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In-depth analysis of the current patient transportation to care units and a simulation-optimization approach to do better

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Abstract: This paper investigates the current patient transportation between services in a large hospital and provides a simulation-optimization solution to reduce completion times of demands. Historical data of the service calls is available and an in-depth analysis is conducted to identify popular routes and current assignment of demands to patient transport employees. We present a mixed-integer model to determine the best distribution of the employees throughout the most popular routes of the hospital to minimize demand completion time. Experiments are conducted on real data from CHU de Québec-Université Laval, Hôpital de l'Enfant Jésus, in the province of Québec, Canada.

Keywords: Optimization, Scheduling, Integer programming, Patient transportation

1 Introduction

Hospitals are complex facilities to manage. The logistics dimension of such an institution comprises transport, production, and supply and replenishment [3]. Many transports are to be managed in the daily operations of an hospital: patients, drugs, food, waste, equipment and laboratory tests for instance. Looking only at patient transportation, logistics must account for intra-hospital patient transports as well as inter-hospital transport. Intra-hospital patient movement is concerned with the transportation of patients in between different services thourghout the hospital and is the focus of this paper. The patient transportation department is essential in providing cares to the patients, but is often neglected in the planning and management of services. Currently, the studied hospital has a system to manage the service calls and a dedicated team, however the division of employees is mainly based on a historic planning of activities and a satisfaction level given by clinical services. The hospital logistic services lacking a real-time decision tool. In Canada, 70% of hospital funding is provided from public funds and 38% of the provinces budgets are spent on healthcare [1]. Therefore, it is in the hospitals interest to manage efficiently all of their operations, in order to do the most out of the available budget that is also often a constraint in the development of teams such as patient transport to increase the level of service. Many example are available in the literature to demonstrate that healthcare facilities want to do better. In Québec [12], two hospitals were followed during 10 years to document the initiatives that led to improvements in the logistics. In the United States [11], an academic medical center serving from 7000 to 9000 requests for transportation per month was studied to determine the transportation staff schedules. In [10], a dynamic dial-a-ride problem is developed with specific constraints related to the German hospital studied. Their study, which brought significant improvements to the patient transportation system, also spread the word that improved hospital logistics leads to savings and patient satisfaction. Finally, in Belgium [15], the transportation department was studied since there were many dissatisfaction among patients and staff given long wait times before a transport.

The CHU of Québec currently has a team of 14 employees dedicated to patient transports. Over 100,000 demands are carried out throughout the year and there is currently limited optimization in regards with the assignment of the employees in the hospital. The goal of this paper is to propose a methodology to improve the efficiency of the patient transportation department. In this study, we are concerned with a small patient transportation department which serves the transports demands as first come first served. As a lot of data is available, one year of the database, we conduct an in-depth analysis of the annual data for patient transportation at the CHU de Québec-Université Laval, Hôpital de l'Enfant Jésus, and proposes a mixed-integer optimization model to change the schedules of the patient transportation department employees, in order to minimize the total time to complete demands. Also, popular routes are identified throughout the hospital zones to better distribute the employees among the hospital. As this is on-going research, a deterministic model is proposed in this paper.

The paper is organized as follows. Section 2 exposes relevant literature. In Section 3, the case study is presented. Section 4 exposes the optimization model developed to minimize total completion time of demands, as well as the data analysis. The methodology used to propose new schedules is also exposed. Numerical results are reported in Section 5. Final remarks are presented in Section 6.

2 Literature review

In this study, patient transportation in between the different clinical services is conducted with a wheelchair, a stretcher or a hospital bed. When a transport is required, a service call is made to the main dispatching system, and broadcast to employees of the patient transportation department. An employee takes the call and completes the service call.

Delays in treating the service calls can lead to treatment delays causing longer stays in the hospital or unnecessary cost increase. Scheduling the patient transports is studied in the field of optimization and operations research. Few papers have looked specifically into patient transportation intra-hospital with wheelchairs, stretchers or beds, but have shown that there is an advantage in doing so. Most of the literature is concerned with vehicle routing problems [16, 17, 18] or dial-a-ride problems [6, 5].

