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Abstract

In this paper, we address a green delivery-pickup problem for Home Hemodialysis Machines (HHMs) categorized as scarce commodities. The system supplies the HHMs either from the central depot of the company or from the individual owners. Based on the sharing economy concept, the individuals who own the HHM devices can involve in this home health care system and share them with others through the fleet of the company to make money. After delivery of portable HHM devices to the clients (patients), they will be collected, disinfected and reallocated to fulfill the demands of the other customers. Moreover, respecting the environmental concerns, the vehicles' fuel consumption and consequently the GHG emissions are realistically assumed as a function of the vehicles' load, such that the company and especially the individual owners contribute to reducing GHG emissions, in addition to the primary economic motivations. Current research provides a bi-objective mixed-integer linear programming model which seeks minimizing total system cost and total carbon emissions. In order to solve the problem, Torabi and Hassini's (TH) technique is applied and then a multi-objective meta-heuristic algorithm, self-learning non-dominated sorting genetic algorithm (SNSGA-II), is developed for medium- and large-sized problems. Finally, the application of the problem is investigated by a real case study from the healthcare sector. Numerical analyses indicate that the proposed green sharing-enabled model has a meaningful impact on both operational-level logistics determinations as well as the environmental important attainment indicators. As notable savings are guaranteed in terms of total system cost and emission, the proposed model has a great potential to provide the item sharing activities with a proper sustainable solution.

Keywords:

Sharing economy, Delivery and pickup problem, Green transportation, Multi-objective optimization, Self-learning NSGA-II

1. Introduction

Nowadays, a large number of people in the world are dialysis patients who suffer from a reduction in the kidney's ability to dispose of urea. To benefit from dialysis machines, these patients usually have to go to a hospital according to a pre-specified schedule. Home Hemodialysis Machine (HHM) as a portable generator of hemodialysis machines is powerful enough for in-center treatment but simplified for use in a patient's home. It provides patients with a reliable and robust dialysis experience (less than 2 hours) where they are most comfortable, at home.

Research has shown that patients who regularly have used HHM have less blood pressure and can survive without kidney transplant (Weinhandl et al. 2012). It implies that medication is effective when it consumed at the right time, at the appropriate place and the desired amount and desired intensity. Due to the high price of HHM and the ever-increasing number of consumers, sharing economy concept can be utilized to provide an inexpensive substitute solution for the patients rather than the HHM ownership. The sharing economy is a term for the distributing process of assets or services in a way that differs from the traditional model of corporations hiring employees and selling products to customers. In the sharing economy, individuals are contributed to rent or "share" items like their house, car and personal time to other people who need them (Hamari et al., 2016). The sharing economy is expanding rapidly in terms of the number of users, service providers and innovative concepts. In recent years, many entrepreneurs and researchers have paid attention on the issue of sharing or leasing scarce assets with high economic and reusable value. In 2016, 44.8 million U.S. adults used the sharing economy, and it is expected to grow to 86.5 million U.S. users by 2021 (Statista, 2019), and it is expected that by 2025 the share-economy market will be $335 billion (PricewaterhouseCoopers, 2015).

Today’s immense and growing potential for competitive pricing, consumers' desire to novel experience, socialization, accessibility, and sustainability portend that the sharing economy will inescapably spread and considered as part of the global economic order (Kathan et al., 2016). However, sharing policy's efficiency depends on the existence of an efficient distribution and sharing system as well as transportation as one of the most important sectors of logistics and a significant infrastructure for economic growth. Despite the key role of transport in international competitiveness, its striking effect on releasing CO_2 emissions cannot be ignored (Mohammadi et al., 2019).

As reported by ECOFYS (2010), the transportation sector is responsible for the release of about 15% of 2010 greenhouse gas emissions and in urban areas, this number increases by more than 80% (United Nations Economic and Social Council, 2009). It is therefore important that, in addition to examining the economic advantages of transport in sharing economy, to control its negative and destructive effects on the environment and reduce its carbon emissions.

Knowing the above considerations, this paper aims to improve the classic pickup and delivery models, to make them more useful for decision-makers to enhance the performance of the sharing operations while serving the customers with a timely home health services and provides the individuals a compact source of income. To integrate a kind of crowdsourcing into a for-profit corporation, a scarce delivery-pickup problem (SDPP) is investigated which attempts to find the optimal routes for a fleet of capacitated vehicles to deliver identical scarce commodities like HHM to customers and pickup used HHMs from customers after requested service time. Accordingly, after the first visit, the "delivery customers" who received the HHM will change to "pickup customers" who must get a pickup service. One key feature of SDPP is that the HHMs collected from a client can be immediately applied to meet the demand of another client with no very time-consuming setup time (including the disinfection process), which in turn affects the vehicle load capacity and designated routes. As a result of that, the healthcare provider can improve HHM utilization by performing item-sharing and delivery then pickup platform instead of using direct deliveries, which leads to less need for an initial investment.

This study, to the best of our knowledge, is the first attempt in demonstrating how the integration of the item-sharing concept into the business model of a private home health care service provider increases the company's profit and provides a compact source of income for the individual owners, and also makes remarkably the positive impacts on the environment. Our bi-objective mathematical model with the above-mentioned characteristics is distinguished from the classic pickup-delivery Problem by allowing the system to supply the HHMs either from the central depot of the company or from the individual owners. The developed optimization model incorporates two objective functions: (i) minimizing the company's total loss through minimization of transportation-related costs, including fuel consumption cost based on travel distance, plus the penalty cost on waiting and/or delay time, and payment of the rent to the individual owners of HHMs, from which the total rental income is subtracted and (ii) minimizing the total carbon emissions generated by the vehicles.

In this model, the volume of CO_2 emissions produced by the system is based on the load and the distances in which the loads are carried by the vehicles. Then, a linear form of the mathematical model is formulated and solved by an exact approach; the fuzzy aggregated method proposed by Torabi and Hassini (2008). Subsequently, the performance of the model for medium- and large-sized problems is evaluated with a meta-heuristic based on a well-known evaluative strategy, self-learning NSGA-II (non-dominated sorting genetic algorithm-II). The self-learning consists of modifying the amount of crossing and mutation probabilities according to the changes in the fitness function value that occurred after operations in the next iteration of the algorithm. Eventually, to compare the foregoing approaches, a comprehensive sensitivity analysis is performed.

In addition to the benefits of proposed SDPP in the home health sector, this model can be also realized in item-sharing, meaning that the customers who already owned a HHM, can involve in this home health service to contribute in the company's income, by temporarily renting their HHM. This idea is particularly beneficial for items which are demanded on rare (like tools, ie lathe, air compressor, lawnmowers, etc.) or just temporal occasions (like items for recreational activities, ie party and event supplies or camping accessories), or even treatment equipment. This allows low rental fees for desired items, concurrently with the chance of more sustainable consumption (Lamberton and Rose, 2012). In a real case from the health sector which motivated this research, a limited number of portal HHMs is used as depicts in **Fig. 1** to serve the patients.

The remainder of the study is arranged as follows. Section 2 provides a brief review of the relevant academic studies in this area. The problem description and developed mathematical formulation are presented in Sections 3 and 4, respectively. Section 5 provides the solution methods for the investigated SDPP. In Sections 6, a real case from the health sector is studied and the efficiency of the proposed model and solving methods are examined, accordingly. Eventually, Section 7 concludes the main findings of the research and provides directions for further research.

Fig. 1. Company offer the comfort of hemodialysis at home by portal dialysis machines (The National, 2018).

2. Literature review

The sharing economy has grown over the past few years where it now serves as an all-encompassing term which indicates to activities of acquiring, presenting or sharing access to goods and services (see Reim et al., 2015; Tukker, 2015). The benefit of delivery-pickup service in a sharing system is that many people can sequentially utilize the same thing instead of individually purchasing one such thing (Bardhi and Eckhardt, 2012). The literature on sharing economy is an emerging field of research in diverse systems which involves but is not restricted to well-known parts such as bike-, car-, and ride-sharing (see Furuhata et al., 2013; Lei and Ouyang, 2018; Ricci, 2015; Ho and Szeto, 2017; Shaheen and Cohen, 2013, Yu et al., 2019b).

Previous studies on item-sharing have coordinated the assignment of supplied items to demands. Carrying a good from its current place to the place where it is requested remains in the user obligation (see Bardhi and Eckhardt, 2012). Although the duty of moving can be outsourced to transport companies like DHL or Airbnb, the prices charged in this way and the long sending time can be a threat to accept item-sharing by customers. They may decide to take responsibility for carrying that needs time and effort and consequently leads to decreasing of user acceptance. Such an item-sharing system asks for practical mechanisms to coordinate the provided items with the requests, but the aforementioned concept and their operational decision are not lectured by research so far.

Pickup and delivery problems (PDPs) generalize the vehicle routing problem (VRP). The PDP investigates planning routes for multiple requests, and for each request, a commodity is transported from a pickup point to a delivery point (for an overview on routing problems with pickup and delivery see Ho and Szeto, 2016). In this study, the PDPs are referred for an overview of sharing problems with pickup and delivery structure which have been surveyed by researches for a long time (see Battarra et al., 2014; Mirzapour Al-e-Hashem and Rekik, 2014; Berbeglia et al., 2007). To the best of our knowledge, a sharing-enabled PDP for HHMs has not been addressed in the literature so far.

The PDPs can be categorized based on the transportation patterns of items, the features of the depots and customers, and constraints on items carried by vehicles. In the routing problem, a depot is a place where goods are kept until they are sent somewhere to be used, a building that vehicles leave from. The proposed model introduces a new entity is called an individual, which is neither a customer nor a depot. Individuals can act as a depot and the truck can load there. While the trucks do not pay for the use of the depot, they are charged by the individuals for renting HHMs. On the other hand, they are similar to customers, because when the item is rented from an individual, it must be returned to him, although trucks are not required to visit them. Besides, ignoring them has not a direct cost for the company such as lost sales.

Based on a comprehensive survey of the PDP presented by Parragh et al. (2008, Parts I and II), PDP outlines can be split into transmission among the depot and clients as well as conveyance between clients. The first structure includes goods picked from and delivered to the customers in which a vehicle leaves the depot, picks up items from and concurrently delivers items to clients and eventually returns to the depot (Zhu and Sheu, 2018; Shi et al., 2018; Karimi, 2018). The second type is applied in carrying to satisfy a set of delivery points with goods gathered from different pickup points (Ho and Szeto, 2016; Archetti et al., 2018; Wang et al., 2018a; Anily and Bramel, 1999). The literature can also be categorized according to the size of the employed fleet. Multi-vehicle transportation problems are straight branches of single-vehicle versions and more realistic (Sun, et al., 2019; Rey et al., 2019; Heng, et al., 2015). Another pickup and delivery routing problem are investigated by Sun et al. (2018), where the authors provide an optimization-based structure for variants of the PDP with time windows that can specify time-dependent travel as well as recognize vehicle start times. In our proposed model, the vehicle leaving time is formulated with continuous-time variables which makes modeling straightforward and many of associated researches are completely related to the real applications (e.g. Ropke and Cordeau, 2009; Naccache et al., 2018; Sun et al., 2018 and Z. Al Chami et al., 2017). In other underlying models like Iassinovskaia et al. (2017) and Ghilas et al. (2016), the time is discretized in periods in which a sailing leg or a stop in port (demand point) may consist of several time intervals.

According to the schemes laid out by Berbeglia et al. (2007), Ho and Szeto (2016) presented an overview to 2015 and compares different variants of the PDPs. In **Table 1**, we summarize recent articles related to operational PDPs published since 2016. The first column shows the references. Then, the feature of models, the solution methods and the main variants of the problems are provided. The headings of the column represent considering sharing economy (SE), greenness (G), multi-objective (MO) and objective function (Obj). P/D, P-D, D-P, and PD stand respectively for pickup or delivery, pickup then delivery, delivery then pickup, and simultaneous pickup and delivery. Homogeneous and heterogeneous fleets are indicated by Ho and Ht. Ct, Dc, Sf, and Hd correspond respectively to investigating continuous period, discrete period, soft time window, and hard time window. Dn, Cap, 1, and >1 also use for dynamic control of capacity, studying capacitated vehicles, a single vehicle, and more than one vehicle in the fleet, respectively. In the variants column, we will refer to the classification based on a coding system by where problems are highlighted.

