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ScienceDirect

Procedia Manufacturing 42 (2020) 483–487

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

International Conference on Industry 4.0 and Smart Manufacturing (ISM 2019)

Crowd-shipping: a new efficient and eco-friendly delivery strategy

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Abstract

In this work, we study the concept of crowd-sourced delivery that aims at exploiting the space of ordinary vehicles, that usually travel on the roads, for delivering parcels. In particular, we introduce a variant of the vehicle routing problem with crowd-shipping. A company makes deliveries by using an own fleet of conventional vehicles as well as some occasional drivers. The occasional drivers are ordinary people, who decide to make a deviation from their routes for delivering parcels to other people, for a small compensation. We show the benefits of using crowd-shipping in terms of saving costs, improving quality of service and decreasing environmental impacts.

Keywords: Crowd-shipping, Vehicle routing, Occasional drivers;

1. Introduction

The rapid growth of e-commerce has lead to new interesting and difficult challenges for on-line retailers. There are several advantages and benefits for customers in on-line shopping: saving time, better price, wide variety and more privacy for personal purchases are some of them. Thus, more and more people prefer buying things on-line over do shopping in the conventional stores. Since the on-line sales are expected to continue to grow as well as the number of on-line retailers, customers are becoming increasingly demanding in terms of quality of service. In this context, the key factors to success for on-line retailers are high speed and low costs deliveries. On one hand, receiving the purchases in few hours is one of the major cause of satisfaction for customers, on the other hand it has a great negative impact on environment. In the last years, people are becoming very concerned about the serious environmental problems. Thus, offering a low environmental impacts service to customers is another important challenge for on-line retailers. Several companies have started to propose innovative ideas for last-mile and same-day deliveries, in order to satisfy the high quality requests of their customers as well as reducing negative environmental impacts, by considering sustainability goals. The environmental protection becomes a crucial focus.

In logistics sector, transportation is one of the bigger producer of polluting emissions; thus, researchers proposed and studied numerous new variants of the vehicle routing problem (VRP). In particular, we distinguish two classes of VRP focused on environmental issues: the pollution routing problem (PRP), which aims at minimizing the polluting emissions of conventional vehicles (i.e., engine fuelled vehicles), and the green vehicle routing problem (GVRP), which aims at optimizing the route of alternative fuel vehicles, such as electrical vehicles. Bektaş and Laporte [3] introduced and modeled the PRP, then, many authors studied and extended this problem (e.g., see Demir et al. [6], Jabali et al. [10], Koç et al. [11], Costa et al. [4]). The GRP was introduced by Erdoğan and Miller-Hooks [8] and widely studied by several authors (e.g., see Felipe et al. [9], Montoya et al. [19], Schneider et al. [20], Macrina et al. [15], Macrina et al. [14]). For a detailed review of these classes of problem the reader is referred to Lin et al. [13] and Erdelić and Carić [7].

Within several innovative delivery strategies, crowd-shipping has gained great popularity among on-line retailers, such as Walmart, DHL and Amazon. The main idea of crowd-shipping, which exploits the concept of sharing economy, is to involve ordinary people in delivering packages to final consumers. Arslan et al. [2] presented an overview on advantages and benefits of crowd-shipping. Archetti et al. [1] introduced the vehicle routing problem with occasional drivers (VRPOD). In the VRPOD a company has to serve a set of customers by using its own fleet of conventional vehicles and, in addition, it can employ some people, i.e. occasional drivers (ODs), who

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10.1016/j.promfg.2020.02.048

decide to make a deviation from their ordinary route for delivering parcels to other people, for a small compensation. They show the benefits of using ODs for delivering parcels in terms of reduction of costs. Macrina et al. [16] extended this work by considering time windows and the possibility of ODs to bring multiple parcels. Recently, Macrina et al. [17] introduced the VRPOD with transshipment nodes and Dahle et al. [5] studied the VRPOD with pickup and deliveries.

