Hybridization of game theory and ridesharing to optimize reverse logistics of healthcare textiles

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Abstract. The reverse logistic of Healthcare Textile has become nowadays a major concern in Morocco. Consequently, it imposes to authorities and professionals the obligation to perform a sustainable reverse logistic model. Through this study, we are going to hybridize game theory and ridesharing to optimize a multi-objective reverse logistics of healthcare textiles. We opted for the Genetic algorithm to face the complexity of the ridesharing model. For cost allocation, the allocation based on volume give best results compared to Alternative Cost Avoided Method. Besides, it allows a higher gain for players with the most important activity.

1. Introduction
Healthcare Textiles (HT) reverse logistics, as a source of contamination, increasingly affects the quality of life of citizens[1]. Therefore, a considerable amount of recommendations has been cited in the GIZ report to limit the impact of this contamination[2]. These recommendations have not been successfully implemented in Morocco[3]. Thus, clinics use their own transport to transport the used HT to laundries. This situation has led to excessive transport costs that are beginning to weigh on the cash flow of these clinics. Then, while waiting for a logistic operator, allowing the launch of the project of outsourcing, we aim through this study to provide an adequate solution to the clinics located in the city of Casablanca.

Ridesharing (RS) as a solution to minimize transportation costs and respect for the environment has recently gained prominence on social networks. This success has encouraged researchers to study the implementation of RS in various fields [4-5-6]. Indeed, this solution can reduce transportation costs, but it is necessary to build homogeneous coalitions and distribute costs equitably among the clinics that make up each coalition. Our objective is to study the best way to implement RS in the case of HT logistics. Thus, the second section presents the proposed solution and outline the state of the art of the RS and game theory (GT). The third part exposes the model formulation of our projected solution. The remaining part of the paper carries out a series of experiments and results discussion.

2. Problem definition and state of art:
The motivation of our work is to exploit the benefits of RS to ensure a temporary solution for clinics that reduces their transport costs, while minimizing the risk of contamination from HT. The latter is fundamental for the clinics involved in our study. Indeed, some clinics are unambitious to participate in high-risk coalitions. The origin of this potential risk is associated with the transport of HT, where the possibility of contamination exists between HT coming from different clinics. Therefore, we will take in consideration the main criteria, stated in interviews with clinic managers, to avoid such high-risk
coalitions. RS is defined as a mode of transportation in which several travelers share a vehicle for a trip and split the trip costs[7]. several research studies have shown that RS can bring many environmental and economic benefits, including reducing traffic congestion and carbon emissions[8-9]. In the literature, RS is often formulated as an optimization problem aimed at maximizing customer coverage, maximizing driver income and many other objectives. The latter are subject to constraints from the origin-destination pairs, the time windows (TW) and so on. The complexity of these models is supported by meta-heuristics such as genetic algorithms [10] or other algorithms like greedy-matching[11]. For a better implementation of the RS solution in our case study, we propose the model illustrated in figure 1, where our model select the starting clinic corresponding to the driver. Then, it will constitute a coalition of clinics and corresponding laundries to ensure both the collection and deposit of HT.

As shown in the figure 1, our model try to set up routings, with picking-up of HT (case of clinics) or delivering of HT (case of laundries), using heterogeneous capacitated vehicle, with requirements in terms of TW. Consequently, one can conclude that we face a Heterogeneous Capacitated Vehicle Routing Problem Pickup and Delivery with TW (HCVRPPDTW). Once coalitions are formed, the other challenge is to distribute the costs fairly among the coalition members, also ensuring an economic gain for each member to encourage them to join the coalition. The main problem in cooperation is cost allocation [12], more than 40 different cost allocation methods have been used in the literature on collaborative transportation[13], and each solution concept satisfy a number of characteristics. However, no concept fulfils all criteria listed in literature. A simple approach for cost allocation is to use a proportional allocation that can be based on the overall volume or weight of the products transported[14]. Moreover, other methods are commonly used in the case of joint distribution and RS like Shapley value and methods based on separable and non-separable cost as ACAM[15]. According to [16], ACAM and Volume can provide an interesting result in the case of transportation problem, insuring individual rationality. Therefore, we will use these methods to allocate costs.

