AN AGILE AND REACTIVE BIASED-RANDOMIZED HEURISTIC FOR AN AGRI-FOOD RICH VEHICLE ROUTING PROBLEM

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ABSTRACT

Operational problems in agri-food supply chains usually show characteristics that are scarcely addressed by traditional academic approaches. These characteristics make an already NP-hard problem even more challenging; hence, this problem requires the use of tailor-made algorithms in order to solve it efficiently. This work addresses a rich vehicle routing problem in a real-world agri-food supply chain. Different types of animal food products are distributed to raising-pig farms. These products are incompatible, i.e., multi-compartment heterogeneous vehicles must be employed to perform the distribution activities. The problem considers constraints regarding visit priorities among farms, and not-allowed access of large vehicles to a subset of farms. Finally, a set of flat tariffs are employed to formulate the cost function. This problem is solved employing a reactive savings-based biased-randomized heuristic, which does not require any time-costly parameter fine-tuning process. Our results show savings in both cost and traveled distance when compared with the real supply chain performance.

1. INTRODUCTION

Feeding pigs in the pork production industry is a highly relevant activity to achieve successfully the supply chain goals (Rodríguez, 2014). Such activity requires a precise logistics from the production plant to the farms where the pigs are raised. Hence, our work consists in designing a set of vehicle routes that meet the feed demand of a set of pig farms, considering the real case of a pork production company in Spain. From an academic point of view, the analyzed problem can be considered as a rich vehicle routing problem (RVRP) (Caceres-Cruz et al., 2014), since: *(i)* vehicles are heterogeneous and have multiple compartments to separate different types of incompatible products that must be distributed to a set of farms; *(ii)* each farm may require multiple products; *(iii)* some farms admit only that a small-medium vehicle deliver the feed; *(iv)* a visit priority must be met, which indicates that some farms must be visited as soon as possible, whereas other farms must be the last to be served; and *(v)* the cost function considers a set of flat tariffs, which depend on both the location of the farm and the number of farms visited in the same route.

A flexible and enriched heuristic is then proposed to address this problem. Apart from the multi-product and multi-compartment RVRP, this heuristic must be able to deal with an objective function that relies on a flat-rate policy instead of the traditional distance-based minimization. Then, this enriched savings-based heuristic is extended into a biased-randomized algorithm (BRA), which is able to provide multiple solution configurations in short computational times. As described in Grasas et al. (2017), biased-randomized techniques are based on the introduction of an oriented (non-uniform) randomization process inside the constructive stage of a given heuristic. By doing so, a deterministic heuristic is transformed into a randomized algorithm that can be run multiple times (either in sequential or in parallel) without losing the logic behind the heuristic. Hence, the main contributions of our paper can be stated as follows: *(i)* the consideration of a flat-rate cost function, together with multi-product and multi-compartment characteristics; *(ii)* the design of a flexible and agile heuristic, which enriches the traditional savings heuristic, to solve a rich and real-life problem in the agri-food distribution industry; *(iii)* the extension of the former heuristic into a biased-randomized algorithm capable of providing, in short computational times, a set of alternative solution configurations to the problem, each of these including different dimensions; and *(iv)* the introduction of a reactive (automatic) fine-tuning process for the main parameter of the biased-randomization process.

Rich vehicle routing problems have been increasingly addressed by the academic community, since they incorporate highly realistic constraints, especially when these are considered simultaneously (Azadeh and Farrokhi-Asl, 2019). Characteristics regarding input data, decision management components, vehicles, time constraints, among others, turns a classical VRP into a rich VRP (Lahyani et al., 2015b). For instance, Alemany et al. (2016) combine the well-known savings heuristic (Clarke and Wright, 1964) with Monte Carlo simulation to solve a heterogeneous-fleet, multi-depot, multi-compartment, multi-product, and multi-trip VRP. In general, vehicles can be classified according to their physical characteristics, e.g., they can be homogeneous or heterogeneous, or compartmentalized or not. The relevance of considering compartmentalized vehicles emerges whenever different types of products are demanded and they are incompatible, i.e., products must be carried separately into the same vehicle and not be mixed. Despite the practical applications of this strategy for addressing real-world problems, the multi-compartment VRP has been scarcely studied (Derigs et al., 2011). Both theoretical and real-world cases can be found in the multi-compartment VRP literature. Silvestrin and Ritt (2017) and Muyldermans and Pang (2010) show examples of the former.

