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A cost-based tool for the comparison of different e-grocery supply chain strategies

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ABSTRACT

E-commerce is always a more diffused sales channel around the whole world market. The grocery market has been interested in the expansion of this phenomenon, especially during the COVID-19 pandemic emergency, when electronic grocery (e-grocery) shopping increased considerably. Moreover, it has remained a diffused selling channel also later, in the non-emergency state. To satisfy this specific market demand, grocery chains are facing the need for a redesign with a new logistic perspective. A grocer can carry out online orders in several ways; it can process them directly in stores using internal staff to shop from the shelves during off-peak hours. Alternatively, some local stores can be closed to customers and dedicated to online orders (dark stores). Another strategy is to carry out online orders from a single distribution centre (e-hub), using stores to complete orders with very fresh products and from which to carry out deliveries. Finally, online orders can be wholly managed by multi e-hubs. Each solution has different logistics costs and performances, influenced by online demand.

For this reason, this work aims to present a cost-based function for grocery chains that compares four strategies to respond to e-grocery shopping. The cost function considers picking, refilling, and transport costs by varying orders and articles quantity. Further, we aim to minimise costs according to online order characteristics and volumes. We identify five decision variables to select the most suitable strategy for the design of the e-grocery network. Finally, a decision support system (DSS) is developed to define the best strategy based on the decision variables.

1. Introduction

Electronic commerce (e-commerce) includes any form of economic activity conducted through electronic connections and, in the last few decades, its growth has considerably changed the role of logistics in the supply chain (SC) (Lu and Liu, 2015). Online shopping for grocery products is quickly accelerating worldwide, particularly following the impact of the COVID-19 pandemic. However, compared to other sectors, grocery has been slower to adopt the online channel (Klepek and Bauerová, 2020). The main gap is represented by the fact that customers are used to seeing, touching, and smelling the product, and buying online implies renouncing these quality tests and trust in the retailer (Boyer and Hult, 2006).

E-grocers' orders are different from typical e-commerce sales, as they usually contain many products in multiple quantities, often including items characterised by high levels of perishability and fragility (Mangiaracina et al., 2018). Furthermore, food SC is characterised by factors such as food quality and safety and sustainability, which consequently influence the design, planning, and transportation (Accorsi et al., 2014; Gharehgozli et al., 2017). To satisfy this specific market demand, most grocers are switching to a multichannel SC by developing an online channel (Lu and Liu, 2015; Hübner et al., 2016; Badenhop and Frasquet, 2021; Siawsolit and Gaukler, 2021). Here, some issues could arise since activities related to storing, picking, and carrying out home deliveries are more complex and expensive than other products (Wollenburg et al., 2018; Van Zelst et al., 2009). Furthermore, grocers have lower value-to-bulk ratios, more significant handling problems, and low margins (Boyer et al., 2003; Barnett and Alexander, 2004).

As emerged from the literature review of Zennaro et al. (2022), many contributions are focused on e-grocery due to the rapid development of the demand for e-commerce of fresh products, also caused by the COVID-19 emergency (Zheng et al., 2021; Tsang et al., 2021; Jiang et al., 2021; Fikar and Braekers, 2022; Delasay et al., 2022). However, many of these focused on the home delivery problem. Few works investigated the distribution problem of goods in the e-grocery sector with regard to distribution network design and logistics strategies to maximise

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profitability. Seghezzi et al., 2022b proposed a conceptual framework that identified nine logistics challenges for e-grocery distributed in four research areas, i.e., the distribution network design, the order fulfilment process, logistics-related choices from other domains, and the automation level. They acknowledged the main gaps which required further investigation, such as order picking and storage and stock-out management. Defining optimal online order allocation is a critical issue for e-grocers (Vazquez-Noguerol et al., 2021). Scott and Scott (2006) and Mangiaracina et al. (2018) studied two different strategies for e-grocers order allocation, i.e., the warehouse-based and the store-based models. In the first strategy, online orders are carried out in warehouses with store orders; this strategy requires a separate area, since store orders are made of cartons per product, while online orders are made of pieces per product. In addition, fresh and frozen products are critical to be managed. The store-based strategy, instead, provides on-line orders to be handled directly in the store by retailers, i.e. they do the shop for on-line customers directly in the shop as the physical ones. Marchet et al. (2018) and Wollenburg et al. (2018) presented a different strategy in which online orders are separate from the physical channel and carried out in a new type of distribution centre, called the online fulfilment centre or the online distribution centre. All these strategies are attractive and competitive, but no comprehensive study summarizes all of their characteristics and logistics parameters to assess which one best fits a certain grocery SC.

In this context, grocers facing an increase in online demand should define the best logistic strategy to improve profits. Therefore, this work proposes a cost function based on logistics costs to compare four strategies by varying online customers and, consequently, online volumes. These four strategies have been derived from the work of Wollenburg et al. (2018), Giuffrida et al. (2017) and the experience of the authors. The first strategy is the In-Store (IS) one, in which the fulfilment of online orders is managed directly by stores, as in the 'traditional bricks-and-mortar structures for online order fulfilment' of Wollenburg et al. (2018). In the second strategy, the Dark Store (DS) one, online orders are fulfilled in dedicated stores closed to customers, that are exactly called dark stores (Giuffrida et al., 2017). The third strategy, the Single e-Hub (SH), provides the integrated fulfilment of online orders from a dedicated hub and from the stores, as in the 'integrated DC for all orders' network configuration of Wollenburg et al. (2018). SH differs from DS due to the management of ultra-fresh products, representing a critical point for online orders. Finally, the fourth strategy is the Multi e-Hub (MH) strategy, where online orders are managed in dedicated online distribution centres (e-hubs) and delivered directly to customers, in line with the 'dedicated DC for online orders' network configuration of Wollenburg et al. (2018).

The main difference between the SH and the MH strategies is the fulfilment of ultra-fresh products for online orders. In fact, in the MH strategy, the fulfilment of these products for online orders is carried out directly in the e-hubs with the other products, while in the SH strategy, they are prepared in the stores. For each strategy, the logistic hub (including stocking, refilling, picking, and transport costs), the e-hub (including stocking, refilling, picking, packing, and transport costs), the store (including refilling, picking, and the packing costs), and delivery costs are defined from a logistics perspective. The study aims to identify the best strategy based on online order volumes, that is, the one that allows a reduction of the total yearly logistics costs. The cost function also leads to the development of a DSS useful for defining which strategy best fits a specific grocery chain.

The paper is organized as follows: Section 2 presents the review of the recent literature, while Section 3 focuses on the description of the problem and the purpose of the study. Section 4 presents the cost-based function, while Section 5 and section 6 are about its parametrical analysis and its practical application to a real case study, respectively. Finally, Section 7 presents discussion and managerial insights while Section 8 is for the conclusions and some ideas for further research.

2. Literature review

The grocery sector is characterised by a large product variety with low profit margins (Holzapfel et al., 2016). High product variety requires large and flexible warehouses, since products are characterised by different physical characteristics, such as size, weight, and fragility, which influence storage and picking strategies (Chabot et al., 2017). Furthermore, food products have different temperature requirements, such as frozen, fresh and ambient, which can be defined by law or applied to increase quality (Ostermeier and Hübner, 2018). Different temperatures entail different warehouses (or sections) managed with different service plants and staff. Furthermore, the delivery of perishable goods is deeply influenced by temperature and requires other solutions than traditional delivery, like electronic products (Shafiee et al., 2021).

The literature on omnichannel and multichannel logistics in grocery retail is limited as it is a relatively new market, significantly increased during the COVID-19 pandemic, and studied more from a marketing perspective than from a logistics perspective (Galipoglu et al., 2018; Kembro et al., 2018; Eriksson et al., 2019).

The analysis of the current literature focused on e-grocery logistics issues highlights two main critical points in e-grocers with an e-commerce channel: the decision of the online order allocation point, that is, where online orders should be prepared in the SC, which has an impact on the design of the whole SC network, and the choice of the home delivery strategy, dealing with the way of managing orders delivery to customers' homes.

The home delivery issue has been deeply investigated, considering influential factors such as time windows, balancing demand throughout the day, and food perishability (Fikar et al., 2021; Dethlefs et al., 2022), as well as the "not at home problem" (Xu et al., 2008). Furthermore, several strategies have been proposed, for example using pick-up points and box systems with different temperature zones in congested areas to shorten the customer's last mile and bundle orders (Eriksson et al., 2019).

In contrast, the order allocation point is still less investigated. From the literature analysis, as far as the online order allocation is concerned, this can be assigned directly to stores (as in the store-based strategy) or a dedicated hub for online orders (as in the warehouse-based strategy).

2.1. In-store-based strategy

Although it presents some weaknesses, the store-based strategy is the most common for now (Mangiaracina et al., 2018). Here, online orders are prepared by store staff directly in the stores visited by physical customers taking products from the same shelves and along the same aisles; consequently, congestion in stores increases the risk of missing products due to inventory management. In fact, in this strategy, the store stocks of online and offline customers are shared and control over the inventory level is more critical (Xu and Cao, 2019). Furthermore, congestions affect the efficiency of fulfilment activities, since the more people there are, the slower the order preparation; congestions are very variable, since the number of physical customers depends on the time and day of the week (Zhang et al., 2020). Finally, the exposition of products in stores is typically organized according to a marketing-based expository logic and not to increase picking efficiency (Hübner et al., 2016). Many works focused on store-based strategy optimisation, investigating models and tools to reduce picking time and costs and to increase online order fulfilment. Gorczynski and Kooijman (2015) proposed an ad hoc area for large and heavy products to save time and energy for pickers; however, online orders usually have a low percentage of this kind of products. Difrancesco et al. (2021) presented a model that analyzed the fulfilment of online orders prepared directly in stores. Through a simulation-based approach, their model defined the optimal preparation and picking time and the optimal number of pickers and packers, with the related performance measures. Giuffrida et al. (2017), instead, compared two different models for the store-based strategy. The first one is the "click and drive" (C&D) model, in which online orders are collected in a separate area for picking activities, called dark store, and the customer does not get off the car. The second one is the "click and store" (C&S) model, in which online orders are prepared in stores and online customers enter the store to collect their order. Mangiaracina et al. (2018) proposed an in-store model in which items are classified into A, B and C classes. Class A items are picked in a back area dedicated to online orders, while class B and C items are chosen from the shelves in the store. The objective is to reduce the picking time, although this strategy requires more space and doubles up the locations of the items. Vazquez-Noguerol et al. (2020) presented a linear programming model for a store-based strategy in which order picking and delivery processes are optimised, considering picking and delivery costs jointly. Pietri et al. (2021) investigated picking and packing processes in a store-based strategy by applying a mathematical model that guides employees on how to organize the articles in different shopping bags during the picking process. Chou et al. (2021) focused on the picking process of online orders in stores; their application aimed to model and optimise products picking throughout the store shelves considering the characteristics of the goods, such as fragility and weight. Siawsolit and Gaukler (2021) investigated the optimal replenishment policy, quantifying how next-day or two-day orders influence profitability, but focussing mainly on perishable products. More recently, Vazquez-Noguerol et al. (2022) studied factors that affect order preparation time in store-based strategy, that are, store size, assortment size, backroom availability and congestion. Urquhart et al. (2022) investigated online grocery fulfilment capacity at the store, focussing on the impact of capacity constraints related to storage and delivery in limiting the success of this strategy. Finally, Seghezzi et al. (2022a) proposed an empirical-based model to improve in-store picking performance, which combined store-based and warehouse-based logic. In their strategy, they defined an area dedicated to the most online required canned and non-food items in the back of stores. In this way, the congestion due to physical customers decreased, as well as the risk of missing products.

2.2. Warehouse-based strategy

Another diffused strategy is to prepare online orders directly in the central warehouse or a dedicated hub (warehouse-based strategy). A traditional grocery distribution centre is used mainly for store replenishment, and commonly it is a carton-picking warehouse which uses multi-product rolltainer for store replenishment (Agatz et al., 2008). Here, grocers receive products in carton packs (secondary packaging) from their suppliers but sell these products in customer units (primary packaging). The supplier carton pack facilitates handling of multiple customer units in the supply chain and protects the products during picking and transportation (Broekmeulen et al., 2017). Retailers receive items in carton units and then refill stores with customer units. Since online orders are made up of customer units, preparing online orders in the warehouse means that an area of it, or a separate hub, should be dedicated to online orders picking in the primary packaging. The main difference between the two warehouses is the order characteristics; store replenishment orders and online customer orders are different in terms of volumes, item variety, unit, and uncertainty (Kembro et al., 2018; Wollenburg et al., 2018; Zhang et al., 2020). Warehouses dedicated to storing replenishment should reflect the layout of the store to facilitate store replenishment, which has a marketing-based logic and is inefficient for picking. On the other hand, a warehouse dedicated to online orders (e-hub) preparation can ignore the marketing logic and focus on maximising picking efficiency (Kämäräinen et al., 2001). In this context, Lunce et al. (2006) compared two companies adopting this strategy and analysing strategic management, logistics infrastructure, information technologies, and marketing strategies, and derived factors related to the success or failure of this strategy. Bindi et al. (2009) analyzed and compared different storage allocation rules in grocery warehouses based on the principle that frequently ordered products in multi-item, less than unit load customer orders should be stored near each other. Vazquez--Noguerol et al. (2021) proposed a planning tool for managers' decision-making process regarding online orders fulfilment in e-hubs, i.e., a linear programming model which determined the time windows during which picking and transport should take place and the assignment of trucks to delivery routes. Finally, Eriksson et al. (2019) investigated the characteristics of e-hubs and the factors that influence their design; they identified four contextual factors, i.e., customer characteristics, product characteristics, order characteristics and delivery and shipment.