In this work, following the idea of the work of Macrina and Guerriero [18], where a green VRPOD (GVRPOD) is addressed, we combine features of GVRP with crowd-shipping. In particular, we studied the impact of using ODs on overall polluting emission as well as the benefits in terms of costs. Thus, we start from the work of Macrina et al. [16], but we introduce a cost related to the fuel used and the polluting emissions in the objective function, then, we study how the use of ODs may lead to both more effective and sustainable transportation plans. The remainder of the paper is organized as follows. In Section 2 we describe the mathematical model proposed by Macrina et al. [16] and we introduce two new objective functions, Section 3 describes our computational results, Section 4 summarizes the conclusions.

2. Mathematical Formulation

In this section we describe the integer linear programming formulation for the VRPOD with multiple deliveries (VRPODmd) of Macrina et al. [16].

Sets. Let C be the set of customers. Let s be the depot node in which each route of conventional vehicles starts and ends. We duplicate the depot, thus we denote with t the destination node. Let K be the set of ODs and V the set of v_k destinations associated with the ODs. The node set is defined as $N = C \cup \{s, t\} \cup V$. The VRPODmd is formulated on on a complete directed graph $G = (N, A)$, where A is the set of arcs.

Parameters. Each arc $(i, j) \in A$ has a cost c_{ij}, a distance d_{ij} and a travel time t_{ij} associated with it. Note that c_{ij}, d_{ij} and t_{ij} satisfy the triangle inequality. Each node $i \in C \cup V$ has a time window $[e_i, l_i]$, and each customer $i \in C$ has a demand d_i. Q is the capacity of the conventional vehicles, P is the number of available conventional vehicles and Q_k is the capacity of OD $k \in K$.

Variables. Let x_{ij} be a binary variable equal to 1 if and only if a classical vehicle traverses arc (i, j). For each node $i \in N$, let y_i be the available capacity of a classical vehicle after visiting customer i, and let s_i be the arrival time of a classical vehicle at customer i. Moreover r^k_{ij} is a binary variable equal to 1 if and only if OD $k \in K$ traverses arc (i, j). Let f^k_i indicate the arrival time of OD k at customer i, and let w^k_i be the available capacity of the vehicle associated with OD k after visiting customer i.

The constraints of VRPODTWmd are modeled as follows:

$$\sum_{j \in C \cup \{t\}} x_{ij} - \sum_{j \in C \cup \{s\}} x_{ji} = 0 \qquad i \in C \tag{1}$$

$$\sum_{j \in C} x_{sj} - \sum_{j \in C} x_{jt} = 0 \tag{2}$$

$$y_j \geq y_i + d_j x_{ij} - Q(1 - x_{ij}) \qquad j \in C \cup \{t\}, i \in C \cup \{s\} \tag{3}$$

$$y_s \leq Q \tag{4}$$

$$s_j \geq s_i + t_{ij} x_{ij} - \alpha(1 - x_{ij}) \qquad i \in C, j \in C \tag{5}$$

$$e_i \leq s_i \leq l_i \qquad i \in C \tag{6}$$

$$\sum_{j \in C} x_{sj} \leq P \tag{7}$$

$$\sum_{j \in C \cup \{v_k\}} r^k_{ij} - \sum_{h \in C \cup \{s\}} r^k_{hi} = 0 \qquad i \in C, k \in K \tag{8}$$

$$\sum_{j \in C \cup \{v_k\}} r^k_{sj} - \sum_{j \in C \cup \{s\}} r^k_{jv_k} = 0 \qquad k \in K \tag{9}$$

$$\sum_{k \in K} \sum_{j \in C \cup \{v_k\}} r^k_{sj} \leq |K| \tag{10}$$

$$\sum_{j \in C} r^k_{sj} \leq 1 \qquad k \in K \tag{11}$$

$$w^k_j \geq w^k_i + d_i r^k_{ij} - Q_k(1 - r^k_{ij}) \qquad j \in C \cup \{v_k\}, i \in C \cup \{s\}, k \in K \tag{12}$$