These works propose metaheuristic approaches given the combinatorial nature of this problem. Regarding real-world cases, products as diverse as apparel, fuel, food, and waste require the use of compartmentalized vehicles for performing an appropriate transport (Wang et al., 2014; Reed et al., 2014; Vidovic et al., 2014; Coelho and Laporte, 2015).

Agri-food supply chains represent also a field where the multi-compartment VRP has been addressed. These chains have special characteristics that should be taken into account in its modelling, such as products perishability (Tordecilla-Madera et al., 2018) or supply and demand seasonality (Vlajic et al., 2012). For instance, Lahyani et al. (2015a) propose a branch-and-cut algorithm to solve a multi-period and multi-compartment VRP with heterogeneous vehicles. A real case from the olive-oil collection process in Tunisia is considered, where compartments cleaning activities are considered. Oppen et al. (2010) address also cleaning activities in a multi-compartment VRP where inventory constraints are considered. Different types of animals are transported in this case, as well as a heterogeneous fleet and multiple trips. An exact method based on column generation is used as solving approach. Alternatively, employing approximate methods is a usual approach in agri-food multi-compartment VRPs. For instance, Caramia and Guerriero (2010) propose a hybrid approach combining mathematical programming and local search techniques to solve a real-life case regarding the collection of different types of milk in Italy. Finally, the number and capacity of compartments can also be a variable to consider, i.e., compartments are flexible. For instance, a large neighborhood search algorithm is proposed by Hübner and Ostermeier (2019) to solve this variant of the multi-compartment VRP. A relevant contribution of this paper is the consideration of loading and unloading costs, which are a function of the number of compartments.

The remainder of this paper is structured as follows: Section 2 shows the main characteristics of our addressed problem, and Section 3 describes the algorithm employed to solve it. Section 4 shows our main found results based on a real case study, and Section 5 shows the concluding remarks and future work.

2. PROBLEM DESCRIPTION

The part of the supply chain addressed in this paper is that in charge of distributing the animal food from central depots to the farms, as displayed in Figure 1. We consider each day as an independent instance, where the subset of farms requiring service can be different. Each farm generates an order, and each order may be composed of different types of feed, e.g., Figure 1 displays circles, hexagons and triangles representing three different products. In general, products can be classified in medicated and non-medicated.

Also, the characteristics of each type of product depend on the growth stage of each herd, i.e., the required diet mix is different according to the age (in weeks) of each individual.

The demand of each product in each farm is deterministic. The feed distribution is carried out from a depot through a set of compartmentalized heterogeneous vehicles. For instance, Figure 1 shows two types of vehicles with three and four compartments, respectively.

Compartments are also heterogeneous, i.e., each compartment has a different known capacity. The demanded quantity per product and farm is at most the capacity of a vehicle.

Hence, each vehicle can visit multiple farms in the same route, as long as the aggregate demand does not exceed the vehicle's capacity. Split deliveries are not allowed, i.e., a single farm must be served by a single vehicle. The objective of using compartmentalized vehicles is to separate each type of feed, since they cannot be mixed during a trip. In addition, if the demand of a product is higher than the capacity of a single compartment, it can be split into two or more compartments in the same vehicle. Nevertheless, in general, medicated feed cannot be transported in the same route as non-medicated feed. Not all types of vehicles can visit all customers, since some farms have access constraints. That is, a subset of farms can be served by all types of vehicles, whereas another subset cannot be served by large vehicles. An additional constraint assigns a sanitary priority indicator, which determines a specific order in which a subset of farms must be visited in case they are in the same route. The company classifies the farms into 3 types according to this sanitary priority: *(i)* a subset of farms with an assigned priority according to a consecutive natural number. These farms must always be served in ascending order whenever they are in the same route, e.g., a farm with a priority of 2 must always be visited before a farm with a priority of 5; *(ii)* a subset of farms with no priority; and *(iii)* a subset of farms with a "negative" priority, which indicates that they must be the last to be served in any route.

