Analysis of the Hiring Cost Impact with a Bi-objective Model for the Multi-depot Open Location Routing Problem

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Abstract: This paper investigates the effect of the hiring cost over transportation cost and the capacity utilization for the vehicles used. This analysis is conducted on a multi-depot open location-routing problem. The problem consists of determining the optimal number of depots to open, as well as the design of the open routes in order to satisfy the demand for all of the customers while seeking the best trade-off between the total traveling and opening cost. To solve the problem, we propose a bi-objective mixed-integer linear model, which is solved using two different approaches: the augmented epsilon constraint 2 (AUGMECON2) method and the weighting revised multi-choice goal programming (WRMCGP) method. Both approaches are implemented, solving benchmark instances and comparing the quality of the Pareto fronts in terms of multi-objective metrics. Accordingly, the results indicate that AUGMECON2 performs better than WRMCGP concerning the quality of the Pareto Front and the elapsed CPU time, for instances with a homogeneous fleet. However, the WRMCGP reported the best solution time in the heterogeneous instances. In summary, considering heterogeneous fleets, the results demonstrate that the hiring cost can be reduced up to 85%, with 73% more vehicle utilization on average.

1 INTRODUCTION

The vehicle routing problem (VRP) is one of the most studied problems in Operations Research due to the diverse applications where it can be implemented. Its practical relevance and theoretical complexity make this topic so attractive, as this provides solutions to several kinds of logistics and transportation problems (Elshaer & Awad, 2020; Irnich et al., 2014; Kardar et al., 2011). A particular variant of the VRP, known as the multi-depot location-routing problem (MDOLRP), determines the number of depots to open, the location of those depots, and the routes' design simultaneously. The problem studied in this work is inspired by the situation faced by a Mexican company, which imports material from suppliers in the USA. The firm agrees with a third-party company an exclusive contract transport the raw material. This translates into high costs. The reason for the high cost comes from the supplier agreement since it requires to contract a homogeneous fleet. The company is interested in analyzing the hiring of different transportation suppliers and considering a heterogeneous fleet. Given the specific context, the MDOLRP can be used to solve the problem. The purpose is to determine the impact of hiring costs over the total cost. In the single-objective version of this problem (Nucamendi-Guillén et al., 2020), the authors focused on minimizing the total incurred cost expressed as the sum of the traveling and vehicle's hiring cost. However, the study did not evaluate the effect of the hiring cost over the traveling cost. The purpose of this work is to conduct a bi-objective analysis to show if reducing the number of vehicles used forces to create routes that increase the cost significantly.

The present study follows two objectives: (i) to solve the bi-objective problem model with exact methods, and (ii) to solve and compare the performance of each solution method based on the

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quality of the Pareto fronts, using multi-objective metrics. In addition, the analysis of the costs between homogeneous and heterogeneous fleets is conducted.

The remainder of the paper is organized as follows. Section 2 presents the literature review of the MDOLRP. Section 3 describes the multi-objective optimization model, the solution methods, and the characteristics of the set of instances. Section 4 reports the results obtained, including the comparison with the multi-objective metrics and the hiring cost analysis. Finally, the concluding remarks of this work are presented in section 5.

2 LITERATURE REVIEW

The location-routing problem (LRP) is a generalization of the VRP in which the optimal number of open depots and optimal design of the routes are simultaneously determined (Wu et al., 2002). As a generalization of the VRP, the LRP is considered as an NP-hard problem. Because of this, it is difficult to obtain optimal solutions to large instances in reasonable computational time, justifying the use of metaheuristics (Adhi et al., 2019; Rabbani et al., 2017). Nevertheless, small instances can be solved with exact methods, with standard computational capacity and enough time to solve (Braekers et al., 2016; Ramos et al., 2014).

In the LRP, the selection of the depot represents a strategical decision, while the design of the routes is an operational decision. However, additional features can affect the decision of location and routing, for instance, to have a limit in the number of depots to open or when facilities have limited capacity (Schneider & Drexl, 2017). Finally, the characteristic of considering open routes denote that the vehicle is not required to return to the depot after visiting the last customer, which is common when a third party executes the distribution since they assume the cost of the "empty" return (Braekers et al., 2016).

