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Bi-objective Sustainable Crowdshipping with Multi Types of Occasional Drivers

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Abstract: The current work presents a deterministic bi-objective sustainable crowdshipping problem optimizing both the cost and CO₂ emissions, referred to as the Bi-Objective Vehicle Routing Problem with Multi types of Occasional Drivers and Time Windows (BO-VRPMODTW). The goals of this work are to verify the trade-off between transportation cost and environmental emissions generation, considering different types of ODs, and to verify the impact in different location spreading for customers. Preliminary experimental results show the gain both in terms of cost and CO₂ emissions of having ODs of different types. The use of ODs in the non-dominated solutions is also analyzed.

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Keywords: Sustainability, Crowdshipping, Multi-objective optimization, Transportation types

1. INTRODUCTION

In the last years, Business-to-Consumer (B2C) E-commerce operations had an exponential increase, representing approximately one-quarter of total global retail sales in 2023. This growth involves an increasing requirement for urban delivery and last-mile delivery solutions. Last-mile delivery is renowned as the most complex, expensive, and time-consuming part of delivery logistics. The key challenges for retailers are guaranteeing faster delivery to meet customers' need while minimizing costs. Therefore, the generation of innovative solutions to enhance same-day and last-mile delivery is a priority (Elsokkary et al., 2023).

One of the innovative solutions considered among online retailers is crowdshipping, also referred to as crowd-sourced delivery or crowd logistics (Strulak-Wójcikiewicz and Wagner, 2021). It is a part of a sharing economy trend focused on freight transportation, which addresses distribution issues by using people who have the willingness to execute deliveries on the way to their normal destinations, without affecting their habitual route. This use of Occasional Drivers - (ODs) aims to exploit underused capacity to cover the businesses' transportation needs (Archetti et al., 2016).

Because crowdshipping reuses excess capacity of vehicle, it is presented as a sustainable option. However, the industrial crowdshipping initiatives have shown that in a large-scale adoption, it does not necessarily imply sustainability, indeed the compensation schemes defined for the ODs can attract more drivers, executing deliveries out of their normal routes, increasing generated emissions and vehicle density. It is frequently mentioned that a way to secure the sustainable value in crowdshipping is to consider the

use of sustainable modes that could replace the regular transportation modes based on fossil fuels. However, the transportation mode effectively used has not yet explicitly been defined (de Oliveira Leite Nascimento et al., 2023).

In this work, we present a bi-objective crowdshipping problem optimizing both the cost and CO₂ emissions, referred to as the Bi-Objective Vehicle Routing Problem with Multi types of Occasional Drivers and Time Windows (BO-VRPMODTW). The goal of this work is to answer to the following research questions: (1) What is the cost of reducing emissions in this context? (2) What is the economical and environmental gain to consider different vehicle types for the ODs? (3) How does the geographical spreading of customers and ODs impact the solutions?.

The remainder of this paper is organized as follows: In Section 2 a literature review is presented, in Section 3 the mathematical model is developed, in Section 4 the computational experiment and the results are described, and the conclusions are summarized in Section 5.

2. LITERATURE REVIEW

The first crowdshipping model is proposed in (Archetti et al., 2016), referred to as the Vehicle Routing Problem with Occasional Drivers (VRPOD), which is a variant of the classic capacitated VRP (CVRP), where the company considers a set of in-store customers, which are customers already located in a company store or depot and identified by their expected final destinations, as occasional drivers able to do a single delivery, in addition to a fleet of capacitated vehicles. The authors aim to minimize the total cost of the regular fleet and the compensation given

to the occasional drivers. Their results provide evidence of the use of occasional drivers to reduce total cost.

This problem was extended in (Macrina et al., 2017) with a variant of the VRPOD including Time Windows (VRPODTW). The occasional drivers can make multiple deliveries, according to compensation and a split delivery policy. A variant of the green VRP with crowdshipping and time windows is introduced in (Macrina and Guerriero, 2018). The authors considered a mixed regular fleet composed of conventional combustion engine and electric vehicles, and the possibility to use occasional drivers. The objective was to reduce the cost of regular fleet fuel and energy consumption, and occasional drivers' compensation. Their results exhibit how the use of occasional drivers may complement the electric regular fleet, leading reduced polluting emissions.

