., 2017).

Logistic Network				Food Products		
Node	Country	Type	Average Temp. [°C]	Product	Weight [g/unit]	Energy content [kWh/unit]
Vignola	Italy	Supplier	26	Ice cream	125	0.30073
Valsamoggia	Italy	Processing node	26	Apple	155	0.09423
Beihai	China	Storage node	25			
Ürümqi	China	Storage node	27			
Venice	Italy	Storage node	25			
Kazan	Russia	Storage node	22			
Moscow	Russia	Storage node	20			
Novosibirsk	Russia	Storage node	20			
Istanbul	Turkey	Storage node	27			
Zhengzhou	China	Client	28			

The energy requirements are calculated based on the equations provided in Section 3.10 and the shelf life decay according to the equations in Section 2.2.

The MILP model is solved with the Gurobi solver with Quad Core 2.4 GHz processors and 8 GB of RAM within 5 min. The instance of the model involved 2,107,085 continuous variables, 15,480 integer variables, of which 840 are binary, and 84,608 constraints. The energy consumption of the FSCS connecting Italy to China was calculated, and the IS metric was quantified for the two products. Since the goal is to assess the sustainability of alternative routes and transport modes for food distribution along the new Silk Road, some assumptions on the capacities of the nodes have been made:

- The suppliers are able to satisfy the client's order completely;
- The processing node is able to process all the incoming products;
- The capacity constraint at the storage nodes is relaxed.

(a)

(b)

Figure 58. Optimal routes for the distribution of (a) ice cream and (b) apples along the Silk Road (Gallo et al., 2017).

The optimal solutions in terms of route and transport mode vary with the product, as illustrated in Figure 58. The maritime route is not suitable for the ice cream since its shelf life is shorter than the required traveling time. Ice cream should be shipped by train via the northern route, which requires less than three weeks, compared to more than five along the maritime route. It is worth noting that the optimal route for ice cream from an energy perspective passes from the Novosibirsk's node, instead of from Kazan and Ürümqi, even though the latter would last one day less. The motivation for such behavior must be found in the different expected external temperatures experienced by the shipment across different regions, justifying the adoption of a climate-driven approach. The northern route is indeed colder than the central one and requires less energy for refrigeration.

Conversely, apples are characterized by a higher conservation temperature set-point. Consequently, they are shipped by vessel, which increases the travel time but is less energy-consuming. According to the optimal solution, the unit (i.e., per-package) energy consumption to supply both ice cream and apples from a Northern Italian producer (i.e., Vignola) to a southern Chinese Market (i.e., Zhengzhou) is 314.86 kWh. The corresponding sustainability metric calculated for the global FSCS of ice cream is $IS_{ice\ cream} = 760$, while, for apples, it is is $IS_{apple} = 913$. These food items consume, respectively, seven and nine hundred times the energy they provide to the consumer. Therefore, energy consumption and the associated environmental impacts should be considered at the planning and design stages. Renewable energy sources might be established to power the food operations from farm to table toward climate-stability goals (Accorsi et al., 2016). Indeed, the adoption of renewable energy sources would decrease FSCS reliance on conventional fossils and reduce the associated environmental impacts and climate change effects.

The obtained solution suggests that the maritime route allows the overall energy consumed for food transportation to be reduced. However, it requires about five weeks to reach the Chinese market, which might not be suitable for all perishable products. To meet the economic and environmental sustainability goals, incorporating the energy waste due to food losses along the supply chain is essential. By incorporating this contribution, the model identifies the optimal route that preserves product quality. For products with a short shelf life, the optimal route selection is time-driven instead of temperature-driven, since the product is distributed as quickly as possible to avoid losses. Given the longer shelf life of apples in comparison with ice cream, the resulting optimal routes are, respectively, temperature-driven and time-driven, and apples account for less energy consumption than ice cream.

Figure 59 shows the energy consumption attributed to each alternative route in the case of the distribution of apples. The dots are the nodes crossed by the route. The slope of the line connecting two nodes represents the energy consumption rate. The maritime corridor, i.e., the blue line, is the most energy-effective, and the vessel's adoption between Venice and Beihai contributes to contain the energy consumption of the FSCS significantly. Figure 59 also highlights that the first arc traveled by truck has the highest energy consumption rate out of the four alternatives.

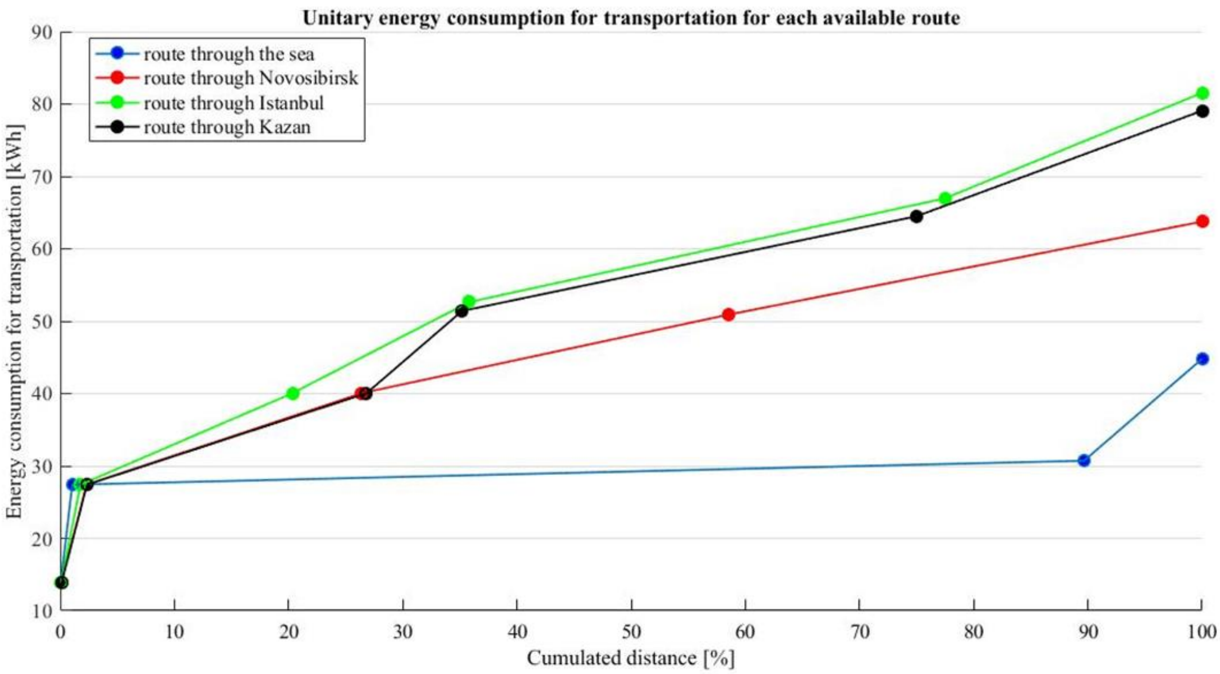


Figure 59. Cumulative energy consumption of the alternative routes of the apple FSCS (Gallo et al., 2017).

According to the proposed model, the optimal solution for the FSCS results from a combination of the following factors:

- The energy consumption of the vehicles;
- The total distance traveled and the travel time, including the fixed setup time of multi-modal transport;
- The need for refrigeration power along the routes.

Another consideration involving the different climate conditions experienced during mid-range and long-range cold chains comes from interpreting the results. Typically, the sea provides thermal mitigation and keeps the temperature stationary, avoiding those peaks experienced upon roads and railways during daily sun hours (Accorsi et al., 2014[b]). Consequently, despite the longer travel, the maritime path is chosen by a temperature-driven solution to minimize the energy consumption for distribution (i.e., as in the case of apples).

These consumptions are increasingly predominant along global FSCS, and their reduction is crucial to sustainable food provision. Therefore, the decision on the route and the transport mode to adopt is of extreme importance in designing energy-effective cold chains. This aspect is explored in Figure 60, which shows the trade-off between the best route via railways (i.e., the route through Novosibirsk) and the maritime route (i.e., the route through Beihai). Figure 60 summarizes the results of the analysis conducted on the external temperatures experienced during the journey. By maintaining all the other parameters as fixed, the line in the figure represents the points at which the two alternative routes and transport modes are equivalent in terms of the energy consumption for refrigeration, considering the external temperature stresses they will experience. For example, when the average external temperature experienced along the railway route is 22.5 °C, the maritime route is preferable for energy minimization if the vessel's average external temperature is below 25 °C.

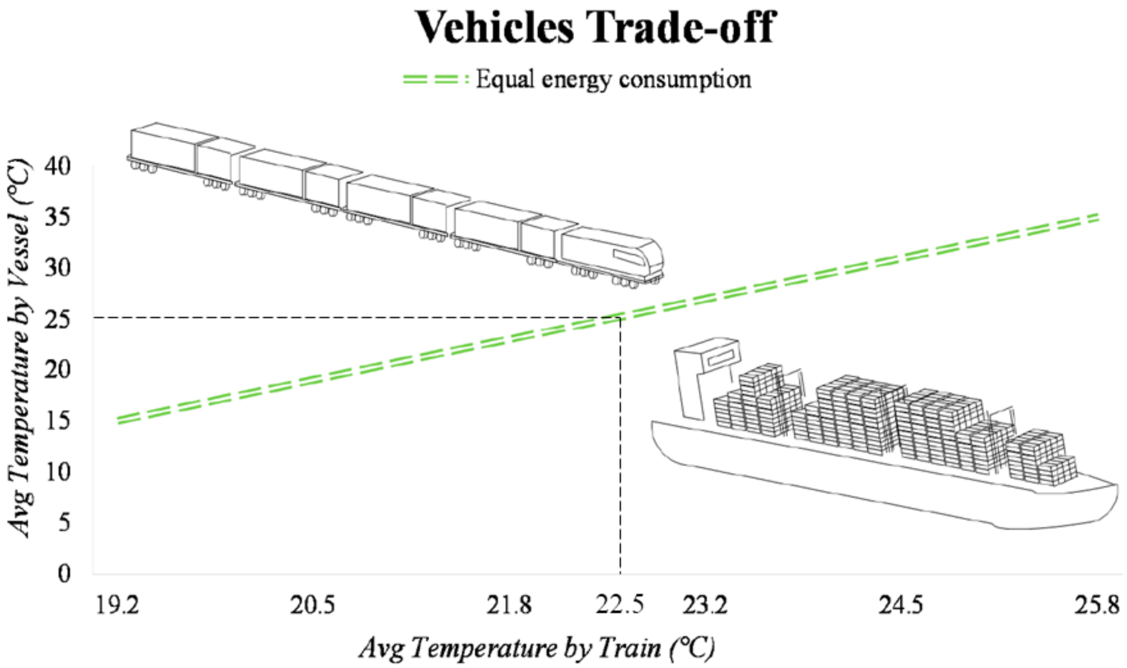


Figure 60. Energy trade-off between rail and maritime routes based on temperatures (Gallo et al., 2017).

5.10 An integrated model to manage the flows of by-products and losses

The previous climate-driven models integrated the logistics flows of products in all the stages of PLC from production to the final distribution. In order to guarantee the delivery of high-quality products, they furtherly introduced the estimation of quality decay of products and the assessment of product disposals. The sustainability of the supply chain can be further enhanced by properly managing the flows of discarded products and valorizing them with the preparation of by-products.

In this section, a model for the valorization of by-products and waste management of the meat industry is provided. The production of beef is undoubtedly the highest environmental stressor in the meat industry. Different concerns contribute to the environmental impact associated with this industry (Elferink et al., 2008). In addition to the energy, water, and land consumption (Virtanen et al., 2011), beef processing results in large flows of waste and by-products (Accorsi et al., 2017 [b], Accorsi et al., 2017 [c]).

One of the main factors influencing decisions in the meat industry is the so-called slaughtering yield, defined as the ratio between the weight of the carcass and the cattle weight (Bhaskar et al., 2007). The slaughtering yield results in 65% for females and 68% for males, on average. The production step removes bones, fats, and muscles. As a result, just 225kg of meat is sold out of the 450kg of the average animal's weight. Therefore, about 1.2 million tons of organic wastes are produced by the Italian meat industry with significant sustainability impacts (Bustillo-Lecompte & Mehrvar, 2017).

5.10.1 Model formulation

For the design of the FSCS of meat by-products, the following logistics nodes are identified:

- Meat production facilities (slaughterhouses), where cattle from the farms are killed and slaughtered. The whole production of meat cuts is carried out at these nodes;
- Treatment facilities involved in the transformation of secondary materials received from the slaughterhouses;
- Distribution nodes represent the customers for the by-products market;
- Disposal facilities, where the waste from the second transformation is collected because it is no longer revenue-generating.

The flows of primary meat cuts from the slaughterhouse to clients are not considered because they are not differential in our problem. Figure 61 presents problem boundaries.

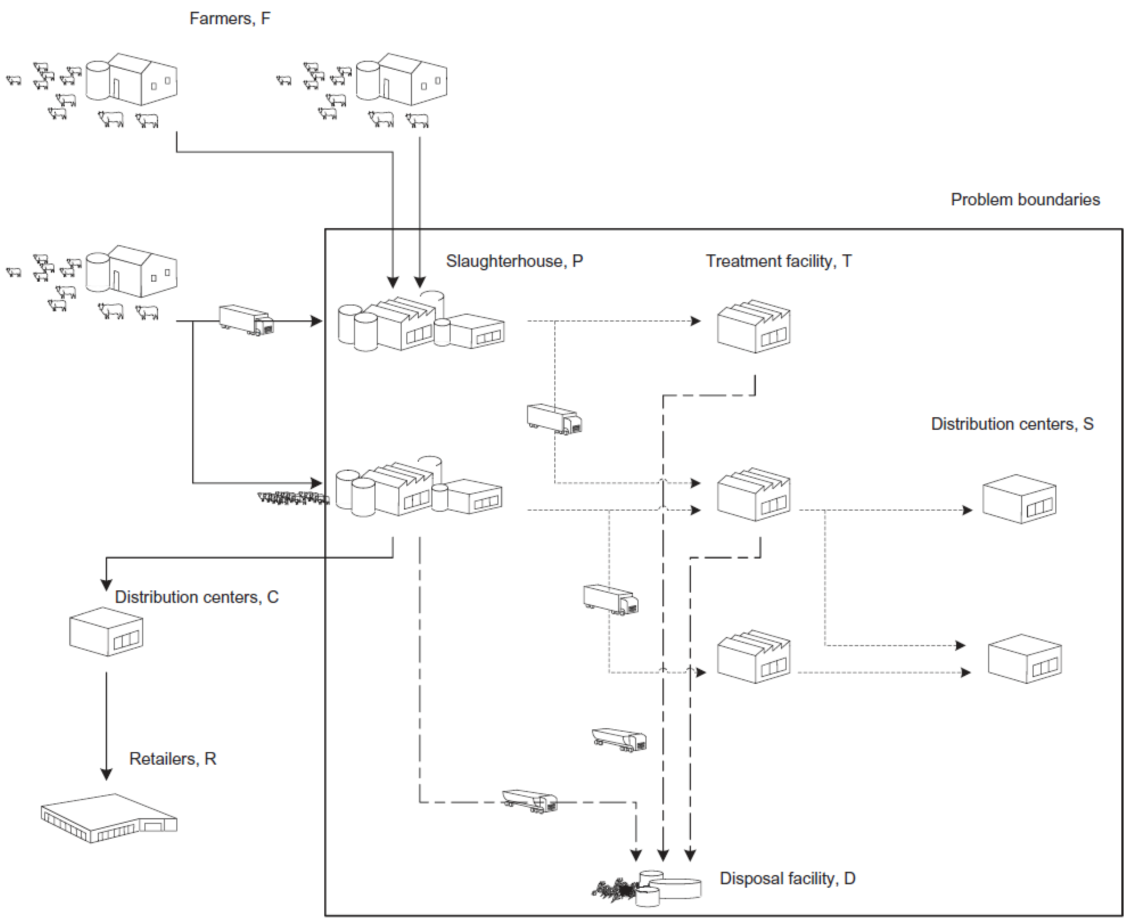


Figure 61. FSCS boundaries (Accorsi et al., 2019).

Sets:

B	Set of by-products
C_b	Set of secondary materials to produce by-products
P	Set of slaughterhouses
T	Set of treatment nodes
S	Set of storage nodes
D	Set of disposal nodes
Ψ	Set of time periods

Parameters:

$dem_{sb\tau}$	Demand of by-product b by storage node s at period τ.
cf_t	Fixed cost at the treatment node t.
cd_{bt}	Variable cost for disposal of by-product b at the treatment node t.
cd_{c_bt}	Variable cost for disposal of secondary material c_b at the treatment node t.

cv_{tb}	Variable treatment cost for each by-product *b* at the treatment node *t*.
pr_b	Price of the by-product *b.*
$tcap_{tb}$	Treatment capacity of the by-product *b* by the treatment node *t*.
$cattle_{p\tau}$	Slaughtered cattle at the slaughterhouse *p* during period τ.
w_{cattle}	Average weight of cattle.
w_b	Weight of one unit of by-product *b*.
w_{c_b}	Weight of one unit of secondary material c_b.
cut_{c_b}	Fraction of cattle generating secondary material c_b.
wst_b	Waste fraction for by-product *b*.
uf_{bc_b}	Usage factor of component c_b on by-product *b*.
ctr	Transportation cost.
α_{tr}	Incremental factor for transportation costs.
$dist_{ab}$	Distance between the generic nodes *a* and *b*.

Decision variables:

$x_{c_b pt\tau}$	Product flow of secondary material c_b from the slaughterhouse *p* to treatment node *t* during period τ.
$x_{bts\tau}$	Product flow of by-product *b* from the treatment node *t* to the storage node *s* during period τ.

Objective function:

$$
\begin{aligned}
& max \sum_{b\in B}\sum_{t\in T}\sum_{s\in S}\sum_{\tau\in\Psi} x_{bst\tau} pr_b \\
& +\sum_{\tau\in\Psi} cf_t|\Psi| \\
& +\sum_{b\in B}\sum_{t\in T}\sum_{s\in S}\sum_{\tau\in\Psi} x_{bst\tau}(w_b dist_{ts} ctr\ \alpha_{tr} + cs_{tb} w_b wst_b cd_{bt}) \\
& +\ \sum_{b\in B}\sum_{t\in T}\sum_{s\in S}\sum_{\tau\in\Psi}\sum_{d\in D} x_{bst\tau}(w_b dist_{td} ctr\ \alpha_{tr} wst_b) \\
& +\sum_{b\in B}\sum_{p\in P}\sum_{t\in T}\sum_{\tau\in\Psi}\sum_{c_b\in C_b} x_{c_b pt\tau}\left(w_{c_b} dist_{pt} ctr\ \alpha_{tr} - cd_{c_b p}\right) \\
& +\ \sum_{c_b\in C_b}\sum_{p\in P}\sum_{b\in B}\sum_{\tau\in\Psi}\sum_{d\in D}\sum_{t\in T} x_{c_b pt\tau}\left(w_{c_b} dist_{pd} ctr\right)
\end{aligned} \quad (5.65)
$$

Subjected to

$$\sum_{t\in T} x_{bts\tau} \le dem_{sb\tau} \ \ \forall s\in S, b\in B, \tau\in\Psi \quad (5.66)$$

$$\sum_{s\in S} x_{bts\tau} \le tcap_{tb} \ \ \forall t\in T, b\in B, \tau\in\Psi \quad (5.67)$$

$$\sum_{t \in T} x_{c_b p t \tau} \le cattle_{p\tau} cut_{c_b} w_{cattle} \;\; \forall p \in P, c_b \in C_b, b \in B, \tau \in \Psi \tag{5.68}$$

$$\sum_{c_b \in C_b} \sum_{p \in P} x_{c_b p t \tau} \ge \sum_{s \in S} x_{b t s \tau} (1 + wst_b) uf_{bc_b} \; \forall \, t \in T, b \in B: uf_{bc_b} > 0, \tau \in \Psi \tag{5.69}$$

$$x_{c_b p t \tau} \ge 0 \; \forall \, t \in T, p \in P, c_b \in C_b, \tau \in \Psi \tag{5.70}$$

$$x_{b t s \tau} \ge 0 \; \forall \, t \in T, s \in S, b \in B, \tau \in \Psi \tag{5.71}$$

The objective function (5.65) maximizes the meat producers' profit as the price of the by-products multiplied by the quantity delivered to fulfill the secondary demand, minus the costs of management (i.e., treatment and disposal) and transportation of logistics flows. Fixed costs paid by the treatment plants are included in the function, although they are not differential. The avoided costs of waste disposal and waste transportation at the slaughterhouses are considered in the function with a positive value. Constraints (5.66) guarantee that the flow of by-products meets the demand. Constraints (5.67) and (5.68) impose the respect of the transformation capacity at the treatment nodes, and the respect of the weight and number of slaughtered animals for the outgoing flows. Constraints (5.69) balance the flows throughout the nodes, while Constraints (5.70) and (5.71) define the domain of the decision variables.

5.10.2 The case of a meat FSCS

The proposed model has been applied to a case study of the main Italian meat producer. Five secondary materials and waste from primary production are considered to produce five different by-products. These secondary materials are valve tissues, skin, fats, bones, and blood, while the resulting by-products are heart valves, bags and clothes, soaps, toys, and organic fertilizers intended for the biomedical, clothing, and agricultural industries.

Table 20 reports the address and location of each slaughterhouse p and treatment node t involved in the network and their traveling distance to the closest disposal center d. The table also reports the monthly fixed costs cf_t for each treatment node. In Table 21, the records report the parameters regarding the nature of the secondary materials and the associated by-products. Specifically, it provides the selling prices of by-products supplied to the distribution centers, their weights, and the waste percentage at the treatment node. Furthermore, this table shows the weight of each secondary material and the usage factor uf_{bc_b}, which represents the weight of secondary material necessary to generate one unit of by-product. It is worth noting how one secondary material is associated with just one by-product in this numerical example. However, the proposed formulation allows defining a set of secondary materials involved in producing each by-product.

Table 20. Meat FSCS network data (Accorsi et al., 2019).

Slaughterhouse (p)	City	$dist_{pd}$ (km)	
$p = 1$	Castelvetro	19.5	
$p = 2$	Ospedaletto	22.5	
$p = 3$	Flumeri	47.0	
$p = 4$	Rieti	3.8	
Treatment facility (t)	City	$dist_{pd}$ (km)	cf_t (€/month)
$t = 1$	Nonantola	9.6	75.56
$t = 2$	San Rocco al Porto	41.0	98.28
$t = 3$	Sant'Angelo dei Lombardi	49.2	133.57
$t = 4$	San Giorgio di Lomellina	34.0	112.73
$t = 5$	Belgioioso	15.4	166.56
$t = 6$	Faenza	8.1	98.12
$t = 7$	Perugia	9.6	62.15

Table 21. By-products and secondary materials parameters (Accorsi et al., 2019).

