Optimising Patient Transportation in Hospitals

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1 Introduction

In large hospitals several hundreds of transports of patients and goods are carried out during a day. For planning these transports the acuteness and punctuality have to be considered just as much as an economic management of resources such as transport staff and vehicles [3]. Today, modern software like Opti-TRANS (see www.opti-trans.com) supports the human scheduler in planning transports in hospitals. Using that software framework we have developed new planning approaches and tested them with data provided by a hospital.

In Section 2 of this paper we discuss a mathematical model of the problem which is formulated as a multiobjective dial-a-ride problem with time windows and various additional constraints. Different approaches for finding good solutions are analysed in Section 3. Computational results for some approaches are presented in Section 4. The paper ends with the Conclusions in Section 5.

2 Patient Transports as a Multiobjective Dial-a-ride Problem

Dial-a-ride problems concern routing and scheduling vehicles in order to satisfy a given set of transportation requests. Each request has an origin location, a destination location, the required capacity, and a desired pickup or drop-off time. Transportation is supplied by a given fleet of vehicles. The aim is to design a set of optimal vehicle routes accommodating all requests under given constraints.

The common restrictions in dial-a-ride problems relate to the vehicle capacities and the maximum ride time, i.e. the time allowed for transporting goods or passengers. For transports in the hospital environment there are several other specific constraints in addition (see [2] for a more detailed description of the problem). Hospital inherent aspects include, among others, accounting for transport priorities, for transportation aids, accompanying medical equipment and/or personnel, for different vehicle types and personnel skills, and for (soft) time windows with respect to the desired pickup or drop-off times. The following additional restrictions are be considered as well:

- loading variants of vehicles implying different capacity constraints
- transports involving changing transport equipment
- requirements of individual shipment (e.g. because of infection risks)
- availability of transport teams
- qualifications of transport teams or additional accompanying personnel

These constraints significantly complicate the construction and modification of high-quality feasible schedules. Another difficulty is that good schedules for the transport of patients have to be generated in a dynamic environment with strict limits on computation time, say 2 or 3 minutes maximally.

In our problem the objective function reflects a variety of preferences through the minimization of the following subgoals:

- total lateness,
- total earliness,
- total driving time,
- total transport time of patients.

Since the time windows for pickup or delivery are soft, deviations from their lower or upper limits should be avoided by incurring penalties for earliness or lateness. These penalty functions also depend on the priority class of a request. Late arrivals are particularly undesirable from the viewpoint of the patient but also from an economical perspective since it incurs idleness of staff or equipment.

The total driving time can be considered as a cost criterion measuring the usage of transport employees and vehicles. The total transport time measures the time during which patients or goods are enroute. In contrast to the total driving time the time for approaching a pickup location is not considered but times of consolidated transports are counted double.

The overall objective is finally built using a weighted sum of the four single objectives. The considered weights for the objectives are adapted so that the specific preferences of the hospital are reflected.

3 Planning Methods

Due to the combinatorial nature of the problem and the requirements of real-life usage, it is not possible to calculate optimal solutions to practical size problems. Transport teams must be informed within a very short time about their next destinations. Therefore, we discuss several procedures to find near optimal or good solutions to the problem that work under strict limits on computational time.

Basically these methods are based on an approach for assigning a transport order to a transport team and, secondly, on a procedure for constructing a feasible route for each vehicle with the previously assigned requests. In a possibly third step, unassigned requests of the previous phases may be inserted into the different vehicle routes.

3.1 Assignment of Orders

Usually several transport teams are feasible for carrying out a given transport order. The specific assignment of a team influences the quality of the obtained solution. Prior to the determination of specific tours, it is, however, not obvious how a good assignment of orders would look like.

Therefore, two rather simple heuristics have been considered which allow to assign an order to a feasible transport team. A simple criterion for choosing a team for an order is to consider the number of orders already assigned to that team. To avoid overload for teams (which might result in undesirable solutions, e.g. because of delays) we select a team with a minimal workload for a new order. Considering this, the transport teams are sorted according the number of assigned orders and, as the second ordering criterion, their earliest availability. A transport order to be planned is then assigned to the first team according to that order which is feasible.

A more time consuming approach would be to consider every possible assignment of a team. If a team is feasible for executing an order, a corresponding solution is calculated by determining a resulting tour for that assignment. The best of all resulting solutions is finally chosen, i.e. the corresponding team assignment is accepted. Without considering the effects on the finally resulting solution for all planned transports, this approach would yield better results than the load balancing method.

