Planning Oncologists of Ambulatory Care Units

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Abstract: This paper addresses the problem of determining the work schedule, called medical planning, of oncologists for chemotherapy of oncology patients at ambulatory care units. A mixed integer programming (MIP) model is proposed for medical planning in order to best balance bed capacity requirements over time under capacity constraints of key resources such as beds and oncologists. The most salient feature of the MIP model is the explicit modelling of specific features of chemotherapy such as the patient treatment protocols. The medical planning problem is proved to be NP-complete. A three-stage approach is proposed for determining good medical planning in reasonable computational time. Numerical experiments based on field data show that the three-stage approach that takes less than 10 minutes always outperforms the direct application of MIP solvers with 10h CPU time. Compared with the current planning, the three-stage approach reduces the peak daily bed capacity requirement by 20h to 45h while the maximum theoretical daily bed capacity is 162h.

Keywords: Oncology, ambulatory care, medical planning, bed capacity, mixed integer programming.
1 INTRODUCTION

This paper addresses the medical planning problem of oncology outpatient cares that consists in determining the work schedule for oncologists in order to balance the bed capacity requirement of the oncologist ambulatory care unit (ACU) while taking into treatment protocols of patients.

This research is performed in close collaboration with the cancer center ICL. The « Institut de Cancérologie de la Loire » (Loire Cancer Institute), a.k.a. ICL, is a French public comprehensive cancer center providing oncology, hematology, pediatric oncology and radiotherapy services. ICL is also the linchpin of the Oncoloire network, which is the care network for cancer patients and aims to ensure that all cancer patients in the Loire department can be treated equally regardless of where they live. In 2008 ICL delivered: 12 000 chemotherapy sessions, 10679 hospitalization days in oncology for 1843 direct entrances, 5623 days of hospitalization in hematology for 411 direct entrances, 2361 days of hospitalization in pediatric oncology for 454 direct entrances and 39266 radiotherapy sessions for 1706 patients. ICL provides an academic teaching and research environment; it serves to train medical students and interns from many disciplines. Also, numerous patients participate in clinical trials. All this complicate the center resource planning.

The problem considered in this paper was brought to our attention by the ICL ambulatory care unit which provides chemotherapy treatment for outpatients in oncology and is common to most oncology ambulatory care units in France. As the demand for oncology care increases, ICL faces serious capacity problem. The ACU unit is often overcrowded and the ACU staff was asking the management to increase the number of beds. We were asked to assess the bed requirement of the ACU unit. Data collected from field show that the actual daily bed capacity requirement (see Figure 1) is highly unbalanced. This observation motivates the research presented in this paper to best smooth the daily bed capacity requirement in order to avoid the bed crises of the ACU unit.
Figure 1: Actual daily beds capacity requirement

More specifically, this paper addresses the problem of determining the work schedule of oncologists, called medical planning, in order to best balance the bed capacity requirement over time. To the best of our knowledge, this problem has not been addressed in the literature. This paper pursues our preliminary work (Mazier and Xie[13]) which shows that peak bed capacity requirement can be reduced by standard optimization solvers provided that computation time over 10h and sometime over 1 days is acceptable.

In this paper, we first propose a mixed integer programming (MIP) model that takes into account obvious capacity constraints of resources such as beds needed during chemotherapy and consultation capacity of oncologists. The most important feature of the MIP model is the explicit modeling of patient treatment protocols that leads to precise estimation of resource requirement of patients over time. The medical planning problem is proved to be NP-complete and it takes standard MIP solvers over 10h to determine acceptable solutions. We then propose a three-stages approach which first determine the morning medical planning, then the afternoon medical planning with given morning medical planning, and local search for improvement of the resulting medical planning. Numerical experiments with field data show that the three-stage approach that takes less than 10 minutes CPU time always outperforms the direct application of MIP solvers to the MIP model with 10h CPU time. Further, the three-stage approach outperforms the current planning in both bed capacity requirement balancing and extra consultation capacity needed. Over 10 problem instances tested, the peak bed capacity requirement is reduced by 20h to 45h per day while the theoretical maximum bed capacity is 162h per day.

The literature on operation management of oncology care centers is poor Conforti et al [5] is the work closest to this paper and proposed an optimization model for outpatient scheduling within a radiotherapy department defined in such a way to represent different real-life situa-
tions. The objective was to minimize the excessive waiting time and waiting lists for radiotherapy treatments. Santibáñez et al [15] used simulation to analyze the impact of operations, scheduling, and resource allocation on patient wait time, clinic overtime, and resource utilization at British Columbia Cancer Agency’s ambulatory care unit. Blay et al [2] conducted a three-month work sampling to evaluate the roles and workload of nurses within an outpatient cancer care center. They identified the range of nursing activities performed by the oncology outpatient nurses. The nurses were found to have a large administrative role while their nursing activities ranged from basic nursing tasks to more specialist activities including patient counseling and complex chemotherapy regimens. Delaney et al [6] presented a multivariate analysis in order to evaluate the chemotherapy treatment duration based on patient–tumor and treatment related factors. They found that the variables which most impact on treatment duration are the type of infusion and the chemotherapy protocol that have been prescribed. While the daily number of patients remained stable, wide fluctuations of workload were observed. Matta and Patterson [12] addressed the problem of multiple responses in simulation experiments of outpatient clinics by developing a stratification framework and an evaluation construct by which managers can compare several operationally different outpatient systems across multiple performance measure dimensions. This approach was applied to a discrete-event simulation model of a real-life, large-scale oncology center to evaluate its operational performance as improvement initiatives affecting scheduling practices, process flow, and resource levels change.

This paper is also related to the general area of appointment scheduling or outpatient scheduling for which is rich literature is available. Cayirli and Veral [3] provided a comprehensive review of the literature of research on appointment scheduling in outpatient services. Gupta and Denton [8] summarized key issues in designing and managing patient appointment systems for health services. This was intended to clarify the level of complexity encountered in the health care environment. They provided taxonomy of complicating factors, which made it easier to summarize the contributions of previous research in this area. Hereafter, we briefly reviewed some related work.