This green initiative was extended in (Macrina et al., 2020) where the impact of using ODs on polluting emissions and costs, in a single objective approach for each objective was studied. The results show a sensitive reduction of CO2 emissions when more competitive compensation schemes are used for all ODs. Simoni et al. (2020) developed a simulation based approach to analyze environmental impacts of crowdshipping. It includes delivery routes, traffic and pollution. Their results exhibit the negative environmental impacts of crowdshipping in terms of generated emissions if the right transport mode is not used. Also, the authors point out the additional affectation of occasional drivers' tendency to execute dedicated delivery trips. Pourrahmani and Jaller (2021) reiterate the tendency of ODs to affect their normal routes, increasing vehicle use and generated emissions. They also mention that a way to secure the sustainable value in crowdshipping is to consider the use of sustainable modes that could replace the regular transportation modes based on fossil fuels.

According to our literature exploration, there is scarce development related to multi-objective approaches to crowdshipping extensions of VRPOD or VRPODTW. Also, current mathematical approaches only consider one type of vehicle for ODs and compensation. Studies generally restrict the ODs and over-simplify the CO2 emissions impact on the ODs route. Despite the multiples recommendations on sustainable vehicle use, no decision making tools have been proposed.

3. MATHEMATICAL MODEL

This problem considers ODs that can be located out of the depot, referred to as "out-store" ODs, to complement a regular vehicle delivery fleet. Specifically, the problem generalizes the participation of different numbers of ODs using different types of vehicles (fueled and non-fueled vehicles), for which the origin and destination are known and different. To encourage the use of sustainable transport modes, the compensation policy assigns higher compensation to the non-fueled type. For each type of vehicle, the speed, capacity, emissions factors are different. The time windows are considered for each client and for each OD final destination. The problem is referred to as the Bi-Objective Vehicle Routing Problem with Multi types of Occasional Drivers and Time Windows (BO-VRPMODTW).

3.1 Description

The problem is defined as follows. P is the number of available regular vehicles. T is the set of vehicle types to consider, and K_t is the set of available ODs of type t . Consider a directed graph $G = (N, A)$, with node set $N = C \cup s \cup O_t \cup V_t$, where C is the set of customers, s represents the depot. O_t represents the set of o_{kt} origins for the ODs of type t , and V_t is the set of v_{kt} destinations associated with the ODs of type t . Each node i in $C \cup v_{kt} \cup o_{kt}$ has a hard time window defined as $[e_i, l_i]$. Each customer $i \in C$ has a demand a_i . Q^R, Q_{kt}^{OD} are the capacity values for regular vehicles and for OD k of type t respectively.

SP^R, SP_t^{OD} represent average speed for regular vehicles and for ODs of type t respectively. E^R, E_{kt}^{OD} are the CO2/fuel conversion factor (kg CO2/L) considered for the regular vehicles and for the vehicles of the ODs of type t respectively. A represents the set of arcs. Each arc (i, j) in A has cost c_{ij} and distance $dist_{ij}$. The value γ represents the price per liter of fuel for regular vehicles. $crmin^R, crmin_t^{OD}$ represent the minimum values of fuel or energy consumption per distance unit if the vehicle is empty (L/km), and $crmax^R, crmax_t^{OD}$ are the maximum values of fuel or energy consumption per distance unit for regular vehicles and for ODs of type t respectively (L/km). Let ρ_t the compensation factor for ODs of type t .

Let x_{ij} be a binary variable that represents if a regular vehicle traverses the arc (i, j) , and r_{ij}^{tk} is a binary variable that indicates if the OD k of type t traverses the arc (i, j) . For each node $i \in N$, y_i represents the current load of the regular vehicle right after visiting the customer i and s_i is the arrival time of the regular vehicle to the customer i . Let w_i^{tk} be the current load of OD k of type t after visiting customer and f_i^{tk} indicates the arrival time of OD k of type t . Let tf_{ij}^R be the total fuel consumption if regular vehicle traverses arc (i, j) , related to the current load of the regular vehicle after visiting the customer i , and tf_{ij}^{ODtk} be the total fuel consumption if OD k of type t traverses arc (i, j) , related to the current load of the OD k of type t after visiting the customer i . Let β_{itk} be a binary parameter equals to 1 if OD k of type t can serve client in node i .

