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Environmentally sustainable inventory control for perishable products: A bi-objective reorder-level policy ☆

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ABSTRACT

In order to improve sustainability and transparency in the decision making for inventory control, this paper presents a reorder-level model that considers product perishability. Conversely to most inventory control policies, the classical economic perspective is paired with an environmental one for a stochastic bi-objective optimization approach to reduce inventory logistics emissions and costs. In order to contrast stockouts, lost-sale costing and a service level constraint are integrated for a more comprehensive approach. Results show how the two objectives may be in contrast, and how Pareto-efficient solutions can help to analyze and select the proper trade-offs during decision making. Experiments indicate, for a case-study application, how the most relevant aspects affecting system performance are product shelf life and the possible need of temperature control during storage. Moreover, considering multiple sustainability perspectives in inventory management can help businesses consolidate and future-proof their operations, as well as meet environmental standards and customer demand for greener products and processes.

1. Introduction

In the current global context, logistics continues to play a key role in many types of supply chains. Due to the high business costs for maintaining reliable flows of goods, totaling near to 7.9% of GDP in the US in 2015 (Monahan et al., 2016), both practitioners and researchers strive for making such processes efficient in order to keep businesses economically sustainable. From the coexisting standpoint of environmental sustainability, logistics buildings and related transport activities are responsible for up to 15% of the total greenhouse gas (GHG) emissions in the life cycle of a product (World Economic Forum, 2009). In this multi-sustainability context, implementing quantitative measures for environmental efficiency is an essential step to reduce emissions (World Economic Forum, 2021).

Additionally, some supply chains are strongly characterized by the economic and environmental driver of waste. For example, the distribution of food produce is responsible for waste at different echelons, adding up to nearly 300 kilograms of food losses per capita each year both in Europe and in North America (Gustavsson et al., 2011). Regarding waste reduction, Gore et al. (2022) reported how only about one third of the surveyed producers and retailers adopt sustainability-related metrics to reduce wastage. In addition, Gustavsson et al. (2011) pointed out that waste is directly related to GHG emissions, as they are not beneficial to any actor in the (food) supply chain. Businesses should therefore implement the environmental sustainability aspect in addition to the economic one, especially when waste is a major factor. Inventory control policies catered to this multi-objective outlook can serve as a major tool for decarbonizing supply chains, bringing also other benefits, such as attracting new clients, improving customer opinion of a brand, and motivating employees who might embrace such values, thus possibly allowing for more sustainable practices for future-proofing businesses (van der Veen and Venugopal, 2014). Within this context, continuous review policies allow for effective and easily-interpretable inventory programs that can benefit the decision making of multiple conflicting sustainability objectives, considering also that order quantity approaches are already commonly adopted in real applications (Andriolo et al., 2014).

In the last decade, environmental sustainability has become an increasingly considered topic in the inventory control literature, as it provides important opportunities for enhancing different perspectives. In particular, the space utilization for storing products is responsible for GHG emissions due to energy usage to maintain a warehouse operational (Fichtinger et al., 2015), and inventory replenishments

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require recurring transport activities. Although efforts have been made to integrate inventory policies with these environmental aspects, most of the proposed models deal with deterministic problems (Daryanto et al., 2021) by considering cost emission factors (e.g., Battini et al., 2014; Bonney and Jaber, 2011; Kazemi et al., 2018) or by following a multi-objective approach. Including GHG emissions as costs may be representative of carbon tax scenarios, nevertheless, businesses should seek environmental sustainability regardless of external regulations. Conversely, the less used multi-objective approaches, aim at increasing transparency in the decision making process by formulating distinct objective functions (van der Veen and Venugopal, 2014).

Moreover, inventory choices may be directly related to the amount of discarded products. The necessity for discarding items can be caused by physical degradation, loss of functionality, or perceived loss in value of items that need to be discarded (Pahl and Voß, 2014). Products with a best-before date, such as medicine or food items, can cause waste due to degradation and are often present in both brick-and-mortar and e-commerce retail stores. Within this scenarios, where the final customer does not have to pick the product, FIFO policy is often considered when dealing with perishable items. Regarding policies for perishables with fixed lifetimes and non-negligible lead times, Berk and Gürler (2008) have suggested how reorder policies of fixed size represent a reasonable policy class, taking into account their potential applicability to real scenarios. Efforts have also been made to approximate optimal inventory policies for perishable products. For example, Haijema (2013) proposed a new hybrid policy class with a mix of base stock and fixed quantity replenishments and optimized it with the use of simulation. Hybrid policies for perishables can bring benefits compared to base stock policies, while for large ratios between lead time and shelf life constant order quantity models have been shown to reduce inventory costs (Haijema and Minner, 2016). Implementing waste in a reordering policy is a key aspect to allow for a holistic model that considers this additional driver from both economic and environmental perspectives. Moreover, careful modeling of outdating items during lead times is especially necessary when lead time grows.

This paper follows the proposal of Andriolo et al. (2014) to pair economic performance with the environmental one following a multi-objective approach by presenting a stochastic reorder-level inventory policy, with the aim of optimizing the management of a perishable product by considering both costs and GHG emissions through quantitative measures. Demand during the lead time is considered as stochastic and modeled with a continuous distribution function, which may include lead time variability other than the one related to demand. The relevance of both sustainability aspects is key especially when dealing with perishable items such as food or medicines, as this product characteristic introduces an additional component for the economic and environmental performance. Additionally, products with shelf lives are often linked to different storing requirements, for example allowing for frozen products to be stored longer with respect to chilled ones. Outdating items, i.e. products that exceed their fixed shelf life, are estimated under the assumption of a single outstanding order per inventory cycle depending on the realization of demand random variables, namely, either if a portion of the reorder quantity outdates in the current or in subsequent reorder cycles. In particular, these two estimations depend on the demand during the cycle, other than during the product shelf life, since if customer request for the product is high enough, no items will perish. This proposed estimation is validated via comparison with a discrete event simulation model, which shows the quality of the estimation of outdated products for several scenarios of input factors and the relation with economic performance. Moreover, the decision process for multiple sustainability in a lost-sale stochastic context requires increased transparency, obtained thanks to the explicit multi-objective identification of efficient solutions. This approach does not appear to be yet addressed in the inventory management literature with stochastic demand. In addition, the considered problem deals with products with limited shelf life and is constrained by customer service level. Increased awareness of the negative impacts of inventory choices is given by the interaction between the two perspectives depending on the system variables, considering that perishability also affects the estimation of the other inventory performance components.

The remainder of this paper is organized as follows. The next section is dedicated to a literature review on reorder-level inventory policies, with a particular focus on stockout modeling, perishability, and sustainability. Section 3 sets the problem context and assumptions by describing the model characteristics. Then, Section 4 is dedicated to presenting the mathematical formulation for the objective functions and the estimation of each component that constitute the objective functions, followed by the multi-objective approach for the constrained optimization problem. To provide managerial insights, Section 5 is catered at presenting relevant results and related analysis for a case study that allowed the estimation of cost and emission factors for the proposed inventory policy. Closing with Section 6, additional considerations and possible future developments are discussed.

2. Literature review

Due to the wide contexts in which inventory is held and the many possible approaches to make this component of supply chain management efficient, the literature on inventory control policies is vast. This section focuses first on scientific contributions regarding continuous-review policies, and more specifically on reorder-level approaches. Then, the focus shifts to how the literature has modeled environmental metrics for inventory management. Finally, the main contributions regarding the inclusion of perishability in reorder-level approaches are analyzed by focusing mainly on inventory models with fixed-lifetime products.

In reorder-level policies, the inventory level is reviewed continuously, and whenever it reaches the reorder level, a fixed-size replenishment is issued to the supplier and received after a lead time. These approaches to inventory control are often referred to as (r, Q) policies, where r is the reorder level, or point, and Q the reorder quantity. Reorder-level models are developed to adapt the concept of economic order quantity to a stochastic setting (Eksioglu, 2008). Andriolo et al. (2014) provided a detailed review on the state of the art of different extensions for order-quantity models, categorizing contributions based on deterministic, stochastic, or fuzzy approaches. This work suggested a lack of environmental sustainability focus in stochastic models.

A relevant distinction to be made when considering an inventory system is the customer behavior whenever a stockout happens. Customers may wait until the requested product becomes available again, or their demand may be lost (Musalem et al., 2010). These scenarios are often referred to as backlogging and lost sales respectively. Although backlogging is widely used in industrial environments, unmet demand is often lost in retail (Bijvank and Vis, 2011), or whenever customers are impatient (Babiloni and Guijarro, 2020). The impact of a stockout is quite different in these two scenarios, since the lost-sales context is deeply related to customer retention other than short-term effects (Jing and Lewis, 2011), and this should be reflected in the quantification of inventory model features. In particular, Bijvank and Vis (2011) focused on lost sales by performing a literature review of different inventory control policies, pointing out how both backorders and lost sales has been included in some contributions by considering probabilities of backordering an order whenever in stockout. Whenever a stockout happens, customers may wait until the requested product becomes available again, or their demand may be lost (Musalem et al., 2010). Including lost sales or backorders in an inventory model can be performed via stockout costing and service level constraints. Liberopoulos et al. (2010) referred to the former as penalized backorder models, and the same concept was adopted for lost sales (e.g., Kouki et al., 2015; Berk and Gürler, 2008). Due to the complexity of assessing stockout-related costs (Chen and Krass, 2001), given by both short- and long-term effects (Andersen et al., 2006), service level measures have been developed to tackle stockout occurrence via constraints. Chen and Krass (2001) define two kinds of service level measures depending on whether average or worst case performance is quantified, namely through mean or minimal service levels. They refer to a service level constrained model as partial costing, stating how minimal measures cannot be directly declined to a full cost model where backorders or lost sales are economically penalized. In this work, the focus will be put on integrating a type I service level measure within a bi-objective optimization framework, computed as the probability of avoiding stockout at every reorder cycle. In particular, Escalona et al. (2021) show how ensuring a low probability of stockouts at any reorder cycle also ensures high values of other service level measures.

