Improved models and heuristics for the biomedical transportation problem

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***Résumé* –** La collecte et le transport des échantillons biomédicaux représente un défi de taille dans la logistique hospitalière. Les hôpitaux, les cliniques ou les centres de prélèvement, génèrent à chaque jour des milliers d'échantillons qui doivent être transportés rapidement vers les laboratoires afin d'être analysés. Puisque les échantillons se détériorent rapidement dans les conditions environnementales non-contrôlées du transport, les autorités ont fixé à trois heures le temps maximal que tout échantillon peut passer entre le moment où il quitte son point de cueillette et l'arrivée au laboratoire d'analyse. Cette contrainte, combinée aux fenêtres de temps et aux multiples passages requis par les centres de collectes, complexifient grandement ce problème de confection de tournées de véhicules. Proposé récemment par [Anaya-Arenas et al. 2015], qui développa deux modèles mathématiques ainsi que des heuristiques rapides afin d'aider à leur résolution, le problème du transport d'échantillons biomédicaux restait beaucoup trop complexe pour être résolu à l'optimalité dans le cas d'instances de taille réelle. Dans cet article nous proposons un algorithme de type *multi-start* très performant qui, testé sur un ensemble de problèmes réels, atteint régulièrement l'optimum sur les problèmes de taille moyenne et améliore régulièrement les meilleures solutions connues sur les problèmes de grande taille.

***Abstract* -** The collection and transport of biomedical samples represents a major challenge in hospital logistics. Hospitals, clinics or collection centers, generate every day thousands of samples that must be transported to laboratories to be analyzed. Since samples deteriorate rapidly in the uncontrolled environmental conditions of transport, the authorities have set to three hours the maximum time that any sample can pass between the time it leaves its collection point and its arrival at the laboratory. This constraint, along with the time windows and multiple visits required by the collection centers, greatly complicate this vehicle routing problem. Anaya Arenas et al. 2015 proposed two mathematical models and fast heuristics to solve the biomedical samples' transportation problem, but it remained far too complex to be solved to optimality for real-life sized instances. In this paper we propose a high-performance multi-start algorithm which regularly reached the optimum on medium-sized problems and improved the best known solutions for several larger-sized problems.

***Mots clés* – Tournées de véhicules, logistique hospitalière, fenêtres de temps, heuristique**
***Keywords* – Vehicle routing, health logistics, time windows, heuristic**

1 INTRODUCTION

Vehicle routing and scheduling is a key component in the efficiency of modern supply chain where quantities of goods and raw materials should be continuously exchanged in the most regular way as possible. In its most common version, the *vehicle routing problem* (VRP) is to distribute goods from a depot to a set of customers [Laporte 2009, Semet *et al.* 2014] subject to some constraints like time windows, vehicle restrictions and many other practical considerations. In other situations, products are exchanged between the customers which lead to pickup and delivery VRP [Berbeglia et al. 2010]. Vehicles can also be used to bring back goods from the customers to a central depot, or consolidation point, like in waste collection problem [Ghiani et al. 2014]. These practical routing problems deal with many real-world constraints and are often referred as *rich* VRP [Lahyani et al. 2015].

In this article we are interested with an application in the healthcare supply chain which corresponds to the transportation of biomedical samples from their *collection point* (CP) to the *laboratory* (Lab) where they will be analyzed. In this transportation problem, CPs refer to hospitals or clinics, where different kinds of sample are taken. As the lifespan of these samples is limited, CPs often require multiple collection requests on a given day and each collection request is generally bounded by a time window. Samples are handled in cold boxes and once collected, boxes must arrive to the Lab within a specified time limit in order to preserve samples' integrity. At the Lab, the boxes are opened and each sample is manually checked and bar-coded in order to be followed in the next steps of the analysis process.

