A pattern-based approach of radiotherapy scheduling
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Abstract: In any cancer treatment, waiting times are critical, the faster the patient is treated the more effective the treatment is. Minimizing waiting times is especially difficult in the context of radiotherapy where material and human resources are usually scarce. Although healthcare scheduling is extensively documented, few studies have addressed the specific radiotherapy problem. In this paper we develop an original model of radiotherapy scheduling using an integer linear optimization of a non-block scheduling strategy. In order to outperform previous works, we have introduced the concept of treatment patterns over the entire patient treatment allowing realistic treatment protocols to take place. Results achieved show an improvement of radiotherapy treatment room utilization, a higher number of patients treated along with a decrease in patient waiting times.

Keywords: Scheduling, Linear programming, healthcare, radiotherapy

1. INTRODUCTION

For several decades, the number of radiotherapy patients have been steadily increasing, this growth in demand is explained for one part by the global ageing of the population and for another part by the easier access to more accurate radiotherapy treatment. More people can be treated and more pathology can now be cured. Radiotherapy treatment is a complex process involving several steps and most of these steps have to be performed in a specific order by highly skilled workers and take place at a precise time within a usually small delay. Furthermore, linear accelerators (i.e., linacs) are expensive machines, and oncologists, nurses and physicians, working in synergy, are also critical resources. These constraints result in a long waiting-times in a process where decreasing these waiting-times are directly proportional to the effectiveness of the treatment. The goal of an efficient scheduling in this context is to minimize costs (i.e., increased resources utilization) and waiting times while keeping service quality at least at the same level (with respect to both the patient and the staff). Numerous approaches were, and still are, developed to solve this kind of complex problems albeit mostly in industrial context, which provide us a great amount of tools and methods to define optimal schedules although several modifications are needed to apply theses industrial methods in healthcare. Within the healthcare field, several operation research approaches were used to model and schedule hospital services. One particular area of interest is the costlier service in any hospital: operating rooms. Simulations (Marcon et al. 2003) and scheduling approaches (Augusto et al. 2010) were published on the better way to schedule surgeries and staff shifts along with choosing the appropriate staff size (for a review see Cardoen et al. 2008).

What renders radiotherapy scheduling so specific is the amount of repetitive tasks, encountered neither in industrial context nor in other hospital services. For the most part, treatment protocols last many successive weeks resulting in dozens of treatment sessions for each patient and several constraints taken into account. However, for the specific subject of radiotherapy scheduling, few studies have been published. Two main approaches were designed; the first one from Coventry and Nottingham Universities resulted in several constructive algorithms consecutively optimized with parameters tuning, GRASP optimization (Petrovic et al. 2006, 2008). The second approach from (Conforti et al. 2006, 2010), described an integer linear optimization program specifically designed to solve radiotherapy scheduling. In their first publication, they introduced their model and in the second one they extended and improved it. In the last version their algorithm works with two patients’ list, one of Booked Patients and one of Waiting Patients weighted accordingly to their emergency status and their arrival order. Their objective function is to maximize the number of new patients starting their treatment. They included several constraints ensuring an accurate treatment such as: the numbers of sessions per week, the session duration, the maximum number of utilization hours per day for the linacs and the availability of already booked patients. Results are obtained for a set of artificial data over one week.

Our first contribution (Jacquemin et al. 2010) combined the best of these both approaches by scheduling simplified real-world data using a linear integer optimization approach. After establishing efficiency bounds of the Conforti’s approach, we showed how our models improved linacs utilization, ensured a better quality of service for the patients and decreased the delays before the first session. We achieved this improvement through several modifications such as increasing the planning horizon and adding some new constraints. We also showed that taking into account radiotherapist availabilities only slightly decrease scheduling performances. In this publication, we suggest a new approach allowing us to
further improve the scheduling methods and its results. The first part explains our approach and the datasets we used, the second part describes our notations and model and the third part shows our results. Finally, some concluding remarks and perspectives close this article.