By-product	Name	pr_b (€/unit)	w_b (kg/unit)	wst_b (%)
$b = 1$	Heart valves	78	0.6	0.21
$b = 2$	Leather bags	23	3.2	0.16
$b = 3$	Soaps	0.72	0.2	0.09
$b = 4$	Pet toys	5.9	0.7	0.13
$b = 5$	Fertilizers	2.1	1	0.08
Secondary material	Name		w_{c_b} (kg/unit)	uf_{bc} (kg/unit)
c_1	Valve tissues		4.5	$uf_{11} = 0.5$
c_2	Skin		45	$uf_{22} = 2.9$
c_3	Fats		13.5	$uf_{33} = 0.18$
c_4	Bones		76.5	$uf_{44} = 0.6$
c_5	Blood		22.5	$uf_{55} = 0.85$

Figure 62 illustrates the 30 distribution centers s considered as secondary markets for the meat by-products on the Italian landscape. Finally, figure 62 shows the average number of cattle slaughtered by the four meat plants along the observed time horizon. The parameters of transportation and disposal costs are set to 0.015 $(\frac{€}{kg \cdot km})$ and 0.126 $(\frac{€}{kg})$, respectively.

Figure 62. Distribution centers *s* served by the treatment nodes *t* (Accorsi et al., 2019).

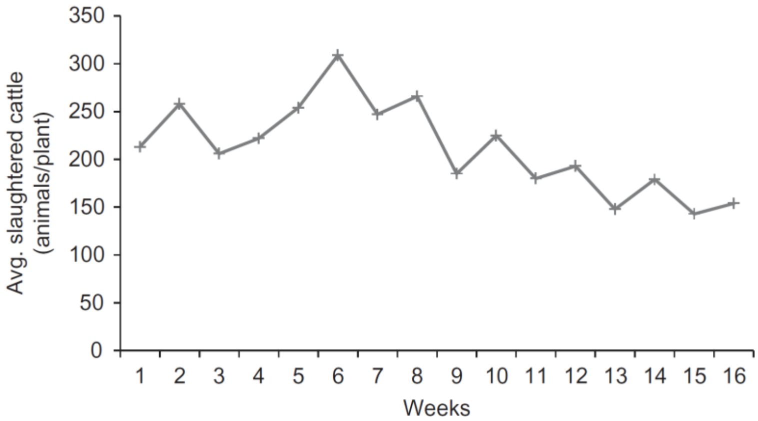


Figure 63. Slaughtered animals over weeks (Accorsi et al., 2019).

The instance was solved in a few seconds through the solver Gurobi run on a workstation configured with Intel Quad Core 2.4-GHz processors and 8GB of RAM. The first finding deals with the flows of secondary materials supplied from the slaughterhouses to the treatment nodes instead of being disposed as waste at the disposal centers. The results for the first four weeks of the planning horizon are reported in figure 64.

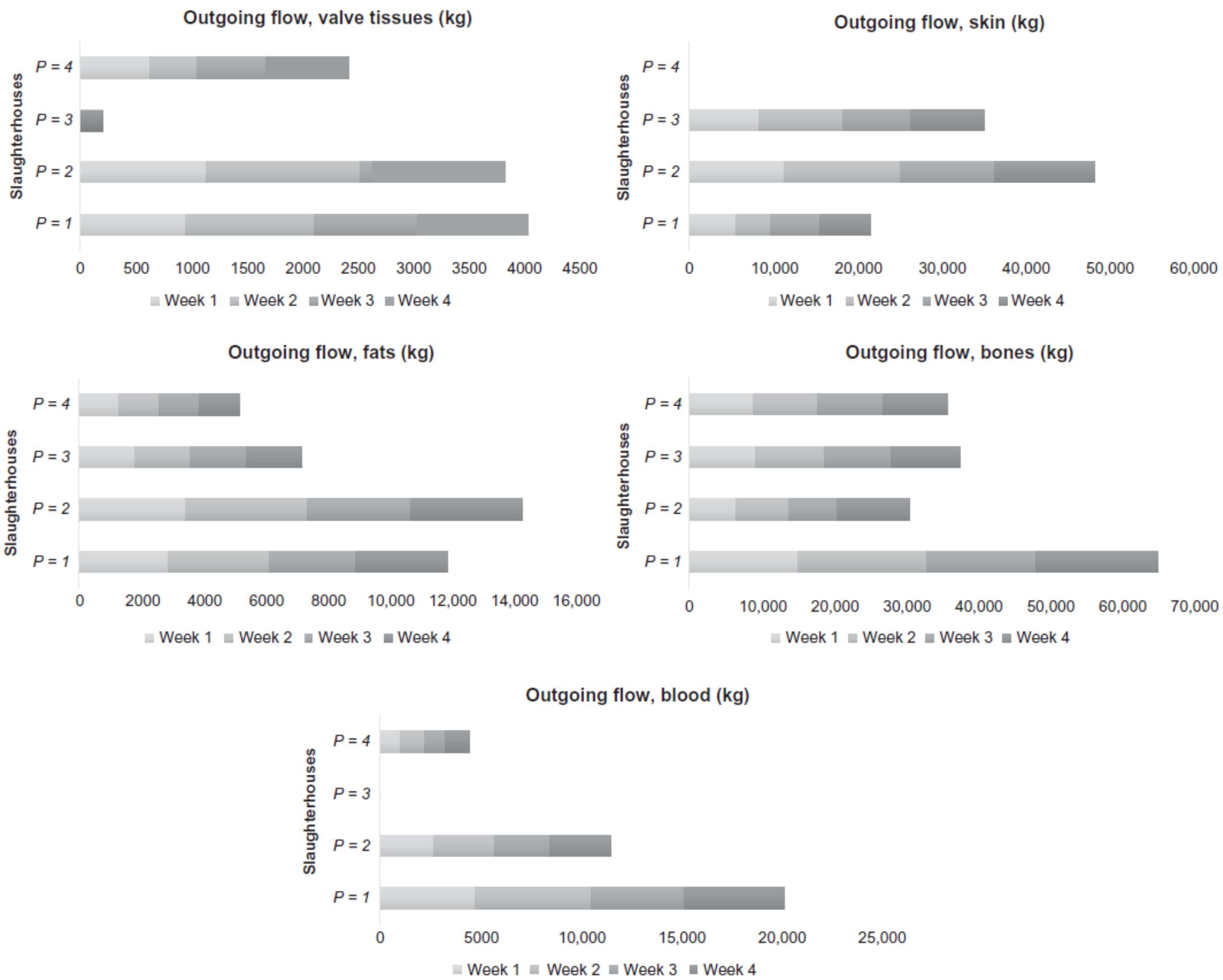


Figure 64. Flows of secondary materials from the slaughterhouses to the treatment facilities (Accorsi et al., 2019).

The figure shows how the traveling distance and the logistics network configuration play a crucial role in managing product flows. In particular, the distance from the disposal centers discourages a plant from disposing the waste and paying for its transportation without any revenue. Furthermore, the location of the plant with respect to the treatment nodes is a lever to use to enhance the valorization of secondary materials into by-products. These drivers lead to the different behaviors of the slaughterhouses, as illustrated by the histograms. Similar findings are obtained from figure 65, which illustrates the flow of by-products resulting from the treatment process and delivered to the distribution centers. Further drivers contribute to the optimal flow allocation, such as the price of the by-products, their weight and waste fraction, as well as the distance between the treatment facilities and the distribution centers.

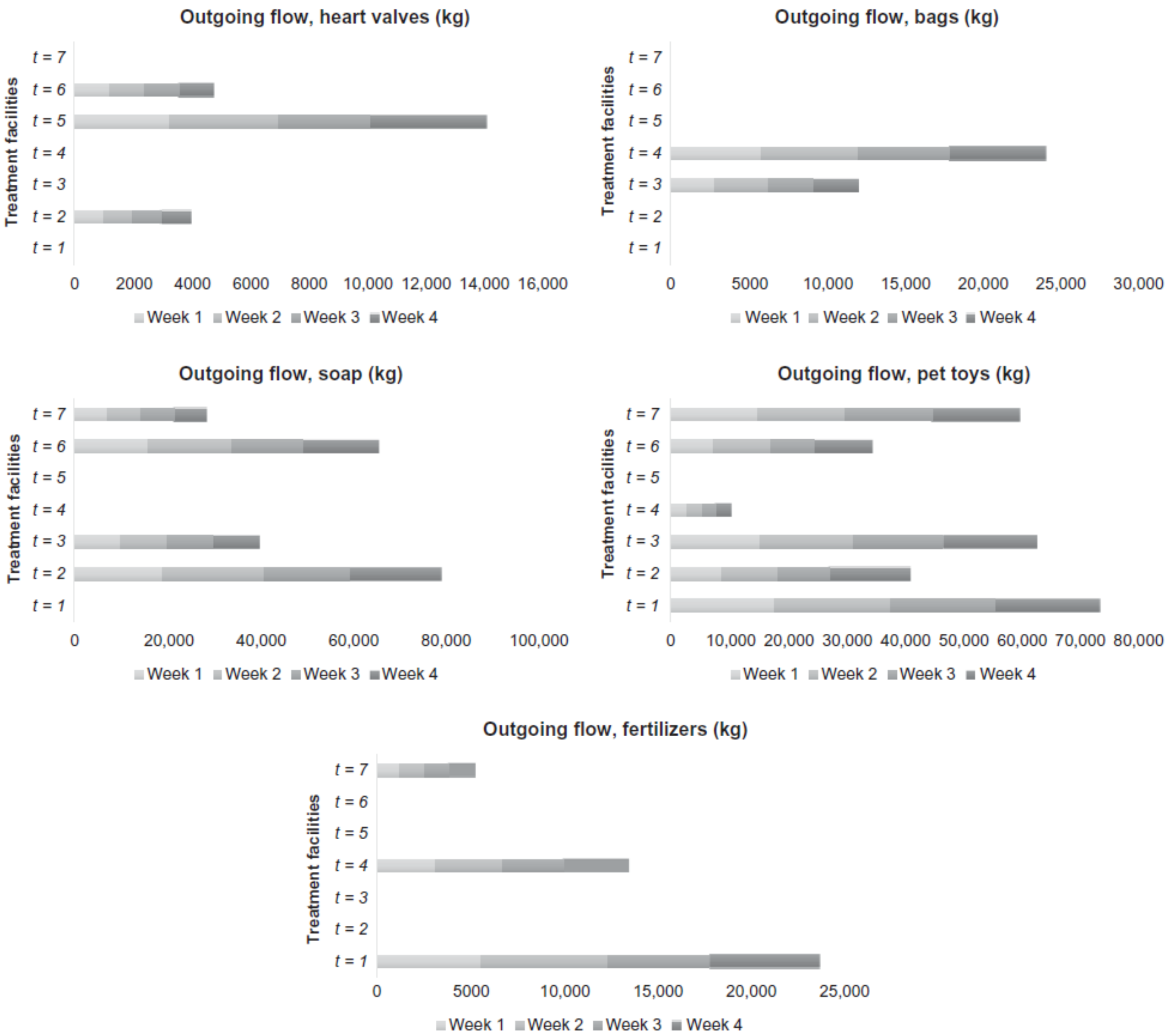


Figure 65. Flows of by-products from the treatment facilities to their customers (Accorsi et al., 2019).

A sensitivity analysis is proposed to investigate the impact of logistics and transportation activities on the valorization of by-products. The parameter α_{tr} scale the transportation costs between the network nodes linearly and measure the impacts of higher costs generated by the by-product valorization. Specifically, 11 scenarios are generated by varying α_{tr} from 1 to 6 with a step of 0.5. This variation is intended to discern how the overall profit decreases with traveling distances among the nodes. Compared to the as-is scenario (i.e., $\alpha_{tr} = 1$), figure 66 shows the percentage decrease of flows of by-products delivered to the distribution centers per each scenario.

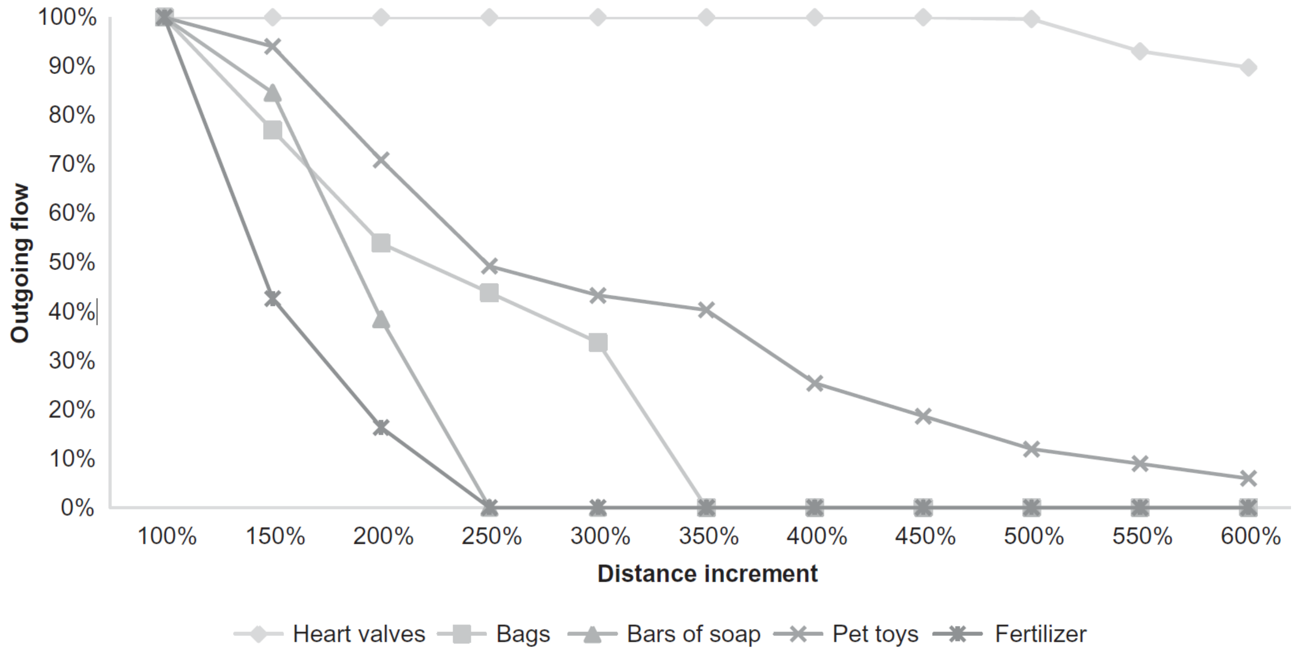


Figure 66. Optimal by-products flow with increasing distances (Accorsi et al., 2019).

Different by-products show different behaviors based on their weight and value, the waste they generate across the network, and the geographic distribution of the demand. For example, when the network sprawl is two and a half times the as-is configuration (i.e., distances are multiplied by 2.5), the treatment of bones into pet toys and their distribution to the customers is no longer convenient. Conversely, the high value of biomedical by-products such as heart valves makes these flows less sensitive to the distances among nodes.

5.11 Integrated climate-driven modeling remarks

This section presents some concluding remarks about the issues and the decision-support models and methods introduced in this chapter. Modern FSCS are not economically, environmentally, and socially sustainable, and the resulting costs, disposal valorization, GHG emissions, energy consumption, and wastes should be minimized to make the food supply finally sustainable. Logistics plays a crucial role in improving the sustainability of the FSCS but require cooperations among the stakeholder of the supply chain and the implementation of innovative, interdisciplinary models. The decision-making process for the distribution of food items should consider the criticality of network design and traveling distances on sustainability. This is particularly important in a global context, as the current one.

The expansion of the cold chain infrastructures would significantly decrease perishable food losses also in developing countries. Still, it would further increase the energy request and the associated costs and carbon emissions. Since the environmental temperature affects the cold chain's performance, the interaction between climate and the distribution of perishable products cannot be ignored.

This chapter proposed several models and introduced the climate-driven modeling approach to reduce the impact of cold chains while guaranteeing the delivery of high-quality products to the consumers. Through the integration of models supporting the strategical, tactical, and operational decision level, this chapter aims to provide practical tools to support decision-makers in improving their supply chains' performances without renouncing to the increase of their profits. The models are formulated to support well-known logistics decisions, but they provide an innovative approach tailored to perishable products integrating quality issues and the effect of climate conditions.

Furthermore, as a percentage of disposals is not avoidable in global supply chains, the remaining disposals should be valorized according to the model proposed in section 5.10, and their costs and environmental impacts should be minimized.

5.12 Chapter’s highlights

- Currently, global FSCS are hardly sustainable due to the high fraction of food losses and wastes, the costs, and the carbon emissions associated with the logistics decisions such as refrigeration, delivery routes, and waste management.
- An increase in FSCS performances can be achieved by implementing innovative, integrated, and interdisciplinary approaches based on cooperation among the stakeholders of the supply chain system.
- This chapter introduces several models and algorithms tailored to perishable products to optimize the FSCS from the strategical to the operational level. By subsequently applying these methods, decision-makers are supported from the decisions about network design and the location of storage nodes to the allocation of logistics flows and on the integration of production, processing, storage, and distribution decisions with an integrated perspective.
- The introduction of the climate-driven modeling approach reduces the impact of FSCS while guaranteeing the delivery of high-quality products to the consumers representing the best solution for global FSCS of fast perishable items.

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6. Uncertainty management in FSCS

The quality degradation process of food is accelerated by the stresses (e.g., temperature, humidity, vibrations, waiting) affecting it throughout the PLC. Although effective operation planning, weather forecasts, and the statistical analysis of the environmental context can provide some estimation of such stresses, they are hardly predictable. The identification of environmental stresses and climate-driven methods previously introduced are based on including the knowledge of these stresses in FSCS analysis. Therefore, their estimation should be very accurate.

As introduced in section 5.7, the exploitation of favorable climate conditions requires cooperation amongst FSCS stakeholders and perfect synchronization of logistics operations. The dynamic nature of environmental stresses threatens this synchronization. An ideal operation scheduling can become useless due to a delay in product arrival time, and an energy-effective route can become high energy-consuming due to a sudden change in weather.

This chapter focuses on this issue to provide methods to control the uncertainty in FSCS optimization by providing an innovative stochastic mathematical model and a stochastic metaheuristic tailored to FSCS. The proposed solutions aim to support decision-makers in one of the most challenging logistics strategies due to its complexity and the further importance assumed by synchronization: the cross-docking. Finally, it is worth noting how the methods provided in this section introduce an additional complexity: their generalization to any kind of product processed in a cross-dock. This complexity is due to the real case study presented at the end of the chapter concerning the delivery of products of different and unknown nature, where perishables could not be distinguished a priori from other products.

The methods illustrated in this chapter are the results of a research period at the Operations Research and Logistics Group of the Wageningen University & Research.

6.1 Cross-docking solutions for fast-moving items

Storage nodes represent a solution to consolidate logistics flows of products after production and before being distributed to the clients in order to satisfy their demand in a timely manner (Accorsi et al., 2014). These hubs intrinsically represent a logistic solution to cope with the uncertainty. They protect the company from fluctuations in demand and supply of goods, as in the well-known bullwhip effect

(Braz et al., 2018). The storage nodes achieve this goal by performing five basic functions: receiving, sorting, storing, retrieving, and shipping (Yu & Egbelu, 2008). Since 30% of an item price is incurred in the distribution process, companies strive to reduce the expenses (Musa et al., 2010). The costs of performing such operations can be reduced by optimizing them. However, the biggest economic advantage can be reached by avoiding them. The objective of cross-docking is to avoid the most expensive of these operations: storage and retrieval. Indeed, by reducing such activities, cross-docking can decrease warehousing costs up to 70 percent. Furthermore, these two steps frequently represent the most time-consuming warehousing activities. This fostered the adoption of cross-docking solutions for fast-moving items and companies distributing large volumes to a large number of stores (Yu & Egbelu, 2008), such as the distribution of fruits and vegetables (Rahbari et al., 2019). Therefore, cross-docking is an efficient solution to cut down storage costs and reduce time consumption, hence representing an effective strategy against quality decay to deliver fresh food to the consumers.

From a time-dependent scale, cross-docking decisions can be subdivided into: (1) strategic decisions such as infrastructure design, determination of locations, and the capacity of cross-docks (Kheirkhah & Rezaei, 2016; Mousavi & Tavakkoli-Moghaddam, 2013); (2) tactical decisions such as the allocation of resources and material flow (Bartholdi & Gue, 2000); and (3) operational decisions such as inbound and outbound operations scheduling and vehicle routing (Larbi et al., 2011; Ahmadizar et al., 2015). The main strategical and tactical decisions concerning cross-docking can be managed effectively with the same approaches developed for other types of storage nodes. For example, the optimal location of the cross-dock can be identified by applying the center-of-gravity model introduced in section 5.1, and the allocation of logistics flows to cross-docks or direct shipments can be determined with the model presented in section 5.4. Furthermore, the optimal layout strategies to design a new cross-dock can be identified with existing models (Bartholdi & Gue, 2000). The most critical decisions about cross-docking concerns the operational decision level, which is the decision level addressed in this chapter.

At the inbound side, incoming vehicles are unloaded, and the load is verified, labeled, consolidated, sorted, handled to the outbound area, loaded into departing vehicles, and shipped within 24 h. Figure 67 shows a sketch of the main operations carried out within a cross-docking hub, summarizes the decisional environment, and identifies material flows, some sources of uncertainty, and the main objective functions.

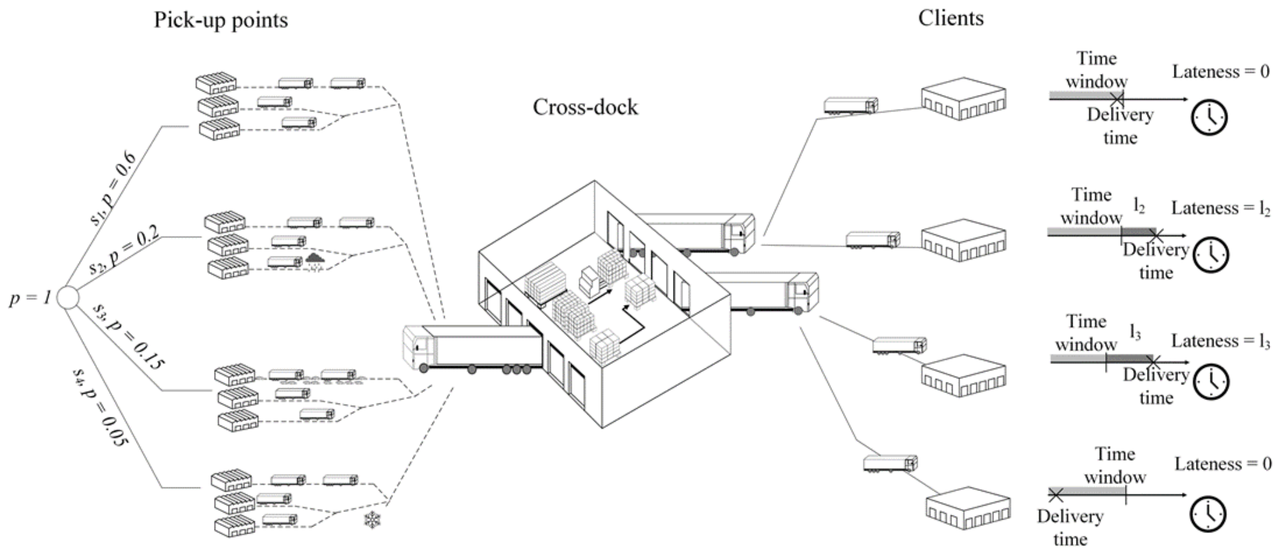


Figure 67. Schematic of the cross-docking network, activities, and objective functions.