$$w^k_s \leq Q_k \qquad k \in K \tag{13}$$

$$f^k_i + t_{ij} r^k_{ij} - \alpha(1 - r^k_{ij}) \leq f^k_j \qquad i \in C, j \in C, k \in K \tag{14}$$

$$f^k_i \geq e_{v_k} + t_{si} \qquad i \in C, k \in K \tag{15}$$

$$f^k_{v_k} \leq l_{v_k} \qquad k \in K \tag{16}$$

$$f^k_i + t_{iv_k} r^k_{iv_k} - \alpha(1 - r^k_{iv_k}) \leq f^k_{v_k} \qquad i \in C, k \in K \tag{17}$$

$$e_i \leq f^k_i \leq l_i \qquad i \in C \tag{18}$$

$$\sum_{j \in C \cup \{t\}} x_{ij} + \sum_{h \in C \cup \{v_k\}} \sum_{k \in K} r^k_{ih} = 1 \qquad i \in C \tag{19}$$

$$x_{ij} \in \{0, 1\} \qquad (i, j) \in A \tag{20}$$

$$r^k_{ij} \in \{0, 1\} \qquad (i, j) \in A, k \in K \tag{21}$$

$$0 \leq y_i \leq Q \qquad i \in C \cup \{s, t\} \tag{22}$$

$$0 \leq w^k_i \leq Q_k \qquad i \in C \cup \{s, v_k\}, k \in K \tag{23}$$

$$f^k_i \geq 0 \qquad i \in C \cup \{s, v_k\}, k \in K. \tag{24}$$

Constraints (1) to (7) are linked to the classical vehicles. In particular, constraints (1) and (2) are the flow conservation constraints. Constraints (3) and (4) are the capacity constraints. Conditions (5) allow the determination of the arrival time at node j and conditions (6) represent the time windows constraints. Constraint (7) imposes a maximum number of available vehicles. Constraints (8) to (18) are linked to the ODs. Conditions (8) and (9) are the flow conservation constraints. Constraints (10) and (11) impose a limit on the number of available ODs and on the number of departures from the depot, respectively. Conditions (12) and (13) are the capacity constraints. Constraints (14) compute the arrival time at node j. Conditions (15) and (16) are the time window constraints and also define the time at which the ODs are available to perform deliveries, while constraints (17) compute the arrival time at the destination node v_k. Constraints (18) guarantee that each customer is served within its time window. Constraints (19) impose that each customer is visited at most once, either by a classical vehicle or by an OD. Constraints (20) to (24) define the domains of variables.

In order to model the CO_2 emissions, we consider the estimation made by Ubeda et al. [21]. Thus, we indicate as $f(y_i)$ the function which calculates the amount of CO_2 produced.

We consider two objective functions in order to evaluate the impacts of ODs on both the costs and the CO_2 emissions.

The first objective function for the VRPODTWmd minimizes the overall costs:

$$min\ obj_1 = \sum_{i\in C\cup\{s\}}\sum_{j\in C\cup\{t\}} c_{ij}x_{ij} + \beta(1/\epsilon)\sum_{i\in C\cup\{s\}}\sum_{j\in C\cup\{t\}} f(y_i)d_{ij}x_{ij} +$$

$$+\sum_{k\in K}\sum_{i\in C\cup\{s\}}\sum_{j\in C}\rho c_{ij}r^k_{ij} - \sum_{k\in K}\sum_{j\in C} c_{sv_k}r^k_{sj}, \qquad (25)$$

It is obtained by the sum of four terms: the first term is the routing cost of conventional vehicles, the second one is the diesel cost with $\beta > 0$ and ϵ the fuel conversion factor (2.61 CO_2 / litre of diesel (Lichty [12]), the third term is the cost of compensation of the OD $k \in K$ for the delivery service with $\rho > 0$, the fourth one is the cost of the OD $k \in K$ when it does not perform the delivery service.