2. PATTERN APPROACH

In our previous studies, we encountered several limitations inherent to the models: i) fixed pattern of treatment over the whole treatment (i.e., 4 or 5 sessions per week), ii) no rest allowed within a week and iii) impossibility to start a treatment except in the beginning of the week (see Table 1). Regarding iii), our main concern was the impossibility to smoothen the workload over the week. In order to overcome these issues, we developed and original model using the notions of patterns. Each pattern defines treatment protocol in terms of treatment days and rest days. This feature allows for patient-dependant patterns as well as pathology-dependant patterns, furthermore each treatment can start as soon as possible within the week under the constraint of the protocol treatment.

Table 1. Treatment sessions with previous models and Pattern model.

<table>
<thead>
<tr>
<th>Week #1</th>
<th>Week #2</th>
</tr>
</thead>
<tbody>
<tr>
<td>With previous models</td>
<td>With Pattern model</td>
</tr>
<tr>
<td>M T W T F SS</td>
<td>M T W T F SS</td>
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<td>M T W T F SS</td>
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</tbody>
</table>

Despite this increased complexity, this modelization uses much less constraints than previous works as most of them are integrated within the patterns. In addition this modelization allows a smoother workload but also follows current radiotherapy best practices. Our objective is to schedule patient’s treatment sessions while respecting constraints of patients and radiotherapists availabilities.

3. PATTERN MODEL

3.1 Notations

In this section, we describe the notation we used in this new model which differs from Conforti’s notation on several features.

Data:
- $H$, Set of days in the planning horizon, indexed by $r$.
- $F$, Set of shifts per day, indexed by $j$.
- $M$, Set of linear accelerator or machines, indexed by $w$.
- $WP$, Set of waiting patients, indexed by $j$.
- $R$, Set of radiotherapists indexed by $j$.

Binary decision variables:
- $B_{w,m,f}$, Decision to start the treatment of patient $w$ on machine $m$ during shift $f$ of day $t$.
- $S_{w,m,f}$, Decision to assign patient $w$ on machine $m$ during shift $f$ of day $t$ for a classic session treatment.
- $C_w$, Decision to change assigned radiotherapist for the patient $w$.

Input parameters:
- $W_w$, Weight of patient $w$ (i.e., priority).
- $Nd_w$, Number of days between the first and the last treatment sessions for the patient $w$.
- $Nt_w$, Number of treatment sessions for the patient $w$.
- $D_{1,w}$, Duration of the first session for the patient $w$.
- $D_{w}$, Duration of classic sessions for the patient $w$.
- $P_w$, Pattern assigned to the patient $w$.
- $R_{w}$, Radiotherapist assigned to the patient $w$.
- $Ar_{w,f}$, Availability of patient $w$ for the $f$ shift of day $t$, 1 if available 0 otherwise.
- $Ar_{r,f}$, Availability of radiotherapist $r$ for the $f$ shift of day $t$, 1 if available 0 otherwise.
- $T_{p,e}$, Treatment information for pattern $p$ on day $e$.
- $Patt_{p,e}$, Start information for pattern $p$ on day $e$.
- $O_{m,f}$, Opening hours i.e. capacity of machine $m$ during shift $f$ of day $t$.
- $M$, Large constant value.

3.2 Pattern Model

Objective function:

$$\max \sum_{w=1}^{w_{\text{max}}} \sum_{m=1}^{m_{\text{max}}} \sum_{f=1}^{f_{\text{max}}} w_w Nt_w (B_{w,m,f} (H - t) - C_w |H|)$$

