

Alternative Job-Shop Scheduling For Proton Therapy

Cyrille Dejemeppe

ICTEAM, Université Catholique de Louvain (UCLouvain), Belgium,
cyrille.dejemeppe@uclouvain.be

Director: Yves Deville (ICTEAM, UCLouvain)

Abstract. Proton Therapy (PT) is a recent radiotherapy technique in which a beam of protons is used to irradiate tumors. The schedule of daily patient treatments in a PT center is a hard problem since it has offline and online components and attempts to optimize several non-trivial objectives. To date, no computer tool allows to optimize the daily schedule of patients inside a PT center. The problem contains several research challenges: new scheduling objective functions, multiobjective scheduling optimization and online/adaptive scheduling are three of them. In this paper, we propose a scheduling model for the PT scheduling problem and we describe our envisioned approach to generate optimized schedules.

Keywords: proton therapy, alternative job-shop, constraint programming, multiobjective optimization, online/adaptive scheduling

1 Introduction

Proton Therapy (PT) is a recent technique in which a beam of protons is used to treat cancer. It offers many advantages over classical radiotherapy techniques. Even if this technique is recent and still under study, treatments performed so far have shown promising results. The management of the schedule of patient treatment is complex and subject to many constraints. To date, no computer procedure exists to optimize the schedule of patient treatments within PT centers. Ion Beam Applications (IBA) proposed to study this problem and a PhD thesis in collaboration with IBA has begun.

The Proton Therapy Problem (PTP) consists in optimizing both offline and online/adaptive schedule of the workflow of patients within a PT center. Furthermore, this problem considers the optimization of several non-trivial objectives which can depend on the specific configuration of the PT center considered. This paper describes the envisioned model representing the daily schedule of patients inside a PT center and the search approaches we consider to generate optimized feasible schedules.

We begin by describing the research challenges of this problem in Section 2 and we provide a definition of the PTP in Section 3. Then, in Section 4, we describe a Constraint Optimization Problem (COP) scheduling model to express the PTP. Finally in Section 5, we describe our random instance generator and we discuss the envisioned refining of the model and search techniques to solve the problem.

2 The Research Challenges

The PT problem is a challenging problem opening several research questions. We identified three main research challenges the PhD thesis will study: new scheduling objective functions, multiobjective scheduling optimization and online/adaptive scheduling.

The PT problem brings us to consider scheduling optimization objectives different from the traditional makespan minimization. Even if several optimization criteria are mentioned in the literature, such as those presented in [7], some objectives needed by PTP have not been studied before. Nowadays, several improvements have been discovered in the search strategies and heuristics for other well known scheduling optimization objectives such as for example the results stated in [9]. We intend to bring further improvement on the optimization of non-classical scheduling objective functions.

The multiobjective part of the problem is another research challenge. We intend to perform multiobjective optimization on several objective functions without aggregating them. Few works consider multiobjective optimization for scheduling without aggregation. Furthermore, most multiobjective problems considered in the literature are restricted to biobjective problems, as stated in [6]. Multiobjective scheduling on hard problems containing more than two objectives is still an open field of research.

The last main research challenge is to perform *online scheduling*. The online scheduling approach differs from the classical offline scheduling approach. Several researches on online scheduling optimization have been performed, such as in [5], but they mainly focus on simple trivial problems. Our purpose is to adapt the online scheduling techniques to hard real-world problems such as the PTP.

Other research challenges arise when considering the PT scheduling problems. First, the addition of variable duration implications between activities has not been studied yet. What we mean is that we consider activity pairs with variable durations such that the duration of the second activity is defined with an analytical function whose input is the duration of the first activity. Then, the PT problem considers perishable resources, i.e. resources whose capacity decreases over time according to an analytical function. Finally, the number of jobs and tasks considered by this problem exceeds most of current scheduling problems already considered in the literature. The size of the problem will force us to adapt state-of-the-art search techniques. Other research challenges should appear when continuing our work on the PTP.

The purpose of our research is to combine the research challenges we mentioned above. Our study will thus focus on multiobjective online scheduling optimization with non-classical objective functions.