2.1. Environmental considerations

Starting from the 2000s, environmental sustainability started to play an important role in inventory policies (Drake and Marley, 2014). Absi et al. (2013), D'Urso et al. (2018) underlined how the majority of order-quantity model extensions include environmental aspects within the total cost objective function. For example, regarding continuous-review policies, Battini et al. (2014) presented a deterministic economic lot-sizing model that includes cost factors for storing, waste, and transport. Similarly, Bonney and Jaber (2011) included waste and transport environmental cost factors in an illustrative model by associating an additional cost factor for each replenishment that depends on supply transport time, and Daryanto et al. (2021) incorporated average carbon emission costs for both storing and transport. Additionally, Kazemi et al. (2018) considered an emission cost for obsolescence disposal for imperfect quality items, and repartitioned storing emission costs with respect to volume occupied by the average inventory.

On the other hand, other researchers consider the environmental perspective as an integral part of the optimization models by developing multi-objective formulations. Similarly to the bi-objective formulation of van der Veen and Venugopal (2014) and Bouchery et al. (2012) developed a n-criteria interactive decision making procedure aimed at identifying all the non-dominated solutions to a deterministic lot sizing model with storage and transport components for the selection of the reorder quantity. The goal for explicit multi-objective optimization is to identify the efficient frontier of the considered objectives. Arıkan et al. (2014) proposed a simulation of a two-echelon supply chain and different freight modes to highlight the effect of lead time variations. Furthermore, Bozorgi et al. (2014), Bouchery et al. (2016) proposed a bi-objective approach by modeling two objective functions for economic and environmental performance separately, depending on the reorder quantity variable, by focusing on the deterministic problems of limited storage and transport capacities for cold items and of different transport modes respectively. Moreover, based on the available literature, there do not appear to be any contributions tackling a stochastic reorder-level inventory problem with explicit multi-objective modeling. The proposed optimization model builds on the consideration of the sustainability aspects of inventory costs and GHG emissions as separate for a reorder-level policy. More specifically, the environmental effects of products that need to be disposed of due to perishability are considered. In addition, the environmental drawbacks of order issue and product storage are integrated, in relation with required number of shipments and average space occupied respectively, considering how different products might not only have different shelf lives but how they might require different storage conditions with different environmental impact.

2.2. Product perishability

Integrating perishability is a further relevant aspect in inventory control. In their literature survey about lifetime considerations in supply chain management, Pahl and Voß (2014) defined perishable goods as products that maintain quality during their shelf life, but need to be discarded afterwards with related economic drawbacks. Moreover, the authors stated that this kind of waste is also related to greenhouse gas emissions and energy consumption. Additionally, Kouki et al. (2013) distinguished between fixed lifetime, stochastic lifetime, and continuous deterioration inventory models, while Janssen et al. (2016) offered a literature review on perishability and deteriorating inventory models, highlighting how service level has been hardly included, even though it plays a relevant role in retail or food sectors. Moreover, regarding continuous-review systems, they underlined how perishability is related to an additional economic component for long-run costs due to outdating products. This product characteristic has been investigated also for multi-period inventory approaches, see for example Haijema and Minner (2019) for a review on stock-age dependent policies, also by considering service level constraints per fixed period (e.g., Minner and Transchel, 2010; Transchel and Hansen, 2019; Kouki et al., 2014). Multi-period problems have also been integrated with other decision problems, such as the inventory routing problems (IRPs), where routing decisions are sometimes paired with perishability considerations. For example, Soysal et al. (2015) studied an IRP that considers a type I service level measure for perishable products, as well as emissions of transport as additional cost components. In a similar perishability setting, where products are characterized by a limited shelf life, Biuki et al. (2020) included sustainability implications in IRP decisions related to supplier selection with the objective of minimizing costs. Since these categories of problems deal with a periodic review setting, product shelf life needs to be considered also for continuous systems. In addition, sustainability considerations should not be limited to the transport component.

Regarding inventory policies and variable lot sizes, one of the approaches in the literature deals with Markov chain representations of inventory. In particular Baron et al. (2020) considered stochastic lead time and shelf life, both distributed as exponential, and the assumption that the inventory drops to zero whenever end-of-life is reached, while Gong et al. (2022) considered the objective function of profit rates under zero lead time and a Brownian demand model. Nevertheless, the impact of perishables on inventory performance should be also considered for (r, Q) policies for non-zero lead times and taking into account that, if there is safety stock, the impact of products that outdate can be only partial on the available inventory level. For additional details on other categories and policies see, for example, Nahmias (2011) for state-of-the-art inventory models for perishable products, and Karaesmen et al. (2011) for future directions in inventory models with perishability by encompassing aspects such as multi-echelon and multi-products considerations. Additionally, Baron (2010) focused on a taxonomy on continuous-review policies.

Regarding reorder-level policies with known shelf lives, for example, Muriana (2016) considers a (r, Q) policy modeled through differential equations, where stock decreases due to customer demand rate and the safety stock is computed a priori depending on the standard deviation of demand and by setting a safety factor. On another note, Berk and Gürler (2008) model a Markov process where demand follows a Poisson distribution, highlighting that reorder-level policies can perform generally well also with respect to more complex time-based policies. Barron and Baron (2020) also employ a Markov chain approach for a single outstanding order per cycle, where optimal values of the decision variables are identified for the lost sales scenario where lead time is random. The proposed estimation regarding perishability builds on the similar idea of considering the effect of outdating items on the performance of an inventory system, with the goal of optimizing not only costs, but also GHG emissions while constrained by service level. In particular, the random variable of demand during lead time is modeled as a continuous distribution that might include variability in lead time duration and a single outstanding order is permitted per reorder cycle.

Other approaches focus directly on the demand distribution in order to quantify the items that exceeded their shelf life. In this regard, Chiu

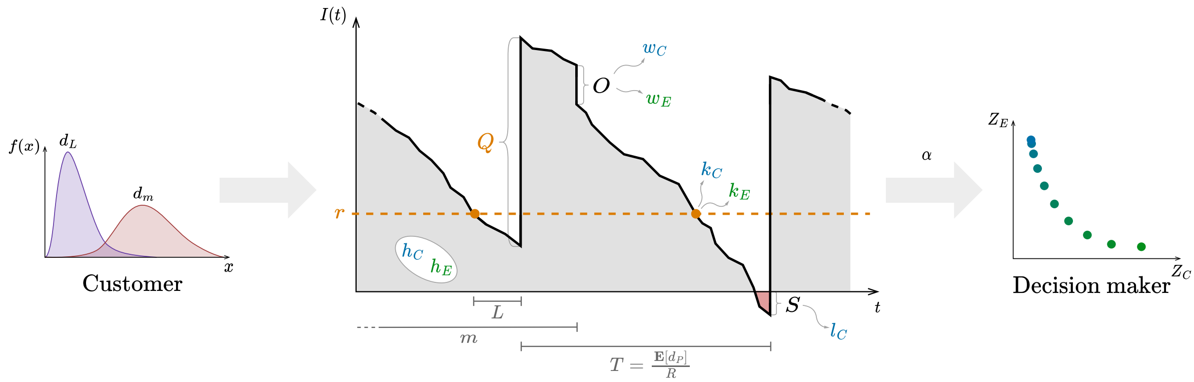

Fig. 1. Representation of a (r, Q) policy with identification of the model components, variables, and parameters used to produce a transparent output for sustainable inventory control decisions.

(1995) models the expected value of outdating products per cycle in a backorder setting, where they assume no products can perish during lead time. Their estimation for outdating units is modeled, as a function of r and Q, by considering different scenarios where products can outdate. Moreover, they point out the impact that lost sales would have on the expected length of a reorder cycle. Following a similar approach and assumption, Kouki et al. (2015) consider the demand during stockouts as lost and include the possibility of multiple outstanding supply orders. Both full-costing formulations estimate outdating products depending on demand distributions during lead time and shelf life, assuming that no product may outdate during the resupply lead time. On the other hand, the model proposed in this work takes into account the possibility of product perishability during the lead time. The estimation is centered on the modeling of all the possible scenarios in which product may outdate, which are based on the distributions of demand during a reorder cycle and during product shelf life. In particular, a more accurate modeling of the amount of products that outdate due to perishability should lead to lower inventory costs with respects to literature benchmarks for an (r,Q) policy. In addition, a minimal service level constraint is considered as well within a bi-objective optimization framework.

3. Problem description

The problem addressed in this study is the inventory control of a perishable product through a reorder-level policy. The classical economic perspective is coupled with an environmental one within a bi-objective optimization framework aimed at increasing transparency in the decision making process in a (r, Q) policy. In particular, the decision variables are the reorder level r and the reorder quantity Q. Namely, whenever the available inventory level reaches r, or surpasses it due to the fact that products have outdated, a fixed-quantity order of size Q is issued to the supplier. This approach for inventory control results in possibly different reordering cycle durations, defined as the difference between the arrival times of two subsequent reorders, due to the variability of the customer demand. A stationary stochastic problem is considered, where uncertain product demand is modeled thanks to probability density functions (PDFs) that remain constant within the planning horizon.

Product perishability is modeled as shelf life, which is representative of products with a best-before date. Unmet customer demand due to inventory shortages is considered as lost, with an incurred cost for each lost-sale unit. Furthermore, a minimal customer service level restricts inventory-control decisions by taking into account the probability of stockouts.

The model considers that economic costs and negative environmental externalities have four main determinants: (i) issuing and transport of resupply orders, (ii) storing of items in the warehouse or dedicated storage space, (iii) quantity of lost sales, and (iv) amount of perishable products that can outdate during inventory holding. The latter component, in particular, is related to both reduction in available stock and to waste management, which can have an impact on both the considered objectives.

The goal is thus to support the decision making for managing the inventory of a product by minimizing the related long-term average costs and emissions. Following the modeling of each component and the objective functions, the bi-objective constrained minimization process increases transparency and communicability in the optimal selection of the decision variables r and Q.

