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QUANTITATIVE APPROACHES FOR THE INTEGRATED MANAGEMENT OF AGRI-FOOD SUPPLY CHAINS

Settore Scientifico Disciplinare ING-IND/17

Coordinatore: Ch.mo Prof. Enrico Conte

Firma

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Supervisore/Tutor: Ch.mo Prof. Giovanni Mirabelli

Firma

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Dottorando: Dott. Vittorio Solina

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Abstract (English)

In recent years, the development of global markets and higher expectations from end customers have forced the supply chain players to better coordinate and integrate their plans, in order to maintain high levels of performance and be competitive on the market. Today, in fact, companies compete not only on product price or quality, but also on the reliability and timeliness of deliveries. Managing a supply chain in an integrated and coordinated manner is even more complicated and challenging, with reference to the agri-food context, where the constraints about quality and safety of goods, that are usually perishable, are much more stringent than in other sectors.

By coordinating the various activities, it is possible to make supply chains more efficient and sustainable, as products can be made and distributed in the right quantity, at the right time and to the right customer. In support of integrated planning, new technologies are recently spreading, with the aim of making the sharing of data and information between the various actors safe and efficient. In this regard, the blockchain is among those technologies, whose interest has grown the most in recent months, both from the academic and business world.

The present dissertation mainly aims to develop, test and validate novel quantitative approaches for the integrated management of agri-food chains.

- In Chapter 2, a review of the main scientific works published in the last 15 years is proposed, referring to the integration of production, storage and distribution activities, via optimization strategies, within perishable supply chains. In this context, in order to identify effectively the different research gaps and to suggest possible future challenges, a five-dimension classification framework is proposed. This review is the starting point for the following 3 chapters, which address as many case studies.
- In Chapter 3, an optimization model is designed for the simultaneous management of the storage and distribution of agricultural products. It is used to maximize the profits of a real company, which deals with the planting, growing, harvesting, storage and distribution of cauliflowers to a main customer and to spot customers. A hybrid fresh-/old-first inventory management policy is modeled to balance the quality of the delivered product and limit the amount wasted. The model improves the current practices of the firm and supports effectively the day-to-day decision-making regarding the quantities of product, for each age, to be stored and distributed to each customer.

- In Chapter 4, a model is instead developed and tested to integrate the activities of production (i.e., harvesting), storage, distribution and routing of perishable agri-products. The case study refers to two companies, located in Southern Italy. At the tactical level, the proposed model determines the optimal value of two important operating parameters: the frequency of the harvesting activities and the service level to be guaranteed to customers. At the operational level, instead, the model is a valid tool to suggest to the company, day-to-day, the optimal quantities to harvest, store, distribute, and the routes to travel to reach customers, in order to maximize profits and contain waste. In this context, considering that the companies of the case study share some customers and are not in competition, as they are heterogeneous in terms of marketed products, the possibility of horizontal collaboration is also explored. The collaboration, as intended in this Chapter, implies that one of the two actors makes its own fleet of vehicles available, in exchange for a fee. In this context, a heuristic framework is proposed and validated. It suggests collaborating day by day, only if collaboration is economically convenient for both the companies. Computational tests, carried out on randomly generated instances, reveal that the collaboration can guarantee significant savings in terms of CO_2 emissions and therefore make the supply chain more sustainable.
- Chapter 5 deals with the integration of the production, storage and distribution activities of a company in the vegetable sector. In the production field, a scheduling problem is solved, which takes into account the set-up times of the production line, the hourly fluctuations in the energy price and the perishable nature of raw materials. In the distribution field, instead, it is necessary to schedule deliveries in terms of quantity of shipped products and days. The proposed model allows to schedule both production and distribution in an integrated way. Two rescheduling strategies are tested, to adequately react to customer demand, which occurs on a weekly basis. The first reproduces the current behavior of the company, while the second allows to improve current practices and jointly minimize the costs of energy, storage and distribution.
- In Chapter 6, considering the recent proliferation of scientific works on the theoretical or practical use of blockchain technology in the agri-food sector, a literature review on this topic is proposed. This tool, since it allows the real-time sharing of information between the various players in the supply chain in a safe and efficient way, can facilitate the coordination of production and distribution plans, which is the main subject of the previous chapters of this thesis work. The aim is to identify current research trends and inform the reader about the degree

of maturity of this technology, which appears promising but still few oriented towards practical applications.

- The possible future developments of this dissertation are presented in Chapter 7 and, first of all, concern new variants of the models presented in Chapters 3, 4, 5. Furthermore, starting from Chapter 6, the idea is to apply blockchain technology to track and trace a real agri-food chain, in order to evaluate the benefits from a quantitative point of view. A further future objective is to use the knowledge acquired about the particular features of agri-food chains to support them in this difficult pandemic period, linked to the spread of COVID-19. A simulation model that takes into account multiple scenarios in terms of supply- and demand-side shocks is currently being developed and tested, in order to support economies both globally and locally.

Abstract (Italiano)

Negli ultimi anni, lo sviluppo dei mercati globali e le maggiori aspettative da parte dei clienti finali hanno portato i vari attori delle filiere a coordinare e integrare maggiormente i loro piani, allo scopo di mantenere elevati livelli di performance ed essere competitivi sul mercato. Oggigiorno, infatti, le aziende si confrontano non solo sul prezzo o sulla qualità del prodotto, ma anche e soprattutto sull'affidabilità e la tempestività delle consegne. Gestire in maniera integrata e coordinata una filiera diventa ancora più complicato e sfidante, se si fa riferimento al contesto agro-alimentare, dove i vincoli legati alla qualità e alla sicurezza dei beni, tipicamente deperibili, sono molto più stringenti rispetto agli altri settori. Attraverso il coordinamento delle varie attività, è possibile rendere più efficienti e sostenibili le filiere, in quanto i prodotti possono essere realizzati e distribuiti nelle giuste quantità, al momento giusto e al cliente giusto. Proprio a supporto della pianificazione integrata, recentemente si stanno diffondendo nuove tecnologie, con il fine di rendere sicura ed efficiente la condivisione di dati e informazioni tra i vari attori. A questo proposito, la blockchain è fra quelle il cui interesse è cresciuto maggiormente negli ultimi mesi, sia da parte del mondo accademico che imprenditoriale.

Il presente lavoro di tesi si propone principalmente di sviluppare, testare e validare nuovi approcci quantitativi per la gestione integrata delle filiere agro-alimentari.

- Nel Capitolo 2, viene proposta una rassegna dei principali lavori scientifici pubblicati negli ultimi 15 anni, relativamente all'integrazione delle attività di produzione, immagazzinamento e distribuzione nelle filiere caratterizzate da prodotti deperibili, attraverso strategie di ottimizzazione. In questo contesto, allo scopo di individuare nel migliore dei modi i differenti gap di ricerca e suggerire possibili sfide future, viene sviluppato un framework, per classificare su 5 principali dimensioni i vari articoli scientifici. Tale rassegna è il punto di partenza per i successivi 3 capitoli, che propongono altrettanti casi studio.
- Nel Capitolo 3, viene costruito un modello di ottimizzazione per la gestione simultanea dell'immagazzinamento e della distribuzione di prodotti agricoli. Esso viene utilizzato per massimizzare i profitti di un'azienda agricola, che si occupa della piantumazione, della coltivazione, della raccolta, dell'immagazzinamento e della distribuzione del cavolfiore a un cliente principale e a dei clienti spot. Una politica ibrida fresh-/old-first di gestione dell'inventario viene modellata per bilanciare la qualità del prodotto consegnato e limitarne l'ammontare deperito. Il modello consente di migliorare le pratiche correnti dell'azienda e di supportare giorno

per giorno il decision-making circa le quantità di prodotto, per ogni età, da immagazzinare e da distribuire ai rispettivi i clienti.

- All'interno del Capitolo 4, viene invece sviluppato e testato un modello per integrare le attività di produzione (intesa come raccolta), immagazzinamento, distribuzione e instradamento di prodotti agricoli deperibili. Il caso di studio fa riferimento a due aziende del Sud Italia. A livello tattico, viene individuato il valore ottimale di due parametri fondamentali: la frequenza delle attività di raccolta e il livello di servizio da garantire ai clienti. A livello operativo, invece, il modello è un valido tool per suggerire all'azienda, giorno per giorno, le quantità ottimali da raccogliere, immagazzinare, distribuire, e le rotte da utilizzare per raggiungere i clienti, allo scopo di massimizzare i profitti e contenere gli sprechi. In questo contesto, considerando che le aziende del caso di studio condividono dei clienti e non sono in competizione, viene esplorata anche la possibilità di collaborazione orizzontale. La collaborazione, come intesa all'interno di questo Capitolo, comporta che uno dei due attori metta a disposizione la propria flotta di veicoli, in cambio di una commissione. A tal proposito, viene proposto e validato un framework euristico che suggerisce giorno per giorno di collaborare, solo se la collaborazione è economicamente conveniente per entrambi gli attori. Test eseguiti su istanze opportunamente generate, rivelano che la collaborazione può garantire significativi risparmi in termini di emissioni di CO_2 e rendere quindi più sostenibile la filiera.
- Il Capitolo 5 prevede un'integrazione tra le attività di produzione, immagazzinamento e distribuzione di un'azienda del comparto vegetale. In ambito produttivo, viene risolto un problema di scheduling, che tiene conto dei tempi di set-up della linea produttiva, delle fluttuazioni orarie del prezzo dell'energia e della deperibilità delle materie prime. In ambito distributivo, invece, è necessario schedulare le consegne in termini di quantità e giorni. Il modello proposto consente di schedulare in maniera integrata sia la produzione che la distribuzione. In questo contesto, vengono testate due strategie di rescheduling, per reagire adeguatamente alla domanda dei clienti, che si verifica su base settimanale. La prima riproduce il comportamento dell'azienda, mentre la seconda consente di migliorarne le pratiche correnti e di minimizzare congiuntamente i costi di energia, stoccaggio e distribuzione.
- Nel Capitolo 6, considerando il recente proliferare di lavori scientifici circa l'utilizzo teorico o pratico della tecnologia blockchain in ambito agro-alimentare, viene proposta una literature review su questo tema. Tale strumento, poiché consente in maniera sicura ed efficiente la condivisione in tempo-reale delle informazioni tra i vari attori della filiera, si presta al

coordinamento dei piani di produzione e distribuzione, oggetto dei precedenti capitoli di questo lavoro di tesi. Lo scopo è individuare i trend di ricerca correnti e informare il lettore circa il grado di maturità di questa tecnologia, che appare promettente ma ancora poco orientata alle applicazioni pratiche.

- I possibili sviluppi futuri del presente lavoro di tesi sono contenuti all'interno del Capitolo 7 e, prima di tutto, riguardano nuove varianti dei modelli presentati nei Capitoli 3, 4, 5. Inoltre, a partire dal Capitolo 6, l'idea è di applicare la tecnologia blockchain per tracciare e rintracciare completamente una reale filiera agro-alimentare, allo scopo di valutarne i benefici dal punto di vista quantitativo. Un ulteriore obiettivo futuro è utilizzare le conoscenze acquisite circa la specificità delle filiere agro-alimentari per supportarle in questo difficile periodo pandemico, legato alla diffusione del COVID-19. Attualmente, è infatti in fase di sviluppo e testing un modello di simulazione che tiene conto di molteplici scenari in termini di shock lato domanda e offerta, con il fine di supportare le economie sia a livello globale che locale.

1. Introduction

Generally, a supply chain is defined as the network of organizations, activities, people, information and resources involved in the flow of products from suppliers to customers (Guo et al., 2016). The supply chain management is crucial, in order to optimize the use of resources involved at each stage.

In recent years, the development of global markets and the increased expectations of end consumers have forced supply chain players to increasingly coordinate their plans, in order to maintain high levels of performance (Kumar et al., 2020). In fact, today, companies compete not only on price and/or quality, but also on reliability and timeliness of deliveries (Viergutz and Knust, 2014). Integrated supply chain management is more complex and challenging when products are perishable, as lack of coordination can easily cause waste, lost sales and other additional costs (Liu and Liu, 2020; Chan et al., 2020).

Historically, decisions about production, inventory and distribution activities were made separately. This means that each actor in the supply chain seeks to minimize its own costs, without worrying about upstream or downstream impacts. This kind of approach allows to minimize the costs of each stage, but the overall costs of the supply chain become usually very high. Basically, the minimization of the costs of each level leads to a local optimum, but not a global optimum (Hiassat et al., 2017; Neves-Moreira et al., 2019). For example, the lack of coordination between production and distribution activities can have two opposite impacts: (i) when production is completed in advance, products may remain in the warehouse for too long, before being distributed, until they lose quality and are not desirable for customers; (ii) when production is completed late, transportation resources (e.g., vehicles, drivers) may no longer be available and delivery time worsens (Marandi and Zegordi, 2017; Stecke and Zhao, 2007).

Increasing global competitive pressure has forced companies to collaborate and then integrate their activities (Kumar et al., 2020). Organizations can become more competitive through integration and interactive collaboration. Sharing information in real-time on supply and demand improves coordination, so that goods can be produced and distributed in right quantities, at right times, to right locations (Simchi-Levi et al., 2000). Moreover, a higher level of integration in designing and managing a supply chain facilitates the achievement of the goal of sustainable development (Benn et al., 2014). Coordination is really critical in agri-food supply chains to obtain a high service level because they are usually characterized by highly frequent orders of small volumes, high product variety, short customer delivery time windows, variability of demand and prices, uncertain yield of the crop (Ahumada and Villalobos, 2009; Trienekens et al., 2014; Fredriksson and Liljestrand, 2015). Coordination between production and distribution can significantly reduce delivery time, that really affects customer satisfaction, then profits

(Vahdani et al., 2017). In the literature, several papers prove that considerable cost savings are achievable through planning integration (Chandra and Fisher, 1994; Nagy and Salhi, 2007; Moin and Salhi, 2007; Amorim et al., 2012). However, it is very important to remark that when many decisions are jointly optimized in a single monolithic model, the result is often that the relative problem is computationally very complex to be solved, then heuristic approaches are necessary to find near-optimal solutions in a reasonable time (Biuki et al., 2020; Chan et al., 2020; Li et al., 2020). Basically, the coordination of production and delivery planning is a very important issue in perishable food industry and urgently needs further studies (Chen et al., 2009).

Therefore, this dissertation mainly focuses on the review and consequent proposal of quantitative approaches for the integrated management of agri-food supply chains, with the aim of improving their performance.

The body of the present thesis is organized as follows:

- Chapter 2 is entitled "Optimization strategies for the integrated management of perishable supply chains: literature review and classification framework proposal". It provides an extensive literature review about the papers, published in the last 15 years, dealing with the integration of production, inventory and distribution activities within perishable supply chains. A rigorous research methodology is applied and a five-dimension classification framework is proposed, with the aim to identify the main research gaps and the possible future challenges. This chapter can be considered an important point of reference for the next three chapters.
- Chapter 3 is entitled "Optimal inventory and distribution management of perishable agricultural products with a hybrid inventory policy". It provides a novel optimization model for the simultaneous management of storage and shipping of agricultural products, with the aim of maximizing profit, taking into account the perishable nature of the goods. The model uses a fresh/old-first hybrid policy in order to balance the quality of the products delivered to customers. The goodness of the model is demonstrated through its application to a real-life case study, which refers to a company in Southern Italy, that deals with planting, growing, harvesting, and distributing cauliflowers. In particular, at the strategic level, the optimal number of vehicles for distribution and the maximum in-stock time of perishable goods is determined. At the operational level, on the other hand, the model can support the company in the day-by-day practices, through the implementation of a rolling horizon framework.

- Chapter 4 is entitled "Modelling and solving an integrated and collaborative harvesting-inventory-routing problem in the perishable food supply chain". In this case, a novel model has been proposed to integrate the harvesting, inventory and distribution activities of a company, that deals with perishable agri-products. At the tactical level, the model gives important information about the most profitable configuration in terms of harvesting frequency and level of service to be guaranteed to end customers. In addition, a further model is proposed that enables the collaboration, in distribution activities, between heterogeneous companies that share part or all of the customers. At the operational level, a heuristic framework, that suggests to companies if and when to collaborate, has been designed and tested. The computational results, related to a real-life case study, show that collaboration can improve the profits of the companies involved and allows to reduce significantly CO_2 emissions.
- Chapter 5 is entitled "Integrated production-distribution scheduling with raw materials perishability and energy considerations". It provides a model, with the aim to integrate production and distribution activities, taking into account the fluctuations in energy prices and raw materials perishability. Changeover times are also considered, while energy, inventory and distribution costs are jointly minimized. The model has been applied to a real-life company and two rescheduling strategies have been tested. The first one, named partial rescheduling, reproduces the current behavior of the company, while the second one is indicated in the literature as complete rescheduling. The computational results show that the current practices of the firm can be significantly improved, exploiting the complete rescheduling characteristics.
- Chapter 6 is entitled "A new trend for improving supply chain performance in the agri-food sector: the blockchain technology". Considering the very strong and recent interest by scholars and entrepreneurs towards blockchain technology, this chapter provides a literature review in order to determine the current state of this technology in the agri-food sector. 34 papers are reviewed and divided into 6 main categories, based on the objectives related to the implementation of the blockchain: traceability in the generic agri-food supply chains, traceability in the specific agri-food supply chains, traceability and middleman focus, reward mechanisms, employment, other smart farming applications. The main future challenges are also outlined.
- Final remarks and possible future developments of the research are outlined in Chapter 7.

2. Optimization strategies for the integrated management of perishable supply chains: literature review and classification framework proposal

The main purpose of this chapter is to systematically review the papers published in the last 15 years about the integration of production, inventory and distribution activities in perishable supply chains. A five-dimension classification framework is proposed, with the aim to identify the main research gaps and to address the most challenging future research directions.

2.1. Introduction

In its most traditional form, a supply chain (SC) is characterized by four main actors or stages: suppliers, manufacturers, distributors and customers (Kumar et al., 2020). Variety and heterogeneity of stakeholders, who often have conflicting objectives, make the design and management of supply chains an extremely difficult task (Diabat et al., 2016; Hammami et al., 2017). According to Bank et al., (2020), supply chain management (SCM) is the process that aims to efficiently integrate the different stages of the supply chain with the aim of delivering the right number of products at the right time to end users. SCM usually means making decisions at different levels: strategic, tactical, and operational, based on the temporal impact (Diabat and Theodorou, 2015; Miller, 2002). Strategic decisions have a long-term impact, usually years, in fact they cannot be easily changed as they involve significant investments (e.g., location-allocation decisions). Tactical decisions, on the other hand, have mid-term effects (i.e., months) and most often concern inventory management. Finally, operational decisions usually have a daily or weekly impact and frequently concern scheduling and routing decisions (Hiassat et al., 2017; Rafie-Majd et al., 2018).

Growing globalization is leading companies around the world to compete not only on price and product quality, but also on the reliability of deliveries. For these reasons, research in the area of SCM has undergone a dramatic increase in recent years, focusing on the integrated planning of production, storage and distribution activities (Viergutz et al., 2014). The integration between different levels of supply chain decisions usually leads to multiple benefits. The pioneeristic research work by Chandra and Fisher, 1994, states that 3-20 % cost savings can be achieved through integrated planning of production and distribution activities. In the literature, there are many other pioneering experiments in integrated planning, with good results in terms of overall efficiency (Thomas and Griffin, 1996; Fumero and Vercellis, 1999). Supply chain integration increases flexibility with respect to customer requests, reduces waste, then promotes a more sustainable perspective (Dai et al., 2020). It should be emphasized that traditional and conventional approaches were based on the separate and sequential optimization of each SC stage. Optimizing independently the costs of each actor leads to an increase in SC total costs, due to the lack of coordination. On the contrary, coordinated SCs are characterized by lower overall costs and higher profits (Bank et al., 2020; Chan et al., 2020). Basically, the optimization of a certain local problem can significantly affect the solution quality of subsequent problems, to the detriment of the overall SC solution (Neves-Moreira et al., 2019). Integrated planning is extremely useful especially in make-to-order (MTO) environments, where finished products usually have to be delivered to the customers shortly after production, in order to guarantee a good service level. In this case, the lack of production-distribution alignment could lead to: (i) significant quality decay such as to make the product undesirable for the customer (e.g., production activities are scheduled too in advance with respect to distribution operations), (ii) failure to meet delivery deadlines (e.g., the completion of production activities occurs too late with respect to the availability of means of transport for distribution) (Marandi and Zegordi, 2017; Armstrong et al., 2008; Stecke and Zhao, 2007).

SCM is even more challenging when dealing with perishable products. According to Amorim et al., (2013), a good can be considered perishable if at least one of the following conditions takes place during a well-defined planning horizon: (i) its physical status deteriorates, (ii) its value decreases according to an internal or external customer, (iii) there is the risk of possible future reduced functionality, based on the opinion of some authority. These authors generically refer to raw materials, semi-finished products, or finished products. In the literature, there are two main types of perishable products. In the first case, we can speak of fixed-lifetime products because they are characterized by a well-defined expiry date, beyond which they must be discarded; traditional examples are dairy products and pharmaceuticals (i.e., when the shelf-life is printed on the product). This category also includes products that become obsolete after a relatively short time period, for example Christmas items, hi-tech goods, fashion apparel, calendars, yearbooks (Jadidi et al., 2017; Coelho and Laporte, 2014). In the second case, instead, deterioration occurs over time in such a way that the product gradually loses its value during storage, until it becomes non-consumable. Fruits, vegetables, flowers, bread are only a few examples (Rong et al., 2011). Basically, in the latter case, shelf-life is not predetermined and the inventory replenishment decisions are extremely critical and challenging (Palak et al., 2018; Rohmer et al., 2019). Perishability affects multiple fields. In the health sector, kidney or heart transplants are strongly influenced by the perishable nature of the organ (Zahiri et al., 2014), in the pharmaceutical field, chemical composition of medicines determines the period of time within which they are still effective (Chung and Kwon, 2016), in hospitals a correct blood bank management is crucial for patient health (Najafi et al., 2017). However, the agri-food sector is probably the one in which the perishable nature of goods affects decision-making the most. The agri-food supply chains are often characterized by frequent customer orders of small quantities, tight time windows for deliveries, yield and demand uncertainty. In this context, real-time information sharing between the players in the chain becomes a key-factor to ensure an adequate service level while minimizing costs. The lack of coordination in the food supply chains mainly causes (i) unharvested fruits and/or vegetables upstream, while (ii) unsold products downstream. In both cases, bad operations management causes waste, which must be disposed of with consequent increase in costs and pollution, due to further transport.

2.2. Other literature reviews and contribution of the present research work

This subsection aims to inform the reader about the literature reviews that have been proposed over the years by other authors, about the integration of production, inventory and distribution activities in the supply chains. The aim is to demonstrate that there is an evident research gap, which will be filled by the subsequent subsections of the current chapter.

Bilgen and Ozkarahan, (2012) provide a literature survey on supply chain management at the strategic, tactical and operational levels. In particular, they focus their attention on models concerning the problems of production and distribution. The goal is to provide a classification according to the solution approach used: optimization-based methodologies, meta-heuristic-based models, information-technology-driven models, hybrid models. Finally, the most significant research trends are revealed. Mula et al., (2010) propose a literature review on mathematical programming models for supply chain production and transport planning. The 44 reviewed papers, covering a period of 20 years (i.e., 1989-2009), are classified and discussed on the basis of the following criteria: supply chain structure, decision level, modeling approach, purpose, shared information, limitations, novelty and application. Fahimnia et al., (2013) present a critical review on integrated production-distribution planning models. First, the papers are divided into seven categories according to the supply chain degree of complexity (e.g., single-product models, multiple-product single-plant models). Then, they are classified based on the solution approach (e.g., mixed integer programming, simulation, genetic algorithms). Wang et al., (2015) review the integrated scheduling problems, which are divided into two main categories: (i) integrated scheduling of production-distribution problems, (ii) integrated scheduling of production-inventory-distribution problems. The first category is then further detailed based on objectives and due date constraints. A rich review of tactical optimization models for integrated production and transport routing planning decisions is presented by Diaz-Madronero et al., (2015). The authors analyze 22 papers over 20 years (i.e., 1994-2014) and propose a classification framework, based on the following criteria: production, inventory, and routing aspects, objective function, solution approach. Soto-Silva et al., (2016) propose an interesting survey about the application of operational research models to the fresh fruit supply chain. The selected papers are classified according to several criteria: decision level (i.e., strategic, tactical, operational), modeling approach, purpose, applicability, novelty. The literature review by Moons et al., (2017) focuses on the integration of production scheduling and vehicle routing decisions at the operational level. The 33 selected papers are first divided into 3 main groups (i.e., single-machine environment, parallel-machine environment, other machine environments) and then classified according to production, inventory, and distribution features, objective, solution approaches. Very recently, Kumar et al., (2020) have proposed a systematic literature review on the quantitative approaches for the integration of production and distribution planning in the supply chain. The 74 selected papers cover a significant time horizon (i.e., 2000-2019) and are classified according to specific criteria.

In Table 1, this chapter is compared with the other examined literature reviews. Some important research gaps emerge. First of all, there is no survey focused on all the five dimensions of the proposed framework. In particular, there is no categorization of papers, based on perishability issues, which strongly affect supply chain performance. In the proposed literature review, all the papers dealing with perishable items are collected and classified. One of the main goals is to highlight the most used approaches to address perishability and limit food waste, in order to make supply chains more sustainable. Perishability significantly affects revenue, as goods subject to deterioration are usually sold in accordance with discount policies (Chen, 2019), but also costs, as it is necessary to take into account additional requirements regarding production (Lutke Entrup et al., 2005), storage (Ali et al., 2013; Meneghetti and Monti, 2015), and transportation activities (e.g., refrigerated vehicles) (Meneghetti and Ceschia, 2020). Furthermore, the main consequences of decay are lost sales and disposal costs (Li et al., 2020). According to Rohmer et al., (2019), in today's competitive markets, the quality and freshness of food products significantly influence customer satisfaction (Guido et al., 2020), therefore they are fundamental aspects for the survival of each business. Moreover, 54 articles are reviewed, which is quite a significant number when compared to many past literature reviews.

Table 1. Comparison between this chapter and the other literature reviews

Reference	# Papers reviewed	Time horizon	SCS	OF	SOA	AV	PI
Bilgen and Ozkarahan, (2004)	N.A.	N.A.	-	-	✓	-	-
Mula et al., (2010)	44	1989-2009	✓	✓	✓	✓	-
Fahimnia et al., (2013)	N.A.	1988-2011	✓	✓	✓	-	-
Wang et al., (2015)	79	1979-2013	-	-	-	-	-
Diaz-Madronero et al., (2015)	22	1994-2014	-	✓	✓	-	-
Soto-Silva et al., (2016)	44	1976-2015	-	-	✓	-	-
Moons et al., (2017)	33	1996-2016	-	✓	✓	-	-
Kumar et al., (2020)	74	2000-2019	✓	✓	✓	-	-
This chapter	54	2005-2020	✓	✓	✓	✓	✓

AV – Approach Validation; OF – Objective Function; PI – Perishability Issues; SOA – Solution Approach; SCS – Supply Chain Structure

2.3. Research methodology

The research methodology used to carry out the literature review, subject of this chapter, is characterized by several steps in sequence, as shown in Figure 1.

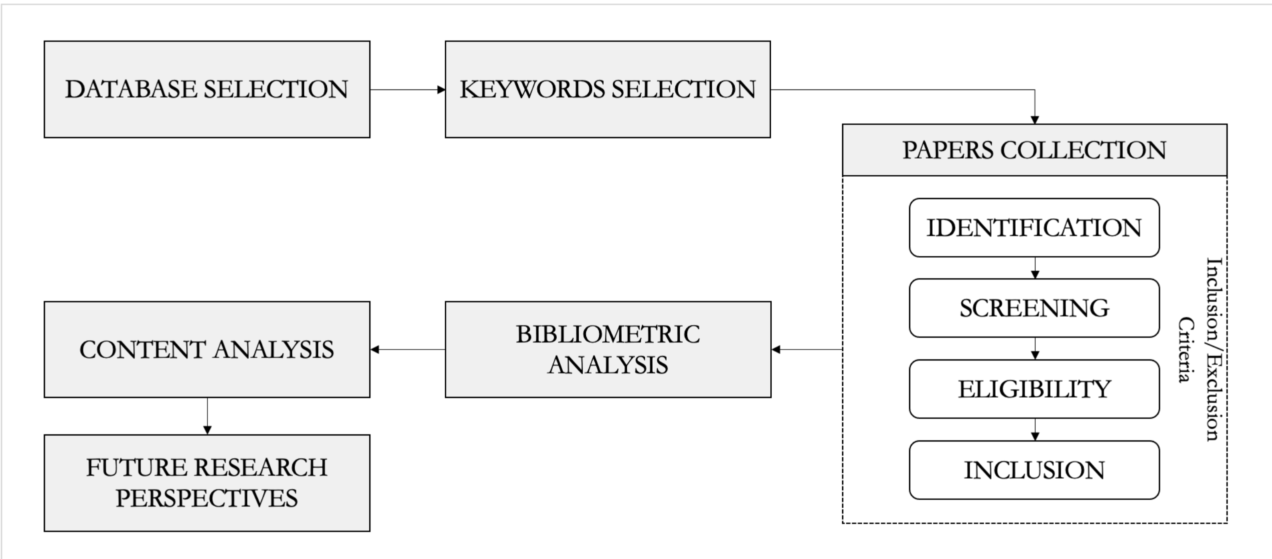

Figure 1. Research methodology scheme

First of all, it is necessary to select one or more databases within which to retrieve the records useful for conducting the survey. Several scientific databases exist. It was decided to query Scopus, which is currently one of the most recognized and comprehensive databases. It contains more than 20,000 peer-reviewed journals related to different publishers (e.g., Elsevier, Taylor \& Francis, IEEE) and is much more exhaustive than others (e.g., Web of Science, IEEE Explore). Scopus was queried on September 8, 2020. The second step of the methodology concerns the keywords selection to carry out the database queries. The main purpose of the current study is to collect research works, where quantitative approaches to integrate decisions related to production, storage and distribution activities, are proposed. Therefore, it was decided (i) to combine the keywords linked to these 3 areas, and (ii) to consider in any case the distribution issues and the perishable nature of the products. Altogether, six queries were conducted, the results of which are shown in Table 2. Specific search criteria have been used, as shown in Table 3.

Table 2. Database queries: results

# Search	Keywords	# Papers
1	"production distribution" AND "perishable	109
2	"production transportation" AND "perishable"	64
3	"Production routing" AND "perishable"	30
4	"Inventory routing" AND "perishable"	51
5	"Inventory transportation" AND "perishable"	68
6	"Inventory distribution" AND "perishable"	192
	Total (after removing duplicates)	366

Table 3. Search criteria

Search criterion	Selection
Search field	Article title, Abstract, Keywords
Years	2005-2020
Subject areas	All
Document type	Journal Article
Language	English
Date of search	8-Sep-2020

The result of this first search was a set of 366 documents, which were reduced to 88 after reading their title and abstract. Then, after reading the full-text, it was decided to include only the 54 articles that use optimization strategies for supply chain integration (Zanoni and Zavanella, 2007; Naso et al., 2007; Chen, 2009; Ahumada and Villalobos, 2011, 2011a; Ahumada et al., 2012; Amorim et al., 2012; Farahani et al., 2012; Amorim et al., 2013; AriaNezhad et al., 2013; Le et al., 2013; Coelho and Laporte, 2014; Seyedhosseini and Ghoreyshi, 2014,a; Viergutz and Knust, 2014; Soysal et al., 2015; Mirzaei and Seifi, 2015; Seyedhosseini and Ghoreyshi, 2015; Belo-Filho et al., 2015; Wu et al., 2015; Bortolini et al., 2016; Shaabani and Kamalabadi, 2016; Li et al., 2016; Diabat et al., 2016; Vahdani et al., 2017; Rahimi et al., 2017; Devapriya et al., 2017; Marandi and Zegordi, 2017; Li et al., 2017; Azadeh et al., 2017; Hiassat et al., 2017; Accorsi et al., 2017; Lacomme et al., 2018; Crama et al., 2018; Ra_e-Majd et al., 2018; Soysal et al., 2018; Hu et al., 2018; Dolgui et al., 2018; Neves-Moreira et al., 2019; Chao et al., 2019; Qiu et al., 2019; Ghasemkhani et al., 2019; Onggo et al., 2019; Rohmer et al., 2019; Violi et al., 2020; Li et al., 2020; Wei et al., 2020; Manoucheri et al., 2020; Sinha and Anand, 2020; Chan et al., 2020; Liu and Liu, 2020; Bank et al., 2020; Biuki et al., 2020; Dai et al., 2020).

2.4. Bibliometric analysis

This subsection shows the results of the bibliometric analysis, which was partly supported by the free software VOSviewer (1.6.13 version) (Van Eck and Waltman, 2009). Only the 54 selected papers were analyzed.

2.4.1. Publishing sources

In Table 4, the distribution of the 54 reviewed articles across the journals is shown. The top 9 journals have published around 60 % of the articles (i.e., 32), and the International Journal of Production Economics is the most prolific, with 6 papers. It is followed by Annals of Operations Research, Computers and Industrial Engineering, Computers and Operations Research, International Journal of Production Research, all with 4 contributions.

Table 4. Distribution of the 54 selected papers across the journals

Journal	# Articles	% Contribution
International Journal of Production Economics	6	11.11
Annals of Operations Research	4	7.41

Computers and Industrial Engineering	4	7.41
Computers and Operations Research	4	7.41
International Journal of Production Research	4	7.41
IFAC-PapersOnLine	3	5.56
Journal of Cleaner Production	3	5.56
European Journal of Operational Research	2	3.70
Omega	2	3.70
Others	22	40.74
Total	54	100.00

2.4.2. Chronological distribution

With the aim to have an idea about the interest over the years in supply chain coordination strategies in the case of perishable products, in Figure 2, a graph relating to the temporal distribution of the selected papers with reference to the period 2005-2020, is shown. As it can easily be seen, interest in the topic of this literature review has grown considerably in recent years. Indeed, despite this study considers the articles published up to September 2020, 2020 is currently the year with the highest number of publications (i.e., 10).

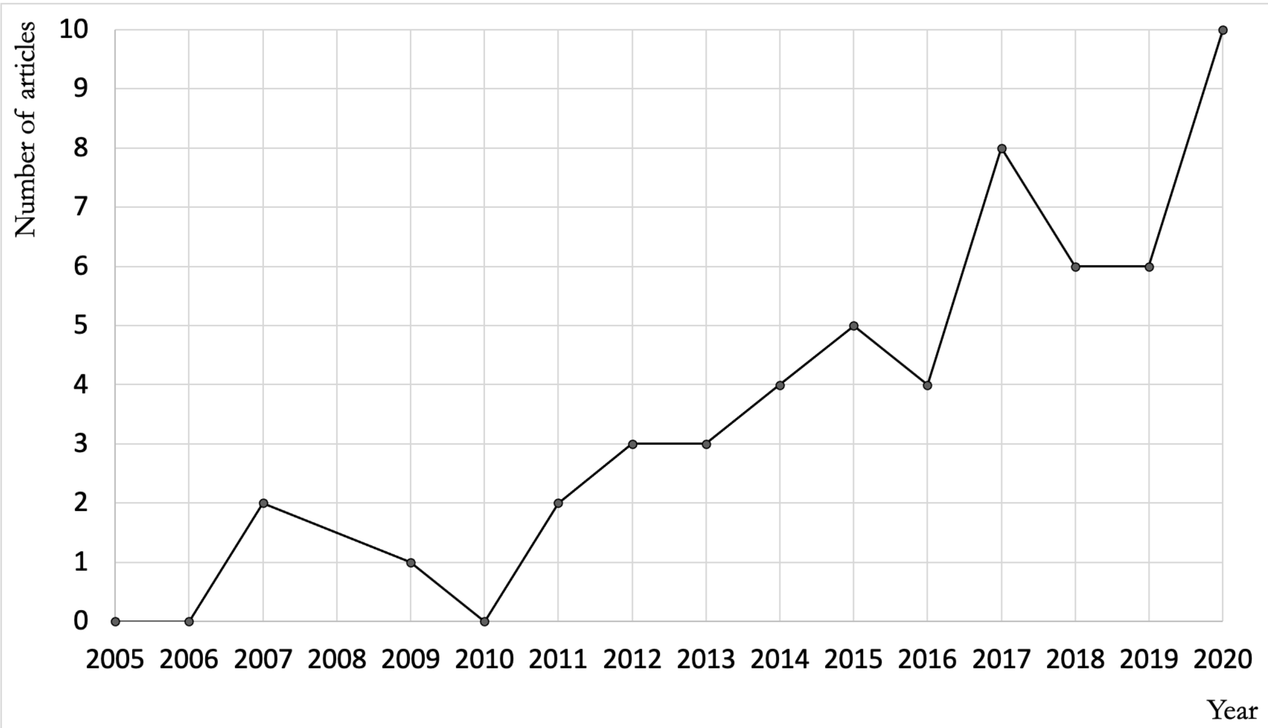

Figure 2 Distribution of the 54 selected papers over the period 2005-2020

2.4.3. Keywords statistics

It is also very interesting to highlight the keywords most frequently used by the authors, in order to identify the most recurring research areas. Since the VOSviewer software is unable neither to distinguish between singular and plural nor between words that have the same root and meaning, similar keywords have been merged. In Table 5, for each final keyword, the list of keywords from which it derives, and the overall number of occurrences, are shown. A hyphen means that the related final keyword has not changed from the original one.

Table 5. Keywords statistics

Original keywords	Final keyword	# Occurrences
Perishable good, Perishable goods, Perishable product, Perishable products	Perishable good(s)/product(s)	38
Inventory-routing, Inventory routing, Inventory routing problem	Inventory routing (problem)	13
Vehicle routing, Vehicle routing problem	Vehicle routing (problem)	7
-	Supply chain	6
-	Perishability	6
Genetic algorithm, Genetic algorithm(s)	Genetic algorithm(s)	6
-	Food quality	4
-	Production scheduling	4
Metaheuristic, Meta-heuristic, Meta-heuristic algorithm, Metaheuristics	Metaheuristic(s) (algorithm)	4
Production and distribution, Production and distribution planning	Production and distribution (planning)	4
Time window, Time windows	Time window(s)	4

As expected, the perishability-related keywords are the most frequently used. However, from the keywords analysis, some important research trends emerge. First of all, it is possible to say that the distribution stage is often addressed and modelled through a vehicle routing problem (VRP). In its most traditional form, a VRP aims to find an optimal set of routes for a vehicle fleet to serve a certain number of customers, while minimizing the total traveling cost (Vidal et al., 2020). The final keyword "Time window(s)" suggests that the requirement to serving customers within delivery time windows is also taken into account. Moreover, many papers deal with an inventory routing problem (IRP), which is an extension of the VRP, where inventory control and routing decisions are combined (Rafie-Majd et al., 2018). The occurrence of the final keywords "Genetic algorithm(s)" and "Metaheuristic(s) (algorithm)" is not a surprise because when different supply chain stages are integrated into a single monolithic problem, non-exact approaches are often necessary to find good solutions in a reasonable time. In fact, the large set of decisions and factors to be jointly considered often result in computationally intractable problems (Neves-Moreira et al., 2019).

2.4.4. Featured authors

In Table 6, the information about the top contributing authors and their relative institution and country, is shown.

Table 6. Top contributing authors

Author	Insitution	Country	# Articles
Almada-Lobo, B.	Universidade do Porto	Portugal	4
Amorim, P.	Universidade do Porto	Portugal	3
Chu, F.	Université Paris-Saclay, Fuzhou University	France, China	3
Li, Y.	Université Paris-Saclay, Academy of Military Science of the Chinese People's Liberation Army	France, China	3
Ghoreyshi, S.M.	Iran University of Science & Technology	Iran	3
Seyedhosseini, M.	Iran University of Science & Technology	Iran	3
Ahumada, O.	Universidad Autonoma de Occidente	Mexico	3

Diabat, A.	New York University Abu Dhabi, New York University	United Arab Emirates, United States	3

Almada-Lobo B. is the most prolific author with 4 publications. He has co-authored three of them with Amorim P. (Amorim et al., 2012, 2013; Belo-Filho et al., 2015). Their research area has mainly focused on addressing the integrated production and distribution planning with perishable products, from an operational point of view. A quite similar topic has been treated by Ghoreyshi S.M. and Seyedhosseini M. in their co-authored papers (Seyedhosseini and Ghoreyshi, 2014, 2014a, 2015). Chu F. and Li Y. has instead co-authored 3 articles, mainly focused on modelling and solving some interesting variants of the production-inventory-routing problem with perishable goods (Li et al., 2016, 2017, 2020). The peculiarity of the three Ahumada's papers concerns the study of agro-food supply chains (i.e., pepper and tomato), with a lot of attention to the harvesting stage and the possibility of multiple transportation modes (e.g., trucking, railroad, air) for what concerns the distribution stage (Ahumada and Villalobos, 2011, 2011a; Ahumada et al., 2012). Diabat, A. has considered both the location-inventory-routing problem and the inventory-routing problem in his studies (Le et al., 2013; Diabat et al., 2016; Hiassat et al., 2017).

2.5. Content analysis

In this section, the content of the 54 selected papers is widely discussed. A five-level classification framework, as shown in Figure 3, is proposed, with the aim to classify the papers according to: supply chain structure, objective, perishability issues, solution approach and approach validation.

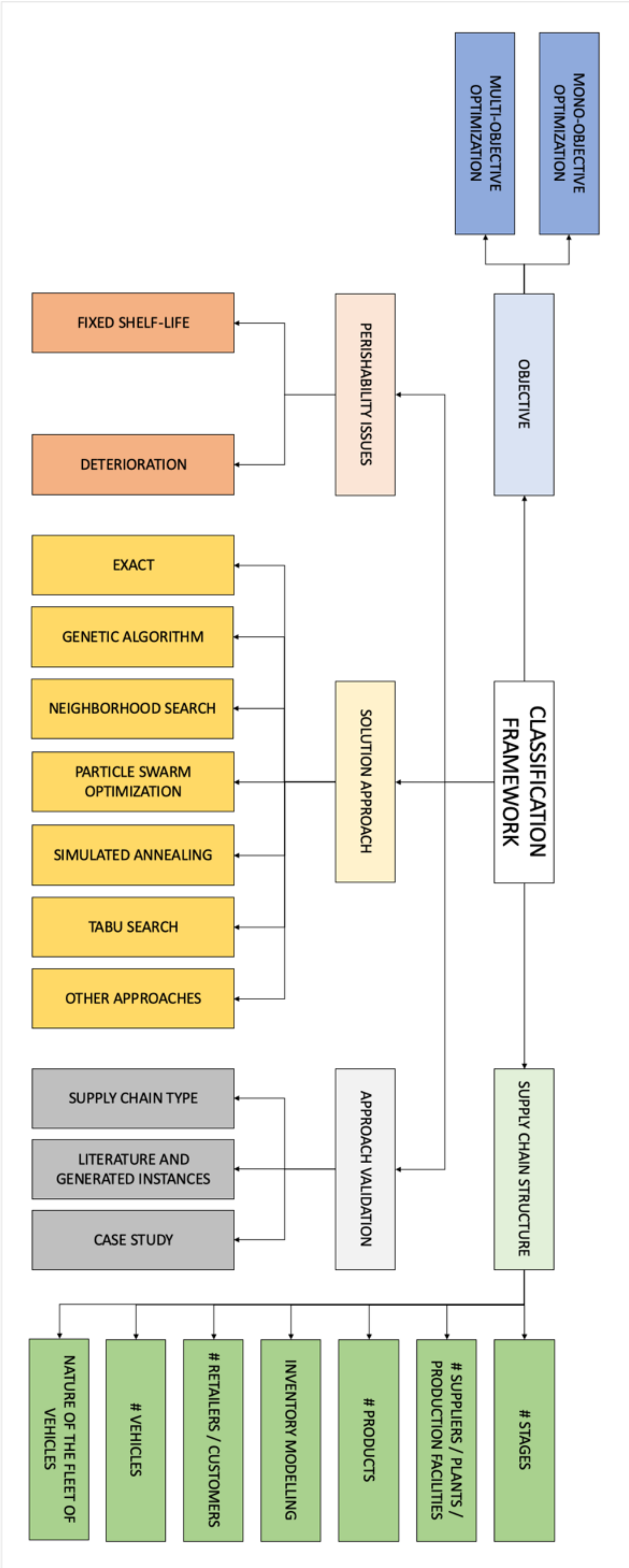

Figure 3. Classification framework

2.5.1. Main contribution

In Table 7, the main contribution of the selected articles is summarized.

Table 7. Main contribution of the 54 selected papers

Reference	Main contribution
Zanoni and Zavanella, (2007)	A Mixed Integer Linear Programming (MILP) Model for addressing the problem of jointly minimizing the transportation and inventory costs related to the shipment of multiple perishable products in a single-origin single-destination supply chain. Six heuristic algorithms to solve the problem in reasonable time.
Naso et al., (2007)	A mathematical model to tackle the problem of coordinating the production and distribution activities of a network of production centers, which supply rapidly perishable goods. A hybrid metaheuristic approach, which combines a genetic algorithm with some constructive heuristics.
Chen, (2009)	A non-linear mathematical model, which simultaneously takes into account production scheduling and vehicle routing with time windows, in the case of perishable products with fixed deterioration rate. A solution algorithm, which relies on the constrained Nelder-Mead method (Nelder and Mead, 1965) and a heuristic.
Ahumada and Vilalobos, (2011)	A tactical planning model for the integrated production and distribution of perishable agri-products. Perishability is addressed in two different ways, (i) by limiting the maximum storage time and (ii) by considering a loss term, into the objective function, for the decay of the products over time.
Ahumada and Villalobos, (2011a)	An operational model, with the aim to support production and distribution decisions about perishable agri-products, during the harvesting season. Quality of crops, management of labor costs, different transportation modes are the most challenging factors taken into account. Revenue is maximized, with reference to a hypothetical producer of tomatoes and peppers.
Ahumada et al., (2012)	A stochastic tactical planning model for supporting the production and distribution of fresh agricultural products. The two-stage stochastic programming is used as modeling approach and applied to a case study in Mexico, which includes all the assumptions made in (Ahumada and

	Villalobos, 2011). The stochastic approach, at the same risk level, guarantees an increase in the expected profit greater than 50 %.
Amorim et al., (2012)	A multi-objective framework, aimed at integrating production and distribution planning for highly perishable products, at an operational level. Perishability is addressed under the two most common cases, i.e., fixed and loose shelf-life. The integrated approach is compared with the decoupled one, with good results.
Farahani et al., (2012)	An integrated approach for short-term production and distribution planning, with reference to a real catering company located in Denmark. The right trade-off between total costs and quality of delivered products is achieved. The production scheduling problem is tackled by a heuristic batching procedure, while the distribution problem is solved through a large neighborhood search algorithm.
Amorim et al., (2013)	A detailed comparison between lot-sizing and batching in the joint production and distribution planning of perishable goods, at an operational level.
AriaNezhad et al., (2013)	A two-echelon model to control the inventory of perishable items. Production and distribution decisions are jointly tackled. Perishability is addressed considering a fixed shelf-life and a penalty related to perished goods, within the objective function. A genetic algorithm applied to the proposed model, considering real-life instances, shows the applicability of the approach.
Le et al., (2013)	A column generation-based approach for solving an inventory-routing problem with perishable goods. The sum of transportation and inventory costs is minimized, while product shelf-life is assumed fixed and known.
Coelho et al., (2013)	Modeling and solving the problem of joint replenishment and inventory control of perishable products, by branch-and-cut. Two selling priority policies (i.e., old-first and fresh-first) are implemented and compared with an optimized policy. The results show that the model can successfully maximize profit and control spoilage, under several scenarios.
Seyedhosseini and Ghoreyshi, (2014)	Formulation of an integrated production and distribution planning model for perishable products. The problem is solved using a heuristic method, where

	the production model is tackled using an exact solver while the distribution one is solved through particle swarm optimization.
Seyedhosseini and Ghoreyshi, (2014)	An integrated production-distribution planning model for a perishable product, which is distributed from a single production facility to multiple distribution centers, using a set of pre-defined feasible delivery routes. Considering the computational complexity of the problem, a heuristic algorithm is designed and then tested, with good results, on some randomly generated instances.
Viergutz and Knust, (2014)	Improvement of a branch-and-bound algorithm, already existing in the literature (Armstrong et al., 2008), with reference to an integrated production and distribution scheduling problem, characterized by a short lifespan product in a make-to-order scenario. Model extensions are introduced and efficient heuristic solution algorithms are developed and applied to randomly generated instances.
Soysal et al., (2015)	Formulation and solution of an inventory-routing problem, characterized by additional features such as CO_2 emissions, fuel consumption, service level, demand uncertainty, product perishability. The application to a case study on the fresh tomato supply chain confirms the goodness of the proposed model, whose several variants are presented.
Mirzaei and Seifi, (2015)	A non-linear mixed integer programming model for an inventory routing problem, in the case of perishable items. The aim is to minimize the cost of transportation, inventory, and lost sale, that is modeled as a linear or an exponential function of the inventory age. The proposed model is solved optimally for small instances, while a meta-heuristic algorithm is designed to tackle larger instances.
Seyedhosseini and Ghoreyshi, (2015)	A formulation for the integration of production and distribution planning of perishable products, through lot sizing and inventory routing. An efficient heuristic algorithm is tested, with the aim to find good solutions in a reasonable time.
Belo-Filho et al., (2015)	An adaptive large neighborhood search framework to tackle the operational integrated production and distribution problem with perishable products. Main decisions are about the sizing and scheduling of production lots, and

	the vehicle routing. The proposed solution approach, tested on randomly generated instances, outperforms traditional methods (e.g., exact methods, fix-and-optimize procedures).
Wu et al., (2015)	A multi-period location model, where several decisions are integrated: the location of facilities, the retailer-to-facility allocation, the shipping plan from the single supplier to the multiple retailers (i.e., the perishable inventory replenishment). The facilities work as cross-docking points, while economies-of-scale are assumed for the transportation stage. A greedy heuristic within a column generation procedure is designed for solving the proposed mixed integer non-linear programming model.
Bortolini et al., (2016)	A tool to support the tactical planning of multi-modal distribution networks in the case of perishable products. Three objectives are jointly optimized: operating cost, carbon footprint, delivery time. The application of the proposed expert system to a real case study, which refers to the fruit and vegetables sector, confirms its effectiveness and efficiency.
Shaabani and Kamalabadi, (2016)	A population-based simulated annealing algorithm for solving an inventory routing problem with perishable products. The comparison with alternative solution methods (i.e., simulated annealing, genetic algorithms) and the use of upper and lower bounds demonstrate the high efficiency of the proposed approach.
Li et al., (2016)	Formulation of a production-inventory-routing problem, where food quality levels are explicitly taken into account throughout the supply chain. The aim is to maximize the total profit.
Diabat et al., (2016)	An innovative arc-based formulation and a tabu search algorithm for the periodic distribution-inventory problem for perishable goods, considering a vendor managed inventory configuration. The proposed approach, tested on a set of randomly generated instances, outperforms the column generation algorithm, and is more efficient than CPLEX.
Vahdani et al., (2017)	A mathematical programming model to address a production-inventory-routing problem with capacity and time window constraints for perishable items. Product quality loss is explicitly taken into account. Two efficient solution approaches are presented, an adaptive large neighborhood search

	algorithm and a meta-heuristic (i.e., water cycle procedure). The computational tests, performed on a set of instances derived from the literature, demonstrate the goodness of the proposed approaches.
Rahimi et al., (2017)	A multi-objective version of the traditional inventory-routing problem, where additional features are taken into account: service level and greenhouse gases emissions (GHG). Demand and transportation costs are supposed uncertain and modeled considering fuzzy distributions. The Non-dominated Sorting Genetic Algorithm (NSGA) II designed by Deb et al., (2002) is used to solve the problem and to derive the Pareto frontier.
Devapriya et al., (2017)	A mixed integer linear programming formulation for the integrated production and distribution scheduling problem with a perishable product. Two heuristics, based on evolutionary algorithms, are designed and tested to solve the problem.
Marandi and Zagordi, (2017)	A mixed-integer nonlinear programming model, that integrates permutation flow shop scheduling (production stage) and vehicle routing (distribution stage), with the aim to minimize delivery and tardy cost, referring to due date violation. An Improved Particle Swarm Optimization algorithm is proposed for solving the problem. The comparison with a known genetic algorithm (Ullrich, 2013) and the solutions returned by LINGO, demonstrates the efficiency of the designed algorithm.
Li et al., (2017)	A production inventory routing model, where quality levels of perishable items are explicitly considered. A set of randomly generated instances are efficiently solved through a two-phase iterative approach, derived from the literature.
Azadeh et al., (2017)	A mathematical formulation for an inventory-routing problem with transshipment in the presence of a single product, that perishes according to an exponential deterioration rate. Considering the NP-hard nature of the model, a genetic algorithm characterized by Taguchi-based parameters tuning, is proposed. The validity of the proposed approach is proved through the application to a real-life case study, with reference to the dairy supply chain.

Hiassat et al., (2017)	Adding the location decisions to the inventory-routing problem with the aim to make it more practical and to integrate strategic, tactical and operational levels. An efficient genetic algorithm is developed for efficiently solving the problem.
Accorsi et al., (2017)	A mixed-integer linear programming model for the integrated planning of production, storage and distribution of perishable products, considering also the interactions with the weather conditions. The application to an illustrative case study, referring to cherries supply chain, shows that significant environmental savings can be achieved.
Lacomme et al., (2018)	The authors address the production and transportation scheduling problem in order to extend the case with a single vehicle, treated in (Geismar et al., 2008). A Greedy Randomized Adaptive Search Procedure (GRASP) with Evolutionary Local Search is proposed to solve the problem in a coordinated way, overperforming the classical approach, where the two sub-problems (i.e., production scheduling and transportation scheduling) are treated sequentially.
Crama et al., (2018)	Proposal of several methods to solve an inventory-routing problem for a single perishable product with stochastic demand. The solution approaches are compared considering different indicators such as profit, service level, freshness. Managerial insights regarding the impact of shelf life and inventory capacity on profit are also provided.
Rafie-Majd et al., (2018)	An integrated inventory-location-routing problem to model a three-echelon supply chain (i.e., supplier, distribution center(s), customers), characterized by perishable goods. The mixed integer nonlinear programming model is solved by GAMS with a fixed time limit. Lower and upper bounds, computed respectively through a Lagrangian Relaxation and a heuristic algorithm, enable the evaluation of the goodness of the obtained solutions.
Soysal et al., (2018)	Analysis of the impact of horizontal collaboration on some critical key performance indicators (i.e., CO_2 emissions, driving time, routing cost, inventory and wage cost), in the case of an inventory-routing problem with multiple suppliers and customers. The application of the proposed chance-constrained programming model to a real-life case study shows its validity.