Although a review of the literature implies PDPs are more diverse, most of them are limited to simultaneous pickup and delivery problems or delivery of the commodities from a node to another node. Regarding **Table 1**, delivering the scarce items to customers and then picking up the used-items from the consumers (indicated by D-P in the column of characteristics) and involving the individual owners with the aim of improving the profitability, service level and environmental factors gained by sharing platforms, collectively is not addressed by researches so far. Furthermore, the green concern associated with logistics activities with less harm to the environment has been rarely discussed and the lack of such approaches can be inferred from **Table 1**. Thus, the necessity of green delivery-pickup service with item-sharing is quite evident.

As **Table 1** shows, in a very few PDP studies, different objectives have been considered despite its importance in realistic applications. Among them, Wang et al. (2018b) considered the operational cost and the number of vehicles utilized as the first and second objective functions, respectively. Although Wang et al. (2018a) and Soysal et al. (2018) have estimated CO_2 emissions of the vehicles as a function of load and speed, they considered a homogenous fleet, converse to the heterogeneous fleet in the proposed SDPP where the different carrier types with unequal capacity, fuel consumption rates, and environmental index are accessible and consequently an appropriate fleet assignment would be embedded in the model (for an overview on green routing problems see Bektaş and Laporte, 2011, Bektaş et al., 2016, Demir et al., 2014a, Demir et al., 2014b, Lin et al., 2014, and Yu et al., 2019a).

This paper aims to bridge over the aforementioned gaps by developing a multi-objective mathematical model to formulate a green sharing-enabled SDPP and improve the profitability, accessibility and even eco-friendliness achieved by item-sharing platforms.

Table 1
Characteristics of earlier studies on PDPs.

Study authors (Year)	SE	G	MO	Obj	Characteristics	Modeling	Solution procedure	Variants
Ghilas et al. (2016)				1	P-D, Ht, Dc, Hd, Cap, >1	MIP	Heuristic	Scenario-based
Ho and Szeto (2016)				1	P/D, Cap, 1	MILP	Heuristic	
Abbasi-Pooya and H. Kashan (2017)				5	PD, Ct, Cap, 1	2 MIP	Heuristic	
Al Chami et al. (2017)			✓	1, 4	P-D, Ht, Ct, Hd, Cap, >1	MILP	Meta-heuristic	
Azadian et al. (2017)				1	P-D, Ho, Ct, Hd, >1	MILP	Heuristic	
Furtado et al. (2017)				1	P-D, Ho, Ct, Hd, Cap, >1	MIP	Exact method	
Iassinovskaia et al. (2017)				1, 2, 3	PD, Dc, Sf, Cap, 1	MILP	Exact method	Inventory-routing problem
Ho and Szeto (2017)				2, 5	P-D, Ho, Ct, Cap, >1	MILP	Meta-heuristic	
Qiu et al. (2017)				1, 4	P-D, Ho, Ct, Hd, Cap, >1	MIP	Heuristic	
Ting et al. (2017)				1	P-D, Ho, Cap, >1	MIP	Meta-heuristic	Multi-vehicle selective
Veenstra et al. (2017a)				1	P-D, Ho, Ct, Hd, Cap, >1	MILP	Exact method	
Veenstra et al. (2017b)				1	P-D, 1	MILP	Meta-heuristic	Traveling salesman problem
Xu et al. (2017)				1	PD, Ho, Ct, Cap, >1	MILP	Meta-heuristic	Multi-visit unpaired
Ahkamiraad and Wang (2018)				1	P-D, Ho, Ct, Hd, Cap, >1	MILP	Meta-heuristic	Vehicle routing problem
Archetti et al. (2018)				1, 2	P-D, Ho, Dc, Cap, 1	MILP	Exact method	Inventory-routing problem
Györgyi and Kis (2018)				1, 3	P-D, Ho, Ct, Hd, >1	SMIP	Exact method	
Karimi (2018)				1	PD, Ho, Ct, Cap, >1	MIP	Meta-heuristic	Hub location-routing problem
Lei and Ouyang (2018)				1, 4	P-D, Ht, Ct, Cap, >1	MINLP	Heuristic	
Lv et al. (2018)				1	PD, Ho, Cap, >1	MIP	Heuristic	Collaborative
Madankumar and Rajendran (2018)		✓		1	P-D, Ho, Ct, Hd, Cap, >1	MILP	Exact method	Vehicle routing problem
Malaguti et al. (2018)				1	P-D, Cap, 1	ILP	Heuristic	Traveling salesman problem
Naccache et al. (2018)				1	P-D, Ho, Ct, Hd, >1	ILP	Heuristic	
Shi et al. (2018)				1, 3	PD, Ho, Ct, Sf, Cap, >1	SMIP	Meta-heuristic	
Soleimani et al. (2018)		✓	✓	1, 6	PD, Ht, Cap, >1	MINLP	Heuristic	Vehicle routing problem
Soysal et al. (2018)		✓		1, 3	P-D, Ht, Ct, Sf Cap, >1	MINLP	Exact method	
Sun et al. (2018)				1, 4	P-D, Ho, Ct, Hd, Cap, >1	ILP	Exact method	Time-dependent
Wang et al. (2018a)		✓		1, 6	P-D, Ho, Cap, 1	ILP	Exact method	Collaborative
Wang et al. (2018b)			✓	1, 4	P-D, Ht, Cap, >1	ILP	Heuristic	
Yu et al. (2017)				1	P-D, Ho, Ct, Hd, Cap, >1	MIP	Exact method	Collaborative
Zhu and Sheu (2018)				1	PD, Ho, Cap, >1	SMIP	Heuristic	
Benavent et al. (2019)				1	P-D, Ho, 1	SMIP	Heuristic	Traveling salesman problem
Goeke (2019)				1	P-D, Ho, Ct, Hd, Cap, 1	MIP	Meta-heuristic	
Rey et al. (2019)				1	P-D, Ho, Cap, >1	MIP	Heuristic	
Sun, et al. (2019)		✓		6	P-D, Ht, Ct, Hd, Cap, >1	MILP	Exact method	
Zhang et al. (2019)				1	PD, Ho, Cap, >1	MIP	Heuristic	
This study	✓	✓	✓	1, 3, 4, 6	D-P, Ht, Ct, Sf, Hd, Cap, Dn, >1	MINLP	Meta-heuristic	

1: Total distance/refueling cost, 2: Inventory cost, 3: Penalty for violated time windows, 4: Profit/Revenue, 5: Total makespan (duration), 6: Emission/fuel consumption, ILP: Integer linear programming, MIP: Mixed integer programming, MILP: Mixed integer linear programming, MINLP: Mixed integer non-linear programming, SMIP: Stochastic mixed integer programming

3. Problem definition

The proposed SDPP is a comprehensive model in which a company is willing to serve its customers (kidney patients) with a limited set of portable hemodialysis machines through its capacitated heterogeneous fleet of vehicles. To address the distribution activities, commodities (HHMs) are supplied either from the central depot or individual owners of HHMs who make them available for the company to rent for a short period. The patients' requests usually in terms of time windows and the individuals' HHMs pickup time window and maximum rental time are both received by the company in advance. The company is, therefore, attempting to pickup the HHMs from the depot or from the available individual's locations to carry them to the patients based on the given time windows. There are two main differences between the depot and individuals; depot is compulsory the starting point of the fleet tour, while the individuals are not necessarily the starting point. Picking up the HHM from the individuals imposes an extra renting cost to the system based on the rental period, which is not the case for the depot. We will discuss how this concept affects the economic and ecologic aspects of the proposed pickup-delivery system.

The patients need the HHMs only for a few hours (≤ 2hrs). The used HHMs picked up by the vehicles can be prepared for the next use after the necessary disinfection and safety checks (it takes a few minutes). Therefore, the distribution is a mixed sequence of pickup-delivery activities. A small example with **Fig. 2** is helpful to illustrate the main features considered in this problem. In this figure, the trip of different vehicles is shown with red, blue and green arrows from the depot to applicants and/or owners nodes. As shown in this figure, the vehicles can pass through the links backward and forward. After the delivery of HHMs to the customer, any other vehicle can be contacted to the customer for taking HHMs back. The nodes are, therefore, allowed to be visited more than once by different vehicles. The HHMs collected from costumers are then prepared to be reallocated to fulfill the demands of other customers. In this paper, we suggest a bi-objective programming model for home health service that aims to determine the best configuration of the routes and vehicle types, and the ideal sequence of deliveries and pickups in order to satisfy the patients' needs, and provide a compact source of income for the individual owners of HHMs such that the two following conflicting objective are being met, simultaneously; minimizing the total costs of the item sharing system and minimizing the carbon emissions generated by the vehicles.

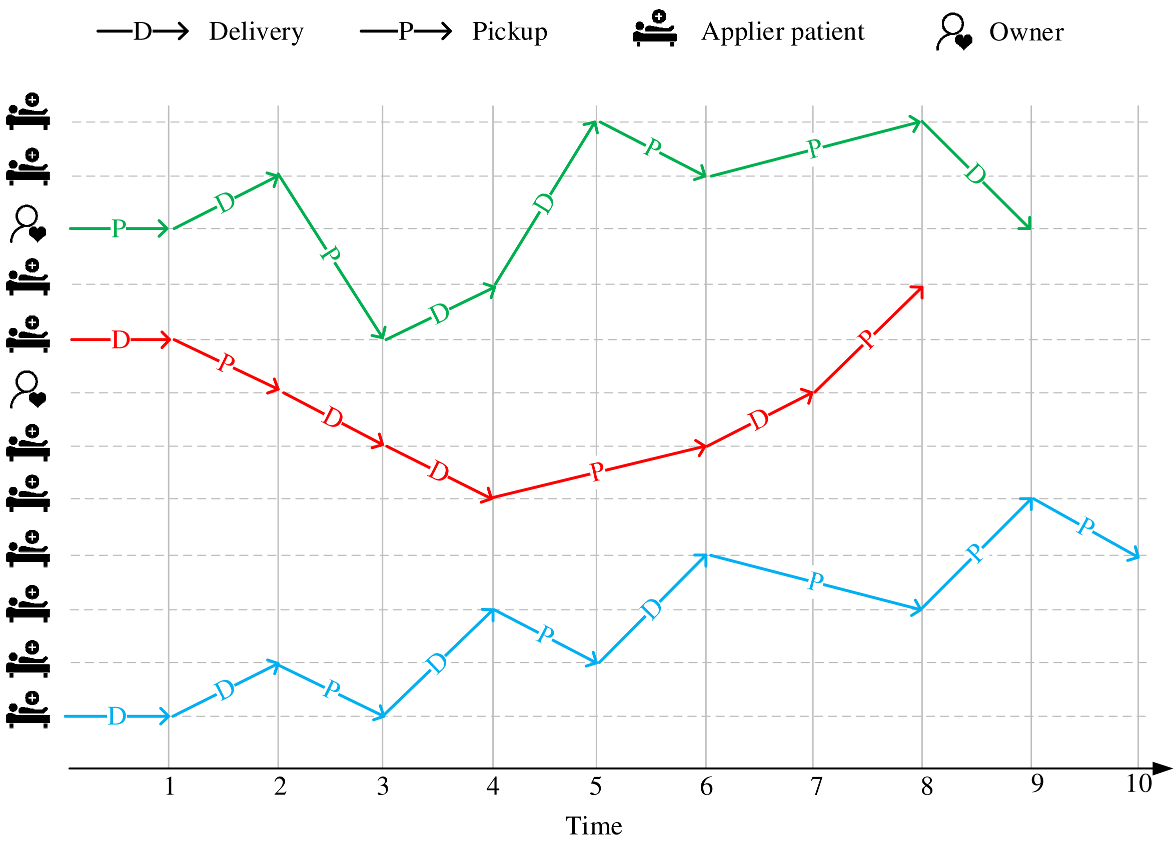

Fig. 2. General schema of a SDPP through a set of customers.

To present the mathematical model, it is essential to examine different assumptions, parameters, and decision variables. To facilitate formulation, the perspectives of assumptions are classified into four sections: 1) assumptions relating to transportation especially the vehicles, 2) assumptions concerning the customers, 3) assumptions relating to the goods, and 4) the assumptions relating to the carbon emission of vehicles. In the following, the assumptions, sets, parameters, and decision variables are given:

3.1. Assumptions

a) Transportation

- A fleet of different vehicles types is assigned to deliver and pickup HHMs throughout the network.
- The vehicles are heterogeneous and have different CO_2 emission indices, and different engine standards e.g. Euro 4, 5, etc.
- Each vehicle has a limited capacity.
- All the vehicles have the same working time.
- All vehicle starts from and ends at a single depot.

b) Customers

- The number of clients is fixed.
- Setup/Pickup time at each customer is constant.
- The demands of all customers are met.
- For each commodity, the total supply is limited and can be less than the total demand. In addition to the available HHMs which the company is owning, they also count on the HHMs are shared by the individuals. It is especially important when a vehicle encounters with a lack of HHM. In this case, the customer's demand can be satisfied through sharing and inter-client transferring.
- The split delivery to a customer is not allowed.
- All customers have a soft time window for taking the commodity.

c) Commodity

- The HHMs are similar and have an identical service time.
- At the end of a lease, the delivered HHMs must be taken back by one of the fleet vehicles at most at the end of working hours.
- When the taken HHMs are prepared in the vehicle, they are returned to the system and can be used to satisfy the demand of another customer.

d) Carbon emissions

- Amount of emitted CO_2 by each vehicle for one unit of goods per kilometer is known and can be different from vehicle to vehicle.