Dealing with the proposed reorder-level policy, it is assumed that the inventory position is reviewed continuously and that only one order can be outstanding per each reorder cycle. Perishable products have a fixed shelf life that begins upon their arrival in stock. In order to meet customer demand, items are then picked with a FIFO policy.

The notation used in the remainder of the paper is listed in Table 1, where the previously-described components, their related costs, and environmental factors are reported, in addition to the notation regarding customer demand. In particular, the unit measure considered for the environmental objective function is the mass of equivalent carbon dioxide, which allows for evaluating the global warming potential of different greenhouse gasses over a given timeframe relative to CO_2 (Allen and Pentland, 2011).

A visual interpretation of the modeled system is given by Fig. 1, which shows a possible realization of inventory level and highlights the relationship between the previously introduced (four) components of the system and cost or emission factors. Such a realization depends on customer parameters, which also affect inventory decisions. In particular, an informed sustainable decision of system variables can be performed only with a clear and easily-interpretable understanding of their impact on the considered objective functions. More specifically, the output given to the decision maker is composed of all the pairs of (r, Q) associated with Pareto efficient solutions, of which the economic and environmental anchor points are but two. The final selection of reorder level and quantity, restricted by the service level, will then determine the progression of the inventory level.

4. Optimization model

This section presents first the model components' baseline estimation by accounting for product perishability. This preliminary step enables the formulation of the total costs and the total emissions objective functions, denoted by Z_C and Z_E respectively. In addition, some insights are provided on the relevance and interpretation of environmental factors. Finally, the bi-objective constrained minimization problem is approached with the aim of maintaining the economic and environmental objective functions as independent as possible in order to provide the decision maker with a quantitative and clear understanding of inventory choices with respect to both the considered perspectives.

Table 1
Notation of objective functions' components and parameters for the proposed reorder-level policy of perishable goods.

Objective functions	
$Z_C(r,Q)$	Economic objective function of total costs in the considered planning horizon [€]
$Z_E(r,Q)$	Environmental objective function of total equivalent carbon-dioxide emissions in the considered planning horizon [kgCO_2e]
Decision variables	
r	Reorder level [items]
Q	Reorder quantity [items]
Components of objective functions	
$R(r,Q)$	Expected number of replenishments in the considered planning horizon
$A(r,Q)$	Expected average inventory [items]
$S(r,Q)$	Expected lost sales per reordering cycle [items]
$O(r,Q)$	Expected outdating products per reordering cycle [items]
Parameters	
α	Minimal service level to be maintained [%]
Demand parameters	
m, L, P	Duration of shelf life [weeks], of lead time, and planning horizon [days] respectively
d_m, d_L, d_T	Demand during shelf life, replenishment lead time, and reordering cycle (r.v.)
$\overline{d}_T, \overline{d}_P$	Expected value of demand during reordering cycle and planning horizon respectively
f_m, f_L	Probability density functions of demand during shelf life and lead time respectively
F_L	Cumulative distribution function of demand during replenishment lead time
Cost and emission factors	
k_C	Cost of a replenishment [€]
h_C	Cost of inventory holding per item in the considered planning horizon [€/item]
l_C	Cost of a lost sale [€/item]
w_C	Cost per outdated unit [€/item]
k_E	Emissions of a replenishment [kgCO_2e]
h_E	Emissions of inventory holding per item in the considered planning horizon [kgCO_2e/item]
w_E	Emissions per outdated unit [kgCO_2e/item]

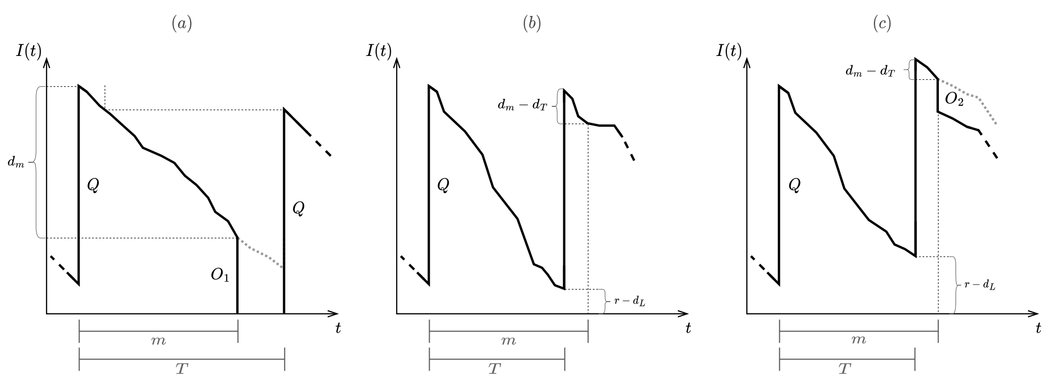

Fig. 2. Visual representation of the possible perishability realizations depending on the demand random variables $d_{\cdot}$c.

4.1. Estimation of inventory components due to perishability

The shelf life of items can lead to outdated items in a reordering cycle, which need to be discarded. This product characteristic influences the estimation of other often-considered components for inventory control, for example, related to lost sales quantities or average inventory level. The modeling of such elements serves as a baseline for the economic and environmental objective functions presented in Section 4.2.

Outdating products
$O = O_1 + O_2$

$d_m < d_T$: $O_1 = (Q - (d_m - B)^+)^+$

$d_m > d_T$: $O_2 = ((r - d_L)^+ - (d_m - d_T)^+)^+$

Fig. 3. Possible realizations and related estimations of expected values of outdating products per reordering cycle, depending on the random variables of demand during shelf life d_m and reordering cycle time d_T.

4.1.1. Outdating products

The estimation of the amount of outdating quantity per reordering cycle takes into account, other than the shelf life of the products, the volatility of customer demand during both their useful lifespan and supply lead time. Demand is modeled with PDFs f_L, f_m for demand during lead time, and shelf life respectively.

Due to the stochasticity of the problem, products can perish both in the same inventory cycle in which they arrive or a subsequent one, depending on different realizations of demand. Under the single outstanding order assumption and FIFO policy, items with fixed shelf life from a reorder quantity cannot be in the inventory for more than two inventory cycles. It is thus sufficient to model the number of items that can outdate within these two cycles. Specifically, if $T > 0$ is the expected value of cycle length, then items can outdate both within the cycle ($m \leq T$) or after the end of the cycle ($m > T$). This is shown in Fig. 3, where, given an order Q and a level r, the expected value of outdated products, O is the sum of those expected to expire within the same cycle (O_1) and those expected to expire in the next one (O_2). The differentiation between these two quantities is based on the relationship between the random variables of demand during shelf life d_m and during the reordering cycle d_T to identify the possible scenarios that results in the quantities reported in Fig. 2, where B is the buffer stock and notation $(\cdot)^+ = \max\{\cdot, 0\}$ indicates the estimation of solely positive values.

The expected number of items expiring within the cycle, O_1, is given by all the items remaining after demand d_m has been satisfied, as per the first portion of Fig. 3. The expected value of O_1 can be computed

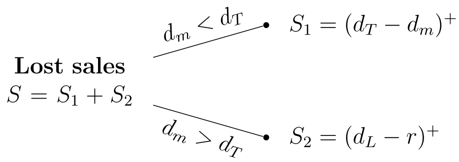

Fig. 4. Possible realizations and related estimations of expected values of lost sales per reordering cycle, depending on the random variables of demand during shelf life d_m and reordering cycle time d_T.

as:

$$O_1 = \int_0^B Q f_m(x)\mathrm{d}x + \int_B^{\bar{d}_T} (Q - x + B) f_m(x)\mathrm{d}x \tag{1}$$

where B is the leftover buffer of safety stock of the previous reorder and $\bar{d}_T$ is the expected value of the random variable of demand during an inventory cycle, with cycle length equal to the expected value of T assuming no product perish. This assumption allows to estimate $\bar{d}_T$ as the expected demand value during this cycle length, and thus the other estimations of the related objective function components that depend on it. As per Fig. 2-a, the initial portion of demand is satisfied by the buffer stock according to the FIFO policy. Therefore, if all the customer demand received during the new batch shelf life is fully satisfied from buffer stock, all the reorder batch will perish. In particular, B is estimated as the steady-state remaining inventory level given by the difference between reorder level and demand during lead time as per the inner integral of Eq. (5). It is important to note that this estimation for O_1 assumes that the buffer stock does not outdate in this time. This estimation is conservative since if outdating of B happened, then less outdating of the current batch would happen.

The other portion of outdating items considers instead the possible perishability in a subsequent cycle with respect to the arrival in stock, estimated as per the second part of Fig. 3. If there is sufficient customer demand, namely if $d_m - d_T \geq r - d_L$, every item in the remaining buffer stock is sold before the shelf life is reached (Fig. 2-b). On the other hand, if $d_m - d_T < r - d_L$, then some items will outdate. This portion can be estimated depending on the remaining buffer stock:

$$O_2 = \int_0^r \int_{\bar{d}_T}^{\bar{d}_T + r - y} \left(\bar{d}_T + r - y - x\right) f_m(x) f_L(y)\mathrm{d}x\mathrm{d}y \tag{2}$$

This estimation refers to the scenario of Fig. 2-c, where it can be seen that some products can outdate due to the difference between buffer stock $(r - d_L)^+$ and demand during the remainder of the shelf life of the order batch $(d_m - d_T)^+$.

4.1.2. Lost sales

Following the same process used for outdating items, the estimation of lost sales depends on to the relation between demand during shelf life d_m and reordering cycle time d_T.