2.3. Order allocation point analysis

Other works investigated the e-grocery SC design comparing these two main strategies and analysing new configurations, proposing decision making tools, a model for cost minimization, and the analysis of influential factors. Kämäräinen et al., (2001) proposed a model to compare the store-based and warehouse-based strategies based on picking efficiency, concluding that e-hubs are more efficient in picking speed, labour costs, and space utilisation, but volumes need to be sufficient. The model of Scott and Scott (2006), instead, analyzed the two strategies for efficient allocation of online grocery orders focussing on the delivery budget and the overall utilisation on store congestion. Zheng et al. (2021) analyzed and proposed a model to decide whether it is better to use the store-based strategy or the warehouse-based one in the case of fresh products, considering customer perception and profit.

Many works compared different case studies and strategies to isolate the main successful factors and criticalities of e-grocers SC (Tanskanen et al., 2002; Jeyaraj et al., 2007; Beatriz and Fernando, 2011; Mkansi et al., 2018; Hüseyinoğlu, 2019; de Magalhães, 2021; Eriksson et al., 2022). Mkansi and Nsakanda, 2021 conducted a qualitative multi-case study on the e-grocery market, highlighting the trade-offs between fulfilment responsiveness, last-mile operation costs, and a seamless customer experience. Hübner et al. (2016) compared different e-grocers' strategies for orders fulfilment (in-store, separated hubs or central dedicated hub) and last-mile distribution concepts (like home delivery and click and collect). Furthermore, they investigated the influence of some factors on SC design, such as country specifics, retailer specifics, and customer behaviour. Finally, Wollenburg et al. (2018) and Hübner et al. (2019), analyzed various types of e-grocer SC and summarised them into three main different types of grocery omnichannel SCs through interviews with 12 companies in six European countries. In the first one, online orders are managed together with store orders in the central warehouse, and are prepared directly in stores and delivered to customers or to pick up points. In the second, dedicated warehouses are built to fulfil online orders, while in the third configuration integrated warehouses fulfil online orders and deliver them to customers and stores. As already reported in the Introduction section, some of the network configurations proposed by Wollenburg et al. (2018) are also investigated in this paper. However, Wollenburg et al. (2018) studied also hybrid configurations of the three main categories, which are not the focus of this study.

Table 1 summarizes the literature review on the order allocation point. In particular, it can be seen that much research is focused on the store-based strategy, developing optimisation models about order picking and stocking (11), while few papers are focused on the warehouse-based strategy (4). The remaining contributions (14) focus on the best order allocation point analysis, investigating influential factors and best practices based on case studies analysis (11). Only three papers develop a decision support model based on cost optimisation, even if they do not consider more than two strategies. In addition, Table 1 highlights the increasing importance of this issue, showing the growing number of works per year.

In this context, our work aims to propose a novel decision support model for SC network design for e-grocers, comparing four different main strategies. With respect to the existing literature, it focuses on

Table 1
Detailed literature analysis on order allocation point.

Reference	Year	Focus			Approach			
		Store-based strategy	Warehouse-based strategy	Order Allocation Point Analysis	Optimisation model	Case study analysis	Influential factors and best practices analysis	Decision Support Systems
Eriksson E. et al.	2022			x			x	
Seghezzi A. et al.	2022	x			x			
Urquhart R. et al.	2022	x				x		
Vazquez-Noguerol M. et al.	2022	x			x			
Chou X. et al.	2021	x			x			
de Magalhães D. et al.	2021			x			x	
Difrancesco R. et al.	2021	x			x			
Mkansi M. et al.	2021			x			x	
Pietri N. et al.	2021	x			x			
Siawsolit C. et al.	2021	x			x			
Vazquez-Noguerol M. et al.	2021		x		x			
Zheng Q. et al.	2021			x				x
Vazquez-Noguerol M. et al.	2020	x			x			
Eriksson E. et al.	2019		x				x	
Hübner A. et al.	2019			x			x	
Hüseyinoğlu I. et al.	2019			x			x	
Mangiaracina R. et al.	2018	x			x			
Mkansi M. et al.	2018			x			x	
Wollenburg J. et al.	2018			x			x	
Giuffrida M. et al.	2017	x			x			
Hübner A. et al.	2016			x			x	
Gorczynski T. et al.	2015	x			x			
Beatriz G. et al.	2011			x			x	
Bindi F. et al.	2009		x		x			
Janson M. et al.	2007			x			x	
Lunce et al.	2006		x				x	
Scott C. et al.	2006			x				x
Tanskanen K. et al.	2002			x			x	
Kämäräinen V. et al.	2001			x				x

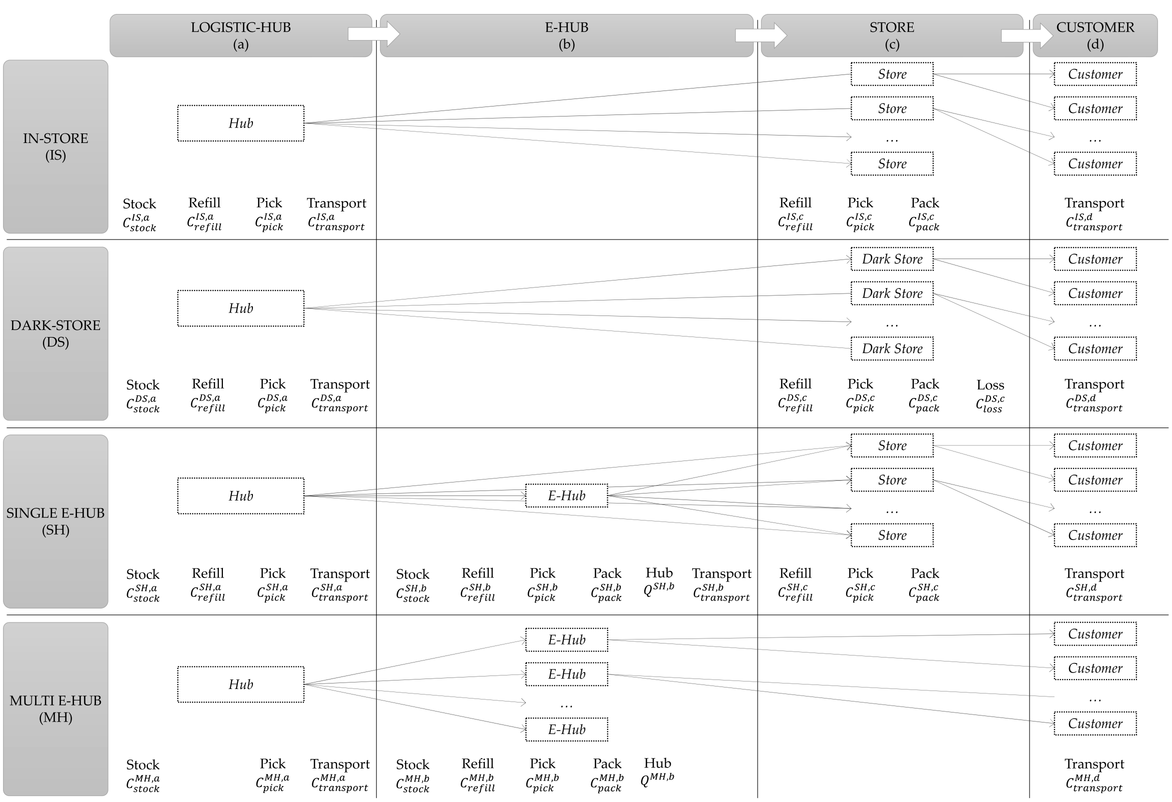


Fig. 1. E-grocery strategies and cost components considered for carrying out online orders.

order allocation point analysis, proposing a cost-based function to compare four different logistic strategies for e-grocery SC network. It considers not only the store-based strategy and the warehouse-based one, such as Seghezzi et al., 2022a, Urquhart et al. (2022), Vazquez-Noguerol et al. (2022), but also other two strategies, which are a mix of the characteristics of the previous ones. Moreover, it proposes a useful decision support system (DSS) to easily evaluate the most suitable strategy with few input data.

3. Problem description

Grocery chains are facing the need for a redesign with a new logistic perspective in order to satisfy the increasing e-grocery demand, characterised by orders with multiple products in considerable quantities. Generally, grocers can carry out online orders in several ways. In this study, based on the experience of the authors and on Wollenburg et al. (2018) configurations, we identify four main strategies, represented in Fig. 1: In-Store (IS) strategy, Dark Store (DS) strategy, Single e-Hub (SH) strategy and Multi e-Hub (MH) strategy.

3.1. In-store strategy

In the IS strategy, online orders are processed directly in stores by the store staff, shopping from the shelves during off-peak hours.

The grocery chain is composed of a single distribution centre (the logistic hub) that serves a certain number of stores n; goods for online orders are collected together with store orders and transported in cages to the served stores. In each store i, while physical customers are shopping, store staff pick the products off the shelves for online orders. Then, the orders are delivered to online customers when the order is completed and packed. Each store manages the demands of an average number of customers m_i.

This strategy is very flexible and easy to apply; initially, it does not require any specific investment, as online orders can be placed by the store staff during off-peak hours. On the other hand, when the number of online orders increases, dedicated staff are required to prepare the orders in stores, since off-peak hours are no longer enough. The available staff could also become not sufficient to process all the required orders. This increase in online orders can lead to store congestion, with a potential rise in online orders preparation time (picking and packing) and the risk of missing products (Scott and Scott, 2006). Moreover, this increase would require performing more replenishment activities to make the products available on the shelves for their next pick.

3.2. Dark-store strategy

Instead of increasing staff and congestion in stores and, consequently, to avoid a worsening in online orders preparation performance, grocers can decide to close some minor stores (e.g., those with the lower profit) to physical customers and dedicate these 'dark stores' to carry out online orders.

In the DS strategy, the grocer's chain is the same as the IS strategy, with a single hub and n stores; no further investment is required. As orders increase, there is no congestion with physical customers during picking; consequently, the performance of online order preparation remains the same, and the risk of missing products is stable. On the other hand, this strategy is limited by the number of stores that can be converted into dark stores; the more they are, the greater the risk of loss of physical customers and overall profit. The daily online customers per dark store m_i are more than the ones in the IS strategy, since it is supposed that total online customers are the same, with the dark stores that tend to group online orders of more stores.

3.3. Single e-hub strategy

Grocers can also evaluate the possibility of employing a dedicated hub to fulfil online orders, as in the SH strategy. The e-hub, a single-piece warehouse, is refilled directly by the logistic hub, a cartons warehouse, with different times and performances. The e-hub carries out most of all online orders: only very fresh products f_i (e.g., dairy products, fish, vegetables) are still picked and packed in the stores. In this strategy, the online orders processed in the e-hub are then transported to stores, where they are completed with very fresh products and then delivered to customers' homes. The e-hub, if possible, should be located near the logistic hub to reduce the transport costs from the hub to the e-hub. In this way, delivery costs are the same as the IS strategy and lower than those of the DS strategy, also with a reduction of congestion in stores.

3.4. Multi e-hub strategy

In the MH strategy, K e-hubs are wholly dedicated to carrying out online orders. The e-hubs are refilled by the logistic hub, as in the SH strategy; however, orders are fully processed in these automated dedicated distribution centres, including fresh products, so they can be delivered directly to online customers. Each e-hub k manages the orders of an average number of customers m_k. E-hubs, in this case, are located closer to customers, as are the stores, to reduce delivery costs; moreover, their investment cost is higher, since they should be highly automated to satisfy online demand.

4. Cost-based function

The cost-based function proposed for the evaluation and comparison of the four strategies aims to derive, starting from some practical input parameters and according to various characteristics, the best strategy, i.e. the one that leads to the lower total costs. Costs are defined from the SC level point of view; that is, the costs of the logistic hub, the e-hub, the stores and the final customer are presented separately. Each cost is the sum of different logistic costs (as shown in Fig. 1), such as refilling costs, picking costs, delivery costs. Logistics costs are transversal and can be found at different levels of the supply chain. It is important to specify both the level of the SC and the transversal logistics costs to compare the impact of each cost; for example, the logistic hub, the e-hub and the stores have all the picking costs, but picking is carried out in three different ways in the three SC levels and, consequently, it has different impacts on the final cost.

4.1. Notations and assumptions

Table 2 presents all the indices, parameters, and variables used.

For our purpose, we assume the following.

- Our research focuses on the logistic costs related to online orders and the annual logistic costs of the physical orders are not considered in the analysis, since it is assumed that for the same e-grocer SC the store costs are the same, regardless of the logistic strategy.
- The yearly amortized cost of the logistic hub (Q) is not taken into account, as this does not represent a new investment, and it is considered to be equal for all strategies. Moreover, this cost impacts not only online orders but also in-stores ones; therefore, it would be misleading to assign it only to online orders.
- Dark stores replace regular stores by serving online customers, previously served by the network of regular stores. However, since dark stores are fewer than regular stores, the distances that have to be covered to serve all online customers with the dark stores network are considered to be, on average, higher; then, home delivery costs are assumed to be greater for the DS strategy than for the IS one.
- Finally, in the DS strategy, we assume that physical customers of the dark stores are ideally redistributed to the remaining stores. However, we are aware that as the number of dark-stores increases, the revenue loss caused by the closure of stores increases always more as

Table 2
Indexes, variables, and parameters.