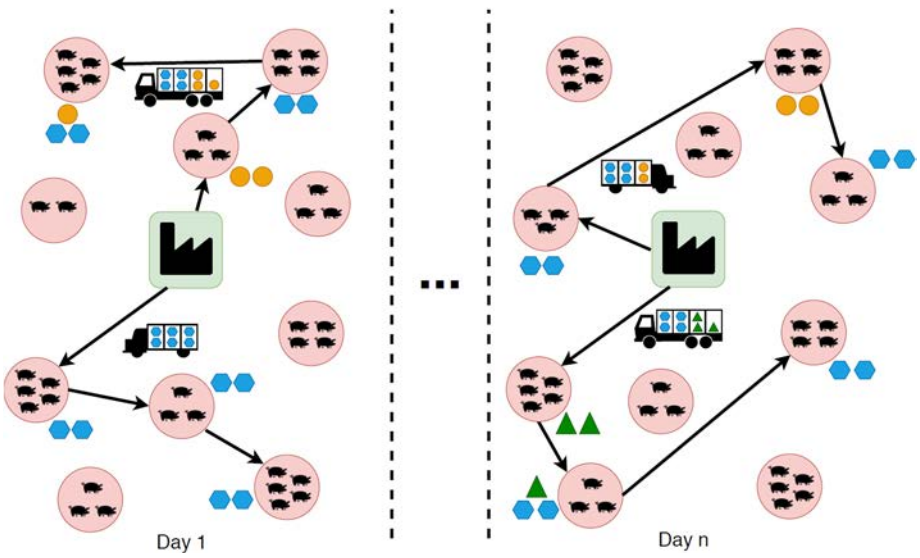

Fig. 1 – Representation of our real-life problem.

Our main objective is to minimize the total distribution cost.

As the company outsources the feed transportation, the distribution cost calculation has been settled in a distribution agreement. This cost is computed as the product of the delivered quantity and a pre-established tariff. The whole distribution region is clustered in zones, so that the tariff $c(n, z)$ depends on both the zone z where the customer is located and the number of farms n visited in the same route. Each customer has three different tariffs according to n (Equation 1), where $c_1(z) < c_2(z) < c_3(z)$.

$$c(n,z) = \begin{cases} c_1(z), & \text{if } n = 1 \\ c_2(z), & \text{if } n = 2 \\ c_3(z), & \text{if } n \geq 3 \end{cases} \quad (1)$$

Figure 2 displays a few examples of tariffs (expressed in €/t) employed by the company.

Figure 2a shows the case in which each farm is the only one visited in its route. Hence, the tariff of all customers in the Zone 1 is $c_1(1) = 7.74$ and the tariff of the customer 4, located in the Zone 2, is $c_1(2) = 8.98$. Figure 2b shows the case in which all customers in the Zone 1 form a single route, therefore, the employed tariff is $c_3(1) = 8.76$. The customer 4's tariff remains the same as in the former case. Finally, Figure 2c shows the case in which customers of different zones form a unique route. Under these circumstances, the distribution agreement indicates that the employed tariff must be the greatest one. Hence, as $c_3(1) = 8.76$ and $c_3(2) = 9.24$, the final distribution tariff for the route in this instance is 9.24 €/t. Since the total satisfied demand is the same in the 3 cases of Figure 2, and the total variable cost depends on the supplied food-load in tonnes, the case in Figure 2b incurs a higher variable cost than the instance in Figure 2a, and the case in Figure 2c incurs the highest variable cost in the example. This means that merging routes increases the variable cost in our problem, which is the opposite of merging routes in traditional routing problems. This behavior is caused by the flat tariffs indicated in the distribution agreement.

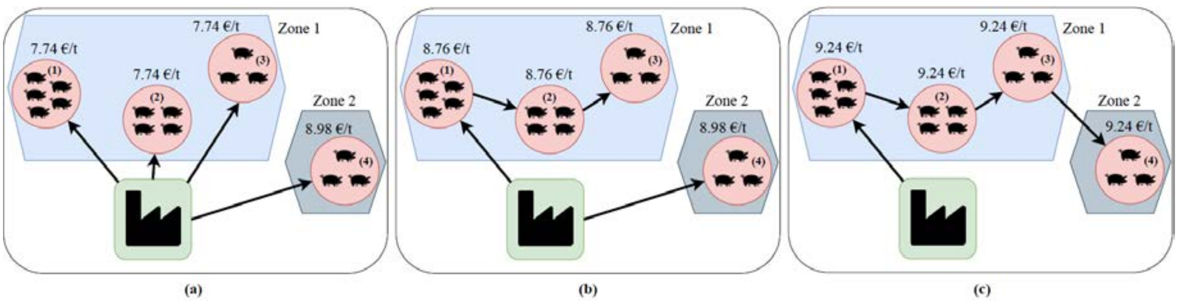

Fig. 2 – Examples of tariffs used by the company.