The single objective approach of the location-routing problem usually requires minimizing a combination, sometimes weighted, of fixed and variable costs. Differently, the multi-objective approach optimizes conflicting objectives, for instance, minimizing the travel cost and maximizing the level of service (Drexl & Schneider, 2015; Tavakkoli-Moghaddam et al., 2010). When the conflicting objectives belong to different dimensions, a normalization process is performed before implementing the model.

One of the methods commonly used is weighted goal programming (WGP), which has been previously applied in multi-objective location-routing problems (Zhao & Verter, 2015; Rabbani et al., 2017; Asefi et al., 2019; Yousefi et al., 2017).

In the specific case of bi-objective problems, the Epsilon-constraint method arises as an approach to be applied in multi-objective routing problems (Kabadurmus et al., 2019; Toro et al., 2017; Arango González et al., 2017). An improved version of the ε-constraint, the augmented epsilon-constraint method (AUGMECON) has gained researchers' attention to solve multi-objective routing problems (Wang et al., 2018; Amini et al., 2019).

The literature review illustrates the tendency to solve realistic routing problems via exact multi-objective methods, from the weighting method, weighting goal programming, to epsilon-constraint based method. These techniques optimize objectives that belong to different nature and in quantity, even if they are conflicting. Even when, in general, the WGP and its variations are frequently used to solve multi-objective routing problems, they present complications when solving large-scale instances, justifying the use of methods as the ones proposed in the present work, which are enough to solve and analyze the bi-objective location-routing problem.

3 MATHEMATICAL MODEL AND SOLUTION METHODS

This work provides a detailed analysis of the bi-objective version of the MDOLRP (Nucamendi-Guillén et al., 2020), following two different strategies. The details and characteristics of the problem, the assumptions, and the model formulation are presented next. The MDOLRP model is functional to analyze the impact of hiring cost in minimizing the total cost. For practical purposes, the following assumptions are made:

- The routes generated should be finished in the manufacturing company;
- The return cost of the supplier transport to the depot is considered on the hiring cost. It means the open routes;
- The demand is deterministic and quantified in pallets;
- The traveled distance is translated into monetary terms.

3.1 Problem Definition

The following notation is used:
$n := Number\ of\ suppliers$
$m := Number\ of\ carriers$

$Q_{\max} :=$ *Maximum capacity per any vehicle*
$w_i^l :=$ *Hiring cost per vehicle l per carrier i*
$D_{ij} :=$ *Transport cost between depot i and supplier j*
$C_{ij} :=$ *Transport cost between suppliers i and j*

Let $P = \{1,..,n+1\}$, be the set that denotes the nodes to visit. Let $Pp = \{1,..,n\}$, the node-set for the suppliers (where n represents the number of suppliers to serve) to collect whereas the node $n+1$ denotes the final node (i.e., the manufacturing plant). Let $F = \{1,\dots,m\}$ be the set of potential carriers (where m represents the number of carriers to contract), where $R_i = \{1,\dots,k_i\}$ denotes the set of vehicles per each carrier, where k_i represents the number of vehicles per each carrier. The capacity and the hiring cost of each vehicle l belonging to carrier i are denoted as Q_i^l and w_i^l, respectively. The demand per supplier j is in d_j. The transport cost is due to the next matrix: depot i to supplier j is in D_{ij}, and supplier i to supplier j is in C_{ij}.

Regarding the variable set, let o_{ij}^l be a binary variable equal to 1, if the arc (i,j) is active to travel from the depot i and the first node j using the vehicle l, and equal to 0 otherwise. Let x_{ij} be a binary variable equal to 1, if the arc (i,j) is traveled between nodes i and j, and equal to 0 otherwise. Let z_i^l be equal to 1, if vehicle l is contracted from the carrier i, and equal to 0 otherwise. Furthermore, let the auxiliary variable v_{ij}^l be a continuous variable that denotes the sum of the demands of the remaining nodes of the route after departing from carrier i using vehicle l when $o_{ij}^l = 1$. In addition, let the auxiliary variable r_{ij} be a continuous variable that denotes the sum of the demands of the remaining nodes of the route after visiting supplier i when $x_{ij} = 1$.

