Medical planning and patient assignment of an oncology outpatient unit

CLARA day on operations research in cancer treatment and operation management

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This work is part of the initiative of CLARA (Cancéropôle Lyon-Auvergne-Rhône-Alpes) on cancer care delivery engineering in order to improve the efficiency of cancer patient cares.

We collaborate with ICL (the Institute of Cancerology of the Loire region) on the optimization of cancer care delivery.

It is part of the Ph.D. thesis of Abdellah Sadki co-supervised by Xiaolan Xie (ENSMSE) and Franck Chauvin (professor of public health in ICL specialized in cancer treatments).
Outline

- Introduction
- Problem Description
- Medical planning
- Patient assignment
- Experiments and results
- Conclusion
Bad utilization of clinical resources

Patient flow badly controlled

High patients waiting time

Consultation capacity overcrowding

Large variations of daily workload → medical staff stressed
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Outpatient concept

- Patients come to the hospital to receive care (chemotherapy)
- They receive one or more injections without requiring an overnight stay
- … and go back home
A right combination of cytotoxic drugs (-> injection time)

- Treatment according to some cyclic pattern with cycle of 4 weeks
- Treatment spread over long time (about 6 months)
- Important variability of injection time (15 minutes to 7h) for 9h opening time of the outpatient unit.

### Chemotherapy protocols

<table>
<thead>
<tr>
<th>Chemotherapy protocols</th>
<th>Periodicity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Week 1</td>
</tr>
<tr>
<td>Avastin</td>
<td>1</td>
</tr>
<tr>
<td>Cisplatin</td>
<td>1</td>
</tr>
<tr>
<td>Rituximab</td>
<td>1</td>
</tr>
<tr>
<td>Vinorelbin</td>
<td>1</td>
</tr>
</tbody>
</table>
Chemotherapy process

Day – 1

- Blood test at outside lab
- Test report sent to the oncologist
- Postpone care session if needed

Day 0

- Registration
- **Medical consultation by oncologist (OK Chemo)**
- Production of chemotherapy (if OK Chemo)
- Installation of the patient in a bed
- **Injection**
- Appointment for next session and departure
- **Outpatient major operation decisions**

  **Medical planning** (once a year)
  - To plan working periods of each oncologist

  **Patient assignment** (for each new patient)
  - To select a weekday for chemotherapy of each patient

  **Appointment scheduling** (daily)
  - To determine for each patient the appointment time for his/her next care session

  **Chemotherapy drug production scheduling** (daily)
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### Decision variables

**Medical planning**

- $y_{jt} = 1/0$ if oncologist $j$ consults in time period $t$ of each week (AM/PM)

**Patient assignment**

- $x_{it} = 1/0$ if patient $i$ comes in time period $t$ of each week (the same day during the whole treatment process)

**Work of the Intern**

- $z_{jwt} = \text{Nb patients of oncologist } j \text{ seen by the intern in time slot } t \text{ of week } w$

**Extra consultation capacity**

- $e_{jwt} = \text{number of patients of oncologist } j \text{ consulted in period } t \text{ of the week } w \text{ with extra consultation capacity}$
• Derived from combination of protocols and patient flow

\[ a_{iw} = 1 \text{ if patient } i \text{ requires a chemo. session in week } w, \]
\[ a_{iw} = 0 \text{ otherwise} \]

• The day is determined by patient assignment variable \( x_{it} \)

<table>
<thead>
<tr>
<th>Chemo</th>
<th>week1</th>
<th>week2</th>
<th>week3</th>
<th>week4</th>
<th>week5</th>
<th>week6</th>
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</thead>
<tbody>
<tr>
<td>Patient1-Avastin</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Patient2-Cisplatin</td>
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<td>1</td>
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<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Patient3-Rituximab</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Patient4-Vinorelbin</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Referee oncologist: patient assigned to one of consultation periods of his referee oncologist