The considered problem requires that the total delivery cost is not the only key performance indicator (KPI), i.e., the approach used to solve this problem must show enough flexibility to consider additional KPIs, such as the number of designed routes and the total traveled distance.

Despite its non-typical objective function and unique constraints, the problem can be classified as a rich variant of a multi-product and multi-compartment open VRP (RVRP). Hence, it is an *NP-hard* problem and, as such, the use of heuristic-based approaches (Londoño et al., 2020) is justified whenever the size of the problem goes beyond a certain level.

3. FROM A FLEXIBLE AND FAST HEURISTIC TO A REACTIVE BIASED-RANDOMIZED ALGORITHM

This section shows our approach for dealing with the described RVRP. This approach is based on both multi-start (Martí et al., 2013) and biased-randomized algorithms (BR) (Grasas et al., 2017). Algorithm 1 provides a general view of the proposed heuristic to solve the RVRP. The core of our approach is a flexible and fast two-stage heuristic, which includes all problem characteristics considering multiple KPIs. In the stage 1, a first initial solution is generated, in which each customer is assigned to a vehicle in a single round-trip, meeting all the considered constraints. Once this initial solution is generated, the algorithm merges routes in stage 2 as much as possible, reducing the number of used vehicles. Algorithm 2 outlines the stage 2, which consists of the following steps: firstly, it computes the *savings* associated with potential route merges. These savings are computed for every edge and are based on both the distance between farms and the tariff per zone.

Then, a list of edges associated with the savings values is created and sorted in decreasing order. The main loop iterates on the sorted savings list, where each edge is selected to be part of the solution only if it meets the following merging conditions: *(i)* both customers in the origin and the end of the edge belong to different routes; and *(ii)* these customers are adjacent to the depot. Unlike the traditional savings method, we do not consider the total vehicle capacity. Instead, it is evaluated whether the demand of each product fits in the available compartments, considering both their capacity and a feasible layout. When a feasible assignment is found, the algorithm merges the routes and updates the solution; otherwise, the current edge is rejected and the algorithm proceeds to the next iteration with a new alternative. The current solution is updated by removing the routes at both extremes of the selected edge and adding the resulting new merged route. All KPIs are then updated, including the cost, which considers the flat-rate delivery tariffs (Figure 2). Again, notice that this approach is different to the distance-based cost computation employed in most articles on the VRP, which do not consider a flat-rate tariff. Finally, the current edge is removed from the list, and the whole process is repeated until the savings list is empty, returning a complete new solution *sol*.

Algorithm 1 Multi-Start R-BR

Require: $inputParameters$
$sol \leftarrow Stage_1(inputParameters)$
$\beta_1, \beta_2 \leftarrow T(0, 0.5, 1)$
$newsol_1 \leftarrow Stage_2(sol, \beta_1)$
$newsol_2 \leftarrow Stage_2(sol, \beta_2)$
$sol, m^* \leftarrow best(newsol_1, newsol_2), best(\beta_1, \beta_2)$
while time **not** reaches the limit **do**
  $\beta_s \leftarrow T(0, m^*, 1)$
  $newsol \leftarrow Stage_1(inputParameters)$
  $newsol \leftarrow Stage_2(newsol, \beta_s)$
  $sol, m^* \leftarrow best(sol, newsol), best(m^*, \beta_s)$
  if $sol \notin S^*$ **then**
    $S^* \leftarrow add(S^*, sol)$
  end if
end while
Ensure: S^*

Algorithm 2 Stage$_2$

Require: sol, β
$savings \leftarrow computeSavingsSorted(sol)$
while $savings \neq \emptyset$ **do**
  $edge \leftarrow selectNextArc(savings, \beta)$
  $savings \leftarrow remove(savings, edge)$
  if $isMergePossible(edge)$ **then**
    $sol \leftarrow updateSolution(sol, edge)$
  end if
end while
Ensure: sol

The previous heuristic is extended into a reactive BR algorithm (R-BR). This procedure allows not only to diversify the search for good solutions, but also to generate alternative solutions assessed in terms of multiple KPIs. Our proposed methodology in Algorithm 1 uses both stages 1 and 2 (Algorithm 2) as the base for the R-BR. Previously described steps are followed the same, except for the selection of the next edge in the savings list.

This selection is now performed by considering a skewed probability distribution, which introduces a sort of randomness into this process. In our case, the selection of the next element is performed according to a geometric distribution with parameter $0 < \beta < 1$.