3.2 Formulation

$$\begin{aligned} \min \quad & \sum_{i \in C \cup s} \sum_{j \in C \cup s} c_{ij} x_{ij} + \gamma \sum_{i \in C \cup s} \sum_{j \in C \cup s} tf_{ij}^R \\ & + \sum_{i \in C \cup s} \sum_{j \in C \cup s \cup v_{kt}} \sum_{t \in T} \sum_{k \in K_t} \rho_t dist_{ij} r_{ij}^{tk} \\ & - \sum_{j \in C} \sum_{t \in T} \sum_{k \in K_t} \rho_t dist_{o_{kt} v_{kt}} r_{sj}^{tk} \end{aligned} \quad (1)$$

$$\begin{aligned} \min \quad & \sum_{i \in C \cup s} \sum_{j \in C \cup s} E^R t f_{ij}^R \\ & + \sum_{i \in C \cup s} \sum_{j \in C \cup s \cup v_{kt}} \sum_{t \in T} \sum_{k \in K_t} E_t^{OD} t f_{ij}^{ODtk} \\ & - \sum_{j \in C} \sum_{t \in T} \sum_{k \in K_t} E_t^{OD} crmin_t^{OD} dist_{o_{kt} v_{kt}} r_{sj}^{tk} \end{aligned} \quad (2)$$

$$\sum_{j \in C \cup d} x_{ij} - \sum_{j \in C \cup s} x_{ji} = 0 \quad \forall i \in C \quad (3)$$

$$\sum_{j \in C} x_{sj} - \sum_{j \in C} x_{js} = 0 \quad (4)$$

$$\sum_{j \in C} x_{sj} \leq P \quad (5)$$

$$\sum_{j \in C \cup v_{kt}} r_{ij}^{tk} - \sum_{j \in C \cup s} r_{ji}^{tk} = 0 \quad \forall i \in C, t \in T, k \in K_t \quad (6)$$

$$\sum_{j \in C \cup v_{kt}} r_{sj}^{tk} - \sum_{j \in C \cup s} r_{jv_{kt}}^{tk} = 0 \quad \forall t \in T, k \in K_t \quad (7)$$

$$\sum_{j \in C} r_{sj}^{tk} - r_{o_{kt}s}^{tk} = 0 \quad \forall t \in T, k \in K_t \quad (8)$$

$$\sum_{h \in C \cup s} r_{hi}^{tk} \leq \beta_{itk} \quad \forall i \in C, t \in T, k \in K_t \quad (9)$$

$$\sum_{j \in C} r_{sj}^{tk} \leq 1 \quad \forall t \in T, k \in K_t \quad (10)$$

$$y_j \leq y_i - a_i x_{ij} + Q^R(1 - x_{ij}) \quad \forall j \in C, i \in C \cup s \quad (11)$$

$$w_{jtk} \leq w_{itk} - a_i r_{ij}^{tk} + Q_{kt}^{OD}(1 - r_{ij}^{tk}) \quad \forall j \in C, i \in C \cup s, t \in T, k \in K_t \quad (12)$$

$$s_j \geq s_i + \frac{dist_{ij}}{SP^R} x_{ij} - M_1(1 - x_{ij}) \quad \forall i \in C \cup s, j \in C \quad (13)$$

$$e_i \leq s_i \leq l_i \quad \forall i \in C \quad (14)$$

$$f_{jtk} \geq f_{itk} + \frac{dist_{ij}}{SP_t^{OD}} r_{ij}^{tk} - M_1(1 - r_{ij}^{tk}) \quad \forall i \in C \cup s \cup o_{kt}, j \in C \cup s \cup v_{kt}, t \in T, k \in K_t \quad (15)$$

$$f_{itk} \geq e_{v_{kt}} + \frac{dist_{ij}}{SP_t^{OD}} dist_{sj} \quad \forall i \in C, t \in T, k \in K_t \quad (16)$$