Bailey [1] reports one of the first studies on scheduling appointment rules focused on patient wait times. Cayirli et al [4] used simulation to evaluate patient and doctor-related performance measures of different appointment rules and to investigate the interactions among appointment system elements and patient panel characteristics. They showed that patient sequencing
has a greater effect on ambulatory care performance than the choice of an appointment rule, and that panel characteristics influence the effectiveness of appointment systems. Liu and Liu[10], [11]addressed two factors appeared in our study: late arrival of physicians and multiple copies of identical resources. They considered these issues by assuming that there is a random lateness for each physician’s arrival at the clinic, resulting in a random number of physicians (variable capacity) available at the beginning. Under this assumption, this system cannot be effectively handled with traditional queuing models and a specific queuing analysis was proposed. Klassen and Rohleder [9] compared various scheduling rules in order to minimize the waiting time of patients as well as the idle time of doctors. Walczak et al [17] used neural network to design a decision support tool for allocating hospital beds and determining required acuity of care. Schaus and Hentenryck [16] considered the daily assignment of newborn infant patients to nurses in a hospital. The objective is to balance the workload of the nurses, while satisfying a variety of constraints. They showed how to decompose the problem in two steps: an assignment of nurses to zones followed by the assignment of nurses to patients and used a constraint programming approach to solve this problem.

There are several major differences between medical planning for oncologists and existing patient appointment models. First, oncology patients have to follow specific treatment protocols which lead to complex dynamic variations for bed capacity requirement. Second, a patient assigned a chemotherapy day will come always the same day for all chemotherapy sessions over the treatment protocol. Finally, each oncology patient is assigned a referee oncologist for better follow-up and the patient should be assigned a day for chemotherapy when his referee oncologist works. These specific features of oncology cares make the medical planning for oncologists different from all existing patient appointment models.

The rest of the paper is organized as follows: Section 2 describes the chemotherapy process at an ACU. Section 3 presents assumptions of our medical planning model, provides a formal mixed integer programming formulation and proves the complexity of the problem. Section 4 proposes a three stage approach to solve the problem. Section 5 presents numerical results to assess the benefits of medical planning optimization and the performance of the three-stage approach. Section 6 is a conclusion.
2 CHEMOTHERAPY PROCESS

Cancer disease is destructive and in many cases fatal. Chemotherapy has shown success in treating the disease. Chemotherapy uses drugs to kill cancer cells and to prevent them from growing or multiplying. The type of chemotherapy treatment of a patient is determined after initial consultation with an oncologist and the assessment by the team of oncologists. Chemotherapy is given in several ways: intravenously, orally, through an injection, or topically (applied on the skin). The most common method of delivering chemotherapy is intravenously and the procedures range from 15 minutes to 7 hours or longer. These variations complicate appointment scheduling and bed allocation.

The chemotherapy is often given in cycles that include treatment sessions separated by rest periods. The length of each cycle and the number of cycles in the treatment plan are defined in a protocol according to the type of the cancer. Table 1 gives some examples of protocols with their periodicity. With Avastin, a patient receives the chemotherapy injection once every two weeks. With Cisplatin, a patient receives the chemotherapy in week 1 and week 2, rests for week 3. The treatment plan repeats over several months as needed.

<table>
<thead>
<tr>
<th>Protocol</th>
<th>Periodicity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Week1</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>

Every patient is assigned a referee oncologist who ensures the follow-up of the treatment. Hence, a patient has to come the day when his referee oncologist works. If necessary, the patient can be seen by another oncologist or an intern, but he has to come always the same day of the week.

Each chemotherapy session on a day \( D \) follows the following process. On day \( D-1 \), a series of blood tests must be performed by an outside medical analysis laboratory in order to determine whether the patient is in a good enough health condition to receive the chemotherapy. The two most important measures in these blood tests are blood counts and liver health. It is important that the liver be healthy, as it will be needed to help remove the chemotherapy drugs from the body. Blood counts are also important as they indicate whether the immune system
is healthy enough to help heal cells that may be damaged during the chemotherapy process. These balance sheets are communicated to the ACU the day before the chemotherapy by the laboratory.

On the day $D$ of chemotherapy, the treatment process is illustrated in Figure 2. Upon the arrival at the hospital, the patient checks in at the reception, goes to the waiting room and stays there until the referee physician is available. The consultation takes place in a consultation box. Depending on the results of blood test and patient's health condition, the physician then decides on the patient's ability to receive the chemotherapy. If not, the physician either postpones the treatment session for some days (one week in most case) or alters the treatment protocol. If the patient is good health condition, the physician prescribes medicines of the chemotherapy and signs the prescription which will be sent to the pharmacy to initiate the preparation of the chemotherapy drugs. The patient returns to the waiting room after the consultation. When a bed becomes available, an ACU nurse places the patient in a bed and prepares the patient for injection. Once the drug is ready and the patient has been prepared, the injection starts. After the injection of the corresponding chemotherapy drug, the patient is given appointment for his next chemotherapy session and leaves the hospital.

![Diagram of chemotherapy process]

Figure 2 : Care process of a chemotherapy session

For an oncology Ambulatory Care Unit (ACU), the major operation decisions include: (i) medical planning once a year to determine the working periods of oncologists, (ii) patient assignment which determine the day of chemotherapy for each incoming patient; (iii) ap-
pointment scheduling which determines the appointment time for the next chemotherapy ses-
sion of each patient; (iv) the production scheduling of chemotherapy drugs. This paper focuses on medical planning.

3 PROBLEM SETTING AND COMPLEXITY

This section provides a formal description of the medical planning problem in order to best balance the bed capacity requirement over time. We first present assumptions of medical planning model, then proposes a mixed integer programming formulation, and analyzes the complexity of the problem.

3.1 Assumptions

Some assumptions are needed in order to simplify the problem.

**Assumption A1.** Only the day of chemotherapy of a patient is determined and the exact appointment time is not considered.

**Assumption A2.** The preparation of the drug at the pharmacy is not considered and the chemotherapy drug is assumed ready when a bed is available for the patient and the patient is prepared for injection.

**Assumption A3.** Enough ACU nurses are available. The preparation of the patient can start when a bed becomes available and the injection starts after the preparation.