3.2. Sets

J : Set of all nodes ($i, j \in \{0, 1, \dots, J\} = \{0 \cup K \cup L\}$), which *0* designates the depot (arrival and departure node for the vehicles). In addition, K and L denotes the set of applicants (kidney patients) ($k \in K$) and the set of individual HHM owners ($l \in L$), respectively.

V : Set of all vehicles ($v \in \{1, 2, \dots, V\}$)

3.3. Parameters

start :	Starting time of service
end :	Ending time of service
st_j :	Setup time for delivering and checking the commodity in advance at node *j*
pt_j :	Pickup time for taking the commodity, disinfection and safety checks at node *j*
d_{ij} :	Symmetrical distance between point *i* and *j*
dr_k :	Rental time of the commodity by customer *k*
pr :	Rental price of the commodity
mr_l :	Maximum returning time determined by the individual owner *l*
re :	Rental cost paid to the individual owners
q_v :	Capacity of vehicle *v*
cap :	Total inventory of HHMs at the depot
c_{ijv}:	The variable cost of vehicle *v* per distance unit traveled from node *i* to node *j*
f_v :	Fuel consumption rate of vehicle *v* per 100 kilometers.
t_{ij} :	Travel time from node *i* to node *j*
$[e_l^{Ind}, l_l^{Ind}]$	Pickup time window of individual point *l*
$[e_k^A, l_k^A]$:	Earliest and latest arrival time at applier node *k*

ρ_k : Penalty coefficient for unit-time violations of the specified time window for applier node *k*

M : A sufficient large number

3.4. *Decision variables*

X_{ijv}^{DD} : 1, if *i* immediately precedes *j* by vehicle *v* to deliver the commodity when we have a delivery in the previous node (*i*); 0, otherwise.

X_{ijv}^{PD} : 1, if *i* immediately precedes *j* by vehicle *v* to deliver the commodity when we have a pickup in the previous node (*i*); 0, otherwise.

X_{ijv}^{D} : 1, if *i* immediately precedes *j* by vehicle *v* to deliver the commodity; 0, otherwise ($X_{ijv}^{D} = X_{ijv}^{DD} + X_{ijv}^{PD}$).

X_{ijv}^{DP} : 1, if *i* immediately precedes *j* by vehicle *v* for taking the commodity when we have a delivery in the previous node (*i*); 0, otherwise.

X_{ijv}^{PP} : 1, if *i* immediately precedes *j* by vehicle *v* for taking the commodity when we have a pickup in the previous node (*i*); 0, otherwise.

X_{ijv}^{P} : 1, if *i* immediately precedes *j* by vehicle *v* for taking the commodity; 0, otherwise ($X_{ijv}^{P} = X_{ijv}^{DP} + X_{ijv}^{PP}$).

Q_{jv}^{D} : Load of vehicle *v* when it arrives at the customer *j* for delivering the commodity

Q_{jv}^{P} : Load of vehicle *v* when it arrives at the customer *j* for taking the commodity

I_v : Initial inventory allocated to the vehicle *v*

T_j^D: Arrival time at node *j* for delivering the commodity

T_j^P: Arrival time at node *j* for taking the commodity

$\Delta\alpha_k$: Time window violation due to early service at applicant node *k*

$\Delta\beta_k$: Time window violation due to late service at applicant node *k*

Considering a vehicle of transport mode, the emitted carbon emission depends on its fuel consumption and its fuel emission factor (Hoen et al., 2014). In view of the environmental concerns, the corresponding generated carbon emission by vehicle v per kilometer is calculated as follows:

$$\varphi_v = f_v . \delta_v . \vartheta . w \tag{1}$$

Where ϑ denotes increasing rate in fuel consumption for the load carried by the vehicle, w is defined as the actual weight of the commodity and δ_v denotes fuel emission of vehicle v, which is described as amount of CO_2 emitted per liter of fuel.

4. Mathematical formulation

Base on the aforementioned explanations and indices, we develop a bi-objective mixed integer nonlinear mathematical model as follows:

$$\text{Min} \sum_{\substack{i,j \in J \\ v \in V}} d_{ij} \, . \, c_{ijv} . \left(X_{ijv}^{D} + X_{ijv}^{P} \right) + \sum_{k \in K} \rho_k . \left(\Delta\alpha_k + \Delta\beta_k \right) + re. \sum_{\substack{i \in J \\ l \in L \\ v \in V}} X_{ilv}^{P} - pr. \sum_{\substack{i \in J \\ k \in K \\ v \in V}} dr_k . X_{ikv}^{D} \tag{2}$$

$$\text{Min} \sum_{\substack{i,j \in J \\ v \in V}} d_{ij} \, . \, \varphi_v . \left(X_{ijv}^{D} . Q_{jv}^{D} + X_{ijv}^{P} . Q_{jv}^{P} \right) \tag{3}$$

The first objective function of the offered model is given in the equation (2), itself has three components; transportation-related cost (including but not limited to fuel cost, driver salary, toll costs, maintenance costs, traffic fines) that is considered as a linear function of travel distance, penalty on waiting and delay time, and the rental cost paid to the individual owners, from which the company's total revenue is subtracted. The second objective function of the offered model is given in the equation (3) which relates to the carbon emissions generated by the load-dependent combustion of fuels in vehicles. It should be noted that in the second objective function the Q and X, both are the decision variables and the two bilinear terms $X_{ijv}^{D} . Q_{jv}^{D}$ and $X_{ijv}^{P} . Q_{jv}^{P}$ consider loads carried by the vehicles. Based on the definition of fuel consumption given by Bektas and Laporte (2011), the fuel emission factor (φ_v) is determined as kilogram of CO_2 released per liter of fuel.

Subject to

Routing and flow constraints

$$\left\{\sum_{i\in J}\sum_{v\in V} X_{ikv}^{D}, \sum_{i\in J}\sum_{v\in V} X_{ikv}^{P}\right\} = 1 \qquad \forall k \in K \qquad (4)$$

$$\sum_{i\in J}\sum_{v\in V}\left(X_{ilv}^{P} - X_{ilv}^{D}\right) = 0 \qquad \forall l \in L \qquad (5)$$

$$\left\{\sum_{j\in J}\left(X_{0jv}^{D} + X_{0jv}^{P}\right), \sum_{i\in J}\left(X_{i0v}^{D} + X_{i0v}^{P}\right)\right\} = 1 \qquad \forall v \in V \qquad (6)$$

$$\sum_{i\in J} X_{ijv}^{D} = \sum_{i\in J}\left(X_{jiv}^{DD} + X_{jiv}^{DP}\right) \qquad \forall j \in J, \forall v \in V \qquad (7)$$

$$\sum_{i\in J} X_{ijv}^{P} = \sum_{i\in J}\left(X_{jiv}^{PD} + X_{jiv}^{PP}\right) \qquad \forall j \in J, \forall v \in V \qquad (8)$$

$$\sum_{i\in J}\sum_{v\in V} X_{ijv}^{D} + X_{ijv}^{P} = \sum_{i\in J}\sum_{v\in V} X_{jiv}^{D} + X_{jiv}^{P} \qquad \forall j \in J \qquad (9)$$

Equation (4) ensures that the demand of all customers (kidney patients) is satisfied. Equation (5) indicates that if the commodities are rented from an individual, it must be returned to him. Equation (6) states that all vehicles must begin their journey from the depot and eventually they must return to the depot. Equations (7-9) specify the constraints of flow conservation.

Inventory constraints

$$Q_{jv}^{D} = I_v . X_{0jv}^{D} + \sum_{i\in J}\left(X_{ijv}^{PD} . \left(Q_{iv}^{P} + 1\right) + X_{ijv}^{DD} . \left(Q_{iv}^{D} - 1\right)\right) \qquad \forall j \in J, \forall v \in V \qquad (10)$$

$$Q_{jv}^{P} = I_v . X_{0jv}^{P} + \sum_{i\in J}\left(X_{ijv}^{PP} . \left(Q_{iv}^{P} + 1\right) + X_{ijv}^{DP} . \left(Q_{iv}^{D} - 1\right)\right) \qquad \forall j \in J, \forall v \in V \qquad (11)$$

$$\sum_{v\in V} I_v \leq cap \qquad (12)$$

$$I_v \leq q_v \qquad \forall v \in V \qquad (13)$$

$$\sum_{i\in J} X_{ijv}^{D} \leq Q_{jv}^{D} \qquad \forall j \in J, \forall v \in V \qquad (14)$$

$$\sum_{i \in J} X_{ijv}^{P} \leq q_v - Q_{jv}^{P} \qquad \forall j \in J, \forall v \in V \qquad (15)$$

Equation (10) shows the vehicle's inventory for delivering HHMs when it reaches a client or owner node. The vehicle's inventory when arriving at the first customer after the depot is equal to the initial stock allocated to the vehicle. In future visits, if delivery is done in the previous node, the vehicle's inventory is reduced. Conversely, the vehicle's inventory is added, if a pickup action is done in the previous node. Equation (11) is similar to the equation (10), except that this shows the vehicle's inventory for picking up HHMs when it reaches a client or owner node. Equation (12) shows the initial allocation of HHMs to various vehicles that cannot be more than the depot's primal inventory. Equation (13) ensures that none of the vehicles can have an initial inventory greater than its capacity. Equation (14) states that a vehicle is assigned to a node for the delivery of goods when its inventory is sufficient to meet the customer's demand. Equation (15) is similar to the previous equation, a vehicle is assigned to a node for the pickup of goods when the vehicle's vacancy capacity is enough for accepting the used HHMs in the node.

Scheduling constraints

$$start + t_{0j} \leq \{T_j^D, T_j^P\} \qquad \forall j \in J \qquad (16)$$

$$\{T_j^D, T_j^P\} \leq end - t_{j0} \qquad \forall j \in J \qquad (17)$$

$$T_k^D + dr_k \leq T_k^P \qquad \forall k \in K \qquad (18)$$

$$T_l^D - T_l^P \leq mr_l \qquad \forall l \in L \qquad (19)$$

$$(T_i^D + st_i + t_{ij}) \leq T_j^D + M\left(1 - \sum_{v \in V} X_{ijv}^{DD}\right) \qquad \forall i, j \in J \qquad (20)$$

$$(T_i^P + pt_i + t_{ij}) \leq T_j^D + M\left(1 - \sum_{v \in V} X_{ijv}^{PD}\right) \qquad \forall i, j \in J \qquad (21)$$

$$(T_i^D + st_i + t_{ij}) \leq T_j^P + M\left(1 - \sum_{v \in V} X_{ijv}^{DP}\right) \qquad \forall i, j \in J \qquad (22)$$

$$(T_i^P + pt_i + t_{ij}) \leq T_j^P + M\left(1 - \sum_{v \in V} X_{ijv}^{PP}\right) \qquad \forall i, j \in J \qquad (23)$$

$$\Delta\alpha_k = Max\{e_k^A - T_k^D, 0\} \qquad \forall k \in K \qquad (24)$$

$$\Delta\beta_k = Max\{0, T_k^D - l_k^A\} \qquad \forall k \in K \qquad (25)$$

$$e_l^{Ind} - M\left(1 - \sum_{v\in V} X_{ijv}^{P}\right) \le T_l^{P} \le l_l^{Ind} + M\left(1 - \sum_{v\in V} X_{ijv}^{P}\right) \qquad \forall j \in J, \forall l \in L \qquad (26)$$

Equation (16) ensures that the delivery/pickup time to/from the first customer cannot be less than the start of the vehicle's working hours with the travel time between the depot and the node. Equation (17) ensures that the delivery/pickup time to/from the last customer delivery the travel time between that node and the depot cannot exceed from vehicle's working hours. Equation (18) states that pickup from an applicant should be done after delivery time plus rental time. Constraint (19) ensures that the commodity rented from an individual must be returned before the time specified by the owner. Equations (20-23) guarantee that when the node *j* is visited after node *i*, the start time of the service to node *j* cannot be less than the start time of the service to node *i*, plus the service time at the node *i*, and the travel time between the two nodes. Equation (24) expresses the relation between the arrival time, its earliest time of the service and the earliness variable and constraint (25) specifies the service tardiness. Equation (26) ensures that the individual points are visited within their pickup time windows.