We assume that, according to the *Ministère de la santé et des services sociaux* (Ministry of Health and Social Services – MSSS) of Quebec, these transportation requests will be satisfied by external carriers, and these external carriers will be paid on the basis of the traveled distance. We also assume that each driver may perform multiple routes during the working day. More precisely, drivers must begin routes at the Lab, where they get empty sample boxes to exchange with full boxes at every visited CP. Drivers return to the Lab to deliver the collected samples before starting any other route. Finally, the drivers' schedule must respect the maximum number of driving hours per day set by the Quebec province regulation. Since the MSSS intends to count on external carriers, we assume that there isn't any a priori limitation on the number of available vehicles. Finally, emergency requests may probably occur. If it is the case, they will be handled by on-call taxis, or as exceptions by the transportation supplier who will plan them outside the regular routes.

The biomedical samples' collection from CP to the Lab has some characteristics that make it a challenging optimization problem. The hardest constraints are the samples' maximum transportation time and the multiple transportation requests at each SCC. Unlike other related contexts, such as blood collecting [Doerner et al., 2008], which considers that the product starts deteriorating right after the donation, we assume that as long as samples are kept at CPs, their deterioration is slowed down due to the controlled temperature and optimal storage conditions. However, as soon as samples are out of the CP, the samples integrity cannot be guaranteed, even if they are transported in cooler boxes. Therefore, we modeled this limitation as a *maximal transportation time*, which depends on the type of the particular samples collected, to preserve the samples' lifespan. Thus, after collection, each sample box must arrive at the Lab within a given time frame. Otherwise, samples deteriorate and may become unusable, increasing tremendously both the Lab's costs and affecting the quality of the service. In fact, an unusable sample forces the patient to make a second collection, which delays the analysis and doubles the operations costs of the entire process (collecting, transporting and analyzing).

On the other hand, and despite the ideal environmental conditions at CPs, the samples maximum lifespan is limited, so CPs doesn't want to keep the collected specimens for a too long time. This is why each CP may make a different number of samples transportation requests, depending on its daily opening hours. Hence, we allowed CPs to propose time windows for theirs transportation requests according to the particularities of their own clients and practices. These multiple pick-ups are also desirable because they contribute to ensure a smoother supply of sample boxes to Labs and thus help balancing their workload.

Given the particular underlying context of the biomedical sample transportation described, the aim of this research was to find the minimum distance set of routes in order to satisfy all the transportation requests of each CP, while respecting the imposed time windows, the maximum transportation times of all the collected samples and the drivers' maximum working time.

The biomedical samples' transportation problem (BSTP) was introduced by [Anaya-Arenas et al. 2015] and shown to be very difficult to solve both by mathematical models and by heuristics. With the exception of the mentioned article, to the best of our knowledge, this problem is original and has never been addressed before. In this article we build on previous works and our contribution is to propose a new multi-start algorithm which outperforms the previous ones. The algorithm considers all the constraints imposed by the Ministry of Health and Social Services. We also developed an efficient data structure and updating procedure to manage the maximal transportation time constraint for the collected samples.

The remainder of this article is as follows. In Section 2 we review the relevant works and Section 3 defines the problem in more details. A multi-start heuristic is developed in Section 4. The efficiency of this heuristic is evaluated in Section 4 on a set of real instances obtained from the MSSS of Quebec, Canada. Our conclusions are presented in Section 5.

2 REVIEW OF RELEVANT WORKS

Our review of the related literature allowed us to identify six specific works which deals with the collection or transportation of biomedical products or presents characteristics making them appear to be very close to the BSTP. Therefore, it is worth positioning the BST with respect to them. First, [Liu et al. 2013] studied a routing problem where biomedical samples needed to be collected and delivered to laboratories. In their case, four types of deliveries and pick-up requirements were considered. The two following papers, [Doerner et al. 2008 and Doerner and Hartl 2008], dealt with a blood collection problem. As in our context, they assumed a limit on the transportation time to preserve the blood's quality, and allowed the planning of multiple pick-ups at each customer location. However, as mentioned previously, they considered that the product's deterioration process began right after the donation so, assuming that a donation is performed just after a pickup is done, a limit on the next pickup time is automatically imposed.