Assumption A3 is reasonable as the ACU is usually staffed according to the standard nurse to bed ratio. Assumption A1 is natural with regard to medical planning which is a long term decision made yearly or when major change occurs. Assumption A2 is a consequence of Assumption A1. Further, by better balancing the bed capacity requirement at the ACU, it is expected that the workload of the nurses will be better balanced. This, together with appropriate patient appointment scheduling that is not addressed in this paper, will allow better synchronization between the drug preparation at the pharmacy and the patient treatment.

Three major resources are considered: physicians, beds, and consultation boxes. Physicians include oncologists and interns. A limited number of consultation boxes are available for oncologists. The consultation boxes for the interns are not considered. Bed capacity is
important as the bed is needed during the injection of the chemotherapy drug and the injection
time is very long.

An ACU is open five days a week (Monday to Friday). Each day is divided into two periods
(morning and afternoon). Each period is characterized by the number of consultation boxes
available and the number of patients an oncologist can consult. There is only one intern in the
ICL-ACU who is always available and can consult patients for all oncologists under their
supervision. However the approaches proposed in this paper can be easily extended to the
general case with any number of interns. The approaches also apply if the intern can only
consult patients of some physicians.

**Assumption A4.** A time horizon of $W$ weeks is considered and the set $P$ of patients treated
over the horizon is assumed known. Each patient starts the chemotherapy at a given week
according to a given protocol with a given referee oncologist.

This is actually a very important assumption. Practically, we consider patients treated during a
period of time in the past and try to optimize the medical planning and patient assignment
with respect to this set of patients. As the medical planning will be applied for the future, the
key question is the goodness of such an approach with respect to unknown future patient flow.
This issue is addressed in a separate study [14] which shows that the medical planning derived
from historical data, together with an efficient patient assignment strategy, remains efficient
with respect to unknown future patient flow.

Under Assumption A4, each patient $i$ is also assigned to a referee oncologist and the set $P$ of
patients can be partitioned into disjoint subsets of patients, $P = \bigcup_{j \in J} P_j$, where $P_j$ denotes the
set of patients of oncologist $j$ and $J$ is the set of oncologists.

Chemotherapy sessions of a patient $i$ can be represented by a $W$-dimension binary vector $a_i$
based on the treatment protocol and the arrival date of the patient. An entry $a_{iw}$ is equal to 1 if
patient $i$ requires a chemotherapy session in week $w$, $a_{iw} = 0$ otherwise. Of course, for a
patient $i$ starting its treatment plan on week $w_0$ and ends its treatment plan on week $w_1$, $a_{iw} =
0$, for all $w < w_0$ or $w > w_1$. All other entries are determined according to the corresponding
protocol.
Table 2: Chemotherapy sessions over 8 weeks

<table>
<thead>
<tr>
<th>patient</th>
<th>start</th>
<th>end</th>
<th>protocol</th>
<th>week1</th>
<th>week2</th>
<th>week3</th>
<th>week4</th>
<th>week5</th>
<th>week6</th>
<th>week7</th>
<th>week8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>4</td>
<td>Avastin</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>7</td>
<td>Avastin</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>16</td>
<td>Cisplatin</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>8</td>
<td>Vinorelbin</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

3.2 Mixed integer programming model

Under Assumptions A1-A4, the medical planning problem is characterized mainly by a set of oncologists, interns, a planning horizon of $W$ weeks, a set of patients with for each patients a treatment protocol and a referee oncologist. Other relevant data include: consultation capacity, beds, injection times and consultation boxes available that will be described later. The objective is to best balance the bed capacity requirement over the planning horizon.

Four sets of decisions need to be made. The first one is the so-called medical planning which indicates for each oncologist the time periods he consults. The medical planning is denoted by binary variables $y_{jt}$ with

$$y_{jt} = \begin{cases} 1, & \text{if oncologist } j \text{ consults in period } t. \\ 0, & \text{otherwise} \end{cases}$$

for all oncologists $j \in J$ and for all time periods $t \in T$ where $T$ is the set of the ten time periods in a week. The same medical planning is applied for different weeks over the planning horizon. This is natural as the oncology protocols require each patient to come the same weekday in different weeks for different treatment sessions.

The second set of decisions concerns the patient assignment which indicates which time period of the week a patient comes for the chemotherapy. Patient assignment is denoted by binary variables $x_{it}$ with

$$x_{it} = \begin{cases} 1, & \text{if patient } i \text{ have chemotherapy in period } t. \\ 0, & \text{otherwise} \end{cases}$$

for all patients $i \in P$ and for all $t \in T$. In this paper, we do not postpone the start of the treatment plan decided by oncologists but select the day patient comes for chemotherapy.

According to the treatment protocols, each patient $i$ comes in time period $t$ of week $w$ if $a_{iw} = 1$ and $x_{it} = 1$. Note that, due to the length of chemotherapy, a chemotherapy session started in
the morning can finish in the afternoon of the same day. We do not consider chemotherapy sessions that last for more than one day. Such treatments are not performed in the ACU.

The third set of decisions concerns patients consulted by interns. It is denoted by non-negative integer variables

$$z_{jwt}$$

denoting the number of patients of oncologist \( j \) consulted by intern in period \( t \) of the week \( w \).

The last set of decisions concerns the extra consultation capacity needed for each period. It is denoted by non-negative integer variable

$$e_{jwt}$$

denoting the number of patients of oncologist \( j \) consulted in period \( t \) of the week \( w \) with extra consultation capacity.

The decisions should be made under the following conditions. First, the number of oncologists that consult in period \( t \) should not exceed the number \( B_t \) of consulting boxes available, i.e.

$$\sum_{j \in J} y_{jt} \leq B_t, \ \forall t \in T$$

Each patient should be assigned a time period, i.e.

$$\sum_{i \in P} x_{it} = 1, \ \forall i \in P$$

The number of patients that come a period in any week should not exceed the consultation capacity of the oncologists, the interns and the extra consultation capacity. More specifically,

$$\sum_{i \in P_j} a_{iw} x_{it} \leq N_t y_{jt} + z_{jwt} + e_{jwt}, \ \forall j \in J, t \in T, w \in W$$

$$\sum_{j \in J} z_{jwt} \leq N'_t, \ \forall t \in T, w \in W$$

where \( N_t \) is the maximum number of patients an oncologist can consult in period \( t \), \( N'_t \) is the maximal number of patients the interns can consult. Note that, for simplicity, the same consultation capacity is assumed for all oncologists. Extension to different consultation capacity is trivial.
In order to ensure the possibility of each patient to be seen by the referee oncologist, it is assumed that each patient should be assigned a time period where the referee oncologist consults. This is ensured jointly by the above consultation capacity constraints and the following constraints that forbid the delegation of patients of oncologist \( j \) and the use of extra consultation capacity if he does not consult in period \( t \).