Decision variable domains

$$Q_{jv}^{D}, Q_{jv}^{P}, T_j^{D}, T_j^{P}, I_v, \Delta\alpha_k, \Delta\beta_k \in R^{+} \qquad \forall j \in J, \forall v \in V \qquad (27)$$

$$X_{ijv}^{DD}, X_{ijv}^{DP}, X_{ijv}^{PD}, X_{ijv}^{PP}, X_{ijv}^{D}, X_{ijv}^{P} \in \{0,1\} \qquad \forall i,j \in J, \forall v \in V \qquad (28)$$

Ultimately, the set (27) makes the non-negativity constraints on the corresponding decision variables and the set (28) makes the integrality constraints on the binary variables.

4.1. *Linearization of the model*

Since a linear form is solved much faster than a nonlinear one and significantly improves its efficiency, it is expedient to convert the proposed mathematical model into the linear form. As the model is currently nonlinear due to the multiplication of variables in the second objective and two nonlinear constraints (10) and (11), we use a linearization method presented by Mirzaei and Seifi (2015). In objective function (3), we have the two bilinear terms $X_{ijv}^{D}.Q_{jv}^{D}$ and $X_{ijv}^{P}.Q_{jv}^{P}$ which can be linearized by the help of the following new variables:

$$X_{ijv}^{D}.Q_{jv}^{D} \rightarrow Y_{ijv}^{D} \qquad \forall i,j \in J, \forall v \in V \qquad (29)$$

$$X^P_{ijv}.Q^P_{jv} \rightarrow Y^P_{ijv} \qquad \forall i,j \in J, \forall v \in V \qquad (30)$$

Using (29) and (30), the objective function (3) would be simply rewritten as follows:

$$\sum_{i,j\in\{0\cup J\}} d_{ij} \, . \sum_{v\in V} \varphi_v . \left(Y^D_{ijv} + Y^P_{ijv}\right) \qquad (31)$$

The following constraints should also be added to the model:

$$Y^D_{ijv} \le \left\{Q^D_{jv}, M.X^D_{ijv}\right\} \qquad \forall i,j \in J, \forall v \in V \qquad (32)$$

$$Y^D_{ijv} \ge \left\{0, Q^D_{jv} + M.\left(X^D_{ijv} - 1\right)\right\} \qquad \forall i,j \in J, \forall v \in V \qquad (33)$$

$$Y^P_{ijv} \le \left\{Q^P_{jv}, M.X^P_{ijv}\right\} \qquad \forall i,j \in J, \forall v \in V \qquad (34)$$

$$Y^P_{ijv} \ge \left\{0, Q^P_{jv} + M.\left(X^P_{ijv} - 1\right)\right\} \qquad \forall i,j \in J, \forall v \in V \qquad (35)$$

Like above, to linearize constraints (10) and (11), new binary variables Z^{DD}_{ijv}, Z^{PD}_{ijv}, Z^{DP}_{ijv} and Z^{PP}_{ijv} are defined as the multiplication of $X^{DD}_{ijv}.Q^D_{iv}$, $X^{PD}_{ijv}.Q^P_{iv}$, $X^{DP}_{ijv}.Q^D_{iv}$ and $X^{PP}_{ijv}.Q^P_{iv}$ respectively. Also, the bilinear terms $I_v.X^D_{0jv}$ and $I_v.X^P_{0jv}$ are replaced with two new variables W^D_{jv} and W^P_{jv}, respectively. Constraints (10) and (11) are also replaced by the following constraints:

$$Q^D_{jv} = W^D_{jv} + \sum_{i\in J}\left(Z^{PD}_{ijv} + Z^{DD}_{ijv} + X^{PD}_{ijv} - X^{DD}_{ijv}\right) \qquad \forall j \in J, \forall v \in V \qquad (36)$$

$$Q^P_{jv} = W^P_{jv} + \sum_{i\in J}\left(Z^{PP}_{ijv} + Z^{DP}_{ijv} + X^{PP}_{ijv} - X^{DP}_{ijv}\right) \qquad \forall j \in J, \forall v \in V \qquad (37)$$

And in the end, the following constraints are also added to the problem

$$Z^{DD}_{ijv} \le \left\{Q^D_{iv}, M.X^{DD}_{ijv}\right\} \qquad \forall i,j \in J, \forall v \in V \qquad (38)$$

$$Z^{DD}_{ijv} \ge \left\{0, Q^D_{iv} + M.\left(X^{DD}_{ijv} - 1\right)\right\} \qquad \forall i,j \in J, \forall v \in V \qquad (39)$$

$$Z^{PD}_{ijv} \le \left\{Q^P_{iv}, M.X^{PD}_{ijv}\right\} \qquad \forall i,j \in J, \forall v \in V \qquad (40)$$

$$Z^{PD}_{ijv} \ge \left\{0, Q^P_{iv} + M.\left(X^{PD}_{ijv} - 1\right)\right\} \qquad \forall i,j \in J, \forall v \in V \qquad (41)$$

$$Z_{ijv}^{DP} \le \{Q_{iv}^{D}, M.X_{ijv}^{DP}\} \qquad \forall i,j \in J, \forall v \in V \qquad (42)$$

$$Z_{ijv}^{DP} \ge \{0, Q_{iv}^{D} + M.(X_{ijv}^{DP} - 1)\} \qquad \forall i,j \in J, \forall v \in V \qquad (43)$$

$$Z_{ijv}^{PP} \le \{Q_{iv}^{P}, M.X_{ijv}^{PP}\} \qquad \forall i,j \in J, \forall v \in V \qquad (44)$$

$$Z_{ijv}^{PP} \ge \{0, Q_{iv}^{P} + M.(X_{ijv}^{PP} - 1)\} \qquad \forall i,j \in J, \forall v \in V \qquad (45)$$

$$W_{jv}^{D} \le \{I_v, M.X_{0jv}^{D}\} \qquad \forall j \in J, \forall v \in V \qquad (46)$$

$$W_{jv}^{D} \ge \{0, I_v + M.(X_{0jv}^{D} - 1)\} \qquad \forall j \in J, \forall v \in V \qquad (47)$$

$$W_{jv}^{P} \le \{I_v, M.X_{0jv}^{P}\} \qquad \forall j \in J, \forall v \in V \qquad (48)$$

$$W_{jv}^{P} \ge \{0, I_v + M.(X_{0jv}^{P} - 1)\} \qquad \forall j \in J, \forall v \in V \qquad (49)$$

5. Solution procedure

There are numerous ways to solve a multi-objective mathematical model. To achieve the compromise solution for the proposed multi-objective optimization problem in small-scaled instances, we use the recently introduced the Torabi and Hassini's (TH) technique. Nonetheless, this method cannot solve the large-scale problems within a reasonable time, forcing us to apply a self-learning version of the NSGA-II.

5.1. *Torabi and Hassini's (TH)*

TH method provides non-dominated solutions and converts the original multi-objective mathematical model to an equivalent single objective one. The related optimization problem, including the aggregated objective function, is compiled as follows:

$$\max \tau(x) = \lambda\tau_0 + (1-\lambda)\sum_{h} \theta_h \mu_h(x) \qquad (50)$$

s.t.

$$\tau_0 \le \mu_h(x) \qquad h \in \{1,2\} \qquad (51)$$

$$x \in F(x) \qquad (52)$$

τ_0 and $\lambda \in [0, 1]$ (53)

Where $F(x)$ denotes the feasible area related to the constraints of the main model. Besides, λ and θ_h represent the coefficient of reimbursement and the weight of the h^{th} objective function, respectively. It is important to note that $\mu_h(x)$ indicates the satisfaction amount of h^{th} objective function and the optimal value of variable $\tau_0 = \min\{\mu_h(x)\}$ expresses the smallest satisfaction degree of the objective functions. To generate a balanced compromise solution, the aggregation function of the TH method surveys for a middle value among the lower bound for satisfaction level of objectives and the weighted sum of these attainment levels, based on the value of λ. Actually, arbitrary solutions can be achieved by trading off the amounts of parameters θ_h and λ (Wang and Shu, 2007). The algorithm can be summarized as follows:

i. For each objective function, determine the positive ideal solution (PIS) and the negative ideal solution (NIS). To obtain PISs, i.e., (Z_1^{PIS}, x_1^{PIS}) and (Z_2^{PIS}, x_2^{PIS}), it is needed to solve the main bi-objective problem for each objective function separately. The NIS for each objective function can be attained by Eqs. (54) and (55).

$$Z_1^{NIS} = Z_1\left(x_2^{PIS}\right) \quad (54)$$

$$Z_2^{NIS} = Z_2\left(x_1^{PIS}\right) \quad (55)$$

ii. For each objective function, determine a linear membership function by Eqs. (56) and (57). The membership functions are illustrated in **Fig. 3**.

$$\mu_1(x) = \begin{cases} 1 & if\ Z_1 < Z_1^{PIS} \\ \dfrac{Z_1^{NIS} - Z_1}{Z_1^{NIS} - Z_1^{PIS}} & if\ Z_1^{PIS} \leq Z_1 \leq Z_1^{NIS} \\ 0 & if\ Z_1 > Z_1^{NIS} \end{cases} \quad (56)$$

$$\mu_2(x) = \begin{cases} 1 & if\ Z_2 < Z_2^{PIS} \\ \dfrac{Z_2^{NIS} - Z_2}{Z_2^{NIS} - Z_2^{PIS}} & if\ Z_2^{PIS} \leq Z_2 \leq Z_2^{NIS} \\ 0 & if\ Z_2 > Z_2^{NIS} \end{cases} \quad (57)$$

iii. Replace the main multi-objective MILP into a single-objective one by the TH compromising method.

iv. Specify the amount of the reimbursement coefficient (λ) and the related weight of the fuzzy goals (θ_h), and then solve the relative single-objective MILP. Other solutions can be rendered using different values of λ and θ_h if required.

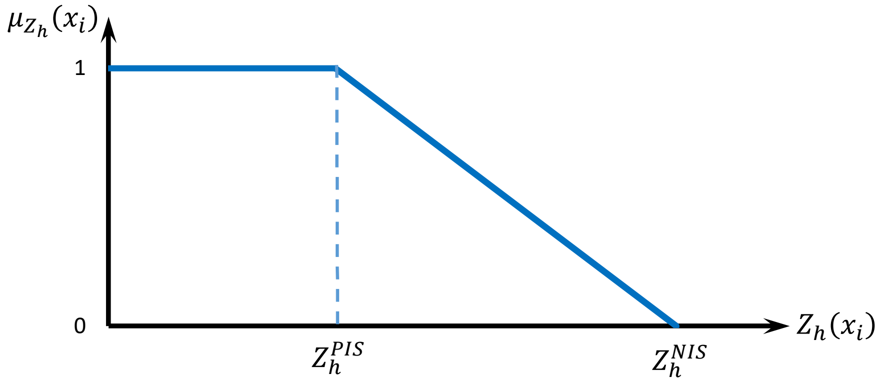

Fig. 3. Membership function related to objectives.

5.2. Self-learning non-dominated sorting genetic algorithm (SNSGA-II)

In order to evaluate the qualities of the proposed model with the consideration of both environmental and economic aspects, it is necessary to design heuristic or meta-heuristic algorithms to examine the problem in large-sized examples. To solve the multi-objective optimization problems, Deb et al. (2000) introduced an algorithm called NSGA-II. It is a completely affirmed algorithm in the research on multi-objective optimization (Mohammadi et al., 2019; Maiyar and Thakkar, 2019; Timajchi et al., 2019; Sazvar et al., 2016). To have a profound effect on the efficiency of the algorithm, the occurrence probabilities of the mutation and crossover are considered as dynamic parameters in developing NSGA-II. The proposed algorithm is inspired by a self-learning genetic algorithm proposed by Kostenko and Frolov (2015) for solving the single-objective optimization problems. The different sub-procedures of the algorithm are succinctly explained as follows:

5.2.1. Initial population

To make the initial population, some members composed of several routes including customers and individuals must be randomly generated whose number is determined by the population size. In this paper, the size of the first generation is shown by *npob* and we assume that every member involves the whole data related to a solution (*S*).

5.2.2. Fitness function

The evolutionary computation and search of the algorithm is done based on the fitness function upon which the fitness merits of all members are determined and assessed continuously. Thereafter, the members will be prioritized, picked and decided whether to remain in the next generation. For the problem in this paper, we take the objective functions, the total transportation cost and emissions generated by vehicles, as the fitness functions.