Index	Description	Unit
i	Index for stores/dark stores served by the logistic-hub	–
j	Index for online customers served by store i.$j = 1 \ldots m_i$	–
k	Index for e-hubs, $k = 1 \ldots. K$	–
e	Index for supply chain echelon, e = a, b, c, d	–
s	Index for strategy, s = IS, DS, SH, MH	–
Parameter	**Description**	**Unit**
V	number of pieces sold per year online	*pieces/ year*
v_i	number of pieces sold per year online in store i	*pieces/ year*
n'	Total number of dark stores	–
g_i	average number of no very fresh products per online order	*pieces*
D	working days per year	*days/year*
$Q^{s,e}$	yearly amortized cost of the logistic hub/e-hub (s = IS, DS, SH, MH e = a, b)	*k€/year*
$Q_k^{s,e}$	yearly amortized cost of the e-hub k (s = MH, e = b)	*k€/year*
F	average revenue per store	*k€/year*
p_{loss}	% of lost customers due to the closing of a store	-
C_{w-op}	hourly cost of warehouse operator	*€/h*
C_{picker}	hourly cost of picking operator	*€/h*
$C_{store-op}$	hourly cost of store operator	*€/h*
$C_{truck-store}$	average cost of one truck from logistic-hub till store	*€/truck*
$C_{truck-hub}$	average cost of one truck from logistic-hub till e-hubs	*€/truck*
z	average number of pieces per pallet	*pieces/ pallet*
y	average number of pieces per package	*pieces/ pack*
w	average number of pieces per cage	*pieces/ cage*
Z	number of equivalent pallets of online volume V	*pallet/day*
Y	number of equivalent cartons of online volume V	*cartons/ day*
W	number of equivalent cages of online volume V	*cages/day*
W_{truck}	average number of cages per truck	*cages/ truck*
Z_{truck}	average number of pallets per truck	*pallet/ truck*
O_{van}	average number of online customers handled with one van	*orders/van*
O_{truck}	average number of orders per truck	*orders/ truck*
Ca_{DS}	average capacity of a dark store in terms of online orders per day	*pieces/day*
Ca_{ME}	average capacity of an e-hub in terms of online orders per day	*pieces/day*
C^s_{route}	average cost of one delivery (route)	*€/van*
$t^{s,e}_{dep}$	average time for stocking a pallet	*s/pallet*
$t^{s,e}_{refill}$	average time for refilling a pallet	*s/pallet*
$t^{s,e}_{pick}$	average time for picking a package	*s/carton*
$t^{s,e}_{pack}$	average time for packing online sales	*s/order*
Variable	**Description**	**Unit**
n	Total number of stores	–
m_i	number of online customers per store/dark store i	-
s_i	average number of pieces per online order in store i	*pieces*
f_i	average number of very fresh products per online order	*pieces*
$\%_{c\&c}$	% of online customers with in-store pick-up (click and collect)	-

redistributing customers to the remaining stores becomes more difficult.

4.2. Cost function definition

The comparison of the four strategies is based on the calculation of the logistic unit cost per piece sold online, calculated for each strategy s:

$$C_u^s = \frac{C^s}{V} \ [€ / piece] \tag{1}$$

with s = IS, DS, SH, MH.

Here, C^s is the general cost function, based on the sum of the costs related to the management of online orders and emerging in the four main echelons of the considered supply chain, i.e. the logistic hub ($e = a$), the e-hub(s) ($e = b$), the stores ($e = c$) and the customers ($e = d$):

$$C^s = C^s_{logistic-hub} + C^s_{e-hub} + C^s_{store} + C^s_{customer} \ [€ / year] \tag{2}$$

Still considering equation (1), V is the daily volume of online orders, defined as:

$$V = \sum_{i=1}^{n} v_i = \sum_{i=1}^{n} m_i \cdot s_i \cdot D \ [pieces / year] \tag{3}$$

where v_i is the online sales volume of store i, obtained by multiplying the average daily number of online customers of store i (m_i) with the average number of pieces sold per online customer in-store i (s_i) and the number of working days per year D. An online order is considered to correspond to a single online customer.

The logistic unit cost per piece sold online C_u^s can also be defined as the sum of four unit costs, the logistic hub unit cost, the e-hub unit cost, the store unit cost and the customers unit cost per piece sold online:

$$C_u^s = C^s_{u,logistic-hub} + C^s_{u,e-hub} + C^s_{u,store} + C^s_{u,customer} \ [€ / piece] \tag{4}$$

Of course, the costs must be considered depending on the strategy, as shown in the following sub-sections.

The daily volume of online orders V can also be expressed as an equivalent number of pallets Z, cartons Y and cages W as follows:

$$Z = \frac{V}{z} \ [pallets] \tag{5}$$

$$Y = \frac{V}{y} \ [cartons] \tag{6}$$

$$W = \frac{V}{w} \ [cages] \tag{7}$$

where z, y and w are the average number of pieces per pallet, carton and cage, respectively.

Moreover, each online order is made of a certain number of pieces s_i, obtained as the sum of the average number of very fresh products per online order f_i and the average number of not very fresh products per online order of store i g_i:

$$s_i = f_i + g_i \ [pieces] \tag{8}$$

The cost function considers also the click and collect option, in which a certain percentage ($\%_{C\&C}$) of customers (m_i) can go to the stores to collect the items of their orders. In the following, the cost components of (2) are detailed according to the four considered strategies.

4.2.1. Logistic hub cost

The logistic hub cost $C^s_{logistic-hub}$ considers the yearly amortized cost of the hub ($Q^{s,a}$) and the cost of stocking ($C^{s,a}_{stock}$), refilling ($C^{s,a}_{refill}$), picking ($C^{s,a}_{pick}$) and transporting ($C^{s,a}_{transport}$) the online sales volume V:

$$C^s_{logistic-hub} = C^{s,a}_{stock} + C^{s,a}_{refill} + C^{s,a}_{pick} + C^{s,a}_{transport} + Q^{s,a} \tag{9}$$

In (9), the cost of stocking $C^{s,a}_{stock}$ considers the cost of the warehouse operator to stock the daily volume of sales, expressed in pallets Z, and it is equal for all strategies:

$$C^{IS,a}_{stock} = C^{DS,a}_{stock} = C^{SH,a}_{stock} = C^{MH,a}_{stock} = Z \cdot C_{w-op} \cdot t^{s,a}_{dep} \tag{10}$$

Similarly, the cost of refilling $C^{s,a}_{refill}$ considers the cost of the warehouse operator to refill the daily volume of sales. Here, for the IS and DS strategies, the daily volume is Z, while for the SH strategy, it refers only to the very fresh products f_i. For the MH strategy, there is no refill activity since all units are continuously handled and directly moved to the e-hub in pallets:

$$C_{refill}^{IS,a} = C_{refill}^{DS,a} = Z \cdot C_{w-op} \cdot t_{refill}^{s,a} \tag{11}$$

$$C_{refill}^{SH,a} = \frac{\sum_{i=1}^{n} m_i \cdot f_i \cdot D}{z} \cdot C_{w-op} \cdot t_{refill}^{SH,a} \tag{12}$$

$$C_{refill}^{MH,a} = 0 \tag{13}$$

The cost of picking $C_{pick}^{s,a}$ depends on the time spent picking the online volume and on the cost of the operators. For IS and DS strategies, it considers the picker cost and the daily sales volume expressed in cartons Y. The SH strategy includes the cost of picking the cartons of no very fresh products and the pallets of very fresh products that are moved to the e-hub. The MH strategy considers that Y is moved by the warehouse operators in pallets:

$$C_{pick}^{IS,a} = C_{pick}^{DS,a} = Y \cdot C_{picker} \cdot t_{pick-c}^{a} \tag{14}$$

$$C_{pick}^{SH,a} = \frac{\sum_{i=1}^{n} m_i \cdot f_i \cdot D}{y} \cdot C_{picker} \cdot t_{pick-c}^{s,e} + \frac{\sum_{i=1}^{n} m_i \cdot g_i \cdot D}{z} \cdot C_{w-op} \cdot t_{pick-p}^{s,e} \tag{15}$$

$$C_{pick}^{MH,a} = Y \cdot C_{w-op} \cdot t_{pick-p}^{s,e} \tag{16}$$

Finally, the transport cost $C_{transport}^{s,a}$ is the yearly cost for moving the goods from the logistic hub to the stores for IS, DS and MH strategies and from the logistic hub to the e-hub for the SH strategy. In each case, this is obtained by multiplying the total number of needed trucks, calculated based on the volume and the handling units that must be moved, with the average cost of one truck $C_{truck-store}$ or $C_{truck-hub}$:

$$C_{transport}^{IS,a} = C_{transport}^{DS,a} = \frac{W}{W_{truck}} \cdot C_{truck-store} \tag{17}$$

$$C_{transport}^{SH,a} = \frac{\sum_{i=1}^{n} m_i \cdot f_i \cdot D}{w \cdot W_{truck}} \cdot C_{truck-store} + \frac{\sum_{i=1}^{n} m_i \cdot g_i \cdot D}{z \cdot Y_{truck}} \cdot C_{truck-hub} \tag{18}$$

$$C_{transport}^{MH,a} = \frac{V}{z \cdot \cdot Y_{truck}} \cdot C_{truck-hub} \tag{19}$$

4.2.2. E-hub cost

The e-hub cost refers only to the strategies having e-hub(s) in their supply chain, i.e. SH and MH strategies; hence, $C_{e-hub}^{IS,b} = C_{e-hub}^{DS,b} = 0$. The cost items are similar to the ones for the logistic hub (9), including the cost of stocking, refilling, picking, packing, and transporting to the stores a part of online orders:

$$C_{e-hub}^{s,b} = C_{stock}^{s,b} + C_{refill}^{s,b} + C_{pick}^{s,b} + C_{pack}^{s,b} + C_{transport}^{s,b} + Q^{s,b} \tag{20}$$

with

$$C_{stock}^{SH,b} = \frac{\sum_{i=1}^{n} m_i \cdot g_i \cdot D}{z} \cdot C_{w-op} \cdot t_{dep}^{SH,b} \tag{21}$$

$$C_{stock}^{MH,b} = \sum_{k=1}^{K} \frac{v_k}{z} \cdot C_{w-op} \cdot t_{dep}^{MH,b} \tag{22}$$

$$C_{refill}^{SH,b} = \sum_{i=1}^{n} m_i \cdot D \cdot g_i \cdot C_{w-op} \cdot t_{refill}^{SH,b} \tag{23}$$

$$C_{refill}^{MH,b} = \sum_{k=1}^{K} v_k \cdot C_{w-op} \cdot t_{refill}^{MH,b} \tag{24}$$

$$C_{pick}^{SH,b} = \sum_{i=1}^{n} m_i \cdot D \cdot g_i \cdot C_{picker} \cdot t_{pick}^{SH,b} \tag{25}$$

$$C_{pick}^{MH,b} = \sum_{k=1}^{K} v_k \cdot C_{picker} \cdot t_{pick}^{MH,b} \tag{26}$$

$$C_{pack}^{SH,b} = \sum_{i=1}^{n} m_i \cdot D \cdot C_{picker} \cdot t_{pack}^{SH,b} \tag{27}$$

$$C_{pack}^{MH,b} = \sum_{k=1}^{K} v_k \cdot C_{picker} \cdot t_{pack}^{MH,b} \tag{28}$$

$$C_{transport}^{SH,b} = \frac{\sum_{i=1}^{n} m_i \cdot D}{O_{truck}} \cdot C_{truck} \tag{29}$$

$$C_{transport}^{MH,b} = 0 \tag{30}$$

The stock costs of Equations (21) and (22) multiply the number of average pallets moved in each strategy by the cost of the warehouse operator and the time needed to store a pallet in the warehouse. Similarly, the refill costs (23), (24), the picking costs (25), (26) and the packing costs (27), (28) consider the number of refilled pieces. Finally, the transport cost for the SH strategy (29) calculates the number of needed trucks, with O_{truck} average number of online orders transported in a truck.