Regarding the number of lost sales per cycle S, whose estimation is summarized in Fig. 4 as the sum of components S_1 and S_2, the second term S_2 is modeled by adapting the widely-used formula for stockout size per reordering cycle (Silver et al., 2016, p. 261) to the perishable case:

$$S_2 = \int_r^\infty \int_{\bar{d}_T}^\infty (y - r) f_m(x) f_L(y)\mathrm{d}x\mathrm{d}y \tag{3}$$

On the other hand, whenever $d_m < d_T$ the number of lost sales is the total demand of the reordering cycle other than the one during shelf life that cannot be covered due to the fact that products outdate, as shown in Fig. 5, which can be estimated as:

$$S_1 = \int_0^{\bar{d}_T} (\bar{d}_T - x) f_m(x)\mathrm{d}x \tag{4}$$

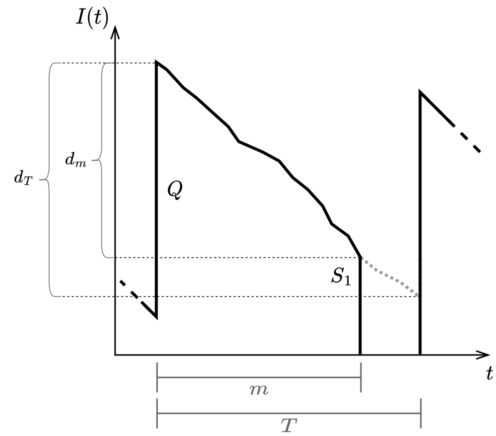

Fig. 5. Visual representation of the lost sale quantity S_1.

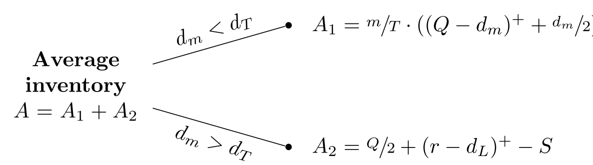

Fig. 6. Possible realizations and related estimations of expected values of average inventory, depending on the random variables of demand during shelf life d_m and reordering cycle time d_T.

4.1.3. Average inventory

As mentioned above, perishability affects the inventory level too, and thus the estimation of the expected average inventory. Similarly to the lost-sales estimation, Fig. 6 summarizes the two realizations for average inventory, which depend on r and Q.

The second of the two realizations is derived from the non-perishable case as follows:

$$A_2 = \int_{\bar{d}_T}^\infty \left(\frac{Q}{2} + \int_0^r (r - y) f_L(y)\mathrm{d}y - S\right) f_m(x)\mathrm{d}x \tag{5}$$

where the inner portion of the integral represents, in relation to the PDF of demand during lead time, the average inventory for a reorder-level policy of a non-perishable product. Conversely, the estimation of the term A_1 of the average inventory should take into account the outdating of products in the current reordering cycle. In this scenario, it is assumed that storage space is used only during the shelf life of the product, after which outdated items are discarded. The factor $(Q - d_m) + {}^{d_m}/_2$ of Fig. 6 represents the average inventory during m, which is then scaled with respect to the overall reordering cycle duration T as follows:

$$A_1 = \frac{m}{T} \int_0^{\bar{d}_T} \left(Q - \frac{x}{2}\right) f_m(x)\mathrm{d}x \tag{6}$$

4.1.4. Number of reorders

The frequency of supply orders needed to replenish the inventory of the product is itself dependent on perishability, as well as on the lost sale setting. For this reason, the estimation of the number of reorders takes into account the expected number of lost sales and outdating products per cycle. This results in the estimation of R of Eq. (7), obtained by adapting the formulation of Kouki et al. (2015) for the expected cycle length.

$$R(r, Q) = \frac{\bar{d}_P}{Q + S(r, Q) - O(r, Q)} \tag{7}$$

4.2. Objective functions

The economic and environmental perspectives are modeled as separate objective functions that depend on the decision variables r and

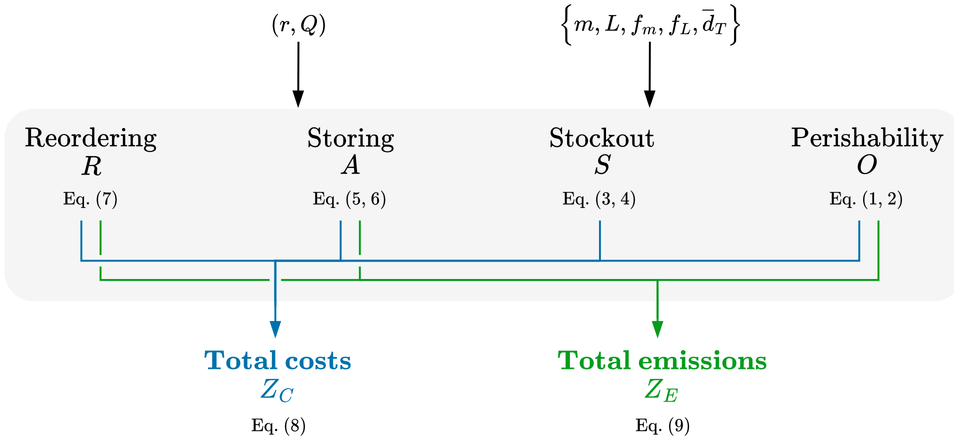

Fig. 7. Relationship between macroscopic model components and objective functions. Numbers refer to the equations for their estimation.

Q, on cost and emission factors, and on probability distributions of the demand. These objective functions become the baseline of an explicit multi-objective approach. Fig. 7 shows how the estimated model components are considered for formulating both objective functions. In particular, lost sales S and outdated items O are estimated per reordering cycle, which allows for obtaining total expected lost sales and outdating items in the planning horizon through the expected number of replenishment orders R.

From a high-level perspective, referring to the notation of Table 1, the total costs of managing the inventory of a perishable product in the considered planning horizon are given by:

$$Z_C(r,Q) = \left(k_C + l_C\, S(r,Q) + w_C\, O(r,Q)\right) R(r,Q) + h_C\, A(r,Q) \tag{8}$$

where the estimation of the objective function of total cost encompasses all the previously-defined components depicted in Fig. 7, which also references the equations for their estimation. In particular, a cost is incurred for every replenishment order (k_C), and for each lost sale (l_C) and outdated item (w_C). Storage costs (h_C) are instead related to the average inventory occupied during the optimization horizon by one item.

Similarly to the economic perspective, the total-emission objective function can be written as:

$$Z_E(r,Q) = \left(k_E + w_E\, O(r,Q)\right) R(r,Q) + h_E\, A(r,Q) \tag{9}$$

where the lost sales do not have a direct impact on emissions related to the inventory control of a product, but they affect the estimation of the other model elements.

Focusing on the emission factors, the environmental objective function takes into account the CO_2e emissions for transport and issuing of every reorder quantity through the parameter k_E. Holding products in stock yields emissions due to energy usage needed to keep the warehouse operational, such as lighting, air conditioning, and heating. Perishable products might also require temperature control during storing and/or transport, which is strictly related both to costs and emissions. Furthermore, the factor h_E can consider the embodied carbon related to the warehouse as fixed overhead emissions that depend on building characterization and useful lifetime. Finally, when products outdate they need to be disposed of, which requires further potentially-polluting actions such as transport to a landfill site. Perished products lead to emissions due to the need for disposal (Tiwari et al., 2018). Each outdated item is responsible for w_E emissions, both due to waste disposal and considering the emissions related to the portion of the product life cycle prior to outdating, since they were incurred without any benefit to customers or the organization.

4.3. Constraints

Although the proposed formulation is general enough to consider lost sales through a full-costing approach, to guarantee a lower bound on the quality of the service, it may be desirable to constrain the problem. In practice, this can be done by imposing the following minimal service level constraint:

$$F_L(r) = \int_0^r f_L(x)\mathrm{d}x \geq \alpha \tag{10}$$

which guarantees that the ready rate, defined as the probability of avoiding a stockout in every reordering cycle, exceeds the desired threshold of $\alpha > 0$. Note that the definition of average inventory of Eq. (5) assumes that the desired service level α or the lost sales cost l_C are sufficient for non-negative safety stock.

Moreover, since only one order can be outstanding for the considered policy, the reorder level r must be lower than the reorder quantity Q (Bijvank and Vis, 2011), further restricting the minimization of both objective functions.

4.4. Multi-objective optimization approach

Following the definition of the objective functions for both economic and environmental perspectives, it is possible to approach the minimization of total costs and emissions related to the inventory control of a perishable product. This approach to multi-objective optimization for the reorder-level policy enables explicit sensitivity analysis and exploration of the trade-off between economic and environmental as functions of the variables and parameters of the problem. The aim is thus to identify all feasible and relevant solutions to support environmentally-responsible decision making for the inventory control of a perishable product. Feasible solutions are the combinations of r and Q that comply with the constraints detailed in Section 4.3. Since the goal is to minimize costs and emissions, the focus is laid only on a portion of the feasible solutions, in particular on the non-dominated ones. In general, a solution is defined as non-dominated if there are no other solutions that improve the performance in every considered objective function. Identifying such combinations of system variables is essential for a decision maker to select the appropriate trade-off solution based on quantitative information on the effect of r and Q on the objective functions.

The problem can be therefore written as:

$$\underset{r,Q\in\mathbb{N}}{\text{minimize}} \quad \langle\, Z_C(r,Q), Z_E(r,Q)\,\rangle \tag{11}$$

$$\text{subject to} \quad \int_0^r f_L(x)\mathrm{d}x \geq \alpha, \tag{12}$$

$$r < Q, \tag{13}$$

Table 2
Case-study warehouse storage parameters, made anonymous with bias and random noise.

	Annual storage costs [€/year]	Storage capacity [m^3]
Standard	106 379	8742
Cold	431 194	4464
Frozen	519 537	4802

Note that, as non-negative quantities of non-divisible products are considered, it is necessary to also specify that the variables are natural numbers. Eqs. (12) and (13) refer respectively to the constraints of minimal ready rate and single outstanding replenishment order and identify the feasibility region $\Omega = \{(r, Q) \mid r < Q,\ F_L(r) \geq \alpha\}$ of the decision space for the selection of reorder level and quantity.

The set of non-dominated solutions $\mathcal{P} \subseteq \Omega$ to be identified is then given by all the combinations of decision variables that do not perform worse in one or both objective functions. As better shown visually in the results of Section 5, non-dominated solutions can be represented by focusing on the objective space through the Pareto front relating all $\langle Z_C(r^*, Q^*), Z_E(r^*, Q^*)\rangle\ \forall\,(r^*, Q^*) \in \mathcal{P}$, thus giving a decision maker all the relevant information needed for a clear selection of the appropriate variables.