\[
z_{jwt} + e_{jwt} \leq \left| P_{j} \right| y_{jw}, \quad \forall j \in J, t \in T, w \in W
\]

This constraint can also be replaced by the following equivalent constraints:

\[
x_{iwt} \leq y_{jw}, \quad \forall j \in J, i \in P_{j}, t \in T
\]

Another constraint is the bed capacity of the afternoon periods which is ensured jointly by two constraint sets. The first forbids a lengthy chemotherapy that cannot start and finish in the afternoon. More specifically,

\[
x_{iwt} = 0, \quad \forall i \in P / d_{i} \geq L_{t}, t \in PM
\]

where \( d_{i} \) is the time patient \( i \) spent in a bed for a treatment session including injection time and patient preparation time, \( L_{t} \) is the ACU opening time during the afternoon, \( PM \) is the set of afternoon time periods. A second constraint restricts the total bed capacity requirement of chemotherapy sessions starting in the afternoon. More specifically,

\[
\sum_{i \in P} a_{iw} d_{i} x_{iwt} \leq Q_{w}, \quad \forall w \in W, t \in PM
\]

where \( Q_{w} \) is the maximum bed capacity of the afternoon, i.e. \( Q_{w} = l L_{t} \) where \( l \) is the number of beds available in the ACU.

In this paper, \( d_{i} \) is called injection time for simplicity. Further, it is assumed to be a positive integer. Practically, all injection times are expressed as integer multiples of some base time unit \( \Delta \). In our numerical experiments, \( \Delta = 15 \) minutes.

The goal is to best balance the bed capacity requirement during different weeks and to use as less as possible the extra consultation capacity. More specifically,

\[
MIN \sum_{w \in W} \left( \bar{C}_{w} - C_{w} \right) + M \sum_{j \in J} \sum_{w \in W} \sum_{t \in T} e_{jwt}
\]

where \( M \) is a positive integer serving as weighting factor for extra consultation capacity, \( \bar{C}_{w} \) and \( C_{w} \) denote respectively the maximum and minimum bed capacity requirements of week \( w \) with
\[
\sum_{i \in P} a_{iw} d_i (x_{it} + x_{it+1}) \leq \widetilde{C}_w, \quad \forall w \in W, t \in AM
\]
\[
\sum_{i \in P} a_{iw} d_i (x_{it} + x_{it+1}) \geq C_w, \quad \forall w \in W, t \in AM
\]

where \( AM \) is the set of morning time periods and \((x_{it} + x_{it+1})\) indicates whether patient \( i \) is treated in morning period \( t \) of the day.

The mathematical model of the medical planning problem described above is a mixed integer programming problem summarized as follows:

\[
\text{MIP:} \quad J^* = \text{MIN} \sum_{w \in W} (\widetilde{C}_w - C_w) + M \sum_{j \in J} \sum_{w \in W} \sum_{t \in T} e_{jtw}
\]

Subject to:

\[
\sum_{t \in T} x_{it} = 1, \quad \forall i \in P \tag{2}
\]
\[
\sum_{j \in J} y_{jt} \leq B_j, \quad \forall t \in T \tag{3}
\]
\[
\sum_{i \in P} a_{iw} x_{it} \leq N_j y_{jt} + z_{jtw} + e_{jtw}, \quad \forall j \in J, t \in T, w \in W \tag{4}
\]
\[
\sum_{j \in J} z_{jtw} \leq N'_j, \quad \forall t \in T, w \in W \tag{5}
\]
\[
z_{jtw} + e_{jtw} \leq |P_j| y_{jt}, \quad \forall j \in J, t \in T, w \in W \tag{6}
\]
\[
\sum_{i \in P} a_{iw} d_i x_{it} \leq Q_t, \quad \forall w \in W, t \in PM \tag{7}
\]
\[
\sum_{i \in P} a_{iw} d_i (x_{it} + x_{it+1}) \leq \widetilde{C}_w, \quad \forall w \in W, t \in AM \tag{8}
\]
\[
\sum_{i \in P} a_{iw} d_i (x_{it} + x_{it+1}) \geq C_w, \quad \forall w \in W, t \in AM \tag{9}
\]
\[
x_{it} = 0, \quad \forall i \in P / d_i \geq L_t, t \in PM \tag{10}
\]
\[
x_{it}, y_{jt}, e_{jtw}, z_{jtw} \geq 0 \tag{11}
\]

Compared to our previous work [13], the above MIP formulation aims at smoothing the bed capacity requirement of each week instead of smoothing the bed capacity requirement over the whole planning horizon. Given the patient arrivals and patient treatment plan characterized by \( a_{iw} \), the total weekly bed capacity requirements are given by \( \sum_{i \in P} a_{iw} d_i \). As a result, the new MIP formulation seems more reasonable and takes into account given
variations of week capacity requirement. Another new ingredient of the new MIP formulation is the relaxation of the consultation capacity constraint and hence, the new MIP model has at least one solution.

3.3 Problem complexity analysis

This subsection introduces the MIP model complexity analysis.

**Theorem 1:** The medical planning problem is NP-complete.

**Proof:** The proof is done by reducing polynomially the BIN-PACKING problem to a special case of the medical planning problem. BIN-PACKING can be defined as follows: given a finite set of items $U$, a size $s(u) \in \mathbb{Z}^+$ for each $u \in U$, a positive integer bin capacity $G$, and a positive integer $K$, is there a partition of $U$ into disjoint sets $U_1, U_2, \ldots, U_K$ such that the sum of the sizes of the items in each $U_i$ is $G$ or less? Consider also the PARTITION problem defines as follows: given a finite set $U$, a size $s(u) \in \mathbb{Z}^+$ for each $u \in U$, is there a subset $U' \subseteq U$ such that $\sum_{u \in U'} s(u) = \sum_{u \in U \setminus U'} s(u)$? PARTITION is known to be NP-complete ([7]).