Since this work aims to analyze the impact of the hiring cost ($F2$) above the traveling cost ($F1$), the objective is conflicted naturally, as proportionally contrary to the problem. The bi-objective model approach is addressed. The mathematical formulation is:

$$F1 = min \sum_{i=1}^{m}\sum_{j=1}^{n} D_{ij} \sum_{l=1}^{R_i} o_{ij}^l + \sum_{i=1}^{n}\sum_{\substack{j=1\\ j\neq i}}^{n} C_{ij}x_{ij}, \tag{1}$$

$$F2 = min \sum_{i=1}^{m}\sum_{l=1}^{R_i} w_i^l z_i^l \tag{2}$$

Subject to:

$$\sum_{j=1}^{n} o_{ij}^l \leq 1, \forall\, i\, \in F; l \in R_i, \tag{3}$$

$$\sum_{i=1}^{m}\sum_{l=1}^{R_i} o_{ij}^l + \sum_{\substack{i=1\\ i\neq j}}^{n} x_{ij} = 1, \forall\, j\, \in Pp, \tag{4}$$

$$\sum_{\substack{i=1\\ i\neq j}}^{n+1} x_{ji} = 1, \forall\, j\, \in Pp, \tag{5}$$

$$z_i^l \geq \sum_{i=1}^{n} o_{ij}^l,\ \forall\, i\, \in F; l \in R_i, \tag{6}$$

$$v_{ij}^l \geq d_j o_{ij}^l, \forall\, i\, \in F; j \in Pp;\ l \in R_i, \tag{7}$$

$$v_{ij}^l \leq Q_i^l o_{ij}^l, \forall\, i\, \in F; j \in Pp;\ l \in R_i, \tag{8}$$

$$r_{ij} \geq d_j x_{ij}, \forall\, i \in Pp; j \in Pp;\ i \neq j, \tag{9}$$

$$r_{ij} \leq (Q_{max} - d_i)x_{ij}, \forall\, i \in Pp; j \in Pp;\ i \neq j, \tag{10}$$

$$\sum_{i=1}^{m}\sum_{l=1}^{R_i} v_{ih}^l + \sum_{\substack{i=1\\ i\neq h}}^{n} r_{ih} - \sum_{\substack{j=1\\ j\neq h}}^{n+1} r_{hj} = d_h, \forall\, h\, \in Pp, \tag{11}$$

$$o_{ij}^l \in \{0,1\}, \forall\, i\, \in F; j \in Pp;\ l \in R_i, \tag{12}$$

$$x_{ij} \in \{0,1\}, \forall\, i \in Pp; j \in P, \tag{13}$$

$$z_i^l \in \{0,1\}, \forall\, i\, \in F; l \in R_i, \tag{14}$$

$$v_{ij}^l \geq 0, \forall\, i\, \in F; j \in Pp;\ l \in R_i, \tag{15}$$

$$r_{ij} \geq 0, \forall\, i \in Pp; j \in P. \tag{16}$$

The objective functions (1) and (2) minimizes the sum of the transportation and contracting costs, respectively. Constraints (3) ensure that, for each vehicle, at most, one departing arc must be activated. In contrast, the group of constraints (4) assure each supplier node must be visited only once, either from the depot or from other nodes. Constraints (5) ensure that all of the routes end at node *n+1*. The constraints (6) activates the carriers for the selected vehicles (departing nodes). On the other hand, constraints (7) ensure that the demand of each departing node must be satisfied. Also, the constraints (8) ensure that the cumulative demand of each route does not exceed the capacity Q_i^l. Constraints (9) and (10) operate in the same way as (7) and (8) but involving only the supplier nodes. Constraints (11) avoid having sub-tours by controlling demand. Finally, constraints (12)-(16) denote the nature of the variables.