5. Results and discussion

The proposed model and bi-objective resolution approach for the sustainable reordering of perishable products are applied in representative scenarios for an industrial case study, presented in the first portion of this section. In particular, by focusing first on a single instance of the problem, the aim is to show the outputs of the model. Finally, by comparing different realistic and relevant scenarios, further results and considerations are obtained for analysis. Impactful considerations are drawn to support the decisions making for the inventory control at a managerial level.

5.1. Case study

The considered case study is a European company specializing in the distribution of food products and operates at a multi-regional level from a single distribution center. The company's warehouse is mainly responsible for receiving, storing, and distributing to retailers, restaurants, and final customers. Over the span of the years 2017 to 2019, the company has managed about five-thousands stock keeping units, accounting for more than 45'000 inventory replenishment orders performed by the procurement office. In order to keep the distribution center running, the company incurs yearly storage costs related to energy consumption and depreciation of the warehouse building and material handling equipment. Moreover, further costs are incurred for procurement due to personnel and overhead costs. Since the business deals mostly with food items, some require temperature control during storage. For this reason, produce categories are defined as standard products, which are shelf-stable items that can be stored in a regular environment, cold products that require refrigeration at 4–8 °C, and frozen products at minus 20 °C. These storage cost values are listed, together with storage capacities in Table 2, depending on the product category.

Overall storage and procurement costs, can be used to derive cost factors for the optimization model. In particular, considering one of the most representative standard products managed by the company, Table 3 lists the available and computed parameters for optimizing its inventory choices in a sustainable manner. The considered product, stored at ambient temperature, has a shelf life of two weeks and its demand distribution has been estimated from the historical company data, which results as an exponentially distributed daily customer demand with rate parameter $\lambda = 3.46$ items per day, while its procurement lead time is estimated to be of four days. Moreover, each unit of product has a value of 15€, occupies 0.008 m^3 during storage, and has a mass of 0.7 kg. The company incurs costs for each lost sale equal to 20% of the item value and 70% for each outdated item due to purchase cost and waste management. Additionally, the input of minimal service level α is set by management to be of 70%.

Similarly to the economic perspective, emission factors related to storage are computed starting from data on yearly energy consumption. Such values are estimated thanks to relevant literature contributions regarding similar warehousing scenarios and assuming a carbon footprint related to the energy mix of the company of 0.6 kgCO_2e/kWh (Allen and Pentland, 2011). More specifically, the energy profile of a warehouse is mainly driven by temperature control for thermal comfort and by lighting (Ries et al., 2017) for standard products. The considered parameters are listed in Table 3. In particular, supply is by road via truck, and the emission factor k_E is estimated depending on the order quantity, since this variable impacts both the number of required shipments $\lceil Q/Q_{max}\rceil$ and the fuel consumption, i.e., more emissions are incurred for an heavier vehicle and for multiple resupply trips (Bozorgi et al., 2014). The emission factor is computed, depending on the travel distance D, as:

$$k_E(Q) = \left(e_0 + e_w \cdot Q \Bigg/ \left\lceil \frac{Q}{Q_{max}} \right\rceil\right) \cdot D \left\lceil \frac{Q}{Q_{max}} \right\rceil \tag{14}$$

where e_0 is the emission fact per traveled distance for an empty vehicle, e_w the factor per item per transport distance that contributes to the increase in transport emissions due to an increase in shipped weight. Q_{max} is the transport capacity for the considered product. In particular, each transshipment can carry 300 units of product, and it is assumed that each unit contributes to 1 gCO_2e per unit distance. Moreover, the emission factor is related to a medium-speed diesel truck (Grigoratos et al., 2019) for a travel route of 62.8 kilometers. Additionally, Eriksson et al. (2015) allow estimating emissions per item of equivalent food product taking into account the carbon-equivalent emissions due to waste management, assuming a landfill end-of-life scenario.

5.2. Validation

This section is dedicated to comparing the results of the proposed model, in particular by focusing on the validity of the estimation of outdating products due to perishability. The comparison is performed with both a simulation model built in Arena Simulation Software 16.2 and with the estimation of Kouki et al. (2015) due to its connection with the presented work. In order to enable the comparison and to reflect on the quality of the estimate of outdating products, the bi-objective setting and service level constraint are disregarded in the current section.

The discrete simulation event experiments consider the shelf life and its effect on inventory level both if the products outdate in the same inventory cycle in which they are received at inventory, or in one of the subsequent cycles. Each result is the average value over 25 replication runs, each with a duration equivalent to four years of stochastic demand and inventory simulation in which an order of fixed size is issued whenever the reorder level is reached or surpassed, and received after a constant lead time. Whenever in stockout, demand is lost, and when shelf life of products in a batch is reached, the remaining items, if any, are discarded. For the comparison with the model of Kouki et al. (2015), their estimations for lost sales, outdating products, and average inventory were implemented within the total cost function assuming a planning horizon of one year.

Model validation is performed starting from the input parameters presented in the previous section, for which the economic anchor point (APC) is computed by minimizing total expected costs of Eq. (8). This minimization results in the optimal values of the variables of reorder level and quantity $r = 14, Q = 29$. Table 4 presents the results of

Table 3
Case study input parameters. (C) indicates case-study data, while the citations allowed the estimation of the related parameters.

Param.	Value	Unit measure	Source
α	70	%	(C)
m	14	days	(C)
P	365	days	(C)
L	4	days	(C)
λ	3.46	items/day	(C)
k_C	11.2	€	(C); Bortolini et al. (2016)
h_C	0.0973	€/item	(C)
l_C	3.0	€/item	(C)
w_C	10.5	€/item	(C)
D	62.8	km	(C)
e_0	0.528	$kgCO_2e$/km	Grigoratos et al. (2019)
e_w	10^{-3}	$kgCO_2e$/item/km	
Q_{max}	300	items	(C)
h_E	0.484	$kgCO_2e$/item	Ries et al. (2017)
w_E	1.47	$kgCO_2e$/item	Eriksson et al. (2015)

Table 4
Total outdated products per year for economic anchor point and related variation of parameters. Positive differences with respect to simulation are related to an overestimation.

	$O \times R$	$O^{(k)} \times R^{(k)}$	$O_{tot}^{(sim)}$	$\%\Delta_{sim}$	$\%\Delta_{sim}^{(k)}$	$\%\Delta$
APC	12.3	17.6	8.8	**40.7**	100.8	−59.6
$Q+5$	26.0	39.7	22.7	**14.5**	74.7	−80.6
$Q+10$	50.7	74.9	46.1	**9.9**	62.3	−84.1
$Q+15$	88.1	122.9	83.7	**5.2**	46.8	−88.9
$m=7$	272.1	370.3	260.4	**4.5**	42.2	−89.3
$m=9$	129.1	190.7	118.3	**9.1**	61.2	−85.2
$m=11$	53.2	83.3	118.3	−55.0	**−29.6**	85.6
$cv^2=.25$	0.2	0.1	0.0	351.2	**180.6**	94.4
$cv^2=.50$	2.6	2.6	1.2	**111.5**	114.0	−2.2
$cv^2=.75$	7.0	8.9	4.7	**48.7**	87.6	−44.4

the comparison in terms of total outdating products for the proposed model, the model of Kouki et al. (2015) denoted by (k), and the simulation results denoted by (sim). In particular, the difference with respect to simulation for both models, $\%\Delta_{sim}$ and $\%\Delta_{sim}^{(k)}$ respectively, is shown for each test, where only one parameter is changed starting from APC parameters and variables. Additionally, the percentage difference $\%\Delta$ between the two models for each parameter variation is also reported. Since it is to be expected that ordering more leads to more wasted items, the effect of increasing order quantity on total outdated products is tested. The other parameters subject to study are the product shelf life, and coefficient of variation of daily demand cv with same demand mean. In particular, the starting point of APC is computed with unitary coefficient of variation and with a shelf life of two weeks. The results of Table 4 show an accuracy of the presented model for almost every instance of input variation. On average, the proposed formulation for outdating products is over 35% more accurate compared to Kouki et al. (2015). Moreover, a better estimation is achieved for all varying order quantities, ranging from close to 60% of error difference for the economic anchor point to over 88%.

Other validation tests on the quality of the outdating estimate are performed taking into account the anchor point obtained with the model and the input parameters of Kouki et al. (2015). In particular, following their work, two main scenarios with shelf life $m = 3$ are compared by varying the lead time between 1 or 2 days. In addition, the cost parameters used are $\{k_C, h_C, wC\} = \{200, 1, 5\}$, and daily demand follows a gamma distribution with mean 10 and unitary coefficient of variation. Regarding this, Table 5 presents the results for the anchor point $\text{APC}_1^{(k)}$ with $n_L = 1$ and $\text{APC}_2^{(k)}$ with $n_L = 2$ respectively. Starting from these anchor points, the effect of variation of cost per outdating unit and of coefficient of variation on the estimates of total outdated items are analyzed. For each variation of waste cost and demand variability the anchor points are recomputed and tested in the simulation model. Within these scenarios, the presented model leads to underestimation of outdating products for higher lead time and high-variability demand. Nevertheless, the accuracy of the estimation is closer to simulation results for every instance compared with the results obtained with Kouki et al. (2015) estimates. It is important to note that all the studied scenarios lead to the optimal choice of a single outstanding order per cycle.

Table 5
Total outdated products per year for anchor points obtained with variation of parameters. Positive differences with respect to simulation are related to an overestimation.