5.2.3. Non-dominated sorting

In the proposed algorithm, the basis of listing and sorting solutions is comparing with some available solutions that are better than others. When there are not any better solutions than one reached solution, it is considered as a non-dominated solution and benefits from more points. Moreover, the degree of competency and appropriateness assigned to any solution is determined based on the ranking of that solution and the lack of overcoming other solutions.

5.2.4. Crowding distance assignment

Crowding distance assignment is a density measure of solutions in the neighborhood which ensures that the optimization procedure keeps the variety of a population. Crowding distance attributes were used in order to set the solutions dispersion more eligible so that they can be distributed uniformly in the feasible solution space. After the non-dominated sorting and crowding distance sorting, all members have two features: non-domination status and crowding distance which can be applied in selecting members with more desirability.

5.2.5. Crossover and mutation

In each iteration of the self-learning NSGA-II, the child members can be generated by doing the crossover and mutation operation on some of the solutions which are chosen as parents. The selection of parents is conducted based on the occurrence probabilities of crossover and mutation. Convers to the traditional NSGA-II, these occurrence probabilities are not constant in the self-learning version and can vary from generation to generation, i.e. $\alpha m_{is}$and αc_{is}, where i is the index of generation and s is the index of the solution. So after applying the mutation or crossover, the fitness function value for each chromosome is calculated and the occurrence probabilities of mutation and crossover are updated accordingly (Kostenko and Frolov 2015). The fineness function is not the only factor to update the probabilities, the similarity index of the generation effects too, meaning that, if the mutation operator in a generation leads to a mating pool with many duplications, the mutation probability will decrease for the next generation accordingly, and vice versa.

As illustrated in **Fig. 4,** the offspring can inherit part of the genes from each parent. In order to achieve this purpose, first of all, we randomly select two solutions (based on the occurrence probability of crossover, αc_{is}) among the population as parents (f_1 and f_2) and apply the crossover. According to the proposed crossover operator, at first, a route in Parent 1 is selected randomly and a sub-route is randomly chosen from that route. The sub-route contains at least one node and at most the whole route. Then, the sub-route is inserted in the best possible place, which is found by a greedy heuristic called Best-Insertion (Bjarnadottir, 2004). After inserting the sub-route into Parent 2, if pickup from a customer happened before delivery to that customer (the inverse occurred for the individuals), the order of the two operations is changed.

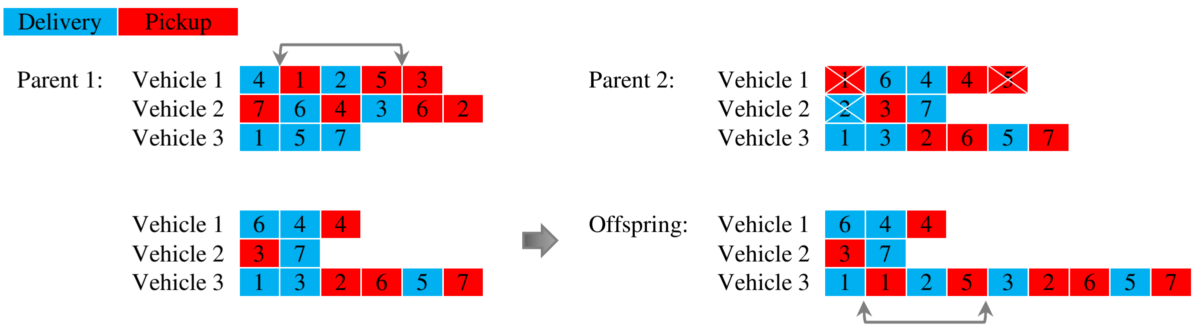

Fig. 4. A representation of the linear crossover operator.

Next, to generate some mutated populations, the mutation operator is employed. To achieve this, at first, based on the mutation probability (αm_{is}), we choose a member of the main population by the binary selection operator (f) and perform a uniform mutation method as presented in Eq. (58):

$$f^{next} \leq f + \pi.\left(f^{max} - f^{min}\right) \qquad \pi \in [1, 2] \qquad (58)$$

Where f^{next} is the offspring, f^{max} and f^{min} are the lower and upper bound of the variable, and π is a random value in the range of 0 to 1. The process continues until the mutated population touches the predetermined size. Ultimately, new generated members have to be integrated with the main community. Among merged populations, some members as much as the initial population should be picked while other members must be relinquished. At this stage, the more desirable members would be chosen. This operation is repeated until a stop criterion is fulfilled. The pseudo code of the self-learning NSGA-II is presented in Pseudo code 1.

Pseudo code 1. The Self-learning Non-dominated Sorting Genetic Algorithm-II (SNSGA-II)

Step 1. Set parameters

Step 2. Generate an initial population P with size npob and set $i = 1$

Step 3. Evaluate objective functions; $f_1(s)$ and $f_2(s)$ $\forall s \in P$

Step 4. Divide the population into non-dominance sorting

Repeat:

Step 5. Calculate crowding distance for every member of P_i

Step 6. Update the occurrence probabilities of mutation and crossover; $\alpha m_{is}$and αc_{is}.

Step 7. Generate a new population of offspring, P_{aux}, based on P_i

Step 8. Apply crossover and mutation operator to each solution of P_{aux}, and calculate $f_1(s)$ and $f_2(s)$ $\forall s \in P_{aux}$

Step 9. Combine parent population P_i and offspring population P_{aux}, perform non-dominate sorting

Step 10. Build P_{i+1} with the first npob elements of $P_i \cup P_{aux}$ following partial order and set $i = i + 1$;

Until a stop criterion is fulfilled

6. Computational results and sensitivity analysis

In this section, to illustrate the validity and practicality of the proposed mathematical model and concerning solution methods, we first apply them on a real case inspired by a home health service. Then, to test the performance of our SDPP, we will conduct a comparison experiment with two closely related PDP.

6.1. A case study

To verify the applicability of the model as well as the effectiveness of the fuzzy multi-objective method and self-learning NSGA-II, we provide real numerical evidence based on the collected data from a real home health service provider in the Middle East and run the SDPP on this case.

The company is a local home care business selling and renting a wide range of goods in patients' homes and providing basic care. In the urban area, approximately 13 clients daily take the rental service of HHMs from the company. The 13 clients and 3 owners are respectively labeled as purple and blue stars on the map displayed in **Fig. 5**, where the depot is labeled as a red triangle. Every morning, collected HHMs at the main depot and those that are rented from individuals are delivered to the clients. The capacity, generated emission and the traveling cost of the used vehicles are known. The demands and the time windows of each customer and the duration of their rent are assumed constant and estimated based on the records and requests of each customer. The customers' addresses and requests are detailed in Appendix A.

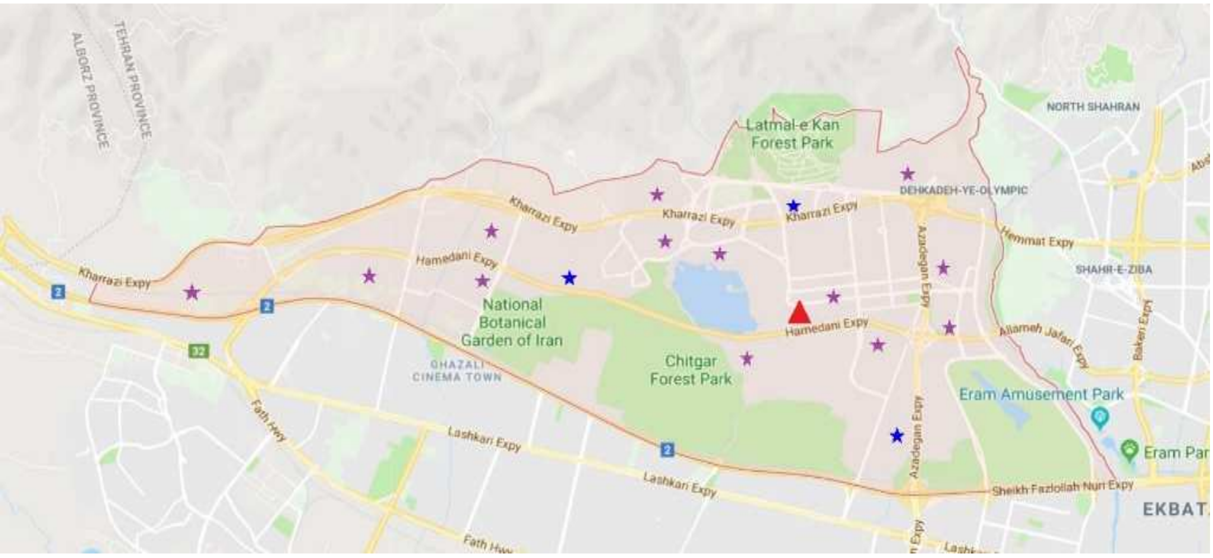

Fig. 5. Location of main office of the company, 13 clients and 3 owners.

At the first step of the computational analysis, the equivalent crisp model is solved in terms of the amounts of the objective function and relative membership function. In the simulated example, it is assumed to have thirteen applicants, three individual owners, and four vehicles. Each vehicle starts its service from the depot at 7:00 AM until the end of that day at 20:00. We set the penalty coefficient in the objective function for unit-time violations of the specified time window between 2-12 and the setup/pickup time between 15-30 minutes. We also consider a free pickup time window and a maximum returning time of 8 hours. These settings are determined according to the delivery and pickup and operations incurred under the real situation. Also, the time of traveling between each pair of points is assumed follows the uniform distribution. Moreover, the carbon emission for different types of vehicles can be estimated based on standard rules as suggested by Mirzapour Al-e-hashem et al. (2013). To analyze the mixed-integer linear model, the case is carried out using IBM ILOG CPLEX version 12.8 on a computer Intel(R), Core (TM) i3-M330 CPU at 2.13 GHz and 4.0 GB of RAM.

Lower and upper bounds of objective functions are calculated separately to make fuzzy membership functions. **Table 2** reveals the details regarding the case problem. The numerical results of the exact approach on the case study are summarized in **Table 3**. The corresponding solutions show that the amounts of objective functions are approximately close to the obtained ideal solutions and there is not any appreciable difference among various λ-values in the TH method. The quality of the acquired solutions depends on the designated parameters, in spite of some vacillations, they are relatively acceptable. The results of the case study are shown in **Fig. 6**.

Table 2

Nadir and ideal solutions.

Objective function	Z^L	Z^U
Z_1	-4.38E+04	-2.23E+04
Z_2	2.14E+03	10.52E+03

Table 3

Computational results for case study.

Method	λ-values	Objective function		Membership function	
		Z_1	Z_2	$\mu(Z_1)$	$\mu(Z_2)$
TH	0	-4.38E+04	2.36E+03	1	0.974
	0.3	-4.38E+04	2.30E+03	0.998	0.981
	0.5	-4.36E+04	2.28E+03	0.991	0.983
	0.7	-4.34E+04	2.13E+03	0.982	1

