An optimisation approach for the e-grocery order picking and delivery problem

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Abstract Traditional supermarket chains that are adopting an omni-channel approach must now carry out the order picking and delivery processes to serve online orders, previously done by the customer. The complexity of the logistics processes has increased, therefore modelling and optimising e-grocery operations becomes definitely important. Since there are few studies modelling order picking and delivery processes, we propose an approach that simultaneously optimises the decision variables of different functions which have traditionally been treated separately. In this study, we present a linear programming model for store-based e-fulfilment strategies with multiple picking locations. The proposed model optimises the allocation of online orders to stores, based on the e-fulfilment costs. As well as minimising the picking and delivery costs, the proposed approach consolidates workloads in order to avoid idle times and reduce the amount of resources required. A weighted sum method is applied to compute the solution, integrating parameters that represent different store features such as the product range, sales mode and physical store activities. The proposed model has been tested on one of the largest grocery sellers, showing that substantial savings can be achieved by reallocating orders to different stores, time windows and delivery vehicles. By focusing on optimising e-fulfilment resources, this approach serves as a guide for traditional grocery sellers to redesign their supply chains and to facilitate decision-making at a managerial level.

Keywords MILP · e-commerce · e-grocery · omni-channel retailing · order fulfilment · optimisation

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1 Introduction

The emergence of e-commerce has provided companies with a great opportunity to ensure their presence in the most attractive of showcases, the Internet. Omni-channel is becoming the latest retailing trend, which offers an improved customer experience by integrating physical and online sales channels (Herhausen *et al.*, 2015). This trend has brought with it significant logistical difficulties, which results in retail success being linked to supply chain efficiency (Bhattacharjya *et al.*, 2016).

Online retail sales have grown at a faster rate than in-store sales. Along 2018 the online grocery orders increased by 13% and online grocery customers spent 20% more than traditional consumers (Kantar Worldpanel, 2018; Murfield *et al.*, 2017). Grocery sellers that are adopting an omni-channel approach must now carry out the order picking and delivery processes, previously done by the customer. Consequently, both the number and the complexity of the processes that are managed by companies have increased (Boyer *et al.*, 2003). Unlike other online businesses, picking process in e-grocery is slower because the large number, variety and complexity of products. An online order may contain products that require different preparations, such as perishable dry products, frozen food products or products that require specific processes. Moreover, not only does the difficulty lie in the products and processes, there are also transport demands in response to the tight time windows required to meet consumer needs (Wollenburg *et al.*, 2018).

Grocery sellers have various options to meet the online demand: use current distribution centres, create online distribution centres, acquire goods from different vendors at multiple locations or use existing physical stores. When dealing with a small number of orders, products can be selected from in-store stock. However, for higher volumes of demand, it is often more efficient to prepare the orders in a warehouse and send them to the store (De Koster, 2002). Despite the increase in online demand in the large-scale consumer sector, some grocery sellers that expanded their business online have collapsed (Lin & Mahmassani, 2002; Scott & Scott, 2006). The main reason is the large investment required in technology and infrastructures, which has a high fixed cost. Another reason for major monetary losses is the incorrect integration of traditional and online sales channels (Aspray *et al.*, 2013).

In the context of dealing with frequent business failures and logistical challenges, modelling e-grocery operations becomes definitely important for traditional vendors. Numerous publications have highlighted the key processes of e-commerce (Ishfaq & Bajwa, 2019). Our study focuses on a store-based model since it is the most representative thus far. This order picking model stands out for the importance placed on defining order scheduling through an integrated picking and delivery strategy (Fikar, 2018). Although there are many models focused on transport, it is desirable to offer an integrated vision which also includes order picking processes.

Since there are few studies which model both order picking and delivery processes, our aim is to develop an approach that simultaneously optimises logistics decision variables which have traditionally been treated separately. Identifying online demand, the model allows to make the daily scheduling of each store taking into account the capacity of the resources for order picking and delivery. Furthermore, there are no models that work with the characteristics of elements of the e-grocery supply chain. Consequently, our mixed integer mathematical model (MILP) allocates orders to online stores by considering the order, store and transport features. With the goal of minimising the total costs, the key activities are identified and the main picking and delivery assignments are calculated. As well as minimising those costs, our model allows to optimise qualitative variables related to the use of resources that are not reflected in the e-fulfilment costs. In this way, the proposed approach consolidates workloads in order to avoid idle times and reduce the amount of resources required. The cost of each alternative is calculated to serve the market demand in the time windows chosen by customers with the aim to improve the business profitability. Furthermore, we extend research in this area by reporting managerial insights grounded in empirical data from a real-world case study.

The remainder of the paper is organised as follows. Section 2 presents an overview of the related literature, and highlights the contribution of our model for combined order picking and delivery processes. Section 3 presents the problem description. Section 4 provides the methodology and the notation used in the mathematical model to obtain the optimal order allocation. Section 5 presents the results obtained when applying the model to a real-world e-grocer. Two optimisation scenarios are developed according to the managerial priorities of the e-grocer. The outcomes are then analysed and discussed to obtain information on the optimal allocation for order fulfilment and to know how weighting parameters modify the objective function. Finally, Section 6 include the unique contributions, theorical and managerial implications, limitations and directions for future research.

2 Related literature

Our study is related to online supermarket chain research, in which early studies indicated that opening new sales channels increases profits and improves customer service. For this reason, companies operating traditional stores have been reorganising their business processes in order to attract customers to their online channel (Bernstein *et al.*, 2008; Ishfaq & Bajwa, 2019; Ofek *et al.*, 2011). E-grocers have focused particularly on e-fulfilment, which encompasses the high cost tasks of order picking and delivery (Kuijpers *et al.*, 2018). Accordingly, several studies have focused on understanding the profitability of e-fulfilment by analysing the known low gross margins for omni-channel grocery sellers (Cai, 2010; Cao *et al,* 2016). We extend these studies by presenting a more in-depth evaluation of costs for the grocery sellers that evolved to an online channel by adapting their traditional stores. This has allowed e-grocers to enter online business almost immediately, though some authors question the profitability of this online channel (Fernie *et al.*, 2010).

In this sense, Belavina *et al.* (2016) compares the financial performance of two revenue models for online grocery retail: the order-by-order model, where customers pay for each delivery, and the subscription model, where customers pay a fixed fee and receive free deliveries. The mathematical model incorporates customers who choose to shop online or offline. Moreover, some researchers have compared traditional and online store processes, such as the study addressed by Chintagunta *et al.* (2012) that concludes that the highest costs for online services are the picking and packaging processes. The poor optimisation of the picking process can be attributed to the fact that originally the product distribution in stores was designed for exhibition, and not for picking efficiency (Hübner *et al.*, 2016). Consequently, authors such as Valle *et al.* (2017) focus their integer programming models on order picking and batching. However, this approach does not address order picking related activities such as product replenishment. Regarding the warehouse preparation model, the existing studies have focused on improving picking efficiency, as it is a great advantage over store preparation. In this sense, Kämäräinen *et al.* (2001) have focused their research on optimising order preparation and consolidation processes. With the aim of reducing operational costs, these authors focus on the design of the picking area. To achieve the optimal design, it is necessary to calculate the break-even point from which the investment made in the automation of logistics operations is justified. In the context of order picking in traditional stores, the Scott & Scott (2006) study presents an allocation model that searches for the most suitable location for order preparation. Typically, this preparation is done at the store closest to the consumer. However, this model shows that due to the congestion caused by the interaction of both channels, the closest store is not always the best option. However, one of the limitations of the model is that a constant demand is assumed throughout the week.

Recent studies have concentrated on modelling the capacity of time windows because of their key role in order scheduling. These time windows are defined as the time intervals in which the order must be served to the customer (Emeç *et al.*, 2016). Punakivi & Saranen (2001) simulate different scenarios to optimise order picking, with a view to defining the ideal capacity of time windows. This study was later complemented by relating picking scheduling to delivery time windows, in compliance with service requirements (Agatz *et al.*, 2011). However, their analysis is limited because they suggest a constant demand where all time windows have the same occupation. This does not allow for the adjustment of time window capacity to the actual order demand. As regarding transport, their study is limited because order occupation and vehicle capacity are not considered. It is important to define the occupation of the orders based on the number of items, units and type of product, in order to select the most appropriate type of vehicle.