[Azi et al. 2010] and [Hernández et al. 2014] addressed variants of the multi-trip vehicle routing problem with time windows where the total duration of each route was limited. To do so, they require the last customer in the route to be served no later than a maximum time after the route departure. [Anaya-Arenas et al. 2015] formally introduced the BSTP. They proposed two mathematical formulations, but it wasn't possible to solve them efficiently for real size instances. Therefore, they developed some fast heuristics to generate initial feasible solutions which are given to the mathematical models to fasten their resolution. This strategy was proven successful in improving the formulations' performance, particularly in the case of small and medium-sized instances. However, BTSP remained far too complex to be solved to optimality for real-life sized instances.

3 PROBLEM DEFINITION

In order to define the biomedical sample transportation problem we need to identify both the locations of the CPs and the collections requests. The n CPs are represented by $V' = \{v'_1, \dots, v'_n\}$ and each CP i requires Q_i collection requests leading to a total of $p = \sum_{i=1}^{n} Q_i$ requests. Then we define a complete graph $G = \{V, A\}$, where $V = \{v_0, v_1, \dots, v_p, v_{p+1}\}$ is the set of nodes in the network, which includes the laboratory as nodes $\{v_0, v_{p+1}\}$ where every route must start and end, and the set $P = \{v_1, v_2, \dots, v_p\}$, being the collection points associated to the p transportation requests of the CPs. In set P, CPs are duplicated as many times as they request a sample transport. Thus we define P_i as the set of nodes in V which corresponds to the original CP v'_i and $P = \bigcup_{i=1}^{n} P_i$. We consider the arc set $A = \{(v_i, v_j): v_i, v_j \in V, i \neq j, i = 0, \dots, p, j = 1, \dots p+1\}$ and a travel time (t_{ij}) and a travel distance (d_{ij}) is assigned to each arc (v_i, v_j). Clearly, t_{ij} and d_{ij} are equal to zero for every (v_i, v_j) if i and $j \in P_k$ (i.e., nodes i and j correspond to two requests from a same CP k). In addition, each request needs to be performed within a time window $[a_j, b_j]$. Finally, any two requests cannot be on the same route if they are related to the same collection point. K uncapacited vehicles are available for satisfying the transportation requests and each vehicle can perform multiple routes $(r = 1, \dots, R)$ within a work shift, but it must respect a limit on the length of its working day (T_k). In addition, we need to consider a loading time (τ_i) for each transportation request and the unloading time (τ_0) of the vehicle at the Lab before a new route can be started. Furthermore, let T^i_{max} be the maximal transportation time for the samples collected at CP i. The objective is to minimize the total traveling distance.

4 HEURISTIC ALGORITHM

In this section, we develop a multi-start algorithm for the BSTP. In the next sections we describe each part of the algorithm.

4.1 Multi-start algorithm

The multi-start algorithm is based on three procedures: *Construction*, *Extraction-reinsertion* and *Swap*. The multi-start algorithm sets a level of randomization which impacts two important parameters of the problem, the maximal sample transportation time (T_{max}) and the maximum length of a vehicle working day (T_k). These parameters impact the *Construction* algorithm which provides an initial feasible solution. The developed multi-start algorithm always works with feasible solutions.

4.2 Construction procedure

We have developed a sequential method to construct an initial feasible solution. We use the following rules in a lexicographic order to select the first node to be visited by a route.

- $N_1 = \text{argmax}_{i \in P}\{t_{0i}\}$ i.e., the set of nodes $i \in P = \{v_1, v_2, \dots, v_p\}$ whose travel time from the lab is the greatest.
- $N_2 = \text{argmin}_{i \in N_1}\{b_i\}$ i.e., the set of nodes $i \in N_1$ whose time window upper bound is the lowest.
- n_1 = Choose a node from N_2 randomly.