Employing this distribution introduces diversification to explore other regions of the solution space, preserving at the same time the savings heuristic original purpose. Unlike previous works, our algorithm is *reactive*, since the parameter β is automatically fine-tuned. The R-BR implementation procedure is described next: firstly, initialize parameters β_1 and β_2 using a symmetric Triangular probability distribution with mode $m = 0.5$. Secondly, generate two complete solutions using β_1 and β_2, respectively.

Then, compare the yielded costs (or any other KPI) to obtain the best-found mode m^* and the best-found solution *sol* so far. Then, the algorithm iterates while the time limit is not reached. For each iteration, a new β_s is computed using a Triangular distribution with mode equal to m^*.

Later, generate a new complete solution *newsol* using β_s. Again, obtain the best-found mode m^* and solution *sol*. Finally, introduce the new solution *sol* in the pool of solutions S^*.

4. CASE STUDY

Real-world instances representing multiple products demands from 44 workdays have been provided by the company. They represent daily deliveries made to 214 farms. Currently, the company performs a delivery only when the customer generates an order. Hence, only a subset of farms is served each day. Furthermore, the delivered product mix also changes every day, and each customer may require multiple types of food at the same day. The feed shelf life is greater than one day; therefore, perishability is not included in our case study.

The number of vehicle types are 3: a vehicle type with 6 compartments and a total capacity of 26 t, a vehicle type with 6 compartments and a total capacity of 21 t, and a vehicle type with 5 compartments and a total capacity of 21 t. A single product demand can vary between 1 t and 26 t. Our approach yields 4 KPIs: *(i)* total distance, computed as an approximation by employing the Euclidean distance between two farms, considering their real Cartesian coordinates; *(ii)* total cost, computed employing the flat tariffs described in Section 2; *(iii)* total number of routes; and *(iv)* average utilization of vehicles, computed considering the utilization percentage of every vehicle used in every route of a complete solution. The algorithm is implemented in Python 3 and executed in a personal computer with 16 GB RAM and a 2.8 GHz Intel Core i7-1165G7 processor.

Table 1 shows the average results after running our biased-randomized algorithm employing 44 instances. This table compares the results obtained when considering a non-reactive and a reactive biased-randomized (BR) heuristic. The latter refers to the procedure described in Section 3. The former refers to the case already described in the literature, in which the parameter β of the geometric probability distribution must be fine-tuned by hand. In our experiments, our manual fine-tuning process found the best results when β follows a uniform probability distribution between 0.01 and 0.40. Both BR procedures employ a time limit of 60 seconds. Table 1 also shows the results obtained by the company in its real daily operations. Obviously, these results are independent of our both BR procedures. Four types of solutions are generated, where each one is the best-found solution assessed in terms of each aforementioned KPI. For instance, the *Best-distance* solution is the one that achieves the minimum distance. Hence, the reached value of the KPI *Distance* is underlined for this solution.

The reasoning in this example can be extended for the rest of the KPIs. The greater the utilization, the better. The other KPIs have an opposite interpretation. Values obtained by the non-reactive BR are only slightly better than the ones yielded by the reactive BR, i.e., differences are minimal. Nevertheless, the non-reactive BR requires a few work hours for performing the fine-tuning process, whereas the reactive BR is automatic and does not require any fine-tuning.

The average percentage difference between our solution and the company solution is shown in the columns *Gap* of Table 1. This indicator is computed considering the gap between each KPI obtained for each instance. A negative gap indicates that our solution outperforms the company's. If the gap is positive, then the smaller the gap, the better.

Hence, a few results can be highlighted. Firstly, our heuristic always reaches a smaller cost than the company, regardless of the type of solution. Secondly, savings in distance provided by our heuristic are high when considering the *Best-distance* solution. Thirdly, the company slightly outperforms our algorithm when considering the number of routes and the vehicle utilization. Finally, the cost is a KPI whose behavior is opposite to the rest of the indicators', i.e., when the cost improves, the other KPIs worsen. This behavior is a result of considering the flat tariffs explained in Section 2.