First, BIN-PACKING with $G = \sum_{u \in U'} s(u)/K$ is also NP-complete for each fixed $K \geq 2$ as any PARTITION instance can be polynomially transformed into an equivalent instance of BIN-PACKING for any fixed $K \geq 2$ in which the set $U'$ of items contains $U$ plus $K-2$ items of size $G$ and $G = \sum_{u \in U'} s(u)/2 = \sum_{u \in U'} s(u)/K$.

For each instance of BIN-PACKING with $K = 5$ and $G = \sum_{u \in U'} s(u)/K$, we associate an instance of the medical planning problem defined as follows: there are $|U|$ patients with injection times $d_u = s(u)$. A horizon of one week $W=1$ is considered. Each weekday corresponds to a bin, i.e. $K=5$. There is one oncologist with consultation capacity $N_t = |U|$, a single consultation box, $B_t=1$ and afternoon bed capacity $Q_t = \sum_{i \in P} d_i$. The question is whether there is a medical planning solution such that $J^* = 0$, i.e., $\bar{C}_w = C_w$ and the bed capacity requirement is the same over the week.
If BIN-PACKING has a solution, then $\sum_{u \in U} s(u) = G$ for each bin $U_i$. Assign all patients corresponding to bin $U_i$ to the day $j$ leads to a medical planning solution with $\bar{C}_w = C_w$ and $J^* = 0$. The reverse is also true. Q.E.D.

Given the mathematical formulation, a straightforward method for medical planning is to solve directly the mixed integer programming model MIP using standard optimization engines. Unfortunately this turns out to be highly time consuming. It takes CPLEX solver over 10h to provide an acceptable solution for problem instances related to our case study. This confirms the complexity of the medical planning problem. The computation time of over 10 hours is too long for real life application in oncology ACUs and efficient optimization methods are needed.

4 A THREE-STAGE APPROACH FOR MEDICAL PLANNING

This section proposes a three-stage approach. It relies on our observation that the MIP model can be quickly solved if the medical planning is given. The first stage determines the medical planning for morning time periods. The second stage determines medical planning for afternoon periods by fixing the morning medical planning. The resulting medical planning is then improved with local optimization in the third stage. In order to limit the computational effort, the two first stages are based on a subset $W' \subset W$ of weeks of the highest weekly bed capacity requirement, i.e. the highest $\sum_{i \in P} a_{w,t} d_i$.

4.1 Morning medical planning

The first stage of our approach determines the medical planning for the morning periods $t \in AM$. As only morning periods are considered, it is not possible to assign all patients and constraints (2) of MIP model on the assignment of all patients are relaxed as follows:

$$\sum_{t \in T} y_{it} \leq 1, \quad \forall i \in P$$  \hspace{1cm} (12)

Extra consultation capacity is not allowed. The objective of this stage is to insert as many patients as possible and to best balance the daily bedload. More specifically, the first stage solves the following mixed integer programming problem:
In the above criterion (13), \( M' \) is a positive integer constant corresponding to a penalty factor in order to assign as many patients as possible.

### 4.2 Afternoon medical planning

The morning medical planning being given, the second stage extends the morning medical planning formulation to schedule afternoon time slots. More specifically, it solves the following mixed integer programming problem:

\[
\text{MIP}^{\text{PM}}: \quad \text{MIN } \sum_{w \in W} \left( \mathcal{C}_w - \mathcal{C}_w \right) + M' \cdot \sum_{i \in P} \left( 1 - \sum_{t \in AM} x_{it} \right)
\]

subject to constraints (12), (3)-(6) and (11) with \( e_{wt} = 0 \), \( T \) replaced by the set \( AM \) of morning periods and \( W \) replaced by the set \( W' \) of selected weeks and

\[
\sum_{i \in P} a_{iw} d_{x_{it}} \leq \mathcal{C}_w, \quad \forall w \in W', t \in AM
\]

\[
\sum_{i \in P} a_{iw} d_{x_{it}} \geq \mathcal{C}_w, \quad \forall w \in W', t \in AM
\]

Note that the afternoon medical planning could also be determined by using \( \text{MIP} \) model with morning medical planning being given. Numerical experiments show that the two approaches leads to similar results. However, the \( \text{MIP}^{\text{PM}} \) is less time consuming as continuous variables \( e_{jw} \) are not considered.

### 4.3 Local optimization of the medical planning

Starting from the complete medical planning determining in stages 1 and 2, the third stage iteratively improves the medical planning by local search and some approximation scheme for evaluation of local solutions.

A medical planning \( \{ y_{jt} \ \forall t \in T \} \) can be equivalently represented by a subset of oncologists assigned to each time period. Each time period \( t \) has \( B_t \) consultation boxes and hence \( B_t \) time slots for consultation. An unused time slot is assumed to be assigned to a fictitious oncologist.
The neighborhood of a given medical planning contains the set of all medical planning obtained by one of the two local moves: (i) interchange an oncologist $i$ in time slot $t_i$ with an oncologist $j$ in another time slot $t_j$ with obvious convention that $t_i$ and $t_j$ belongs to different time periods; (ii) replacing an oncologist in a time slot $t_i$ by a real oncologist $j$ with the convention that oncologist $j$ is not given another time slot in the same time period. Move (ii) changes the number of consultation boxes to each oncologist while move (i) modifies the schedule.

The neighborhood structure is illustrated by Figure 3. The medical planning is represented by a matrix and an entry $(j, t_i)$ with a black token indicates that oncologist $j_i$ works in period $t_i$. The two dark arrows illustrate a type (i) move and the grey arrow a type (ii) move.

![Figure 3: Locals moves](image)

The starting point of the local search is the medical planning $y^0$ determined in stages 1-2. Its quality is evaluated by solving the MIP model by fixing the medical planning. Let $MIP(y^0)$ be the corresponding criterion value.

Starting from $y^0$, the local search algorithm determines all neighbor solutions $y$ of $y^0$. Let $NH(y^0)$ be the set of neighbor solutions of $y^0$. The neighborhood is large with about 300 neighbors in our numerical experiments and solving the MIP model exactly for each neighbor solution $y$ in order to identify the best neighbor solution is very time consuming. Instead, linear relaxation is used to identify the most promising neighbor.

