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# Master Chemotherapy Planning and Clinicians Rostering in a hospital outpatient cancer centre

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**Abstract** In the past years, the number of patients needing chemotherapy treatments has been constantly increasing. Chemotherapy treatments must be carefully planned to provide a suitable and timely cure. They are often provided within an outpatient setting. Clinicians and nurses staff must face the increasing demand for chemotherapy treatment with limited resources, such as exam rooms, beds, and seats. In this work, we consider a cancer centre shared among different oncologist specialties, as suggested by the Organisation of European Cancer Institutes. We focus on the oncologist visit that each patient must undergo before the drug infusion, to check if the patient's conditions are compatible with the drug infusion. We consider the problem of planning the weekly assignment of consultation rooms to cancer pathologies, referred to as Master Chemotherapy Planning. Further, we jointly address the problem of selecting a clinician with suitable skills to cover each consultation room in the weekly schedule, given the clinicians' availability over the month. Several criteria are considered, such as the number of visits in overtime, the amount of served demand and the clinicians' workload. The problem is formulated as a lexicographic multiobjective optimisation problem and solved using a sequence of MIP models. Further, we use a rolling horizon approach to consider a long planning horizon up to one year, aiming also at keeping the change of weekly

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plans from one month to the other as small as possible. The models and rolling horizon procedure are tested on real data from an Italian hospital.

**Keywords** Chemotherapy planning · Oncologists rostering · Multiobjective optimisation · MIP models · Rolling horizon procedure

## 1 Introduction

The increase of elder population, and the reduction of mortality for several diseases have led to an increase of cancer incidence in most of the western and industrialised countries. Age is one of the most studied risk factors for cancer in the international literature, and cancer is an age-related disease, as the incidence increases with age, especially in the midlife where it begins to rise faster [1]. As reported by the World Health Organisation (WHO), cancer is the second leading cause of death globally (with 9.6 million deaths worldwide in 2018), accounting around the 17% of overall deaths [2].

The cancer care pathway is composed by the following steps: onset of symptoms, diagnosis, and treatment. The onset of symptoms is usually the moment when the person understands that there might be the presence of cancer and decides to discuss with the general practitioner to better evaluate if diagnostic tests are needed, also considering patient risk factors. The diagnosis is usually performed in secondary care with outpatient visits and might includes lab tests (e.g. Faecal immunochemical test, blood tests with cancer markers) or imaging (CT scan, ultrasounds, X-rays). Once the diagnosis states the presence of cancer, the patient is addressed to the adequate and effective treatment. For each type of cancer there is a specific treatment regimen that might include radiotherapy, chemotherapy and surgical intervention. Amongst the therapies, chemotherapy is the one with the largest use, considering most of the cancer types [3]. An effective care requires specific clinician skills and volumes that guarantees the proper clinician training [4].

The rise of cancer incidence is reported in the cancer care report published by WHO in 2020. The variation of the global burden of cancer increased from 12.6 million in 2008 to 18.1 million of new cases in 2018. The projection of the global burden of cancer estimated for 2040 will rise to 29.4 million, with an increase of the 62% [2]. Indeed, between 2018 and 2040, the number of patients requiring first-course chemotherapy annually will increase from 9.8 million to 15.0 million, with a relative increase of 53% [5]. This increase will require to find more efficient ways to organise the care process and to use the resources involved in the chemotherapy treatments.

Cancer care is provided in secondary care settings, where treatments could be provided in large cancer centres (called comprehensive cancer centres), or medium or small centres. The Organisation of European Cancer Institutes (OECI) suggested to concentrate the patient treatment activities in a dedicated area, referred to as *outpatient cancer centre*, where all the patients from different hospital specialties who need chemotherapy treatments are treated [6].

In our study we assume that chemotherapy treatments are provided in a *shared cancer centre*, namely an outpatient cancer centre, where material and human resources (seats and beds, exam rooms, nurses, drugs, pharmacists and paramedical personnel) are shared among different specialities or pathologies. Besides, the clinicians (oncologists) work both in the centre and the ward or specialty they belong to, and must divide their working time between the assistance and care of patients needing chemotherapy treatments delivered in the cancer centre and the other and many activities in their ward. Hospitals and specialties involved in the cancer treatment have to change the organizational and care model of chemotherapy activities in a shared perspective, to improve resource use and patient care.

In general, the problem of scheduling chemotherapy treatments belongs to the family of multi-appointment scheduling problems. Usually in the same day, or in two consecutive ones, patients enter the clinic and, needing a chemotherapy treatment, must first have a blood sample test, then they must be visited by a clinician who, depending on the overall patient condition, should decide if they can take the drug infusion or not. If they are postponed, a new appointment is fixed and the treatment is cancelled, otherwise they are assigned to a seat or bed in the infusion rooms for the chemotherapy treatment.

The overall chemotherapy treatments planning and scheduling problem in a shared cancer centre involves several decisions and can be viewed as a three levels decision problem.

First, at a strategic level, the capacity planning of the main resources involved, i.e. medical and paramedical personnel staff, number of seats and beds available for the patient treatments, number of exam rooms dedicated to the clinician consultations, must be determined. Then, at a tactical planning level, the capacity of some resources (in particular consultation or exam room blocks) should be allocated to the clinical specialties. However, a pathology-based approach can be also assumed instead of a specialty-based assignment. Following a specialty-based approach, the exam room blocks for clinician consultation are cyclically assigned to the wards or specialties, while using a pathology-based strategy the blocks are assigned to groups of cancer pathologies, not considering the ward to which the patient to visit belongs. In the latter approach, the problem can be viewed as a case mix planning problem aiming at maximising the number of treatments performed for each group/type of cancer pathology. Once the number of blocks assigned to the specialties or the pathologies is fixed, the cyclic timetable determines the days when the different cancer groups are treated, referred to as Master Chemotherapy Planning (MCP). In this phase, the clinician rostering over a mid-term planning horizon that covers the cyclic schedule should be determined as well. Finally, at an operational level, two sub-problems are tackled. The first sub-problem entails the assignment of patients needing chemotherapy to a specific chemotherapy session/day over a given planning horizon (usually a week). The second sub-problem consists in determining the sequence of patients' appointments for each chemotherapy session.

As will be mentioned and described in the next section, most of the studies on chemotherapy planning and scheduling problems are focused on the operational scheduling of the treatments accounting for different types of resources (nurses, beds and seats, clinicians, etc).

In this paper we deal with the tactical level decision problem that lies behind the chemotherapy scheduling. The decisions addressed aim at determining the days of the week when each pathology is scheduled as well as the clinician coverage of each day depending on clinicians' skills and availability over one month. We formulate the problem as an optimisation problem with different criteria, such as minimising the overtime visits, minimising the unmet demand and minimizing the maximum workload over all clinicians. As the objectives are not equally important, we model it as a lexicographic problem and solve it by optimising a sequence of MIP models. Then, we tackle the problem in a long planning horizon, namely one year, with a rolling horizon approach that keeps the number of changes in the weekly pattern with respect to the previous month as small as possible. Indeed, avoiding widely fluctuating weekly rosters is highly relevant in practice.

This research started by a collaboration with a medium sized Italian public hospital that recently set up an outpatient shared cancer centre. Thanks to the cooperation and involvement of the hospital managers and oncologists the models and the rolling horizon approach have been tested on real data.

The main difficulty in planning the chemotherapy treatments and, in particular in scheduling the consultation rooms and setting the medical agendas, lied in the resistance to change from a *per-specialty* to a *per-pathology* paradigm. In this direction, the research herein presented aims at supporting the hospital managers and clinicians in making shared optimal decisions, while taking into account different criteria and practical requirements, usually with a clear priority among them.

The solution of the problem herein addressed is important for the overall chemotherapy planning and scheduling process when several pathologies are considered, as it creates a feasible planning schedule to be further used to solve the operational multi-appointment scheduling phase.