Deriving out of these publications, some authors have focused on time windows management. In addition to calculating the cost of the routes, an approximation of the opportunity cost has been incorporated into them, based on the study of consumer behavior. On the one hand, Klein *et al.* (2018) present a model to statically determine the price at which time windows must be offered to ensure a certain profitability. This study is completed a year later with the aim of calculating this price dynamically, considering the forecast of demand (Klein *et al.,* 2019). On the other hand, Mackert *et al.* (2019) develop a model that statically determines the selection of time windows that are offered to the consumer. In this way, only the choice of those that represent a viable operating cost with a certain level of service is allowed. Likewise, this study is subsequently completed with a dynamic approach that combines orders with demand forecasting (Mackert, 2019). Despite delving into the management of time windows, none of these studies consider the limitations of the different product typologies and do not define the operational routes either.

Focusing on evaluating supply chain decisions in last mile delivery, Al-Nawayseh *et al.* (2013) model the different costs in terms of time and distance, for home delivery and pick-up points. Their study concludes that time has a greater effect on cost than distance. This is because the time factor is directly affected by other costs, such as driving distance, driver cost and the number of orders. Their findings show that the best options are pick-up points, such as click & collect or click & drive. However, for home delivery they define fixed routes with a five-hour maximum duration, without considering the limitations of fresh and frozen products and the large monetary losses they normally incur (Ghezavati *et al*., 2017; He *et al.*, 2019). There are also last mile logistics studies such as Kovačić *et al.* (2015), which takes the time limitation into account in routes with perishable products. However, this study does not consider how the type of products affects the packaging process, and also permits that demand is not met owing to transport fleet or time window limitations. Accordingly, there is a growing research flow that has examined the importance of order fulfilment (Griffis *et al.*, 2012; Koufteros *et al.*, 2014; Peinkofer *et al.*, 2015). Nonetheless, alternatives such as inter-store shipments or changes to order allocations to accommodate demand have not been widely addressed.

In this context, e-grocery delivery costs play a key role in the different order fulfilment options (Netessine & Rudi, 2006). A first adaptation to e-grocery routing problems is the incorporation of maximum time on each route to avoid long routes. The mathematical model by Wang *et al.* (2014) define online order delivery routes, limiting the maximum route time of vehicles in order to ensure the preservation of perishable products. Moreover, different mathematical models have been developed over the last few years in order to improve delivery route related aspects. Some transport modelling studies, design and implement a network system to optimise delivery routes when online orders include both premium and standard products (Emeç *et al.*, 2016; Yanik & Bozkaya, 2014). Logistical difficulties increase when the consumer chooses the home delivery mode, since the fact that the customer is not at home at the time of delivery represents a considerable loss of logistical efficiency and waste of perishable products. For this reason, authors such as Pan *et al.* (2017) have developed a transportation model that tries to maximize the probability of delivery of an order while minimizing distances in the distribution of online orders. Some authors focused on online food shopping delivery highlight the importance of dividing the delivery area into smaller areas in order to reduce the total distance travelled by the fleet and to measure the viability of the service per area of delivery (Zissis *et al.,* 2017). Their results suggest that it is theoretically possible to collaborate and reduce economic aspects, derived environmental and social costs. However, the implementation of these ideas still poses a great challenge due to the extremely competitive nature of the food retail market. Subsequently, the same authors extended the mathematical model to the possibility of collaborative distribution among several supermarkets (Zissis *et al.,* 2018). The main objective of this study is to create a sustainable model that achieves a significant reduction in shipping time and distance by creating a network of micro warehouses. However, it is highlighted that the profitability of this model is limited by the necessary investment and by the difficulty of managing route times. That is why one of the main limitations of the developed models is the lack of analysis on logistics costs. In this regard, Herrel (2014) also organizes delivery to clients according to predefined distribution areas, each of which functions as a business unit. In his supply chain optimisation engine, the author considers several factors that can vary over time: traffic congestion, population density, delivery charges by region, and order and truck earnings. However, the main limitation of the model is that it does not include time windows for clients with a maximum route time of vehicles.

However, these models do not consider store characteristics, which would determine the most appropriate store to prepare each order. Hübner and Ostermeier (2018) consider the problem of routing vehicles with multiple compartments that are technically able to maintain different range of temperatures. Martins *et al.* (2019) expand on this study by addressing a multi-period setting with time window allocations oriented towards the product complexity. In this context, mathematical modelling plays a fundamental role. Recent systematic literature review of the main e-grocery topics by Martín *et al.* (2019) stands out logistics as one of the key competitive aspects. Nonetheless, they confirm that the use of mathematical modelling is practically null. In this way, studies focusing on optimising order distribution do not take into account the importance of planning this activity together with picking, despite being an aspect of great importance due to the sensitivity of the products. As indicated by De Kervenoael *et al.* (2016), most of the existing models focus on reducing costs, neglecting the use of existing mathematical tools to optimise those processes. For this reason, supermarket chains must focus their efforts on redesigning their logistics models, rather than trying to reduce the costs of current models, which become unsustainable with the growth of the online channel.

The review of literature presented above shows that there are different researches that optimise either picking or delivery processes of e-grocery. However, e-fulfilment processes have not been studied together and in depth in the omni-channel context of supermarkets. Having reviewed the research in this area, our study fills this gap by focusing on e-fulfilment processes so that e-grocers may improve the daily allocation of online orders to the different stores and delivery vehicles. In addition, the proposed approach includes all those online features of the stores, orders and vehicles that have not been studied so far. The proposed MILP allows to meet the online demand minimizing the costs associated with the supply chain, grouping orders and avoiding idle times in order to reduce the amount of logistics resources required. The research contributions of this paper could be marginal with respect to innovation in operations research, but offer the rigor with respect to existing literature. The paper offers the scientific rigor and the application of operations research on picking and delivery in e-grocery since the proposed approach was tested in one of the best known e-grocers. As a result, supermarket chains can use the proposed model in order to ensure their business profitability.

3 Problem definition

This study involves logistics activities in e-grocery e-fulfilment processes to meet the daily demand by optimising the logistics costs. Our problem arises from a practical e-commerce environment, where each client must be served within the selected range of time windows. According to store policies, the capacities of these time windows must be limited in order to fulfil 100% of orders, taking into account the requirements of the different days of the week. It should be noted that the first time window is never offered to the customer, and the second time window is only available for click & collect and click & drive orders. With regard to store characteristics, this approach has been created with the understanding that all stores offer the same range of products. That fact that the product range is the same does not imply that the stores have the same dimensions.

The product delivery is unique, so each complete order must be sent using the same vehicle. Since this is a store-based model, customers can choose between home delivery and pick up at the store, via the click & collect or click & drive services. Each order must be prepared in a single store and in the same time window. In this sense, it is not allowed that an order is left half-finished to be prepared in another store or in the next time window. The fact that an order is collected in a specific store does not imply that the order must be prepared there. In this context, inter-store deliveries are allowed but transfers between vehicles are not permitted. These inter-store deliveries provide logistical flexibility, representing a great opportunity to meet the demand while optimising the picking and delivery time windows. The cost associated with these internal transports between stores affects the delivery cost motivated by traveling more kilometres and shipping arrangement, among others. For its major importance, only travelling costs have been considered. Although the MILP is not aimed at optimising delivery routes, some constraints have been set for minimum vehicle filling and maximum vehicle capacity. Each store and each time window have an associated vehicle; therefore, as a starting condition, that vehicle must finish the route before starting the next time window. The maximum transport capacity ensures that the route associated with these orders is always completed and that the maximum route time of is not exceeded, so as not to affect the cold chain (Archetti *et al.*, 2014). In the case of fresh or frozen products, the interval between order picking and delivery cannot exceed that of the time window. The routes must be defined so that each vehicle can always complete its route within a time window.

The mathematical model should allocate online orders by considering the different characteristics of the stores, the orders and the available vehicles. A daily order schedule should be thereby obtained by taking into account the demand and the different picking options. The solution obtained should indicate where each order should be prepared, and what is the most appropriate picking time window, so as to minimise the associated costs of e-fulfilment and the number of logistics resources used inefficiently. Figure 1 shows the logical flow of the proposed approach.