3 The Proton Therapy Problem

In this section we explain how PT centers are used in cancer treatment. Then, we explain the workflow of patients inside PT centers. Finally, we define the objectives of patient scheduling inside PT centers.

3.1 PT Centers

To date, according to [8], there are more than 40 PT centers in operation around the world. The rooms of PT centers are not described in this document but more details

are provided in [2]. While these centers differ on many points, most of them have a common structure which allow to use the same reasoning for scheduling purposes.

3.2 Patient Workflow

When a patient is diagnosed with cancer, a given number of PT treatment sessions is determined for his treatment. To each treatment session of a patient corresponds a workflow, i.e. a sequence of steps the patient has to follow. The workflow assigned to a given treatment session is defined according to the type of cancer, the location and size of the tumor, the advancement in the treatment as well as other factors. The workflow of patients may differ even if they have the same cancer type. For example, a child workflow systematically begins with an anesthesia while this is not always the case for an adult workflow. The time spent at every step of the workflow of a patient may be approximated but it varies due to human factors.

3.3 PT Problem Objectives

There are two main objectives when scheduling the workflow of patients inside a PT center. The first objective is to generate a daily offline schedule of patient treatments. This means we have to define the time at which every event in the workflow of every patient considered takes place. The second objective is to perform online/adaptive scheduling to re-arrange a previously computed offline schedule. This has to be done in order to react to unexpected events occurring in the PT center such as delays, technical failures, medical complications, etc. Both offline and online scheduling must be generated such that they optimize a given set of criteria. The criteria on which optimization is made might differ when considering offline and online scheduling. Furthermore, the criteria considered depend on the PT center considered. Some examples of these criteria are the staff welfare, the patient comfort, the patient throughput and the respect of the appointment times of patient treatment sessions.

In this section, we defined how PT center work and how patients are treated in these ones. We have also given a definition of the objectives the PT problem attempts to achieve. In the next section, we define a scheduling model for the PTP.

4 Modeling the PTP with Scheduling

We propose to express the PTP as a scheduling problem whose focus is set on patient workflows. As stated in [1], a scheduling model can be divided in four main components: activities, resources, constraints and objective functions. This section describes the four main components of our scheduling model.

4.1 Activities

The activities of our model are parts of patient workflows. Every workflow of the treatment session of a patient contains a succession of steps through which the patient must go. To every step of a given workflow corresponds an non-preemptive activity in our model. Most of our activities have a fixed duration except those with the property mentioned in Section 2. These latter ones have a max and min duration. The activities of a single patient treatment session are modelled as a job. These jobs impose an order on the succession of activities it contains.

4.2 Resources

We have different types of resources to consider for our problem. First, activities corresponding to patient workflow steps occur in the PT center rooms which are modelled either as disjunctive or alternative resources. Rooms that are present in a single instance, e.g. an anesthesia preparation room, in the considered PT center are modelled as disjunctive resources. On the other hand, rooms present in multiple instances, e.g. treatment preparation rooms, are modelled as alternative resources. As defined in [3], an alternative resource is a set of resources for which a given activity requirement can be fulfilled by any of the resource from the set. Each resource from this set of possibilities is modelled by a disjunctive resource. The proton beam is modelled as a disjunctive resource. The staff members are also modelled with alternative resources following the same reasoning as the one applied for the PT center rooms.

4.3 Constraints

We can distinguish here two types of constraints: temporal constraints and resource constraints.

Temporal Constraints As a sequence of activities from the same workflow is modelled as a job in which activities must be executed in order, every job imposes sequential precedence constraints between the activities it contains:

$$\forall p : \text{end}(a_{p,i}) \leq \text{start}(a_{p,i+1}) \text{ with } 1 \leq i \leq n - 1 \quad (1)$$

where p represents a patient, $a_{p,i}$ is the i^{th} activity of the workflow of patient p which contains n activities.