By limiting storage tasks, cross-docking enhances the customer service level in terms of on-time deliveries while decreasing holding costs (Joo & Kim 2013). The effectiveness of cross-docking relies on the simultaneous arrival of vehicles (Lee et al. 2006), the prioritization of unloading and loading operations at the inbound/outbound docks, and the consolidation of loads in agreement with the vehicle routing strategy. Synchronizing such processes is vital and determines the ability of cross-docking to achieve the efficiency goals in practice (Buijs et al. 2014).

6.2 Literature on cross-docking models and algorithms

The available literature on cross-docking is quite recent. In the 1990s, the pressure to increase customer service levels and reduce delivery lead times motivated scholars to provide approaches to facilitate fast handling at warehouses. Some years later, early models for cross-docking underlined the challenging nature of synchronizing operations (Ting & Weng, 2003).

Since then, many efforts have been devoted to decision-support models to aid the synchronization of cross-docking processes. Lee et al. (2006) proposed the integration of vehicle routing in a cross-docking assignment model by managing vehicle arrivals and consolidation simultaneously without temporary storage. Yu and Egbelu (2008) introduced the vehicle-docking scheduling problem to set the priority of dock assignments, while the transfer from inbound to outbound docks was automated through conveyors. Musa et al. (2010) developed an algorithm that established the loads to be delivered through a cross-docking hub and the gains realized from consolidation. Other studies have formulated objective functions for the makespan to minimize the time spent at the cross-dock (Vahdani & Zandieh, 2010;

Arabani et al., 2011). Joo & Kim (2013) also considered compound vehicles as service vehicles used both at the inbound and outbound sides. Agustina et al. (2014) integrated vehicle scheduling and routing into a cross-docking model for food products. Moghadam et al. (2014) provided a model allowing more than one vehicle to visit a delivery node. Ahmadizar et al. (2015) illustrated a two-level vehicle routing problem to assign vehicles to consolidation through cross-docking systems and vehicles for last-mile deliveries. Küçükoğlu & Öztürk (2015) included a packing problem to determine how to assign loads to vehicles departing from the cross-dock. Mohtashami et al. (2015) proposed a multi-objective model to minimize both the makespan of cross-docking operations and transportation costs simultaneously. To provide an exhaustive formulation of an operational cross-docking model, Küçükoğlu & Öztürk (2016) proposed a two-stage model to allocate physical flows from the supplier to customers through cross-docks and to assign vehicles to docks. Other studies have considered environmental impacts (Yin & Chuang, 2016; Abad et al., 2018) and worker requirements (Rezaei & Kheirkhah, 2018). Other studies have included the reverse logistics of end-of-life products to investigate the benefits of cross-docking throughout closed-loop supply chains (Rezaei & Kheirkhah, 2017).

Given the complexity of cross-docking models, lots of the proposed models are paired with solution methods to solve real cross-docking instances in a reasonable time (Joo & Kim, 2013). Indeed, operational models are notoriously NP-hard (Abad et al., 2018).

Table 22 classifies thirty-five recently proposed operational models for cross-docking according to their main scopes, type of formulation, objective function, solution method (i.e., heuristics or metaheuristics to solve large instances), and level of robustness in addressing uncertainty.

The scopes include:

- Dock door assignment;
- Vehicle routing;
- Operations scheduling;
- Temporary storage management.

The type of formulation of the models includes:

- Integer Programming (IP);
- Mixed-Integer Programming (MIP);
- Mixed-Integer Linear Programming (MILP);
- Dynamic Programming (DP).

The solution methods, instead, include:

- Branch-and-price algorithm (BP);
- Tabu Search algorithm (TS);
- Simulated Anneaing (SA);
- Artificial Bee Colony (ABC);
- Ant Colony Optimization (ACO);
- Genetic Algorithm (GA);
- Large Neighborhood Search (LNS);
- Differential Evolution algorithm (DE);
- Imperialist Competitive Algorithm (ICA);
- Particle Swarm Optimization (PSO);
- Cuckoo Optimization Algorithm (COA);
- Column Generation (CG);
- Self-Evolution Algorithm (SEA);
- Variable Neighborhood Search (VNS).

Table 22. Classification of models and algorithms for cross-docking models.

Authors	Year	Dock door assignment	Vehicle routing	Operations scheduling	Temporary storage	Model type	Objective Function	Meta-heuristics	Heuristics	Solution method	Uncertainty
Sung & Song	2003	X	✓	X	X	IP	Cost	✓	X	TS	X
Lee, et al.	2006	X	✓	X	X	IP	Cost	✓	X	TS	X
Sung & Yang	2008	X	✓	X	X	IP	Cost	X	✓	BP	X
Yu & Egbelu	2008	X	X	✓	✓	MILP	Makespan	X	✓		X
Wen et al.	2009	X	✓	✓	X	MILP	Travel time	✓	X	TS	X
Musa et al.	2010	X	✓	✓	✓	IP	Cost	✓	X	ACO	X
Vahdani & Zandieh	2010	X	X	✓	✓	MILP	Makespan	✓	X	GA,TS, SA…	X
Alpan & Penz	2011	✓	✓	✓	✓	DP	Cost	X	X		X
Arabani et al.	2011	X	X	✓	✓	MILP	Makespan	✓	X	GA,TS,P SO,ACO, DE	X
Larbi et al.	2011	X	X	✓	✓		Cost	X	✓		✓
Santos et al.	2011	X	✓	X	X	IP	Cost	X	✓	CG,BP	X
Arabani et al.	2012	X	✓	✓	✓	MILP	Makespan, lateness	✓	X	GA,PSO, DE	X
Liao et al.	2012						Makespan	✓	X	DE	X
Joo & Kim	2013	✓	X	✓	✓	MILP	Makespan	✓	X	GA,SEA	X

Kuo	2013	X	X	✓	✓		Makespan	✓	X	SA,VNS	X
Mousavi & Tavakkoli-Moghaddam	2013	X	✓	X	X	MIP	Cost	✓	X	SA,TS	X
Santos et al.	2013	X	✓	X	X	IP	Cost	X	✓	BP	X
Agustina et al.	2014	✓	✓	✓	✓	MILP	Cost	X	X		X
Moghadam et al.	2014	X	✓	✓	X	MIP	Cost	✓	X	SA,ACO	X
Mousavi et al.	2014	X	✓	✓	✓	MILP	Cost	X	✓		✓
Ahmadizar et al.	2015	X	✓	X	✓	MILP	Cost	✓	X	GA	X
Kucukoglu & Ozturk	2015	X	✓	X	X	MILP	Cost	✓	X	SA,TS	X
Mohtashami et al.	2015	X	✓	✓	X	MILP	Makespan, cost, trips	✓	X	GA,PSO	X
Mohtashami	2015	X	X	✓	✓		Min. makespan	✓	X	GA	X
Mokhtarinejad et al.	2015	X	✓	✓	X	MILP	Cost, waiting time	✓	X	GA	X
Kheirkhah & Rezaei	2016	X	✓	X	X	MILP	Cost	X	X		X
Kucukoglu & Ozturk	2016	✓	✓	✓	X	MILP	Cost	✓	X	GA	X
Yin & Chuang	2016	X	✓	X	X	IP	Cost	✓	X	ABC	X
Yu et al.	2016	X	✓	X	X	MILP	Cost	✓	X	SA	X
Grangier et al.	2017	X	✓	✓	X		Cost	✓	X	LNS	X
Mousavi & Vahdani	2017	X	✓	✓	✓	MILP	Cost	✓	X	ICA	✓
Rezaei & Kheirkhah	2017	X	✓	X	X	MILP	Sustainability	X	X		X
Wisittipanich & Hengmeechai	2017	✓	X	✓	✓	MIP	Makespan	✓	X	PSO	X
Abad et al.	2018	X	✓	✓	✓	MILP	Cost, fuel	✓	X	GA,PSO	X
Rezaei & Kheirkhah	2018	X	✓	X	X	MILP	Sustainability	✓	X	COA	X
Proposed method		✓	X	✓	✓	MILP	Min. costs	✓	X	GA	✓

The table shows that most of the research on operations scheduling has focused on minimizing the makespan of cross-docking tasks. Nevertheless, minimizing the makespan may not necessarily lead to increased customer service levels. Makespan-driven objective functions prioritize vehicles intending to minimize the time for unloading and loading operations, regardless of the earliness or tardiness of deliveries. Hence, transportation aspects should be included in the objective function in order to meet the customers' expected time windows (Agustina et al. 2014). This is of particular importance in FSCS, where unmet delivery time windows can affect the product quality and result in losses. However, most of the research in the literature integrates operations scheduling with vehicle routing to optimize transportation costs without considering violations of the time windows. Furthermore, the solution method proposed in this chapter, a stochastic metaheuristic genetic algorithm for cross-docking implementing a two-stage scenarios tree, has never been implemented before. The scenario tree represents the probability distribution of the uncertain parameters like the vehicle arrival time.

The innovative methods proposed in this chapter aim to fill this gap in the literature by providing a stochastic mixed-integer model and a stochastic genetic algorithm with scenario tree (SGA-ST) to minimize the costs resulting from the violation of customer time windows, thereby enforcing an increase in the service level. This decision-support model integrates dock assignments, operations (i.e., unloading, handling, and loading), temporary storage management, and minimization of delays in the deliveries while considering the uncertainty of the vehicle arrival times.

6.3 Problem formulation

Consider a pallet delivery company with a cross-docking hub for collecting pallet loads, consolidating, and delivering them to a set of clients, C. Both the supplier and the client are companies operating in various industrial sectors. The company handles the physical flows of pallets on behalf of its clients, ensuring their delivery within a predetermined time window. For client $c \in C$, the time window closes at time ctw_c. The company offers a delivery service to the suppliers within a predetermined time interval, starting from the departure of inbound vehicles from the suppliers. The size of the time window depends on the service level agreement between the pallet delivery company and its client. Whenever a delivery exceeds the due time window, a penalty must be paid to the client. As the logistic service is intended for less-than-unit-load pallets, the clients prefer receiving partial deliveries on time rather than full orders delivered late. This yields a penalty cost paid for a pallet unit delivered to client c one time-unit after the due date, denoted by upc_c.

Let IT be the set of inbound vehicles arriving at the cross-dock. Each of the vehicles $i \in IT$ delivers products $p \in P$ with a quantity $iq_{i,p}$. Each incoming vehicle must be assigned to one of the inbound dock doors, ID. Then, the vehicle is unloaded by the workers. Each pallet unit is unloaded in a time interval denoted by ut. Pallets are held in temporary storage in front of the door while waiting for transfer. Pallets are assigned to one of the available departing vehicles, OT. Each vehicle in an outbound dock has a capacity of cap pallet units. The whole supply/distribution process is prompted by a demand for each product $p \in P$ by client $c \in C$, as specified by parameter $dem_{p,c}$. According to the schedule, workers transfer the pallets from the temporary storage area to the outbound area. The mean transfer time between the inbound and outbound areas is equal to trt. Once an outbound vehicle is available at the outbound dock door and workers are also available, each pallet is loaded into the vehicle in time lt.

As soon as the outbound vehicle is loaded, it departs from the cross-docking hub for delivery to the clients. The shipping time to reach client $c \in C$ is tt_c. In order to limit late deliveries, the cross-docker might split a delivery in two. This implies that the available pallets could be loaded into a departing vehicle on time, whilst others from the same order could be shipped with a second vehicle. This second vehicle reaches the cross-docking hub after an urgent call and incurs a further cost, $ucsd_c$, for the extra delivery per each client $c \in C$.

6.3.1 Uncertain vehicles arrival times

Each inbound vehicle has an independent arrival time τ_i expressed by a probability distribution function $f(\tau_i)$ defined on the interval $[\tau_i^{dep} + t_i^{min}, \tau_i^{dep} + t_i^{max}]$ where τ_i^{dep} is the departure time of vehicle i and t_i^{min} and t_i^{max} are two positive numbers representing the minimum and maximum travel time of inbound vehicles at the cross-dock. The distribution of this random variable $\widetilde{\tau_i}$ can be discretized by applying a frequency analysis on the historical travel time along the same route. Each realization of the stochastic variables is expressed by the scenarios $s \in S$, where the base scenario with no late arrivals (i.e., all the inbound vehicles arrive at the expected time) is defined by s_0. By introducing the set of scenarios S, the stochastic arrival time of inbound vehicles τ_i can be denoted by τ_{is}. The alternative scenarios constitute a scenario tree, where each branch of the tree represents a scenario characterized by a probability of its realization p_s. When historical data about arrival time are available, the probability of scenario s is estimated as the relative frequency of the realization of that scenario.

6.3.2 Assumptions

The proposed model and algorithm make the following assumptions:

- The temporary storage capacity inside the hub is unlimited, as products typically flow quite fast through cross-docking locations.
- Both the vehicles and the dock door are dedicated to inbound or outbound operations only (i.e., there are neither compound vehicles nor bivalent doors).
- Cross-dock yard space for vehicles is unlimited.
- There are unlimited outbound vehicles available for secondary deliveries.
- Once operators start serving a vehicle, all of the pallets must be unloaded/loaded before the next vehicle can be served at the same dock door (no preemption is allowed).
- There is no temporary storage available at the cross-dock at the starting time.

6.3.3 Estimation of outbound travel time

In order to decrease the complexity of the defined problem, all of the clients served by a single vehicle are considered to be a single node cumulating their individual demands as follows:

$$dem_{p,c} = \sum_{i \in I_c} dem_{p,i}, \text{ where } I_c \subseteq C. \tag{6.1}$$

This prompts implementing the vehicle routing separately to estimate the total travel time and evaluate the violation of time windows. Good approximations can be obtained with simplified vehicle routing models and quasi-optimal methods, as showcased by Figliozzi (2008). Figliozzi demonstrated that the following approximation of the VRP for a set C of the clients leads to good results with a limited number of parameters, thus providing a simple and easily interpreted equation:

$$VRP(C) \approx k_1 \frac{n-m}{n} \sqrt{An} + 2\bar{r}m \tag{6.2}$$

Where:

- k_l is a parameter estimated by linear regression;
- m is the number of routes;
- n is the number of clients (belonging to set C) to be visited;
- A is the area where the n clients are distributed;
- $\bar{r}$ is the average distance between the clients and the storage node.

The allocation of clients to vehicles can be done with the cluster-first route-second method introduced in section 5.5, further simplifying the VRP problem. In such a case, equation (6.2) can be applied to each cluster, where m can be set to 1, and n is the number of clients associated with the cluster by the chosen clustering algorithm. According to Figliozzi (2008) the value of k_l varies with the spatial distribution of clients between 0.62 and 0.9. In particular, it is highest for randomly distributed clients and lowest for clustered clients. Therefore, in this dissertation, k_l is approximated by the following equation:

$$k_l = 0.62 + (0.9 - 0.62)C_r \tag{6.3}$$

C_r is the clustered ratio: $C_r = \frac{\sum_{n,m \in C} dist_{nm}/|C|}{\sum_{n \in C} dist_{dn}}$ where C is the set of client, $dist_{nm}$ is the distance between clients n and m and $dist_{dn}$ is the distance between client n and the storage node d.

Finally, the estimation of the area A is conducted by ordering nodes counterclockwise with respect to the origin (i.e., the storage node) of a system of Cartesian axis and by summing the areas given by the triangles made of each couple of subsequent nodes and the depot until all these areas are cumulated.

The approximation of the vehicle routing time leads to several simplifications of the model:

- The scheduling model does not take into account the vehicle routing for each of the outbound vehicles.
- The number of clients $c \in C$ is a subset of the initial set as it contains a group of delivery points served by the same outbound vehicle; this significantly reduces the size of the instance.
- Each outbound vehicle serves a cluster of clients assigned to it by the vehicle routing approximation, denoted by c.

Each vehicle must deliver its products within a single time window.

6.3.4 Two-stage stochastic model

This subsection introduces the variables of the proposed model and illustrates the objective function and constraints characterizing the two-stage stochastic formulation.

Figure 68 shows an overview of the main features of the proposed model. Specifically, variables are defined in agreement with the decisional flow diagram illustrated in the figure. The constraints ensure that the decisional precedence graph is respected and define the relationships among the variables (e.g., an inbound vehicle must be assigned to a dock door before the unloading operation can begin).

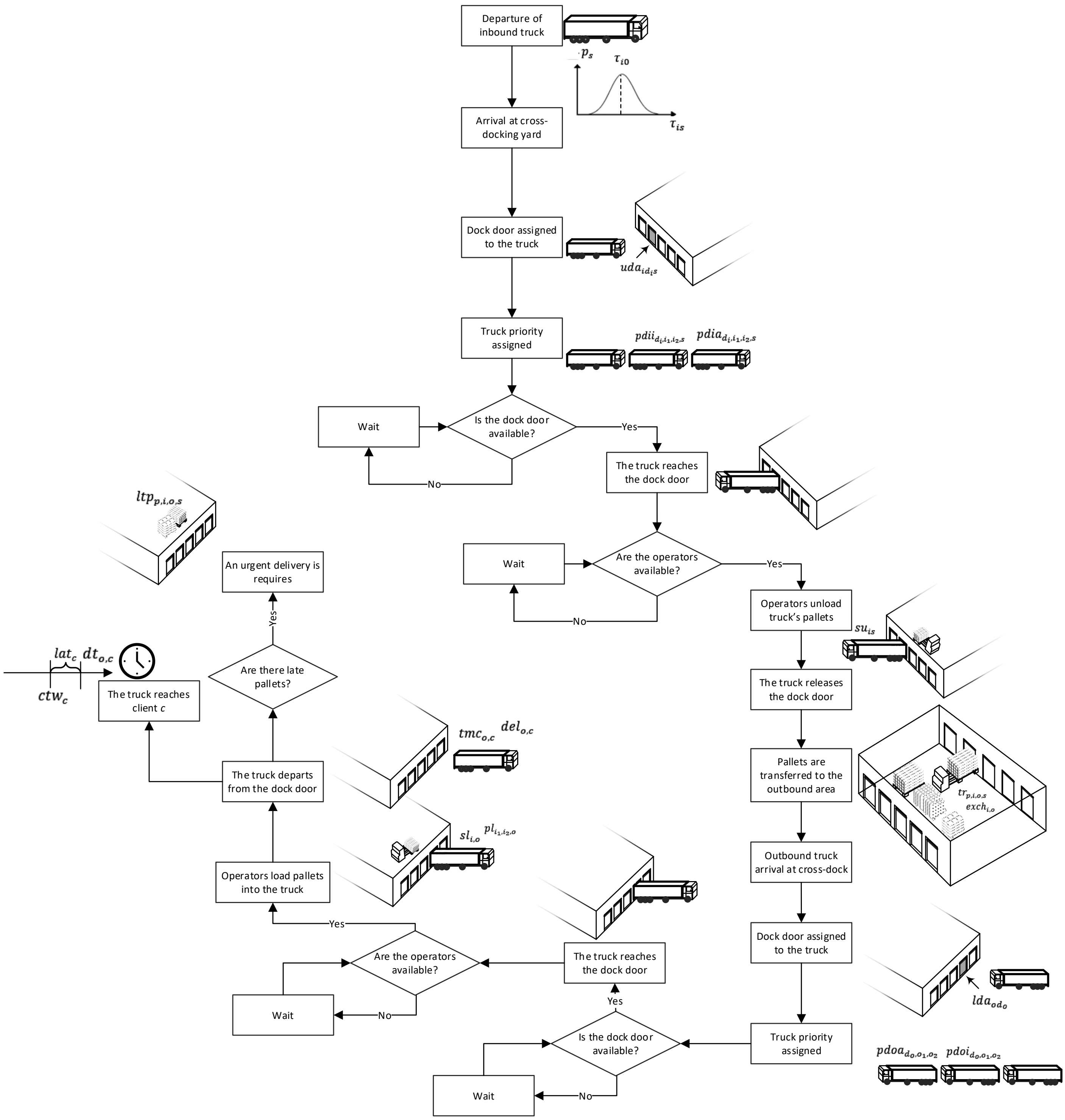


Figure 68. Decisions supported by the proposed stochastic model.

Decision variables:

lat_c absolute lateness value of the load delivered to customer c

$dt_{o,c}$ delivery time of outbound vehicle o to client c; $dt_{o,c} = 0$ if outbound vehicle o does not serve client c

$del_{o,c}$ = 1 if outbound vehicle o serves client c (0, otherwise)

su_{is} starting time of the unloading process of inbound vehicle i in scenario s

$pl_{i_1,i_2,o}$ = 1 if the products from inbound vehicle i_1 are loaded into outbound vehicle o before products from inbound vehicle i_2 (0, otherwise)

$sl_{i,o}$ starting time of the loading process for products coming from inbound vehicle i into outbound vehicle o

$tr_{p,i,o,s}$ number of pallets of product p transferred from inbound vehicle i to outbound vehicle o in scenario s

$ltp_{c,p,i,o,s}$ number of pallets of product p from inbound vehicle i that should have been carried by outbound vehicle o to customer c but arrived late and must be delivered with a second vehicle

$exch_{i,o}$ = 1 if inbound vehicle i transfers products to outbound vehicle o (0, otherwise)

uda_{id_is} = 1 if inbound vehicle i is assigned to inbound dock door d_i in scenario s (0, otherwise)

lda_{od_o} = 1 if outbound vehicle o is assigned to outbound dock door d_o (0, otherwise)

$pdii_{d_i,i_1,i_2,s}$ = 1 if inbound vehicle i_1 immediately precedes inbound vehicle i_2 at dock door d_i in scenario s (0, otherwise)

$pdia_{d_i,i_1,i_2,s}$ = 1 if inbound vehicle i_1 precedes inbound vehicle i_2 at dock door d_i in scenario s (0, otherwise)

$pdoi_{d_o,o_1,o_2}$ = 1 if outbound vehicle o_1 immediately precedes outbound vehicle o_2 at dock door d_o (0, otherwise)

$pdoa_{d_o,o_1,o_2}$ = 1 if outbound vehicle o_1 precedes outbound vehicle o_2 at dock door d_o (0, otherwise)

$tmc_{o,c}$ departure time of outbound vehicle o from the cross-dock traveling to client c; $tmc_{o,c}$ = 0 if outbound vehicle o does not serve client c

Objective function:

The objective of the model is to minimize the penalty costs incurred by violating the time windows. These costs are split into the penalties for late delivery (i.e., the first vehicle) or late extra-delivery (i.e., the second vehicle). All of the cross-docking operations are scheduled and prioritized according to this goal, which results in maximizing the customer service level. As the model does not distinguish among different products, the management of perishable products, whose value is highly sensitive to storage and delivery time, is incorporated as a function of the service level agreement signed between the company and a client.

The proposed objective function is expressed as follows:

$$\min \sum_{c\in C}\sum_{p\in P} lat_c upc_c dem_{p,c} + \sum_{s\in S}\sum_{c\in C}\sum_{i\in IT}\sum_{p\in P} p_s ltp_{c,p,i,o,s} ucsd_c. \qquad (6.4)$$

The first term in Eq. (6.4) aims to minimize the total costs for earliness and tardiness for the vehicles responsible for pallet deliveries. This cost is avoided when the vehicle delivers the load within the due time window. Whenever a vehicle is early or late, the cross-docker pays a unit cost per pallet and per time unit.

The costs of extra deliveries are not time-dependent, as urgent vehicle calls are significantly more expensive than the penalties paid to clients.