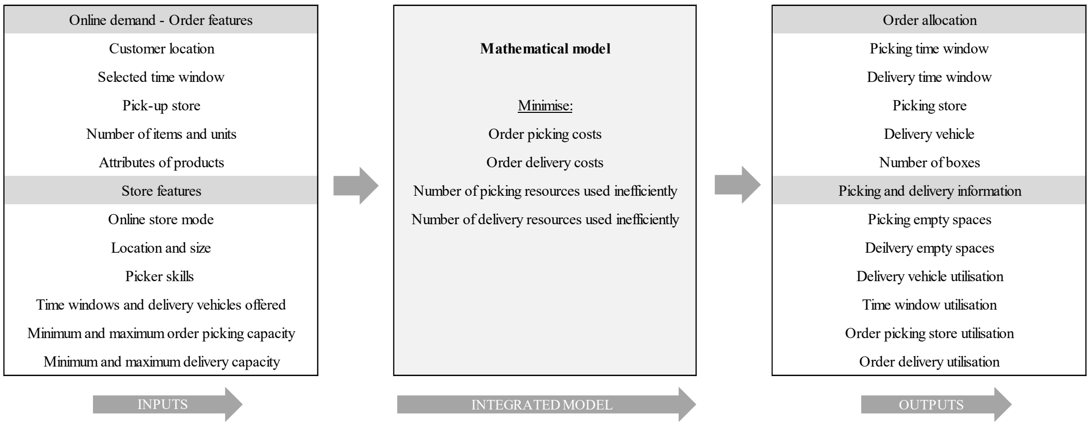

Fig. 1 Logical flow with the elements under consideration of the proposed approach

The input data for the MILP model comes from the order characteristics and store features, collected in the website database of the company. As well as minimising the order picking and delivery costs, our model allows to optimise the use of logistics resources. In order to improve the logistical efficiency, two variables called "qualitative variables" have been added because these are not reflected in the e-fulfilment costs. The qualitative variable associated with the picking activity determines if a time window has idle times, that is, more orders could be prepared in that time range because the maximum capacity is not reached. The qualitative variable referring to order delivery determines if a vehicle has enough space to send more orders in the same trip. These qualitative elements promote the filling of the picking time windows and trucks, grouping the orders in the minimum preparation windows and sending them using the minimum number of trucks. Thanks to this optimisation of the utilisation, the workload is consolidated in order to avoid idle times and reduce the amount of resources required. In this way, we are illustrating a problem that combines both a quantitative and qualitative approach. As a result, the proposed approach is a daily schedule which allocates orders to the different stores with their corresponding vehicle so as to obtain the best possible solution.

4 Mathematical formulation of the problem

The proposed linear programming model combines the simultaneous optimisation of costs and qualitative e-fulfilment factors. The model calculates the costs of preparation and transportation of online orders for each of the possible alternatives, grouping at the same time the workload in order to avoid idle times and to reduce the amount of resources required. This section describes the problem of scheduling online orders for the optimisation of a grocery seller supply chain. The deterministic problem is expressed as follows:

Input data:

- A group of picking stores I that prepare online orders OSi and the distance between customers and stores D_{ik}.
- Time windows J available in each store in which orders K are prepared. Order picking activity is limited by the number of earlier e_k and latest l_k time window selected by the customer to receive or pick up the order.
- The cost SCi associated with preparing an order in a store, including features such as: picker skills, traditional store activity, picking capacity within each time window MPC_{ij} *y* MOP_{ij}, product replenishment model and store size.
- Delivery considerations: cost per kilometre KC, minimum vehicle filling $MDCij$ and maximum order occupation of each vehicle MBD_{ij}.
- Online demand: the number of orders placed for a defined scheduling period with the distinctive characteristics of each order k: product characteristics P_k, delivery mode SM_k, collection store CS_k, number of items R_k and number of boxes generated by purchased units B_k

Output of the model:

- In which store and at which time window each order is prepared PA_{ijk}.

- From which store and at which time window each order is delivered DA_{ijk}.
- The time window with order picking capacity PU_{ij} and the vehicles used inefficiently DU_{ij}.
- The necessary inter-store shipments CPP_{ik}.

4.1 Notation

The following section outlines the notation employed in the proposed linear programming model.

Indices

i : Indices of stores, i = {1…I}

j : Indices of time windows, j= {1…J}

k : Indices of orders, k = {1…K}

Parameters

e_k : Earlier time window selected by the customer to receive or pick up the order k

l_k : Latest time window selected by the customer to receive or pick up the order k

R_k : Total quantity of items per order k

CS_k : Collection store chosen by the customer of the order k

B_k : Total quantity of boxes of the order k

SCi : Mean value in currency units of the order picking cost per item for each store i

KC : Currency units of cost associated with each kilometre travelled

MPC_{ij} : Maximum picking capacity measured in number of orders for store i at time window j

MDC_{ij} : Maximum delivery capacity measured in number of boxes for store i at time window j

MBD_{ij} : Minimum number of boxes needed to make a shipment from store i at time window j

MOP_{ij} : Minimum number of orders needed to prepare in store i at time window j

M : Large number

D_{ik} : Delivery distance measured in kilometres from store i to the customer or pick-up store of the order k

$$\mathrm{OD_{ik}} = \begin{cases} 1 & \text{if the parameter } Dik > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{P_k} = \begin{cases} 1 & \text{if the order } k \text{ has perishable products} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{SM_k} = \begin{cases} 1 & \text{if the order } k \text{ is home delivery} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{OS_i} = \begin{cases} 1 & \text{if the store } i \text{ is ready to prepare online orders} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{OA_{ik}} = \begin{cases} 1 & \text{if the parameter } OSi \geq SMk \\ 0 & \text{otherwise} \end{cases}$$

Decision variables

$$\mathrm{PA_{ijk}} = \begin{cases} 1 & \text{if the order } k \text{ is prepared at time window } j \text{ in store } i \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{DA_{ijk}} = \begin{cases} 1 & \text{if the order } k \text{ is deliveried at time window } j \text{ in store } i \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{DU_{ij}} = \begin{cases} 1 & \text{if delivery capacity is used at time window } j \text{ in store } i \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{PU_{ij}} = \begin{cases} 1 & \text{if order picking capacity is used at time window } j \text{ in store } i \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{VDU_{ij}} = \begin{cases} 1 & \text{if a vehicle is used at time window } j \text{ in store } i \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{TWU_{ij}} = \begin{cases} 1 & \text{if there is a picking process at } j \text{ in } i \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{CPP_{ik}} = \begin{cases} 1 & \text{if the order } k \text{ is prepared in a different store } i \text{ where it is collected} \\ 0 & \text{otherwise} \end{cases}$$

Weighting parameters

εC : Weighting of e-fulfilment cost

εD : Weighting of delivery inefficiency

εP : Weighting of order picking inefficiency

The correct definition of these parameters plays a highly important role in the model. For this reason, it is recommended that the 'weighting of e-fulfilment cost' by default has a value of 1. Taking this weight as a reference, the user who applies the model must define the other two parameters based on the company priorities. On the one hand, the 'weighting of order picking inefficiency' has been defined by authors such as Peidro *et al.* (2010) to avoid idle time in the picking time windows. It is typically associated with the availability of pickers in an attempt to avoid low occupancy time windows by bundling online orders together. This condition for filling time windows is closely linked to the minimum order picking allowed for an order to be allocated to a picking time window for a pre-established minimum number of orders. On the other hand, the 'weighting of delivery inefficiency' is used to promote the occupation of vehicles, in both customer and inter-store deliveries. Vehicle occupation is encouraged by penalising vehicles that have empty spaces (Belavina *et al.*, 2016). Similarly, the allocation of vehicles is linked to the minimum filling allowed, which does not permit an order to be allocated to a vehicle if the number of orders does not exceed a pre-established figure. The correct assignment of weightings is very important in the search for the model's effectiveness, since small changes in these weightings give rise to significant changes in the solution of the objective function. It should be noted that the objective is not focused on optimising the weights; they are simply user-defined input elements taking arbitrary values.