Roughly speaking our case is a RS multi-objective case (cost, coalition risk) with HCVRPPDTW. The present study fills a gap in the literature by adding some particularities compared to the existing models: Multi-objective (MO) model, Heterogeneous fleet (HF), Multiple Depot (MD), Strict TW, Hazardous Materials (HT), PD, RS and GT (Allocation cost).

3. Model Formulation

3.1. HFCVRPPDTW model:
The HFCVRPPDTW can be defined on a directed graph G = (N, A), where: N = {0, …, n-1, n, ..., 2n-1, 2n,…, 3n-1} is the set of nodes, A is the set of arcs where n= the number of clinics = the number of laundries = the number of virtual depots and K is a set of heterogeneous vehicles.

Decision variables:
\( x_{ijk} \): a binary variable (BV) equal to 1 if arc \((i, j)\) is used by vehicle \(k\), 0 otherwise, \((i, j) \in N, k \in K\)

\( Z_i \): total cost of routing (Variable cost + fixed cost of used vehicles)

The model that govern the CVRP-PDTW is the same as presented in [17].

3.2. Risk Calculation:
As aforementioned above, based on interviews with clinics, we have specified the list of criteria for assessing the risk of contamination. Then, we applied weighting vote method [18] to established a risk matrix, which give the risk contamination when two clinics are on the same coalition. The total \(Z_2\) risk calculation is calculated with the same objective-function and constraints as presented in [17]. We denote \(\alpha, \beta\) as the Weighting parameters of cost function and risk function respectively.

We express our aggregate multi-objective function as follows:

\[
\text{Minimize } \alpha \cdot Z_1 + \beta \cdot Z_2
\]  

(1)

3.3. RS constraints:
The aim of our model is to limit the number of vehicle used by clinics. Roughly speaking, some clinics will engaged their vehicle to transport their HT and those of other clinics taking into account transport cost and coalition preference. Thus, we will enhance our model with constraints linked to RS. Let:

\( u_i \): a CV which represent node potentials indicating the visit order of node \(i\) in the tour

\[
x_{0ik} = x_{i+n0k} \quad i \in \{n, \ldots, 2n - 1\}, k \in K
\]  

(2)

\[
x_{0i+nk} = x_{i0k} = 0 \quad i \in \{n, \ldots, 2n - 1\}, k \in K
\]  

(3)

\[
\sum_{j=0}^{3n-1} x_{ijk} = \sum_{p=0}^{3n-1} x_{i+njk} \quad i \in \{n, \ldots, 2n - 1\}, k \in K
\]  

(4)

\[
u_i - u_j \leq (1 - \delta_{ij}) \cdot n - 1 \quad i, j \in \{n, \ldots, 3n - 1\}, i \neq j, k \in K
\]  

(5)

\[
u_i \leq u_{i+n} \quad i \in \{n, \ldots, 2n - 1\}
\]  

(6)

\[
u_i \geq 0 \quad i \in \{n, \ldots, 3n - 1\}
\]  

(7)

Equation (2) make sure that a tour begins from the clinic and ends at his destination. However, constraint (3) prevent starting from laundries or ending at clinics. Constraint (4) ensure the use of the same vehicle by origin and destination. Constraints (5) and (6) eliminate sub tours and ensure that each clinic precedes its corresponding laundry. Finally, constraint (7) defines the non-negativity of \(u\).

