A comprehensive heuristic toolbox for the optimal location, routing, and fleet choice of urban consolidation centers

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Abstract

Urban Consolidation Centers (UCCs), facilities where deliveries directed towards the city center can be dropped off, sorted, and consolidated in smaller and more environmentally friendly vehicles represent a good opportunity to reduce the negative impacts of urban freight movements. However, in the past twenty years only a few of the real-world applications have succeeded due to several operational, financial, and regulatory issues. In this report, we present a model to address the optimal facility location, fleet, and route choice problem for UCCs based on the heuristic genetic algorithm. The model, which is presented in the form of a toolbox, allows minimizing the total costs and the environmental impacts of UCC configurations, in order to reproduce perspectives of different stakeholders and policy scenarios. The model features two sequential sub-models to address the location-allocation and heterogeneous routing problem. It also accounts for specific aspects of the last-mile distribution problem, such as the different costs, speeds, and capacities of available vehicles. The applicability of the toolbox is demonstrated showing different potential scenarios for the implementation of UCCs in the city of Austin, Texas.

Keywords: *Urban Freight Distribution; Urban Consolidation Centers; Location-Routing Models; Fleet Choice; Genetic Algorithms*

1. Introduction

Urban freight distribution plays a critical role in the sustainable development of urban regions as it determines up to 15-20% of vehicular traffic in cities (Dablanc, 2011). The several negative effects of the “last mile” freight distribution threaten the livability of cities and they can outweigh the benefits of economic development and flourishing of commercial activities. Indeed, the presence of trucks in urban areas increases the use of nonrenewable resources and the levels of emission of associated pollutants (global and local), triggers traffic jams, and decreases the throughput of traffic. It can also lead to traffic accidents and can cause considerable noise and visual intrusion (Quak, 2008; Browne et al., 2012).

Consequently, in recent decades a series of initiatives, including new regulations, infrastructure improvements, and measures concerning sharing space and time have been adopted throughout the world, especially Europe and Japan (Muñuzuri et al., 2005). A particularly promising solution features Urban Consolidation Centers (UCCs): transshipment points situated in the proximity of a city center, where deliveries from logistic companies are dropped off, sorted, and consolidated in smaller and more environmentally friendly vehicles such as electric vans and cargo-bikes (Crainic et al., 2004; Allen et al., 2007). In addition to the reduced emissions, another

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advantage of these “alternative” vehicles would be the transshipment in smaller vehicles that would allow higher load factors and ultimately decrease the amount of traffic entering the city. Moreover, a series of additional logistics and retail services can also be provided at the UCC (Huschebeck and Allen, 2005).

In the last twenty years several UCCs have been implemented mainly in European cities in the U.K., Italy, France, Germany and the Netherlands, but also in Motomachi in Yokohama, Japan. However, the majority of these projects did not last longer than a few years (Schoemaker, 2002; Browne et al., 2005). Real-world experiences highlighted different reasons behind the failure of UCCs initiatives. Some can be ascribed to a lack of planning and to relatively ambitious forecasts in terms of public acceptance and carrier compliance (Rooijen and Quak, 2010). Other factors might be attributed to the UCCs’ vital dependency on local authorities to subsidize the high investment and operating costs (Dablanc and Rodrigue, 2014). Finally, erroneous operational choices concerning the location of the facilities and the characteristics of the fleet in charge of the “last mile” deliveries may have led to eventual negative results of implementation of UCCs. The efficiency of this measure depends particularly on the distance between the UCCs and customers and on the features of vehicles used for the final leg of distribution (speed, operating costs, capacity, emissions, etc.). This is the case of Leiden, Netherlands, where the UCC was located relatively far away from the city center (Schoemaker, 2002) and Kassel, Germany where the additional operation costs outweighed the transportation savings (Browne et al., 2005).

Clearly, introducing UCCs involves extra-costs, risks, and delays in the delivery process that could jeopardize the success of this measure. For this reason, identification of optimal solutions in terms of facility location, fleet, and delivery routes would be beneficial in the preliminary assessment of UCC initiatives, prior to financial and institutional considerations. To date, in the field of urban logistics, important studies have been conducted to determine efficient and sustainable configurations of urban distribution systems by identifying the best location of these facilities (Crainic et al., 2004; Munuzuri et al., 2012) and the optimal fleet choice for the last-mile delivery (Figliozzi et al., 2011); more complex problems have also been investigated, including the optimal combination of “satellites” and delivery routes (Crainic et al., 2010), and the optimal configuration of routes and mix of vehicles (van Duin et al., 2013).

This study follows similar lines, but aims to cover several of these aspects simultaneously, thereby providing a broader perspective involving different goals. To our knowledge, a similar comprehensive model considering the optimal location of UCCs, along with the mix of vehicles and their routes to accomplish last mile deliveries has not yet been developed. A study addressing this type of problem has been published by Wu et al. (2002) who developed a model for the multi-depot location-routing problem with a heterogeneous fleet. However, in this report, the capacity is the only distinguishing factor among the different types of vehicles. Our model, by contrast, is formulated as a Mixed-Integer Linear Program (MILP) where the decision variables are whether to use a facility or not, the number of certain vehicle types to be used, characterized by different capacities, speeds, costs, and emissions, and the routes to be taken to serve all customers. In order to bring a higher level of realism, additional constraints concerning the time to accomplish deliveries and the maximum service range of certain vehicles (e.g. cargo-bikes) were introduced to our model.

Given the complexity of the problem, the model is decomposed into two sub-models: the first one consists of a facility location problem with capacity and budget constraints; the second one consists of a mixed-vehicle routing problem with time, capacity, and budget constraints. In order to apply the model to large-scale real world cases to solve the MILP, we adopted the heuristic technique of genetic algorithms.

This model has been implemented in the form of a user-friendly “toolbox” that allows users to customize their own study by defining the main parameters, including demand, features of vehicles and facilities, and financial and environmental constraints. Another important feature of our toolbox is the possibility to choose between two different objective functions: the minimization of daily operating costs and the minimization of the daily cost of emissions. This component of our model is included in order to provide a broader view regarding the alternative opportunities for implementing UCC solutions. The main rationale behind this choice is to allow a comparison among perspectives of the several stakeholders (carriers, retailers, consumers, municipalities, etc.) involved in the distribution process, who often have different priorities (e.g. providing a cost-effective service and minimizing negative externalities of truck deliveries).

In the remainder of this paper, we first introduce the different operational issues related with the implementation and operation of the UCCs considered in our model. Then, we provide the model formulation and the description of the computational approach based on the heuristic technique of genetic algorithms used to solve the optimization problem. Finally, we illustrate the capabilities of the toolbox by showing the results corresponding to different scenarios in the city of Austin, Texas. We conclude with a number of general remarks and recommendations for future research.