The main contributions of the paper are:

- focus on a highly relevant and fairly complicated real-world tactical level planning problem of scheduling consultation rooms and setting the medical agendas, which, has not been sufficiently studied in the literature;
- mathematical modeling and lexicographic approach to efficiently solve the optimisation problem for a one month planning period;
- rolling horizon procedure to deal with long-term planning horizon;
- practical orientation of the research that is reinforced by the use of real data and the cooperation of hospital managers and oncologists.

The organization of the paper is the following. In Section 2 the main contributions from the literature on multi-appointment scheduling and planning in chemotherapy are listed. The problem description is reported in Section 3. The models and the rolling horizon approach are introduced in Section 4. Results are discussed in Section 5 and conclusions and further developments are reported in Section 6.

## 2 Literature review

Chemotherapy planning involves many different decisions about the management of the limited resources related to the problem, such as exam and consultation rooms, bed and chairs, clinicians, nurses, pharmacists, and so on.

In fact, the chemotherapy planning involves not only the chemotherapy infusion, but several activities, such as the periodic diagnostic and lab tests, the physicians and nurses' services, the drug prescriptions for outpatients and the home and community care [7], and medical and paramedical staff are involved.

The shared cancer centre paradigm, where several specialties and pathologies share the same place and facility, human and physical resources, has been proposed only recently [6]. When the drug infusion is administered, the pathology the patient is affected is not relevant anymore: any nurse can provide the care, and beds and chairs can be assigned to any type of patients. The only difference among pathologies relies in the chemotherapy regimen and corresponding infusion time. Instead, looking at the overall process, the oncologist consultation visit before the infusion can be performed only by an oncologist with the proper expertise and required skills on the specific cancer pathology of the patient.

The literature on outpatient chemotherapy activities is sparse compared to other areas of application with similar features, such as multi-appointment scheduling in healthcare [8] and rostering issues in hospitals [9].

In [10] a literature review for outpatient chemotherapy planning and scheduling, with a broad view on the chemotherapy processes and care delivery, is proposed. The study analyses the literature focusing on several dimensions, such as planning level (strategic, tactical and operational), key performance indexes (costs, outcomes, qualitative), resource involved and level of uncertainty considered. The authors also provide the opportunities and the challenges of modelling and analysis based on a real case study.

The largest part of the studies addresses the patient appointment scheduling for the infusion activity and the assignment of the daily slots to nurses, focusing on the operational level, rather than tactical or strategic levels [11].

The assignment and scheduling of appointments for chemotherapy treatment is a complex problem that has been investigated for its combinatorial characteristics and challenges [10]. It is configured as multiobjective problem with conflicting criteria, such as minimisation of staff workload (nurses, physicians, phlebotomists), reduction of patient waiting time for infusion, minimisation of overtime, avoiding appointment delays or cancellations for service disruptions or late presentation of the patient.

The methods adopted in the studies published in the literature usually have a multi-level approach using exact methods, heuristics and meta-heuristics.

In [12] an online two-stage procedure for chemotherapy appointment scheduling and nurse assignment to patient was developed with the aim of maximising the number of patients scheduled and minimising the number of nurses needed.

An optimisation model to define the sequence of patients to be scheduled for chemotherapy infusion is presented by [13]. The model considers the uncertainty around the deferral given by the patient ability to receive the treatment. The deferring time of appointment was faced also by [14], using a multi-criteria MIP model, based on a three-stage heuristics. The aim is to minimise the number of deferring times for appointments scheduled for the minimum feasible number of nurse's full time equivalent. The study is mostly focused on nurse workload and it determines the variation of nurses needed when deferring time are present in the appointment scheduling approach. Liang and Turkan [15] develop two separate models for the delivery of chemotherapy for outpatients focusing on nurses assignment, patient scheduling and drug administration. The models are aimed at minimising the total patient waiting time and the overall clinic overtime as excess workload.

In [16] is proposed a MIP model aimed at providing the best appointment scheduling for patients, considering the availability of nurses and pharmacists.

A model aimed at improving patient service and nurse satisfaction for outpatient chemotherapy scheduling was proposed by [17]. The model schedules different types of patients on the basis of their treatment duration, with the aim of optimising nurse staff utilisation and minimising constraint violations such as beds or chairs, time constraints and patient-to-nurse ratios. The model smooths the volume of patients during the daytime and reduces the overload of pharmacy orders (with a consequent reduction of delays in the distribution of medication to patients).

In [18] the chemotherapy outpatient scheduling problem is solved accounting for the requests for appointments that arrive in real time and uncertainty due to last minute scheduling changes. They propose dynamic template scheduling combining proactive and online optimisation.

Only one study considered the consultation capacity of oncologists and clinicians [19]. The authors propose a MIP model for determining the work schedule of oncologists for chemotherapy of oncology patients at ambulatory care units. The study includes different resource capacity constraints, such as beds for patients that will attend the chemotherapy, rooms for consultations, oncologists and nurses. The proposed three-phases solution approach aims at balancing the daily bed capacity and increasing the number of patients treated.

The analysis of the recent literature shows that the inclusion of oncologists as relevant resource for solving the scheduling for chemotherapy appointments is treated in few studies. Table 1 recaps the main features of the mentioned papers, namely the resources considered and the decision level: operational (o), tactical (t), or strategic (s).

However, the above mentioned studies do not consider the clinical or anatomical cancer pathology and the related oncologists' skills, that, instead, become relevant in a shared cancer centre based on a per-pathology paradigm. Clinicians are the critical resource and their skill, availability and workload must be accounted for successfully and efficiently managing a shared cancer centre.

Indeed, all the studies cover the decisions at operational level and four of them consider also the decisions at tactical level, while none of them cover the strategic level.

In this paper we want to fill the gap in the literature in two directions. First, we concentrate the analysis only on the tactical level decision problem that lies behind the operational chemotherapy appointment scheduling. In detail, focusing on a cancer centre where resources are shared among several specialties and pathologies, we address the problem of determining the days of the week when each pathology is scheduled, namely the MCP. Jointly, we account for the clinicians availability and skills on the clinical and anatomical cancer pathology to determine the monthly clinicians' rostering to cover the weekly timetable. The solution of the problem herein addressed is particularly important in the overall chemotherapy planning and scheduling process because it creates a feasible per pathology planning pattern that can be further used in the operational multi-appointment scheduling phase.

| Authors and year | Nurse | Oncologist | Beds or chairs | Pharmacy | Decision level |
|---|---|---|---|---|---|
| Alvarado et al. 2017 [20] | ◆ | | ◆ | ◆ | $o$ |
| Benzaid et al. 2019 [12] | ◆ | | ◆ | ◆ | $t, o$ |
| Garaix et al. 2020 [13] | | ◆ | ◆ | | $o$ |
| Hesaraki et al. 2020[14] | ◆ | | ◆ | | $t, o$ |
| Hesmat & Eltawil 2019[16] | ◆ | | ◆ | ◆ | $t, o$ |
| Huang et al. 2018 [17] | ◆ | | ◆ | | $o$ |
| Liang & Turkan 2016 [15] | ◆ | | | | $o$ |
| Sadki et al. 2013 [19] | ◆ | ◆ | ◆ | | $t, o$ |

