Radiation Therapy Patient Scheduling

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Introduction

Radiation therapy (RT), chemotherapy and surgery are the most commonly used cancer therapies worldwide. RT treatments are generally divided into a number of occasions delivered once a day that together sum up to the planned radiation dose. The length of the daily sessions vary between patients. In this work, we use combinatorial optimization to schedule RT patients taking future patient arrivals into account.

A long waiting time between the day when a patient is ready for RT and the day treatment starts negatively affects the outcome of the treatment (see e.g. [1]). As a result, many cancer institutes around the world have adopted waiting time targets that determine the date by which a patient should start treatment. The waiting time targets differ depending on the urgency level of the patient.

There are many uncertainties in the RT process, including for example the random arrival of new patients, time spent on treatment planning and machine failures. Creating patient schedules is a considerable challenge for RT clinics, where in most cases the scheduling is done manually. Designing more efficient schedules would be of great significance and could potentially save lives.

Scheduling of radiotherapy patients has been relatively sparsely studied over the years. In [4], the authors show that patient scheduling in RT clinics can be seen as a special case of a dynamic job-shop problem. The patient allocation problem is solved for a one-week horizon using a MIP-model in [2]. In [6], the advance patient scheduling problem is modeled as a discounted infinite horizon Markov Decision Process, and this was later further developed to include cancellations in [3]. Previous work also include online optimization approaches, when the patient must leave the clinic with the schedule in hand [5].

In this work, we develop two different models; a MIP model and a Constraint Programming (CP) model. We aim to find the optimal treatment allocation for patients in a three month planning horizon, while taking expected future patient arrivals into account. It is, to the best of our knowledge, the first time the radiotherapy patient scheduling problem is modeled using CP, and also the first time expected future patient arrivals are included in a MIP model.

Models

The patient scheduling is done in batches once a day. The batch consists of patients that have arrived during the day, previous patients who still have not been informed of a start day since it is more than one week away, and expected future patient arrivals.

Currently, we consider a single machine type, which all patients can be scheduled on. Patients are assumed to be assigned to a treatment protocol, i.e., a plan stating waiting time target, frequency of treatment sessions, session duration and what days of the week treatment is allowed to start.

Both the CP and MIP models are time indexed with time discretized into 5 minute segments. Furthermore, the day is divided into time windows that all contain equally many 5 minute slots. The aim is to assign patients to time windows on each day. The reason for scheduling patients to time windows instead of specific starting times is because it greatly increases computational speed while it maintains an adequate level of detail from a clinical perspective.

The main objective is to minimize a weighted sum of the violations of the waiting time targets. From a clinical perspective, it is favorable to schedule the patients in the same time window each day of the treatment, and therefore this is included as a secondary objective.

The MIP model uses binary variables that capture which day a patient first starts their treatment and in which time window the patient is scheduled during each day of treatment, while at the same time ensuring that the patient follows the given treatment protocol.

In the CP model, the main decision variables determine in which time window each patient is treated on each day. The `cumulative` global constraint is used to ensure that patients follow their treatment protocols. When solving the model, deterministic and random search strategies are combined to rapidly reach good feasible solutions.

Preliminary Results and Future Work

The MIP model is solved in CPLEX 12.8 using the Python API and the CP modeling is done in MiniZinc 2.2.2 using the Gecode solver. In both cases, we simulate patient arrivals according to a Poisson process and create patient schedules for many consecutive days using a simulation engine built in Python 3.6. The arrival rates are approximated from data from a well known cancer clinic in Europe.

Preliminary results look promising for both the MIP and the CP model. For the MIP model, the time to find an optimal solution (with some tolerance) for a batch consisting of a total of 30 patients ranges from a few minutes to around 30 minutes. The CP model finds feasible solutions within seconds, but reaching optimality is in general slower than for the MIP model.

The simulations have so far been run on approximated arrival rates and protocols that are related to the real data, but that include some simplifications. Going forward, the focus is to extract relevant treatment protocols from the data and use these to test the models. We will also investigate improving the CP model using, e.g., a `regular` global constraint. Another future direction is to extend the models to include multiple machines.

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