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Efficient hierarchical hybrid delivery in the last mile logistics

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Abstract: An efficient hierarchical hybrid delivery (EHHD) model is proposed by integrating a location-allocation optimisation model with a dynamic data envelopment analysis (DEA) model in this paper. The proposed model is characterised by having a periodic measurement assessing customer behaviour using the dynamic DEA, as well as developing a hierarchical connection among home delivery, the pickup point and the locker station options. The developed model considers uncertain conditions for transportation costs and customer behaviour. To solve this model, a meta-goal programming approach has been used. Based on the results of the numerical experiments, the developed model has a better performance than other competing models in terms of generating feasible and optimal solutions. Moreover, the application of the developed model is demonstrated in a case study. To the best of our knowledge, the model presented in this paper is the first attempt to simultaneously integrate customer behaviour with last-mile logistics. [Received: 23 April 2021; Accepted: 27 August 2022]

Keywords: last-mile delivery; customer behaviour data; delivery options; hierarchical; efficient; supply chain.

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1 Introduction

One of the significant resources of energy consumption and greenhouse gas emission is urban transportation (Savelsbergh and Woensel, 2016). Meanwhile, transportation activities are known as an important element in the supply chain and logistics management (Lambert and Cooper, 2000; Mason and Lalwani, 2006). In this regard, some researchers focus on transportation planning in the supply chain as well as logistics management with the aim of optimising the transportation problem (Petridis et al., 2017; Mehlawat et al., 2019). In the literature, logistics management is defined as "the process of planning, implementing, and controlling the efficient, effective flow and storage of goods, services, and related information from the point of origin to the point of consumption for the purpose of confirming to customer requirements", where it is a part of the supply chain management (Lummus et al., 2001). On the other hand, the last-mile logistics, which is generally related to the last stage of the customer demand satisfaction process in terms of the delivery of goods to the destination point, is one of the most polluted, costly and inefficient parts of the supply chain (Olsson et al., 2019). It is worth noting that the flow of goods, as mentioned in Olsson et al. (2019), can be reversed in the last-mile logistics. An example of reverse flow is when vehicles transport the flow of returned goods to a collection point (Tighazoui et al., 2018). Particularly, due to the rapid growth of e-commerce leading to increased online customer demand, last-mile city logistics has got a significant role in influencing urban transportation (Viu-Roig and Alvarez-Palau, 2020). The COVID-19 pandemic crisis has also led to further growth in e-commerce as online demand has increased due to social distance restrictions (Statista, 2020). In this regard, the labour shortage caused by the pandemic threatens the demand satisfaction process (Nagurney, 2021a, 2021b). In addition, the process of satisfying demand becomes more and more complex as statistics show that the demand for parcel delivery has tripled in less than a decade by 2020, and is expected to nearly double from 2020 to 2026 (Mazareanu, 2020). Thus, planning and optimisation of the last-mile logistics problems for the supply chain and logistics managers is essential, especially where there are constraints on supply and transportation (Balcik et al., 2008).

In case of the lack of effective last-mile solutions, the goods delivery leads to the increase of logistic costs, lead time, traffic problems, and decrease of social networking activities. Therefore, the conventional delivery networks should be upgraded. For example, when the customers are not present in the reception location, delivery is failed and it imposes a lot of cost on the delivery system. Hence, an appropriate solution is to deliver the good to a place near the absent customer's location. This solution is referred to as crowdsourced delivery. It should be noted that crowdsourced delivery cannot be fully replaced for the traditional parcel delivery system. However, the combination of these two delivery approaches leads to the improvement of last-mile logistics (Guo et al., 2020). Halldórsson and Wehner (2020) proposed and investigated six last-mile fulfilment options. In the first option, the end consumer buys the product from a retailer's store and the end consumer is responsible for transportation. The second option is similar to the first option, except that the end consumer makes an online order. In the third option, after registering an order, the end consumer goes to the points located in a close distance to pick up the goods. The fourth option is similar to the third one while in this option, the end consumer is faced with no time limitation to pick up the goods. In the fifth option, after aligning the sender and receptor's time, the sender delivers the goods to the customer in the reception location. Finally, in the sixth option, the goods are delivered when the end consumer' car is parked in a specific region in the city. When the customer is not present in the delivery location, the retailer can temporarily deliver the goods to the collection and delivery point (CDP), so that the customer can pick up the goods from CDP, later. The CDP location is affected by customer behaviour and depending on the shopper's attendance and service time, CDPs are divided into two categories. The first category is attended CDP in which, the logistic provider contracts with supermarkets, so that the human workers provide services for the customer at a specific time. The second category is unattended CDP in which, the customer picks up the goods from the smart locker within 24 hours (Xu et al., 2020). The unattended CDP is useful in high security areas (Janjevic and Winkenbach, 2020).

Based on a thorough review of the literature, few studies have been focused on optimisation models for CDP location and demand allocation. Also, the quantitative approaches regarding the customer behaviour and mobile CDPs are very limited in the literature (Xu et al., 2020; Deutsch and Golany, 2018; Schwerdfeger and Boysen, 2020). Due to insufficient planning and lack of focus on optimisation in relation to delivery points, some serious challenges arise, such as reduced levels of service, increased traffic congestion, higher transportation costs and lack of attention to customer characteristics. In this regard, the main research questions are as follows:

- Which network structure of last-mile fulfilment options can improve the demand satisfaction process?
- How is customer behaviour integrated with the delivery points location-allocation optimisation model?
- How is transportation cost minimised in relation to customer congestion?

This paper aims to examine the value of customers as an influential factor in locating CDPs through the development of a multi-objective mathematical optimisation model. On the other hand, the hierarchical connections among different categories of CDPs have been considered in this paper in order to improve the level of service. Finally, the customer's desire to reduce the transportation and delivery costs considering congestion levels is addressed in this paper as a supply-related objective function.

The rest of the paper is organised as follows: The related literature is reviewed in Section 2. The problem of efficient hierarchical hybrid delivery (EHHD) is defined in Section 3, and the optimisation model is formulated in Section 4. In Section 5, a reformulated model is proposed given the linearisation of optimisation model. In Section 6, the solution approach is introduced. The numerical experiments are presented in Section 7. In Section 8, a sensitivity analysis is performed on some important parameters. A real-world case study is provided in Section 9, and finally, the concluding remarks are provided in Section 10.

2 Literature review

The logistic last-mile problems have created some challenges for the cities, logistic careers and retailers. In the research performed by Deutsch and Golany (2018), the parcel locker network has been designed for reducing the logistic flows and the number of failed deliveries, and increasing the transportation network flexibility. However, this paper has some limitations including inconsideration of the dynamic approach and customer preferences. In the research performed by Schwerdfeger and Boysen (2020), the mobile parcel lockers have been introduced as a solution for last-mile distribution which can decrease the traffic congestion, environmental impacts and negative health consequences in big cities. The relocation of the lockers can facilitate the access to customers whose locations vary during the day. They proved that the fleet size required in the mobile parcel lockers is less than the fleet size required in stationary lockers. When the recipient provides the sender with the possibility of delivery in more than one delivery location, the delivery process becomes flexible; i.e., this process takes place with a lower cost and in a shortest time. For this purpose, Orenstein et al. (2019) developed a logistic model for delivery of small parcels to the service points. They suggested to perform the future studies by regarding multi-period problems to achieve efficient delivery. Zhou et al. (2016) proposed a model which considers two kinds of services including the home delivery (HD) and customer's pick-up (CP), simultaneously, in order to reduce the costs and pollution, and increase the effectiveness of supply chain. Their findings showed that the proposed model has a lot of advantages over the HD-only service. On the other hand, distance is an important criterion for the customer to choose the pickup point. However, their model decides to provide service for the customer by either HD or customer's pickup.

There exist a number of factors which affect the location of delivery points. Janjevic et al. (2019) developed a last-mile multi-echelon distribution network by formulating a nonlinear optimisation model based on CDPs. The ratio of the demands attracted to these points is assumed as a function of the distance between the demands and CDPs. The results showed that observance of CDPs can reduce the costs. Xu et al. (2020) proposed a data-driven method for location of CDPs based on the customer behaviour data. The online retailers' location is determined by integrating the data mining models and facility location. The results were analysed based on the trade-off between the consumer service level and the total logistic costs. However, they have not considered the traffic congestion in their proposed model which is one of the main limitations of their research. It should be noted that the possibility of crimes such as impersonating courier is one of the disadvantages of HD. In this regard, Lee et al. (2019) developed a decision model for installation of unmanned parcel lockers. The demand and distance have been considered in their model while some important factors such as the environment and performance components have been ignored. Noyan and Kahvecioglu (2017) proposed a two-stage stochastic programming model for designing a last-mile distribution network. This model observes the uncertain aspects in a post-disaster environment and it has been concluded that observance of the capacity leads to a reduced response time. In this model, customer access is only provided by the distribution points. Chauhan et al. (2019) presented a facility location model with the aim of maximising the customer coverage. Drones are launched from these locations and return to these locations after serving the customers. In this model, both the battery capacity of the drones and the capacity of the locations have been considered. They showed that considering the battery capacity of drones is critical to such delivery systems.

On the other hand, last-mile logistics are effective in routing. The growth of demands and customer expectations has made the companies to design a faster last-mile network in terms of cost, efficiency and delivery time. In this regard, Salama and Srinivas (2020) determined several points as a truck park location by clustering the delivery locations where, the other demand points in each cluster are satisfied by drones. The truck park location can be either one of the points in which the customer is present or any point in the delivery area. In this paper, the objective functions of time and cost have been compromised by epsilon-constraint method. Jahangiriesmaili et al. (2017) developed a two-echelon delivery structure for last-mile deliveries where, heavy trucks deliver the goods to the terminals and then, small trucks transfer the goods from the terminal to the customers. This delivery structure can reduce the road congestion and fuel consumption and increase accessibility. They concluded that the location of terminals in congested regions is not economically justifiable. Sitek et al. (2020) developed a binary integer programming model for vehicle routing problem (VRP). This model is distinct from the other VRPs due to the fact that it considers the alternative delivery points and parcel lockers in the distribution networks. They showed that increase in the number of delivery points leads to increase in the travelled distance and the number of service providers. Baldi et al. (2019) proposed a model for last-mile logistics by which, the items are accommodated in bins. It should be noted that the items have been divided into two categories where, a group of items should be accommodated in the bins while there is no compulsion for accommodation of the other group. The items are classified before modelling and hence, these two groups of items are considered as the inputs of the model. Moshref-Javadi et al. (2021) proposed mathematical models in which trucks and drones are synchronised in order to minimise the waiting time of customers for the last mile delivery problems. The goods can be delivered to the customer via a drone that launches from the truck. After meeting the customer demand, the drone returns to the truck according to the updated location of the truck. They showed that synchronisation of the truck and the drone can significantly reduce the customer's waiting time compared to a truck-only scenario. In this regard, Kuo et al. (2021) synchronised the trucks and drones so that the customer's node is served in a specific time window. Luo et al. (2021) investigated customer service with collaboration between drones and trucks, where there is a tolerable time for serving, i.e., the time window is flexible. They showed that an increase in the number of drones leads to less transportation costs and higher customer satisfaction. Thomas et al. (2022) criticises the body of research related to the delivery system that is based on the collaboration of trucks and drones in that it neglects the scheduling problem. Deploying multiple drones simultaneously in a delivery network regardless of scheduling may lead to drone collisions and this reduces the safety of the delivery system. For this purpose, they presented a mixed integer linear programming model to consider the truck routing and drone scheduling decisions in an integrated manner. Salama and Srinivas (2022) introduced a new variant of drone-truck collaboration through a mixed integer linear programming model, in which there is a truck and a heterogeneous fleet of drones. This paper simultaneously focuses on three types of decisions which include assignment (each customer location to a vehicle), routing (truck and drones) and scheduling (drone and truck operator activities) in the last mile of the delivery problem. In addition, Salama and Srinivas (2022) considered the recovery and launch operations of drones as flexible. In other words, such operations are not limited to the location of the customer. Jackson and Srinivas (2021) compared three strategies of truck-only, truck-tandem and drone-only through a discrete event simulation to better serve customers in the healthcare industry. The results showed that in terms of cost and time, the drone-only strategy is the most efficient strategy where a large number of drones are available.

The research papers in the literature of the subject are summarised in Table 1 where, five characteristics are specified in this table to represent the differences between these papers. The first characteristic determines the objective function in terms of the costs (installation, operational, and transportation costs, etc.), the fleet size, delivery in the intervals preferred by the customer, delivery time, route length, unsatisfied demand of the retailer, greenhouse gas emission rate, customer service level, and customer value. The second characteristic is related to the constraints of the mathematical program regarding the full or partial service provision for the customers, service provision capacity, guarantee of opening the facilities in the case of customer allocation, customer service level, dynamic service provision based on the time periods, the limited number of candidate locations, and the budget amount. The uncertain data can have an exact distribution, a subjective uncertainty, or an approach to control conservatism along with computational flexibility. Accordingly, the third characteristic is determined based on the stochastic programming, fuzzy programming and robust optimisation. The fourth characteristic presents the location based on last-mile fulfilment options. The last column of the fourth characteristic presents the combination of the options and their relationships. Finally, the fifth characteristic considers the effect of customer behaviour on location. The periods in which the customer's behaviour is observed can be independent or dependent in a time horizon.