4.2 Objective function

The objective function consists of two addends. As well as minimising the order picking and delivery costs, our model allows to optimise the use of logistics resources. These qualitative elements promote the filling of the picking time windows and trucks, grouping the orders in the minimum preparation windows and sending orders in the minimum number of trucks. Thanks to this optimisation of the utilisation, the workload is consolidated in order to avoid idle times and reduce the amount of resources required, serving as a decision-making model. E-grocers are the ones that decide the weight that multiplies those qualitative variables which are not reflected in the e-fulfilment costs. This is the main reason why the weighted sum approach (Zadeh, 1963) has been used to solve the objective function. In the weighted sum method, the different terms of the objective function are summed up with varying scalar weights and this sum is optimised. If weights change, each different single objective optimisation determines a different optimal solution that focus on a priori articulation of preferences (Marler & Arora, 2010). This approach has been used by different authors to transform a multi-objective problem into one single-objective scalar function (Aksoy, 2019; Vahidinasab & Jadid, 2010). There are other procedures such as normalization or the transformation of qualitative variables to monetary values that could be applied to transform into a mono-objective function. Since the variability of workload is not measurable in monetary values, in this study the objective function has been constructed through a weighted sum on logistics costs and on the use of logistics resources.

The first term in the objective function represents the 'e-fulfilment cost' for each order. To evaluate the different options, we only need to identify the costs that vary depending on the volume of orders from a store, ignoring the fixed costs because they do not affect the process of allocating orders to stores. Two different cost parameter are determined for this study. These 'e-fulfilment costs' are based on the cost per kilometre travelled and the picking cost of each order in each store. The 'delivery cost' is calculated by multiplying the distance in kilometres between the assigned store and the customer, by 'the cost per kilometre'. At this stage it is also necessary to define the 'delivery cost per kilometre'. Authors such as Rodríguez García *et al.* (2018) have developed a cost model for this calculation based on repairs, fuel and the driver related cost. Their model integrates a value for the cost of starting the route, which ensures that orders are sent in as few vehicles as possible. The 'delivery cost' calculated for each order is not only based on home delivery, but also includes the cost of transfer between stores. This cost is zero for click & collect and click & drive orders because the distance is zero in that case. Likewise, the 'order picking cost' is calculated by multiplying the cost associated with each store by the number of items in each order. The ‘order picking cost per item’ must be defined by the company. E-grocer could determine that cost for each store based on the location, size, product range and internal activity of a given traditional store. This first term of the objective function is then multiplied by the weighting εC, which by default has a value of 1. Thus, the weights referring to uses (εD and εP) should be defined in relation to that value. If this weighting of e-fulfilment cost is modified, the qualitative weightings should be relativized.

The second term of the objective function includes the qualitative aspects. On the one hand, the ‘weighting of delivery inefficiency’ (εD) is multiplied by the number of vehicles that have empty space, to group orders that can wait to be transported. On the other hand, εP represents the ‘weighting of order picking inefficiency’, which is multiplied by the number of time windows with the capacity to prepare orders. This second qualitative term tries to reduce the use of picking time windows which are not working at maximum preparation capacity due to idle time of the associated resources. The values of the weights must be defined to optimise either the logistics costs or the amount of resources used. The higher the weightings values, the greater the bundling of orders to consolidate workloads of online resources. In this way, we are illustrating a problem with a single objective function, in a scalar function that combines both a quantitative and qualitative approach. Once the result is obtained, it is possible to return to define other weightings, so as to compare the resulting logistics optimisations. The objective function is represented according to the equation (1) as:

$$\min \quad \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}(D_{ik}\cdot PA_{ijk}\cdot KC + SC_i\cdot R_k\cdot PA_{ijk})\cdot \varepsilon C + \sum_{i\in I}\sum_{j\in J}(DU_{ij}\cdot \varepsilon D + PU_{ij}\cdot \varepsilon P) \qquad (1)$$

4.3 Constraints

Below are the constraints grouped by typology:

Capacity limitation

$\sum_{k\in K} PA_{ijk} \le MPC_{ij}$ $\quad \forall I, \forall j$ *(2)*

$MPC_{ij}\cdot TWU_{ij} - \sum_{k\in K} PA_{ijk} \le M\cdot PU_{ij}$ $\quad \forall I, \forall j$ *(3)*

$MPC_{ij}\cdot TWU_{ij} - \sum_{k\in K} PA_{ijk} \ge PU_{ij}$ $\quad \forall I, \forall j$ *(4)*

$\sum_{i\in I}\sum_{j\in J} PA_{ijk}\cdot OA_{ik} = 1$ $\quad \forall i$ *(5)*

$\sum_{k\in K} OD_{ik}\cdot DA_{ijk}\cdot B_k \le MDC_{ij}$ $\quad \forall I, \forall j$ *(6)*

$MDC_{ij}\cdot VDU_{ij} - \sum_{k\in K} OD_{ik}\cdot DA_{ijk}\cdot B_k \le M\cdot DU_{ij}$ $\quad \forall I, \forall j$ *(7)*

$MDC_{ij}\cdot VDU_{ij} - \sum_{k\in K} OD_{ik}\cdot DA_{ijk}\cdot B_k \ge DU_{ij}$ $\quad \forall I, \forall j$ *(8)*

Minimum filling

$\sum_{k\in K} OD_{ik}\cdot DA_{ijk}\cdot B_k \ge MBD_{ij}\cdot VDU_{ij}$ $\quad \forall I, \forall j$ *(9)*

$\sum_{k\in K} OD_{ik}\cdot DA_{ijk}\cdot B_k \le M\cdot VDU_{ij}$ $\quad \forall I, \forall j$ *(10)*

$\sum_{k\in K} PA_{ijk} \ge MOP_{ij}\cdot TWU_{ij}$ $\quad \forall I, \forall j$ *(11)*

$\sum_{k\in K} PA_{ijk} \le M\cdot TWU_{ij}$ $\quad \forall I, \forall j$ *(12)*

Time window allocation

$\sum_{i\in I}\sum_{j\in J} DA_{ijk}\cdot j \ge e_k$ $\quad \forall k/SM_k = 1$ *(13)*

$\sum_{i\in I}\sum_{j\in J} DA_{ijk}\cdot j \le e_k$ $\quad \forall k/SM_k = 0$ *(14)*

$\sum_{i\in I}\sum_{j\in J} DA_{ijk}\cdot j \le l_k$ $\quad \forall k$ *(15)*

$\sum_{i\in I}\sum_{j\in J} DA_{ijk} = 1$ $\quad \forall k$ *(16)*

$\sum_{i\in I}\sum_{j\in J} PA_{ijk}\cdot j \le \sum_{i\in I}\sum_{j\in J} DA_{ijk}\cdot j - 1$ $\quad \forall k/P_k = 0$ *(17)*

$\sum_{i\in I}\sum_{j\in J} PA_{ijk}\cdot j = \sum_{i\in I}\sum_{j\in J} DA_{ijk}\cdot j - 1$ $\quad \forall k/P_k = 1$ *(18)*

$\sum_{i\in I}\sum_{j\in J} PA_{ijk}\cdot i = \sum_{i\in I}\sum_{j\in J} DA_{ijk}\cdot i$ $\quad \forall k$ *(19)*

Order collection

$\sum_{j\in J} DA_{ijk}\cdot j \le e_k$ $\quad \forall i, \forall k/SM_k = 0, P_k = 0, i = CS_k$ *(20)*

$\sum_{j\in J} DA_{ijk}\cdot j = e_k$ $\quad \forall i, \forall k/SM_k = 0, P_k = 1, i = CS_k$ *(21)*

$\sum_{j \in J} DA_{ijk} \cdot j \leq e_k - 1 \qquad \forall i, \forall k / SM_k = 0, i \neq CS_k \qquad (22)$

$\sum_{j \in J} DA_{ijk} \cdot j \geq (e_k - 1) - M \cdot (1 - CPP_{ik}) \qquad \forall i, \forall k / SM_k = 0, P_k = 1, i \neq CS_k \qquad (23)$

$\sum_{j \in J} DA_{ijk} \cdot j \leq M \cdot CPP_{ik} \qquad \forall i, \forall k / SM_k = 0, P_k = 1, i \neq CS_k \qquad (24)$

Constraints (2), (3) and (4) correspond to capacity limitation. The equations prevent the store picking time windows from exceeding their capacity of picking online orders by calculating the occupation and the excess for each time window. The constraint (5) guarantees that the order will be prepared in one, and only one, of the available time windows. The variable OA_{ik} prevents any not an online order picking store from being assigned. In this situation, there may be stores that do not prepare orders but do act as order pick-up points. Constraints (6), (7) and (8) related to delivery vehicle capacity, avoid the occupation from being exceeded. For this, we first consider the orders transported through OD_{ik}. These orders are either home delivery, or orders prepared in a different store from where the customer has chosen to collect. The occupancy of each order (B_k) is calculated according to the number of items and the product type, and expressed as a number of boxes to be transported. The result provides a figure for the occupancy and excess for each delivery vehicle.

