Impact of urban satellites in fast fashion last mile distribution

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Purpose – The paper addresses how urban satellites affect profit based on inventory management policies and different operational conditions. An Italian retailer fast fashion supply chain is used as a case study. The case study also aims at capturing the consumers' purchasing attitudes under order-and-wait sales scenarios that consider the time customers are willing to wait for their in-store unavailable products.

Design/Methodology/Approach - In this paper, the impact of urban satellites on the operations of fast fashion supply chains is evaluated using discrete event simulation. The simulation replicated the case study supply chain, and the input data were fitted from the case study.

Findings - Results show that urban satellites can decrease store inventory levels for on-shelf items, thus increasing lost demand and impacting on transportation cost. However, adding satellites allows to increasing product assortment through the available retail store space room, thus attracting new customers, increasing sales and reaching higher profit. The study eventually gives managerial implications for urban satellites on store floors space usage, assortment and distribution policies.

Originality/Value – The paper overcome the gap of the literature about the operational and economic adavantages and disadvantages of including urban satellites in fast fashion supply chains.

Keywords - city logistics; last-mile logistics; fast fashion supply chains; inventory control; transportation systems; optimization and simulation

1. **Introduction**

Fast fashion retailers constantly exhibit new products at retail stores located in the city centers or popular shopping malls to attract consumers in repeated shopping experience and stimulate impulse purchasing behaviors (Gabrielli et al. 2013). Fast fashion products typically have short life cycles and are exposed to a highly variable and seasonal demand (Christopher et al. 2004). This requires the fast fashion industry to create responsive supply chains as a way to promptly react to uncertainty in demand. To do so, retailers have to trade stylish fresh apparel assortments with very short production and distribution lead times (Cachon and Swinney 2011). A variety of novel product are lately designed to conform to the newest fashion trends and produced in sufficient amounts to avoid the risk of stock-out and lost sales.

Several solutions are used to build these types of responsive and flexible supply chains, including multi-channel and city logistics (Galipoglu et al., 2018), with the purpose of rapidly and frequently shipping items to retail stores and assuring a high service level (fill rate) (Christopher et al. 2004). In this context, to stay profitable, retailers must meet a wide apparel assortment while optimizing their inventory level to fulfill customers' requests as a way to both sustaining sales revenue and minimizing operations expenditures (Ketzenberg et al., 2000). This is the challenge that the fast fashion industry is seeking to respond by exploring new operational models such as the implemention of city logistics solutions. In fact, fast fashion retailers typically have a centralized consolidation center (CC) that receives shipments from internal and external suppliers and then sorts, packs and ships orders to all worldwide retail stores. The centralized logistics model is a key element to build and maintain a responsive supply chain, but it can result in expensive store allocation and transportation practices (Ghemawat and Nueno, 2006). This is why, to minimize some of the disadvantages of the centralized distribution system and meet the goal of both low inventory levels, wide fresh assortments, and high customer service levels, satellite warehouses and urban satellites can be added to the distribution model (Crainic et al. 2010). Urban satellites promise to reduce last-mile delivery distance and time, include buffer storage services and speed up replenishment frequencies, which can result, in turn, in larger free retail store capacity and higher assortment in line with the fast fashion industry paradigm (Van Rooijen and Quak 2010). Urban satellites can affect inventory management policies, operational conditions, and subsequent increased revenue and cost savings. In other words, urban satellites promise to provide many impacts to sales and operations that can, in turn, generate significant economic benefits. However, urban satellites are a rather new city logistics solution and little has been reported about the operational and economic adavantages and disadvantages of such solutions.

To overcome this gap, this paper analyzes the operational advantages and reduced operations costs that can be obtained from adding urban satellites into the centralized distribution model of a large fast fashion retailer headquartered in Italy (named as the Company in the following). In particular, this work aims at understanding the impacts of urban satellites to logistics operations, store inventories and floor space areas, and related cost and revenue benefits. A discrete event simulation framework is adopted to compare the performance and cost of the Company under an *as is* scenario of centralized distribution compared to a *to be* scenario that simulates the addition of urban satellites to the network. Actually, the *to be* scenario considers the insertion of urban satellites in three key Italian cities. Also, the simulation model is used to analyze the conditions that make adding urban satellites to the distribution system profitable and present a profit analysis through assessment of operations cost and sales revenue under multiple scenarios. The analysis includes various operational characteristics, such as the replenishment policy and the different ways of distributing inventories between the echelons of the supply chain with associated cost analysis. It also aims at capturing the consumers' purchasing attitudes under order-and-wait sales scenarios that consider the time customers are willing to wait for their in-store unavailable products (Gao & Su, 2017).

The remainder of the paper is structured as follows. Section 2 presents the relevant literature. The empirical context and the simulation methodology are introduced in section 3. Section 4 points out the model used for simulation and the experimental setting, while results are discussed in section 5. Finally, managerial implications are discussed in section 6 and conclusions drawn in the last section.

2. Literature review

The academic literature has largely discussed how the apparel industry has been leading changes and innovations in supply chain management, distribution, and retail operations for long times (Barnes and Lea-Greenwood, 2006). In particular, the emerging dynamics of the fast fashion sector have called retailers to desire low cost and flexibility in design and quality and to implement quick-response strategies to maintain profitability in increasingly demanding markets (Bhardwaj and Fairhurst, 2010). Targeting both lower cost and higher fill rate has an impact on all echelons of the supply chain and especially for distribution operations (Baker, 2004).

Thus, a key component of the fast fashion paradigm is searching for an effective centralized distribution policy, whereas consolidation and distribution centers can assure a high level of rapid responsiveness to market demand with reduced central inventory (Baker, 2008; Mehrjoo and Pasek, 2016). Consequently, scholars have mainly focused on solving various problems at the retail level, such as: determining product replenishment order quantities and frequencies that minimize the cost of lost sales, backorders, and obsolete inventory (Fisher et al., 2001); choosing apparel assortment to maximize profits (Rajaram, 2001); optimizing retail store sales and backroom areas (Pires et al., 2019); optimizing transportations among the nodes of the supply chain (Sung and Jang, 2018).

However, recent studies in the city logistics arena (Dolati Neghabadi, 2019) have been addressing issues inherent with a centralized distribution system when it comes to sustainability, shipping cost, and retail store capacity and discussions are still open about innovations that help more efficiently handling the last mile delivery in urban areas (Ranieri et al., 2018).

In this perspective, second-tier satellite storages located in urban areas can reduce last-mile transportation costs and substantially contribute to improving the service level. For example, da Costa Fontes and Goncalves (2019) demonstrated that “lower transport costs are achievable by a hub-and-spoke with sub-hub structure because the economy of scale this model provides is combined with shorter alternative paths”. Besides, from a retailer point of view, urban satellites are reported to allow for a short lead time (specifically for the last-mile delivery) and an increase in the product assortment (Van Rooijen and Quak 2010) together with a reduction in the inventory level of the individual products (Chen et al. 2016).

Due to their proximity to the points of sale, urban satellites, also allow for higher frequencies of retail store replenishment and subsequent decrease in capital and operations cost of store inventories (Greasley and Assi 2012). In turn, reduced inventories allow releasing storage capacity that can be filled with larger product assortment to generate increased sales revenue in compliance with the fast fashion paradigm. With urban satellites, released storage capacity may also be shared with other retail companies operating in different (e.g., complementary) markets to decrease running costs (Matzler et al., 2015).

Research is also associated with developing models that evaluate the impact of introducing urban satellites in the fast fashion retail supply chain. In the operations research area, in particular, some works are intended to solve the two-echelon vehicle routing problem when satellites are added to a distribution network. For example, Crainic et al. (2012) proposed a model that minimizes the global routing costs of a two-echelon network where freight is delivered from distribution centers to intermediate satellites, and then to end retail stores. Similarly, Darvish et al. (2019) explored an integrated routing problem in which a supplier delivers a commodity to its customers through a two-echelon supply network. In this case, the objective is to minimize the total cost of shipping (from the CC to the satellite, and from satellite to a retail store), the rental cost of the satellite, and the penalty incurred for unmet shipping due dates. Other similar vehicle routing algorithms are proposed for planning and managing integrated short-term scheduling of operations with two-tiered distribution structures (Crainic et al. 2009) or designing the routes for a vehicle fleet located at the CC to transport demand to a subset of satellites (Zhou et al., 2018; Dridi et al., 2019).