	The most relevant result is that horizontal collaboration leads to significant cost savings and minimizes emissions.
Hu et al., (2018)	An iterative framework characterized by a decomposition procedure and a local search scheme, with the aim to efficiently solve an optimization model, where inventory routing and freight consolidation, with perishable products, are integrated. Computational experiments, based on real data from the cut flower supply chain in California, validate the proposed approach.
Dolgui et al., (2018)	A mathematical model for solving a production-inventory distribution problem in a three-stage supply chain with perishable products and truckload discounts. An exponential deterioration rate is supposed for the goods, in accordance with the literature about the growth rate of the micro-organisms, that cause the deterioration. The proposed non-revisiting genetic algorithm is efficient and outputs near-optimal solutions in short computational time, if compared with CPLEX.
Neves-Moreira et al., (2019)	A fix-and-optimize matheuristic for solving a production-routing problem with time windows. The application of the proposed solution approach to both literature instances and a real meat supply chain, prove its goodness.
Chao et al., (2019)	An Improved Ant Colony Optimization algorithm with distance-based clustering approach for solving a two-stage location-routing-inventory problem with time windows in a distribution network characterized by perishable items. Energy costs and perished foods during the transportation stage are explicitly considered. The application of the proposed approach to randomly generated instances and to a Chinese case study confirm its validity and usefulness.
Qiu et al., (2019)	Design and development of an exact branch and cut algorithm for solving a generalized production-inventory-routing problem with perishable inventory. Multiple inventory management policies are implemented. The application of the proposed approach to a real-life case study, with reference to a Chinese fresh meat supply chain, confirms its validity.
Ghasemkhani et al., (2019)	Modeling and solving an integrated production-inventory-routing problem with time windows in a network characterized by a single depot and multiple retailers. The demand of perishable products is tackled through a fuzzy

	approach. Different quality levels are used to take into account product deterioration and introduce price-discount policies. The optimal solution is found through CPLEX in a reasonable time, with reference to small- and medium-size randomly generated instances.
Onggo et al., (2019)	A simheuristic algorithm, which integrates Montecarlo Simulation within an iterated local search for solving a perishable inventory routing problem with stochastic demand. The aim is to minimize the total costs related to a supply chain, made by a single fresh food supplier and several retail centers.
Rohmer et al., (2019)	A two-stage matheuristic combining an adaptive large neighborhood search with a MILP formulation for solving an inventory-routing problem with perishable products. The aim is to minimize transportation and inventory costs, while considering items deteriorating linearly over the time. Different variants of the proposed approach are tested, the results are very promising.
Violi et al., (2020)	A rolling horizon algorithm to solve an inventory-routing problem under uncertainty with perishable agri-products. The objective function is a convex combination of the expected cost and a certain risk measure. The application of the proposed approach to a real tangerine supply chain in the South of Italy confirms its efficiency and effectiveness.
Li et al., (2020)	A hybrid matheuristic for a production routing problem, where product perishability is related to packaging considerations. Computational tests on a set of randomly generated instances show the high performance of the proposed approach. The impact of different kinds of price discounts is also discussed. Moreover, two branch-and-cut algorithms are developed and implemented.
Wei et al., (2020)	A mixed-integer programming model is formulated to simultaneously optimize production, replenishment, inventory, and routing decisions about perishable products, which deteriorate over the considered planning horizon. Different inventory strategies are tested. The proposed branch-and-cut algorithm is very efficient in solving the problem, when compared with the results returned by CPLEX.
Manoucheri et al., (2020)	A hybrid search algorithm, which combines the variable neighborhood search and the simulated annealing, for solving a production routing problem with

	perishable products. Food degradation is addressed through the Gompertz equation, while temperature levels at warehouse and (refrigerated) vehicles are explicitly considered to estimate product quality. The application of the proposed approach to a real chicken-packing plant in Iran confirms its great usefulness.
Sinha and Anand, (2020)	Formulation of a holistic model and proposal of an improved bacteria foraging algorithm for a three-stage supply chain problem, where products deterioration increase with the time. The validation of the proposed approach consists in comparing it with a traditional bacteria foraging algorithm, on two case studies, with good results in terms of performance.
Chan et al., (2020)	A modified multi-objective particle swarm optimization (PSO) algorithm for solving a four-objective mixed integer linear programming model, which deals with an integrated production-inventory-routing problem with perishable goods. Different quality levels are considered to clearly take into account product deterioration. Computational tests on a real case study, which refers to a Chinese meat supply chain, shows the efficiency of the designed approach, where compared to other PSO-based algorithms.
Liu and Liu, (2020)	A mathematical model, which jointly optimizes production scheduling and vehicle routing. Given a single machine, a set of customers, served by homogeneous vehicles, the objective is to minimize the total weighted delivery time of the orders, that represents a measure of customer service level. The improved large neighborhood search algorithm, proposed for solving the model, outperforms CPLEX and a genetic algorithm, available in the literature.
Bank et al., (2020)	A mixed integer programming model for an integrated production and distribution problem in a two-stage supply chain. A hybrid simulated annealing and a genetic algorithm are proposed, with good results, in the solution of the problem.
Biuki et al., (2020)	A two-phase approach to design a green supply chain. In the first phase, the most sustainable suppliers are selected through the PROMETHEE method (Rabbani et al., 2018). Then, a multi-objective mixed integer programming model is designed, that is solved by using two metaheuristics based on

	Genetic Algorithm and Particle Swarm Optimization. The computational tests, executed on a set of randomly generated instances, confirm the validity of the proposed approach.
Dai et al., (2020)	Formulation of three cyclic inventory-routing models, under the vendor-managed-inventory policy. A constant deterioration rate is supposed for the perishable products, whose demand is dependent on price and stock. A hybrid heuristic algorithm, which combines cuckoo and Clarke-Wright savings algorithms, is developed for solving with good results all the proposed models.

2.5.2. Supply chain structure

In Tables 8-9, the 54 selected papers are classified, based on some factors related to the 3 main areas of this literature review: production, inventory, distribution. Furthermore, with the aim to give an idea about the complexity of each supply chain, an extremely important indicator is defined and used: the number of modeled supply chain stages. It is really important to specify that the two items # suppliers/plants/production facilities and # retailers/customers refer respectively to the first and last level of the considered supply chain. They give to the reader a significant indication about the product flow, that could be: one-to-one, one-to-many, many-to-one, many-to-many.

Table 8. Production and inventory features

Reference	# Supply chain stages	Production Area				Inventory Area	
		# Suppliers/ Plants/ Production facilities		# Products		Suppliers/ Plants/ Production facilities	Retailers/ Customers
		S	M	S	M		
Zanoni and Zavanella, (2007)	2	✓	-	-	✓	✓	✓
Naso et al., (2007)	2	-	✓	✓	-	-	-

Chen, (2009)	2	✓	-	-	✓	-	-
Ahumada and Villalobos, (2011)	5	-	✓	-	✓	✓	-
Ahumada and Villalobos, (2011a)	5	-	✓	-	✓	✓	-
Ahumada et al., (2012)	5	-	✓	-	✓	✓	-
Amorim et al., (2012)	2	-	✓	-	✓	-	✓
Farahani et al., (2012)	2	✓	-	-	✓	-	-
Amorim et al., (2013)	2	✓	-	-	✓	-	-
AriaNezhad et al., (2013)	2	✓	-	-	✓	✓	✓
Le et al., (2013)	2	✓	-	✓	-	-	✓
Coelho and Laporte, (2014)	2	✓	-	✓	-	✓	✓
Seyedhosseini and Ghoreyshi, (2014)	2	✓	-	✓	-	✓	✓
Seyedhosseini and Ghoreyshi, (2014a)	2	✓	-	✓	-	✓	✓
Viergutz and Knust, (2014)	2	✓	-	✓	-	-	-
Soysal et al., (2015)	2	✓	-	✓	-	-	✓
Mirzaei and Seifi, (2015)	2	✓	-	✓	-	-	✓

Seyedhosseini and Ghoreyshi, (2015)	2	✓	-	✓	-	✓	✓
Belo-Filho et al., (2015)	2	✓	-	-	✓	-	-
Wu et al., (2015)	3	✓	-	✓	-	-	✓
Bortolini et al., (2016)	4	-	✓	-	✓	-	-
Shaabani and Kamalabadi, (2016)	2	✓	-	-	✓	✓	✓
Li et al., (2016)	2	✓	-	✓	-	✓	✓
Diabat et al., (2016)	2	✓	-	✓	-	-	✓
Vahdani et al., (2017)	3	-	✓	-	✓	✓	-
Rahimi et al., (2017)	2	✓	-	-	✓	-	✓
Devapriya et al., (2017)	2	✓	-	✓	-	-	-
Marandi and Zegordi, (2017)	2	✓	-	-	-	-	-
Li et al., (2017)	2	✓	-	✓	-	✓	✓
Azadeh et al., (2017)	2	✓	-	✓	-	✓	✓
Hiassat et al., (2017)	2	-	✓	✓	-	-	✓
Accorsi et al., (2017)	2	-	✓	-	✓	-	✓

Lacomme et al., (2018)	2	✓	-	✓	-	-	-
Crama et al., (2018)	2	✓	-	✓	-	-	✓
Rafie-Majd et al., (2018)	3	✓	-	-	✓	✓	✓
Soysal et al., (2018)	2	-	✓	-	✓	-	✓
Hu et al., (2018)	3	✓	-	✓	-	✓	-
Dolgui et al., (2018)	3	-	✓	✓	-	-	✓
Neves-Moreira et al., (2019)	2	✓	-	-	✓	✓	✓
Chao et al., (2019)	3	-	✓	✓	-	-	✓
Qiu et al., (2019)	2	✓	-	✓	-	✓	✓
Ghasemkhani et al., (2019)	2	✓	-	-	✓	-	✓
Onggo et al., (2019)	2	✓	-	✓	-	-	✓
Rohmer et al., (2019)	3	✓	-	✓	-	✓	-
Violi et al., (2020)	3	-	✓	✓	-	✓	✓
Li et al., (2020)	2	-	✓	✓	-	✓	✓
Wei et al., (2020)	3	✓	-	✓	-	✓	✓
Manoucheri et al., (2020)	2	✓	-	-	✓	✓	✓

Sinha and Anand, (2020)	3	-	✓	✓	-	-	✓
Chan et al., (2020)	2	✓	-	✓	-	✓	✓
Liu and Liu, (2020)	2	✓	-	✓	-	-	-
Bank et al., (2020)	2	-	✓	-	-	-	-
Biuki et al., (2020)	4	-	✓	-	✓	✓	✓
Dai et al., (2020)	2	✓	-	✓	-	✓	✓

S – Single; M – Multiple

Table 9. Distribution features

Reference	Distribution Area					
	# Retailers/ Customers		# Vehicles		Nature of the fleet of vehicles	
	S	M	S	M	Homogeneous	Heterogeneous
Zanoni and Zavanella, (2007)	✓	-	-	✓	✓	-
Naso et al., (2007)	-	✓	-	✓	✓	-
Chen, (2009)	-	✓	-	✓	✓	-
Ahumada and Villalobos, (2011)	-	✓	-	-	-	-
Ahumada and Villalobos, (2011a)	-	✓	-	-	-	-

Ahumada et al., (2012)	-	✓	-	-	-	-
Amorim et al., (2012)	-	✓	-	-	-	-
Farahani et al., (2012)	-	✓	-	✓	✓	-
Amorim et al., (2013)	-	✓	-	✓	✓	-
AriaNezhad et al., (2013)	-	✓	-	-	-	-
Le et al., (2013)	-	✓	-	✓	✓	-
Coelho and Laporte, (2014)	-	✓	-	✓	-	✓
Seyedhosseini and Ghoreyshi, (2014)	-	✓	-	✓	✓	-
Seyedhosseini and Ghoreyshi, (2014a)	-	✓	-	✓	✓	-
Viergutz and Knust, (2014)	-	✓	✓	-	-	-
Soysal et al., (2015)	-	✓	-	✓	✓	-
Mirzaei and Seifi, (2015)	-	✓	-	✓	✓	-
Seyedhosseini and Ghoreyshi, (2015)	-	✓	-	✓	✓	-
Belo-Filho et al., (2015)	-	✓	-	✓	✓	-
Wu et al., (2015)	-	✓	-	-	-	-

Bortolini et al., (2016)	-	✓	-	-	-	-
Shaabani and Kamalabadi, (2016)	-	✓	-	✓	-	✓
Li et al., (2016)	-	✓	-	✓	✓	-
Diabat et al., (2016)	-	✓	-	✓	✓	-
Vahdani et al., (2017)	-	✓	-	✓	-	✓
Rahimi et al., (2017)	-	✓	-	✓	-	✓
Devapriya et al., (2017)	-	✓	-	✓	✓	-
Marandi and Zegordi, (2017)	-	✓	-	✓	-	✓
Li et al., (2017)	-	✓	-	✓	✓	-
Azadeh et al., (2017)	-	✓	✓	-	-	-
Hiassat et al., (2017)	-	✓	-	✓	✓	-
Accorsi et al., (2017)	-	✓	-	✓	-	✓
Lacomme et al., (2018)	-	✓	✓	✓	✓	-
Crama et al., (2018)	-	✓	-	✓	✓	-
Rafie-Majd et al., (2018)	-	✓	-	✓	-	✓
Soysal et al., (2018)	-	✓	-	✓	-	✓

Hu et al., (2018)	-	✓	-	✓	-	✓
Dolgui et al., (2018)	-	✓	-	✓	-	✓
Neves-Moreira et al., (2019)	-	✓	-	✓	-	✓
Chao et al., (2019)	-	✓	-	✓	✓	-
Qiu et al., (2019)	-	✓	-	✓	✓	-
Ghasemkhani et al., (2019)	-	✓	-	✓	-	✓
Onggo et al., (2019)	-	✓	-	✓	✓	-
Rohmer et al., (2019)	-	✓	-	✓	✓	-
Violi et al., (2020)	-	✓	-	✓	✓	-
Li et al., (2020)	-	✓	-	✓	✓	-
Wei et al., (2020)	-	✓	-	✓	✓	-
Manoucheri et al., (2020)	-	✓	-	✓	✓	-
Sinha and Anand, (2020)	-	✓	-	✓	-	✓
Chan et al., (2020)	-	✓	-	✓	✓	-
Liu and Liu, (2020)	-	✓	-	✓	✓	-
Bank et al., (2020)	-	✓	✓	-	-	-

Biuki et al., (2020)	-	✓	-	✓	-	✓
Dai et al., (2020)	-	✓	-	✓	✓	-

S – Single; M – Multiple

72 % of the papers analyzed concern a two-level structure. The retailers/customers are always multiple, except for the research work by Zanoni and Zavanella, (2007), where a single-vendor-to-single-buyer model is addressed. The suppliers/plants/production facilities are single in 32 papers, while multiple in 7 cases.

The remaining papers address a more complex supply chain structure. Wu et al., (2015) tackle a problem characterized by three main levels: a single supplier, a set of potential facility locations, a set of retailers. One of the main contributions is the modeling of the facilities as cross-docking points. Similarly, Dolgui et al., (2018) address a supply chain, made up of multiple plants, multiple cross-docks, multiple markets. Cross-docking is a logistics concept, which aims to coordinate as much as possible the arrival of goods and their next shipment in order to minimize storage times and optimize distribution to end customers. This approach favors economies of transportation and, above all, enables hub-and-spoke networks which replace the more traditional point-to-point structures (Stephan and Boysen, 2011). A similar concept is used by Hu et al., (2018), who consider a set of growers, a consolidation center, and a set of retailers/wholesalers. Basically, the perishable product is transferred from local growers to a consolidation center via short-haul routing, while long-haul routing is necessary for the shipment from the consolidation center to geographically dispersed nodes. Vahdani et al., (2017) formulate and solve a mathematical programming model for simultaneous scheduling of production and delivery of perishable products to customers. The production system is divided into two stages, each of them having several production sites. The last level includes, instead, a set of retailers, that place the different orders. Rafie-Majd et al., (2018) consider a three-echelon supply chain, characterized by a supplier, a set of distribution centers, a certain number of retailers, within an integrated inventory-location-routing problem. This structure is very similar to that by Chao, (2019), where instead the suppliers/manufacturers are multiple. Rohmer et al., (2019) consider an intermediate depot between a single supplier and multiple customers. Violi et al., (2020) take into account a real agriculture supply chain in Italy, where a single perishable product is moved from a set production plants to a set of retailers, through a supplier located in the middle.

Only two papers consider a four-echelon supply chain. Bortolini et al., (2016) place two intermodal hubs between multiple producers and multiple retailers. Biuki et al., (2020) take into account suppliers, manufacturers, distribution centers, and customers. Lastly, the three papers written by Omar Ahumada and J. Rene Villalobos (Ahumada and Vilallobos, 2011; Ahumada and Villalobos, 2011a; Ahumada et al., 2012), with the aim to replicate as much as possible the behavior of the fresh agricultural supply chains, model explicitly five different stages: harvesting, packing, warehousing, distribution centers, customers.

In Figures 4-7, the main statistics about the supply chain structure of the analyzed papers are summarized.

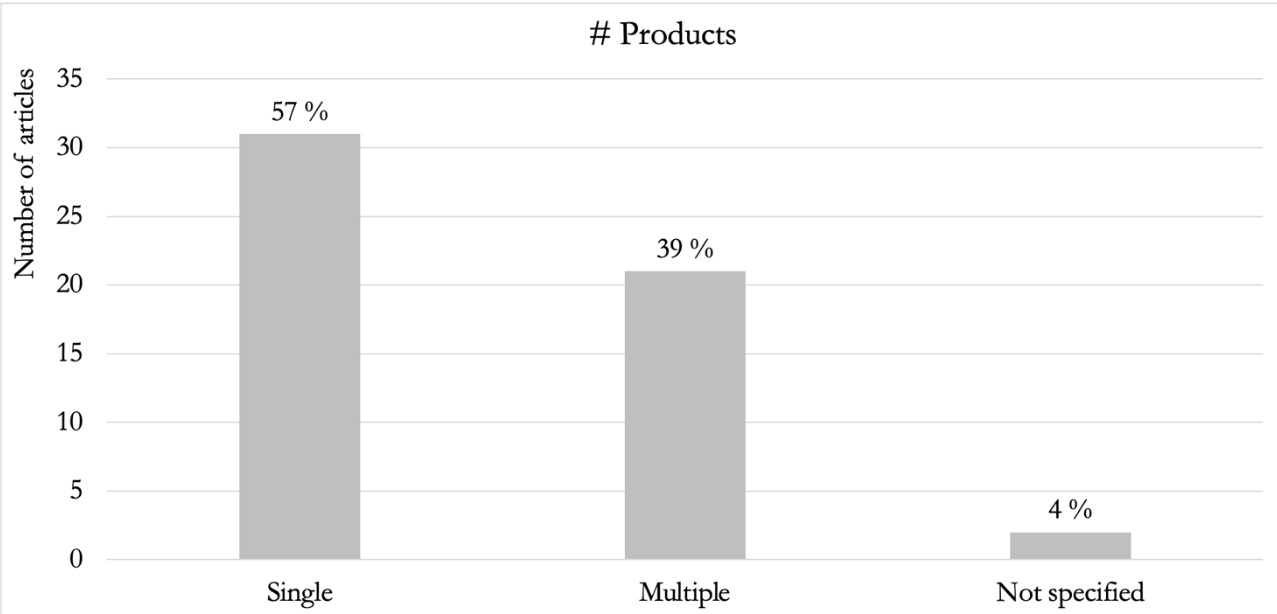

Figure 4. Statistics on supply chain structure: # products

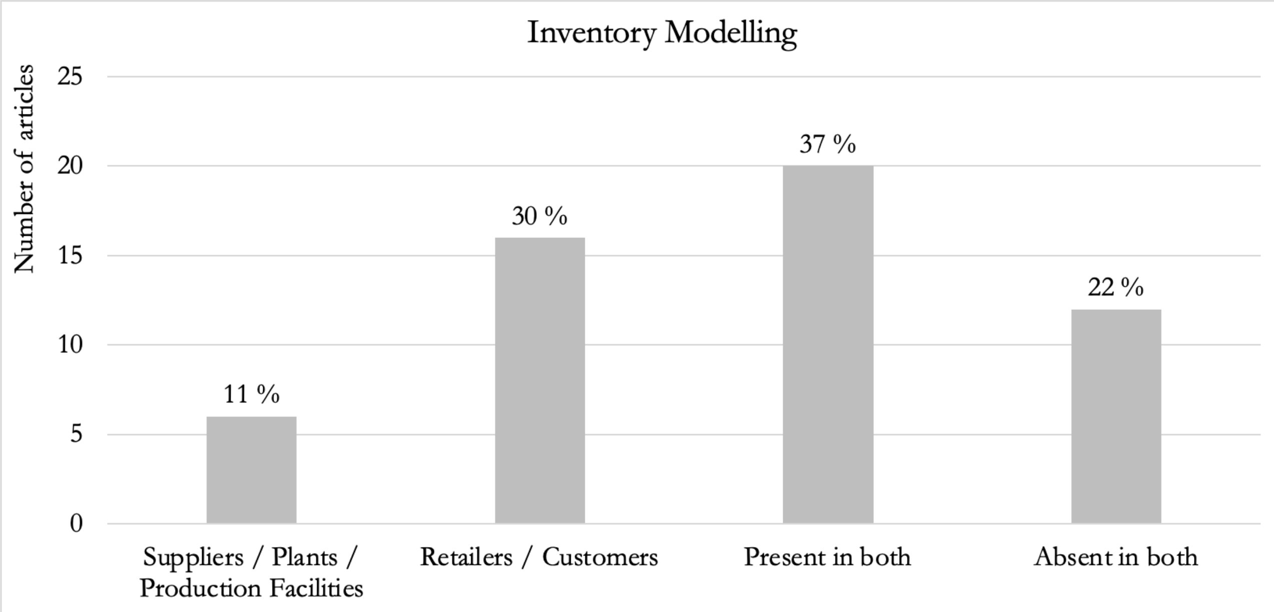

Figure 5. Statistics on supply chain structure: inventory modelling

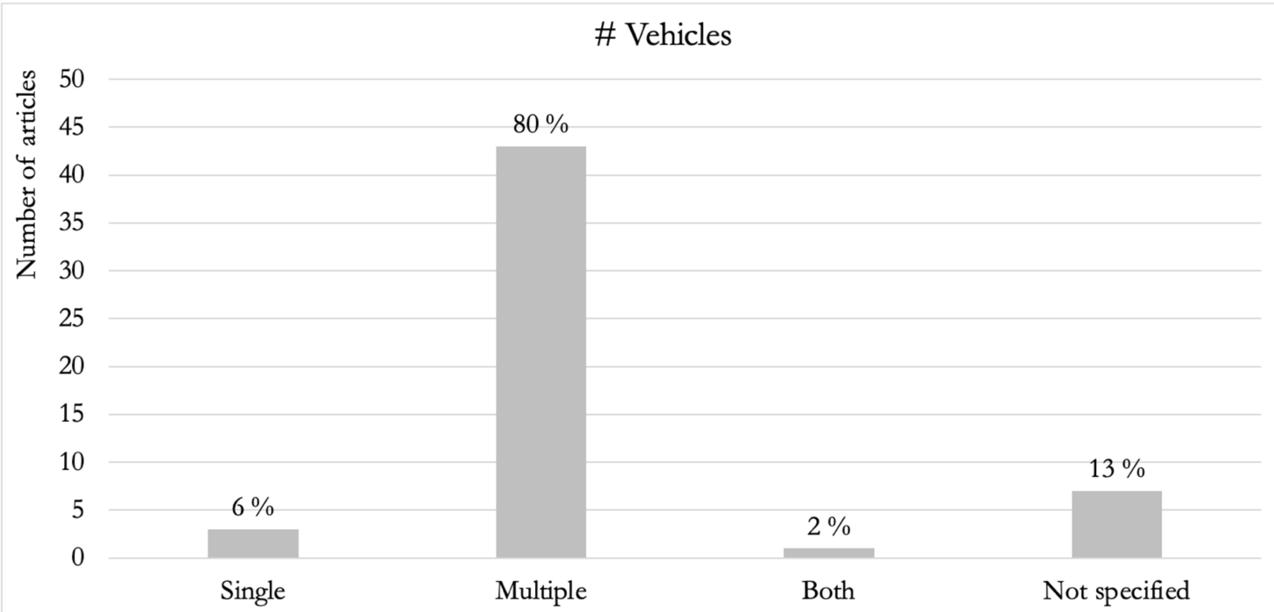

Figure 6. Statistics on supply chain structure: # vehicles

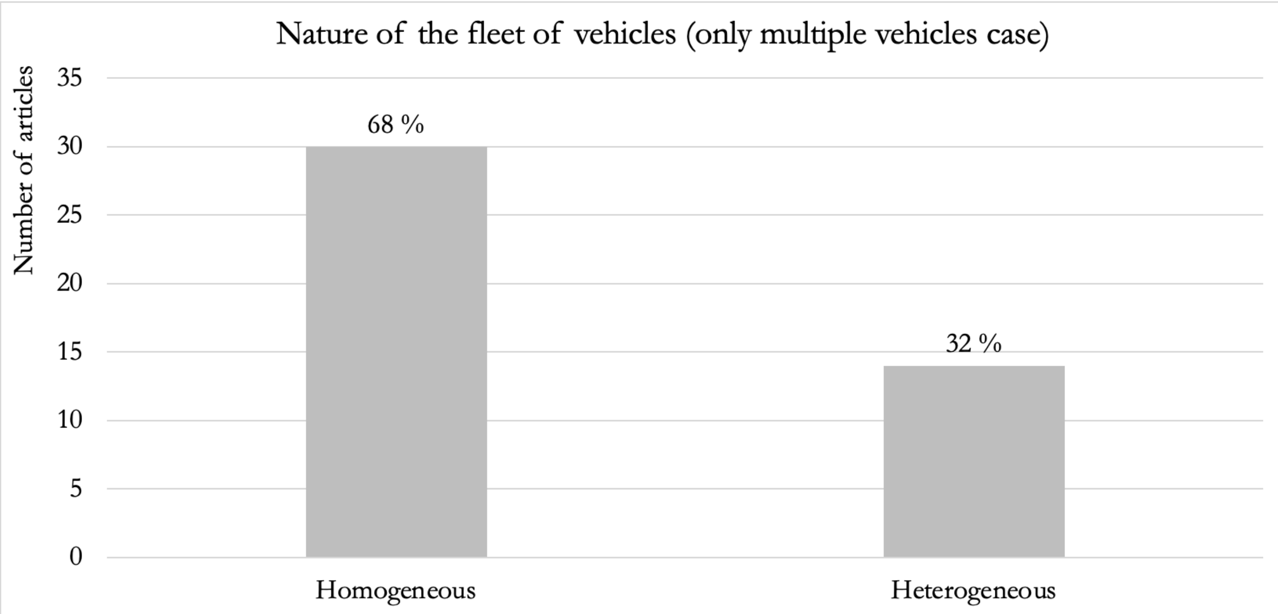

Figure 7. Statistics on supply chain structure: nature of the fleet of vehicles (only multiple vehicles case)

The number of products is in most cases single. With reference to 2 papers (Marandi and Zegordi, 2017; Bank et al., 2020), a hyphen has been inserted, as the relative authors speak of jobs rather than products. Inventory is modeled both upstream and downstream in most papers. Instead, it is completely absent in 22 % of cases, especially when authors model production-distribution problems, in which it is not necessary to store finished products before their distribution. The vehicles are multiple and homogeneous in the vast majority of cases. It should be noted that Lacomme et al., (2018) refer to both a single vehicle case (i.e., literature instances) and a multiple vehicle case (i.e., new instances). With reference to some papers, the number of vehicles is not explicitly specified, because the possibility of multiple transportation modes is taken into account (e.g., trucking, railroad, air) (Ahumada and Villalobos, 2011; Ahumada and Villalobos, 2011a; Ahumada et al., 2012; AriaNezhad et al., 2013; Bortolini et al., 2016) or third-party logistics service providers (3PL) are considered for what concerns the distribution phase (Amorim et al., 2012).

2.5.3. Objective

In Tables 10-12, the 54 selected papers are classified according to their objective.

Table 10. Mono-objective minimization

Reference	PC	IC	DC	Other
Zanoni and Zavanella, (2007)	-	✓	✓	-
Naso et al., (2007)	✓	-	✓	Truck loading and unloading waiting times
Farahani et al., (2012)	✓	-	✓	-
Amorim et al., (2013)	✓	-	✓	-
AriaNezhad et al., (2013)	✓	✓	✓	Cost of delayed or earlier delivery; cost of perished goods
Le et al., (2013)	-	✓	✓	-
Seyedhosseini and Ghoreyshi, (2014)	✓	✓	✓	-
Seyedhosseini and Ghoreyshi, (2014a)	✓	✓	✓	-
Soysal et al., (2015)	-	✓	✓	Cost of waste
Mirzaei and Seifi, (2015)	-	✓	✓	Cost of lost sale
Seyedhosseini and Ghoreyshi, (2015)	✓	✓	✓	-
Belo-Filho et al., (2015)	✓	-	✓	-
Wu et al., (2015)	-	✓	✓	Cost of facilities set-up
Shaabani and Kamalabadi, (2016)	✓	✓	✓	-
Diabat et al., (2016)	-	-	✓	-
Devapriya et al., (2017)	-	-	✓	-
Marandi and Zagordi, (2017)	-	-	✓	Tardy cost
Azadeh et al., (2017)	-	✓	✓	Cost of spoilage; cost of transshipment
Hiassat et al., (2017)	-	✓	✓	Cost of warehouses opening
Accorsi et al., (2017)	-	✓	✓	Disposal cost
Lacomme et al., (2018)	-	-	-	Makespan (i.e., arrival time of the last vehicle at the depot)

Rafie-Majd et al., (2018)	-	✓	✓	Cost of opening the distribution centers; cost of waste; cost of order
Soysal et al., (2018)	-	✓	✓	Cost of waste
Hu et al., (2018)	-	✓	✓	-
Dolgui et al., (2018)	✓	✓	✓	Cost of ordering; cost of handling; cost of deteriorated units (i.e., lost sales)
Neves-Moreira et al., (2019)	-	✓	✓	-
Chao et al., (2019)	-	✓	✓	Vehicle maintenance cost; ordering cost; time window violation penalty cost; cargo damage cost of perishable food; energy cost (referred to vehicle)
Qiu et al., (2019)	✓	✓	✓	-
Onggo et al., (2019)	-	✓	✓	Stock-out cost; deterioration cost
Rohmer et al., (2019)	-	✓	✓	-
Violi et al., (2020)	-	✓	✓	Cost of loss products; risk measure
Wei et al., (2020)	✓	✓	✓	-
Manoucheri et al., (2020)	✓	✓	✓	-
Sinha and Anand, (2020)	✓	✓	✓	Ordering costs; deterioration cost
Liu and Liu, (2020)	-	-	-	Total weighted delivery time of the orders
Bank et al., (2020)	-	-	-	Makespan
Dai et al., (2020)	✓	✓	✓	Ordering cost; shortage cost of retailers

PC – Production Costs; IC – Inventory Costs; DC – Distribution/Transportation Costs

Table 11. Mono-objective maximization

Reference	Profit	Satisfied demand
Chen, (2009)	✓	-
Ahumada and Villalobos, (2011)	✓	-
Ahumada and Villalobos, (2011a)	✓	-
Ahumada et al., (2012)	✓	-

Coelho and Laporte, (2014)	✓	-
Viergutz and Knust, (2014)	-	✓
Li et al., (2016)	✓	-
Vahdani et al., (2017)	✓	-
Li et al., (2017)	✓	-
Crama et al., (2018)	✓	-
Ghasemkhani et al., (2019)	✓	-
Li et al., (2020)	✓	-

Table 12. Multi-objective optimization

Reference	# Objectives	List of objectives
Amorim et al., (2012)	2	Minimization of total costs (i.e., production costs, transportation costs, spoilage costs); Maximization of the freshness of the products delivered to the distribution centers (i.e., customers' willingness to pay)
Bortolini et al., (2016)	3	Minimization of operating cost; Minimization of carbon footprint; Minimization of delivery time
Rahimi et al., (2017)	3	Maximization of profit; maximization of service level (i.e., minimization of rate of delays, minimization of the number of backordered products, minimization of backorder frequency rate); minimization of greenhouse gas emissions
Chan et al., (2020)	4	Minimization of production, inventory, and routing costs; maximization of the average food quality; minimization of CO_2 emissions; minimization of weighted delivery lead time
Biuki et al., (2020)	3	Minimization of cost of the network; maximization of environmental efficiency of the logistics chain network; maximization of social sustainability

It can be easily noted that the vast majority of the papers are mono-objective and aim to minimize the costs. In some cases, production, inventory, and distribution/transportation costs are jointly minimized (AriaNezhad et al., 2013; Seyedhosseini and Ghoreyshi, 2014; Seyedhosseini and Ghoreyshi, 2014a; Seyedhosseini and Ghoreyshi, 2015; Shaabani and Kamalabadi, 2016; Dolgui et al., 2018; Qiu et al., 2019; Wei et al., 2020; Manoucheri et al., 2020; Sinha and Anand, 2020; Dai et al., 2020). When dealing with perishable supply chains, it is common to find cost items associated with the perishable nature of goods: cost of perished goods (AriaNezhad et al., 2013; Chao et al., 2019), cost of waste (Soysal et al., 2015; Rafie-Majd et al., 2018; Soysal et al., 2018), cost of spoilage (Azadeh et al., 2017), disposal cost (Accorsi et al., 2017), cost of deteriorated units (i.e., lost sales) (Mirzaei and Seifi, 2015; Dolgui et al., 2018; Sinha and Anand, 2020; Violi et al., 2020). Two papers minimize the makespan (Lacomme et al., 2018; Bank et al., 2020). The cost of ordering has been written in the last column of Table 10, only when explicitly considered; in fact, in many cases, it is implicitly included into the inventory costs. Only one paper introduces a risk measure within the objective function (Violi et al., 2020). They give a mean-risk structure to the objective, that is written as a convex combination of two terms: the expected value of the overall costs and a risk measure, that is the conditional value at risk (CVaR) (Rockafellar and Uryasev, 2000). Except for one case (Viergutz and Knust, 2014), the maximization of the objective function is always about profit. In only five papers, the multi-objective optimization is addressed. In this case, some sustainability-oriented objectives are considered, such as carbon foot print minimization (Bortolini et al., 2016; Rahimi et al., 2017; Chan et al., 2020), environmental efficiency of the logistics chain network and social sustainability maximization (Biuki et al., 2020).

2.5.4. Perishability issues

Supply chain management in the case of perishable items is quite complicated and time-critical (Biuki et al., 2020; Alkaabneh et al., 2020). The main aim of this part is to provide a picture of the ways in which the different authors have addressed perishability. In the literature, the most recognized classification of perishability concerns two types of items: (i) fixed-lifetime and (ii) age-dependent. Fixed-lifetime goods have a well-defined expiration date, beyond which they perish (e.g., dairy products, pharmaceuticals). Age-dependent goods, instead, are subject to deterioration, then they lose value over time (e.g., agricultural products); although they have an expiration date, it is not predetermined (Coelho and Laporte, 2014; Palak et al., 2018). The 54 selected papers are classified according to such a taxonomy in Table 13.

Table 13. Perishability type

Reference	Fixed shelf-life	Deterioration
Zanoni and Zavanella, (2007)	✓	-
Naso et al., (2007)	✓	-
Chen, (2009)	-	✓
Ahumada and Villalobos, (2011)	-	✓
Ahumada and Villalobos, (2011a)	-	✓
Ahumada et al., (2012)	-	✓
Amorim et al., (2012)	✓	✓
Farahani et al., (2012)	-	✓
Amorim et al., (2013)	✓	-
AriaNezhad et al., (2013)	✓	-
Le et al., (2013)	✓	-
Coelho and Laporte, (2014)	✓	✓
Seyedhosseini and Ghoreyshi, (2014)	✓	-
Seyedhosseini and Ghoreyshi, (2014a)	✓	-
Viergutz and Knust, (2014)	✓	-
Soysal et al., (2015)	✓	-
Mirzaei and Seifi, (2015)	-	✓
Seyedhosseini and Ghoreyshi, (2015)	✓	-
Belo-Filho et al., (2015)	✓	-
Wu et al., (2015)	-	✓
Bortolini et al., (2016)	✓	-
Shaabani and Kamalabadi, (2016)	✓	-
Li et al., (2016)	-	✓
Diabat et al., (2016)	✓	-
Vahdani et al., (2017)	-	✓

Rahimi et al., (2017)	✓	-
Devapriya et al., (2017)	✓	-
Marandi and Zegordi, (2017)	-	-
Li et al., (2017)	-	✓
Azadeh et al., (2017)	-	✓
Hiassat et al., (2017)	✓	-
Accorsi et al., (2017)	-	✓
Lacomme et al., (2018)	✓	-
Crama et al., (2018)	✓	-
Rafie-Majd et al., (2018)	✓	-
Soysal et al., (2018)	✓	-
Hu et al., (2018)	✓	-
Dolgui et al., (2018)	-	✓
Neves-Moreira et al., (2019)	✓	-
Chao et al., (2019)	-	✓
Qiu et al., (2019)	-	✓
Ghasemkhani et al., (2019)	-	✓
Onggo et al., (2019)	-	✓
Rohmer et al., (2019)	-	✓
Violi et al., (2020)	-	✓
Li et al., (2020)	✓	-
Wei et al., (2020)	-	✓
Manoucheri et al., (2020)	-	✓
Sinha and Anand, (2020)	-	✓
Chan et al., (2020)	-	✓
Liu and Liu, (2020)	-	-
Bank et al., (2020)	✓	-

Biuki et al., (2020)	✓	-
Dai et al., (2020)	-	✓

2.5.4.1. Fixed shelf-life

28 papers deal with products with fixed shelf-life. Some of them introduce interesting and challenging features. Given a two-echelon supply chain (i.e., single producer and multiple customers), AriaNezhad et al., (2013) consider in the objective function the cost from perishing the goods in the original factory warehouse. Bortolini et al., (2016) use a particular function, aimed at estimating the market purchase probability (Osvald and Stirn, 2008); basically, they take into account explicitly the loss of product quality over time. Coelho and Laporte, (2014) define a discrete set for the product age, and they study the impact of item age on revenue and inventory holding costs. They claim that their approach can also be used in the case of products subject to deterioration. Amorim et al., (2012) formulate two different models to consider respectively the cases of fixed and loose shelf-life. In this latter case, the authors link the shelf-life to the knowledge of predictive microbiology, then to the stocking temperature. The use of a multi-objective framework allows to take into account, in both cases, the freshness of the product, therefore the customers' willingness to pay. S.M. Seyedhosseini and S.M. Ghoreyshi claim that, although their optimization models were designed for perishable products with fixed lifetime, they can be extended to deteriorating goods that decrease their value throughout the lifetime. In this case, the quality loss of goods should be included in the inventory costs (Seyedhosseini and Ghoreyshi, 2014a; Seyedhosseini and Ghoreyshi, 2015). In some papers, reaching the expiration date is penalized in the objective function through the waste cost (Soysal et al., 2015; Soysal et al., 2018; Rafie-Majd et al., 2018). In order to limit the amount of unsold products, Rahimi et al., (2017) introduce a step-wise nonlinear holding cost. They take into consideration that non-fresh products need extra-inspections before they are carried to the next period. The proposed holding cost function replicates the price discounts for non-fresh products, and guarantees a trade-off between economic, service level and environmental criteria. Li et al., (2020) take into consideration different shelf-lives, depending on the packaging. Their article is mainly based on the following assumption: the same item can have a different shelf-life depending on the packaging used. Basically, innovative food packaging can significantly lengthen the expiration date of products, lowering the decay rate (Rizzo and Muratore, 2009; Li et al., 2017a). The authors investigate the tradeoff between packaging costs and shelf-life benefits. One of the main contributions of Biuki et al., (2020) is instead to

consider both the shelf-life of raw materials and finished products, within the proposed Mixed-Integer Programming (MIP) model.

2.5.4.2. Deterioration

In 26 papers, the shelf-life is not fixed and known a priori, but the aspects related to deterioration and loss of quality are emphasized.

A set of research works trace explicitly the food quality throughout the supply chain, by using a quality level index (Li et al., 2016; Li et al., 2017; Ghasemkhani et al., 2019; Chan et al., 2020). They stress the assumption that food quality significantly affects selling price and customer demand.

Most papers propose a fixed decay rate, which implies a linear deterioration of the product (Chen, 2009; Ahumada and Villalobos, 2011; Ahumada et al., 2012; Farahani et al., 2012; Rohmer et al., 2019; Violi et al., 2020; Dai et al., 2020). It must be noted that Chao et al., (2019) take into account both the deterioration due to the transport time and that due to a break during the transportation process (e.g., turning on/off frequently the door of a truck).

Ahumada and Villalobos, (2011a) focus their attention on the loss of value of agri-products, once harvested. They use a post-harvest color function (Hertog et al., 2004), assuming to store the products at a constant temperature. Basically, in the objective function of the proposed optimization model, an expected cost is used, derived from rejected or discounted shipments, which depend on the color of the product when it reaches the customer. Deterioration is addressed by Mirzaei and Seifi, (2015), by considering lost sale as a linear or exponential function of the inventory age. A couple of papers assume exponential deterioration rate (Azadeh et al., 2017; Dolgui et al., 2018). This assumption takes into account the growth of micro-organisms within the product, which in many cases follows an exponential behavior. Although Accorsi et al., (2017) consider a set of shelf-life values in their model, they explicitly take into account the quality decay of perishable products. In particular, they refer to kinetic models, based on the Arrhenius equation and the accelerated aging factor (Lee et al., 2008; Tsironi et al., 2017). Common thermodynamic models are instead considered to replicate the heat transfer mechanism in refrigerated storage rooms and vehicles. In some models, the deterioration rate is time-dependent (Wu et al., 2015; Vahdani et al., 2017; Qiu et al., 2019; Wei et al., 2020; Sinha and Anand, 2020). Onggo et al., (2019) consider the case of inventory of products with different ages. They address product perishability, by considering multiple degradation speed levels. Manoucheri et al., (2020) use the Gompertz equation (Gil et al., 2011), with the aim to estimate microbial growth.

Lastly, a couple of papers address only implicitly perishability (Marandi and Zegordi, 2017; Liu and Liu, 2020).

2.5.5. Solution approach

In Table 14, the solution approach used by the different authors to validate their optimization models is detailed. It should be noted that the expression "heuristic algorithm" (HA) is used, when the related approach does not have a well-recognized and known name in the literature.

Table 14. Solution approach

Reference	Solution Approach									
	BC	CG	GA	HA	NS	OS	PSO	SA	TS	Other
Zanoni and Zavanella, (2007)	-	-	-	✓	-	-	-	-	-	-
Naso et al., (2007)	-	-	✓	✓	-	-	-	-	-	-
Chen, (2009)	-	-	-	✓	-	-	-	-	-	Constrained Nelder-Mead Method
Ahumada and Villalobos, (2011)	-	-	-	-	-	✓*	-	-	-	-
Ahumada and Villalobos, (2011a)	-	-	-	-	-	✓*	-	-	-	-

Ahumada et al., (2012)	-	-	-	-	-	-	-	-	-	Stochastic Version and Multi-Cut Version of Bender's Decomposition. A Multicut for Risk Stochastic Programs
Amorim et al., (2012)	-	-	✓	-	-	✓	-	-	-	-
Farahani et al., (2012)	-	-	-	✓	✓	-	-	-	-	-
Amorim et al., (2013)	-	-	-	-	-	✓*	-	-	-	-
AriaNezhad et al., (2013)	-	-	✓	-	-	-	-	-	-	-
Le et al., (2013)	-	✓	-	-	-	-	-	-	-	-
Coelho and Laporte, (2014)	✓	-	-	-	-	-	-	-	-	-
Seyedhosseini and Ghoreyshi, (2014)	-	-	-	-	-	✓	✓	-	-	-
Seyedhosseini and Ghoreyshi, (2014a)	-	-	-	✓	-	✓*	-	-	-	-

Viergutz and Knust, (2014)	-	-	-	-	-	-	-	-	✓	BB, Iterated LS
Soysal et al., (2015)	-	-	-	-	-	✓	-	-	-	Simulation Model Algorithm
Mirzaei and Seifi, (2015)	-	-	-	-	-	✓	-	✓	✓	-
Seyedhosseini and Ghoreyshi, (2015)	-	-	-	✓	-	✓	-	-	-	-
Belo-Filho et al., (2015)	-	-	-	✓	✓	✓*	-	-	-	FO
Wu et al., (2015)	-	✓	-	-	-	-	-	-	-	-
Bortolini et al., (2016)	-	-	-	-	-	✓	-	-	-	Empirical Rules (Pareto Frontier)
Shaabani and Kamalabadi, (2016)	✓	-	✓	-	-	✓*	-	✓	-	LR
Li et al., (2016)	-	-	-	-	-	✓*	-	-	-	-
Diabat et al., (2016)	-	✓	-	-	-	✓*	-	-	✓	-
Vahdani et al., (2017)	-	-	-	✓	✓	✓	-	✓	-	WCA, 4 LS Procedures, Beam Search, Nawaz-Enscore-Ham Method

Rahimi et al., (2017)	-	-	✓	-	-	-	-	-	-	NSGA-II
Devapriya et al., (2017)	-	-	✓	-	-	✓*	-	-	-	MA
Marandi and Zegordi, (2017)	-	-	✓	-	-	✓*	✓	-	-	-
Li et al., (2017)	-	-	-	-	-	-	-	-	-	Two-Phase Iterative Approach
Azadeh et al., (2017)	-	-	✓	-	-	-	-	-	-	-
Hiassat et al., (2017)	-	-	✓	-	-	✓*	-	-	-	-
Accorsi et al., (2017)	-	-	-	-	-	✓	-	-	-	-
Lacomme et al., (2018)	-	-	-	-	-	-	-	-	-	GRASP with Evolutionary LS
Crama et al., (2018)	-	-	-	✓	-	-	-	-	-	Matheuristic Algorithm
Rafie-Majd et al., (2018)	-	-	-	✓	-	✓*	-	-	-	LR
Soysal et al., (2018)	-	-	-	-	-	✓	-	-	-	-
Hu et al., (2018)	-	-	-	-	-	✓*	-	-	-	Decomposition and Optimization-Based LS
Dolgui et al., (2018)	-	-	✓	-	-	✓	-	-	-	-

Neves-Moreira et al., (2019)	-	-	-	-	-	-	-	-	-	FO Matheuristics, RH
Chao et al., (2019)	-	-	-	-	-	✓*	-	-	-	Improved ACO with Distance-Based Clustering Approach
Qiu et al., (2019)	✓	-	-	-	-	-	-	-	-	-
Ghasemkhani et al., (2019)	-	-	-	-	-	✓	-	-	-	-
Onggo et al., (2019)	-	-	-	-	-	-	-	-	-	Simheuristic Algorithm: Montecarlo Simulation and Iterated LS
Rohmer et al., (2019)	-	-	-	-	✓	✓*	-	-	-	Adaptive Large NS, Decompositi on Strategies
Violi et al., (2020)	-	-	-	-	-	-	-	-	-	RH
Li et al., (2020)	✓	-	-	-	-	-	-	-	-	Hybrid Matheuristic
Wei et al., (2020)	✓	-	-	-	-	✓*	-	-	-	-
Manoucheri et al., (2020)	-	-	-	-	✓	✓	-	✓	-	-

Sinha and Anand, (2020)	-	-	-	-	-	-	-	-	-	BFA and Improved BFA
Chan et al., (2020)	-	-	-	-	-	-	✓	-	-	-
Liu and Liu, (2020)	-	-	✓	-	✓	✓	-	-	-	-
Bank et al., (2020)	-	-	✓	-	-	✓	-	✓	-	-
Biuki et al., (2020)	-	-	✓	-	-	✓	✓	-	-	-
Dai et al., (2020)	-	-	-	✓	-	✓	-	-	-	Improved Clarke-Wright Savings Algorithm and Cuckoo Algorithm

ACO – Ant Colony Optimization; BB – Branch and Bound; BC – Branch and Cut; BFA – Bacteria Foraging Algorithm; CG – Column Generation; FO – Fix-and-Optimize; GA – Genetic Algorithm; GRASP – Greedy Randomized Adaptive Search Procedure; HA – Heuristic Algorithm; LR – Lagrangian Relaxation; LS – Local Search; MA – Memetic Algorithm; NS – Neighborhood Search; NSGA – Non-dominated Sorting Genetic Algorithm; OS – Optimal Solution via Optimization Software; PSO – Particle Swarm Optimization; RH – Rolling Horizon; SA – Simulated Annealing; TS – Tabu Search; WCA – Water Cycle Algorithm

2.5.5.1. Exact approaches

In many research works, the proposed solution approach is the main contribution. The models that integrate the planning of production, storage and distribution activities are generally very complex from a computational point of view, therefore they require heuristic approaches (i.e., not exact), to find a good solution in reasonable time. For this reason, in a few papers the solution is determined solely through an optimal approach by using a software (e.g., CPLEX, LINGO, MATLAB) (Soysal et al., 2015; Accorsi et al., 2017; Soysal et al., 2018; Ghasemkhani et al., 2019). Some authors do not use heuristic approaches, but impose an optimality gap, represented by an asterisk in Table 14, with the aim to limit the computational time (Ahumada and Villalobos, 2011; Ahumada and Villalobos, 2011a; Amorim et al., 2013). The branch-and-cut is adopted within different papers (Coelho and Laporte, 2014; Shaabani and Kamalabadi, 2016; Qiu et al., 2019; Li et al., 2020; Wei et al., 2020), while Viergutz and Knust, (2014) use the branch-and-bound algorithm. In many other cases, the optimal or sub-optimal solutions are determined, only with the aim to demonstrate the efficiency, in terms of computational time, of the proposed algorithm, through a specific comparison.

2.5.5.2. Genetic algorithms

Genetic algorithms aim to mimic biological evolutionary processes and have been successfully used for solving many optimization problems (Godinho Filho et al., 2012; Lee, 2018).

Naso et al., (2007), with the aim to solve the problem of coordinating the production and distribution planning within a network of independent supply centers, propose a hybrid metaheuristic approach, where genetic algorithms and constructive heuristics are integrated. Amorim et al., (2012) formulate models for the integrated production and distribution planning, where perishable goods have fixed or loose shelf-life. For the second case, a hybrid genetic heuristic is proposed. A genetic algorithm, coded in MATLAB, is designed by AriaNezhad et al., (2013) for a two-echelon model, aimed to control the inventory of perishable goods. Rahimi et al., (2017) use the NSGA-II for a multi-objective inventory-routing problem. Devapriya et al., (2017) use a genetic algorithm and two memetic algorithms for an integrated production-distribution scheduling problem. Azadeh et al., (2017) integrate a genetic algorithm and the Taguchi approach to solve an inventory routing problem with transshipment. Dolgui et al., (2018) propose a non-revisiting genetic algorithm (NrGA), which represents a novel version of traditional genetic algorithms.

2.5.5.3. Neighborhood search

Some meta-heuristics exploit the concept of solution neighborhood: variable neighborhood search (VNS) and large neighborhood search (LNS) are among the most used approaches in this context. VNS is based on two main steps: a descent phase to find a local optimum and a perturbation to "escape" from the corresponding valley (Hansen et al., 2010). About LNS, instead, an initial solution is gradually improved through some phases of destruction and reparation (Pisinger and Ropke, 2010.

Farahani et al., (2012) design a novel approach, that integrates short-term production and distribution planning, within an iterative scheme. The distribution problem is solved through an LNS algorithm. Belo-Filho et al., (2015) develop an adaptive LNS for solving the operational integrated production and distribution problem with perishable products. The adaptiveness of the approach is related to the destroy and repair operators, that are chosen adaptively. The authors demonstrate that the adaptive LNS outperforms exact approaches and the fix-and-optimize method. An adaptive LNS metaheuristic is also developed by Rohmer et al., (2019) for tackling an inventory-routing problem. An LNS-based heuristic is used by Vahdani et al., (2017) for a production-inventory-routing problem. Such an approach appears quite promising, when compared with LINGO and a water cycle algorithm (Eskandar et al., 2012). The hybrid search algorithm proposed by Manoucheri et al., (2020) combines VNS and SA with good results for a production routing problem. Liu et al., (2020) use an improved LNS, which outperforms a genetic algorithm, in solving an integrated production and distribution problem with a minimum total order weighted delivery time.

2.5.5.4. Particle swarm optimization

PSO replicates some social behaviors of natural organisms (Banks et al., 2007).
Seyedhosseini and Ghoreyshi study an integrated model for production and distribution planning of perishable products. While the production submodel is solved by LINGO, a PSO-based heuristic is proposed with good results for the distribution part. Marandi and Zagordi, (2017) design and apply an improved PSO to deal with a production-distribution scheduling problem. The contribution mainly lies in the use of additional operators (i.e., 1-exchanged and 2-opt), with the aim to prevent the premature convergence of the algorithm. Chan et al., (2020) propose a modified multi-objective particle swarm optimization algorithm with multiple social structures. With the aim to efficiently solve an integrated location-routing-inventory problem, Biuki et al., (2020) propose two hybrid metaheuristics as parallel and series combinations of GA and PSO. The computational experience shows that the parallel approach is better than the series one.

2.5.5.5. Simulated annealing

SA is a technique that has gained a lot of popularity in recent years in solving optimization problems. It is based on an analogy with the behavior of physical systems during the cooling process (Suman and Kumar, 2010).

Mirzaei and Seifi, (2015) combine SA and TS for an inventory routing problem. Shaabani and Kamalabadi, (2016) present a population-based simulated annealing algorithm (PBSA) for a multi-product multi-retailer perishable inventory routing problem. The PBSA has been compared with SA and GA, to show its superiority in terms of efficiency. Bank et al., (2020) propose a low-level co-evolutionary hybrid algorithm to solve an integrated production-distribution problem. The approach combines SA and GA, because the features of GA are applied in the local search process of SA.

2.5.5.6. Tabu search

For what is known, TS was proposed by Glover, (1986) and is nowadays one of the most used heuristic methods for combinatorial optimization.

Viergutz and Knust, (2014) propose model extensions with reference to the research work by Armstrong et al., (2008), which addresses an integrated production-distribution scheduling problem. They solve some of them by a tabu search approach. Diabat et al., (2016) design a hybrid tabu search, which outperforms a column generation approach in solving a periodic distribution inventory problem.