The second objective function for the VRPODTWmd, to be minimized, represents the total emissions of conventional vehicles:

$$min\ obj_2 = \sum_{i\in C\cup\{s\}}\sum_{j\in C\cup\{t\}} f(y_i)d_{ij}x_{ij}, \qquad (26)$$

3. Potential benefits of using ODs: the computational study

In this section, we describe the results of our computational study. In particular, we focused on two main factors: the compensation scheme for ODs and the impact of crowd-shipping on the polluting emissions.

We carried out our experimental tests by solving the mathematical model presented in Section 2, using the two different objective functions (25) and (26). All the experiments are conducted using an Intel 2.60 GHz processor, with 16 GB of RAM. The model was implemented in Java and solved with CPLEX. We conducted the computational study on different small-size instances with five, 10 and 15 customers, based on Solomon VRP with time windows instances, taken from the work of Macrina et al. [16].

3.1. Computational results minimizing costs

For the first phase of our computational study, we used the objective function (25). We fixed the cost β to 0.8 [€/L], and to calculate ODs compensation ρ is set to 1.10, 1.20 and 2.10. Table 3.1 presents the comparison results for each VRPODmd instance, varying the value of ρ. For each value of ρ and for each instance, table 3.1 shows the value of the objective function under the column *cost*, the number of conventional vehicles (CVs) and ODs under the columns CVs and ODs, respectively. In addition, the last two columns report two gaps: $GAP_1 = (obj_b - obj_a)/obj_a$, $GAP_2 = (obj_c - obj_b)/obj_b$, where obj_a is the value of objective function obtained when $\rho = 1.10$, while obj_b and obj_c the values of objective function when $\rho = 1.20$ and $\rho = 2.10$, respectively. In addition, for each class of instances, we give the average results in the row *avg*. Looking at results in Table 3.1, it is evident that the best solutions are obtained when $\rho = 1.10$. For instances with five customers, the value of GAP_1 is 17.4%, however the configuration of the solutions is almost the same if we consider the results of the two compensation schemes $\rho = 1.10$ and $\rho = 1.20$. Indeed, the number of CVs and ODs remains unchanged for the majority of the instances. The overall costs dramatically increase when $\rho = 2.10$. Indeed,GAP_2 is 32.6%. The number of ODs is reduced and for six instances out of 12, ODs are never used. We can observe the same trend for instances with 10 and 15 customers. These results clearly confirm that the use of ODs leads to more convenient solutions, even if the compensation scheme is not the optimal one.

Figures 1 – 3 show the graphical results obtained for RC208C10 instance. In particular, Figure 1 shows the locations of customers (the circles), ODs (the squares) and the depot (the triangle). Figure 2 shows the planning obtained when $\rho = 2.10$, thus no ODs are used, while Figure 3 shows the delivery routes obtained when $\rho = 1.10$. Looking at Figure1, we can observe that we have two clusters of customers: one composed of 6,10 and 11 and one composed of 12,13 and 14. The other customers are randomly placed around the central depot. Looking at Figure 2, we have a classical solution of a VRP, indeed, all the customers are served by three CVs. More interesting is the Figure 3. The ODs serve the majority of farther and inconvenient customers in the network, such as 7, 16, 18 and 19. Configuration represented in Figure 3 seems the more suitable one, because of the strategic use of ODs in the organization of the deliveries. Indeed, if we focus on customer 7, it is one of the farther customer in the network. In the Figure 2, customer 7 is the last one served by the conventional truck. Instead, it is the first and the only one served by the OD 1 in the Figure 3. Thus, the use of ODs may lead to more efficient solutions which do not penalize farther customers, by offering a better quality service to all the shoppers.

Fig. 1. Customers, ODs and depot of RC108C10 instance. Customers locations are the blue circles, orange rhombs are ODs and grey triangle represents the central depot.