In order to develop marketing strategies, companies classify the customers in terms of their characteristics. Hence, it is necessary to classify the customers because "as companies have limited resources, they have to use their resources effectively by selecting the valuable customers and making effort to keep them". On the other hand, "companies should first segment their customers and then determine the special offerings and priorities in order fulfilling and required degree of relationship for each segment" (Gucdemir and Selim, 2015). Based on a thorough literature of review:

Table 1 Summary of the most relevant papers in the literature

	Objective function									*Constraints*								*Uncertain conditions*			*Last-mile fulfillment options*					*Customers' behaviour*	
	Cost	*Fleet size*	*Preference*	*Time*	*Distance*	*Unsatisfied demand*	*Greenhouse gas emission*	*Level of service*	*Customer value*	*Full-service provision*	*Partial service provision*	*Capacity*	*Opening of the facilities*	*Customer service level*	*Dynamic service provision*	*The number of candidate locations*	*Budget*	*Stochastic programming*	*Fuzzy programming*	*Robust optimisation*	*Conventional shopping*	*Home delivery*	*Locker station*	*Pickup point*	*Hierarchical Hybrid*[1]	*independent*	*dependent*
Zhou et al. (2016)	✔									✔		✔	✔									✔		✔			
Noyan and Kahvecioglu (2017)				✔		✔				✔		✔				✔	✔	✔			✔						
Jahangiriesmaili et al. (2017)	✔									✔			✔									✔					
Deutsch and Golany (2018)	✔									✔			✔										✔				
Janjevic et al. (2019)	✔									✔		✔										✔					
Baldi et al. (2019)	✔									✔	✔	✔															
Orenstein et al. (2019)	✔										✔	✔															
Lee et al. (2019)					✔					✔			✔										✔				
Chauhan et al. (2019)								✔			✔	✔	✔									✔					
Schwerdfeger and Boysen (2020)		✔								✔		✔			✔								✔				
Xu et al. (2020)	✔									✔		✔		✔	✔								✔	✔		✔	
Salama and Srinivas (2020)	✔			✔						✔		✔	✔			✔						✔					
Sitek et al. (2020)					✔					✔		✔										✔					
Kuo et al. (2021)	✔									✔		✔			✔							✔					
Luo et al. (2021)	✔			✔						✔					✔							✔					
Moshref-Javadi et al. (2021)				✔						✔		✔										✔					
Jackson and Srinivas (2021)	✔									✔		✔						✔				✔					
Thomas et al. (2022)				✔						✔		✔										✔					
Salama and Srinivas (2022)				✔						✔		✔										✔					
This paper	✔		✔				✔	✔	✔		✔	✔			✔		✔		✔	✔					✔		✔

Note: [1]Hierarchy.

All the researchers, other than Xu et al. (2020), formulated the location model regardless of the customer behaviour data. While Xu et al. (2020) considered the customer behaviour data, they have not integrated the customer behaviour model into the location model. Hence, all the research efforts investigating the location of last-mile fulfilment options have assumed that all the customers are provided with services, while the priorities of order fulfilment and valuable customers have been ignored. Considering the papers in Table 1, there exist a lack of enough attention to the behaviour and value of customers in the location-allocation problems.

- In addition, Xu et al. (2020) do not mention the reasons for choosing the features used for extraction and analysis of the customer behaviour model and therefore, it is not specified whether these features have the capacity of describing the customer behaviour. Although Gucdemir and Selim (2015) introduced several variables for business customer classification, the relationships between these variables have been ignored.
- None of the objective functions of the mathematical programming models proposed in Table 1 has simultaneously considered the environment, customer service level, and customer value.
- Customer behaviour data have been studied, in the literature, regardless of the uncertain conditions. Meanwhile, the uncertain conditions have not been defined for transportation costs in terms of the customer congestion.
- In the research literature, it has been invariably assumed that the customers are the same in terms of value and they are fully served. Both of these assumptions do not reflect the real-world situation. In addition, the congestion of customers receiving services has not been considered in the research literature.
- Finally, there has been no distribution network to integrate the last-mile fulfilment options and investigate their connections.

In light of the above-mentioned research gaps in the literature, the main contributions of this paper in addressing these gaps, are listed as follows:

- Due to the importance of customer characteristics, the location-allocation optimisation model is integrated with a developed dynamic data envelopment analysis (DDEA) model to measure the value of customers periodically.
- The customer features introduced by Gucdemir and Selim (2015) have been adopted in our paper, in which the relationship between the features has been examined based on the developed DDEA model.
- A multi-objective optimisation model is proposed to consider, simultaneously, the objective functions related to the environment, the customer service level and customer value.
- The fuzzy and robust approaches have been applied to consider uncertain conditions for customer value and transportation costs.

- A comprehensive analysis is presented for situations, where service is provided for efficient and a fraction of customers. In addition, customer congestion is incorporated into the objective function of the optimisation model via the supply function presented in this paper.
- The last-mile fulfilment options have been integrated and the connections among the options have been defined hierarchically.

To the best of our knowledge, it is the first work in the field of delivery options and last-mile logistics that simultaneously considers all the above-mentioned contributions by focusing on the customer behaviour, network of delivery options, uncertain conditions, various types of services, and multiple objectives.

3 Problem statement

In this paper, it is assumed that the online retailer needs to determine the optimal strategic locations to integrate the HD, pickup point and locker station options in the last-mile distribution network in every contract period. For choosing the location, the retailer should establish a trade-off between:

1 transportation cost

2 environmental cost

3 customer value

4 customer service level

5 customer time preference.

In this regard,

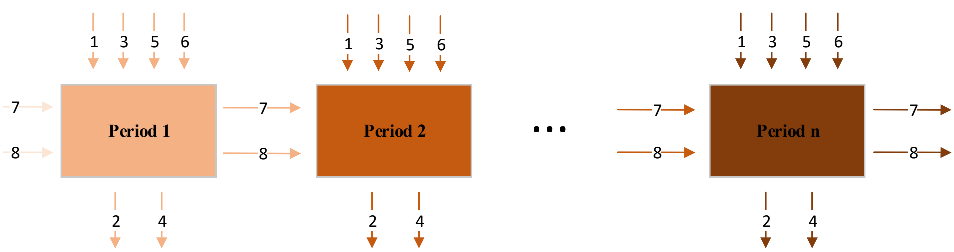
1 The transportation cost paid by the customer is calculated based on the supply function determined by the retailer. According to Khisty and Lall (2002), the supply function is presented by $p^{re} = \alpha + \beta n^d$ where, p^{re} represents the price for retailer and the cost for customer, α represents the fixed cost, β is variable cost, and n^d represents the demand. Also, it should be noted that an increase in the number of demands results in an increase in the delivery congestion.

2 In order to determine the environmental impacts, the greenhouse gas emission rate for a specific travelled distance is considered as the basis of calculating the environmental costs. Also, it is necessary to use some variables for business customer segmentation, in order to determine the customer value and the customer service level. Hence, the eight variables introduced by Gucdemir and Selim (2015) have been used in this paper. The first variable is recency which indicates the live relationship between the customer and the company. The second variable is loyalty which indicates the customers' repeated behaviour. The ratio of the total demand to the observed period of time constitutes the average annual demand (AAD), and the average expenditure of a customer during the observed period of time constitutes the average annual sales revenue (AASR). The AAD and AASR are the third and fourth variables. The fifth variable is frequency which indicates the average number of

transactions conducted during the observed period. The sixth variable considers both the loyalty and recency simultaneously, and it is referred to as the long-term relationship potential. Finally, the average percentage changes in AAD and AASR are considered as the seventh and eighth variables, and they are calculated based on two consecutive periods.

3 The DDEA is used, in this paper, for customer valuation. Data envelopment analysis (DEA) measures the relative efficiency of a set of decision-making units (DMUs), such that it focuses on the ratio of production of multiple outputs to application of multiple inputs. DDEA evaluates the performance of DMUs in interrelated time periods. Compared to DEA, DDEA includes quasi-fixed inputs and intermediate products in addition to the inputs and outputs, and they present the dependence between the consecutive periods (Kao, 2013). In this paper, the first, third, fifth and sixth variables are considered as inputs; the second and fourth variables are considered as outputs; the seventh variable is considered as quasi-fixed input, and the eighth variable is considered as intermediate product. A dynamic system of each customer's behaviour is presented in Figure 1, based on the above-mentioned variables.

Figure 1 The dynamic system of a customer's behaviour (see online version for colours)

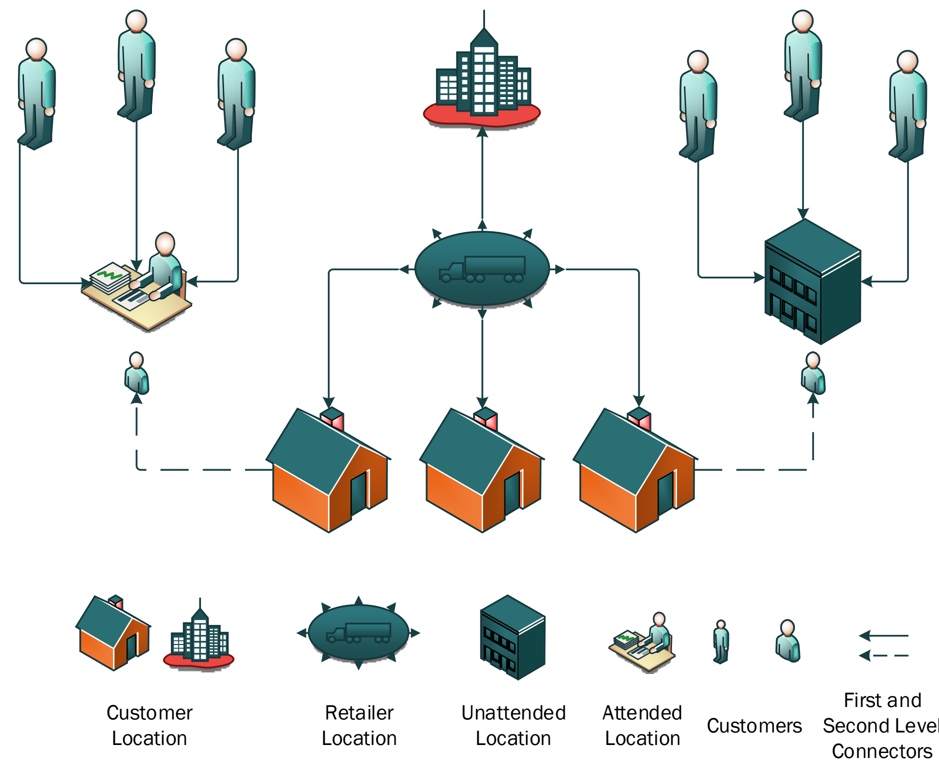


4 The customer value is determined based on the customer behaviour's data in different periods of time and the variables related to the business customer segmentation and, the retailer can optimise the last-mile distribution network, based on the customer value. Accordingly, the patterns should be detected which are both optimal and efficient. Therefore, in this paper, the location-allocation decisions are combined with DDEA (Klimberg and Ratick, 2008).

5 Finally, unlike the pickup point, the reception of service by the customer in the locker station point does not depend on the opening hours of the service provider facility. On the other hand, in the HD, the delivery time should be aligned by customer and the service provider. Therefore, it is necessary to consider the customer preferences about the time interval of receiving the service.

The structure of the delivery system proposed in this paper is presented in Figure 2. In this structure, there are two assumed levels for delivery of the parcels to the customers. In the first level, there are three groups of customers. The first group chooses the HD option and hence, the parcels are sent from the retailer location to the customer location. The second group chooses the pickup point option and hence, they go to the attended locations to receive the goods. The third group chooses the locker station option and accordingly, they go to the unattended locations to receive the goods. In the second level, there are two groups of customers. These two groups include the customers who have chosen the HD option but, they were not present in their location at the delivery time. Therefore, they go to the attended or unattended locations to receive their parcels. The structure proposed in this paper considers the transportation costs, environmental costs, customer service level, customer value and the customer's time preference for parcel delivery and at the same time, it integrates and connects the delivery options to each other. In this regard, this structure is referred to as the EHHD structure.

Figure 2 The EHHD structure (see online version for colours)



In the following, the assumptions of the mathematical model, proposed in this paper, are explained.

- Since customer behaviour varies according to their needs at different time periods, the online retailers develop their plans based on the customers' dynamic demands.
- The conditions in the real world are uncertain. In particular, transportation and customer behaviour, which depend on several uncontrollable factors, are among the parameters that should be considered under uncertainty. That said, the customer behaviour data and the transportation costs are uncertain.

- Due to space constraints in cities, the locations are selected among a set of known potential points.
- In order to improve customer convenience and enhance the level of service, failed deliveries due to the absence of the customer are rescheduled through other delivery points. Therefore, if those customers who choose the HD option are not present in the delivery location, they should receive their goods from either the pickup point or the locker station, depending on the information provided for the online retailer.
- Budget, space and facilities, etc. are among factors that naturally lead to limitations in the provision of services. As a result, the service provision locations have a limited capacity.

4 Problem formulation

In this section, the formulation of the EHHD problem based on a multi-objective programming model is presented. In this regard, Table 2 describes the indices, parameters and the decision variables of the model.