More specifically, for each neighbor solution $y$, we first check whether the linear relaxation system defined by (2)-(11) and

$$\sum_{w \in W} (C_w - C_w) + M \sum_{j \in J} \sum_{w \in W} \sum_{t \in T} e_{jwt} \leq MIP(y^0) - 1$$

(17)

has a solution. If the system does not has a solution, then the medical planning is not strictly better than $MIP(y^0)$ as $MIP(y)$ is an integer for any medical planning $y$ due to the assumptions of
integer injection times and integer weight factor $M$. Otherwise, the linear relaxation of $MIP$ model with given medical planning $y$ is solved. Let $LB_{MIP}(y)$ be the corresponding criterion value which is a lower bound of the exact criterion of the medical planning $y$.

The neighbor solution $y^j$ with the smallest lower bound $LB_{MIP}(y)$ is selected. $MIP$ model is then solved exactly for medical planning $y^j$ to obtain the exact criterion value $MIP(y^j)$. If $MIP(y^j) < MIP(y^0)$, the local search continues with $y^j$. Otherwise, the local search stops.

The overall optimization method can be summarized as follows:

**MIP-based physician schedule heuristic:**

Step 1: Select the $K$ busiest weeks $W'$;

Step 2: Solve $MIP^{AM}$ to determine the morning medical planning;

Step 3: Solve $MIP^{PM}$ to determine the afternoon medical planning. Let $y^0$ be the resulting complete medical planning;

Step 4: Solve $MIP$ with the complete planning horizon for medical planning $y^0$. Let $MIP(y^0)$ be the resulting criterion value;

Step 5: Let $LB^* = \infty$;

Step 6: For each medical planning $y$ obtained by any of the two local moves,

5.1: If the linear relaxation system defined by (2)-(11) and (17) does not have a solution, then go to next medical planning;

5.2: Solve the linear relaxation of $MIP$ model for medical planning $y$. Let $LB_{MIP}(y)$ the criterion value;

5.3: If $LB^* > LB_{MIP}(y)$, then $LB^* = LB_{MIP}(y)$ and $y^j = y$.

Step 7: If $LB^* = \infty$, stop; otherwise, solve $MIP$ for medical planning $y^j$.

Step 8: If $MIP(y^j) < MIP(y^0)$, set $y^0 := y^j$ and go to Step 5. Otherwise, stop.

In our numerical experiments, $K = 4$ busiest weeks are used in Stages 1 and 2. Further, a stopping criterion of a CPU time of 5 minutes and a gap of 2% is used in $MIP^{AM}$ and $MIP^{PM}$. The
evaluation of each medical planning \( MIP(y) \) is implemented with a stopping criterion of a CPU time of 1 minute.

5 NUMERICAL RESULTS

This section presents numerical results based on data collected from the field to evaluate the effectiveness of the three-stage approach with respect to current practice.

5.1 Experimental setting

The numerical experiments of this paper are based on field data collected from the ambulatory care unit of ICL for the year 2008.

The ACU has 10 oncologists and one intern. It has 18 beds for oncology patients. With a maximum possible utilization of 9h per bed per day, the maximum daily bed capacity for 18 beds is 162 hours.

The ACU is open Monday to Friday and with 10 consultation periods per week corresponding to morning periods from 8h30 to 12h and afternoon periods from 13h30 to 15h30. There is no consultation on Friday afternoon. Chemotherapy sessions longer than 4 hours are assigned to morning periods, i.e. \( x_i = 0, \forall i \in P/d_i \geq L_t = 4h, t \in PM \). The maximum bed capacity requirement of chemotherapy sessions planned for each afternoon is limited to \( Q_t = 18 L_t = 72h \).

There are 3 consultation boxes in the morning and 2 in the afternoon. One consultation box is dedicated to the intern. As a result, the 10 oncologists share the 14 consultation slots. A consultation takes about 15 to 30 minutes depending only on the physician skills. We assume that a physician can make until 14 consultations in the morning and 8 in the afternoon, i.e. \( N_t = N_t' = 14 \), for all morning period \( t \), \( N_t = N_t' = 8 \), for all afternoon period \( t \) except Friday afternoon, \( N_t = N_t' = 0 \), for the Friday afternoon period \( t \).

The penalty factor is defined with the value \( M = 250 \) in order to avoid using extra consultation capacity whenever it is possible. The penalty factor \( M' = 250 \) is also used in Stage 1 of our approach.
The numerical experiments are conducted with data of the first two trimesters of year 2008. The \textit{MIP} model is solved for each of these trimesters with a time horizon of $W = 12$ weeks. The ACU delivered 2178 chemotherapy sessions for over 750 patients in the first trimester and 2084 chemotherapy sessions for 709 patients during the second trimester. Unfortunately, data collection turned out to be difficult and some data are untraceable. The injection time $d_i$ for about 5% patients are missing. In the numerical experiments, missing injection times are generated by uniform random sampling from all known injections times. Five different problem instances for each trimester are generated and are denoted as $i_0, i_1, i_2, i_3,$ and $i_4$ for instances of trimester $i$ with $i = 1, 2$.

5.2 Comparison of different medical planning strategies

This subsection compares three medical planning strategies: the current planning, the \textit{MIP} strategy and the 3-stage approach. The current planning is the actual medical planning and patient assignment used by the ACU during the first two trimesters of year 2008. It is available from the field data. The criterion value of the current planning for each problem instance can be easily estimated from the data of the problem instance and the \textit{MIP} model. Note that the current planning strategy places each new patient in the first available time slot according to the medical planning. As a result, the medical planning and patient assignment are determined without taking into account impact on the bed capacity requirement.

The \textit{MIP} strategy consists in solving directly the \textit{MIP} model by means of a Branch and Bound algorithm with the commercial optimization engine ILOG CPLEX Concert 11 API for C++ running on a 2.4 GHz Intel Core processor. We limit the computation time to 10 hours in order to be sure of having a good enough feasible solution. The computation time is very long partly because of much symmetry of the problem and the large number of patients. For example, patients with the same protocol and the same referee oncologist and starting treatment in the same week are completely interchangeable.

The three-stage approach is implemented by using CPLEX to solve all optimization problems including $MIP(y), LBMIP(y), MIP^{AM}, MIP^{PM}$, and the existence of a solution of linear relaxation system defined by (2)-(11) and (17).