2.5.5.7. Other approaches

In the previous subsections, the most used approaches to solve the problems addressed within this literature review have been highlighted. However, other important algorithms have been recently adopted: local search (Viergutz and Knust, 2014; Vahdani et al., 2017; Hu et al., 2018; Onggo et al., 2019), lagrangian relaxation (Shaabani and Kamalabadi, 2016; Rafie-Majd et al., 2018), matheuristic algorithms (Crama et al., 2018; Neves-Moreira et al., 2019; Li et al., 2020), ACO (Chao et al., 2019), rolling horizon (Neves-Moreira et al., 2019; Violi et al., 2020), BFA (Sinha and Anand, 2020), simulation (Soysal et al., 2015; Onggo et al., 2019), column-generation based algorithms (Le et al., 2013; Wu et al., 2015; Diabat et al., 2016).

2.5.6. Approach validation

Each proposed solution approach needs to be properly validated. In this subsection, the selected papers are classified according to the nature of the instances through which the goodness of each algorithm has been demonstrated, see Table 15. Some authors use instances already known in the literature. Others, introducing completely new problems, are forced to randomly generate new data. While, in some cases, real data are used, derived from specific case studies. Furthermore, the supply chain type is reported; obviously, it is specific, only when referring to a case study (real or hypothetical).

Table 15. Approach validation

Reference	Supply Chain Type	Literature Instances	Generation of Instances	Case Study
Zanoni and Zavanella, (2007)	Generic	-	✓	-
Naso et al., (2007)	Ready-mixed concrete	-	✓	✓
Chen, (2009)	Generic	✓	✓	-
Ahumada and Villalobos, (2011)	Pepper, Tomato	-	-	✓
Ahumada and Villalobos, (2011a)	Pepper, Tomato	-	-	✓
Ahumada et al., (2012)	Pepper, Tomato	-	-	✓
Amorim et al., (2012)	Generic	-	✓	-
Farahani et al., (2012)	Catering	✓	✓	✓
Amorim et al., (2013)	Generic	-	✓	-
AriaNezhad et al., (2013)	Conserved wax bean and jam	-	-	✓
Le et al., (2013)	Generic	-	✓	-
Coelho and Laporte, (2014)	Generic	-	✓	-

Seyedhosseini and Ghoreyshi, (2014)	Generic	-	✓	-
Seyedhosseini and Ghoreyshi, (2014a)	Generic	-	✓	-
Viergutz and Knust, (2014)	Generic	-	✓	-
Soysal et al., (2015)	Fresh tomato	-	-	✓
Mirzaei and Seifi, (2015)	Generic	✓	✓	-
Seyedhosseini and Ghoreyshi, (2015)	Generic	-	✓	-
Belo-Filho et al., (2015)	Generic	-	✓	-
Wu et al., (2015)	Generic	-	✓	-
Bortolini et al., (2016)	Fruit and vegetables	-	-	✓
Shaabani and Kamalabadi, (2016)	Generic	✓	✓	-
Li et al., (2016)	Generic	-	✓	-
Diabat et al., (2016)	Generic	-	✓	-
Vahdani et al., (2017)	Generic	✓	✓	-
Rahimi et al., (2017)	Generic	-	✓	-
Devapriya et al., (2017)	Generic	-	✓	-
Marandi and Zegordi, (2017)	Generic	-	✓	-
Li et al., (2017)	Generic	✓	✓	-
Azadeh et al., (2017)	Dairy	-	-	✓
Hiassat et al., (2017)	Generic	-	✓	-
Accorsi et al., (2017)	Cherry	-	-	✓
Lacomme et al., (2018)	Generic	✓	✓	-
Crama et al., (2018)	Generic	✓	✓	-
Rafie-Majd et al., (2018)	Generic	-	✓	-

Soysal et al., (2018)	Fig, cherry	-	-	✓
Hu et al., (2018)	Cut flower	-	-	✓
Dolgui et al., (2018)	Generic	✓	✓	-
Neves-Moreira et al., (2019)	Meat	✓	-	✓
Chao et al., (2019)	Fresh seafood	✓	✓	✓
Qiu et al., (2019)	Fresh meat	✓	✓	✓
Ghasemkhani et al., (2019)	Generic	✓	✓	-
Onggo et al., (2019)	Generic	✓	-	-
Rohmer et al., (2019)	Generic	-	✓	-
Violi et al., (2020)	Tangerine	-	-	✓
Li et al., (2020)	Generic	-	✓	-
Wei et al., (2020)	Generic	✓	✓	-
Manoucheri et al., (2020)	Chicken	-	✓	✓
Sinha and Anand, (2020)	Generic (glass industry)	-	✓	✓
Chan et al., (2020)	Meat	-	✓	✓
Liu and Liu, (2020)	Generic	✓	✓	-
Bank et al., (2020)	Generic	-	✓	-
Biuki et al., (2020)	Generic	-	✓	-
Dai et al., (2020)	Generic	-	✓	-

19 out of the 54 selected papers demonstrate the goodness of the proposed solution approach via case study.

Only a couple of papers refer to non-food products. Naso et al., (2007) focus on the production of ready-mixed concrete for construction engineering and refer to a supply network in Northern Europe. The instances replicate the typical workdays of the different nodes of the network. The authors claim that the perishability features of ready-mixed concrete have many similarities with agri-food products. Sinha and

Anand, (2020) refer, instead, to an Iranian glass industry, whose main information is reported in (Hajiaghaei-Keshteli and Fathollahi Fard, 2019).

10 papers are about fruit and/or vegetables. The three articles by Omar Ahumada and J. Rene Villalobos (Ahumada and Villalobos, 2011; Ahumada and Villalobos, 2011a; Ahumada et al., 2012) refer to a hypothetical producer of peppers and tomatoes, based in Mexico. Farahani et al., (2012) develop a main set of instances, based on the real setting of a catering company in Denmark. Additional test sets are included, in order to validate the solution approach under different problem sizes. Some parameters are randomly generated, while others are derived from the Solomon instances (Solomon, 1987). AriaNezhad et al., (2013) consider a manufacturing company of conserved wax bean and jam. Soysal et al., (2015) apply their model to a real supply chain located in Turkey, where a distribution center provides fresh tomatoes to 11 supermarkets. Several Key Performance Indicators (KPIs) are introduced to highlight the benefits, coming from the proposed mathematical approach: average vehicle load, number of vehicles used, total emissions, total driving time, total fuel cost, total inventory cost, total waste cost, total cost. Bortolini et al., (2016) address the distribution of six fruits and vegetables (i.e., potatoes, apples, pears, Brussels sprouts, oranges, tomatoes) cultivated by a set of Italian producers to supply a set of European retailers. They consider and compare three different transportation modes (i.e., truck, train, airplane). The proposed expert system, called Food Distribution Planner, can effectively manage product perishability and limit CO_2 emissions. Accorsi et al., (2017) consider an Italian supply chain of fresh cherries, characterized by 4 production plants aimed at processing raw cherries and packaging, and 3 warehouses. The application of the proposed MILP model can significantly impact on economic and environmental aspects of the considered cold chain. Soysal et al., (2018) prove the benefits of horizontal collaboration between two real suppliers, which produce figs and cherries, respectively. The data used by Violi et al., (2020) come from an Italian supply chain, where a medium agri-food company supplies tangerines to a set of retailers.

4 papers refer to meat products. A very challenging case study is addressed by Neves-Moreira et al., (2019): 175 multiple meat products are manufactured by a meat processing center and delivered to 185 meat stores, by using 35 heterogeneous vehicles. The proposed integrated approach can guarantee a cost saving of 21.73 %, compared to the company's solution. Qiu et al., (2019) consider a Chinese chain, where a food company provides fresh meat products to some stores. The proposed approach ensures a decrease of 12 % in the total cost. Manoucheri et al., (2020) refer to a company in Iran, that supplies packed chicken to a set of customers, by refrigerated vehicles. The developed optimization model returns

the production lot size, inventory levels and optimal routes for each vehicle. The Chinese supply chain considered by Chan et al., (2020) is made by a company, which provides a single fresh meat product to 40 retail stores. 3 homogeneous vehicles are used for the distribution phase, under a planning horizon of one week. The model designed by the authors provides a 15.51 % cost reduction.

Three papers concern dairy products (Azadeh et al., 2017), cut flowers (Hu et al., 2018), fresh seafood (Chao et al., 2019). All the remaining papers randomly generate new data, or refer to some well-known literature instances.

2.6. Research trends and possible future challenges

In this review chapter, framework for classifying scientific articles, which address the coordination of activities in perishable supply chains, via optimization strategies, has been proposed. This framework contains five dimensions: objective, perishability issues, solution approach, approach validation, supply chain structure. Some important research trends can be detected:

- Most of the publishing journals belong to the areas "management science and operations research", "industrial and manufacturing engineering".
- Interest in the application of optimization models for integrated decision-making along perishable supply chains is strongly growing. More than 50 % of the articles published in the last 15 years refer to the period 2016-2020.
- A careful analysis of the selected documents shows a strong interest in the following main problems: the integrated production-distribution problem (Ahumada and Villalobos, 2011; Ahumada and Villalobos, 2011a; Ahumada et al., 2012; Amorim et al., 2012; Farahani et al., 2012; Amorim et al., 2013; Seyedhosseini and Ghoreyshi, 2014; Seyedhosseini and Ghoreyshi, 2014a; Viergutz and Knust, 2014; Seyedhosseini and Ghoreyshi, 2015; Belo-Filho et al., 2015; Devapriya et al., 2017; Marandi and Zegordi, 2017; Lacomme et al., 2018; Liu and Liu, 2020; Bank et al., 2020), the inventory-routing problem (Le et al., 2013; Soysal et al., 2015; Mirzaei and Seifi, 2015; Shaabani and Kamalabadi, 2016; Rahimi et al., 2017; Azadeh et al., 2017; Soysal et al., 2018; Hu et al., 2018; Onggo et al., 2019; Dai et al., 2019; Rohmer et al., 2019; Violi et al., 2020; Dai et al., 2020), the production-routing and the production-inventory-routing problem (Li et al., 2016; Vahdani et al., 2017; Li et al., 2017; Ghasemkhani et al., 2019; Neves-Moreira et al., 2019; Manoucheri et al., 2020; Li et al., 2020), the location-inventory-routing problem (Hiassat et al., 2017; Rafie-Majd et al., 2018; Chao et al., 2019; Biuki et al., 2020).

- Integrating multiple stages of the supply chain into a single framework is complex, especially when referring to perishable products. The vast majority of the problems addressed are then NP-Hard, therefore non-exact approaches are needed to find a sub-optimal solution in reasonable time. Currently, evolutionary algorithms (e.g. genetic algorithms) are among the most preferred by researchers.
- A very high percentage of the reviewed research works deal with two-level supply chains, i.e. supplier(s)-to-customer(s). When the supply chain is 3-tier, a cross-docking or consolidation node is often placed halfway.

As a consequence, there are some significant challenges that need to be addressed in the next future:

- In more recent years, the research branch concerning electric vehicles is spreading significantly (Macrina et al., 2019; Zhen et al., 2020). Erdogan and Miller-Hooks defined the green vehicle routing problem, where the fleet is composed of alternative fuel vehicles, which have a very positive environmental impact. Currently, this topic is very little explored within the perishable supply chains. Furthermore, only a few of the reviewed research works use CO_2 emissions as a supply chain KPI.
- As for the distribution phase, very few papers evaluate the possibility of using transportation modes different to truck (e.g., train or airplane) and even intermodal ones. This research line deserves to be further investigated because it could make perishable supply chain more efficient and guarantee a higher service level to the end customer.
- Only one of the reviewed papers (Soysal et al., 2018) deals with horizontal collaboration as regards the distribution of goods with limited shelf-life. This topic deserves to be better developed in the coming years because it is very sustainability-oriented. Sharing vehicles for shipping means limiting CO_2 emissions and then protecting environment (Pan et al., 2019).
- Recently, a new set of hybrid optimization strategies named matheuristics has emerged. They combine mathematical programming algorithms and metaheuristics in a cooperative way (Jourdan et al., 2009; Ball et al., 2011). Matheuristic strategies have been attracting the interest of many scholars and have already been successfully applied to solve some combinatorial optimization problems. Some examples are: vehicle routing (Fikar et al., 2015), patient admission scheduling problem with operating rooms (Guido et al., 2018), flow shop (Della Croce et al., 2014), workforce planning (Valeva et al., 2017), cloud manufacturing scheduling (Vahedi-Nouri et al., 2020). There is a clear shortage of matheuristic strategies applied to

integrated planning problems in perishable supply chains, although they are very promising and, in most cases, efficient.

- The potential of Industry 4.0 (Ivanov et al., 2020) is little explored. Blockchain is an emerging technology, which has a significant impact on efficiency and sustainability of supply chains (Saberi et al., 2019; Mirabelli and Solina, 2020; Saurabh and Dey, 2020; Astarita et al., 2020). It would be very interesting to understand how improving the quality of information exchange between the various nodes of the chain can impact on the coordination of activities. Basically, blockchain could better guarantee the demand-supply matching, which would result in the reduction of perished products (i.e., waste). Moreover, many of the documents examined deal with production planning, but the features of smart manufacturing appear very little exploited until now.
- There is a significant need to give impetus to the development of multi-objective models, in order to pursue not only economic, but also environmental and social sustainability.
- Only one of the reviewed papers explores the relationship between product shelf-life and packaging used (Li et al., 2020). More research is needed addressing this emerging topic. More expensive packaging is usually also more sustainable and extends the product lifetime. In this context, it would be very useful to have more investigations on the impact that different packaging can have on the economic and environmental sustainability of the perishable supply chains.
- Only 35% of the selected papers aim to solve real-life case studies. There is a need for further research, which is capable of modeling and quantitatively improving existing supply chains. In fact, it is very important to have useful approaches available to practitioners and entrepreneurs, in order to create a stronger link between academia and industry.

The main purpose is that this extensive review of quantitative approaches to optimize the integrated management of perishable supply chains can be a starting point for all scholars who want to study and deepen this topic in the coming years.

3. Optimal inventory and distribution management of perishable agricultural products with a hybrid inventory policy

3.1. Introduction and scientific background

Agriculture supply chains deal with products whose relevant features, like perishability, seasonality, or yield uncertainty, generally make the management of such chains very complex. In particular, at every stage of the chain, decision-makers face very challenging issues due to weather-related uncertainty, limited shelf-life, demand and price variability, safety and quality standards. For such reasons, the application of quantitative approaches has become increasingly popular in the agri-food supply chains to achieve economic, environmental, and social sustainability (Plà et al., 2014; Esteso et al., 2018; Zhu et al., 2018).

Accounting for perishability in critical tasks like production, storage, and distribution planning of agri- and food-products has become a very popular topic in recent years (Ahumada and Villalobos, 2009; Kusumastuti et al., 2016; Soto-Silva et al., 2016; Shukla and Jharkharia, 2013). A commodity is called perishable if its quality is subject to deterioration. Foods such as fruit, vegetables and meat need to be controlled and stored at certain temperatures in order to maintain high their quality. In particular, it is important to monitor both the duration of storage in the warehouse and the transport time along the supply chain. Basically, a tight coordination between production and distribution systems is absolutely necessary (Farahani et al., 2012). Hence, perishability considerably influences the contractual agreements between grower and wholesaler (Huang et al., 2019), the inventory management (Ali et al., 2013; Pan, 2016; Agi and Soni, 2020), the shipping operations (Viet et al., 2020), and in general the decision-making process along the whole agri-food supply chain.

Starting from a real-life agricultural firm that deals with planting, growing, harvesting and distributing cauliflowers, the problem of jointly managing storage and shipment of perishable agricultural products, with the aim of maximizing profits, is taken into account within this chapter. In particular, the firm has entered into a contract according to which a main customer prepares a planting plan for a given product, and the firm commits itself to supply to the main customer at least an agreed percentage of the harvested products along a given time horizon. In order to maximize profits, the firm has some degrees of freedom in terms of inventory management, being allowed to catch the opportunities offered on the spot market for the excess production with respect to the agreed threshold. With the aim of supporting the upgrade of the current practices, where the firm does not have complete control of the shipment management, an optimization model for the simultaneous planning of storage and shipment is proposed. The model aims at maximizing profits whose revenue components are represented by sales to the main customers and to the spot customers, while the cost components are represented by the production, storage, and shipment costs. Given the nature of the products, the relevant constraints aim at representing the dynamic inventory mechanism for perishable products adopted by the firm, whose hybrid fresh/old-first priority policy aims to balance quality of products delivered to the main customer. Further constraints ensure the fulfillment of the contract with the main customer and the resource availability of the vehicle fleet. The model can be suited to either tactical or operational decision-making. As for the former, the model has been adopted to select the fleet size and the maximum in-stock time of perishable products. As for the latter, the model has been used for the day-by-day planning of storage and shipment to both the main and the spot customers.

The proposed approach falls in the broad class of optimization models for supporting the decision-making about planting, harvesting, storage, production, distribution (and in some cases, purchasing) of perishable agri- and food-products. Ahumada and Villalobos, (2011) propose an integrated tactical planning model for the production and distribution of fresh products. They consider some factors usually neglected in the literature, such as transportation and inventory costs, price dynamics, product decay. The problem is addressed using a MIP model, whose objective is the revenue maximization. The model is validated referring to a hypothetical producer based in Mexico. Ahumada and Villalobos, (2011a) present an operational model for supporting the production and distribution decisions of perishable agricultural products, during the harvest season. They take into account some significant factors, such as the preservation of the quality of perishable crops, the management of labor costs, the different possible transportation modes (i.e., trucking, railroad and air). The proposed MIP model is validated using a hypothetical producer of tomatoes and bell peppers. Ferrer et al., (2008) use a mixed integer programming model for scheduling the harvesting activities in the wine industry. The decision-making about manpower allocation and routing of harvest operations is also supported. Product quality loss related to early or delayed harvest with respect to an optimal date is considered. The validation of the proposed model, which can be used at both a tactical and operational level, is carried out using a real industrial case in Chile. Rong et al., (2011) propose a methodology to model food quality degradation and integrate it in a MILP model, useful for production and distribution planning. The quality loss is modelled considering two main factors, time and temperature. The proposed approach is applied to an illustrative case study, which concerns a supply chain for bell peppers. The aim is to minimize the cost of production, transportation, cooling, storage, and disposal. Tan and Comden, (2012) develop a planning methodology, which considers the uncertainty in both the supply of fruits and vegetables from some contracted farms and the demand from the retailers. The proposed approach suggests the farm areas and the seeding times for annual plants, in order to maximize the total expected profit. Accorsi et al., (2017) focus on the interaction between climate and the distribution of perishable products. In particular, they propose a MILP model for the planning of production, storage and distribution of perishable products. The model takes into account the weather conditions and is validated through an illustrative case study of a cold chain for cherries. The proposed approach contains many sustainable features, in fact the main aim is the minimization of energy consumption for the product refrigeration, exploiting the information about weather conditions. Soto-Silva et al., (2017) present three optimization models, which deal with some important decisions in the horticulture context. The first two are respectively for purchasing and storing the fresh produce. The third one is an integrated model for purchasing and storing fresh produce for a processing plant. The proposed tools are validated considering a real Chilean apple supply chain. Abedi and Zhu, (2017) propose a MILP model to help decision-making of a real trout fish farm. The main decisions are on the spawn purchase quantity, the best time to harvest fish, the distribution of the harvested fish. The objective is profit maximization and the delivery of fresh fish to the most profitable customers is prioritized. Jiang et al., (2018) develop a mixed integer nonlinear programming model (MINLP) for supporting, in an integrated way, the decisions about harvesting and distribution activities of perishable agri-products. The model is formulated as a vehicle routing problem with time windows. Ahumada et al., (2012) propose a stochastic tactical planning model for the production and distribution of fresh agricultural products. The model takes into account some significant uncertainties like the variability of weather and demand. It is tested and validated using the stochastic version of the same case study presented in Ahumada and Villalobos, (2011a). Jiang et al., (2019) integrate the decisions about harvest and farm-to-door distribution scheduling for vegetables online retailing. They propose a quadratic vehicle routing programming model with time windows and solve it through a genetic algorithm with adaptive operators. A quadratic post-harvest quality deterioration function is used to take into account vegetables perishability. Grillo et al., (2017) propose a MILP model, with the aim to maximize two conflicting objectives, profit and mean product freshness. By varying the weight assigned to each objective, shelf-life length, and pricing policy, different scenarios are defined and addressed through a rolling horizon approach. The computational experiments, conducted on real-life data from a Spanish orange and tangerine supply chain, show the validity of the proposed approach. Higgins et al., (2006) develop a MIP model, with the aim to efficiently plan the production of the different sugar brands by the various mills and the shipping activities through the different ports, with reference to an Australian case study. The model is solved through two local-search based meta-heuristics, which can provide better solutions than manual methods.

A mathematical model to maximize the profit of a real distributor of fresh tomato in Iran is presented by Ghezavati et al., (2017). They take into account product quality changes, by considering three different quality loss functions, related to ripeness, freshness, and coolness. Since the proposed model is hard to be solved, a Benders' decomposition algorithm is used. Chan et al., (2020) focus on sustainability and efficiency of food supply chains, looking at people's quality of life. They propose a multi-objective production inventory routing problem and an efficient particle swarm algorithm for solving it. The total cost (production, inventory, routing), the overall amount of CO_2 emissions, and the delivery time are minimized, while the average food quality is maximized. A Chinese meat supply chain network is used for the validation of the proposed model and algorithm. Belo-Filho et al., (2015) address the operational integrated production and distribution planning problem with perishable products. In this context, the main decisions are on sizing and scheduling of production batches, and vehicle routing. An adaptive large neighborhood framework is used to tackle such a problem, with the aim to minimize the total production and distribution costs. Amorim et al., (2012) integrate the decisions on production and distribution planning of perishable products. They consider the two cases of fixed or loose shelf-life. The use of a multi-objective framework proves the benefits of the integrated approach instead of the decoupled one. Merener et al., (2016) propose and implement a deterministic optimization model to support a real-life firm located in South America, which deals with an intermediation service between grain producers and end-users. The computational results reveal the optimal storing and shipping policy for profit maximization. Dolgui et al., (2018) propose a mathematical model to integrate production, inventory, and distribution activities in a multi-stage supply chain with perishable products and truckload discounts. Near-optimal solutions are obtained by using a non-revisiting genetic algorithm.

3.1.1 Contribution

Basically, this chapter aims to fill the following research gaps:

- First of all, as highlighted in Chapter 2, numerous articles dealing with the integrated management of perishable supply chains, use instances known in the literature or generated randomly to validate the proposed models. A low proportion of articles in the literature (i.e., about 35 %) use real-life data, then case studies, to test and demonstrate the goodness of their approaches. This is a major limitation. In this chapter, the proposed optimization model is validated under multiple scenarios, which refer to a real agricultural company. Instances are generated, starting from historical data, therefore the proposed approach aims to be an important reference not only for academics, but also for practitioners and entrepreneurs.

- A very recent literature review by Kumar et al., (2020) on the use of quantitative approaches for coordinated planning of production and distribution activities, analyzes more than 70 articles from the point of view of the decision-making level. None of them offer managerial insights on all the three traditional decision levels (i.e., strategic, tactical and operational). In this chapter, the optimization model is used at a strategic-tactical level to upgrade current practices of the real firm, in such a way it is able to have full control of both warehouse management and deliveries. While, at the operational level, day-by-day support is provided to the decision-maker, to better plan deliveries to the main customer and spot customers, and adequately manage the warehouse with the aim to preserve product quality and avoid waste.
- As far as is known, mathematical modeling of inventory management in order to enable a hybrid priority policy is quite new and little explored in the literature. The starting point is the interesting paper by Coelho and Laporte, (2014). Hybrid inventory management serves to ensure a balance of the quality of the delivered product.
- At the operational level, a heuristic approach, called rolling horizon, is used to solve the model. Although it is well known in the literature, it has so far been little used for problems, in which there is integration between inventory and distribution activities along perishable supply chains, as highlighted in Chapter 2. Only Violi et al., (2020) have been recently used a rolling horizon scheme to tackle an inventory routing problem in the agri-food context.

3.2. Problem statement and model formulation

This chapter focuses on storage and shipment problems faced by an agricultural firm whose aim, along a discrete time horizon $\mathcal{T} = \{1, \dots, T\}$ is to supply a main contract customer, wishing to catch market opportunities offered by the demand expressed by spot customers. Without loss of generality, the time horizon $\mathcal{T}$ refers to the harvesting/distribution season, prior to which planting and growing of crop occur, while $t \in \mathcal{T}$ is a generic period index, hence $t = 1$ represents the time period when the harvest/distribution season starts.

The agricultural firm and the main customer agree on a planting/growing/harvesting plan according to which the main customer commits to buy, along $\mathcal{T}$, up to 100 % of the total amount harvested, while the firm commits to supply at least a fraction γ of such amount to the main customer. Q_t is the amount of product harvested at period t, hence Q_t represents the amount of fresh product entering the system at t. The fresh product can be either immediately used as partial fulfillment of the main customer, or stored for later delivery. While the demand D_t of spot customers at period t, can only be fulfilled by the stored products. Then, q_{max} is the maximum amount of product that can be received at each period by the main customer, while I_{max} refers to the capacity of the cooled warehouse.

Distribution is made by using a fleet of at most N vehicles, each vehicle i having a capacity C_i and a renting/shipping cost K_{it} per period t. Each vehicle can execute at most one delivery-trip per period, and no further transportation costs are considered. Inventory costs are related to temperature control of the cooled warehouse. The unit inventory cost per time period, from the end of period t to the end of period t is denoted by h_t. Stored products are subject to perishability. Adopting a fixed lifetime scheme, τ is the maximum in-stock time (MIST) of each product. Thus, at the end of period t the amount of product that entered the system at $(t - \tau)$, and has not yet been delivered, must be disposed. Possible additional costs for the disposal of outdated products are neglected. R is the unit production cost related to planting, growing and harvesting, while unit sale-prices per period t to main customer and spot customers are denoted by p_t and v_t, respectively, with $p_t < v_t$. In Table 16, the notation of all problem data is reported and briefly explained. All the random parameters, namely, the amount of harvested product Q_t, the demand of spot customers D_t, and the market prices p_t and v_t, are represented by their expected values.

Table 16. Notation of all the problem data

$\mathcal{T}$	Harvesting/distribution time horizon, with $\mathcal{T} = \{1, \dots, T\}$;
τ	Maximum in-stock time;
N	Number of vehicles;
Q_t	Amount harvested during period t (i.e., fresh product);
D_t	Amount required by spot customers at period t;
I_{max}	Inventory capacity;
q_{max}	Maximum amount of product, that can be received by the main customer, per period;
C_i	Capacity of vehicle i, $i = 1, \dots, N$

p_t	Unit selling price to main customer at period t
v_t	Unit selling price to spot customers at period t
K_{it}	Renting/shipping cost of vehicle I per period t
h_t	Carrying/holding cost per product unit from the end of period $(t-1)$ to the end of period t
R	Unit production (i.e., planting/growing, harvesting) cost
γ	Minimal fraction of the total harvested products to be delivered to the main customer along the entire season, $\gamma \in (0,1)$

The goal is to maximize profits related to storage and shipping of products, fulfilling contractual agreements with the main customer. Here, revenues are related to selling products, while costs are related to production (planting/growing/harvesting), shipment and storage management. In particular, it is very important to highlight that production costs are independent of the decision-making process along the time horizon. Indeed, decisions at each period t are about the amount x_t of fresh product and y_t of in-stock product to deliver to the main customer, and the amount w_t of in-stock product to deliver to spot customers. In order to represent different ages of products stored in the warehouse, similar to Coelho and Laporte, (2014), the inventory level at the end of period t related to products harvested at period $(t-s)$ (with $s \leq \tau$) is denoted by $I_t^{(s)}$. As for the inventory policy, a hybrid fresh/old-first approach is adopted. The company sells stored products according to an old-first policy, but the simultaneous selling of fresh products is not prevented. More precisely, in a period when deliveries are made, the firm tries to fill the vehicles with fresh (i.e., just harvested) products, and in case in-stock products are also considered for deliveries, for such products an old-first priority is adopted. The latter one is also the policy adopted to meet spot customer requests. This clarifies why the total deliveries at period t were decomposed in the three decision variables x_t, y_t, and w_t. Auxiliary continuous variables $\delta_t^{(s)}$ are introduced to represent such hybrid fresh/old-first priority policy. In fact, $\delta_t^{(s)}$ is the cumulate amount of in-stock products harvested between $(t-s+1)$ and $(t-1)$, which are selected at period t to ensure the shipping of $(y_t + w_t)$ in-stock products. Hence, δ_t^{τ} is set equal to $(y_t + w_t)$, and a set of binary variables $\eta_t^{(s)}$, that are used to force the deliveries from the oldest parts of the inventory, in case $(y_t + w_t) > 0$. The resulting constraint structure guarantees that $\delta_t^{(s)} = max\{0, y_t + w_t - \sum_{l=s-1}^{\tau-1} I_{t-1}^{(l)}\}$. In Table 17, the notation for all the decision variables of the proposed model is reported.

Table 17. Notation of all the decision variables

$x_t \geq 0$	Amount of fresh products delivered to main customer at period t;
$y_t \geq 0$	Amount of in-stock products delivered to main customer at period t;
$w_t \geq 0$	Amount of in-stock products delivered to spot customers at period t;
$I_t^{(s)} \geq 0$	Amount of products harvested at period $(t - s + 1)$, that are still in stock at the end of period t, with $s = 1, \dots, \tau$;
$\delta_t^{(s)} \geq 0$	Amount of in-stock products harvested from period $(t - s + 1)$ to period $(t - 1)$, that are delivered at period t, with $s = 2, \dots, \tau$;
$\eta_t^s \in \{0,1\}$	Binary variable equal to one if the total amount of in-stock products $(y_t + w_t)$ delivered at time t is larger than $\sum_{l=s-1}^{\tau-1} I_{t-1}^l$, 0 otherwise, with $s = 2, \dots, \tau$;
$z_{ti} \in \{0,1\}$	Binary variable equal to one if vehicle i is selected for delivery at period t

Next, the model formulation is presented.

Max $\quad \sum_{t=1}^{T}(p_t(x_t + y_t) + v_t w_t) - \sum_{t=1}^{T}\sum_{i=1}^{N} K_{it} z_{ti} - \sum_{t=1}^{T}\sum_{s=1}^{\tau} h_t I_t^{(s)} - R \sum_{t=1}^{T} Q_t \qquad (1)$

s.t.

$$\sum_{t=1}^{T}(x_t + y_t) \geq \gamma \sum_{t=1}^{T} Q_t \qquad (2)$$

$$x_t + y_t \leq q_{max} \qquad t = 1, \dots, T \qquad (3)$$

$$x_t + y_t \leq \sum_{i=1}^{N} C_i z_{ti} \qquad t = 1, \dots, T \qquad (4)$$

$$w_t \leq D_t \qquad t = 1, \dots, T \qquad (5)$$

$$I_t^{(1)} = Q_t - x_t \qquad t = 1, \dots, T \qquad (6)$$

$$I_t^{(s)} = I_{t-1}^{(s-1)} - \delta_t^{(s)} + \delta_t^{(s-1)} \qquad t = 1, \dots, T, s = 2, \dots, \tau \qquad (7)$$

$$I_1^{(s)} = 0 \qquad s = 2, \dots, \tau \qquad (8)$$

$$\delta_t^{(\tau)} = y_t + w_t \qquad t = 1, \dots, T \tag{9}$$

$$\delta_t^{(s)} \geq \delta_t^{(s-1)} \qquad t = 1, \dots, T, s = 2, \dots, \tau \tag{10}$$

$$\delta_t^{(1)} = 0 \qquad t = 1, \dots, T \tag{11}$$

$$\delta_t^{(\tau)} - \sum_{l=s-1}^{\tau-1} I_{t-1}^{(l)} \leq I_{max}\, \eta_t^{(s)} \qquad t = 2, \dots, T, s = 2, \dots, \tau \tag{12}$$

$$\sum_{l=s-1}^{\tau-1} I_{t-1}^{(l)} - \delta_t^{(\tau)} \leq I_{max}(1 - \eta_t^{(s)}) \qquad t = 2, \dots, T, s = 2, \dots, \tau \tag{13}$$

$$\delta_t^{(s)} - \delta_t^{(s-1)} + I_{max}(1 - \eta_t^{(s)}) \geq I_{t-1}^{(s-1)} \qquad t = 2, \dots, T, s = 2, \dots, \tau \tag{14}$$

$$\delta_t^{(s)} \leq I_{max}\, \eta_t^{(s+1)} \qquad t = 2, \dots, T, s = 2, \dots, \tau - 1 \tag{15}$$

$$\sum_{s=1}^{\tau} I_t^{(s)} \leq I_{max} \qquad t = 1, \dots, T \tag{16}$$

$$I_t^{(s)} \geq 0 \qquad t = 1, \dots, T, s = 1, \dots, \tau \tag{17}$$

$$\delta_t^{(s)} \geq 0 \qquad t = 1, \dots, T, s = 2, \dots, \tau \tag{18}$$

$$x_t, y_t, w_t \geq 0 \qquad t = 1, \dots, T \tag{19}$$

$$z_{ti} \in \{0,1\} \qquad t = 1, \dots, T, i = 1, \dots, N \tag{20}$$

$$\eta_t^{(s)} \in \{0,1\} \qquad t = 2, \dots, T, s = 2, \dots, \tau \tag{21}$$

Some explanations are in order. Constraint (2) enforces the fulfillment of the supply contract with the main customer. The amount of product delivered to the main customer each day is guaranteed not to exceed both the daily threshold q_{max}, in view of constraints (3), and the capacity of the adopted vehicles, in view of constraints (4). Constraints (5) ensure that sales to spot customers do not exceed their demand, while constraints (6) allow to decouple the fresh products from the in-stock ones. An old first priority strategy is forced for in-stock products by means of constraints (7) to (15), assuming an empty inventory at the beginning of the time horizon, while constraints (16) ensure that the storage capacity is not exceeded. The objective function (1) is the profit along the harvesting/distribution season, accounting for the sale revenues, the transportation cost, the inventory cost, and the production cost (here, the main assumption is that the total amount $\sum_{t=1}^{T} Q_t$ of harvested product along $\mathcal{T}$ equals the total amount of planted products).

3.3. Case study

In the following, the real-life case study that has given the motivation to develop the modeling approach presented above, is introduced. An agricultural firm, located in the Southern Italy, deals with planting, growing, harvesting and distributing cauliflowers to a main contract customer and several spot customers. It should be noted that cauliflower variety ranges from very early maturing (less than 60 days from planting to maturity) to late maturing (more than 100 days). Post-harvest cauliflower has an expected shelf-life of 3-4 weeks, but only under some particular storage conditions. Indeed, cauliflower is highly perishable. Romo-Parada et al., (1989) have proved that under a controlled atmosphere of 3 % O_2 and 2.5 % to 5 % CO_2, cauliflower is still marketable after 52 days of storage. More in general, storage temperature should be between 0 °C and 4 °C because higher value would cause quality worsening and shelf-life reduction, see Raja et al., (2011).

The relevant features of the contract between the firm and the main customer are perfectly overlapping with those described earlier. Furthermore, actual planting and shipping operations are entirely managed by the main customer. In fact, at the beginning of the season (first half of August), a planting plan, in terms of cauliflower species, total amount and scheduling, is issued by the main customer, with the aim of ensuring a reasonably balanced maturing season from the end of November until the end of April.

Besides, during the harvesting/distribution season, it is the main customer that takes care of the cauliflower collection at the firm warehouse, in terms of vehicle operations and scheduling. The current shipping policy is based on a fleet of two vehicles (with capacity of 11,040 cauliflowers) whose schedule makes the MIST not greater than three days. The warehouse capacity is 50,000 cauliflowers, while the total amount of planted products is generally around 700,000.

The agricultural firm is willing to upgrade current operation practices. In particular, two relevant issues arise. In terms of tactical decisions, the firm wants to select the fleet size (and capacity) along with the appropriate MIST, while in terms of operational decisions, the firm wants to plan the daily operations with respect to storage and shipping, accounting for perishability. In the following, before reporting on the computational experience, the set of test-instances, that have been built on the basis of historical data, is described.

3.3.1. Instance generation

From the analysis of historical data, it can be stated that at the beginning and at the end of the harvesting season, the amount of harvested cauliflowers is usually quite limited, while the central weeks are the most prolific. Hence, a whole harvesting/distribution season can be divided into 4 main intervals in sequence. The first and the fourth interval are characterized by low amount of harvested products (i.e., *low season*), while while the two central intervals are the ones with high amount of harvested products (i.e., *high season*). During each low season interval of the horizon the amount of harvested cauliflowers is around 130,000, while during each high season interval such amount increases up to 235,000.

With the aim to address the problem under different scenarios, the instances have been designed by adopting two higher-level parameters, i.e., the total amount of harvested products per time horizon, and the variability of random parameters per period. 4 sets of short-term instances have been generated, adopting as length of the time horizon 35 days, next referred to as low season-low variability (LS-LV), low season-high variability (LS-HV), high season-low variability (HS-LV), high season-high variability (HS-HV). Every set contains 20 instances, and the initial inventory level has been set to null. Subsequently, in order to test the proposed model also over a whole season, two sets of long-term instances have been generated, next referred to as whole season-low variability (WS-LV), whole season-high variability (WS-HV). Every long-term instance consists of 4 short-term instances, placed in the order LS-HS-HS-LS. Twenty instances have been generated for each long-term set. Independent of the harvesting scenario, the actual length of each harvesting/distribution time horizon is increased of 5 days in order to guarantee the warehouse emptying.

In the remainder of this chapter, all the parameters and variables related to the quantity of product are expressed in cauliflower units, while those related to monetary aspects are expressed in Euro [€]. For each instance, the following data have been generated: Q_t, D_t, p_t, v_t. Q_t has been generated by sampling from a normal distribution, with coefficient of variation equal to 0.15 and 0.40 for the two scenarios of low and high variability, respectively; the mean has been estimated on the basis of the historical data. In Figures 8-9, a historical data sample related to the 2018-2019 season, and a generated long-term data sample, in terms of amount harvested, are respectively shown.

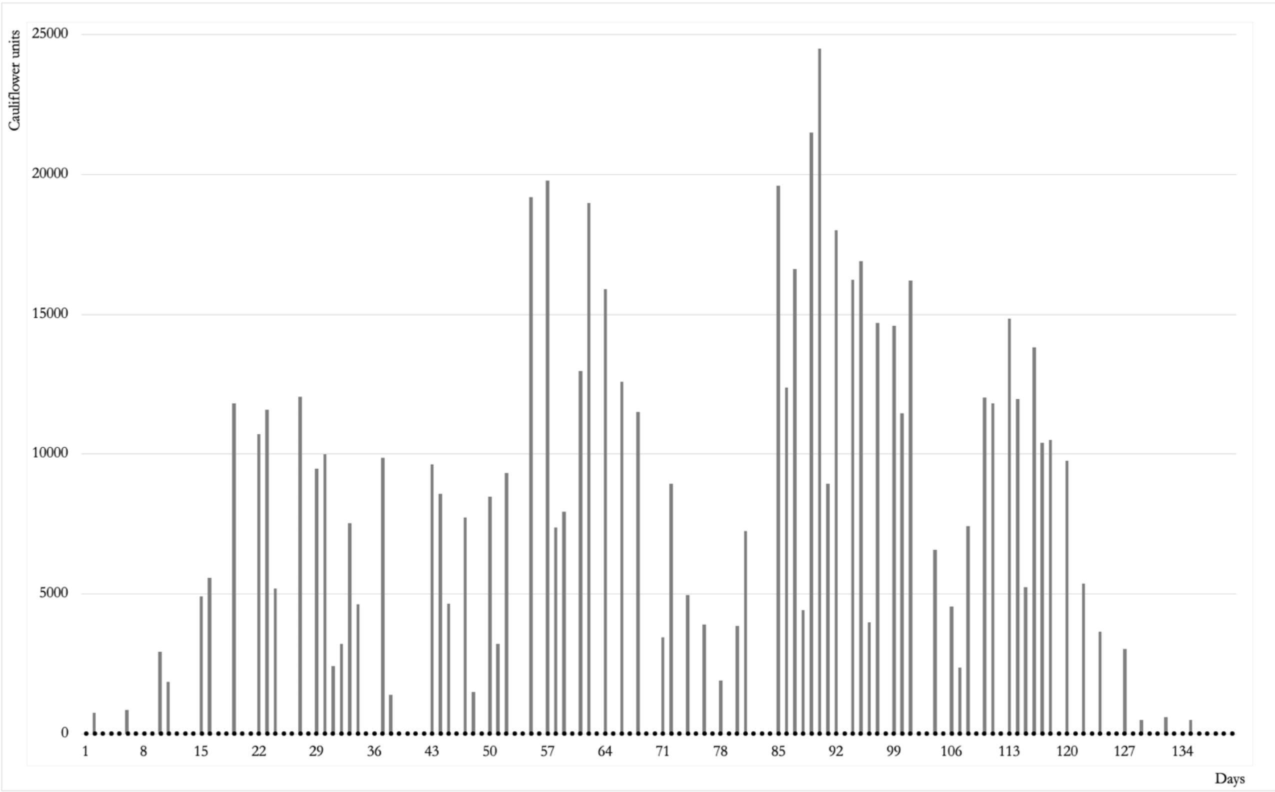

Figure 8. Harvested cauliflower units per day: historical data (2018-2019 season)

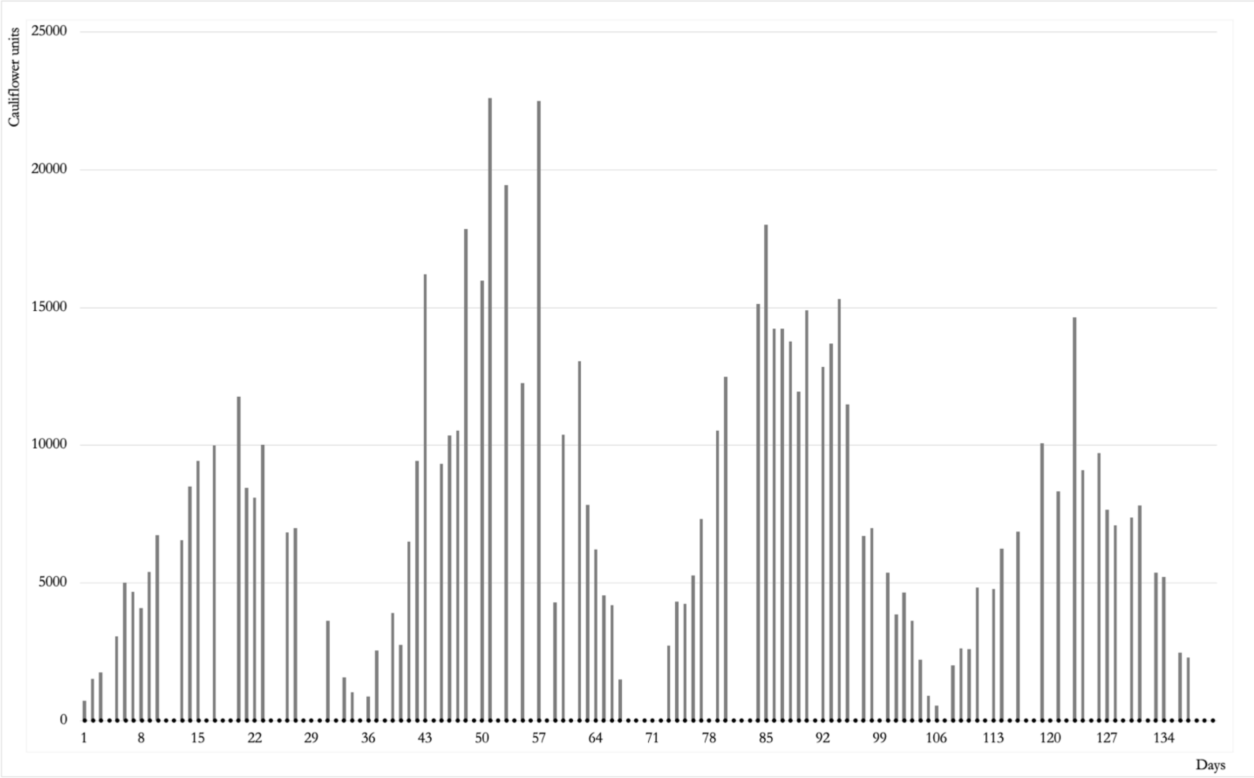

Figure 9. Harvested cauliflower units per day: generated data (2018-2019 season)

As it can be seen, the two graphs share the same characteristics: in both cases, in fact, the daily amount of harvested product fluctuates between very high and very low values, and in some days, it can be zero. Furthermore, as already highlighted above, at the beginning and at the end of the season the harvested quantity is usually quite limited, while the middle weeks are the most prolific.

D_t and p_t have been generated by sampling from a normal distribution, with coefficient of variation equal to 0.05 and 0.10 for the two scenarios of low and high variability, respectively. Referring to the amount required by spot customers, the mean has been set to 170 and 230 respectively for the two scenarios of low and high season. About the unit selling price to the main customer, the mean has been estimated based on the historical data, retrieved from the official website of the Italian Institute of Services for the Agricultural Food Market (Ismea, 2020). v_t has been generated assuming a 5 % increase in the price to the main customer. The remaining relevant data, whose setting is based on the current operating conditions of the firm, are reported in Table 18.

Table 18. Relevant data of the case study

$\sum_{t=1}^{T} Q_t$	I_{max}	C_i	K_{it}	h_t	R	γ
[units]	[units]	[units]	[units]	[€/unit*day]	[€/unit]	-
~730,000	50,000	11,040	400.00	0.02	0.25	0.95

3.3.2. Computational experience and managerial insights

The computational experiments have been carried out on a Server running Windows 10 Pro with AMD Ryzen 7 2700X Eight-Core Processor 4.00 GHz/16GB. The proposed optimization model has been solved by CPLEX 12.8, Academic License. The computational tests have been performed at two different decision levels (i.e., strategic-tactical and operational), with the aim of highlighting some significant managerial insights.

3.3.2.1. Strategic-tactical level

At the strategic-tactical level, the optimization model was adopted to support decisions of the firm regarding the maximum in-stock time (τ) and the size of the fleet (N). The choice of τ influences the average quality of the shipped product. Several alternatives have been explored, but for the sake of presentation simplicity, only the results related to $\tau \in \{3,5,7\}$ are reported. On the other hand, the decision about N has an important economic impact due to bearing additional costs for purchase, maintenance, insurance, etc. In this case, six alternatives have been assessed, i.e., $N \in \{1, 2, \dots, 6\}$.

Table 19 shows the total profit, averaged over the 20 instances per short-term test-set, as τ and N vary. These results, in more detailed form, are reported in the next subsection.

Table 19. Average total profit for the short-term instances [€]

Set	τ	$N=1$	$N=2$	$N=3$	$N=4$	$N=5$	$N=6$
LS-LV	3	42,232.66	42,313.95	42,313.95	42,313.95	42,313.95	42,313.95
	5	42,934.02	43,039.89	43,039.95	43,039.95	43,039.95	43,039.95
	7	43,293.69	43,401.85	43,401.85	43,401.85	43,401.85	43,401.85
LS-HV	3	42,859.14	43,234.41	43,243.93	43,243.93	43,243.93	43,243.93
	5	44,048.55	44,366.46	44,378.03	44,378.03	44,378.03	44,378.03
	7	44,573.14	45,073.50	45,177.91	45,199.31	45,199.31	45,199.31
HS-LV	3	118,560.09	122,869.68	123,052.99	123,086.22	123,096.36	123,096.36
	5	120,409.60	123,866.42	124,311.55	124,489.16	124,561.01	124,567.28
	7	120,433.05	124,029.14	124,596.30	124,812.08	124,937.95	124,959.70
	3	123,264.97	129,634.94	129,976.46	130,060.45	130,079.82	130,079.82

HS-HV	5	126,590.04	132,034.26	132,890.64	133,123.92	133,246.12	133,284.28
	7	126,846.68	132,621.94	133,640.03	133,926.03	134,092.80	134,166.46

In general, the average profit increases as τ and/or N increase. Nonetheless, for any given $\tau \in \{3,5,7\}$ the average profit tends to stabilize as soon as N gets sufficiently high. This is due to the combination of the warehouse capacity, the setting of τ, and the total capacity of the vehicles. In fact, once that τ, I_{max}, C_i have been fixed, it is easy to see that a threshold on the number N of vehicles exists such that any further vehicle would result useless in the shipment operations.

The computational effort required for solving each short-term instance is reasonably low (less than 5 seconds per instance), hence it was decided to test also the long-term ones, the results of which are reported in Table 20. They give an exhaustive overview about the amount of profit over a whole season and this is very important for strategic-tactical decision-making.

Table 20. Average total profit for the long-term instances [€]

Set	τ	$N = 1$	$N = 2$	$N = 3$	$N = 4$	$N = 5$	$N = 6$
	3	313,674.87	331,102.28	331,726.91	331,859.01	331,878.81	331,892.13
HS-LV	5	325,609.98	334,483.03	335,674.53	336,058.50	336,160.42	336,195.25
	7	326,658.11	335,574.06	336,954.53	337,466.25	337,657.79	337,729.49
	3	307,076.61	325,725.97	326,580.50	326,748.40	326,852.77	326,870.25
HS-HV	5	321,415.57	332,201.19	333,480.85	333,833.01	334,067.75	334,153.04
	7	323,081.39	334,610.72	336,309.18	336,830.85	337,097.17	337,243.01

As expected, the average profit increases as τ and N increase. However, when τ is fixed, the most significant increase occurs when N varies from 1 to 2. Likewise, when N is fixed, the average profit rises significantly only when τ varies from 3 to 5. As a consequence, combining the insights coming from such results with the experience of the decision-maker, the most appropriate setting of the parameters is $\tau = 5$ and $N = 2$. In fact, although a higher average profit could be obtained adopting a larger value of τ, the resulting average loss of product quality is not considered acceptable by the firm, namely, the expected increase of the profit could be canceled by an actual reduction of the unit selling price. Similarly, any investment in more than 2 vehicles is not recoverable in the short-term, given the limited expected profit increase. For example, when $\tau = 5$, the average profit increases by around 1,000 € per year passing from $N = 2$ to $N = 3$. As for the average computational effort required for solving a long-term instance, the CPU time has never been higher than 250 seconds.

3.3.2.1.1 Short-term instances: detailed results

In this subsection, detailed results about the short-term instances are reported. Seven Key Performance Indicators (KPIs) have been taken into account: revenue from the main customer, revenue from the spot customers, inventory cost, shipping cost, production (planting/growing/harvesting) cost, % waste (i.e., percentage of perished products), profit.

Tables 21-34 show how the 7 considered KPIs vary for each of the twenty instances of the LS-LV set, depending on: the number of vehicles used for delivery (i.e., N) and the MIST (i.e., τ). The instances are named respectively LL-1, LL-2, ..., LL-20. Figures 10-12 show, instead, 6 out of the 7 KPIs, averaged over the twenty instances (production cost is here neglected because is obviously constant, in terms of average value).