Table 1: Resources and decision level considered in the literature

## 3 Problem description

We consider the problem of organising the activity of a shared cancer centre, over a long term planning horizon of several months up to one year. Patients with different cancer pathologies receive chemotherapy treatments in the center. In particular, we focus on the visit that each patient must undergo before receiving the drug infusion, while we do not consider the infusion management itself. Let us describe the problem of assigning days and consultation rooms to a set of pathologies $J$ and setting the medical agendas on a single month, described by a set of days $G$. The center is closed on weekends and holidays, thus $G$ includes only the working days ($|G|$ is usually between 20 and 23). The cancer centre has a set $K$ of available exam rooms for clinicians' consultation and it works according to a weekly pattern: let $D$ be the set of working days in a week (Monday to Friday). An exam room can be assigned to only one pathology in each day. As a result, a set of weekly blocks $B$ is built, each weekly block $b \in B$ being described by a working day of the week $d$ (Monday to Friday) and a consultation room $k$. We have to assign the pathologies to exam rooms and days, thus building a weekly pattern. The weekly pattern is then repeated along the working days of month $G$. An additional parameter $p_{gd}$ is introduced to link the day indices $g$ and $d$, such that $p_{gd}$ is equal to 1 if the working day $g$ in the monthly horizon corresponds to day $d$ of the week, and 0 otherwise (e.g. if day 1 in $G$ is a Wednesday then $p_{13} = 1$). A set of clinicians $I$ is considered, and we assume that clinicians are not always available and have not the skills to treat any pathology. Clinicians provides their availability on a monthly basis. The availability of clinicians is described by a parameter $a_{ig}$ defined for each clinician $i \in I$ and day $g \in G$. The parameter is equal to 1 if clinician $i$ is available on day $g$ and 0 otherwise. Similarly, the skills of clinicians are described by parameter $s_{ij}$, defined for each clinician $i$ and each pathology $j$: $s_{ij}$ is equal to 1 if $i$ can treat pathology $j$ and 0 otherwise. Each block assigned to a pathology must be covered by an available clinician with the specific and appropriate skills: for instance, if a pathology $j$ is assigned to a consultation room on Tuesday, then, for each Tuesday in the month (e.g. each day $g$ such that $p_{g2} = 1$) there must be an available clinician $i$ such that $s_{ij} = 1$ who can visit the patients in day $g$ and in the assigned room.

Given the length of a visit, it is possible to compute the number of visits $\Gamma_j^{dk}$ that can be performed in day $d$ of the weekly pattern and room $k$ for pathology $j$. The weekly pattern must be able to meet the requests for visits. The number of patients requiring a visit is not known, but an estimation can be provided based on the historical data: let us denote with $l_j$ the reference number (it can be the average or the median value of the observed data) of visits for pathology $j$ in a week and $m_j$ the highest considered value, i.e. the maximum number that corresponds to the most loaded week. In some cases, the maximum value could be very sensitive to the presence of outliers and the use of percentiles, e.g. the 90th, might be more appropriate, depending on the features of the centre and on the historical data.

The problem is to assign each room to a pathology in each day of the weekly schedule. On each working day $g$ of the month $G$, a clinician able to treat a pathology must be assigned to each block reserved for the pathology itself. Besides, a clinician must also be assigned to the emergency care service every working day and a clinician must cover the continuity of care service each working day, both performed in dedicated ambulatories. The emergency ambulatory is located in an extra exam room of the cancer centre and follows the same timetabling of the ordinary ambulatories. Instead, the continuity of care ambulatory covers the closing hours of the cancer centre in the working days. If a clinician is assigned to an ordinary ambulatory during in a day, he/she cannot be assigned to the emergency or the continuity of care ambulatory in the same day. Further, if a clinician is assigned to the continuity of care service in day $d$ he/she should not works in the center in the next day. As for the clinician's duties in the wards or in other hospital facilities, we assume that they are included in parameter $a_{ig}$.

| | |
|---|---|
| $J$ | set of pathologies |
| $G$ | monthly planning horizon |
| $D$ | working days in the week (Monday to Friday) |
| $K$ | set of rooms |
| $B$ | set of blocks |
| $I$ | set of clinicians |

Table 2: List of sets used in the model

| | |
|---|---|
| $\Gamma_j^{dk}$ | capacity of each block $b = (d, k)$, w.r.t. pathology $j$ |
| $a_{ig}$ | clinician availability: equal to one if clinician $i$ is available in day $g$, zero otherwise |
| $s_{ij}$ | clinician skill: equal to one if clinician $i$ can treat pathology $j$, zero otherwise |
| $l_j$ | reference number of required visits per week for pathology $j$ |
| $m_j$ | highest considered number of required visits per week for pathology $j$ |
| $p_{gd}$ | equal to 1 if day $g \in G$ occurs on working day $d \in D$ |

Table 3: List of parameters used in the model

As for the longer planning horizon that includes several months, up to one year, the weekly schedule must be kept unchanged during a single month, but it can be slightly changed from a month to another. We aim at keeping the weekly pattern as similar as possible throughout the year, and especially in consecutive months.
Several stakeholders are involved in the process and each one has a different perspective, leading to a multiobjective problem. Cancer centre management is interested in guaranteeing treatment to each patient while limiting the overtime. Clinicians are interested in keeping the workload tolerable. As for the patients, and the overall healthcare system, it is important not to neglect any pathology. However, such goals have not the same importance, resulting in a lexicographic multi-criteria problem. In planning the weekly pattern, the main goal is to provide treatment to all the patients with the minimum overtime. If this goal is met, clinicians perspective is accounted for, and the highest workload over all clinicians is minimised. Then, the unmet demand of the different pathologies must be balanced.

When considering the long planning horizon, the main goal is still to treat as many patients as possible, but we also want to keep as small as possible the deviations in the weekly pattern in consecutive months.

The list of the sets used in the model are reported in Table 2, while the list of the parameters is reported in Table 3.

## 4 Models and rolling horizon scheme

We tackle the problem over the several months planning horizon with a rolling horizon approach, where each month is optimized by solving a lexicographic multiobjective problem. The number of changes in the weekly pattern with respect to the previous month is kept as small as possible. In the following, we describe the models used in optimizing the single month in Section 4.1 and the rolling horizon approach in Section 4.2.

## 4.1 Single month models

The lexicographic multiobjective problem on a single month is solved optimising a sequence of models: we optimise first an overtime related metric, trying to obtain a solution able to serve all the reference demand without incurring overtime, or if it is not possible, a solution that minimises the total overtime. Then, we consider the clinicians' perspective, minimising the maximum workload among the clinicians, while keeping the overtime equal to the optimal one. Then, we optimise the demand-related objective minimising the maximum percentage, among the pathologies, of unmet demand w.r.t. the highest considered value of required visits.

In the next subsections we will describe the variables and constraints common to all the models, then we describe the lexicographic objective function problem and the approach and finally we describe the single objective models.

### *4.1.1 Variables*

The assignment of blocks to pathologies in the weekly pattern is described by binary variables $x_j^{dk}$, such that

$$x_j^{dk} = \begin{cases} 1 & \text{if block } b = (d,k) \text{ is reserved for pathology } j, \text{ with } d \in D, k \in K \\ 0 & \text{otherwise.} \end{cases}$$

The assignments of clinicians to consultation rooms and pathologies in each day of the month $G$ are described by binary variables $w_{ij}^{gk}$, such that

$$w_{ij}^{gk} = \begin{cases} 1 & \text{if clinician } i \text{ treats pathology } j \text{ in day } g \in G \text{ and room } k \in K \\ 0 & \text{otherwise.} \end{cases}$$

Other two families of binary variables are needed to represent the coverage of the emergency and continuity of care services:

$$u_i^g = \begin{cases} 1 & \text{if clinician } i \text{ covers the urgency ambulatory in day } g \in G \\ 0 & \text{otherwise,} \end{cases}$$

$$v_i^g = \begin{cases} 1 & \text{if clinician } i \text{ covers the continuity of care ambulatory in day } g \in G \\ 0 & \text{otherwise.} \end{cases}$$

As some overtime may be needed to guarantee the feasibility in terms of reference demand satisfaction, a non-negative variable $\beta_j^{dk}$ is defined which represents the number of visits in overtime for pathology $j$ in day $d$ and room

$k$. Additional variables are needed to represent the other goals: let $\lambda$ be the maximum workload assigned over all clinicians, and $z$ the maximum unmet demand, w.r.t. the weekly highest number of request $m_j$, among the pathologies.