Constraints (9), (10), (11) and (12) guarantee that the minimum filling for vehicles, and the minimum picking in each time window are met. These minimum filling allowed does not permit that an order to be allocated to a vehicle if the number of orders does not exceed a pre-established figure.

Constraints (13), (14) and (15) ensure that each order is delivered within the customer's chosen time window. The first time window is not offered to the customer so as to allow time to prepare the order. Equation (13) affects home delivery orders, indicating that delivery will take place at or after the earlier time window selected by the customer (e_k). Equation (14) refers to click & collect and click & drive orders, where the delivery must take place either before or within the customer's selected time window. Equation (15) guarantees that the order is delivered before the latest time window selected by the customer (l_k). Constraint (16) ensures that orders are delivered in a single delivery vehicle. Constraints (17) and (18) guarantee that orders are picked in a single time window and order delivery takes place at least one-time window after it is picked. For orders that contain perishable products, the time elapsed between picking and delivery of orders cannot exceed the length of a picking time window. Equation (19) ensures that each order is delivered from the store where it is prepared.

Constraints (20), (21), (22), (23) and (24) are associated with click & collect and click & drive orders. Orders that are transported between stores are also subject to a picking time window. The last two equations are associated with orders that include inter-store shipments, and with perishable products. These logical expressions depend on the value of M, which is a sufficiently large number so that the condition always remains true (Williams, 2013). In the case of the last restriction, multiplying the equation by the M value ensures that the order must have been transported between stores before collection.

5 Application to a real-world case study

This section outlines the results of quantitative and qualitative optimisation scenarios with a case study. The aim of these experiments is to evaluate and validate the quality of the proposed optimisation model in real problems. This case study uses the linear programming model to obtain the optimum order allocation, while integrating e-fulfilment processes. First, we describe the company's initial condition as a leading e-grocer in the Spanish market, and then we present two optimisation scenarios selected by the company. Finally, we conducted a series of computational experiments to empirically evaluate the impact of e-fulfilment aspects.

5.1 Company description

The proposed model has been evaluated by using real data from a Spanish e-grocer. We have applied our approach for e-fulfilment scheduling with a view to evaluating the potential savings. Actually, this e-grocer offers more than 15,000 product items, with 80% of their sales including fresh produce. To develop the case study, we used demand related data from the year 2019, focusing on a specific area of activity that includes 28 order picking stores. The company was the market leader in distribution within the defined area of activity at the end of 2018, obtaining a 16.2% market share. In the online channel in particular, it is the market leader with a share of close to 30%. In this channel they operate a store-based model, delivering products from their supermarkets with their own transport fleet. Figure 2 shows the geographical distribution of stores offering the home delivery service and the click & collect and click & drive services in the specific area of activity selected for the study. Moreover, the map shows the distribution of the warehouses that supply products to the online stores, in reference to the chosen country, Spain. In total there are three warehouses differentiated by the type of products they supply. Each depot has different facilities depending on whether these products are fresh, frozen or dried.

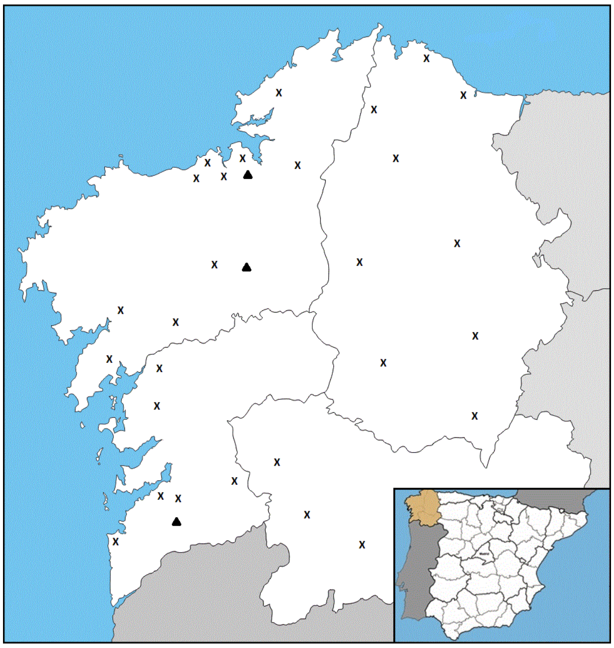

Fig. 2 Locations of e-fulfilment online stores (cross) and warehouses (triangle)

The problem to be solved focuses on the actual demand corresponding to one full working day, since orders can be placed up to one day before their collection. The daily demand of home delivery, click & collect and click & drive services for the 28 stores consists of 200 online orders. Of these orders, 50% contain perishable products and 49% contain frozen products. Each order contains an average of 58 units and 46 items.

5.2 Assumptions

The main characteristics and assumptions of this experiment are as follows:

- All the stores permit home delivery orders, but only 9 stores offer the click & collect and click & drive service.
- Each picking store has 6 picking time windows, each one lasting 3 hours and with a picking capacity of up to 5 orders.
- Each store has its own associated vehicle, each with the capacity to transport up to 8 boxes.
- For both delivery and picking processes, there is a minimum filling number required for a given time window to be used; in this case it is one unit.

As illustrated in Figure 3, the input data for our model comes from a database with the information that customers provide when they order online on the company's website. This database is completed with the company's characteristics in relation to store and delivery particularities, and available resources. Our proposed model determines the optimum scheduling for a full day based on the online demand of customer orders. The proposed linear programming model is coded in MPL (Mathematical Programming Language) which provides capabilities for generating model instances with the data stored in the database. The model instance is solved with Gurobi Optimiser. The results of the model were run in an Intel Core i5-6200U, at 2.3 GHz. The obtained solution is stored in the database and evaluated by the decision-maker.

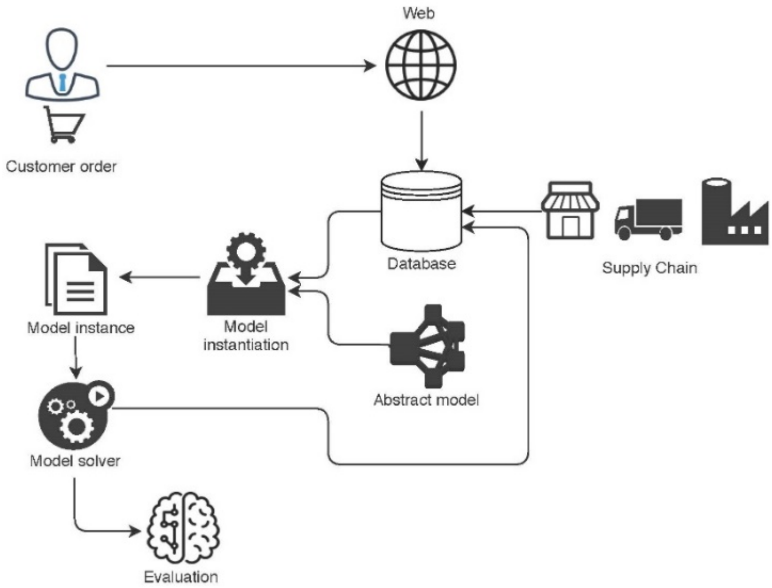

Fig. 3 Diagram of the computational experiment

With a view to comparing the results of each optimisation scenario, it is necessary to simulate the company's initial situation. Initially, the company allocated its orders according to postcodes. In this situation, the same store could serve orders to a specific grouping of postcodes. To do this, the MILP must include a constraint that reflect the company's currently defined allocation model. The constraint included in the model is $\sum_{i \in I} \sum_{j \in J} PA_{ijk} \cdot i$ = i where 'k' represents each order and 'i' represents the store currently assigned for its preparation and delivery. This limits the allocation of orders to stores, thereby freeing up the allocation of picking time windows. It should be noted that 'weighting of order picking inefficiency' and 'weighting of delivery inefficiency' are 0.