Dial-a-ride problems are similar to vehicle routing problems, but are also concerned with service quality. In [2], a dynamic transportation of patients is proposed. When a request is made, the origin of the patient is given, the destination location is known, a time window for pickup or delivery is given and finally, the mode of transportation. To consider service quality, the maximum ride time is an input to the problem. The routes are updated as the service calls are made, which increases the complexity of the problem. This study was suitable for a very large hospital, but is too complex for the size of the patient transportation department of this study. A bi-objective dial-a-ride problem is proposed in [13]. Multiobjective problems require insight from the user to take the final decision, therefore adding complexity to the implementation in practice of the solution proposed, since the models are to be used by the decision makers. In [16], as the transports are known in advance, there are many decision variables such as: arrival time, start time and assignment variables. In this study, the transports are not known in advance, therefore this formulation cannot be used. In [9], queueing theory, integer programming and simulation is used to compute the minimum number of employees to conduct all of the transports. Their model decreases variations in pickup times and increases patient satisfaction. This study is interesting but the number of employees are the decision variables, which is not always the case in practice. An interesting model considers the number of available stretchers [4] and the dependencies between transports. In that paper, the model also considers the patient treatment time, but this is not an information that is available for this study. Other studies based on evolutionary algorithms [14] are available, but are more concerned with the field of machine learning and artificial intelligence.

All of the above references are interesting, but are mostly concerned with complex patient transports. In this study, we aim at providing a solution that is easily understandable by the decision makers in the context of a small patient transport department. Also, as this is the first phase of the project, a deterministic model is developed, in order to validate the modelling of the problem.

3 Case study

Patients in a hospital require to be transported between different clinical services, for example from the emergency toward radiology. The patient transport team is in charge of transporting patients in the hospital, given demands that are placed through a telephonic system. The first employee that is available takes the call, completes the demand then closes the demand in the system. Currently, there are fourteen employees in the department and the minimum and maximum number of available employees per hour are presented in Table 1. The schedule is available per 15 minutes periods, therefore the minimum and maximum number of employees per hour is considered. There is no specific assignment of the employees in the hospital zones. Currently, all employees cover all of the hospital.

Table 1: Minimum and maximum number of employees per hour.

Hour (h)	Min.	Max.	Hour (h)	Min.	Max.
7	1	4	15	8	12
8	7	9	16	4	6
9	6	9	17	2	2
10	9	11	18	3	3
11	7	9	19	2	3
12	5	8	20	2	3
13	9	11	21	0	2
14	12	13			

Without entering into details, there are between 1 and 13 available employees during the same period throughout the weekday, from 7 am to 10 pm, considering lunch, dinner and break periods.

The CHU de Québec-Université Laval, Hôpital de l'Enfant Jésus (HEJ) is located in Québec city, Canada and part of a five-hospital, 1700 beds university health centre. HEJ being the trauma and neuro-science reference hospital of the region and also have extensive mission in specialty such as orthopedic, intensive cares and general medicine. This hospital have 355 hospitalization beds, 24 intensives care unit beds, 13 operation rooms and a total of 48 stretchers in emergency department often in over capacity. The different hospital zones in which patient transportation occurs are visible in Figure 1.

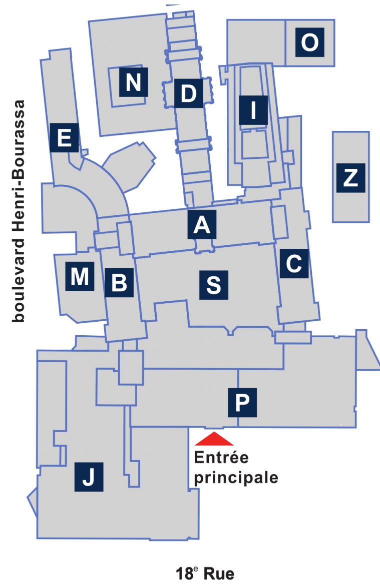


Figure 1: Hospital zones.