	$O \times R$	$O^{(k)} \times R^{(k)}$	$O_{tot}^{(sim)}$	$\%\Delta_{sim}$	$\%\Delta_{sim}^{(k)}$	$\%\Delta$
$\text{APC}_1^{(k)}$	834.5	1123.6	865.0	**−3.5**	29.9	−111.8
$w_C=10$	584.5	770.7	576.2	**1.4**	33.8	−95.7
$w_C=15$	415.4	565.1	410.9	**1.1**	37.5	−97.1
$w_C=20$	332.2	472.5	340.5	**−2.4**	38.8	−106.3
$cv^2=0.23$	256.3	379.7	202.7	**26.5**	87.3	−69.7
$cv^2=0.4$	416.0	560.2	364.9	**14.0**	53.5	−73.9
$cv^2=0.63$	628.8	800.7	608.6	**3.3**	31.6	−89.5
$\text{APC}_2^{(k)}$	663.2	877.8	671.4	**−1.2**	30.8	−104.0
$w_C=10$	404.9	597.7	437.7	**−7.5**	36.5	−120.5
$w_C=15$	272.8	473.2	330.2	**−17.4**	43.3	−140.1
$w_C=20$	161.8	382.1	270.5	**−40.2**	41.2	−197.5
$cv^2=0.23$	264.1	448.6	159.2	**65.9**	181.8	−63.7
$cv^2=0.4$	322.2	530.1	232.0	**38.9**	128.5	−69.8
$cv^2=0.63$	446.3	659.4	375.2	**19.0**	75.7	−75.0

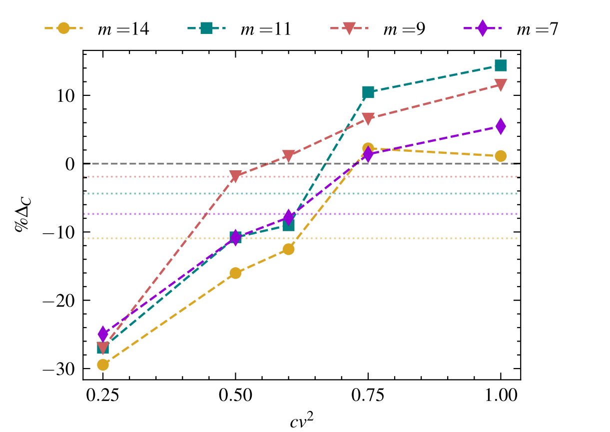

Fig. 8. Percentage difference on simulated total costs between the proposed model anchor point and the one of Kouki et al. (2015). Dotted horizontal lines depict the average value for each shelf life. Negative values are related to lower actual inventory costs for the proposed formulation.

The third set of tests for validation is centered on showing the effects of the difference in estimation of the components of the objective functions on total economic performance. For showing the impact of inventory decisions on total costs, the economic anchor point was computed starting from case study parameters for the two different

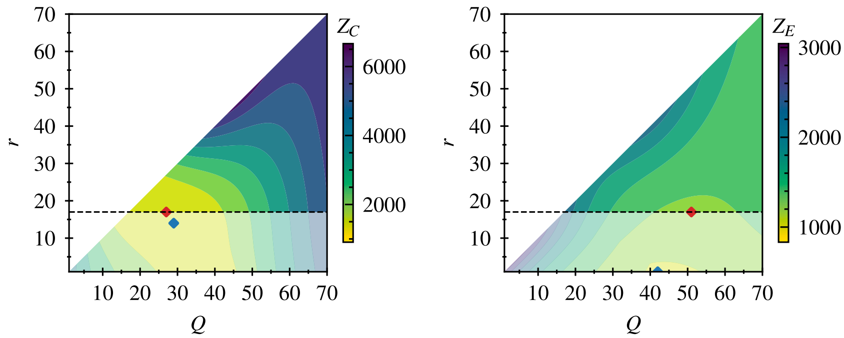

Fig. 9. Contour plots of objective functions at varying values of decision variables reorder level r and quantity Q. The dashed line identifies the lower bound for r due to service level. Blue and red points represent optimal pairs of Q and r with respect to the unconstrained and constrained problem respectively.

models for varying demand variability and for several values of shelf life and subsequently plugged in the simulation model. Fig. 8 shows the difference between the presented model and the one of Kouki et al. (2015), where negative values mean that the proposed model of this study leads to lower inventory costs. Results show that, on average with respect to demand variability, an improvement of up to almost 11% of total yearly inventory costs compared to Kouki et al. (2015) can be achieved. This is especially prevalent for low demand variability, where resulting inventory costs are more than 27% lower over the different shelf lives.

5.3. Multi-objective results

The proposed optimization model is applied along with the multi-objective approach to the perishable product described previously, whose model parameters are summarized in Table 3. The goal is to minimize yearly costs and emissions while maintaining the desired minimal service level.

Starting from the daily demand distribution, the other required demand distributions are obtained through convolution, resulting in skewed gamma density functions (e.g., for demand during the lead time or shelf life). Fig. 9 depicts the resulting contours from the numerical computation of such performance for economic and environmental objectives, evaluated using Eqs. (8) and (9) respectively. The two performance metrics behave differently for varying values of the decision variables r and Q in the decision space allowed by the single outstanding order assumption. For example, a higher variation in total emissions is observed for lower values of r while maintaining the reorder quantity constant.

The constrained problem requires the identification of a lower bound for reorder-level. This value is given by the minimum amount of items that guarantees the required minimal service level, defined as ready rate α. The service level function for this scenario is depicted in Fig. 10, together with the requested service level. This results in a lower-bound value of $r = 17$ units, which is related to a service level of 72.3% and allows the identification of the feasibility region Ω, thus restricting the selection of the optimal values for each objective function by reducing the decision space as presented in Fig. 9 for both the considered perspectives.

By implementing initially a single-objective optimization, it is possible to minimize separately the two objective functions. This results in the anchor points $(r_C^*, Q_C^*) = (17, 27)$ and $(r_E^*, Q_E^*) = (17, 51)$, that are related to the economic minima (915.6€) and environmental minima (1144.3 $kgCO_2e$). These results are also shown graphically in Fig. 9, where the constrained optima points are distinguished from unconstrained ones and it can be clearly seen how they vary due to the introduced minimal service level requirement. Each of these anchor points is related to different values of model components, which would result in different inventory patterns. For example, the resulting average inventory of a solely-economic choice is 16.9 items, while an

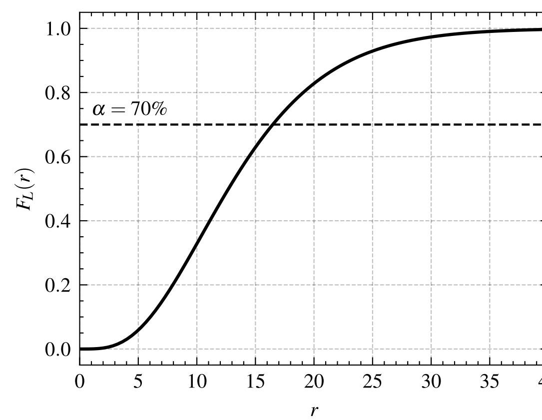

Fig. 10. Ready rate service level function at varying values of reorder level r.

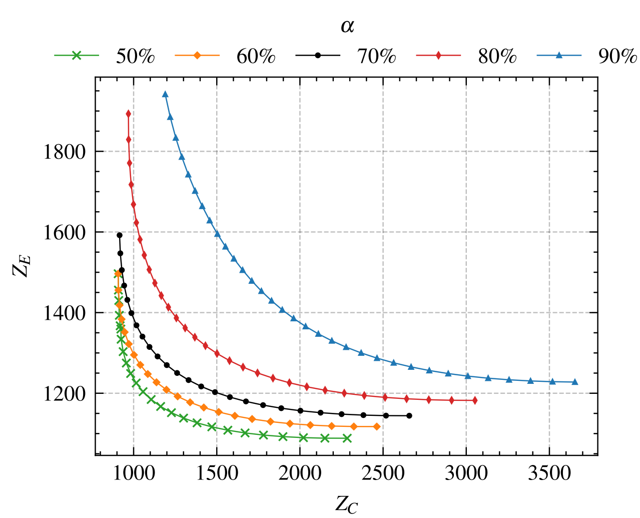

Fig. 11. Pareto fronts for total costs and emissions in the case of varying minimal service level α.

environmentally responsible optimization would result in a value of 26.2.

Since the considered problem is bi-objective, it is necessary to follow the approach described in Section 4.4 for multi-objective optimization in order to obtain an efficient solution in terms of both total costs and emissions. The set $\mathcal{P}$ of non-dominated solutions is derived numerically, and the resulting Pareto front in the decision space is shown in Fig. 11 for the service level of 70%.

The performance of each point of this frontier is reported in Table A.1. This information about the economic and environmental

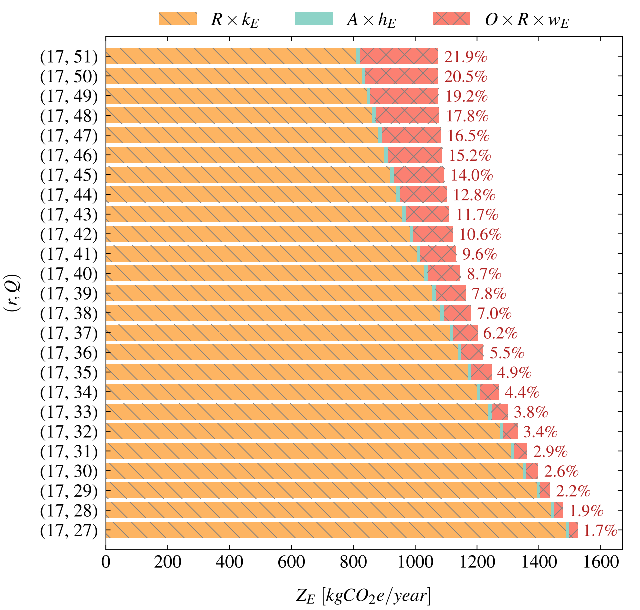

Fig. 12. Environmental performance and emission components depending on each Pareto frontier pair. Percentages indicate the relative contribution of outdating products on total emissions.

performance for each identified efficient pair of variables allows for the quantitative information needed to make an informed decision regarding the inventory control of the considered product. Moreover, due to the relevance of the performance measure of the number of wasted products due to perishability, Fig. 12 depicts the absolute environmental performance depending on the selected efficient pair. In addition, the inventory components of total emissions are distinguished, including the relative contribution of outdating products on the environmental performance.