1	-4.33E+04	2.25E+03	0.979	0.986
Mean	-4.36E+04	2.26E+03	0.990	0.985

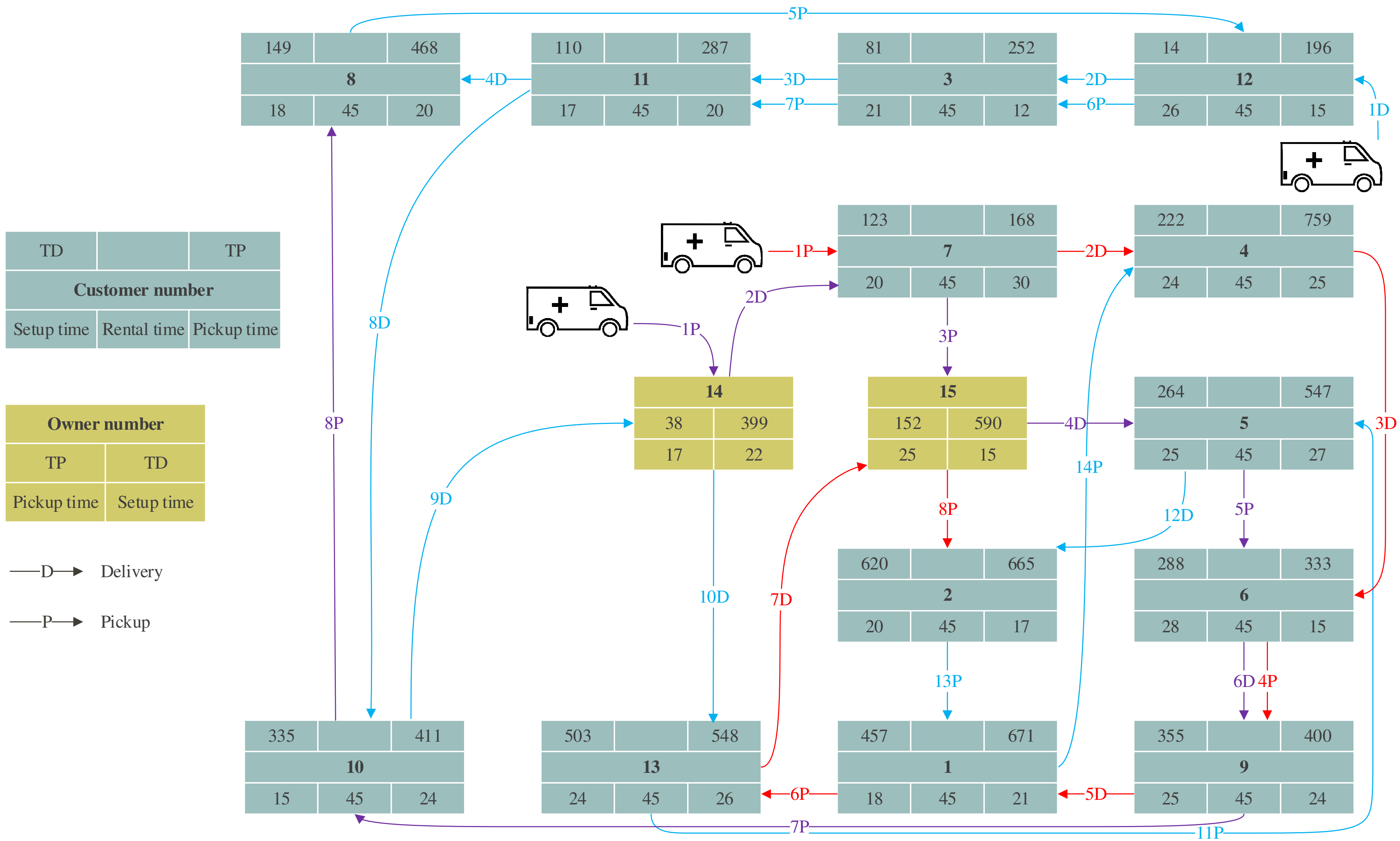

Fig. 6. Optimized routing plan considering three vehicles.

6.2. Trade-offs between economic and environmental objectives

In order to expose compromises between economic and environmental objectives in our case study, with changing the weight of objective functions three components the results are investigated. **Fig. 7** shows the analysis of the objective functions yielded by the company's case where the λ-value is set to 0.5. The results expose the comparison between economic and environmental objectives by changing the weights. As expected, the values of the objective functions are reduced when we increase the corresponding weight. It can be also observed that there are numerous non-dominated solutions for the TH method. Although the reduction in the second objective, total emissions, from 2556 to 2139 arises in cost from -43821 to -42946, win-win situations can be similarly detected. As it is observed amid instances 5 and 6, both transportation-related costs and total emissions can be decreased simultaneously. With a higher change in weights, lower total cost and emissions in points 1 and 8, respectively, results. In these cases, while the weights in the integrate function are reduced, transportation costs and total emissions increase. It is worthwhile to note that setting sustainability targets requires an evaluation of economic and environmental effects and such evaluations could be valuable for decision-makers.

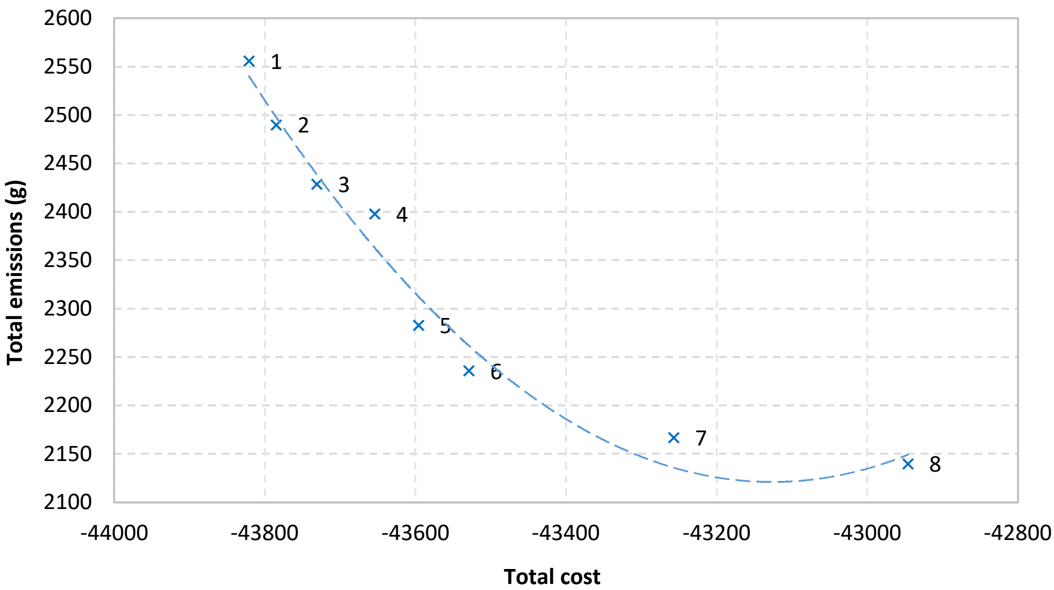

Fig. 7. Trade-offs between economic and environmental objectives.

6.3. Performance of self-learning NSGA-II

To examine the effectiveness of the proposed algorithm in comparison with the exact approach, different illustrative examples have been carried out. To do so, the parameters are generated randomly using uniform distributions which their lower and upper bounds specified in Appendix B. Thereat, figures in the bracket denote lower and upper bound of the uniform distribution, respectively. For this comparison, the TH method is used and λ-value set to 0.5.

Then, the self-learning NSGA-II was executed taking the following parameters to show the detail results of our instances: the population size is 2×|the number of non-dominated solutions recorded by exact methods|, the initial crossover rate is 0.9, and the initial mutation rate is 0.15. The self-learning NSGA-II stop criterion was reached when after finalizing an iteration, the computation time employed by CPLEX was exceeded. Several tests have been done to adjust these parameters, based also on the results reported by some bi-objective routing problems.

Table 4 provides a summary of the results reported by our SDPP for two points of the Pareto set. In this manner, all test problems are first solved via CPLEX and then are solved by self-learning NSGA-II. In this table, columns 2-4 show the size of instances, characterized respectively by the vehicles of the fleet, the number of owners and applier patients. Columns 5-7 show the results reported by CPLEX (Z_i^E) including economic (Z_1) and environmental (Z_2) objectives and the best-known execute time, respectively. Columns 8-10 show the computational results obtained by self-learning NSGA-II (Z_i^H). The last two columns report the gap among them which is determined by $\Delta_i = \frac{Z_i^H - Z_i^E}{\|Z_i^E\|}$. It should be noted that CPLEX was not able to solve the larger-scale instances. Therefore, for medium and large-sized problems, the best bounds of CPLEX obtained after two hours are used to calculate the gaps. In test problems 9 and 10, CPLEX is discontinued as "out of memory", and until the reported time, it could not reach a feasible solution.

Table 4

Comparison of solution approaches performance on different instances.

Instance	Dimension			CPLEX				Self-learning NSGA-II			Gap	
	V	L	K	Z_1	Time (Sec.)	Z_2	Time (Sec.)	Z_1	Z_2	Time (Sec.)	Δ_1	Δ_2
1	1	1	4	-1.66E+04	316	2.85E+02	255	-1.62E+04	2.91E+02	364	0.025	0.019
2	2	2	7	-3.14E+04	799	4.38E+02	605	-3.10E+04	4.59E+02	1,022	0.012	0.047
3	2	2	10	-3.98E+04	1,391	1.01E+03	1,030	-3.74E+04	1.02E+03	1,456	0.06	0.011
4	3	3	13	-4.36E+04	2,323	2.14E+03	1,671	-4.13E+04	2.22E+03	1,645	0.052	0.037
5	3	4	15	-5.17E+04	3,185	2.27E+03	2,275	-4.50E+04	2.42E+03	2,051	0.13	0.065
6	4	4	17	-5.65 E+04	6,393	2.36E+03	4,349	-4.68E+04	2.61E+03	3,171	0.172	0.106
7	5	5	17	-5.71E+04	7,200	2.84E+03	7,200	-4.91E+04	3.11E+03	3,843	0.141	0.095
8	5	6	19	-6.43E+04	7,200	3.29E+03	7,200	-5.72E+04	3.59E+03	4,977	0.11	0.091
9	6	4	24	N/A	10,800	N/A	10,800	-7.00E+04	5.65E+03	7,714	-	-
10	7	5	30	N/A	10,800	N/A	10,800	-9.12E+04	6.17E+03	12,614	-	-
Average											0.088	0.059

V: the number of available vehicles in the fleet

L: the number of applicants

K: the number of available individual owners

These two approaches are compared for different instances and **Table 4** shows the computational results. As seen in **Table 4**, CPLEX cannot solve the large-scale problems optimally in a reasonable time, we rely on the lower bound reported after two hours. On this matter, self-learning NSGA-II, on average, has a better performance in larger-sized cases in terms of computational time. Moreover, the differences between the results of the CPLEX software and the best solutions of self-learning NSGA-II are adequately small and it converges to near-optimum solutions in less than three hours. To have an idea of the execution time, **Fig. 8** depicts the computational time (in seconds), expended by self-learning NSGA-II and CPLEX for different instances. Here we can note that, in medium and large-sized problems, without any exception, the execution time of self-learning NSGA-II is shorter than the exact methods.

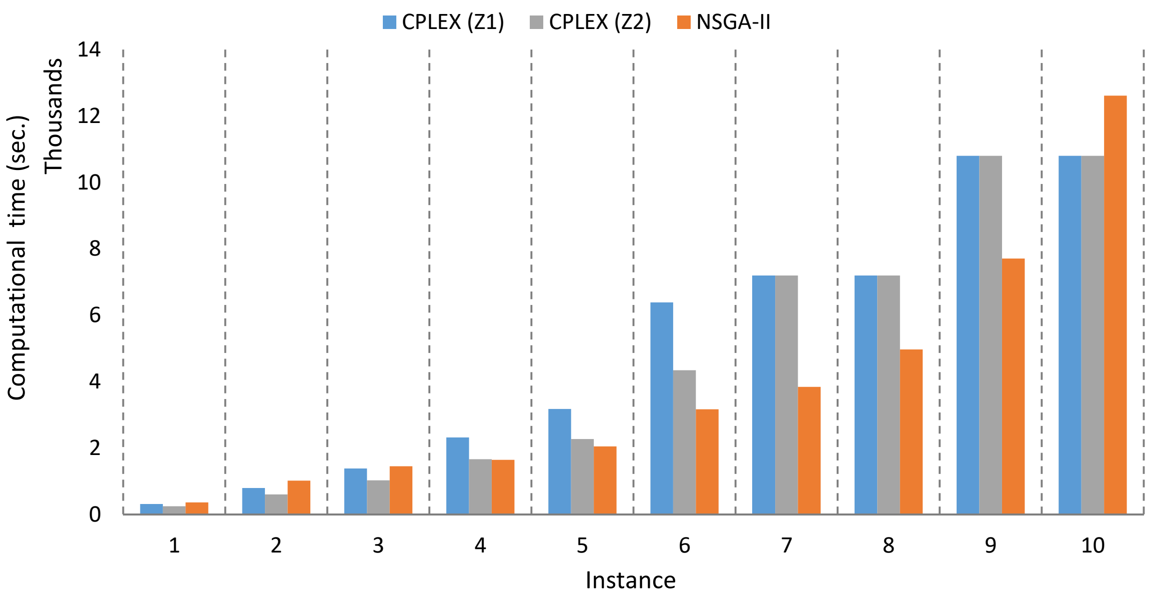

Fig. 8. Computational time, categorized by different instances.

The set of non-dominated points obtained by self-learning NSGA-II for the test problem 9 are shown in **Fig. 9**. As illustrated in **Fig. 9**, the number of non-dominated points increases in further iterations. The last case results in a larger feasible solution space, where the algorithm has a higher probability to generate several new feasible solutions, leads to updating more constantly the non-dominated set.