$$e_i \leq f_{itk} \leq l_i \quad \forall i \in C \cup s \cup v_{kt} \quad (17)$$

$$tf_{ij}^R \geq crmin^R dist_{ij} + crmax^R \left(\frac{y_j}{Q^R} \right) dist_{ij} - crmin^R \left(\frac{y_j}{Q^R} \right) dist_{ij} - crmax^R dist_{ij}(1 - x_{ij}) \quad \forall i \in C \cup s, j \in C \cup s \quad (18)$$

$$tf_{ij}^{ODtk} \geq crmin_t^{OD} dist_{ij} + crmax_t^{OD} \left(\frac{w_i^{tk}}{Q_{kt}} \right) dist_{ij} - crmin_t^{OD} \left(\frac{w_i^{tk}}{Q_{kt}} \right) dist_{ij} - crmax_t^{OD} dist_{ij}(1 - r_{ij}^{tk}) \quad \forall i \in C \cup s \cup o_{kt}, j \in C \cup s \cup v_{kt}, t \in T, k \in K_t \quad (19)$$

$$\sum_{j \in C \cup t} x_{ij} + \sum_{k \in K_t} \sum_{t \in T} \sum_{j \in C \cup s} r_{ji}^{tk} = 1 \quad \forall i \in C \quad (20)$$

$$x_{ij} \in \{0, 1\} \quad \forall (i, j) \in A \quad (21)$$

$$r_{ij}^{tk} \in \{0, 1\} \quad \forall (i, j) \in A, k \in K_t, t \in T \quad (22)$$

$$0 \leq y_i \leq Q^R \quad \forall i \in C \cup s \quad (23)$$

$$s_i \geq 0 \quad \forall i \in C \cup s \quad (24)$$

$$0 \leq w_i^{tk} \leq Q_{kt}^{OD} \quad \forall i \in C \cup s \cup v_{kt}, k \in K_t, t \in T \quad (25)$$

$$f_i^{tk} \geq 0 \quad \forall i \in C \cup s \cup v_{kt}, k \in K_t, t \in T \quad (26)$$

$$tf_{ij}^{ODtk} \leq crmax_t^{OD} dist_{ij} r_{ij}^{tk} \quad \forall i \in C \cup s \cup o_{kt}, j \in C \cup s \cup v_{kt}, t \in T, k \in K_t \quad (27)$$

$$tf_{ij}^{ODtk} \geq 0 \quad \forall i \in C \cup s \cup o_{kt}, j \in C \cup s \cup v_{kt}, t \in T, k \in K_t \quad (28)$$

$$tf_{ij}^R \geq 0 \quad \forall i \in C \cup s, j \in C \cup s \quad (29)$$

The objective function (1) represents the transportation cost. The terms represent respectively the cost associated with regular vehicles, the total fuel cost associated with regular vehicles, the cost of compensation of the ODs of type t , the cost for the original travel of the ODs of type t . The objective function (2) represents the CO2 emissions. It is composed of the CO2 emissions generated by regular drivers' travel, by ODs, and the one generated in the original travel by ODs.

Constraint (3)-(4) are the flow constraints for regular vehicles. Constraint (5) restricts the number of available regular vehicles. Constraints (6)-(7) are the flow constraints for ODs. Constraint (8) specifies that all ODs making a delivery must go through the depot first. Constraint (9) indicates if OD k of type t can serve client in node i . Constraint (10) limits the number of departures from depot for each ODs of type t .

Constraint (11) represents the total load in the regular vehicles after visiting a customer. Constraint (12) is the total load for ODs of type t after visiting a customer. Constraints (13)-(14) represent the time windows accomplishment for regular vehicles. Constraints (15)-(17) represent the time windows constraints for ODs. Constraint (15) includes the M_1 number, defined as the maximum value between the customers and ODs final destinations time windows latest times l_i . Constraints (18)-(19) represent the total fuel consumption calculation for regular vehicles and ODs respectively. Constraint (20) guarantees that each customer is visited only once, by a regular vehicle or an OD. Constraints (21)-(29) represent decision variable domains.