Table 2 Notations

Symbol	*Description*
Indices	
$i \in I = \{1, 2, \ldots, r^h\}$	The set of customers choosing the home delivery option.
$a \in A = \{1, 2, \ldots, r^p\}$	The set of customers choosing the pickup point option.
$u \in U = \{1, 2, \ldots, r^l\}$	The set of customers choosing the locker station option.
$f \in F = \{1, 2, \ldots, m^h\}$	The potential set of the locations providing service for home delivery option.
$j \in J = \{1, 2, \ldots, m^p\}$	The potential set of the locations providing service for pickup point option.
$k \in K = \{1, 2, \ldots, m^l\}$	The potential set of the locations providing service for locker station option.
$t \in T = \{1, 2, \ldots, n\}$	The time horizon considered by the retailer for locating and providing services to the customer.
$t' \in T' = \{1, 2, \ldots, n'\}$	The set of periods in which, the retailer can provide the service, based to the customer preferences.
$g \in G = \{1, 2, \ldots, s^{in}\}$	Inputs
$q \in Q = \{1, 2, \ldots, s^{ou}\}$	Outputs
$z \in Z = \{1, 2, \ldots, s^{io}\}$	Intermediate inputs and outputs

Table 2 Notations (continued)

Symbol	*Description*
Parameters	
c_f^h	The fixed cost of activation of the location providing home delivery service
c_j^p	The fixed cost of activation of the location providing pickup point service
c_k^l	The fixed cost of activation of the location providing locker station service
e^h	The greenhouse gas emission rate for home delivery option
e^p	The greenhouse gas emission rate for pickup point option
e^l	The greenhouse gas emission rate for locker station option
e^{hp}	The greenhouse gas emission rate for hybrid home delivery and pickup point options
e^{hl}	The greenhouse gas emission rate for hybrid home delivery and locker station options
d_{if}^h	The distance between the customer *i* and the location of the service provider *f*
d_{ij}^{hp}	The distance between the customer *i* and the location of the service provider *j*
d_{ik}^{hl}	The distance between the customer *i* and the location of the service provider *k*
d_{aj}^p	The distance between the customer *a* and the location of the service provider *j*
d_{uk}^l	The distance between the customer *u* and the location of the service provider *k*
c_{kt}^r	The cost of relocating the service provider to the locker station option in each period
α^h, α^p, α^l	The fixed transportation cost of home delivery (h), pickup point (p), and locker station (l) options in the first level
α^{hp}, α^{hl}	The fixed transportation cost of the hybrid home delivery-pickup point (hp) and home delivery-locker station (hl) options in the second level
β^h, β^p, β^l	The variable transportation cost of home delivery (h), pickup point (p), and locker station (l) options in the first level
β^{hp}, β^{hl}	The variable transportation cost of the hybrid home delivery-pickup point (hp) and home delivery-locker station (hl) options in the second level
$\overline{c}_{ft}^h$	The maximum capacity of the location of the home delivery service provider
$\overline{c}_{jt}^p$	The maximum capacity of the location of the pickup point service provider
$\overline{c}_{kt}^l$	The maximum capacity of the location of the locker station service provider
I_{git}^h	The amount of the g^{th} input for i^{th} customer in period t

Table 2 Notations (continued)

Symbol	*Description*
Parameters	
I^{p}_{gat}	The amount of the g^{th} input for a^{th} customer in period t
I^{l}_{gut}	The amount of the g^{th} input for u^{th} customer in period t
O^{h}_{qit}	The amount of the q^{th} output for i^{th} customer in period t
O^{p}_{qat}	The amount of the q^{th} output for a^{th} customer in period t
O^{l}_{qut}	The amount of the q^{th} output for u^{th} customer in period t
R^{h}_{zit}	The amount of the z^{th} quasi-fixed input or the intermediate product for i^{th} customer in period t
R^{p}_{zat}	The amount of the z^{th} quasi-fixed input or the intermediate product for a^{th} customer in period t
R^{l}_{zut}	The amount of the z^{th} quasi-fixed input or the intermediate product for u^{th} customer in period t
γ^{p}_{i}	The customer i who needs the service provided by the pickup point option in the second level
γ^{l}_{i}	The customer i who needs the service provided by the locker station option in the second level
$c^{u}_{t'}$	Unwillingness of the customer i to receive the service in period ct
B	The available budget
ε	small non-Archimedean number
Γ^{h}	The uncertainty budget for the customer choosing the home delivery option
Γ^{p}	The uncertainty budget for the customer choosing the pickup point option
Γ^{l}	The uncertainty budget for the customer choosing the locker station option
$(\overline{t_1}^{M}, \overline{t_2}^{M}, \overline{t_3}^{M}, \overline{t_4}^{M}, \overline{t_5}^{M})$	The target value for each objective function
Q^{b}	Certain bound
$\delta_1, \delta_2, \delta_3, \delta_4, \delta_5$	Preferential weight for each goal
Δ	A small positive number
M^{bn}	A large number
Decision variables	
x^{h}_{ft}	$x^{h}_{ft} = 1,$ if a home delivery service provider is located at location f in period t; $x^{h}_{ft} = 0,$ otherwise
x^{p}_{jt}	$x^{p}_{jt} = 1,$ if a pickup point service provider is located at location j in period t; $x^{p}_{jt} = 0,$ otherwise
x^{l}_{kt}	$x^{l}_{kt} = 1,$ if a locker station service provider is located at location k in period t; $x^{l}_{kt} = 0,$ otherwise

Table 2 Notations (continued)

Symbol	*Description*
Decision variables	
y^{h}_{ift}	$y^{h}_{ift}=1$, if demand point i is covered by location f in period t; $y^{h}_{ift}=0$, otherwise
y^{p}_{ajt}	$y^{p}_{ajt}=1$, if demand point a is covered by location j in period t; $y^{p}_{ajt}=0$, otherwise
y^{l}_{ukt}	$y^{l}_{ukt}=1$, if demand point u is covered by location k in period t; $y^{l}_{ukt}=0$, otherwise
y^{hp}_{ijt}	$y^{hp}_{ijt}=1$, if demand point i is covered by location j in period t; $y^{hp}_{ijt}=0$, otherwise
y^{hl}_{ikt}	$y^{hl}_{ikt}=1$, if demand point i is covered by location k in period t; $y^{hl}_{ikt}=0$, otherwise
$y^{pr}_{it'}$	$y^{pr}_{it'}=1$, if the demand point i is covered in period t'; $y^{pr}_{it'}=0$, otherwise
x^{Lh}_{ift}	The linearisation variable for customer i which is covered by location f in period t
x^{Lp}_{ajt}	The linearisation variable for customer a which is covered by location j in period t
x^{Ll}_{ukt}	The linearisation variable for customer u which is covered by location k in period t
x^{Lhp}_{ijt}	The linearisation variable for customer i which is covered by location j in period t
x^{Lhl}_{ikt}	The linearisation variable for customer i which is covered by location k in period t
y^{Lh}_{ift}	The linearisation variable indicating the efficiency of customer i covered by location f in period t
y^{Lp}_{ajt}	The linearisation variable indicating the efficiency of customer a covered by location j in period t
y^{Ll}_{ukt}	The linearisation variable indicating the efficiency of customer u covered by location k in period t
y^{Lhp}_{ijt}	The linearisation variable indicating the efficiency of customer i covered by location j in period t
y^{Lhl}_{ikt}	The linearisation variable indicating the efficiency of customer i covered by location k in period t
θ_{kt}	The slack variable of linearisation
z^{Rh}, b^{Rh}_{if}	The decision variables related to the robust programming for customer i receiving service from location f
z^{Rp}, b^{Rp}_{aj}	The decision variables related to the robust programming for customer a receiving service from location j

Table 2 Notations (continued)

Symbol	*Description*
Decision variables	
z^{Rl}, b_{uk}^{Rl}	The decision variables related to the robust programming for customer *u* receiving service from location *k*
$d_{if}^{Rh}, d_{aj}^{Rp}, d_{uk}^{Rl}$	Deviations from the nominal values are related to home delivery, pickup points and locker stations, respectively, in the robust approach
v_{gi}^{h}	The weight assigned to the g^{th} input for customer i
v_{ga}^{p}	The weight assigned to the g^{th} input for customer *a*
v_{gu}^{l}	The weight assigned to the g^{th} input for customer *u*
u_{qi}^{h}	The weight assigned to the q^{th} output for customer *i*
u_{qa}^{p}	The weight assigned to the q^{th} output for customer *a*
u_{qu}^{l}	The weight assigned to the q^{th} output for customer *u*
w_{zi}^{h}	The weight assigned to z^{th} quasi-fixed input or intermediate product for customer *i*
w_{za}^{p}	The weight assigned to z^{th} quasi-fixed input or intermediate product for customer *a*
w_{zu}^{l}	The weight assigned to z^{th} quasi-fixed input or intermediate product for customer *u*
d_{i}^{eh}	The inefficiency level of customer *i*
d_{a}^{ep}	The inefficiency level of customer *a*
d_{u}^{el}	The inefficiency level of customer *u*
w_{i}^{eh}	The efficiency level of customer *i*
w_{a}^{ep}	The efficiency level of customer *a*
w_{u}^{el}	The efficiency level of customer *u*
$d_1^{M-}, d_2^{M-}, d_3^{M-}, d_4^{M-}, d_5^{M-}$	The negative deviation variables
$d_1^{M+}, d_2^{M+}, d_3^{M+}, d_4^{M+}, d_5^{M+}$	The positive deviation variables
α^{D}, β^{D}	The positive and negative deviation variables for meta-goal programming
$y_{ift}^{FRh}, y_{ajt}^{FRp}, y_{ukt}^{FRl}, y_{ijt}^{FRhp}, y_{ikt}^{FRhl}$	The binary variables assigning the customer to the service provider location.

The formulation of the EHHD problem based on a multi-objective programming model is presented in equations (1)–(37). In this model, there are three customer sets *I*, *A*, and *U*, who chose the HD option, delivery points, and locker stations to receive service, respectively. Similarly, there are three sets of service locations *F*, *J*, and *K*, where the demand of each of these customers is fulfilled in the time horizon *T* with respect to the customer preferred periods *T′*. *G*, *Q*, and *Z* represent the sets of criteria for DDEA that measures the value of the customer in accordance with the Figure 1. Equations (1)–(5) represent the objective functions of the model where:

1 the first objective function minimises the transportation cost to reduce the congestion level and minimise the relocation cost

2 the second objective function maximises the customer service level

3 the third objective function minimises the greenhouse gas emission

4 the fourth objective function maximises the efficiency to determine the customer value

5 the fifth objective function minimises the customers' unwillingness to receive service in non-preferred periods.

$$\begin{aligned} Min\ OF_1 = & \sum_{i\in I}\sum_{f\in F}\sum_{t\in T}\left(\alpha^h + \beta^h y_{ift}^h\right)x_{ft}^h \\ & +\sum_{a\in A}\sum_{j\in J}\sum_{t\in T}\left(\alpha^p + \beta^p y_{ajt}^p\right)x_{jt}^p \\ & +\sum_{u\in U}\sum_{k\in K}\sum_{t\in T}\left(\alpha^l + \beta^l y_{ukt}^l\right)x_{kt}^l \\ & +\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\left(\alpha^{hp} + \beta^{hp} y_{ijt}^{hp}\right)x_{jt}^p \\ & +\sum_{i\in I}\sum_{k\in K}\sum_{t\in T}\left(\alpha^{hl} + \beta^{hl} y_{ikt}^{hl}\right)x_{kt}^l \\ & +\sum_{k\in K}\sum_{t\in T} c_{kt}^r \left|x_{kt}^l - x_{kt-1}^l\right|, \end{aligned} \tag{1}$$

$$\begin{aligned} Max\ OF_2 = & \sum_{i\in I}\sum_{f\in F}\sum_{t\in T} w_i^{eh} y_{ift}^h + \sum_{a\in A}\sum_{j\in J}\sum_{t\in T} w_a^{ep} y_{ajt}^p \\ & +\sum_{u\in U}\sum_{k\in K}\sum_{t\in T} w_u^{el} y_{ukt}^l + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} w_i^{eh} y_{ijt}^{hp} \\ & +\sum_{i\in I}\sum_{k\in K}\sum_{t\in T} w_i^{eh} y_{ikt}^{hl}, \end{aligned} \tag{2}$$

$$\begin{aligned} Min\ OF_3 = & \sum_{i\in I}\sum_{f\in F}\sum_{t\in T} e^h d_{if}^h y_{ift}^h + \sum_{a\in A}\sum_{j\in J}\sum_{t\in T} e^p d_{aj}^p y_{ajt}^p \\ & +\sum_{u\in U}\sum_{k\in K}\sum_{t\in T} e^l d_{uk}^l y_{ukt}^l + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} e^{hp} d_{ij}^{hp} y_{ijt}^{hp} \\ & +\sum_{i\in I}\sum_{k\in K}\sum_{t\in T} e^{hl} d_{ik}^{hl} y_{ikt}^{hl}, \end{aligned} \tag{3}$$

$$Max\ OF_4 = \sum_{i\in I} w_i^{eh} + \sum_{a\in A} w_a^{ep} + \sum_{u\in U} w_u^{el}, \tag{4}$$

$$Min\ OF_5 = \sum_{i\in I}\sum_{t'\in T'} c_{t'}^u y_{it'}^{pr}, \tag{5}$$

s.t.