5.4. Scenario analysis

To further investigate the tackled problem, several realistic scenarios are considered in order to analyze the optimization model outcomes in different conditions. By focusing on variations of the baseline setting solved above, further results and considerations can be drawn.

5.4.1. Minimal service level

Adopting the same input parameters and optimization approach used above, different service levels are tested for the considered product. Input values of α affect the resulting Pareto front of the bi-objective optimization. In this regard, Fig. 11 shows such frontiers, which are not only shifted to higher values of emissions and costs, but also change the trade-off behavior. Whereas the environmental anchor point is always affected by the service level, low-enough values of α do not affect the economic anchor point. Moreover, the degree of change between the frontiers due to different service levels can be analyzed through the metric of (standard) hypervolume (Zitzler et al., 2007). In particular, the hypervolume indicator is computed for each frontier and scaled to the value of the initial Pareto front, given by $\alpha = 70\%$. By shifting from a service level of 60% to 70%, a relative change of 4.2 of hypervolume is observed, while from 50% to 60% the change is of 3.7. Similarly, from 70% to 80% the change of hypervolume is 8.4, and from 80% to 90% of 17.3. As a result of the restricted selection of decision variables, the service level to be maintained at each reordering cycle plays a huge role in the inventory system performance, with increasing impact for large enough minimal ready rate values.

5.4.2. Shelf life

Since the proposed optimization model considers product perishability, the effect of the shelf life m on the anchor point computation is tested. Specifically, an increase is experienced in both economic and environmental order quantities, while only the reorder level of the economic objective function is affected by a variation of 6 items between one and four week shelf lives (Fig. 13).

Additionally, Fig. 14 depicts the estimation of average inventory and outdating products per cycle for each of the anchor points as m changes. Due to the increase of both economic and environmental reorder quantities, that happen at a different trends with respect to shelf life as shown in Fig. 13, the resulting average inventory increases. On the other hand, the outdating products per inventory cycle decrease with shelf life, especially prominent for the environmental anchor points at varying m.

5.4.3. Product category

Whenever specific temperature control is needed in order to preserve product quality and safety requirements, additional costs and emissions are caused by inventory storage. Additionally, due to the need to maintain temperature control over the whole supply chain, transport factors are also influenced. In particular, Tassou et al. (2009) suggested how the fuel consumption during transport can increase of 20.1% and 26.7% with respect to ambient for chilled and frozen products respectively, and similarly how carbon dioxide emissions can increase of 19.9% and 27.1% . These parameters related to each product category are listed in Table 6, where the difference estimated from the case study data about shelf life and lead time per product category is also reported.

As products in different categories are related to different input parameters, the computation of the anchor points for both objective functions and their performance needs to consider the different factors also for cold items and for frozen items reported in Table 6. Results show that there is an increase in total emissions and total costs due to different product requirements and characteristics, as it can be expected. Moreover, the relative contribution of different objective function components on total costs and emissions, computed in the respective anchor points, shift depending on product category. For example for the economic performance, an increase in transport costs is observed from around 55% to more than 71% (Fig. 15). On the other hand, for environmental performance the increase related to transport emissions is not true for cold items, possibly to the greater effect of perishability given by the shorter shelf life. The resulting performance of both objective functions are thus considerably affected by the type of product, since they require different holding and transport conditions, which are related to different economic and environmental factors, and are characterized by different shelf lives and procurement lead times.

Additionally, Fig. 16 depicts the estimation of lost sales for each product category as both lead time and shelf life change. Starting from the data related to each category, the economic anchor points are computed for increasing values of lead time and shelf life respectively via a multiplication factor. These results show how the lost sales per inventory cycle decrease with shelf life, while an opposite trend is observable for increasing lead time durations.

Focusing now only on the frozen product type, the results in Fig. 17 show the impact of different transport environmental factors on the expected number of reorders for the environmental anchor point. In particular, different waste emission factors are tested, starting from the case study emissions per outdated product. For each, it can be observed how the trend is an increase in the number of reorders. Moreover, for a given waste factor, a greater emission per unit distance is related to a lower number of reorders. In particular, different values of emissions per travel distance e_0 are tested, scaled with respect to the case study emission factor.

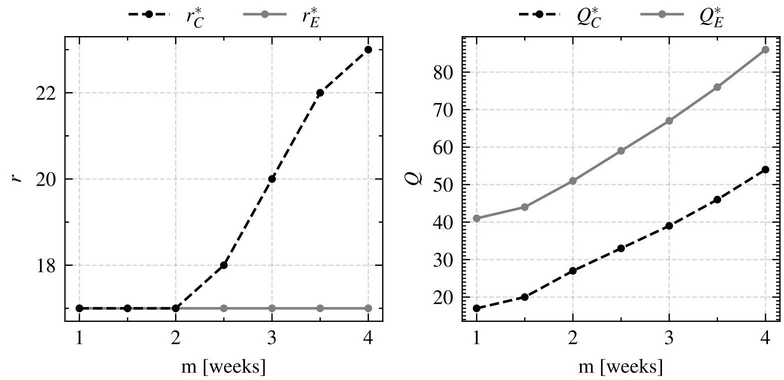

Fig. 13. Effect of shelf life on the economic and environmental anchor point variables.

Table 6
Case study input parameters per product category. (C) indicates case-study data, while the citations allowed the estimation of the related parameters.

	Standard	*Cold*	*Frozen*	Unit measure	Source
k_C	11.2	13.5	14.2	€	(C); Bortolini et al. (2016) and Tassou et al. (2009)
h_C	0.0973	0.7723	0.866	€/item	(C)
e_0	0.528	0.634	0.671	kgCO$_2$e/km	Grigoratos et al. (2019) and Tassou et al. (2009)
h_E	0.484	1.53	1.71	kgCO$_2$e/item	Ries et al. (2017), Nunes et al. (2014) and Gil-Lopez et al. (2014)
m	14	10	28	days	(C)
L	4	2	5	days	(C)

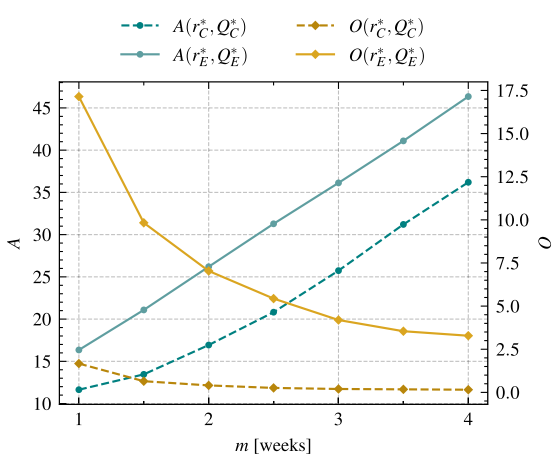

Fig. 14. Effect of shelf life on the average inventory value and on the number of outdating items per cycle for economic and environmental anchor points.

5.5. Managerial insights

The identification of the Pareto front is an essential tool for a simple but quantitative analysis of trade-offs in inventory control and the interplay among decision variables and each objective function of the considered optimization problem. The proposed model and methodology suggests that focusing only on the economic objective can have strong negative environmental drawbacks, which could be the result of the different behavior of the objective functions due to cost and emission factors. Other than the economic and environmental anchor points, the other non-dominated solutions are the key to make a sustainable decision for inventory management in a more transparent setting, where losses and gains of switching from one point of the frontier to the other can be quantitatively estimated and used for an evidence-based selection of the decision variables. For example, it could be possible to considerably reduce emissions related to the inventory control of a product at virtually no deprecation of the economic objective function, but further increasing costs would lessen such environmental gains. This consideration is in fact true in the case-study results presented in Table A.1, where, by moving away from the economic anchor point, an improvement almost 8% in emission can be obtained at less about 3% of total costs. Moreover, the Pareto front allows for identifying efficient solutions, meaning that a possible choice of r and Q that is not based on the proposed multi-objective optimization approach might be far from the identified efficient solutions.

As might be expected, the performance of economic and environmental objective functions depending on the decision variables can be quite different, meaning that optimizing either objective would lead to poor performance of the other. In addition to this, the constrained problem causes a great degree of control on the reorder level variable, which restricts the decision space for the selection of the variables r and Q. In fact, the inclusion of the service level does not only change the value of r due to the related lower bound, but makes the anchor points shift also to different values of Q, which can be quite different from the non-constrained case, for example for the economic anchor point. Even though the double inclusion of stockouts in terms of both lost sale cost and service level constraint might seem redundant, from the environmental perspective it would not make sense to deprecate customer satisfaction even if prioritizing emissions was the main objective. This behavior is due to the lack of connection between lost sales and emissions, since there is no drawback in emissions of not being able to meet customer demand from available inventory. Moreover, the integrated service level and stockout-costing approach is valuable also from the economic point of view due to the difficulty often connected with measuring accurately lost sale costs (Andersen et al., 2006). Based on this connection between the two objective functions and service level, it is possible to notice that an increase in service level is always

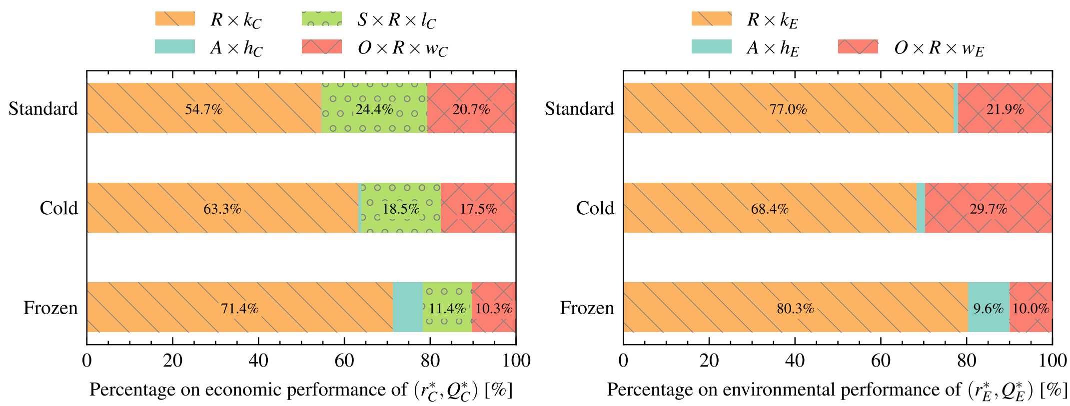

Fig. 15. Percentage of each model component on total costs (left) and emissions (right) computed in the relative anchor points for each product category.