2. Operational issues involved with the implementation of UCCs and comprehensive model formulation

The main operational barriers to the implementation of UCCs can be summarized in the extra costs of developing dedicated facilities for the transshipment of goods (and possibly added logistic services), operating these facilities, purchasing the fleet in charge of the last-mile deliveries, and providing the delivery service to customers. In addition, other operational issues, such as increased delivery time due to the transshipment and limitations of lower capacity, service range, and speed of vehicles like cargo-bikes and electric vans, could arise when implementing UCCs. Most of these barriers have been thoroughly investigated in the field of urban freight distribution and they have been typically studied by adopting different techniques from the Operations Research field.

The optimal location of UCCs, which is a central aspect of the efficiency of the city distribution (Browne et al., 2007), relies on identifying the optimal candidate sites where freight can be transshipped from trucks to smaller and more eco-friendly vehicles to accomplish the last leg of distribution. The problem has been traditionally formulated as a location–allocation model for the multi-echelon distribution setting (Taniguchi et al., 1999; Crainic et al. 2004; Crainic et al., 2010) where the main considered costs are those related to the investment and operation of the facilities and the transportation costs inbound and outbound the UCCs. Different constraints concerning the capacity of facilities and budget conditions have been typically included to increase the realism of the models. Clearly, since each context represents a unique setting in terms of costs (rent, handling and transportation), accessibility of customers (traffic conditions), and urban morphology (land-use and road network layout), the location-allocation model might yield to various results. For example, in a situation characterized by high infrastructure costs and limited available space in the city center, few larger facilities in the periphery of the city would probably be a more efficient solution. Otherwise, in case of heavy traffic conditions, cargo-bikes might demonstrate more advantages than larger vehicles because in these conditions larger vehicles (most often) cannot exhibit a speed advantage over cargo-bikes. Interestingly, in most of the previous studies the adopted perspective was the one of local authorities, made in an attempt to minimize externalities.

Another critical issue to guarantee a satisfactory delivery service and implement efficient UCC solutions consists of the fleet of vehicles used for the last-mile distribution. In this case, different choices would reflect distinct priorities as each typology of vehicle is characterized by specific strengths and weaknesses. For example, cargo-bikes are characterized by lower purchase costs and zero emissions, but they have limited capacity and service range, and have lower speeds; on the other hand, "traditional" vans have higher capacities and speeds, but also considerably higher purchasing costs and several negative externalities. In the last few years, within the literature of urban logistics, a growing number of studies have been carried out to investigate the competitiveness of alternative modes, such as electric vans or cargo-bikes (Feng and Figliozzi, 2013; Davis and Figliozzi, 2013; Tipagornwong and Figliozzi, 2014). Browne and Leonardi (2011) have provided an ex-post evaluation of a trial in London where deliveries made by traditional vans were replaced by electrically assisted tricycles and electric vans departing from a UCC. Furthermore, an extensive number of papers have combined this issue with the vehicle routing problem (VRP), aiming to provide an accurate solution to what is referred to as the heterogeneous vehicle routing problem (HVRP). Within the field of sustainable urban freight distribution, van Duin et al. (2013) have proposed a model for the Fleet Size and Mix Vehicle Routing Problem (FSMVRP) with time-windows for electric-vehicles.

The model developed in this study has the following main goals: to determine the optimal locations among different candidate sites for UCCs; to determine the optimal fleet mix given different typologies of vehicles; and to determine the optimal delivery routes from UCCs to their assigned customers. It includes considerations of different categories of costs, including transportation costs (truck trips to the UCC and last mile deliveries from the UCCs) and investment costs (rent and upgrades of facilities and purchase of fleet).

Our model was made by introducing a few assumptions. First, we consider a single depot (e.g. a major distribution center or warehouse) located in the outskirts of the city from which one or more trucks depart to serve all the UCCs being used. Second, we consider the three following options for the last-mile distribution: vans, electric vans, and cargo-bikes. However, the model could be easily adapted to analyze additional typologies of vehicles. The objective of our model is to either minimize cumulative costs or to minimize cumulative emissions; the user may choose which of the two categories should be minimized.

Under these circumstances, the following sets of decision variables are identified:

1. Location binary variables y_s of UCCs corresponding to 1 if the UCC is open and 0 otherwise; *s* is an index from *S*, the set of candidate facilities.

2. Flow distribution variables f_{sk} representing the quantity of goods being sent from UCC *s* to the customer *k*; where *k* is an index from *K,* the set of customers that have to be served.

3. Delivery route binary variables: $x_{i,j}^{v,s}$, $y_{i,j}^{e,s}$, $z_{i,j}^{b,s}$ representing respectively the van (*v*), electric van (*e*) and cargo-bike (*b*) departing from UCC *s*, that serves customer *j* after having served customer *i;* V is the set of available vans, E is the set of available electric vans and B is the set of available cargo-bikes.

The optimization program of the comprehensive UCC implementation model is formulated using equations 1-18. The presented formulation has a goal to minimize costs; however, with minor adjustments to the formulation, the objective to minimize emissions can also be used, as discussed later.

$$\min Z(y_s, f_{sk}, x_{i,j}^{v,s}, y_{i,j}^{e,s}, z_{i,j}^{b,s}) = \sum_{s\epsilon S}\Bigg(\Big(y_s i_s + \sum_{k\epsilon K}(h_s f_{sk} + \alpha_s f_{sk}\frac{1}{k_0}p_0)\Big) + \sum_{v\epsilon V}\Big(\big(\sum_{i\epsilon K'}\sum_{j\epsilon K'}\beta_{i,j}p_1 x_{i,j}^{v,s}\big)\Big) + \sum_{e\epsilon E}\Big(\big(\sum_{i\epsilon K'}\sum_{j\epsilon K'}\beta_{i,j}p_2 y_{i,j}^{e,s}\big)\Big) + \sum_{b\epsilon B}\Big(\big(\sum_{i\epsilon K'}\sum_{j\epsilon K'}\beta_{i,j}p_3 z_{i,j}^{b,s}\big)\Big)\Bigg) + \sum_{v\epsilon V}(r_1) + \sum_{e\epsilon E}(r_2) + \sum_{b\epsilon B}(r_3) \quad (1)$$