Constraints:

$$lat_c \geq \sum_{o\in OT} dt_{oc} - ctw_c \qquad \forall\, c \in C \qquad (6.5)$$

$$\sum_{o\in OT} del_{oc} \geq 1 \qquad \forall\, c \in C \qquad (6.6)$$

$$\sum_{c\in C} del_{o,c} = 1 \qquad \forall\, o \in OT \qquad (6.7)$$

$$dt_{o,c} \leq M \cdot del_{o,c} \qquad \forall\, o \in OT, c \in C \qquad (6.8)$$

$$tmc_{o,c} \leq M \cdot del_{o,c} \qquad \forall\, o \in OT, c \in C \qquad (6.9)$$

$$\left(tmc_{o,c} + del_{o,c} \cdot tt_c\right) = dt_{o,c} \qquad \forall\, o \in OT, c \in C \qquad (6.10)$$

$$\sum_{s\in S}\sum_{i\in IT}\left(tr_{p,i,o,s} + ltp_{c,p,i,o,s}\right) \geq \sum_{c\in C} dem_{p,c} \cdot del_{o,c} \qquad \forall\, p \in P,\ o \in OT, s \in S \qquad (6.11)$$

$$\begin{cases} tr_{p,i,o,s} \leq iq_{i,p} \\ \qquad if\ sl_{i,o} \geq su_{i,s} + \sum_{p\in P} iq_{i,p}(ut + trt) - M\left(1 - exch_{i,o}\right) \\ tr_{p,i,o,s} = 0 \\ \qquad otherwise \end{cases} \qquad \forall\, p \in P, i \in I, s \in S \qquad (6.12)$$

$$\sum_{p\in P} tr_{p,i,o,s} \leq M \cdot exch_{i,o} \qquad \forall\, i \in IT, o \in OT, s \in S \qquad (6.13)$$

$$\sum_{o\in OT}\left(tr_{p,i,o,s} + \sum_{c\in C} ltp_{c,p,i,o,s}\right) \leq iq_{i,p} \qquad \forall\, p \in P, i \in I, s \in S \qquad (6.14)$$

$$tmc_{o,c} \geq sl_{i,o} + \sum_{p\in P} lt_{i,o} \cdot tr_{p,i,o,1} - M\left(1 - exch_{i,o}\right) \qquad \forall\, o \in OT, c \in C, i \in IT \qquad (6.15)$$

$$sl_{i,o} \geq su_{i,1} + \sum_{p\in P} iq_{i,p} \cdot (ut + trt) - M\left(1 - exch_{i,o}\right) \qquad \forall\, i \in IT, o \in OT \qquad (6.16)$$

$$su_{i,s} \geq \tau_{is} \qquad \forall\, i \in IT, s \in S \qquad (6.17)$$

$$\sum_{i_1\in IT, i_1} pl_{i_1,i_2,o} = exch_{i_2,o} \qquad \forall\, i_2 \in IT, o \in OT \qquad (6.18)$$

$$\sum_{i_1\in IT} pl_{i_2,i_1,o} = exch_{i_2,o} \qquad \forall\, i_2 \in IT, o \in OT \qquad (6.19)$$

$$\sum_{i\in IT} pl_{0,i,o} = 1 \qquad \forall\, o \in OT \qquad (6.20)$$

$$\sum_{i\in IT} pl_{i,H,o} = 1 \qquad \forall\, o \in OT \qquad (6.21)$$

$$sl_{i,o} \geq sl_{i_2,o_2} + \sum_{p \in P} lt \cdot tr_{p,i_2,o_2,s_0} - M\left(1 - \sum_{d \in OD} pdoi_{d,o_2,o}\right) \qquad \forall\, i, i_2 \in IT, o, o_2 \in OT \qquad (6.22)$$

$$sl_{i,o} \geq sl_{i1,o} + \sum_{p \in P} lt \cdot tr_{p,i_1,o,s_0} - M\left(1 - pl_{i_1,i,o}\right) \qquad \forall\, i, i_1 \in IT, o \in OT \qquad (6.23)$$

$$su_{i,s} \geq su_{i_{1,s}} + \sum_{p \in P} ut \cdot iq_{i_1,p} - M\left(1 - \sum_{d \in ID} pdii_{d,i_1,i,s}\right) \qquad \forall\, i, i_1 \in IT, s \in S \qquad (6.24)$$

$$\sum_{d \in ID} uda_{d,i,s} = 1 \qquad \forall\, i \in IT, s \in S \qquad (6.25)$$

$$\sum_{d \in OD} lda_{d,o} = 1 \qquad \forall\, o \in OT \qquad (6.26)$$

$$uda_{0,d,s} = 1 \qquad \forall\, d \in ID, s \in S \qquad (6.27)$$

$$uda_{H,d,s} = 1 \qquad \forall\, d \in ID, s \in S \qquad (6.28)$$

$$lda_{0,d} = 1 \qquad \forall\, d \in OD \qquad (6.29)$$

$$lda_{H,d} = 1 \qquad \forall\, d \in OD \qquad (6.30)$$

$$\sum_{i_1 \in IT:\, i_1 < H} pdii_{d,i_1,i,s} = uda_{i,d,s} \geq pdia_{d,i,i_2,s} \qquad \forall\, i, i_2 \in IT, d \in ID, s \in S \qquad (6.31)$$

$$\sum_{o_1 \in OT:\, o_1 < H} pdoi_{d,o_1,o} = lda_{o,d} \geq pdoa_{d,o,o_2} \qquad \forall\, o, o_2 \in OT, d \in OD \qquad (6.32)$$

$$\sum_{i_1 \in IT:\, i_1 > 0} pdii_{d,i,i_1,s} = uda_{i,d,s} \geq pdia_{d,i_2,i,s} \qquad \forall\, i, i_2 \in IT, d \in ID, s \in S \qquad (6.33)$$

$$\sum_{o_1 \in OT:\, o_1 > 0} pdoi_{d,o,o_1} = lda_{o,d} \geq pdoa_{d,o_2,o} \qquad \forall\, o, o_2 \in OT, d \in OD \qquad (6.34)$$

$$pdii_{d,i_1,i_2,s} \leq pdia_{d,i_1,i_2,s} \leq 1 - pdia_{d,i_2,i_1,s} \qquad \forall\, i_1, i_2 \in IT, d \in ID, s \in S \qquad (6.35)$$

$$pdoi_{d,o_1,o_2} \leq pdoa_{d,o_1,o_2} \leq 1 - pdoa_{d,o_2,o_1} \qquad \forall\, o_1, o_2 \in OT, d \in OD \qquad (6.36)$$

$$pdia_{d,0,i,s} \leq uda_{i,d,s} \geq pdia_{d,i,H,s} \qquad \forall\, i \in IT, d \in ID, s \in S \qquad (6.37)$$

$$pdoa_{d,0,o} \leq lda_{o,d} \geq pdoa_{d,o,H} \qquad \forall\, o \in OT, d \in OD \qquad (6.38)$$

$$pdia_{d,i,0,s} = pdia_{d,H,i,s} = 0 \qquad \forall\, i \in IT, d \in ID, s \in S \qquad (6.39)$$

$$pdoa_{d,o,0} = pdoa_{d,H,o} = 0 \qquad \forall\, o \in OT, d \in OD \qquad (6.40)$$

$$pdia_{d,i_2 i_3,s} \geq pdii_{d,i_1 i_2,s} + pdia_{d,i_1 i_3,s} - 1 \qquad \forall\, d \in \mathrm{I}D, i_1, i_2, i_3 \in \mathrm{IT}, s \in S \qquad (6.41)$$

$$pdoa_{d,o_2 o_3} \geq pdoi_{d,o_1 o_2} + pdoa_{d,o_1 o_3} - 1 \qquad \forall\, d \in \mathrm{O}D, o_1, o_2, o_3 \in \mathrm{OT} \qquad (6.42)$$

$$del_{o,c}, pl_{i_1,i_2,o}, exch_{i,o}, uda_{i,d_i,s}, lda_{o,d_o}, pdii_{d_i,i_1,i_2,s}, pdia_{d_i,i_1,i_2,s}, pdoi_{d_o,o_1,o_2}, pdoa_{d_o,o_1,o_2} \in \{0,1\}, \forall\, c \in C, o, o_1, o_2 \in OT, \forall\, i, i_1, i_2 \in IT, d_i \in ID, d_o \in OD, s \in S \qquad (6.43)$$

$$lat_c, dt_{o,c}, su_{i,s}, sl_{i,o}, tmc_{o,c} \in \mathbb{R}^+, \forall\, c \in C, o \in OT, \forall\, i \in IT, s \in S \qquad (6.44)$$

$$tr_{p,i,o,s}, ltp_{c,p,i,o,s} \in \mathbb{Z}^+, \forall\, c \in C, p \in P, \forall\, i \in IT, o \in OT, s \in S \qquad (6.45)$$

Constraints 6.5 define the absolute lateness value. Constraints 6.6, 6.7, and 6.8 ensure that each client is served by one of the scheduled outbound vehicles. The delivery time of each vehicle is determined based on the departure time from the cross-dock plus the travel time required for the delivery tour (Constraints 6.9 and 6.10). The demand of each client must be fulfilled, either with the scheduled vehicle or through an extra delivery (Constraints 6.11 and 6.14). Constraints 6.12 and 6.13 require that each outbound vehicle must distribute only loads available at the hub.

The following group of inequalities defines the timing of the cross-dock operations. An outbound vehicle can depart from the hub only after the loading activities have been carried out by workers (Constraint 6.15). Loading processes must begin after unloading and load handling to the selected outbound door have been completed (Constraint 6.16). Furthermore, inbound vehicles only trigger unloading activities after arriving at the cross-dock (Constraint 6.17).

Constraints 6.18 and 6.19 define priorities in the loading operations, imposing that products coming from an inbound vehicle must be loaded into an outbound vehicle in agreement with their precedence order. Each vehicle is preceded by the dummy vehicle *0* (Constraint 6.20) and succeeded by the dummy vehicle H (Constraint 6.21).

Inequalities (6.22) and (6.23) define the minimum time to begin loading operations for an outbound vehicle. Loading operations can begin when all of the pallets of the previous vehicle devoted to that door have been loaded (Constraint 6.22). Priorities are defined by the objective function and considered, when feasible, in agreement with the first-in-first-out policy (Constraint 6.23). The minimum loading times are estimated based on the expected arrival times of inbound vehicles given by the base scenario s_0 (i.e., no late arrivals).

For inbound vehicles, the unloading process can begin once the previous vehicle allocated to the same door has been unloaded (Constraint 6.24). The unloading operations are driven by the current arrival time of the inbound vehicle so that the unloading time is determined for each possible value of the stochastic variable (i.e., the vehicle arrival time). Conversely, for outbound vehicles, the cross-docker decides when to start loading operations for each vehicle.

Each inbound and outbound vehicle is assigned to a corresponding dock door (Constraints 6.25 and 6.26), except for dummy vehicles *0* and H, which are assigned to all of the dock doors at the same time (Constraints 6.27–6.30). The constraints (6.31)–(6.42) define the precedence order of inbound and outbound vehicles at the corresponding dock doors, prioritizing the operations at the hub. The remaining constraints define the domain of the decision variables.

All of the inbound operations are dependent on scenario s. Outbound operations need to be scheduled in advance in order to guarantee the availability of the vehicles. This requires such operations to be scheduled in advance without knowledge of the exact arrival times of inbound vehicles.

The proposed formulation is a two-stage stochastic model with complete recourse so that the feasibility of the solution at the second stage is always guaranteed. This assumption is not excessive, owing to the broad availability of extra-paid delivery vehicles in the transport market. If all of the carriers are unavailable at a given time, they will reach the cross-docking hub as soon as they complete their previous missions.

6.4 Stochastic genetic algorithm with scenario tree to solve the cross-docking problem

In this section, a stochastic genetic algorithm is provided to provide a quasi-optimal solution for complex issues with hundreds of vehicles. Genetic algorithms are meta-heuristics inspired by evolutionary principles (Ahmadizar et al., 2015). As in genetics, populations of chromosomes evolve progressively through generations. A set of genes composes each chromosome. The first iteration generates chromosomes as a sequence of randomly disposed genes. At each iteration, genes are rearranged according to some operations (i.e., selection, cross over, mutation). The resulting chromosomes that better fit the ecosystem further proceed to the next generations, while others are discarded. The evolution proceeds to the next generations until a termination criterion is met. In the following subsections, these principles are applied to the cross-docking problem.

The proposed algorithm steps are illustrated in figure 69 and provide a solution to the same problem illustrated in the two-stage stochastic models. These procedures, described in detail in the next subsections, are tailored to the model introduced in the previous sections as they include all the parameters, the variables, the objective function, and the logical constraints of the model.

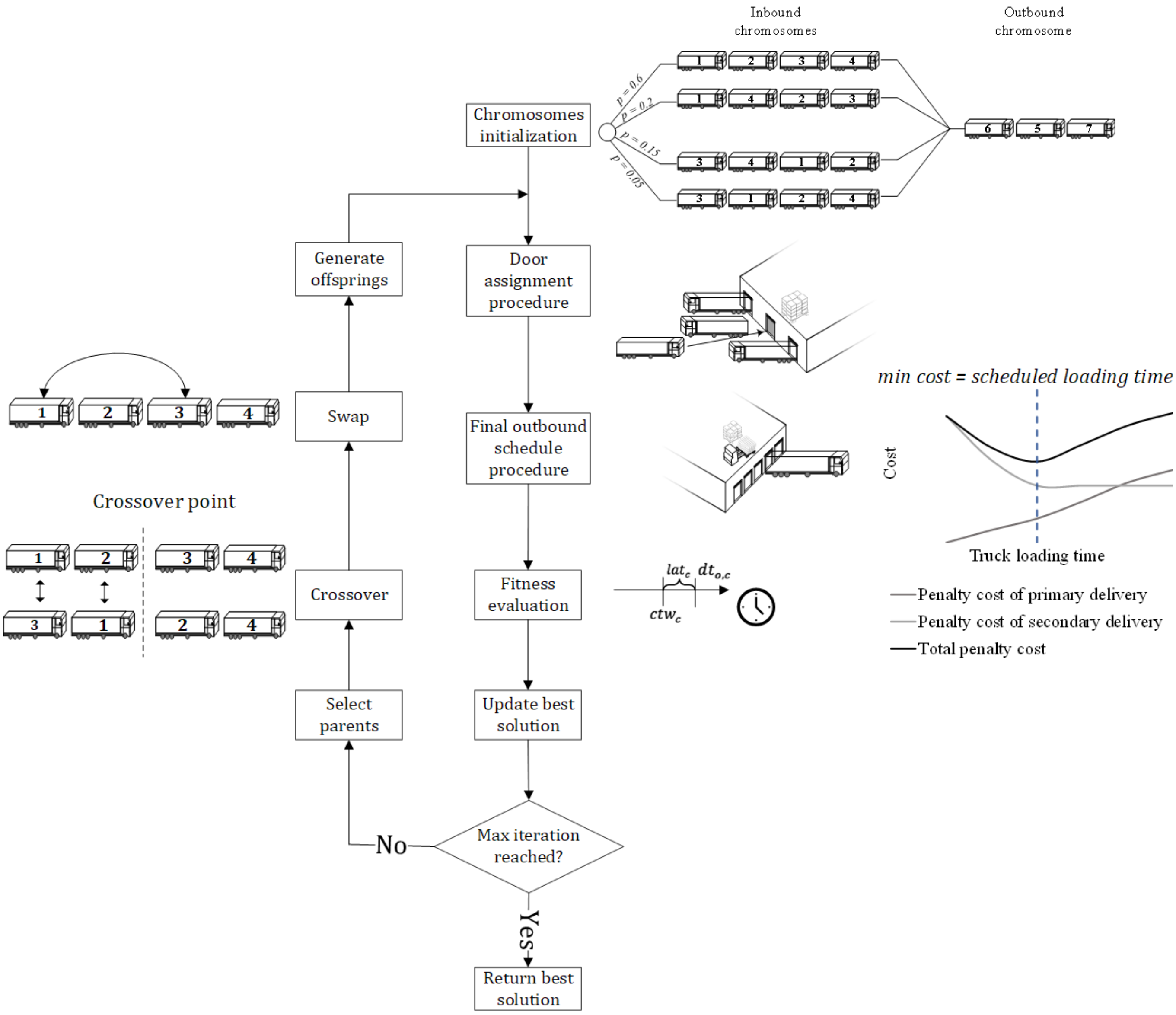


Figure 69. Steps of the genetic algorithm.

6.4.1 Chromosome representation

The definition of chromosomes is essential to model our problem as a genetic algorithm. Each chromosome is represented as an array of symbols, known as genes. Each gene represents an entity from the real problem that must be encoded into this representation. The proposed algorithm encodes a random sequence of vehicles into each chromosome. Each gene represents a vehicle. As there are no compound vehicles and each vehicle can be either devoted to inbound or outbound, two types of chromosomes are introduced: inbound chromosomes and outbound chromosomes.

Inbound chromosomes have a length equal to the number of inbound vehicles. The sequence of vehicles mapped into such chromosomes represents the prioritization of the unloading operations for inbound vehicles, which is then converted in the final schedule according to the procedure illustrated in subsection 6.4.3. Similarly, outbound vehicles have a length equal to the number of outbound vehicles.

The random sequence of vehicles mapped into the chromosome represents the prioritization of loading operations at outbound dock doors, then converted into the schedule of loading operations according to the procedure of subsection 6.4.3.

Furthermore, in order to encode a scenario tree in the proposed algorithm, each solution consists of a number of inbound chromosomes equal to the number of scenarios. As each scenario represents different vehicles' arrival times, they require different prioritization of vehicles and lead to different optimal schedules. For this reason, the algorithm proposes a schedule for each possible vehicle arrival time, similarly to what the stochastic model does by providing an optimal unloading time for each inbound vehicle and each scenario (i.e., variables su_{is}).

Conversely, outbound vehicles must be necessarily planned earlier to avoid delays and expensive urgent calls for unplanned deliveries. Therefore, the schedule of outbound vehicles must be decided ex-ante (first-stage decision), and each solution of the genetic algorithm only includes one outbound chromosome.

As the chromosomes represent a prioritization of vehicles and there are separate chromosomes for inbound and outbound vehicles, all the possible solutions are feasible without requiring further procedures to guarantee the feasibility (e.g., avoiding the loading operations of unavailable products). Figure 69 illustrates the chromosomes representation with one outbound chromosome and a number of inbound chromosomes corresponding to the number of scenarios in the scenario tree.

6.4.2 Fitness function

A fitness function determines the most promising chromosomes that will evolve to the next generation. As chromosomes represent feasible solutions for the cross-docking scheduling problem, the value of the objective function determines the formulation of the fitness function.

This algorithm aims to minimize the penalty costs charged to the cross-docker when a delivery violates the time window. The objective function of the proposed algorithm is the same used in the stochastic model (Eq. 6.4). Therefore, the evaluation of equation (6.4) is used to assess how well the chromosomes fit the environment and should be selected as parents evolving in the next generation.

6.4.3 Decision rules

The algorithm randomly generates the array representing a chromosome. Based on this prioritization, a set of rules is applied to quantify the decision variables and calculate the fitness value corresponding to the solution.

Door assignment procedure

The procedure assigns the vehicle encoded in the first genes (i.e., with the highest priority) to the first available dock door. When there are no empty doors, the algorithm assigns the vehicle to the first dock released by the previously assigned vehicles.

As the arrival time is uncertain, the door assignment procedure described in the following pseudo-code is repeated for each scenario s thus repeating the door assignment procedures for $|S|$ times and providing the same amount of inbound schedules.

Two procedures determine the loading sequence of pallets into outbound vehicles (door assignment for outbound vehicles) and determine the departure time of vehicles along with the estimated number of pallets to be delivered with an urgent delivery (final outbound schedule).

Door assignment algorithm for inbound vehicles i

$rt := 0$
$door := 1$
for each inbound dock door d
  if *there are no vehicles assigned to d*
    $door := d$
    $rt := 0$
  else
    Pick the last vehicle i_0 assigned to door d
    $time := su_{i_0,s} + \sum_{p \in P} ut \cdot iq_{i_0,p}$
    if $time < rt$
      $door := d$
      $rt := time$
    end
  end
end
Add vehicle i to the list of vehicles assigned to *door*
$uda_{i,door,s} := 1$
$su_{i,s} := rt$

Door assignment algorithm for outbound vehicles o

rt := 0
door := 1
for each outbound dock door d
  if *there are no vehicles assigned to d*
    door := *d*
    rt := 0
  else
    Pick the last vehicle o_0 assigned to door *d*
    time := $\sum_{i \in I} sl_{i,o,s} + \sum_{p \in P} \sum_{i \in I} lt \cdot tr_{p,i,o_0,s}$
    if *time* < *rt*
      rt := *time*
      door := *d*
    end
  end
end
Pick the client *c* assigned to vehicle *o*
for each product *p*
  if $dem_{p,c} > 0$
    for each inbound vehicle *i*
      if $tr_{p,i,o,s} > 0$
        availTime := $su_{i_0 s} + \sum_{p \in P} ut \cdot iq_{i_0,p} + trt \cdot tr_{p,i,o,s}$
        $sl_{i,o,s}$:= *availTime*
        if *availTime* > *rt*
          rt := *availTime*
        end
      end
    end
  end
end
$lda_{i,door}$:= 1

Final outbound schedule

The door assignment procedure determines a schedule for the inbound operations per each realization of the stochastic parameter τ_{is}. However, in order to have all outbound vehicles available at the right time and dock door, their schedule must be determined before having complete information on inbound flows. Specifically, the final outbound schedule procedure determines the optimal schedule of outbound vehicles based on the value of the fitness function described in Equation (6.4).

The proposed procedure evaluates the expected penalty cost resulting from an incorrect schedule based on the probability of each scenario p_s and on the number of late pallets $ltp_{c,p,i,o,s}$ that will require an urgent delivery.

Final outbound schedule for outbound vehicle o serving client c

$optScen$:= 0
$optCost$:= ∞
for each scenario s_1
  $latePal$:= 0
  $cost$:= 0
  for each scenario s_2
    for each inbound vehicle i
      if $\sum_{p\in P} tr_{p,i,o,s_2} > 0$
        if $su_{i,s_2} + \sum_{p\in P} ut \cdot iq_{i_0,p} + trt \cdot tr_{p,i,o,s_2} > sl_{i,o,s_1}$
          $latePal := \sum_{p\in P} tr_{p,i,o,s_2}$
          $ltp_{c,p,i,o,s_1} := ltp_{c,p,i,o,s_1} + tr_{p,i,o,s_2}$
          $delTime := \sum_{i\in I} sl_{i,o,s_2} + \sum_{p\in P} \sum_{i\in I} lt \cdot tr_{p,i,o,s_2} + tt_c$
          $lat_c := 0$
          if $delTime > ctw_c$
            $lat_c := ctw_c - delTime$
          end
          $cost := cost + upc_c \cdot (\sum_{p\in P} dem_{p,c} - latePal) \cdot lat_c + latePal \cdot ucsd_c \cdot p_{s_2}$
          if $cost < optCost$
            $optCost := cost$
            $optScen := s_2$
          end
        end
      end
    end
  end
end

Parents' selection

The parents' selection procedure is the step connecting two consecutive iterations of genetic algorithms. Chromosomes that best adapt to the environment (i.e., with high fitness value) are more likely to hand their characteristics over to the next generations according to a roulette wheel mechanism (Ahmadizar et al., 2015).