4. COMPUTATIONAL EXPERIMENT

In this section the computational experiment executed to validate BO-VRPMODTW is presented. The problem was solved on 20 instances and compared with the VRPTW bi-objective results (which can be achieved by modifying the right-hand side of constraints (9) and (10) to 0). The model was implemented and solved using the ϵ -constraint approach minimizing the CO2 emissions and controlling the transportation cost, implemented in Python with Gurobi version 10.0.1, and run in a PC with an Intel 2.30 GHz processor and 32 GB of RAM. The parameters settings for all the experiments are presented in the table 1. The number of vehicles, capacity and speed are based on the structure presented in (Macrina et al., 2017). For the fuel or energy consumption and CO2 conversion factor, the values are based on the ones presented in (Muñoz-Villamizar et al., 2017) and (Úbeda et al., 2014).

Table 1. Experiment parameters

Type	Number	Q_{kt}^R Q_{kt}^{OD}	SP_t^R SP_t^{OD}	$crmin_t^R$ $crmin_t^{OD}$	$crmax_t^R$ $crmax_t^{OD}$	E_{kt}^R E_{kt}^{OD}	c_{ij} ρ_t
Regular drivers	5	200	50	0.254	0.379	2.61	1
ODs type 1	5	50	50	0.254	0.285	2.61	1.1
ODs type 2	2	25	40	0.002	0.004	1	1.2

The remainder of this section presents the generation of instances, a comparison for all instances result, and the detailed results for two instances.

4.1 Generation of Instances

The instances used to check the proposed model are based on the Solomon VRPTW instances (see Solomon, 1987). For this case the clustered geographical distribution (C), and random geographical distribution (R) classes of customer locations were selected. A set of 10 clustered small instances and 10 random small instances were created, considering a total of 13 customers. For each instance, the origin and destination for the occasional drivers were generated randomly with a uniform distribution, according to the customers location coordinates. Also, the destinations time windows were randomly generated with a uniform distribution according to customers latest time windows.

4.2 All instances comparison

The summary results for all instances are presented. The comparison for each instance between the BO-

VRPMODTW and VRPTW is presented in table 2, considering that the instance names correspond to the original Solomon reference. Specifically, the minimum and maximum cost and CO2 emissions values, number of solutions in the Pareto front (#SP), Pareto front total computational time for both problems, and hypervolume gap are included. For each instance, a normalized hypervolume is computed using as a reference point the maximum values of both objectives, increased by 10%, and the normalized values for cost and CO2 emissions of each solution in the Pareto front. The HV gap is the ratio of the BO-VRPMODTW hypervolume minus the VRPTW hypervolume, to the VRPTW hypervolume. In this case a 0.0% gap means no difference between BO-VRPMODTW and VRPTW fronts, and a higher value of gap implies that VRPTW front is dominated by BO-VRPMODTW front.