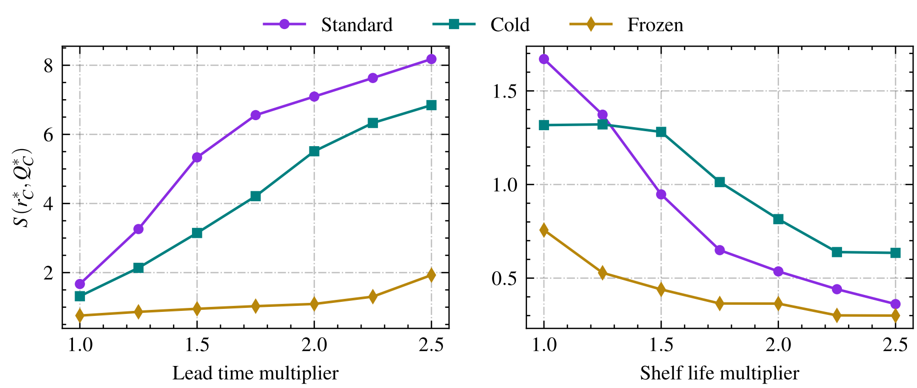

Fig. 16. Effect of lead time shelf life increase on the number of the expected lost sales per cycle for economic anchor points.

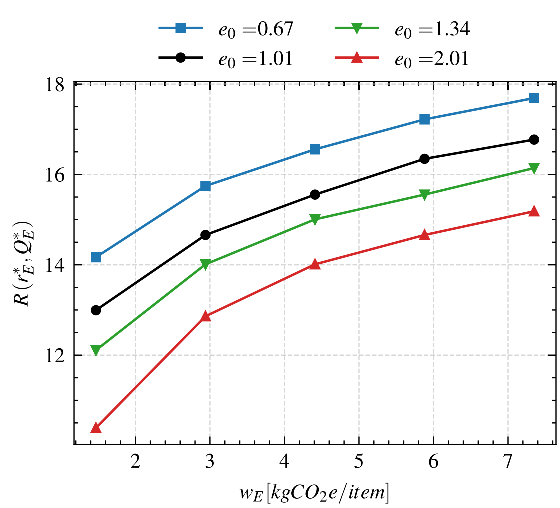

Fig. 17. Effect of variation in waste and transport emissions on the expected number of reorders in the planning horizon for environmental anchor points.

related to increased emissions since the constraint limits the selection of decision variables in a way that directly affects the objective functions. On the other hand, solely optimal economic performance might not be affected by different service levels, since the cost component of lost sales already allows to comply with the constraint. The opposite results true for very high service level values, that require both high costs and emissions in order to be guaranteed.

A further hint from the managerial perspective is that perishability has an important effect on the inventory control problem components. In fact, products with short shelf lives tend to require smaller and thus more frequent replenishments, forcing the optimal choice of decision variables to deviate from the non-perishable case. On the other hand, as perishability decreases, more stock can be kept in inventory, including higher values of safety stock. In particular, an highly perishable product leads to overall higher values of total costs and emissions since this component highly influences also the others, in addition to begin a driver for costs and emissions itself.

Finally, it is important to consider that practitioners often deal with many food products that are not only characterized by perishability, but also by the requirement of temperature control during storage and transport. This feature of products, paired with other characteristics that might be specific of a product category such as lead time or shelf life, influences the inventory choices also in multi-objective setting, due for example to the rise in cost and emission factors for storage and transport. While increasing total cost and emissions, the optimization of these different product categories leads to a greater impact of the storing component on total performance. In particular, both storage costs and emissions play a bigger role on total performance for products that require temperature control during storage. Such variation in characteristics and factors per product category also leads in a shift in relative importance of other components, such as on the contribution of lost sales and outdating products on total costs or emissions. Moreover, over different product types the effect of lead time is also relevant. As products with longer shelf lives might be characterized also by larger procurement lead times in a realistic scenario, it is important to consider how this aspects play a contrasting role in the number of lost sales, which is closely connected with the fact that products can outdate due to perishability.

6. Conclusion

This paper presents a model to manage the inventory by considering multiple sustainability perspectives. Perishability is tackled via

Table A.1
Pareto front decision variables combinations with relative value of total economic and environmental performance, losses and gains with respect to anchor points, and component of objective functions values.

r	Q	$Z_C(r,Q)$	$Z_E(r,Q)$	Z_C loss [%]	Z_E gain [%]	Z_E loss [%]	Z_C gain [%]	R	A	$S \times R$	$O \times R$
17	27	915.6	1592.0	0.0	−0.0	39.1	65.5	44.7	16.9	74.6	18.1
17	28	920.0	1547.1	0.5	2.8	35.2	65.4	43.2	17.5	73.5	20.4
17	29	929.2	1505.5	1.5	5.4	31.6	65.0	41.8	18.0	72.8	22.9
17	30	943.2	1467.1	3.0	7.8	28.2	64.5	40.5	18.5	72.6	25.7
17	31	962.3	1431.6	5.1	10.1	25.1	63.8	39.3	19.1	72.9	28.7
17	32	986.8	1398.8	7.8	12.1	22.2	62.9	38.2	19.6	73.7	32.0
17	33	1017.0	1368.5	11.1	14.0	19.6	61.7	37.1	20.1	75.0	35.7
17	34	1053.1	1340.5	15.0	15.8	17.1	60.4	36.0	20.6	76.9	39.7
17	35	1095.3	1314.9	19.6	17.4	14.9	58.8	35.1	21.1	79.5	44.0
17	36	1144.0	1291.3	25.0	18.9	12.8	57.0	34.1	21.5	82.6	48.7
17	37	1199.3	1269.8	31.0	20.2	11.0	54.9	33.3	22.0	86.3	53.9
17	38	1261.4	1250.3	37.8	21.5	9.3	52.5	32.4	22.4	90.7	59.4
17	39	1330.4	1232.7	45.3	22.6	7.7	49.9	31.6	22.8	95.7	65.4
17	40	1406.3	1216.9	53.6	23.6	6.3	47.1	30.8	23.2	101.3	71.9
17	41	1489.2	1202.8	62.7	24.4	5.1	44.0	30.1	23.5	107.5	78.8
17	42	1578.9	1190.5	72.5	25.2	4.0	40.6	29.4	23.9	114.3	86.1
17	43	1675.4	1179.8	83.0	25.9	3.1	37.0	28.7	24.2	121.7	93.9
17	44	1778.4	1170.6	94.2	26.5	2.3	33.1	28.1	24.5	129.6	102.2
17	45	1887.7	1162.9	106.2	27.0	1.6	29.0	27.5	24.7	138.1	110.8
17	46	2003.1	1156.7	118.8	27.3	1.1	24.6	26.9	25.0	147.0	119.9
17	47	2124.1	1151.8	132.0	27.7	0.7	20.1	26.3	25.3	156.4	129.3
17	48	2250.5	1148.2	145.8	27.9	0.3	15.3	25.7	25.5	166.2	139.1
17	49	2381.8	1145.8	160.1	28.0	0.1	10.4	25.2	25.7	176.4	149.3
17	50	2517.6	1144.5	175.0	28.1	0.0	5.3	24.7	26.0	186.9	159.8
17	51	2657.4	1144.3	190.3	28.1	0.0	−0.0	24.2	26.2	197.7	170.5

the estimation of outdating products and it is shown how this aspect affects other objective functions components, allowing for assessing the dual performance of the proposed reorder-level policy. The bi-objective nature of the problem was evaluated with the identification of the Pareto front while considering lost sales and the service level constraint. In particular, the identification of Pareto-efficient solutions is key for increased awareness at the decision level.

One of the more significant findings of this study is that merely considering lost sales through costing could have a major effect on the probability of stockouts, highlighting the importance of constraining the minimization through service level. Moreover, shelf life and product category emerged as important factors affecting the choice of decision variables and the related performance. The findings suggest that, in general, environmental performance is not only related to the efficiency of emission factors but also to the inventory choices taken at the tactical level. In addition, evidence shows how optimal reorder level and quantity values differ from cost and emission perspectives. Without the multi-objective approach to sustainability, it would not be possible to estimate the effect of decision variables on economic and environmental performance simultaneously for a perishable product in a stochastic setting. The insights gained from this research could help to improve awareness of inventory choices and enhance the understanding of their impact on the considered objectives.

To conclude, further research might explore different service level measures, and how they affect, for example, perishability estimations. Moreover, extending the model to two or more outstanding orders could improve the applicability of the model in other real scenarios. The performance of the reorder level policy could be also further studied by comparing it to other approaches, such as base stock policies, for the multi-objective problem. Another possible progression of this research could be the analysis of environmental drivers in order to assess emission factors, for example by modeling storage emissions as a result of warehouse characterization, location, and energy sources. Continued efforts are hence needed to encourage more sustainable decisions in logistics via quantitative implications of managerial decisions.

CRediT authorship contribution statement

Francesco Pilati: Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Marco Giacomelli:** Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Matteo Brunelli:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization.

Data availability

Data will be made available on request.

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Appendix

Detailed data on each of the identified Pareto pairs of decision variables for the single product analysis is given in Table A.1, where for each pair of r and Q the total performance is computed, as well as the estimation of each objective functions component. In addition, the percentage gains and losses obtained from moving from the economic and environmental respectively anchor points are tabulated as well, showing how, for example, optimizing solely for emissions would come at a worsening in economic performance of more than 190%.

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