Injection time of each patient

Consultation capacity of oncologists and interns in period t

Number of consultation boxes in period t

Maximal bed capacity of afternoon periods
Balance daily bedload

Minimize extra-consultation capacity

Patient assignment

Nb of Consultation boxes

Max nb of patients of oncologist j

Max workload of the intern

Treatment of patient during the presence of its referee oncologist

Max bed capacity for PM periods

Max daily bedload

Min daily bedload

\[
\text{Minimize:} \quad \sum_w (C_{\text{max}} - C_{\text{min}}) + \sum_j \sum_w \sum_t e_{jw} \cdot M \\
\text{Subject to:} \\
\sum_{t \in T} x_{it} = 1 \quad \forall i \in P \\
\sum_{t \in T} y_{jt} \leq B_t \quad \forall i \in P \\
\sum_{i \in P_j} a_{iw} \cdot x_{it} \leq N^t \cdot y_{jt} + e_{jw} + z_{jwt} \quad \forall j \in J, w \in W, t \in T \\
\sum_{j \in J} z_{jwt} \leq N^t \quad \forall w \in W, \forall t \in T \\
z_{jwt} + e_{jw} \leq |P_j| \cdot y_{jt} \quad \forall j \in J, w \in W, \forall t \in T \\
\sum_{i \in P} a_{iw} \cdot d_i \cdot x_{it} \leq Q_t \quad \forall w \in W, \forall t \in PM \\
\sum_{i \in P} a_{iw} \cdot d_i \cdot (x_{it} + x_{it+1}) \leq C_{\text{max}} \quad \forall w \in W, \forall t \in AM \\
\sum_{i \in P} a_{iw} \cdot d_i \cdot (x_{it} + x_{it+1}) \geq C_{\text{min}} \quad \forall w \in W, \forall t \in AM \\
x_{it} \in \{0, 1\} \quad \forall i \in P, \quad e_{jw}, z_{jwt} \geq 0
Problem complexity

- The LP model for medical planning is built on past historical data of over 800 patients over one trimester
- The LP model is NP-complete
- The LP model takes over 10h for LP solvers to get reasonable solution
Tree-stages approach

- Mixed-integer programming-based heuristic
- Target the most critical weeks
- Problem resolution in tree stages

First stage: Morning periods scheduling

- Only morning periods are considered
- Only most critical weeks (Reduced horizon)
**Second stage : Afternoon periods scheduling**

- Extends the morning medical planning formulation to schedule afternoon periods
- Constraints related to afternoon medical planning

**Third stage : Local optimization of the medical planning**

- Improvement of the medical planning by local search including interchange oncologists on two time slots and replace oncologist on a time slot
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Basic patient assignment scheme

- For a given medical planning \( Y_{jt} = 1/0 \), at the end of each week:
  - Select a set \( P^N \) of patients including at least new patients of the next week
  - Consider the set \( P \) of patients including those in \( P^N \) and all on-going patients
  - Select a planning horizon of \( W \) weeks
  - Determine the treatment weekday of each new patients.
Basic patient assignment scheme

- Decisions to be made each week

**Patient assignment**

- \( x_{it} = 1/0 \) if patient \( i \) comes in time slot \( t \) of each week

**Work of the Intern**

- \( z_{jwt} = \text{Nb patients of oncologist } j \text{ seen by the intern in time slot } t \text{ of week } w \)

**Extra consultation capacity**

- \( e_{jwt} = \text{number of patients of oncologist } j \text{ consulted in period } t \text{ of the week } w \text{ with extra consultation capacity} \)
Daily bedload balancing and extra-capacity minimization

\[ \text{Min } \sum_w (C_{\text{max}_w} - C_{\text{min}_w}) + \sum_j \sum_w \sum_t e_{jw}t \cdot M \]

Subject to:

Patient assignment
\[ \sum_{t \in T} x_{it} = 1 \quad \forall i \in P \]

Max nb of patients of oncologist j
\[ \sum_{i \in P_j} a_{lw} \cdot x_{it} \leq N^r \cdot y_{jt} + e_{jw}t + z_{jw}t \quad \forall j \in J, w \in W, t \in T \]

Max workload of the intern
\[ \sum_{j \in J} z_{jw}t \leq N^l \quad \forall w \in W, \forall t \in T \]

