Environmental Sustainable Fleet Planning in B2C e-Commerce Urban Distribution Networks

Francesco Carrabs, Raffaele Cerulli and Anna Sciomachen

Abstract Sustainable distribution is one of the topics concerning the smart city concept. In this chapter we face the problem of delivering a given amount of goods in urban areas arising from e-channel department stores, with the aim of minimizing the overall distribution costs; costs take into account traveling components, loading and other operative aspects, and environmental issues. More precisely, in the present business to consumer distribution problem, we have to determine the fleet of not homogeneous vehicles (trucks, wagons, vans and picks-up) to be used for satisfying the demands of clients coming from e-channels, and their related itineraries, given the traveling limits imposed by the urban government; in particular, we have to respect the maximum route length constraints and use the appropriate vehicles for each kind of street. We propose a mathematical programming model to solve this computationally difficult problem, which is strategic for being able to implement sustainable distribution plans in a smart city context. Preliminary results of test bed cases related to different sized urban distribution networks are reported and analyzed.

Keywords City logistics • Sustainable distribution • e-Channel • Network models • Vehicle routing problem

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1 Introduction

Nowadays, both large and small cities are proposing a new model, called "the smart city", which represents high technological, sustainable, comfortable and secure living environment. Following this idea, a number of models have been developed and deployed with the help of technological advances in computer and communication, such as Information and Communication Technology (ICT) and Intelligent Transport Systems (ITS), which constitute precisely the basis of the smart city model [2, 12].

Sustainable distribution is one of the topics concerning the smart city concept. Recently, increasing attention has been particularly devoted to sustainable development of urban areas as well as mobility of goods for ensuring the wellbeing of community. The aim of a sustainable urban distribution network is to analyze how society intends to provide the means to properly meet economic, environmental and social needs efficiently and equitably, while minimizing negative impacts and their associated costs, including environmental issues, such as congestion, noise and air pollution. In this sense, the idea of city logistics has been proposed to establish efficient and environmentally friendly urban logistics systems [5, 11].

A difficulty in modeling city logistics comes from the complex interactions between private and public stakeholders involved in urban freight transport: shippers, freight carriers, administrators and residents (consumers). In fact, city logistics requires advanced optimization and simulation modeling approaches and tools to assist in the design, implementation and evaluation of schemes that satisfy the needs of all the above stakeholders, who hold different concerns and objectives. While the recent growth of research into urban distribution and city logistics is encouraging (see e.g. [6, 13]), only few works have been concerned with examining the likely impact of policy measures on distribution operations. A review of emerging techniques for enhancing the practical application of city logistics models is presented in [7, 12]; focuses on the evaluation of urban tours traveled by different types of commercial vehicles and their related costs. In Anderson et al. [1] a project is presented having the aim of investigating the ways in which alternative policy measures, such as weight and access time restrictions, can result in changes in the vehicle activities involved in urban distribution operations. New challenges have been observed for distribution systems designed within smart city frameworks. In particular, models of vehicle routing problems (VRP) are considered basic tools for implementing sustainable good distribution channels in urban areas. In this direction, a number of chapters on VRP have been published by operations researchers and practitioners (see, e.g. [9, 10]) with the aim of providing advances for the development of ITS within smart city models. In the present chapter we consider a particular case of VRP, originating from the need of delivering goods in an urban context arising from e-channel department stores. More precisely, in this urban business to consumer (B2C) distribution problem we have to determine the fleet of not homogeneous vehicles (trucks, wagons, vans and pick-up) to be used for the delivery of a given amount of goods in urban areas. Note that the management of the fleet and the global routing of vehicles in the urban network are key elements for sustainable goods distribution plans. Our problem is strongly connected to the design of city logistics systems for medium–large cities, where it provides the means to efficiently keep large trucks out of the city center, with small and environment-friendly vehicles providing the last leg of distribution activities [5]. Following this direction, in this chapter, each vehicle involved in the distribution process is characterized by two parameters: (1) the size (which allows it to cross only some types of roads) and (2) the maximum load capacity. Starting from a depot (to be determined) each vehicle must pass through the streets of the city (compatible with its size) to deliver the required goods along that road and go back to the chosen depot. The considered cost components, to be minimized, take into account traveling, loading and environmental issues.

