Patients assignment for an Oncology Outpatient Unit

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Abstract—This paper considers an oncology ambulatory care unit (ACU) in a cancer center. Recently, the ACU we consider in this paper is facing increasing demand for oncologic care and increasingly sophisticated care technologies. The ACU is often over-capacitated leading to high overtime and long patient waiting times. This paper proposes a method for optimizing patients’ assignment in order to best smooth the bed utilization, also called bedload, while taking into account constraints such as the care protocols. A simulation model is then proposed to assess the effectiveness of the proposed patient assignment policy. Numerical experiments based data collected from the field show the capability of the proposed method to smooth the bedload.

I. INTRODUCTION

HEALTHCARE industry has experienced enormous pressures during the past decades because of the intense competition for patients among healthcare providers, increasing demand for healthcare and limited budget for healthcare. The quality of patient care has become a vital concern. Therefore, it is very important to continually improve the health care delivery and reduce the cost.

This research is motivated by our collaboration with the « Institut de Cancérologie de la Loire » (Loire Cancer Institute), a.k.a. ICL. It is a public comprehensive cancer center providing Oncology, Hematology, Pediatric oncology and Radiotherapy services. ICL is also the linchpin of the Oncolooire network, which is the care network for cancer patients and aims to ensure that all cancer patients in Loire 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; and serves to train medical students and interns from many disciplines. Also, numerous patients participate in clinical trials. All these make the center resource planning complicated.

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 then asked to assess the bed requirement of the ACU unit. However, as it will be shown in our previous study [1], field data show that the daily bed capacity requirement 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. In [1], we considered the working period planning of oncologists of the ICL ambulatory care unit which provides chemotherapy treatment for outpatients in oncology. The problem consists in determining the working periods of the oncologists and the day of treatment of each patient in order to best balance the bed capacity requirements.

This paper pursues the research started in [1] and addresses the problem of assignment of new incoming patients. Our goal is to find a schedule for new incoming patients, while balancing the daily bed capacity requirement, under various constraints such as the total bed capacity, the consultation capacity of oncologists and patients care protocols.

The chemotherapy treatment protocol for a patient is often determined after initial consultation with an oncologist and the assessment by the team of oncologists. The chemotherapy is often given in cycles that include treatment periods 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 kind 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, week 2 and rests for week 3. The treatment plan repeats over several months as needed.

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

<table>
<thead>
<tr>
<th>Example of Protocols of Chemotherapy</th>
<th>Periodicity</th>
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<tbody>
<tr>
<td>Chemotherapy protocols</td>
<td>Week 1</td>
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<tr>
<td>Avastin</td>
<td>1</td>
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<tr>
<td>Cisplatin</td>
<td>1</td>
</tr>
<tr>
<td>Rituximab</td>
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<td>Vinorelbin</td>
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from 15 minutes to 7 hours or longer. This large variability complicates the patient assignment schedule and beds allocation.

In oncology care, every patient is associated with a referee physician who ensures the follow-up of the care. Hence, a patient has to come the day when his referee physician works. If necessary, the patient can be seen by another physician or an intern, but he has to come the same day of the week.

Operation management of outpatient care units has been addressed in the literature. Mazier and Xie [2] proposed a scheduling method for physician working period based on an integer linear program model. Santibañez et al [3] used simulation to analyze the impact of simultaneous operations, scheduling, and resource allocation on patient wait time, clinic overtime, and resource utilization at British Columbia Cancer Agency’s ambulatory care unit. Cayirli et al [4] used simulation and classification scheme of “new return patient” to analyze the effects of sequencing policy at the time of booking an appointment in outpatient unit.

The rest of the paper is organized as follows: Section 2 describes the chemotherapy process at the ACU. For completeness, Section 3 describes briefly the three-stage heuristic presented in [1] for working periods planning of oncologists. Section 4 presents and discusses the patient assignment strategy. Section 5 presents simulation model for evaluation of the patient assignment strategy. Section 6 presents numerical results of the simulation and compares the proposed patient assignment strategy with the one currently used in practice.

II. CHEMOTHERAPY PROCESS

The appointment time of patients for chemotherapy is determined according to the schedule of physicians and treatment protocols of patients. Each patient makes blood analysis one day before each chemotherapy, in order to allow his referee physician to check the effects of the treatment and the way the patient’s metabolism tolerates the toxicity of the drug. These balance sheets are communicated to the ACU the day before by the External laboratories. The physician then decides on the patient’s ability to receive the chemotherapy. In the case of a negative test, the treatment is postponed for some days, one week in most case. The physician can also determine to alter the treatment protocol.