Once the parents have been selected, they undergo some recombination of their genes, creating the offsprings, new individuals with different characteristics (vehicle prioritization) and fitness values. These offsprings form the next generation together with a set of new randomly generated chromosomes, which reduce the risk of getting stuck in a local optimum.

Crossover

The crossover operator rearranges the genes to create two new solutions (Arabani et al., 2011). Firstly, a random number r between 1 and the total number of genes is generated. Then, starting from the first position in the chromosome, each couple of genes of the two parents are exchanged. The exchange procedure continues until position r is reached.

The results are two individuals constituted by a first block of genes from one parent and the remaining ones coming from the other parent, mixing the two genomes. However, the two new solutions could not be feasible as they can have doubled genes (i.e., the same vehicle with two priorities), while other vehicles could be missing.

Consider, for example, the following couple of parents: *1-2-3-4-5* and *5-4-3-2-1*. If the crossover exchanges the genes until the third one, the resulting offspring are *1-2-3-2-1* and *5-4-3-4-5*. So, vehicles *1* and *2* are duplicated while *4* and *5* are missing in the first offspring and vice versa.

In order to form feasible solutions, the duplicated values are removed from the chromosomes and they are replaced by the missing values with a randomly generated order.

Swap

The swap operator performs another random rearrangement of the genes. It is applied locally to a single chromosome and swaps two random genes to form a new solution (Joo and Kim, 2013). As the solutions of the proposed approach separate chromosomes for inbound vehicles and outbound vehicles, the resulting solution exchanges the priorities of two vehicles while ensuring the feasibility of the solutions.

Firstly, two random numbers r_1 and r_2 ranging between 1 and the number of genes are generated. Then, the swap operators move the gene in position r_1 to position r_2 and vice versa.

6.5 Model and algorithm validation

6.5.1 Algorithm lower and upper bounds

In order to assess the quality of the solutions proposed by this algorithm, a gap estimation procedure is carried out. The metaheuristic performs this procedure at the first iteration of the proposed SGA-ST. It consists of two consecutive steps for estimating both a lower bound and an upper bound. The lower bound could not be feasible in practice due to the relaxation of some constraints, while the upper bound estimation always generates a feasible solution.

Lower bound estimation

The lower bound estimation procedure relaxes the constraints (6.22)-(6.24) on dock doors' availability of the stochastic model. Each inbound vehicle can be processed as soon as it reaches the cross-dock, without waiting in a queue based on its priority. The same relaxation applies to outbound dock doors, where vehicles can be immediately loaded without waiting for an available dock door.

The algorithm then calculates the fitness function by applying the procedures described above for any other solution, therefore providing a lower bound as a benchmark for the obtained solutions.

Upper bound estimation

The upper bound estimation procedure generates a feasible solution by applying a prioritization algorithm for inbound and outbound vehicles.

Inbound vehicles are scheduled according to the First In First Out prioritization order. The first vehicle arriving at the cross-dock has the highest priority, and therefore its gene is the first in the chromosome and so on. Once inbound vehicles are scheduled, and the products' availability at the cross-dock has been deduced with the door assignment algorithm, the priority of outbound vehicles is estimated based on the chronological order of arrival of their demanded products. As soon as all the products requested by an outbound vehicle are available, the vehicle's gene is added to the chromosome.

The chromosomes are then evaluated according to the procedure illustrated in the previous sections, and the fitness value of the upper bound is deduced accordingly.

6.5.2 Performances evaluation

Mathematical models to optimize the operations in a cross-dock are notoriously NP-hard. Indeed, these models cannot be solved in a reasonable time when the total number of vehicles goes beyond just ten units (Joo & Kim, 2013). Therefore, the validation of the model and the algorithm and their performance evaluation is tested on small instances. Table 23 presents the input data for the instances, which includes four inbound vehicles, five outbound vehicles, two inbound dock doors, and two outbound dock doors. The scenario tree of this instance includes two scenarios. The first is the base scenario with the probability of 60%, while the other has a probability of 40%. The five clients order a total amount of 70 pallets, which must be received from the suppliers. Both the unloading and loading times for each pallet are 0.2 h. The unloading time includes the time for weighing and checking each pallet. The loading time includes the time for consolidation and labeling. Pallets are transferred from inbound docks to outbound docks in 0.1 h each. Finally, the unit penalty cost for the scheduled deliveries is $upc_c = 0.6$ for each pallet delivered one hour late, and the cost for second deliveries is $ucsd_c = 50$ for each pallet delivered with the second vehicle.

Table 23. Input data for the validation instance.

Inbound data				Outbound data		
Inbound vehicle i	Arrival time τ_{is} [h]	Scenario probability p_s	Inbound quantity iq_{ip} [pallet]	Client	Order quantity dem_{pc} [pallet]	End of time-window ctw_c [h]
1	$\tau_{11} = 11.133$ $\tau_{12} = 11.9$	$p_1 = 0.6$ $p_2 = 0.4$	$iq_{13} = 10$ $iq_{15} = 5$	1	$dem_{11} = 10$	$ctw_1 = 30.8$
2	$\tau_{21} = 11.767$ $\tau_{22} = 13.2$	$p_1 = 0.6$ $p_2 = 0.4$	$iq_{23} = 15$	2	$dem_{22} = 15$	$ctw_2 = 33.92$
3	$\tau_{31} = 13$ $\tau_{32} = 16.2$	$p_1 = 0.6$ $p_2 = 0.4$	$iq_{31} = 10$ $iq_{32} = 15$ $iq_{34} = 10$	3	$dem_{33} = 25$	$ctw_3 = 28.13$
4	$\tau_{41} = 12.783$ $\tau_{42} = 17.5$	$p_1 = 0.6$ $p_2 = 0.4$	$iq_{45} = 5$	4	$dem_{44} = 10$	$ctw_4 = 30.23$
				5	$dem_{55} = 10$	$ctw_5 = 36.83$

Two different instances of the problem have been solved. The first neglects the second scenario and consider that the first one is certain $p_1 = 1$, while the second instance considers the second scenario according to the probability shown in table 23. The stochastic mixed-integer model was implemented in AMPL and solved using the Gurobi solver running on a 2.59 GHz Dual Core PC with 12 GB of RAM. In contrast, the genetic algorithm has been implemented in a custom C# application and solved with the same PC, therefore having the same computing performances.

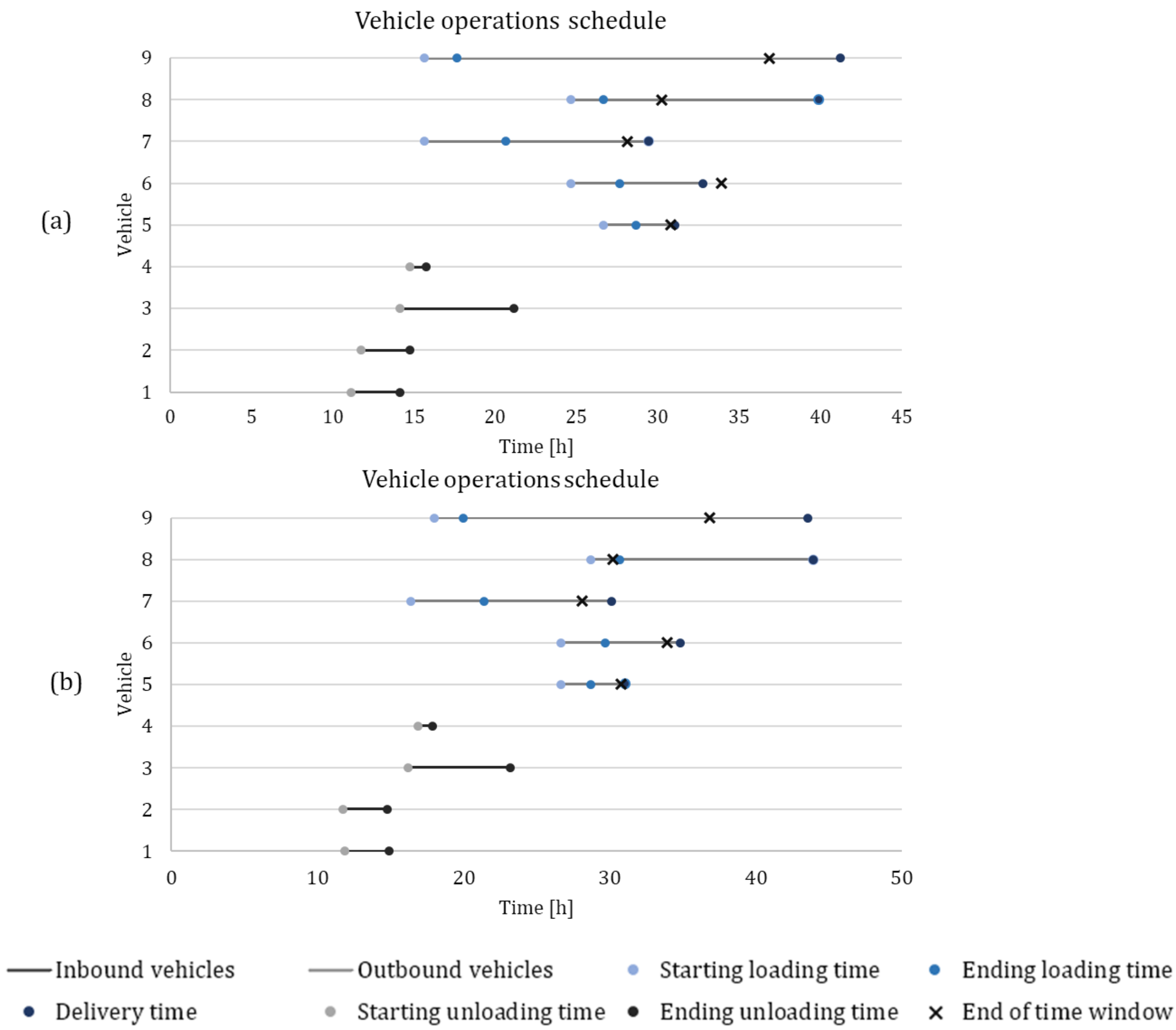


Figure 70. Operation schedule results with (a) one scenario and (b) two scenarios.

The two-stage stochastic model and the genetic algorithm returned the same results for the two instances, which are shown in figure 70 as a series of chronological activities performed at the cross-docking hub. Vehicles 1–4 are the inbound vehicles, while the others are outbound vehicles. The cross-dock processes vehicles in the time interval represented by a continuous line in the figure. The lines on the left of the chart indicate vehicles with higher priority than those on the right. When two vehicles are processed at the same time, they have been assigned to different dock doors. Furthermore, the figure shows the starting and ending times of the unloading activities for each inbound vehicle, and the starting and ending times of the loading activities, and the delivery time for each outbound vehicle. A black cross denotes the ending time of the client's time window. Whenever the delivery time exceeds this ending time, the lateness value is greater than zero.

The results illustrate how the uncertainty of vehicle arrival times affects optimal decisions. The operations of vehicles are preempted or delayed according to the total penalty cost estimated based on the expected arrival time of vehicles. For instance, as inbound vehicles 3 and 4 are the most affected by uncertainties, their operations are delayed in the second instance. As a result, the expected starting time of loading operations for outbound vehicles is delayed accordingly (e.g., outbound vehicle 6, which contains products from vehicle 3).

Two additional instances with a higher number of vehicles were implemented to test the performances of the model and compare them with the results given by the SGA-ST. The comparison between the two methods is shown in table 24. The results highlight that the proposed SGA-ST achieves the optimum very quickly. The table also reports the estimated upper and lower bounds. When the number of vehicles exceeds 20, the optimization model lacks to solve in an acceptable time while the SGA-ST finds its best solution within 12 seconds.

Whenever both the model and the genetic algorithm find a solution, they always coincide in the tested instances.

Table 24. Comparison of the performances of the stochastic model and the stochastic algorithm.

	Inbound data		Outbound data		Scenarios	SMILP solving time [s]	SGA-ST solving time [s]	SMILP optimal solution	SGA-ST best solution	Upper bound	Lower bound
	Vehicles	Doors	Vehicles	Doors							
1	4	2	5	2	1	399	0	104.364	104.364	118.93	90.32
2	4	2	5	2	2	47	0	118.785	118.785	127.76	112.58
3	6	2	8	2	1	140	1	174.32	174.32	196.52	170.12
4	10	2	10	2	1	…	12	…	208.88	309.87	195.48

6.6 The case of a pallet delivery company

The proposed solution method has been applied to a real case study of an Italian pallet delivery company delivering tens of thousands of pallets to about 400 nodes every day from four different logistics hubs. The company provides a delivery service for fast-moving items. Clients request two different services that set delivery time fences, service levels, and penalties. The cross-docker offers a delivery service within 24 hours, known as α service, intended for perishable products and urgent orders. Otherwise, the cheaper β service guarantees delivery within 48 hours. The allowed time interval for the deliveries starts when the order departs from the supplier node.

The proposed case study will focus on the deliveries assigned to one of the company's hubs during a working day. Incoming vehicles can be assigned to 14 dock doors, half devoted to inbound vehicles, and the other half to outbound vehicles. Table 25 summarizes the main input data of the case study. Unloading, loading, and transfer time data are estimated with a frequency analysis conducted on the field. Figure 71 shows the distribution of the expected arrival time of the inbound vehicles. The company delivers several product types, including perishable products. However, the type of products they will handle on a working day is unknown in advance, so different solutions based on products can hardly be applied. Therefore, the company aims to minimize the delays in the delivery to clients to increase the service level and avoid losses for perishable products processed in their cross-docks.

The analysis of historical arrival times of inbound vehicles from each supplier led to identifying 33 different scenarios. Each scenario is characterized by different vehicles' arrival times and probability. Table 25 also shows the cumulative distribution function of the probability of such scenarios.

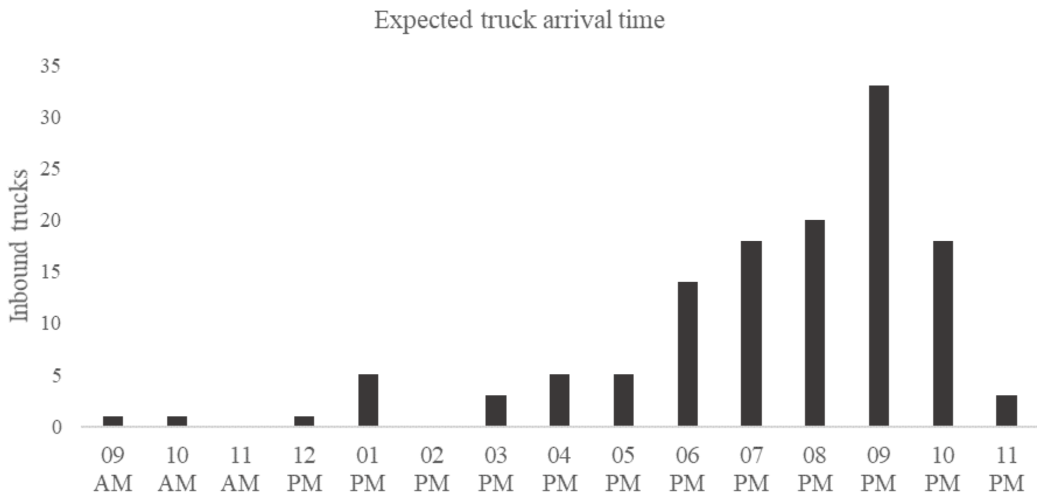
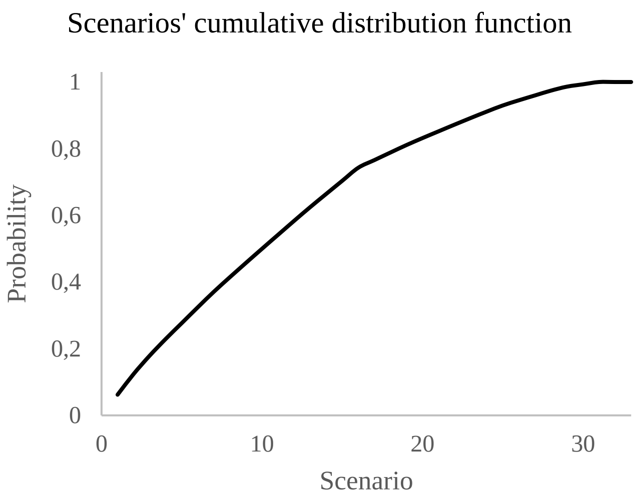


Figure 71. Frequency distribution of expected vehicle arrival time.

Table 25. Input data of the cross-docking problem.

	Value
Inbound vehicles	130
Outbound vehicles	141
α service deliveries	70
β service deliveries	71
Inbound dock doors	7
Outbound dock doors	7
Average demand of pallets	30
ut [s]	55
trt [s]	46
lt [s]	55
upc_c	1
$ucsd_c$	10



The user interface of the software application developed to implement the genetic algorithm allows setting the number of iterations of the algorithm and the size of the chromosomes population. At the first iteration, the software calculates the upper and lower bounds. The interface is then updated at each iteration with the current best solution, the number of late deliveries, the best generation, and the corresponding gap with the lower bound.

In order to solve the illustrated case study, the software generates ten chromosomes at each iteration. As the algorithm requires one random chromosome for outbound vehicles and one chromosome per each scenario for inbound vehicles, each feasible solution is made up of 34 chromosomes. Each inbound chromosome schedules 130 vehicles while outbound chromosomes schedule 141 vehicles. The number of iterations for this case study is set to 1,000. Therefore, the resulting number of chromosomes generated during the simulation is 340,000.

Figure 72 shows the main interface of the developed software application and the results of each iteration of the algorithm in a dot plot. The utilization of the dock doors is then assessed through a sensitivity analysis. Doors utilization in the AS-IS is compared with the results obtained with 12 dock doors (i.e., 6 inbound doors and 6 outbound doors) and 16 dock doors (i.e., 8 inbound doors and 8 outbound doors). These charts clearly show how the dock doors' utilization rate increases and reduces according to the number of dock doors. Furthermore, Table 26 shows how, as most inbound vehicles arrive between 06 PM and 10 PM, doors utilization is maximized in this interval. Few doors increase vehicles’ waiting time and the penalty costs paid by the cross-docker to the clients. This consideration provides support to the estimation of the pay-back period of new investment in infrastructure.

Table 26. Results of the case study and sensitivity analysis on dock doors.

Simulation	Iterations	Solutions generated at each generation	Best fitness value	Number of late deliveries	Upper bound	Lower bound
7+7 dock doors	1000	10	45.78	3	303.91	1.97
6+6 dock doors	1000	10	135.69	5	1043.7	
8+8 dock doors	1000	10	9.96	2	37.6	
AS-IS (7+7 doors)	1000	10	111.76	6	-	-

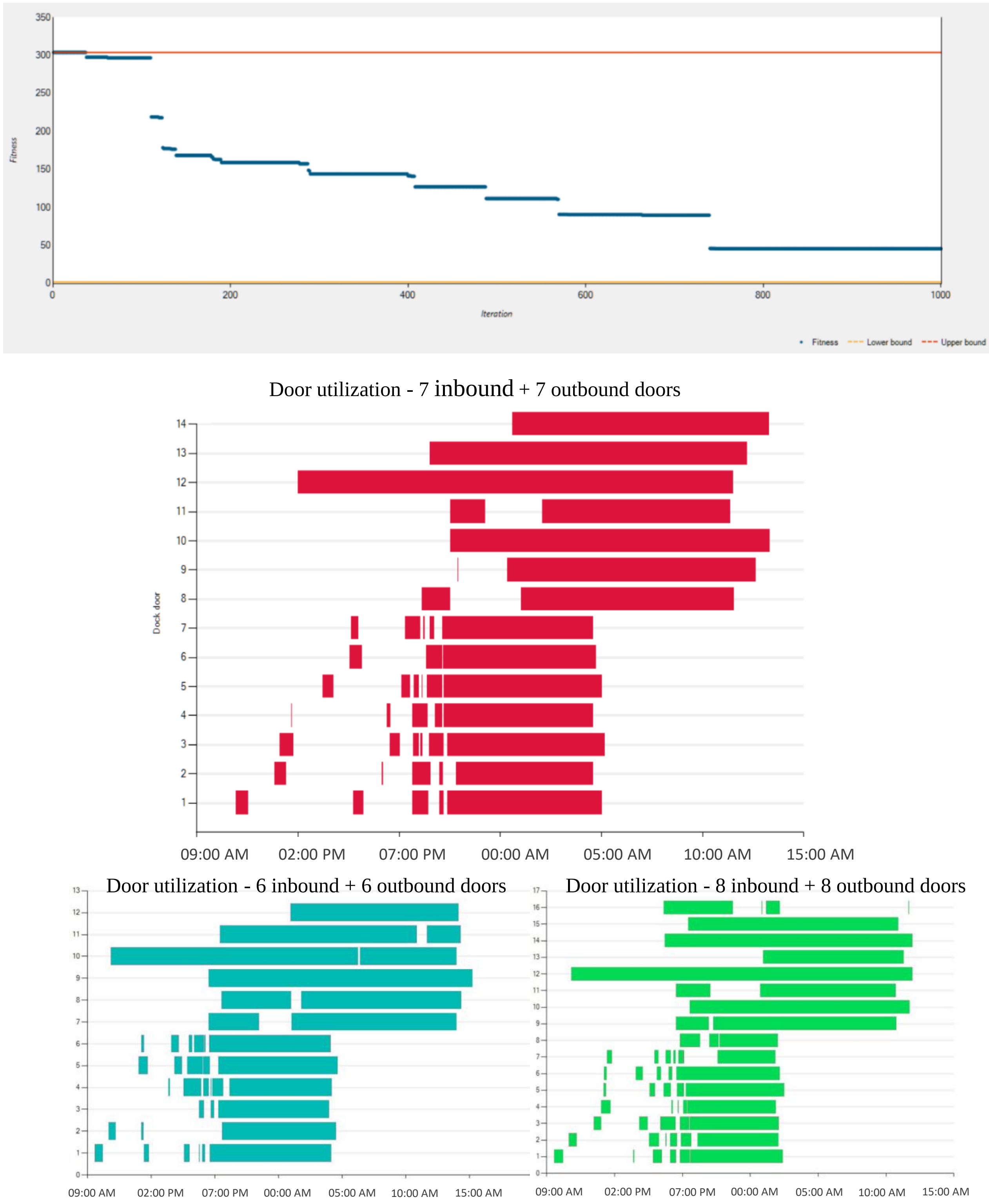


Figure 72. Main interface of the application and results of the case study.

The proposed algorithm scheduled 271 vehicles with an expected penalty costs of 45.78. Only three deliveries are expected to be late. The total lateness is equal to 6.19 hours, which is mainly due to one delivery point that is 23 driving hours far from the cross-dock. The value of the upper bound is equal to 303.91, with 28 late deliveries, while the lower bound is equal to 1.97 with one late delivery.

As shown in Table 26, the lower bound does not change when the dock doors increase. As introduced in the previous section, the lower bound assesses the fitness value when the door availability constraint is relaxed. Therefore, its value is independent of the actual number of docks. The results have been compared with the AS-IS solution, which is characterized by a penalty cost of 111.76, with six late deliveries and the total lateness equal to 7.5 hours, far worse than the solution provided by the proposed method.