Since this study aims to analyze the behavior of the vehicles' hiring and traveling cost over the total cost, for both the case of the heterogeneous and homogeneous fleet, it is necessary to use the multi-objective optimization method. This optimization approach is useful to manage decision-making problems involving two or more conflicting objectives. Given the characteristics of the problem, this procedure is followed.

3.2 Solution Methods

The computational experiments were executed using both approaches, WRMCGP and AUGMECON2. Figure 1 describes the implementation of WRMCGP. Figure 2 exhibits the implementation of AUGMECON2.

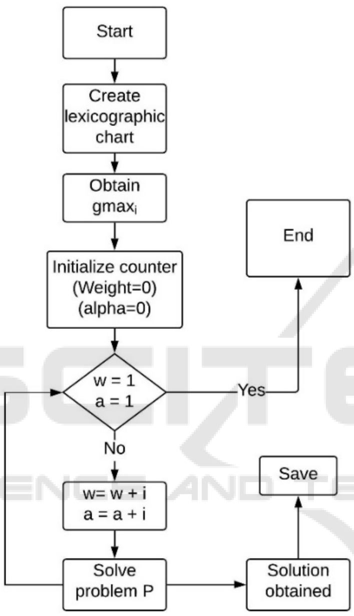

Figure 1: WRMCGP diagram.

4 COMPUTATIONAL EXPERIENCE

4.1 Set of Instances

For computational experimentation, we considered two different sets of instances. The first set belongs to the instances used for the multi-depot vehicle routing problem, proposed in (Cordeau et al., 1997) and labeled P and Pr. The second set involves the instances with a heterogeneous fleet (Wang & Wu, 2015). For the heterogeneous instances, different opening costs per each depot were considered. In the instances involving a homogeneous fleet, all the vehicles have the same opening cost.

After implementing the model, only three instances of each group could be entirely solved (six in total). Tables 1 and 2 indicate the description of those instances. In these tables, columns 1-5 indicate the name of the instance, number of suppliers (*n*), number of depots (*m*), number of vehicles (*k*), and vehicles' hiring costs, respectively.

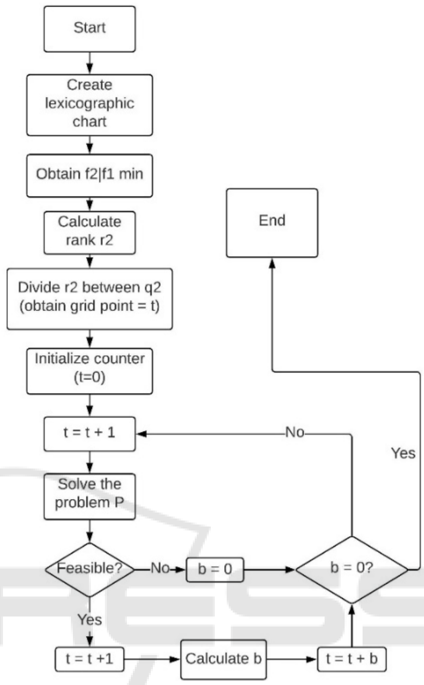

Figure 2: AUGMECON2 diagram.

Table 1: Description of the homogeneous instances.

Instance name	*n*	*m*	*k*	Vehicle capacity	Hiring cost
P_02	50	4	5	160	31.80
Pr_01	48	4	4	200	63.13
Pr_02	96	4	7	195	60.70

Table 2: Description of the heterogeneous instances.

Instance name	*n*	*m*	*k*	Vehicles Capacities		Hiring costs	
				min	max	min	max
Wa-W15O1	20	2	15	4	8	20	35
Wa-W15O2	24	3	15	4	5	15	20
Wa-W15O3	25	3	15	4	5	15	20

The formulation was coded using the optimization language AMPL and solved using Gurobi 9.0.0 using computational equipment with an Intel Core i7-6600U @ 2.6GHz processor with 16 GB of RAM, under Windows 10 as OS. The computational time limit is set to 7200 seconds per iteration in the Pareto Front.