Subject to:

$$\sum_{k\epsilon K} f_{sk} \leq y_s c_{max} \quad \forall\, s\epsilon S \quad (2)$$
$$\sum_{s\epsilon S} f_{sk} = d_k \quad \forall\, k\epsilon K \quad (3)$$
$$\sum_{s\epsilon S}\sum_{k\epsilon K}\alpha_s f_{sk}\frac{1}{k_0}e_0 \leq \varepsilon_0 \quad (4)$$
$$\sum_{i\epsilon K}\sum_{k\epsilon K} d_k x_{i,k}^{v,s} \leq k_1 \quad \forall\, v\epsilon V, \forall\, s\epsilon S \quad (5)$$
$$\sum_{i\epsilon K}\sum_{k\epsilon K} d_k y_{i,k}^{e,s} \leq k_2 \quad \forall\, e\epsilon E, \forall\, s\epsilon S \quad (6)$$
$$\sum_{i\epsilon K}\sum_{k\epsilon K} d_k z_{i,k}^{b,s} \leq k_3 \quad \forall\, b\epsilon B, \forall\, s\epsilon S \quad (7)$$
$$\sum_{i\epsilon K'} x_{i,p}^{v,s} - \sum_{j\epsilon K'} x_{p,j}^{v,s} = 0 \quad \forall\, v\epsilon V, \forall\, s\epsilon S, \forall\, p\epsilon K' \quad (8)$$
$$\sum_{i\epsilon K'} y_{i,p}^{e,s} - \sum_{j\epsilon K'} y_{p,j}^{e,s} = 0 \quad \forall\, e\epsilon E, \forall\, s\epsilon S, \forall\, p\epsilon K' \quad (9)$$
$$\sum_{i\epsilon K'} z_{i,p}^{b,s} - \sum_{j\epsilon K'} z_{p,j}^{b,s} = 0 \quad \forall\, b\epsilon B, \forall\, s\epsilon S, \forall\, p\epsilon K' \quad (10)$$
$$\sum_{k\epsilon K} x_{0,k}^{v,s} = y_s \quad \forall\, v\epsilon V, \forall\, s\epsilon S \quad (11)$$
$$\sum_{k\epsilon K} y_{0,k}^{e,s} = y_s \quad \forall\, e\epsilon E, \forall\, s\epsilon S \quad (12)$$
$$\sum_{k\epsilon K} z_{0,k}^{b,s} = y_s \quad \forall\, b\epsilon B, \forall\, s\epsilon S \quad (13)$$
$$\sum_{s\in S}\sum_{v\in V}\sum_{p\in K} x_{p,j}^{v,s} + \sum_{s\in S}\sum_{e\in E}\sum_{p\in K} y_{p,j}^{e,s} + \sum_{s\in S}\sum_{b\in B}\sum_{p\in K} z_{p,j}^{b,s} = 1 \quad \forall\, j\epsilon K \quad (14)$$
$$\sum_{i\epsilon K'}\sum_{j\epsilon K'}\beta_{i,j}x_{i,j}^{v,s}\frac{1}{\gamma_1} \leq \tau \quad \forall\, v\epsilon V, \forall\, s\epsilon S \quad (15)$$
$$\sum_{i\epsilon K'}\sum_{j\epsilon K'}\beta_{i,j}y_{i,j}^{e,s}\frac{1}{\gamma_2} \leq \tau \quad \forall\, e\epsilon E, \forall\, s\epsilon S \quad (16)$$
$$\sum_{i\epsilon K'}\sum_{j\epsilon K'}\beta_{i,j}z_{i,j}^{b,s}\frac{1}{\gamma_3} \leq \tau \quad \forall\, b\epsilon B, \forall\, s\epsilon S \quad (17)$$
$$\sum_{s\epsilon S}\sum_{v\epsilon V}\sum_{i\epsilon K'}\sum_{j\epsilon K'}\beta_{i,j}e_1 x_{i,j}^{v,s} + \sum_{s\epsilon S}\sum_{ev\epsilon EV}\sum_{i\epsilon K'}\sum_{j\epsilon K'}\beta_{i,j}e_2 y_{i,j}^{e,s} + \sum_{s\epsilon S}\sum_{b\epsilon B}\sum_{i\epsilon K'}\sum_{j\epsilon K'}\beta_{i,j}e_3 z_{i,j}^{b,s} \leq \varepsilon_1 \quad (18)$$

In this formulation, the decision variables are:

$y_s = 1$ if UCC *s* is used, 0 otherwise.
$f_{sk} = \{0, d_k\}$ is the daily amount (volume) of shipment that goes from UCC *s* to customer k.
$x_{i,p}^{v,s} = 1$ if the van v departing from UCC *s* serves customer *j* after having served customer *i*, 0 otherwise.
$y_{i,j}^{e,s} = 1$ if electric van *e* departing from UCC *s* serves customer *j* after having served customer *i*, 0 otherwise.
$z_{i,j}^{b,s} = 1$ if cargo-bike *b* departing from UCC *s* serves customer *j* after having served customer *i*, 0 otherwise.

The other notation in the model is:

S: the set of available UCCs.
V: set of all available vans.
E: set of all available electric vans.
B: set of all available cargo-bikes.
K: set of customers.
K': $K \cup s$, union of the set K with a specific UCC s.
i_s: fixed cost of purchasing/renting UCC s (daily basis).
h_s: cost of handling a unit of demand for UCC s.
d_k: demand of customer k (daily basis)
α_s: distance from the warehouse to UCC s.
k_0: capacity per truck.
k_1: capacity per van.
k_2: capacity per electric van.
k_3: capacity per cargo-bike.
c_{max}: capacity of all UCCs.
p_0: shipment costs per distance traveled by truck.
p_1: shipment costs per distance traveled by van.
p_2: shipment costs per distance traveled by electric van.
p_3: shipment costs per distance traveled by cargo-bike.
e_0: emission per distance traveled by truck.
e_1: emission per distance traveled by van.
e_2: emission per distance traveled by electric van.
e_3: emission per distance traveled by cargo-bike (always assumed zero).
ε_0: maximum amount of pollution allowed for all shipments from the warehouse to all UCCs.
ε_1: maximum amount of pollution allowed for all shipments from the UCCs to all customers.
$\beta_{i,j}$: distance from customer *i* to *j.*
r_1: purchase price of a van (daily basis).
r_2: purchase price of an electric van (daily basis).
r_3: purchase price of a cargo-bike (daily basis).
τ: maximum time allowed for delivery
$\gamma 1$: average speed of vans.
$\gamma 2$: average speed of electric vans.
$\gamma 3$: average speed of cargo-bikes.

Constraint (2) ensures that UCCs' capacities are not exceeded. Satisfaction of demand is enforced by Constraint (3). Constraint (4) ensures that the total emissions produced by trucks are below the allowable limit. The capacities of vans, electric vans, and cargo-bikes are enforced by Constraint (5), Constraint (6) and Constraint (7), respectively. Constraints (8-10) ensure the conservation of flows at nodes (customers) for vans, electric vans, and cargo-bikes. Constraints (11-13) ensure that each van, electric van, and cargo-bike can travel to only one customer at a time. Constraint (14) ensures that each customer is served only once. Constraints (15-17) represent the time constraint for deliveries of vans, electric vans, and cargo-bikes. Constraint (18) ensures that emissions produced by all the deliveries accomplished by vans, electric vans, and cargo-bikes together are below the allowable limit.