Table 2. Instances comparison

Inst.	BO-VRPMODTW				VRPTW				HV Gap (%)
	Lex optimal		#SP	Time (s)	Lex optimal		#SP	Time (s)	
	Cost	CO2			Cost	CO2			
C101	232.96	146.43	10	10.622	232.96	146.43	1	0.062	550
	444.92	135.34			220.22	138.01			
	220.22	138.01			262.05	162.23			
C102	356.35	127.53	4	46.330	220.22	138.01	1	2.695	423
	262.05	162.23			263.79	162.09			
	400.10	121.30			154.17	97.82			
C103	131.53	89.15	15	708.122	263.79	162.09	2	0.677	193
	200.95	68.83			154.17	97.82			
	160.48	101.93			154.72	96.58			
C104	160.48	101.93	11	8386.268	154.72	96.58	3	942.421	750
	340.46	83.34			170.70	104.84			
	132.89	90.31			170.70	104.84			
C105	340.46	83.34	9	28.636	170.70	104.84	1	0.109	888
	199.78	69.21			154.40	96.86			
	199.78	69.21			154.40	96.86			
C109	227.50	140.30	7	1148.846	154.40	96.86	1	7.478	1080
	389.00	126.00			154.40	96.86			
	219.51	137.23			154.40	96.86			
C201	227.50	140.30	8	52.451	227.50	140.30	1	0.113	657
	389.00	126.00			219.51	137.23			
	219.51	137.23			219.51	137.23			
C202	258.30	110.38	7	107.471	219.51	137.23	1	0.265	381
	174.59	105.82			182.84	114.29			
	180.87	97.53			182.84	114.29			
C204	220.09	138.36	4	2383.915	182.84	114.29	1	1098.741	8717
	389.58	125.10			220.09	138.36			
	369.29	224.36			220.09	138.36			
C208	369.29	224.36	10	13773.098	220.09	138.36	1	70.318	425
	465.28	187.79			220.09	138.36			
	398.72	269.76			220.09	138.36			
R101	465.28	187.79	7	2.416	417.95	247.52	1	0.055	1381
	398.72	269.76			513.33	305.48			
	464.23	179.52			516.02	304.21			
R102	247.86	153.28	9	138.550	340.46	208.11	2	0.391	7783
	408.97	97.19			350.44	206.76			
	371.09	233.25			417.47	254.75			
R110	514.70	173.09	19	1310.317	420.25	253.78	2	13.170	1513
	249.97	152.85			417.47	254.75			
	371.09	233.25			417.47	254.75			
R111	514.70	173.09	14	352.972	420.25	253.78	2	1.155	758
	249.97	152.85			417.47	254.75			
	371.09	233.25			417.47	254.75			
R112	378.84	128.89	11	654.509	276.99	173.35	1	265.056	963
	315.69	202.23			437.17	267.25			
	431.77	129.15			441.55	263.34			
R201	431.77	129.15	11	21.728	437.17	267.25	2	0.152	6508
	284.32	173.12			441.55	263.34			
	336.80	165.36			347.18	215.69			
R202	336.80	165.36	8	75.313	353.25	214.20	3	1.127	4809
	312.90	187.95			357.73	225.44			
	400.09	164.85			347.27	214.23			
R209	311.66	198.91	4	11.476	364.69	220.32	6	2.385	849
	311.66	198.91			347.27	214.23			
	352.76	146.52			347.27	214.23			
R210	323.15	205.44	7	52.069	341.50	219.18	2	0.751	1624
	323.15	205.44			341.50	219.18			
	480.20	158.48			341.50	219.18			
R211	323.15	205.44	10	368.190	323.15	205.44	1	11.285	541
	480.20	158.48			323.15	205.44			
	480.20	158.48			323.15	205.44			

For all the instances results, the solutions hypervolumes obtained in the proposed model are significantly larger than the ones obtained with the VRPTW. In 5 clustered instances (C101, C102, C201, C202, and C208) and 1 random instance (R211), the original solutions obtained in VRPTW are also efficient for BO-VRPMODTW, concerning the cost. For the other instances, all the original VRPTW solutions are dominated by the BO-VRPMODTW Pareto front. According to this, it can be implied that for a clustered class, there is a relevant participation of a regular fleet in terms of minimizing total cost, considering the ODs compensation. However, from the emissions perspective, the minimum value of CO2 is obtained in the BO-VRPMODTW. For random class, there is a higher participation of ODs of both types in terms of minimizing total cost and emissions.

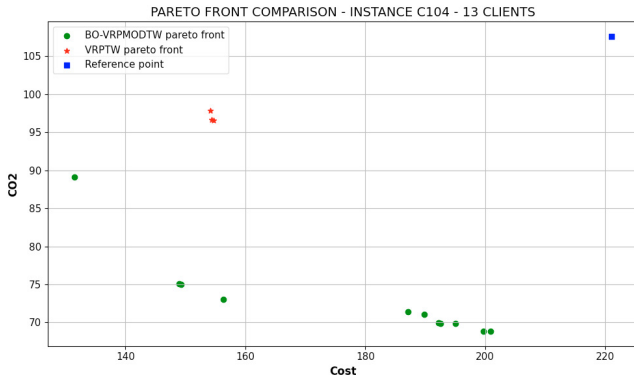


Fig. 1. Pareto front comparison - Instance C104 - 13 clients

Also, the proposed problem allows to obtain a higher number of possible solutions to generate an expected trade-off between the cost and emissions minimization including different types of ODs, in contrast to only considering a regular fleet, which for clustered class normally presents only 1 feasible solution, and for random class an average of 2 feasible solutions for both objectives. The difference of computational time between the problems was expected and can be explained considering that the single-objective approach of the BO-VRPMDTW solved in each iteration of the ϵ -constraint is more complex than the VRPTW, thus the solving is more time consuming. Also, since the BO-VRPMDTW is a bi-objective problem, several solutions are sought and the solving time increases with the number of these solutions.