Finally, some research has provided case studies related to centralized distribution systems where different solution approaches are applied. Adopted methodologies include genetic algorithms (Çelebi, 2015), system dynamics modeling (Cagliano et al., 2012), and discrete event simulation, which is the approach used for this study.

Discrete event simulation was used in Alfieri et al. (2019) to analyze, using a case study, the benefits that can be obtained from entering urban satellites into a fast fashion distribution system. The results revealed that the increase in transportation and inventory costs could be balanced by higher revenue that is made from selling a wider range of product assortment present in the stores.

All in all, the literature reports that including urban satellites tends to raise the performance of the supply chain. However, beyond reduced operations cost, it is still unclear how urban satellites can unlock additional operational and economic value that they promise in running last mile logistics of responsive supply chains. This paper aims at bridging this gap by analyzing the operational advantages and associated economic benefits of urban satellites in supply chains by addressing an Italian fast fashion case study.

3. Empirical context

This work uses a case study based methodology. It builds on a case-study to gather empirical data and run simulations to inductively elaborate considerations that can be valuable for other similar firms (McCutcheon and Meredith, 1993). The addressed case is a multi-national fast fashion Company headquartered in Italy that claims anonymity due to confidentiality reasons. In the Company stores, customers can independently serve themselves or can ask the help of store assistants, i.e., what is called *assisted sales*.

The Company supply chain is represented in Figure 1(a). It has three echelons: production, distribution, and retail levels. At the production levels, several production facilities, represented with squares in Figure 1, are placed in various European sites. Instead, differently from production, distribution, and retail levels are both located in Italy. Specifically, distribution is centralized, i.e., the distribution level consists of a single consolidation center (CC – the triangle in Figure 1(a)) located in the north-west of Italy. The lower level of the supply chain (i.e., the retail level), instead, is composed of 220 retail stores (circles in Figure 1(a)), spread over all the entire country, and the Company owns (or directly manages) all of them. As the Company directly controls production, distribution and retail, the supply chain is vertically integrated.

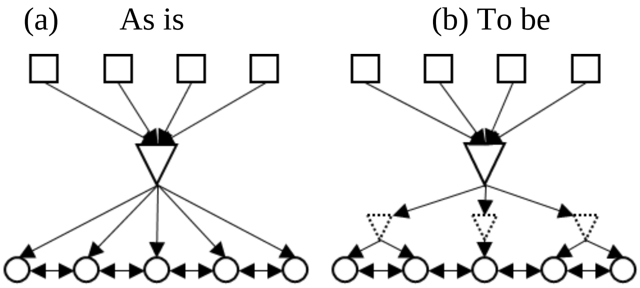

Figure 1. Supply chain structure

As it is common in fashion companies, there are two selling seasons per year (autumn/winter and spring/summer seasons), and the product assortment completely changes from one season to the other. Moreover, in each season, different items are *pushed* to customers each month. When an item is pushed, it is said that the item is *on theme*; hence, in each month of the season, some of the items are on theme, and some are not. As it will be explained in the following, being or not being on theme has an impact on the item replenishment policy.

The distribution process starts with the so-called initial allocation at the beginning of each selling season. Within the first allocation, the CC sends 90% of the product assortment to the retailers and keeps the remaining 10%. Each store receives a number of products that is proportional to its expected demand. To allow the fulfillment of the demand, the inventories at retail stores can be re-allocated among them during the entire selling season. Moreover, if an item is on theme, every day, the retailers can place replenishment orders for the item, to the CC. The inventory is managed by a (Q, R) policy, which implies that Q units are ordered to the CC each time the inventory position (i.e., on-hand inventory plus already placed replenishments minus backorders) decreases below a threshold R. In the event of a stock-out, i.e., if a customer order cannot be fulfilled, the retailers can ask the CC and the other retailers if they have sufficient amount to send it for that order fulfillment, even if the requested item is not on theme. A delivery lead time from 1 to 3 days is needed between each pair of (not production) nodes in the network.

Urban satellites (i.e., intermediate warehouses located closer to the stores with respect to the CC) are recognized as a means to increase the supply chain efficiency in terms of inventory levels, replenishment frequency, and assortment. To increase replenishment frequency and assortment while decreasing inventory levels, the satellites can be located in the nodes of the network that are more critical from a market point of view. The supply chain modified with the addition of urban satellites, named *to be*, is represented in Figure 1(b). In the figure, the dotted triangles represent the urban satellites. To be effective, satellites must be placed close to the stores so as they can keep the safety stocks for the city stores. Two choices are generally possible for them: place a new warehouse within the city boundaries or have one of the largest city stores to play the satellite role. As each satellite and the stores related to it are quite close, no more point-to-point transportation is needed to replenish stores from the satellite, but milk run deliveries can be used for this purpose. Specifically, when satellites are added to the supply chain, stores can be replenished twice a day, i.e., once in the morning and once in the afternoon. The increase in the replenishment frequency has as a first direct effect the decrease of the store inventory levels for the current products. The inventory reduction could save space for the retailer, and a smaller store would be needed. However, it is not so easy to reduce the store space without changing the store location, and this could harm loyal customers. Thus, firms can decide to keep the same stores and to exploit the freed up space to increase the product seasonal assortment, i.e., to allow a larger number of different items in each store. This larger assortment can, in turn, push sales in a fast fashion context where customer are more driven by impulse-purchasing behaviors rather than by specific needs (Liapati et al., 2015).

In the *to be* supply chain, the item amount initially allocated to urban satellites serves as safety stock for the retail stores. However, urban satellites, differently from retail stores, cannot place any replenishment order during the season, i.e., the initial allocation is the only product amount they receive in each season. The assumption of no replenishment in satellites has been made according to the Company requirement to exploit them as a temporary buffer between the CC and the stores.

4. Simulation model

Discrete Event Simulation (DES) has been chosen as a tool to model and evaluate the Company supply chain operations when urban satellites are introduced, and to understand both the operational and economic effects of such an introduction. The simulation model is used to replicate, on a daily basis, the two supply chain configurations described in the previous section (i.e., the *as is* and the *to be* scenarios) in terms of inventory planning and allocation process. Inventory, lost sale and transportation costs are the only costs included in the analysis. Costs related to urban satellite rental fees, depreciation of assets, and store labor are not considered. The fill rate and the inventory level are also taken into account together with the customer's order lead time, referred to as the time needed to fulfill an order received from a customer. While inventory level and fill rate are directly related to inventory and lost sale costs, respectively, the customer order lead time impacts on lost sale amount, depending on how long customers are willing to wait for the desired product.

The DES models of the two supply chain configurations are very similar, with the main difference that the *to be* scenario has the urban satellite echelon, which is not present in the *as is* scenario. In the experiments, the values of the replenishment policy parameters (i.e., when and how much to order) and the type of replenishment policy (namely (Q, R) and order-up-to (OUT) policy) have been considered to evaluate their effectiveness when urban satellites are added to the supply chain.

Three main processes can be identified in the Company inventory management: (1) demand satisfaction, (2) order planning, and (3) allocation policy. The first process is related to customers, while the other two are related to retail stores. Specifically, the order planning is about how stores plan replenishments, and the allocation policy regards how item inventories are partitioned to stores. Each of these processes is modeled through a separate block in the simulation models, while variables are used to represent their interactions.