In the case that the environmental objective is adopted in the model (i.e. minimizing emissions), the main objective function (1) would be replaced by the sum of Constraint (4) and Constraint (18) and it would itself become a constraint; the first part of the objective function that deals with the cost of purchasing a UCC, handling demand at each UCC, and transporting goods from the warehouse to each UCC would become Constraint (4) while the rest of the objective function which deals with the distribution of goods from each UCC to all of its customers would become Constraint (18). These two new constraints would have to be below a value expressing a monetary budget. Thus, the right hand side of Constraint (4) and Constraint (18), ε_0 and ε_1, would now have a cost interpretation rather than an emission interpretation.

3. Computational approach

In order to solve the defined mathematical problem, the model is divided into two joint sub-models aimed at solving separately the optimal location and mixed vehicle routing components, as Figure 1 shows. The first sub-model aims at identifying a set of best performing configurations of UCCs and the customers that will be assigned to each UCC according to the objective selected. The second sub-model, which is fed with the output of the first sub-model, aims at identifying the optimal routes and corresponding vehicles serving customers departing from the facilities identified in the first sub-model. Unlike other approaches, where different sub-models are iterated back and forth to consider inter-dependencies among the different design problems, our two sub-problems are solved sequentially. In order to provide a fair estimation of the last-mile costs within the location-allocation model (i.e. the first sub-model), the length of routes departing from the UCCs are derived through an analytical approximation model (see Section 3.1). Given the computational burden of deriving heterogeneous routes for large problems, the exact last-mile delivery costs are derived only within the second-model for a smaller set of optimal solutions. In short, when the first sub-model is solved (a set of optimal UCC locations is determined and each customer is assigned to a specific UCC), work begins on the next sub-model, where the aim is formulate routes and choose vehicle types in such a way as to minimize the cost (or emissions) of routing for each UCC.

The approach adopted to solve the two sub-models is based on the search heuristic technique of the genetic algorithm (GA), which is an optimization strategy where a set of randomly generated solutions (initial population) is improved by means of an iterative procedure. This iterative process consists of selecting the best performing solutions (parents) and “breeding” them to create new “generations”, until an optimal solution is found. During the breeding process mutations are randomly applied (i.e. random changes in a solution that occur at a predetermined probability) in order to maintain a higher diversity in the population. The interested reader may refer to Yang (2010) for a more detailed explanation of this heuristic. Besides the typical steps used in the genetic algorithm, we provide a more detailed description of some peculiarities of the optimal location-allocation sub-model and optimal fleet choice-routing sub-model in Section 3.1 and Section 3.2.

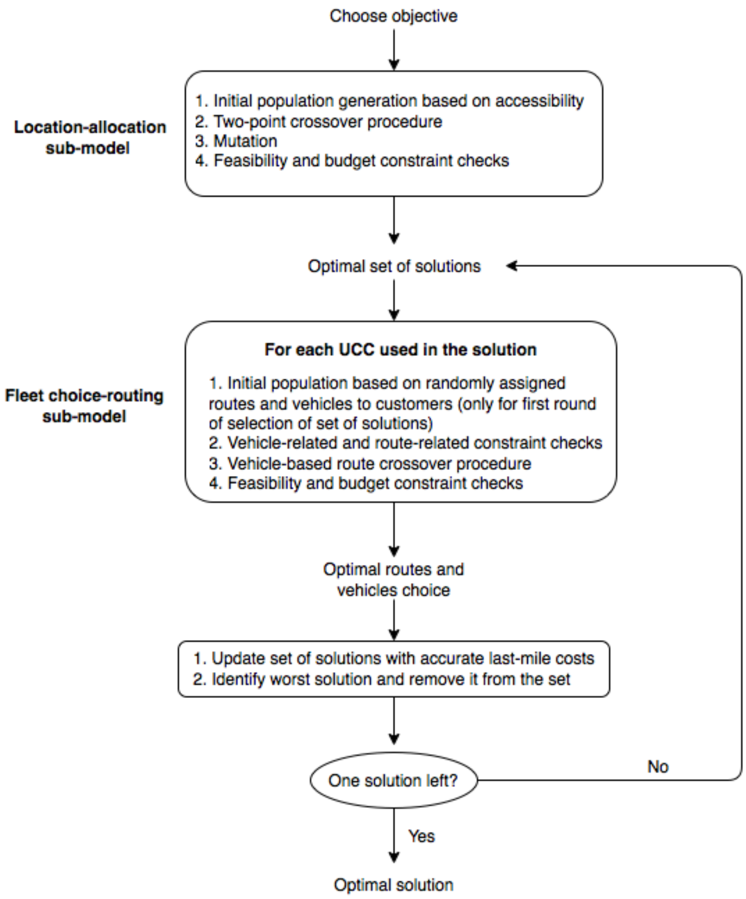

Figure 1: Descriptive Map of the adopted optimization approach

3.1 Location-allocation sub-model

The method used to fill the initial population of solutions is not completely random, but it is based on the relative accessibility of the available UCCs for each customer. Hence, as an initial step, all the customers are assigned to a UCC *i* with a probability P_i which is derived from

$$P_i = \frac{(\sum_i^N d_i)/d_i}{\sum_i^N((\sum_i^N d_i)/d_i)} \tag{19}$$

where d_i represents the distance between the customer and UCC *i* among the available set of *N* facilities.

At this point, a random number of facilities between 1 and (*N*-1) are removed and the "unassigned" customers (i.e. customers whose UCC has been removed) are re-assigned to the remaining UCCs according to their relative accessibility with a probability derived by means of Equation (19).

The selection of "parent" solutions is based on the tournament selection method where the best performing solution is identified among a set of randomly selected solutions. The breeding procedure into "child" solutions is rather straightforward and is accomplished by means of a two-point crossover where the assigned UCCs of two corresponding groups of customers in the parent solutions are swapped. The mutation of child solutions is applied such that some customers are randomly re-assigned to the available facilities.

To provide an estimate of the last-mile delivery costs, the lengths of routes are determined by means of the approximation approach proposed by Robusté et al. (2004), based on the prior studies of Eilon (1971) and Daganzo (1984), where analytical formulations are empirically derived depending on different features of demand. Hence, we adopt the following equation representing the distance D of the routes departing from a single facility, obtained from the Clarke and Wright Algorithm in the elliptic VRP:

$$D \approx 0.603a\sqrt{1+\beta^2}\left(\frac{N}{C}\right) + 0.725\sqrt{AN} \tag{20}$$

where "*a*" corresponds to the major semi-axis of the ellipse circumscribing the customers served by the UCC, β represents the ratio between the major and minor semi-axis of the ellipse, *N* corresponds to the number of customers served (in our case by each utilized UCC), *C* indicates the average amount of customers that can be served given the average capacity of the fleet, and *A* represents the area containing the scattered customers.
When the amount of customers served by the UCC is low (N<3) instead, we adopt the original formulation by Daganzo (1984) where the total length *D* of the routes is given by:

$$D \approx \frac{2rN}{C} + 0.73\sqrt{AN} \tag{21}$$

where *r* corresponds to the average distance between the customers and the UCC. The results of these estimations are face-validated by analyzing the results produced in the case studies examined in Section 4.