We present a mathematical formulation of this novel urban B2C distribution problem for solving it. The referring urban B2C network problem (UB2CNP) is presented in more details in the next section. Section 3 reports the proposed network model and the related Mixed Integer Programming (MIP) formulation. Finally, some preliminary results and outlines for future works are given.

2 Problem Definition

The proposed urban logistic network problem (UB2CNP) can be seen as an extension of the classical vehicle routing problem VRP, encountered very frequently in making decisions about the distribution of goods and services. Given a number of customers with known demands and a fleet of not identical vehicles with known capacities, the problem consists in finding a set of routes originating and terminating at a central depot and serving all the customers exactly once. The routes cannot violate the capacity constraints on the vehicles. Differently from the classical VRP formulation, in addition, we must meet the size constraints on the streets, which specify which kind of vehicle can cross the street. All problem parameters, such as customer demand and typologies of streets, are assumed to be known with certainty. The standard objective of the UB2CNP problem consists of minimizing the total travel cost.

The UB2CNP is a basic distribution-management problem that can be used to model many real world problems. Some of the most useful applications of the UB2CNP include bank deliveries, postal deliveries, industrial refuse collection, national franchise restaurant services, school bus routing, security patrol services, and vendor deliveries for just-in-time manufacturing.

Here, the UB2CNP applies to deliver groceries ordered from e-channel department stores to customers who reside at their homes. The management of the department stores has hence to collect the orders and group them according to the allowable vehicles. Further, customers are identified according to their address with reference to the corresponding kind of street, for being able to define the routes necessary to satisfy the overall demand and choose the best vehicle to use for the delivery which minimizes costs and the environmental impact. The problem, as particular case of the classical VRP problem, is NP-complete [8] that is computational difficult to be solved, and instances involving more than 100 customers are very hard to solve optimally. For this reason it makes sense to focus on the development of efficient mixed integer programming formulation models, possibly accomplished by the creation of heuristics approach to solve the problem. For recent surveys on the state of the art in VRP research we recommend the survey by Cordeau et al. [4] that describes both exact and heuristic methods, and the survey by Bräysy and Gendreau [3] that focuses on metaheuristics.

3 The Urban Logistic Problem

Formally the UB2CNP is defined as follow. Let $G = (V \cup \{0\}, E, L)$ be a connected digraph where V is the set of locations, 0 is a special vertex representing the depot, L is the set of different typologies (label) of streets, A is a set of arcs to which two values are associated: (1) a nonnegative weight t_{ij}, denoting the travel time (or the edge length) and (2) a label indicating the edge (street) type. Let n, m and l be the cardinality of V, E and L, respectively. A service requirement q_i, which can be delivery from the depot, associated with each customer. Vehicles of different type and different capacity must be routed to serve all the customers. A feasible vehicle route $\rho = \{0, v_1, v_2, \ldots, v_{\ell-1}, v_\ell, 0\}$ of length l is an ordered sequence of different customers to be served such that the total capacity of the vehicle is not exceeded and, the streets constraints are satisfied. A feasible solution $S = \{\rho_1, \rho_2, \ldots, \rho_k\}$ of the problem is a collection of feasible routes. We denote by $c(\rho)$ the total length of route ρ and by $c(S) = \sum_{\rho_i \in S} c(\rho_i)$ the total length of the feasible solution S. The UB2CNP problem consists in computing the minimum cardinality set $S = \{\rho_1, \rho_2, \ldots, \rho_k\}$ of feasible routes such that all the customers are served and each customer is visited by a single vehicle. Note that this objective implies the minimization of the number of vehicles used for delivering the required goods, thus in turn reducing both the congestion and the pollution in the city tours as well as the final cost.

3.1 The Urban Logistic Network Model

To model this problem we use an edge labeled graph. The nodes represent intersections and the arcs the streets of the city. The nodes are classified as: depot nodes (where goods are stored), costumer nodes (where goods have to be delivered) and the transshipment nodes. We assign a different label to each type of street according to its width. Moreover, each label will be associated to a particular type of vehicle. Without loss of generality, we assume that the labels are ordered according to the width of the street. For example, if there are three types of roads there are three different labels: A, B and C. The vehicles associated to label A can travel along the streets of type A, B and C, labeled B vehicles can travel along streets B and C, while vehicles with label C are allowed to pass only through streets of type C. Each vehicle is characterized by two parameters: (1) the size (which allows it to cross only some types of roads) and (2) the maximum load capacity. Starting from a depot each