$$\sum_{i\in I} y_{ift}^h \le \bar{c}_{ft}^h x_{ft}^h, \qquad \forall f \in F, t \in T. \tag{6}$$

$$\sum_{a\in A} y_{ajt}^p + \sum_{i\in I} y_{ijt}^{hp} \le \bar{c}_{jt}^p x_{jt}^p, \qquad \forall j \in J, t \in T. \tag{7}$$

$$\sum_{u\in U} y_{ukt}^l + \sum_{i\in I} y_{ikt}^{hl} \le \bar{c}_{kt}^l x_{kt}^l, \qquad \forall k \in K, t \in T. \tag{8}$$

$$\sum_{j\in J} y_{ijt}^{hp} = \sum_{f\in F} \gamma_i^p y_{ift}^h, \qquad \forall i\in I, t\in T. \tag{9}$$

$$\sum_{k\in K} y_{ikt}^{hl} = \sum_{f\in F} \gamma_i^l y_{ift}^h, \qquad \forall i\in I, t\in T. \tag{10}$$

$$\sum_{i\in I} y_{ift}^h \geq x_{ft}^h, \qquad \forall f\in F, t\in T. \tag{11}$$

$$\sum_{a\in A} y_{ajt}^p + \sum_{i\in I} y_{ijt}^{hp} \geq x_{jt}^p, \qquad \forall j\in J, t\in T. \tag{12}$$

$$\sum_{u\in U} y_{ukt}^l + \sum_{i\in I} y_{ikt}^{hl} \geq x_{kt}^l, \qquad \forall k\in K, t\in T. \tag{13}$$

$$\sum_{f\in F} y_{ift}^h \leq 1, \qquad \forall i\in I, t\in T. \tag{14}$$

$$\sum_{j\in J} y_{ajt}^p \leq 1, \qquad \forall a\in A, t\in T. \tag{15}$$

$$\sum_{k\in K} y_{ukt}^l \leq 1, \qquad \forall u\in U, t\in T. \tag{16}$$

$$\sum_{j\in J} y_{ijt}^{hp} \leq 1, \qquad \forall i\in I, t\in T. \tag{17}$$

$$\sum_{k\in K} y_{ikt}^{hl} \leq 1, \qquad \forall i\in I, t\in T. \tag{18}$$

$$y_{ift}^h \leq \sum_{ct\in CT} y_{it'}^{pr}, \qquad \forall i\in I, f\in F, t\in T. \tag{19}$$

$$\sum_{ct\in CT} y_{it'}^{pr} \leq 1, \qquad \forall i\in I. \tag{20}$$

$$\sum_{f\in F}\sum_{t\in T} c_f^h x_{ft}^h + \sum_{j\in J}\sum_{t\in T} c_j^p x_{jt}^p + \sum_{k\in K}\sum_{t\in T} c_k^l x_{kt}^l \leq B, \tag{21}$$

$$\sum_{g\in G}\sum_{t\in T} v_{gi}^h I_{git}^h + \sum_{z\in Z} w_{zi}^h R_{zit_1}^h = 1, \qquad \forall i\in I. \tag{22}$$

$$\sum_{g\in G}\sum_{t\in T} v_{ga}^p I_{gat}^p + \sum_{z\in Z} w_{za}^p R_{zat_1}^p = 1, \qquad \forall a\in A. \tag{23}$$

$$\sum_{g\in G}\sum_{t\in T} v_{gu}^l I_{gut}^l + \sum_{z\in Z} w_{zu}^l R_{zut_1}^l = 1, \qquad \forall u\in U. \tag{24}$$

$$\sum_{q\in Q}\sum_{t\in T} u_{qi}^h O_{qit}^h + \sum_{z\in Z} w_{zi}^h R_{zit_n}^h + d_i^{eh} = 1, \qquad \forall i\in I. \tag{25}$$

$$\sum_{q\in Q}\sum_{t\in T} u_{qa}^p O_{qat}^p + \sum_{z\in Z} w_{za}^p R_{zat_n}^p + d_a^{ep} = 1, \qquad \forall a\in A. \tag{26}$$

$$\sum_{q\in Q}\sum_{t\in T} u_{qu}^l O_{qut}^l + \sum_{z\in Z} w_{zu}^l R_{zut_n}^l + d_u^{el} = 1, \qquad \forall u\in U. \tag{27}$$

$$\left(\sum_{g\in G} v_{gi}^h I_{gi't}^h + \sum_{z\in Z} w_{zi}^h R_{zi'(t-1)}^h\right) - \left(\sum_{q\in Q} u_{qi}^h O_{qi't}^h + \sum_{z\in Z} w_{zi}^h R_{zi't}^h\right) \geq 0, \quad \forall i\in I, i'\in I, i'\neq i, t\in T. \tag{28}$$

$$\left(\sum_{g\in G} v_{ga}^{p} I_{ga't}^{p} + \sum_{z\in Z} w_{za}^{p} R_{za'(t-1)}^{p}\right) - \left(\sum_{q\in Q} u_{qa}^{p} O_{qa't}^{p} + \sum_{z\in Z} w_{za}^{p} R_{za't}^{p}\right) \geq 0, \quad \forall a\in A, a'\in A, a'\neq a, t\in T. \tag{29}$$

$$\left(\sum_{g\in G} v_{gu}^{l} I_{gu't}^{l} + \sum_{z\in Z} w_{zu}^{l} R_{zu'(t-1)}^{l}\right) - \left(\sum_{q\in Q} u_{qu}^{l} R_{zu't}^{l} + \sum_{z\in Z} w_{zu}^{l} R_{zu't}^{l}\right) \geq 0, \quad \forall u\in U, u'\in U, u'\neq u, t\in T. \tag{30}$$

$$w_i^{eh} = 1 - d_i^{eh}, \qquad \forall i\in I. \tag{31}$$

$$w_a^{ep} = 1 - d_u^{el}, \qquad \forall a\in A. \tag{32}$$

$$w_u^{el} = 1 - d_u^{el}, \qquad \forall u\in U. \tag{33}$$

$$x_{ft}^{h}, x_{jt}^{p}, x_{kt}^{l}, y_{ift}^{h}, y_{ajt}^{p}, y_{ukt}^{l}, y_{ijt}^{hp}, y_{ikt}^{hl}, y_{it'}^{pr} \in \{0,1\}, \quad \forall f\in F, j\in J, k\in K, i\in I, t\in T, ct\in CT. \tag{34}$$

$$v_{gi}^{h}, v_{ga}^{p}, v_{gu}^{l}, u_{qi}^{h}, u_{qa}^{p}, u_{qu}^{l}, w_{zi}^{h}, w_{za}^{p}, w_{zu}^{l} \geq \varepsilon, \quad \forall g\in G, i\in I, a\in A, q\in Q, u\in U, z\in Z. \tag{35}$$

$$d_i^{eh}, d_a^{ep}, d_u^{el} \geq 0, \qquad \forall i\in I, a\in A, u\in U. \tag{36}$$

$$w_i^{eh}, w_a^{ep}, w_u^{el} \ \textit{free variables}, \qquad \forall i\in I, a\in A, u\in U. \tag{37}$$

In addition, the constraints of the model are represented in equations (6)–(37). In this regard, equations (6)–(8) consider the capacity limitation at each location providing the HD service, pickup point service and locker station service, respectively, equations (9)–(10) represent the referral of a number of the first-level demands to the second level in order to use the pickup point option and locker station option, respectively, equation (11) specifies that if the service provider location is established for providing services through HD option, at least one customer is supplied by it, equation (12) specifies that if the service provider location is established for providing services through pickup point option, at least one customer is supplied by its first or second level, equation (13) specifies that if the service provider location is established for providing services through locker station option, at least one customer is supplied by its first or second level, equations (14)–(18) indicate that the customer choosing, respectively, the HD option, pickup point option, locker station option, HD and pickup point options, and HD and locker station options, is covered at most once in each period, equation (19) indicates the customers having chosen the HD option receive their parcel in their preferred time period, equation (20) indicates that the customers receive their parcel at most in one of their preferred periods, equation (21) consider the budget limitation for activation of the service provider locations, equations (22)–(24) indicate the weighted sum of the inputs and quasi-fixed inputs for the customers choosing, respectively, the HD option, pickup point option and locker station option is arbitrarily set equal to 1, equations (25)–(27) represent the inefficiency level for the customer choosing the HD option, pickup point option and locker station option, respectively, equations (28)–(30) indicate the ratio of the weighted sum of the outputs and intermediate products to the weighted sum of the inputs and quasi-fixed inputs for the customers choosing, respectively, the home delivery option, pickup point option and locker station option, is not more than 1, equations (31)–(33) consider the efficiency level for the customers choosing the HD option, pickup point option and locker station option, respectively, equation (34) represents the binary decision variables, equation (35) represents the non-negative continuous decision variables to avoid ignoring any factor in calculating efficiency, equation (36) demonstrates the non-negative continuous decision variables, and finally, equation (37) represents the decision variables unconstrained in sign.

5 Problem re-formulation

In this section, the linearisation process of the model is described to produce a formulation which simplifies the problem solving. In the first objective function (1), multiplication of the location decision variable and the covering decision variable makes the model nonlinear. Hence, equations (38)–(58) are used for transforming the nonlinear model to an equivalent linear representation (Orsun et al., 1999). In this regard, equations (38)–(41) indicate the linear transformation of the term $x_{ft}^{h} y_{ift}^{h}$, equations (42)–(45) indicate the linear transformation of the term $x_{jt}^{p} y_{ajt}^{p}$, equations (46)–(49) indicate the linear transformation of the term $x_{kt}^{l} y_{ukt}^{l}$, equations (50)–(53) indicate the linear transformation of the term $x_{jt}^{p} y_{ijt}^{hp}$, equations (54)–(57) indicate the linear transformation of the term $x_{kt}^{l} y_{ikt}^{hl}$, and finally, equation (58) indicates the binary decision variables for linearisation process.

$$x_{ift}^{Lh} = x_{ft}^{h} y_{ift}^{h}, \qquad \forall i \in I, f \in F, t \in T. \tag{38}$$

$$x_{ift}^{Lh} \le x_{ft}^{h}, \qquad \forall i \in I, f \in F, t \in T. \tag{39}$$

$$x_{ift}^{Lh} \le x_{ift}^{h}, \qquad \forall i \in I, f \in F, t \in T. \tag{40}$$

$$x_{ift}^{Lh} \ge x_{ft}^{h} + y_{ift}^{h} - 1, \qquad \forall i \in I, f \in F, t \in T. \tag{41}$$

$$x_{ajt}^{Lp} = x_{jt}^{p} y_{ajt}^{p}, \qquad \forall a \in A, j \in J, t \in T. \tag{42}$$

$$x_{ajt}^{Lp} \le x_{jt}^{p}, \qquad \forall a \in A, j \in J, t \in T. \tag{43}$$

$$x_{ajt}^{Lp} \le y_{ajt}^{p}, \qquad \forall a \in A, j \in J, t \in T. \tag{44}$$

$$x_{ajt}^{Lp} \ge x_{jt}^{p} + y_{ajt}^{p} - 1, \qquad \forall a \in A, j \in J, t \in T. \tag{45}$$

$$x_{ukt}^{Ll} = x_{kt}^{l} y_{ukt}^{l}, \qquad \forall u \in U, k \in K, t \in T. \tag{46}$$

$$x_{ukt}^{Ll} \le x_{kt}^{l}, \qquad \forall u \in U, k \in K, t \in T. \tag{47}$$

$$x_{ukt}^{Ll} \le y_{ukt}^{l}, \qquad \forall u \in U, k \in K, t \in T. \tag{48}$$

$$x_{ukt}^{Ll} \ge x_{kt}^{l} + y_{ukt}^{l} - 1, \qquad \forall u \in U, k \in K, t \in T. \tag{49}$$

$$x_{ijt}^{Lhp} = x_{jt}^{p} y_{ijt}^{hp}, \qquad \forall i \in I, j \in J, t \in T. \tag{50}$$

$$x_{ijt}^{Lhp} \le x_{jt}^{p}, \qquad \forall i \in I, j \in J, t \in T. \tag{51}$$

$$x_{ijt}^{Lhp} \le y_{ijt}^{hp}, \qquad \forall i \in I, j \in J, t \in T. \tag{52}$$

$$x_{ijt}^{Lhp} \ge x_{jt}^{p} + y_{ijt}^{hp} - 1, \qquad \forall i \in I, j \in J, t \in T. \tag{53}$$

$$x_{ikt}^{Lhl} = x_{kt}^{l} y_{ikt}^{hl}, \qquad \forall i \in I, k \in K, t \in T. \tag{54}$$

$$x_{ikt}^{Lhl} \le x_{kt}^{l}, \qquad \forall i \in I, k \in K, t \in T. \tag{55}$$

$$x_{ikt}^{Lhl} \le y_{ikt}^{hl}, \qquad \forall i \in I, k \in K, t \in T. \tag{56}$$

$$x_{ikt}^{Lhl} \ge x_{kt}^{l} + y_{ikt}^{hl} - 1, \qquad \forall i \in I, k \in K, t \in T. \tag{57}$$

$$x_{ift}^{Lh}, x_{ajt}^{Lp}, x_{ukt}^{Ll}, x_{ijt}^{Lhp}, x_{ikt}^{Lhl} \in \{0,1\} \quad \forall i \in I, f \in F, t \in T, a \in A, j \in J, u \in U, k \in K. \tag{58}$$

In addition, there exist an absolute term in the objective function (1) that is used for calculation of the relocation cost. The linear equivalent of this term is presented in equations (59)–(61) (Yu and Li, 2000).

$$\sum_{k \in K} \sum_{t \in T} c_{kt}^{r} \left| x_{kt}^{l} - x_{kt-1}^{l} \right| = \sum_{k \in K} \sum_{t \in T} c_{kt}^{r} \left(x_{kt}^{l} - x_{kt-1}^{l} + 2\theta_{kt} \right), \tag{59}$$

$$x_{kt}^{l} - x_{kt-1}^{l} + \theta_{kt} \ge 0, \qquad \forall k \in k, t \in T. \tag{60}$$

$$\theta_{kt} \ge 0, \qquad \forall k \in K, t \in T. \tag{61}$$

In the objective function (2), multiplication of the continuous efficiency decision variable and the covering decision variable makes the model nonlinear. Equations (62)–(82) represent the equivalent linear model (Tan and Khoshnevis, 2004).