Finally, over the several generations a set of *m* candidate optimal solutions is created in order to provide the input for the second sub-model. The size of the set, M, can be varied according to the scale of the problem and level of accuracy sought in the solutions of the overall problem. In the case studies presented in Section 4, we typically used sizes ranging between 2 and 10 based on the size of the case studies.

3.2 Fleet choice-routing sub-model

The output of the location-allocation sub-model consists of *M* solutions, each of which may use up to *N* UCCs. This means that if all of the available UCCs are used, the fleet choice-routing sub-model needs to optimize M*N UCC/customer configurations.

The main algorithmic steps of the sub-model can be summarized as follows. For a particular solution $m \in M$, the used UCC $n \in N_m$ is selected and each customer serviced by UCC *n* is assigned to a random route that is served by a random vehicle type. Then, once the feasibility of the routes in terms of delivery time and capacity is verified, additional routes are created with random vehicles (always ensuring that constraints are satisfied) until all customers served by UCC *n* have been assigned to a route. Then, we proceed to check the constraints that pertain to the entire UCC (either emission or budget constraints). Constraint (18), shown earlier, states that we need to check emission and budget constraints not just for UCCs but for the entire solution that may use up to *N* UCCs. Thus, in order to check emission or budget constraints for each UCC separately, each UCC was linked to its own constraints. The constraints are directly proportional to the number of assigned customers to that UCC divided by the total number of customers in the network. These steps outline the creation of one random solution for UCC *n*. They are then repeated many times (usually ranging between 100 to 500 times) to create an original population for UCC *n* in solution *m*.

The following step of the genetic algorithm procedure creates better solutions by "breeding" the best solutions of the initial population (identified with a tournament selection procedure); this process is then repeated over several generations in order to produce higher quality solutions. The breeding approach used is based on the crossover method described by Prins (2004) where customers of the first Parent solution are randomly assigned to a new route corresponding to the one serving the same customers in the second Parent solution. Since in our sub-model, vehicle typologies are required to be "bred" as well, we propose the following approach to extend Prins's breeding process: It is assumed that when a customer is re-assigned to a new route, the customer also inherits this route's vehicle typology; this approach is used when possible but sometime the addition of a new customer does not allow for the same vehicle type to be used because some constraint may no longer be satisfied. For example, if a cargo-bike was originally used, the addition of a new customer may exceed its capacity. In this case, a new vehicle type, either an electric van or a van is randomly assigned. As with any genetic algorithm, a mutation may also occur with a predetermined probability. This mutation would allow for random customers to be placed on new routes and to inherit a new vehicle. Also, another mutation may allow for the switching of vehicle typologies on any one route if and only if the new vehicle type would be able to meet all constraints.

The preceding steps describe the approach for finding the best set of routes for one particular UCC in one particular solution. With that, all steps must be repeated for each UCC selected in the first sub-model in order to find the total costs (or emissions). These steps are applied to all the solutions in the set, allowing for the calculation of their total costs (or emissions) and ultimately yielding to the removal of the worst one. The breeding procedure is applied to the remaining solutions in the set in order to further improve the value of the objective function. The whole procedure is iterated among the set of solutions until the optimal one is identified.

4. Application to a realistic case study: Austin

In order to show the applicability of the toolbox, we present the results of several simulations performed with different settings reflecting different UCC implementation scenarios in the city of Austin, Texas. Austin accounts for a population of about 900,000 inhabitants and is considered one of the fastest growing cities in the US with annual growth rates between 2.5 and 3.0 percent (U.S. Census Bureau, 2015). This rapid growth gives UCCs an important opportunity to address the current and future issues associated with local congestion and pollution.

Since conducting a data collection, validation, and analysis exercise was beyond the scope and means of this research, the case study was built based on previous studies and publicly available data sources concerning the demand and costs of UCCs. Hence, the two following alternative configurations for the application of the model are used for our demonstration. The first one, represented in Figure 2a, corresponds to a situation of relatively low number of 48 daily customers (represented by the blue markers) mainly located in the central districts and 12 available facilities (represented by the green markers). The locations of both customers and facilities are spread rather homogeneously over the network. Different sizes of the deliveries are randomly assigned with values between 1 ft^3 and 40 ft^3 to the each of the customers. The second one, represented in Figure 2b, corresponds to a situation of a higher amount of daily customers (149) distributed over a larger area of the city (Figure 2b). Similar to the "small scale" configuration, the sizes of deliveries are randomly assigned to customers.

In both cases, the main depot (represented by the purple marker) is located in the Southeastern limit of the city, close to Austin-Bergstrom International Airport and Interstate 35, two major sources of freight trips for Austin.

The road network used in the simulations covers the majority of the city districts and consists of 3561 links and 1369 nodes.

In this study, we assume the size of available UCCs to be relatively small (about 4000 ft^2) due to the urban location and the absence of added logistic services of these facilities. As a result, the estimated handling capacity corresponds to around 2,900 ft^3 of goods per day and the investment costs correspond to an approximate annualized value of \$40,000 (assuming depreciation of 20 years and an interest rate of 5%). The costs derived from the operation of satellites are given by the product of amount of goods transshipped (in ft^3) and the average handling cost which is assumed to be \$0.025 /ft^3.