Demand satisfaction block: this block simulates the customer arrival to the network, i.e., in one of the retail stores. The daily demand for each product is stochastic, and its distribution is fitted using the Company real data. The data have been collected at SKU-store level, i.e., no aggregation has been made on stores, products, variants or sizes. Once the demand is received, the inventory of the requested product is checked and, if the on-hand inventory is larger than the required quantity, the received order is fulfilled, the inventory level is decreased by the required quantity, and the demand is accounted for as fulfilled. On the contrary, if the on-hand inventory is not sufficient, but the customer is patient, the demand can be backlogged. In this case, the requested items are searched for in the network: the store manager asks other nodes of the supply chain to satisfy her demand. Other nodes include either the CC and other retail stores in the *as is* scenario or the city urban satellite, the CC, and other retail stores in the *to be* scenario.

The orders sent to the network are called *backlog orders*, to disntiguish them from the replenishment orders. If the whole backlog order is available in one of the other nodes of the supply chain, the requested items are delivered to the requesting retailer, the customer order is fulfilled, and the demand is considered as satisfied, although not immediately. If no node can fulfill the order, it is accounted for as lost sale. The possibility to fulfill a single backlog order by using items from different nodes in the supply chain at the same time is not considered (i.e. the horizontal transhipment is allowed only if the sending node has the entire backlog quantity), as it is not allowed in the Company procedures because the transportation costs would be higher than the value of the possible lost sale. The frequency used for backlog orders deliveries strictly depends on the value of the lead time. In the *as is* scenario, where it takes from 1 to 3 days to deliver an order, it is not possible to send orders more than once a day; hence, at the end of each day, the orders collected during it are sent altogether. Instead, with urban satellites (i.e., *to be* scenario), backlog orders can be sent twice a day, provided that inventory is available at the urban satellite. The deliveries of backlog orders are included, from a simulation point of view, in the allocation policy block.

Replenishment planning block: in this block the replenishment process of the Company retail stores is modeled. The current replenishment policy, for each retail store, is a continuous (Q, R) policy, as in use at the Company: each time a quantity is taken from the inventory to satisfy an order, the replenishment system checks if the level falls below the threshold R and, in this case, an order of Q items is sent to the CC. The values of Q and R vary in the experiments.

Allocation policy block: this block models the allocation of the available quantity of products at the CC or at satellites to the retail stores when the two types of orders (backlog and replenishment) are received. Backlog and replenishment orders are very different from the customer point of view, and then, in reality, the allocation process is performed through the so-called rationing policies (Alfieri et al. 2017, Teunter and Haneveld 2008).

In the case study considered in this paper, however, no difference is assumed between them because the Company gives no priority to backlog orders; hence, no rationing is needed, and a simple FIFO strategy is applied. In the *as is* scenario, both backlog and replenishment orders are received by the CC, which satisfies them (by allocating the requested amount) as long as it has available inventory. When the available inventory is no longer enough to fulfill the received orders, replenishment orders are simply no longer fulfilled, while horizontal transshipments between stores are allowed for the backlog orders. In this case, a request for a quantity equal to the backlog order is sent to the network. If another store has it and is willing to fulfill the backlog order, it will ship the items from its available inventory. In this process, no distance or other rule is used to select the retail store that will fulfill the order: if more than one is available, the first retailer that has declared to be available to satisfy the backlog orders is picked. In the simulation model, to mimic such behavior, a mechanism that randomly selects the retail store that will fulfill the backlog order (among the stores with enough inventory to do it) is used. In the *to be* scenario, the fulfillment mechanism is different from city to city. For the stores located in the towns without an available urban satellite, the fulfillment of both replenishment and backlog orders is equal to that of the *as is* scenario. For stores located in a city with an urban satellite, the backlog order is sent to the urban satellite. In the case it does not have the requested amount, the order is sent to the CC and, only if the CC does not have it, the other network stores will be taken into consideration for the order fulfillment. Once orders (either backlog or replenishment ones) are assigned to the sender (CC, urban satellite or another retail store), the requested quantity is shipped to destination and will be available after a given lead time. At the beginning of each season, an initial amount of each product is allocated to each node of the network (CC, urban satellites, and retail stores). This is called *initial allocation*. The quantity allocated to the

CC and urban satellites will be used to fulfill retail store replenishment and backlog orders. However, as operated by the Company, both the CC and urban satellites do not have any further replenishment possibility. When their inventory is over, no store replenishment order will be any longer satisfied, while backlog orders will be sent to the other stores in the network, as previously described.

From the simulation, three main performance indicators are collected, which take into account the standard operational performance measures (Stevenson, 2007):

- average inventory levels for each product, at each store / urban satellite / CC, over the selling season;
- supply chain service level for each product, measured by the supply chain fill rate, i.e., the ratio of fulfilled demand (satisfied from the store and through backlog orders) to the total demand;
- immediate service level for each product, measured by the immediate fill rate, i.e., the ratio of demand fulfilled by the retail store inventory to the total demand.

By comparing the average inventory levels of the *as is* and the *to be* scenario, the average freed up store space can be calculated, i.e., the amount of space made available on the shelf when an urban satellite is added. Moreover, by comparing the supply chain and the immediate fill rates of the *as is* and the *to be* scenario, the impact of the urban satellite on final customers can be evaluated. The performance measures are only computed over the stores of the cities where the urban satellites are added, as in all the other stores no planning rules change between the *as is* and the *to be* scenario.

5. Experimental results

The simulation model has been developed using Arena Rockwell software and replicates an eight-month selling season of the Company. In the simulation, only fast-moving products have been included, because the introduction of satellites should have the main effects on replenishment mechanisms of this class of items. All the fashion categories have been simulated (e.g., trousers, accessories, jersey, and so on), and within the categories, a subset of seven products has been selected and modeled. In this way, the complete typical Company store selection has been included in the analysis. All the variants and sizes of each product have been separately simulated, leading to a simulation of 39 SKUs. Using real data, the demand distribution of each SKU has been selected and fitted from the available demand observations. The Poisson distribution has been fitted from the daily demand data. As in the *to be* scenario replenishments can be delivered twice a day, the daily demand has to be split into two parts, representing the morning demand and the afternoon demand. Real data showed that 30% of customers buy in the morning and 70% in the afternoon. Two different distributions have been used in this case for each store, by decomposing the rate λ of the daily Poisson store demand in 0.3λ for the morning Poisson distribution and 0.7λ for the afternoon Poisson distribution[1].

On the contrary, the initial inventory allocation at the CC, the stores and the satellites has been varied in the experiments. As far as replenishment lead times are concerned, for those from the CC to retail stores and those in between the stores, a symmetric triangular distribution has been used for data fitting, with one day as a minimum and three days as maximum threshold values. For the shipping lead time that incurs from the urban satellite to the city stores, it has been assumed as a fixed 4 hour time period.

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[1] The Poisson process composition property is used:

$$\text{Poisson}(\alpha+\beta)= \text{Poisson}(\alpha)+ \text{Poisson}(\beta).$$

During the simulation, for each node of the supply chain, the following data have been collected: fulfilled demand, lost final demand, inventory levels. From the data, information about fill rates and inventory costs could be obtained at the end of the simulation. For each simulation, 100 replications have been performed to address the variability of demand and lead times in the model. The simulation model has been verified and validated usig the real case data.

In the following, three experiments are discussed. (1) The first experiment addresses the case study of the Company. The *as is* simulation model exactly replicates the Company supply chain in the selling season at study, whereas the *to be* model simulates the same season for the Company supply chain, including the satellites. The aim of the first experiment is the analysis of the economic profitability that could be achieved if satellites are added to the supply chain. The second and third experiments, instead, investigate the conditions under which including the satellites in the fast fashion supply chains can be profitable. Specifically, (2) the second experiment tests the profitability of adding hubs in various scenarios in which the replenishment policy and its parameters are varied. Two different policies are modeled: a continuous (Q, R) policy (as in the current Company setting), and a periodic Order-Up-To (OUT) level policy. The parameters of the policy are also varied to test how the profitability of adding the satellites changes. (3) The third experiment, instead, investigates the effect of the initial allocation on the profitability of adding the satellites. In the *as is* scenario, the percentage of the initial inventory of the CC is varied; in the *to be* scenario, the quantity initially allocated to the urban satellites is varied to test how the profitability of the *to be* scenario changes with larger or smaller urban satellites.