As uncertainty significantly affects the schedule of the cross-docking operations, the adoption of deterministic decision-making approaches, quite common in the literature, is discouraged in practice. Indeed, it does not lead to significant savings within an environment characterized by uncertainty. The proposed methods highlighted the benefits of a stochastic approach. The comparison with the deterministic solution is obtained through the expected value of the solution, which approximates the stochastic parameters with their expected values and represents a typical solution currently applied in uncertain environments (Birge & Louveaux, 2011). The optimal solution given by this approximation is equal to 362.52, worse than the upper bound provided by the SGA-ST and even worse than the AS-IS solution. Conversely, the proposed methods significantly improved the performance of the FSCS, reducing the cost to 45.78. This illustrates the Benefit of the Stochastic Solution (BSS). The BSS quantifies the savings (i.e., 316.74) reached when shifting from a deterministic to a stochastic approach.

In order to find another benchmark for the proposed method, the expected value of perfect information (EVPI) is calculated. It represents the further savings the decision-maker would gain in case of complete information availability. The perfect information lies in the actual arrival time of each inbound vehicle before the scheduling. The EVPI was estimated by considering only one scenario with a 100% probability where the vehicles' arrival times have been set to the actual arrival time in the monitored working day. As the PI scenario accounts for a cost of 36.68, the EVPI is equal to 9.1 when compared to 45.78. With respect to these results, having an optimal schedule for every scenario as provided by the two-stage model and algorithm supports the decision-maker for adopting a solution not far from the EVPI, either under uncertainty. This avoids the need for continuously updating the schedule without disturbing the ongoing operations.

The sensitivity analysis summarized in Table 26 might support the practitioners while assessing the impact of infrastructural investments to increase the number of docks on the clients' service level and the related penalty costs. The conducted analysis considers two dimensions: the number of dock doors and the processing times (i.e., unloading, transfer, and loading time).

In conclusion, the proposed stochastic model and algorithm enable predicting the time and cost savings generated daily when the number of doors increased. The case study reveals a reduction of penalty costs of 80% with just one door added. Similarly, the proposed SGA-ST can be applied to assess the reduction of penalty costs associated with a reduction of the handling time (i.e., unloading, loading, and transfer time) and other operational tasks.

6.7 Chapter's highlights

- The quality degradation of perishable items is affected by environmental stresses that are usually dynamic and uncertain by nature (e.g., weather, waiting times).
- The previous chapters have introduced methods to optimize FSCS with deterministic approaches, which require approximating these stochastic processes leading to a suboptimal solution when applied in practice.
- This chapter aims to include this uncertainty in the input parameters representing the environmental stresses by solving the problem of the optimal scheduling in the logistics solution that requires the highest synchronization between materials and information flows: cross-docking.
- Although the literature proposes several models to support the operational decision level in cross-docking, no evidence has been found out of a two-stage stochastic model with a stochastic metaheuristic solution approach with scenario tree to solve these problems in an uncertain environment.
- The chapter introduced an innovative stochastic model and an innovative stochastic genetic algorithm with scenario tree to fill this gap in the literature and to provide stochastic methods to face uncertainty in FSCSs that can be extended to other logistics problems.
- The application of the proposed methods to a real case study of a pallet delivery company demonstrates that a stochastic approach can provide significant savings and increase the clients' service level compared to a deterministic method. Furthermore, the introduction of a novel solution method for stochastic models provides solutions very close to the optimal ones while overcoming the issue of the complexity of stochastic models for cross-docking.

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7. The case study of a global FSCS

This chapter retraces the main contents of the proposed thesis by applying the methods, models, and algorithms introduced and validated in the previous chapters to a real case study. It aims to show how the combination of the proposed approaches can provide practice-ready tools to support the decision-making process in the optimization of a complex real-world FSCS. The content of this case study is intended to demonstrate how the proposed method can be integrated to increase the performance of the supply chain system and follow the perishable products throughout their life cycle from a logistic perspective.

7.1 Description of the case study

The case study presented in this chapter concerns the global FSCS of a company providing logistics services to customers distributed in more than 100 countries worldwide. The company is a Fourth Party Logistic Service Provider (4PL). Compared to the logistics services provided by 3PLs (transportation, warehousing, distribution, and financial services), 4PLs establish a partnership with the clients in order to better integrate their services with those of their clients and implement integrated logistics solutions proactively (Büyüközkan et al., 2009). The 4PL company presented in this chapter has partnerships with companies producing and selling food globally.

This chapter will focus on the Italian nodes of this FSCS, but the same methods can be generalized to optimize it globally. The Italian network includes 2105 suppliers, five storage nodes, and 1652 clients' nodes. 460 out of the 2105 suppliers providing products to the Italian storage nodes (hubs and DCs) are located abroad. Figure 73 shows the map of the Italian network: the green pins represent the suppliers; the blue flags represent the storage nodes; the red pins represent the clients. The company usually makes two deliveries a week for each client. However, some clients even require daily deliveries.

Figure 74 focuses only on the Italian landscape, where most of the nodes are located to provide a better awareness of the geographical distribution of the nodes.

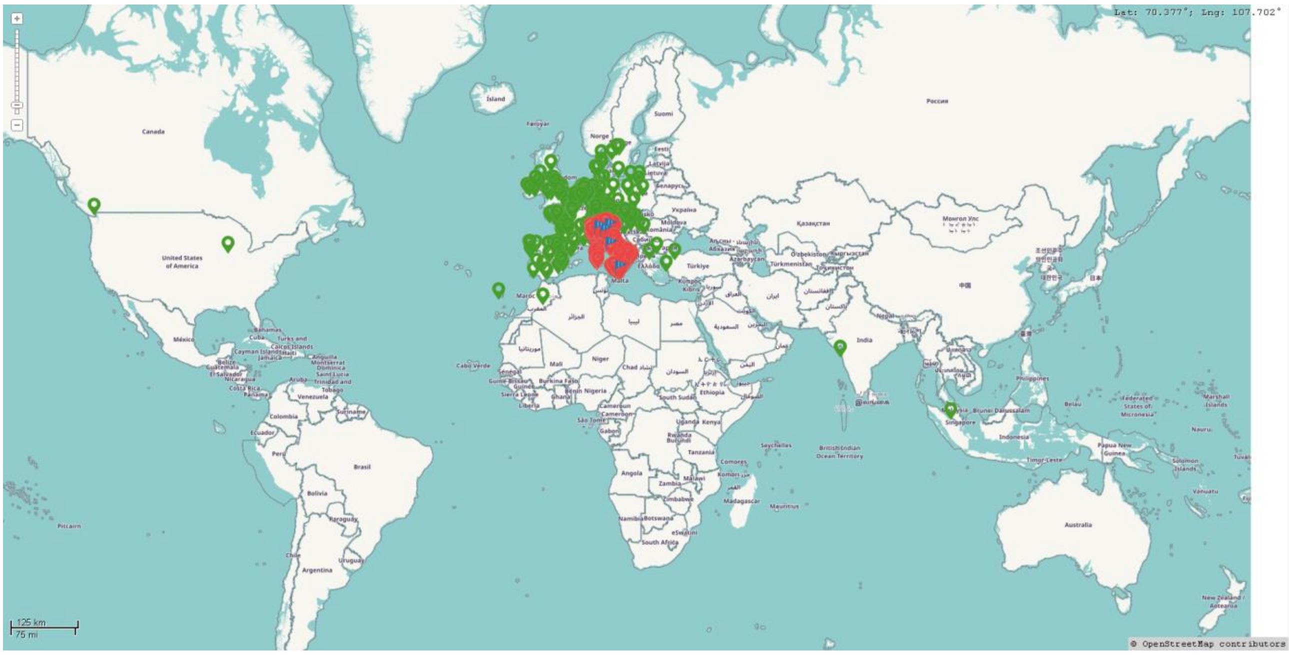


Figure 73. Map of the FSCS.

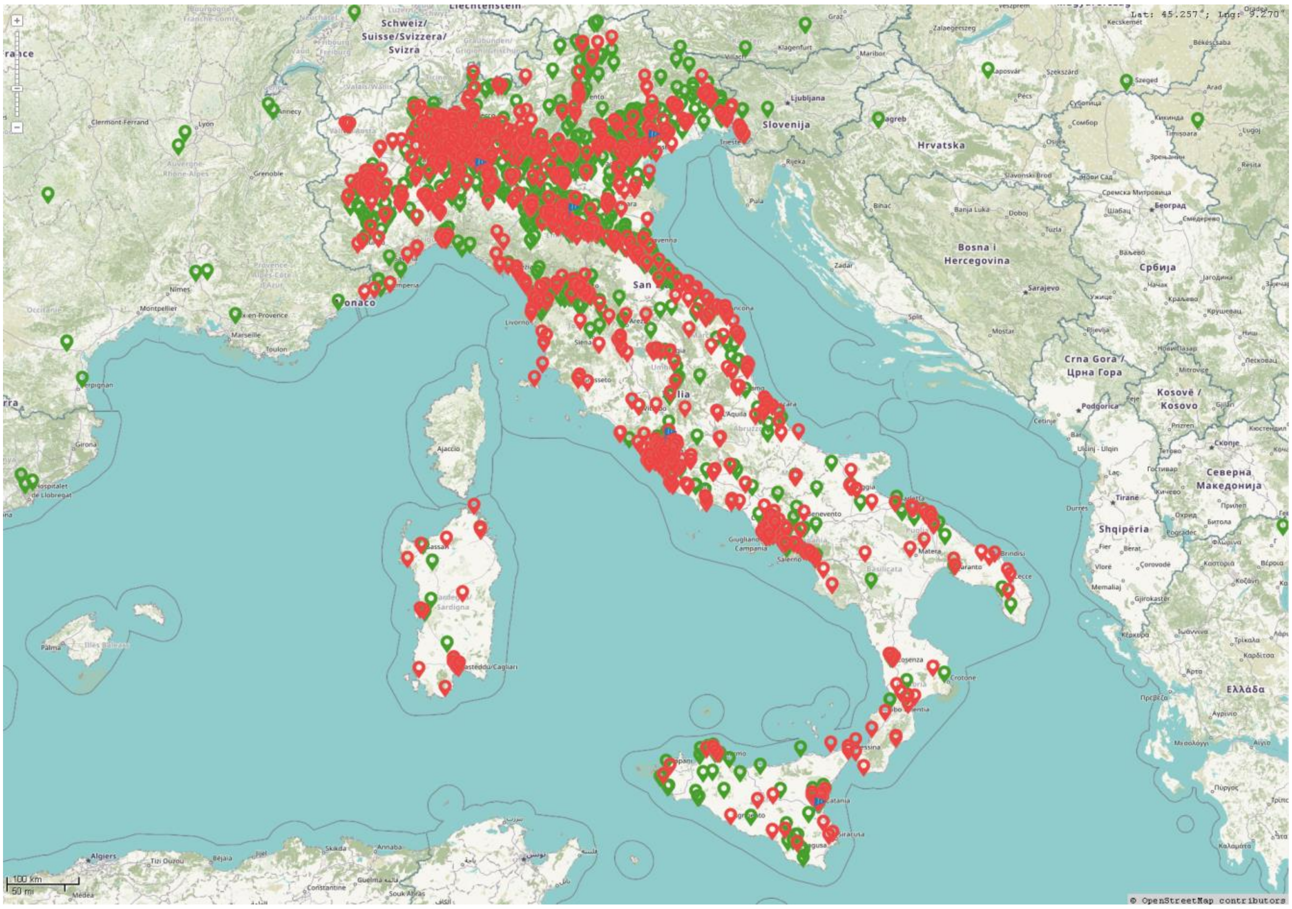


Figure 74. Nodes in the Italian landscapes.

The total number of SKUs managed by the company is more than 30,000, including products' variants. Excluding the variants of the same product, the number of items is reduced by half. 64% of the

SKUs are stored only in one of the five storage nodes to avoid redundancy. The products distributed by the company are very different from each other but can be grouped into three categories:

- 8% of products are dried;
- 80% of products are chilled;
- 12% of the products are frozen.

Figure 75 shows the distribution of the shelf life of the SKUs, excluding the non-perishable items. The shelf life is distinguished between the actual shelf life of the SKUs and the minimum accepted shelf life according to service level agreements with clients. A significant number of SKUs has a short shelf life, from 1 to 100 days. However, the number of clients demanding the delivery of products with a higher remaining shelf life is low, giving more flexibility to the 4PL company to manage such products' logistics flows.

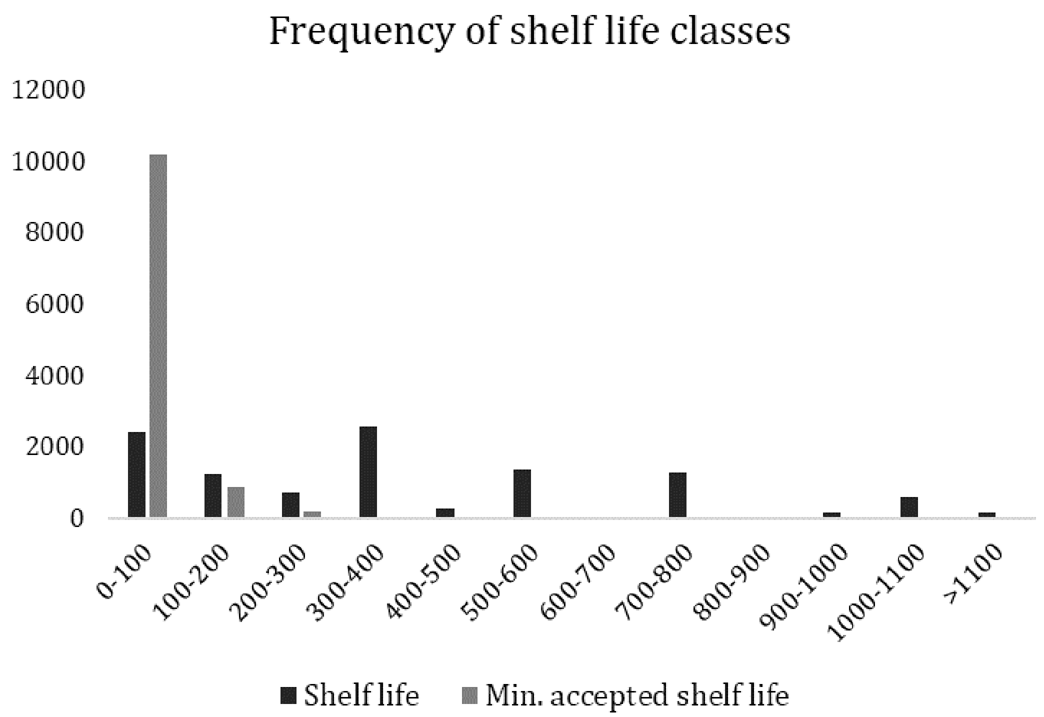


Figure 75. Frequency of shelf life classes [days].

Products are packed in 10 different packages. The packages' distribution is shown in figure 76, along with the percentages of SKUs they pack and flows distributed with them in the last year. The total net weight of products distributed throughout the year was about 50,000 tons.

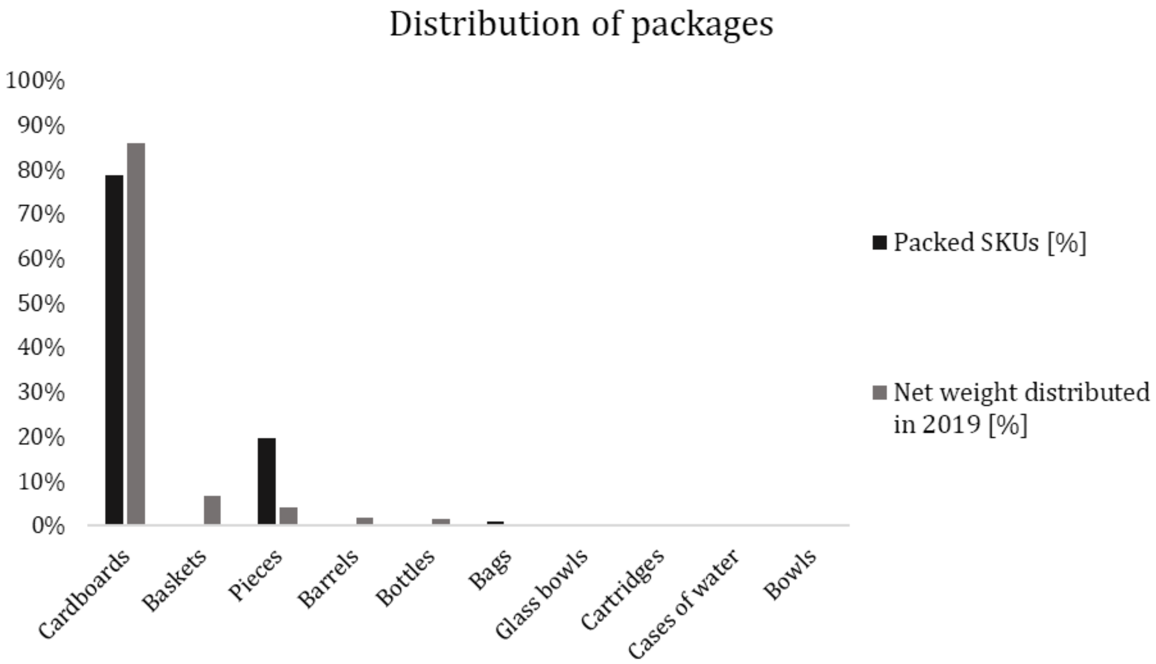


Figure 76. Distribution of packages adopted to pack the SKUs and to move products flows in 2019.

The company distributes products with a fleet of about 150 vehicles: half of them are vehicles of their own, while the other half represent vehicles of subcontractors. All the vehicles are refrigerated as most of the products are temperature-sensitive products with ideal conditions far from the average Italian temperature. The vehicles have two or three different temperature-controlled chambers each in order to allow the distribution of products with different characteristics with the same vehicle. Furthermore, most of the vehicles are equipped with a kit to transport exhausted oils as the company provides this service to improve the environmental sustainability of the FSCS.

The company has provided the case study input data as Microsoft Excel files extracted from the company ERP. The data were then imported into Microsoft Access tables. The primary and foreign keys have been defined, and the relations between different tables have been established according to the schema illustrated in figure 77. The result is a database containing nine tables with 11 relations based on foreign keys and about 6.5 million records. All the input data refers to the year 2019, from the 1st of January to the 31th of December.

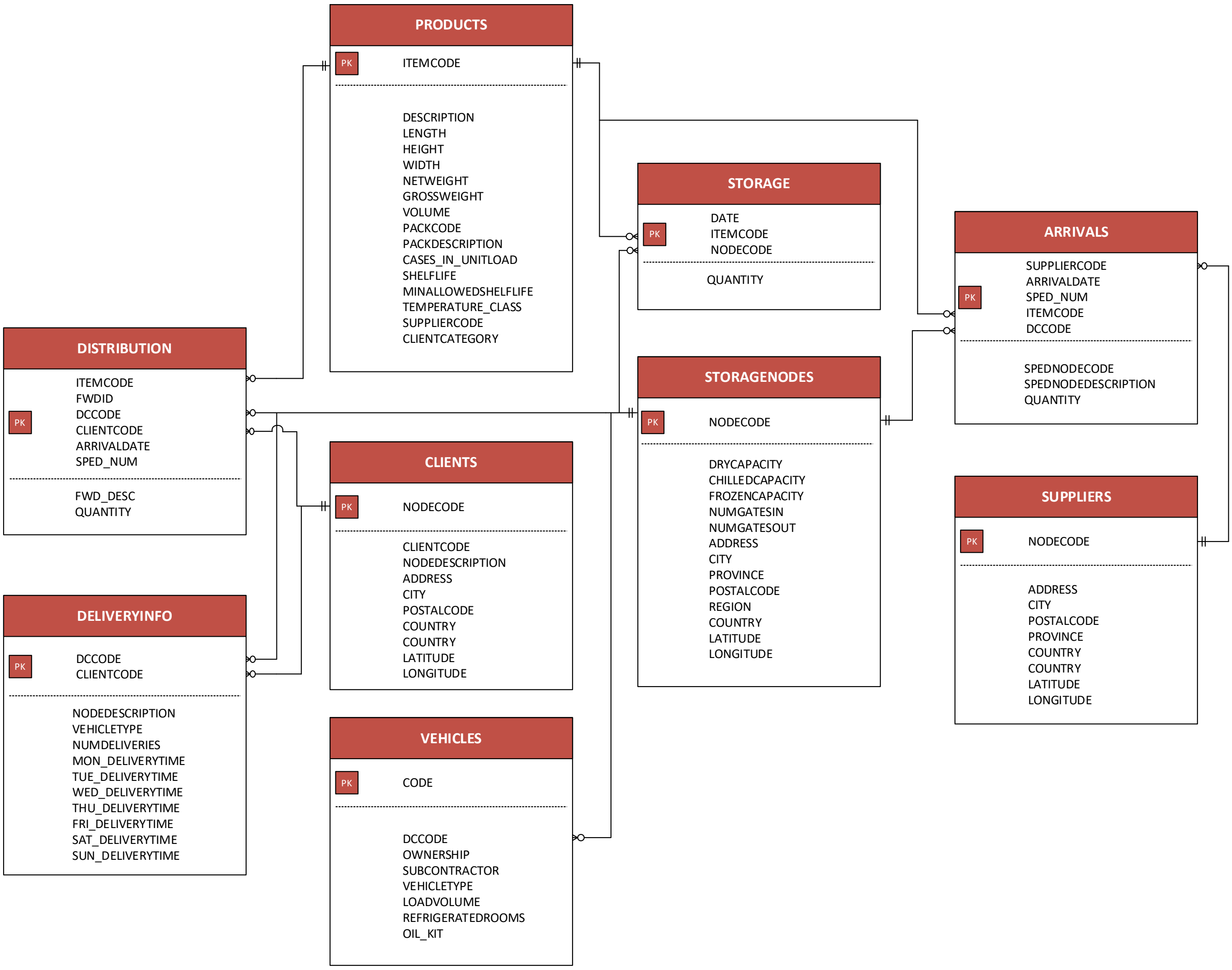


Figure 77. Database architecture for input data of the case study.

The intrinsic characteristics of the products distributed by the company, with lots of fruits and vegetables that must be stored near 0°C and more than 90% of products that are chilled or frozen, determine a high criticality of environmental conditions for such products. Furthermore, the average climate conditions in Italy are significantly different from their ideal conditions. Therefore, the intensive use of refrigeration for this FSCS is essential, justifying the approach of the company that is only equipped with refrigerated vehicles. These vehicles have at least two temperature-controlled chambers each. Indeed, as most of the products distributed by the company are chilled or frozen, they are much more temperature-sensitive than the fresh fruits and vegetables shown in Table 1. The storage nodes are equipped with several refrigerated rooms to store the different SKUs at their optimal conditions.

In this FSCS, the adoption of a climate-driven approach exploiting favorable environmental conditions during the distribution of the items could lead to significant savings compared to the AS-IS scenario.

7.2 Determination of the optimal location of storage nodes

7.2.1 Location of a new warehouse in Sardinia

Given the growing intensity of the logistics flows in Sardinia and the high traveling time from the company's storage nodes to this island, the company aims to create a new warehouse. The storage node would currently serve about 30 clients demanding about 850 tons of products. The nodes are shown in table 27, along with their geographical information and the total net weight demanded in 2019.