3.2 Determination of Tours

During the planning of orders, several planning approaches for generating a specific tour are considered. A simple and quick approach to tour building is to insert a new order at the first feasible position. This approach may most resemble the manual planning which does not allow for considering many alternative insertion possibilities or the revision of previous plans. In first fit planning it is not obvious that good solutions are found, in particular when the sequence of orders to be planned is disadvantageous.

A more promising approach with respect to the solution quality is to consider each insertion possibility, i.e. the existing tour of a team is checked for gaps for inserting the pickup or delivery of a new order. In that approach it is not allowed to revise the given planning, i.e. inserting a new pickup or delivery such that already planned transports would require a shifting. Compared with the first fit planning, this approach is more time consuming.

An even more promising approach is to consider each feasible insertion point in a tour and to allow for a shifting of already planned orders. This, of course, may lead to undesired delays of orders being planned to be executed after the inserted one, but possibly an avoided delay of the inserted order and other advantages (e.g. reduced travel costs) compensate that effect in the overall objective function. Since more insertion possibilities (and resulting tours) are checked this approach is more time consuming than the best fit planning of tours.

3.3 An Evolutionary Algorithm

In a recent study [1], a novel evolutionary algorithm (EA) for solving the considered transport problems is presented. The basic idea of the EA is that there is a set of entities (called a population) which represent solutions to an optimization problem under consideration. This set of entities is evolved through a number of generations. In each generation step, an offspring population is generated using the data of the previous population (the parents) and random and other modifications (mutation & recombination). Among the parents and offspring population, the best entities are selected to become parents of the subsequent generation. The whole process starts with a population of randomly generated entities and results in the best entity of the final population, the solution to the problem.

For the considered transport planning problem, the EA controls the assignment of orders to transport teams, i.e. each entity consists of an array of numbers specifying the assigned transport team for each transport order. Mutations are simply done by assigning randomly a new feasible team to an order. Recombination is done by mixing two different sets of assignments in some consistent way. For the selection of best solutions an entity needs some evaluation which means that specific tours are build by an underlying tour construction procedure. Selection criterion is then the overall objective function discussed in Section 2.

4 Computational Results

Numerical tests of the planning approaches have been performed using real live master data from a hospital. For the given topology of the hospital, 60 patient transport orders are generated with earliest pickup times lying in an 1 hour interval. For executing these orders 21 transport employees (single person teams) are available. Thus, on the average about 3 transports are to be done by one transport employee. The transport orders have different priorities (low, average, high) and require varying transport equipment.

Different combinations of the heuristics for order assignment and tour determination are considered (see Table 1). As expected, load balancing is in general faster than best fit as an assignment strategy but does not lead to equally good results. A first fit tour construction is faster but worse than a best fit tour building. Best insert tour building leads to even better results but requires the longest time.

Table 1. Results of heuristic procedures

assignment of orders	construction of tours	objective value	runtime [s]
load balancing	first fit	445	10
load balancing	best fit	289	20
load balancing	best insert	271	32
best fit	first fit	333	36
best fit	best fit	269	109
best fit	best insert	244	210

The EA is controlled by a parameter prescribing the allowed running time. The generational loop stops when this time limit is reached. As can be observed (see Table 2) this allows for an effective control of

Table 2. Results of the Evolutionary algorithm

runtime limit [s]	objective value	unplanned orders	runtime [s]
30	250	3	41
60	232	3	69
120	243	0	132
180	239	0	191
600	230	0	610

the runtime. The additional amount of about 10s is required for initialization and finishing of a generation step. As can be seen, the EA needs a specific time to obtain results of competitive quality. In particular, the current implementation allows for unassigned orders which are punished by a penalty function. After about 2 minutes running time, unassigned orders are not observed any more and the results become better than those of the best heuristics.

5 Conclusions

We have shown that there are effective methods for planning transports of patients and goods in hospitals under real-life requirements. Assuming typical hospital conditions in planning these approaches provide feasible solutions within an acceptable amount of time. As our experiments show, there are differences in the quality of results and the required computation time. It is therefore up to the preferences (and circumstances) of a specific hospital to decide in favor of a specific approach. During the further development of the Opti-TRANS software we will provide these novel approaches to hospitals for their daily planning of transports.

References

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