*4.1.2 Constraints*

$$\sum_{j \in J} x_j^{dk} = 1 \qquad \forall d \in D, k \in K \tag{1}$$

$$\sum_{\substack{d \in D,\\ k \in K}} \left( \Gamma_j^{dk} x_j^{dk} + \beta_j^{dk} \right) \geq l_j \qquad \forall j \in J \tag{2}$$

$$\beta_j^{dk} \leq M x_j^{dk} \qquad \forall j \in J, d \in D, k \in K \tag{3}$$

$$x_j^{dk} \leq |i \in I : s_{ij} = a_{ig} = 1| \qquad \forall j \in J, d \in D, g \in G, k \in K : p_{gd} = 1 \tag{4}$$

$$x_j^{dk} = \sum_{i \in I : s_{ij} = 1} w_{ij}^{gk} \qquad \forall j \in J, d \in D, g \in G, k \in K : p_{gd} = 1 \tag{5}$$

$$\sum_{i \in I} u_i^g = 1 \qquad \forall g \in G \tag{6}$$

$$\sum_{i \in I} v_i^g = 1 \qquad \forall g \in G \tag{7}$$

$$\sum_{j \in J, k \in K} w_{ij}^{gk} + u_i^g + v_i^g \leq a_{ig} \qquad \forall i \in I, g \in G \tag{8}$$

$$v_i^g + u_i^{g+1} + v_i^{g+1} + \sum_{\substack{j \in J : s_{ij} = 1\\ k \in K}} w_{ij}^{gk} \leq 1 \qquad \forall i \in I, g \in G : (g+1) \in G, p_{g5} = 0 \tag{9}$$

$$\lambda \geq \sum_{\substack{j \in J, g \in G,\\ k \in K}} w_{ij}^{gk} + \sum_{g \in G} (u_i^g + v_i^g) \qquad \forall i \in I \tag{10}$$

$$z \geq 100 \frac{m_j - \sum_{b=(d,k) \in B} \Gamma_j^{dk} x_j^{dk}}{m_j} \qquad \forall i \in I, j \in J \tag{11}$$

Constraints (1) guarantee that each block $(d, k)$ is assigned to one and only one pathology. Constraints (2) guarantee that the blocks allocated to a pathology $j$ in a week are sufficient to deal with the weekly reference demand, possibly with some overtime visits, represented by variables $\beta_j^{dk}$. Inequalities (3) state that overtime visits for a pathology can be activated in a block only if the pathology is assigned to the block. Constraints (4) forbid to assign a pathology to a day $d$ in the weekly pattern if during the considered month $G$ there is one occurrence of the day for which none of the suitably skilled clinicians is available $(s_{ij} = a_{ig} = 1)$. For instance, let us consider Monday $(d = 1)$ and a pathology $j$. Then we have to check each Monday of the month (e.g. each day $g$ such that $p_{g1} = 1$) and compute the number of clinicians who are able to treat pathology $j$ and available in day $g$. A consultation room can be assigned to $j$ on Monday in the weekly pattern only if such number is strictly positive. Constraints (5) guarantee that each block assigned to pathology $j$ in day $d$ of the week is covered in day $g$ by a suitably skilled clinician. Similarly, Equations (6) and (7) guarantee that the urgency and the continuity of care services are covered and assigned to a clinician in each day. Equations (8) forbid a clinician to be assigned to any services or ambulatories in day $g$ if he/she is not available. Constraints (9) guarantee that a clinician cannot work in the center the day after a continuity shift (the constraints are not enforced on Fridays). Finally, the value of variable $\lambda$ is set by Constraints (10), while Constraints (11) set the value of $z$ variable.

#### *4.1.3 Multi-criteria model and approach*

The different goals are combined into a lexicographic objective function. The obtained model is the following:

$$\begin{aligned} \min\ & h_1 \textstyle\sum_{\substack{j\in J, d\in D,\\ k\in K}} \beta_j^{dk} + h_2\lambda + h_3 z \\ \text{s.t.}\quad & (1)-(11), \end{aligned} \tag{12}$$

where $h_1, h_2$ and $h_3$ are three parameters such that $h_1 >> h_2 >> h_3$.

We propose to solve in sequence three models to deal with the lexicographic problem. First a minimum overtime solution is found and then refined solutions are generated to account for the other objectives.

The aim of the first model is then to generate a minimum overtime solution able to meet the reference number of visits for each pathology. The model, denoted as FEASibility (FEAS), is the following:

$$\begin{aligned} \text{(FEAS)} \qquad \min & \sum_{\substack{j\in J, d\in D,\\ k\in K}} \beta_j^{dk} \\ \text{s.t.} \qquad & (1)-(9) \end{aligned} \tag{13}$$

The objective function (13) minimises the total number of overtime visits. The optimal solution of FEAS is stored in parameter $\overline{\beta}$. Then the following constraint (14) can be added to force overtime to be equal to the optimal value:

$$\sum_{\substack{j\in J, d\in D,\\ k\in K}} \beta_j^{dk} \leq \overline{\beta}. \tag{14}$$

To account for the clinicians' perspective we minimise the workload of the most loaded clinician. The resulting workLOAD (LOAD) model is the following:

$$\begin{aligned} \text{(LOAD)} \qquad & \min \lambda \\ & \text{s.t.} (1)-(10), (14). \end{aligned} \tag{15}$$

The maximum workload among all the clinicians is minimised by the objective function (15) and the optimal value is stored in the parameter $\overline{\lambda}$.

The solution found by FEAS and LOAD may provide an unfair service among the pathologies. Thus, we consider a fairness-based objective which minimises the highest percentage of unmet demands with respect to the highest considered number of weekly requested visits $m_j$ among the pathologies. The resulting FAIRness (FAIR) model is the following:

$$\text{(FAIR)} \qquad \min z \tag{16}$$
$$\text{s.t.}(1)-(9),(11),(14).$$

The maximum percentage of unmet demand is minimised by (16). Constraint (14) is added so as to prevent the overtime to increase too much to reduce the unmet demand.

We also impose that the clinicians' workload does not exceed the value $\overline{\lambda}$, thus resulting in FAIRness and balanced Maximum workLOAD (FAIR-ML) model:

$$\text{(FAIR}-\text{ML)} \qquad \min z \tag{17}$$
$$\bar{\lambda} \geq \sum_{\substack{j\in J, g\in G,\\ k\in K,}} w_{ij}^{gk} + \sum_{g\in G}(u_i^g + v_i^g) \qquad \forall i \in I \tag{18}$$
$$\text{s.t.} \qquad (1)-(9),(11),(14).$$

The goal of guaranteeing a similar level of demand satisfaction and treatment to all the pathologies can be formulated also with variable $\alpha$ that represents the possible increase of the treated demand w.r.t. the reference value $l_j$. The resulting model is the following:

$$\max \alpha \tag{19}$$
$$\sum_{\substack{d\in D\\ k\in K}} \mathit{\Gamma}_j^{dk} x_j^{dk} \geq \alpha l_j \qquad \forall j \in J \tag{20}$$
$$\text{s.t.} \qquad (1)-(9),(14).$$

Equations (20) force $\alpha$ to be equal to the minimum possible increase among the pathologies; $\alpha$ is then maximised by the objective function (19). In the tests considered in the paper, such a model provides almost always the same results as the FAIR one.

## 4.2 Rolling horizon

When dealing with a long horizon, we may consider an extended set $G$. However, keeping the same weekly pattern for long periods may lead to unfeasibility, due to the clinicians' availability. Therefore, we decided to optimize each month separately, but linking consecutive months in a rolling horizon framework.