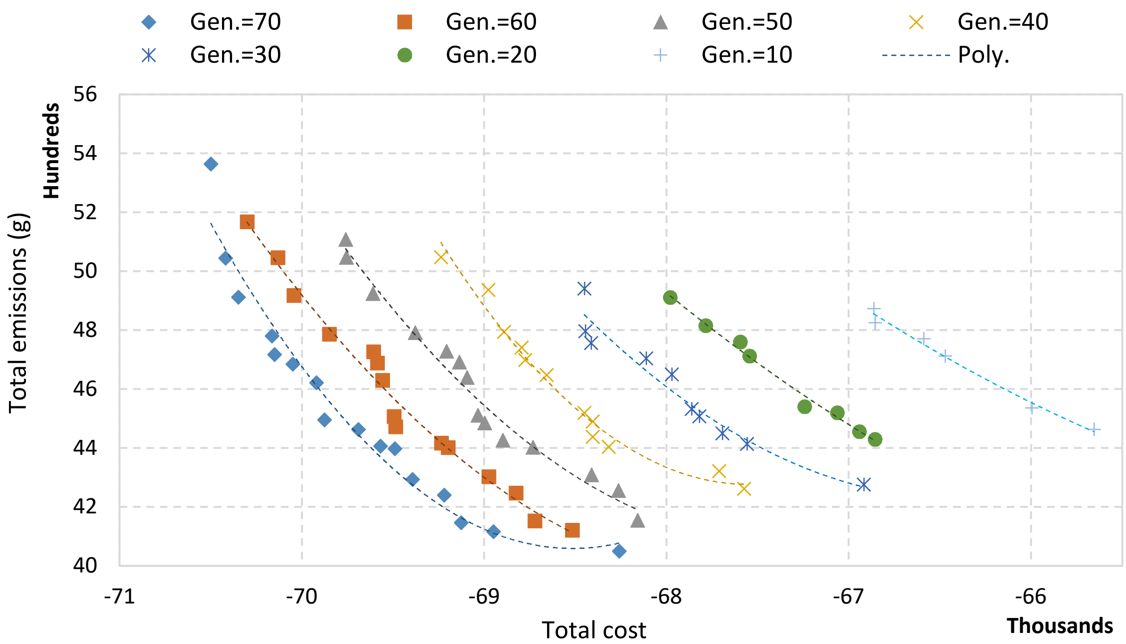

Fig. 9. Pareto solutions of different generations for instance 9.

To assess the performance of the proposed self-learning NSGA-II and their relative dispersion in the Pareto frontier, we employed the following metrics and it is compared with TH method:

Spacing metric (*SM*):

Spacing is one of the metrics used to estimate the distance variance and distribution of neighboring solutions in a known Pareto front. Lower SM displays a better dispersion of the solutions in the frontier (Srinivas and Deb, 1994). Eq. (59) outlines the spacing metric.

$$SM = \sum_{i=1}^{n-1} \left| d_i - \bar{d} \right| \Big/ (n-1).\bar{d} \tag{59}$$

where n is the number of Pareto solutions, $\bar{d}$ is the average Euclidean distance in sorted Pareto solutions and

$$d_i = \sqrt{\left(Z_1^{i+1} - Z_1^{i}\right)^2 + \left(Z_2^{i+1} - Z_2^{i}\right)^2} \tag{60}$$

Mean ideal distance (*MID*):

This metric, which was proposed by Zitzler and Thiele (1998), describes the average distance between solutions in the Pareto frontier and a hypothetical ideal solution. The smaller value of MID signs a better performance of the method. The following equation defines the MID metric.

$$MID = \sum_{i=1}^{n} \sqrt{\left(\frac{Z_1^i - Z_1^{best}}{Z_1^{max} - Z_1^{min}}\right)^2 + \left(\frac{Z_2^i - Z_2^{best}}{Z_2^{max} - Z_2^{min}}\right)^2} \Big/ n \tag{61}$$

where Z_j^{max} and Z_j^{min} are maximum and minimum amounts of j^{th} objective among solutions in Pareto frontier and Z_j^{best} is the ideal solution in all problems.

Fig. 10 summarizes the value of the Spacing metric for the TH method and self-learning NSGA-II for different instances. Notably, lower values of spacing metric specify that solutions be distributed evenly. Based on this figure, although the TH has less spacing metric than the self-learning NSGA-II in most cases, the respective gaps are not significant and both approaches reach a further solution space and diversify the search procedure.

Fig. 11, which compares the performance of the TH method and self-learning NSGA-II based on the MID metric, confirms that obtained solutions by CPLEX are closer to true Pareto front. According to the diagram, in all cases, the TH method has the monotony and higher quality of the Pareto frontier.

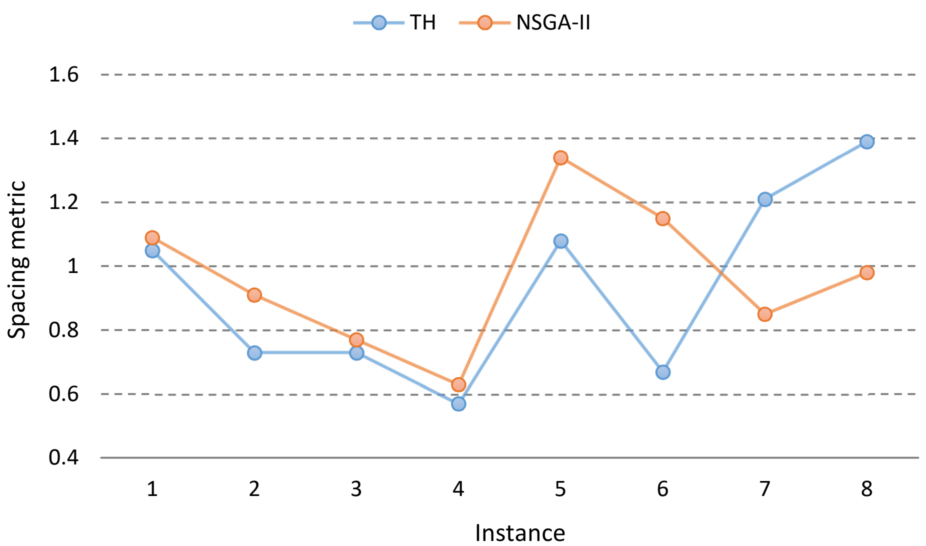

Fig. 10. SM in TH method versus self-learning NSGA-II.

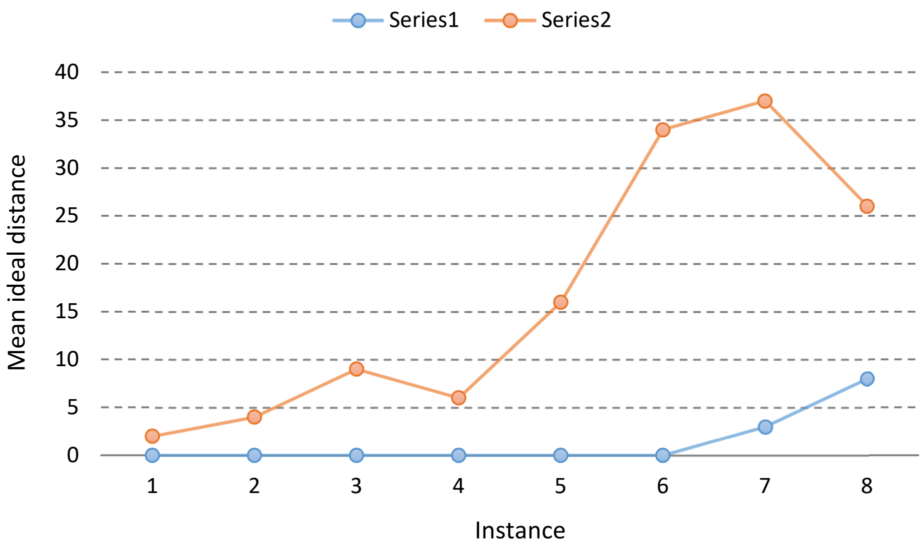

Fig. 11. MID in TH method versus self-learning NSGA-II.

6.4. Sharing versus no-sharing scenarios

Now we turn our attention to an analysis of the most important ingredients of the sharing policy, we compare the solutions with and without the sharing policy to show that it is not only profitable for individuals to make money and for the company to save cost through saving in traveling but also it reduces the total generated emission which is considered as a secondary objective in this study. Therefore, to demonstrate the impact of the sharing policies on the optimal solution, several numerical examples are developed while the parameters remain unchanged and generated according to Appendix B.

For this purpose, 10 test problems are solved twice; with sharing policies and without sharing policies. **Table 5** provides a summary of the results reported by the CPLEX on a computer Intel(R), Core (TM) i7-4790K CPU at 4.00GHz and 16.0 GB of RAM. As **Table 5** shows, the minimum, maximum and average of Δ_1 are 0.17, 0.53 and 0.31 respectively. Similarly, the minimum, maximum and average of Δ_2 are 0.09, 0.31 and 0.19 respectively. It has conclusively been shown that the sharing policy simultaneously generates better solutions concerning transportation-related cost and total emissions. For 4th example, the sharing policy enables a 25% saving in the total cost, and a drop of 21% in the total carbon emissions. As seen in **Fig. 12**, these are in addition to the financial benefits that individuals will receive and the benefits of expediting services to patients at a lower cost.

Table 5

The overall impact of sharing economy on objective functions.

Instance	Dimension			With sharing policies		Without sharing policies		Gap	
	V	L	K	Z_1	Z_2	Z_1	Z_2	Δ_1	Δ_2
1	1	1	4	-1.66E+04	2.85E+02	-1.32E+04	3.45E+02	0.26	0.17
2	2	2	7	-3.14E+04	4.38E+02	-2.68E+04	4.90E+02	0.17	0.11
3	2	2	10	-3.98E+04	1.01E+03	-3.02E+04	1.25E+03	0.32	0.19
4	3	3	13	-4.36E+04	2.14E+03	-3.49E+04	2.70E+03	0.25	0.21
5	3	4	15	-5.17E+04	2.27E+03	-4.05E+04	2.49E+03	0.28	0.09
6	4	4	17	-5.65 E+04	2.36E+03	-4.18E+04	3.43E+03	0.35	0.31
7	5	5	17	-5.91E+04	2.66E+03	-4.54E+04	3.03E+03	0.30	0.12
8	5	6	19	-6.70E+04	3.17E+03	-5.29E+04	3.83E+03	0.27	0.17
9	6	4	24	-8.44E+04	4.69E+03	-6.21E+04	6.56E+03	0.36	0.29
10	7	5	30	-1.15E+05	5.33E+03	-7.50E+04	7.40E+03	0.53	0.28
Average								0.31	0.19

V: the number of available vehicles in the fleet

L: the number of applicants

K: the number of available individual owners

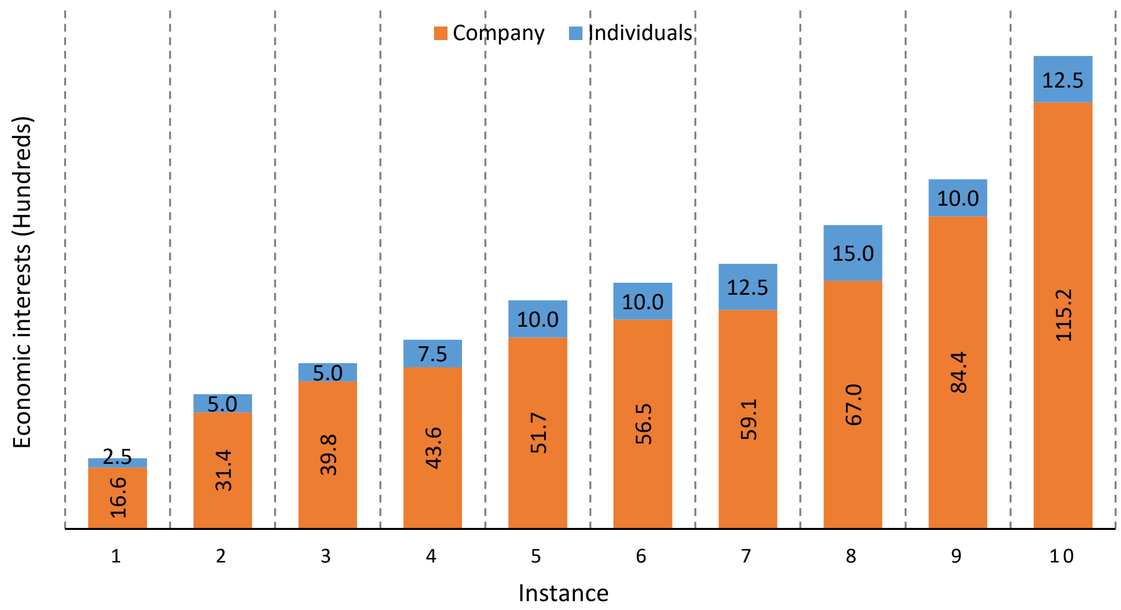

Fig. 12. The company's economic benefits versus individuals'.