We first compare the bed capacity requirements of the current planning and the \textit{MIP} strategy in order to show the benefit of optimization. Figure 4 illustrates the daily bed capacity
requirements, also called **bedload** in this section, of the two strategies for one problem instance of the first trimester of year 2008 (problem instance 1_4 in Table 3). The current planning strategy leads to large fluctuations for bed capacity requirements (see for example the last week of the trimester), the peak bed capacity requirement is about 160h and the lowest bed capacity requirement is less than 40h. Further the bed capacity requirement frequently approaches the theoretical maximal daily capacity of 162h. This is the root cause of the bed crisis observed in practice. For days of high bed capacity requirement, the ACU faces stressed medical staff, unsatisfied patients as the high bed capacity requirement is expected to result in long waiting times, and heavy workload of the pharmacy to prepare drugs. On the other side, for days of light bed capacity requirement, medical staff and beds are most often left unused.

Compared with the current planning, the **MIP** strategy is able to better balance the daily bed capacity requirement. Further, extra consultation capacity is used in the current planning while it is not used in the **MIP** strategy. Unfortunately the computation time of 10 hours is too long for a real life application.

![Figure 4: MIP strategy vs current planning.](image)

Table 3 compares the bedload balancing, extra consultation capacity and the criterion value (1) of the current planning, the **MIP** strategy and the three-stage approach. The first column gives the problem instance where 1_i (resp. 2_i) corresponds a problem instance of the first (resp. second) trimester. Columns Min and Max represent the minimum and the maximum daily bed capacity requirement (in hour) over the whole planning horizon of one trimester (W = 12 weeks). Column Extra gives the extra consultation capacity used. Column **Obj** gives the criterion value of the corresponding strategy. Column **CPU** gives the CPU time (in seconds).
From Table 3, for all problem instances, the 3-stage approach gives the best criterion value in a reasonable computation time of less than 10 minutes and does not use any extra consultation capacity. Compared with the current planning, MIP strategy balances much better the bed capacity requirement with less extra consultation capacity and hence smaller criterion value but requires very long computation time.

Apart from the gain in extra consultation capacity, let us evaluate the gain in peak daily bed capacity requirement, i.e. the columns Max. Compared with the current planning, for the 10 problem instances, the 3-stage approach reduces the peak daily bed requirement by 20h to 45h with an average gain of 30h. The MIP approach reduces the peak daily bed requirement by 19h to 46h with an average gain of 30.5h. The above gains should be compared with the maximum theoretical bed capacity of 162h for 18 beds with a maximum usage of 9h each. The bed capacity requirement balancing allows the partner hospital ICL to avoid the bed crisis and to provide its medical staff with smoothed workload. It also allows ICL to accept more patients.

Note that it seems that the MIP approach sometimes leads to lower peak bed capacity requirement. However, detailed bed capacity requirements show that the 3-stage approach actually better balances bed capacity requirement in each week and hence leads to better criterion value.

Table 3: Bedload for 1st and 2nd trimesters of year 2008

<table>
<thead>
<tr>
<th>Instance</th>
<th>Current planning</th>
<th>MIP</th>
<th>3-stage approach</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Max</td>
<td>Obj</td>
</tr>
<tr>
<td>1_0</td>
<td>38,5</td>
<td>162,2</td>
<td>835,5</td>
</tr>
<tr>
<td>1_1</td>
<td>32,5</td>
<td>159,2</td>
<td>801</td>
</tr>
<tr>
<td>1_2</td>
<td>32,5</td>
<td>167,75</td>
<td>869,25</td>
</tr>
<tr>
<td>1_3</td>
<td>31,25</td>
<td>155,5</td>
<td>791</td>
</tr>
<tr>
<td>1_4</td>
<td>67,8</td>
<td>162,3</td>
<td>1225</td>
</tr>
<tr>
<td>2_0</td>
<td>41,75</td>
<td>146</td>
<td>698,7</td>
</tr>
<tr>
<td>2_1</td>
<td>42,25</td>
<td>151</td>
<td>726,5</td>
</tr>
<tr>
<td>2_2</td>
<td>43,25</td>
<td>142</td>
<td>719</td>
</tr>
<tr>
<td>2_3</td>
<td>48,75</td>
<td>152,5</td>
<td>693,7</td>
</tr>
<tr>
<td>2_4</td>
<td>42,25</td>
<td>138,5</td>
<td>696,2</td>
</tr>
</tbody>
</table>

Table 4 gives the current medical planning for the first trimester 2008 for problem instance 1_4. There are three consultation boxes available for the morning periods AM1 to AM3 and two consultation boxes, PM1 and PM2, available for the afternoon periods. For each box and each period, we give the ID of the oncologist scheduled. In this medical planning, a
consultation box is sometime shared by several physicians in the same time period. Such organisation causes conflicts between oncologists. Consultation times fluctuate from 15 to 30 minutes. Often, the first oncologist cannot finish his planned consultations on time. As a result, the second oncologist sharing the same consultation box has to wait and his patients also. This results in higher patients waiting time.

Table 5 gives the average number of patients seen by each oncologist including those seen by the intern and their induced bedload during the first trimester 2008 in the current planning. For each oncologist, the table gives the average number of patients consulted in each weekday with shadowed cells corresponding to consultations within the medical planning. Consultations outside the medical planning are due to assignment of new patients to the first available time slot of their referee oncologist without taking into account resulting consultation capacity requirement. As a result, the consultation capacity is often exceeded and oncologists have to consult outside their medical planning to meet the demands.