Zones of interest in this study are mostly A, B-E (referred as B in the text), P and J. B zone is the radiology on the ground floor and care units on others, P is the main hall, neuro-science care units, physical rehabilitation services as well as the intensive care units and J is the emergency room and operating block.

4 Methodology

Currently, a demand placed into the system is fulfilled by the nearest, or first available employee. This paper proposes a methodology to change the schedules of the employees to minimize demand completion times, and to distribute the employees among popular routes of the hospital. This sections presents the data analysis and the optimization model used to distribute the employees throughout the hospital.

4.1 Data analysis

The hospital provided us with a full year of data from the telephonic system used to dispatch the patient transport employees. Many crucial information is available but the most relevant for this study are: demand completion time, origin and destination. Figure 2 presents the boxplots of demand completion times, for every day of the week. The lower part of the box is the first quartile, the top of the box the third quartile and the median is represented by the line in the box. Below and over the box are the lines representing minimum and maximum of the demand completion times. One can clearly see that there is a trend for the weekdays and another trend for the week-end days. This study concentrates on weekdays only.

The median demand time completion is 12 minutes, while minimum is 2 minutes and maximum 30 minutes. Also, 75% of the service calls are completed under 18 minutes.

After analyzing the data under all of its angles, it was decided that the most used routes throughout the hospital should be retained to dispatch the employees in the different zones, as per Figure 1. In order for one to grasp the number of demands, Table 2 presents the total number of demands per year and the average per day, for the 10 most popular routes in the hospital, either as origin or destination.

There are a total of 55,518 demands throughout the year on the 10 most popular routes.

In the optic of scheduling employees on given routes, origins and destinations per zones are combined to determine the total number of transports on a given route. Figure 3 presents the most used routes during weekdays in the entire hospital.

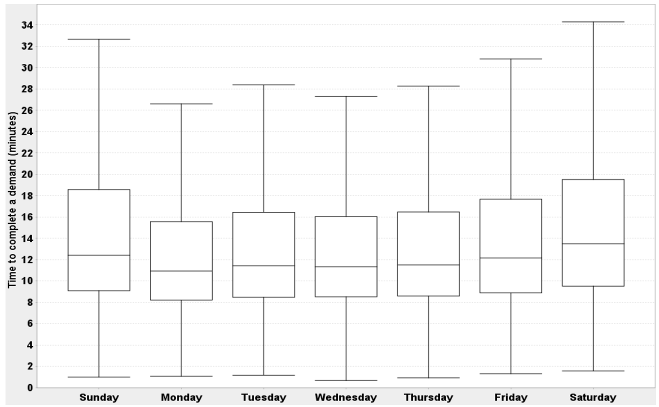


Figure 2: Boxplot of the demand completion times for every day of the week.

Table 2: Number of demands and average per day, per route.

Route	Number of demands	Average per day
P-P	8127	31.3
J-B	7040	27.1
J-J	6888	26.5
B-J	5906	22.7
J-P	5247	20.2
P-B	5224	20.1
B-B	4634	17.8
B-P	4409	17.0
J-A	4083	15.7
P-J	3960	15.2
Total	55,518	213.5

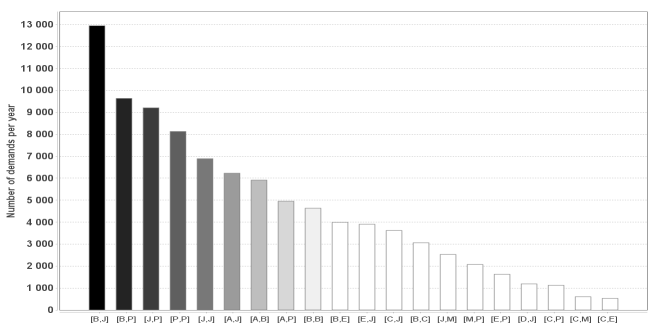


Figure 3: Most popular routes, origin and destination combined.

For example, route [B,J] also represents transports on route [J,B].

4.2 Problem description

This section presents the optimization model used to assign the employees on a specific route. At the moment, there is no optimization of the schedule of the employees, and the goal of this model is to propose a new scheduling of the employees to improve the patient transportation in the hospital.