In order to obtain the corresponding cost, it is necessary to define the input elements that feed into the mathematical model. The input data can be consulted in the RiuNet repository with the DOI: https://doi.org/10.4995/Dataset/10251/148730. In this case study the company defined the e-fulfilment costs in the following way. The 'delivery cost per kilometre' is a constant mean value (€1.29 per kilometre) defined based on account repairs, and driver and fuel related costs. By contrast, the 'order picking cost per item' varies depending on the store and ranged from €0.29 per item to €0.55 per item. These costs were defined by considering the characteristics of each store such as size, range of products, picker skills and distance to the supply warehouse. Adding this input data to the MILP gives us the initial order picking and delivery costs, following the initial allocation criteria. Table 1 shows the initial e-fulfilment costs and the resulting qualitative aspects when simulating the demand for one working day.

Table 1 Results of initial scenario of the company

	Initial values
E-fulfilment cost	8.553 €
Order picking cost	4.309 €
Delivery cost	4.244€
Delivery vehicles used	89
Delivery vehicles used inefficiently	66
Delivery empty spaces (boxes)	266
Order picking time windows used	81
Order time windows used inefficiently	67

Analysing the solution, it can be stated that, from the 89 vehicles used, only 23 use their maximum vehicle capacity. Likewise, 83% of the picking time windows have some degree of inefficiency. Given the level of resource workload, different experimental analyses are carried out to improve order allocation. These results were validated with the logistics data of the company.

5.4 Problem optimisation

Once the company's initial situation is calculated and analysed, it can be optimised according to their specific business interests. Since the company's objective is to achieve a balance between improving the qualitative aspects and minimising costs, there are two different scenarios to simulate. Both scenarios require the values 'weighting of order picking inefficiency' and 'weighting of delivery inefficiency' to be defined, relative to the 'weighting of e-fulfilment cost'. The first scenario prioritises the qualitative part of the objective function. This can lead to varying costs so as to ensure that picking and delivery time windows are filled. In contrast, the second scenario affords a greater importance to quantitative optimisation, where the order allocation results in a minimum cost, and the qualitative aspects are not minimised. The results of each optimisation process are presented and compared with the company's initial situation.

5.4.1 Optimisation with qualitative priorities

This optimisation is focused on improving the filling of picking and delivery time windows. The e-fulfilment costs are balanced against the qualitative aspects, without minimising the total cost, the proposed optimisation scenario consolidates workloads in order to avoid idle times, reducing the amount of resources required. This does not imply that the result obtained represents the minimum costs, since qualitative parameters are prioritized over the logistics costs. To achieve this, the values of the 'qualitative weightings' εP and εD play a vital role and must be sufficiently high with respect to εC (that is equal to 1), thereby minimising the variables DU_{ij} and PU_{ij}. As figure 4 shows, the values of the qualitative weightings εP and εD greatly affect how the model is solved. The different values for the qualitative weightings are represented on the horizontal axis. The 'order picking inefficiency' and 'delivery inefficiency' weightings have the same values. On the ordinate axis, the e-fulfilment costs are represented on the left vertical axis, while the right vertical axis shows the qualitative variables that are optimised. It is important to bear in mind that picking time window occupancy is measured in the number of orders, whereas delivery time window occupancy is measured in boxes. This is why the delivery vehicle occupancy is usually greater than one box for orders that contain perishable products. The range of values of both variables is usually different, so even if 'order picking inefficiency' and 'delivery inefficiency' have the same weighting, the minimisation is not necessarily the same. This is important to bear in mind, although the minimisation can be compensated if to 'weighting of order picking inefficiency' is assigned a different value of 'weighting of delivery inefficiency'.

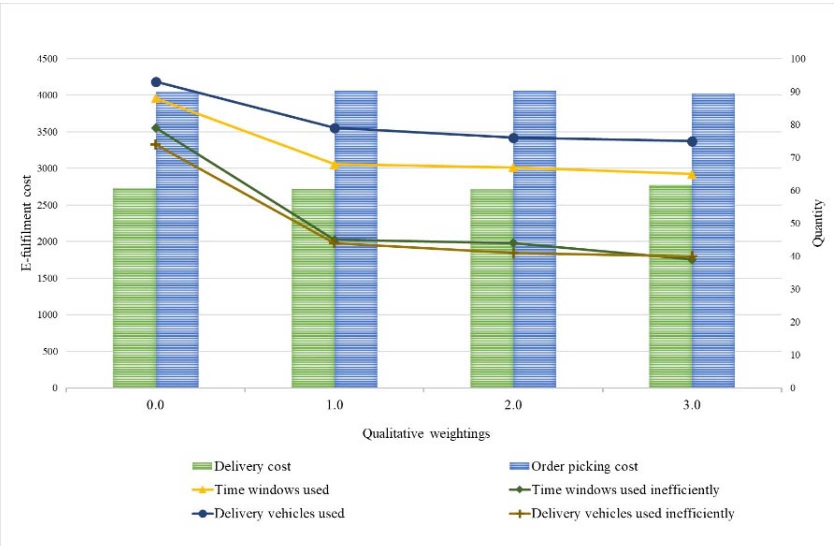

Fig. 4 Experiments on the values of qualitative inefficiencies

Figure 4 illustrates that small increases in the e-fulfilment cost lead to significant qualitative improvements. For example, in the case of $\varepsilon = 3$, the "time windows used" is reduced by 23 time windows and the "delivery vehicles used" is reduced by 18 vehicles from the corresponding value when $\varepsilon = 0$. The results indicate a 26 % reduction in the order picking time windows used, and a 19% reduction in the vehicles used, merely with an increase of only 2% in delivery costs. This cost addition is due to an increase according to the distance travelled by the delivery vehicles, but the improvement in the occupation of delivery vehicles and picking time windows allow pickers to prepare a greater number of orders in the same time window. Furthermore, there is a small reduction in the order picking costs. In conclusion, this optimisation indicates that bundling the online orders so as to minimise their availability, which only slightly increase costs, should be highly regarded in logistics business decisions.

5.4.2 Optimisation with quantitative priorities

This scenario minimises the picking cost to meet the online demand. The resulting order allocation allows all orders to be picked and delivered in the most cost-effective manner. If the values of the qualitative weightings, εP and εD, are zero, the second term of the objective function does not affect the optimisation process. Due to this situation, we do not take into account the occupation of the picking time windows or the last mile delivery vehicles. It is also possible to minimise the e-fulfilment costs and reduce order dispersion in the picking time windows and delivery vehicles. Consequently, the values of the qualitative weightings should always be lower than the value for 'weighting of e-fulfilment cost'. This ensures that the increase in occupation does not affect the picking and delivery costs. Therefore, this scenario gives rise to two situations.

In the first situation the qualitative elements are equal to zero, so the objective function only minimises the e-fulfilment costs. In the second situation the qualitative weightings for picking and delivery inefficiency are given values between zero and one, because one is the value of 'weighting of e-fulfilment cost'. If the objective function only consists of the quantitative term, our model for order allocation produces the costs and qualitative values, for one working day, shown in Table 2 below.