Fig. 1 describes the chemotherapy process of patients at the ACU during a cycle of protocol on the day of chemotherapy. Upon the arrival at the hospital, the patient checks-in at the reception, goes to the waiting room and stays there until his referee physician comes to look for him. The consultation takes place in a consultation Box. This consultation can last between 15 and 30 minutes. The physician prescribes medicines of the chemotherapy and signs the prescription which will be sent to the pharmacy. 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 cure and the patient leaves the hospital.

In this paper we do not consider the duration of preparation of the drug by the pharmacy and we suppose that the drug can be prepared on time.

III. WORKING PERIODS PLANNING OF ONCOLOGISTS

A. Principle

Previously we proposed in [1] a mixed-integer programming-based three-stage heuristic approach for planning oncologists working periods (see Fig. 2). The first stage determines the scheduling of physicians for morning time slots. The second stage optimizes the allocation of afternoon time slots under the constraints of the previous morning schedule. The third stage uses a local search to improve iteratively the global solution. The neighborhood structure of local search is defined by two local moves: (i) exchanging a time slot $t_i$ assigned to a physician $i$ with another time slot $t_j$ assigned to another physician $j$. (ii) replacing physician $i$ by physician $j$ on a time slot $t_i$. Readers is referred to [1] for more details of the working periods planning and the three-stage approach.

B. Limitation of the three-Stage approach

The three-stage heuristic relies on complete historical data over a planning horizon (3 months in [1]) concerning number of patients arrived each week and the treatment protocol of each patient. The working periods planning of physicians and the assignment of patients are optimized based on the full knowledge of all patients involved. This means the assignment of a patient arriving in week $w$ is determined by taking into account patients arrived in all subsequent weeks.

While this approach seems reasonable for physicians working periods planning. It is not applicable to assignment of patients. Patients for oncology care are known at most

![Fig. 1. Patient process in the ICL outpatient unit.](#)

![Fig. 2. Three-Stage Heuristic.](#)
two weeks before the start of the protocol.

Further, the heuristic modifies simultaneously the schedule of patients and the working periods planning of oncologists. But before using a new working periods planning, we should check the impact on the entire oncology service. Physician do not work only for the ACU unit, they have activities in some other units of the center. If we change the day oncologist works for the outpatient unit, it could disturb the working way of the center.

For these reasons, in the following, we focus on patient assignment and develop implementable patient assignment strategies.

IV. PATIENT ASSIGNMENT STRATEGIES

In the ICL center, physicians working periods planning is established at least for six months based on historical data from the database for a horizon long enough or generated data for the horizon by a stochastic model.

A. Patient flow analysis

To design a stochastic model generating a flow of patients that corresponds to reality, we retrieve historical data from the appointment booking system of ICL which contains scheduled appointment information for all patients during 2008 and 2009.

Fig. 3 provides an overview of the number of new patients per week recorded for 2009. We note that there is no effect of seasonality. Statistical analysis shows that the patients flow follows a Poisson distribution with an average of \( \lambda = 21 \) new patients per weeks. Fig. 3 further shows that the stochastic patient arrival model fits the observed patient flow.

The stochastic model allows us to predict the arrival of new patients and thus build optimal patient assignment strategies.

B. Basic scheme for new patient assignment

The working periods planning of physicians being given, we try to compute the new patient schedule for each week. The problem arises at the beginning of each week. Existing patients are already assigned an appointment date. There is a set of new patients. The problem consists in determining the appointment date of each new patient in order to best balance the bed requirement.

The mathematical formulation we use to assign new patients is similar to the MIP model of [1] for working periods planning of physicians. The problem is characterized by the notation of Table II where \( a_{iw} \) for all weeks \( w \) represent all chemotherapy sessions which depends on both treatment protocol and patient arrival week.

The following base model denoted MIP1 will be used to design different patient assignment strategies by varying the planning horizon \( W \) and the set of new patients to consider.

Decision variables:

- \( x_{it} \): patient assignment with \( x_{it} = 1 \) if patient \( i \) comes in period \( t \), \( x_{it} = 0 \) otherwise. By convention, the assignment \( x_{it} \) is given for existing patients. In order to respect the treatment protocol, a patient always comes the same period for any week where a chemotherapy session is needed, i.e. \( a_{iw} = 1 \);
- \( Z_j \): number of patients delegated by the physician \( j \) in week \( w \) in period \( t \) to the intern;
- \( E_j \): number of patients beyond the normal consultation capacity of physician \( j \) in week \( w \) in period \( t \).