Generally, the MH e-hub cost $C_{e-hub}^{MH,b}$ refers to better times and performance concerning the SH strategy, thanks to the higher processed volumes. However, due to the higher automation required, the investment costs are higher ($Q^{MH,b} > Q^{SH,b}$) and are calculated as the sum of the costs of each hub k:

$$Q^{MH,b} = \sum_{k=1}^{K} Q_k^{MH,b} \tag{31}$$

4.3. Store cost

The store cost $C_{store}^{s,c}$ is the sum of the cost of refilling, picking and packing the sales volumes of all stores and the cost related to the loss of physical customers:

$$C_{store}^{s,c} = C_{refill}^{s,c} + C_{pick}^{s,c} + C_{pack}^{s,c} + C_{loss}^{s,c} \tag{32}$$

Since the MH strategy does not use stores, $C_{store}^{MH,c} = 0$. For the other strategies, the refilling cost $C_{refill}^{s,c}$ considers the yearly cost of the store operator to refill the volume related to online sales in all stores:

$$C_{refill}^{IS,c} = \sum_{i=1}^{n} v_i \cdot C_{store-op} \cdot t_{refill}^{IS,c} \tag{33}$$

$$C_{refill}^{DS,c} = \sum_{i=1}^{n'} v_i \cdot C_{store-op} \cdot t_{refill}^{DS,c} \tag{34}$$

$$C_{refill}^{SH,c} = \sum_{i=1}^{n} m_i \cdot f_i \cdot D \cdot C_{store-op} \cdot t_{refill}^{SH,c} \tag{35}$$

Similarly, the picking cost $C_{pick}^{s,c}$ includes the yearly cost of the store operator to pick the volume related to online sales in all stores:

$$C_{pick}^{IS,c} = \sum_{i=1}^{n} v_i \cdot C_{store-op} \cdot t_{pick}^{IS,c} \tag{36}$$

$$C_{pick}^{DS,c} = \sum_{i=1}^{n'} v_i \cdot C_{store-op} \cdot t_{pick}^{DS,c} \tag{37}$$

$$C_{pick}^{SH,c} = \sum_{i=1}^{n} m_i \cdot f_i \cdot D \cdot C_{store-op} \cdot t_{pick}^{SH,c} \tag{38}$$

Here, the times for the refilling and picking activities performed with the DS strategy can be considered to be lower than those of the IS one since, in the dark stores, there are no congestion phenomena. Moreover, in (35) and (38) the costs refer only to the online volume of very fresh products.

The packing cost $C_{pack}^{s,c}$ is based on the time the store operators spend packing each order:

$$C_{pack}^{IS,c} = C_{pack}^{SH,c} = \sum_{i=1}^{n} m_i \cdot D \cdot C_{store-op} \cdot t_{pack}^{s,c} \tag{39}$$

$$C_{pack}^{DS,c} = \sum_{i=1}^{n'} m_i \cdot D \cdot C_{store-op} \cdot t_{pack}^{DS,c} \tag{40}$$

The loss cost $C_{loss}^{s,c}$ is specific for the DS strategy, since it is assumed that converting some stores to dark stores leads to decreased physical customers. It multiplies the total number of dark stores n', the average annual revenue of one store F and the percentage of customers lost per dark store p_{loss}:

$$C_{loss}^{DS,c} = n' \cdot F \cdot p_{loss} \tag{41}$$

$$C_{loss}^{IS,c} = C_{loss}^{SH,c} = C_{loss}^{MH,c} = 0 \tag{42}$$

4.3.1. Customer cost

Finally, the customer cost $C_{customer}^{s,d}$ refers only to the yearly cost of transportation of the orders to the house of the customers, starting from the stores (IS, DS and SH strategies) or the e-hubs (MH strategy):

$$C_{customer}^{s,d} = C_{transport}^{s,d} \tag{43}$$

The transportation cost considers the average cost of one route from store i (i.e. average cost of serving a certain number of online customers with one single van from store i) $C_{route\ i}^{s}$ multiplied by the average number of vans required per day per store i. Here, $\%_{c\&c}$ is the percentage of online customers who collect their shopping directly in the store i, hence, who do not need the delivery (as in the click and collect strategy).

$$C_{transport}^{IS,d} = C_{transport}^{SH,d} = \sum_{i=1}^{n} \frac{m_i \cdot (1 - \%_{c\&c})}{O_{van\,i}} \cdot C_{route\ i}^{s} \cdot D \tag{44}$$

$$C_{transport}^{DS,d} = \sum_{i=1}^{n'} \frac{m_i \cdot (1 - \%_{c\&c})}{O_{van\,i}} \cdot C_{route\ i}^{DS} \cdot D \tag{45}$$

$$C_{transport}^{MH,d} = \sum_{k=1}^{K} \frac{m_k}{O_{van\,k}} \cdot C_{route\ k}^{MH} \cdot D \tag{46}$$

By comparing (44) and (45) we can say that, generally, $C_{route\ i}^{DS} > C_{route\ i}^{IS}$, since the number of dark stores n' is lower than the number of stores n and, consequently, distances are on average higher.

The transportation cost (46) for the MH strategy is obtained by adding the yearly delivery costs of each e-hub k. In addition, in this strategy, click-and-collect orders are assumed to be delivered to stores that are already available for normal orders, with the same vans used for the deliveries to customers' homes.

5. Parametrical analysis and DSS proposal

This section aims to study the four strategies by applying the cost-based function to real data, varying all parameters. The objective is to understand the behaviour of the cost-function for the four strategies according to different input values, reported in Section 5.1.

Section 5.2 shows the Design of Experiments (DOE) analysis, while Section 5.3 is for the investigation of the possible trends of the logistic costs, including an analysis focused on how some specific parameters (the number of stores n, the average pieces sold per customer s_i, the percentage of click and collect customers $\%_{C\&C}$ and the percentage of very fresh products f_i) influence the total logistic unit cost of the various strategies. This is done by keeping an intermediate value of the other parameters and comparing the total logistics unit costs trend of each strategy.

5.1. Parameters and values settings

While in the case study reported in Section 6 the values of all input parameters are directly derived from field data, here, to compare different scenarios and to carry out generalized results, some input parameters of the model have been estimated. In particular, the refilling, picking and packing times, the truck capacities ($W_{truck}, Y_{truck}, O_{truck}$) and the average number of pieces per pallet, cage and carton (z, w and w) have been directly measured by the authors in the stores and in the logistic hubs of large-scale distribution players. To define the number of needed dark stores n' and the number of required e-hubs K for different scenarios, the volume of the daily online orders has been considered as a dependent variable, and the capacities of the dark stores and the e-hubs are calculated in terms of online pieces processed per day (Ca_{DS}, Ca_{MH}, respectively). Finally, similarly to what has been seen in practice, the e-hub in the SH strategy is assumed to be located near the logistic hub to reduce transport costs. In this way, transport costs from the logistic hub to the e-hub can be considered internal refilling costs, and the transport from the e-hub to stores is the same as the one for the store orders. This assumption can easily be derived also from the last network configuration of Wollenburg et al. (2018). Our model application refers to this favourable scenario; alternatively, transport costs from the logistic hub to the e-hub should be considered.

Table 3 presents the values of all input parameters used.

Table 3
Parameters and Values.

Parameters	Unit	Value(s)	Parameters	Unit	Value (s)
n	-	50,100,150,200	F	k€/year	2250
m_i	-	5 ÷ 100	p_{loss}	-	5 ÷ 80%
$\%_{c\&c}$	-	0 ÷ 100%	w	pieces/cage	1000
s_i	pieces	5 ÷ 100	z	pieces/pallet	1700
g_i	pieces	0 ÷ 100% s_i	y	pieces/carton	20
f_i	pieces	0 ÷ 100% s_i	$t_{dep}^{s,a}$	s/pallet	120
D	days	270	$t_{refill}^{s,a}$	s/pallet	180
Q^{SH}	k€/year	1000 ÷ 5000	$t_{pick}^{s,a}$	s/carton	30
Q_k^{MH}	k€/year	2000 ÷ 6000	$t_{refill}^{IS,c}, t_{refill}^{SH,c}$	s/piece	5 ÷ 10
C_{w-op}	€/h	20–50	$t_{refill}^{DS,c}$	s/piece	3 ÷ 6
C_{picker}	€/h	30–55	$t_{pick}^{IS,c}, t_{pick}^{SH,c}$	s/piece	40 ÷ 100
$C_{store-op}$	€/h	35–60	$t_{pick}^{DS,c}$	s/piece	20 ÷ 50
$C_{truck-store}$	€/truck	20	$t_{pack}^{IS,c}$, $t_{pack}^{SH,c}$	s/order	480 ÷ 660
$C_{truck-hub}$	€/truck	20	$t_{pack}^{DS,c}$	s/order	300 ÷ 500
$C_{route\ i}^{IS}$, $C_{route\ i}^{SH}$	€/van	20 ÷ 60	$t_{dep}^{SH,b}$	s/pallet	120
$C_{route\ d}^{DS}$	€/van	40 ÷ 100	$t_{dep}^{MH,b}$	s/pallet	120
$C_{route\ k}^{MH}$	€/van	80 ÷ 250	$t_{refill}^{SH,b}$	s/piece	3 ÷ 5
O_{van}	orders/van	10	$t_{refill}^{MH,b}$	s/piece	2 ÷ 4
W_{truck}	cages/truck	40	$t_{pick}^{SH,b}$	s/piece	15 ÷ 40
Y_{truck}	pallet/truck	33	$t_{pick}^{MH,b}$	s/piece	5 ÷ 30
O_{truck}	orders/truck	100	$t_{pack}^{SH,b}$	s/order	300 ÷ 500
Ca_{DS}	pieces/day	3000–1000	$t_{pack}^{MH,b}$	s/order	120 ÷ 240
Ca_{MH}	pieces/day	50,000–500,000			

5.2. Design of Experiments analysis

Fig. 2 presents the Design of Experiments (DOE) analysis carried out for each strategy to compare the impact of each logistic cost C_u^s using Minitab© software.

The DOE analysis shows that in the IS strategy (Fig. 2a), the store cost , $C_{store}^{IS,c}$ is the one that most influences the logistic cost, followed by the logistic hub cost $C_{logistic-hub}^{IS,a}$. As online orders increase, it is expected that the number of store operators will increase too, increasing costs, performances and congestions. Similarly, in the DS strategy (Fig. 2b), the store cost $C_{store}^{DS,c}$ is the one that most affects the final logistic cost, followed by the customers' cost of home-delivery $C_{customer}^{DS,d}$. In this case, the benefit acquired by closing the stores to the public is certainly reduced by the loss of revenues linked to the closure. Moreover, as mentioned before, since home delivery is managed from dark stores that are fewer and less distributed compared to the IS strategy, the routes are, on average, longer and, consequently, higher. The SH strategy (Fig. 2c) is equally influenced by the e-hub cost $C_{e-hub}^{SH,b}$ and the store cost $C_{store}^{SH,c}$. Finally, in the MH strategy (Fig. 2d), both the logistic hub cost $C_{logistic-hub}^{MH,a}$ and the e-hub cost $C_{e-hub}^{MH,b}$ influence the total logistic costs, since the first has a higher value due to the additional transport costs between the logistic-hub and the e-hubs. In contrast, the second has higher investment costs due to the high picking performance required and the high level of automation.

5.3. Logistic costs analysis

To better understand how each logistic cost influences the four strategies, the unit cost of the logistic hub $C_{u,logistic-hub}^s$, of the e-hubs $C_{u,e-hub}^s$, of the stores $C_{u,store}^s$, and of the customers $C_{u,customer}^s$ already introduced in (4) are analyzed by varying the number of customers m_i and the number of stores n, maintaining average values for the other parameters.

Fig. 3 presents the single logistic unit costs (in order: $C_{u,logistic-hub}^s$, $C_{u,e-hub}^s$, $C_{u,store}^s$, and $C_{u,customer}^s$) in relation with m_i in two configurations, i.e. $n = 50$ stores (on the left side) and $n = 200$ stores (on the right side). In the first case, it is evident that the strategies mainly influenced by the logistic hub are the IS and DS ones, due to the costs of picking the cartons and transporting the cages. After, there is the SH strategy, with an intermediate logistic hub cost, and finally the MH strategy, which has the lowest volumes of cartons and cages.

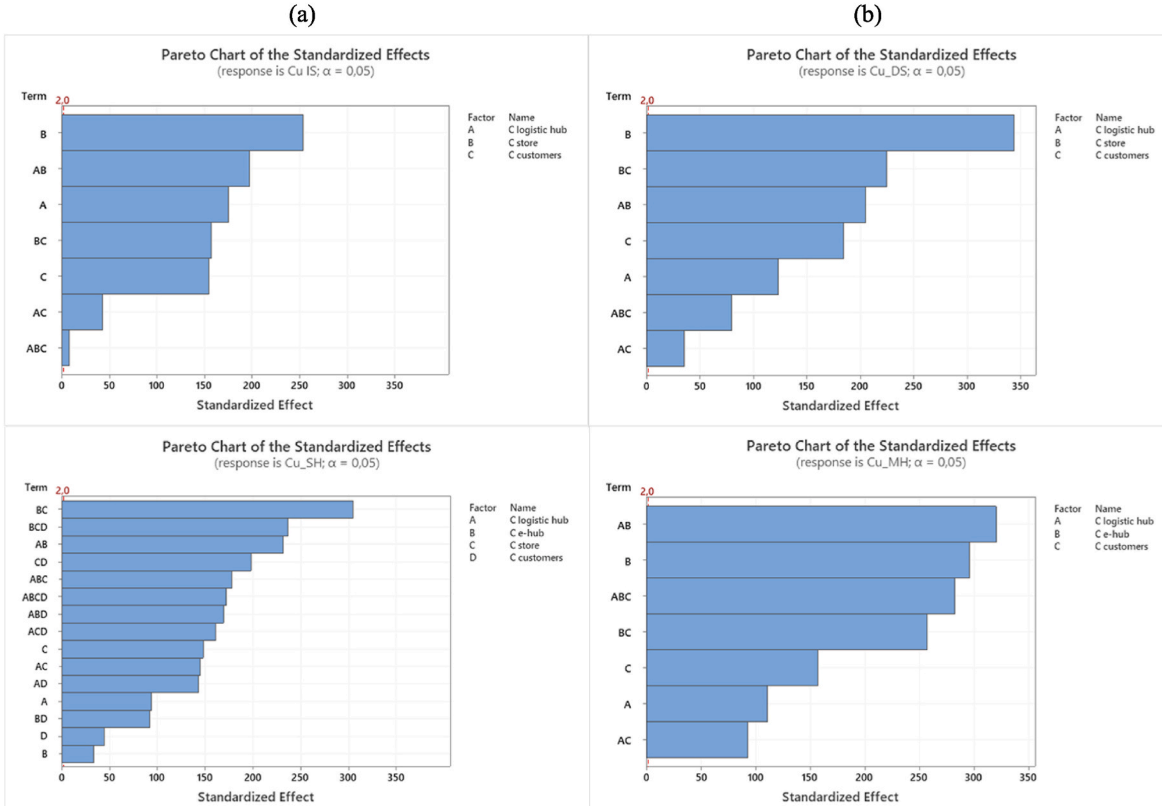
Considering the $C_{u,e-hub}^s$, instead, it is equal to zero in IS and DS strategies, while in SH strategy it has a decreasing trend depending on the online volumes until reaching a relatively constant value; in the MH strategy, instead, it has a decreasing trend but with some fluctuations due to the opening of new e-hubs.