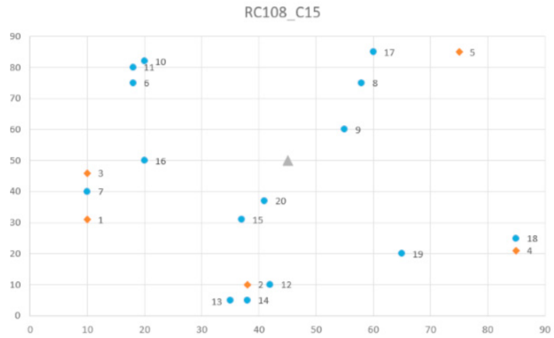


Fig. 2. VRPODmd solution for RC108C10 instance when $\rho = 2.10$. Dashed tours are conventional routes, no ODs are used

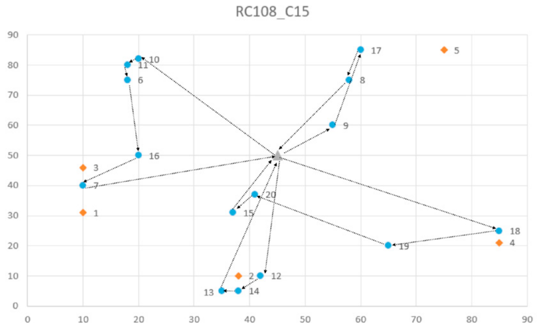
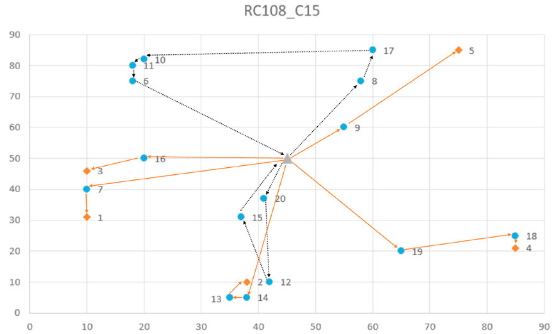


Fig. 3. VRPODmd solution for RC108C10 instance when $\rho = 1.10$. Dashed tours are conventional routes, full lines are ODs trajectory.



The use of ODs becomes very competitive if we analyse the reduction of CO_2 emissions, due to the reduction of conventional vehicles used. Indeed, we know that the major impact on polluting emissions is related to the conventional vehicles. The quantity of CO_2 emitted grows with the increasing of the load and the curb weight of the vehicle. Table 2 reports the quantity of CO_2 [kg] produced, on average. We can observe a sensitive reduction of CO_2 emissions when more competitive compensation schemes are used. Thus, even if the objective function focuses on the reduction of overall costs, the use of ODs leads to more sustainable planning solutions.