Table 21. KPIs for the case $\tau = 3$, $N = 1$ (LS-LV, Instances: LL1-to-LL10)

KPI	Instances									
	LL-1	LL-2	LL-3	LL-4	LL-5	LL-6	LL-7	LL-8	LL-9	LL-10
Revenue Main	79,789.78	80,614.02	77,695.87	74,619.13	79,461.09	78,470.31	79,096.37	73,458.82	78,549.16	74,966.25
Revenue Spot	2,775.26	3,016.05	2,732.75	3,159.54	2,948.67	3,172.10	3,098.72	2,618.08	2,571.53	2,085.69
Inventory Cost	1,094.46	1,183.84	1,044.98	910.00	808.00	1,078.86	1,649.14	1,468.34	1,409.44	670.60
Shipping Cost	6,000.00	5,600.00	5,600.00	6,000.00	6,000.00	6,000.00	6,000.00	6,000.00	5,600.00	6,400.00
Production Cost	31,878.00	31,803.00	31,735.25	31,316.25	31,583.50	31,316.25	31,684.50	31,631.00	31,632.00	31,365.50
% Waste	0.00	0.06	0.38	0.20	0.25	0.20	0.00	0.25	0.00	0.00
Profit	43,592.58	45,043.23	42,048.39	39,552.42	44,018.26	43,247.30	42,861.45	36,977.56	42,479.25	38,615.84

Table 22. KPIs for the case $\tau = 3$, $N = 1$ (LS-LV, Instances: LL11-to-LL20)

KPI	Instances									
	LL-11	LL-12	LL-13	LL-14	LL-15	LL-16	LL-17	LL-18	LL-19	LL-20
Revenue Main	79,775.90	77,628.47	77,625.29	78,844.37	77,499.97	75,509.67	80,457.08	77,365.43	80,723.07	78,827.77
Revenue Spot	2,454.41	2,444.94	2,547.90	2,811.16	2,315.21	2,567.05	2,780.38	2,338.35	3,141.85	2,843.86
Inventory Cost	1,070.16	1,150.92	884.42	1,049.66	767.06	875.44	1,113.18	1,278.34	957.64	1,027.96
Shipping Cost	5,600.00	5,600.00	6,400.00	6,000.00	6,800.00	5,600.00	5,600.00	6,000.00	5,600.00	5,200.00
Production	31,715.00	31,891.75	31,525.75	31,616.50	31,439.50	31,295.75	31,679.75	31,754.00	31,392.25	31,400.25

Cost										
% Waste	0,25	0,17	0.00	0.00	0.00	0,05	0.00	0.00	0.00	0,75
Profit	43,845.15	41,430.74	41,363.02	42,989.37	40,808.62	40,305.53	44,844.53	40,671.44	45,915.03	44,043.42

Table 23. KPIs for the cases $\tau = 3, N = 2, 3, 4, 5, 6$ (LS-LV, Instances: LL1-to-LL10)

KPI	Instances									
	LL-1	LL-2	LL-3	LL-4	LL-5	LL-6	LL-7	LL-8	LL-9	LL-10
Revenue Main	80,321.34	80,614.02	77,695.87	74,619.13	79,461.09	78,788.35	79,096.37	73,572.34	78,458.16	74,972.82
Revenue Spot	2,681.84	3,016.05	2,732.75	3,159.54	2,948.67	3,172.10	3,098.72	2,499.40	2,666.17	2,077.45
Inventory Cost	1,311.80	1,183.84	1,044.98	910.00	808.00	1,605.16	1,428.34	1,266.26	1,413.08	603.56
Shipping Cost	6,000.00	5,600.00	5,600.00	6,000.00	6,000.00	5,600.00	6,000.00	6,000.00	5,600.00	6,400.00
Production Cost	31,878.00	31,803.00	31,735.25	31,316.25	31,583.5	31,316.25	31,684.50	31,631.00	31,632.00	31,365.50
% Waste	0.00	0.06	0.38	0.20	0.25	0,20	0.00	0,25	0.00	0.00
Profit	43,813.38	45,043.23	42,048.39	39,552.42	44,018.26	43,439.04	43,082.25	37,174.48	42,479.25	38,681.21

Table 24. KPIs for the cases $\tau = 3, N = 2, 3, 4, 5, 6$ (LS-LV, Instances: LL11-to-LL20)

KPI	Instances									
	LL-11	LL-12	LL-13	LL-14	LL-15	LL-16	LL-17	LL-18	LL-19	LL-20
Revenue Main	79,884.89	77,555.57	77,625.29	79,427.09	77,499.97	75,610.47	80,370.24	77,581.95	80,723.07	78,912.53
Revenue Spot	2,340.23	2,521.08	2,547.90	2,711.32	2,315.21	2,461.45	2,870.56	2,111.51	3,141.85	2,755.84
Inventory Cost	1,022.40	1,154.16	884.42	1,169.18	767.06	846.34	1,116.52	968.04	957.64	1,024.7
Shipping Cost	5,600.00	5,600.00	6,400.00	6,000.00	6,800.00	5,600.00	5,600.00	6,000.00	5,600.00	5,200.00
Production Cost	31,715.00	31,891.75	31,525.75	31,616.50	31,439.50	31,295.75	31,679.75	31,754.00	31,392.25	31,400.25
% Waste	0,25	0,17	0.00	0.00	0.00	0,05	0.00	0.00	0.00	0,75
Profit	43,887.72	41,430.74	41,363.02	43,352.73	40,808.62	40,329.83	44,844.53	40,971.42	45,915.03	44,043.42

Figure 10. Average value of revenue, cost, % waste, profit, when $\tau = 3$ (LS-LV)

Table 25. KPIs for the case $\tau = 5, N = 1$ (LS-LV, Instances: LL1-to-LL10)

KPI	Instances									
	LL-1	LL-2	LL-3	LL-4	LL-5	LL-6	LL-7	LL-8	LL-9	LL-10
Revenue Main	80,755.60	81,935.49	78,095.55	75,425.62	80,548.33	78,685.78	79,640.87	73,902.58	78,808.9	75,429.13
Revenue Spot	2,708.63	3,242.66	2,850.00	3,088.83	3,173.77	3,382.2	3,007.85	3,131.60	2,597.57	3,063.67
Inventory Cost	2,137.22	2,273.44	1,539.52	1,569.74	1,382.44	1,624.86	2,260.28	1,920.44	1,568.7	1,961.54
Shipping Cost	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,600.00	5,200.00
Production Cost	31,878.00	31,803.00	31,735.25	31,316.25	31,583.50	31,316.25	31,684.50	31,631.00	31,632.00	31,365.50
% Waste	0.00	0.00	0.00	0.20	0,067282	0.18	0.00	0.00	0.00	0.00
Profit	44,249.01	45,901.71	42,470.78	40,428.46	45,556.16	43,926.87	43,503.94	38,282.74	42,605.77	39,965.76

Table 26. KPIs for the case $\tau = 5, N = 1$ (LS-LV, Instances: LL11-to-LL20)

KPI	Instances									
	LL-11	LL-12	LL-13	LL-14	LL-15	LL-16	LL-17	LL-18	LL-19	LL-20
Revenue Main	79,426.25	78,584.12	78,462.48	79,038.33	77,859.46	75,310.64	79,730.89	76,816.92	80,816.33	79,560.51
Revenue Spot	3,030.96	2,365.04	2,591.44	3,615.88	2,806.99	2,811.67	3,398.68	3,174.15	3,272.67	3,180.04
Inventory Cost	1,092.34	1,455.98	1,520.58	1,902.68	1,803.58	946.86	1,227.5	1,763.16	1,827.5	1,613.62
Shipping Cost	5,600.00	5,600.00	5,600.00	5,600.00	5,600.00	5,200.00	5,200.00	5,200.00	4,800.00	4,800.00
Production Cost	31,715.00	31,891.75	31,525.75	31,616.50	31,439.50	31,295.75	31,679.75	31,754.00	31,392.25	31,400.25
% Waste	0,01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0,21
Profit	44,049.87	42,001.43	42,407.59	43,535.03	41,823.37	40,679.70	45,022.32	41,273.91	46.069.25	44,926.68

Table 27. KPIs for the case $\tau = 5, N = 2$ (LS-LV, Instances: LL1-to-LL10)

KPI	Instances									
	LL-1	LL-2	LL-3	LL-4	LL-5	LL-6	LL-7	LL-8	LL-9	LL-10
Revenue Main	81,292.36	82,210.39	78,203.43	75,425.62	80,548.33	79,108.21	79,640.87	74,789.08	78,876.54	75,429.13
Revenue Spot	2,609.81	2,982.06	2,756.04	3,088.83	3,173.77	3,334.53	3,007.85	2,825.39	2,684.93	3,063.67
Inventory Cost	2,354.36	1,908.16	1,553.44	1,569.74	1,378.2	1,792.32	2,039.48	2,290.48	1,723.7	1,961.54
Shipping Cost	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,600.00	5,200.00
Production Cost	31,878.00	31,803.00	31,735.25	31,316.25	31,583.50	31,316.25	31,684.50	31,631.00	31,632.00	31,365.50
% Waste	0.00	0.00	0.00	0,20	0,07	0,18	0.00	0.00	0.00	0.00
Profit	44,469.81	46,281.29	42,470.78	40,428.46	45,560.40	44,134.17	43,724.74	38,492.99	42,605.77	39,965.76

Table 28. KPIs for the case $\tau = 5, N = 2$ (LS-LV, Instances: LL11-to-LL20)

KPI	Instances									
	LL-11	LL-12	LL-13	LL-14	LL-15	LL-16	LL-17	LL-18	LL-19	LL-20
Revenue Main	80,087.24	78,584.12	78,462.48	79,131.98	77,859.46	75,310.64	79,644.05	77,969.80	80,816.33	79,560.51
Revenue Spot	2,916.78	2,365.04	2,591.44	3,567.49	2,806.99	2,811.67	3,488.86	2,421.94	3,272.67	3,180.04
Inventory Cost	1,486.18	1,455.98	1,520.58	1,620.76	1,803.58	946.86	1,230.84	1,369.42	1,827.5	1,613.62
Shipping Cost	5,600.00	5,600.00	5,600.00	5,600.00	5,600.00	5,200.00	5,200.00	5,600.00	4,800.00	4,800.00

Production Cost	31,715.00	31,891.75	31,525.75	31,616.50	31,439.50	31,295.75	31,679.75	31,754.00	31,392.25	31,400.25
% Waste	0,01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0,21
Profit	44,202.84	42,001.43	42,407.59	43,862.21	41,823.37	40,679.70	45,022.32	41,668.32	46,069.25	44,926.68

Table 29. KPIs for the case $\tau = 5, N = 3, 4, 5, 6$ (LS-LV, Instances: LL1-to-LL10)

KPI	Instances									
	LL-1	LL-2	LL-3	LL-4	LL-5	LL-6	LL-7	LL-8	LL-9	LL-10
Revenue Main	81,100.56	82,274.87	78,203.43	75,425.62	80,548.33	79,108.21	79,549.07	74,884.84	78,876.54	75,504.28
Revenue Spot	2,790.17	2,914.46	2,756.04	3,088.83	3,173.77	3,334.53	3,103.25	2,726.27	2,684.93	2,985.18
Inventory Cost	2,342.92	1,904.00	1,553.44	1,569.74	1,378.20	1,792.32	2,043.08	2,287.12	1,723.70	1,958.20
Shipping Cost	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,600.00	5,200.00
Production Cost	31,878.00	31,803.00	31,735.25	31,316.25	31,583.50	31,316.25	31,684.50	31,631.00	31,632.00	31,365.50
% Waste	0	0	0	0.20	0.07	0.18	0.00	0.00	0.00	0.00
Profit	44,469.81	46,282.33	42,470.78	40,428.46	45,560.40	44,134.17	43,724.74	38,492.99	42,605.77	39,965.76

Table 30. KPIs for the case $\tau = 5, N = 3, 4, 5, 6$ (LS-LV, Instances: LL11-to-LL20)

KPI	Instances									
	LL-11	LL-12	LL-13	LL-14	LL-15	LL-16	LL-17	LL-18	LL-19	LL-20
Revenue Main	80,087.24	78,584.12	78,462.48	79,131.98	77,859.46	75,310.64	79,644.05	78,053.54	80,816.33	79,560.51
Revenue Spot	2,916.78	2,365.04	2,591.44	3,567.49	2,806.99	2,811.67	3,487.70	2,335.04	3,272.67	3,180.04
Inventory Cost	1,486.18	1,455.98	1,520.58	1,620.76	1,803.58	946.86	1,229.68	1,366.26	1,827.50	1,613.62
Shipping Cost	5,600.00	5,600.00	5,600.00	5,600.00	5,600.00	5,200.00	5,200.00	5,600.00	4,800.00	4,800.00
Production Cost	31,715.00	31,891.75	31,525.75	31,616.50	31,439.50	31,295.75	31,679.75	31,754.00	31,392.25	31,400.25
% Waste	0,01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0,21
Profit	44,202.84	42,001.43	42,407.59	43,862.21	41,823.37	40,679.70	45,022.32	41,668.32	46,069.25	44,926.68

Figure 11. Average value of revenue, cost, % waste, profit, when $\tau = 5$ (LS-LV)

Table 31. KPIs for the case $\tau = 7, N = 1$ (LS-LV, Instances: LL1-to-LL10)

KPI	Instances									
	LL-1	LL-2	LL-3	LL-4	LL-5	LL-6	LL-7	LL-8	LL-9	LL-10
Revenue Main	80,466.28	81,270.13	78,373.25	75,565.24	80,548.33	78,895.78	79,269.35	73,902.58	78,666.28	76,046.95
Revenue Spot	3,074.21	3,242.66	3,170.27	3,301.84	3,233.27	3,653.49	3,466.86	3,131.60	2,963.67	3,199.97
Inventory Cost	2,286.96	1,608.08	2,192.82	1,438.10	1,378.20	1,859.04	2,444.06	1,920.44	2,048.68	2,287.26
Shipping Cost	4,800.00	5,200.00	4,800.00	5,200.00	5,200.00	4,800.00	4,800.00	5,200.00	4,800.00	4,800.00
Production Cost	31,878.00	31,803.00	31,735.25	31,316.25	31,583.50	31,316.25	31,684.50	31,631.00	31,632.00	31,365.50
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00
Profit	44,575.53	45,901.71	42,815.45	40,912.73	45,619.90	44,573.98	43,807.65	38,282.74	43,149.27	40,794.16

Table 32. KPIs for the case $\tau = 7, N = 1$ (LS-LV, Instances: LL11-to-LL20)

KPI	Instances									
	LL-11	LL-12	LL-13	LL-14	LL-15	LL-16	LL-17	LL-18	LL-19	LL-20
Revenue Main	79,563.21	78,767.27	78,462.48	79,360.29	77,550.69	75,195.40	80,032.01	78,128.24	81,618.35	79,662.81
Revenue Spot	3,429.52	2,489.53	2,591.44	3,539.44	3,598.25	3,101.52	3,487.70	3,382.03	2,968.95	3,244.48
Inventory Cost	1,502.96	1,718.78	1,520.58	2,077.16	2,519.16	1,268.64	1,604.78	3,238.60	1,946.58	1,625.18
Shipping Cost	5,200.00	5,200.00	5,600.00	5,200.00	4,800.00	4,800.00	4,800.00	4,800.00	4,800.00	4,800.00
Production Cost	31,715.00	31,891.75	31,525.75	31,616.50	31,439.50	31,295.75	31,679.75	31,754.00	31,392.25	31,400.25
% Waste	0.00	0.00	0.00	0.00	0,02	0.00	0.00	0.05	0.00	0.00
Profit	44,574.77	42,446.27	42,407.59	44,006.07	42,390.28	40,932.53	45,435.18	41,717.67	46,448.47	45,081.86

Table 33. KPIs for the case $\tau = 7, N = 2, 3, 4, 5, 6$ (LS-LV, Instances: LL1-to-LL10)

KPI	Instances									
	LL-1	LL-2	LL-3	LL-4	LL-5	LL-6	LL-7	LL-8	LL-9	LL-10
Revenue Main	80,907.88	82,274.87	77,997.21	75,565.24	80,548.33	79,401.02	79,269.35	74,888.26	78,666.28	76,046.95
Revenue Spot	3,074.21	2,914.46	3,170.27	3,301.84	3,233.27	3,519.63	3,466.86	2,722.73	2,963.67	3,199.97
Inventory Cost	2,507.76	1,904.00	1,816.78	1,438.10	1,378.20	2,023.12	2,223.26	2,287.00	2,048.68	2,287.26
Shipping Cost	4,800.00	5,200.00	4,800.00	5,200.00	5,200.00	4,800.00	4,800.00	5,200.00	4,800.00	4,800.00
Production Cost	31,878.00	31,803.00	31,735.25	31,316.25	31,583.50	31,316.25	31,684.50	31,631.00	31,632.00	31.365.50
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00
Profit	44,796.33	46,282.33	42,815.45	40,912.73	45,619.90	44,781.28	44,028.45	38,492.99	43,149.27	40,794.16

Table 34. KPIs for the case $\tau = 7, N = 2, 3, 4, 5, 6$ (LS-LV, Instances: LL11-to-LL20)

KPI	Instances									
	LL-11	LL-12	LL-13	LL-14	LL-15	LL-16	LL-17	LL-18	LL-19	LL-20
Revenue Main	80,240.43	78,767.27	78,462.48	80,019.94	77,333.04	75,195.40	79,918.09	78,455.64	81,618.35	79,671.39
Revenue Spot	3,062.58	2,489.53	2,591.44	3,206.16	3,830.07	3,101.52	3,584.98	3,039.27	2,968.95	3,235.51
Inventory Cost	1,678.20	1,718.78	1,520.58	1,726.26	2,492.36	1,268.64	1,588.14	2,754.26	1,946.58	1,623.70
Shipping Cost	5,200.00	5,200.00	5,600.00	5,600.00	4,800.00	4,800.00	4,800.00	4,800.00	4,800.00	4,800.00
Production	31,715.00	31,891.75	31,525.75	31,616.50	31,439.50	31,295.75	31,679.75	31,754.00	31,392.25	31,400.25

Cost										
% Waste	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.05	0.00	0.00
Profit	44,709.81	42,446.27	42,407.59	44,283.34	42,431.25	40,932.53	45,435.18	42,186.65	46,448.47	45,082.95

Figure 12. Average value of revenue, cost, % waste, profit, when $\tau = 7$ (LS-LV)

Tables 35-54 show how the 7 considered KPIs vary for each of the twenty instances of the LS-HV set, depending on: the number of vehicles used for delivery (i.e., N) and the MIST (i.e., τ). The instances are named respectively LH-1, LH-2, ..., LH-20. Figures 13-15 show, instead, 6 out of the 7 KPIs, averaged over the twenty instances (production cost is here neglected because is obviously constant, in terms of average value).

Table 35. KPIs for the case $\tau = 3, N = 1$ (LS-HV, Instances: LH1-to-LH10)

KPI	Instances									
	LH-1	LH-2	LH-3	LH-4	LH-5	LH-6	LH-7	LH-8	LH-9	LH-10
Revenue Main	74,300.14	76,517.52	79,942.86	82,438.05	76,566.18	78,905.73	77,256.76	75,083.99	79,478.93	78,746.66
Revenue Spot	2,596.59	2,799.74	3,104.78	2,605.77	2,444.69	1,898.93	1,731.62	2,630.57	2,367.98	2,444.18
Inventory Cost	856.40	855.26	911.44	964,68	1,342.68	1,212.06	861.46	914.70	599.76	1,242.24
Shipping Cost	6,000.00	6,000.00	6,000.00	6,400.00	6,000.00	6,800.00	6,000.00	6,000.00	6,400.00	6,000.00
Production Cost	31,570.50	31,364.50	31,538.50	31,883.50	31,889.50	31,533.50	31,427.00	31,699.75	31,894.00	31,554.50
% Waste	0.00	0.00	0.09	0.04	0.00	0.00	0.00	0.16	0.00	0.00
Profit	38,469.83	41,097.50	44,597.70	45,795.64	39,778.69	41,259.10	40,699.92	39,100.11	42,953.15	42,394.10

Table 36. KPIs for the case $\tau = 3$, $N = 1$ (LS-HV, Instances: LH11-to-LH20)

KPI	Instances									
	LH-11	LH-12	LH-13	LH-14	LH-15	LH-16	LH-17	LH-18	LH-19	LH-20
Revenue Main	82,895.93	82,109.49	79,852.53	91,109.27	81,564.82	81,271.92	75,061.82	81,535.29	74,178.92	79,931.08
Revenue Spot	2.844.08	2,580.13	3,185.34	2,647.93	1,934.76	2,517.81	2,177.83	2,371.55	2,969.39	1,845.41
Inventory Cost	565.86	860.52	1,446.84	1,721.32	1,097.44	824.88	917.50	1,131.00	1,406.58	1,145.4
Shipping Cost	6,000.00	6,000.00	5,600.00	6,000.00	6,000.00	6,000.00	6,000.00	5,600.00	5,600.00	5,600.00
Production Cost	31,279.00	31,818.25	31,798.00	31,442.75	31,644.75	31,719.75	31,779.75	31,442.25	31,595.75	31,814.75
% Waste	0.20	0.00	0.49	0.00	0.00	0.06	0.34	0.24	0,73	0.19
Profit	47,895.15	46,010.85	44,193.03	54,593.13	44,757.39	45,245.10	38,542.40	45,733.59	38,545.98	43,216.34

Table 37. KPIs for the case $\tau = 3$, $N = 2$ (LS-HV, Instances: LH1-to-LH10)

KPI	Instances									
	LH-1	LH-2	LH-3	LH-4	LH-5	LH-6	LH-7	LH-8	LH-9	LH-10
Revenue Main	74,300.14	76,517.52	79,942.86	82,438.05	76,566.18	78,905.73	77,256.76	75,083.99	79,478.93	78,746.66
Revenue Spot	2,596.59	2,799.74	3,104.78	2,605.77	2,444.69	1,898.93	1,731.62	2,630.57	2,367.98	2,444.18
Inventory Cost	856.40	855.26	911.44	964.68	1342.68	1212.06	861.46	914.70	599.76	1,242.24
Shipping Cost	6,000.00	6,000.00	6,000.00	6,400.00	6,000.00	6,800.00	6,000.00	6,000.00	6,400.00	6,000.00
Production Cost	31,570.50	31,364.50	31,538.50	31,883.50	31,889.50	31,533.50	31,427.00	31.699.75	31,894.00	31.554.50
% Waste	0.00	0.00	0.09	0.04	0.00	0.00	0.00	0.16	0.00	0.00
Profit	38,469.83	41,097.50	44,597.70	45,795.64	39,778.69	41,259.10	40,699.92	39,100.11	42,953.15	42,394.10

Table 38. KPIs for the case $\tau = 3$, $N = 2$ (LS-HV, Instances: LH11-to-LH20)

KPI	Instances									
	LH-11	LH-12	LH-13	LH-14	LH-15	LH-16	LH-17	LH-18	LH-19	LH-20
Revenue Main	82,895.93	82,109.49	79,852.53	91,109.27	81,564.82	81,271.92	75,061.82	81,535.29	74,178.92	79,931.08
Revenue Spot	2,844.08	2,580.13	3,185.34	2,647.93	1,934.76	2,517.81	2,177.83	2,371.55	2,969.39	1,845.41
Inventory Cost	565.86	860.52	1,446.84	1,721.32	1,097.44	824.88	917.50	1,131.00	1,406.58	1,145.40
Shipping Cost	6,000.00	6,000.00	5,600.00	6,000.00	6,000.00	6,000.00	6,000.00	5,600.00	5,600.00	5,600.00
Production Cost	31,279.00	31,818.25	31,798.00	31,442.75	31,644.75	31,719.75	31,779.75	31,442.25	31,595.75	31,814.75
% Waste	0.20	0.00	0.49	0.00	0.00	0.06	0.34	0.24	0.73	0.19
Profit	47,895.15	46,010.85	44,193.03	54,593.13	44,757.39	45,245.10	38,542.40	45,733.59	38,545.98	43,216.34

Table 39. KPIs for the case $\tau = 3$, $N = 3, 4, 5, 6$ (LS-HV, Instances: LH1-to-LH10)

KPI	Instances									
	LH-1	LH-2	LH-3	LH-4	LH-5	LH-6	LH-7	LH-8	LH-9	LH-10
Revenue Main	74,300.14	76,517.52	79,942.86	82,438.05	76,566.18	78,905.73	77,256.76	75,083.99	79,478.93	78,746.66
Revenue Spot	2,596.59	2,799.74	3,104.78	2,605.77	2,444.69	1,898.93	1,731.62	2,630.57	2,367.98	2,444.18
Inventory Cost	856.40	855.26	911.44	964.68	1,342.68	1,212.06	861.46	914.70	599.76	1,242.24
Shipping Cost	6,000.00	6,000.00	6,000.00	6,400.00	6,000.00	6,800.00	6,000.00	6,000.00	6,400.00	6,000.00
Production Cost	31,570.5	31,364.5	31,538.5	31,883.5	31,889.5	31,533.5	31,427.00	31,699.75	31,894.00	31,554.50
% Waste	0.00	0.00	0.09	0.04	0.00	0.00	0.00	0.16	0.00	0.00
Profit	38,469.83	41,097.50	44,597.70	45,795.64	39,778.69	41,259.10	40,699.92	39,100.11	42,953.15	42,394.10

Table 40. KPIs for the case $\tau = 3$, $N = 3, 4, 5, 6$ (LS-HV, Instances: LH11-to-LH20)

KPI	Instances									
	LH-11	LH-12	LH-13	LH-14	LH-15	LH-16	LH-17	LH-18	LH-19	LH-20
Revenue Main	82,895.93	82,109.49	79,852.53	91,109.27	81,564.82	81,271.92	75,061.82	81,535.29	74,178.92	79,931.08
Revenue Spot	2,844.08	2,580.13	3,185.34	2,647.93	1,934.76	2,517.81	2,177.83	2,371.55	2,969.39	1,845.41
Inventory Cost	565.86	860.52	1,446.84	1,721.32	1,097.44	824.88	917.50	1,131.00	1,406.58	1,145.4
Shipping Cost	6,000.00	6,000.00	5,600.00	6,000.00	6,000.00	6,000.00	6,000.00	5,600.00	5,600.00	5,600.00

Production Cost	31,279.00	31,818.25	31,798.00	31,442.75	31,644.75	31,719.75	31,779.75	31,442.25	31,595.75	31,814.75
% Waste	0.20	0.00	0.49	0.00	0.00	0,06	0.34	0.24	0.73	0.19
Profit	47,895.15	46,010.85	44,193.03	54,593.13	44,757.39	45,245.10	38,542.40	45,733.59	38,545.98	43,216.34

Figure 13. Average value of revenue, cost, % waste, profit, when $\tau = 3$ (LS-HV)

Table 41. KPIs for the case $\tau = 5$, $N = 1$ (LS-HV, Instances: LH1-to-LH10)

KPI	Instances									
	LH-1	LH-2	LH-3	LH-4	LH-5	LH-6	LH-7	LH-8	LH-9	LH-10
Revenue Main	76,682.51	79,032.44	81,689.15	82,712.71	76,664.4	78,540.41	77,577.69	76,309.06	81,357.76	80,875.58
Revenue Spot	2,431.08	2,687.67	3,014.35	3,147.24	2,896.61	3,122.84	2,109.83	2,314.61	2,602.8	2,412.86
Inventory Cost	2,082.34	1,912.76	2,183.78	2,275.58	2,140.82	2,998.06	1,721.96	1,305.64	2,098.38	2,926.82

Shipping Cost	5,600.00	5,600.00	5,600.00	5,200.00	5,200.00	5,200.00	5,200.00	5,600.00	5,600.00	5,200.00
Production Cost	31,570.50	31,364.50	31,538.50	31,883.50	31,889.50	31,533.50	31,427.00	31,699.75	31,894.00	31,554.50
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	39,860.75	42,842.85	45,381.22	46,500.87	40,330.69	41,931.69	41,338.56	40,018.28	44,368.18	43,607.12

Table 42. KPIs for the case $\tau = 5, N = 1$ (LS-HV, Instances: LH11-to-LH20)

KPI	Instances									
	LH-11	LH-12	LH-13	LH-14	LH-15	LH-16	LH-17	LH-18	LH-19	LH-20
Revenue Main	82,667.79	82,184.73	79,024.68	89,689.46	82,141.63	81,849.99	77,366.15	81,506.41	77,792.33	78,965.47
Revenue Spot	3,423.95	2,501.47	3,716.50	3,288.57	2,184.64	3,337.24	2,688.91	2,611.19	2,782.63	2,633.21
Inventory Cost	1,342.84	857.10	1,918.54	1,914.54	2,059.46	2,057.62	2,430.86	1,408.28	2,606.32	1,835.56
Shipping Cost	4,800.00	6,000.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,200.00	5,600.00	5,200.00
Production Cost	31,279.00	31,818.25	31,798.00	31,442.75	31,644.75	31,719.75	31,779.75	31,442.25	31,595.75	31,814.75
% Waste	0.00	0.00	0.03	0.00	0.00	0.00	0.29	0.00	0.23	0.00
Profit	48,669.90	46,010.85	43,824.64	54,420.74	45,422.06	46,209.86	40,644.45	46,067.07	40,772.89	42,748.37

Table 43. KPIs for the case $\tau = 5, N = 2$ (LS-HV, Instances: LH1-to-LH10)

KPI	Instances									
	LH-1	LH-2	LH-3	LH-4	LH-5	LH-6	LH-7	LH-8	LH-9	LH-10
Revenue Main	76,868.32	78,790.37	81,738.85	83,429.33	78,586.96	78,540.41	77,677.86	76,095.64	81,433.63	80,887.86
Revenue Spot	2,237.33	2,884.70	2,962.52	2,955.09	2,337.95	3,115.94	2,004.89	2,521.31	2,523.41	2,398.85
Inventory Cost	1,749.64	2,064.3	1,909.08	2,193.28	2,454.5	2,549.56	1,381.38	1,298.92	1,474.98	2,533.14
Shipping Cost	5,600.00	5,200.00	5,600.00	5,600.00	5,600.00	5,200.00	5,200.00	5,600.00	5,600.00	5,200.00
Production Cost	31,570.50	31,364.50	31,538.50	31,883.50	31,889.50	31,533.50	31,427.00	31,699.75	31,894.00	31,554.50
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	40,185.51	43,046.27	45,653.79	46,707.64	40,980.91	42,373.29	41,674.37	40,018.28	44,988.06	43,999.07

Table 44. KPIs for the case $\tau = 5, N = 2$ (LS-HV, Instances: LH11-to-LH20)

KPI	Instances									
	LH-11	LH-12	LH-13	LH-14	LH-15	LH-16	LH-17	LH-18	LH-19	LH-20
Revenue Main	82,667.79	82,109.49	79,797.48	89,784.62	82,528.69	82,685.07	77,846.85	81,547.17	77,930.78	79,783.19

Revenue Spot	3,423.95	2,580.13	3,716.50	3,189.75	1,845.67	2,563.57	2,688.91	2,568.41	2,638.33	2,312.20
Inventory Cost	1,342.84	860.52	1,918.54	1,690.08	1,423.04	1,717.74	2,525.72	1,195.08	2,438.86	1,459.08
Shipping Cost	4,800.00	6,000.00	5,200.00	5,200.00	5,600.00	5,600.00	5,200.00	5,200.00	5,600.00	5,200.00
Production Cost	31,279.00	31,818.25	31,798.00	31,442.75	31,644.75	31,719.75	31,779.75	31,442.25	31,595.75	31,814.75
% Waste	0.00	0.00	0,03	0.00	0.00	0.00	0.29	0.00	0,23	0.00
Profit	48,669.90	46,010.85	44,597.44	54,641.54	45,706.57	46,211.15	41,030.29	46,278.25	40,934.50	43,621.56

Table 45. KPIs for the case $\tau = 5, N = 3, 4, 5, 6$ (LS-HV, Instances: LH1-to-LH10)

KPI	Instances									
	LH-1	LH-2	LH-3	LH-4	LH-5	LH-6	LH-7	LH-8	LH-9	LH-10
Revenue Main	76,868.32	78,790.37	81,738.85	83,429.33	78,486.16	78,540.41	77,677.86	76,221.31	81,433.63	81,764.28
Revenue Spot	2,237.33	2,884.7	2,962.52	2,955.09	2,428.67	3,115.94	2,004.89	2,406.26	2,523.41	2,171.95
Inventory Cost	1,749.64	2,064.3	1,909.08	2,193.28	2,444.42	2,549.56	1,381.38	1,309.54	1,474.98	2,770.82
Shipping Cost	5,600.00	5,200.00	5,600.00	5,600.00	5,600.00	5,200.00	5,200.00	5,600.00	5,600.00	5,600.00
Production Cost	31,570.50	31,364.50	31,538.50	31,883.50	31,889.50	31,533.50	31,427.00	31,699.75	31,894.00	31,554.50
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	40,185.51	43,046.27	45,653.79	46,707.64	40,980.91	42,373.29	41,674.37	40,018.28	44,988.06	44,010.91

Table 46. KPIs for the case $\tau = 5, N = 3, 4, 5, 6$ (LS-HV, Instances: LH11-to-LH20)

KPI	Instances									
	LH-11	LH-12	LH-13	LH-14	LH-15	LH-16	LH-17	LH-18	LH-19	LH-20
Revenue Main	82,667.79	82,109.49	79,797.48	91,051.16	82,528.69	82,588.17	78,185.65	81,547.17	78,052.32	79,674.95
Revenue Spot	3,423.95	2,580.13	3,716.5	2,941.51	1,845.67	2,663.87	2,368.19	2,568.41	2,512.67	2,417.16
Inventory Cost	1,342.84	860.52	1,918.54	2,494.54	1,423.04	1,721.14	2,137.96	1,195.08	2,434.74	1,455.8
Shipping Cost	4,800.00	6,000.00	5,200.00	5,200.00	5,600.00	5,600.00	5,600.00	5,200.00	5,600.00	5,200.00
Production Cost	31,279.00	31,818.25	31,798.00	31,442.75	31,644.75	31,719.75	31,779.75	31,442.25	31,595.75	31,814.75
% Waste	0	0	0,0283037	0	0	0	0,2949992	0	0,2334175	0
Profit	48669,90	46010,85	44597,44	54855,38	45706,57	46211,15	41036,13	46278,25	40934,50	43621,56

Figure 14. Average value of revenue, cost, % waste, profit, when $\tau = 5$ (LS-HV)

Table 47. KPIs for the case $\tau = 7, N = 1$ (LS-HV, Instances: LH1-to-LH10)

KPI	Instances									
	LH-1	LH-2	LH-3	LH-4	LH-5	LH-6	LH-7	LH-8	LH-9	LH-10
Revenue Main	77,876.01	79,423.46	82,248.48	82,752.68	78,853.04	78,865.46	77,559.92	76,559.84	86,040.51	81,378.96
Revenue Spot	2,258.30	2,795.81	3,658.43	3,266.64	3,096.80	3,587.91	2,143.49	2,500.16	2,716.50	2,328.58
Inventory Cost	3,010.46	2,510.60	3,428.44	2,269.32	4,766.94	3,945.94	1,736.12	1,675.98	5,557.92	3,243.00
Shipping Cost	4,800.00	5,200.00	4,800.00	5,200.00	4,800.00	4,800.00	5,200.00	5,200.00	5,200.00	4,800.00
Production Cost	31,570.50	31,364.50	31,538.50	31,883.50	31,889.50	31,533.50	31,427.00	31.699.75	31,894.00	31,554.50
% Waste	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	40,753.35	43,144.17	46,139.97	46,666.50	40,493.40	42,173.93	41,340.29	40,484.27	46,105.09	44,110.04

Table 48. KPIs for the case $\tau = 7, N = 1$ (LS-HV, Instances: LH11-to-LH20)

KPI	Instances									
	LH-11	LH-12	LH-13	LH-14	LH-15	LH-16	LH-17	LH-18	LH-19	LH-20
Revenue Main	83,067.30	82,882.39	78,844.62	90,657.84	85,688.15	84,282.48	81,871.82	80,574.62	78,843.17	78,847.87
Revenue Spot	3,128.66	2,425.57	3,948.84	2,904.63	2,114.26	2,919.97	2,746.23	3,523.17	2,468.23	2,774.33
Inventory Cost	1,385.70	1,094.54	2,170.14	2,641.34	4,445.42	3,503.64	6,064.46	1,739.70	3,223.66	1,858.76
Shipping Cost	4,800.00	5,600.00	4,800.00	4,800.00	4,800.00	5,200.00	4,800.00	4,800.00	5,200.00	5,200.00
Production Cost	31,279.00	31,818.25	31,798.00	31,442.75	31,644.75	31,719.75	31,779.75	31,442.25	31,595.75	31,814.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.29	0.00	0.00
Profit	48,731.26	46,795.17	44,025.32	54,678.38	46,912.24	46,779.06	41,973.84	46,115.84	41,291.99	42,748.69

Table 49. KPIs for the case $\tau = 7, N = 2$ (LS-HV, Instances: LH1-to-LH10)

KPI	Instances									
	LH-1	LH-2	LH-3	LH-4	LH-5	LH-6	LH-7	LH-8	LH-9	LH-10
Revenue Main	78,053.31	79,346.42	82,277.78	83,592.68	79,082.84	78,865.46	78,122.60	76,685.51	88,116.54	82,624.10
Revenue Spot	2,258.30	2,858.75	3,320.85	3,266.64	2,874.05	3,587.91	2,131.18	2,385.11	2,685.33	2,300.57
Inventory Cost	2,757.98	2,693.08	2,225.66	2,888.52	3,920.28	3,504.34	1,840.28	1,686.60	5,912.94	3,594.40
Shipping Cost	4,800.00	4,800.00	5,200.00	5,200.00	4,800.00	4,800.00	5,200.00	5,200.00	5,600.00	5,200.00
Production Cost	31,570.50	31,364.50	31,538.50	31,883.50	31,889.50	31,533.50	31,427.00	31,699.75	31,894.00	31,554.50
% Waste	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	41,183.13	43,347.59	46,634.47	46,887.30	41,347.11	42,615.53	41,786.50	40,484.27	47,394.93	44,575.77

Table 50. KPIs for the case $\tau = 7, N = 2$ (LS-HV, Instances: LH11-to-LH20)

KPI	Instances									
	LH-11	LH-12	LH-13	LH-14	LH-15	LH-16	LH-17	LH-18	LH-19	LH-20
Revenue Main	83,067.30	82,809.25	79,617.42	91,408.38	85,929.80	86,048.88	82,412.74	82,442.65	78,828.77	79,710.73
Revenue Spot	3,128.66	2,501.47	3,948.84	2,904.63	2,264.31	2,919.97	2,274.25	2,759.39	2,483.23	2,411.88
Inventory Cost	1,385.70	1,097.30	2,170.14	3,097.18	3,976.36	4,607.64	4,650.48	2,460.64	2,993.30	1,485.24
Shipping Cost	4,800.00	5,600.00	4,800.00	4,800.00	4,800.00	5,200.00	5,200.00	4,800.00	5,200.00	5,200.00
Production	31,279.00	31,818.25	31,798.00	31,44.,75	31,644.75	31,719.75	31,779.75	31,442.25	31,595.75	31,814.75

Cost										
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.29	0.00	0.00
Profit	48,731.26	46,795.17	44,798.12	54,973.08	47,773.00	47,441.46	43,056.76	46,499.15	41,522.95	43,622.62

Table 51. KPIs for the case $\tau = 7, N = 3$ (LS-HV, Instances: LH1-to-LH10)

KPI	Instances									
	LH-1	LH-2	LH-3	LH-4	LH-5	LH-6	LH-7	LH-8	LH-9	LH-10
Revenue Main	79,244.52	79,212.83	82,277.78	83,592.68	79,107.32	79,449.26	78,122.60	76,559.84	88,278.38	82,734.00
Revenue Spot	2,325.71	2,985.02	3,320.85	3,266.64	2,875.27	3,029.19	2,131.18	2,500.16	2,517.30	2,185.96
Inventory Cost	3,864.98	2,685.76	2,225.66	2,888.52	3,733.92	3,049.08	1,840.28	1,675.98	5,521.54	3,411.30
Shipping Cost	4,800.00	4,800.00	5,200.00	5,200.00	4,800.00	5,200.00	5,200.00	5,200.00	5,600.00	5,200.00
Production Cost	31,570.50	31,364.50	31,538.50	31,883.50	31,889.50	31,533.50	31,427.00	31,699.75	31,894.00	31,554.50
% Waste	0.10	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	41,334.75	43,347.59	46,634.47	46,887.30	41,559.17	42,695.87	41,786.50	40,484.27	47,780.14	44,754.16

Table 52. KPIs for the case $\tau = 7, N = 3$ (LS-HV, Instances: LH11-to-LH20)

KPI	Instances									
	LH-11	LH-12	LH-13	LH-14	LH-15	LH-16	LH-17	LH-18	LH-19	LH-20
Revenue Main	83,067.30	82,809.25	79,617.42	91,408.38	85,929.80	86,048.88	82,412.74	82,442.65	79,993.51	79,602.49
Revenue Spot	3,128.66	2,501.47	3,948.84	2,904.63	2,264.31	2,919.97	2,274.25	2,759.39	2,554.26	2,516.84
Inventory Cost	1,385.70	1,097.30	2,170.14	2,876.38	3,755.56	4,386.84	4,429.68	2,460.64	4,031.66	1,481.96
Shipping Cost	4,800.00	5,600.00	4,800.00	4,800.00	4,800.00	5,200.00	5,200.00	4,800.00	5,200.00	5,200.00
Production Cost	31,279.00	31,818.25	31,798.00	31,442.75	31,644.75	31,719.75	31,779.75	31,442.25	31,595.75	31,814.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.29	0.00	0.00
Profit	48,731.26	46,795.17	44,798.12	55,193.88	47,993.80	47,662.26	43,277.56	46,499.15	41,720.36	43,622.62

Table 53. KPIs for the case $\tau = 7, N = 4, 5, 6$ (LS-HV, Instances: LH1-to-LH10)

KPI	Instances									
	LH-1	LH-2	LH-3	LH-4	LH-5	LH-6	LH-7	LH-8	LH-9	LH-10
Revenue Main	79,244.52	79,346.42	82,277.78	83,592.68	79,107.32	79,449.26	78,122.60	76,559.84	88,278.38	82,734.00
Revenue Spot	2,325.71	2,858.75	3,320.85	3,266.64	2,875.27	3,029.19	2,131.18	2,500.16	2,517.30	2,185.96
Inventory Cost	3,864.98	2,693.08	2,225.66	2,888.52	3,733.92	3,049.08	1,840.28	1,675.98	5,300.74	3,411.30

Shipping Cost	4,800.00	4,800.00	5,200.00	5,200.00	4,800.00	5,200.00	5,200.00	5,200.00	5,600.00	5,200.00
Production Cost	31,570.50	31,364.50	31,538.50	31,883.50	31,889.50	31,533.50	31,427.00	31,699.75	31,894.00	31,554.50
% Waste	0.10	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	41,334.75	43,347.59	46,634.47	46,887.30	41,559.17	42,695.87	41,786.50	40,484.27	48,000.94	44,754.16

Table 54. KPIs for the case $\tau = 7, N = 4, 5, 6$ (LS-HV, Instances: LH11-to-LH20)

KPI	Instances									
	LH-11	LH-12	LH-13	LH-14	LH-15	LH-16	LH-17	LH-18	LH-19	LH-20
Revenue Main	83,067.30	82,915.65	79,617.42	91,408.38	85,929.80	86,048.88	82,526.84	82,442.65	79,993.51	79,602.49
Revenue Spot	3,128.66	2,388.99	3,948.84	2,904.63	2,264.31	2,919.97	2,155.26	2,759.39	2,554.26	2,516.84
Inventory Cost	1,385.70	1,091.22	2,170.14	2,876.38	3,755.56	4,386.84	4,217.6	2,460.64	4,031.66	1,481.96
Shipping Cost	4,800.00	5,600.00	4,800.00	4,800.00	4,800.00	5,200.00	5,200.00	4,800.00	5,200.00	5,200.00
Production Cost	31,279.00	31,818.25	31,798.00	31,442.75	31,644.75	31,719.75	31,779.75	31,442.25	31,595.75	31,814.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.29	0.00	0.00
Profit	48,731.26	46,795.17	44,798.12	55,193.88	47,993.80	47,662.26	43,484.75	46,499.15	41,720.36	43,622.62

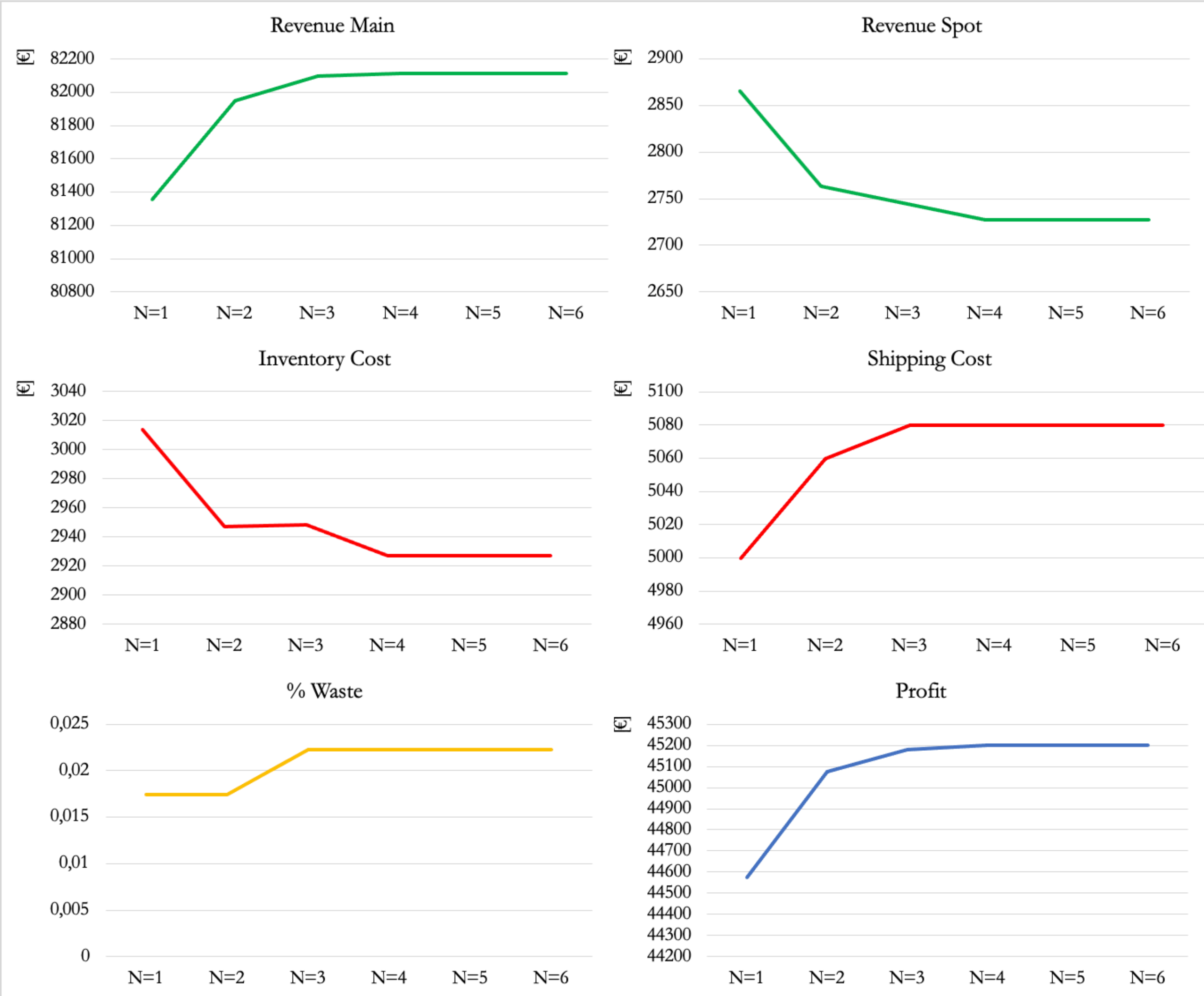

Figure 15. Average value of revenue, cost, % waste, profit, when $\tau = 7$ (LS-HV)

Tables 55-86 show how the 7 considered KPIs vary for each of the twenty instances of the HS-LV set, depending on: the number of vehicles used for delivery (i.e., N) and the MIST (i.e., τ). The instances are named respectively HL-1, HL-2, ..., HL-20. Figures 16-18 show, instead, 6 out of the 7 KPIs, averaged over the twenty instances (production cost is here neglected because is obviously constant, in terms of average value).

Table 55. KPIs for the case $\tau = 3$, $N = 1$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,490.26	183,670.16	186,512.48	178,322.74	194,655.81	184,674.88	186,974.62	190,886.34	193,781.59	187,713.85

Revenue Spot	5,495.51	5,535.58	5,873.39	5,059.32	6,015.68	5,670.21	6,025.68	4,952.15	5,113.57	5,541.66
Inventory Cost	3,021.34	2,749.84	4,425.44	3,276.78	2,483.42	2,854.48	3,867.30	3,855.86	3,871.80	2,750.50
Shipping Cost	9,600.00	9,600.00	9,200.00	9,600.00	9,200.00	9,600.00	9,200.00	9,200.00	9,600.00	10,000.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.77	0.00	0.00	1.49	1.91	0.17	0.00
Profit	114,145.93	117,397.40	119,401.93	111,583.28	129,602.82	118,769.36	120,456.50	123,688.38	126,412.11	121,342.76

Table 56. KPIs for the case $\tau = 3, N = 1$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	185,384.54	190,370.54	189,650.83	186,660.34	175,987.92	183,440.11	171,420.28	184,904.91	188,450.05	182,081.16
Revenue Spot	5,252.59	5,210.50	5,727.37	5,490.98	1,500.75	5,582.98	5,171.73	5,872.62	5,610.98	5,602.53
Inventory Cost	3,338.22	3,041.88	4,930.20	3,279.68	2,808.20	3,209.12	3,966.20	2,035.90	3,498.40	4,184.44
Shipping Cost	9,600.00	10,000.00	9,200.00	9,600.00	8,800.00	9,600.00	9,200.00	10,000.00	10,000.00	9,200.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	1.92	2.20	0.41	0.00	4.27	0.00	2.05	0.00	0.00	1.50
Profit	118,297.16	123,050.91	122,061.50	120,303.64	106,562.72	117,287.22	104,223.06	119,538.63	121,626.13	115,450.50

Table 57. KPIs for the case $\tau = 3, N = 2$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,706.85	186,645.86	188,919.83	182,292.83	198,366.63	185,042.35	190,115.32	199,436.70	198,796.67	187,842.05
Revenue Spot	5,129.76	5,356.73	5,170.47	4,269.60	5,638.73	5,875.80	5,837.76	4,559.13	4,714.53	5,407.58
Inventory Cost	1,629.74	2,616.32	2,289.88	2,206.12	2,065.76	2,288.68	2,008.64	2,500.86	2,517.44	1,073.10
Shipping Cost	9,600.00	9,600.00	10,000.00	9,600.00	9,600.00	9,600.00	9,600.00	9,600.00	9,600.00	10,000.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	115,388.37	120,327.77	122,441.92	115,83431	132,954.35	119,908.22	124,867.94	132,800.72	132,382.51	123,014.28

Table 58. KPIs for the case $\tau = 3$, $N = 2$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	189,204.02	196,730.94	193,276.41	188,315.94	183,070.32	184,320.70	176,017.62	185,151.38	189,723.65	187,966.33
Revenue Spot	5,092.09	5,044.90	5,366.50	5,128.37	5,083.32	5,621.98	5,007.72	5,706.30	5,573.98	5,208.87
Inventory Cost	519.96	1,680.52	1,930.82	2,666.06	1,780.36	2,643.88	2,167.42	1,553.04	2,239.68	2,876.22
Shipping Cost	10,400.00	10,400.00	9,600.00	9,600.00	9,600.00	9,600.00	9,600.00	9,600.00	10,000.00	9,200.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	123,974.40	130,207.07	127,925.59	122,210.25	117,455.53	118,772.05	110,055.17	120,501.64	124,121.45	122,250.23

Table 59. KPIs for the case $\tau = 3$, $N = 3$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,706.85	186,645.86	188,919.83	182,583.87	198,366.63	185,932.59	190,115.32	199,436.70	198,820.21	187,842.05
Revenue Spot	5,129.76	5,356.73	5,170.47	4,269.60	5,638.73	5,695.62	5,837.76	4,559.13	4,714.53	5,407.58
Inventory Cost	1,629.74	2,174.72	2,289.88	2,196.18	1,979.60	2,909.66	2,008.64	2,059.26	2,096.12	1,073.10
Shipping Cost	9,600.00	9,600.00	10,000.00	9,600.00	9,600.00	9,600.00	9,600.00	9,600.00	9,600.00	10,000.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	115,388.37	120,769.37	122,441.92	116,135.29	133,040.51	119,997.30	124,867.94	133,242.32	132,827.37	123,014.28

Table 60. KPIs for the case $\tau = 3$, $N = 3$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	189,249.74	196,730.94	193,276.41	188,315.94	183,070.32	184,320.70	176,364.77	185,151.38	189,723.65	187,966.33
Revenue Spot	5,092.09	5,044.90	5,366.50	5,128.37	5,083.32	5,621.98	4,825.98	5,706.30	5,573.98	5,208.87
Inventory Cost	959.72	1,501.20	1,728.58	2,479.38	1,600.24	2,464.06	1,832.70	1,553.04	1,853.80	2,434.62
Shipping Cost	10,000.00	10,400.00	9,600.00	9,600.00	9,600.00	9,600.00	10,000.00	9,600.00	10,000.00	9,200.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75

% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	123,980.36	130,386.39	128,127.83	122,396.93	117,635.65	118,951.87	110,155.30	120,501.64	124,507.33	122,691.83

Table 61. KPIs for the case $\tau = 3, N = 4, 5, 6$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,706.85	186,645.86	189,110.79	182,656.11	198,366.63	185,487.75	190,115.32	199,436.70	198,820.21	187,842.05
Revenue Spot	5,129.76	5,356.73	4,970.83	4,478.76	5,638.73	5,875.80	5,837.76	4,559.13	4,714.53	5,407.58
Inventory Cost	1,629.74	2,174.72	2,281.20	2,256.78	1,979.60	2,645.00	2,008.64	1,838.46	1,926.12	1,073.10
Shipping Cost	9,600.00	9,600.00	10,000.00	9,600.00	9,600.00	9,600.00	9,600.00	9,600.00	9,600.00	10,000.00
Production Cost	59,218,50	59,458,50	59,358,50	58,922,00	59,385,25	59,121,25	59,476,50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	115,388.37	120,769.37	122,441.92	116,356.09	133,040.51	119,997.30	124,867.94	133,463.12	132,997.37	123,014.28

Table 62. KPIs for the case $\tau = 3, N = 4, 5, 6$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	189,204.02	196,730.94	193,276.41	188,315.94	183,070.32	184,320.70	176,364.77	185,151.38	189,723.65	187,983.37
Revenue Spot	5,092.09	5,044.90	5,366.50	5,128.37	5,083.32	5,621.98	4,825.98	5,706.30	5,573.98	5,208.87
Inventory Cost	519.96	1,501.20	1,728.58	2,479.38	1,600.24	2,464.06	1,832.70	1,553.04	1,853.80	2,392.68
Shipping Cost	10,400.00	10,400.00	9,600.00	9,600.00	9,600.00	9,600.00	10,000.00	9,600,00	10,000.00	9,200.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	123,974.40	130,386.39	128,127.83	122,396.93	117,635.65	118,951.87	110,155.30	120,501.64	124,507.33	122,750.81

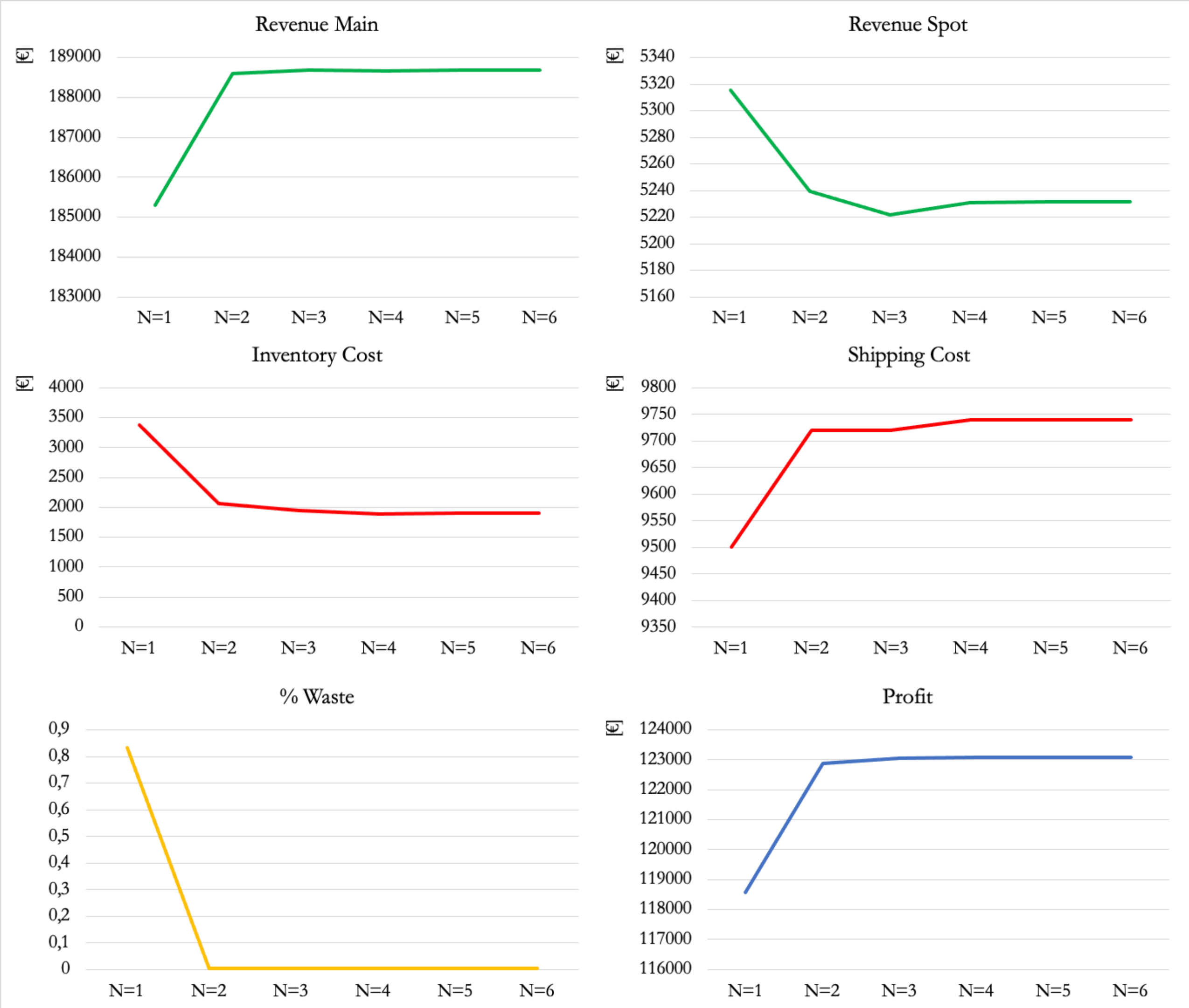

Figure 16. Average value of revenue, cost, % waste, profit, when $\tau = 3$ (HS-LV)