Due to the probability nature of the participation rate and the number of shared devices, we present a sensitivity analysis on the number of shared HHMs by individuals to prove the attractiveness of the sharing policy. To do so, the test problem 10 with 30 customers is solved for different numbers of HHMs. As illustrated in **Fig. 13**, not only the increasing individual's participation has a significant impact on the revenues, but also it obviously indicates the positive role of the sharing policy on reducing carbon emissions.

In **Fig. 14** a sensitivity analysis is done to examine the impact of the fleet size on the optimal solution and identify the sufficient size of the fleet over which keeps the sharing policy on its profitable role. As observed in **Fig. 14**, five vehicles in the last example lead to the reduction of the aggregated objective function.

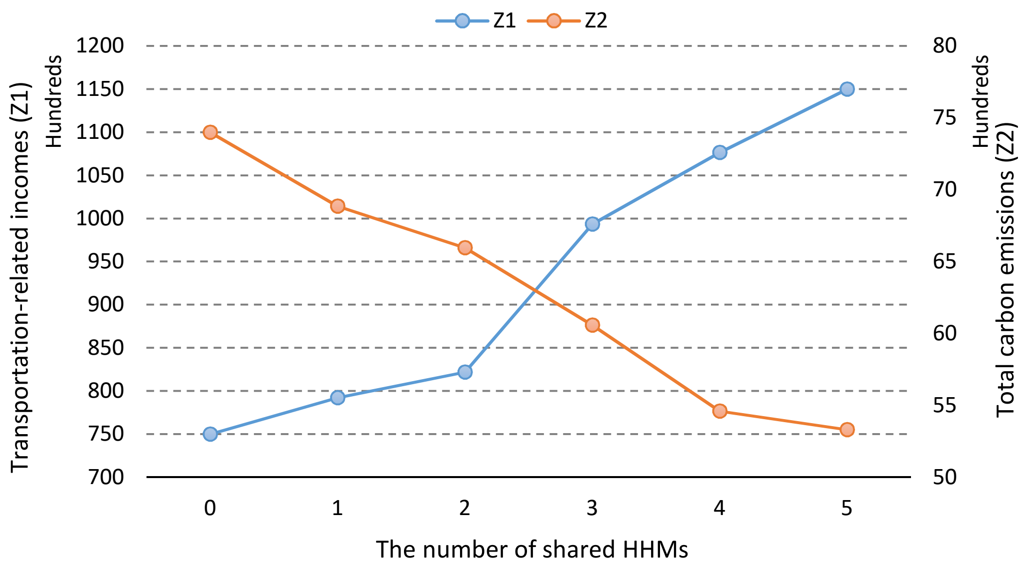

Fig. 13. Total system profits and total emissions as a function of the number of shared HHMs by individuals.

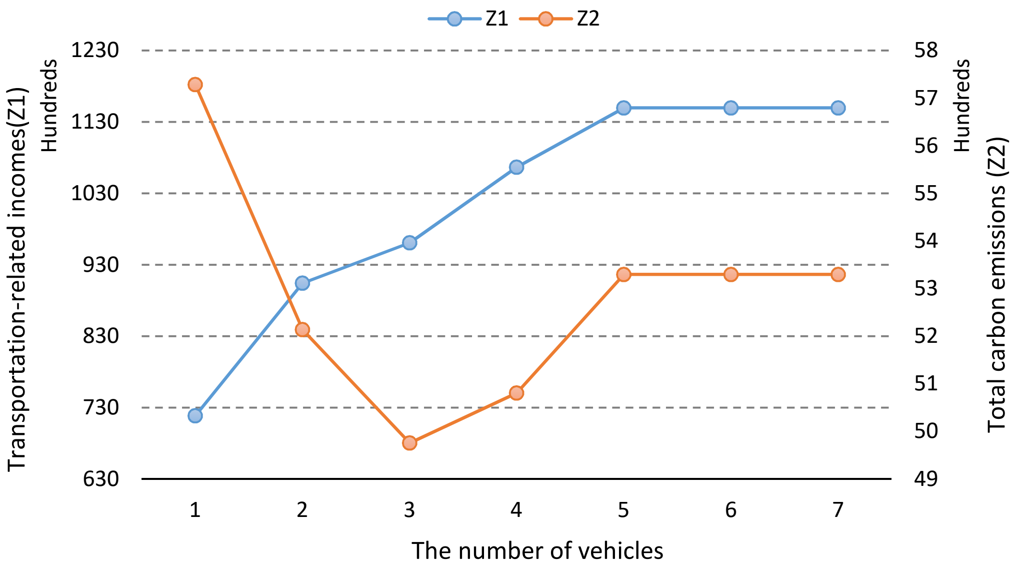

Fig. 14. Relationship between the objective functions and the number of vehicles in fleet.

In order to represent the impact of increasing individuals' participation in the amount of time windows violation, we provide a boxplot graph to compare the changes in the average latency and early arrival time for each considered number of shared HHMs. As seen in **Fig. 15**, it leads to a noticeable decrease in the average time window violation. As intuitively expected, when the number of shared HHMs increases, the arrival time in delivering HHMs to the patients will reduce, thus it led to increasing applier satisfaction.

In summary, the computational experiments demonstrate that the proposed model can be successfully used by the practitioners to stablish a transportation service in an item sharing business to guarantee the minimum transportation costs which motivate the individual owners further to involve and concurrently respect the increasing concerns about GHG emissions through omitting the direct transportations from patients to hospitals and vice versa.

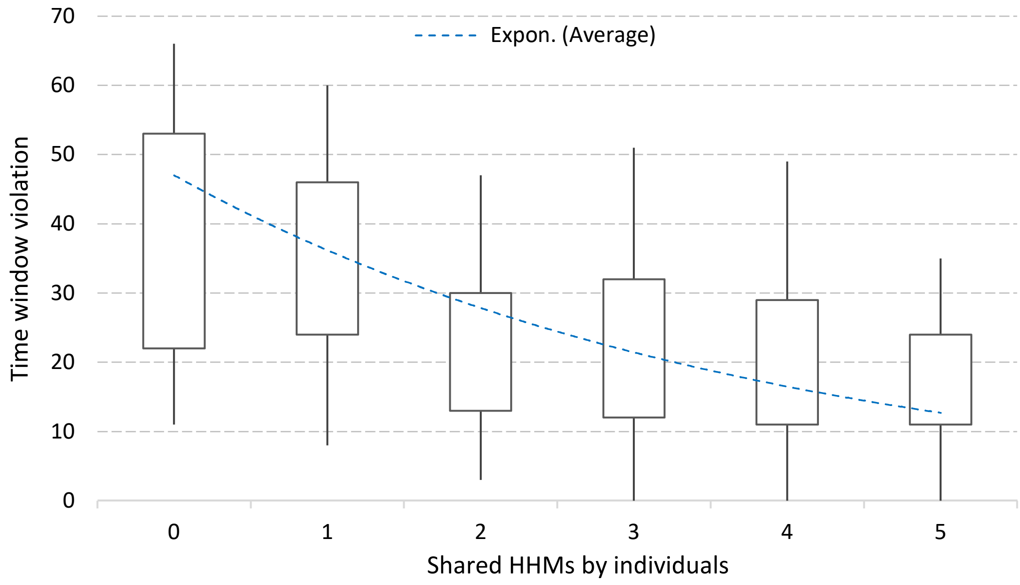

Fig. 15. Boxplots of the average latency and early arrival time for each considered number of shared HHMs.

7. Conclusions

This research is the first try to introduce and investigate the potentials of sharing concept on the green delivery-pickup problem of scarce commodities like HHMs, which considers a framework naturally extensible for variants of items. We formulated a mathematical model of the problem that allows coordinating the transfer of HHMs among clients through the various modes for delivering and picking up. When HHMs is delivered to the customer, any other vehicle can be contacted to the customer for taking HHMs back, therefore locations in the SDPP are allowed to be visited more than once. To solve the bi-objective mathematical model, first an exact approach, the Torabi and Hassini's method was applied. Then, to solve the medium- and large-sized problems in a reasonable time, a self-learning non-dominated sorting genetic algorithm is then proposed, and validated by solving an extensive set of test problems.

Finally, the effectiveness and applicability of the proposed model are demonstrated by the computational results on a real case. Our tests confirm that the economic and environmental benefit of a scarce delivery-pickup platform significantly profits from economies of sharing in both solution techniques. Therefore, our sustainable and sharing structure is gained as a result of healthcare transportation planning.

Our findings in this study open up numerous directions. This collaborative platform can be developed in other industries like transportation (e.g. car and bike-sharing system), consumer goods (e.g. sharing a book and toy) and services (e.g. crowdfunding and lending), and facilitated the increase of quality through transparency and a stable relationship between providers and customers. The proposed model can be employed to allow the reuse and already utilizing of different commodities when not in use and provide maximum benefits for individuals and consumers. The sharing pattern is dominated by a centralized platform that provides a trusted marketplace for exchange and enforces standards; however, some activities can be moved to more distributed networks and the problem is formulated as a bi-level model.

The article has some limitations that will be the subject of future researches. For example, in order to improve the results, better routing decisions can be made when aiming at extending more factors such as multiple supply depots, the speed of the vehicles, customer priority and road condition in a general framework. Furthermore, the effects of dynamic and stochastic routing can be investigated in future works. These issues also will turn our idea toward more practical via trade-off among economics, services, risks, and environmental issues. In addition, the use of different exact methods such as column generation techniques might be interesting ideas.

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Appendix A. A detailed explanation of the case study's data

The distance data and the other information used for the company' case is shown in the following table. The capacity of all vehicles is 5 items. For each vehicle of the fleet, we set the rate of fuel consumption and carbon emission to 8 and 2, respectively, and we assume a fixed gas-oil price of 50 cents per liter per kilometer.

- The No. 0 stands for the main office of the company that can be regarded as the depot.
- The longitude and latitude of the locations are taken from the Google map coordinate system.
- Both the earliest and the latest times are presented in minutes beginning from 7 am.
- When the vehicles are ready to give service, the earliest arrival time set 0 which corresponds to 7 am of a day.

No.	Longitude	Latitude	Earliest arrival time	Latest arrival time	Rental Time	Setup time	Pickup time
0	35/7473	51/2138	0	-	-	-	-
1	35/7214	51/2130	30	90	45	18	21
2	35/7549	51/1955	75	105	45	20	17
3	35/7415	51/1576	205	240	45	21	12
4	35/7212	51/1744	130	170	45	24	25
5	35/7542	51/1900	280	320	45	25	27
6	35/7275	51/1717	35	70	45	28	15
7	35/7424	51/2122	90	135	45	20	30
8	35/7505	51/1860	65	100	45	18	20
9	35/7248	51/1913	315	350	45	25	24
10	35/7482	51/1944	420	465	45	15	24
11	35/7211	51/2006	45	85	45	17	20
12	35/7278	51/1589	90	110	45	26	15
13	35/7504	51/2235	120	140	45	24	26
14*	35/7204	51/1696	-	-	-	22	17
15*	35/7324	51/1824	-	-	-	15	25
16*	35/7201	51/2126	-	-	-	21	27

* Individual owners

Appendix B. Sources of the nominal data generated randomly.

Parameter	Symbol	Range
Setup time	st_j	~ uni[15,30]
Pickup time	pt_j	~ uni[15,30]
Distance	d_{ij}	~ uni[2,20]
Customer rental time	dr_k	~ uni[30,60]
Rental price	pr	~ uni[100,200]
Returning time	mr_l	~ uni[480,600]
Payment to owners	re	~ uni[1500,3000]
Capacity	q_v	~ uni[5,10]
Total inventory at the depot	cap	~ uni[5,10]
Fuel consumption rate	f_v	~ uni[1,4]
variable costs	c_{ijv}	~ uni[0.5,3.2]
Travel time	t_{ij}	~ uni[10,90]
Earliest pickup time	e_l^{Ind}	~ uni[0,30]
Latest pickup time	l_l^{Ind}	~ uni[750,780]
Earliest delivery time	e_k^A	~ uni[30,480]
Latest delivery time	l_k^A	~ uni[45,540]
Penalty	ρ_k	~ uni[2,12]
Carbon emission	φ_v	~ uni[8,15]