We start planning the first month of the considered planning horizon and then move on with the next month, and so on and so forth. When optimising the single month the main goal is to provide treatment to all the patients with a minimum overtime. As mentioned, when passing from a month to another, we may change the weekly pattern. However we want to keep the changes as small as possible, and this becomes a further objective. Finally, we still want to avoid excessive workloads and guarantee fairness. The overall objective function is:

$$\min\, h_1 \sum_{\substack{j \in J, d \in D,\\ k \in K}} \beta_j^{dk} + h_\Delta \Delta + h_2 \lambda + h_3 z \tag{21}$$

where $\Delta$ represents the number of changes w.r.t. the previous month weekly pattern and $h_1 >> h_\Delta >> h_2 >> h_3$.

Let us denote with $\bar{x}_i^{dk}$ the weekly pattern obtained for the previous month. We want to keep small the differences between the number of consultation rooms assigned to pathology $j$ in day $d$ in the previous month's weekly schedule and the number of consultation rooms assigned to pathology $j$ in day $d$ in the current month's schedule, namely

$$\left| \sum_{k \in K} x_j^{dk} - \sum_{k \in K} \bar{x}_j^{dk} \right|. \tag{22}$$

We denote such absolute value as $\delta_{dj}$ for each pathology $j$ and day $d$. The changes in the weekly pattern are the sum of the absolute values described in (22). Then, we force $\Delta$ to be at least the number of changes in the weekly schedule from the previous month to the current one through the following constraints:

$$\delta_{dj} \geq \sum_{k \in K} x_j^{dk} - \sum_{k \in K} \bar{x}_j^{dk} \qquad \forall d \in D, j \in J \tag{23}$$

$$\delta_{dj} \geq \sum_{k \in K} \bar{x}_j^{dk} - \sum_{k \in K} x_j^{dk} \qquad \forall d \in D, j \in J \tag{24}$$

$$\sum_{d \in D} \sum_{j \in J} \delta_{dj} \leq \Delta \tag{25}$$

When optimising the single month within the rolling horizon framework, we apply the scheme described in Figure 1.

First we compute the best possible overtime value $\beta^*$, solving FEAS model in a stand-alone fashion. Then we force the overtime to be at most $(1+\varepsilon)\beta^*$ through the following constraint:

$$\sum_{\substack{j \in J, d \in D,\\ k \in K}} \beta_j^{dk} \leq (1+\varepsilon)\beta^* \tag{26}$$

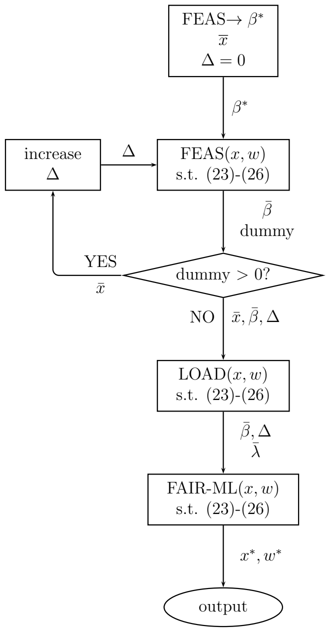


Fig. 1: Single month rolling horizon scheme.

We start forcing $\Delta$ equal to zero, namely we try to apply the previous month's weekly schedule $\bar{x}$, and we try to obtain a feasible clinicians' coverage solving FEAS model including constraint (23)-(26).

To account for the possible infeasibility when using the weekly schedule previously computed in the new month, we add a dummy clinician who can treat any pathology and is always available. We penalised the workload of the dummy clinician, so that workload is assigned to the dummy clinician only if the problem is not feasible. If the problem is not feasible, namely some blocks cannot be covered due to clinicians unavailability, the dummy clinician is assigned a strictly positive workload. Then, we increase the value of $\Delta$, allowing the new weekly pattern to be farther from the previous one. We continue increasing the value of $\Delta$ until a feasible solution can be found (the workload of the dummy clinicians is null).

When the value of $\Delta$ allows us to find a feasible solution, we store it together with the minimum overtime $\bar{\beta}$ and we solve the LOAD and FAIR-ML models to get the clinicians rostering $w^*$. Additional ergonomic constraints, similar to (9), are added to link the last day of a month to the first day of the following month.

## 5 Computational results

The models and rolling horizon procedure presented in Section 4 have been implemented with AMPL and solved with CPLEX 20.1.0.0 on an Intel CORE i7 at 2.80 Ghz with 8Gb RAM, running under Windows 8.1 Pro. All the models and procedures are fast and able to obtain optimal solutions for all instances, however we set a one hour time limit for each model solution and 1000 Mb memory limit. The models and the rolling horizon procedure have been tested on a set of twelve instances based on real data collected in a medium-size Italian public hospital. Historical data collected in 2018 have been used to create twelve single month instances that refers to the planning period January-December 2019. The instances differ with respect to the monthly patter $G$, the clinicians availability (parameter $a_{ig}$) and the demand parameters $l_j$ and $m_j$. The case study and the instances are described in Section 5.1.
In Section 5.2, we analyse the behavior of the models introduced in 4.1.3, sequentially optimized in the lexicographic approach, when solving single month instances. We compare the values of all the metrics introduced in Section 4.1.1, i.e. the number of visits in overtime, the maximum workload over all clinicians, the maximum unmet demand and the possible percentage increase of treated demand. The number of weekly visit blocks assigned to each cancer pathology and the number of monthly visit blocks assigned to each clinicians are also analyzed. Further, we run other 24 instances, obtained by doubling and tripling the number of clinicians and consultation rooms, and increasing the demand accordingly, to evaluate the computational time required by the models to solve larger instances. Then, in Section 5.3 the behavior of the rolling horizon procedure is analysed.

### 5.1 Case study and instances description

The models have been applied to the real case study of the outpatient cancer centre recently set up in the San Martino Hospital in Genoa (Italy). About two years ago, the hospital, based on the OECI (Organisation of European Cancer Institutes) advice, underwent an important reorganization of the outpatient chemotherapy activities. In the centre patients from seven different specialties (three related to haematology specialties and four related to oncology specialties) are treated. Besides, 45 clinicians are involved in the centre.

During 2018, 32,000 accesses for chemotherapy treatments were recorded. Among them we remove the treatments performed to hematological patients and concentrate the analysis on patients affected by solid tumor (oncological patients).

In this study, we use and adapt the classification, reported by the American Joint Committee on Cancer (AJCC) [21], to classify the more than twenty types of solid tumors into seven cancer pathologies, namely cancer Macro-Groups (cMG), depending mainly on the specific body site or organ affected by the cancer, e.g. lymphatic system, gastrointestinal, breast, lung, etc. (Table 4).

| **AJCC specific-site group** | **cancer Macro Group (cMG)** |
|---|---|
| Breast | Breast(MA) |
| Female Reproductive Organs | Gynecology (GY) |
| Thorax | Lung–respiratory (PO) |
| Lower Gastrointestinal tract<br>Upper Gastrointestinal tract | Gastrointestinal (GI) |
| Male Genital Organs<br>Urinary tract | Urology (GU) |
| Bone<br>Central Nervous System<br>Endocrine System<br>Head & Neck<br>Hepatobiliary System<br>Neuroendocrine<br>Ophthalmic Sites<br>Skin<br>Soft Tissue Sarcoma | Other (OT) |

Table 4: Classification of AJCC specific-site cancer groups and relationship with the cancer Macro Groups of the case study

We collected the historical data of all the chemotherapy treatments performed by the hospital in 2018, before the start of the activity of the new outpatient cancer centre.

In Table 5 the weekly indexes and total number of chemotherapy outpatient accesses for each cMG are reported. The data reported in the table are the sum with respect to the cMG of the data coming from the seven specialties that treated, in different percentage, almost all cancer pathologies in their own outpatient ambulatories, usually located near the ward stay area. The number of accesses corresponds to the number of consultation visits performed, since all patients accessing the outpatient cancer ambulatories, after the blood tests, had been visited by a clinician, who decided if the patient can or not undergo the chemotherapy treatment. For each cMG, the weekly average, median, maximum, minimum, Standard Deviation (ST.Dev.), 10th and 90th percentile values are reported in the first six columns. In the last column the total number of accesses is also given.