Table 63. KPIs for the case $\tau = 5, N = 1$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	179,467.78	183,317.33	188,768.73	179,036.11	194,674.91	184,058.87	189,800.63	194,265.00	193,723.16	189,120.27
Revenue Spot	6,490.37	5,942.18	6,210.89	5,831.73	6,232.82	6,241.29	6,573.82	5,707.85	5,510.36	5,744.16
Inventory Cost	3,078.36	3,102.04	6,603.80	3,730.92	2,655.84	2,777.72	5,113.62	5,526.56	3,985.86	3,827.40
Shipping Cost	9,200.00	8,800.00	8,800.00	9,200.00	9,200.00	9,200.00	8,800.00	8,800.00	9,200.00	9,200.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Profit	114,461.29	117,898.97	120,217.32	113,014.92	129,666.64	119,201.19	122,984.33	126,552.04	127,036.41	122,674.78

Table 64. KPIs for the case $\tau = 5, N = 1$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	189,145.84	194,835.14	190,953.54	187,229.60	180,937.83	183,582.38	174,719.36	185,371.18	187,360.57	185,168.62
Revenue Spot	6.287.66	5,601.74	6,231.18	6,728.75	5,450.94	6,148.73	6,069.22	5,903.70	6,680.40	5,255.78
Inventory Cost	4,530.48	4,436.00	6,259.28	4,968.68	3,695.72	3,824.42	5,564.32	2,662.48	3,990.86	4,565.74
Shipping Cost	8,800.00	8,800.00	8,400.00	8,800.00	9,200.00	9,200.00	8,800.00	9,200.00	8,800.00	9,200.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.07	0.00	0.00
Profit	122,701.27	127,712.63	123,338.94	121,221.67	114,175.30	117,779.94	107,221.51	120,209.40	122,313.61	117,809.91

Table 65. KPIs for the case $\tau = 5, N = 2$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,367.87	188,157.09	190,337.96	181,443.56	200,274.87	184,883.57	190,900.21	199,688.92	198,857.76	191,285.19
Revenue Spot	6,119.79	5,763.54	5,726.10	4,970.33	6,040.73	6,241.29	6,415.06	4,747.05	4,920.07	6,292.06
Inventory Cost	2,297.90	4,027.82	4,031.22	2,578.26	4,389.16	2,552.76	3,523.18	3,204.18	3,147.64	4,262.92
Shipping Cost	9,200.00	9,200.00	8,800.00	8,800.00	8,800.00	9,200.00	8,800.00	9,200.00	9,200.00	8,800.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	115,771.26	121,234.31	123,874.34	116,113.63	133,741.19	120,250.85	125,515.59	132,937.54	132,418.94	125,352.08

Table 66. KPIs for the case $\tau = 5, N = 2$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	190,666.66	199,276.29	194,077.95	190,575.54	184,557.86	186,268.09	177,413.59	188,720.75	191,274.90	187,498.78
Revenue Spot	5,919.86	5,261.90	5,601.22	6,169.43	5,083.32	6,150.11	5,042.03	5,747.46	6,515.38	5,193.54
Inventory Cost	2,220.12	3,270.76	3,169.62	5,094.24	2,748.26	4,739.36	3,064.22	3,329.26	4,486.48	2,493.58
Shipping	9,200.00	9,200.00	9,200.00	8,800.00	9,200.00	9,200.00	9,200.00	9,200.00	8,800.00	8,800.00

Cost										
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0..00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00
Profit	125,764.65	132,579.18	128,123.05	123,882.73	118,375.17	119,552.09	110,988.65	122,735.95	125,567.30	122,549.99

Table 67. KPIs for the case $\tau = 5, N = 3$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,759.83	188,157.09	192,520.74	182,800.04	201,610.24	186,097.97	190,900.21	201,506.76	200,007.92	191,285.19
Revenue Spot	5,751.73	5,763.54	4,934.42	4,685.13	5,495.07	6,241.29	6,415.06	4,546.45	4,920.07	6,292.06
Inventory Cost	2,216.52	3,365.42	4,722.00	2,785.20	4,125.18	3,435.96	3,302.38	3,809.54	3,495.76	4,042.12
Shipping Cost	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	8,800.00	9,200.00	9,200.00	8,800.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	115,876.54	121,896.71	124,174.66	116,577.97	134,394.88	120,582.05	125,736.39	133,949.42	133,220.98	125,572.88

Table 68. KPIs for the case $\tau = 5, N = 3$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	190,508.56	199,276.29	194,077.95	191,720.20	185,849.02	186,478.30	177,413.59	189,002.48	192,450.63	189,976.32
Revenue Spot	6,133.16	5,261.90	5,601.22	5,152.02	4,927.80	5,949.14	5,042.03	5,582.58	6,180.16	4,835.11
Inventory Cost	2,448.56	3,049.96	2,967.38	4,528.96	3,118.14	4,442.22	2,843.42	3,071.40	4,121.58	3,498.14
Shipping Cost	8,800.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00
Profit	125,991.41	132,799.98	128,325.29	124,175.26	119,140.93	119,858.47	111,209,45	123,110.66	126,372.71	123,264.54

Table 69. KPIs for the case $\tau = 5, N = 4$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,759.83	189,669.79	192,520.74	182,800.04	201,796.39	186,097.97	192,508.76	201,904.84	200,203.90	191,285.19
Revenue	5,751.73	5,213.06	4,934.42	4,685.13	5,300.16	6,241.29	5,660.89	4,157.93	4,714.53	6,292.06

Spot										
Inventory Cost	2,216.52	3,585.88	4,722.00	2,564.40	3,895.62	3,435.96	3,611.00	3,098.96	2,867.78	3,821.32
Shipping Cost	9,200.00	9,600.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,600.00	9,600.00	8,800.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121,25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	115,876.54	122,238.47	124,174.66	116,798.77	134,615.68	120,582.05	125,882.15	134,269.56	133,439.40	125,793.68

Table 70. KPIs for the case $\tau = 5, N = 4$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	191,877.96	199,276.29	194,077.95	191,720.20	186,038.56	186,478.30	178,296.79	189,002.48	192,644.99	190,691.76
Revenue Spot	5,754.11	5,261.90	5,601.22	5,152.02	4,728.90	5,949.14	5,042.03	5,582.58	5,976.76	4,835.11
Inventory Cost	2,898.54	2,829.16	2,967.38	4,308.16	2,887.98	4,221.42	3,505.82	3,071.40	3,714.14	3,992.78
Shipping Cost	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00
Profit	126,131.78	133,020.78	128,325.29	124,396.06	119,361.73	120,079.27	111,430.25	123,110.66	126,771.11	123,485.34

Table 71. KPIs for the case $\tau = 5, N = 5$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,759.83	189,669.79	191,891.28	182,800.04	201,610.24	186,097.97	192,508.76	201,723.88	200,409.04	191,285.19
Revenue Spot	5,751.73	5,213.06	4,934.42	4,685.13	5,495.07	6,241.29	5,660.89	4,345.85	4,549.47	6,292.06
Inventory Cost	2,216.52	3,365.08	4,092.54	2,343.60	3,847.38	3,435.96	3,611.00	3,284.72	3,184.00	3,821.32
Shipping Cost	9,200.00	9,600.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	8,800.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	115,876.54	122,459.27	124,174.66	117,019.57	134,672.68	120,582.05	125,882.15	134,490.76	133,563.26	125,793.68

Table 72. KPIs for the case $\tau = 5, N = 5$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20

Revenue Main	191,877.96	199,276.29	194,077.95	191,720.20	185,849.02	186,899.15	178,296.79	189,002.48	192,644.99	190,691.76
Revenue Spot	5,754.11	5,261.90	5,601.22	5,152.02	4,927.80	5,590.01	5,042.03	5,582.58	5,976.76	4,835.11
Inventory Cost	2,898.54	2,829.16	2,967.38	4,213.50	2,897.34	4,226.08	3,505.82	3,071.40	3,493.34	3,771.98
Shipping Cost	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,07	0,00	0,00
Profit	126,131.78	133,020.78	128,325.29	124,490.72	119,361.73	120,136.33	111,430.25	123,110.66	126,991.91	123,706.14

Table 73. KPIs for the case $\tau = 5, N = 6$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,759.83	189,669.79	192,520.74	183,534.99	201,796.39	186,097.97	192,508.76	201,723.88	200,409.04	191,285.19
Revenue Spot	5,751.73	5,213.06	4,934.42	4.525.23	5,300.16	6,241.29	5,660.89	4,345.85	4,549.47	6,292.06
Inventory Cost	2,216.52	3,365.08	4,722.00	2,841.10	3,838.62	3,435.96	3,611.00	3,284.72	3,184.00	3,821.32
Shipping Cost	9,200.00	9,600.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	8,800.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0..00	0.00	0.00	0.00	0.00	0.00
Profit	115,876.54	122,459.27	124,174.66	117,097.12	134,672.68	120,582.05	125,882.15	134,490.76	133,563.26	125,793.68

Table 74. KPIs for the case $\tau = 5, N = 6$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	191,674.14	199,276.29	194,077.95	191,720.20	185,849.02	186,899.15	178,296.79	189,002.48	192,450.63	190,691.76
Revenue Spot	5,967.41	5,261.90	5,601.22	5,152.02	4,927.80	5,590.01	5,042.03	5,582.58	6,180.16	4,835.11
Inventory Cost	2,908.02	2,829.16	2,967.38	4,213.50	2,897.34	4,226.08	3,505.82	3,071.40	3,454.54	3,771.98
Shipping Cost	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00
Profit	126,131.78	133,020.78	128,325.29	124,490.72	119,361.73	120,136.33	111,430.25	123,110.66	127,039.75	123,706.14

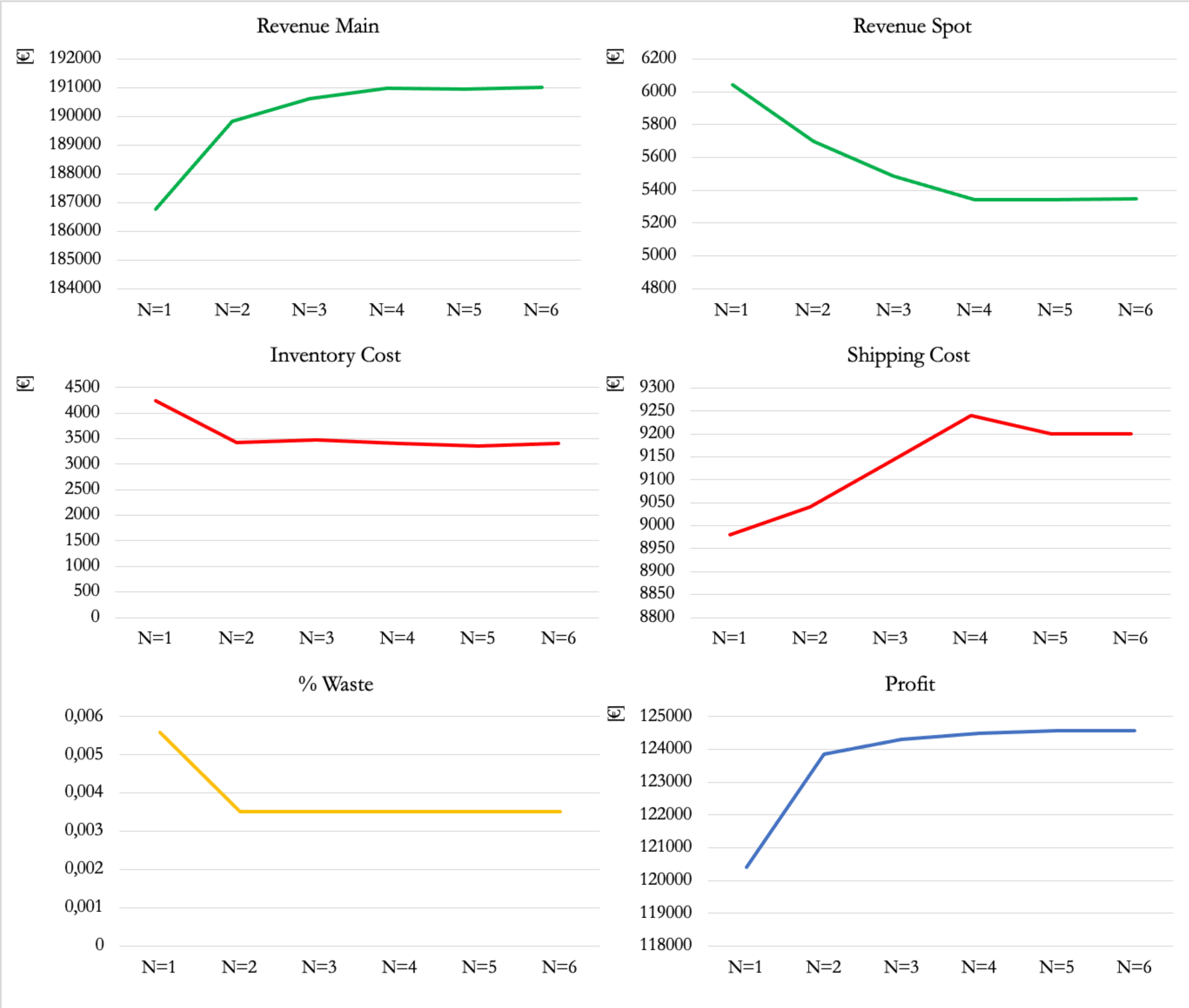

Figure 17. Average value of revenue, cost, % waste, profit, when $\tau = 5$ (HS-LV)

Table 75. KPIs for the case $\tau = 7, N = 1$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	179,467.78	183,317.33	188,768.73	178,883.34	194,674.91	184,058.87	189,800.63	194,372.10	193,723.16	188,899.11
Revenue Spot	6,490.37	5,942.18	6,210.89	6,029.97	6,232.82	6,241.29	6,573.82	5,881.59	5,510.36	6,068.63
Inventory Cost	3,078.36	3,102.04	6,603.80	4,162.44	2,655.84	2,777.72	5,113.62	6,068.86	3,985.86	4,254.62
Shipping Cost	9,200.00	8,800.00	8,800.00	8,800.00	9,200.00	9,200.00	8,800.00	8,400.00	9,200.00	8,800.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Profit	114,461.29	117,898.97	120,217.32	113,028.87	129,666.64	119,201.19	122,984.33	126,690.58	127,036.41	122,750.87

Table 76. KPIs for the case $\tau = 7, N = 1$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	189,349.66	194,835.14	190,953.54	187,229.60	180,937.83	183,261.78	174,719.36	185,425.90	187,360.57	184,327.78
Revenue Spot	6,074.36	5,601.74	6,231.18	6,728.75	5,450.94	6,148.73	6,141.49	5,903.70	6,680.40	6,107.40
Inventory Cost	4,521.00	4,436.00	6,259.28	4,968.68	3,695.72	3,503.82	5,564.32	2,584.40	3,990.86	4,541.08
Shipping Cost	8,800.00	8,800.00	8,400.00	8,800.00	9,200.00	9,200.00	8,800.00	9,200.00	8,800.00	9,200.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	122,701.27	127,712.63	123,338.94	121,221.67	114,175.30	117,779.94	107,293.78	120,342.20	122,313.61	117,845.35

Table 77. KPIs for the case $\tau = 7, N = 2$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,151.84	188,157.09	191,515.35	181,633.16	200,274.87	184,760.90	192,792.63	199,409.91	199,335.38	192,277.00
Revenue Spot	6,817.27	5,763.54	5,667.16	4,771.25	6,040.73	6,574.29	6,317.27	5,290.77	4,920.07	6,283.61
Inventory Cost	2,991.78	4,027.82	4,888.08	2,568.78	4,389.16	3,118.84	5,050.32	3,547.04	3,581.84	5,595.12
Shipping Cost	8,800.00	9,200.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00	9,200.00	8,400.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	115,958.83	121,234.31	124,135.93	116,113.63	133,741.19	120,295.10	125,783.08	133,259.39	132,462.36	125,403.24

Table 78. KPIs for the case $\tau = 7, N = 2$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	191,859.95	199,418.41	196,894.92	190,699.76	184,557.86	186,107.35	176,642.51	189,904.47	191,274.90	186,657.94
Revenue Spot	6,133.16	5,261.90	5,407.39	6,479.75	5,083.32	6,459.23	5,802.69	6,070.02	6,515.38	6,045.16
Inventory Cost	3,298.44	3,405.40	5,214.76	5,371.52	2,748.26	5,062.46	3,030.58	4,913.44	4,486.48	2,468.92
Shipping Cost	9,200.00	9,200.00	8,800.00	8,800.00	9,200.00	8,800.00	9,200.00	8,800.00	8,800.00	8,800.00

Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	126,092.92	132,586.66	129,101.05	124,039.99	118,375.17	119,777.37	111,011.87	123,058.05	125,567.30	122,585.43

Table 79. KPIs for the case $\tau = 7, N = 3$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,543.80	188,157.09	192,514.79	182,800.04	201,710.07	185,975.30	191,868.74	201,070.14	200,332.04	194,613.23
Revenue Spot	6,449.21	5,763.54	5,362.48	4,685.13	6,040.73	6,574.29	6,128.48	5,290.77	5,447.85	5,545.46
Inventory Cost	2,910.40	3,365.42	5,125.34	2,785.20	5,051.56	4,002.04	3,716.84	4,194.50	4,565.68	6,165.38
Shipping Cost	8,800.00	9,200.00	8,800.00	9,200.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	116,064.11	121,896.71	124,593.43	116,577.97	134,513.99	120,626.30	126,003.88	134,272.16	133,402.96	126,031.06

Table 80. KPIs for the case $\tau = 7, N = 3$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	193,295.15	199,418.41	199,287.51	191,867.12	187,119.66	186,517.76	177,525.71	191,359.17	192,672.93	189,634.90
Revenue Spot	6,133.16	5,261.90	5,468.66	5,462.34	4,927.80	6,066.86	5,802.69	5,892.90	6,180.16	6,045.16
Inventory Cost	4,402.44	3,184.60	6,679.58	4,828.94	4,167.98	4,774.12	3,692.98	5,388.50	4,329.06	4,668.28
Shipping Cost	9,200.00	9,200.00	8,800.00	9,200.00	9,200.00	8,800.00	9,200.00	8,800.00	9,200.00	8,800.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	126.424.12	132,807.46	130,090.09	124,332.52	119,361.73	120,083.75	111,232.67	123,860.57	126,387.53	123,363.03

Table 81. KPIs for the case $\tau = 7, N = 4$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,543.80	189,669.79	192,514.79	182,989.64	201,710.07	186,637.70	192,792.63	201,723.34	200,332.04	194,418.87
Revenue Spot	6,449.21	5,213.06	5,362.48	4,486.05	6,040.73	6,574.29	6,317.27	4,715.83	5,447.85	5,748.86
Inventory	2,910.40	3,585.88	5,125.34	2,554.92	4,830.76	4,664.44	4,608.72	3,934.50	4,344.88	5,953.62

Cost										
Shipping Cost	8,800.00	9,600.00	8,800.00	9,200.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	116,064.11	122,238.47	124,593.43	116,798.77	134,734.79	120,626.30	126,224.68	134,610.42	133,623.76	126,251.86

Table 82. KPIs for the case $\tau = 7, N = 4$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	193,340.87	199,418.41	199,287.51	192,937.52	187,119.66	186,317.56	177,525.71	191,359.17	192,867.29	191,732.50
Revenue Spot	6,133.16	5,261.90	5,468.66	5,462.34	4,927.80	6,258.26	5,802.69	5,892.90	5,976.76	6,045.16
Inventory Cost	4,621.40	2,963.80	6,458.78	5,678.54	3,947.18	4,544.52	3,472.18	5,167.70	3,891.98	6,434.68
Shipping Cost	8,800.00	9,200.00	8,800.00	9,200.00	9,200.00	8,800.00	9,200.00	8,800.00	9,200.00	8,800.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	126,650.88	133,028.26	130,310.89	124,553.32	119,582.53	120,304.55	111,453.47	124,081.37	126,815.57	123,694.23

Table 83. KPIs for the case $\tau = 7, N = 5$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,543.80	189,669.79	192,514.79	182,800.04	201,902.67	185,975.30	192,792.63	201,723.34	200,332.04	194,943.35
Revenue Spot	6,449.21	5,213.06	5,362.48	4,685.13	5,869.53	6,574.29	6,317.27	4,715.83	5,447.85	5,545.46
Inventory Cost	2,910.40	3,365.08	5,125.34	2,343.60	4,631.36	4,002.04	4,608.72	3,713.70	4,124.08	6,053.90
Shipping Cost	8,800.00	9,600.00	8,800.00	9,200.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	116.064.11	122,459.27	124,593.43	117,019.57	134,955.59	120,626.30	126,224.68	134,831.22	133,844.56	126,472.66

Table 84. KPIs for the case $\tau = 7, N = 5$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	193,295.15	199,418.41	199,287.51	192,937.52	187,119.66	186,517.76	177,525.71	191,359.17	192,867.29	191,732.50

Revenue Spot	6,133.16	5,261.90	5,468.66	5,462.34	4,927.80	6,066.86	5,802.69	5,892.90	5,976.76	6,045.16
Inventory Cost	3,960.84	2,963.80	6,237.98	5,583.88	3,726.38	4,562.42	3,472.18	5,167.70	3,671.18	6,213.88
Shipping Cost	9,200.00	9,200.00	8,800.00	9,200.00	9,200.00	8,800.00	9,200.00	8,800.00	9,200.00	8,800.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	126,865.72	133,028.26	130,531.69	124,647.98	119,803.33	120,295.45	111,453.47	124,081.37	127,036.37	123,915.03

Table 85. KPIs for the case $\tau = 7$, $N = 6$ (HS-LV, Instances: HL1-to-HL10)

KPI	Instances									
	HL-1	HL-2	HL-3	HL-4	HL-5	HL-6	HL-7	HL-8	HL-9	HL-10
Revenue Main	180,543.80	189,669.79	192,514.79	183,534.99	201,710.07	185,975.30	192,792.63	201,723.34	200,332.04	194,748.99
Revenue Spot	6,449.21	5,213.06	5,362.48	4,525.23	6,040.73	6,574.29	6,317.27	4,715.83	5,447.85	5,748.86
Inventory Cost	2,910.40	3,365.08	5,125.34	2,841.10	4,609.96	4,002.04	4,608.72	3,713.70	4,124.08	5,842.14
Shipping Cost	8,800.00	9,600.00	8,800.00	9,200.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00
Production Cost	59,218.50	59,458.50	59,358.50	58,922.00	59,385.25	59,121.25	59,476.50	59,094.25	59,011.25	59,162.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	116,064.11	122,459.27	124,593.43	117,097.12	134,955.59	120,626.30	126,224.68	134,831.22	133,844.56	126,693.46

Table 86. KPIs for the case $\tau = 7$, $N = 6$ (HS-LV, Instances: HL11-to-HL20)

KPI	Instances									
	HL-11	HL-12	HL-13	HL-14	HL-15	HL-16	HL-17	HL-18	HL-19	HL-20
Revenue Main	193,528.72	199,418.41	199,287.51	192,937.52	187,119.66	186,517.76	177,525.71	191,359.17	192,672.93	191,943.99
Revenue Spot	5,967.41	5,261.90	5,468.66	5,462.34	4,927.80	6,066.86	5,802.69	5,892.90	6,180.16	5,864.11
Inventory Cost	4,422.70	2,963.80	6,237.98	5,583.88	3,726.38	4,553.32	3,472.18	5,167.70	3,602.74	6,191.10
Shipping Cost	8,800.00	9,200.00	8,800.00	9,200.00	9,200.00	8,800.00	9,200.00	8,800.00	9,200.00	8,800.00
Production Cost	59,401.75	59,488.25	59,186.50	58,968.00	59,317.75	58,926.75	59,202.75	59,203.00	58,936.50	58,848.75
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	126,871.68	133,028.26	130,531.69	124,647.98	119,803.33	120,304.55	111,453.47	124,081.37	127,113.85	123,968.25

Figure 18. Average value of revenue, cost, % waste, profit, when $\tau = 7$ (HS-LV)

Tables 87-120 show how the 7 considered KPIs vary for each of the twenty instances of the HS-HV set, depending on: the number of vehicles used for delivery (i.e., N) and the MIST (i.e., τ). The instances are named respectively HH-1, HH-2, ..., HH-20. Figures 19-21 show, instead, 6 out of the 7 KPIs, averaged over the twenty instances (production cost is here neglected because is obviously constant, in terms of average value).

Table 87. KPIs for the case $\tau = 3$, $N = 1$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	193,407.32	175,471.68	182,323.63	182,100.54	194,030.24	175,287.84	182,776.02	202,113.81	194,400.76	193,866.35

Revenue Spot	6,120.65	5,770.24	5,937.76	5,285.53	5,677.86	5,377.12	3,855.06	6,738.15	5,744.02	6,042.03
Inventory Cost	3,314.44	3,931.18	3,787.58	3,854.1	3,012.36	2,976.06	2,908.8	3,031.4	2,033.44	4,517.58
Shipping Cost	9,200.00	9,600.00	9,600.00	9,200.00	9,600.00	9,200.00	8,800.00	9,200.00	10,000.00	9,200.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.68	1.81	0.00	2,14	0.00	0.02	3.09	0.00	0.00	0.00
Profit	128,177.78	108,732.99	115,560.56	115,140.72	127,857.24	109,500.15	116,120.78	137,857.31	129,018.84	126,896.80

Table 88. KPIs for the case $\tau = 3$, $N = 1$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	193,484.24	184,550.72	202,539.71	192,758.92	188,622.48	190,303.69	185,351.94	190,009.44	204,551.86	192,282.09
Revenue Spot	4,355.96	5,029.18	6,668.08	5,899.68	6,501.93	5,944.06	2,241.9	1,794.98	4,559.53	4,436.95
Inventory Cost	4,683.24	3,669.42	2,830.34	3,846.32	3,253.84	3,384.68	3,540.08	3,951.94	4,994.76	3,936.22
Shipping Cost	9,600.00	10,000.00	9,200.00	8,800.00	9,200.00	9,600.00	9,200.00	8,800.00	9,200.00	9,200.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	3.01	0.00	0.23	0.00	0.53	0.00	3.95	4.11	2.98	2.96
Profit	124,070.96	117,190.73	138,250.45	126,534.53	123,742.32	124,372.32	116,054.01	120,243.73	135,687.63	124,289.57

Table 89. KPIs for the case $\tau = 3$, $N = 2$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	197,991.38	182,086.80	185,694.96	188,902.26	197,965.88	178,700.60	189,904.38	203,280.90	195,038.21	195,492.52
Revenue Spot	6,120.65	5,770.24	5,421.58	4,685.08	5,531.96	5,012.14	5,473.19	6,514.63	5,584.15	5,738.03
Inventory Cost	3,631.40	3,388.52	1,750.88	1,565.64	2,581.66	1,760.3	2,015.02	2,059.34	1,578.36	1,667.14
Shipping Cost	9,200.00	9,600.00	9,600.00	10,000.00	9,600.00	9,600.00	9,600.00	9,200.00	9,600.00	9,600.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.12	0.00	0.11	0.00	0.00	0.02	0.00	0.00	0.00	0.00
Profit	132,444.88	115,890.77	120,452.41	122,830.45	132,077.68	113,363.69	124,961.05	139,772.94	130,351.50	130,669.41

Table 90. KPIs for the case $\tau = 3$, $N = 2$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances

	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	199,084.52	190,162.4	208,191.08	196,362.41	192,503.89	191,195.29	194,904.49	193,764.84	217,077.41	200,708.7
Revenue Spot	5,874.68	4,749.80	6,472.30	5,823.75	6,186.73	5,793.66	5,396.94	6,202.39	5,210.20	5,528.63
Inventory Cost	1,901.34	3,452.66	2,533.06	4,398.52	3,262.98	1,043.40	1,505.58	1,673.32	3,050.62	2,328.30
Shipping Cost	10,400.00	9,200.00	9,600.00	9,200.00	9,200.00	10,000.00	9,600.00	9,200.00	9,600.00	9,600.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.09	0.00	0.02
Profit	133,171.86	123,539.79	143,603.32	129,109.89	127,299.39	127,054.80	130,396.10	130,285.16	150,407.99	135,015.78

Table 91. KPIs for the case $\tau = 3$, $N = 3$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	198,268.76	182,716.69	185,694.96	188,902.26	197,965.88	178,700.60	190,660.39	204,072.00	194,830.51	195,492.52
Revenue Spot	6,120.65	5,444.64	5,421.58	4,685.08	5,531.96	5.012.14	5,290.41	6,315.37	5,584.15	5,738.03
Inventory Cost	3,055.12	2,650.06	1,530.08	1,324.20	2,140.06	1,723.48	1,539.32	1,860.98	1,370.66	1,667.14
Shipping Cost	9,200.00	10,000.00	9,600.00	10,000.00	9,600.00	9,600.00	10,000.00	9,600.00	9,600.00	9,600.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.14	0.00	0.11	0.00	0.00	0.02	0.00	0.00	0.00	0.00
Profit	133.29.,54	116,533.52	120,673.21	123,071.89	132,519.28	113,400.51	125,609.98	140,163.14	130,351.50	130,669.41

Table 92. KPIs for the case $\tau = 3$, $N = 3$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	199,084.52	190,162.40	208,191.08	196,469.66	193,088.27	191,195.29	194,904.49	193,991.22	218,267.62	201,218.53
Revenue Spot	5,874.68	4,749.80	6,472.30	5,716.50	5,991.53	5,793.66	5,396.94	6,202.39	5,027.00	5,133.35
Inventory Cost	1,832.56	3,015.30	2,312.26	3,733.26	3,086.84	877.10	1,505.58	1,720.56	2,860.54	1,788.64
Shipping Cost	10,400.00	9,200.00	9,600.00	9,200.00	9,200.00	10.000.00	9,600.00	9,200.00	10,000.00	10,000.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.09	0.00	0.02
Profit	133,240.64	123,977.15	143,824.12	129,775.15	127,864.71	127,221.10	130,396.10	130,464.30	151,205.08	135,269.99

Table 93. KPIs for the case $\tau = 3, N = 4$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	198,901.94	182,716.69	185,694.96	188,902.26	197,965.88	178,700.60	190,660.39	204,072.00	194,830.51	195,492.52
Revenue Spot	5,951.93	5,444.64	5,421.58	4,685.08	5,531.96	5,012.14	5,290.41	6,315.37	5,584.15	5,738.03
Inventory Cost	2,818.54	2,429.26	1,530.08	1,324.2	1,919.26	1,723.48	1,539.32	1,860.98	1,370.66	1,667.14
Shipping Cost	9,600.00	10,000.00	9,600.00	10,000.00	9,600.00	9,600.00	10,000.00	9,600.00	9,600.00	9,600.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.5	58,763.25	59,092.50	59,294.00
% Waste	0.14	0.00	0.11	0.00	0.00	0.02	0.00	0.00	0.00	0.00
Profit	133,599.58	116,754.32	120,673.21	123,071.89	132,740.08	113,400.51	125,609.98	140,163.14	130,351.50	130,669.41

Table 94. KPIs for the case $\tau = 3, N = 4$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	199,084.52	190,162.4	208,191.08	196,469.66	193,088.27	191,392.69	194,904.49	193,770.42	218,267.62	201,218.53
Revenue Spot	5,874.68	4,749.8	6,472.3	5,716.5	5,991.53	5,587.86	5,396.94	6,202.39	5,027.00	5,133.35
Inventory Cost	1,832.56	3,015.30	2,091.46	3,458.58	2,866.04	868.70	1,505.58	1,499.76	2,639.74	1,788.64
Shipping Cost	10,400.00	9,200.00	9,600.00	9,200.00	9,200.00	10,000.00	9,600.00	9,200.00	10,000.00	10,000.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.09	0.00	0.02
Profit	133,240.64	123,977.15	144,044.92	130,049.83	128,085.51	127,221.10	130,396.10	130,464.30	151,425.88	135,269.99

Table 95. KPIs for the case $\tau = 3, N = 5, 6$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	198,901.94	182,866.07	185,694.96	188,902.26	197,965.88	178,700.60	190,660.39	204,072.00	194,830.51	195,492.52
Revenue Spot	5,951.93	5,289.44	5,421.58	4,685.08	5,531.96	5,012.14	5,290.41	6,315.37	5,584.15	5,738.03
Inventory Cost	2,818.54	2,210.74	1,530.08	1,324.20	1,919.26	1,723.48	1,539.32	1,860.98	1,370.66	1,667.14
Shipping Cost	9,600.00	10,000.00	9,600.00	10,000.00	9,600.00	9,600.00	10,000.00	9,600.00	9,600.00	9,600.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00

% Waste	0.14	0.00	0.11	0.00	0.00	0.02	0.00	0.00	0.00	0.00
Profit	133,599.58	116,967.02	120,673.21	123,071.89	132,740.08	113,400.51	125,609.98	140,163.14	130,351.50	130,669.41

Table 96. KPIs for the case $\tau = 3, N = 5, 6$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	199,285.63	190,162.4	208,191.08	196,469.66	193,088.27	191,195.29	194,904.49	193,991.22	218,267.62	201,218.53
Revenue Spot	5,664.73	4,749.80	6,472.30	5,716.50	5,991.53	5,793.66	5,396.94	6,202.39	5,027.00	5,133.35
Inventory Cost	1,823.72	3,015.3	2,091.46	3,458.58	2,866.04	877.10	1,505.58	1,720.56	2,465.06	1,788.64
Shipping Cost	10,400.00	9,200.00	9,600.00	9,200.00	9,200.00	10,000.00	9,600.00	9,200.00	10,000.00	10,000.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.09	0.00	0.025
Profit	133,240.64	123,977.15	144,044.92	130,049.83	128,085.51	127,221.10	130,396.10	130,464.30	151,600.56	135,269.99

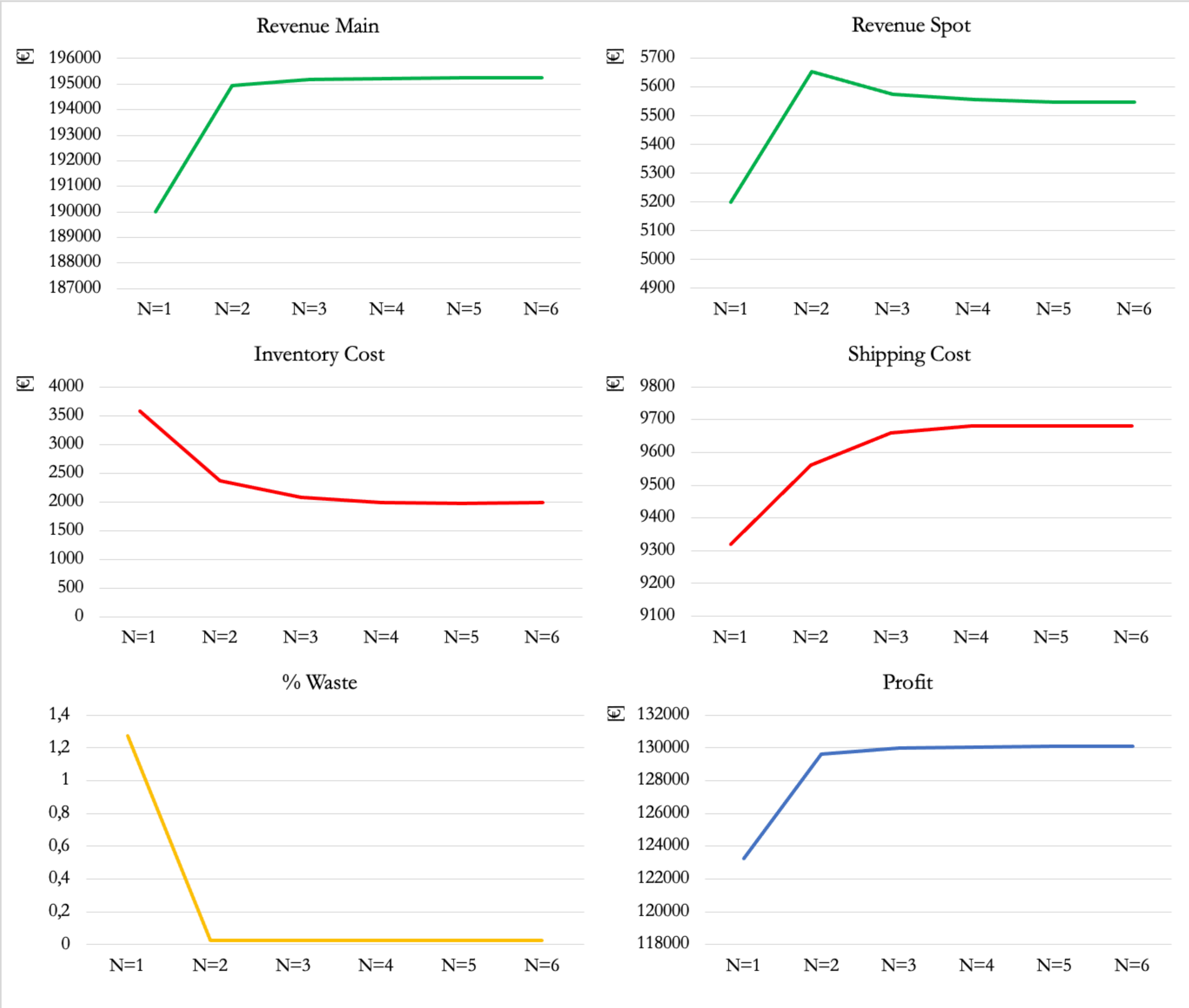

Figure 19. Average value of revenue, cost, % waste, profit, when $\tau = 3$ (HS-HV)

Table 97. KPIs for the case $\tau = 5, N = 1$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	193,988.27	181,849.44	182,517.21	190,937.34	195186.56	175,587.16	189,077.47	204,686.01	195,914.63	194,837.54
Revenue Spot	7,067.02	6,345.30	6,129.34	5,823.19	5,402.85	5,779.04	5,882.06	6,956.40	5,888.13	5,860.41
Inventory Cost	4,238.02	8,316.52	4,676.18	7,291.34	3,889.42	3,685.68	5,887.98	5,213.62	2,593.06	4,869.34
Shipping Cost	8,400.00	8,400.00	8,800.00	8,800.00	9,200.00	8,800.00	8,800.00	8,800.00	9,600.00	9,200.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.5	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Profit	129,581.52	112,500.47	115,857.12	121,477.94	128,261.49	109,891.77	121,470.05	138,865.54	130,517.20	127,334.61

Table 98. KPIs for the case $\tau = 5, N = 1$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	205,907.2	190,000.93	204,748.23	193,918.60	191,767.15	194,669.37	192,012.53	195,039.97	210,667.14	195,577.71
Revenue Spot	6,978.50	5,763.94	7,103.25	5,899.68	6,870.53	6,731.24	6,212.05	5,976.88	5,777.14	6,153.16
Inventory Cost	9,456.14	6,047.26	4,863.32	4,847.76	5,842.18	7,513.88	4,954.60	4,887.06	7,847.28	4,512.36
Shipping Cost	8,800.00	9,200.00	9,200.00	8,800.00	8,800.00	8,800.00	9,200.00	9,200.00	9,200.00	9,200.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0,22
Profit	135,143.56	121,797.86	138,861.16	126,692.77	125,067.25	126,195.98	125,270.23	128,121.04	140,168.00	128,725.26

Table 99. KPIs for the case $\tau = 5, N = 2$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	200,902.66	186,071.16	192,765.93	195,511.30	202,131.52	182,868.09	193,047.11	207,608.61	200,414.64	201,440.04
Revenue Spot	6,898.30	5,991.70	5,527.96	4,620.40	5,384.99	5,062.30	5,329.51	6,157.58	5,167.30	5,399.61
Inventory Cost	6,927.96	7,374.24	6,126.62	4,644.28	4,445.42	5,065.26	4,775.88	3,765.26	3,223.42	3,358.98
Shipping Cost	8,400.00	8,800.00	9,200.00	9,600.00	9,600.00	8,800.00	9,200.00	9,200.00	9,600.00	9,600.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	133,637.25	116,910.87	123,654.02	126,696.17	134,232.59	115,076.38	125,599.24	142,037.68	133,666.02	134,586.67

Table 100. KPIs for the case $\tau = 5, N = 2$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	210,658.03	193,233.96	212,537.52	198,839.26	195,037.92	197,402.24	199,914.96	195,059.73	220,237.92	207,346.88
Revenue Spot	5,796.43	5,235.45	6,285.69	5,552.25	5,992.13	5,879.85	6,230.64	5,820.13	5,058.17	4,618.03
Inventory Cost	7,402.80	5,302.92	5,396.90	6,233.86	4,976.72	4,648.90	3,536.22	1,751.22	4,948.32	5,790.58
Shipping Cost	9,200.00	8,800.00	9,200.00	8,800.00	8,800.00	9,200.00	9,200.00	9,600.00	9,200.00	9,600.00

Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	140,365.66	125,646.74	145,299.31	129,879.90	128,325.08	130,542.44	134,609.63	130,719.89	151,918.77	137,281.08

Table 101. KPIs for the case $\tau = 5, N = 3$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	201,156.36	186,146.81	192,949.27	195,748.66	202,131.52	183,596.16	193,170.47	208,293.63	200,206.94	201,440.04
Revenue Spot	6,674.10	5,936.45	5,336.38	4,372.72	5,384.99	5,093.90	5,329.51	6,134.09	5,167.30	5,399.61
Inventory Cost	5,639.60	5,849.04	4,602.30	4,028.70	3,666.56	4,151.38	3,282.88	3,985.48	2,711.22	3,138.18
Shipping Cost	8,400.00	8,800.00	9,200.00	9,600.00	9,600.00	9,200.00	9,200.00	9,200.00	9,600.00	9,600.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	134,955.11	118,456.47	125,170.10	127,301.43	135,011.45	116,349.93	127,215.60	142,478.99	133,970.52	134,807.47

Table 102. KPIs for the case $\tau = 5, N = 3$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	211,290.89	193,407.51	212,629.50	198,839.26	194,375.52	199,569.26	199,914.96	195,096.43	220,155.08	207,286.43
Revenue Spot	5,206.73	5,054.10	6,058.28	5,552.25	5,992.13	5,311.20	6,230.64	5,820.13	5,270.20	4,669.38
Inventory Cost	6,655.40	4,678.22	3,628.02	5,350.66	3,651.92	4,902.64	3,315.42	1,629.74	4,415.08	4,446.64
Shipping Cost	9,200.00	8,800.00	9,600.00	8,800.00	8,800.00	9,600.00	9,200.00	9,600.00	9,200.00	9,600.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	141,156.22	126,263.64	146,532.76	130,763.10	128,987.48	131,487.07	134,830.43	130,878.07	152,581.20	138,615.92

Table 103. KPIs for the case $\tau = 5, N = 4$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	201,059.18	186,071.16	192,949.27	195,748.66	202,131.52	183,596.16	193,170.47	209,113.11	200,414.64	201,440.04
Revenue Spot	6,759.98	5,991.70	5,336.38	4,372.72	5,384.99	5,093.90	5,329.51	5,938.07	5,167.30	5,399.61
Inventory	5,186.70	5,387.04	4,381.50	3,807.90	3,315.20	3,930.58	3,062.08	4,385.72	2,918.92	3,138.18

Cost										
Shipping Cost	8,400.00	8,800.00	9,200.00	9,600.00	9,600.00	9,200.00	9,200.00	9,200.00	9,600.00	9,600.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	135,396.71	118,898.07	125,390.90	127,522.23	135,362.81	116,570.73	127,436.40	142,702.21	133,970.52	134,807.47

Table 104. KPIs for the case $\tau = 5, N = 4$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	211,290.89	193,407.51	212,402.96	199,967.44	195,037.92	199,569.26	199,914.96	194,875.63	220,155.08	207,346.88
Revenue Spot	5,206.73	5,054.10	6,294.46	5,414.25	5,992.13	5,311.20	6,230.64	5,820.13	5,270.20	4,618.03
Inventory Cost	6,434.60	4,457.42	3,416.86	5,885.78	4,093.52	4,681.84	3,183.46	1,408.94	4,194.28	4,043.10
Shipping Cost	9,200.00	8,800.00	9,600.00	8,800.00	8,800.00	9,600.00	9,200.00	9,600.00	9,200.00	9,600.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	141,377.02	126,484.44	146,753.56	131,218.16	129,208.28	131,707.87	134,962.39	130,878.07	152,802.00	139,028.56

Table 105. KPIs for the case $\tau = 5, N = 5$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	201,059.18	186,636.24	192,949.27	195,918.86	202,131.52	183,596.16	193,170.47	209,285.31	200,206.94	201,440.04
Revenue Spot	6,759.98	5,717.90	5,336.38	4,195.12	5,384.99	5,093.90	5,329.51	5,793.75	5,167.30	5,399.61
Inventory Cost	4,965.90	4,979.66	4,160.70	3,633.14	3,094.40	3,918.96	3,062.08	3,919.50	2,711.22	3,138.18
Shipping Cost	8,400.00	9,200.00	9,200.00	9,600.00	9,600.00	9,200.00	9,200.00	9,600.00	9,600.00	9,600.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	135,617.51	119,196.73	125,611.70	127,689.59	135,583.61	116,582.35	127,436.40	142,796.31	133,970.52	134,807.47

Table 106. KPIs for the case $\tau = 5, N = 5$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20

Revenue Main	211,290.89	193,407.51	212,402.96	200,116.90	194,375.52	199,569.26	199,914.96	194,875.63	220,155.08	207,346.88
Revenue Spot	5,206.73	5,054.10	6,294.46	5,277.51	5,992.13	5,311.20	6,230.64	5,820.13	5,270.20	4,618.03
Inventory Cost	6,434.12	4,457.42	3,196.06	5,552.74	3,431.12	4,480.52	3,183.46	1,408.94	3,973.48	3,822.30
Shipping Cost	9,200.00	8,800.00	9,600.00	8,800.00	8,800.00	9,600.00	9,200.00	9,600.00	9,200.00	9,600.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	141,377.50	126,484.44	146,974.36	131,563.92	129,208.28	131,909.19	134,962.39	130,878.07	153,022.80	139,249.36

Table 107. KPIs for the case $\tau = 5, N = 6$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	201,059.18	186,605.44	192,949.27	195,918.86	202,316.44	183,596.16	193,170.47	209,285.31	200,414.64	201,440.04
Revenue Spot	6,759.98	5,743.90	5,336.38	4,195.12	5,192.03	5,093.90	5,329.51	5,793.75	5,167.30	5,399.61
Inventory Cost	4,965.90	4,757.26	3,941.50	3,633.14	2,921.64	3,918.96	3,062.08	3,919.50	2,918.92	3,138.18
Shipping Cost	8,400.00	9,200.00	9,200.00	9,600.00	9,600.00	9,200.00	9,200.00	9,600.00	9,600.00	9,600.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	135,617.51	119,414.33	125,830.90	127,689.59	135,748.33	116,582.35	127,436.40	142,796.31	133,970.52	134,807.47

Table 108. KPIs for the case $\tau = 5, N = 6$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	211,290.89	193,407.51	212,402.96	200,116.90	195,037.92	199,569.26	199,914.96	194,875.63	220,155.08	207,346.88
Revenue Spot	5,206.73	5,054.10	6,294.46	5,277.51	5,992.13	5,311.20	6,230.64	5,820.13	5,270.20	4,618.03
Inventory Cost	6,434.12	4,457.42	3,034.38	5,552.74	4,093.52	4,480.52	3,183.46	1,408.94	3,973.48	3,822.30
Shipping Cost	9,200.00	8,800.00	9,600.00	8,800.00	8,800.00	9,600.00	9,200.00	9,600.00	9,200.00	9,600.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	141,377.50	126,484.44	147,136.04	131,563.92	129,208.28	131,909.19	134,962.39	130,878.07	153,022.80	139,249.36

Figure 20. Average value of revenue, cost, % waste, profit, when $\tau = 5$ (HS-HV)

Table 109. KPIs for the case $\tau = 7$, $N = 1$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	193,988.27	183,174.24	182,517.21	190,937.34	195,186.56	175,587.16	189,077.47	204,686.01	194,592.46	194,837.54
Revenue Spot	7,091.82	6,345.3	6,129.34	5,823.19	5,402.85	5,779.04	5,882.06	6,956.4	6,759.63	5,860.41
Inventory Cost	4,241.12	9,641.32	4,676.18	7,291.34	3,889.42	3,685.68	5,887.98	5,213.62	2,470.2	4,869.34
Shipping Cost	8,400.00	8,400.00	8,800.00	8,800.00	9,200.00	8,800.00	8,800.00	8,800.00	9,200.00	9,200.00
Production Cost	58,835.75	58.977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Profit	129,603.22	112,500.47	115,857.12	121,477.94	128.261.49	109,891.77	121,470.05	138,865.54	130,589.39	127,334.61

Table 110. KPIs for the case $\tau = 7, N = 1$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	211,424.20	192,284.88	204,971.01	193,945.72	191,767.15	194,669.37	191,522.96	195,359.96	210,607.08	199,329.75
Revenue Spot	6,978.50	5,583.99	6.870.99	5,899.68	6,870.53	6,731.24	6,589.21	6,141.80	5,828.62	6,326.96
Inventory Cost	13,846.42	7,383.76	4,853.84	4,874.88	5,842.18	7,513.88	5,214.86	5,410.94	8,021.36	5,899.22
Shipping Cost	8,800.00	9,200.00	9,200.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00	8,800.00	9,200.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04
Profit	136,270.28	122,565.36	138,861.16	126,692.77	125,067.25	126,195.98	125,297.56	128,482.07	140,385.34	131,264.24

Table 111. KPIs for the case $\tau = 7, N = 2$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	200,902.66	187,872.40	192,765.93	196,691.26	202,131.52	185,046.16	193,170.47	209,322.81	200,606.36	207,092.34
Revenue Spot	6,923.10	5,474.85	5,527.96	5,565.61	5,384.99	5,093.90	5,329.51	6,956.40	6,202.34	5,118.01
Inventory Cost	6,931.06	8,398.30	6,126.62	6,471.14	4,445.42	6,862.86	4,899.24	6,096.82	4,511.28	6,600.46
Shipping Cost	8,400.00	8,800.00	9,200.00	9,200.00	9,600.00	8.800.00	9,200.00	8,800.00	8,800.00	9,200.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	133,658.95	117,171.20	123,654.02	127,394.48	134,232.59	115,488.45	125,599.24	142,619.14	134,404.92	137,115.89

Table 112. KPIs for the case $\tau = 7, N = 2$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	213,643.50	193,233.96	212,537.52	198,839.26	195,041.71	199,720.93	202,072.10	195,379.72	219,532.01	211,485.64
Revenue Spot	5,651.19	5,235.45	6,285.69	5,552.25	6,539.01	6,605.80	5,910.96	5,985.05	5,792.60	5,285.56
Inventory Cost	9,128.06	5,302.92	5,396.90	6,233.86	5,815.86	7,336.20	4,848.40	2,154.02	5,259.84	7,993.52
Shipping Cost	9,200.00	8,800.00	9,200.00	8,800.00	8,400.00	8,800.00	8,800.00	9,200.00	8,800.00	9,200.00

Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	141,480.63	125,646.74	145,299.31	129,879.90	128,436.61	131,299.78	135,534.91	131,202.00	152,035.77	140,284.43

Table 113. KPIs for the case $\tau = 7, N = 3$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	201,341.26	188,486.96	192,949.27	196,928.62	202,131.52	185,837.96	193,170.47	212,240.61	200,625.72	207,092.34
Revenue Spot	6,520.38	5,080.05	5,336.38	5,317.93	5,384.99	5,093.90	5,329.51	6,124.79	6,399.44	5,118.01
Inventory Cost	5,649.08	6,865.30	4,602.30	5,716.62	3,666.56	5,720.64	3,282.88	6,751.56	4,286.14	5,496.46
Shipping Cost	8,400.00	8,800.00	9,200.00	9,200.00	9,600.00	9,200.00	9,200.00	9,200.00	8,800.00	9,200.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	134,976.81	118,923.96	125,170.10	128,138.68	135,011.45	117,022.47	127,215.60	143,650.59	134,846.52	138,219.89

Table 114. KPIs for the case $\tau = 7, N = 3$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	214,439.90	193,407.51	212,402.96	198,839.26	194,379.31	200,915.79	202,366.36	195,390.10	219,652.27	212,267.96
Revenue Spot	5,578.53	5,054.10	6,294.46	5,552.25	6,539.01	6,005.80	6,160.08	5,781.73	5,792.60	5,084.92
Inventory Cost	8,802.70	4,678.22	3,637.66	5,350.66	4,491.06	6,319.22	4,654.84	1,802.90	4,717.70	6,865.12
Shipping Cost	9,200.00	8,800.00	9,600.00	8,800.00	8,400.00	9,200.00	9,200.00	9,200.00	8,800.00	9,200.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	142,529.73	126,263.64	146,532.76	130,763.10	129,099.01	132,511.62	135,871.85	131,360.18	152,698.17	141,994.51