The following sets are defined:

I: set of routes
K: set of periods

The parameters are as follows:

t_{ik}: average time to complete a demand on route i at period k.
B_k: number of employees available at period k.
N_{ik}: average number of demands on route i at period k.
M: penalty associated with overtime to complete demands.
l_k: minimum number of employees during period k.
D_k: length of period k in minutes.

The decision variables are:

x_{ik}: number of employees on route i at period k.
δ_{ik}: overload, in minutes, during period k to complete demands.

The objective function minimizes the total completion time of demands and penalizes overtime:

$$\min_{x,\delta} \qquad \sum_{i\in I}\sum_{k\in K} t_{ik}x_{ik} + M\delta_{ik} \tag{1}$$

$$\begin{aligned}
\text{s.t.:} \quad \sum_{i\in I} x_{ik} &\le B_k, && \forall k \in K, && (2)\\
N_{ik}t_{ik} - D_k x_{ik} &\le \delta_{ik}, && \forall i \in I, \forall k \in K, && (3)\\
x_{ik} &\ge 0, && \forall i \in I, \forall k \in K, && (4)\\
\delta_{ik} &\ge l_k, && \forall i \in I, \forall k \in K, && (5)\\
x_{ik} &\in \mathbb{N}, && \forall i \in I, \forall k \in K, && (6)\\
\delta_{ik} &\in \mathbb{R}, && \forall i \in I, \forall k \in K && (7)
\end{aligned}$$

Constraints (2) schedules a maximum number of employees on each route for each time period. Constraints (3) ensure that the median of the demands is completed with the number of assigned employees, but allows an overtime to validate the constraint. This overtime is then penalized in the objective function. Non-negativity constraints are enforced with constraints (4)–(5) and variables domain is given by constraints (6)–(7).

The idea with this formulation is that, coupled with the analysis of the popular routes in the hospital, the model determines the optimal number of employees to assign on each route in order to respond to the median demands, as well as the median demand completion times.

Overtime, in this specific case, is only used to validate the constraints. Therefore, as we are minimizing the total demand completion time and that the overtime is penalized, the optimization model will seek for a solution leading to the less overtime possible.

As this is a preliminary study on the hospital analysis, a simple deterministic model is developed to show that there is room for improvement in the schedule of the patient transportation team.

5 Computational experiments

This section presents the computational experiment conducted on data provided from the hospital, which consists of one year of service calls for patient transportation. The optimization model developed in Section 4.2 is used to dispatch the employees among the most popular routes, on an hourly basis.

5.1 Benchmark without bounds

A benchmark is created to compare results further obtained from optimized dispatch of employees. The optimization problem described in Section 4.2 is used to determine the optimal number of employees required every hour, without assigning them to routes. Therefore, the same model is solved, but the index for routes is dropped. The Cplex [7] solver is used to compute the solution through AMPL [8] mathematical modelling.

Periods of one hour are chosen for the period length D_k in the optimization problem. The median time to complete a demand t_{ik} and median number of demands N_{ik} are computed from the database. The number of employees available B_k was set to 14 for all periods, given this is the total number of employees in the department. Finally, the minimum number of employees l_k was set to 0 and the penalty M arbitrarily to 1000.

Results are shown in Table 3. The Min. and Max. columns show the number of available employees every hour. These values were calculated with the available schedule, considering breaks and lunch periods. The column of interest is the fourth, more precisely Opt. without bounds. No bounds were fixed for the variables x_{ik}, therefore results show the number of employees required every hour of the day. Of course, this is a deterministic model, but it still exposes the fact that the current schedule can be improved, in order to minimize completion times of demands. For this optimal solution, all overtime variables δ_{ik} are equal to 0. This benchmark solution shows that critical periods in the day are hours 9, 10, 11 and 17, since they would required more employees than currently available in the schedule.

5.2 Benchmark with bounds

The same optimization model as Section 5.1 is solved, but bounds on the optimization variables x_{ik} were fixed to the actual minimum and maximum number of available employees, more precisely second and third column of Table 3.