3.4. Cost allocation methods:

3.4.1. Alternative Cost Avoided Method (ACAM). The Alternative Cost Avoided Method uses the weights \(w_i = \frac{C(N) - C(N \setminus \{i\})}{C(N) - \sum_{j \in (i)} C(N \setminus \{j\})}\), expressing savings that are made for each participant by joining the grand coalition instead of operating alone.

\[
\varphi_i(C) = C(N) - C(N \setminus \{i\}) + w_i \cdot [C(N) - \sum_{j \in (i)} C(N \setminus \{j\})]
\]  

(8)

3.4.2. Allocation based on volume. Volume weights is based on distributing the total cost of the grand coalition, \(C(N)\), among the participants according to a volume or a cost weighted measure.

\[
\varphi_i(C) = \frac{C(N) - C(N \setminus \{i\})}{\sum_{j \in (i)} C(N \setminus \{j\})} C(N)
\]  

(9)

For choosing an adequate allocation method, it should be decided which axioms and characteristics are relevant for the case at hand. No cost allocation method fulfills all listed characteristics.

3.5. Data of computational study:
We study 18 clinics disseminated in the whole region of Casablanca. The HT generated historical data of each clinic show the stability of HT’s boxes generated. Consequently, we consider the demand as the average number of daily HT’s boxes generated. We have a set of heterogeneous vehicle. Each clinic has its own vehicle and we get from the clinic the fixed and variable costs.

4. Solution methodology
The resolution by the exact approach has shown its limitations because the research space is too large, especially in the case of the MO problem[19]. Based on a very broad field of studies, the genetic algorithm (GA) is a promising approximation algorithm that has addressed hard problems in recent decades [20]. For this reason, we propose the GA to deal with this case. The next section will show experimentation of the chosen GA. Then, we will use GT in order to allocate cost and ensure adequate profit and individual rationality for each clinic.

4.1. Heuristic Approach:

4.1.1. Genetic Algorithm. The GA is one of the best known evolutionary optimization techniques, this Meta-heuristic covers several optimization problems such as VRPTW [21]. Alba et al. 2004 proposed a cellular Genetic Algorithm (cGA) to solve CVRP [22]. The interesting results from the operators of cGA will guide our choice towards the Alba’s operators. The proposed GA and the case studied are coded and implemented on the platform HeuristicLab 3.3.15.15587[23] and experiments are carried out on an Intel® CORE(TM) i5-4200 CPU with a 2.3 Ghz processor and 4 GB installed memory RAM.

4.1.2. Validation and analysis of the approach. The benchmarking is the best way to validate the meta-heuristic proposed in the case of RS HCVRPDDTW. However, this is the first work, to our knowledge, that dealt with multi-objective RS in case of HCVRPDDTW. Nonetheless, we can generate our GA for small instances to compare the results with the Exact Approach (EA). The benchmark results, exposed in table1, show a little difference between EA and GA, however the execution time (ET) in GA is very interesting. These results encouraged us to justify the acceptability of a proposed GA’s performance and to perform the experimentation of the GA in large instances. To do so, we carried out 50 tests for real instance. The GA, gave the best solutions within a reasonable time. The table 2 represents the best results from GA. The RS constraints chose clinics 5, 13 and 7 as a starting point. Therefore, their vehicles will be used to cover the collection from clinics and delivery to laundries according to the sequences specified in the table 2. The tuning experiments showed that there is a compromise range between cost and risk. Consequently, we can perform RS as an alternative solution to manage the logistic of HT.

| Algorithm | Objective Function | GAP to Global optimum | ET (Minutes) |
|-----------|--------------------|-----------------------|--------------|
| EA        | 684                |                       | 23:49.0      |
| GA        | 686.5              | 0.36%                 | 01:05.1      |

Table 2. Best result coming from real instance experiments.

| Pickup and Delivery Sequence | Cost \( ^{c} \) | Risk |
|------------------------------|-----------------|------|
| Routing 1                    | 1066.9          | 87   |
| Routing 2                    | 1318.3          | 416  |
| Routing 3                    | 1287.1          | 105  |
| Total                        | 3672.3          | 608  |

\(^{a}\) C: Clinics
\(^{b}\) L: Laundry
\(^{c}\) MAD: Moroccan Dirhams
4.2. Cost allocation
The stand-alone cost of each clinic and the cost of every coalition (Routing 1, 2, 3) generated by the heuristic approach are used to share the total cost according to Volume method. As basis for computation of ACAM, we use the heuristic approach to solve the transportation problem for each coalition when one clinic is missing. This will allow us to calculate the marginal cost of each clinic. In this section, cost refers to normalization between cost (MAD) and risk introduced before.