Experiment 1: case study

The first experiment addresses the economic profitability that could be achieved if urban satellites are introduced in the supply chain of the Company. The objective is to increase the flexibility of the supply chain, by decreasing the store replenishment lead time. With the urban satellite, the stores of the city can be replenished in 4 hours instead of waiting for one to three days if replenished by the CC. Three satellites are added, one in each of the three most critical cities from the market standpoint. The *as is* simulation model replicates the current supply chain, the *to be* model adds the three urban satellites to the network. The planning policy is the one in use at the Company. Specifically, in the *as is* simulation, the initial allocation is as follows: the initial inventory distributed in the supply chain is equal to the average seasonal demand, and the CC receives 10% of this quantity, whereas the rest is sent to the stores of the Company. In the *to be* simulation, the CC still receives the same amount, whereas a single item of each SKU is sent to each store, and the rest is sent to the satellites. The choice of placing only 1 item for each SKU to each store reflects the Company requirements to implement the *to be* scenario. The initial allocation is the only replenishment introduced in the network during the selling season; however, during the season, the items are moved from one node to the other within the supply chain. Replenishments occur from the CC to the stores for the items *on theme,* and the *theme* planning policy is a continuous (Q, R) with R=0 and Q=2. Instead, backlog orders are always allowed, and their size strictly depends on the demanded quantity.

The results of the simulations are used to evaluate the profit that can be created with three urban satellites in the Company network. The profit is expressed in terms of transportation, storage, and inventory costs. These are estimated through the data collected in the simulation of service levels and freed inventory space at the stores.

Table 1 shows the simulation results. For each cell of the table, the average is followed by its standard error between brackets.

	as is	**to be**
Supply chain SL	89.28 % (0.22%)	88.49 % (0.23 %)
Immediate SL	82.56 % (0.28%)	74.71 % (0.24 %)
Total store inventory	2941 (2.52)	507 (0.81)

Table 1. Experiment 1: Company case study simulation results

The supply chain and immediate service levels are the averages of the single-product service levels over all the products, again averaged over all the replicates. The total store inventory, instead, is the average over all the replicates of the sum of the inventories over all the stores of the networks. By adding the three urban satellites, the supply chain service level does not consistently change. This reflects the possibility of issuing backlog orders to all the nodes of the supply chain: if a store cannot fulfill a customer request, the request is sent to the network. Thus, the *as is* supply chain service level reflects the maximum service level achievable with the given initial allocation, in the case of customers willing to wait as long as needed for their product. The *to be* supply chain SL, instead, slightly decreases: if a store cannot fulfill a customer request, the request is sent to the urban satellite of the city, to the CC, to all the other stores, but it cannot be sent to the urban satellites of other cities. Thus, a tiny portion of the total demand should have been fulfilled by an urban satellite of another city, but, as this is not possible, it becomes lost. The immediate service level, instead, largely decreases. While in the *as is* scenario the initial allocation gives on average five items at each store for each product, in the *to be* scenario the initial allocation is equal to one item at each store for each product. Although the stores can be replenished when the product is *on theme*, the theme only lasts one month out of 8 (which is the season length). For these reasons, the portion of customers that can be served in stores decreases in the *to be* scenario. The effect of the allocation policy is also reflected in the total store inventory values: the *to be* inventory is around 17% of the *as is* inventory, as expected from the changes in the initial allocation. The results suggest the following consideration. If customers are willing to wait (i.e., backlog orders are issued and the supply chain SL is the only SL to consider), then adding urban satellites does not influence the service given to the customers, and it frees spaces at the stores. The freed up store space can be used to enlarge the assortment and attract more customers, thus increasing the store profit. Moreover, as backlog orders are placed first to the urban satellites, customers only have to wait around 4 hours to receive their orders, instead of from 1 to 3 days. If consumers are inpatient to receive their orders (thus, backlog orders are not placed, and the immediate SL is the only SL to consider), then both the inventory levels and the service level decreases. Thus, as long as a small decrease in service level is acceptable (i.e., a small increase in lost sales), a smaller store could be rented (thus decreasing inventory costs) (Greasley and Assi, 2012). However, instead of changing the store size, the freed store space could be used to introduce new product assortment (Van Rooijen and Quak, 2010). The sales of the new assortment could then counterbalance the greater lost demand.

To check whether adding satellites creates new sales revenue and/or savings in operations expenditure (in case customers are either willing or unwilling to wait for their items), a profit analysis has been performed.

The Net Profit (NP) of adding the satellites is calculated through the comparison between *as is* and *to be* scenarios. The NP is given by:

$$NP = \alpha \, NR - LDC - TC, \qquad (1)$$

where NR is the new revenue, i.e., the additional revenue that can be earned in the *to be* scenario by selling new assortment placed in the freed store space; α is the selling percentage, which will be discussed later in the paragraph; LDC is the cost of the lost demand increase in the *to be* in comparison with the *as is* scenario; TC is the difference in transportation costs between the *as is* and the *to be* scenarios. There is no need to account for the inventory cost, as the two scenarios are assumed to have the same inventory levels, as in the *to be* the freed store space is filled with new assortment, which will create the new revenue NR. Although this assumption is realistic, this new assortment might not be completely sold. Thus, various selling percentages of new assortment (α in equation (1)) are considered.

LCD is based on product margins, which is 20% of the average selling price. Specifically, LCD is calculated as the sum over all the products in a specific product category of the difference between the lost demand of the *as is* and the *to be* scenarios, multiplied by its margin. It takes a negative value because the lost demand in the *as is* scenario is smaller than the one in the *to be* scenarios, as shown by service level values in Table 1.

TC is calculated according to the following assumption: both the shipments among stores and from the CC to the stores are single direct shipments, whereas milk runs are used from the urban satellite to the city stores. In the *to be* scenario, the 4-hour lead time has been set for the milk runs to respect the store time constraints (i.e., every day, replenishments can only occur from 11 am to 1 pm, in the morning, and from 5 pm to 7 pm, in the afternoon). The number of milk runs needed from each satellite to replenish all the city stores have been estimated with a simulation based on the travel distances given by Google Maps among the stores of the same city. The calculation of TC can be expressed either in terms of unit cost per distance or in terms of a fixed cost for each milk run. In equation (1), TC is the difference between all the transportation costs of the *as is* and the *to be* scenario.

Customers willing to wait for their product. If customers are willing to wait when the product they ordered is not available, the supply chain SL (collected in the simulations) is considered in the analysis to evaluate the lost demand cost. Also, for transportation costs, the cases of cost depending on the distance and on the number of deliveries are considered separately. Figure 2 and Figure 3 show the net profit NP for the two transportation cases (distance in Figure 2, deliveries in Figure 3), for various values of the unit transportation cost (each line of the graph shows NP for a specific value of unit transportation cost) and for different selling percentage α (horizontal axis). Figure 2 shows that profit is created in many cases. If customers are willing to wait, the new assortment generates a margin able to justify the small increase of lost demand, and the transportation costs also decrease with urban satellites, thus increasing the net profit. Thus, if transportation cost is 0.50 €/km, the profit is made if at least 20 % of the new assortment is sold. As stores are characterized by an *assisted sale* strategy, selling 20% of the new assortment is likely to occur. More in general, if the transportation cost is higher than 0.80 €/km, then the NP is positive even in the case of α = 0%, i.e., completely unsold new assortment. On the contrary, if transportation cost depends on the single delivery (i.e., there is a fixed cost for each delivery), higher transportation costs are required. Figure 3 shows that if the cost of delivery is equal to 5 €, then the profit is positive only if at least 90% of the new assortment is sold during the selling season. If the cost of delivery is more than 27 € (which is quite unrealistic), then the profit is not positive regardless of the value of α.