Table 2 Results of the optimisation with quantitative priorities

	Initial values	Current optimal values
E-fulfilment cost	8.553 €	6.773 €
Order picking cost	4.309 €	4.048 €
Delivery cost	4.244€	2.725 €
Delivery vehicles used	89	93
Delivery vehicles used inefficiently	66	74
Delivery empty spaces (boxes)	266	298
Order picking time windows used	81	88
Order time windows used inefficiently	67	79

The initial costs and qualitative values are compared with these optimised values. The results of the optimisation show that the e-fulfilment costs have decreased, while the qualitative aspect values have increased. The overall saving in e-fulfilment costs is almost 21%. This might seem to be a small improvement, but it should be remembered that profit margins are small in this e-grocery market. If we multiply this daily saving to get annual figures, the annual saving is approximately €650,000. This result is obtained by optimising the delivery costs, which decreased by 36% compared to initial situation of the company. On the other hand, order picking costs hardly vary. Since there are no qualitative weightings, the model returns a solution in which the economic aspects have improved but the qualitative aspects have not. The dispersion of orders in delivery vehicles and in picking time windows is greater than in the initial situation, so there are filling inefficiencies for each picking and delivery time window used. As a result, only 10 % of the order picking time windows are fully occupied. This corresponds to 9 order picking time windows operating at maximum occupation, while the remaining order picking time windows have idle time. Likewise, for transport purposes, just 20% of the delivery vehicles used are fully filled, corresponding to only 19 vehicles operating at their maximum capacity of 8 boxes per route.

Once the first scenario where the weightings were zero was shown, the second scenario is described below in order to improve the qualitative aspects while maintaining the objective of minimising e-fulfilment costs. To do this, the qualitative weightings should be given relatively small values with respect to εC. In this situation, the objective function tries to optimise both terms, although prioritising cost optimisation. This result brings considerable qualitative improvements, while keeping the e-fulfilment costs to a minimum. Figure 5 shows the qualitative improvements obtained for the 'order picking inefficiency' and 'delivery inefficiency' weightings equal to 0.20, with respect to the default value of 'weighting of e-fulfilment cost'.

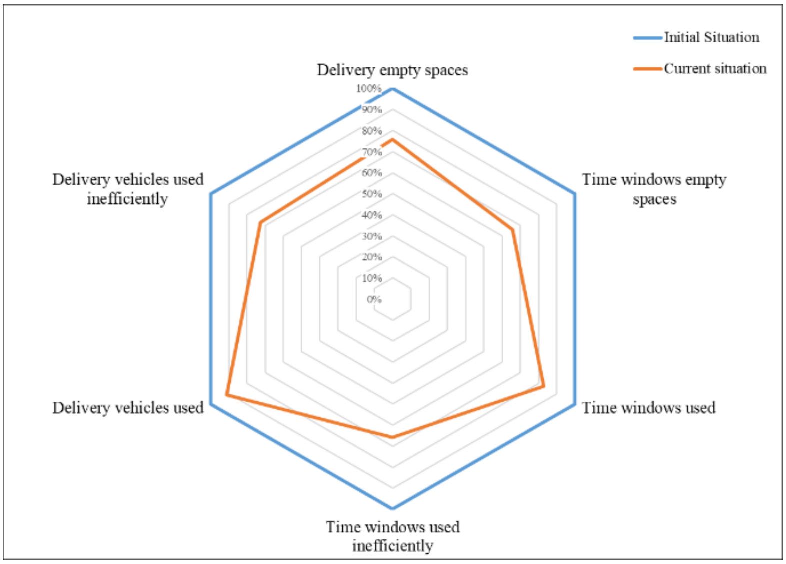

Fig. 5 Qualitative analysis of optimisation prioritising economic aspects

On the one hand, the order picking time windows used are reduced by 17%. As a result of this improvement, the idle time in picking time windows is reduced by 34%. On the other hand, 9% less vehicles are used in the delivery task, which leads to a reduction of 27% in the number of delivery vehicles that are not working at their maximum capacity.

5.5 Computational experiments

After presenting the case study, this section shows how the model can be generalized. A series of experiments have been conducted in order to empirically validate the model's optimisation quality at the same time that evaluate the impact of the qualitative weightings. The results of the model were appraised based on the decision variable data stored in each run. Three different scenarios are developed with the aim of observing how the objective function varies with different input data. It is important to note that, by default, the value for 'weighting of e-fulfilment cost' (εC) that multiplies the total cost in the objective function is one. By contrast, in the optimisation scenarios, the values for order picking weighting (εP) and delivery inefficiency weighting (εD) that multiply the qualitative variables are modified. Firstly, the results are shown for the situation where εD has a constant value of one. Secondly, the results are presented for the scenario where εP is one. Finally, the results are modelled for the case when the qualitative weightings have equal values. Table 3 shows these three scenarios, where column T (sec) denotes the total time elapsed in seconds, column DC represents the delivery cost, while column PC represents the order picking cost. Column TC gives the sum of the previous two terms to express the e-fulfilment cost of each order allocation model. Finally, column V shows the number of delivery vehicles used and column P represents the order picking time windows used.

Table 3 Results of weighting parameters variation

εD = 1							εP = 1							εP = εD						
εP	T(sec)	DC	PC	TC	V	P	εD	T(sec)	DC	PC	TC	V	P	ε	T(sec)	DC	PC	TC	V	P
0	54	2725	4051	6776	88	66	0	27	2736	4042	6778	78	84	0	15	2725	4049	6774	95	89
0.25	45	2743	4033	6776	80	66	0.25	48	2722	4056	6778	78	68	0.25	42	2722	4052	6774	81	67
0.5	85	2743	4033	6776	80	66	0.5	58	2722	4056	6778	77	68	0.5	50	2722	4052	6774	80	68
0.75	56	2743	4033	6776	79	66	0.75	39	2713	4063	6776	79	68	0.75	49	2713	4063	6776	78	68
1	92	2713	4063	6776	78	68	1	81	2713	4063	6776	78	68	1	81	2713	4063	6776	78	68

εD = 1							εP = 1							εP = εD						
εP	T(sec)	DC	PC	TC	V	P	εD	T(sec)	DC	PC	TC	V	P	ε	T(sec)	DC	PC	TC	V	P
1.25	61	2704	4076	6780	76	68	1.25	55	2743	4033	6776	79	66	1.25	69	2704	4076	6780	77	68
1.5	73	2704	4076	6780	77	68	1.5	72	2743	4033	6776	79	66	1.5	100	2704	4076	6780	77	68
1.75	73	2704	4076	6780	77	68	1.75	100	2743	4033	6776	80	66	1.75	125	2704	4076	6780	77	68
2	111	2704	4076	6780	77	68	2	171	2756	4022	6778	79	65	2	188	2717	4065	6782	76	67
2.25	128	2719	4064	6783	76	68	2.25	199	2756	4022	6778	79	65	2.25	504	2717	4067	6784	77	66
2.5	101	2719	4064	6783	76	68	2.5	289	2759	4022	6781	79	65	2.5	817	2717	4067	6784	76	67

From this table we can observe how the problem is quickly solved since all the scenarios give a solution before a computational time of 13 minutes. This fact assesses the optimisation quality of the model. However, the large computing time differences that occur when varying the qualitative parameters are noteworthy. This aspect was already highlighted in Section 3, when emphasizing the need to correctly define the weightings parameters. In general, the computing time is not proportional to the increase in the value of the qualitative weightings until the weights take on values greater than 1. In these cases, the higher the weighting, the greater the execution time. Comparing the three scenarios, it can be highlighted that for the same epsilon values, the 3 scenarios maintain similar computing times. The time is significantly increased only in the third scenario, when epsilon takes values between 2 and 2.5. Observing the second exploratory study, it could be noted that εP is the parameter that mostly influence the computational performance.

Focusing on performance based on optimising costs, table 3 shows that the higher the values of the weightings, the greater importance of the qualitative aspects to minimise the e-fulfilment costs. The scenario that achieves the greatest reduction in TC is the third scenario. To focus solely on improving the PC, scenario 2 reaches the solution with a lower cost for values of εP around 2. Instead, in order to minimize DC, the user should focus on both scenarios 1 and 3 when epsilon is between 1.25 and y 1.75.

In order to improve the qualitative aspects, the corresponding epsilon should be promoted. If the objective is to reduce the number of delivery vehicles used, scenario 2 is ideal. In contrast, scenario 1 greatly improves the number of order picking time windows used. In general, for the three scenarios, a non-zero epsilon value achieves great qualitative results since the total cost is maintained and the number of resources required is reduced. The results represented highlight that the number of resources required for picking and delivery activities can be greatly reduced. The corresponding epsilon should be promoted to improve the qualitative aspects. If the objective is to reduce the number of delivery vehicles used, scenario 2 is the most ideal. In contrast, scenario 1 greatly improves the order picking time windows used.