Table 115. KPIs for the case $\tau = 7, N = 4$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	201,059.18	188,486.96	192,949.27	196,928.62	202,131.52	185,177.06	193,170.47	213,107.61	201,031.58	207,092.34
Revenue Spot	6,784.78	5,080.05	5,336.38	5,317.93	5,384.99	5,093.90	5,329.51	5,911.39	6,069.40	5,118.01
Inventory	5,189.80	6,423.70	4,381.50	5,495.82	3,315.20	4,619.14	3,062.08	7,184.36	3,888.02	5,275.66

Cost										
Shipping Cost	8,400.00	8,800.00	9,200.00	9,200.00	9,600.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	135,418.41	119,365.56	125,390.90	128,359.48	135,362.81	117,463.07	127,436.40	143,871.39	134,920.46	138,440.69

Table 116. KPIs for the case $\tau = 7, N = 4$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	214,439.90	193,407.51	212,402.96	200,089.79	194,379.31	200,915.79	202,366.36	195,610.90	220,120.01	212,207.51
Revenue Spot	5,578.53	5,054.10	6,294.46	5,284.30	6,539.01	6,005.80	6,160.08	5,781.73	5,350.74	5,136.27
Inventory Cost	8,361.10	4,457.42	3,416.86	5,882.52	4,270.26	5,877.62	4,434.04	2,023.70	4,123.70	6,426.12
Shipping Cost	9,200.00	8,800.00	9,600.00	8,800.00	8,400.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	142,971.33	126,484.44	146,753.56	131,213.82	129,319.81	132,953.22	136,092.65	131,360.18	152,918.05	142,424.41

Table 117. KPIs for the case $\tau = 7, N = 5$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	201,248.38	188,253.84	192,949.27	196,928.62	202,131.52	185,837.96	193,170.47	213,107.61	201,031.58	207,092.34
Revenue Spot	6,617.58	5,337.05	5,336.38	5,317.93	5,384.99	5,093.90	5,329.51	5,911.39	6,069.40	5,118.01
Inventory Cost	4,991.00	6,007.58	4,160.70	5,275.02	3,094.40	5,058.24	3,062.08	6,963.56	3,888.02	5,275.66
Shipping Cost	8,400.00	8,800.00	9,200.00	9,200.00	9,600.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	135,639.21	119,805.56	125,611.70	128,580.28	135,583.61	117,684.87	127,436.40	144,092.19	134,920.46	138,440.69

Table 118. KPIs for the case $\tau = 7, N = 5$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	214,439.90	193,407.51	212,629.50	200,116.90	194,379.31	200,915.79	202,366.36	195,195.62	220,120.01	212,267.96

KPI										
Revenue Spot	5,578.53	5,054.10	6,058.28	5,277.51	6,539.01	6,005.80	6,160.08	5,985.05	5,350.74	5,084.92
Inventory Cost	8,140.30	4,457.42	3,186.42	5,552.74	4,270.26	5,656.82	4,330.12	1,811.74	3,902.90	6,202.72
Shipping Cost	9,200.00	8,800.00	9,600.00	8,800.00	8,400.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	143,192.13	126.484.44	146,974.36	131,563.92	129,319.81	133,174.02	136,196.57	131,360.18	153,138.85	142,656.91

Table 119. KPIs for the case $\tau = 7, N = 6$ (HS-HV, Instances: HH1-to-HH10)

KPI	Instances									
	HH-1	HH-2	HH-3	HH-4	HH-5	HH-6	HH-7	HH-8	HH-9	HH-10
Revenue Main	201,059.18	189,113.75	192,949.27	197,098.82	202,131.52	185,837.96	193,170.47	213,107.61	200,823.88	207,092.34
Revenue Spot	6,784.78	5,474.85	5,336.38	5,134.33	5,384.99	5,093.90	5,329.51	5,911.39	6,069.40	5,118.01
Inventory Cost	4,969.00	6,610.48	3,939.90	5,155.88	2,929.68	5,039.86	3,062.08	6,742.76	3,680.32	5,275.66
Shipping Cost	8,400.00	8,800.00	9,200.00	9,200.00	9,600.00	9,200.00	9,200.00	9,200.00	9,200.00	9,200.00
Production Cost	58,835.75	58,977.75	59,313.25	59,191.25	59,238.50	58,988.75	58,801.50	58,763.25	59,092.50	59,294.00
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	135,639.21	120,200.37	125,832.50	128,686.02	135,748.33	117,703.25	127,436.40	144,312.99	134,920.46	138,440.69

Table 120. KPIs for the case $\tau = 7, N = 6$ (HS-HV, Instances: HH11-to-HH20)

KPI	Instances									
	HH-11	HH-12	HH-13	HH-14	HH-15	HH-16	HH-17	HH-18	HH-19	HH-20
Revenue Main	214,591.13	193,407.51	212,402.96	200,060.65	195,041.71	202,350.99	202,366.36	195,416.42	220,120.01	212,933.96
Revenue Spot	5,440.08	5,054.10	6,294.46	5,333.76	6,539.01	6,005.80	6,160.08	5,985.05	5,350.74	5,084.92
Inventory Cost	8,153.08	4,457.42	3,034.38	5,557.08	4,932.66	6,981.62	4,330.12	2,032.54	3,902.90	6,388.56
Shipping Cost	9,200.00	8,800.00	9,600.00	8,800.00	8,400.00	9,200.00	9,200.00	9,200.00	9,200.00	9,600.00
Production Cost	59,486.00	58,719.75	58,927.00	59,477.75	58,928.25	58,890.75	58,799.75	58,808.75	59,229.00	59,293.25
% Waste	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Profit	143,192.13	126,484.44	147,136.04	131,559.58	129,319.81	133,284.42	136,196.57	131,360.18	153,138.85	142,737.07

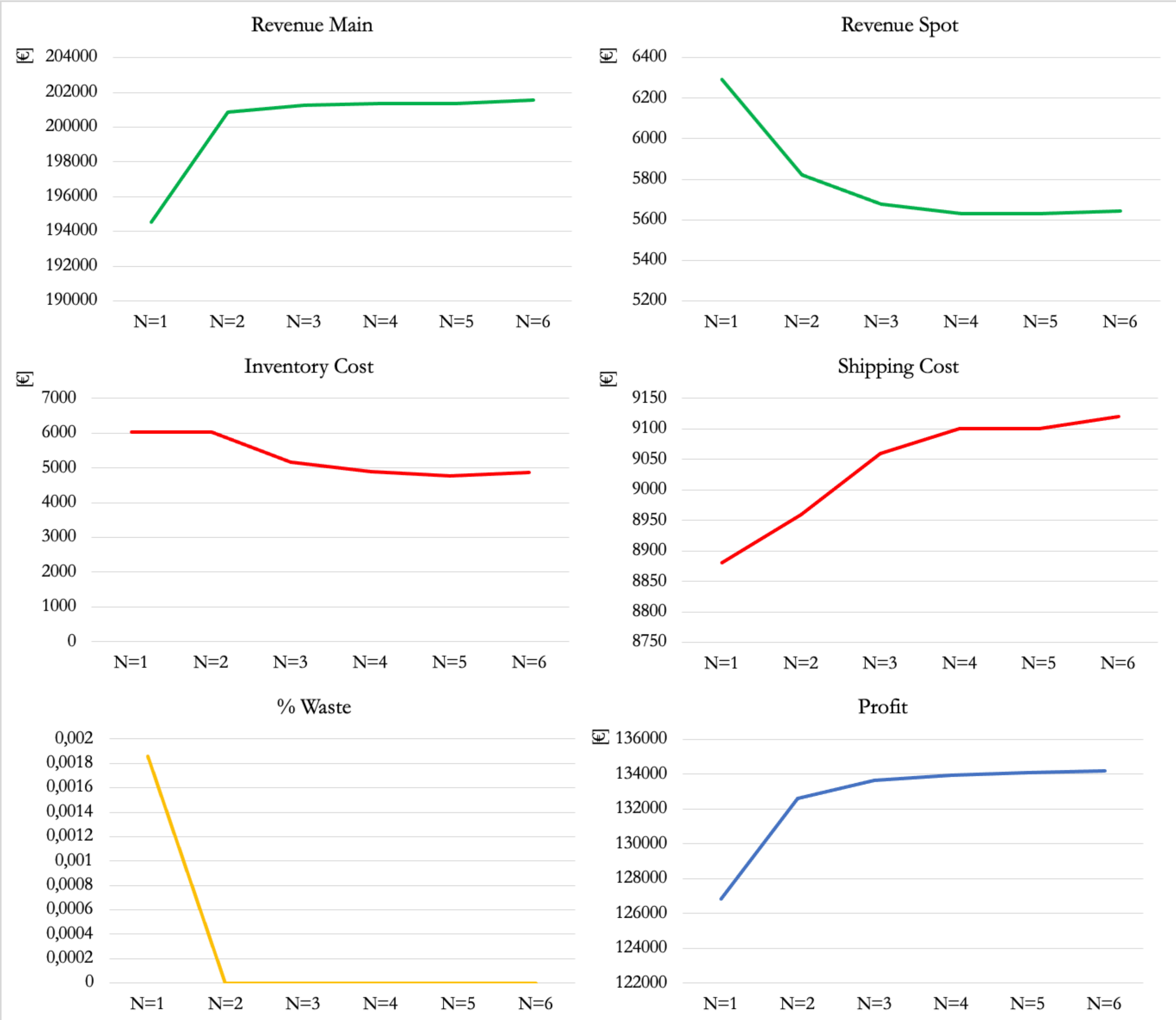

Figure 21. Average value of revenue, cost, % waste, profit, when $\tau = 7$ (HS-HV)

3.3.2.2. Operational level

Once fixed the relevant parameters at the strategic-tactical level (i.e., $\tau = 5$ and $N = 2$), the problem has been addressed at the operational level. In this case, the tests have been conducted on the 40 long-term instances. With the aim to reproduce the real operating conditions of the company, a rolling horizon approach has been implemented. Basically, the model is solved every week, considering $T = 14$ days. After each run, only the decisions made on the first 7 days are saved, while the others are made only when a new week becomes available. In Figure 22, a scheme of the used rolling horizon approach is shown.

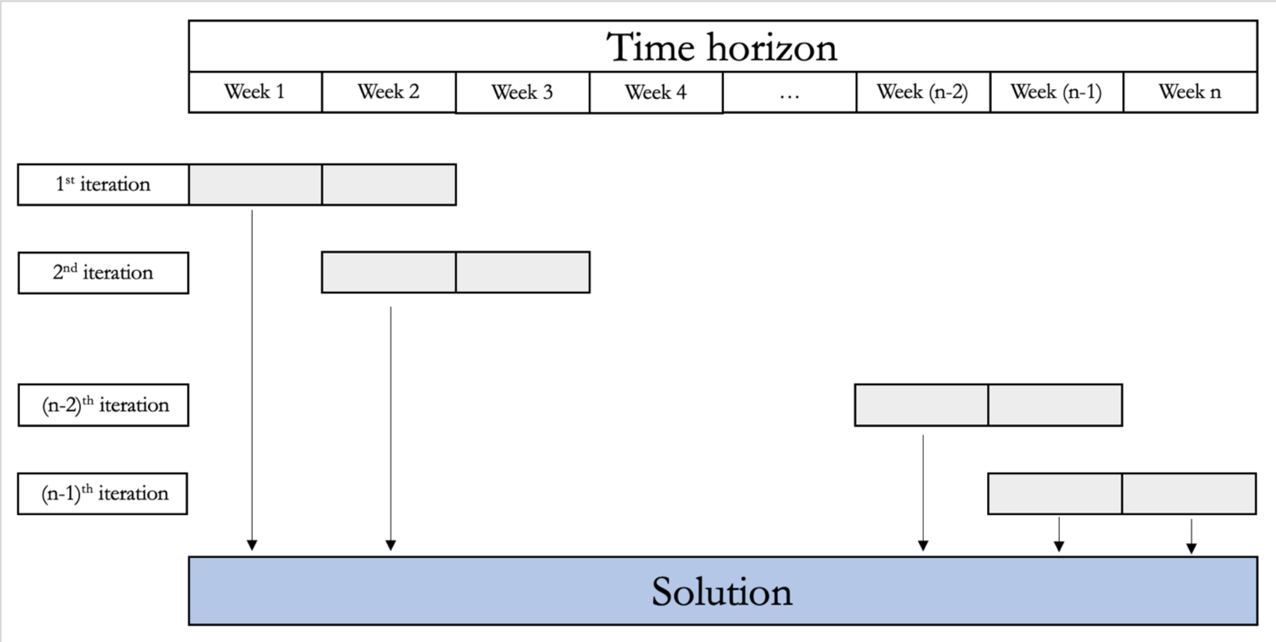

Figure 22. Rolling horizon approach

Given an overall time horizon of n weeks, $n = 21$ in the present experiments, $(n-1)$ iterations are necessary to solve the problem. At the first iteration, the model is solved on the first two weeks, but only the decisions made on the first week become part of the solution. At the second iteration, the time horizon concerns the second and third week; in this case, the decisions made on the second week (i.e., the first week of the current time horizon) are the only inserted into the solution. At the final iteration, the decisions made on both the remaining weeks are saved.

One of the main purposes of the proposed model is to support the decision maker in catching the market opportunities offered by the spot customers, taking into account that, along the whole season, a certain fraction γ of the amount harvested has to be guaranteed to the main customer. In this context, two different configurations of Constraint (2) have been considered, called respectively $\gamma - soft$ and $\gamma - hard$: the first one is that contained within the proposed model, using $T = 14$; the second one, instead, forces the weekly shipment to the main customer to be at least a fraction γ of the amount harvested in the same week. In this latter case, Constraint (2) is replaced by:

$$\sum_{t=1}^{7}(x_t + y_t) \geq \gamma \sum_{t=1}^{7} Q_t \tag{22}$$

$$\sum_{t=8}^{14}(x_t + y_t) \geq \gamma \sum_{t=8}^{14} Q_t \tag{23}$$

Observe that the second configuration, unlike the first one, certainly ensures that at the end of the season, at least a fraction γ of the total amount harvested will be shipped to the main customer, in the spirit of the original description of the contract.

In Tables 121-122 and 123-124, the results of the computational experiments on the WS-LV and WS-HV instances are shown, respectively. More specifically, in Tables 121 and 123, the reader can find the minimum-, average-, and maximum-profit over the twenty instances of each test-set, referring to both configurations $\gamma - hard$ and $\gamma - soft$. While, in Tables 122 and 124, the contribution of revenues and costs to the average profits is reported.

Table 121. Profit for the WS-LV instances [€]

	$\gamma - hard$	$\gamma - hard$
Max	337,227.63	343,602.82
Avg	326,516.30	334,390.93
Min	317,678.22	324,332.80

Table 122. Revenue, cost, and waste for the WS-LV instances

$\gamma - hard$				$\gamma - soft$			
	Avg	Share [%]			Avg	Share [%]	
Revenue [€]	542,453.23	Main	97.62	Revenue [€]	554,614.27	Main	97.14
		Spot	2.38			Spot	2.86
Cost [€]	215,936.93	Inventory	1.89	Cost [€]	220,223.34	Inventory	4.39
		Shipment	14.09			Shipment	13.22
		Production	84.02			Production	82.39
Waste [%]	0.02			Waste [%]	0.67		

Table 123. Profit for the WS-HV instances [€]

	$\gamma - hard$	$\gamma - hard$
Max	341,432.44	359,922.48
Avg	317,482.89	332,096.96
Min	293,630.42	305,737.30

Table 124. Revenue, cost, and waste for the WS-HV instances

$\gamma - hard$				$\gamma - soft$			
	Avg	Share [%]			Avg	Share [%]	
Revenue [€]	534,118.14	Main	97.62	Revenue [€]	554,786.63	Main	97.15
		Spot	2.38			Spot	2.85
Cost [€]	216,635.25	Inventory	2.12	Cost [€]	222,689.67	Inventory	5.38
		Shipment	14.11			Shipment	13.13
		Production	83.77			Production	81.49
Waste [%]	0.08			Waste [%]	0.27		

Some important managerial insights can be detected from the computational results. First of all, it is possible to state that the $\gamma - soft$ setting is more profitable than the $\gamma - hard$. This is mainly due to a significant increase in the revenue. The $\gamma - hard$ configuration implies an almost total emptying of the warehouse by the end of each week, having to ship to the main customer a very large part of the amount harvested. On the contrary, the $\gamma - soft$ setting allows to better catch the market opportunities (i.e., higher unit selling prices) because it is possible to store a higher amount of product between a week and the next one. This means that the inventory costs increase considerably, but also the revenue. As expected, the average age of the product shipped increases, shifting from $\gamma - hard$ to $\gamma - soft$, but in both the cases it is not greater than two days, that is an acceptable value (here, the main assumption is that the age of the fresh product is equal to one). Waste is intended as product which remains in the inventory for more than τ days. It is in all cases very low, not exceeding on average 0.67 %. More than 97 % of revenues come from sales to the main customer. Most of the costs relate to the production of cauliflower, whose extent does not depend on the company's decisions. Although the choice of the $\gamma - soft$ option appears more profitable, it is very important to remark that possible violation of the contractual agreement is not prevented in such a case. However, within the computational experiments of this work, such drawback has never been detected.

3.4. Brief conclusions

Aiming to support a decision-maker in simultaneously planning the storage and shipment of harvested agri-products, a MILP model has been introduced, and its application to an agricultural firm, located in the Southern Italy, that deals with planting, growing, harvesting and distributing cauliflowers, has been studied and validated. Along the entire harvesting/distribution season, for contractual reasons, the firm must reserve at least a given share of the harvested products to a main customer; however, it can also catch the opportunities offered by more profitable spot customers. In order to balance quality of products delivered to the main customer, the firm adopts a hybrid fresh/old first priority policy. Current operations practices have very low flexibility in terms of shipment, which is under the control of the main customer, thus affecting the inventory management as well. The optimization model, whose aim is profit maximization, enables the company to upgrade its practices, in order to have full control of storage and shipment planning. At the strategic-tactical level, the model has been adopted to select a good combination of fleet size and maximum in-stock time of cauliflowers. At the operational level, the model has been tailored to the day-by-day planning of storage and shipment, by means of a rolling horizon approach. The computational experiments, carried out on instances generated from real-life data, have demonstrated the suitability of the presented model to both decision scenarios.

Future enhancement of the model will consider the dependency of unit selling-prices on the product quality loss, and the possible extension to a multi-product version.

4. Modelling and solving an integrated and collaborative harvesting-inventory-routing problem in the perishable food supply chain

4.1. Introduction

In the coming years, an increase in global food demand is expected, due to the growth in the world population. This trend has been going on for several decades. Fresh fruit and vegetables are and will be among the most demanded products also because their consumption has several beneficial effects on human health (Cox et al., 2000; Wang et al., 2015). Therefore, one of today most significant challenges concerns the design and management of efficient fresh-produce supply chains, which can effectively face the variability of demand and prices, the perishable nature of the products, the complexity of the logistic systems (Villalobos et al., 2019). In recent decades, globalization has forced companies all over the world to rethink market strategies in a sustainable and collaborative way, in order to contain costs and offer a higher quality product to customers, who are increasingly demanding and knowledgeable (Guido et al., 2020). While in the past there was a tendency to locally and sequentially optimize the various phases of the supply chain, today the research world is moving towards integrated approaches, which reduce lead times and offer quicker reactions to the frequent market changes (Fahimnia et al., 2013).

Considering this global trend, the main aim of this Chapter is to address the integrated and collaborative harvesting inventory distribution problem (HIDP) with perishable products. It belongs to the class of the production-inventory-routing problems, which aim to jointly optimize production, inventory, distribution, and routing decisions. In the most classic configuration, such problem involves a supplier, who produces a commodity and replenish a set of customers through the use of a fleet of vehicles, within a well-defined time horizon. Then, the most common decisions concern: when and how much to produce, the inventory level at the supplier and/or at each customer, when and how much to deliver, which vehicle routes to use (Li et al., 2020; Neves-Moreira et al., 2019).

The contribution of this Chapter can be briefly summarized as follows:

- A new optimization model is proposed, to support in an integrated way an agricultural company in the harvesting, storage, and distribution decisions. Such a model can be very useful at the tactical level to define the most profitable configuration of the main operating parameters.

- A further optimization model to support horizontal collaboration, in terms of distribution activities, between two or more heterogeneous agri-companies, which share part of their customers. The model can increase profit and limit considerably CO_2 emissions.
- A heuristic framework which can deal with the two proposed optimization models and invite day-by-day to collaboration, only when profitable for all the suppliers.

4.2. Scientific background

The reduction in total operating cost achieved by coordination of production and distribution planning can range from 3 % and 20 %, as reported in the work of Chandra and Fisher, (1994). The integration of production and distribution activities can bring innumerable advantages, such as reduction in delivery time, increase in product quality for the benefit of customer satisfaction, improvement in the overall performance of the food supply chain (Vahdani et al., 2017). The study of Amorim et al., (2012) highlights the economic advantages in using an integrated approach compared to a decoupled one. Moreover, the coordination of the different steps of the supply chain has a very positive environmental impact, limiting pollution (Al Shamsi et al., 2014) and food waste (de Moraes et al., 2020). As reported in (De Steur et al., 2016; Papargyropoulou et al., 2014), a very large part of food waste is currently due to inefficiencies in the fresh food supply chain.

The coordination of production, storage and distribution activities is much more complex and critical when the supply chain deals with perishable products. Perishability and shelf-life are among the main issues for achieving sustainability and efficiency in food logistics (Fredriksson and Liljestrand, 2015). Products such as fruits, vegetables, and flowers are characterized by continuous deterioration (Chen et al., 2009), which influences the profits achievable from their sale to customers. Basically, the selling price is not constant, but depends on the quality, which usually begins to decline immediately after production, or harvesting in the case of agricultural products (Bustos and Moors, 2018). In the case of fresh fruits and vegetables, the expiry date is not printed, then their shelf-life is defined loose because it can be only estimated based on some information (e.g., physical status, date of harvesting) (Amorim et al., 2012). For all these reasons, a branch of research which concerns the inventory management with deteriorating items has developed over the years. The work of Nahmias (1982) was pioneering, while for some quite recent studies, see Coelho and Laporte, (2014); Hsiao et al., (2017); Huang et al., (2018).

In the following, the most relevant contributions in the literature, where decisions about production, inventory, and routing of perishable products are simultaneously optimized, are analyzed. However, it is important to say that more detailed information about the production-inventory-routing problems can be found in some comprehensive and quite recent reviews, see Diaz-Madronero et al., (2015); Adulyasak et al., (2015); Fahimnia et al., (2013).

Rong et al., (2011) propose a MILP model for planning the production and distribution activities in a multi-level food supply chain. The total costs are minimized, namely production, transportation, storage, disposal, and cooling costs for transportation equipment and storage facilities. The authors mainly focus on product quality, whose decay is strongly related to the temperature along the chain. In particular, they include linear or exponential product quality degradation models in their MILP. The aim is to find a sort of trade-off between quality preservation costs and costs for waste. Since the proposed modelling approach refers to a generic food supply chain configuration, it can successfully be applied in several food industries. Jia et al., (2014) consider a two-echelon supply chain, where a single supplier distributes a single product to a set of retailers, using a fleet of homogeneous vehicles. They propose a MILP model, which supports the decision-making of the supplier about the production plan, the customers' delivery time, the routing in each period of the planning horizon. The vehicles loading costs are explicitly taken into account. Considering the computational complexity of the problem, the authors propose a two-phase algorithm to solve it efficiently. The computational results and a sensitivity analysis show that the model can be a very useful tool for planning supply chain activities, when dealing with perishable items. Seyedhosseini and Ghoreyshi, (2014) consider a supply chain characterized by a production facility and multiple distribution centers. With the aim to minimize the total cost, the proposed production-inventory-routing model supports the decision-making about the production quantities, the distribution centers to be visited, the quantities to be delivered. To solve the problem efficiently, the authors divide it into two sub-problems, which deal respectively with the production and distribution activities. The first one is optimally solved, while a particle swarm heuristic is designed to tackle the distribution submodel. Computational experiments on a set of randomly generated instances prove the goodness of the proposed approach in terms of solution quality and time performance. Li et al., (2016) use a MILP model to define a production-inventory-routing problem where quality of perishable products is explicitly considered, and profit maximized. They test their generic supply chain model on some randomly generated instances and analyze how food perishability impacts on the solution. Vahdani et al., (2017) propose a mathematical programming approach to integrate some common operational decisions, like production scheduling, inventory management, and vehicle routing. In particular, the considered production system is multi-stage and multi-site, while at the delivery level different transporting vehicles with different capacities are taken into account. The multi-period nature and the use of time windows make the problem quite difficult to be optimally solved. Therefore, two heuristic and meta-heuristic algorithms are proposed and applied to some benchmark instances, with good results. Ghasemkhani et al., (2019) present a multi-product and multi-period integrated production-inventory-routing problem with time windows, where the fleet of vehicles is heterogenous. The uncertainty in customers demand is tackled through two fuzzy approaches. The proposed model is tested and validated on a set of randomly generated numerical examples, which are solved optimally. Neves-Moreira et al., (2019) address a production-inventory-routing-problem in a meat supply chain, where the producer has a single meat processing center with several production lines, and a fleet of vehicles for the distribution to the customers. The authors take into account many real-life features such as product family setups, food perishability, delivery time windows. Since the dimension of the problem is very large, a three-phase methodology is proposed, in order to find good solutions in a reasonable time. At the first step, the size of the problem is reduced, then an initial solution is found and iteratively improved with a fix-and-optimize based matheuristic. The approach is tested both on some simple instances from the literature and on a real-life case study. Qiu et al., (2019) present a generalized production-inventory-routing model with perishable inventory. With the aim of making their model close to reality, they discuss and analyze three different delivery, and selling priority policies, for a total of nine combinations of inventory management policies. An exact branch-and-cut algorithm is developed to solve the model, which can significanlty improve the current operating conditions of a food company located in China. The use of different work scenarios allows the identification of useful managerial implications. With the aim to determine an integrated food production, inventory, and distribution plan, Li et al., (2019) formulate a bi-objective MILP model which considers two main objectives: the minimization of production, inventory, and transportations costs, the maximization of average food quality. The high computational complexity of the problem requires the use of heuristic approaches to solve it in a reasonable time. Therefore, the authors propose an ε-constraint-based two-phase iterative heuristic and a fuzzy logic method. The computational results, carried out on a case study and on a set of randomly generated instances, show the goodness of the proposed approach. Chan et al., (2020) propose an MILP model which aims to balance the following three P's in the food supply chain: profit, people, planet. In fact, multiple objectives are jointly taken into account: maximization of the average food quality, minimization of the amount of CO_2 emissions, minimization of the total weighted delivery time, minimization of the total expense of the system (i.e., fixed and variable production cost, total inventory cost, total routing cost). A particle swarm optimization algorithm is proposed to solve efficiently a real-life case, which refers to a meat supply chain. Manoucheri et al., (2020) focus their attention on product quality, and on warehouse and vehicle temperature. The proposed production-inventory-routing problem is solved through a hybrid search algorithm, which combines the advantages of the variable neighborhood search and simulated annealing. The application to a real chicken-packing plant in Iran reveals the opportunity to reduce distribution and inventory costs, and minimizing food waste. A sensitivity analysis is carried out to determine the most suitable temperature for vehicles and warehouse. Li et al., (2020) consider a multi-plant perishable-food production-routing problem. Since, in many real-life situations, the package can influence the quality decay rate of the food products, they integrate the package selection decision within a MILP model, which is solved by a hybrid matheuristic. The results of the computational experience show that integrating package selection into the production routing planning is profitable. Moreover, a study on different discount policies is carried out, in order to understand how they impact the profit.

Some considerations can be drawn from the above literature review. First of all, the most significant contributions about the production-inventory-routing problem in the case of perishable products are recent, then this topic is currently of great interest in the scientific landscape. This aspect is also highlighted in Chapter 2. Moreover, the review shows that, as regards the production activities, there is no focus on the harvesting of perishable agri-products. Then, as far as is known, this Chapter can represent one of the first attempts at an integrated harvesting-inventory-distribution model.

As regards the concept of collaboration (Gansterer and Hartl, 2018), traditionally more emphasis has been given to the vertical collaboration (Vlachos et al., 2008; Treitl et al., 2014; Son and Ghosh, 2020), while the horizontal collaboration (Krajewska et al., 2008; Fernandez et al., 2016; Soysal et al., 2018) has been less explored over the years.

4.3. Problem Description and Model Formulation

In the following, two optimization models are introduced. The first one aims to support in an integrated way the decision-making about the harvesting, storage, and distribution activities of a single-supplier. The second one manages horizontal collaboration between two or more suppliers, as regards the distribution activities. The need for horizontal collaboration between suppliers arises given their heterogeneous and therefore not competitive nature, but also because they have in common some of the customers of the network. The two mathematical models have as their main motivation the case study that will be presented later.

4.3.1. Model for single supplier

The current Chapter refers refer to harvesting, storage, and distribution issues faced by an agricultural company, along a discrete time horizon $\mathcal{T} = \{1, 2, \ldots, T\}$, which belongs to the harvesting/distribution season, prior to which planting and growing of crop occur. A generic period index is denoted by $t \in \mathcal{T}$.

The company, which deals with a single perishable agri-product, has contractual obligations to a main customer, but can also exploit the favorable opportunities offered by spot customers. The main customer has a set of distribution centers (DCs) to be served along $\mathcal{T}$. The company agrees with the main customer a planting plan, in order to guarantee the availability of the product to the DCs during $\mathcal{T}$. ρ is the unit production cost, which takes into account planting and growing activities. Based on the planting plan, $\bar{Q}_w$ indicates the amount of product, which is ripe to be harvested during the week w of $\mathcal{T}$. The harvesting activities can be carried out γ days per week and each harvesting day implies a fixed cost η, related to the rental of specialized equipment. Each product unit (kg), once harvested can be immediately shipped to the customers or stored for later deliveries. The depot has a capacity I_{max}, each product unit has a storage cost per period h_t and is arranged according to its age s ($s = 1$ means fresh product, $s = 2$ means that the product was harvested yesterday, etc.). According to company policies, the product cannot be stored for more than τ time periods, after which it must be discarded. Disposal costs are not taken into account explicitly. The freshness of the product determines its market value, then $\bar{p}_t^s$ and b_t^s ($b_t^s > \bar{p}_t^s$) indicate the unit selling price of product of age s at period t, to the main customer and spot customers, respectively. A reward β can be earned by the company for each product unit shipped to the main customer, depending on the quality of service. This latter is related to the agreed daily shipping time limit θ, and/or to the agreed fraction δ of the demand, which must be guaranteed to each DC at each period. Therefore, the unit revenue p_t^s of product of age s at period t can be computed as follows:

$$p_t^s = \bar{p}_t^s + \beta(\theta, \delta) \qquad t = 1, \ldots, T, \qquad s = 1, \ldots, \tau \qquad (1)$$

The amount of product marketable at each period depends on the market demand; D_{tj} represents the demand by the distribution center j at period t, while G_t is the demand by spot customers at period t.

K vehicles, each vehicle k having the same load capacity L, are available for the distribution to the DCs. The set of customers (i.e., DCs) is denoted by $\mathcal{V} = \{1,2, \dots, V\}$, while 0 is the node-depot of the company. Then, the problem can be defined on a complete graph $G = \{\mathcal{N}, \mathcal{A}\}$, where $\mathcal{N} = \mathcal{V} \cup \{0\}$ is the set of nodes, while $\mathcal{A} = \{(i,j): i,j \in \mathcal{N}, i \neq j\}$ is the set of arcs. d_{ij} and t_{ij} are the kilometric distance of the arc (i,j) and the time to travel it, respectively. Fuel and driver cost define the overall routing cost. α is the fuel price per kilometer, while λ is the wage rate per minute for the drivers. There are no routing or distribution costs for spot customers sales. In Table 125, the notation of all problem data is shown.

Table 125. Notation of all the problem data

$\mathcal{T}$	Harvesting/distribution time horizon, with $\mathcal{T} = \{1, \dots, T\}$;
$\mathcal{W}$	Set of weeks of the harvesting/distribution time horizon, with $\mathcal{W} = \{1, \dots, W\}$;
$\bar{T}_w$	Set of days of week w;
$\mathcal{V}$	Set of DCs of the main customer, with $\mathcal{V} = \{1, 2, \dots, V\}$;
$\mathcal{N}$	Set of nodes, including the company 0, with $N = \mathcal{V} \cup \{0\}$;
$\mathcal{A}$	Set of arcs, with $\mathcal{A} = \{(i,j): i,j \in \mathcal{N}, i \neq j\}$;
$\mathcal{K}$	Set of vehicles, with $\mathcal{K} = \{1,2, \dots, K\}$;
L	Load capacity of each vehicle;
d_{ij}	Kilometric distance between node i and node j, $(i,j) \in A$;
t_{ij}	Time distance in minutes between node i and node j, $(i,j) \in A$;
α	Fuel price per kilometer;
λ	Wage rate per minute for the drivers;
$\bar{Q}_w$	Amount of ripe product at week w;
$\bar{p}_t^s$	Unit selling price of product of age s at period t to the main customer;
p_t^s	Unit revenue of product of age s at period t to the main customer;
D_{tj}	Demand of product at period t by DC j;
h_t	Unit storage cost at period t;
τ	Maximum storage time;
δ	Fraction of demand of the main customer to be satisfied at each period (i.e., service level)

M_1, M_2	Sufficiently high constants;
b_t^s	Unit selling price of product of age s at period t to the spot customer;
G_t	Demand of product at period t by spot customers;
I_{max}	Inventory capacity;
θ	Daily shipping time limit, referring to the DCs of the main customer;
β	Unit reward related to the quality of service offered to the main customer;
ρ	Unit production cost;
η	Fixed daily harvesting cost (i.e., rental of specialized equipment);
γ	Number of harvesting days per week.

The goal is to maximize profit. Revenue depends on sales to the main customer and spot customer. Cost depends on the inventory management, the routing of the vehicles, the production (planting/growing) and harvesting activities. The decisions to be made at each period t concern the amount Q_t of product harvested, the amount y_{jkt}^s of product of age s shipped to distribution center j by vehicle k, the amount z_t^s of product of age s sold to spot customers. Binary variables r_t represent the possibility to choose whether or not to carry out the harvesting at each period. The inventory management is guaranteed by the variables I_t^s, which define the inventory level of product of age s at the end of period t. The inventory level at the beginning of the time horizon is supposed null. Continuous variables f_{jt} determine the time to serve DC-customer j at period t, while binary variables x_{ijkt} are active in case arc (i,j) is traveled by vehicle k at period t. In Table 126, the notation for the decision variables of the proposed optimization model is shown.

Table 126. Notation of all the decision variables

$Q_t \geq 0$	Amount of product harvested at period t;
$r_t \in \{0,1\}$	Binary variable equal to 1 if harvesting is made at period t;
$y_{jkt}^s \geq 0$	Amount of product of age s shipped to DC j by vehicle k at period t;
$I_t^s \geq 0$	Inventory level of product of age s at the end of period t;
$x_{ijkt} \in \{0,1\}$	Binary variable equal to 1 if vehicle k travels arc (i,j) at period t;
$f_{jt} \geq 0$	Time to serve DC j at period t;
$z_t^s \geq 0$	Amount of product of age s sold at period t to spot customers.

Next, the model formulation is introduced:

$$\text{Max} \quad \sum_{j\in\mathcal{V}}\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{s=1}^{\tau} p_t^s y_{jkt}^s + \sum_{t=1}^{T}\sum_{s=1}^{\tau} b_t^s z_t^s - \sum_{t=1}^{T}\sum_{s=1}^{\tau} h_t I_t^s$$
$$-\alpha \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{(i,j)\in\mathcal{A}} d_{ij}x_{ijkt} - \lambda \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{(i,j)\in\mathcal{A}} t_{ij}x_{ijkt}$$
$$-\rho\sum_{t=1}^{T} Q_t - \eta\sum_{t=1}^{T} r_t \qquad (2)$$

$$\text{s.t.} \quad \sum_{t\in\bar{T}_w} Q_t = \bar{Q}_w \qquad w = 1, \dots, W \qquad (3)$$

$$\sum_{t\in\bar{T}_w} r_t = \gamma \qquad w = 1, \dots, W \qquad (4)$$

$$Q_t \leq M_1 r_t \qquad t = 1, \dots, T \qquad (5)$$

$$\sum_{k=1}^{K}\sum_{s=1}^{\tau} y_{jkt}^s \leq D_{tj} \qquad t = 1, \dots, T, j \in \mathcal{V} \qquad (6)$$

$$\sum_{k=1}^{K}\sum_{s=1}^{\tau} y_{jkt}^s \geq \delta D_{tj} \qquad t = 1, \dots, T, j \in \mathcal{V} \qquad (7)$$

$$\sum_{s=1}^{\tau} z_t^s \leq G_t \qquad t = 1, \dots, T \qquad (8)$$

$$I_0^s = 0 \qquad s = 1, \dots, \tau \qquad (9)$$

$$I_t^1 = Q_t - \sum_{j\in\mathcal{V}}\sum_{k=1}^{K} y_{jkt}^1 - z_t^1 \qquad t = 1, \dots, T \qquad (10)$$

$$I_t^s = I_{t-1}^{s-1} - \sum_{j\in\mathcal{V}}\sum_{k=1}^{K} y_{jkt}^s - z_t^s \qquad t = 1, \dots, T, s = 2, \dots, \tau \qquad (11)$$

$$\sum_{s=1}^{\tau} I_t^s \leq I_{max} \qquad t = 1, \dots, T \tag{12}$$

$$\sum_{k=1}^{K} \sum_{j \in \mathcal{V}} x_{0jkt} = \sum_{k=1}^{K} \sum_{i \in \mathcal{V}} x_{i0kt} \qquad t = 1, \dots, T \tag{13}$$

$$\sum_{j \in \mathcal{V}} x_{0jkt} \leq 1 \qquad t = 1, \dots, T, k = 1, \dots, K \tag{14}$$

$$\sum_{i \in \mathcal{N}, i \neq j} x_{ijkt} = \sum_{i \in \mathcal{N}, i \neq j} x_{jikt} \qquad t = 1, \dots, T, k = 1, \dots, K, \; j \in \mathcal{V} \tag{15}$$

$$\sum_{j \in \mathcal{V}} \sum_{s=1}^{\tau} y_{jkt}^s \leq L \qquad t = 1, \dots, T, k = 1, \dots, K \tag{16}$$

$$y_{jkt}^s \leq L \sum_{i \in \mathcal{N}, i \neq j} x_{ijkt} \qquad t = 1, \dots, T, k = 1, \dots, K, \; j \in \mathcal{V}, s = 1, \dots, \tau \tag{17}$$

$$x_{ijkt} \leq \sum_{s=1}^{\tau} y_{jkt}^s \qquad i \in \mathcal{N}, j \in \mathcal{V}: i \neq j, \; t = 1, \dots, T, k = 1, \dots, K \tag{18}$$

$$\sum_{k=1}^{K} \sum_{i \in \mathcal{N}: i \neq j} x_{ijkt} \leq 1 \qquad j \in \mathcal{V}, t = 1, \dots, T \tag{19}$$

$$f_{0t} = 0 \qquad t = 1, \dots, T \tag{20}$$

$$f_{jt} \geq f_{it} + t_{ij} x_{ijkt} - M_2 (1 - x_{ijkt}) \qquad i \in \mathcal{N}, j \in \mathcal{V}: i \neq j \; t = 1, \dots, T, k = 1, \dots, K \tag{21}$$

$$f_{jt} \leq \theta \qquad j \in \mathcal{V}, t = 1, \dots, T \tag{22}$$

$$Q_t \geq 0 \qquad t = 1, \dots, T \tag{23}$$

$$r_t \in \{0,1\} \qquad t = 1, \dots, T \tag{24}$$

$$y_{jkt}^s \geq 0 \qquad j \in \mathcal{V}, t = 1, \dots, T, \; k = 1, \dots, K, s = 1, \dots, \tau \tag{25}$$

$$I_t^s \geq 0 \qquad t = 0, \dots T, s = 1, \dots, \tau \tag{26}$$

$$x_{ijkt} \in \{0,1\} \qquad (i,j) \in A, k = 1, \dots, K \; t = 1, \dots, T \tag{27}$$

$$f_{jt} \geq 0 \qquad j \in \mathcal{V}, t = 1, \dots, T \tag{28}$$

$$z_t^s \geq 0 \qquad t = 1, \dots, T, s = 1, \dots, \tau \tag{29}$$

The objective function (2) maximizes the profit and comprises seven parts: revenue from the main customer, revenue from spot customers, inventory cost, fuel and driver cost (i.e., routing cost), production cost, harvesting cost. Constraints (3) and (4) regulate the amount of daily harvested product. The consistency between harvesting variables (Q_t) and harvesting frequency variables (r_t) is ensured by constraints (5). Constraints (6) and (7) state that the amount of product shipped to the DCs must not exceed their demand and must be consistent with the agreed service level at each period, respectively. Constraints (8) ensure that the demand of spot customers is not exceeded at each period. Constraints (9)-(12) regulate the inbound/outbound mechanism of product to/from the inventory, considering its limited capacity and the assumed initial null level. Constraints (13)-(14) and (15) guarantee the flow balancing on the depot of the company and on each node-customer, respectively. Constraints (16) ensure that the load capacity of each vehicle is not exceeded at each period. Constraints (17)-(18) guarantee the consistency between the variables x_{ijkt} and y_{jkt}^s. Constraints (19) prevent the split delivery for each customer, at each period. Constraints (20)-(21) take into account the time to serve each customer and ensure the subtour elimination. Constraints (22) set a time limit within which each customer must necessarily be served at each period. Constraints (23)-(29) are on the nature of the decision variables.

This model is referred as M_{SS} in the remainder of this Chapter.

4.3.2. Model for horizontal collaboration between suppliers

This subsection refers to the possibility of horizontal collaboration between multiple suppliers, who have in common some or all customers. In this context, the main hypothesis is that all suppliers are heterogeneous, that is, not competing with each other. Collaboration is a strategic decision that, in many cases, can lead to a significant reduction in operational costs. Given a set $\mathcal{C} = \{1,2, \dots, C\}$ of supplier companies, collaboration, as intended in this study, implies that one of them makes available its own fleet, and the depot as hub for deliveries. Basically, the remaining $(C-1)$ companies, called spoke-suppliers, send their goods to the hub, where the transshipment of goods from their vehicles to those of the hub is carried out, with the aim of optimizing the routing.

The problem can be defined on a complete graph $G' = \{\mathcal{N}', \mathcal{A}'\}$. The set of all customers (i.e., DCs) is denoted by $\mathcal{V}' = \{1,2, \dots, V'\}$, while 0 is the node-hub. Therefore, $\mathcal{N}' = \mathcal{V}' \cup \{0\}$ is the set of nodes, while $\mathcal{A}' = \{(i,j): i,j \in \mathcal{N}', i \neq j\}$ is the set of arcs. The set of customers of company c is referred as $\mathcal{V}'_c \subset \mathcal{V}'$. d'_{ij} and t'_{ij} are the kilometric length of the arc (i,j) and the time to travel it, respectively.

K' vehicles, each vehicle k having the same load capacity L', are made available by the hub-supplier for the distribution of goods. σ_c and ψ_c are respectively the fixed fuel and driver cost that the spoke-supplier c must bear for the depot-to-hub round trip. τ_c is the maximum storage time according to the inventory policy of company c, while K_C is the number of vehicles owned by company c. Other company-related parameters are known from the solution of model M_{SS}^c for each supplier c, namely $\bar{y}_{jtc}$ and $\bar{K}_{tc}$. $\bar{y}_{jtc}$ is the optimal amount of product to be shipped to DC j at period t by supplier c, and can be formally defined as follows:

$$\bar{y}_{jtc} = \sum_{s=1}^{\tau_c} \sum_{k=1}^{K_c} \tilde{y}_{jkt}^{s} \qquad j \in \mathcal{V}'_c, t = 1, \dots, T \qquad (30)$$

Where $\tilde{y}^s_{jkt}$ is the optimal value of y^s_{jkt}. $\overline{K}_{tc}$ is instead the minimum number of vehicles, according to the load capacity, to be used by company c at period t to carry out the amount of product $\sum_{j\in\mathcal{V'}_c}\bar{y}_{jtc}$. Table 127 summarized the problem data.

Table 127. Model for horizontal collaboration: main data

$\mathcal{C}$	Set of companies, with $\mathcal{C} = \{1,2,\dots,C\}$;
$\mathcal{V}'$	Set of DCs to be served, with $\mathcal{V}' = \{1,2,\dots,V'\}$;
$\mathcal{N}'$	Set of nodes, including the hub 0, with $\mathcal{N}' = \mathcal{V}' \cup \{0\}$;
$\mathcal{A}'$	Set of arcs, with $\mathcal{A}' = \{(i,j): i,j \in \mathcal{N}', i \neq j\}$;
$\mathcal{V}'_c$	Subset of DCs to be served by company c;
$\mathcal{K}'$	Set of vehicles, with $\mathcal{K}' = \{1,2,\dots,K'\}$;
d'_{ij}	Kilometric distance between node i and node j, $(i,j) \in \mathcal{A}'$;
t'_{ij}	Time distance in minutes between node i and node j, $(i,j) \in \mathcal{A}'$;
σ_c	Fixed fuel cost for the depot-to-hub round trip by spoke-supplier c;
ψ_c	Fixed driver cost for the depot-to-hub round trip by spoke-supplier c;
$\bar{y}_{jtc}$	Amount of product to be shipped by company c to DC $j \in \mathcal{V}'_c$ at period t;
$\overline{K}_{tc}$	Number of vehicles to be used for the depot-to-hub round trip by spoke-supplier c at period t.

The goal is to minimize the overall routing cost. Decision variables x_{ijkt} and f_{jt} preserve the same meaning of M_{SS}, while variables y^s_{jkt} are re-defined to take into account the multi-supplier nature of the model. While, variables y_{jktc} represent the amount of product of supplier c shipped to DC j by vehicle k at period t.

In the following, the model formulation is introduced and then explained.

Max

$$\alpha\sum_{k=1}^{K'}\sum_{t=1}^{T}\sum_{(i,j)\in\mathcal{A}'} d_{ij}x_{ijkt} + \sum_{t=1}^{T}\sum_{c=1}^{C}\sigma_c\overline{K}_{tc}$$

$$+\lambda\sum_{k=1}^{K'}\sum_{t=1}^{T}\sum_{(i,j)\in\mathcal{A}'} t_{ij}x_{ijkt} + \sum_{t=1}^{T}\sum_{c=1}^{C}\psi_c\overline{K}_{tc} \quad (31)$$

s.t.
$$\sum_{k=1}^{K\prime} y_{jktc} = \bar{y}_{jtc} \qquad c = 1, \dots, C, t = 1, \dots, T \quad j \in \mathcal{V}'_c \tag{32}$$

$$\sum_{c=1}^{C} \sum_{j\in\mathcal{V}\prime_c} y_{jktc} \leq L' \qquad t = 1, \dots T, k = 1, \dots, K' \tag{33}$$

$$y_{jktc} \leq L' \sum_{i\in\mathcal{N}',i\neq j} x_{ijkt} \qquad c = 1, \dots, C, t = 1, \dots, T, \quad j \in \mathcal{V}'_c, k = 1, \dots, K' \tag{34}$$

$$x_{ijkt} \leq \sum_{c\in C:j\in\mathcal{V}\prime_c} y_{jktc} \qquad i \in \mathcal{N}', j \in \mathcal{V}' \quad t = 1, \dots, T, k = 1, \dots, K' \tag{35}$$

$$y_{jktc} \geq 0 \qquad t = 1, \dots T, k = 1, \dots, K' \quad c = 1, \dots, C, j \in \mathcal{V}'_c \tag{36}$$

The model is characterized by the above constraints and the following constraints, introduced in M_{SS} and now referred to the graph G': (13)-(15), (19)-(22), (27)-(28). The objective function (31) aims to minimize the routing costs, represented by four components: variable fuel cost, fixed fuel cost, variable driver cost, fixed driver cost. Constraints (32) guarantee that the demand from the distribution centers is met at each period. Constraints (33) ensure that the load capacity of each vehicle is not exceeded at each period. Constraints (34)-(35) ensure consistency between variables x_{ijkt} and y_{jktc}, whose non negativity is established by constraints (36).

In the remainder of this Chapter, this collaborative routing model is referred as M_{CR}.

4.4. Case study

With the aim to prove the usefulness and efficiency of the above introduced and explained optimization models, a real-life case study is considered. Two agricultural companies, located in the Southern Italy, deal with planting, growing, harvesting and distributing perishable crops to the same main contract customer, which has several distribution centers scattered throughout Italy, and they can also exploit the more profitable opportunities offered by spot customers. The two companies are respectively referred as C_1 and C_2, respectively. C_1 deals with broccoli, while C_2 with artichokes.

At the beginning of the season, the main customer decides the planting plan of the two supplier companies, in terms of scheduling and quantities, in order to have a balanced amount of goods along the harvesting/distribution season, which usually lasts from December to April. The main customer has seven DCs, which must be periodically supplied. C_1 and C_2 supply respectively five and four DCs, and they share two of them. A fleet of two vehicles with load capacity of 10,000 kg each is owned by C_1, while C_2 uses only one vehicle with load capacity of 4,000 kg for the distribution of the agricultural products.

Currently, the two companies have inefficiencies regarding the coordination of the harvesting, storage and routing activities. These three steps of the supply chain are characterized by conflicting objectives, then an integrated approach is desirable. Once mature, each agricultural product can be harvested within a certain time interval. Therefore, two first fundamental decisions are: how much to harvest at each time period and how often. Once harvested, each product unit can be stored taking into account the limited capacity of the inventory, or immediately sent (as fresh product) to the customers, based on their demand. The inventory capacity of C_1 and C_2 is 30,000 kg and 10,000 kg, respectively. The harvested products are perishable, that is, they are subject to deterioration of their physical state and to the reduction of value perceived by customers, over time. Therefore, they can be stored for a time period not longer than 4 days, based on the contractual agreements. Selling price varies with product age. The main customer recognizes a unit reward to the two suppliers, on the basis of the guaranteed service level, as follows:

$$\beta^{C_1}(\theta,\delta)\begin{cases}0.010\ €/Kg\ for\ \theta = 9\ hours, \delta = 0.85\\ 0.005\ €/Kg\ for\ \theta = 10\ hours, \delta = 0.85\\ 0.000\ €/Kg\ for\ \theta = 11\ hours, \delta = 0.85\end{cases}$$

$$\beta^{C_2}(\theta,\delta)\begin{cases}0.000\ €/Kg\ for\ \theta = 10\ hours, \delta = 0.75\\ 0.015\ €/Kg\ for\ \theta = 10\ hours, \delta = 0.85\end{cases}$$

Model M_{SS} was used for supporting C_1 and C_2 at the tactical and operational level. At the tactical level, in fact, the two companies are willing to determine the most profitable combination between the harvesting frequency and the quality of service guaranteed to the main customer. These are fundamental choices because impact all other decisions. At operational level, they need to be helped by a decision-support system in order to organize in an integrated manner their harvesting, inventory, and routing activities, and maximize profit, on a daily base.

Considering that C_1 and C_2 share a part of their customers, the possibility of horizontal collaboration for what concerns the distribution activities was also explored. In this context, Model M_{CR} was applied, which deals with the routing activities, but receives as input the quantities to be shipped from the solution of M_{SS}. The type of collaboration explored in this Chapter is such that C_2 sends the agricultural products to C_1, which takes care of the distribution to customers in exchange for a fee. There are two main reasons that motivated the analysis of this configuration. First of all, C_1 has a very high vehicle load capacity, which is often largely unused. Moreover, the two suppliers are not competitors, therefore they are aware that some form of collaboration could bring benefits to both, without negatively affecting their respective market share.

4.4.1. Instances

The instances, useful for proving the goodness of the proposed models, refer to a time horizon of six weeks between January and February, which is the most interesting and challenging period in terms of amount of harvested and shipped product, within the overall harvesting/distribution season of the fresh vegetables of this study. During the considered time interval, the amount of harvested broccoli and artichokes is usually around 360,000 kg and 100,000 kg, respectively.

In order to address the problem under different realistic scenarios, 10 instances per company have been generated. In particular, the following data have been generated by using a normal distribution with coefficient of variation equal to 0.10: $\bar{Q}_w, D_{tj}, G_t, p_t^s, b_t^s$. The mean of the amount of weekly ripe product has been set to 60,000 kg and 22,000 kg, respectively for C_1 and C_2. The mean of the daily demand from each DC has been set to 1,600 kg and 600 kg, respectively for the two suppliers, while about spot customers it has been set to 800 kg and 500 kg. The unit selling prices of the fresh product to the main customer has been estimated, from the historical data made available by the official website of the Italian Institute of Services for the Agricultural Food Market (Ismea, 2020). b_t^s has been generated assuming a 10 % increase in the price to the main customer. The perishable nature of the agricultural products of the case study has been taken into consideration, assuming a dependence of the market price on the age of the product, as shown in Figure 23. The two lines represent in what percentage the market value of the product decreases with increasing age: in the case of broccoli (i.e., light gray line), a decrease of 5 % per day has been considered, while this value is 2 % per day for artichokes (i.e., dark gray line).

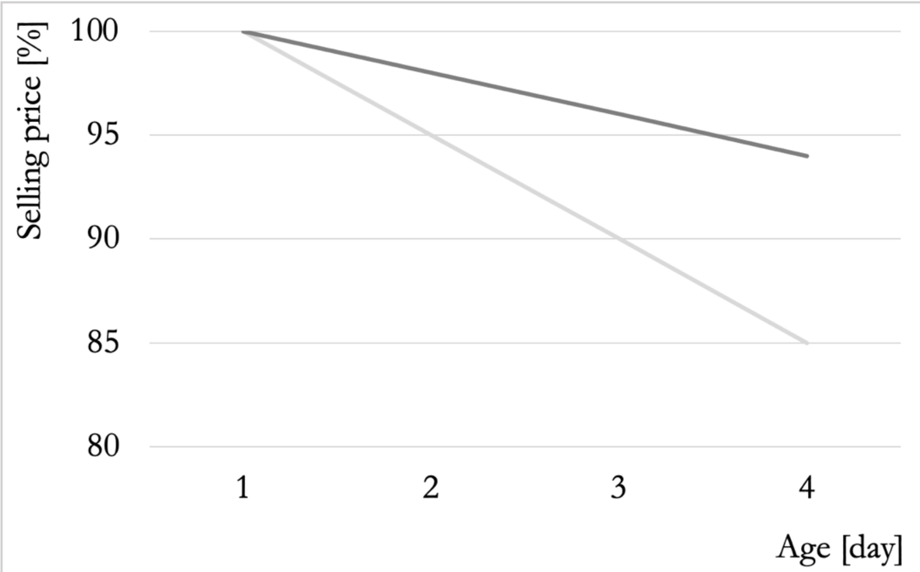

Figure 23. Selling price trend of broccoli and artichokes according to age

Table 128 shows the remaining relevant data, retrieved from the current operating conditions of the two companies. A hyphen means that there is no unique value for the data, then it can be varied within the case study.