3.2. *Computational results minimizing CO_2 emissions*

Table 1. Computational results for VRPODms with objective function 25

	$\rho = 1.10$			$\rho = 1.20$			$\rho = 2.10$				
	cost	CVs	ODs	cost	CVs	ODs	cost	CVs	ODs	GAP_1	GAP_2
C101C5	225.1	2	2	254.7	2	2	292.5	2	1	13.1%	29.9%
C103C5	132.0	1	2	158.4	1	2	194.9	2	1	20.0%	47.6%
C206C5	200.6	1	3	233.3	2	1	260.9	2	1	16.3%	30.1%
C208C5	158.8	1	2	183.0	1	1	198.5	1	0	15.3%	25.0%
R104C5	121.9	1	2	155.8	2	1	166.7	2	0	27.8%	36.8%
R105C5	176.7	2	1	185.7	2	0	185.7	2	0	5.1%	5.1%
R202C5	158.4	2	1	172.4	2	1	177.0	2	0	8.8%	11.8%
R203C5	198.3	1	2	229.7	1	1	238.0	2	0	15.9%	20.0%
RC105C5	196.9	2	2	223.7	2	1	254.3	2	1	13.6%	29.2%
RC108C5	188.3	1	2	240.6	1	2	304.1	2	0	27.8%	61.5%
RC204C5	130.1	1	2	154.1	1	2	185.2	1	1	18.5%	42.4%
RC208C5	146.9	1	2	186.6	1	1	223.2	1	1	27.0%	51.9%
avg	**169.5**	**1.3**	**1.9**	**198.2**	**1.5**	**1.3**	**223.4**	**1.75**	**0.5**	**17.4%**	**32.6%**
C101C10	356.3	2	3	406.9	3	2	442.8	3	1	14.2%	24.3%
C104C10	299.8	2	3	336.4	2	1	359.8	2	1	12.2%	20.0%
C202C10	215.0	2	3	264.6	2	3	303.8	2	1	23.1%	41.3%
C205C10	224.3	2	3	261.7	2	2	280.0	2	0	16.7%	24.8%
R102C10	215.0	2	2	260.6	2	2	291.7	2	1	21.2%	35.7%
R103C10	193.6	2	2	209.8	2	1	233.8	2	1	8.4%	20.8%
R201C10	227.6	3	2	248.3	3	1	259.7	3	1	9.1%	14.1%
R203C10	161.7	1	3	198.3	1	2	251.7	1	2	22.6%	55.6%
RC102C10	416.4	2	2	459.6	2	2	477.0	3	0	10.4%	14.5%
RC108C10	396.8	2	2	428.9	3	0	428.9	3	0	8.1%	8.1%
RC201C10	286.3	2	2	315.8	2	2	357.5	2	1	10.3%	24.9%
RC205C10	315.5	2	2	360.7	2	2	410.5	2	1	14.3%	30.1%
avg	**275.7**	**2.0**	**2.4**	**312.6**	**2.2**	**1.7**	**341.4**	**2.3**	**0.8**	**14.2%**	**26.2%**
C103C15	249.9	1	5	339.5	2	5	421.2	3	1	35.8%	68.5%
C106C15	195.2	2	5	266.4	2	2	312.1	2	1	36.5%	59.9%
C208C15	381.1	3	3	432.6	4	0	432.6	4	0	13.5%	13.5%
C202C15	405.9	2	5	457.6	3	2	479.2	4	0	12.7%	18.1%
R102C15	360.4	3	4	411.9	4	2	448.5	4	2	14.3%	24.4%
R105C15	256.1	2	5	335.5	2	4	398.9	4	0	31.0%	55.7%
R202C15	394.8	3	4	452.0	3	2	462.4	4	0	14.5%	17.1%
R209C15	295.0	3	3	344.6	3	3	399.9	4	0	16.8%	35.6%
RC103C15	423.4	3	3	457.7	3	1	476.2	4	0	8.1%	12.5%
RC108C15	305.4	2	5	401.0	2	5	481.8	3	1	31.3%	57.7%
RC202C15	436.9	3	4	494.5	4	1	523.1	4	0	13.2%	19.7%
RC204C15	409.3	2	2	436.4	3	0	436.4	3	0	6.6%	6.6%
avg	**342.8**	**2.4**	**4.0**	**402.5**	**2.9**	**2.3**	**439.4**	**3.58**	**0.4**	**19.5%**	**32.5%**

Table 2. Evaluation of CO_2 emissions for the VRPODmd with objective function 25

	CO_2		
ρ	1.10	1.20	2.10
| C | =5	76.4	92.5	121.9
| C | =10	142.4	163.0	194.7
| C | =15	184.2	218.2	269.0
avg	**134.3**	**157.9**	**195.2**

In the second phase of our computational study, we solved the VRPODmd model presented in Section 2 by using the objective function 26, that minimizes the CO_2 emissions. We set $\rho = 1.10$ and a time limit on CPLEX running time of 15 minutes. We compared the results with those obtained by using the objective function (25), when $\rho = 1.10$. Table 3.2 summarizes the values of CO_2 [kg], obtained for each instance and compares also the number of CVs and ODs. GAP_3 is calculated as $(CO_2^{obj_2} - CO_2^{obj_1})/CO_2^{obj_1}$, where $CO_2^{obj_1}$ and $CO_2^{obj_2}$ are the values of CO_2 emissions obtained using the objective functions obj_1 (25) and obj_2 (26), respectively.