Subject to:

$$\sum_{d=1}^{d_{\text{max}}} \sum_{f=1}^{f_{\text{max}}} S_{w,m,f} \geq (Nt_w - 1) \sum_{f=1}^{f_{\text{max}}} B_{w,m,f} Patt_{p,e}$$

$$\forall w, \forall m, \forall t \leq |H| - Nd_w + 1 \quad (1)$$
The objective of this model is to schedule the most early \((B_{wmtf}(H-t))\) new starting treatments according to patient’s priority \(w\) and their number of sessions \(N_t\), with a penalty to ensure the minimization of radiotherapist changes \((C_w/H)\). Each patient’s weight is based on the priority of treatment (i.e., urgent or not) and the rank of each patient in the waiting list (First In First Out model). Constraints (1) and (2) use a window mask to ensure that after the treatment starting date the right amount of treatment sessions is set according to the treatment protocol. Constraints (3) prevent the search of solutions with starting dates too late to finish the whole treatment before the end of the considered horizon. Furthermore, every waiting patient should begin their treatment once within horizon (4) according to beginning patterns and its availability (5). Besides, every regular treatment session must follow patterns and patients’ availabilities (6), occurs on the same linac than the starting session (7) and cannot take place the same day than the starting session (8). Finally, the sum of starting and regular session durations should respect shift capacities as specified in (9) while (10) deals with radiotherapist availabilities and the decision variable allowing a change of radiotherapist for this first session.

4. DATASETS

Our virtual center performs treatments on 2 identical linacs, each linac works during 3 240 minutes per week (i.e., 2 * 324 minutes per day, 5 days a week for patterns and 2 * 270 minutes per day, 6 days a week for Rav.). This amount of time is decreased from previous publications (Conforti et al. 2010, Jacquemin et al. 2010) in order to gather enough difference to distinguish each model’s performances. This scheduling takes place each week during 15 consecutive weeks over a 10-weeks span allowing to schedule every session of each patient’s treatment. Because the scheduling optimization is performed during a long period (i.e., 15 weeks), the flow of new patients during the first 4 weeks grows slowly to fill the center which starts with already 45 patients booked. After these 4 warm-up weeks, random amounts of new patients that should be planned is set between 25 to 30 patients per week. We decided to use 1 to 6 weeks treatment protocols with 20% of them with a high priority. We also kept Conforti’s choices in terms of number of treatment sessions per week (i.e., 4 or 5 session for every patient). According to a field study, we defined session durations between 7 to 15 minutes for regular session and twice or thrice this time for the first treatment session. Further, we randomly generated some data like patient availabilities and radiotherapists’ assignment to patients.

Since each patient receives 4 or 5 treatment sessions per week, this provides us two kinds of patterns: the first one consists of 5 successive sessions (5 sessions per week or 5SW) and the second one consists of two sessions followed by at least one rest day (4 sessions per week or 4SW) (see table 1). However, only 2 successive days are needed to start the treatment thus allowing us to start 5SW treatments anywhere between Monday to Tuesday and 4SW treatments Monday or Thursday. Concerning radiotherapists, our virtual center works with 3 radiotherapists available one or two shifts each week and distributed among available starting days (2 days for Rav. and 3 days for patterns), as described in Table 2. This organization ensures two shifts on days where either 4SW or 5SW patients can start their treatment and one shift on Wednesday to start 5SW patients when 4SW patients are not treated.

To assess performances of the model, we compare its results with those obtained from our last best model (i.e., Rav. in Jacquemin et al. 2010) and we use three key performance indicators:

- The percentage of new patients starting their treatments.
- The number of weeks each patient had to wait before starting its treatment.
• The percentage of patients starting their treatment with another radiotherapist i.e. radiotherapist changes.

Table 2. Radiotherapists planning

<table>
<thead>
<tr>
<th></th>
<th>M</th>
<th>T</th>
<th>W</th>
<th>T</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rav.</td>
<td>AM</td>
<td>RT1</td>
<td>RT2</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PM</td>
<td>RT3</td>
<td>RT1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patterns</td>
<td>AM</td>
<td>RT1</td>
<td>RT3</td>
<td>RT2</td>
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</tr>
<tr>
<td>Patterns</td>
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<td>RT2</td>
<td>RT1</td>
<td>RT3</td>
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</tr>
</tbody>
</table>

Treatment session durations, protocols parameters and amount of patients per week were gathered in a major French oncology center (Centre Léon Bérard, CLB).