Column 5 of Table 3 presents the optimal number of employees per hour with current bounds. Results are similar to the benchmark without bounds, except that the overtime variables δ_{ik} are not all equal to 0, since hours 9, 10, 11 and 17 would require more employees than currently available. For hour 9, the overtime variable is 113.6 minutes, for hour 10 it is of 25.8 minutes, for hour 11 the overtime is 8.223 minutes and finally, 16.8 minutes for hour 17. The overtime variables are used to obtain a feasible solution in the optimization model, but if they are not equal to 0, they indicate that delays are to be expected in the transportation of patients.

Table 3: Optimal number of employees per hour with bounds and without bounds and actual minimal and maximum number of employees per hour.

Hour	Actual Min.	Actual Max.	Opt. without bounds	Opt. with bounds
7	1	4	2	2
8	7	9	5	7
9	**6**	**9**	**11**	**9**
10	**9**	**11**	**12**	**11**
11	**7**	**9**	**10**	**9**
12	5	8	6	6
13	9	11	10	10
14	12	13	11	12
15	8	12	8	8
16	4	6	4	4
17	**2**	**2**	**3**	**2**
18	3	3	3	3
19	2	3	2	2
20	2	3	2	2
21	1	2	1	1

5.3 Optimization of routes

The benchmarks show that there is possible improvement in the schedule of the patient transportation department. Currently, the employees are not assigned to any routes and are simply fulfilling the requests as they come. The optimization problem in Section 4.2 is used to optimize the most popular routes. From Table 2, demands from most popular routes, origin and destination combined, are computed and presented in Table 4.

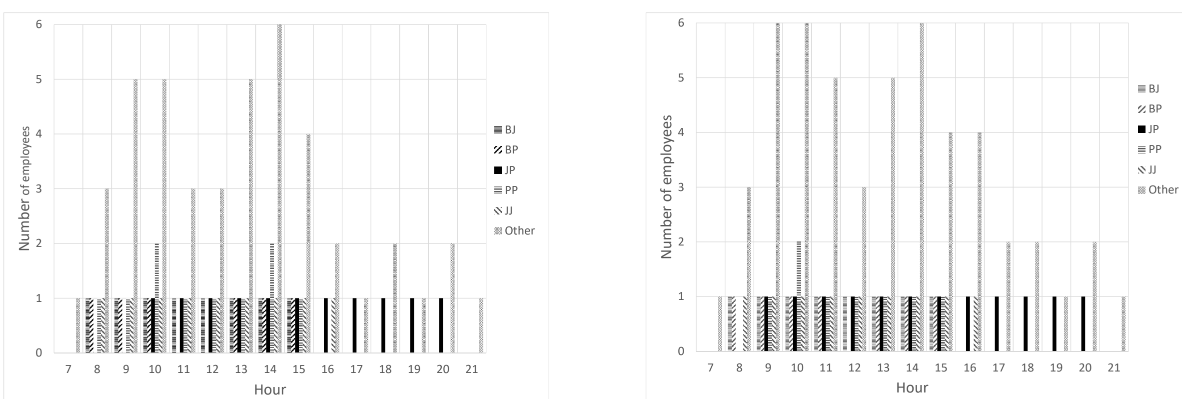
Table 4: Number of demands on most popular routes and average per day.

Route	Number of demands	Average per day
B-J	12946	49.8
B-P	9633	37.1
J-P	9207	35.4
P-P	8127	31.3
J-J	6888	26.5
Other	49527	190.5

The optimization problem was solved using 6 routes $I = \{BJ, BP, JP, PP, JJ, other\}$, where other consists of all the remaining routes in the hospital. The idea with the choice of these routes is that they are the most busy on weekdays. The problem is solved for $K = \{1, 2, \ldots, 21\}$, which represents the hours in the shifts. Values for N_{ik} are shown in Table 4 and t_{ik} are computed from the database. Penalty M is also set to 1000, and l_k and B_k are given as per Table 1 and the lengths D_k of periods are one hour.