Looking at results in Table 3.2 and focusing on instances with five customers, we can observe that for instances where the same number of CVs and ODs is used, the quantity of CO_2 remains almost unchanged, in fact, the gap value is 0.0%. However, looking at C101C5 the value of GAP_3 rises up to 82.0%. Indeed, for C101C5 instance the configuration scheme is different and the number of conventional vehicles used by VRPODmd, when optimizing the objective function obj_1 (25), is higher. We can observe almost a similar trend for all the instances. The use of ODs becomes a strategy choice, indeed, how we mentioned in Section 3.1 the polluting emissions are strongly related to the use of conventional vehicles and we know that the ODs will travel whether performing the delivery or not. Our computational study confirmed that, the more the number of available ODs the less the quantity of polluting emissions.

Table 3. CO_2 emissions evaluations comparing the two objective functions 26 and 25

	Minobj$_2$			*Minobj*$_1$			
	CO_2	CVs	ODs	CO_2	CVs	ODs	GAP_3
C101C5	66.0	1	3	120.1	2	2	82.0%
C103C5	61.2	1	3	61.2	1	2	0.0%
C206C5	57.5	1	3	57.5	1	3	0.0%
C208C5	69.6	1	2	79.2	1	2	13.8%
R104C5	45.8	1	2	45.8	1	2	0.0%
R105C5	53.8	1	3	101.7	2	1	89.0%
R202C5	88.1	2	1	88.1	2	1	0.0%
R203C5	79.6	1	3	79.6	1	2	0.0%
RC105C5	88.4	1	3	106.9	2	2	21.0%
RC108C5	37.5	1	3	37.5	1	2	0.0%
RC204C5	54.0	1	3	71.5	1	2	32.4%
RC208C5	67.9	1	2	67.9	1	2	0.0%
avg	**64.1**	**1.1**	**2.6**	**76.4**	**1.3**	**1.9**	19.2%
C101C10	130.0	2	3	157.1	2	3	20.8%
C104C10	111.7	2	3	176.0	2	3	57.6%
C202C10	111.5	2	3	121.8	2	3	9.2%
C205C10	87.0	1	3	102.7	2	3	18.1%
R102C10	62.0	2	3	92.2	2	2	48.6%
R103C10	64.9	2	3	92.8	2	2	42.9%
R201C10	93.3	2	3	130.2	3	2	39.6%
R203C10	45.3	1	3	90.9	1	3	100.6%
RC102C10	131.2	2	3	226.4	2	2	72.6%
RC108C10	135.5	2	3	210.7	2	2	55.5%
RC201C10	105.2	2	3	138.8	2	2	31.9%
RC205C10	158.5	2	3	169.0	2	2	6.6%
avg	**103.0**	**1.8**	**3.0**	**142.4**	**2.0**	**2.4**	38.2%
C103C15	77.4	1	5	122.3	1	5	58.0%
C106C15	99.0	2	5	102.1	2	5	3.1%
C208C15	180.9	3	5	236.1	3	3	30.6%
C202C15	143.4	3	5	187.5	2	5	30.8%
R102C15	123.4	3	5	185.0	3	4	49.9%
R105C15	93.3	3	5	116.1	2	5	24.4%
R202C15	154.5	2	5	205.2	3	4	32.8%
R209C15	119.4	2	5	172.9	3	3	44.7%
RC103C15	198.0	3	5	253.4	3	3	28.0%
RC108C15	109.6	2	5	168.4	2	5	53.7%
RC202C15	206.1	3	5	253.7	3	4	23.1%
RC204C15	89.4	1	5	208.0	2	2	132.8%
avg	**132.9**	**2.3**	**5.0**	**184.2**	**2.4**	**4.0**	38.7%

4. Conclusions

In this work, we have studied a new promising delivery strategy, named crowd-shipping. The problem of routing a fleet of conventional vehicles and non professional couriers (i.e., occasional drivers (ODs)) to serve a set of customers is known as vehicle routing problem with occasional drivers. The ODs are ordinary people who decide to deliver parcels to other people on their route, for a small compensation. We have shown the benefits of using the ODs in transportation planning, in terms of both costs reduction and environmental impacts.

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