5. RESULTS

Results were obtained by Integer Linear Programming under LINGO© on one core of a 2.8Ghz CPU with 4Go DDRAM. Input data and results were managed by Microsoft Excel 2007© combined with LINGO VBA module and several Microsoft Excel macros. Even if we used an exact resolution method, resolution times over 15 weeks will result in intolerable resolution time hence each algorithm was allowed to run a maximum of 1200 seconds per each week resolution. For determining the running time, we have studied the sensitivity of the planning solutions on the running time and we observed for a majority of cases solved that when the research is cut off after 20 minutes, the planning solution achieved is closer than 2% of solutions obtained with larger cut-offs.

The pattern model schedules every patient in its waiting list despite how late they start hence the percentage of scheduled patients is always 100%. On the other side, as shown in Figure 1, the change in linac capacity results in a great decrease in the number of patients started each week for the Rav. model. However the number of patients scheduled with Patterns is also better than with Rav. with 370 patients scheduled instead of 357 within the first 15 weeks. This results also in slightly more delays with Patterns than with Rav. as show in Figure 2. Furthermore, Patterns performs better on the linac utilization indicator (Fig. 3) with rarely more than 90% of utilization as soon as the center is full (i.e., after the 7th week). Both of these observations lead us to suppose that pattern tends to respect radiotherapist availabilities more than Rav. hence delaying more patients at the beginning of the simulation while performing better as soon as the center is full. Another important behavior of this new model can be observed in its ability to follow load variability more closely than Rav. as seen on Figure 3, for example in low-load weeks such as #10 to #12.

We also developed for this model another key indicator showing the beneficial impact of Pattern model concerning radiotherapists’ changes. Figure 4 shows the percentage of patients whom didn’t start their treatment with their own radiotherapists. These results show the great beneficial impact of pattern model on this indicator although high-load weeks (#9 and #13) result in a greater percentage of changes in the following weeks (#10 and #14). Over the 15 weeks period, Patterns model results in only 8% of radiotherapists’ changes while Rav. results in 21%. In addition, it confirms the possibility to significantly improve quality of care and working conditions without decreasing performances.

Figure 1. Percentage of new patients starting their treatments over the 15 weeks for Rav. model with 300 minutes shifts (dashed line on the top) and 270 minutes shifts (plain line on the bottom). Both results are shown with vertical bars depiction variability over several runs.
Figure 2. Delays for new patients before they can start their treatment with Rav and Patterns models. From left to right: no waiting time (258 vs 248), one week of delay (83 vs 77), two weeks (13 vs 39), three weeks (2 vs 3) and the last one for four weeks (1 vs 9).

Figure 3. Percentage of linacs utilization over the 15 weeks. Dashed line for Rav model’s results; Plain line for Patterns model’s results. Dotted line for expected load added each week on the lower part of the graph.

Figure 4. Percentage of radiotherapists change over the 15 weeks period. Dashed line for Rav model’s results with vertical lines depicting variability over several runs. Plain line for Patterns model’s results.
4. CONCLUSION

In conclusion, we proposed a new approach allowing a greater flexibility in treatment protocols implementation and consequently a better depiction of reality. Furthermore, this “pattern” model performed better on every classical performance indicators in term of resources efficiency and we showed the possibility to take into account radiotherapists’ availabilities without major decrease in performances. Although this model works correctly, the running time for solving the problem increases exponentially with the number of linacs and patients. In order to allow the resolution for “real world” problems with more than 8 linacs (i.e., like in CLB), we plan to develop an heuristic resolution method in order to achieve near real-time scheduling and to provide an useful tool to radiotherapy schedulers.

REFERENCES