<table>
<thead>
<tr>
<th>Box</th>
<th>Mon</th>
<th>Tue</th>
<th>Wed</th>
<th>Thu</th>
<th>Fri</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM1</td>
<td>0</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>AM2</td>
<td>1</td>
<td>1</td>
<td>1/7</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>AM3</td>
<td>8</td>
<td>5</td>
<td>intern</td>
<td>9</td>
<td>intern</td>
</tr>
<tr>
<td>PM1</td>
<td>2/9</td>
<td>6/intern</td>
<td>8</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>PM2</td>
<td>3</td>
<td>5</td>
<td>intern</td>
<td>intern</td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Average number of patients during the 1st trimester 2008 in the current planning

<table>
<thead>
<tr>
<th>Oncologist</th>
<th>Mon</th>
<th>Tue</th>
<th>Wed</th>
<th>Thu</th>
<th>Fri</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>16,8</td>
<td>2,5</td>
<td>1,4</td>
<td>2,1</td>
<td>17,3</td>
</tr>
<tr>
<td>1</td>
<td>11,9</td>
<td>9,1</td>
<td>10,7</td>
<td>3,2</td>
<td>7,5</td>
</tr>
<tr>
<td>2</td>
<td>3,5</td>
<td>0,1</td>
<td>0,5</td>
<td>0,2</td>
<td>9</td>
</tr>
<tr>
<td>3</td>
<td>6,2</td>
<td>0,1</td>
<td>14,3</td>
<td>11,5</td>
<td>1,3</td>
</tr>
<tr>
<td>4</td>
<td>0,9</td>
<td>17,8</td>
<td>0,5</td>
<td>18,8</td>
<td>0,6</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>10,5</td>
<td>0,7</td>
<td>0,6</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>1</td>
<td>0,2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0,3</td>
<td>4,3</td>
<td>6,5</td>
<td>0,3</td>
</tr>
<tr>
<td>8</td>
<td>7,9</td>
<td>0,5</td>
<td>5,7</td>
<td>0,4</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>0,4</td>
<td>0,4</td>
<td>0</td>
<td>2,6</td>
<td>0</td>
</tr>
<tr>
<td>Total nb patient/day</td>
<td>47,6</td>
<td>42,3</td>
<td>38,3</td>
<td>45,9</td>
<td>36</td>
</tr>
<tr>
<td>Total Bedload</td>
<td>111,36</td>
<td>108,42</td>
<td>101,41</td>
<td>130,4</td>
<td>100,6</td>
</tr>
</tbody>
</table>
Table 6 gives a medical planning generated by the three-stage approach for problem instance 1_4 of the 1st trimester 2008. For each box and each period, we give the ID of the oncologist scheduled and the average number of patients in the consultation period. The last two rows give for each day the average number of patients and the average bedload. From this table, the bedload is not proportional to the number of patients. For example, Friday has the least number of patients but the second largest bedload. Tuesday has by far the largest number of patients but the second lowest bedload. As Friday afternoon is closed for consultation, the three-stage approach assign to to Friday patients with lengthy chemotherapy sessions.

Let us compare the current planning and the three-stage planning. Sharing of consultation box in the same time period is allowed in the current planning but forbidden in the three-stage planning. The intern is not always used in the current planning while it is in the three-stage planning. Consultations outside medical planning are allowed in the current planning and forbidden in the three-stage planning. Of course, some of the outside medical planning consultations are due to medical reasons that are not considered in the three-stage planning. Finally, the 3-stage approach smooths the average daily bedload while balancing the average of patients per day.

Table 6: Medical planning for 1st trimester 2008(1_4) of the 3-stages approach

<table>
<thead>
<tr>
<th>Box</th>
<th>Day</th>
<th>Mon</th>
<th>Tue</th>
<th>Wed</th>
<th>The</th>
<th>Fri</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM1</td>
<td>Oncologist</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Nb Patients</td>
<td>14</td>
<td>12,82</td>
<td>14</td>
<td>14</td>
<td>13,2</td>
</tr>
<tr>
<td>AM2</td>
<td>Oncologist</td>
<td>8</td>
<td>4</td>
<td>7</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Nb Patients</td>
<td>13,42</td>
<td>14</td>
<td>11,5</td>
<td>14</td>
<td>10,5</td>
</tr>
<tr>
<td>AM3</td>
<td>Oncologist</td>
<td>intern</td>
<td>intern</td>
<td>intern</td>
<td>intern</td>
<td>intern</td>
</tr>
<tr>
<td></td>
<td>Nb Patients</td>
<td>5,5</td>
<td>9,42</td>
<td>12,2</td>
<td>10,6</td>
<td>9,2</td>
</tr>
<tr>
<td>PM1</td>
<td>Oncologist</td>
<td>4</td>
<td>3</td>
<td>6</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Nb Patients</td>
<td>8,42</td>
<td>8,42</td>
<td>1</td>
<td>3,2</td>
<td></td>
</tr>
<tr>
<td>PM2</td>
<td>Oncologist</td>
<td>intern</td>
<td>intern</td>
<td>intern</td>
<td>intern</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Nb Patients</td>
<td>7,2</td>
<td>3,5</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Total nb patient/day</td>
<td>48,54</td>
<td>48,16</td>
<td>38,7</td>
<td>41,8</td>
<td>32,9</td>
<td></td>
</tr>
<tr>
<td>Total Bedload</td>
<td>109,79</td>
<td>110,5</td>
<td>109,77</td>
<td>111,96</td>
<td>110,17</td>
<td></td>
</tr>
</tbody>
</table>
6 CONCLUSION

This paper considered the medical planning problem of oncology ambulatory cares in order to best balance the bed capacity requirement. We proposed a formal innovative mixed integer programming (MIP) model. The MIP model captures main features of oncology chemotherapy such as treatment protocols and patient-oncologist relationships. Numerical experiments with data collected from the field showed the ability of MIP-based approaches to significantly smooth the bed capacity requirements over time. For the 10 problem instances considered, we were able to reduce about 20 to 45h of the peak bed capacity requirement compared to the maximum ACU bed capacity of 162h.

Future research can be pursued in several directions. One immediate extension of this work is to investigate the benefit of postponing the arrival of new patients for more than one week. A second important research direction is the assignment of incoming patients to different periods of the week. The current work relies on Assumption A4 which assumes full knowledge of all patients and is hence not applicable for patient assignment that is done once a week. Another important research direction is the appointment scheduling for all patients having their chemotherapy sessions the same day. More detailed information is needed and relations with the drug preparation should be taken into account. The simulation of the patient flows together with operations management strategies is another important issue. It requires faithful modelling of patient flows and patient treatment plan changes. Another relevant issue is the medical planning and patient assignment for special weeks of 4 days. The drug preparation scheduling in the pharmacy is another relevant issue. Finally, the impact of the reorganization of the ambulatory care units on other cares units is a difficult issue of research.

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REFERENCES