In clustered instances, BO-VRPMDTW solutions include on average 2 regular vehicles, 1 OD of type 1, and 2 ODs of type 2, giving the higher load amount to regular vehicles and ODs of type 2. This allows to confirm how the inclusion of ODs with sustainable vehicle options, even with a higher compensation than ODs with fossil fuel vehicles, could be beneficial to support a regular fleet to attend deliveries in clustered locations. For random instances, the problem solutions normally include an average of 2 regular vehicles, 3 ODs of type 1, and 2 ODs of type 2, giving a similar load amount to regular vehicles, ODs of type 1, and ODs of type 2. For random locations, the results allow to confirm how the inclusion of ODs in general (type 1 or 2), could generate a representative benefit in terms of cost and emissions minimization, not only as a complement, but having a comparable participation to regular drivers.

4.3 Detailed results on two instances

In this part, we focus on one clustered and one random instance, where VRPTW solutions are fully dominated by BO-VRPMDTW solutions. The clustered instance is C104. The Pareto front results comparison between the two approaches is presented in Fig. 1, including the reference point for hypervolume calculation.

For this instance, in the VRPTW approach, a total of 3 feasible solutions are obtained. All the solutions in this approach involve the use of 2 regular drivers. For BO-VRPMDTW, a total of 11 feasible solutions are obtained. On average, the solutions include 1 regular vehicle, 3 ODs of type 1, and 2 ODs of type 2 are used.

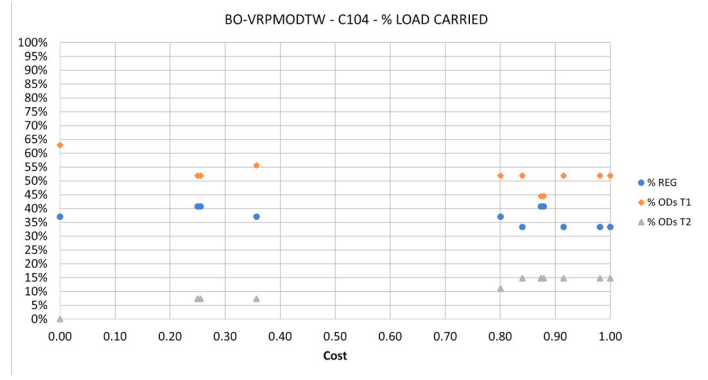


Fig. 2. Load carried by type - Instance C104 - 13 clients

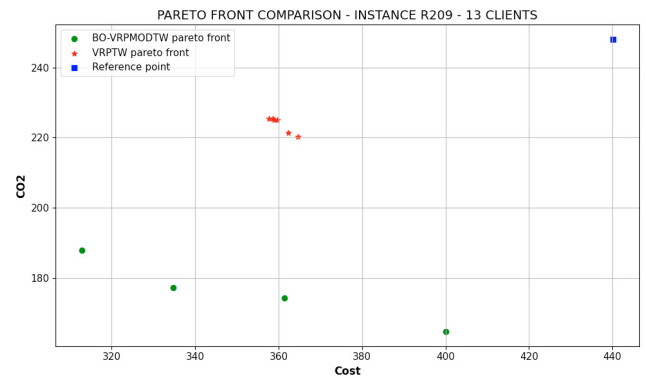


Fig. 3. Pareto front comparison - Instance R209 - 13 clients

According to the results it is stated that BO-VRPMDTW outperforms the VRPTW in the bi-objective perspective. ODs activation guarantees a reduction in the total CO2 emissions generated. Also, for this instance, if the goal is minimizing the total cost, the ODs activation allows a reduction in the total value. Fig. 2 presents the percentage of load carried by each type of vehicle, according to the normalized value of cost for each solution in BO-VRPMDTW, to verify the evolution between value 0 (lex optimal cost) to value 1 (lex optimal CO2).