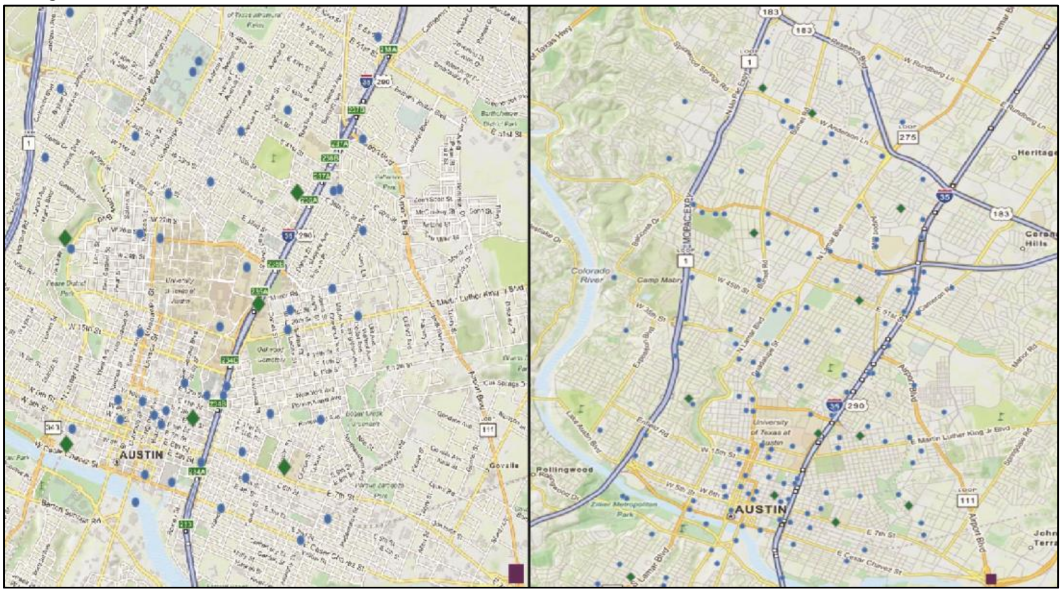

Figure 2 (a): Demand and facility location for the small configuration; (b): Demand and facility location for the large configuration

The main features of the available typologies of vehicles in the model are reported in Table 1. Capacities and purchasing costs are derived from publicly available data about different models (Cyclelogistics, 2011; Cycle Maximus, 2015; Nissan, 2015; Commercial Truck Trader, 2015). The speeds of "traditional" vans and electric vans have been assumed rather low (20 mph) to account for the urban context and lower values have been applied for cargo-bikes to consider for physical limitations of cyclists. The operating costs are derived considering an average hourly wage of \$30/hour and including other costs such as usage of gasoline (for vans) and maintenance. The allowable radius, which is not shown in the table, (the maximum distance that a vehicle is allowed to go from the UCC that it serves) is set to 4 miles for cargo-bikes but is not considered for electric vehicles and vans. The emission costs accounts for both greenhouse and non-greenhouse gas emissions produced per mile (Litman, 2009).

Table 1: Fleet characteristics

	Traditional van	*Electric van*	*Cargo-bike*	*Truck*
Speed (mph)	*20*	*20*	*10*	*30*
Capacity (ft^3)	*180*	*140*	*40*	*1,000*
Purchasing costs (\$)	*25,000*	*30,000*	*7,000*	*-*
Operating costs (\$/mile)	*3*	*2.8*	*3.2*	*3.3*
Emissions costs (\$/mile)	*0.095*	*0.015*	*0*	*0.215*

Finally, here we present a series of different scenarios corresponding to potential situations for the development of UCCs and possible related policy initiatives:

Base Scenario: The distribution costs using UCCs for a single carrier are minimized. This scenario represents a situation where the carrier, evaluating the opportunity to implement UCCs as part of its last mile delivery, seeks the most cost efficient location of facilities, mix of vehicles, and corresponding routes serving its current customers.

Scenario 1: The emissions caused by the distribution for a single carrier are minimized. This scenario represents a situation where the carrier, evaluating the option of using UCCs, seeks for the most environmentally friendly configuration in terms of location of facilities, vehicles in charge of the last mile deliveries, and corresponding routes. A high environmental performance might be sought in cases where a carrier seeks to build an environmentally friendly image or when the local authorities attempt to identify the most sustainable option for the city.

Scenario 2: A single carrier minimizes costs as in the Base Scenario, but the purchase/rent cost of the facilities is reduced to an annualized value of \$7,500 and the handling capacity of facilities is decreased to 600 ft^3. This scenario represents a situation where the local authorities decide to provide inexpensive usage of facilities to the carriers. The reduced capacity instead, might be due to the inability (or unwillingness) of the municipality to provide for large facilities or due to the fact that the same offer is made to several carriers that have to share the same facilities. This kind of scenario may be introduced by local authorities with the goal of having more UCC facilities around its city in hopes of decreasing the total distance that last mile vehicles have to travel which would result in a reduction of emissions.

Scenario 3: A single carrier minimizes costs as in the Base Scenario, but the purchase costs of bikes are reduced to zero and the purchase of costs of electric vans are reduced by 33%. This scenario represents a situation where local authorities decide to subsidize “cleaner” means of freight distribution aiming to improve air quality

5. Results

Since a heuristic technique is used to solve this NP-hard problem, the obtained solutions might be sub-optimal. Hence, it is recommended to test each configuration by changing and calibrating the several parameters used in the problem (population size, tournament size, number of generations, etc.). In this study, for the small configuration, the best results have been obtained by using a population size of 200 and 300 solutions for the location-allocation sub-model and the routing sub-model, respectively. Twenty generations were bred in the location-allocation model, whereas in the routing sub-model five generations were produced for each solution before the worst performing one was eliminated.

The outcomes corresponding to the alternative scenarios for the small configuration are summarized by Figure 3, which shows the UCCs chosen (blue dots) and the routes taken by each vehicle type. Figure 4 resents the total daily distribution costs and Figure 5 presents the total daily total emission costs.

The optimal configuration in the Base Scenario (Figure 3a,) corresponds to a single facility from where 4 routes for vans and 3 routes for electric vans depart. Even though cargo-bikes have a considerably lower purchasing cost and an operating cost similar to other modes, they are not included in the fleet probably because of their limited capacity and service range.

According to these results, we could conclude that cargo-bikes will be seldom used whenever a carrier wants to minimize costs under these conditions. However, in other systems, where customers may be more clustered around the available facilities and where the average demand of a customer is much lower, cargo-bikes could still be a viable option. The corresponding total daily distribution costs of the Base Scenario amounts to $397.7 and the total daily emission costs amount to $4.8.

On the other hand, Scenario 1 (Figure 3b), where the goal is to minimize emissions, is characterized by widespread usage of cargo-bikes and electric-vans for the last mile distribution (respectively 8 and 14 routes). As expected, vans are not used because they pollute much more per mile than the other two vehicle types. Also in this case, one single facility is chosen, relatively close to the main depot to reduce the emissions of trucks, but central enough to serve many customers with cargo-bikes. This scenario results in total daily distribution costs of $624.0 and total daily emission costs of $1.2. Though using only cargo-bikes would result in $0 of daily emissions, using only cargo-bikes is not a feasible solution because it would also result in many more total trips and would exceed the allowable cost constraint.

When the investment cost of opening UCCs is reduced (along with their daily handling capacity) as in Scenario 2 (Figure 3c), the lowest costs are achieved by using two facilities (the same UCC as in the previous scenarios plus an additional one further west). The majority of customers are served with regular vans (7 routes), except for one delivery route assigned to an electric van. As in the Base Scenario, no cargo-bikes are used. The total daily distribution cost of this scenario amounts to $286.2 and the total daily emission cost is $1.9. Compared to the Base Scenario, the operation costs are much lower due to the fact that the facility comes at a much lower price (as well as a lower handling capacity). Interestingly, under these conditions, the total daily cost of emissions is close to the value of Scenario 1, where the objective was to minimize emissions. Hence, this result suggests that the leasing of smaller facilities at cheaper prices might be a beneficial option for the municipality when seeking for more environmentally friendly solutions.