Patients delegation constraints
\[ z_{jw}t + e_{jw}t \leq |P_j| \cdot y_{jt} \quad \forall j \in J, w \in W, \forall t \in T \]

Max bed capacity for PM periods
\[ \sum_{i \in P} a_{lw} \cdot d_i \cdot x_{it} \leq Q_t \quad \forall w \in W, \forall t \in PM \]

Max daily bedload
\[ \sum_{i \in P} a_{lw} \cdot d_i \cdot (x_{it} + x_{it+1}) \leq C_{\text{max}_w} \quad \forall w \in W, \forall t \in AM \]

Min daily bedload
\[ \sum_{i \in P} a_{lw} \cdot d_i \cdot (x_{it} + x_{it+1}) \geq C_{\text{min}_w} \quad \forall w \in W, \forall t \in AM \]

\[ x_{it} \in \{0, 1\} \forall i \in P, \quad e_{jw}t, z_{jw}t \geq 0 \]
Three strategies with the basic assignment scheme

**Strategy 1 (myopic strategy)**

- $P^N =$ new patients of the next week
- Time horizon $W = 1$
- Patients are assigned without considering the impact of the bedloads of subsequent weeks
Strategy 2

- $P^N =$ new patients of the next week
- Time horizon $W > 1$ (12 weeks = one trimester)

Assignment by taking into account

- the future care requirement of known patients via their protocol of care
- but not that of unknown incoming patients of these weeks
Assignment strategies

Strategy 3

- \( P^N \) = new patients of the next week + fictitious patients
- Time horizon \( W > 1 \) (12 weeks = one trimester)

Assignment by taking into account

- the future care requirement of known patients via their protocol of care
- Care requirement of unknown patients via randomly generated fictitious patients
Step 1: Initialization
• Select a week $w = w_0$ in the historical data
• Record the population of existing patients and new patients

Step 2: Patient assignment optimization
• Generate the nb of new incoming patients over planning horizon
• Apply patient sampling process to generate protocols and referee oncologists
• Solve the patient assignment model according to the patient assignment strategy

Step 3: Patient assignment
• Assign incoming patients of week $w$ according to the resulting solution

Step 4: Generate new incoming patients
• Generate the number of new incoming patients for week $w+1$
• Apply patient sampling process to generate protocols and referee oncologists

Step 5: Repeat steps 2-4 until the end of the simulation horizon
Design of a stochastic model

- Derived from historical data of patients in 2008-2009
- More than 2000 patients
- No seasonality is observed
- Poisson distribution seems good enough
Patient flow modeling

• No enough data are available to have a precise stochastic modeling of treatment protocols and a referee oncologists
• We use a sampling population, i.e. the set of more than 2000 patients from the hospital information system.
• New patients are randomly sampled from the sampling population with the same treatment protocol with the same referee oncologist.
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ICL Outpatient unit resources

- Open Monday to Friday with 10 periods
- 2 consultations boxes in the morning, 1 in the afternoon (+ 1 box for intern)
- At most 14 consultations the morning, 8 the afternoon
- 18 beds
- 9 oncologists, 1 intern
- Outpatient care from 9 A.M. To 6 P.M.
- Theoretical bed capacity of 162 hours per day
Experiments

Data sets

- Data collected from the outpatient care unit of ICL
- 5% of injection times are missing and randomly generated
- Simulation over 1 year
- Population of more than 2000 patient

Optimization

- C++
- ILOG CONCERT CPLEX 11.0
### Scheduling physician working period

<table>
<thead>
<tr>
<th>Instance</th>
<th>Current planning</th>
<th>MIP1</th>
<th>3Stages approach</th>
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<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Max</td>
<td>Obj</td>
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<tr>
<td>1_0</td>
<td>38.5</td>
<td>162.25</td>
<td>3342</td>
</tr>
<tr>
<td>1_1</td>
<td>32.5</td>
<td>159.25</td>
<td>3204</td>
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<tr>
<td>1_2</td>
<td>32.5</td>
<td>167.75</td>
<td>3477</td>
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<tr>
<td>1_3</td>
<td>31.25</td>
<td>155.5</td>
<td>3164</td>
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<td>1_4</td>
<td>33</td>
<td>151.25</td>
<td>3159</td>
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<td>2_3</td>
<td>48.75</td>
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<tr>
<td>2_4</td>
<td>42.25</td>
<td>138.5</td>
<td>2785</td>
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</tbody>
</table>