Table 27. Geographical information and demands of the Sardinian nodes.

Node ID	City	Country	Weight [t]
1	Cagliari	Italia	4,46
2	Cagliari	Italia	10,12
3	Sassari	Italia	0,01
4	Quartucciu	Italia	0,01
5	Elmas	Italia	4,09
6	Cagliari	Italia	72,79
7	Cagliari	Italia	37
8	Oristano	Italia	41,95
9	Olbia	Italia	43,59
10	Sassari	Italia	49,11
11	Cagliari	Italia	52,94
12	Alghero	Italia	18,87
13	Cagliari	Italia	34,78
14	Olbia	Italia	53,66
15	Cagliari	Italia	65,83
16	Quartu S. Elena	Italia	47,52
17	Sestu	Italia	92,73
18	Nuoro	Italia	33,6
19	Carbonia-Iglesias	Italia	33,33
20	S.Margherita	Italia	0,01
21	Quartucciu	Italia	31,08
22	Sassari	Italia	19,01
23	Olbia	Italia	29,97
24	Cagliari	Italia	32,08
25	Oristano	Italia	0,01
26	Sestu	Italia	0,01
27	Cagliari	Italia	26,64
28	Quartucciu	Italia	7,83
29	Cagliari	Italia	3,63

Three potential locations have been identified for the new storage nodes: Cagliari, Oristano, and Olbia. The center-of-gravity mathematical model introduced in Section 5.1 has been applied to determine the optimal location for the new storage node based on the Euclidean distances. The mathematical model returned the geographical coordinates of a location within the city of Cagliari, therefore validating one of the options identified by the 4PL company. Figure 78 shows the clients in Sardinia with red pins and the new warehouse locations in green. The three potential locations identified by the 4PL companies are represented by green squares, while the optimal location given by the mathematical model is represented with the green triangle in the South of the island.

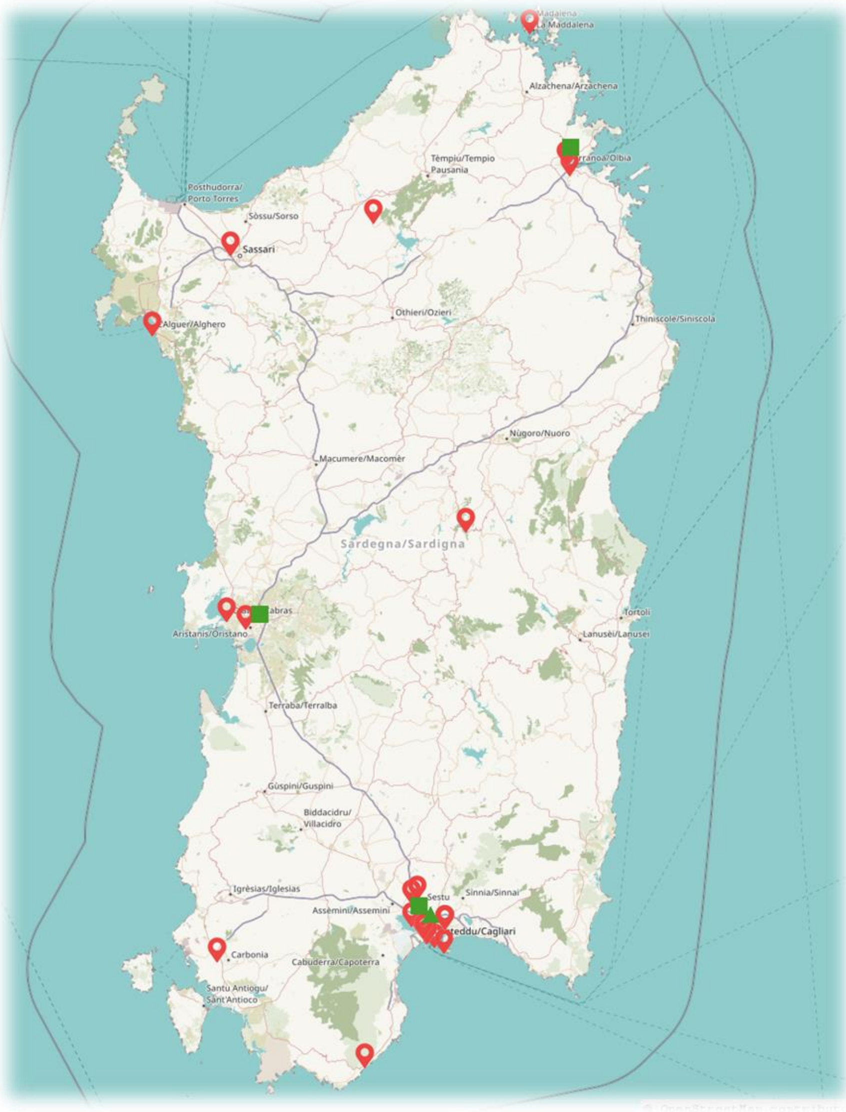


Figure 78. Potential locations of the new warehouse (in red) and clients it will serve (in green).

The optimal location suggested by the mathematical model is within a little park in the city center. Therefore it is unfeasible for the final decision. However, the proximity with one of the three potential alternatives suggests that the optimal decision could be among the location identified by the company, and it is not necessary to explore options in additional cities. When evaluating the driving distances instead of the Euclidean distances, the potential location in Cagliari also outperformed the optimal location calculated with the Euclidean distances due to the proximity to the main roads of the island.

Table 28 shows the results of the analysis with the driving distances, where the node in Cagliari provides much better performances than the locations in Oristano and Olbia. The driving distances are calculated as the minimum road distances provided by the routing tool based on the open-source software Itinero as introduced in chapter 4.

Table 28. Comparison between the potential locations for the new warehouse.

Potential storage locations	Latitude	Longitude	Yearly distance
Optimal Euclidean solution	39.246	9.112	46,628 km
Potential location in Cagliari	39.266	9.078	46,298 km
Potential location in Oristano	39.913	8.619	58,353 km
Potential location in Olbia	40.939	9.515	102,861 km

7.2.2 Optimal location for the existing storage nodes

The 4PL company is also assessing the opportunity to move two of its five current storage nodes due to the changes in their logistics flows in the last years and to expand their capacity.

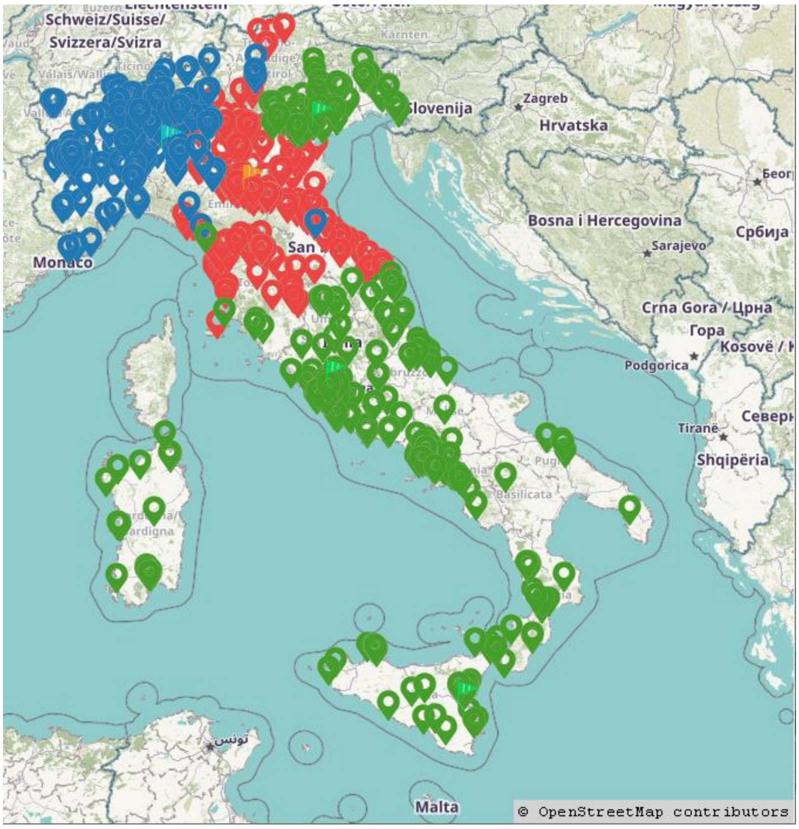


Figure 79. Nodes affected by the relocation of two storage nodes (in red and blue).

The nodes affected by this relocation are shown in figure 79. The two storage nodes that must be relocated are in the provinces of Lodi (pale blue flag) and Modena (orange flag). The clients assigned to these two storage nodes are shown with blue pins and red pins, respectively. This is a tactical allocation of clients to the DCs that can periodically be revised. The total number of nodes served by the two warehouses that will be relocated is 762, demanding about 20,000 tons of products every year. This analysis aims to find out the optimal location for the two storage nodes without changing the allocations of clients to the warehouses. However, the same model and solving method applied to this case study and illustrated in section 5.1 could provide a solution for clients' allocation at the same time if the company would like to revise clients' allocation too.

Despite the significant number of nodes involved in the analysis, the center-of-gravity model illustrated in section 5.1, implemented in AMPL and solved using the Gurobi solver running on a 2.59 GHz Dual Core PC with 12 GB of RAM was able to find out the optimal solution in 1 second.

The optimal locations suggested by the center-of-gravity model are both located near the main roads of the Italian infrastructures. The optimal location for the storage node in Modena is in Anzola dell'Emilia, near the city of Bologna, while the optimal location for the storage node in Lodi is in the city of Milan, close to the clients with the highest demand. The comparison between the AS-IS locations and the solutions of the model is shown in figure 80, with two circles giving a closer look at the locations of the storage nodes.

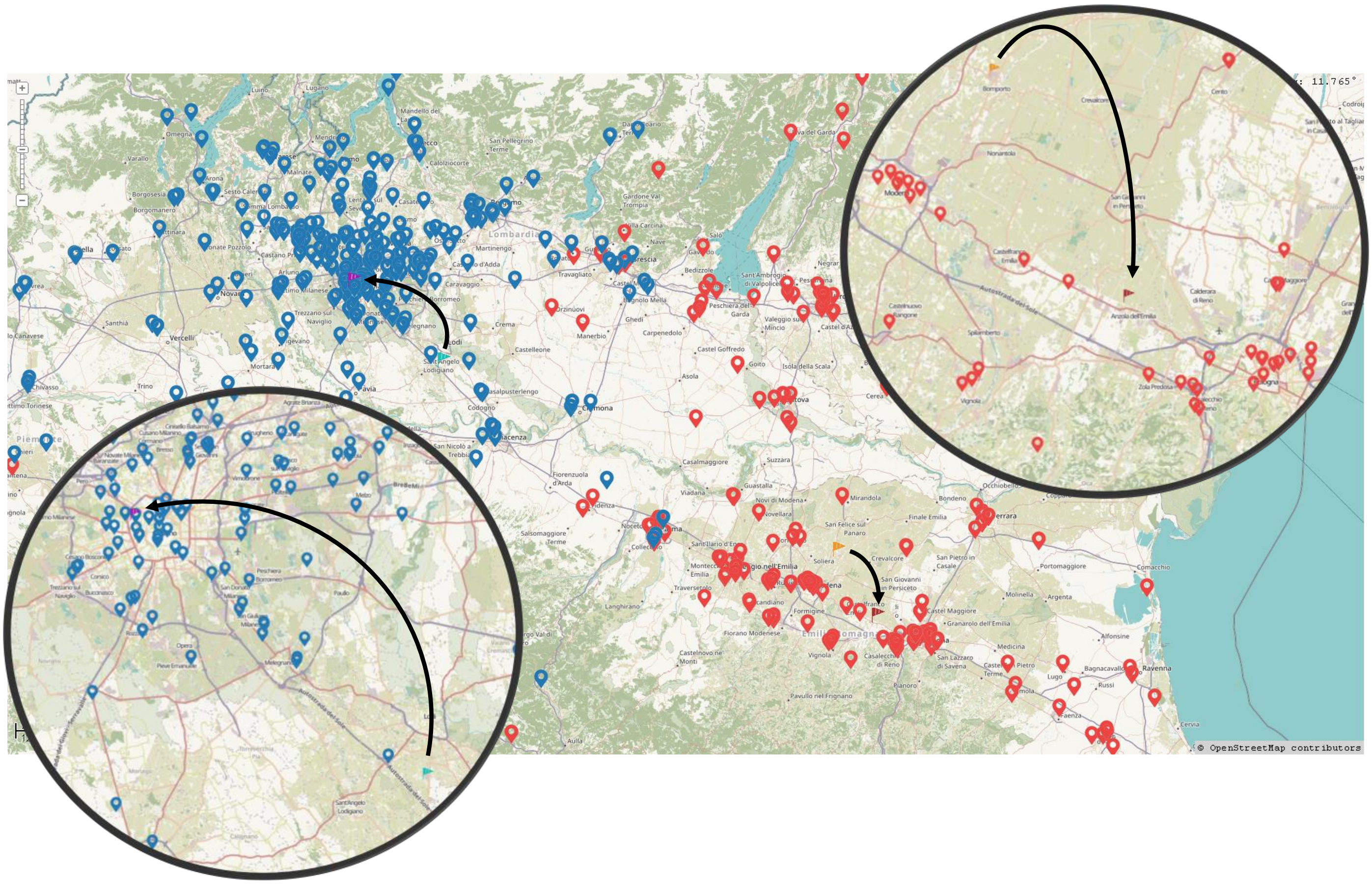


Figure 80. Relocation of the warehouse in Lodi (AS-IS: pale blue flag; TO-BE: violet flag) and Modena (AS-IS: orange flag, TO-BE: burgundy flag).

Table 29 shows the comparison between the AS-IS and the TO-BE scenarios. As the new delivery tours and the vehicle routing problem will be addressed in the next section, the comparison has been made on the average weighted distance between the storage node and the clients, calculated as follows:

$$dist = \frac{\sum_{c \in C} d_{dc} w_c}{\sum_{c \in C} w_c} \qquad \forall\, d \in D \tag{7.1}$$

Where:

d_{dc} is the driving distance between the storage node d and the client c;

w_c is the number of deliveries demanded by client c during 2019.

The relocation of the two warehouses would lead to a reduction of 5.34% of the driving distances for the warehouse in Modena and a reduction of 26.5% of the driving distances for the warehouse in Lodi.

Table 29. Comparison between the AS-IS and TO-BE locations.

	City	Latitude	Longitude	Average weighted distance
Warehouse 1 AS-IS	Modena	44.74	11.04	114.70
Warehouse 2 AS-IS	Lodi	45.61	9.50	85.61
Warehouse 1 TO-BE	Anzola dell'Emilia	44.56	11.19	108.58
Warehouse 2 TO-BE	Milan	45.48	9.15	62.93

7.3 Determination of the delivery tours

The 4PL company currently serves its clients according to a master schedule allocating the demand to storage nodes based on their geographical area. The company currently schedules the deliveries according to tight time windows in order to exploit the hours in the night that are the coolest of the day. Indeed, the company delivers its products only with refrigerated vehicles, as most of them are chilled or frozen, and night deliveries significantly reduce the energy consumption of the FSCS. However, the company does not apply a climate-driven approach that could further enhance the sustainability of the FSCS and lead to significant savings. Every day the company defines the schedule for the day after the next one (e.g., on Monday, it schedule deliveries for Wednesday).

The deliveries are currently scheduled and organized according to an automated proposal made by a planning platform, which is revised manually by the operators. As the company does not follow a climate-driven approach, a traditional vehicle routing approach is adopted. After determining the schedule, the company communicates the expected delivery time to the clients. The time window starts at the expected delivery time and ends 15 minutes later. Early deliveries are not allowed as the deliveries occur during the night, outside the working shift of clients that are not available for collecting products before the time window starts.

This section aims to provide an automated method to find out the best solution to the routing problem according to the methods proposed in chapter 5 and to assess the results of a climate-driven approach to optimize the illustrated supply chain system. Given the high energy consumption of this FSCS that must recur continuously to refrigeration systems to guarantee the safety and quality of its products, a climate-driven approach could be particularly appropriate to address this case study.

Given the significant complexity of the problem, this preliminary analysis will focus on the deliveries of one of the main storage nodes of the company: the one located in the province of Modena. In order to provide a significant and representative analysis of the TO-BE scenario, the optimization of the operational decisions will focus on the most critical day of 2019, the 22nd of February.

7.3.1 Cluster-first approach for allocating the demand to the vehicles

The deliveries involved in the analysis of the selected working day entail 118 clients. As introduced in section 7.1, the company decided to reduce the redundancy of the SKUs in the different storage nodes. Therefore, the nodes served by the warehouse during the selected day are distributed throughout the Italian landscape, as illustrated in figure 81.

In order to reduce the complexity of the problem, a cluster-first, route-second approach has been applied. Therefore, the first step of the analysis consisted of applying a capacitated k-means algorithm to allocate the nodes to the available vehicles without exceeding vehicle capacity (Mostafa & Eltawil, 2017). The vehicles available at the warehouse in Modena have a mean capacity of about 20 pallets. However, the total demand for the selected day was about 260 pallets, thus requiring a minimum number of 13 vehicles to be handled.

Therefore, the capacitated k-means algorithm was applied with $k = 13$, resulting in the tours connecting the nodes shown with the same icon in the map in figure 81, where the storage node is indicated with a blue flag. The minimum number of pallets to be delivered with the resulting tours is 12 pallets, which will be distributed with some of the smallest vehicles of the company's fleet (containing between 10 and 15 pallets), while the maximum is 33 pallets, corresponding to the maximum pallets capacity of the biggest vehicles available.

Table 30. Tours resulting from the cluster-first algorithm.

Tour	Clients visited	Pallets	Total volume [m^3]	Average distance from the warehouse [km]
1	3	15	4.40	265.33
2	10	33	10.16	29.19
3	4	15	3.41	41.52
4	2	14	3	54.117
5	6	20	6.33	117.27
6	24	20	5.99	167.27
7	12	19	5.8	242.99
8	7	33	10.48	145.99
9	38	33	9.3	346.79
10	2	12	2.51	78.28
11	5	20	4.64	129.52
12	3	20	5.32	159.83
13	2	18	4.73	156.75

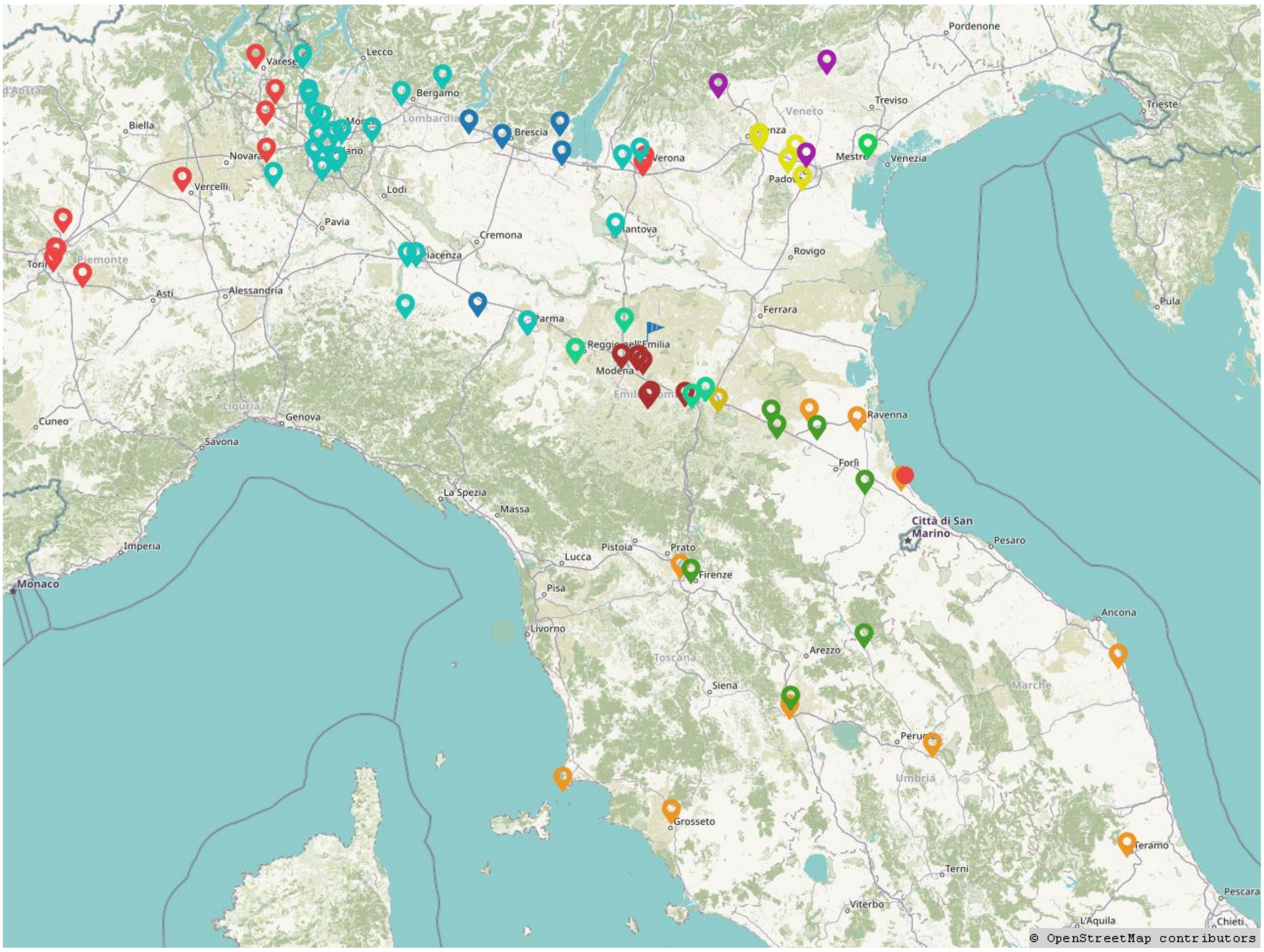


Figure 81. Solution of the cluster-first algorithm.

7.4 Climate-driven optimization of a delivery tour

In order to exemplify the effects of a climate-driven optimization of the delivery tours determined in the previous section, the optimization of one of the tours is illustrated. As the types of products delivered from the company are significantly affected by the climate-conditions, fixed delivery tours are not appropriate for this FSCS, as described in section 5.4.

For the illustrative case of the climate-driven optimization for this FSCS, tour 6 was chosen. As shown in table 30, this is the second tour in terms of the number of nodes involved and therefore is one of the most complex tours to be optimized. Furthermore, the average distance between the clients and the storage node for this tour is equal to 167.27 km, which is a significant distance for this distribution phase.

The climate-driven models proposed in chapter 5 are intended for Full Truckload shipments without constructing the delivery tours. Therefore, the first step of this optimization was the identification of the best vehicle routing strategy to serve the 24 clients included in tour 6. The application of the CVRP model proposed in section 5.4 returned the solution shown in figure 82.