4.2 Multi-objective Metrics

To measure the performance of the method, we use the following metrics:

- NOS/NPS:

The number of optimal solutions in the Pareto Front evidences the best performance between algorithms; a higher NPS value is preferred (Rayat et al., 2017).

- Quality metric (QM):

This metric calculates the proportion between the number of non-dominated Pareto Front solutions of method A and the total non-dominated solutions from the combined Pareto front (Rayat et al., 2017), as shown in equation (17).

$$Q(A) = \frac{Number\ of\ non-dominated\ solutions\ of\ method\ A}{Total\ number\ of\ non\_dominated\ solutions}, \quad (17)$$

The quality of solutions is compared against each other, and the higher value algorithm is desirable.

- RPOS:

The metric determines the ratio of Pareto-optimal solutions in P_i that are not dominated by any other solutions in P, which is the union of the sets of the Pareto-optimal solution, and it is calculated using equation (18) (Altiparmak et al., 2006):

$$RPOS(P_i) = \frac{|\ P_i - \{\ X \in P_i |\ \exists\ Y \in P\ :\ Y \prec X\}|}{|P_i|} \quad (18)$$

Where $Y \prec X$ means the solution X is dominated by the solution Y, and these solutions X are removed from the solution set P_i. The higher value, the better.

- Hyperarea ratio (HR):

The proportion of the generated area (HR) (21) is calculated by dividing the Pareto front area (HA) for each point between the total area (TA) (Zitzler & Thiele, 1999), as shown in eq. (21). The area (HA) of the Pareto Front can be defined as the product of the difference between coordinate $(F1_i, F2_i)$ for each solution S_i and the (highest) maximum point (M), as defined in eq. (19). Lastly, the total area (TA) is the product of the difference between the coordinates $(M, F1_{min})$, and $(M, F2_{min})$ (20). Figure 3 shows an example to calculate Hyperarea of a Pareto front.

$$HA = \sum_{i=1}^{n-1} ((f1_{i+1} - f1_i) * ((f2_M - f2_i)), \quad (19)$$

$$TA = (f2_M - f2_{min}) * (f1_M - f1_{min}), \quad (20)$$

$$HR = HA/TA, \quad (21)$$

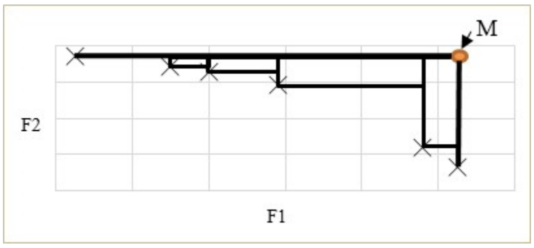

Figure 3: Hyperarea of the Pareto front.

4.3 Experimental Results

This section is devoted to reporting the values of the metrics used to evaluate each method's efficiency over each specific group of instances. First, the values of the NPS and elapsed CPU time is shown. Then, the values of the Q(A), RPOS, and HR are displayed.

Tables 3 and 4 report the value of NPS and the CPU time (in seconds) for each solution approach over each type of instance. These two metrics are first considered since they quickly indicate the method's performance in terms of quality and speed. The columns are identified with an (A) for AUGMECON2 and a (W) for WRMGCP.

Table 3: NPS and computational time of optimality homogeneous instances.

Instance name	NPS		CPU Time (sec)	
	A	W	A	W
P_02	5	8	1054	10373
Pr_01	9	6	34	44
Pr_02	5	3	3108	5023
Average	6.33	5.67	1398	5146

It is evident that AUGMECON2 performs better than WRMCGP, reporting denser fronts in general and in the case of the homogeneous instances, requiring 74.76 % less time on average than WRMCGP. On the other hand, there is a difference of 65.69% on average in the heterogeneous instances in favor of WRMCGP. Since the number of points in the Front differs per method, a detailed analysis is conducted to determine the variation between the minimum and maximum values for the extreme solutions of each Pareto Front. This analysis is shown in section 4.4.