In the MIP1 formulation, \( C_{max} \) and \( C_{min} \) correspond to the largest and the smallest daily bed capacity requirement of week \( w \) which takes into account the total time of patients

\[
\text{MIP1: Min } \sum_w (C_{max} - C_{min}) + \sum_j \sum_w \sum_t E_j \cdot M 
\]
coming a day spent in the bed (preparation time and injection time). The objective function (1) aims in best smoothing the bedload of each week and to reduce the violation of the consultation capacity of physicians and the intern. Constraints (2) ensure that every patient is assigned to a single period. Constraints (3) and (5) ensure that a patient comes only when the referee physician works. Constraints (4) ensure that the sum of patients delegated to the intern does not exceed his consultation capacity. Constraints (6) guarantee that the maximum capacity of beds in each afternoon period is respected.

C. Patients’ assignment scenarios

The previous MIP model is used to schedule patients in three ways, depending on whether we consider the future or not. The characteristics of the three different strategies are reported in what follows.

Strategy 1: MIP1 model is used for patient assignment with \( W=1 \), i.e. patients are assigned without considering the impact of the bedloads of subsequent weeks; see “Fig. 4” (S1).

Strategy 2: MIP1 model is used for patient assignment with \( W > 1 \) and with \( P^b \) corresponding to the set of patients arriving next week. In this strategy, patients are assigned by taking into account bedloads of subsequent weeks but without taking into account incoming patients of these weeks, see “Fig. 4” (S2).

Strategy 3: MIP1 model is used for patient assignment with \( W > 1 \) and with \( P^v \) including both new patients of the next week but also randomly generated incoming patients for all subsequent weeks, see “Fig. 4” (S3).

In strategy 1, new patients of the next week are assigned to best balance the bedload of the next week neglecting the patients who will come / comeback in the following weeks. In this case, the additional information provided by the protocols of care indicating the periodicity of treatment (all weeks when the patient will have a chemotherapy) are not used. Strategy 2 uses this information to better balance the bedload of the following weeks. This improves the quality of the assignment and reduces the probabilities of exceeding physicians’ consultation capacity, but, this strategy does not consider the new arrivals in the future weeks.

So, to improve strategy 2, new patients of the future weeks should be taken into account. Strategy 3 uses the patient’s treatment periodicity provided by the protocol of care -as in strategy 2- and generates predictive patient arrivals to best forecast the bed requirements of the next weeks.

For strategy 3 we introduce the concept of rolling horizon. For each week \( w_i \) we compute a complete patients’ schedule over a horizon of \( W \) future weeks. Patients are generated for week \( w_{i+1} \) to \( w_{i+W} \) (see Fig. 4.S3) according to the stochastic patients flow model described in Section IV.A. These fictive patients serve only for the optimisation of the week \( w_i \). On this rolling horizon we know all patients who will have their chemotherapy over the entire planning horizon. The generation of these fictive patients for optimization purpose is the same as patient generation in the simulation and will be explained in details in Section V.

Each week \( w_i \) MIP1 is used for optimisation of patient assignment. Considering real patients and fictive patients for the optimisation, we keep only the assignment of the patients coming on week \( w_i \). Then, we shift the horizon by one week and schedule patients for week \( w_{i+1} \). So, the new rolling horizon becomes \( w_{i+1} \) to \( w_{i+1+W} \). Strategy 3 reduces the risk of exceeding the physicians consulting capacity and reduces the bedload peaks.

The optimal horizon is determined by trials and is set to \( W = 12 \) weeks. We demonstrated the effectiveness of this strategy for new patient scheduling by simulation in Section IV.

V. SIMULATION

To evaluate the effectiveness of our scheduling strategies, we performed a comprehensive process and data analysis. The primary data source is the appointment booking system, which contains all historical appointment information for all patient visits, including those to the ACU. These historical data are used to build the simulation model.

More precisely, the simulation model contains two parts: (i) the number of new incoming patients for each future week, and (ii) the treatment protocol and the referee physician for each new incoming patient.

As stated in Section IV, the flow of new incoming patients is rather stable without any seasonality. The number of new patients per week follows a Poisson distribution with rate \( (\lambda=21) \) new patients per week. This process will be called "patient flow generation process".

As the number of treatment protocols is rather large (about 150), the historical data are not enough to have a precise stochastic modeling of the probability of a new patient having a specific protocol and a specific referee physician. Further, the treatment protocol may be altered and a particular chemotherapy may be postponed depending on the health status of the patients. Having a precise stochastic model taking into account all this possible change is out of the scope of the current paper.

Instead of building a stochastic model of the protocol and the referee physician for new incoming patients, we use the set of all patients in the ICL appointment booking system containing more than 2000 patients. This set is termed the sampling population. For each new incoming patient, a patient is randomly picked from the sampling population and
we assume that the new incoming patient follows exactly the same treatment protocol with the same referee physician. This sampling procedure helps to preserve the proportions of patients per pathology and the number of patients per physician, while including uncertainties. This process will be called "patient sampling process".