However, the data reported show that each cMG have a standard deviation about 10%: this shows that the demand distribution has a limited variation and data are mostly distributed around the average. The analysis of the time series for each cMG showed a seasonal pattern of 8 weeks, but the largest impact is given by the trend and error. The number of weekly accesses, i.e. visits for each cMG is reported in Figure 2. While for some groups there is a smaller variability (groups GY and OT), other groups present a higher variability (between 20% and 25% for group MA). The seasonality has a common pattern that is given by repeated identical peaks provoked by the booked availabil-

| cMG pathology ($j$) | Average | Median | Max | Min | St.Dev. | 10th Percentile | 90th Percentile | Total (2018) |
|---|---|---|---|---|---|---|---|---|
| GI | 62.8 | 63.0 | 81.0 | 36.0 | 9.0 | 53.2 | 72.9 | 3,279 |
| GU | 36.7 | 36.0 | 51.0 | 24.0 | 6.7 | 29.0 | 45.0 | 1,910 |
| GY | 21.6 | 21.5 | 37.0 | 12.0 | 5.3 | 15.1 | 28.0 | 1,129 |
| MA | 162.7 | 162.5 | 194.0 | 121.0 | 14.9 | 145.3 | 181.8 | 8,483 |
| OT | 77.0 | 77.0 | 94.0 | 60.0 | 8.2 | 66.1 | 88.0 | 4,012 |
| PO | 82.8 | 81.5 | 115.0 | 60.0 | 11.5 | 69.4 | 95.9 | 4,315 |
| | | | | | | | | *23,128* |

Table 5: Weekly measures and total number of accesses for chemotherapy treatments for each cMG (January-December 2018).

ity and programmed activity of outpatient visits. In chemotherapy treatments (much more than in other health care delivery contexts) respecting the timing and cyclicality of the treatments is highly relevant for the care effectiveness. Appointments cannot be delayed and the treatment planning presents a cycle that is due to clinical indications.

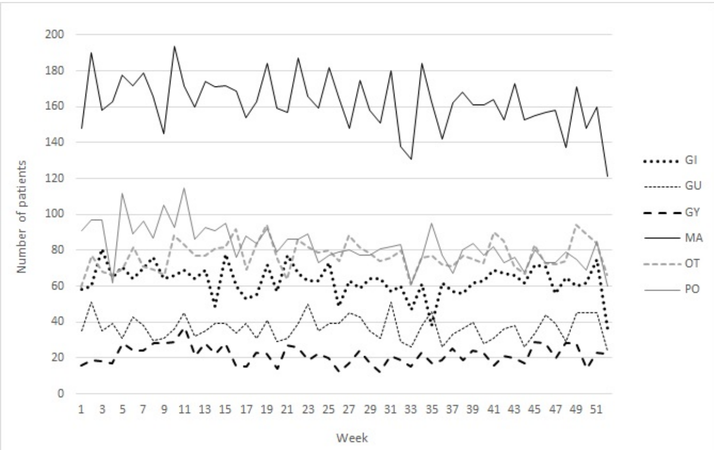


Fig. 2: Number of visits per week for each cMG in 2018

In the results reported in the Section 5 the average and maximum values have been used to set up the reference demand parameters $l_j$ and $m_j$, respectively. However, with different distribution of the observed data and in presence of outliers, the use of the median and 90th percentile might be a more appropriate choice for setting the demand parameters.

We collected the real clinicians availability data for a small period (from February to April 2019). In Figure 3 the clinician availability data for April is reported. The black cells represent the days of the month where clinicians are unavailable due to teaching activities, outpatient and inpatient ward shift, or annual leave and cannot be scheduled to visit in the outpatient cancer centre. Grey cells represent holidays. Based on the real data collected and the weekly unavailability, we generated the clinician availability for the other months using a normal distribution considering the frequency and average availability of clinicians during the different months and days of the week.

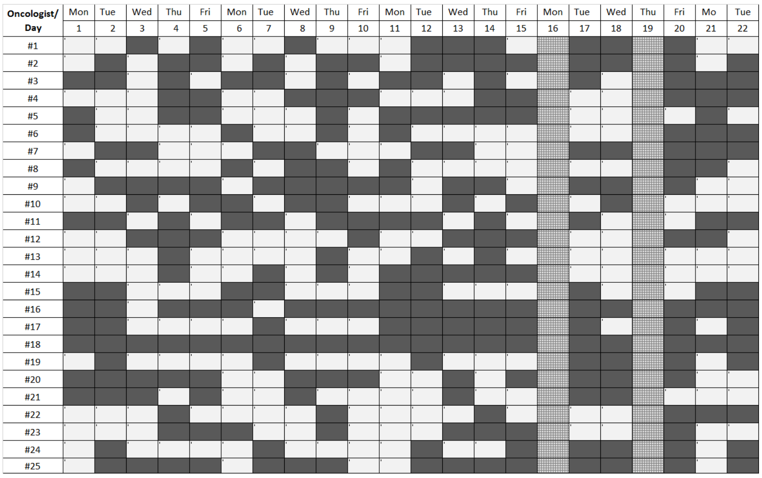


Fig. 3: Example of clinicians availability sheet (April)

The current structure of the new shared cancer centre has three exam rooms and the centre works five days per week. All oncological patients affected by one of the six solid tumors cMGs, as reported in Table 4, are considered. The oncologists of the wards involved in the study are 25. So the set sizes used in the computational tests are: $|I| = 25$, $|J| = 6$, $|K| = 3$, $|D| = 5$, while $|G|$ depends on the working days of the month and is usually between 20 and 23.

### 5.2 Single month results

The models presented in Section 4.1.3 have been tested on the twelve single month instances above described. We analyze the behavior of the lexicographic approach, given by model FAIR-ML, and of FEAS, LOAD and FAIR as stand-alone models. Table 6 reports the value of the metrics obtained by the models in each month. For each model, FEAS, FAIR LOAD and FAIR-ML the overall overtime $\beta$ ($\beta = \sum_{\substack{j \in J, d \in D, \\ k \in K}} \beta_j^{dk}$), the maximum unmet demand $z$, the maximum percentage increase of the treated demand $\alpha$ and the maximum workload over all clinicians $\lambda$, are reported. For FAIR model, the best possible value of $z$ and $\alpha$ is also reported (in brackets), namely the value that can be obtained if the overtime is not limited and can virtually increase indefinitely. It is reported only in those months in which it differs from the value obtained limiting the overtime. The required computational time is also reported in the last column. All the models are solved very quickly: over all the months they always require less than one second. Thus, combining them into a sequence in the lexicographic approach does not require more than few seconds.

Fixing the overtime sets also the value of $z$ and $\alpha$, as it sets the number of blocks assigned to each pathology, and, as a consequence, the unmet demands and the possible increase the centre can deal with. All models always provide the same value of $\beta$, $z$ and $\alpha$ obtained by FEAS. Such values are actually rather good. In seven months the values obtained by FAIR are equal to the best possible ones. When they differ, the difference can be significant. Optimising the unmet demand without overtime limitation can even double the value of $z$, as in June, July and November. However, it is worth pointing out that the highest value is indeed a bound that cannot be reached in practice, as it would imply an overtime of more than a thousand of visits. The increase of the value of $z$ comes at the expense of a decrease of the value of $\alpha$ in four months out of five (about 8.5% in the worst case), only in one month (June) the value of $\alpha$ increases by about 3.5%.

The overtime is very low in most of the months. It is equal to zero in five months, to one in three months and to two in two months. The most critical months are June and July where it rises up to 5 and 3, respectively. The percentage of unmet demand with respect to the maximum varies in the different months: it is below 10% in two months, April and October, but it increases up to almost 30% in June or August. It is worth pointing out that it is anyway possible to satisfy the average demand with a reasonable overtime even in the most critical months. In those months where overtime is not needed (January, February, May, September and October), the demand that the centre can manage is about 5% higher than the reference value. FEAS and FAIR model provide high values of clinicians workload: it is on average 10, never below 8 and may rise up to 14. Besides, when it is accounted for in the LOAD model, it is always small: it is equal to 5 in most of the months and equal to 6 in two months.