- Maximal daily bed-load for 18 beds (9h/bed) = 162h
- Current planning causes a large fluctuation
  - Reduce the peak daily bedload by about 30h over 18 beds
### Scheduling physician working period

<table>
<thead>
<tr>
<th>Day</th>
<th>Oncologist</th>
<th>Mon</th>
<th>Tue</th>
<th>Wed</th>
<th>Thu</th>
<th>Fri</th>
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<tbody>
<tr>
<td>AM1</td>
<td>Oncologist</td>
<td>1</td>
<td>0</td>
<td>6</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Patient nb</td>
<td>11,7</td>
<td>20,1</td>
<td>12,67</td>
<td>4,75</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Bedload (h)</td>
<td>33,28</td>
<td>52,50</td>
<td>50,50</td>
<td>7,63</td>
<td>13,80</td>
</tr>
<tr>
<td>AM2</td>
<td>Oncologist</td>
<td>3</td>
<td>5</td>
<td>9</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Patient nb</td>
<td>9,17</td>
<td>4,5</td>
<td>2,2</td>
<td>20,83</td>
<td>20,4</td>
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<tr>
<td></td>
<td>Bedload (h)</td>
<td>25,65</td>
<td>10,28</td>
<td>7,75</td>
<td>80,13</td>
<td>79,63</td>
</tr>
<tr>
<td>PM</td>
<td>Oncologist</td>
<td>6</td>
<td>4</td>
<td>8</td>
<td>0</td>
<td></td>
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<tr>
<td></td>
<td>Patient nb</td>
<td>12,1</td>
<td>13</td>
<td>12,25</td>
<td>2,9</td>
<td></td>
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<tr>
<td></td>
<td>Bedload (h)</td>
<td>28,60</td>
<td>26,25</td>
<td>32,63</td>
<td>6,50</td>
<td></td>
</tr>
</tbody>
</table>

| Total nb patient /Day | 32,97 | 37,6 | 27,12 | 28,48 | 26,4 |
| Daily Bedload (h)     | 87,53 | 89,03| 90,88 | 94,25 | 93,43 |

✓ The bedload is not proportional to the number of patients
### Patient assignment strategies

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Actual planning</th>
<th>Strategy 1</th>
<th>Strategy 2</th>
<th>Strategy 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max</td>
<td>Min</td>
<td>Obj</td>
<td>Extra</td>
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<td>15</td>
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<td>2</td>
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<td>20</td>
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<td>16</td>
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<td>25</td>
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<td>8</td>
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<tr>
<td>4</td>
<td>118</td>
<td>19</td>
<td>19722</td>
<td>10</td>
</tr>
</tbody>
</table>

- Well balanced bedloads
- Reduced consultation capacity overflow
- Well balanced patients distribution

Extra : Total extra consultation capacity for 1 year
Strategy 3 Vs actual assignment:

- Improved bedload balancing and picks reduction
- Well anticipation of patients arrival
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Conclusion

- We presented a new method to schedule medical planning in an ambulatory care unit.
- We presented a new method to assign patients in an ambulatory care unit.
- The proposed assignment strategies make use of patient treatment protocols and rely on Monte Carlo optimization taking into account unknown random future patients to balance the bedload requirement.
Conclusion

• A simulation model taking into account random patient arrivals and random treatment protocols and referee physicians is proposed for evaluation of different assignment strategies.
• The simulation on a long horizon of one year shows the stability and robustness of patient’s assignment strategies.

• One immediate future research is to design a method for the daily appointment schedule of patients to have a comprehensive planning tool.
• This method should take into account the preparation of drugs in the pharmacy to ensure smoother production.