$$y_{ift}^{Lh} = w_{i}^{eh} y_{ift}^{h}, \qquad \forall i \in I, f \in F, t \in T. \tag{62}$$

$$y_{ift}^{Lh} \le M^{bn} y_{ift}^{h}, \qquad \forall i \in I, f \in F, t \in T. \tag{63}$$

$$y_{ift}^{Lh} \le w_{i}^{eh}, \qquad \forall i \in I, f \in F, t \in T. \tag{64}$$

$$y_{ift}^{Lh} \ge w_{i}^{eh} - M\left(1 - y_{ift}^{h}\right), \qquad \forall i \in I, f \in F, t \in T. \tag{65}$$

$$y_{ajt}^{Lp} = w_{a}^{ep} y_{ajt}^{p}, \qquad \forall a \in A, j \in J, t \in T. \tag{66}$$

$$y_{ajt}^{Lp} \le M^{bn} y_{ajt}^{p}, \qquad \forall a \in A, j \in J, t \in T. \tag{67}$$

$$y_{ajt}^{Lp} \le w_{a}^{ep}, \qquad \forall a \in A, j \in J, t \in T. \tag{68}$$

$$y_{ajt}^{Lp} \ge w_{a}^{ep} - M\left(1 - y_{ajt}^{p}\right), \qquad \forall a \in A, j \in J, t \in T. \tag{69}$$

$$y_{ukt}^{Ll} = w_{u}^{el} y_{ukt}^{l}, \qquad \forall u \in U, k \in K, t \in T. \tag{70}$$

$$y_{ukt}^{Ll} \leq M^{bn} y_{ukt}^{l}, \qquad \forall u \in U, k \in K, t \in T. \tag{71}$$

$$y_{ukt}^{Ll} \leq w_u^{el}, \qquad \forall u \in U, k \in K, t \in T. \tag{72}$$

$$y_{ukt}^{Ll} \geq w_u^{el} - M\left(1 - y_{ukt}^{l}\right), \qquad \forall u \in U, k \in K, t \in T. \tag{73}$$

$$y_{ijt}^{Lhp} = w_i^{eh} y_{ijt}^{hp}, \qquad \forall i \in I, j \in J, t \in T. \tag{74}$$

$$y_{ijt}^{Lhp} \leq M^{bn} y_{ijt}^{hp}, \qquad \forall i \in I, j \in J, t \in T. \tag{75}$$

$$y_{ijt}^{Lhp} \leq w_i^{ep}, \qquad \forall i \in I, j \in J, t \in T. \tag{76}$$

$$y_{ijt}^{Lhp} \geq w_i^{eh} - M\left(1 - y_{ijt}^{hp}\right), \qquad \forall i \in I, j \in J, t \in T. \tag{77}$$

$$y_{ikt}^{Lhl} = w_i^{eh} y_{ikt}^{hl}, \qquad \forall i \in I, k \in K, t \in T. \tag{78}$$

$$y_{ikt}^{Lhl} \leq M^{bn} y_{ikt}^{hl}, \qquad \forall i \in I, k \in K, t \in T. \tag{79}$$

$$y_{ikt}^{Lhl} \leq w_i^{eh}, \qquad \forall i \in I, k \in K, t \in T. \tag{80}$$

$$y_{ikt}^{Lhl} \geq w_i^{eh} - M\left(1 - y_{ikt}^{hl}\right), \qquad \forall i \in I, k \in K, t \in T. \tag{81}$$

$$y_{ift}^{Lh}, y_{ajt}^{Lp}, y_{ukt}^{Ll}, y_{ijt}^{Lhp}, y_{ikt}^{Lhl} \geq 0, \quad \forall i \in I, f \in F, t \in T, a \in A, j \in J, u \in U, k \in K. \tag{82}$$

In this linearisation, equations (62)–(65) indicate the linear transformation of the term $w_i^{eh} y_{ift}^{h}$, equations (66)–(69) indicate the linear transformation of the term $w_a^{ep} y_{ajt}^{p}$, equations (70)–(73) indicate the linear transformation of the term $w_u^{el} y_{ukt}^{l}$, equations (74)–(77) indicate the linear transformation of the term $w_i^{eh} y_{ijt}^{hp}$, equations (78)–(81) indicate the linear transformation of the term $w_i^{eh} y_{ikt}^{hl}$, and equation (82) indicates the continuous decision variables for linearisation process.

6 The solution methodology

In this section, the transportation cost under uncertain conditions, the multi-objective programming solution approach, and the imprecise data of customer behaviour are discussed.

6.1 Uncertain transportation costs

In this paper, it is assumed that the variable transportation costs of the first level are uncertain parameters. The uncertain costs can be resulted from the customer congestion, the traffic in the retailer's area, and different transportation vehicles used in each service provider location. Bertsimas and Sim (2003) proposed a model for solving the binary robust optimisation problems with uncertain cost coefficients. In these problems, the uncertain parameters related to the objective function have a specific range. Hence, the decision maker can control the problem conservatism rate by transportation costs. The robust counterpart of the model is obtained by adding equations (83)–(87) to the model in which, equation (83) indicates the robust programming terms that are added to the first objective function, equations (84)–(86) represent the robust programming constraints and equation (87) represent the non-negative continuous decision variables related to the robust programming.

$$\sum_{i\in I}\sum_{f\in F} b_{if}^{Rh} + z^{Rh}\Gamma^h + \sum_{a\in A}\sum_{j\in J} b_{aj}^{Rp} + z^{Rp}\Gamma^p + \sum_{u\in U}\sum_{k\in K} b_{uk}^{Rl} + z^{Rl}\Gamma^l, \quad (83)$$

$$z^{Rh} + b_{if}^{Rh} \geq d_{if}^{Rh} x_{ift}^{Lh}, \qquad \forall i \in I, f \in F, t \in T. \quad (84)$$

$$z^{Rp} + b_{aj}^{Rp} \geq d_{aj}^{Rp} x_{ajt}^{Lp}, \qquad \forall a \in A, j \in J, t \in T. \quad (85)$$

$$z^{Rl} + b_{uk}^{Rl} \geq d_{uk}^{Rl} x_{ukt}^{Ll}, \qquad \forall u \in U, k \in K, t \in T. \quad (86)$$

$$\begin{aligned} & z^{Rh}, z^{Rp}, z^{Rl}, b_{if}^{Rh}, b_{aj}^{Rp}, b_{uk}^{Rl} \geq 0, \\ & \forall i \in I, f \in F, t \in T, a \in A, j \in J, u \in U, k \in K. \end{aligned} \quad (87)$$

6.2 Goal programming

Goal programming is a multi-criteria decision making (MCDM) approach for solving multi-objective problems. This approach minimises the deviations of the goals from achieving their targets. In fact, it seeks to find the feasible solutions that can satisfy the decision maker. Since goal programming can observe various criteria, it has become a popular approach which is used widely in different areas (Rodriguez Uria et al., 2002; Benítez-Fernández and Ruiz, 2019). Furthermore, the decision maker can set new goals on the original goals where, meta-goal programming has been developed for this purpose. The model proposed in this paper considers the meta-goal programming based on equations (88)–(95).

$$Min\ \beta^D, \quad (88)$$

s.t.

$$OF_1 + d_1^{M-} - d_1^{M+} = \overline{t}_1^M, \quad (89)$$

$$OF_2 + d_2^{M-} - d_2^{M+} = \overline{t}_2^M, \quad (90)$$

$$OF_3 + d_3^{M-} - d_3^{M+} = \overline{t}_3^M, \quad (91)$$

$$OF_4 + d_4^{M-} - d_4^{M+} = \overline{t}_4^M, \quad (92)$$

$$OF_5 + d_5^{M-} - d_5^{M+} = \overline{t}_5^M, \quad (93)$$

$$\delta_1 \frac{d_1^{M+}}{\overline{t}_1^M} + \delta_2 \frac{d_2^{M-}}{\overline{t}_2^M} + \delta_3 \frac{d_3^{M+}}{\overline{t}_3^M} + \delta_4 \frac{d_4^{M-}}{\overline{t}_4^M} + \delta_5 \frac{d_5^{M+}}{\overline{t}_5^M} + \alpha^D - \beta^D = Q^b, \quad (94)$$

$$d_1^{M-}, d_2^{M-}, d_3^{M-}, d_4^{M-}, d_5^{M-}, d_1^{M+}, d_2^{M+}, d_3^{M+}, d_4^{M+}, d_5^{M+}, \alpha^D, \beta^D \geq 0. \quad (95)$$

In this model, equation (88) indicates the achievement function, equations (89)–(93) indicate the goals structure, equation (94) represents the meta-goal constraint and equation (95) represents the non-negative continuous decision variables related to meta-goal programming.

Theorem 1: If Q^b, and $(\overline{t}_1^M, \overline{t}_2^M, \overline{t}_3^M, \overline{t}_4^M, \overline{t}_5^M)$ are the certain bound and the target values of each objective function, respectively, the solution produced by equations (88)–(95) is a Pareto efficient solution for equations (1)–(37).

Proof: Let S^{f*} is the optimal solution of equations (88)–(95), where S^{f*} represents the optimal decision variables. If S^{f*} is not an efficient solution for equations (1)–(37), there exist another feasible solution (S^{f**}) such that it has lower deviation from each goal. Since the preferential weight to each goal is positive, the weighted sum of deviations in S^{f**} is less than that of S^{f*}, and it is in contradiction with optimality of S^{f*}.

6.3 Fuzzy approach

Due to the existence of uncertainty, the customer behaviour data is imprecise. In the interval data envelopment analysis (IDEA) model proposed by Wang et al. (2005), the interval input and output data have been considered as the alternatives of the crisp input and output data. Accordingly, the best upper and lower bounds of efficiency are determined for each DMU. In this regard, the constraints in equations (28)–(30) are converted into the constraints in equations (96)–(98) to achieve both the upper bound and the lower bound of efficiency. Equations (96)–(98) indicate the joint constraints of the upper and lower bounds of efficiency. In equations (96)–(110), the upper and lower bounds of the data are shown with overbar and underbar, respectively.

$$\left(\sum_{g\in G} v_{gi}^h \underline{I}_{gi't}^h + \sum_{z\in Z} w_{zi}^h \underline{R}_{zi'(t-1)}^h\right) - \left(\sum_{q\in Q} u_{qi}^h \overline{O}_{qi't}^h + \sum_{z\in Z} w_{zi}^h \overline{R}_{zi't}^h\right) \geq 0,$$
$$\forall i \in I, i' \in I, i' \neq i, t \in T. \tag{96}$$

$$\left(\sum_{g\in G} v_{ga}^p \underline{I}_{ga't}^p + \sum_{z\in Z} w_{za}^p \underline{R}_{za'(t-1)}^p\right) - \left(\sum_{q\in Q} u_{qa}^p \overline{O}_{qa't}^p + \sum_{z\in Z} w_{za}^p \overline{R}_{za't}^p\right) \geq 0,$$
$$\forall a \in A, a' \in A, a' \neq a, t \in T. \tag{97}$$

$$\left(\sum_{g\in G} v_{gu}^l \underline{I}_{gu't}^l + \sum_{z\in Z} w_{zu}^l \underline{R}_{zu'(t-1)}^l\right) - \left(\sum_{q\in Q} u_{qu}^l \overline{O}_{qu't}^l + \sum_{z\in Z} w_{zu}^l \overline{R}_{zu't}^l\right) \geq 0,$$
$$\forall u \in U, u' \in U, u' \neq u, t \in T. \tag{98}$$

Moreover, the constraints in equations (22)–(27) are converted into the constraints in equations (99)–(104) to achieve the upper bound of efficiency.

$$\sum_{g\in G}\sum_{t\in T} v_{gi}^h \underline{I}_{git}^h + \sum_{z\in Z} w_{zi}^h \underline{R}_{zit_1}^h = 1, \qquad \forall i \in I. \tag{99}$$

$$\sum_{g\in G}\sum_{t\in T} v_{ga}^p \underline{I}_{gat}^p + \sum_{z\in Z} w_{za}^p \underline{R}_{zat_1}^p = 1, \qquad \forall a \in A. \tag{100}$$

$$\sum_{g\in G}\sum_{t\in T} v_{gu}^l \underline{I}_{gut}^l + \sum_{z\in Z} w_{zu}^l \underline{R}_{zut_1}^l = 1, \qquad \forall u \in U. \tag{101}$$

$$\sum_{q\in Q}\sum_{t\in T} u_{qi}^{h}\bar{O}_{qit}^{h} + \sum_{z\in Z} w_{zi}^{h}\bar{R}_{zit_n}^{h} + d_i^{eh} = 1, \qquad \forall i \in I. \tag{102}$$

$$\sum_{q\in Q}\sum_{t\in T} u_{qa}^{p}\bar{O}_{qat}^{p} + \sum_{z\in Z} w_{za}^{p}\bar{R}_{zat_n}^{p} + d_a^{ep} = 1, \qquad \forall a \in A. \tag{103}$$

$$\sum_{q\in Q}\sum_{t\in T} u_{qu}^{l}\bar{O}_{qut}^{l} + \sum_{z\in Z} w_{zu}^{l}\bar{R}_{zut_n}^{l} + d_u^{el} = 1, \qquad \forall u \in U. \tag{104}$$

And finally, the constraints in equations (22)–(27) are converted into the constraints in equations (105)–(110) to achieve the lower bound of efficiency.

$$\sum_{g\in G}\sum_{t\in T} v_{gi}^{h}\bar{I}_{git}^{h} + \sum_{z\in Z} w_{zi}^{h}\bar{R}_{zit_1}^{h} = 1, \qquad \forall i \in I. \tag{105}$$

$$\sum_{g\in G}\sum_{t\in T} v_{ga}^{p}\bar{I}_{gat}^{p} + \sum_{z\in Z} w_{za}^{p}\bar{R}_{zat_1}^{p} = 1, \qquad \forall a \in A. \tag{106}$$

$$\sum_{g\in G}\sum_{t\in T} v_{gu}^{l}\bar{I}_{gut}^{l} + \sum_{z\in Z} w_{zu}^{l}\bar{R}_{zut_1}^{l} = 1, \qquad \forall u \in U. \tag{107}$$

$$\sum_{q\in Q}\sum_{t\in T} u_{qi}^{h}\underline{O}_{qit}^{h} + \sum_{z\in Z} w_{zi}^{h}\underline{R}_{zit_n}^{h} + d_i^{eh} = 1, \qquad \forall i \in I. \tag{108}$$

$$\sum_{q\in Q}\sum_{t\in T} u_{qa}^{p}\underline{O}_{qat}^{p} + \sum_{z\in Z} w_{za}^{p}\underline{R}_{zat_n}^{h} + d_a^{ep} = 1, \qquad \forall a \in A. \tag{109}$$

$$\sum_{q\in Q}\sum_{t\in T} u_{qu}^{l}\underline{O}_{qut}^{l} + \sum_{z\in Z} w_{zu}^{l}\underline{R}_{zut_n}^{l} + d_u^{el} = 1, \qquad \forall u \in U. \tag{110}$$

7 Numerical experiments

In this section, the performance of the proposed model is evaluated based on some numerical experiments and the results are compared to the competing models. A significant point mentioned by Xu et al. (2020) is that "because of the privacy concerns of online customers and potential business competitive advantages gained by the analysis of online customers' private information, online retailers hesitate to share their e-store's user private information, which makes it difficult for researchers and practitioners to collect the customer's location data". In this paper, the analysis of customer behaviour data has been performed based on the real data introduced by Gucdemir and Selim (2015). The range of the parameters in the proposed model is set according to Table 3.