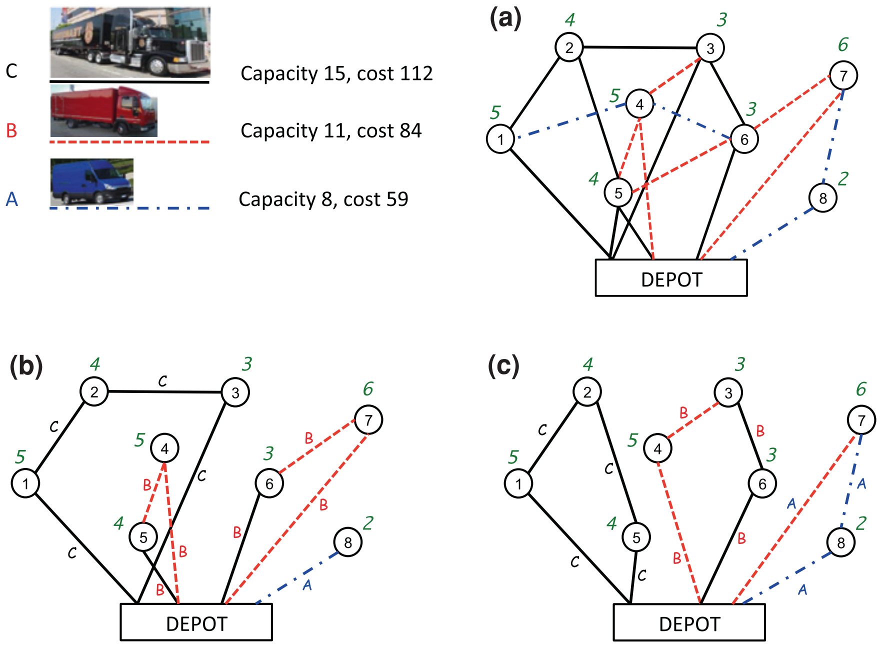

Fig. 1 A simple example of the problem where no cost are associated to the edge of the graph. **a** The labeled graph G. **b** A feasible solution with value 112 + 84 + 84 + 59 = 339 and **c** a better solution with value 112 + 84 + 59 = 255

vehicle must pass through the streets of the city (compatible with its size) to deliver the required goods along that road and go back to the depot. A cost c_k is associated to each type of vehicle. The length of each route cannot exceed a fixed value. A simple example of our referring urban B2C network model is reported in Fig. 1a, which shows a small urban center in which eight customers must be supplied from a single depot by using three type of vehicles. To each vehicle is associated a capacity 8, 11, 15 and a fixed cost 59, 84, 112, respectively. To each edge is associated a label representing the type of vehicle that can cross this edge. In this particular case, the cost of the edges is neglected. The numbers outside the nodes represent the associated goods' demand. In Fig. 1b and c are reported two feasible solutions with cost 339 and 255, respectively. Readers can easily note how the number of the used vehicles impacts on the final cost.

3.2 *Mixed Integer Programming Mathematical Formulation*

In this section we present a integer programming formulation for the UB2CNP. Before presenting the whole model let us summarize the required notations. Consider customers at various locations in the city which must be served by vehicles hosted at a central depot. Denote the central depot by 0 and the locations by $i = 1 \ldots n$. We can represent the input information using a directed network $G = (V \cup \{0\}, E, L)$, where V denotes the set of n vertices, E the set of m arcs (the streets) and L the set of labels associated to the arcs (the streets characteristic).

The following inputs are assumed to be available:

- T = number of vehicle types;
- Q_t = capacity of vehicle type $t (Q_1 < Q_2 < \cdots < Q_T)$;
- f_t = fixed activation cost of vehicle type $t (f_l < f_2 < \cdots < f_T)$;
- d_j = demand of customer j;
- c^t_{ij} cost to pay for each vehicle of type t that crosses the arc (i, j);
- a^t_{ij} that assumes value equal to 1 if the edge (i, j) can be traversed by the vehicles of type t;
- V_d set of demand nodes;
- V_p set of transhipment nodes ($V = V_d \cup V_p \cup \{0\}$ and $V' = V_d \cup V_p$).
- mk = number of vehicles of type k available

In addition, the following decision variables are used:

- binary variable x^k_{ij} that assumes value equal to 1 if a vehicle of type k travels from i to j, and 0 otherwise;
- continuous variable y_{ij} that represents the flow of goods from i to j.