It can be observed that the higher load mobilization for all the solutions corresponds to ODs of type 1 with an average of 52%. Also, it is stated how to generate a reduction of the CO2, the proportion of load assigned to ODs of type 2 evolves from 0% to 15%, with an average of 12%. Finally, for regular vehicles, an average of 36% of the load is carried. This implies that in this case, the most representative type in the bi-objective condition corresponds to ODs with fueled vehicles.

The random instance is R209, for which the Pareto front comparison is presented in Fig. 3. For this instance, from the VRPTW approach, a total of 6 feasible solutions are obtained. This involve the use of 3 regular drivers on average. For BO-VRPMDTW a total of 4 feasible solutions are obtained. On average 2 regular vehicles, 1 ODs of type 1 and 2 ODs of type 2 are used.

For this case, the BO-VRPMDTW also outperforms the VRPTW in the bi-objective perspective, even considering the reduction of the number of available solutions. The ODs activation allows to minimize the total cost and

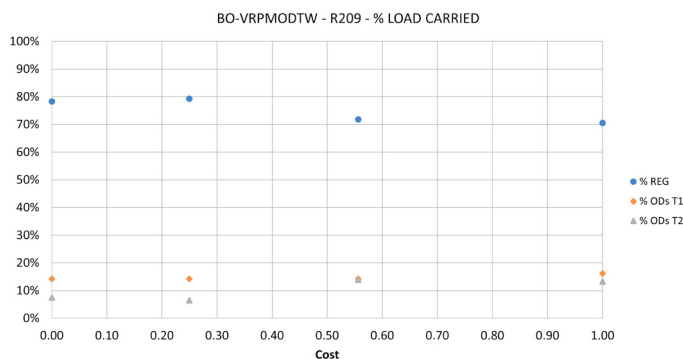


Fig. 4. Load carried by type - Instance R209 - 13 clients

reduce the total CO₂ emissions limits. Fig. 4 presents the percentage of load carried by each type of vehicle for this instance, according to the normalized value of cost for each solution in BO-VRPMDTW. It is observed that for this instance, the higher percentage in load mobilization corresponds to regular driver which on average corresponds to 75%. For ODs, the average for type 1 is 15%, and for type 2 is 10%. In this case, ODs represent a feasible complement for the bi-objective approach, but have as main type the regular fleet.

5. CONCLUSIONS

We proposed a bi-objective crowdshipping problem optimizing both the cost and CO₂ emissions, referred to as the Bi-Objective Vehicle Routing Problem with Multi types of Occasional Drivers and Time Windows (BO-VRPMDTW), generalizing the participation of "out store" ODs using fueled and non-fueled vehicles, having a higher the compensation policy for non-fueled type.

For the BO-VRPMDTW, there is good evidence to consider as good the trade-off from a bi-objective perspective, including cost and CO₂ emissions, considering the possibility of obtaining a wider range of solutions to increase, decrease, or control both objectives, according to possible business interests. The CO₂ emissions reduction reflects positively the use of ODs for deliveries, depending on ODs availability, type, distance to clients, and vehicle capacity.

In random instances, as a deterministic approach, there is a higher use of ODs in both types (fueled and non-fueled) to decrease the assignation of load in Regular vehicles, in terms of reducing CO₂ and controlling transportation costs. In clustered instances, there is a higher utilization of regular vehicles, considering the client's grouping, even from a CO₂ reduction perspective. However, OD intervention could be considered as a complementary approach, mainly with those who can use a sustainable vehicle. There is initial evidence to consider as good, to include a higher incentive for ODs that use more sustainable modes (non-fueled). In both clustered and random instances, it is stated the use and assignation of ODs with sustainable modes guarantee a decrease in CO₂ emissions.

Future works should consider different methods (exact or approximate) to scale up the solution approaches for bigger instances in a bi-objective context. Also, to analyze the inclusion of a third objective, to expand the sustainability

dimensions in the ODs types activation. Other possible approach could be to define multiple availability slots between ODs types, in a deterministic or probabilistic approach, to analyze selection and probability to complement a delivery scheme. Finally, to include an online perspective to the problem.

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