Two models were solved: optimization of routes without bounds, and optimization of routes with bounds, in the same sense as Section 5.1 and Section 5.2.

Figure 4 presents the optimal number of employees on specific routes for every hour. Results show that, with or without bound on the decision variables x_{ik}, there is one or two employees assigned to a specific route, and the rest to the totality of the zones. The benchmark solution with bounds showed that the critical hours were 9, 10, 11 and 17. The results for the optimal number of employees per hour are given in Table 6. It is interesting to note that for the critical hour 9, 9 employees are required, and that currently, 9 employees are available. Therefore, simply by assigning 5 employees to different routes and the remainder to the rest of the hospital, the overtime variables drop from 113.6 minutes to 33.27 minutes, without changing the number of employees. Overtime variables are presented in Table 5. Also, at hour 11, 2 employees less than actual are required, and it only increases the overtime variables of 4.73 minutes. These results show that simply by re-arranging the current schedule and by assigning employees to specific routes, it allows to decrease the possible delays in patient transportation.



(a) Without bounds on variables. (b) Wit bounds on variables.

Figure 4: Number of employees assigned to specific routes per hour.

Table 7 present the difference in the number of employees required if they are assigned to specific routes, versus the current schedule. Note that the upper bound on available employees was taken as a reference, as it is the maximum number of employees available every hour. These results show that, given the actual schedule, it is possible to decrease the overtime variables, and that it is also possible to re-arrange the schedule to decrease the number of available employees per hour, given that the difference is always negative or equal to 0.

Table 5: Comparison of overtime variables, optimization with bounds, with and without routes.

Hour	Overtime variables (minutes) Optimal without routes	Sum of overtime variables (minutes) Optimal with routes
9	113.6	33.27
10	25.8	18.89
11	8.22	12.95
17	16.8	8.67

Table 6: Optimal number of employees per hour considering routes, with and without bounds.

Hour	Min.	Max.	Opt. routes without bounds	Opt.routes with bounds
7	1	4	1	1
8	7	9	6	7
9	**6**	**9**	**11**	**9**
10	**9**	**11**	**12**	**11**
11	**7**	**9**	**10**	**7**
12	5	8	7	7
13	9	11	10	10
14	12	13	11	12
15	8	12	9	9
16	4	6	6	4
17	**2**	**2**	**2**	**2**
18	3	3	3	3
19	2	3	2	2
20	2	3	3	3
21	0	2	1	1

These results are interesting since they show that it is possible to simply re-organize the schedule to obtain a better repartition of the employees in the hospital. For example, there are currently 1 employee that comes in at 7 AM and 3 employees that come in at 7h30 AM. The results show that with one employee at 7 AM, the current demand can be met. Therefore, by shifting the arrival of the 7h30 AM employees later, it would help to spread out the real needs for staff throughout the day. In order to meet the union specifications of schedules, these results will be handed out to the supervisor of the patient transportation department and of course, the new schedule will have to be tested in order to evaluate the real outcome of these results, but this is outside the scope of this paper.

Table 7: Difference of employees required when dispatched per route, compared to actual number of employees.

Hour	Optimal with routes	Actual # employees	Difference
7	1	4	-3
8	7	9	-2
9	9	9	0
10	11	11	0
11	7	9	-2
12	7	8	-1
13	10	11	-1
14	12	13	-1
15	9	12	-3
16	4	6	-2
17	2	2	0
18	3	3	0
19	2	3	-1
20	3	3	0
21	1	2	-1

6 Conclusion

This paper presents a mixed-integer model to determine the best repartition of the employees of the patient transportation department. Currently, the demands are served as first-come first-served by the first available employee. As one year of historical data was available for this study, an in-depth analysis of the demands throughout the course of the year was made in order to establish the most popular routes where the demands occur. Then, an optimization model was used to determine the optimal number of employees on each route in order to minimize the demand completion time. Results are promising, as they show that it is possible to simply re-arrange the schedule of the employees in order to reduce the completion time of demands. As this is on-going research, future work based on this study will involve developing a stochastic model, to consider uncertain number of demands as well as uncertain completion times.

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