As mentioned previously, the performance of the proposed model is evaluated and compared to two competing methods including a traditional location approach entitled the set covering problem technique, and the model proposed by Xu et al. (2020). The EHHD problem considering the HD (type1), pickup point (type2), locker station (type3) options and the hybrid of the three mentioned options (type4) based on the set covering problem technique and the model proposed by Xu et al. (2020) is adjusted. After solving the problem, the sum of the deviation variables is presented in Table 4. Based on the results, the method proposed in this paper can effectively produce both a feasible solution and a solution closer to the decision maker's opinion, compared to the solutions produced by competing methods. Accordingly, the proposed method outperforms the competing ones.

It should be noted that there exist some significant drawbacks in the method proposed by Xu et al. (2020). The first drawback is that it has compared the optimisation model with an approach which provides no guarantee for production of an optimal solution. This comparison is unfair; because before solving the problem, the optimisation model is expected to produce a better solution. The second drawback is that the method proposed by Xu et al. (2020) is evaluated in two independent periods. Therefore, the sum of the periods of their method should be compared by a benchmark approach; because the benchmark approach is planned for both periods. Applying these modifications, the method proposed by Xu et al. (2020) loses its absolute priority.

Table 3 Range of the parameters

Parameters	*Values*	*Parameters*	*Values*
i	{1, 2, 3, 4, 5}	$\beta^h, \beta^p, \beta^l, \beta^{hp}, \beta^{hl}$	1
a	{1, 2, 3, 4, 5}	$\bar{c}^h_{ft}$	[2, 5]
u	{1, 2, 3, 4, 5}	$\bar{c}^p_{jt}$	[1, 5]
f	{1, 2, 3}	$\bar{c}^l_{kt}$	[1, 4]
j	{1, 2, 3}	I^h_{git}	[0.02, 0.999]
k	{1, 2}	I^p_{gat}	[0, 0.996]
t	{1, 2}	I^h_{gut}	[0.167, 1]
t'	{1, 2}	O^h_{qit}	[0.001, 0.935]
g	{1, 2, 3, 4}	O^p_{qat}	[0.007, 1]
q	{1, 2}	O^l_{qut}	[0, 0.547]
z	{1, 2}	R^h_{zit}	[0.008, 0.967]
c^h_f	[100, 200]	R^p_{zat}	[0, 1]
c^p_j	[100, 200]	R^l_{zut}	[0, 1]
c^l_k	[50, 100]	γ^p_i	(1, 0, 0, 0, 0)
$e^h, e^p, e^l, e^{hp}, e^{hl}$	1	γ^l_i	(0, 0, 0, 0, 1)
d^h_{if}	[10, 80]	$c^u_{t'}$	[1, 9]
d^{hp}_{ij}	[2, 90]	B	1,800
d^{hl}_{ik}	[2, 12]	ε	10^{-5}
d^p_{aj}	[6, 10]	$\bar{t}^M_1, \bar{t}^M_2, \bar{t}^M_3, \bar{t}^M_4, \bar{t}^M_5$	(20, 19, 128, 8.9, 2)
d^l_{uk}	[3,4]	Q^b	0.63
c^r_{kt}	[0.25, 0.5]	$\delta_1, \delta_2, \delta_3, \delta_4, \delta_5$	(1, 0.95, 0.98, 1, 1)
$\alpha^h, \alpha^p, \alpha^l, \alpha^{hp}, \alpha^{hl}$	0.1		

Table 4 Comparison of the methods

Method	*Option type*	*Sum of the deviation variables*
Set covering technique	Type 1	159.396
	Type 2	17.299
	Type 3	Infeasible
	Type 4	Infeasible
Xu et al. (2020)	Type 1	Infeasible
	Type 2	18.106
	Type 3	Infeasible
	Type 4	Infeasible
This paper		16.288

8 Sensitivity analysis

In this section, the effects of service level changes, transportation under uncertain conditions, customer ranking under uncertain conditions and regarding the customer's imprecise behaviour data, environmental impacts, efficient service provision, and fractional service provision are investigated.

8.1 Service level changes

In this subsection, a sensitivity analysis is performed to investigate the effect of service level changes on the target value of the second objective function. Based on Figure 3, the retailers intuitively observe the conflicts between the objective functions and create a trade-off between the service level and other goals. In Figure 3, the target value is represented in x-axis and the value of the corresponding objective function or the budget value is represented in y-axis. Based on the results, under $\overline{t}_2^M = 1, 2, \ldots, 8, 10, 11, 13$, the transportation cost is less than the average transportation cost, under $\overline{t}_2^M = 11, 12, 14, 15, \ldots, 21$, the customer service level is higher than the average customer service level, under $\overline{t}_2^M = 7, 8, \ldots, 13, 15, 16, \ldots, 21$, the greenhouse gas emission rate is lower than the average rate of greenhouse gas emission, and under $\overline{t}_2^M = 4, 5, 6, 13, 14, \ldots, 21$, the customer value is higher than the average customer value. The customer's preferred period to receive the service is not sensitive to $\overline{t}_2^M$. Finally, under $\overline{t}_2^M = 1, 2, \ldots, 8, 11, 16$, the budget value is lower than the average budget.

8.2 Transportation under uncertain conditions

In this subsection, the robust counterpart of the proposed model is studied to determine the changes that occur in the objective and budget functions due to inconsideration of the uncertain conditions. For this purpose, it is assumed that Γ^h, Γ^p and Γ^l are the integer values ranging in the intervals [0, 3], [0, 3] and [0, 2], respectively, and as a result, there exist 48 scenarios. Table 5 shows the maximum (Max), arithmetic mean (Ave), minimum (Min) and coefficient of variation (CV) of the results obtained from solving all the

48 scenarios. Based on the results, the uncertain conditions have the strongest effect on B, OF_2, OF_1, OF_3, and OF_4, respectively. In addition, OF_5 indicating the customer preference in receiving the services, is not sensitive to the uncertain transportation conditions. The uncertain condition results in the maximum increase and decrease in OF_2 and B, respectively.

Figure 3 Sensitivity analysis on service level, (a) OF_1 (b) OF_2 (c) OF_3 (d) OF_4 (e) OF_5 (f) B (see online version for colours)

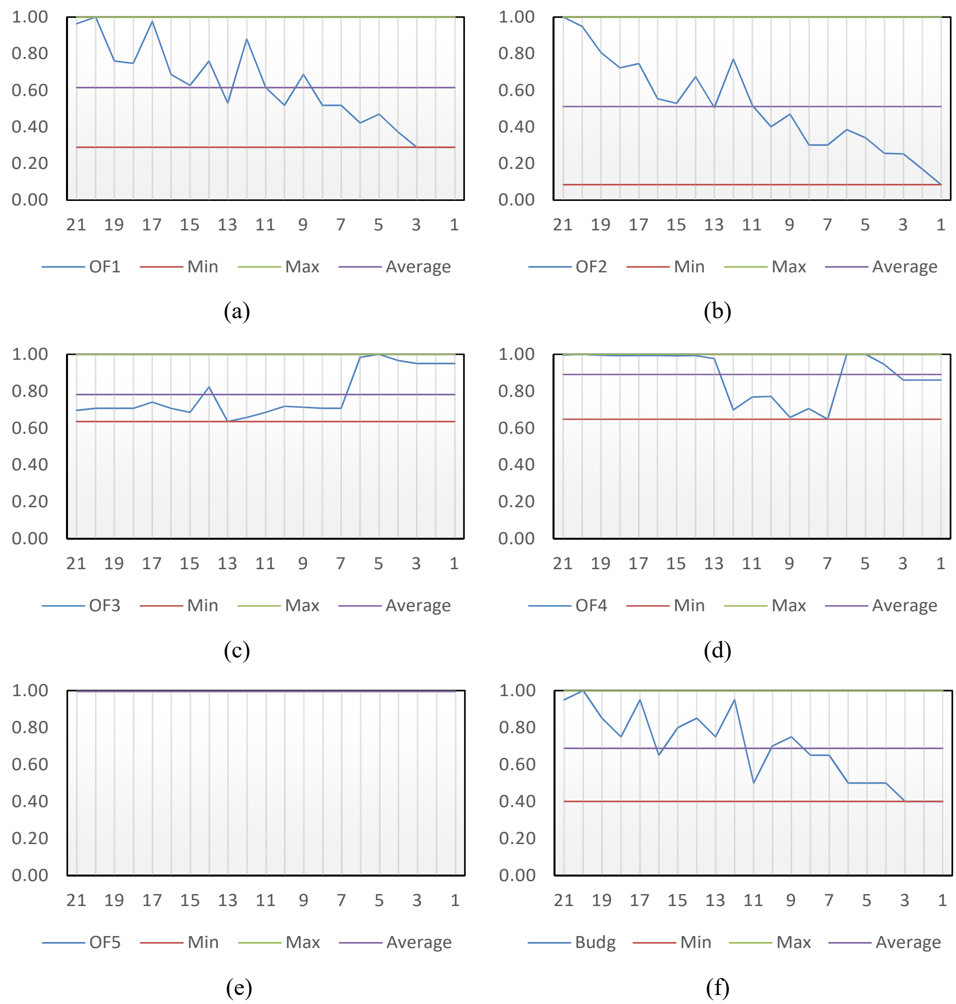


Table 5 The effect of uncertain conditions on transportation

	OF_1	OF_2	OF_3	OF_4	OF_5	B
Max	22.250	11.833	132.000	7.332	1	1,100.100
Ave	20.224	9.976	128.344	7.279	1	944.986
Min	20.000	9.575	125.000	7.107	1	600.100
CV	1.753	3.993	0.965	0.515	0	15.390

Table 6 Uncertain conditions in customer behaviour data

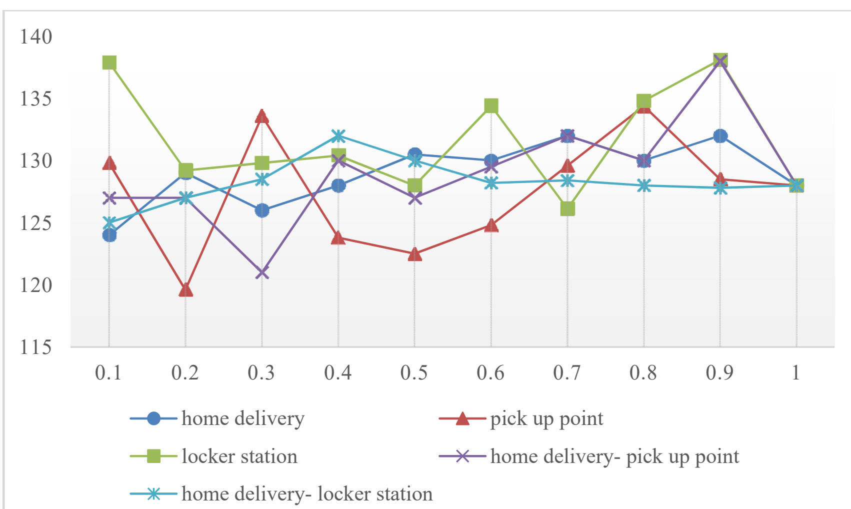
Customer clusters	*This paper*												*Gucdemir and Selim (2015)*
	Home delivery				*Pickup points*				*Locker station*				
	Lower bound 1	*Lower bound 2*	*Lower bound 3*	*Upper bound*	*Lower bound 1*	*Lower bound 2*	*Lower bound 3*	*Upper bound*	*Lower bound 1*	*Lower bound 2*	*Lower bound 3*	*Upper bound*	
1	0.426	0.347	0.281	0.521	1	1	1	1	0.161	0.145	0.128	0.178	0.166
2	0.100	0.091	0.081	0.109	0.274	0.061	0.120	0.297	0.028	0.025	0.022	0.032	0.100
3	0.467	0.425	0.382	0.510	1	1	1	1	0.508	0.452	0.397	0.575	0.243
4	0.046	0.043	0.039	0.049	0.004	0.004	0.003	0.005	0.011	0.011	0.010	0.011	0.044
5	1	1	1	1	1	1	1	1	1	1	1	1	0.546

8.3 Imprecise customer behaviour data

Gucdemir and Selim (2015) segmented the customers in five classes including the best, valuable, average, potentially valuable, and potentially invaluable customers. Gucdemir and Selim (2015) calculated three values for each group of the customers in each segmentation variable while, they performed ranking on, only, one of the values as a representative of other values. Instead, in this paper, each of those three values has been assigned to each group of the customers of every option. In this regard, all the customers using the options are scored based on the solution of the model proposed in this paper and then, the customer behaviour data is changed by 30%. In Table 6, the upper bound represents the score of each customer under deterministic conditions, while the lower bound 1, lower bound 2 and lower bound 3 represent, respectively, 10%, 20% and 30% of uncertainty in data. According to the results, uncertain condition has no effect on the efficient customers. On the other hand, for inefficient customers, the score under deterministic condition is always larger than the score under uncertain condition. The results show that increasing the uncertainty interval leads to decrease in the lower bound of efficiency, except for the second customer choosing the pickup point option.

The results show that the customer cluster 5 belongs to the 'best' cluster, based on both the approaches proposed in this paper and by Gusdemir and Selim (2015). In addition, the customers are segmented, in this paper, as 'potential valuable' and 'potential invaluable', similar to Gusdemir and Selim (2015). The customer 1 that has selected the HD option, is segmented as 'valuable' in deterministic condition and as 'average' in uncertain condition. Moreover, the customers 1, 3 and 5 that selected the pickup points option, are segmented all as 'best'.