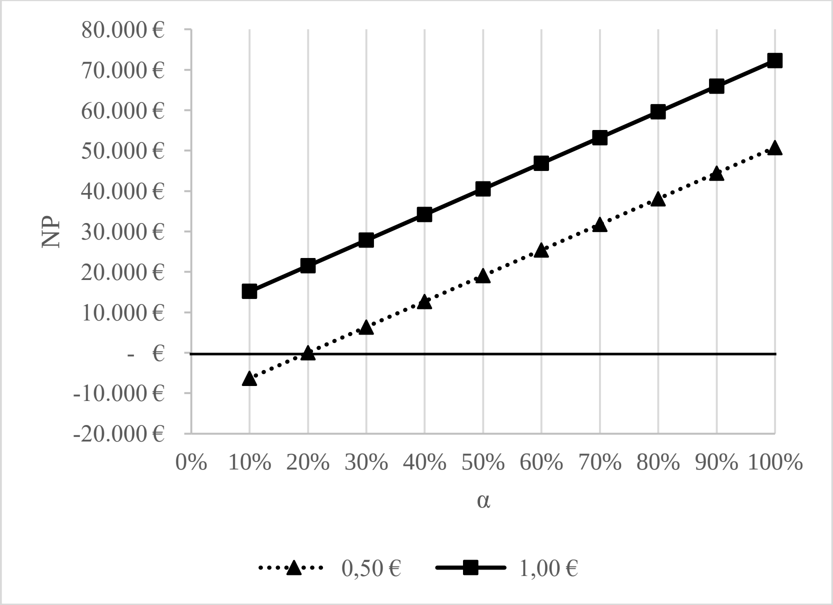

Figure 2. Economic evaluation of operations expenditure with transportation costs depending on distance, and customers willing to wait for their products

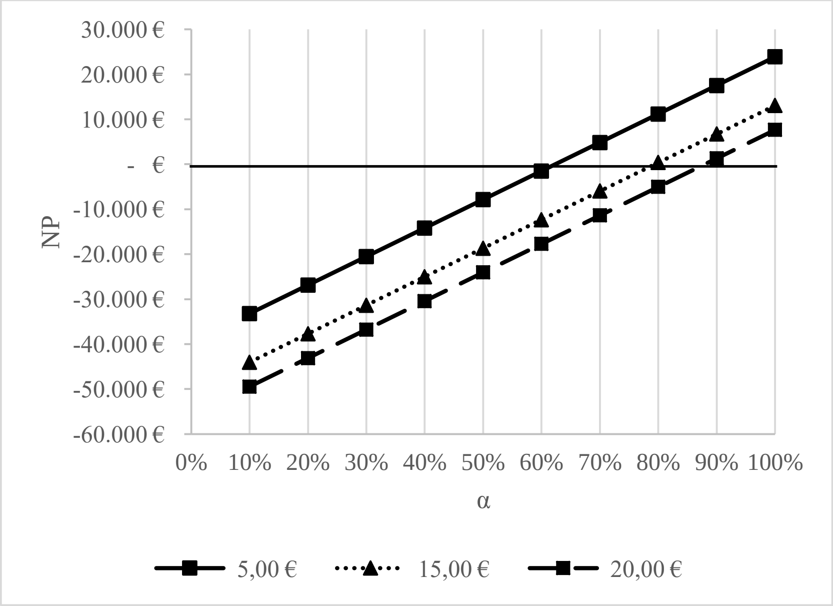

Figure 3. Economic evaluation of the Net Profit with transportation costs depending on deliveries, and customers willing to wait for their products

Customers not willing to wait for their product. If customers do not wait for their product, the lost demand depends on the immediate SL. In this case, Table 1 has already shown that the immediate SL largely decreases; thus, a large lost demand cost is added in NP. In this case, a larger percentage of new assortment α must be sold to make the NP positive. Figure 4 shows how NP changes if customers are not willing to wait and if the transportation cost depends on the traveled distance. If the unit transportation cost is 0.50 €/km, then the profit is positive only if the whole new assortment is sold (α = 100%). For a unit cost equal to 1 €/km, 70% of the new assortment needs to be sold. Although the required values of α are larger than before, the assisted sale strategy should guarantee their achievement. Moreover, if the transportation unit cost is higher than 2 €/km, the profit becomes positive for all the values of α.

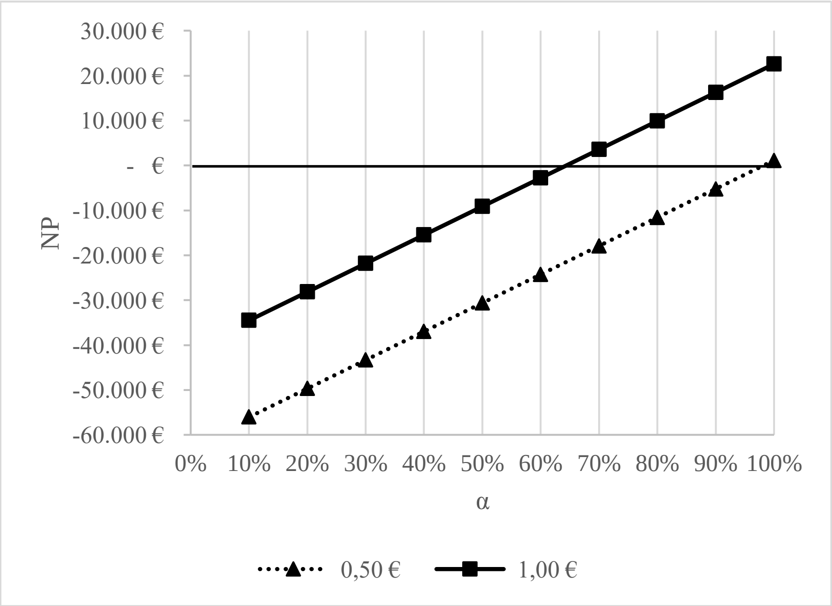

Figure 4. Assessment of Net Profit with transportation cost based on distance, and customers not willing to wait for their products

Instead, if the unit cost per shipment is considered, there is no value of unit cost that makes the NP positive. Indeed, adding the urban satellites increases the number of shipments (replenishments can be sent twice a day instead of once); however, it reduces the lead times and, hence, the total distance.

The profit analysis assumes that the Company owns the urban satellites, and they are used only to replenish the Company stores. As discussed in the literature (Crainic et al., 2009; Van Duin and Muñuzuri, 2015; De Marco et al., 2018), however, the opportuning of sharing storage space can be implemented with companies operating in different (e.g., complementary) markets. Thus, the possibility of sharing the satellite spaces and deliveries with one or two companies can be beneficial, and it will be analyzed in the following. Thanks to the storage sharing, transportation and storage costs can be reduced, thus increasing the profit.

In the case of customers willing to wait for their products and transportation costs depending on the distance, adding the satellites becomes profitable even if the satellites are not shared with other companies, as previously discussed. In the case of shared satellites, the NP increases, as shown in Figure 5, where unit transportation cost equals 0.50 €/km. Sharing the satellites makes operations profitable even if no new assortment is sold. The larger the unit transportation cost, the higher the profit, also in the case of shared satellites. Moreover, sharing the satellites increases the profitability linearly with the number of companies the satellite is shared with.