The influence of the $C_{u,store}^s$ on the four strategies, instead, is higher in the IS and DS ones. The strategy with the highest store cost is the IS strategy, in both configurations, with an increasing trend as online orders increase. On the contrary, the DS strategy is less influenced by store cost with SC with few stores. As the SC becomes more significant, more stores need to be closed and the $C_{u,store}^{DS}$ increases, with fluctuations corresponding to the closing of more stores.

Finally, the IS and the SH strategies have the exact lower customer cost $C_{u,customer}^s$, as the deliveries are managed from the stores, which are closer to customers. The MH strategy has the highest customer cost, with a decreasing trend and fluctuations at the opening of new e-hubs. DS strategy, instead, has a linearly decreasing trend, consistently lowest than MH but higher compared to SH and IS.

In conclusion, the comparison of the four logistics costs shows that the ones which mainly influence the total unit cost, then having the

(a) (b)



(c) (d)

Fig. 2. DOE Analysis of the four strategies based on C_u^s: IS (a), DS (b), SH (c) and MH (d).

(a) (b)

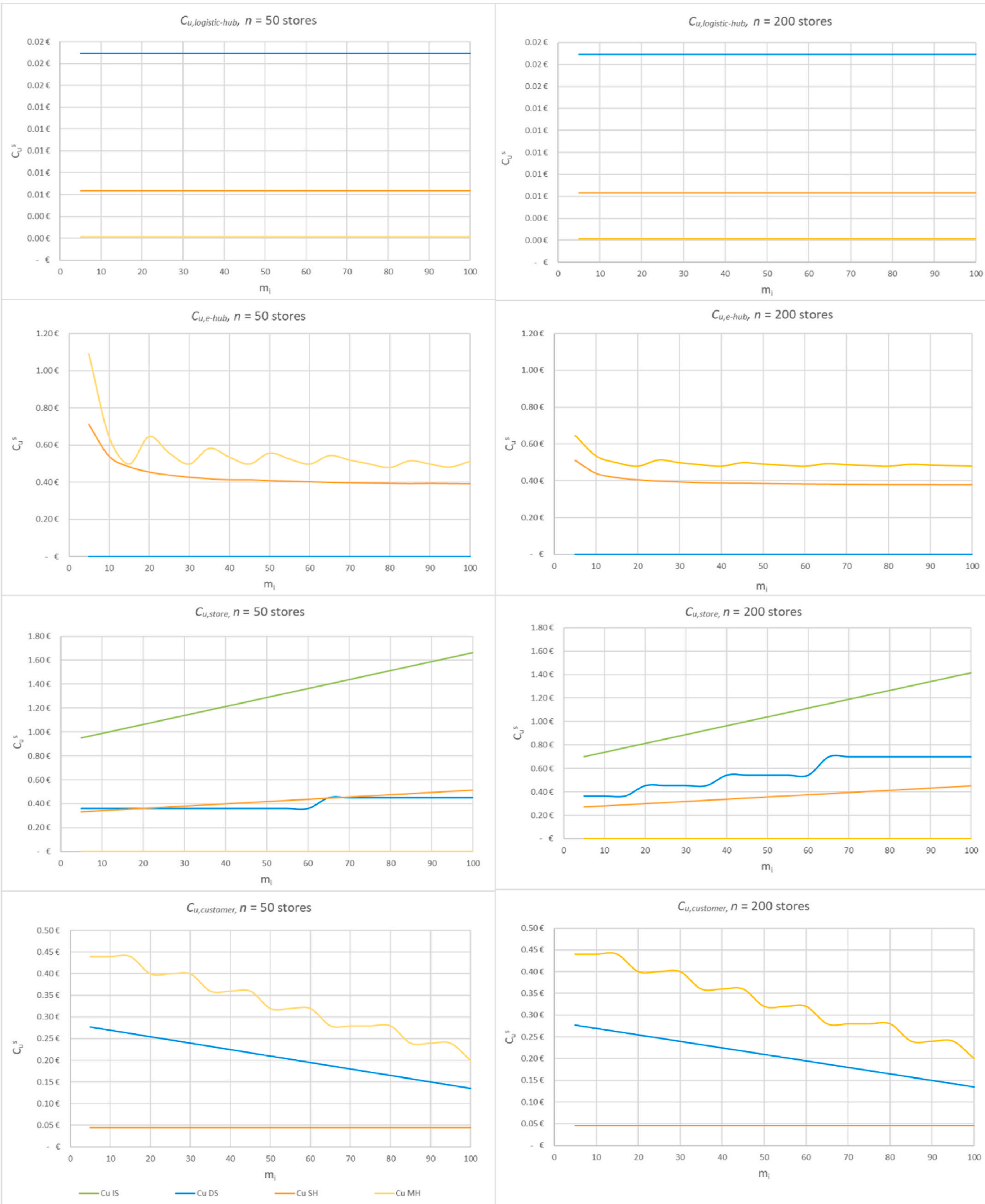


Fig. 3. Comparison of the four strategies based on m_i and in order (per row) $C^s_{u,logistic-hub}$, $C^s_{u,e-hub}$, $C^s_{u,store}$, and $C^s_{u,customer}$ varying n: 50 (column a) and 200 (column b).

highest values, are the store and the e-hubs costs, in order, followed by the customers unit cost and the logistic hub unit cost, which has the lowest values.

5.3.1. Number of stores analysis

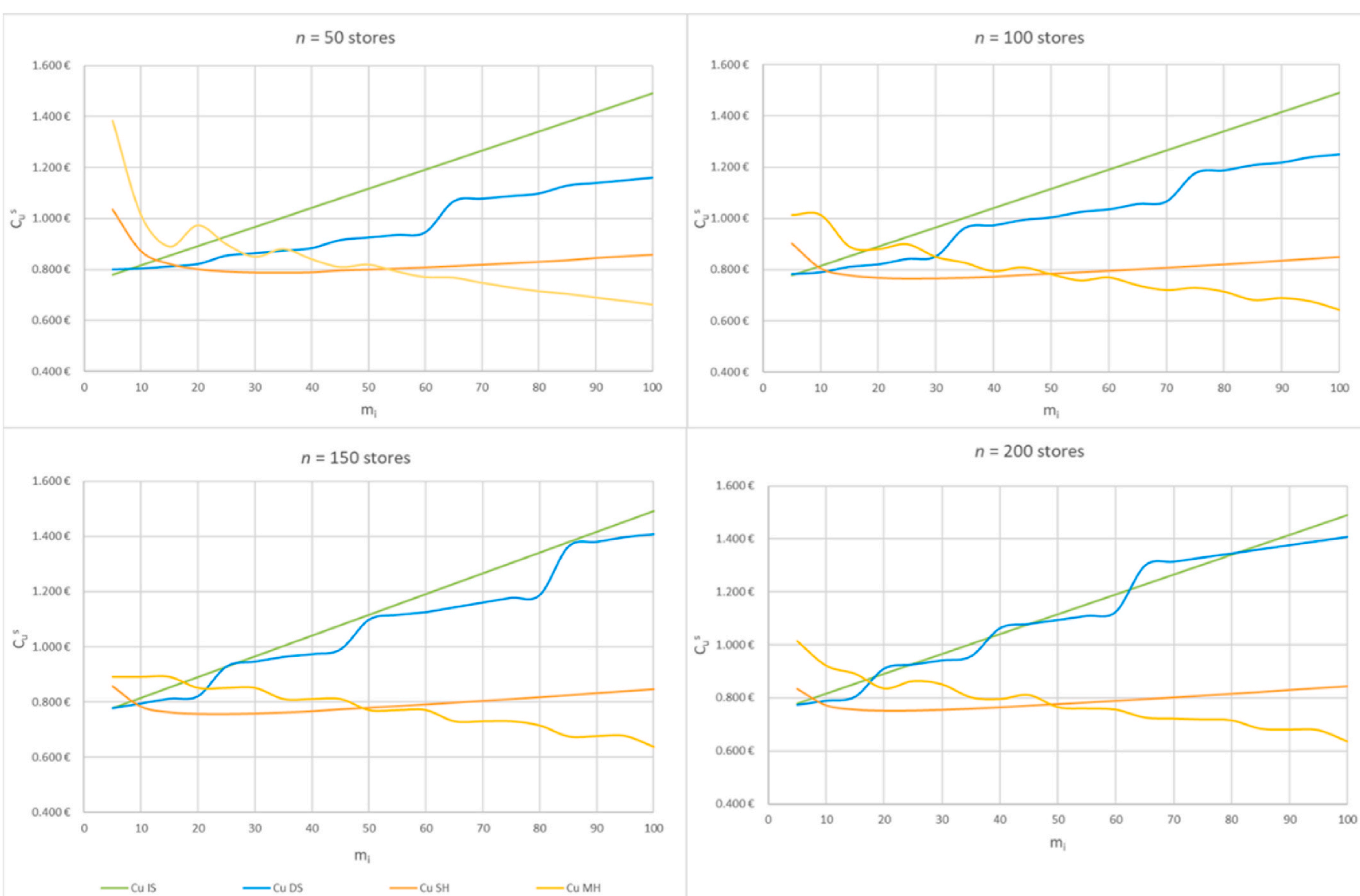
Fig. 4 compares the four strategies showing the relation between the logistic unit cost per piece sold online C_u^s and the average number of online customers per day per store m_i, varying the number of stores in the SC n. In the first configuration with 50 stores (Fig. 4a), IS strategy is the most convenient for a small volume of daily online customers, less than 7–8; in fact, this strategy is the one with the lowest logistics costs as far as the online orders can be carried out with the existing staff during off-peak hours.

On the other hand, it becomes weak when online orders require too many operators, leading to congestion issues. Then, as the number of daily customers m_i increases (8–18), the DS strategy becomes more convenient. However, even if this strategy does not require a high investment, there is an increasing loss of revenue and a higher risk of losing customers. It is because as online customers increase, the number of dark stores has to increase, with the consequent reduction of normal stores, reaching the extreme situation where there are only dark stores. In such a situation, with more online customers that allow paying the initial investment (18–55), the SH strategy becomes the most convenient. Finally, the MH strategy is the most convenient when the number of daily online customers is even higher, more than 55. Although it has higher investment costs it can process more online orders due to its better performance. Moreover, this strategy has a higher delivery cost, since e-hubs are fewer than stores and dark stores, with distances to customers' homes that are on average greater. As the number of stores n increases, the optimal ranges of m_i decrease, as the total number of online customers increases, too. In fact, with 200 stores (Fig. 4d), the IS strategy is never convenient, while the DS strategy is the most suitable with less than eight online customers per day per store; then, for a range of m_i between 8 and 50, the most suitable strategy is the SH one, and for more than 50 the MH one.

5.3.2. Number of pieces sold per online customer analysis

Fig. 5 compares the four strategies showing the relation between the logistic unit cost per piece sold online C_u^s and the average number of online customers per day per store m_i, varying the number of pieces sold per customer s_i. In the first configuration, with $s_i = 10$ (Fig. 5a), the C_u^s is high for MH, SH and DS strategies, and then it decreases with m_i, while it

(a) (b)



(c) (d)

Fig. 4. Comparison of the four strategies based on m_i and C_u^s varying n: 50(a), 100(b), 150(c) and 200(d).