At each step, to add a new node to the set of visited nodes of the working route, we check the possibility of adding each un-routed node to every insertion place of the current route and select the insertion having the smallest detour in time. Given node i to be inserted between nodes j and k, the detour is $t_{ji} + t_{ik} - t_{ij}$. The general framework of the construction phase is given in the following where K is the number of vehicles and R the maximum number of routes per vehicle.

For $(i = 1 \text{ to } K)$ **do**
  For $(r = 1 \text{ to } R)$ **do**
    Initialize the route r by visiting the first node n_1;
    While (there is an un-routed node to be added in a feasible position) **do**
      Add to the route r, the node having the smallest detour in time;
    End While
    $r = r + 1$;
  End For;
  $k = k + 1$;
End For.

Figure 1. The Construction procedure

4.3 Extraction-reinsertion procedure

In this procedure, the goal is to reduce the distance of the solution by repositioning some of the nodes. To improve the solution, a node is extracted from its location and reinserted into its best feasible position. Starting from the first route of vehicle 1, all the nodes are repositioned to try to find an improved solution. As soon as a move leads to an improvement it is accepted and the whole procedure is iterated until we have no improvement by repositioning all the available nodes. During this procedure, we are allowed to create a new route or close an already existing one.

4.4 Swap

In a random order, two nodes are considered and their corresponding positions are swapped. As soon as a move improves the cost of the solution, it will be accepted and the procedure stops whenever we have no improvement by swapping all available nodes.

4.5 Multi-start heuristic algorithm

The general framework of the multi-start algorithm is provided in Figure 2 and consists of two loops. During the execution of the inner loop, the goal is to construct an initial feasible solution. Within this loop, as long as there is no feasible solution we try to run the *Construction* procedure by setting different temporary values for the maximum vehicle travel time (Tem_{T_k}) and the sample travel time ($Tem_{T_{max}}$) parameters. Essentially, at the very first iteration the algorithm is initialized by setting $Tem_{T_{max}} = T_{max}$ and $Tem_{T_k} = T_k$ which automatically produce and initial feasible solution. For the other iterations, if the generated solution by applying the *Construction* procedure is feasible, the corresponding values of Tem_{T_k} and $Temp_{T_{max}}$ are decreased by applying the following updates in which α is an input parameter:

$$Temp_{T_k} = Temp_{T_k} - \alpha T_k$$
$$Temp_{T_{max}} = Temp_{T_{max}} - \alpha T_{max}$$

Otherwise, in order to increase the chance of obtaining a feasible solution the corresponding values of parameters are increased by applying the updates:

$$Temp_{T_k} = Min\{Temp_{T_k} + \alpha T_k; T_k\}$$
$$Temp_{T_{max}} = Min\{Temp_{T_{max}} + \alpha T_{max}; T_{max}\}$$

Finally, the values to be used as the maximum travel and sample times, when running the *Construction* procedure, are set by applying the following relations in which $rand(0, x)$ is a random integer number between 0 and x.

$$r_1 = rand(0, T_k - Temp_{T_k}) + Temp_{T_k}$$
$$r_2 = rand(0, T_{max} - Temp_{T_{max}}) + Temp_{T_{max}}$$

Upon obtaining an initial feasible solution, we apply the *Extraction-Reinsertion* and *Swap* procedures to try to improve the quality of the initial solution.