Figure 4 The effect of the emission rate on *OF*3 (see online version for colours)



8.4 Environmental impacts

The environmental objective function depends on the emission rate of delivery options. Figure 4 presents the effect the emission rate, changing in the interval [0.1, 1], on the environmental objective function. The highest decrease of pollution has occurred in the HD option under $e^h = 0.1$, in the pickup point option under $e^p = 0.2$, in the locker station option under $e^l = 0.7$, in the hybrid HD -pickup point option under $e^{hp} = 0.3$, and in the hybrid HD and locker station option under $e^{hl} = 0.1$. For the emission rate of 0.9, the HD, locker station and hybrid HD-pickup point options resulted in the highest pollution. Based on the results, e^p and e^l play a significant role in the increase/decrease of pollution. The changes in e^p leads to the highest level of changes in the environment objective function while, the changes in e^{hl} leads to the lowest level of changes in the objective function.

8.5 Efficient service provision

The most of the supply chain networks are designed without extraction of efficient solutions while, the optimal structure results from the efficient solutions (Grigoroudis et al., 2014). In this subsection, the solutions are filtered so that their efficiency is guaranteed. For this purpose, equations (14)–(18) are transformed to equations (111)–(115). Based on this transformation, only those solutions are studied which belong to the efficient customers.

$$\sum_{f\in F} y_{ift}^{h} \le w_i^{eh}, \qquad \forall i\in I, t\in T. \tag{111}$$

$$\sum_{j\in J} y_{ajt}^{p} \le w_a^{ep}, \qquad \forall a\in A, t\in T. \tag{112}$$

$$\sum_{k\in K} y_{ukt}^{l} \le w_u^{el}, \qquad \forall u\in E, t\in T. \tag{113}$$

$$\sum_{j\in J} y_{ijt}^{hp} \le w_i^{eh}, \qquad \forall i\in I, t\in T. \tag{114}$$

$$\sum_{k\in K} y_{ikt}^{hl} \le w_i^{eh}, \qquad \forall i\in I, t\in T. \tag{115}$$

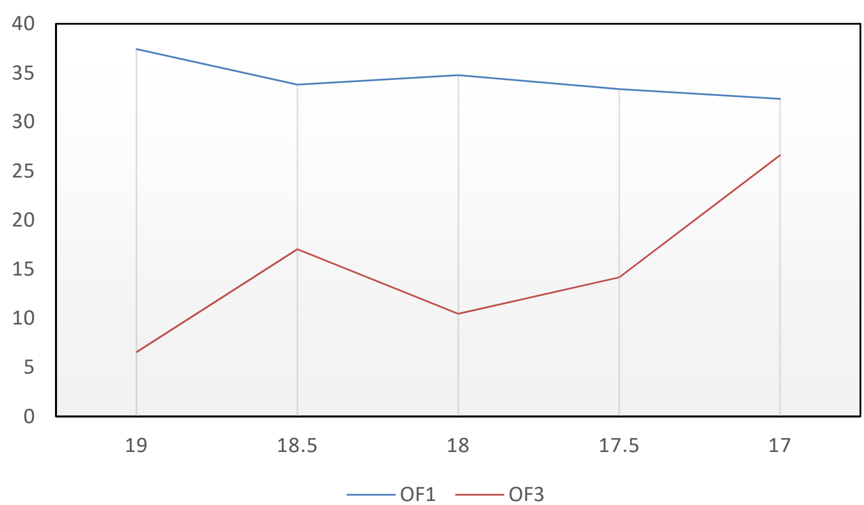
In order to determine the effect of equations (111)–(115) on the first and third objective functions, the proposed model is solved based on the second objective function and then, a sensitivity analysis is performed on the changes in the first and third objective functions. The x-axis in Figure 5, presents the value of $\overline{t}_2^M$ and the y-axis presents the change percentages between the first and third objective functions of the models solved based on equations (14)–(18) and equations (111)–(115), respectively. Based on this figure, the changes in OF_1 have a descending trend while the changes in OF_3 have an ascending trend. In general, the model solved based on equations (111)–(115) resulted in lower transportation cost and environmental impacts compared to the model solved based on equations (14)–(18).

Theorem 2: Let the P^{pr} be the proposed model solved based on equations (14)–(18) and the P^{su} be the proposed model solved based on equations (111)–(115). If S^{pr} is the set of P^{pr} solutions and S^{su} is the set of P^{su} solutions, then, $OF_1^{su} \le OF_1^{pr}$ and $OF_3^{su} \le OF_3^{pr}$ where, OF_1^{pr} and OF_1^{su} are the objective functions of the transportation cost minimisation belonging to P^{pr} and P^{su}, respectively, and OF_3^{pr} and OF_3^{su} are the objective functions of the greenhouse gas emission minimisation belonging to P^{pr} and P^{su}, respectively.

Proof: The binary solutions obtained by the model solved based on equations (14)–(18) and the model solved based on equations (111)–(115) are represented by B^{pr*} and B^{su*}, respectively. Since, at most, all the customers are efficient, $B^{su*} \leq B^{pr*}$ is concluded based on the constraints in equations (111)–(115). It is obvious that the customers who are inefficient in P^{pr} will be inefficient in P^{su}, too, and they will not be provided with service. In other words, in P^{su}, only valuable customers receive the service. Hence, it is concluded that $S^{su} \subseteq S^{pr}$ and accordingly, the following equations are concluded: $OF_1^{su} \leq OF_1^{pr}$ and $OF_3^{su} \leq OF_3^{pr}$.

Corollary: When the number of customers increases, the problem becomes large scale. In other words, cardinality leads to computational complexity. According to Barr and Durchholz (1997), the model proposed in this paper is run for the customer blocks to identify the efficient customers. Based on Theorem 2, the inefficient customers are removed from each block. On the other hand, in each iteration, the customers who are the most inefficient are removed and accordingly, the problem is optimised only for efficient customers. Therefore, based on Theorem 2, the proposed model can deal with and solve the problems with big data.

Figure 5 The changes in OF_1 and OF_3 regarding the efficient solutions (see online version for colours)



8.6 Fractional service provision

In this subsection, it is assumed that the service can be provided only for a fraction of the customers. This assumption is so practical when each demand point represents for a group of the customers. Equations (116)–(127) are used for this purpose where, equations (116)–(125) indicate the constraints guaranteeing that when the customer is assigned to the service provider location, a fraction of the customer receive the service, equation

(126) represent the non-negative continuous decision variables and equation (127) represent the binary decision variables.

$$y_{ift}^{h} \le y_{ift}^{FRh}, \qquad \forall i \in I, f \in F, t \in T. \tag{116}$$

$$y_{ift}^{h} \le 2y_{ift}^{FRh} - (2 - \Delta), \qquad \forall i \in I, f \in F, t \in T. \tag{117}$$

$$y_{ajt}^{p} \le y_{ajt}^{FRp}, \qquad \forall a \in A, j \in J, t \in T. \tag{118}$$

$$y_{ajt}^{p} \ge 2y_{ajt}^{FRp} - (2 - \Delta), \qquad \forall a \in A, j \in J, t \in T. \tag{119}$$

$$y_{ukt}^{l} \le y_{ukt}^{FRl}, \qquad \forall u \in U, k \in K, t \in T. \tag{120}$$

$$y_{ukt}^{l} \ge 2y_{ukt}^{FRl} - (2 - \Delta), \qquad \forall u \in U, k \in K, t \in T. \tag{121}$$

$$y_{ijt}^{hp} \le y_{ijt}^{FRhp}, \qquad \forall i \in I, j \in J, t \in T. \tag{122}$$

$$y_{ijt}^{hp} \ge 2y_{ijt}^{FRhp} - (2 - \Delta), \qquad \forall i \in I, j \in J, t \in T. \tag{123}$$

$$y_{ikt}^{hl} \le y_{ikt}^{FRhl}, \qquad \forall i \in I, k \in K, t \in T. \tag{124}$$

$$y_{ikt}^{hl} \ge 2y_{ikt}^{FRhl} - (2 - \Delta), \qquad \forall i \in I, k \in K, t \in T. \tag{125}$$

$$y_{ift}^{h}, y_{ajt}^{p}, y_{ukt}^{l}, y_{ijt}^{hp}, y_{ikt}^{hl} \ge 0, \qquad \forall f \in F, j \in J, k \in K, i \in I, t \in T. \tag{126}$$

$$y_{ift}^{FRh}, y_{ajt}^{FRp}, y_{ukt}^{FRl}, y_{ijt}^{FRhp}, y_{ikt}^{FRhl} \in \{0, 1\}, \quad \forall f \in F, j \in J, k \in K, i \in I, t \in T. \tag{127}$$

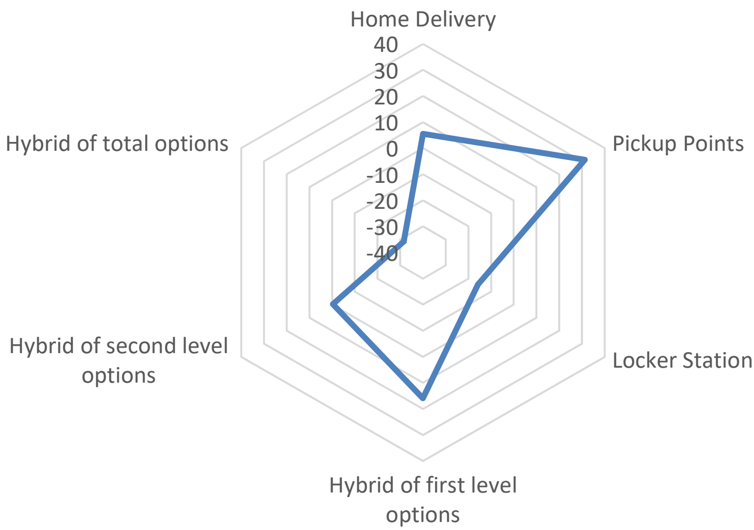
Figure 6 presents the effect of fractional service provision on delivery options regarding the achievement of the target values in terms of percentage changes. Based on the results, the fractional service provision leads to improvement in the achievement of target values compared to the non-fractional service provision under pickup point option, the hybrid of first level options, and HD option. However, the fractional service provision leads to a decrease in the achievement of the target values in case of locker station option, the hybrid of second level options, and the hybrid of total options.

Table 7 Comparison of the results of the two methods based on fractional service provision

Option type	*The sum of the deviation variables*		*Improvement percentage*
	Deutsch & Golany (2018)	*This paper*	
Type 1	159.396	15.387	90.347
Type 2	14.395	11.200	22.195
Type 3	infeasible	18.829	-
Type 4	infeasible	21.422	-

Deutsch and Golany (2018) formulated the fractional service provision for a parcel locker network. The model proposed in this paper has been compared to the method proposed by Deutsch and Golany (2018) based on the type 1, type 2, type 3 and type 4 option types, and the results are reported in Table 7. The results show that the model proposed in this paper provides more satisfactory solutions for the decision maker, under type 1 and type 2 options. Furthermore, the proposed model provided the solution for type 3 and type 4 options while, the model developed by Deutsch and Golany (2018) resulted in infeasible solution and is not able to produce the solution for type 3 and type 4 options. Therefore, the model proposed in this paper provides effectively better solutions and outperforms the competing model proposed by Deutsch and Golany (2018).

Figure 6 The effect of fractional service provision on achievement of the target values (see online version for colours)



9 A case study

In this section, the application of the proposed model is demonstrated through a case study introduced by Petridis et al. (2016). In this case study, a network of supply chain is considered that includes 20 warehouses and five customers and it is intended to design a supply chain based on efficiency. It is assumed that the services are delivered to the customers by ten warehouses (1–10) through the HD, five warehouses (11–15) through the pickup point, and five warehouses (16–20) through the locker station option. In addition, it is assumed that the customers who receive service through the pickup point and locker station options pay the transportation cost in accordance with the transportation cost paid by the customers who receive their service through the HD option. The transportation and warehouses activation cost and the capacity of the warehouses are considered based on the values considered by Petridis et al. (2016). In order to highlight the role of efficiency, it is assumed that $(\delta_1, \delta_2, \delta_3, \delta_4, {}_5) = (0.001, 1, 0.001, 0.001, 0.001)$ and $(\delta_1, \delta_2, \delta_3, \delta_4, \delta_5) = (0.0001, 1, 0.0001, 0.0001, 0.0001)$. In this case study, it is assumed that there are five customers for each option with the features mentioned in the previous section, so that among the customers who choose the HD option, customer 1 can use both the HD and the pickup point options, and customer 5 can use both the HD and the locker station options.

After solving the model, the results of the proposed method and the technique of set covering is shown in Figure 7. The standard deviation of the efficiency values in

Figures 7(a) and 7(b) is 0.0087 and 0.0006, respectively. In Figure 7(a), the efficiency of the proposed method is more than the values of type 1, type 2, type 3 and type 4. The difference between the efficiency values of the proposed method and type 1, type 2, type 3 and type 4 in Figure 7(b) is, respectively, 0.0004, 0.0002, 0.0004, 0.0018. It should be noted that the higher efficiency of the proposed method is obtained under lower budget consumption compared to other methods. Therefore, it is concluded that the proposed method resulted in more efficient solutions and much less budget consumption. All the values in Figure 7 are normalised for better comparison.