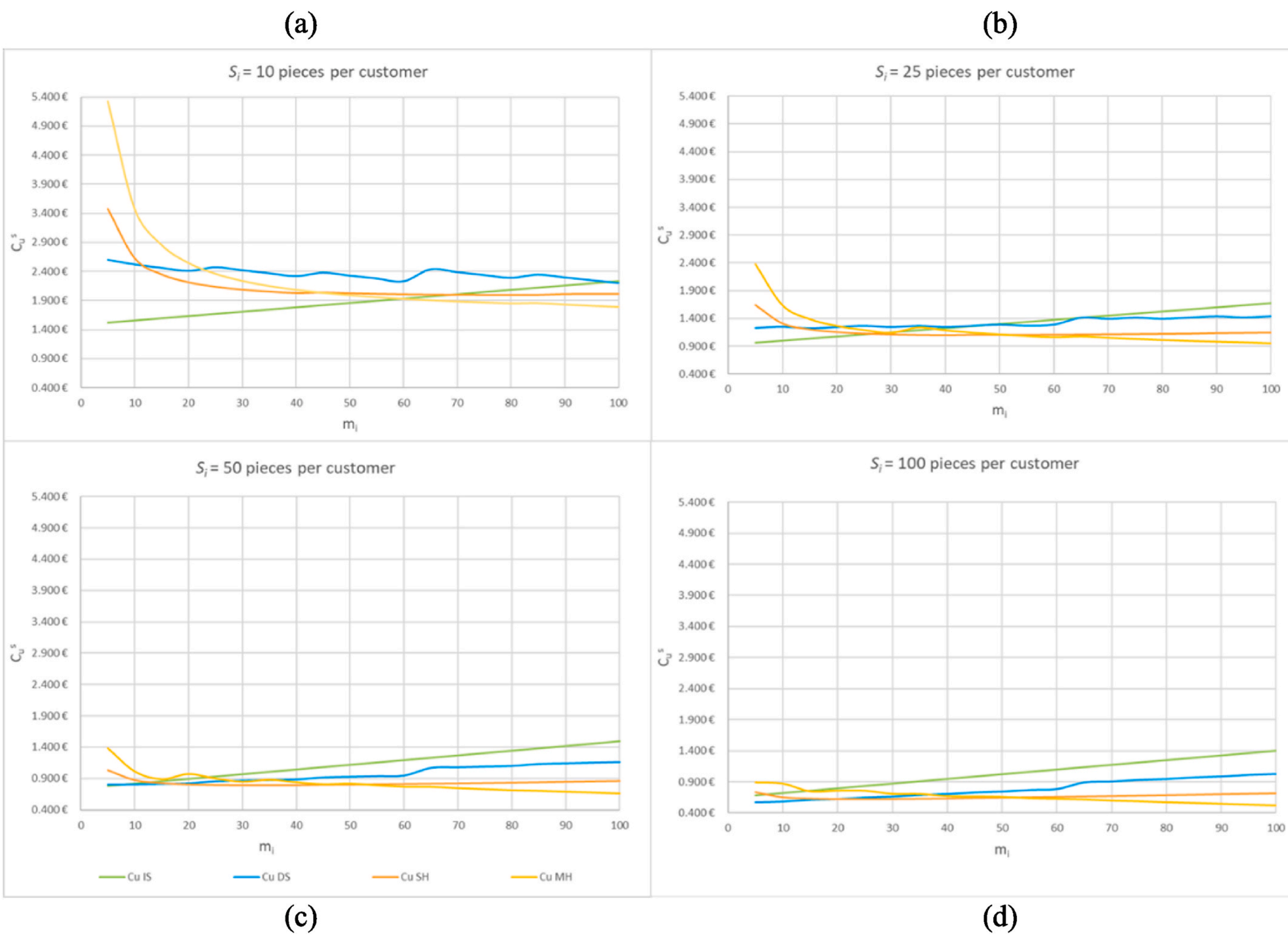


Fig. 5. Comparison of the four strategies based on m_i and C_u^s varying s_i: 10(a), 25(b), 50(c) and 100(d).

is lower in the IS strategy, with an increasing trend. Since we have few pieces sold but the same packing and delivery costs, DS and SH strategies are never convenient. In contrast, IS strategy is suitable for less than 63 customers and, in case of more customers, it is preferable to the MH strategy.

As s_i increases, the C_u^s decreases in general in all strategies, and it maintains the same trend as in the tool shown in Fig. 8: the most suitable strategy for an increasing value of m_i is, in order, IS for few customers per store, then DS, SH and MH. C_u^s has a decreasing trend, justified by the fact that packing and delivery costs depend on the number of customers and not on the pieces sold, that is, the bigger is s_i the lower is C_u^s..

5.3.3. Percentage of click and collect customers analysis

Fig. 6 is focused on the influence of $\%_{C\&C}$, the percentage of customers that will pick up the shop in-store directly by themselves (click and collect), presenting the relation between the logistic unit cost per piece sold online C_u^s and the average number of online customers per day per store m_i of the four strategies. Basically, the click and collect percentage $\%_{C\&C}$ influences the home delivery cost: the bigger it is, the lower is the home delivery cost $C_{customer}^{s,d}$. In the first configuration (Fig. 6a), the click and collect percentage is zero, i.e. all customers receive their orders at home. In this case, the most suitable strategy for an increasing value of m_i is, in order, IS for few customers per store, then DS, SH and finally MH, as in the trend shown in the tool shown in Fig. 8.

As the $\%_{C\&C}$ increases, the logistic unit cost of the DS strategy C_u^{DS} decreases, while this parameter does not influence much the other strategies. The customer cost for home delivery mostly impacts the DS strategy, and the lower it is, the more suitable this strategy is.

5.3.4. Percentage of ultra fresh products analysis

Finally, Fig. 7 compares the four strategies influenced by the number of very fresh products per order f_i. In Fig. 7a $f_i = 0$, then, there are no very fresh products. In this case, the IS strategy is the most suitable when the number of average customers is low (less than 5), and then the best strategy is SH. In fact, without very fresh products, in the SH strategy, online orders are fully managed in the e-hub and the store cost C_{store}^{SH} is zero. As f_i increases, C_u^{SH} increases too, and in the last two configurations, when the number of very fresh products f_i is more than half of s_i (Fig. 7c and d), SH strategy is never convenient.

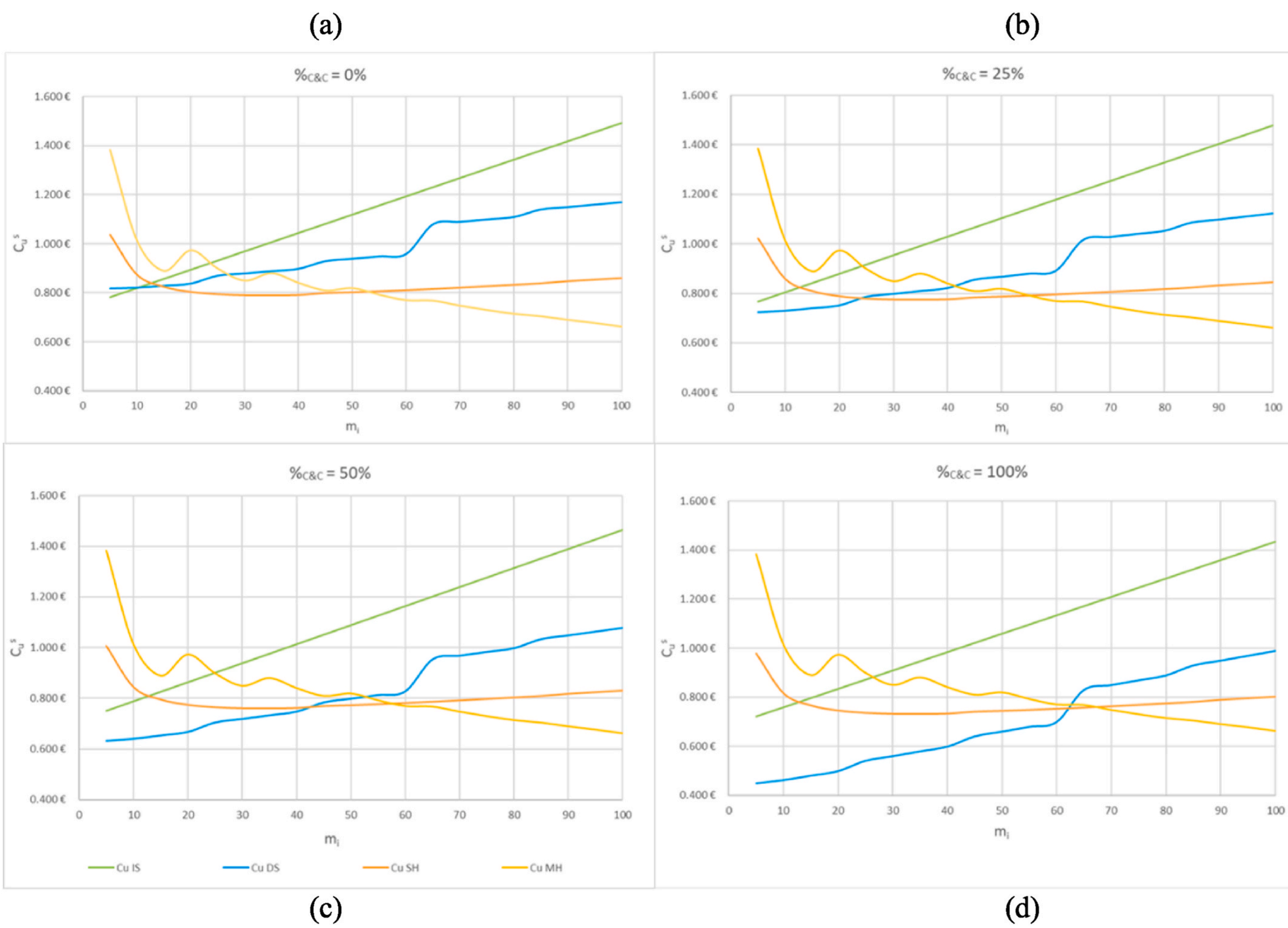


Fig. 6. Comparison of the four strategies based on m_i and C_u^s varying $\%_{C\&C}$: 0(a), 25(b), 50(c) and 100(d).

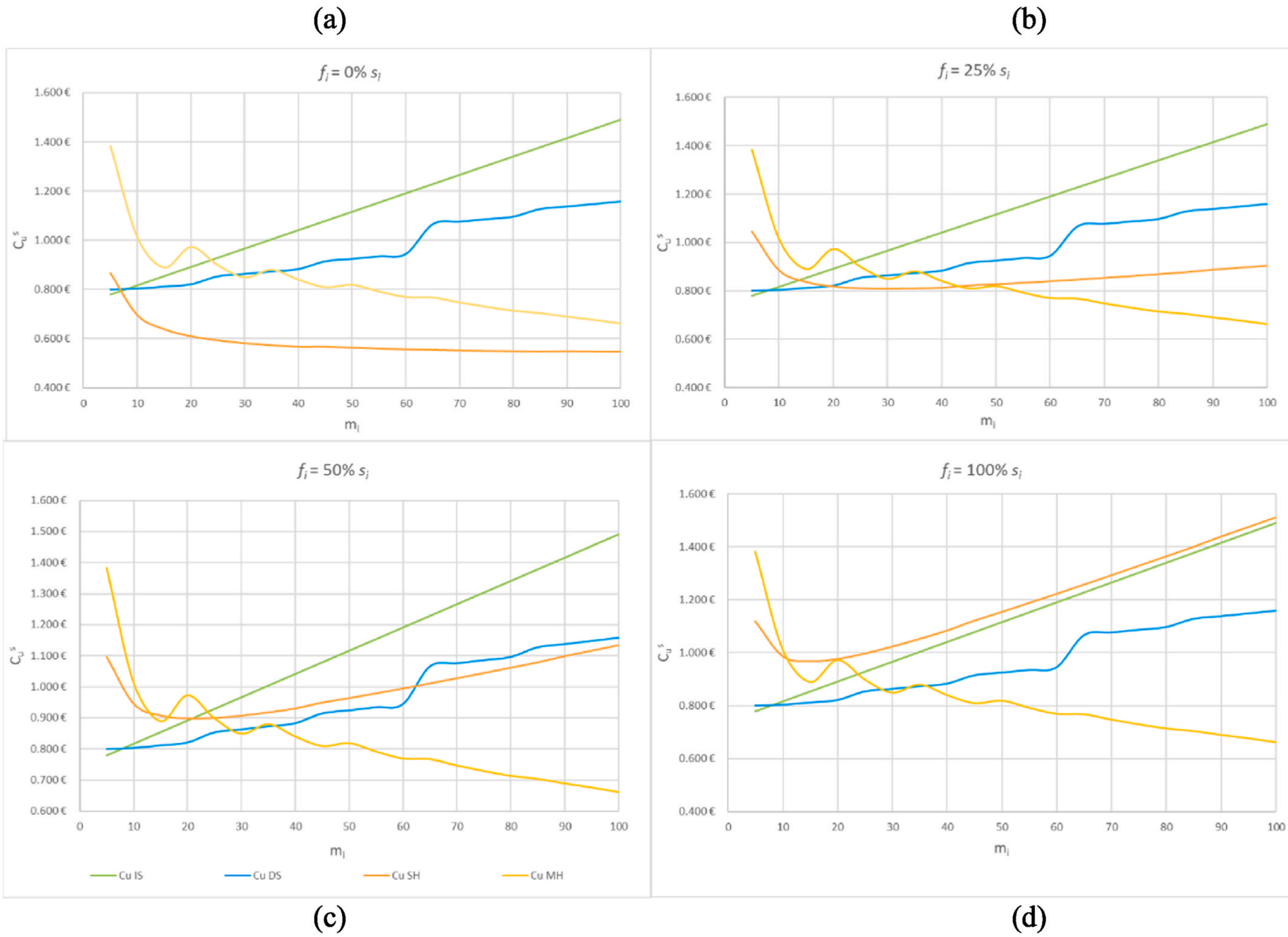


Fig. 7. Comparison of the four strategies based on m_i and C_u^s varying f_i: 0(a), 25(b), 50(c) and 100(d).

5.4. Decision support system

There are many aspects, phenomena and parameters which influence the logistic cost in the e-commerce channel and they all should be considered together to carry out the optimal strategy for grocers' SCs. From this analysis, it arises five main decision variables which should be considered in the online order fulfilment point allocation for groceries: the network of physical stores (n), the average number of daily online customers per store (m_i), the average number of pieces sold per online customer (s_i), the percentage of ultra-fresh products in online orders (f_i), and the percentage of customers with do not require the home delivery service ($\%_{c\&c}$).