In general, for the three scenarios, a non-zero epsilon value achieves great qualitative results since the total cost is maintained and the number of resources required is decreased. Focusing on the first scenario where εD is one and εP is greater than zero, it is possible to reduce PC and keep P values low if the εP values are lower than one. The P value that represents the order picking time windows used increase after the value of εD is greater than εP. Thereby, the optimisation of vehicle used is prioritized so that the value of V is reduced until only 76 vehicles, 14% less than without using qualitative weights. For the second scenario with epsilon values between zero and one, the PC increases. In this situation, the number of P resources remains constant. As the weight value increases, the number P is reduced up to a total of 23% with respect to the initial situation. By contrast, the results of scenario 3 are very different from the previous scenarios since the values of V and P do not fluctuate, but rather decrease as epsilon increases. In addition, it is verified that, when increasing the value of the weights, the TC cost increases proportionally. However, for values less than one, the DCs are higher than for epsilon greater than one. In the case of the PC, the opposite occurs, which is consistent since the TC cost is multiplied in the objective function by εC, which is 1, while the other weights that multiply the qualitative variables are modified and when they exceed the weights of costs affect the result. With this last scenario, the values of epsilon 2.5 reflect that a reduction of 20% in V and 25% in P can be obtained. These are the best results obtained at a qualitative level, because it is possible to greatly reduce the number of resources necessary for the preparation and transportation of online orders.

As a conclusion, the analysis carried out on the parameters helps to clarify that the εP parameter is the one that most influences the model execution time. On the other hand, when it comes to minimizing the resulting cost, it has been shown that weightings with values less than one must be defined. Based on the study, researchers and companies can focus the logistics of their online channel towards an improvement of the costs of preparation or transport, together with the reduction of the resources necessary to carry out these activities.

5.6 Discussion

The retail sale of groceries has always been characterized by a sale made up of a large number of products with low profit margins. As a consequence, the entry into the online business has led to the development of various logistics strategies in search of efficient business where retailers have absorbed part of the tasks that in the traditional model are carried out by the customer (Fisher & Kotha, 2014; Ring & Tigert, 2001). Taking efficient business as a priority, e-grocers must detect the company's nuclear activities, those essential to operate efficiently. The focus of attention should be on those activities that represent the highest cost for the company, which are transport costs (Hübner *et al.,* 2016a) and preparation costs (Vanelslander *et al.,* 2013). Both activities must be optimised, thus researchers recommend to establish the essential resources to carry out the company's activity (Osterwalder *et al.,* 2011). Authors such as Fikar (2018) highlight the advantage of having a large number of picking services in that e-grocers can reach their customers faster. Our results show that using more time windows or vehicles to prepare online orders is not necessarily more efficient. If orders are correctly allocated to both picking stores and picking time windows, idle time and underutilised vehicles can be avoided. The main implication of the proposed approach is that it enables such optimisation to be achieved through the joint management of preparation and transport activities.

Authors such as Pires et al. (2017) stand out that researchers should focus on the evident lack of contributions of practical cases. The presented publication demonstrates the potential benefits and application of academic research to real problems in this field. Having presented the case study and the corresponding computational experiments, we can conclude that the proposed model leads to significant improvements to the real-world case study. For this purpose, it is important to correctly define the qualitative weightings, since their values will greatly affect the e-fulfilment costs. In the different simulations, it can be stated that it is possible to balance the utilisations of the logistics resources and the costs of these activities. This allows companies to compare different scenarios and decide which order allocation strategy better fits their requirements. In this way, the proposed model solves one of the future works of research presented by Wollenburg *et al*. (2018) who ask for quantitative analyses that connect the real costs and sales data of different logistics network designs of e-grocers.

Having observed the results of the case study, the company has chosen to focus on scenario number 2 where the optimisation is based on quantitative priorities. It has eliminated the constraint that allocated orders to stores according to postcodes, and has focused on an optimisation by prioritising the economic aspects. The results in both scenarios show that by simply rescheduling the order allocation, we can achieve an optimum situation which is a vast improvement on the initial situation of the company. The computational experiments indicate that the proposed model is effective in quickly responding to optimisation needs, compared to other mathematical models. Moreover, the results highlight the importance of a correct allocation of resources, those essentials, in order to optimise the e-fulfilment costs. As a result, time slot scheduling has been defined as one of the most challenging directions.

Some authors call for models aimed at process optimisation, which help e-grocers get on the right track and avoid errors (Fernie *et al.,* 2010). Logistics efficiency is one of the keys to success for the e-grocery business. The distribution network design, stock management and time slot scheduling are considered the most important activities for companies that are moving to an omni-channel model (Agatz *et al*., 2011; Melacini *et al*., 2018). These aspects dealt with in the model are what differentiate online grocery stores in their competitive business market.

6 Conclusions

Electronic commerce of supermarket chains is experiencing constant growth, making logistics activities extremely difficult. Furthermore, scheduling online orders has become a complex task due to the different delivery options and means of order allocation. This article proposes to integrate the e-fulfilment processes in a mixed linear programming model for the daily allocation of orders to picking stores and their corresponding transports. This modelling method allows supermarkets to study all possible solutions to the order allocation problems, taking into account the characteristics of the online demand, the supply chain, the different stores and their associated vehicles. In this way, the proposed approach provides relevant academic and management contributions to the world of e-grocers with a model for picking and delivering online orders from traditional stores.

The theoretical contribution is based on the capacity of the analysis carried out to determine the efficient management to respond to online demand. The design characteristics of the online business supply chain could be organized taking into account the singularities of this sector due to perishable products that require special manipulations and delivery conditions, the high average number of items per order that increases picking times, and the high demand of consumers in terms of delivery speed and time windows (Wollenburg et al., 2018). These conditions allow e-grocers to improve their logistics activities in an expanding business market, having to deal with new and varied problems. These are normally the result of inappropriate supply chain management, such as designating a large number of picking stores or not adjusting their resources to order picking requirements. Our proposed model's solution allows supermarkets to know which resources, if any, need to be allocated to the different picking and delivery time windows. As a consequence, grocery sellers must find profitable ways to improve their customer's in-store experience and online operations. Managers need to focus their efforts on a collective approach to all e-fulfilment associated activities, from order picking to delivery. As a result, this linear programming tool extends the research aimed at professionals. The model serves as a guide for e-grocers with store-based model to differentiate them from their competition and will serve to direct improvement actions. The validity of this linear programming approach for e-grocery order allocation has been demonstrated via the evaluation of results of the case study. Furthermore, through the abstraction of knowledge from the exploratory study, the model speed confirms that the improvements are more effective than dealing with deterministic methods in isolation. Furthermore, there is no evidence suggesting that this paper has identified any implications for society. The proposed model facilitates decision-making at a managerial level and allows companies to simulate different scenarios and carry out a sensitivity study in order to find the optimum distribution network.

Previous studies have confirmed the importance of optimising logistics routes and order picking. Due to the complexity associated with transport modelling in urban areas, our model allocates transport to stores based on a time limit per route of three hours. Transport optimisation is based on minimising the cost per kilometre travelled by the total number of vehicles used. This is the main limitation of the model, since it focuses on allocating orders to vehicles, rather than managing the logistics routes in order to travel the minimum possible kilometres.

The proposed linear programming model can be adapted to other logistics configurations. Beyond, there remain several interesting research directions. First, the mathematical model could be developed for the case of companies that pick and deliver online orders from a central warehouse. This study would be interesting because recent literature indicates that picking costs decrease and delivery costs tend to increase. The main reason is that picking processes are usually more optimised in a warehouse than in traditional stores, conversely, delivery routes increase since warehouses are not usually so close to customers. Second, it would be particularly interesting to be able to simulate situations where fresh and dry items are prepared in different stores or even in different time intervals. These products represent one of the singularities of the online business of supermarkets compared to other sectors, since short storage times are more adequate for perishable products. Moreover, fresh and frozen products require special storage and delivery conditions which limit the route time from the store to the customer. Third, another potential line of future research could be to develop a model where some picking stores have different range of products. Including this type of restrictions requires that certain orders cannot be prepared in some stores or that consolidations must be made. The decentralized approaches represent a current trend of research in the online market due to the difficulty of managing split shipments in the order delivery process.

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