Then, the (MIP) formulation of UB2CNP is the following:

$$\min \sum_{k\in T} f_k \sum_{j\in V'} x^k_{0j} + \sum_{k\in T} \sum_{\substack{i,j\in V\\ i\neq j}} c^k_{ij} x^k_{ij} \tag{1}$$

$$s.t. \sum_{k\in T} \sum_{i\in V} x^k_{ij} = 1 \qquad \forall j \in V_d \tag{2}$$

$$\sum_{i\in V} x^k_{ip} - \sum_{j\in V} x^k_{pj} = 0 \qquad \forall p \in V', \forall k \in T \tag{3}$$

$$x^k_{ij} \le a^k_{ij} \qquad \forall i,j \in V,\ i \neq j,\ \forall k \in T \tag{4}$$

$$\sum_{j\in V'} x^k_{0j} \le m_k \qquad \forall k \in T \tag{5}$$

$$\sum_{i\in V} y_{ij} - \sum_{i\in V} y_{ji} = q_j \qquad \forall j \in V_d \tag{6}$$

$$\sum_{i\in V} y_{ij} - \sum_{i\in V} y_{ji} = 0 \qquad \forall j \in V_p \tag{7}$$

$$y_{0j} \le \sum_{k=1}^{T} (Q_k) x^k_{0j} \qquad j \in V' \tag{8}$$

$$y_{ij} \leq M \sum_{k=1}^{T} x_{ij}^{k} \qquad \forall (i, j) \in E \tag{9}$$

$$x_{ij}^{k} \in \{0, 1\} \qquad \forall i, j \in V, \ i \neq j, \ \forall k \in T \tag{10}$$

$$y_{i,j} \geq 0 \qquad \forall (i,j) \in E \tag{11}$$

where M is chosen to be a large number so that (9) becomes redundant if $\sum_{k \in T} \sum_{i \in V} x_{ij}^{k} = 1$. For our problem is easy to see that a correct value for M is $\max_{k \in T}\{Q_k\}$. However, due to the constraints (4) we can associate different value M_{ij} to each arc (i, j) of the graph considering the maximum capacity of the vehicle among those that can traverse the arc (i, j).

In the above formulation, the objective function (1) requires the minimization of the total cost to serve all customers. Note that the cost coefficients depend on the type of the vehicles; in this way we are able to take into a proper account a sort of pollution charge depending on the environmental impact of the vehicle. Moreover we consider a fix cost f_k required to use the vehicle k. Constraints (2) and (3) impose that a customer is visited exactly once and that if a vehicle visits a customer, it must also depart from it. Constraints (4) guarantees that each vehicle can traverse only appropriate streets. The maximum number of vehicles available for each vehicle type is imposed by constraints (5). Constraints (6) and (7) are the commodity flow constraints: they specify that the difference between the quantity of goods a vehicle carries before and after visiting a customer is equal to the demand of that customer (this demand is equal to 0 for the transhipment nodes). The constraints (8) ensure that the vehicle capacity is never exceeded whenever the constraints (9) guarantee that the value y_{ij} can be greater than 0 only if exists at least a vehicle that crosses the arc (i, j). Finally, constraints (10) and (11) are the variables constraints.

4 Computational Tests

The model were coded in C++ and solved by CPLEX 12 on a 2.33 GHz Intel Core2 processor. We carried out the computational tests on a set of scenarios composed by three instances having the same number of vertices, edges and vehicles. In the randomly generated instances, the number of vertices ranges from 10 to 40 and the density ranges from 0.3 to 0.5. We used small instances because, how we will see in the following, the UB2CNP problem appears very hard to solve in particular when the density of the graph increases. Moreover, we generated instances with 2 and 3 different type of vehicles in order to evaluate also the impact of this parameter on the performance of the model; in particular, in our instances we consider two types of urban routes where vans and wagons, and vans, wagons and trucks are allowed, respectively.