However, clinician workload and overtime metrics do not seem too conflicting. Indeed, solving in sequence FEAS and LOAD and FAIR-ML) it is possible to reduce the maximum workload even by more than half, keeping the overtime equal to the optimal value and without worsening other metrics. Using the lexicographic approach as reported in Section 5.2 by sequentially solving FEAS, LOADand FAIR-ML allows to find an equivalent solution with respect to overtime and demand metrics that is better from the clinicians workload point of view. Such behavior is shown by Figure 4, where the workload assigned to each clinician by the different models is reported throughout the first six months of the year. Figure 4 shows that accounting for the workload significantly reduces the unbalances among clinicians. Indeed, the peaks are reduced and the workload of clinicians is evenly balanced. The workload obtained for single clinicians by LOAD and its FAIRness-based version FAIR-ML is the same for all months, with only one exception in February.

Table 6: Models comparison on single month instances

| Instance | FEAS Model | | | | | FAIR Model | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | $z$ | $\alpha$ | $\lambda$ | Time | $\beta$ | $z$ | $\alpha$ | $\lambda$ | Time |
| 1 | 0.00 | 11.11 | 1.04 | 9.00 | 0.08 | 0.00 | 11.11 | 1.04 | 7.00 | 0.08 |
| 2 | 0.00 | 16.28 | 1.00 | 13.00 | 0.13 | 0.00 | 12.20 | 1.00 | 14.00 | 0.13 |
| 3 | 1.00 | 20.00 | 0.97 | 13.00 | 0.17 | 1.00 | 20.00 (18.18) | 0.97 (0.88) | 13.00 | 0.11 |
| 4 | 2.00 | 7.69 | 0.95 | 9.00 | 0.63 | 2.00 | 7.69 | 0.95 | 10.00 | 0.09 |
| 5 | 0.00 | 12.20 | 1.03 | 9.00 | 0.14 | 0.00 | 12.20 | 1.03 | 9.00 | 0.08 |
| 6 | 5.00 | 28.00 | 0.88 | 11.00 | 0.31 | 5.00 | 28.00 (12.19) | 0.88 (0.91) | 11.00 | 0.19 |
| 7 | 3.00 | 20.00 | 0.92 | 8.00 | 0.14 | 3.00 | 20.00 (11.11) | 0.92 (0.91) | 8.00 | 0.09 |
| 8 | 2.00 | 29.41 | 0.95 | 9.00 | 0.09 | 2.00 | 29.41 | 0.95 | 9.00 | 0.05 |
| 9 | 0.00 | 10.00 | 1.06 | 9.00 | 0.11 | 0.00 | 10.00 (6.49) | 1.06 (0.97) | 11.00 | 0.06 |
| 10 | 0.00 | 5.26 | 1.09 | 12.00 | 0.11 | 0.00 | 5.26 | 1.09 | 11.00 | 0.06 |
| 11 | 1.00 | 18.18 | 0.97 | 10.00 | 0.20 | 1.00 | 18.18 (8.86) | 0.97 (0.95) | 10.00 | 0.11 |
| 12 | 1.00 | 15.29 | 0.99 | 9.00 | 0.25 | 1.00 | 15.29 | 0.99 | 12.00 | 0.16 |
| Instance | LOAD Model | | | | | FAIR_ML Model | | | | |
| | $\beta$ | $z$ | $\alpha$ | $\lambda$ | Time | $\beta$ | $z$ | $\alpha$ | $\lambda$ | Time |
| 1 | 0.00 | 11.11 | 1.04 | 5.00 | 0.20 | 0.00 | 11.11 | 1.04 | 5.00 | 0.06 |
| 2 | 0.00 | 16.28 | 1.00 | 5.00 | 0.25 | 0.00 | 12.20 | 1.00 | 5.00 | 0.19 |
| 3 | 1.00 | 20.00 | 0.97 | 6.00 | 0.25 | 1.00 | 20.00 | 0.97 | 6.00 | 0.22 |
| 4 | 2.00 | 7.69 | 0.95 | 5.00 | 0.30 | 2.00 | 7.69 | 0.95 | 5.00 | 0.16 |
| 5 | 0.00 | 12.20 | 1.03 | 5.00 | 0.17 | 0.00 | 12.20 | 1.03 | 5.00 | 0.08 |
| 6 | 5.00 | 28.00 | 0.88 | 5.00 | 0.38 | 5.00 | 28.00 | 0.88 | 5.00 | 0.53 |
| 7 | 3.00 | 20.00 | 0.92 | 6.00 | 0.16 | 3.00 | 20.00 | 0.92 | 6.00 | 0.13 |
| 8 | 2.00 | 29.41 | 0.95 | 5.00 | 0.20 | 2.00 | 29.41 | 0.95 | 5.00 | 0.06 |
| 9 | 0.00 | 10.00 | 1.06 | 5.00 | 0.25 | 0.00 | 10.00 | 1.06 | 5.00 | 0.08 |
| 10 | 0.00 | 5.26 | 1.09 | 5.00 | 0.16 | 0.00 | 5.26 | 1.09 | 5.00 | 0.06 |
| 11 | 1.00 | 18.18 | 0.97 | 5.00 | 0.42 | 1.00 | 18.18 | 0.97 | 5.00 | 0.16 |
| 12 | 1.00 | 15.29 | 0.99 | 5.00 | 0.27 | 1.00 | 15.29 | 0.99 | 5.00 | 0.11 |

In Table 7 the number of blocks assigned to each cancer pathology (cMG) in each month by FAIR-ML is reported. As we fix the overtime, all the models provide the same number of blocks assigned to each pathology. The number of weekly blocks relates to the average required number of visits. In fact, cMG4 (MA=Breast Cancer) is assigned the highest number of blocks, as it has the greatest demand of visits, while cMG3 (GY=Ginecology Tumors) is assigned the minimum number of blocks, as it has the lower number of required visits.

Finally, the computational time required and the models' scalability are evaluated on a set of larger instances. In Table 8 the average, standard deviation, minimum and maximum time required by FEAS, FAIR, LOAD and FAIR-ML to solve the twelve single month instances are compared with the those required to solve the instances obtained by doubling (Scalex2) and tripling (Scalex3) the size of the sets $I$ and $K$, namely the number of clinicians and exam rooms. Even if the size of the problem is doubled, the required computational time is still reasonable and it is on average less than two seconds. All instances can be solved within 14 seconds at most for the FEAS model. Further increasing the instance size does not result in more challenging cases. On the contrary, for FEAS, LOAD and FAIR-ML, the average time is even reduced. Whether it decreases or increases, the difference is quite small.