Resource Constraints The first resource constraint we can express is the one on disjunctive resources (for the beam and rooms or staff members existing in only a single instance). This constraint expresses that disjunctive constraint can be used by only a single activity at any time:

$$\forall t, \forall r_d : \sum_a \text{usage}(a, r_d, t) \leq 1 \quad (2)$$

where t represent a discrete time step, r_d represents a disjunctive resource and $\text{usage}(a, r, t)$ represents the usage of the resource r by activity a at time t . The alternative resources we introduced in Section 4.2 are represented as sets of disjunctive resources. As such, each disjunctive resource in the set of an alternative resource is subject to the constraint expressed in Equation (2).

As explained in Section 3.1, a small amount of time is needed to switch the proton beam from one treatment room to another. This amount of time needed to switch the beam between two treatment rooms is modelled with setup times. The same reasoning is applied for the small amount of time needed between successive irradiations of a patient's treatment session. As stated in [1], the setup time (transition time) $\text{setup}(a_1, a_2)$ between two activities a_1 and a_2 is the amount of time that must elapse between the end

of a_1 and the start of a_2 when a_1 precedes a_2 . In our case, the proton beam switch from one room to another induces the following setup times:

$$\begin{aligned} \forall m, \forall n \neq m, \forall i, \forall j \neq i : & \text{ if } \text{start}(\text{irr}_{n,j}) \leq \text{start}(\text{irr}_{m,i}) \\ & \text{start}(\text{irr}_{m,i}) \geq \text{end}(\text{irr}_{n,j}) + \text{setup}(\text{irr}_{n,j}, \text{irr}_{m,i}) \end{aligned} \quad (3)$$

where $\text{irr}_{m,i}$ represents the i^{th} irradiation of patient m . The small amount of time needed between successive irradiations of a patient is modelled as follows:

$$\forall m, \forall i = 1, \dots, k-1 : \text{start}(\text{irr}_{m,i+1}) \geq \text{end}(\text{irr}_{m,i}) + \text{setup}(\text{irr}_{m,i}, \text{irr}_{m,i+1}) \quad (4)$$

Finally, some resources are used during a sequence of activities and cannot be released between the different activities that the sequence contains. To model this, a new activity starting at the same time as the first activity and ending at the same time as the last activity in the sequence is introduced. Furthermore, the resource usage is set on this new activity. The constraints induced are thus expressed as follows:

$$\forall m, \forall i, \forall j > i : \begin{cases} \text{start}(a_{m,i \rightarrow j}) = \text{start}(a_{m,i}) \\ \text{end}(a_{m,i \rightarrow j}) = \text{end}(a_{m,j}) \end{cases} \quad (5)$$

where $a_{m,i \rightarrow j}$ represents an activity spanning the i^{th} activity to the j^{th} activity of patient m .

4.4 Objective Function

As stated in Section 2, the PT problem considers several non-classical optimization objectives. Until now, we focused on the easiest objective to compute and quantify: maximization of the patient throughput. We modelled this objective as a minimization of the makespan of the generated schedule:

$$\text{minimize makespan} = \text{minimize } \max_a (\text{end}(a)) \quad (6)$$

5 Perspectives

In order to work on PTP instances close to reality, we implemented a random instance generator under several generation rules. First, we can decompose our instances in two parts: a configuration file describing the resources of the center and a list of daily patients and activities to schedule. Using real data and a PT center simulator from [4], we were able to determine a set of patient workflows for given center configurations. To each workflow was bound a frequency of appearance. Thanks to these data, we generated several configuration files describing classical PT center equipment. The daily instance files were generated by considering the set of patient workflows with a probability relative to the frequency from the data.

To test our data, we implemented a simplified version of our problem. This simplified version only considers the minimization of the makespan and disjunctive resources. Treating instances with 60 patients, which is the daily patient throughput in the most important PT centers, we were able to find a solution with a Constraint Programming (CP) search in less than 4 seconds.

Our next move will be to implement a full version of the model containing all the resources and constraints described in Section 4. Then, we will consider other objectives than minimization of the makespan; separately first then together in a multiobjective version of our problem. Finally, we will study the mechanisms that will allow us to perform online/adaptive scheduling in response to unexpected events.

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