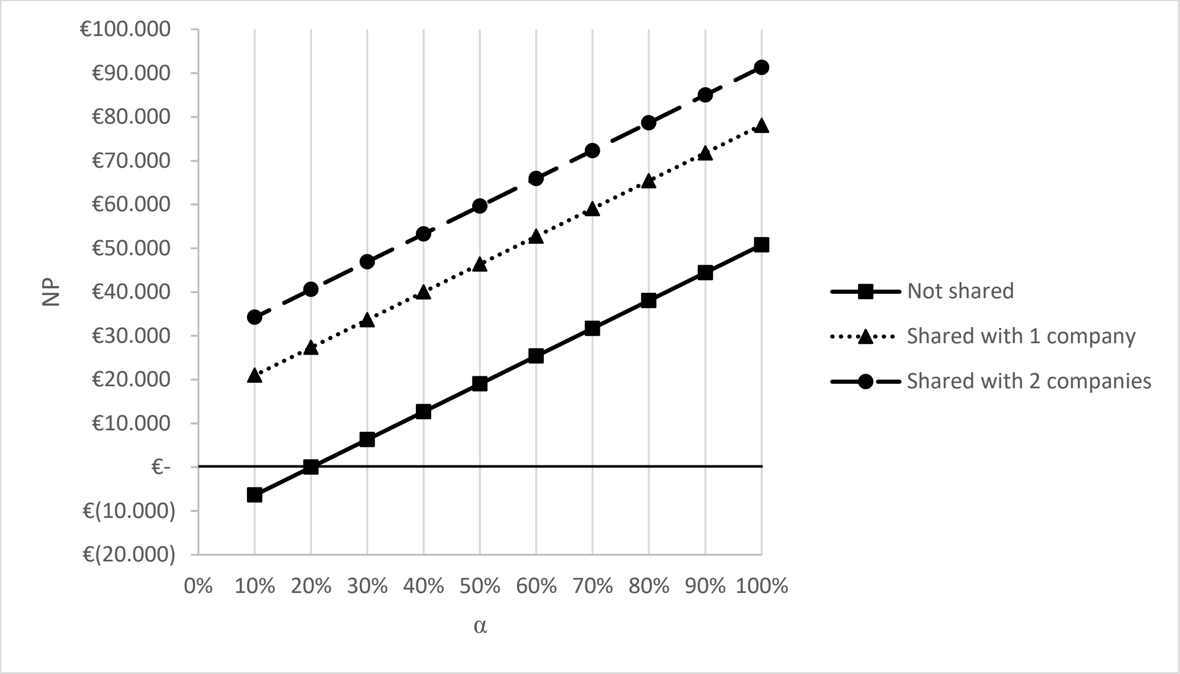

Figure 5. NET Profit with satellite sharing, customers willing to wait and transportation costs depending on the distance

Also, in the case of transportation costs depending on shipments and customers willing to wait for their product, the profitability of satellites increasing with the storage sharing. With a substantial cost of shipment such as 20 €/shipment, the break-even percentage of new assortment moves from 90% with private satellites to 70% with satellites shared with one company, and to 50% with satellites shared with two companies. By changing the unit transportation cost, also the break-even percentages change; despite the value of the unit transportation cost, sharing the satellites increases the profitability linearly.

If customers are not willing to wait, the profit decreases, as previously discussed; however, sharing the satellites with other companies can help. For instance, if the transportation costs depend on the distance, sharing the satellites reduces the break-even percentage of new assortment that has to be sold. If the unit transportation cost is 0.5 €/km, then the percentage moves from 100% of private satellites to 60% if the satellites are shared with one company, and to 40% if they are shared with two companies.

However, if the transportation costs depend on the number of shipments, the profit is still negative even if the satellites are shared with one or two companies.

Experiment 2: the impact of the replenishment policy and its parameters

The second set of experiments aims at evaluating how the replenishment policy affects the decision to add urban satellites to the supply chain. For each product, the replenishment policy is active only in the *theme* period, which is a month out of the eight months of the selling season; thus, its impact should be limited. The simulated replenishment policies are: continuous (Q, R) policy and periodic OUT policy. The values for the policy parameters are summarized in Table 2. A full factorial experiment has been carried; however, only a subset of combinations of factors will be shown in the results below.

POLICY	**PARAMETER**	**VALUES**
(Q, R)	Q	{1,…,4}
(Q, R)	R	{0,…,4}
OUT	OUT level	{1,…,4}

Table 2. Experiment 2: considered policies and their parameter values

In the (Q, R) policy, the parameter Q refers to the lot size and R to threshold level: when the inventory falls below R, Q items are ordered to the CC. In the OUT policy, every week the inventory position is checked, and if it falls below the OUT level, an order is issued to bring the inventory position up to the OUT level. The values of all the parameters are less than 5, as the initial allocation gives no more than five items at each store.

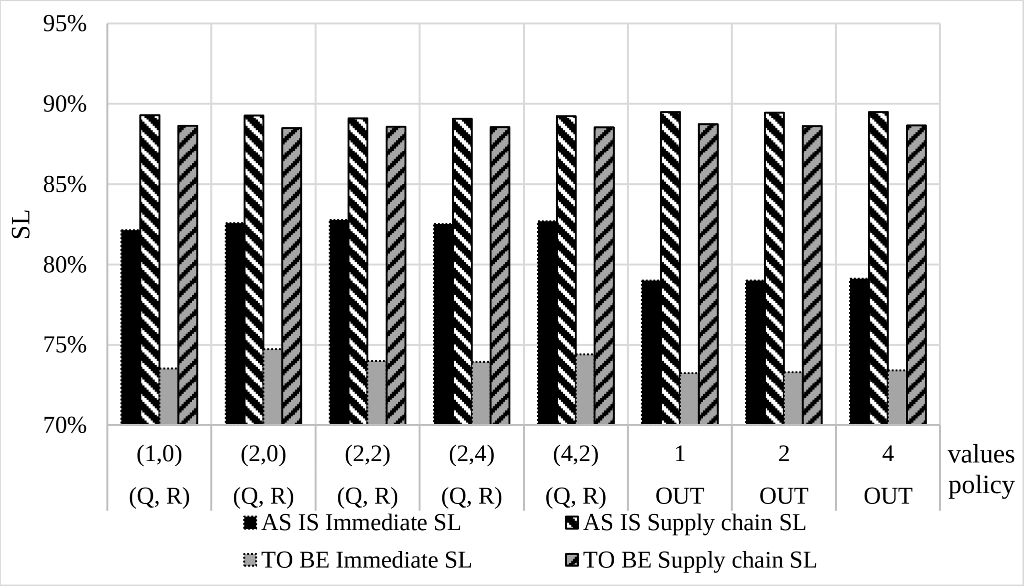

Figure 6. Impact of the replenishment policies and their values on the SL

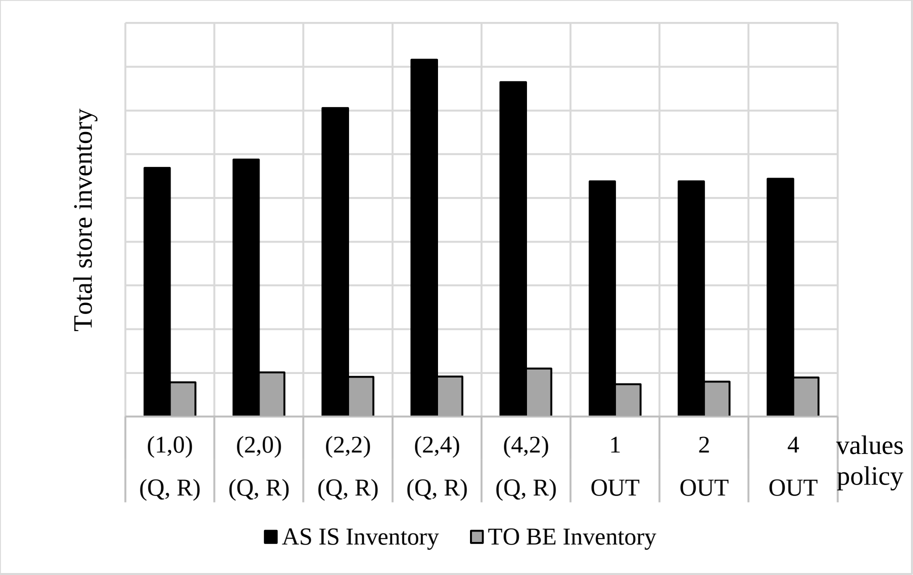

Figure 7. Impact of the replenishment policies and their values on the store inventory

Figure 6 and Figure 7 show how the supply chain performance measures change if the values of the parameters of the two inventory policies are varied. Figure 6 displays the immediate (solid filled bars) and the supply chain (pattern filled bars) service levels, while Figure 7 shows the total store inventory of the *as is* (black bars) and of the *to be* (grey bars) scenarios. The horizontal axis in both figures shows the policy and the values of its parameters, for some of the performed experiments. The supply chain SL is not much affected either by the policies or their parameters, as it is not strictly related to the single store, rather to the whole supply chain. Thus, the supply chain SL is also robust in terms of policies and parameters. Instead, the immediate SL shows some differences. The (Q, R) policy tends to guarantee a larger immediate SL: while with the OUT policy the store can issue an order only on a specific day of the week, with the (Q, R) policy an order can be issued as soon as the inventory falls below R. Thus, with the OUT policy there could be more days with zero inventory than in the (Q, R) case. However, as Figure 7 shows, the total inventory is a bit larger in the (Q, R) policy than in the OUT. For the (Q, R) policy, increasing the value of R (first two bars in Figure 6 and Figure 7) tends to increase the SL, as the number of items always available in inventory increases (as can be seen by the increase in Figure 7). Instead, with an increase of the order size Q, the immediate SL does not change much, but the inventory increases. With the OUT policy, instead, there are no significant changes in performance with different OUT values. To summarize, the type of replenishment policy has an effect on the supply chain performance, while the performance tends to be quite robust with respect to the values of the policy parameters.