Scenario 3 (Figure 3d), which corresponds to the minimization of costs when the upfront costs of cargo-bikes and electric-vans are entirely or partly subsidized, is characterized by the usage of a single UCC from where the deliveries are performed by electric-vans and vans (respectively 7 and 2 routes). Surprisingly, no cargo-bikes are used, even though cargo-bikes were entirely subsidized. The total daily distribution and emission costs correspond to $383.3 and $3.6, respectively. Hence, this outcome suggests that subsidizing both electric-vans and cargo-bikes would yield to only a minor reduction of emissions, particularly when compared to alternative measures like leased smaller facilities.

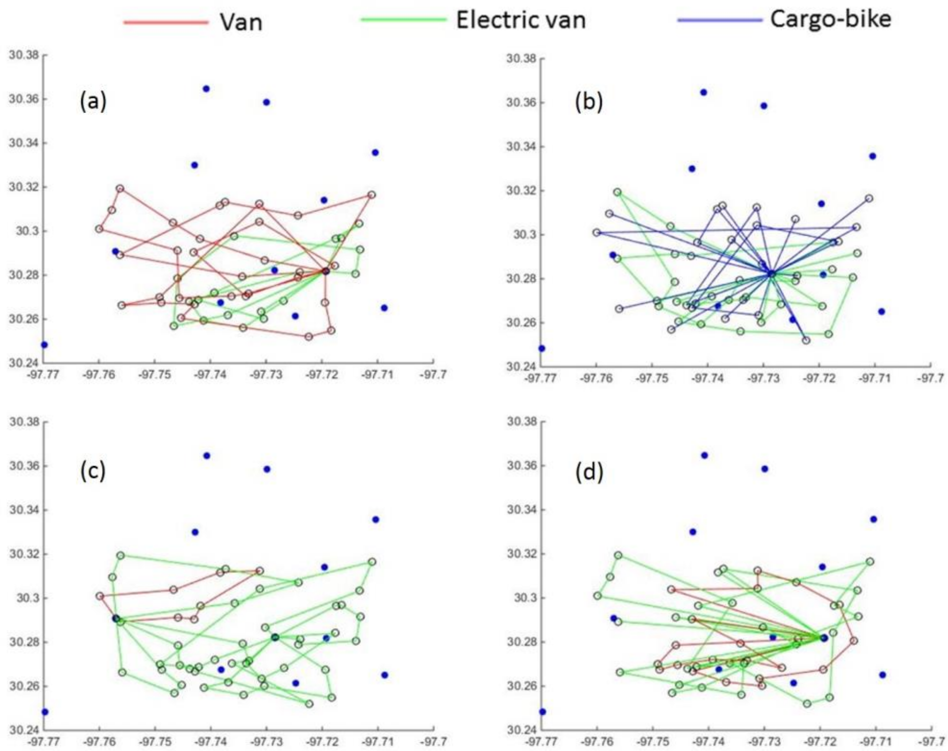

Figure 3 Straight line paths of each of the small configuration scenarios: (a) Base Scenario; (b) Scenario 1; (c) Scenario 2; (d) Scenario 3; the x and y axes represent the latitudes and longitudes.

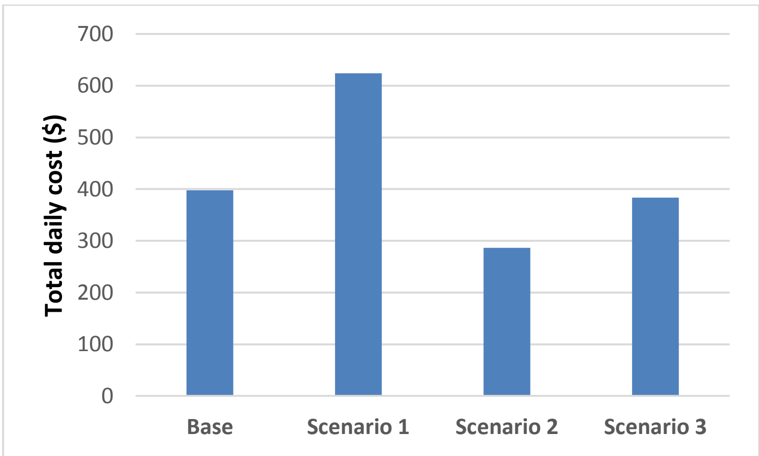

Figure 4: Total daily costs of distribution in the small configuration

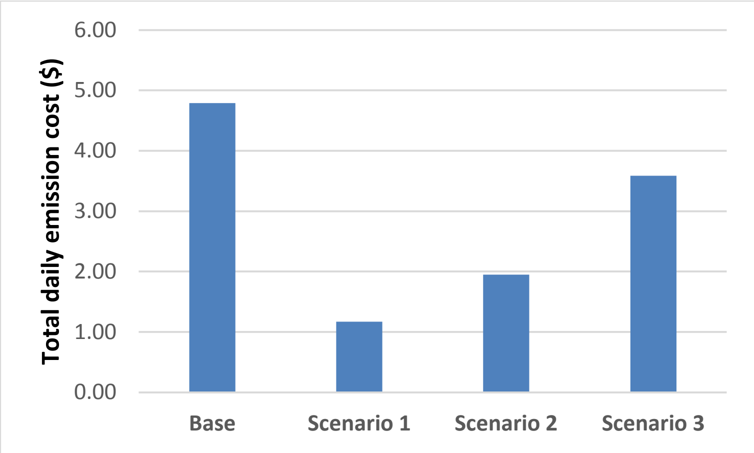

Figure 5: Total daily emission cost of distribution in the small configuration

For the larger configuration of the UCC distribution problem, shown in Figure 2b, the number of generated feasible solutions used in both the location-allocation and the routing sub-model corresponds to 300. The 3 best solutions of the first sub-model obtained after 20 generations of breeding were passed to second sub-model. Here, 5 generations of breeding were produced each time before the worst solution was eliminated.

Figure 6 and Figure 7 show the total daily operating costs and total daily costs of emissions, respectively, for the large configuration. The paths of the routes are not shown due to the great amount of routes overlapping in each scenario. The outcomes of the simulations for the larger scale problem are consistent with ones identified for the small configuration.

In the Base Scenario, the total daily cost of delivery is $1686.0 and the total daily cost of emissions is $20.7. As in the Base Scenario, only a limited number of facilities is used (two UCCs) from where the vehicles in charge of the last-mile distribution are in large part vans (15) and electric vans (19). However, in this case, two cargo-bikes are used (one per facility). This suggests the idea that even though cargo-bikes may not be the most economical mode (in the modeled scenarios), it might still be a good idea for each UCC to have one in case there is a small amount of demand left over than cannot fit into a van or an electric van.