Figure 7 The results of the case study under (a) $(\delta_1, \delta_2, \delta_3, \delta_4, \delta_5) = (0.001, 1, 0.001, 0.001, 0.001)$ and (b) $(\delta_1, \delta_2, \delta_3, \delta_4, \delta_5) = (0.0001, 1, 0.0001, 0.0001, 0.0001)$ (see online version for colours)

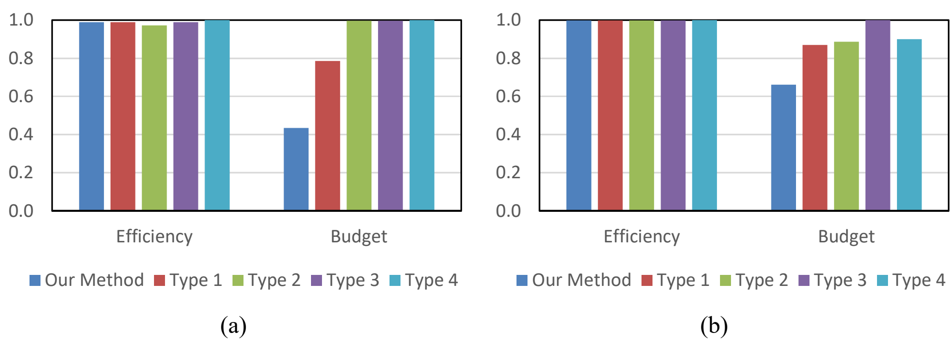
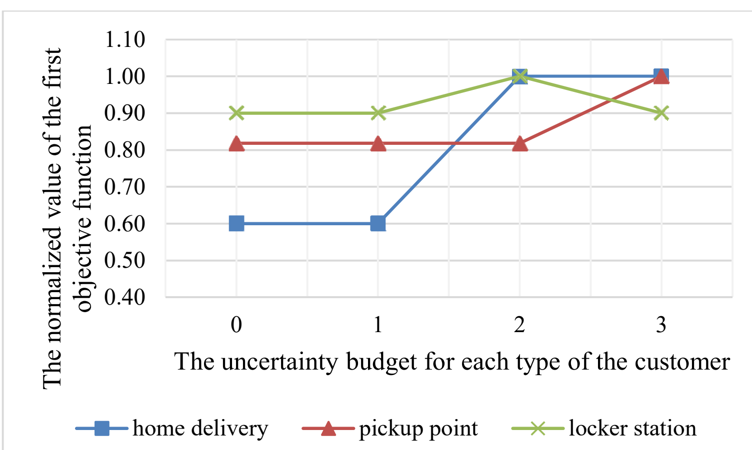


Figure 8 Cost changes vs. uncertainty budgets changes (see online version for colours)



In the following, the robustness and environmental friendliness of the proposed models are analysed as two important decision factors for supply chain managers. Figure 8 shows the cost changes based on the supply function versus changes in the uncertainty budgets $(\Gamma^h, \Gamma^p, \Gamma^l)$ for each of the delivery options. Based on the results, the pickup point option is more robust than other options because it requires a further increase in its uncertainty budget to change costs. For this reason, this option is more appropriate when the strategy of supply chain managers is focused on preserving the level of costs in uncertain conditions. On the other hand, the HD option is less robust than other options, where increasing the uncertainty budget leads to the largest change in cost. Therefore, managers choose such an option, where a sudden increase in cost does not lead to the loss of customers. With the locker station option, increasing the uncertainty budget first leads to increased costs and then to reduced costs. It is worth noting that such a decrease in the costs is due to a decrease in the level of service. Therefore, managers should be aware that increasing uncertainty in this option can lead to loss of customers. Considering the different behaviours of each of these options under uncertainty, a combination of these options can provide more confidence for supply chain managers.

Figure 9 Standard deviations caused by increased uncertainty budgets (see online version for colours)

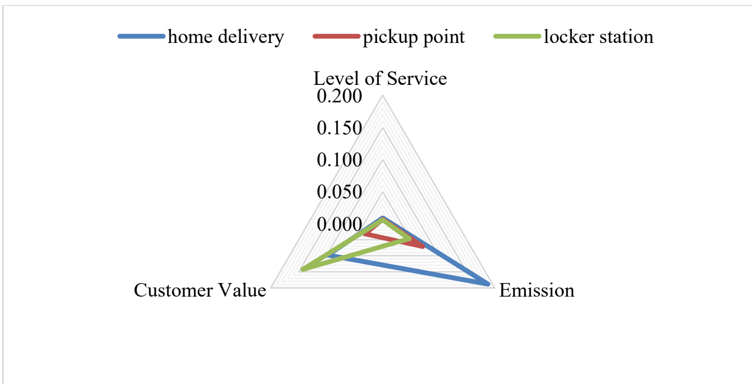
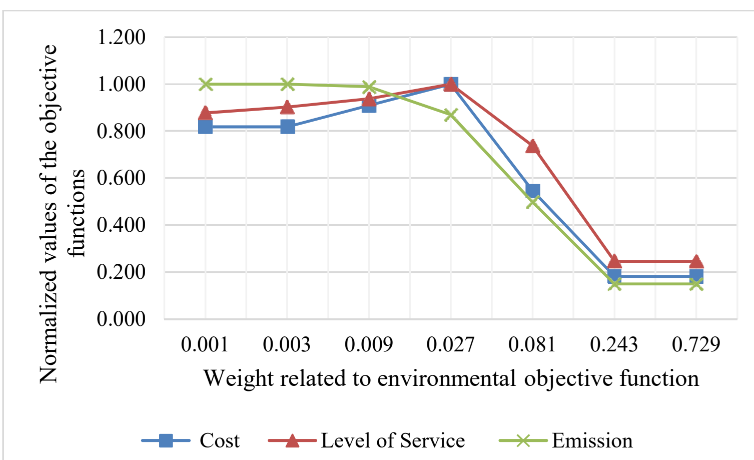
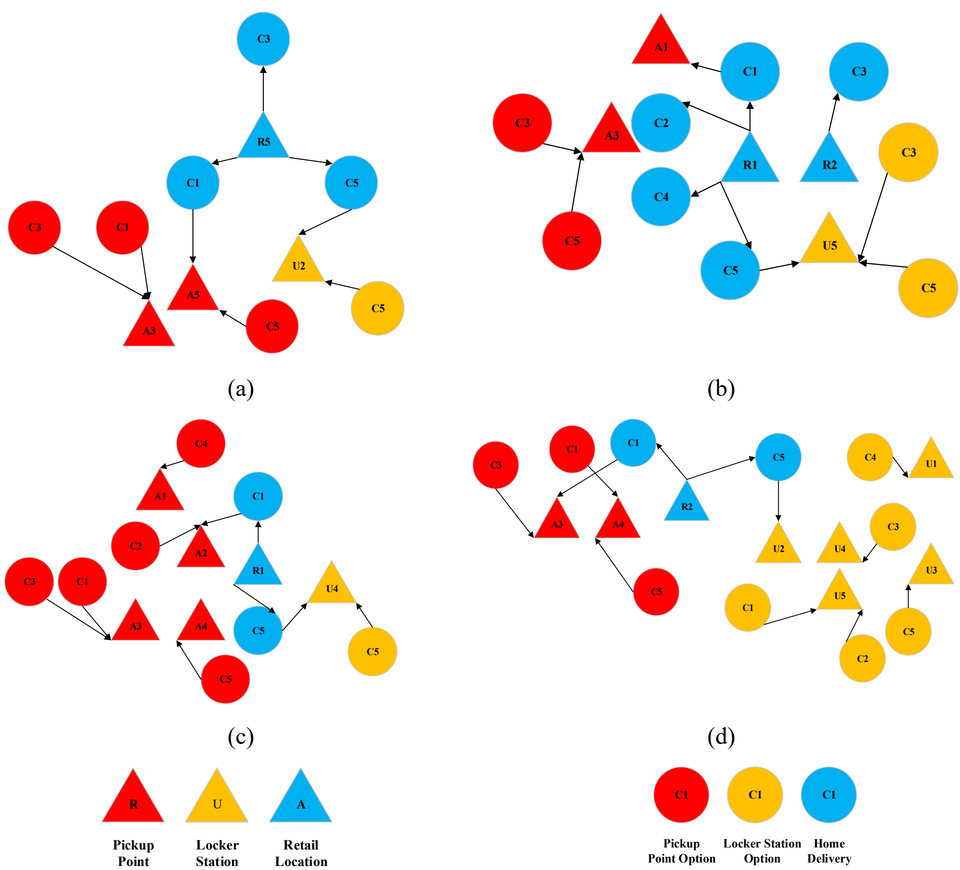


Figure 10 Environmental issues vs. the cost and level of service (see online version for colours)



On the other hand, sometimes owing to obligations that arise from the environmental laws and customer-centric strategies, it is important for supply chain managers that the delivery options structure in conditions of uncertainty generally provide good robustness for environmental and customer-related aspects. In other words, it is crucial that fluctuations in solutions due to uncertain conditions do not greatly jeopardise the robustness of managers' planning. Figure 9 shows the standard deviations of solutions extracted from each of objective functions related to the service level, customer value, and emissions where uncertainty budgets has increased according to Figure 8. As shown in Figure 9, the smallest area belongs to the pickup point option. In other words, uncertainty in this option generally leads to less dispersion of solutions than other options. Therefore, there is good robustness in this option. It is worth noting that uncertain conditions have different effects on each objective function across different delivery options. For example, the pickup point option is more robust from a customer-centric perspective than the locker station option. This is while the locker station option is more robust from an environmental perspective than the pickup point option. Hence, supply chain managers can gain more benefits by combining these options in accordance to their goals, especially where high dispersion of solutions leads to weakness in the supply chain planning.

Figure 11 Instances of optimal decisions for case study, (a) partial service provision (b) full service for HD option (a) full service for pickup point option (d) full service for locker station option (see online version for colours)



As mentioned above, the environment is another important factor which could affect the decisions of supply chain managers. Although, based on the laws that may be in place, the supply chains have to comply with environmental considerations, there are other important factors that could affect the customer service, such as the cost and level of service. Thus, supply chain managers cannot focus on just one factor. Figure 10 shows the effect of increasing the importance of the environmental objective function on the cost and service level. Based on this figure, as the weight of the environmental objective function increases, the amount of emission decreases, while the other two factors, increase initially and then decrease. It should be noted that greater focus on environmental issues could mean making customer service uneconomical for supply chain managers. When the weights are set to 0.003 and 0.009, there is a slight increase in cost, whereby the level of service is improved and greenhouse gas emissions are reduced. Weights set greater than 0.027 are justified for supply chain managers when there are strict rules on environmental issues.

Finally, the optimal decisions regarding locations and allocations are evaluated in four instances. In Figure 11, the locations and customers are represented by triangles and circles, respectively. In Figure 11(a), there is no limit on the satisfaction of all demands, while in Figures 11(b), 11(c), and 11(d) the applicants of the HD option, the pickup point option and the locker station option need to be completely satisfied. In other words, $|I|$ is set to 5 in Figure 11(b), $|A|$ is set to 5 in Figure 11(c), and $|U|$ is set to 5 in Figure 11(d). Based on the results, although partial service provides fewer connections between service locations and service recipients, it covers effective customers, who are also valuable in other instances. It is concluded that if customers did not have the same value, partial service would be more effective in the supply chain network design. This way, most of the supply chain resources are used for attending to valuable customers, and unnecessary focus on low value customers is avoided, thus reducing resource waste.

10 Conclusions

Last-mile logistics serves as a milestone in the supply chain domain, so much so that a lack of sufficient attention on the part of supply chain managers and decision makers to this issue could lead to various challenges in cities, namely, increased logistic costs, environmental impacts and traffic congestion. Hence, it is necessary to find an effective solution for last-mile logistics problem. For this purpose, the EHHD model is developed in this paper. This model is a data-driven method which integrates the location-allocation optimisation model with DDEA model. This integration is done considering the significant effect of the customer behaviour data, which is periodically investigated by the dynamic DEA in the developed model, on the optimal location-allocation decisions. On the other hand, the proposed model considers different delivery options including HD, the pickup point and the locker station options, simultaneously, where these options are hierarchically connected to each other.

Based on the EHHD model, the online retailers can create a trade-off between the transportation costs, environmental impacts, customer value, customer preferences and the service level. Since some of the terms in the proposed model are nonlinear, the linearisation process was implemented on the model. Then, robust and fuzzy approaches are employed to examine uncertain conditions for transportation costs and the customer behaviour data. Since EHHD is a multi-objective optimisation model, meta-goal programming was used as a solution approach for the proposed model. The numerical experiments showed that the proposed model has a higher performance compared to other methods in terms of both producing a feasible solution and a solution which is closer to the decision maker's opinion. In addition, a sensitivity analysis was applied on the service level, uncertain conditions, efficient service provision, environmental impacts and fractional service provision. Based on this analysis, OF_1, OF_2, and B have a similar trend in terms of the service level. Based on the results, the uncertain condition has the strongest effect on OF_2 and B; however, it has no effect on the efficient customers. The two elements that are effective in increasing and decreasing pollution are e^p and e^l. Efficient service provision can decrease the allocation costs, and fractional service provision has the strongest improving effect on the pickup point option. Finally, an application of the developed model on the supply chain network is demonstrated in a case study. The results showed that the developed model is able to provide a high level of service while spending less budget compared to other competing models. On the other hand, the pickup point option was shown to be more robust than other options. A sensitivity analysis on the importance of emissions in the proposed model indicated that higher focus on controlling environmental impacts can lead to a drastic reduction in service level. Finally, the partial service strategy can cover valuable customers and help design the supply chain efficiently. In other words, supply chain resources are planned for more important customers rather than for all customers.

Since this paper is the first attempt to adopt a hierarchical structure for delivery options in accordance with customer behaviours, this has resulted in some limitations in this research. The most important limitation was limited access to private information. Such information is required for location-allocation decisions and evaluation of customer behaviour, while dissemination of such information by institutions and organisations is illegal due to privacy policies and considerations. Important innovations are presented in this research, including the development of a hierarchical structure of delivery options, attention to environmental issues and types of services, measuring the customer value, considering uncertainty conditions for transportation costs and customer behaviour, and addressing customer congestion. Accordingly, this paper provides many research opportunities for future studies. In this regard, it should be noted that the proposed model can be extended to a two-phase approach in which, the first phase optimises the location-allocation model, and the second phase optimises the VRP, regarding the fixed location of the retailers and customers. In addition, the effects of combining the other DEA models with the location-allocation model can be studied. On the other hand, since the optimisation model presented in this paper is general in scope, it can have a wide range of applications in other case studies, where researchers can focus on implementing the proposed model in other studies. Finally, other objective functions and other types of uncertain conditions are the contributions which can be included in the proposed model and are suggested for future researches.

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