Experiment 3: the impact of the initial allocation

The third experiment addresses the changes in the performance of the supply chain when the initial allocation is varied. At the beginning of the selling season, the available inventory is distributed among the nodes of the supply chain, and this certainly influences the performance of each node.

In Experiment 1, the initial allocation was defined as follows:

- *as is* scenario: 10% to the CC, 90% to the stores, according to their expected demand;

- *to be* scenario: 10% to the CC, 1 item of each SKU to each store, and the remaining inventory to the satellites.

In this experiment, the total initial inventory of the supply chain is kept constant at the value used in the *as is* case, but it is distributed in different ways:

- *as is* scenario: the percentage held at the CC is varied from 0% to 100%, the remaining inventory is distributed among stores proportionally to their expected demand;
- *to be* scenario: 10% to the CC, the number of items of each SKU in each store is varied between 1 and 3 items, the remaining inventory is sent to the satellites.

The variations of the *as is* scenario are useful to understand how the performance of the supply chain is influenced by the initial allocation to the stores. The variations of the *to be* scenario are needed to evaluate the possibility of choosing different sizes of the satellites (varying from 1 to 3 the number of items of each SKU sent to the stores, the satellites can be smaller as they need to contain less inventory). The replenishment policies in use in this experiment are both (Q, R) with Q=2 and R=0 (as in the Company practice), and OUT with OUT level = 2 (which is the most comparable to the (Q, R) parameter values).

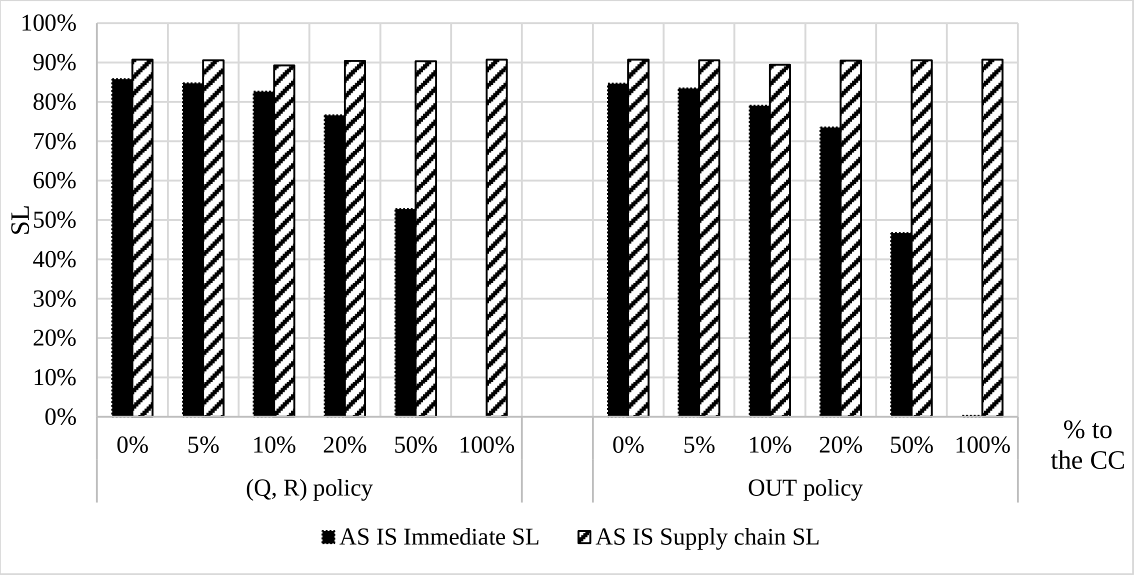

Figure 8. Service levels of the *as is* supply chain with different initial allocations

Variation in the as is scenario. Figure 8 shows the service level of the *as is* supply chain with different initial allocations. The horizontal axis shows the percentage of initial inventory kept at the CC, and the vertical axis the service level. Also, the solid filled bars indicate the immediate SL, and the pattern filled bars the supply chain SL. From the figure, it can be seen that the supply chain SL tends to be constant regardless of the replenishment policy and the percentage of initial inventory kept at the CC. As in the previous experiment, this is explained by the fact that the total inventory in the supply chain is always the same, and, thus, if customers are willing to wait, their product can be searched in the whole supply chain. Instead, the immediate SL drastically changes. If no inventory is kept at the CC, i.e., the entire inventory is shared among the stores proportionally to their expected demand, then the stores have the maximum achievable SL. On the contrary, if the whole initial inventory is given to the CC, then the stores do not have any inventory on hand, thus achieving an almost null immediate SL. Figure 9 confirms the results by showing how the store inventory decreases when the percent initial CC inventory increases.

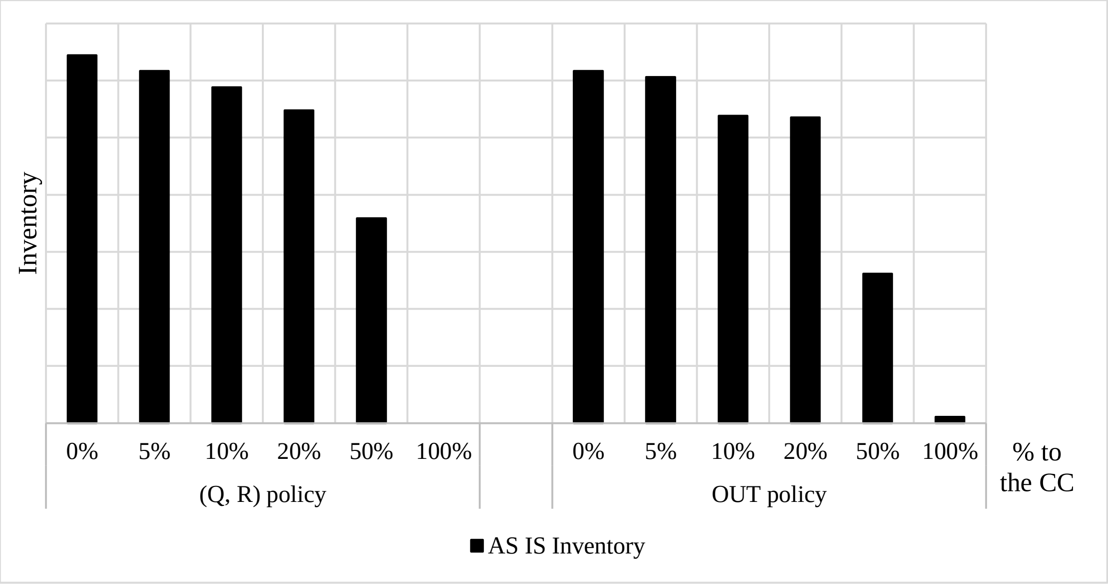

Figure 9. Average total store inventory of the *as is* supply chain with different initial allocations