The next analysis consists of determining which method produces better Pareto fronts with respect to the remaining metrics Q(A), RPOS, and HR. Tables 5 and 6 show the values obtained for the heterogeneous and homogeneous instances, respectively. The columns are identified with an (A) for AUGMECON2 and a (W) for WRMCGP.

Table 4: NPS and computational time of optimality-solved heterogeneous instances.

Instance name	NPS		CPU Time (sec)	
	A	W	A	W
Wa-W15O1	6	5	611	276
Wa-W15O2	4	3	3126	1217
Wa-W15O3	3	3	996	129
Average	4.33	3.67	1578	541

Table 5: Results of multi-objective metrics for the homogeneous instances.

Instances	Q(A)		RPOS		HR	
	A	W	A	W	A	W
P_02	1	0.625	1	1	0.699	0.657
Pr_01	1	0.667	1	0.833	0.695	0.657
Pr_02	1	0.6	1	1	0.616	0.521
Average	1	0.631	1	0.944	0.670	0.612

Table 6: Results of multi-objective metrics for the heterogeneous instances.

Instances	Q(A)		RPOS		HR	
	A	W	A	W	A	W
Wa-W15O1	1	0.833	1	1	0.781	0.78
Wa-W15O2	1	0.75	1	1	0.318	0.258
Wa-W15O3	1	1	1	1	0.736	0.736
Average	1	0.861	1	1	0.612	0.591

From tables 5 and 6, it can be observed that AUGMECON2 performs better, improving by 36.9% in quality, 2.56% in RPOS, and 8.66% in HR for homogeneous instances and improving by 23.9% in quality, 0.0% in RPOS, and 3.43% in HR in heterogeneous instances. In general, AUGMECON2 outperforms WRMCGP, even when WRMCGP presents a competitive computational time performance in the heterogeneous instances.

In summary, it was demonstrated that the vehicles' hiring costs play an essential role when the DM seeks a better trade-off between the number of vehicles to hire and the total distance traveled, representing a metric of customer satisfaction. A detailed analysis is presented next to better understand the impact of hiring cost over travel distance and capacity utilization.

4.4 Detailed Analysis of the Impact of Vehicles' Hiring Cost

As mentioned before, a detailed analysis is conducted to evaluate the impact of the hiring cost over the transportation cost (in both cases) and vehicles' capacity utilization. This study was performed in two stages. First, we calculate the proportion of improvement in the transportation cost (F1) and hiring cost (F2) as the difference between the Front's extreme points. Secondly, the capacity utilization per vehicle was estimated for each extreme point. Figures 4 and 5 illustrate the calculation of these values for the instances Pr_01 and Wa-W15O1, respectively.

Tables 7 and 8 summarize the percentage of reduction in transportation and hiring cost over the homogeneous and heterogeneous fleet instances, respectively. In these tables, the first column indicates the name of the instance. In contrast, columns two and three reports the percentage of reduction (RED) in transportation and increment (INC) in hiring cost, respectively. Finally, columns five and six report the minimum and maximum percentages of capacity utilization, respectively.

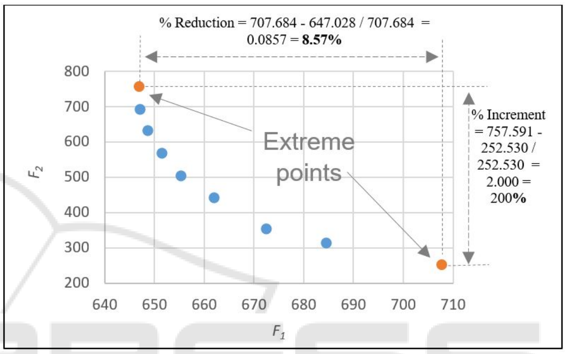

Figure 4: Percentage calculation of cost savings, for instance Pr_01.

Table 7: Percentage of cost reduction and capacity utilization for homogeneous instances.