Table 128. Case study: relevant data

	K	τ	I_{max}	ρ	η	α	λ	δ	θ	h
	[unit]	[day]	[Kg]	[€/Kg]	[€/day]	[€/Km]	[€/minute]	-	[hour]	[€/Kg]
C_1	2	4	30,000	0.10	800	0.30	0.15	0.85	-	0.03
C_2	1	4	10,000	0.15	500	0.30	0.15	-	10	0.10

In Tables 129-130 and 131-132, the spatial and temporal distance between nodes for the case of first and second supplier are respectively shown. They have been recovered from GoogleMaps, taking into account the shortest path between each pair of nodes and the traffic conditions that occur in the part of the day in which the shipment usually takes place.

Table 129. Spatial distance between nodes [Km], referring to the first supplier

	C_1	DC_1	DC_2	DC_3	DC_4	DC_5
C_1	0	392	433	55	277	619
DC_1	392	0	152	367	696	236
DC_2	433	152	0	405	583	337
DC_3	55	367	405	0	362	592
DC_4	277	696	583	362	0	851
DC_5	619	236	337	592	851	0

Table 130. Temporal distance between nodes [minute], referring to the first supplier

	C_1	DC_1	DC_2	DC_3	DC_4	DC_5
C_1	0	235	276	51	188	360
DC_1	235	0	113	222	406	152
DC_2	276	113	0	245	343	215
DC_3	51	222	245	0	226	344
DC_4	188	406	343	226	0	480
DC_5	360	152	215	344	480	0

Table 131. Spatial distance between nodes [Km], referring to the second supplier

	C_1	DC_1	DC_2	DC_3	DC_4
C_1	0	512	739	604	691
DC_1	512	0	236	103	272
DC_2	739	236	0	145	161
DC_3	604	103	145	0	182
DC_4	691	272	161	182	0

Table 132. Temporal distance between nodes [minute], referring to the second supplier

	C_1	DC_1	DC_2	DC_3	DC_4
C_1	0	295	432	369	422

DC_1	295	0	144	73	171
DC_2	432	144	0	98	113
DC_3	369	73	98	0	124
DC_4	422	171	113	124	0

4.4.2. Computational experience and managerial insights – tactical level

The computational experiments have been carried out on a PC running Windows 10 Pro with AMD Ryzen 7 2700X Eight-Core Processor 4.00 GHz/16GB. The proposed optimization model has been solved by CPLEX 12.7, Academic License.

4.4.2.1. Single-supplier model

At the tactical level, M_{SS} has been adopted, with the aim to determine the most profitable combination of two important parameters: the harvesting frequency (i.e., number of harvesting days per week) and the quality of service guaranteed to the DCs.

The choice of γ is quite critical in that, harvesting very frequently corresponds to increase the costs related to the renting of the specialized harvesting equipment, but it allows to ship fresh products quite often; on the other hand, harvesting only in a few days of the week entails greater use of the warehouse to stock up and delivery of products with an average higher age (i.e., lower market value). Six alternatives have been explored, namely $\gamma \in \{2,3,4,5,6,7\}$. Observe that $\gamma = 1$ is not feasible because $\tau = 4$ is not enough to ensure that DCs demand can be met every day.
Moreover, the services level, that maximized the profit, has been determined. In this case, $\theta \in \{9,10,11\}$ and $\delta \in \{0.75, 0.85\}$ have been explored for the two companies, respectively. Observe that the values to be contractually guaranteed are respectively $\theta = 11$ hours and $\delta = 0.75$, but some rewards are ensured in order to encourage the decrease of θ and the increase of δ.

In Tables 133-135, the computational results of the experiments carried out on the 10 instances generated with reference to the first supplier, are reported. The average value of 10 KPIs is highlighted. The first eight KPIs characterize the objective function (2) of M_{SS}. Moreover, the tables show the number of trips and the average age of the product shipped to the main customer and spot customers.

Table 133. Average KPIs for the case of $\theta = 9$ hours (C_1 – first supplier)

KPI	γ					
	2	3	4	5	6	7
Revenue Main [€]	119,336.27	123.304,78	124,484.04	125,568.56	125,946.92	125,724.96
Reward Main [€]	3,282.25	3,287.55	3,274.44	3,277.89	3,270.17	3,252.99
Revenue Spot [€]	11,920.63	12,287.85	13,014.80	12,961.07	13,369.76	14,153.24
Inventory Cost [€]	13,585.96	7,049.99	4,152.71	2,550.25	1,360.49	678,69
Fuel Cost [€]	22,897.35	22,894.17	22,894.26	22,894.17	22,894.26	22,894.17
Driver Cost [€]	7,172.04	7,170.87	7,171.14	7,170.87	7,171.14	7,170.87
Production Cost [€]	36,341.34					
Harvesting Cost [€]	9,600.00	14,400.00	19,200.00	24,000.00	28,800.00	33,600.00
Number of trips [unit]	75.10	75.10	75.10	75.10	75.10	75.10
Average product age [day]	2.18	1.62	1.37	1.22	1.10	1.02
Profit [€]	44,942.56	51,023.81	51,013.84	48,850.89	46,019.62	42,446.12

Table 134. Average KPIs for the case of $\theta = 10$ hours (C_1 – first supplier)

KPI	γ					
	2	3	4	5	6	7
Revenue Main [€]	119,280.69	123,288.01	124,382.05	125,457.42	125,893.95	125,725.60
Reward Main [€]	1,640.31	1,643.21	1,635.84	1,637.65	1,634.26	1,626.49
Revenue Spot [€]	11,976.92	12,331.40	13,127.04	13,072.11	13,436.19	14,153.24
Inventory Cost [€]	13,594.38	7,093.31	4,171.01	2,556.52	1,380.45	680,04
Fuel Cost [€]	20,513.85	20,507.28	20,517.18	20,507.22	20,509.71	20,509.71
Driver Cost [€]	6,520.79	6,517.62	6,521.78	6,517.58	6,518.81	6,518.81
Production Cost [€]	36,341.34					
Harvesting Cost [€]	9,600.00	14,400.00	19,200.00	24,000.00	28,800.00	33,600.00
Number of trips [unit]	72.00	71.80	72.00	71.80	71.90	71.90
Average product age [day]	2.19	1.62	1.37	1.22	1.10	1.02
Profit [€]	46,327.57	52,403.08	52,393.63	50,244.52	47,414.10	43,855.43

Table 135. Average KPIs for the case of $\theta = 11$ hours (C_1 – first supplier)

KPI	γ					
	2	3	4	5	6	7
Revenue Main [€]	119,277.87	123,239.61	124,400.55	125,402.91	125,905.51	125,729.52
Reward Main [€]	0.00	0.00	0.00	0.00	0.00	0.00
Revenue Spot [€]	11,979.01	12,351.49	13,098.85	13,136.66	13,412.93	14,153.24

Inventory Cost [€]	13,587.89	7,056.84	4,159.49	2,561.87	1,363.99	686.19
Fuel Cost [€]	20,210.28	20,194.41	20,196.75	20,194.35	20,196.30	20,195.55
Driver Cost [€]	6,429.46	6,425.54	6,425.69	6,424.73	6,426.14	6,425.03
Production Cost [€]			36,341.34			
Harvesting Cost [€]	9,600.00	14,400.00	19,200.00	24,000.00	28,800.00	33,600.00
Number of trips [unit]	68.50	68.40	68.40	68.30	68.40	68.30
Average product age [day]	2.19	1.62	1.37	1.22	1.10	1.02
Profit [€]	45,087.91	51,172.98	51,176.14	49,017.28	46,190.68	42,634.65

First of all, it is very important to highlight that that the average profit, once fixed θ, initially increases as the harvesting frequency increases until it reaches the peak when $\gamma \in \{3,4\}$. Then, it starts to significantly decrease. The reasons behind this trend are multiple. As it can be noted, the increase in the harvesting frequency has two main effects: the revenue (main and spot) increases because the average age of the product delivered decreases, while storage costs decrease significantly. These two benefits are "paid" through the increase in harvesting costs. When $\gamma \in \{5,6,7\}$, the benefits obtained can no longer offset the additional costs of the harvesting, therefore the average profit significantly reduces. Note that the routing costs remain constant because all the parameters related to the distribution activities remain unchanged. Next, it is critical to also analyze how KPIs change, by fixing γ and varying θ. Here, there are two main contrasting effects: the reward insured by the main customer, and the routing costs. The reward pushes towards a reduction of the daily time limit, but this entails a significant increase in the routing costs because the flexibility in the choice of the routes is reduced (observe that, as expected, the number of trips reduces as θ increases). Basically, it is possible to state that when θ is equal to 10 hours, the additional revenue from the main customer is enough to cover the increase in routing costs and to guarantee the best profitability. At the tactical level, the use of M_{SS} referring to S_1, suggests then the following setting: $\gamma = 3$ and $\theta = 10$. Observe that, when $\gamma \in \{3,4\}$, the average profit is very similar. However, when the harvesting frequency is three days per week, the average quality of the product shipped is higher, and this aspect could favor customer's satisfaction and loyalty in the mid-long term.

In Tables 136-137, the computational results (average values) of the experiments conducted on the 10 instances related to C_2 are shown.

Table 136. Average KPIs for the case of $\delta = 0.75$ (C_2 – second supplier)

KPI	γ					
	2	3	4	5	6	7
Revenue Main [€]	78,878.70	79,015.54	79,048.03	78,371.14	76,767.99	76,219.58
Reward Main [€]	0.00	0.00	0.00	0.00	0.00	0.00
Revenue Spot [€]	14,363.05	15,320.20	15,604.37	16,385.33	17,908.06	18,301.31
Inventory Cost [€]	11,245.55	6,088.89	3,883.02	2,462.91	1,329.36	798.99
Fuel Cost [€]	19,081.74	19,081.74	19,081.74	19,081.74	19,081.74	19,081.74
Driver Cost [€]	5,835.63	5,835.63	5,835.63	5,835.63	5,835.63	5,835.63
Production Cost [€]	10,193.62					
Harvesting Cost [€]	7,200.00	10,800.00	14,400.00	18,000.00	21,600.00	25,200.00
Number of trips [unit]	41,70	41.70	41.70	41.70	41.70	41.70
Average product age [day]	2.02	1.56	1.35	1.23	1.13	1.08
Profit [€]	39,685.21	42,335.75	41,258.39	39,182.57	36,635.70	33,410.91

Table 137. Average KPIs for the case of $\delta = 0.85$ (C_2 – second supplier)

KPI	γ					
	2	3	4	5	6	7
Revenue Main [€]	81,140.74	81,611.02	81,650.38	80,280.37	79,846.40	79,279.38
Reward Main [€]	1,368.48	1,361.19	1,353.19	1,338.96	1,325.22	1,315.94
Revenue Spot [€]	11,439.08	12,254.63	12,570.39	13,562.64	14,414.08	14,699.79
Inventory Cost [€]	11,624.28	6,360.80	4,048.40	2,588.84	1,385.03	719.20
Fuel Cost [€]	19,081.74	19,081.74	19,081.74	19,081.74	19,081.74	19,081.74
Driver Cost [€]	5,835.63	5,835.63	5,835.63	5,835.63	5,835.63	5,835.63
Production Cost [€]	10,193.62					
Harvesting Cost [€]	7,200.00	10,800.00	14,400.00	18,000.00	21,600.00	25,200.00
Number of trips [unit]	41.70	41.70	41.70	41.70	41.70	41.70
Average product age [day]	2.05	1.57	1.36	1.23	1.13	1.08
Profit [€]	40,013.02	42,955.04	42,015.23	40,022.14	37,486.49	34,264.93

When the service level is fixed, the profit varies by varying γ. As the harvesting frequency increases, most of the shipments concern the fresh product, therefore the storage costs decrease drastically. The overall revenue increases because the product delivered is on average "younger" and then better paid. In particular, profit is maximized when γ is equal to 3. If the service level is varied, a reward must be taken into account when δ=0.85. In this case, the larger amount of product to be guaranteed daily to the main customer implies the loss of some market opportunities offered by spot customers. However, the revenue increase from the main customer is higher than the revenue decrease from spot customers, therefore this solution is more convenient, whatever the harvesting frequency. It should be noted that in any case the routing costs do not vary, as parameters related to distribution remain unchanged. Basically, with reference to the second supplier, the proposed optimization model M_{SS} suggests the setting $\gamma = 3$ and δ=0.85.

4.4.2.2. Collaboration between suppliers

Since suppliers $C_1$and C_2 are geographically very close and share two customers, at the tactical level the possibility of collaboration in the distribution of goods has been also explored. In particular, M_{CR} has been solved, by using as input the output of M_{SS} in terms of amount to be shipped to each DC by each supplier at each period. This means that the decisions about harvesting and storage are fixed, while new solutions are possibile for the routing phase. Figure 24 shows a graphical example of horizontal collaboration between the two suppliers. Basically, C_2 sends its goods to C_1 incurring a routing cost for the round trip from its depot to that of the other supplier, which acts as a hub. At the hub, the goods are transferred from the C_2 vehicle to the C_1 fleet, which deals with the delivery of the agri-products to the DCs in exchange for a fee.

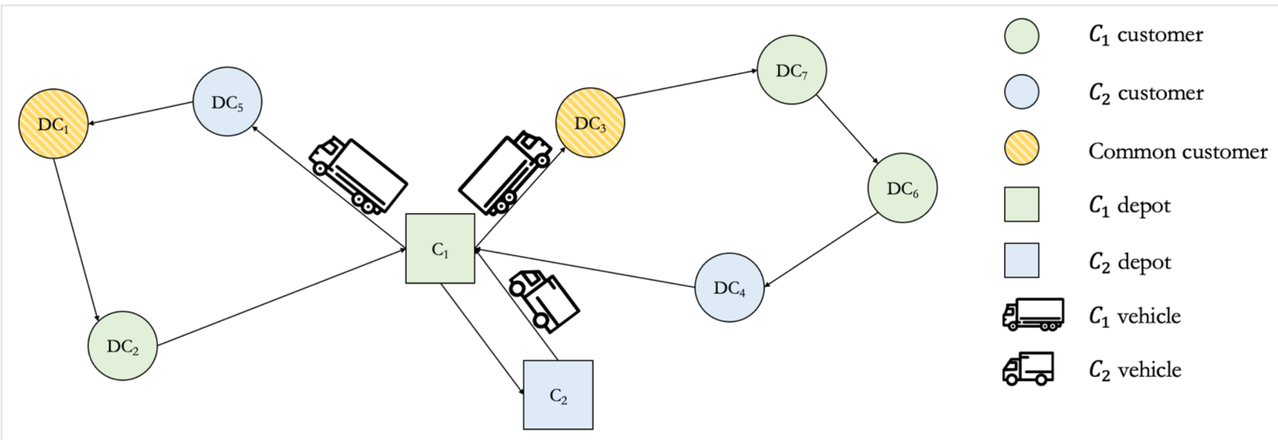

Figure 24. Graphical example of horizontal collaboration between the two suppliers of the case study

M_{CR} has been solved on ten datasets, obtained by randomly combining the ten instances generated for the two companies, and under the most profitable parameter setting, according to the discussion made in the previous subsection. The only exception was that, the time limit was fixed to 11 hours for the DCs of C_1, which are not shared with C_2, in order to guarantee the feasibility of the problem. Here, it was supposed to implement the horizontal collaboration in any period of the time horizon. The mean computational time was around 15 secs, that is a really acceptable value. In Figure 25, it is shown how the routing costs vary in the two cases of autonomous and collaborative distribution.

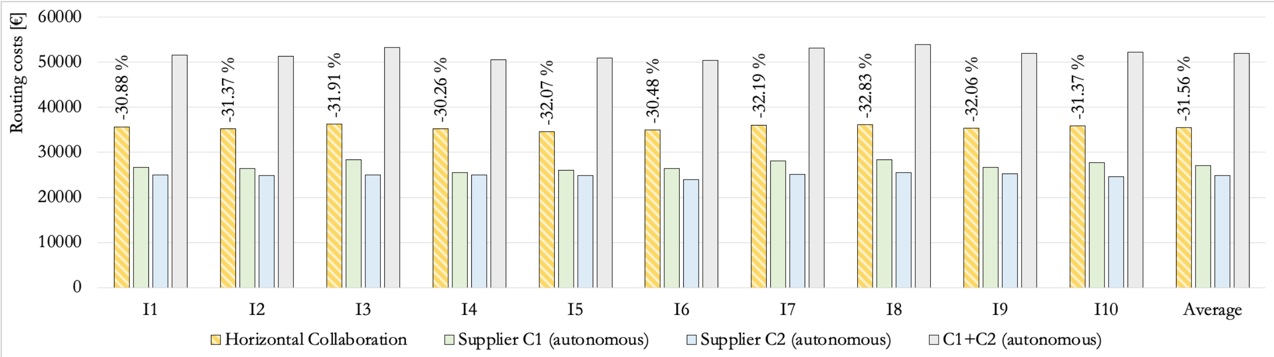

Figure 25. Routing costs [€] in the cases of autonomous and collaborative distribution

As it can be noted, the implementation of the collaborative routing leads to an average reduction in fuel and driver costs of 31.56 %, which corresponds to about 16,400 €. However, an important issue concerns the percentage of sharing of such saving between the two suppliers, which mainly depends on the amount of the fee that C_2 pays to C_1 for having the service. Figure 26 represents how the profit varies between the two suppliers, as the fee varies. If the service was performed free of charge by supplier C_1, this latter would incur a loss of approximately 5,600 € compared to non-collaboration, caused by the additional routing costs and the lack of reward from the main customer. Instead, C_2 would have to bear the only costs to move to and from the C_1 depot, therefore it would have a total saving of about 20,000 €. Looking at the graph, it is possible to state that a fee of at least 140 €/day is required for supplier C_1 to make profitable the collaboration with C_2. However, the amount of fee which makes collaboration, convenient in the same way for the two suppliers, is about 310 €/day because the average profit increase is distributed in the fairest way.

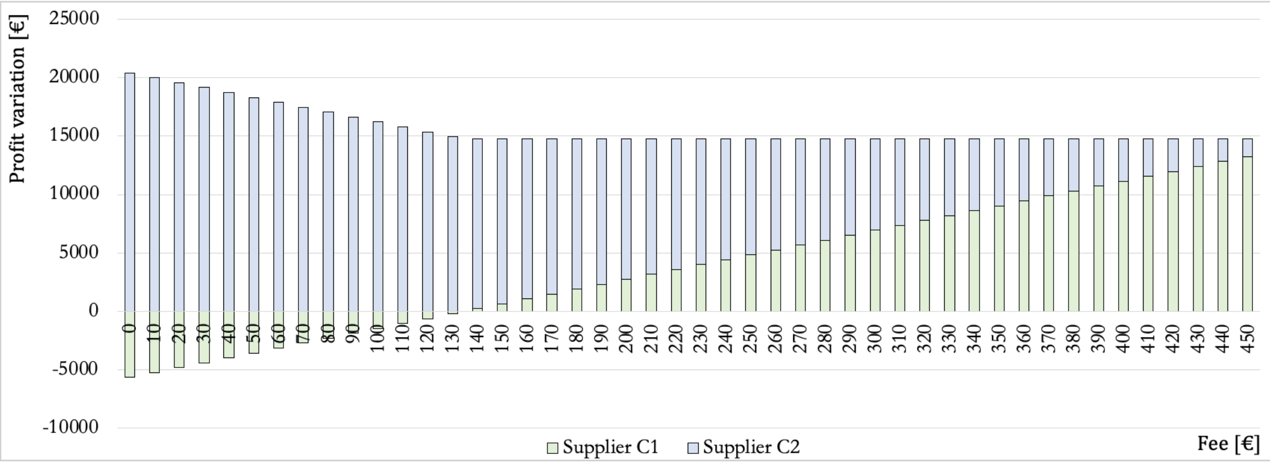

Figure 26. Average profit variation for the two suppliers, by varying the fee

4.4.3. Computational experience and managerial insights – operational level

At the operational level, the two companies must make 4 types of decisions, which are listed below:

- harvesting decisions: if and how much to harvest;
- inventory decisions: amount of product of each age to store;
- shipping decisions: amount of product of each age to ship to the main customer and spot customers;
- routing decisions: route to reach the different DCs.

With the aim to support the two suppliers operationally, a heuristic framework, represented in Figure 27, has been proposed.

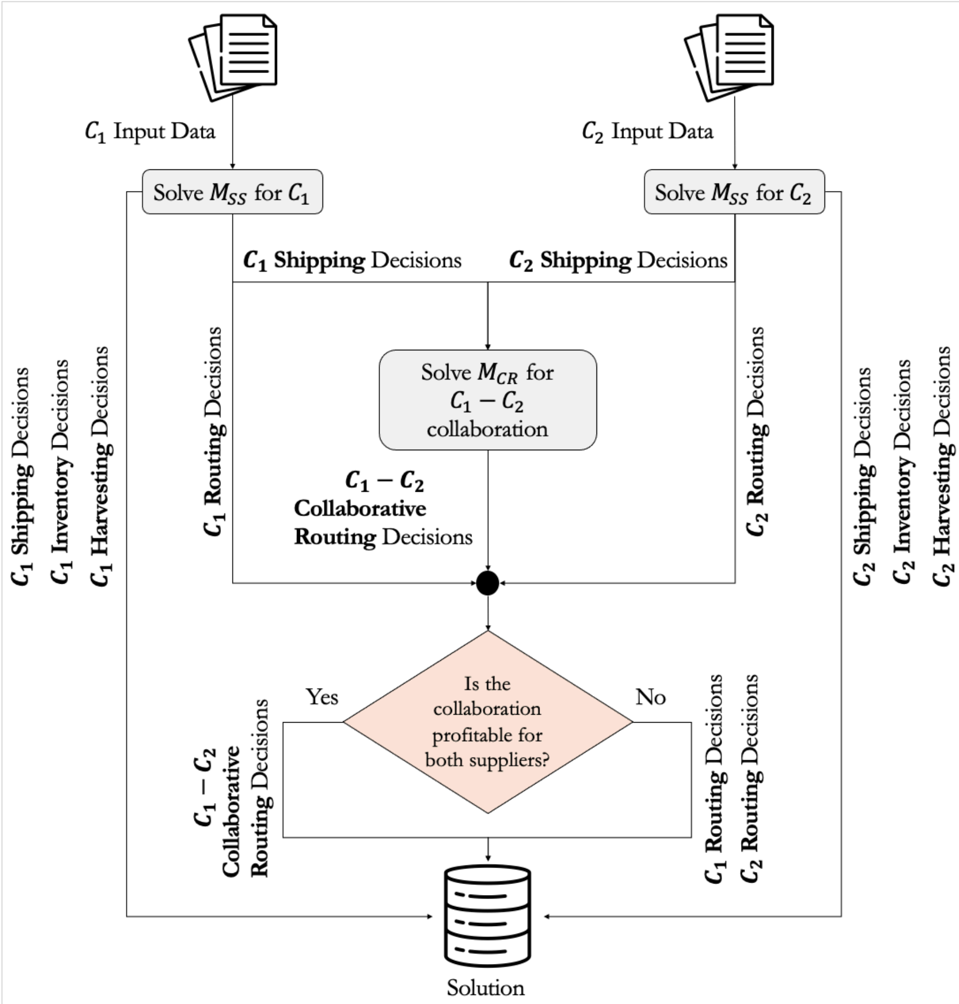

Figure 27. Heuristic framework for the operational level

The framework suggests the best decisions to maximize the overall profit and verifies if horizontal collaboration is convenient or not, once a daily fee ω has been fixed.

Given a well-defined time horizon, the first step is to solve Model M_{SS} separately for the two suppliers. The harvesting, inventory and shipping decisions, output of M_{SS} are inserted into the solution of the overall problem.

At the second step, Model M_{CR} is solved. It receives the shipping decisions as input and returns the collaborative routes and their relative cost.

At the third step, the profitability of the collaboration for both suppliers is checked. If yes, the routing decisions resulting from the M_{CR} model are inserted into the solution. Otherwise, the collaboration is not implemented and autonomous routing decisions, output of the respective models M_{SS}, are inserted into the overall solution.

At the operational level, Model M_{SS} has been solved separately for C_1 and C_2, on the ten instances generated for each company, and considering only one week as time horizon. Then, Model M_{CR} has been launched on the ten datasets, obtained by randomly combining the ten instances generated for each company. Three different scenarios, described in Table 138, have been considered in terms of fee that C_2 pays to C_1 for having the distribution service. The computational time was not longer than 2 minutes in all cases.

Table 138. Different scenarios for the operational level

Scenario	ω [€/day]
Sc1 - C_1 has less bargaining power than C_2	100.00
Sc2 - C_1 has greater bargaining power than C_2	500.00
Sc3 - C_1 and C_2 have the same bargaining power	310.00

In Table 139, the results of the computational experience at the operational level are summarized. The profit in case of autonomous distribution is compared with the three scenarios of collaborative distribution. As expected, the collaboration brings benefits for both suppliers according to all 3 scenarios. The first two scenarios favor the second and the first supplier respectively. While the third scenario allows the maximization of the benefits for both the companies, with an average increase in overall profit of 18.32 %. Observe that under the third scenario, collaboration is implemented on average in 94 % of the days (i.e., “yes” condition with reference to Figure 27), which means that it is almost always profitable for both companies. This percentage drops to 51 % and 44 % respectively for the first two scenarios.

Table 139. Profit comparison between autonomous and collaborative distribution under the three different scenarios

	Profit [€]		Profit increase [%]								
	Autonomy		Collaboration – Sc1			Collaboration – Sc2			Collaboration – Sc3		
	C_1	C_2	C_1	C_2	Total	C_1	C_2	Total	C_1	C_2	Total
I_1	7,142.65	7,414,50	1.04	8.19	4.68	16.25	0.86	8.41	13.03	15.04	14.06
I_2	5,332.24	1,314.29	3.45	100.69	22.68	12.57	3.77	10.83	25.05	78.00	35.52
I_3	9,363.34	3,591.73	1.65	55.66	16.62	13.46	1.58	10.17	16.14	35.70	21.56
I_4	9,589.83	4,583.81	0.78	27.52	9.43	18.45	2.49	13.29	11.09	25.74	15.83
I_5	10,656.91	7,734.92	1.13	19.41	8.82	2.80	0.34	1.76	12.13	15.09	13.38
I_6	6,679.89	1,981.08	1.00	37.98	9.46	9.36	2.27	7.74	13.48	52.40	22.38
I_7	12,762.68	577.99	0.73	203.52	9.51	6.72	8.57	6.80	10.36	217.77	19.35
I_8	4,235.38	4,508.95	5.08	64.68	35.82	61.68	3.11	31.48	39.79	32.08	35.82
I_9	15,232.41	3,969.68	0.57	36.00	7.89	9.50	2.00	7.95	9.16	30.82	13.64
I_{10}	10,251.36	4,542.15	0.67	17.45	5.82	7.97	1.67	6.03	8.01	23.91	12.89
Avg	9,124.64	4,021.91	1.25	34.21	11.33	12.62	1.74	9.29	13.43	29.40	18.32

Moreover, in the following, the benefits that collaboration can bring to the environment are briefly described, in terms of CO_2 emissions, whose conversion factor is estimated at 2.63 kg/l, as in (Soysal et al., 2018). In Figure 28, the amount of CO_2 emissions (kg) in the case of absence of collaboration between the two suppliers is compared with the 3 collaborative scenarios. Basically, the collaboration leads to a significant reduction in CO_2 emissions in all cases. In particular, in the third scenario there is an average reduction of over 31 %, which is one more reason to prefer collaborative routing.

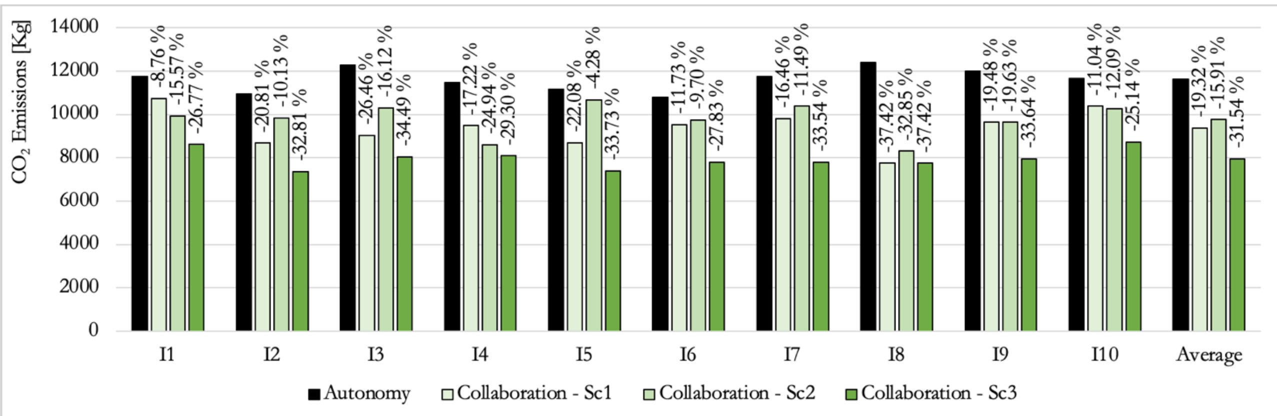

Figure 28. Comparison in terms of CO2 emissions reduction between autonomous and collaborative distribution

4.5. Short conclusions

This Chapter has dealt with the proposal of two optimization models to support the decision-making of two agri-companies, which produce and sell perishable products. In particular, their business concerns planting, growing, harvesting, inventory, and delivery management of fresh vegetables. They have a main contract customer, who has a set of DCs to be daily served, but they can also exploit the opportunities offered by a spot market. The first model aims to maximize profit of a single agri-company and concerns the integration and coordination of the harvesting, storage, delivery and routing decisions. Through a computational experience conducted on a set of real-life instances, it was possible to identify the most profitable parameter setting, in terms of the optimal number of days of the week to be dedicated to harvesting activities and the quality of service to be guaranteed to the customers. The second model instead allowed to explore and assess the benefits achievable from the horizontal collaboration between the two companies of the case study for what concerns the distribution activities. Computational experience under multiple scenarios reveals that overall savings on routing costs are up to 31-32 %. At the operational level a heuristic framework was presented and implemented in order to jointly support the two companies on a daily basis. An average increase in profit of around 18 % and a reduction in CO_2 emissions of up to 31 % are achievable.

5. Integrated production-distribution scheduling, with raw materials perishability and energy consumption

5.1. Brief introduction

Quantitative approaches for the integration of production and distribution planning in the supply chain are attracting the interest of scholars and companies in recent years (Kumar et al., 2020). In the past, there was the tendency to optimize locally every single stage of the supply chain. Recently, instead, research has been moving towards integrated approaches, with the aim to effectively deal with frequent market changes, customer needs, uncertainty (Fahimnia et al., 2013). Specifically, supply chain management is even more complex, when referring to the food context, as it is necessary to take into account additional features such as food quality and safety (Guido et al., 2020; Mirabelli and Solina, 2020), and raw material, semifinished and finished product perishability (Amorim et al., 2013). Considering the expected increase in food demand in the next years, it is crucial to protect sustainability and minimizing food waste. In this challenging context, production systems need to be efficiently managed, especially because energy cost is rising due to the considerable grow of energy demand in the last few years. In fact, the efficient use of energy resources leads to cost savings and reduction in greenhouse gas emissions (Gahm et al. 2016).

Therefore, the aim of this Chapter is to develop and test an optimization model to determine in an integrated manner the production and delivery plan for a company, which operates in the food sector. Energy, inventory and distribution costs are jointly minimized. Two production (re)scheduling strategies (Ouelhadj et al., 2009) are compared, where the first one reproduces the current behavior of the company.

5.2. Scientific background

Considering the topic of this Chapter, the literature review is divided into two main parts. The former collects energy-efficient scheduling models, while the latter concerns the coordination of production and distribution activities in the food supply chain.

5.2.1. Energy-efficient scheduling models

Electricity prices are extremely variable. Power suppliers usually charge higher electricity prices at peak hours, while more reasonable prices are proposed during mid-peak or off-peak hours (Gong et al., 2020). Through an efficient scheduling of production activities, it is possible to save on energy costs by limiting the activities carried out during peak hours. In the following, the most relevant energy-efficient scheduling models, based on the policy of time-of-use (TOU) electricity tariffs, are reviewed. The focus is only on papers which tackle single-machine and/or food-related problems.

A mathematical model to minimize energy consumption costs with reference to a single machine is proposed in (Shrouf et al., 2014). The framework takes into consideration the fluctuations in energy prices, and multiple machine states with own energy consumption: turning on, turning off, idle. Given the model complexity, a genetic algorithm is proposed to solve it. The authors show that heuristic solutions are preferable, especially when the size of the problem is considerable. The mathematical formulation proposed in (Shrouf et al., 2014) is improved in (Aghelinejad, 2016), with the aim to reduce the number of decision variables and make less time-consuming the problem. A MILP model is presented in (Angizeh et al., 2020) to optimize the operations of a real-world food production plant characterized by several production lines and product types. The aim is to minimize the total manufacturing cost, represented by electricity consumption and labor. An ILP is instead designed in (Ramos and Leal, 2017) to address a real-life problem with reference to a Portuguese food retail company. The main goal is to minimize the energy-cost for the production of flake ice, which is very important to preserve fish freshness in food retail stores. The proposed model, tested both on real and randomly generated instances, suggests the production of the best amount of ice at the right time, minimizing waste. The overall results show that it is possible to achieve an average annual saving greater than 30 %.

Several research works aim to jointly minimize two specific objectives, namely makespan and total energy costs. An integer programming model is presented in (Wang et al., 2016) to tackle a single-machine batch scheduling problem with non-identical job sizes. An ε-constraint method and two decomposition-based heuristic approaches are used to solve it. The computational experiments show the applicability of the proposed methods. An MILP model is instead proposed in (Cheng et al., 2017) to address a single-machine batch scheduling problem with machine on/off switching and TOU tariffs. A heuristic based - ε-constraint method is designed to solve efficiently the problem, especially the largest instances. An integrated production scheduling and maintenance planning problem under TOU tariffs is addressed in

(Cui et al., 2019). In this case, the two objectives (i.e., makespan and total energy costs) measure respectively the service level and energy sustainability. The problem is solved through a heuristic framework, characterized by two different layers. The first one (i.e., the inner) is based on a Branch & Bound Algorithm, and optimizes the maintenance decisions. The second one (i.e., the outer) refers to production scheduling and is solved by a hybrid NSGA-II algorithm. The Pareto frontier is used as a tool for supporting the decision-maker.

It is important to point out that more detailed information about decision support systems for energy-efficient production planning can be found in some recent and comprehensive surveys (Biel and Glock, 2016; Gahm et al., 2016).

5.2.2. Integrated production scheduling and distribution planning in the food supply chain

By coordinating production and distribution activities, it is possible to achieve a significant reduction in total operating costs (Chandra and Fisher, 1994). In the following, the most relevant papers, in which the integration of production scheduling and distribution planning, with reference to the food supply chain, is tackled, are reviewed.

The short production scheduling and distribution planning problem within the dairy industry is addressed in (Bilgen and Celebi, 2013). The authors develop an MILP model, which takes into account many real-life features such as sequence-dependent setup times, machine speeds, overtime, minimum and maximum lot-size, shelf life constraints. A hybrid methodology, based on the MILP formulation and a simulation approach, is designed to obtain the optimal production and delivery plan. A case study referring to a company located in Turkey shows the goodness of the proposed approach. A non linear mathematical model is proposed in (Chen et al., 2009) to simultaneously optimize production scheduling and vehicle routing with time windows in the case of perishable food products. The main features of the model are (i) customer demand stochasticity and (ii) finished products deterioration. The goal is the maximization of the expected total profit. Since the problem is computationally complex, a solution algorithm is developed, with good results. A framework for the integrated production-distribution planning problem, referring to multi-product and semi-continuous food processing industries, is proposed in (Kopanos et al., 2012). Changeover times between different product families are explicitly taken into account, and several transportation modes for the deliveries to the customers are compared. The efficiency of the designed approach is demonstrated through two industrial case studies, related to the yogurt sector in Greece. In (Devapriya et al., 2017), a MIP model is used to formulate the single plant, integrated production and distribution scheduling problem. The peculiarity is the perishable nature of the products, which significantly influences the delivery plan. Evolutionary approaches are developed and used to find good solutions for the problem, in reasonable time. The work is an extension of (Geismar et al., 2008). The operational integrated production and distribution planning problem with perishable products is addressed in (Belo-Filho et al., 2015). The main decisions concern line-assignment, lot-sizing/splitting, vehicle routing. The proposed adaptive large neighborhood search (ALNS) framework is very efficient and outperforms the traditional methods (i.e., exact methods, fix-and-optimize) in solving the problem.

More detailed information about integrated production-distribution models can be found in some comprehensive surveys (Kumar et al., 2020; Fahimnia et al., 2013).

5.3. Problem description and mathematical model

The Chapter refers to a make-to-order company, which deals with production, storage and distribution of food products along a discrete time horizon $\mathcal{D} = \{1, \dots, D\}$. Each day of the time horizon is denoted by $d \in \mathcal{D}$ and is divided into a set $\mathcal{S}$ of slots of equal time length. The firm has a single production line and deals with a set $\mathcal{P}$ of products, where a subset $\bar{\mathcal{P}}$ is characterized by highly perishable raw materials, which have a maximum storage time τ_p. We denote by α_p and r_p, respectively, the amount of energy consumption and the capacity of the line per slot, when product p is manufactured. The production line has a product setup β at the beginning of the planning horizon. The energy cost is subject to fluctuations throughout the day, then λ_{sd} is the energy price at slot s of day d. Once manufactured and before being delivered, the products are stored in the inventory, which has a capacity I_{max}. Moreover, h_p the daily unit storage cost referring to product p. Along the time horizon, C customers have to be served. K vehicles are available for the shipping stage, each having a load capacity l_k. An amount of θ_c shipments has to be guaranteed to customer c for each week w of the time horizon. The demand of product p by customer c at week w is denoted by dem_{pcw}, while γ_c^l is the cost for serving customer c by vehicle k. Deliveries are not allowed on some days $d \in \widetilde{\mathcal{D}}$. In Table 140, the notation of all problem data is shown.

Table 140. Notation of all problem data

$\mathcal{D}$	Set of days of the time horizon, with $\mathcal{D} = \{1, \dots, D\}$;
$\tilde{\mathcal{D}} \subset \mathcal{D}$	Set of days, belonging to the time horizon, on which deliveries are not allowed;
$\mathcal{W}$	Set of weeks of the time horizon, with $\mathcal{W} = \{1, \dots, W\}$;
$\bar{\mathcal{D}}_w$	Set of days of week w;
$\mathcal{P}$	Set of products, with $\mathcal{P} = \{1, \dots, P\}$;
$\bar{\mathcal{P}} \subset P$	Set of products, whose raw materials are highly perishable;
$\mathcal{S}$	Set of working slots per day, with $\mathcal{S} = \{1, \dots, S\}$;
$\mathcal{C}$	Set of customers, with $\mathcal{C} = \{1, \dots, C\}$;
$\mathcal{K}$	Set of vehicles, with $\mathcal{K} = \{1, \dots, K\}$;
α_p	Amount of energy consumption per slot when product p is produced;
r_p	Production capacity referring to product p per slot;
β	Initial production line set up;
τ_p	Maximum storage time of highly perishable raw materials with reference to product $p \in \bar{\mathcal{P}}$;
λ_{sd}	Energy price at slot s of day d;
h_p	Daily unit storage cost of product p;
I_{max}	Storage capacity;
dem_{pcw}	Demand of product p expressed by customer c at the beginning of week w;
l_k	Load capacity of vehicle k;
γ_c^k	Shipping cost for customer c with vehicle k;
θ_c	Fixed number of weekly shipments for customer c.

The goal is to simultaneously minimize energy, storage, and distribution costs. For what concerns the production phase, the decisions to be daily made regard the amount Q_{psd} of product p manufactured at each slot s. In addition, the functioning of the single line is regulated by binary variables x_{psd} and y_{psd}, which define the set up and production type at each slot s of day d, respectively. Setups are also managed by binary variables $\delta_{pp'sd}$, which are active in case a changeover from product p to p' occurs at slot s of day d. The inventory management is guaranteed by variables I_{pd}, which define the inventory level of product p at the end of day d. About the distribution stage, variables w_{dc}^k define whether or not to use vehicle k to serve customer c at day d, while the amount of product p shipped to customer c by vehicle

k at day d is defined by continuous variables z_{pdc}^{k}. The notation of the decision variables of the proposed optimization model is shown in Table 141.

Table 141. Notation of all decision variables

x_{psd}	Binary variable equal to one if production line is set up for product p in slot s of day d;
$\delta_{pp'sd}$	Binary variable equal to one if a changeover from product p to p' takes place in slot s of day d;
y_{psd}	Binary variable equal to one if there is production of product p in slot s of day d;
I_{pd}	Inventory level of product p at the end of day d;
Q_{psd}	Amount of product p produced at slot s of day d
w_{dc}^{k}	Binary variable equal to one if customer c is served by vehicle k at day d;
z_{pdc}^{k}	Amount of product p shipped to customer c by vehicle k at day d.

In the following, the model formulation is presented and then explained.

Min
$$\sum_{p\in\mathcal{P}}\sum_{s\in\mathcal{S}}\sum_{d\in\mathcal{D}}\lambda_{sd}\alpha_p y_{psd}+\sum_{p\in\mathcal{P}}\sum_{d\in\mathcal{D}}h_p I_{pd}+\sum_{k\in\mathcal{K}}\sum_{d\in\mathcal{D}}\sum_{c\in C}\gamma_c^k w_{dc}^k \tag{1}$$

s.t.
$$\sum_{p\in\mathcal{P}}x_{psd}=1 \qquad s\in\mathcal{S},d\in\mathcal{D} \tag{2}$$

$$y_{psd}\le x_{psd} \qquad p\in\mathcal{P},s\in\mathcal{S},d\in\mathcal{D} \tag{3}$$

$$Q_{psd}\le r_p y_{psd} \qquad p\in\mathcal{P},s\in\mathcal{S},d\in\mathcal{D} \tag{4}$$

$$\delta_{\beta p'11}\ge x_{p'11} \qquad p'\in\mathcal{P}:\beta\neq p' \tag{5}$$

$$\delta_{pp'sd}\ge x_{ps-1d}+x_{p'sd}-1 \qquad p,p'\in\mathcal{P}:p\neq p',d\in\mathcal{D},\ s\in\mathcal{S}\backslash\{1\} \tag{6}$$

$$\delta_{pp'1d}\ge x_{pSd-1}+x_{p'1d}-1 \qquad p,p'\in\mathcal{P}:p\neq p',$$

$$d \in \mathcal{D} \setminus \{1\} \quad (7)$$

$$1 - y_{p'sd} \geq \delta_{pp'sd} \qquad p, p' \in \mathcal{P}: p \neq p', s \in \mathcal{S}, \; d \in \mathcal{D} \quad (8)$$

$$\sum_{s \in \mathcal{S}} \sum_{d \in \bar{D}_w : d \leq \tau_p} Q_{psd} = \sum_{c \in \mathcal{C}} dem_{pcw} \qquad p \in \bar{\bar{\mathcal{P}}}, w \in \mathcal{W} \quad (9)$$

$$\sum_{k \in \mathcal{K}} \sum_{d \in \bar{D}_w \cup \bar{D}_{w+1}} z_{pdc}^{k} \geq dem_{pcw} \qquad p \in \mathcal{P}, c \in \mathcal{C}, w \in \mathcal{W} \setminus \{W\} \quad (10)$$

$$\sum_{k \in \mathcal{K}} \sum_{d \in \bar{\bar{D}}_w} z_{pdc}^{k} = dem_{pcW} \qquad p \in \mathcal{P}, c \in \mathcal{C} \quad (11)$$

$$\sum_{k \in \mathcal{K}} \sum_{d \in \mathcal{D}} z_{pdc}^{k} = \sum_{w \in \mathcal{W}} dem_{pcw} \qquad p \in \mathcal{P}, c \in \mathcal{C} \quad (12)$$

$$\sum_{c \in \mathcal{C}} w_{dc}^{k} \leq 1 \qquad k \in \mathcal{K}, d \in \mathcal{D} \quad (13)$$

$$\sum_{p \in \mathcal{P}} z_{pdc}^{k} \leq l_k w_{dc}^{k} \qquad k \in \mathcal{K}, d \in \mathcal{D}, c \in \mathcal{C} \quad (14)$$

$$\sum_{p \in P} I_{pd} \leq I_{max} \qquad d \in \mathcal{D} \quad (15)$$

$$I_{p0} = 0 \qquad p \in \mathcal{P} \quad (16)$$

$$I_{pd} = I_{pd-1} + \sum_{s \in \mathcal{S}} Q_{psd} - \sum_{c \in \mathcal{C}} \sum_{k \in \mathcal{K}} z_{pdc}^{k} \qquad p \in \mathcal{P}, d \in \mathcal{D} \quad (17)$$

$$\sum_{k \in \mathcal{K}} \sum_{c \in \mathcal{C}} z_{pdc}^{k} \leq I_{pd-1} \qquad p \in \mathcal{P}, d \in \mathcal{D} \quad (18)$$

$$\sum_{d \in \overline{D}_w} \sum_{k \in \mathcal{K}} w_{dc}^{k} = \theta_c \qquad c \in \mathcal{C}, w \in \mathcal{W} \quad (19)$$

$$\sum_{k \in \mathcal{K}} \sum_{c \in \mathcal{C}} w_{dc}^{k} = 0 \qquad d \in \widetilde{D} \quad (20)$$

$$y_{psd}, x_{psd} \in \{0,1\} \qquad p \in \mathcal{P}, s \in \mathcal{S}, d \in \mathcal{D} \quad (21)$$

$$\delta_{pp'sd} \in \{0,1\} \qquad p, p' \in \mathcal{P}: p \neq p' \quad s \in \mathcal{S}, d \in \mathcal{D} \quad (22)$$

$$I_{pd} \geq 0 \qquad p \in \mathcal{P}, d \in \mathcal{D} \cup \{0\} \quad (23)$$

$$Q_{psd} \geq 0 \qquad p \in \mathcal{P}, s \in \mathcal{S}, d \in \mathcal{D} \quad (24)$$

$$w_{dc}^{k} \in \{0,1\} \qquad d \in \mathcal{D}, c \in \mathcal{C}, k \in \mathcal{K} \quad (25)$$

$$z_{pdc}^{k} \geq 0 \qquad d \in \mathcal{D}, c \in \mathcal{C}, k \in \mathcal{K} \quad p \in \mathcal{P} \quad (26)$$

The objective function (1) minimizes the total costs. The three terms refer to energy, inventory, and shipping costs, respectively. Constraints (2) state that the production line must be set up for exactly one product at each time. However, due to constraints (3), such a set-up does not necessarily follow an actual production. Constraints (4) limit the production capacity of the line. Constraints (5)-(8) regulate the changeovers on the production line. Constraints (9) take into account the perishability of raw materials. Constraints (10)-(11) define the time horizon within which the demand of each customer must be met. While, constraints (12) ensure that demand equals the total amount of shipped products, over the planning horizon. Constraints (13) state that each vehicle can serve not more than one customer per day. Constraints (14) ensure that the load capacity of each vehicle is not exceeded at each day. Constraints

(15)-(17) regulate the inbound/outbound mechanism of product to/from the inventory, considering its limited capacity and assumed initial null level. Constraints (18) state that only products in stock at the beginning of each day can be shipped to the customers. Constraints (19) establish the number of weekly shipments for each customer. Constraints (20) prevent deliveries on some days. Constraints (21)-(26) define the nature of the decision variables.

5.4. Case study

A real-life case study is considered to prove usefulness and efficiency of the proposed optimization model. The Chapter refers to an Italian company that deals with the production, storage and distribution of vegetables. Basically, six types of product are produced ($p_1, p_2, \dots, p_6$). One production line is available and can be set up for one product type at a time both for hygiene reasons and above all because each product type requires its own process parameters. According to the historical data provided by the company, the average changeover time is one hour. Energy consumption of the line varies according to the products processed. Most of the raw materials useful to feed the production cycle are sent directly by the customers for quality reasons. Therefore, the company of this case study transforms and sends them back to customers/suppliers in the form of finished products. Customers, who are wholesalers within the overall food supply chain, express their demand at the beginning of each week and jointly make raw material available. Such demand must be satisfied within two weeks as the products must be placed on the shelves of the retailers in time for the planned promotional offers. It should be noted that as regards p_5 and p_6, the relative raw material is highly perishable then it must necessarily be processed within seven days. The company works on two daily shifts of 8 hours each. After the production process, the finished products, before being be shipped, must be stored in the inventory, whose capacity is 20,000 units. The storage cost concerns maintaining the temperature level to preserve food quality.

For what concerns the distribution phase, two vehicles are available with load capacity of 10,000 units and 3,000 units, respectively. According to the contractual agreements, each customer must be served twice a week. Considering the different geographical positioning of the customers and the different vehicles size, the shipping cost depends on the customer to be served and the vehicle used. In any case, each vehicle can serve at most one customer per day.

5.4.1. Instances

The instances refer to a time horizon of eight weeks between February and March, which is one the most challenging period in terms of amount produced and distributed. During the considered time interval, the amount produced is usually around 60,000 units.

With the aim to address the problem under multiple realistic scenarios, 10 instances have been built. In particular, the following data have been generated, by using a normal distribution with coefficient of variation equal to 0.05: λ_{sd}, dem_{pcw}. The energy price has been estimated from the historical data made available by Gestore dei Mercati Energetici (GME, 2020), which is the company responsible in Italy for the organization and management of the electricity market. Figure 29 shows the energy price trend on a generic day of the time horizon, during the working hours of the company (i.e., 8h00-24h00). In particular, the black line refers to the historical data, while the grey one concerns the generated data. For what regards the mean of the weekly demand of each product type by each customer, it has been estimated considering the historical data provided by the company.

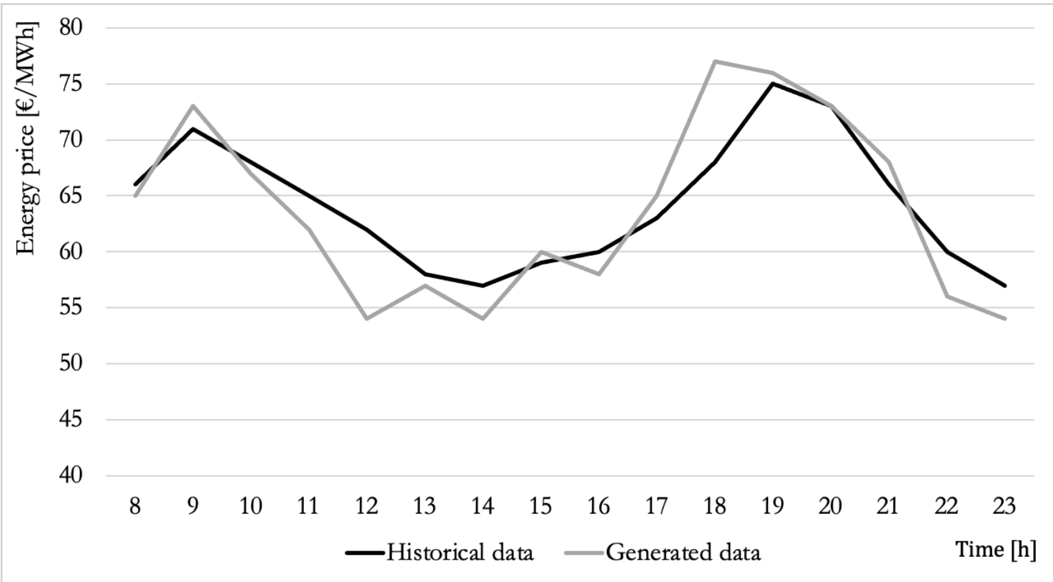

Figure 29. Energy price trend on a generic day of the time horizon: historical data vs. generated data

In Tables 142-143, the relevant data, referring to the current operating conditions of the firm, are summarized.

Table 142. Case study: product data

	p_1	p_2	p_3	p_4	p_5	p_6
r_p [unit/hour]	200.00	285.00	750.00	375.00	185.00	185.00
α_p [kWh]	25.00	22.00	21.00	18.00	12.00	13.00
h_p [€/unit]	0.05	0.04	0.05	0.03	0.08	0.08

Table 143. Case study: other relevant data

C	K	l_1	l_2	I_{max}	γ_1^1, γ_1^2	γ_2^1, γ_2^2	θ_1, θ_2
[unit]	[unit]	[unit]	[unit]	[unit]	[€/shipment]	[€/shipment]	[unit]
2	2	10,000	3,000	20,000	200.00, 150.00	120.00, 80.00	2

The computational experiments have been carried out on a PC running Windows 10 Pro with AMD Ryzen 7 2700X Eight-Core Processor 4.00 GHz/16GB. The presented optimization model has been solved by CPLEX 12.7, Academic License.

5.4.2. Rescheduling strategies and computational results

The proposed optimization model has been adopted with the aim to improve the current practices of the company. In particular, two different strategies have been implemented and compared, named respectively partial rescheduling (PR) and complete rescheduling (CR), within a rolling horizon scheme. It should be noted that the first strategy reproduces the current behavior of the company. In Figure 30, the rolling horizon scheme is shown.