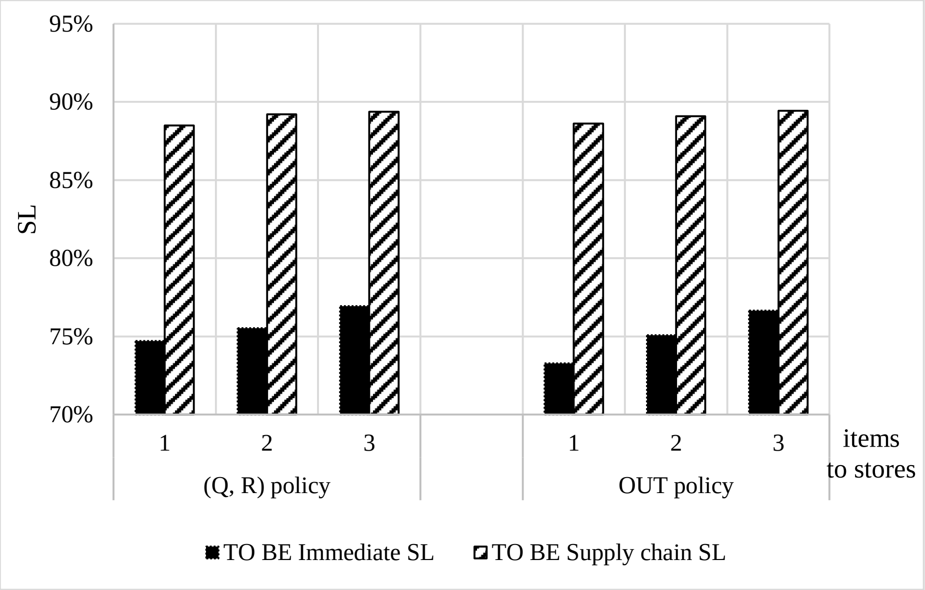

Figure 10. Service levels of the *to be* supply chain with different initial allocations

Variation in the to be scenario. The variations of the initial allocation in the *to be* scenario give insights about how the performance of the supply chain is affected by the size of the satellites. The more items are initially allocated to the retail stores, the smaller the satellite room space can be. Figure 10 and Figure 11 show the performance of the *to be* supply chain with various initial allocations to the stores. Both the supply chain and the immediate SLs are affected by the initial store allocation. The immediate SL increases with the number of items given to each store as there is more inventory available to fulfill the demand immediately. Also, the supply chain SL tends to grow: if the store has not the requested items, it can look for it at its urban satellite, the CC and the other stores, but it cannot ask to the other urban satellites; thus, the smaller the satellites, the more available items can be used to fulfill a backlog order. Moreover, the total store inventory increases with the number of items given to each store (Figure 11).

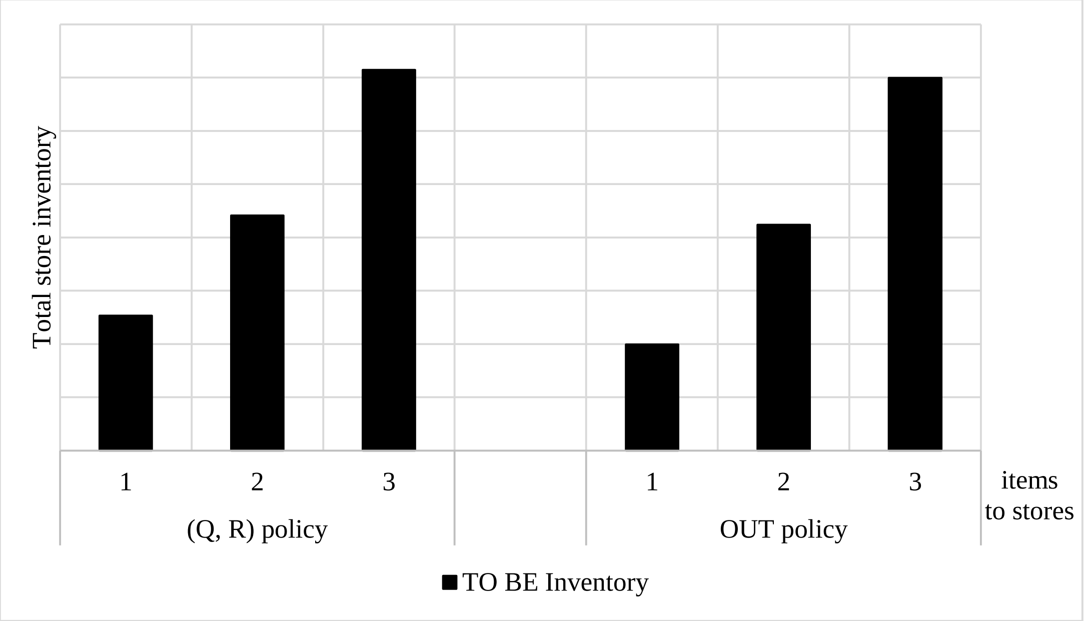

Figure 11. Total store inventory of the to be supply chain with different initial allocations

6. Discussion and implications

This study aims at exploring the operational advantages and associated savings in operations expenditures that can be obtained by adding urban satellites into supply chains and distribution networks. The results prove that urban satellites can decrease store inventory levels, increase lost demand, and impact on transportation costs.

Urban satellites decrease the service level on individual products but improve the overall customer service. Adding satellites allows to increasing product assortment through more floor space available at retail stores, thus attracting more sales and, ideally, new customers.

Also, if customers are willing to wait for their desired product as much as needed, satellites decrease the transportation time and increase replenishment frequency, so that waiting time is reduced. Therefore, whether to add urban satellites or not is a decision affected by the dominant purchasing behavior: if customers are time-sensitive, urban satellites may not give enough sale benefits due to higher probability of stockout for the specific item, while under a dominant order-and-wait attitude (Rajagopalan and Kumar, 1994) customers will benefit from shorter delivery time. However, when time-sensitive customers are also impulse-driven consumers, lost sales for a specific item can be turned into sales of other items from a larger assosrtment.

The profitability of the satellites increases if the transportation cost is based on the traveled distance and not on the number of shipments. These benefits are consistent with both time continuous and time discrete replenishment policies. Moreover, transportation service and satellites could be shared with other companies operating in different (e.g., complementary) markets, thus improving the profitability of adding satellites.

Also, the initial product inventory levels at both the CC, satellites and retail stores allocated at the beginning of the selling season highly impacts the economic benefits that can be obtained from adding satellites.

These results have some managerial policy implications. The decrease of inventories can suggest either to rent smaller stores or to use the freed store space for expanding product assortment. In addition, the available store space could be used to serve as satellites in the distribution system. Shorter traveling distances and reduced freight volume per trip could also suggest using smaller green vehicles for shipments and milk runs, resulting in lower environmental impact and in reduced emissions. As a last remark, adding satellites can be profitable in those industries where assortment, more than specific product availability, is relevant to customers, like in the fast fashion sector (Stavrulaki 2011).

7. Conclusion

To gain a competitive advantage in a sector that exploits the impulse purchasing behaviors of consumers, fast fashion supply chains need to have a high level of flexibility, which can be reached by either large inventories at the points of sales, or very short lead times / very large ordering frequencies. Large store spaces usually imply higher rental fees, especially in the city centers where rents are expensive. Introducing urban satellites to manage the last mile distribution effort could be beneficial in terms of reducing lead times and increasing the replenishment frequency.

Urban satellites prove to provide several operational advantages and related economic benefits in terms of reduced operations expenditures. In fact, urban satellites can be settled close to city stores (or in one of the biggest stores of the city) to shorten lead times and increase the responsiveness of supply chains. Satellites enable refilling store inventories more than once a day and thus allow to reduce store inventory levels and their cost. The reduced inventory levels can be exploited to widen the fashion product assortment with the latest trendy items. Thus, the lost demand for one specific product is counterbalanced by the purchase of one of the new products available on shelves. Moreover, the store operators could also induce customers to buy other available products.

The paper addresses only fast fashion supply chains by focusing on an Italian fast fashion Company. However, other industries could benefit from the introduction of satellites, and industry-specific characteristics should be included in the analysis. Thus, further research will be devoted to addressing this analysis. Moreover, this paper assumed a satellite management internal to the Company; however, interesting results could be achieved by assuming a third party logistic provider. In this case, the profitability might change to assess the provider profits, which might be different from the Company profit. Future research will address also these issues.

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