Results show that ACAM and volume respect the individual rationality in the case of coalition 1 and coalition 3 and there is a certain similarity between allocated costs. While for coalition 2, only the volume respect the individual rationality, since for the ACAM, at least one participant is worse in this allocation comparing to its standing alone. Collaboration in the case of clinics allows optimizing considerably the total cost. The profit made by each clinic and by each coalition is very significant.

Table 3. Comparison between ACAM and Volume.

| Coalition 1 | Clinics | Stand alone | ACAM | Profit | Volume | Profit |
|------------|---------|-------------|------|--------|--------|--------|
|            | 8       | 151.5       | 11.0 | 140.5  | 36.6   | 114.9  |
|            | 14      | 182.5       | 52.2 | 130.2  | 44.1   | 138.4  |
|            | 12      | 182.6       | 58.1 | 124.6  | 44.1   | 138.5  |
|            | 15      | 226.3       | 48.6 | 177.7  | 54.7   | 171.6  |
|            | 16      | 225.5       | 64.0 | 161.5  | 54.5   | 171.0  |
| Sum        |         | 968.4       | 234  | 734.4  | 234    | 734.4  |

| Coalition 2 | Clinics | Stand alone | ACAM | Profit | Volume | Profit |
|------------|---------|-------------|------|--------|--------|--------|
|            | 13      | 183.1       | 87.6 | 95.5   | 77.3   | 105.8  |
|            | 11      | 182.8       | 78.6 | 104.2  | 77.2   | 105.6  |
|            | 7       | 151.6       | 39.9 | 111.7  | 64.0   | 87.6   |
|            | 2       | 76.5        | 55.2 | 21.3   | 32.3   | 44.2   |
|            | 4       | 107.3       | 55.4 | 52.0   | 45.3   | 62.0   |
|            | 1       | 76.9        | 122.0| -45.1  | 32.4   | 44.4   |
|            | 18      | 301.4       | 56.6 | 244.9  | 127.2  | 174.2  |
| Sum        |         | 1306.1      | 551.3| 754.7  | 551.3  | 754.7  |

| Coalition 3 | Clinics | Stand alone | ACAM | Profit | Volume | Profit |
|------------|---------|-------------|------|--------|--------|--------|
|            | 10      | 182.6       | 94.9 | 87.8   | 72.2   | 110.4  |
|            | 5       | 136.3       | 52.3 | 84.0   | 53.9   | 82.4   |
|            | 3       | 106.4       | 48.5 | 57.9   | 42.1   | 64.3   |
|            | 6       | 136.4       | 45.3 | 91.0   | 53.9   | 82.4   |
|            | 9       | 152.2       | 41.3 | 110.9  | 60.2   | 92.0   |
| Sum        |         | 713.9       | 282.3| 339.6  | 282.3  | 339.6  |

5. Conclusion
This research sheds new light on reverse logistics in the case of HT, by proposing a RS MO model of a very complicated case of HCVRPPDTW. Our objective was to support medical instances to find a solution to their sustainable reverse logistics. The affinities between the clinics led us to integrate the RS and the GT to set up homogeneous coalition between clinics and to share properly their transport costs. The simulation coming from the GA helped us to seek a compromise between the main objectives studied. For cost allocation, the practical case studied confirms that the ACAM does not guarantee individual rationality in coalition 2, since in the case of its creation one of the clinics pays more than he would have paid by standing alone. The Volume gives a solution that respects individual rationality and allows a higher gain for players with the most important activity. As perspective of this work, we suggest a deep study of coalition stability.

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