Table 1 Test results carried out on the small instances with (a) 2 type of vehicles and (b) 3 type of vehicles

id	n	m	v	MIP		
				Obj	#Routes	Time
(*a*)						
1	10	13	2	483.33	1	0.02
2	10	18	2	417.66	1	0.02
3	10	21	2	1006.33	3.33	0.07
4	20	54	2	1880.66	5.66	1.06
5	20	73	2	1469.33	5	4.96
6	20	94	2	1983	5.33	20.33
7	30	127	2	3297	8.66	7.91
8	30	170	2	*2938.66**	*8.33**	434.35
9	30	216	2	2879.33	6	1593.98
10	40	233	2	*2735.33**	*8**	2480.98
11	40	307	2	*2545.33**	*7.66**	3142.33
12	40	385	2	*2229**	*7.33**	3748.88
(*b*)						
1	10	13	3	544.66	1	0.02
2	10	18	3	507.33	1	0.02
3	10	21	3	1789.33	4.66	0.18
4	20	54	3	4186	7.33	3.94
5	20	73	3	2909.33	5.33	10.74
6	20	94	3	3515.33	5.66	719.27
7	30	127	3	5324	8	324.07
8	30	170	3	*5078.66**	*8**	2627.9
9	30	216	3	*5174**	*7.33**	3763
10	40	233	3	*5122**	*9**	3971.91
11	40	307	3	*3461**	*7.33**	7210.03
12	40	385	3	N.D.	N.D.	N.D.

* is associated to the computational time if the optimal solution is not found within the fixed time limit.

In Table 1a are reported the results of the model with a number of vehicles equal to 2. The first four columns list the id (*id*), the number of vertices (*n*), the number of edges (*m*) and the number of different vehicles ($|T|$), respectively. The column MIP is divided in three subcolumns (*Obj*, *Routes* and *Time*) reporting the objective function value, the number of the routes found and the CPU time (in seconds) spent. A threshold of 2 h and of 3 GB of memory were imposed for the solution of each instance. The results reported in each line of the table are the average values computed on the three instances of the same scenario. Finally, if for at least an instance of a scenario the model finds a feasible (but not optimal) solution, within the time limit or the memory limit, the marker "*" is reported on the column *Obj* and *Routes* of that scenario. Moreover, if for at least an instance of a scenario the model does not find a feasible solution, within the thresholds, the term N.D. (Not Determined) is reported for this scenario.

From the results of Table 1a we can see that the model is able to solve all the instances up to 30 vertices except for the scenario n°8. On the scenarios up to 20 vertices, the model is very fast while on the instances with 30 vertices the computational time increases meaningfully. Obviously, as the density of the graph grows the computational time increases. However, it is interesting to notice that, in some cases, instances with more vertices and low density require less computational time than instances with less vertices but higher density (see scenarios 6 and 7). On the greatest instances with 40 vertices, the model never finds the optimal solution but, within the thresholds, a feasible solution is always found.

In Table 1b are shown the results of the model with a number of vehicles equal to 3. Comparing the Time columns of the two tables it is evident that the complexity of the instances meaningfully increases when the number of vehicles grows. Indeed, the model finds the optimal solution on the scenarios up to 7. On the remaining five scenarios, the model finds in four cases a feasible solution while on the scenario n°12 it fails to find a feasible solutions. Also in this table, the scenario n°6 required more computational time than the scenario n°7 and this enforces our conjecture that the performance of the model are more affected by the density than by the number of vertices of the graph.

It should be noted that the value of the solution is closely related to the environmental impact of the solution: the smaller the value of the solution (smaller the cost of the objective function), the lower is the congestion of city streets and, therefore, the lower is the emissions of greenhouse gases and air polluting compounds and noise congestion.

5 Conclusion and Outlines for Future Works

In this chapter we propose a variant of the classical vehicle routing problem (VRP). We called "Urban logistic network problem" (UB2CNP) this new variant. For this new problem we propose an integer mathematical formulation; the problem originated from the need of determining a sustainable fleet of vehicles to be used for delivering goods in a urban B2C distribution problem.

We execute some preliminary tests of our mathematical programming model on random generated graph instances, representing urban transportation networks.

In the future experimentation we will highlight the importance of the type of vehicles and how this type affects the optimal solution of the problem; in particular we deeply analyze the environmental impact in the objective function cost component. Moreover one of the aims we want to achieve is to study the relationship between the reduction of the emissions of greenhouse gases and the increased costs of the distribution service. To do this we will use the methodology of sensitivity analysis. From applicative point of view we strongly believe that the proposed novel variant of the classical VRP goes in the direction of the development of ITS which is one of the necessary tools for efficient smart city models.

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