$BestSolution = \emptyset$;
$Temp_{T_k} = T_k$;
$Temp_{T_{max}} = T_{max}$;
For ($Iter$ = 1 to Max_{iter}) **do**
    $flag = 1$;
    While (*flag*) do
        $r_1 = rand(0, T_k - Temp_{T_k}) + Temp_{T_k}$;
        $r_2 = rand(0, T_{max} - Temp_{T_{max}}) + Temp_{T_{max}}$;
        $CurrentSolution$ = *Initialization* (r_1, r_2);
        If ($CurrentSolution$ is feasible**)**
            $Temp_{T_{max}} = Temp_{T_{max}} - \alpha T_{max}$;
            $Temp_{T_k} = Temp_{T_k} - \alpha T_k$;
            $flag = 0$;
        Else
            $Temp_{T_{max}} = Temp_{T_{max}} + \alpha T_{max}$;
            If $(Temp_{T_{max}} > T_{max})$ *Then* $Temp_{T_{max}} = T_{max}$;
            $Temp_{T_k} = Temp_{T_k} + \alpha T_k$;
            If $(Temp_{T_k} > T_k)$ *Then* $Temp_{T_k} = T_k$;
        End If
    End While
    $CurrentSolution$=
        Extraction-Reinsertion($CurrentSolution$);
    $CurrentSolution$ = **Swap**($CurrentSolution$);
    If ($CurrentSolution$ improves the cost of the best known solution)
        $BestSolution = CurrentSolution$;
End For

Figure 2. The Multi-start algorithm

To do so, we use the initial given values for the sample travel time (i.e. T_{max}) and vehicle travel time (i.e. T_k). The termination criterion of the algorithm is a given number of iterations (i.e. Max_{iter}).

4.6 Information update

In order to manage efficiently the time windows and the maximum sample transportation time constraints, we need rules to update the earliest and the latest start time of nodes in the solution. For doing so, we adapted the method proposed by [Campbell and Savelsbergh 2004] for the VRP with time windows.

5 COMPUTATIONAL RESULTS

In this section we will evaluate the performance of the new heuristic on the set of real instances in [Anaya-Arenas et al. 2015]. These instances were obtained from the Quebec's Ministère de la Santé et des Services Sociaux (Ministry of Health and Social Services) and correspond to real transportation of biomedical samples faced by four administrative regions in the province of Quebec. Instances were divided into *Small* (four SCCs for a total of around 10 requests), *Medium* (up to 10 SCCs, around 20 requests) and *Large* (up to 20 SCCs, up to 50 requests) sets. Experts from the MSSS estimated the loading and unloading time to 10 minutes ($\tau_i = 10$ minutes), and T^j_{max} was set to 180 minutes for any CP *j*, which means that a sample will never travel more than 180 minutes. The working shift's maximal length was set to $T_k = 480$ minutes. All travel times and distances were calculated by using GoogleMaps.

All heuristic algorithms have been implemented in C using Microsoft Visual Studio 2010 and run on an Intel Core I-7 with a 3.4GHz processor and 32 Go of RAM.

Table 1 reports numerical results for the 38 instances. Column "Cplex" reports the best total distance produced by Cplex after 3 hours of computing time. These solutions were proven to be optimal for instances 1 to 27. Columns under header "Anaya-Arenas" reports the best solutions produced by the heuristics proposed in [Anaya-Arenas et al. 2015]. Columns under header "Multi-start Heuristic" report the results of the multi-start algorithm developed in Section 4 after 1 and 100 iterations. Heuristics' computing times are not reported as they are negligible. For each heuristic we report the total distance (Dist) and its gap in percentage (Gap) with respect to the best solution produced by Cplex.

The multi-start heuristic with 100 iterations produces all the optimal solutions for small and medium sized instances (1 to 25) It is worth mentioning that the heuristic's initial solution (after only one iteration) was on average 1.72% above the optimal. For the larger instances, the average gap was reduced from 8.25% (for the [Anaya-Arenas 2015] heuristic) to only 4.67% with 1 iteration of the heuristic and to -0.91% with 100 iterations. In the latter, the heuristic improved the best know Cplex solutions five times.