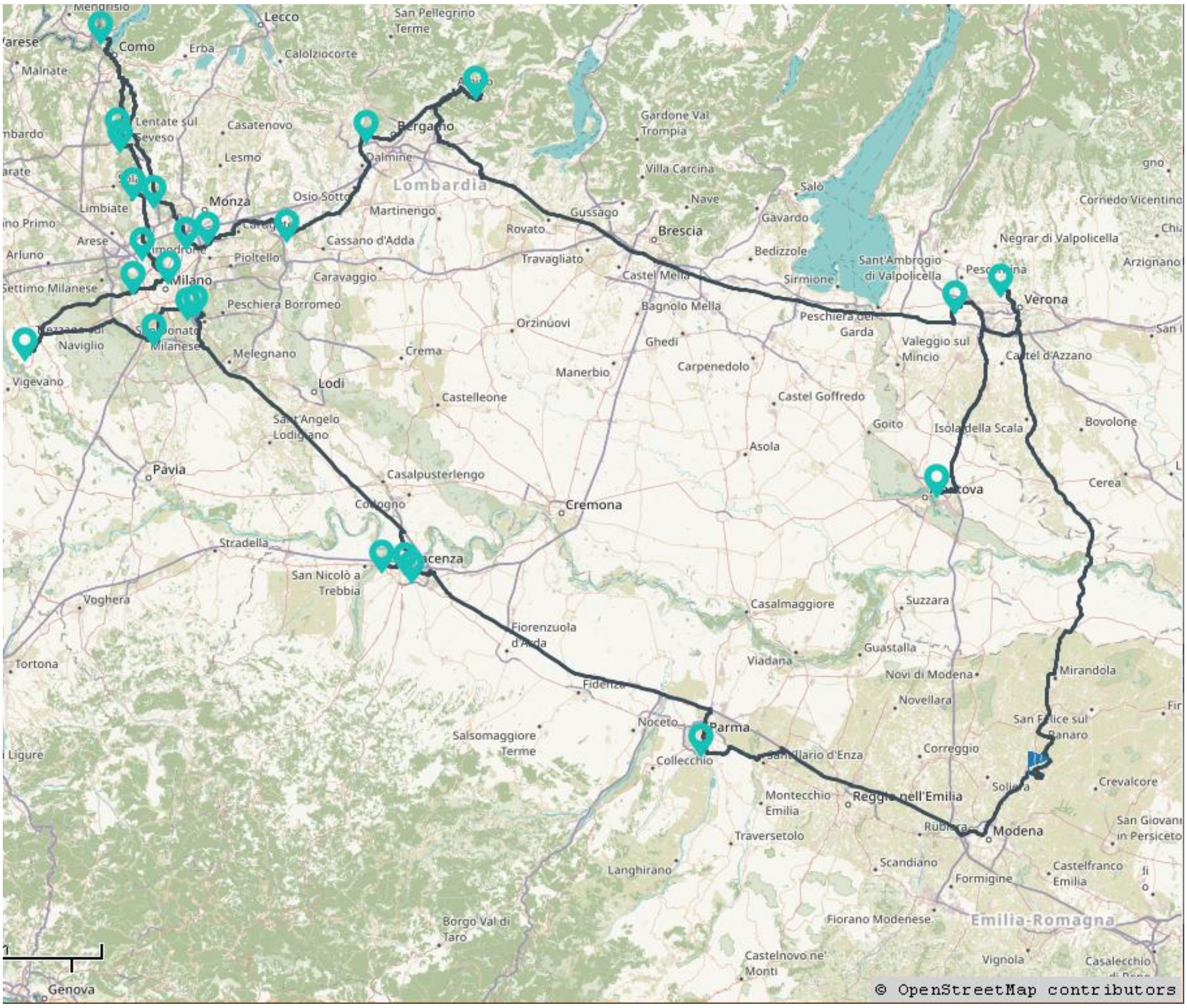


Figure 82. Optimal solution of the Vehicle Routing Problem.

Then, the climate-driven models proposed in sections 5.8.1 and 5.9.2 have been applied to optimize the climate-driven logistics for this tour. The constraints of this instance have been encoded into the proposed models, where the temperature set-points within the two refrigerated chambers of the vehicle are fixed according to the peculiarities of the transported items (0°C for chilled items and -18 °C for frozen items).

Therefore, the models proposed the optimal schedule for vehicle departure according to these constraints and the weather conditions. The temperature in clients' locations during the selected day is shown in Table 31, where the cities are ordered by their visit order.

Table 31. Temperature ranges in clients' cities during the 22nd of February 2019.

	Time								
City	00:00	03:00	06:00	09:00	12:00	15:00	18:00	21:00	24:00
Modena	11	11	9	12	16	18	16	13	11
Verona	9	8	8	11	16	17	14	11	10
Mantova	10	9	8	9	14	18	16	14	11
Bergamo	9	7	7	12	17	19	16	13	10
Curno	9	7	7	12	17	19	16	13	10
Cassano d'Adda	12	10	9	11	16	20	17	14	12
Cologno Monzese	12	10	9	11	16	20	17	14	12
Sesto San Giovanni	12	10	9	11	16	20	17	14	12
Varedo	11	10	9	11	16	20	18	14	12
Tavernola	9	7	7	12	17	19	16	13	10
Paderno Dugnano	11	10	9	11	16	20	18	14	12
Lentate sul Seveso	10	9	8	11	17	19	17	14	11
Limbiate	11	10	9	11	16	20	18	14	12
Novate Milanese	11	10	9	11	16	20	18	14	12
Milano	12	10	9	11	15	19	17	14	12
Abbiategrasso	13	10	10	11	15	19	18	14	12
Rozzano	13	10	10	11	15	20	18	14	12
Paullese	12	10	9	11	15	19	17	14	12
Piacenza	8	8	7	11	15	18	16	12	9
Parma	10	9	8	12	16	18	15	12	11

The results of the climate-driven optimization are shown in figure 83. The different climate conditions experienced by the vehicle distributing the products during the working day determine variations in the refrigeration cost resulting in different total transportation costs. The figure shows the departure time from the warehouse, the arrival time for each of the 24 stops, the costs cumulated in each route, and how these costs vary according to the departure time. The result is a total transportation cost varying from € 463.52 when the departure time is at 12:00 PM on the 22nd of February to € 674.12 at 10:00 AM of the same day. These costs include the costs due to fuel consumption and vehicle refrigeration, according to Eq. (5.20). Costs vary significantly during the day due to the difference between the external temperature, which is more than doubled throughout the day, and the low temperature set-point within the vehicle to keep products chilled or frozen. The minimum value at the end of the day is due to lower temperatures in the night between the 22nd and the 23rd of February. However, as the total driving time for the tour is around ten hours, the optimal departure time would lead to delivering some of the products on the morning of the 23rd of February, which could be too late for the clients. In such a case, the vehicle should depart as soon as possible from the Modena warehouse. Indeed, if all the deliveries should occur within the 22nd of February, the minimum cost is reached when the vehicle departs at 00:00 AM on the 22nd of February (€ 508.67). The energy consumption for refrigeration of this distribution tour has the same trend as the costs represented in figure 83, according to the environmental sustainability model proposed in 5.9.2. The minimum energy consumption is equal to 4671 kWh and the maximum to 7764 kWh, while the energy consumption at 00:00 AM is equal to 5690 kWh.

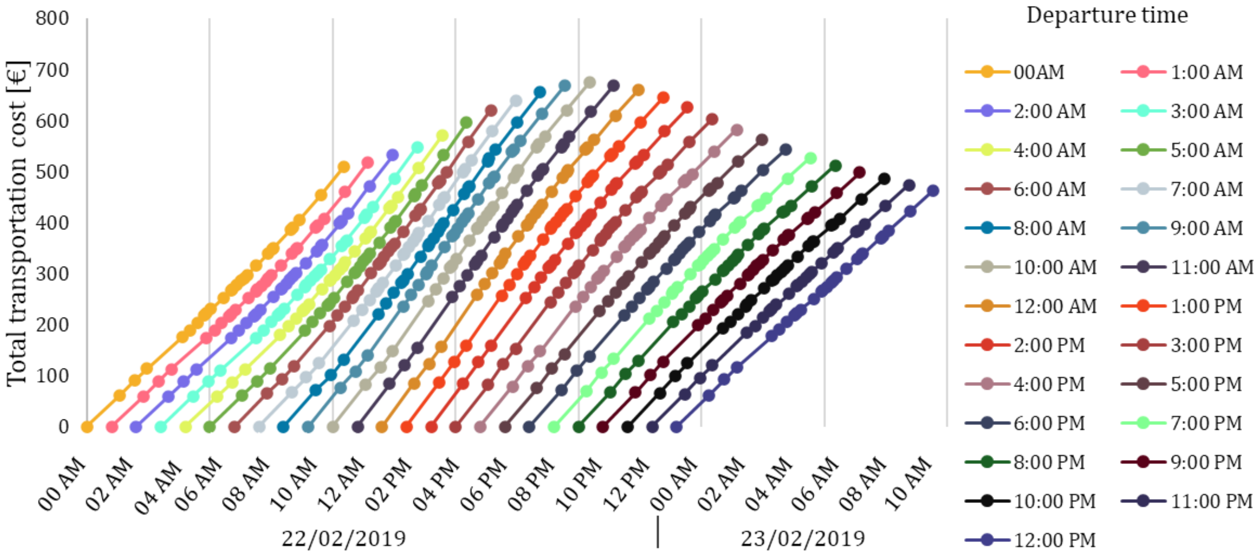


Figure 83. Transportation cost with different departure times from the warehouse.

7.5 Simulation of the AS-IS and TO-BE delivery tour

In order to conclude the analysis of the delivery tours of the FSCS, a simulated comparison between the traceability data of the AS-IS (without climate-driven optimization) and the TO-BE (with climate-driven optimization) scenario for the delivery tour selected in the previous section is proposed. Currently, the selected delivery tour departs around 04:40 AM from the Modena warehouse and reach the first client at 06:00 AM, while the last client is reached around 03:30 PM.

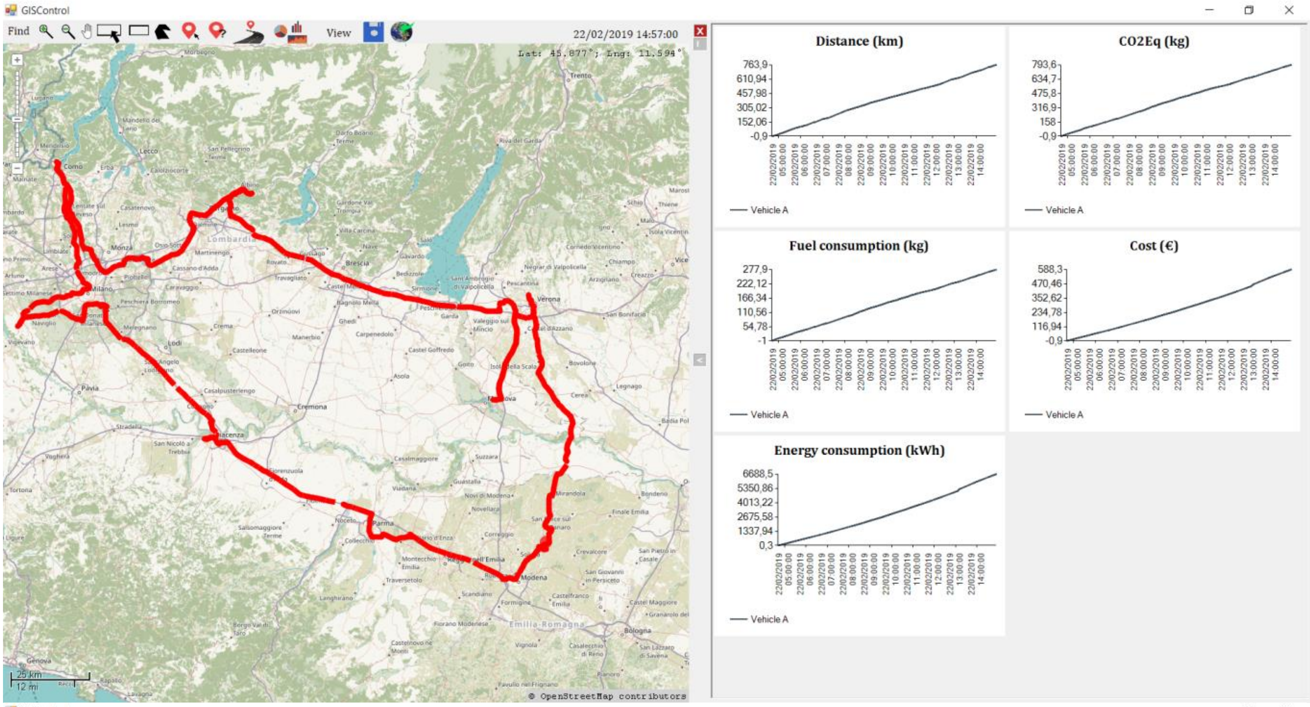
Both the AS-IS and the TO-BE traceability profiles were simulated with the integrated traceability tool proposed in chapter 4, showing the real-time values of:

- Traveled distance;
- CO_{2eq} to move the products along the route, excluding the impact of refrigeration;

- Fuel consumption;
- The total transportation cost, calculated according to the objective function of Eq. (5.20) of the climate-driven model proposed in section 5.8.1;
- The total energy consumption, calculated according to the objective function of Eq. (5.36) of the climate-driven model proposed in section 5.9.2.

The reconstruction of the monitored profiles is shown in figure 84.

(a)



(b)

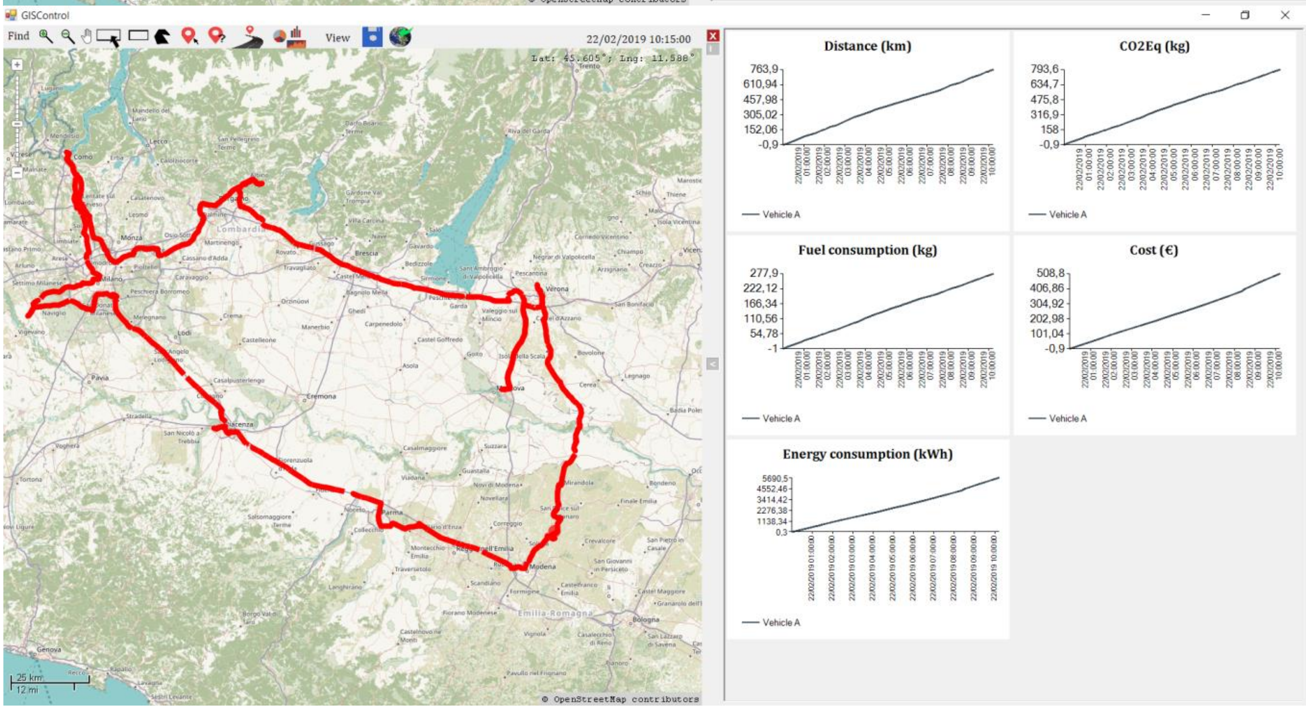


Figure 84. Simulated traceability profile in the (a) AS-IS and (b) TO-BE.

As shown by the simulated traceability profiles, the AS-IS solution consumes about 1000 kWh (+17,5%) more than the TO-BE solution. As a result, the TO-BE solution reduces the total transportation costs by 135€ (-23%). This reduction of the total cost could also be bigger without optimizing the delivery tours provided by the CVRP model proposed in chapter 5, as currently happen in the analyzed FSCS.

7.6 Chapter’s highlights

- This chapter proposed the case study of the global FSCS of a 4PL company distributing perishable products worldwide.
- The case study focused on the Italian network, which still involves several suppliers located abroad.
- The products distributed by the company are particularly temperature-sensitive as most of them are chilled or frozen perishable items.
- Several models, algorithms, applications, and methods proposed throughout the thesis have been applied to this case study, showing a significant impact in increasing the sustainability of the FSCS.

7.7 References

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8. Conclusions

In modern Food Supply Chain Systems (FSCS), the increasing traveled distances due to globalization, the extreme fragmentation and the lack of cooperation among the stakeholders, and the growing variety of distributed products set challenging tasks for logistic managers. Whilst innovative logistic solutions and the increased awareness of both companies and consumers are significantly enhancing the safety of the distributed products, Perishable Product Lifecycle Management (PPLCM) is rarely sustainable.

In order to develop sustainable PPLCM practices, this thesis proposes integrated and interdisciplinary decision-support models and methods for the design, control, and optimization of perishable products lifecycle. The proposed solutions aim to provide practice-ready tools and procedures to guide practitioners and managers in making sustainable decisions tailored to their products.

In particular, after assessing the peculiarities of perishable products and the environmental stresses (e.g., temperature, vibrations) affecting their quality and safety and exploring the recent research trends about PPLM, the thesis describes in detail a top-down approach to optimize FSCSs. Firstly, a framework to identify products' criticalities is proposed. It distinguishes between new FSCSs, for which there are no primary data available, and already existing FSCSs. The former case is analyzed through the classification of products' characteristics and supply chain characteristics. The latter is analyzed through the introduction of an innovative integrated traceability tool. Based on the criticality identified in this first phase, the proposed methodology supports the identification of the best long-term strategy for preserving PLC from environmental stresses: packaging and containment solutions, or infrastructures and refrigeration systems.

Then, decision-support models and platforms are introduced to support the optimization of the FSCS from the strategical to the tactical and operational decision levels to optimize the logistics of the product lifecycle and increase the performance of the supply chain system.

The proposed models support the optimization of the operative decisions with a climate-driven perspective, introducing an ex-ante approach that avoids adverse climate conditions to enhance sustainability while preserving product quality. Indeed, the climate-driven logistic approach exploits favorable climate conditions to deliver high-quality products while reducing the energy consumption, costs, and carbon emissions of the FSCS.

Finally, as the stresses affecting products' quality and supply chain sustainability are frequently uncertain, innovative models and solution methods to control uncertainty in FSCS are proposed. These methods provide robust solutions based on the distribution of data gathered on-field and forecasts to improve the control of processes that are currently addressed as unpredictable.

The proposed models and methods are applied to several real case studies to prove their effectiveness and show the practical implications for practitioners and logistic managers.

Furthermore, the last chapter introduces a complex case study of a global FSCS to show the effects of the consequent application of the proposed models and methods in a real environment. These real applications prove the effectiveness of the proposed approach in designing, controlling, and optimizing the product life cycle and enhancing the sustainability of FSCSs.

The proposed integrated approach based on innovative models and methods aims to provide some practical answers to the sustainability issues raised in the last decades. It combines:

- The need of companies to reduce the costs of the logistics of perishable products and boost the margins of low value-added food items.
- The increasing attention of researchers, regulators, and institutions toward the reduction of carbon emissions by supply chain systems.
- Consumers' demand for safe and high-quality food products, further informing them about the origin of the items and the location of production and processing plants.
- The reduction of food wastes and losses, which still affects a significant share of food items.

Future developments should focus on:

- Developing climate-driven models and methods to support the strategical and tactical decisions.
- Developing stochastic models to choose the best distribution route according to uncertain climate conditions.
- Models and methods to support the other stages of PLC that are not covered by this thesis (e.g., focusing on the harvesting and retail phases).
- The design of innovative packaging solutions to better insulate the perishable products from environmental stresses.

In conclusion, the models and methods proposed in this thesis aim to provide generalizable tools to support managers and practitioners in the design, control, management, and optimization of FSCS. Their adoption and enhancement would aid the sustainable development of these supply chain systems, reducing the impact of food on climate change and its consequences.

Acknowledgments

This dissertation represents the core of a research path that started six years before, with my Bachelor's thesis at the Department of Industrial Engineering (DIN) of the University of Bologna. It represents the closing act of a long and fruitful journey I had the chance to share with lots of enriching people. I know that these years wouldn't be the same without them and therefore I think they should be mentioned in a thorough report of my activities.

First, I want to thank prof. Riccardo Manzini and prof. Riccardo Accorsi for their mentorship, their absolute trust in my potential and the results of my activities, their continuous professional and human support. They taught me how to conduct my research from the basis, inspired me always to give my best, and always proceed one step further. Thanks for the opportunities to take part in research activities, industrial projects, national and international conferences, seminars, and webinars. Thanks for the opportunity to work with outstanding people that shared parts of this long journey with me: professors, researchers, students, friends.

I would like to sincerely thank the research group at the Department of Industrial Engineering, all the professors and colleagues for welcoming me as part of this amazing team. Thanks to Professor Emilio Ferrari, Professor Alberto Regattieri, Professor Mauro Gamberi, Professor Cristina Mora, and Professor Marco Bortolini. I would also like to mention some of my colleagues: Giulia Baruffaldi, Lucia Botti, Francesco Galizia, Francesco Piana, Francesco Pilati, who introduced me to this group when I started my research activities at the DIN. Thanks to Francesca Calabrese, Federica Garbellini, Giovanni Lelli, Lorenzo Mucci, Daniele Santi, Luca Volpe, I am sure that these years wouldn't have been the same if I didn't have the chance to share their passion, creativity, and inspiration. Thanks to Laura Bonacini and Giorgia Cocchi for their ceaseless support during the last year of this journey. Writing this thesis would have been much harder if we didn't have the chance to work together during these tough months. Thanks to all the other colleagues that shared the working space with me. Talking with you inspired me to explore new ideas, research activities, and acquire new competencies.

Thanks to the research group of the Wageningen University & Research for welcoming me into their team and immediately made me feel at home in The Netherlands. Thanks for your help, finding me a home and a bike, for inviting me to take part in your group both during working time and in my spare time. I will always take the WUR bottle with me.

Thanks to Antonio, Giancarlo, Giada, and Michele for the laughs, the discussions, for sharing opinions and ideas, for coffees, and for the video calls during the lockdown. Thanks for the loyal and long-lasting friendship and affection.

Thanks to my family for their presence and support and for sharing my hopes and difficulties.

Above all, thanks to Rita. Thanks for your inspiration, for the endless trust in me and my potential, for encouraging me always to go ahead, and for giving me all the support I needed during these years. The higher the mountain, the higher we climb.