The simulation process is illustrated by Algorithm 1. Note that the fictive new incoming patients generated in Steps 2.1 and 2.2 are only used in the MIP1 model for patient assignment. These patients are discarded after the assignment for patients of week $w$ have been determined in Step 2.3.

**Algorithm 1** (Simulation of a patient assignment strategy with a given physician working period planning)

Step 1: Initialization.
1.1. Select a week $w_0$ in the historical data. The number of patients at the beginning of the simulation is the number of new patients and existing patients of week $w_0$;
1.2. Apply patient sampling process to select for each patient its protocol and referee physician;
1.3. Set $w = 1$;

Step 2: Patient assignment optimization.
2.1. Generate randomly number of fictive new incoming patients for weeks $w+1, w+2, \ldots, w+W-1$;
2.2. Apply patient sampling process to select for each fictive new incoming patient its protocol and referee physician;
2.3. Solve the patient assignment model MIP1 according to the patient assignment strategy;

Step 3: Patient assignment.
Assign incoming patients of week $w$ according to the solution of Step 2.3;

Step 4: Generate new incoming patients.
4.1. Generate randomly number of new incoming patients for week $w+1$;
4.2. Apply patient sampling process to select for each new incoming patient its protocol and referee physician;

Step 5: Repeat steps 2-4 until the end of the simulation horizon.

**VI. COMPUTATIONAL RESULTS**

The ICL ACU is open Monday to Friday with 10 periods per week and has 18 beds. The number of beds is subject to variation because of external activities. In our experiments we assume that this number is constant and equal to 18. This value, according to the ICL staff, gives a good representation of reality. 3 consultation boxes (2 for physicians and 1 for the only intern) are available for consultations in the morning and 2 (1 for physician and 1 for the intern) in the afternoon. There is no consultation Friday afternoon. 10 physicians are sharing the 14 time slots for consultations and work from 8:30AM to 12PM in the morning and from 1:30PM to 3:30PM in the afternoon. A consultation takes about 15 to 30 minutes depending only on the physician skills. As a result, we assume that a physician can make 14 consultations in the morning and 8 in the afternoon. With the ACU open 9 hours a day and 18 beds; the maximum daily bed capacity is 162 hours.

The MIP1 model is solved by means of a Branch and Bound algorithm with the commercial LP solver ILOG CPLEX 11. The simulation runs on a 2.4 GHz Intel Core processor platform.

The existing patient assignment strategy in the ACU is first come first served. It places each patient in the first available time slot according to the physician schedule, without taking into account the impact on the Bedload. Only physician’s consultation capacity is verified and patients with treatment duration longer than three hours are placed on morning time slot to avoid exceeding the ACU opening time.

To compare the ACU assignment strategy with our proposed assignment strategies, algorithm 1 is also used to evaluate the existing strategy with Step 2.3 replaced by the FIFO assignment rule.

The simulation is run for a horizon of one year. Four independent simulation runs are performed by starting with existing patients of the first four weeks of 2008 collected from ICL database. Fig. 8 shows a graphical representation of the bedload (the bedload is given in quarter) and other performance measures are given in Table III.
From Fig. 5, assignment strategy 1 balances the bedload better than the actual FIFO assignment over the entire optimization horizon. Unfortunately, from Table III, strategy 1 mismanages the physicians’ consultation capacity as it does not take into consideration the future patients; it poorly distributes patients and has higher risk of saturating the capacity of physicians.

The overflow of consultation capacity is improved in the strategy 2 see table III. As strategy 2 uses partial data for the rolling horizon see Fig. 4, the bedload balance is less effective and it still has peaks as we can see in Fig. 6. Strategy 3 improves performance of strategy 2. Indeed, as described before, strategy 3 has a complete estimation of future patients’ arrivals over the rolling horizon, it produces balanced bedload (see Fig. 7) and eliminates the major overflow of physicians’ consultation capacity.

Fig. 8 shows graphical comparison of bedload obtained by the actual assignment and the bedload obtained by strategy 3. One can see the effectiveness of the use of strategy 3. The bedload is much balanced and smoothed.

Table III compares the bedload of the actual assignment and our assignment strategies. The first column presents data sets generated with the stochastic model. Columns min and max represent the minimum and the maximum daily bedload (in hours) over the whole planning horizon of one year. Columns TNPO represent the total number of patients overflow during one year. Comparing the max bedload and min bedload of each strategy in Table III, our assignment strategies give much better balanced bedload than the actual assignment in all cases.

VII. CONCLUSION

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. 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.

REFERENCES