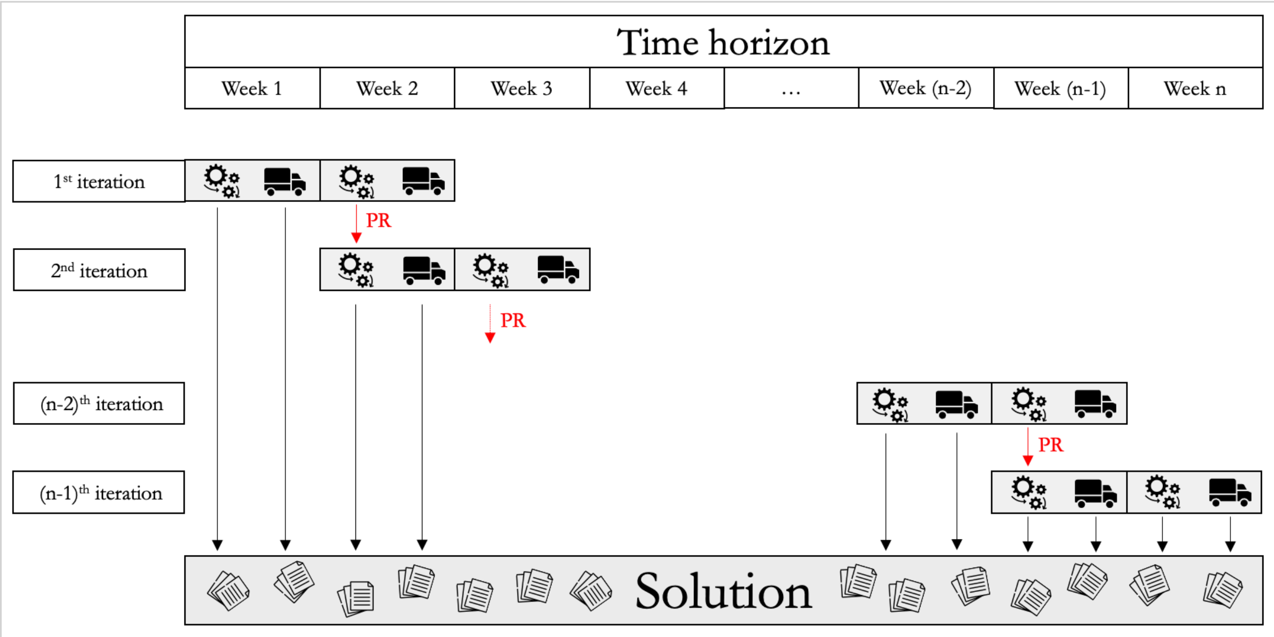

Figure 30. Rolling horizon scheme

Basically, given an overall time horizon of n weeks, $(n-1)$ iterations are necessary to solve the problem. In fact, at each iteration, the optimization model is solved considering a bi-weekly planning horizon. The first iteration concerns the first and second week of the time horizon. The second iteration regards the second and third week of the time horizon. And so on. At each iteration, both strategies require that the decisions made on the first week (of the current planning horizon) must be saved and inserted into the overall problem solution. Two kinds of decisions are taken into account: production plan and distribution plan. The main differences between the two tested rescheduling strategies are in the second week (of the current planning horizon). According to PR, the production decisions made in the second week must be saved and constraint the production plan of the next iteration (see the red arrows in Figure 30), while they must be completely redefined according to CR. For clarity reasons, in Figure 31 shows an illustrative example, which represents the production and distribution decisions, returned by the model, with reference to the first two iterations, under PR and CR. As it can be seen, the first iteration is the same for both strategies. Then, the main difference is that the production decisions made in the second week of the first iteration are saved according to PR (i.e., red cells), while they are completely destroyed and redefined under the complete rescheduling approach.

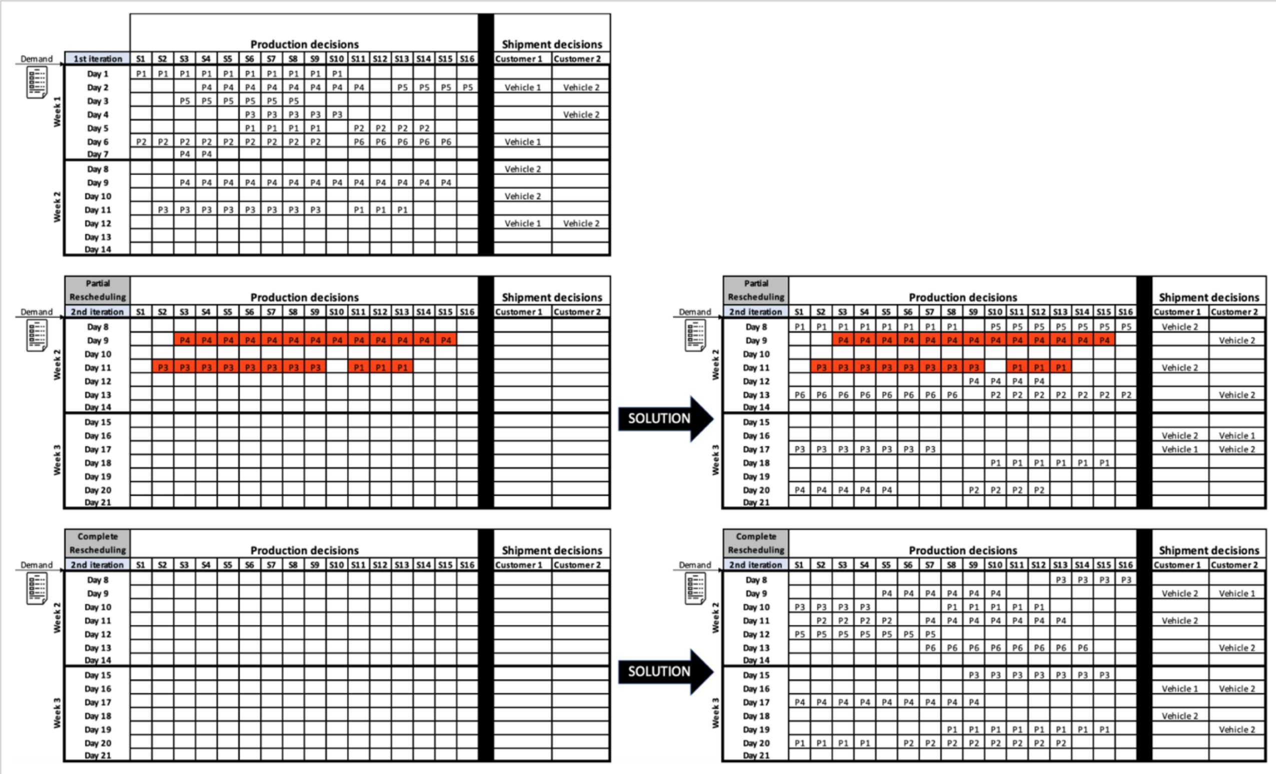

Figure 31. Illustrative example: partial rescheduling and complete rescheduling

The optimization model has been solved on the 10 instances generated. Because of the computational complexity, the gap has been set to 3 %. The mean computational time was 15 seconds for PR and 37 seconds for CR. In Table 144, the results are shown. As it can be noted, the complete rescheduling strategy can improve the current practices of the company. On average, savings greater than 4 % can be achieved. In particular, the energy cost decreases because it is possible to better exploit mid-peak and off-peak hours. In addition, better inventory and delivery management is ensured. The production plan proposed by the model avoids the deterioration of raw materials that have a more stringent shelf-life, minimizing food waste. Given the limited computational time necessary for its solution, it can be a valid tool to support business decisions at an operational level. In fact, it can be effectively and efficiently solved once a week, taking into account the demand that arises from customers.

Table 144. Computational results

	Energy Cost [€]		Inventory Cost [€]		Shipping Cost [€]		Total Cost [€]		
	PR	CR	PR	CR	PR	CR	PR	CR	∆ (%)
I1	259.11	238.51	4,043.94	3,861.28	3,730.00	3,760.00	8,033.05	7,859.79	2.16

I2	275.65	229.94	4,057.72	3,750.78	3,760.00	3,760.00	8,093.37	7,740.72	4.36
I3	269,25	247,01	4,119.27	3,990.14	3,770.00	3,770.00	8,158.52	8,007.15	1.86
I4	268.12	244.88	4,208.05	3,833.49	3,810.00	3,680.00	8,286.17	7,758.37	6.37
I5	256.44	229.15	4,182.10	3,817.32	3,810.00	3,760.00	8,248.54	7,806.47	5.36
I6	274.31	236.17	4,039.37	3,888.81	3,770.00	3,810.00	8,083.68	7,934.98	1.84
I7	265.49	241.50	4,089.34	3,714.83	3,810.00	3,680.00	8,164.83	7,636.33	6.47
I8	263.41	239.79	3,988.33	3,775.37	3,850.00	3,730.00	8,101.74	7,745.16	4.40
I9	266.93	249.43	4,055.23	3,913.58	3,720.00	3,680.00	8,042.16	7,843.01	2.48
I10	266.74	236.57	4,049.07	3,745.18	3,860.00	3,720.00	8,175.81	7,701.75	5.80
Avg	266.55	239.30	4,083.24	3,829.08	3,789.00	3,735.00	8,138.79	7,803.37	4.12

5.5. Brief conclusions

In this Chapter, an optimization model with the aim to support, in an integrated way, a company that deals with production, inventory and distribution of vegetable products, has been designed, implemented and tested. The model considers several real-life features such as the hourly fluctuations in energy price, changeover times on the production line, shelf-life of raw materials. Considering that customer demand occurs weekly and influences production and distribution plans, two rescheduling strategies have been implemented and compared, named respectively (i) partial and (ii) complete rescheduling. The first one reproduces the current behavior of the company. The computational results show that the second strategy works better and can improve the operational practices of the firm.

Future developments include the design of a conceptual framework with the aim to integrate the proposed model into an advanced automated planning system, in accordance with the Industry 4.0 paradigm. Among the enabling technologies of the fourth industrial revolution, the model significantly exploits the value of Big Data, to support and make decision-making more flexible in the context of smart manufacturing. The adoption of smart practices is particularly interesting in the food industry context as they can minimize the amount of wasted food, reduce energy consumption, protecting environmental sustainability.

The future research will be also focused on the possibility of using heuristic approaches to solve larger instances. Moreover, the model will be enhanced considering a multi-line version.

6. A new trend for improving supply chain performance in the agri-food sector: the blockchain technology

6.1. Introduction

Food production must grow significantly in the coming years to meet the needs of the world population, which is expected to increase by about 2.3 billion by the year 2050 (FAO, 2009). Agriculture is undoubtedly one of the activities that provides the greatest food resources to feed the population. In recent years, new techniques and methodologies are being developed to make agricultural supply chains more efficient, with the aim to minimize food waste and protect food quality and safety. In fact, due to the multiple food scandals of recent decades, final consumers have become more demanding and educated about food properties (Guido et al., 2020). In modern society, more importance is given to the quality of life, which is why more and more methods aiming at environmental and social sustainability are spreading. For instance, precision agriculture is an innovative approach, where the field is not treated homogeneously, but is divided into sub-zones according to the different needs. In this way, irrigation water and fertilizers can be used only when and where necessary (Mulla, 2013). In many agricultural fields, the installation of a wireless sensor network (Yin, 2013) is now consolidated, and outputs real-time information on critical environmental parameters such as temperature and humidity, in order to optimize the agricultural practices. The internet of things (IoT) (Netom et al., 2017) is pervading most of the supply chains, with the aim of innovating, improving, and making them more sustainable and safer.

In this ever-changing landscape, the advent of blockchain is an opportunity that deserves to be explored and analyzed. Born in 2008 with the invention of the Bitcoin cryptocurrency, this technology has had a very strong development first in the financial sector, then in various other sectors. In the last few years, there has been a real explosion of scientific research on the blockchain topic, which is also attracting investors and entrepreneurs from all over the world.

In this Chapter, the focus is on the opportunities that this technology can offer the agri-food sector. Recent studies show that blockchain technology appears very promising for tracking and tracing the agricultural supply chains (Mirabelli and Solina, 2020). Considering the high number of scientific papers published in recent years on this topic, there is a strong need to classify and study them. Therefore, the main purpose of this Chapter is to collect and analyze the main scientific contributions published till

April 2020, on the use of blockchain in the agri-food sector, in order to identify current research trends, open issues, and address some possible future challenges.

6.2. The blockchain technology: an overview

The blockchain was conceptualized in 2008, when the paper "Bitcoin: A peer-to-peer electronic cash system" (Nakamoto, 2008) was published. The first applications of blockchain were in the financial sector with the advent of the Bitcoin cryptocurrency (Tschorsch and Scheuermann, 2016). However, today such disruptive technology is used in many other areas with very promising results, biomedical and health care applications (Kuo et al., 2017; Angraal et al., 2017), energy sector (Andoni et al., 2019; Zheng, 2019), transportation (Astarita et al., 2020), supply chain management (Saberi et al., 2019; Pournader et al., 2020), smart home (Dorri et al., 2017), smart city (Sharma et al., 2017), government (Olnes et al., 2017), pharmaceutical industry (Bocek et al., 2017).

6.2.1. Blockchain: what it is and how it works

The blockchain can be defined as a distributed, decentralized, immutable, and shared ledger, composed by a chain of data blocks, which are characterized by cryptographic correlation (Xie et al., 2017). Basically, the information is on multiple distributed computers (i.e., network nodes), which then store the same replicated database (Astarita et al., 2020). In Figures 32 and 33, an example representation of centralized and decentralized infrastructure, is respectively shown.

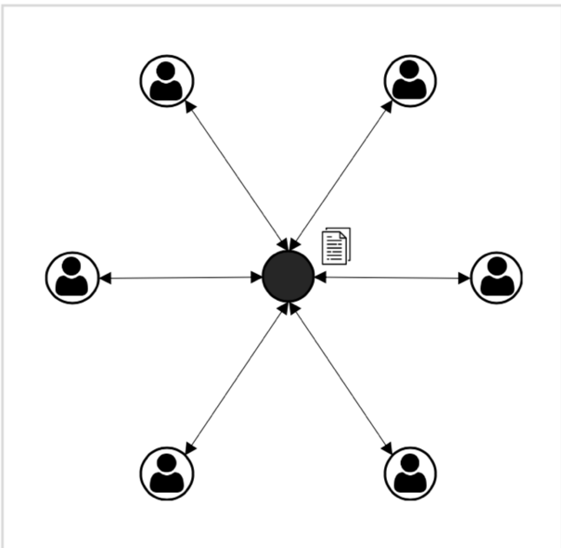

Figure 32. Centralized infrastructure paradigm

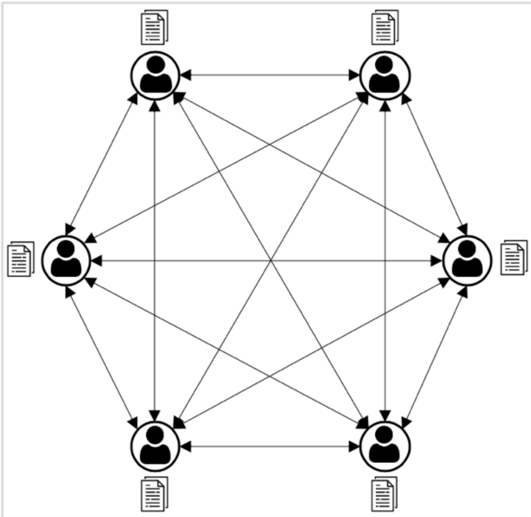

Figure 33. Decentralized infrastructure paradigm

The vast majority of traditional information systems rely on centralized infrastructures, which have a single point of failure, making the overall system highly vulnerable (Caro et al., 2018) Blockchain can overcome this issue because each node has its own copy of the ledger. Each user/node can add data to the blockchain through transactions, which are aggregated into blocks. Before every new block is added to the chain, verification on the validity of the inserted information, through a "mining process", is required. Those who deal with such process are called "miners" and use a consensus algorithm, which is similar to a voting system because each transaction can be validated and stored in the database, only once it has been confirmed by enough nodes/voters. Several consensus mechanisms exist, Proof of Work (PoW) and Prof of Stake (PoS) are among the most popular. PoW has been highly criticized in recent years as requiring high processing power and electricity consumption (Surasak et al., 2019).

Blockchain is often combined with smart contracts. The concept of smart contract was introduced in 1994 by Nick Szabo, as a "computerized transaction protocol that executes the terms of a contract" (Szabo, 1994). It concerns the translation of contractual clauses into code, with the aim of minimizing the need for intermediaries between contractors and the occurrence of malicious exceptions. A smart contract is deterministic in the sense that each input always produces the same output, then it works as an "autonomous actor" (Christidis and Devetsikiotis, 2016).

Around the blockchain topic, a set of interesting projects are being developed, including Ethereum and Hyperledger. The term "Ethereum" refers to three different concepts: the Ethereum protocol, the Ethereum network based on such protocol, and the Ethereum project, which deals with funding the development of the first two. Basically, Ethereum can be considered as an open-source and blockchain-based platform, which can support the creation and implementation of smart contracts. There is also an Ethereum-associated cryptocurrency, namely Ether, which is used as a reward for mining nodes (Danner, 2017). Hyperledger is a project of open-source blockchains, supported by Linux. In this context, it is really important to mention Hyperledger Fabric (Androulaki et al., 2018), a permissioned blockchain infrastructure supported by IBM, and Hyperledger Sawtooth (Olson et al., 2018), which uses the novel "Proof of Elapsed Time" consensus mechanism, and is promoted by Intel.

6.2.2. Blockchain: main features

The great popularity of blockchain is mainly due to some important features, which can be summarized as follows:

- transparency and auditability: all data stored on the blockchain are based on a consensus reached by the majority of the network nodes, therefore this distributed ledger represents a transparent and auditable source of information (Caro et al., 2018). This can enable the development of reliable communities among different stakeholders (Hua et al., 2018);
- decentralization and trust: blockchain applications can work in a decentralized way, without the need for a trusted intermediary (Casado-Vara et al., 2018). This means that a set of assets (e.g., money, data, documents, imagery) can be exchanged between more users in a decentralized way, without a third-party control, supervision or intermediation. Basically, transactions become leaner because they can be managed in an untrustworthy environment (Pinna and Ibba, 2019). Blockchain technology can create belief and trust, by combining smart contracts, consensus algorithms, and its distributed ledger nature (Shyamala Devi et al., 2019). Therefore, it can replace traditional centralized systems (Caro et al., 2018);
- immutability: all actors (e.g., farmers, food processors, wholesalers, retailers) can store information on the blockchain and nobody can tamper with it, once the record is recognized by the whole network (Hua et al., 2018). Basically, transactions can only be added on the distributed ledger, but not removed. The blockchain contains the history of all transactions (Shyamala Devi et al., 2019);

- security: the use of cryptography ensures information security. All the transactions are encrypted, then no unauthorized users can tamper with them (Shyamala Devi et al., 2019);
- traceability: the data stored on the blockchain are accessible by all nodes in the supply chain, in real-time. In particular, on the one hand the final consumer can retrieve a set of information about the origin of the product and the processes it has undergone, then he/she feels more protected. On the other hand, in the event of a food crisis, it is possible to quickly recall unsafe products, minimizing recall costs (Kim et al., 2018).

6.3. Research methodology

The research methodology for carrying out the systematic literature review is based on 4 main steps in sequence, indicated by the PRISMA statement (Moher et al., 2009): identification, screening, eligibility, inclusion. The main goal is to collect the papers which propose models, methodologies, or analysis on the use of the blockchain technology in the agri-food sector.
The following research questions (RQs) are addressed:

- RQ1: How much research has there been in the field of blockchain in the agri-food sector?
- RQ2: What are the possible blockchain-based application in the agri-food sector?
- RQ3: What are the open issues, barriers and future challenges concerning blockchain (in the agri-food sector?

6.3.1. Identification

The first step of the research methodology concerns the collection of documents. Numerous databases exist, from which scientific contributions can be retrieved. In this study, Scopus was used, also because is one of the most recognized by the scientific community. It contains more than 20,000 peer-reviewed journals, and it is more comprehensive than many others databases such as Web of Science, IEEE Xplore, ACM Digital Library.

Scopus was queried in April, 2020, using the following keyword combination: ("blockchain" AND "agriculture") OR ("blockchain" AND "food") OR ("blockchain" AND "agricultural supply chain") OR ("blockchain" AND "harvesting") OR ("blockchain" AND "farmer"). Then, all papers belonging to one of the following types were excluded: conference review, review, note, short survey, editorial, letter.

6.3.2. Screening

During the screening phase, the title and abstract of the documents were read, with the aim of excluding some of them on the basis of the following criteria:

- papers not written in English;
- generic papers on blockchain technology;
- papers focused only on technical and architectural aspects related to blockchain technology.

6.3.3. Eligibility, inclusion, analysis

For the remaining papers, the full text was read and those which do not specifically concern the agri-food sector were excluded. The resulting documents were included in the systematic literature review. They were analyzed based on some criteria including publication year, document type (i.e., article, conference paper, book chapter), journal, topic, blockchain platform (i.e., Ethereum, Hyperledger, other). Then, a broad discussion was provided in order to clearly identify the theoretical or practical applications of blockchain in the agri-food context.

- papers not written in English;
- generic papers on blockchain technology;
- papers focused only on technical and architectural aspects related to blockchain technology.

6.4. Results

Figure 34 summarizes the application of the above explained research methodology through a scheme.

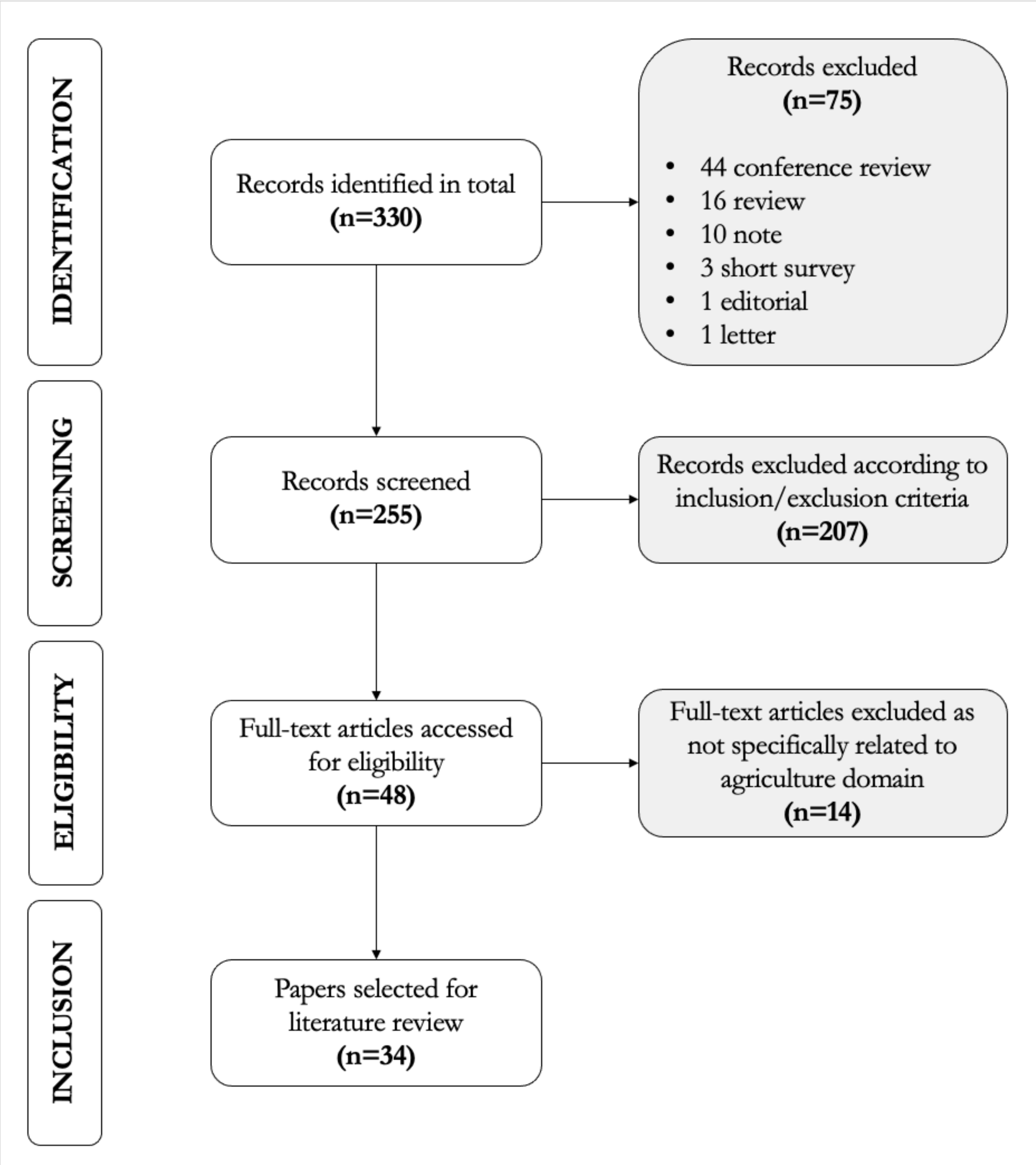

Figure 34. Research methodology

As it can be seen, from the Scopus database query, 330 documents were collected, which were reduced to 225, after applying the exclusion criterion by type. Then, after reading title and abstract, a further 207 papers were excluded, based on the exclusion criteria relating to the screening phase. The full-text of the remaining papers was accessed, in order to include in the systematic literature review, only 34 papers specifically focused on the agri-food domain.

6.4.1. Document analysis

Figure 35 shows the number of publications per year on blockchain technology in the agri-food context. As it can be noted, the trend is strongly growing and this confirms the enormous and recent interest that the scientific community has in this topic. Furthermore, there are no publications before 2016, the year in which the paper "An agri-food supply chain traceability system for China based on RFID & blockchain technology" (Tian, 2016) was published. Without any doubt, such paper can be considered a pioneering work in addressing the opportunities that blockchain technology can offer to track & trace the agri-food supply chains.

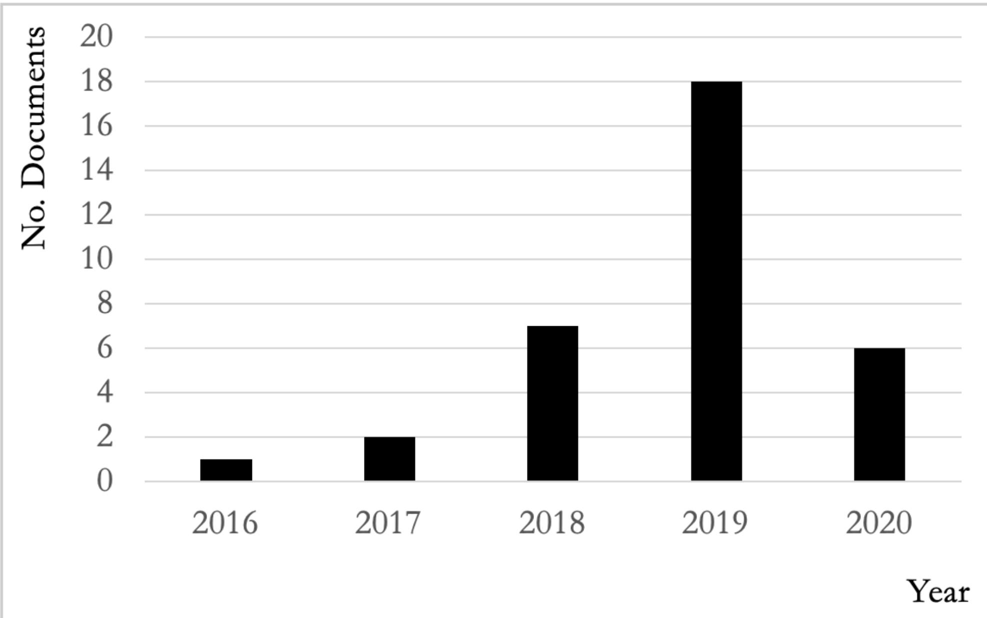

Figure 35. Number of published documents per year

Figure 36 shows instead that the vast majority of the documents are proceedings (i.e., 26 out of 34), confirming that the blockchain topic has been particularly debated in the most recent international scientific conferences.

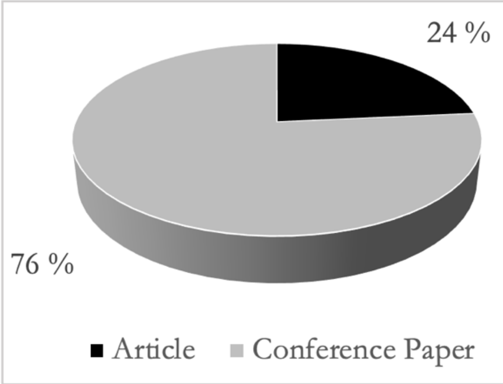

Figure 36. Document type statistics

In Table 145, the peer-reviewed journals, where the only 8 article-type documents were published, is shown.

Table 145. Journals of the article-type documents

Journal	No. Papers
Ad Hoc Networks	1
Cluster Computing	1
Electronics (Switzerland)	1
Future Generation Computer Systems	1
IEEE Access	1
International Journal of Innovative Technology and Exploring Engineering	1
International Journal of Advanced Computer Science and Applications	1
Journal of Communications and Networks	1
Total	8

In Table 146, the 34 selected papers are briefly outlined. The main topic, and the use of Ethereum (E) and/or Hyperledger (H), are highlighted. As it can be noted, Ethereum is a fairly recognized platform in the literature for agri-food applications, in fact it is taken into consideration in 41 % of cases. While, only 3 out of the 34 selected papers propose Hyperledger. In only one case, E and H are compared in terms of performance (Caro et al., 2018).

Table 146. Main aspects of the selected papers

Reference	Topic	E	H
Tian, (2016)	Agri-food supply chain & traceability	-	-
Tian, (2017)	Food supply chain & traceability	-	-
Xie et al., (2017)	Agricultural supply chain & traceability	✓	-
Caro et al., (2018)	Agri-food supply chain & traceability	✓	✓
Casado-Vara et al., (2018)	Agricultural supply chain & traceability	-	-
Leng et al., (2018)	Agricultural supply chain	-	-
Patil et al., (2018)	Greenhouse farming & security	-	-
Hua et al., (2018)	Agricultural supply chain & traceability	-	-
Kim et al., (2018)	Agricultural supply chain & traceability	✓	-
Lin et al., (2018)	Smart agriculture & traceability	-	-
Salah et al., (2019)	Soybean supply chain & traceability	✓	-
Pinna and Ibba, (2019)	Agriculture & temporary employment contracts	-	-
Shyamala Devi et al., (2019)	Smart agriculture	✓	-
Shih et al., (2019)	Agricultural supply chain & organic products traceability	✓	-

Arena et al., (2019)	Extra-virgin olive oil supply chain & traceability	-	✓
Basnayake and Rajapakse, (2019)	Agricultural supply chain & organic foods traceability	✓	-
Surasak et al., (2019)	Agricultural supply chain & traceability	-	-
Giaffreda et al., (2019)	Precision agriculture & reward	✓	-
Harshavardhan Reddy et al., (2019)	Agricultural supply chain	-	-
Wu and Tsai, (2019)	Intelligent agriculture	-	-
Iswari et al., (2019)	Cocoa supply chain & traceability	-	-
Jaiswal et al., (2019)	Food grain supply chain & trading	✓	-
Nazarov et al., (2019)	Russian agri-food supply chain	-	-
Liao and Xu, (2019)	Tea supply chain	✓	-
Madumidha et al., (2019)	Agri-food supply chain & traceability	✓	-
Shaikh et al., (2019)	Agri-food supply chain & traceability	-	-
Branco et al., (2019)	Mushroom production & control	-	-
Zhang, (2019)	Rural waste management & reward	-	-
Alonso et al., (2020)	Dairy industry & crops monitoring	-	-
Iqbal and Butt, (2020)	Safe farming & traceability	-	-

Chun-Ting et al., (2020)	Agricultural supply chain & traceability	✓	-
Balakrishna Reddy and Ratna Kumar, (2020)	Organic food supply chain	✓	-
Miloudi et al., (2020)	Smart farming	✓	-
Saji et al., (2020)	Agricultural supply chain & traceability	-	✓

6.4.2. Findings and discussion

Below, the 34 selected documents are classified according to the purpose of the proposed blockchain-based application.

6.4.2.1. Traceability (generic agri-food supply chain)

The vast majority of the documents examined concern food traceability. According to Kamble et al., (2020), traceability is the main enabler for blockchain adoption in Indian agricultural supply chains. After the occurrence of numerous food scandals, the interest of the scientific community on this issue has grown considerably in recent decades. In this context, it is important to highlight the difference between track and trace. Tracking means gathering all information relating to the processes undergone by the product along the supply chain, from upstream to downstream. While, tracing means being able to reconstruct the history of the product from downstream to upstream, through the information stored at each stage (Pizzuti et al., 2014).

The first paper which addresses the use of the blockchain technology for the traceability of agri-food supply chains was published about four years ago (Tian, 2016). The main aim of such paper is to propose a traceability system based on RFID (Radio-Frequency IDentification) and blockchain to protect food safety and quality and to reduce the losses in the field of logistics, referring to the Chinese agri-food markets. The proposed system can completely track & trace the supply chain, "from farm to fork". One year later, the same author published another paper (Tian, 2017), where a supply chain traceability system jointly based on HACCP (Hazard Analysis and Critical Control Points), blockchain and IoT is proposed. An example scenario is also presented to show how the overall system works. Both papers have as main purpose to solve the numerous problems that characterize the Chinese agro-food supply chains, which are defined "at the primary stage": the regulations are still disordered, and often there is no supply-demand matching due to the information asymmetry between producer and final consumer. Furthermore, traditional traceability systems are centralized and usually subject to fraud, tampering, corruption. As a consequence, several food crisis have occurred over the years, such as "gutter oil" (Lu and Wu, 2014) and milk adulteration with melamine (Pei, 2011), which have significantly reduced consumer confidence. According to Hua et al., (2018), in China many actors in the supply chain have their own traceability systems, which are therefore closed and independent, this means that it is almost impossible to guarantee the traceability of the whole supply chain. Under such conditions, the integration of the multiple and private sub-systems of each company is difficult and expensive. With the aim to solve these issues, the authors propose an architecture for a blockchain-based agricultural traceability system. Since it represents an open data sharing platform, cheating results is very expensive and dangerous, while those who comply with all food standards and regulations can be more appreciated by the final consumer. The proposed system collects the basic planting information (e.g., geographical location, planting time, grower's name) and a provenance record, which stores the data about each agricultural operation (e.g., date time, company, person, operation type). The platform has two types of users: the former can enter and update data on the system, which can be queried by the latter, i.e., consumer-user. Very similar issues are dealt with by Kim et al., (2018), according to whom despite the high scale of world agricultural trade, there are no globally shared protocols between the various actors. In addition, some existing standards at regional level are very often scarcely interoperable. As a consequence, the risks for consumers are significant. The authors introduce Harvest Network (HN), a theoretical application, which can integrate the Ethereum blockchain and IoT devices, leveraging the GS1 standards for message exchange. The aim is to design a distributed ledger for all stakeholders in the supply chain, in order to improve food traceability and transparency. Moreover, the challenging issue of tracking an asset through a token, on the blockchain network, is addressed.

Caro et al., (2018) propose AgriBlockIoT, a fully decentralized and blockchain-based traceability solution, which is able to integrate the IoT devices involved along the whole agri-food supply chain. The authors define, develop and deploy a use-case named "from-farm-to-fork" to prove the feasibility of the proposed solution. In this context, two different blockchain implementations are used: Ethereum and Hyperledger Sawtooth, which are compared in terms of latency, CPU, and network usage. The proposed framework can solve the issues of data integrity, tampering, transparency, auditability. Ethereum is also used by Chun-Ting, (2020) to build a traceability service platform for farm-to-fork traceability, combined with IoT sensors. The proposed system has three different layers: data collecting layer, blockchain layer, and application layer. In this case, the data collecting layer is an IoT agriculture platform, which collects via sensors, environmental data from the farms. The blockchain layer periodically requests data from the data collecting layer, which is then sent to the network of nodes. Once verified, the transaction occurs, and the record is stored in a block of the chain. The application layer queries certified data from the blockchain layer, when necessary. This tiered architecture makes the system highly flexible, as the data collecting layer can be replaced by any given collection platform of an agricultural supply chain. A very detailed description of data structure and system implementation is also provided. The blockchain-IoT integration is also addressed by Surasak et al., (2019), who focus their attention on the quality of agricultural products in the Thai supply chains, which can significantly influence the revenue of farmers and the satisfaction of end customers. The authors use OurSQL (i.e., blockchain + MySQL) combined with IoT, to provide users with real-time product information (e.g., temperature and humidity values). A website and an android application are developed to make the overall system user-friendly. Lin et al., (2018) design a general blockchain and IoT based smart agriculture ecosystem, which involves an Enterprise Resource Planning (ERP) legacy system and an IoT system. Two kinds of data are then stored in the blockchain: the first one is generated from the ERP legacy system (e.g., trade, logistics, warehouse information), while the second one refers to the data collected by the IoT devices on the field, such as humidity, temperature, soil nutrition, etc. This data stored in the chain are easily accessible even via smartphone, by all supply chain entities (e.g., farmers, farming processing plants, logistics companies, retailers) and by the customers, who can retrieve all the information about the processes undergone by the product. Further two papers propose blockchain-based solutions for food traceability, investigating the opportunities offered by IoT and smart contracts (Madumidha et al., 2019; Shaikh et al., 2019). A multi-agent system (MAS), integrated with blockchain and smart contracts is instead proposed by Casado-Vara et al., (2018).

Another important issue, addressed by Iqbal and Butt, (2020), is how to guarantee food traceability in a safe farming environment. Crops are continuously exposed to attacks by animals, and their damage can lead to significant losses for farmer. There are some common techniques (e.g., guarding, fencing, trapping) to prevent vertebrate attacks, but they are not always effective. Therefore, the authors propose an IoT-based prevention system, which uses sensors in the field to detect animal attacks. In the case of danger, such sensors, through the wireless communication, send a warning to a Repelling and Notifying System, which produces ultrasonic sound waves, unbearable for animals. The IoT-based system is well integrated with an agricultural blockchain, to guarantee traceability and transparency.

6.4.2.2. Traceability (specific agri-food supply chain)

Some scholars propose blockchain-based solutions, related to specific agricultural supply chains.
An important research branch concerns the traceability of the organic food supply chains, which today are increasingly appreciated by consumers (Guido et al., 2020). Many agricultural practices, with the aim to increase productivity, involve the use of pesticides, which can be extremely harmful to human health and environment. For this reason, many consumers prefer organic products, which are usually more expensive, but also healthier than others. However, they are very often subject to fraud. In this context, a traceability system plays a very important role because can guarantee product provenance and enhance its healthy characteristics. Shih et al., (2019) propose a blockchain-based organic vegetable production and marketing system, using Ethereum. The system allows to increase the sales of organic vegetables and to reduce the ecological and agricultural environmental pollution. Consumers can verify that the vegetables have been grown according to organic standards. Furthermore, intermediaries cannot establish unjustified prices as the system is completely transparent, while smart contracts enable digital payment collection. Similar objectives are pursued in the paper proposed by Basnayake and Rajapakse, (2019), where the use of a public blockchain is adopted to ensure maximum transparency. With the aim to discourage any attempt at fraud, a token-based mechanism is designed to indicate the farmers' reputation. The system is presented as a prototype and then validated. The authors design also a proof-of-concept, which is adequately tested.

Extra-virgin olive oil is among the most appreciated and recognized Italian products in the world, but it is also among the most counterfeited. It certainly needs an efficiently traceability system to be protected (Guido et al., 2020). Arena et al., (2019) present BRUSCHETTA, a blockchain-based application, specifically dedicated to the traceability and certification of the extra-virgin olive oil supply chain. Also in this case, IoT sensors are leveraged for quality control and can communicate with the blockchain in an integrated manner. The main objective is to ensure that the consumer can transparently access the history of the product. The authors also perform simulations regarding the possible adoption of the proposed system in real industrial scenarios and conclude that it is not always suitable. Therefore, they present and evaluate a mechanism for dynamic auto-tuning of the blockchain parameters in order to guarantee timely and correct operation.

Salah et al., (2019) observe that, although there is a great interest of the scientific community towards the adoption of blockchain technology in agriculture, conceptual applications are often discussed without dealing with the implementation step. The authors aim to fill this gap by presenting a solution based on blockchain and Ethereum smart contracts to track and trace soybean supply chains. The authors explain in detail the characteristics of soybean supply chain, the system design, the entity relationship and sequence diagram, and above all the algorithms behind smart contracts. The proposed solution is generic enough to be applied to other agricultural supply chains, and eliminates the need for trusted intermediaries.

Iswari et al., (2019) focus on the cocoa supply chain in Indonesia. The long length of this supply chain makes data traceability quite difficult and, as a consequence, causes very worrying information asymmetries. Basically, farmers very often do not know the needs of the cocoa industries, which are usually not aware of the quantities produced by the farmers. Even the institutions disagree with each other about the real amount of national cocoa production. In view of a possible future implementation of the blockchain technology, the authors study the structure and interactions of the cocoa supply chain, through a requirement analysis and two UML diagrams (i.e., use case diagram and sequence diagram).

Alonso et al., (2020) present a platform, which concerns the application of IoT, Edge Computing, Artificial Intelligence, and Blockchain, exploiting the Global Edge Computing architecture. The main goal is the real-time monitoring of dairy cattle and feed grain. The authors have the merit of being among the few of this survey, to have performed the testing of the proposed framework within a real scenario, on a dairy firm. The presented agro-industrial platform has significant benefits in terms of traceability, security, and data integrity. In addition, users have the option of accessing data collected by IoT sensors at any time.

Liao and Xu, (2019) focus on the tea supply chain. They propose a blockchain-based traceability system for tea quality and safety, characterized by three main layers: data layer, business logic layer, and presentation layer. The data layer lays on the Ethereum blockchain and a relational database. Transparency and authenticity are ensured to the final consumer, who can retrieve all information about the product, scanning a QR Code with his/her smartphone.

6.4.2.3. Traceability (middleman focus)

A line of research concerns the adoption of blockchain-based systems in agri-food, with a focus on the elimination or reduction of intermediaries within supply chain.

According to Saji et al., (2020), middlemen exploit their position halfway between producers and final consumers to increase their profits by increasing unfairly prices. This way of acting puts both the farmer's economy and the product quality at risk. The authors propose the creation of a permissioned blockchain network, which involves producers and consumers, and aims to reduce the gap between market price and sale price of the farmer, in a fully transparent environment. Through a distributed digital ledger, it is possible to keep track of all movements undergone by the product from the field to delivery, eliminating any malicious intervention by intermediaries.

Balakrishna Reddy and Ratna Kumar, (2020), through an Analytic Hierarchy Process (AHP) analysis, note that the blockchain technology is the most suitable for improving the sustainability and effectiveness of agri-food supply chains. Hence, they propose a blockchain-based framework, to support small and medium-sized farmers who operate locally. Due to the transparency of the network, farmers can get a fair price to remunerate their work. In fact, it is not possible to be cheated by intermediaries, which will inevitably decrease in number. According to Harshavardhan Reddy et al., (2019), the use of the blockchain technology in agriculture, in addition to ensuring the authenticity of the product in real time, ensures farmers the best price they can expect from their product. The authors estimate that the farmer can achieve a 30 % increase in profit in the rice chain in India, eliminating the intermediaries. According to Iswari et al., (2019), farmers in India mainly have two options for selling food grains: the government that buys at minimum price or the private distributors, who buy at a very low fixed price. The presence of many intermediaries along the chain raises the sale price to the final consumer and does not adequately remunerate the growers. Therefore, the authors aim to build a reliable and transparent platform, through which farmers can sell cereals directly to end consumers, without the need for intermediaries. In this context, the use of some smart contracts that can be implemented on the Ethereum blockchain is addressed. For the trading process, the Vickrey auction method (Ausubel and Milgrom, 2006) is used. The experimental results appear very promising in an attempt to overcome the problem of low yields for farmers in India.

Nazarov et al., (2019) provide a broad discussion about the benefits that implementing a blockchain-based framework could bring to the Russian agro-industrial system. They also focus their attention on the concept of intermediation: traditionally, farmers are forced to wait to be paid by their buyers, also due to the presence of middlemen who usually slow down transactions. The blockchain, instead, allows for smart, safe and transparent payments, without third parties (e.g., banks).

6.4.2.4. Reward mechanisms

Some papers try to exploit the blockchain to enable reward mechanisms between the various actors creating a collaborative and environmentally friendly network.

Giaffreda et al., (2019) begin their discussion by pointing out that agriculture consumes around 70 % of water resources worldwide (Gilbert, 2012), which is a much higher share than necessary. This quota can be reduced through the typical practices of precision agriculture, according to which it is possible to irrigate only the areas of the field that really need water. In order to create a sustainable environment, the authors propose a blockchain-based framework that encourages and rewards virtuous behavior in agricultural practices, in a multi-actor ecosystem. In this case, unlike many other contributions analyzed in this survey, this is not only a conceptual proposal, but a real experiment which is ongoing in the Northern Alps region of Italy. IoT and smart contracts are also exploited.

Zhang, (2019) addresses the problem of rural waste, and study the feasibility of a decentralized blockchain-based system in the field of trade in energy from biomass and agricultural products. In particular, it is explained how a digital cryptocurrency can encourage the exchange of waste, energy, fertilizers between farmers and entrepreneurs. Basically, the proposed model consists of 4 main phases: a) generation and collection of waste by the farmer, b) transportation of waste to the energy plant, c) generation of digital coupons as a reward, d) exchange of tokens with energy and/or fertilizers. Although this system has implementation costs (e.g., developing a mobile app or purchasing smart bins), it can improve economic and environmental sustainability in rural regions by stimulating farmers to participate more proactively in the recycling process through incentives.

6.4.2.5. Employment

Blockchain technology can also be used to protect workers' rights. Pinna and Ibba, (2019) focus on temporary work, which allows companies to maintain staffing flexibility, in the difficult and highly competitive global economic context of today. Workers with fixed-term contracts are not always adequately protected. They usually do not have guarantees, wages are low, and professional growth is often very limited. Therefore, a blockchain-based system is proposed to manage temporary work, safeguard workers' rights, make the contract processing procedure automated and quick. Smart contracts are saved permanently on the blockchain and can be checked at any time by the competent authorities. Transparency and security are fully guaranteed. A case study in agriculture is addressed.

6.4.2.6. Other smart farming related applications

Other possible blockchain-based solutions in smart farming environment are listed below.

Miloudi et al., (2020) aim to integrate IoT, blockchain, and geospatial technologies in a smart farming environment, to face some of the most significant challenges in the agricultural world, such as food security, fraud, contamination, transparency, food waste, climate change. Basically, the proposed decentralized infrastructure allows to efficiently manage the data obtained from remote sensing systems, satellites, and environmental databases. In this way, greater attention is given to the management of soil and water resources. The research work of Xie et al., (2017) also involves the use of GPS modules. They design an extremely secure blockchain-based data storage system and a network of sensors, which allow real-time product monitoring. In particular, there is a "sensing layer" including: temperature sensor, humidity sensor, acceleration sensor, pressure, sensor, GPS module and GPRS module. The main contribution of the authors concerns the design of a double chain storage system, which exploits the characteristics of the blockchain to avoid tampering. A double-chain architecture is also proposed by Leng et al., (2018) for a Chinese public service platform, in order to improve: its credibility, the demand-supply matching mechanism, the transparency and security of transaction information, the overall efficiency of the system.

Patil et al., (2018) aim to increase data security within a smart greenhouse farming. The greenhouse is equipped with IoT sensors (e.g., light sensors, water level sensors, humidity and CO_2 sensors), actuators (e.g., LED light, fan, heater and sprinkling), and contains a local blockchain. The proposed security framework can face the threats of availability, integrity, confidentiality, authenticity. Therefore, it allows secure communication of data in smart greenhouse farming. The blockchain-IoT integration is addressed also in (Shyamala Devi et al., 2019).

The control of environmental variables is extremely important within the production departments, especially when food is processed. Branco et al., (2019) propose a conceptual approach that integrates blockchain and IoT, which guarantees the efficient and distributed collection of data relating to environmental indicators in mushroom production. The proposed approach completes the already existing production control system. IoT devices, integrated with the blockchain network, facilitate monitoring of the environmental conditions of the production areas, but they can also be used to detect power outages and other equipment problems. This system, still in the design stage, in case of anomalies, manages to send a warning to all production managers, so as to promptly take corrective actions and minimize food waste.

Wu and Tsai, (2019) deal with intelligent agriculture, which through the use of sensors manages to regulate the amount of water needed for irrigation, based on soil conditions. Their study proposes the use of dark web technology and a private blockchain, in order to ensure the highest level of security.

6.5. Open issues, barriers and future challenges

The numerous research works examined in this Chapter showed that blockchain technology is very promising in agri-food supply chains. However, it remains to be seen how much value it can add in the long term, considering that many frameworks are only conceptual, while the few real implementations refer to small-scale projects. Therefore, before a mass diffusion of this technology in the agri-food sector, it is necessary to address some open issues.

- Scalability: scalability still constitutes one of the most significant barriers to the spread of blockchain technology. For instance, Bitcoin has a significant limit on the number of transactions per unit of time, when compared to other players such as Visa or Mastercard (Vlastelica, 2017). The world of research is working hard to build more efficient distributed consensus algorithms. PoW algorithms have a good degree of maturity, but require a very high use of energy resources. In fact, PoS algorithms have recently become more widespread, because they consume less energy and guarantee greater speed and scalability (Andoni et al., 2019).
- Technical expertise: limited technical knowledge represents a strong barrier to the adoption of this technology in the supply chains. A blockchain-based system is often integrated with the internet of things, which usually involves the use of mobile devices. In the agri-food sector, not all actors in the chain are inclined to learn new technology and/or radically change their habits.
- Data protection: the regulations which protect the data of the network nodes must be clear. Dealing with a distributed system architecture means that, in the event of a malicious attack, the user does not have a central authority to which to direct their complaints as in traditional systems. Therefore, it is necessary that the various governments shed light on the solutions in terms of privacy and data confidentiality (Andoni et al., 2019). Privacy and confidentiality can be a

significant problem for the blockchain, as the information is stored on a public ledger. If on the one hand there are mechanisms for anonymization or based on cryptography (Christidis and Devetsikiotis, 2016), on the other there are also malicious methods to de-anonymize and recover sensitive data (Ron and Shamir, 2013). Just recently, smart contracts demonstrated their vulnerability and fragility with the DAO attack (Mehar et al., 2019), which caused a loss of about $ 50.00 M and the bug in the Parity wallet, from which $ 280.00 M were stolen (Browne, 2017). According to Salah et al., (2019a), the vulnerability issues are mainly due to negligence in writing the smart contracts code. Furthermore, the supply chain actors may not agree with the total transparency guaranteed by the blockchain, as they could be unwilling to share their data, for privacy reasons. In this context, the main challenge is to convince farmers, wholesalers, retailers, and consumers that this new technology can bring value to the overall supply chain through the increase of transparency.

- Development cost: blockchain systems can have significant costs, related to new customized ICT equipment and software, which should be compensated for by the advantages deriving from the elimination of intermediaries, the reliability of data and increased security (Andoni et al., 2019).
- Reputation: blockchain technology still remains too associated with cryptocurrencies such as Bitcoin and some malicious activities (Swan, 2015). This is one of the reasons that has hindered its spread in recent years.
- Standards and interoperability: there is a lack of shared technology standards, which could improve interoperability and integration. Clear rules are needed that can handle unambiguously disputes and especially payments through cryptocurrencies.

6.6. Brief conclusions

In this Chapter, a literature review on the use of the blockchain technology in the agri-food sector was carried out. The aim was to identify the state of the art, the main blockchain-based applications in, the open issues and possible future challenges.

The analysis of the collected documents showed a strongly growing trend in terms of number of publications, which confirms the great and recent interest that the scientific community has in this topic. At the moment, the main application of this technology in agriculture concerns the exploitation of its properties of authenticity and transparency to guarantee the traceability of food products. However, blockchain appears also quite promising to protect workers' rights, decrease the power of supply chain intermediaries, exploit reward mechanisms with the aim to enhance sustainable initiatives.

The main gap in literature is the almost total absence of practical applications. Most of the papers analyzed propose conceptual frameworks, then there is still little evidence about the benefits that this technology can actually bring to real agricultural supply chains. However, the first experimentations seem promising enough, although some open issues remain: today, the major limitation of this technology is scalability, which appears still too low. Furthermore, it would be important to understand what the propensity to adopt blockchain by supply chain actors is, considering that some start-up costs must be faced. Many farmers have habits consolidated over time, which do not contemplate the massive use of technology. Substantially, mush effort is still needed by academia and industry, before blockchain can spread on a large scale and become a well-recognized standard.

7. Final remarks and possible future developments

In this dissertation, it has been shown how the use of quantitative approaches can be useful to support the integrated management of agri-food supply chains and to significantly improve their performance. Chapter 2, through a systematic literature review concerning 54 articles, has highlighted that the interest in models capable of integrating the production, storage and distribution activities is strongly growing in recent years. In addition, it has highlighted several research gaps, some of which have been filled in subsequent chapters.

Future developments are planned, as follows:

- Chapter 3 and 4 will be extended, considering novel variants of the proposed models, respectively. For what concerns the model in Chapter 3, the idea is to develop and test a multi-product model, to design specific strategies for dealing with inventory and distribution of different cauliflower types (i.e., white cauliflower, Roman cauliflower, purple cauliflower, green cauliflower). The first of the two models in Chapter 4, instead, will be improved considering a multi-company version.
- A part of the optimization model proposed in Chapter 5 is about the production scheduling. The idea is to deepen this branch of research. Despite the large body of literature resulting from decades of studies on scheduling problems, several limitations still remain, especially in the food sector. Many food companies still do not have adequate tools to efficiently plan their production activities, with consequent economic losses and waste. Basically, in many cases, schedules are manually generated by production operators, based on their experience. In this context, starting from the real data related to a company that produces vegetables preserved in oil, the purpose is to develop and test a model for solving a multi-product and multi-stage production scheduling problems with earliness-tardiness penalties.
- The main research gap emerging from Chapter 6 concerns the limited number of real applications about the blockchain technology. Therefore, one of the main future aims is to implement a blockchain-based traceability system on a real company belonging to the agri-food sector, in order to assess quantitatively the benefits. The starting point will be a recently published paper (Guido et al., 2020), where a conceptual framework to track&trace an extra-virgin olive oil supply chain has been proposed and tested with good results.

- The novel coronavirus disease, named COVID-19, has recently shown the fragility of many agri-food supply chains and highlighted the need for more resilient systems, able to react adequately to disruptions (Singh et al., 2020). When a pandemic is ongoing, governments are forced to take drastic measures (e.g., partial or full lockdown, social distancing, restrictions on circulation), in order to contain the risk of infections. Such measures obviously have crucial impacts on the global and local economies, and make the management of supply chains much more challenging and difficult (Chowdhury et al., 2020). The forced closure of bars, restaurants, public canteens, shopping centers, local markets and other commercial facilities has impacted consumer habits and increased the pressure on supermarkets (Mishra et al., 2021). Therefore, one the future developments concerns the study of demand- and supply-side shocks within a real supermarket supply chain. The idea is to propose a simulation model and to test different strategies/scenarios, in order to make it more resilient.

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