Fig. 8 proposes a tool which summarizes the effects of all these decision variables on the final logistic unit cost C_u^s, becoming a useful decision support system (DSS) in which it is possible to derive the most suitable e-grocery strategy starting from the decision variables. In fact, from this tool, it is possible to derive the most appropriate strategy based on few simple input data, the decision variables n, m_i,s_i, $\%_{C\&C}$ and f_i. The columns report the average number of customers per store per day m_i, from 10 to 100, and the click and collect percentage $\%_{C\&C}$. The rows identify the number of stores n (50, 100, 150, 200), the average pieces sold per customer s_i, from 10 to 100, and the percentage of very fresh products f_i (0–100%). For example, a grocer with 50 stores, an average of 10 online customers per store, with 25% of them with the click-and-collect choice, with an average order of 50 pieces with 25% of fresh products should apply the SH strategy, as it is the one with the lower unit logistic cost.

Looking at Fig. 8, it is interesting to note that there is no gradual colour scale, unlike what could be expected. In fact, it is not always true that the most suitable strategies are, in order, IS, DS, SH and MH as the online volumes increase. The size of the SC network, the average number of pieces sold per online order, the percentage of ultra-fresh products, and the percentage of click-and-collect customers make the choice less obvious. For example, in almost any combination, if there are no ultra-fresh products, the SH strategy is the most suitable one, with few stores, few online customers and few pieces sold online, while it would be reasonable to think that the IS strategy is always the best with small online volumes. Another reflection concerns the effect that the click-and-collect service could have on the final choice of the strategy. Looking at the online sales volumes, it is reasonable to think that the DS strategy is preferable with low volumes, and then the SH and the MH ad volumes increased. However, if the percentage of click-and-collect customers is not much high, the MH strategy is preferable with low volumes. For example, with 50 stores, 25 pieces sold per order with very fresh products, and 50 customers, MH is preferable for $\%_{c\&c}$ less than 25%, while DS is more suitable if the $\%_{c\&c}$ is higher.

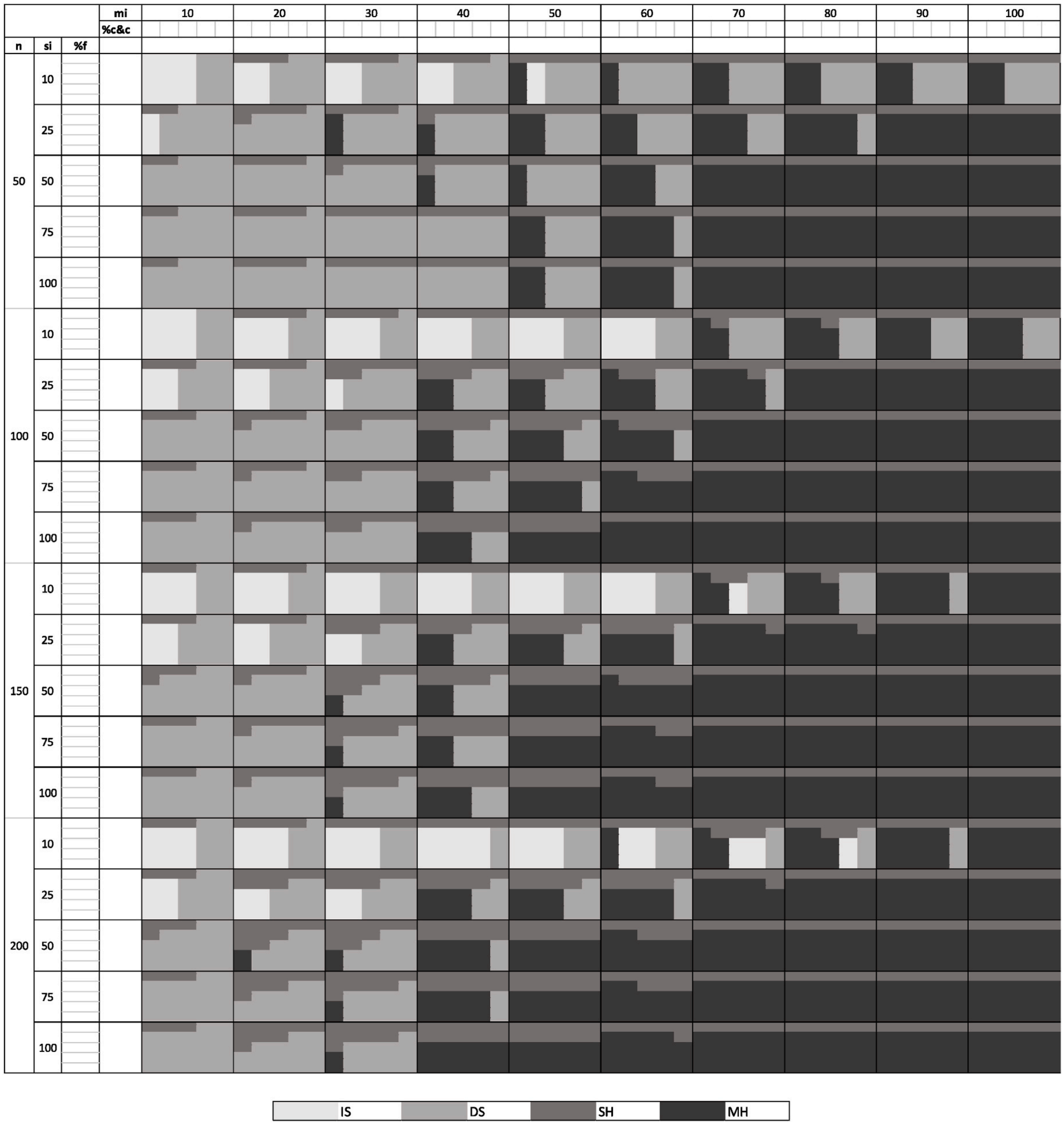


Fig. 8. DSS for strategy selection based on n, s_i, f_i, m_i, $\%_{c\&c}$.

6. Practical application

6.1. Case study

The company chosen for the case study has a logistic hub that serves 134 stores distributed in an area of 250,000 m^2 in 15 main districts; it has a turnover of around 1500 million per year and about 7000 employees. The data used for the model application covers one year. The authors directly measured other data, such as the average picking time in stores. Finally, other average data have been collected in collaboration with the distributor managers. Online orders were initially carried out with an IS strategy, with an average daily volume of 5–10 online orders per store. Due to the increase in online volumes (20–30 daily online orders per store), and the consequent rise in congestion in stores and costs, the presented model has been applied using the data of Table 4. Fig. 10 shows the trend of the four strategies, varying the daily customers per store and the logistic unit cost per piece sold online. Here, it can be seen that the best strategy for this company is the SH one, and that this remains preferable for a wide range of online customers (until $m_i = 70$, when it is suggested to move to an MH strategy).

Fig. 9 reports also which strategy is the best for different ranges of daily online customers per store. The IS strategy turns out to be the most convenient for a small number of daily online customers ($0 \leq m_i \leq 12$): this strategy is the one with the lowest logistics costs as far as the online orders can be carried out with the existing staff during the off-peak hours. Conversely, it becomes weak when online orders require too

Table 4
Parameters of the case study.

Parameters	Unit	Range of Values	Parameters	Unit	Range of Values
n	-	134	F	k€/year	2250
m_i	-	5 ÷ 100	p_{loss}	-	5 ÷ 80%
$\%_{c\&c}$	-	10%	w	*pieces/ cage*	1000
s_i^{online}	*pieces*	50	z	*pieces/ pallet*	1700
g_i^{online}	*pieces*	80% s_i^{online}	y	*pieces/ carton*	20
f_i^{online}	*pieces*	20% s_i^{online}	t^a_{dep}	*s/pallet*	120
D	*days*	270	t^a_{refil}	*s/pallet*	180
Q^{SH}	*k€/year*	1000	t^a_{pick}	*s/carton*	30
Q^{MH}	*k€/year*	2000	$t^{IS,c}_{refil}, t^{SH,c}_{refil}$	*s/piece*	7
C_{w-op}	*€/h*	30	$t^{DS,c}_{refil}$	*s/piece*	5
C_{picker}	*€/h*	40	$t^{IS,c}_{pick}, t^{SH,c}_{pick}$	*s/piece*	40 ÷ 100
$C_{store-op}$	*€/h*	50	$t^{DS,c}_{pick}$	*s/piece*	30
C_{truck}	*€/truck*	20	$t^{IS,c}_{pack}, t^{SH,c}_{pack}$	*s/order*	480
$C^{IS}_{route\ i}, C^{SH}_{route\ i}$	*€/van*	40	$t^{DS,c}_{pack}$	*s/order*	360
$C^{DS}_{route\ d}$	*€/van*	40 ÷ 100	$t^{SH,b}_{dep}$	*s/pallet*	120
$C^{MH}_{route\ k}$	*€/van*	80 ÷ 250	$t^{MH,b}_{dep}$	*s/pallet*	120
Ca_{van}	*orders/ van*	10	$t^{SH,b}_{refil}$	*s/piece*	4
Ca_{truck}	*cages/ truck*	40	$t^{MH,b}_{refil}$	*s/piece*	3
Ca'_{truck}	*pallet/ truck*	33	$t^{SH,b}_{pick}$	*s/piece*	15 ÷ 40
Ca''_{truck}	*orders/ truck*	100	$t^{MH,b}_{pick}$	*s/piece*	5 ÷ 30
Ca_{DS}	*pieces/ day*	3000–1000	$t^{SH,b}_{pack}$	*s/order*	360
Ca_{MH}	*pieces/ day*	50,000–500,000	$t^{MH,b}_{pack}$	s/order	180

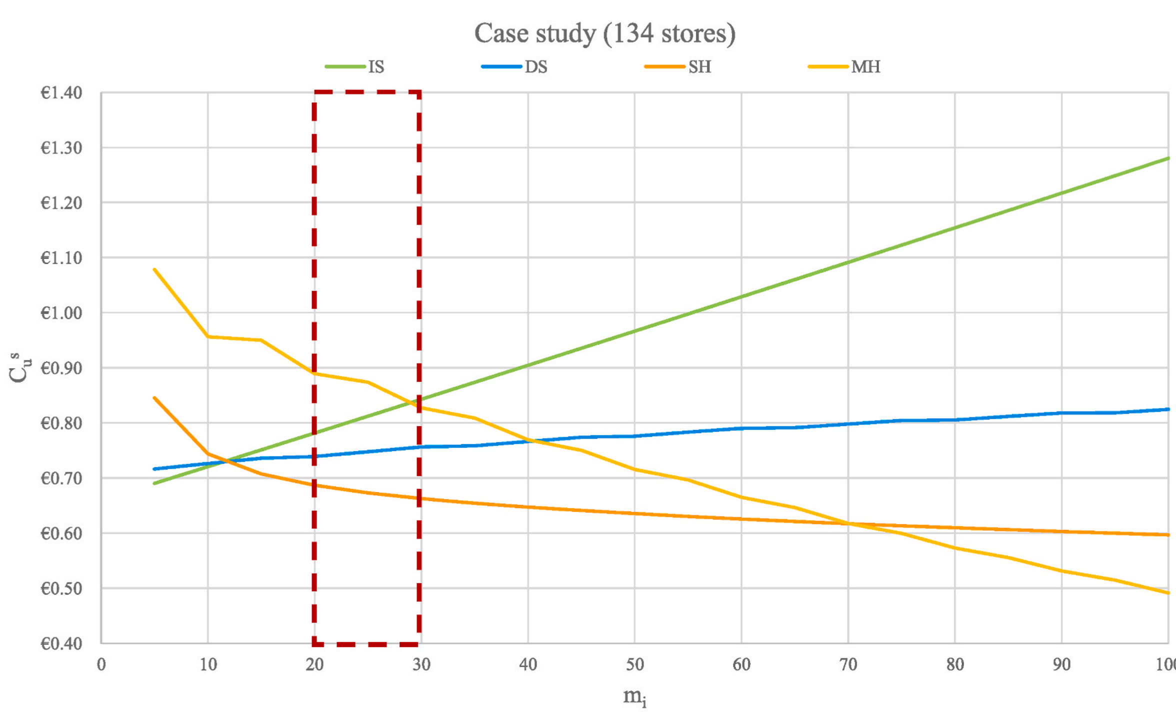
many operators, leading to congestion issues. Then, as the number of daily customers increases, which allows paying the initial investment of the e-hub, the SH strategy becomes the most convenient ($12 \leq m_i \leq 70$). Finally, the MH strategy is the most suitable when the number of daily online customers is higher ($m_i > 70$). On the other hand, the DS strategy here turns to be never convenient. Finally, applying the tool of Fig. 8 to the case study, rounding up to 150 stores, 30 customers per day with 50 pieces per order, the table indicates the same result as Fig. 9, SH as the best strategy.

6.2. Possible extension

In this section we show the possible application of the proposed cost function by considering different mixes of the strategies and the comparisons that can be done from that. For this purpose, we decide to further elaborate the data of the company, and to focus on a case in which there is a group of 26 stores located in a limited area, enough far from the other stores and with a higher $\%_{c\&c}$ and a low m_i. Therefore, all the stores are divided into two groups, group A with these 26 stores, and group B with the 108 remaining ones. Table 5 summarizes the characteristics of the two groups which are different from the previous case (Table 4).