Type of solution	Non-reactive BR				Reactive BR			
	KPI				KPI			
	Distance	Cost	#Routes	Utilization	Distance	Cost	#Routes	Utilization
Real company	1153.6	5555.5	23.9	95.8%	1153.6	5555.5	23.9	95.8%
Best-distance	<u>1104.0</u>	5541.7	24.7	92.5%	<u>1106.6</u>	5540.6	24.8	92.3%
Best-cost	1201.3	<u>5495.7</u>	26.7	86.2%	1196.9	<u>5497.5</u>	26.8	86.1%
Best-#routes	1178.8	5544.3	<u>24.2</u>	94.1%	1173.3	5542.4	<u>24.3</u>	93.8%
Best-utilization	1168.5	5549.6	24.2	<u>94.8%</u>	1174.7	5548.6	24.3	<u>94.6%</u>
	Gap				Gap			
Best-distance	<u>-4.4%</u>	-0.2%	3.5%	3.3%	<u>-4.1%</u>	-0.3%	3.7%	3.5%
Best-cost	4.3%	<u>-1.1%</u>	12.3%	9.6%	4.0%	<u>-1.1%</u>	12.6%	9.6%
Best-#routes	2.0%	-0.2%	<u>1.4%</u>	1.7%	1.5%	-0.2%	<u>1.7%</u>	2.0%
Best-utilization	1.1%	-0.1%	1.4%	<u>1.0%</u>	1.7%	-0.1%	1.7%	<u>1.2%</u>

Table 1 – Average results considering different KPIs.

The best-found distance and best-found cost gaps between our solution and the company solution for the 44 instances are displayed in Figure 3. This figure also shows a comparison between our both tested heuristics, i.e., non-reactive BR (NR-BR) and reactive BR (R-BR). Regarding the distance, only a few instances exceed the 0% limit, i.e., our agile approach is able to outperform the company's distance results for the vast majority of instances. Furthermore, our approach always reaches a negative gap in costs, which is a great result considering the tough restriction imposed by the flat tariffs. Finally, Figure 3 also shows that our reactive BR is able to yield solutions highly similar to the ones achieved by the non-reactive BR.

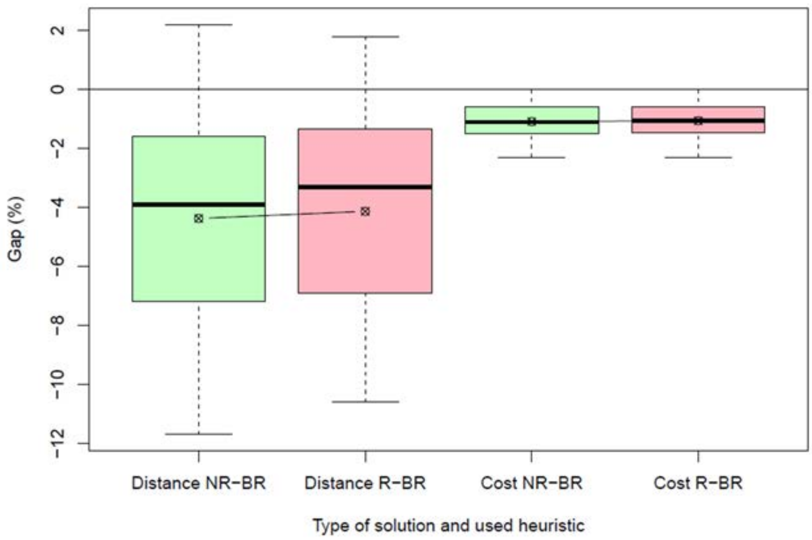

Fig. 3 – Distance and cost gaps of our best-found solutions with respect to the company's.

4. CONCLUSIONS

This work has proposed a reactive biased-randomized heuristic to solve a real-world rich vehicle routing problem for the distribution of animal food. A set of complex constraints have been considered, such as multi-compartment heterogeneous vehicles, flat tariffs, visit priorities, among others. Four KPIs have been proposed to assess the solutions quality.

Advantages of employing our agile approach are mainly twofold. Firstly, our yielded results outperform the real company's outcomes in terms of traveled distance and distribution cost. These results are obtained in only a few seconds, whereas designing these routes by the company takes a few work hours. Secondly, results yielded by our reactive biased-randomized algorithm are highly competitive when compared with a non-reactive one. However, the latter requires a time-costly fine-tuning process, whereas our proposed heuristic does not require to perform this procedure. Future work includes considering inventory planning jointly with the vehicle routing. In this case, both food perishability conditions and a multi-period planning can be included.

ACKNOWLEDGEMENTS

This work has been partially supported by the Doctoral School of the Universitat Oberta de Catalunya (Spain), the Universidad de La Sabana (Colombia, Grant INGPhD-12-2020), and the EU-IoF2020 project (282300206-UC005).

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