In Scenario 1, where the goal is minimizing emissions, in line with the results of the small configuration, the daily operating costs are higher than the Baseline Scenario at $1972.0 and the daily emission costs were lower at $7.4. Also in this case, no van is used, whereas 39 routes consisted of electric vans and 13 routes consisted of cargo-bikes. The facilities selected consist of the same two UCCs used in the Baseline Scenario.

As with the small configuration, the intention of Scenarios 2 and 3 was to investigate the effects of potential alternative policy measures to reduce the daily costs of emissions without compromising the efficiency of the solutions. Unlike in the small configuration where the costs of emissions could be drastically reduced (particularly in Scenario 2), the same cannot be said for the large configuration. While the operating costs are decreased thanks to different types of policy measures, the daily costs of emissions are not considerably reduced ($19.00 and $19.50 respectively for Scenario 2 and 3). This result might be explained by the greater spread of customers in the large configuration, which does not allow for a great emission reduction or by a limited scalability of the model. For this reason, alternative scenarios with different demand patterns are recommended for additional investigations about these measures and for further testing of the model.

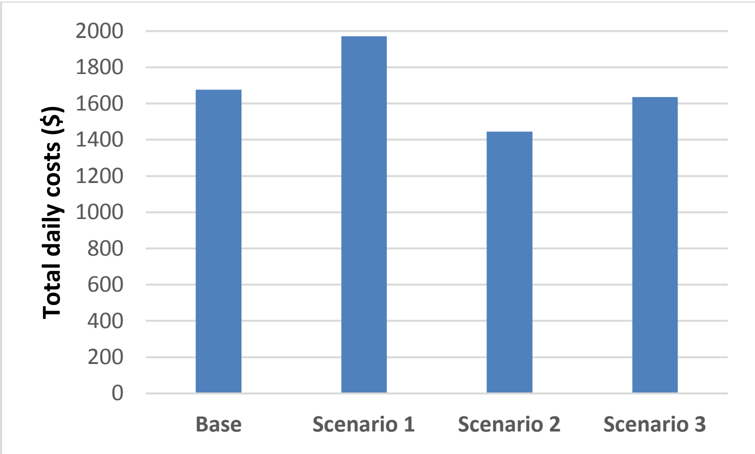

Figure 6: Total daily costs of distribution in the large configuration

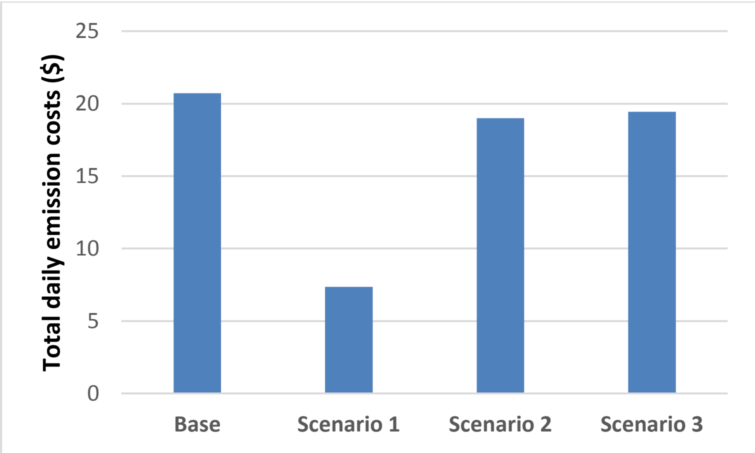

Figure 7: Total daily emission cost of distribution in the large configuration

As shown in the simulations presented above, the toolbox can provide useful information to different stakeholders for the evaluation of alternative UCC solutions.

For example, the possibility of choosing different objectives, as in the Base Scenario and Scenario 1, shows how stakeholders with different goals (i.e. carriers and local authorities) would likely use a different fleet and a different set of routes.

Furthermore, the two additional scenarios designed to reduce the daily costs of emissions while still using the objective function that minimizes operating costs provided an indication of the effectiveness of two alternative policy measures. In the configurations analyzed, Scenario 2, which offers lower prices of facilities with lower handling capacities, looks like the best compromise in terms of costs and emissions produced for both small and large configurations. Indeed, decreasing the price for the usage of facilities would not only reduce the costs for the carriers, but also yield to a decrease of emission costs, particularly in the case of the small configuration. This scenario can be a practical and viable solution for local authorities that are willing to lease their own facilities (with capacity limitations) to multiple carriers. However, it is recommended to perform some sensitivity analyses of the costs and capacities used before coming to conclusions.

6. Conclusions

UCCs represent an innovative approach to reduce the negative impacts associated with the current delivery systems in urban areas. However, to date, most UCC initiatives had to be terminated due to high operating costs and a lack of subsidies. In the last fifteen years, the necessity of identifying the most beneficial setup in order to guarantee the success of UCCs has been the main rationale behind several studies in the urban logistic field. Along these lines, this study combined several issues into an optimization model presented in the form of a toolbox.

In this paper, we formulated an optimization problem that decides where to open UCCs, what vehicle types to use, and what routes to take in order to either minimize costs or minimize emissions. From a theoretical standpoint, this study represents an extension of previous models that typically addressed only one or two of the three decisions variables analyzed in this paper. The decision variables of the problem are the same as those in the model of Wu et al. (2002). However, our problem also considers each typology of vehicle to have additional specific features like costs and speeds.

The methodological approach consists of dividing the problem into two sub-models that are sequentially solved by means of the heuristic genetic algorithm. The main characteristics of the model consist of first determining a set of candidate solutions regarding UCC locations and then feeding these candidate solutions into the second genetic algorithm that determines routes and chooses vehicle types. In order to improve the computational capabilities of the model, the breeding of solutions can be made more efficient by alternative techniques, which would allow only for the best characteristics of each parent solution to survive over the generations. Also, we plan to extend our study to see how the value of the objective function might further decrease if we applied a linear relaxation to the routing sub-model which can currently be characterized as an integer program.

From a policy perspective, this study represents a useful tool to develop partnerships between carrier companies, local businesses, and city authorities in order to identify optimal solutions for all of the stakeholders involved. As an example, in the final part of this paper we provided a demonstration of the potential applications of the toolbox by producing alternative scenarios. Each scenario represents different conditions or policy interventions from the carrier or the local authorities. Some sensitivity analyses of the different parameters used in the toolbox and additional simulations entailing different customer and facility locations are recommended.

There are many methodological and institutional challenges involved with the implementation of UCCs. With this toolbox, we hope to provide an additional level of understanding, which is critical in the preliminary analysis of the problem.

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