Table 1. Heuristics' performance for the BSTP instances

	Cplex	Anaya-Arenas		Multi-start Heuristic			
				1 it.		100 it.	
#	Dist	Dist	Gap	Dist	Gap	Dist	Gap
1	193.9	193.9	0.00	193.9	0.00	193.9	0.00
2	125.3	125.3	0.00	125.3	0.00	125.3	0.00
3	311.8	311.8	0.00	311.8	0.00	311.8	0.00
4	235.8	235.8	0.00	235.8	0.00	235.8	0.00
5	324.2	324.2	0.00	324.2	0.00	324.2	0.00
6	270.7	285.8	5.58	270.7	0.00	270.7	0.00
7	279.9	292.6	4.54	279.9	0.00	279.9	0.00
8	267.9	286.8	7.05	267.9	0.00	267.9	0.00
9	184.0	184.0	0.00	184.0	0.00	184.0	0.00
10	556.8	556.8	0.00	556.8	0.00	556.8	0.00
11	618.9	618.9	0.00	618.9	0.00	618.9	0.00
12	199.4	206.4	3.51	206.1	3.36	199.4	0.00
13	754.4	754.4	0.00	754.4	0.00	754.4	0.00
14	230.3	246.8	7.16	230.3	0.00	230.3	0.00
15	234	234.0	0.00	237.9	1.67	234.0	0.00
16	126	131.0	3.97	126.0	0.00	126.0	0.00
17	193	193.0	0.00	193.0	0.00	193.0	0.00
18	193	193.0	0.00	223.3	15.70	193.0	0.00
19	284.7	284.7	0.00	284.7	0.00	284.7	0.00
20	301.3	330.4	9.66	301.3	0.00	301.3	0.00
21	154.9	160.0	3.29	163.1	5.29	154.9	0.00
22	230.1	244.8	6.39	269.3	17.04	230.1	0.00
23	931.3	949.6	1.96	931.3	0.00	931.3	0.00
24	995.3	1003.2	0.79	995.3	0.00	995.3	0.00
25	990.5	1031.2	4.11	990.5	0.00	990.5	0.00
Avg.	**367.5**	**375.1**	**2.32%**	**371.0**	**1.72%**	**367.8**	**0.00%**
26	1193.0	1229.3	3.04	1257.3	5.39	1193.0	0.00
27	1832.8	1923.3	4.94	1832.8	0.00	1832.8	0.00
28	1932.9	2108.9	9.11	1932.9	0.00	1932.9	0.00
29	468.9	497.0	5.99	468.9	0.00	468.9	0.00
30*	484.3	523.7	8.14	511.0	5.51	484.3	0.00
31	569.6	636.8	11.80	612.4	7.51	572.7	0.54
32	1551.4	1700.7	9.62	1582.5	2.00	1552.5	0.07
33	586.9	638.4	8.77	626.8	6.80	575.2	-1.99
34	1560.3	1787.0	14.53	1658.6	6.30	1560.3	0.00
35	1692.9	1883.1	11.24	1879.1	11.00	1683.2	-0.57
36	1689.6	1888.3	17.76	1886.1	11.63	1688.2	-0.08
37*	1928.5	2022.3	4.86	2011.3	4.29	1793.7	-6.99
38	445.1	460.7	3.50	446.1	0.22	432.6	-2.81
Avg.	**1225.86**	**1330.73**	**8.25%**	**1285.06**	**4.67%**	**1213.10**	**-0.91%**

Presently, the MSSS does not use any formalized approach to plan and optimize their routes. In some cases, contracts have been signed with external carriers, but in others, very costly taxi services are called. In a previous study for the MSSS [Renaud et al. 2013, Chabot 2015], we estimated the annual routing effort for the four administrative regions studied to more and 2,161,000 kilometers per years. In this context, even a small improvement lead to substantial yearly cost savings.

6 CONCLUSIONS

This article presents a new multi-start heuristic to tackle the biomedical samples' transportation problem faced by Quebec's Ministère de la santé et des services sociaux (MSSS). Although this problem is similar to the multi-trip vehicle routing problem with time windows, it presents particular constraints related to the perishable nature of the samples and the organization of work in the network of sample collections centers in Quebec.

The new heuristic outperforms existing method. For medium size real instances, the heuristic always obtain optimal solution in few seconds. For larger instances, the new heuristic improved the best known solution with an average deviation of about -0.91%. We are actually developing improved mathematical models for this problem as well as some new valid inequalities.

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