Table 5
New data for groups A and B.

Parameter	Unit	Group A values	Group B values
n	-	26	108
m_i	-	10 ÷ 15	25 ÷ 35
$\%_{c\&c}$	-	30%	5%
s_i^{online}	*pieces*	50	50
g_i^{online}	*pieces*	80% s_i^{online}	80% s_i^{online}
f_i^{online}	*pieces*	20% s_i^{online}	20% s_i^{online}



IS	SH	MH
0-12	12-70	> 70

Fig. 9. Comparison of the four strategies for the case study.

The model has been applied to both groups; Figs. 10 and 11 show the related results. By grouping the stores, the average daily volume is supposed to become of 10–15 online orders per store for group A: Fig. 10 suggests that DS strategy is the most suitable one, with a unit cost C_u^{DS} of 0.75 €/piece. On the other side, for group B the average daily volume is supposed to become of 25–35 online orders per store, with the SH strategy as the most suitable one, with a C_u^{SH} of 0.71–0.69 €/piece (as shown in Fig. 11). These results suggest the use of two different strategies, DS and SH, for the two groups of stores. However, by comparing these outcomes with the ones of Fig. 9, it is evident that the use of this mix of strategies in this case it is not convenient, since managing all the 134 stores with the SH strategy has a lower unit cost C_u^{SH}, which varies from 0.69 €/piece to 0.65 €/piece. In fact, the mixed strategy here leads to fixed costs for the e-hub as well as for the dark-stores, although volumes are not so high to justify them both.

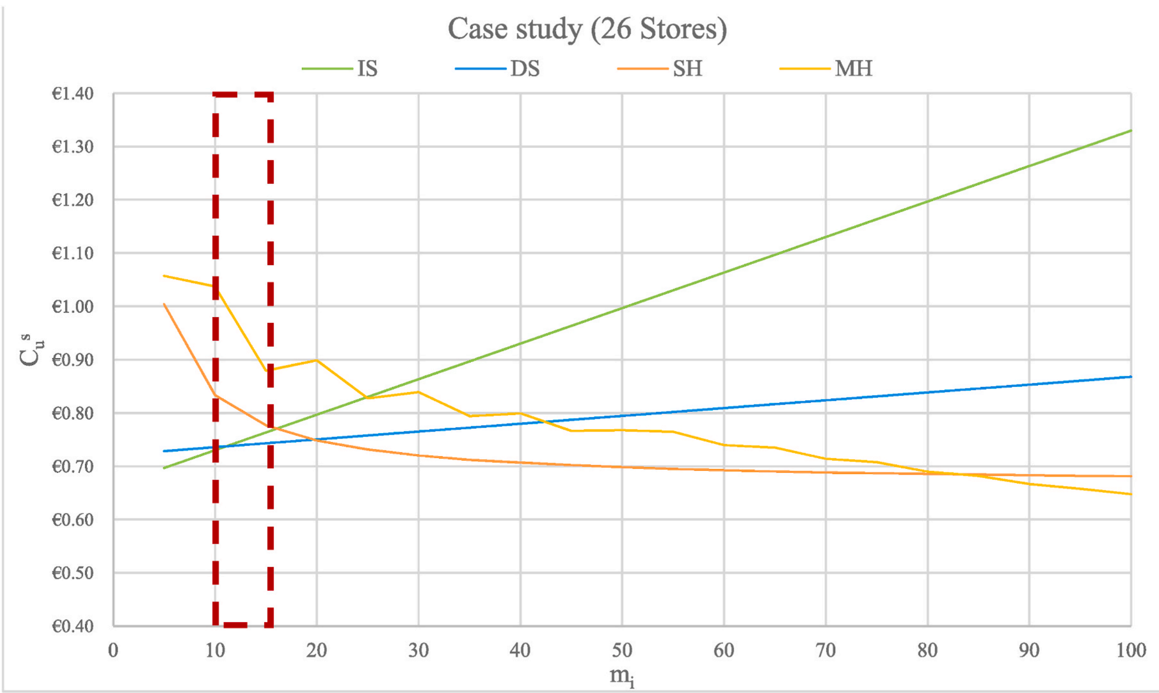


Fig. 10. Comparison of the four strategies for the case study for group A.

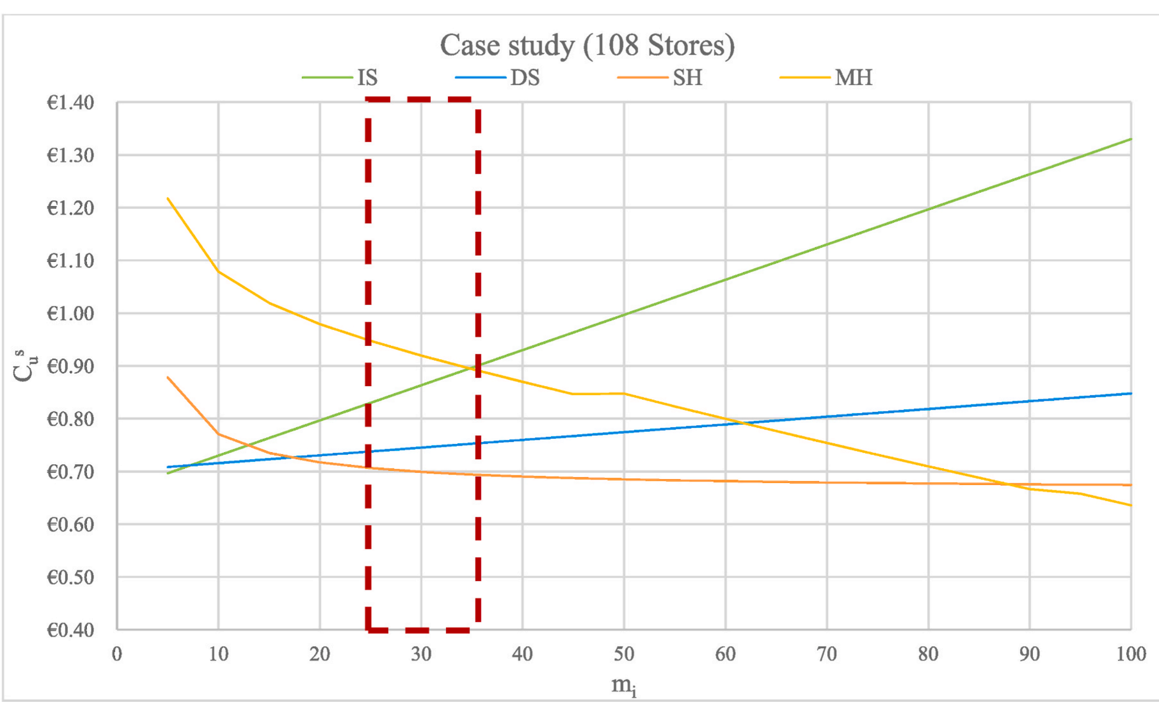


Fig. 11. Comparison of the four strategies for the case study for group B.

Table 6
Advantages and disadvantages of the four logistics strategies.

Strategy	Advantages	Disadvantages
IS	- works well with few online orders - very flexible strategy - easy to apply - no initial investment required	As online orders increase: - dedicated staff required - off-peak hours no longer enough - increase of congestions in stores - increase of time for online orders preparation - increase of risk of having missing products - costs of shelves refilling uselessly greater
DS	- no congestions with customers in stores during picking - high online orders preparation performance high - stable risk of having missing products - no initial investment required	- limited number of stores that can be converted into dark stores (the more they are, the higher the risk of loss of physical customers) - delivery costs higher than IS strategy (online customers are the same, but dark stores are fewer and farther away)
SH	- congestions in stores is lower than IS (only very fresh products are picked in stores) - no risk of loosing physical customers - high picking performance in the e-hub - delivery costs are the same as the IS strategy	- additional transport costs between the logistic hub and the e-hub - high initial investment cost
MH	- high picking performance in the e-hubs - no congestions issues in stores (no stores) - higher level of automation	- additional transport costs between the logistic hub and the e-hubs - higher initial investment cost - higher delivery costs

7. Discussion and managerial insights

With respect to the existing literature, this work presents both a cost-based function and a DSS to evaluate the most suitable logistic strategy for an e-grocer SC. Table 1 shows that most of the works published on this topic is focused only on the store-based strategy and/or the warehouse-based strategy. This work, instead, considers not only the store-based strategy (IS) and the warehouse-based strategy (MH), but also other two different strategies, the DS and the SH ones, which could be considered a mix of the characteriscs of the previous ones. Few works have proposed so far mathematical models to define the optimal order allocation point, such as Kämäräinen et al. (2001), Scott and Scott (2006) and Zheng et al. (2021). Nonetheless, the first one proposed a model to compare the store-based and warehouse-based strategies based on picking efficiency, without considering other logistics variables. The model of Scott and Scott (2006) analyzed the two strategies focussing on the delivery budget and the overall utilisation on store congestion, while Zheng et al. (2021) analyzed the store-based strategy and the warehouse-based convenience in the case of fresh products, considering customer perception and profit. Then, our work extends the available literature by concurrently considering more variables to define the most suitable strategies.

Moreover, the application of our approach to the case study showed the possibility to use the cost-based function directly, or to derive the results through the DSS. In the first case, the solution is more accurate and results indicate also the average final cost per unit; however, it requires a higher amount of input data. On the other side, the decision support tool can indicate only the best strategy, without giving information about the exact cost values. In the case study it is also investigated the possibility to have a mix of the strategies, by dividing the stores into two groups according to their characteristics. Here, the application of the cost function led to the suitability of different strategies for the two groups. However, the comparison of the obtained unit costs with the ones resulting from the consideration of single strategies showed the convenience of applying the SH strategy for all stores. To derive the best strategy for the two groups it is also possible to use the DSS, although with this method it is not possible to identify if it is better to use a unique strategy or a mix of them.

Table 6 summarizes the main advantages and disadvantages in terms of operativity and logistics costs of each strategy that can be used as a reference guide. This table, together with the DSS of Fig. 8, can be used by grocers and managers to know which strategy best suits their online channel to reduce their total logistics costs, knowing or estimating only five input variables: the network of stores of the SC n, the daily average number of customers per store m_i, the average number of pieces per order s_i, the percentage of customers which prefer the click and collect option $\%_{C\&C}$ and the percentage of very fresh products f_i.. Moreover, grocers and managers could be able to evaluate the most suitable strategy in their current situation as well as to consider different future scenarios with a long-term horizon. The DSS rebuts the use of the four strategies in the most intuitive order IS, DS, SH and MH, as online volume increases. In fact, the click-and-collect service, the percentage of ultra-fresh products and the size of online orders per person influence the choice of the final strategy unexpectedly. The MH strategy and the SH one could be preferred with low online sales volumes as the IS strategy, and the DS strategy could be selected with higher online sales volumes, as discussed previously. Consequently, the DSS can effectively support practitioners in network design decisions about the online order allocation point, considering the total online sales volumes and other essential aspects. In fact, the DSS represents an easy to apply tool based on logistic costs which is currently missing in the literature, useful to comprehensively compare the four different strategies, suggesting which is the most suitable one without applying any mathematical model and without the need of having a lot of input data, since it is based only on the setting of five decision variables. Anyway, it remains that the DSS is based on a detailed cost function, which can be applied to have more precise results.

8. Conclusion and further research

This study presented a cost-based function to compare four different e-grocery supply chain configurations with different online order allocation points. The definition of the mathematical formulation and its subsequent application to a parametical analysis have allowed to derive a DSS tool and a summary table that can guide academics and practitioners in e-grocery SC studies. In particular, the performed analyses showed that it is important to consider online order volumes but also other decision variables to determine the best strategy. To ease this job, the proposed DSS summarizes all the findings, and it allows to derive the most suitable strategy based only on five input variables. The results showed that as online orders increase, the best strategy changes, but it is not always following the order IS, DS, SH, and MH, since other factors can come into play. Moreover, in order to ease its comprehension, the proposed approach has been applied also to a real case study of a big Italian large-scale organized distribution player.

As mentioned in the introduction, the strategies analyzed in this study are taken from the works of Wollenburg et al. (2018) and Giuffrida et al. (2017) and integrated with the authors' experience. In this paper, they have been analyzed individually, to understand their general behaviour and which are the main variables affecting their logistics costs. However, in the case study we also showed a possible extension of the proposed approach, by considering the application of two strategies simultaneously. In the same direction, future research should further investigate the possibility of using a mix of the four strategies at the same time with the objective of carrying out a similar integrated DSS tool which can be used as reference by practitioners. Indeed, the SH strategy, in practice, is already a particular mix of the IS and MH one, having the same characteristics of MH (even if only with one e-hub), with the ultra-fresh products that are managed according to the IS strategy. This could also include a different strategy per product typology or differentiate strategies for different geographic areas.

Moreover, this research did not consider the possibility of having pick-up points located in different places with respect to the stores. This configuration could be investigated in the future, especially in those solutions where home delivery costs have a high impact. Future research could also consider new and different strategies for managing the online order allocation point. Finally, the model could be extended to more specific e-grocer SCs, such as SCs with only fresh products or with specific products as housewares chains; in these cases, different results and considerations could emerge.

Data availability

The data that has been used is confidential.

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