Instance name	RED	INC	% Avg. of Capacity utilization	
	T. cost	H. cost		
	F_1	F_2	Min	Max
P_02	5.76%	140.00%	37.36%	97.50%
Pr_01	8.57%	200.00%	27.38%	85.13%
Pr_02	2.78%	57.14%	56.88%	93.11%
Average	5.70%	132.38%	40.54%	91.91%

The average percentage of increment cost for homogeneous instances is 132.38% for hiring cost on average, producing savings of around 5.70% on average for transportation costs. On the other hand, if we choose the minimum Hiring cost, this produces an average increment of 6.12 % in transportation costs.

When analysing the capacity utilization, it raises from 40.54% to 91.91%, which indicates that looking for the best solution in distance tends to sub-utilize the vehicles' capacity. Moreover, when the decision-maker seeks for seizing the vehicle's capacity utilization, the total traveled distance is worsened by less than 10%, but producing increasing in hiring costs up to two times more, which is significant since, for these instances, the contracting costs represent up to 60% of the total value (transportation + hiring costs).

Table 8: Percentage of cost reduction and capacity utilization in heterogeneous instances.

Instance name		RED	INC	% Avg. of Capacity utilization	
		T. cost	H. cost		
		F_1	F_2	Min	Max
Wa-W15	O1	15.58%	36.36%	72.74%	96.00%
	O2	11.02%	10.00%	92.86%	100%
	O3	7.42%	12.50%	87.62%	98.57%
Average		11.34%	19.62%	84.41%	98.19%

In the instances with the heterogeneous fleet, it was observed that savings in transportation costs raised to 11.34% while, for the hiring costs, the increment is around 15.62%, on average. On the other hand, if we choose the Hiring cost minimum, this provokes an average increment of 12.95% in the transport cost. As a conclusion, it can be observed that it is more rentable to have different carriers (heterogeneous) to sacrifice long travel and more vehicle utilized. When having vehicles with different capacities, the model seeks a better combination. It can also be confirmed when observing the minimum and maximum values for capacity utilization because vehicles have a utilization of over 70% in the worst case.

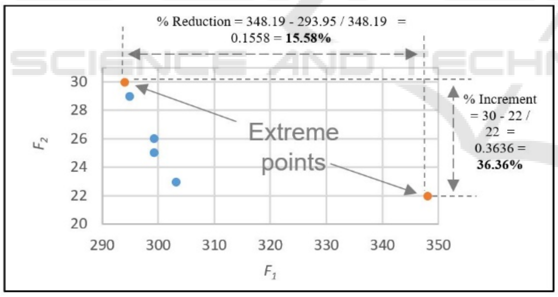

Figure 5: Percentage calculation of cost savings for instance Wa-W15O1.

In summary, considering that contracting costs represent up to 40% of the total cost, we can initially conclude that seizing vehicles utilization should be preferred over total traveling distance for routing problems involving hiring costs.

5 CONCLUSIONS AND FUTURE RESEARCH

This work analyzes the impact of the hiring cost over the transportation cost through a bi-objective model for the MDOLRP, considering vehicles with a homogeneous and heterogeneous fleet. The problem was modeled using a bi-objective model and solved using a commercial solver, testing literature instances and obtaining optimality for instances up to 25 suppliers, 2 to 3 depots, and 15 vehicles for the heterogeneous fleet and, in the case of the homogeneous fleet, instances up to 96 suppliers, 4 depots, and 7 vehicles.

In terms of the methods used, AUGMECON2 outperformed WRMCGP. However, WRMCGP performed faster in heterogeneous instances. In addition, we demonstrate that in the heterogeneous instances, the saving in hiring cost is significant by maximizing the vehicles' capacity utilization without significantly affecting transportation costs. In the case of the homogeneous instances, the savings are less substantial.

Future work involves the application of metaheuristic algorithms to deal with large-scale instances. In addition, the application of different objectives as max time delivery, customer service level, priority index, time windows, split delivery, autonomous vehicles, and drone application can also be interesting to the academic knowledge.

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