Table 7: Number of blocks assigned to each cancer pathology

| Instance | cMG 1 | cMG 2 | cMG 3 | cMG 4 | cMG 5 | cMG 6 |
|---|---|---|---|---|---|---|
| 1 | 2 | 2 | 1 | 5 | 2 | 3 |
| 2 | 3 | 1 | 1 | 5 | 2 | 3 |
| 3 | 2 | 1 | 1 | 5 | 3 | 3 |
| 4 | 2 | 1 | 1 | 5 | 3 | 3 |
| 5 | 2 | 1 | 1 | 5 | 3 | 3 |
| 6 | 2 | 1 | 1 | 5 | 3 | 3 |
| 7 | 2 | 1 | 1 | 5 | 3 | 3 |
| 8 | 2 | 1 | 1 | 5 | 3 | 3 |
| 9 | 2 | 1 | 1 | 5 | 3 | 3 |
| 10 | 2 | 1 | 1 | 5 | 3 | 3 |
| 11 | 2 | 1 | 1 | 5 | 3 | 3 |
| 12 | 2 | 2 | 1 | 5 | 3 | 2 |

Table 8: CPU time comparison on larger instances

| Basic Scenario | | | | |
|---|---|---|---|---|
| | FEAS | FAIR | LOAD | FAIR-ML |
| Average | 0.18 | 0.10 | 0.25 | 0.13 |
| St.Dev. | 0.15 | 0.05 | 0.06 | 0.07 |
| Min | 0.08 | 0.05 | 0.17 | 0.03 |
| Max | 0.59 | 0.20 | 0.36 | 0.28 |
| Scalex2 | | | | |
| | FEAS | FAIR | LOAD | FAIR-ML |
| Average | 16.55 | 0.45 | 0.91 | 1.26 |
| St.Dev. | 53.99 | 0.89 | 0.29 | 2.27 |
| Min | 0.19 | 0.11 | 0.66 | 0.09 |
| Max | 179.33 | 3.13 | 1.58 | 8.00 |
| Scalex3 | | | | |
| | FEAS | FAIR | LOAD | FAIR-ML |
| Average | 0.42 | 0.48 | 1.88 | 1.07 |
| St.Dev. | 0.08 | 0.27 | 0.42 | 0.80 |
| Min | 0.33 | 0.20 | 1.19 | 0.16 |
| Max | 0.61 | 1.09 | 2.59 | 2.80 |

### 5.3 Rolling horizon results

In this section we present the results of the rolling horizon procedure described in Section 4.2. We set $\varepsilon$ equal to 0.1 and the value of $\beta^*$ equal to one if no overtime is requested by the single month solution.

Table 9 compares the metrics' value obtained solving, in a lexicographic fashion, the sequence of FEAS, LOAD and FAIR-ML model for each month separately, and within the rolling horizon approach (RH). The rolling horizon results are given both with ($\varepsilon = 0.1$) and without fixing the overtime with respect to the single month. The number of variations $\Delta$ in the weekly pattern

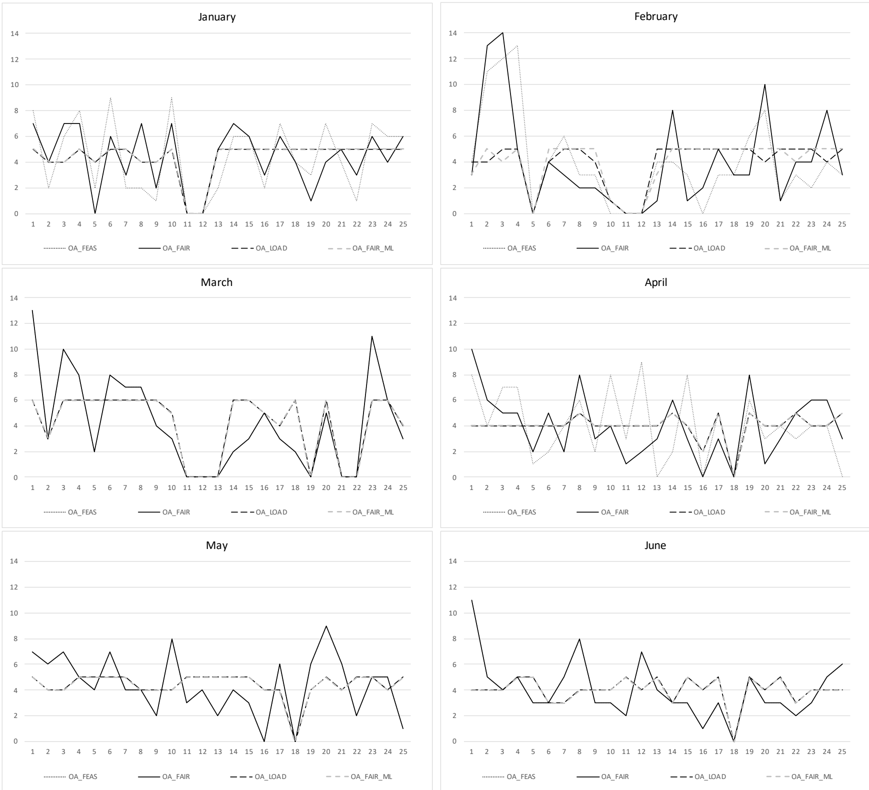


Fig. 4: Oncologist workload (January-June)

is reported, as well. Solving each month separately results in a great number of changes. There are changes in every month (except for January) and in eight months they are 14 or more, which means that we may have about a variation in each day. Excluding the December instance, the variations are never less than 12 and the maximum number, in February, is 20. Instead, within the rolling horizon approach, if the overtime is fixed, the variations are more than halved (from 14.36 to 6.36), without any impact on overtime ($\beta$), demand metrics ($z$ and $\alpha$) and clinicians' workload ($\lambda$). In two months we do not have any variations, in all but 3 months they are 8 or fewer. The maximum of variations needed is 12, in August and September instances. On the other hand, if we focus on reducing the number of changes in the pattern and we do not limit the overtime, we manage to further reduce them in all months except for September where the number of variations is slightly increased. The number of variations can be reduced up to about 30% on average, from 6.36 to 4.55. This comes at the expense of the overtime worsening in all months From February to July it is particularly high, and in two month (March and April) the overtime is 25. On average the overtime increases more than 10 times, passing from 1.25 to 13.17. Without fixing the overtime, the values of all metrics are worsened. In particular the value of $z$ and $\alpha$ increases of 46% and decrease of 10%, respectively.

The different behavior is shown also in Table 10, where the number of blocks assigned to each cMG pathology, fixing and without fixing the overtime, are reported. With respect to the solution obtained optimising each month separately (Table 7), the RH results fixing $\varepsilon = 0.1$ differ just for one block in February and August. Instead, without fixing the overtime, the blocks assignment differs in many months and for many cMG pathologies. Thus, overall, we can obtain a good compromise by limiting overtime with respect to the single month solution within the rolling horizon approach.Keeping limited the overtime to the best possible value can be done accepting an average increase of less than two variations of the weekly schedule over all the months.

As for the computational time, the rolling horizon procedure always requires less than five seconds to generate the pattern for one month and therefore can be applied in practice.

Table 9: Metrics comparison and CPU time

| Instance | Single Month (Lexicographic solution) | | | | | | RH with (26) ($\varepsilon = 0.1$) | | | | | | RH without (26) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | $z$ | $\alpha$ | $\lambda$ | Time | $\Delta$ | $\beta$ | $z$ | $\alpha$ | $\lambda$ | Time | $\Delta$ | $\beta$ | $z$ | $\alpha$ | $\lambda$ | Time | $\Delta$ |
| 1 | 0 | 11.11 | 1.04 | 5 | 0.34 | - | 0 | 11.11 | 1.04 | 5 | 0.22 | - | 0 | 11.11 | 1.04 | 5 | 0.25 | - |
| 2 | 0 | 12.20 | 1.00 | 5 | 0.56 | 20 | 0 | 12.20 | 1.00 | 5 | 0.58 | 0 | 23 | 31.43 | 0.76 | 5 | 0.64 | 0 |
| 3 | 1 | 20.00 | 0.97 | 6 | 0.64 | 18 | 1 | 20.00 | 0.97 | 6 | 1.14 | 4 | 25 | 37.39 | 0.74 | 6 | 1.11 | 2 |
| 4 | 2 | 7.69 | 0.95 | 5 | 1.08 | 16 | 2 | 7.69 | 0.95 | 5 | 2.39 | 8 | 25 | 24.21 | 0.82 | 5 | 1.47 | 4 |
| 5 | 0 | 12.20 | 1.03 | 5 | 0.39 | 14 | 0 | 12.20 | 1.03 | 5 | 1.72 | 6 | 23 | 23.40 | 0.84 | 5 | 1.12 | 4 |
| 6 | 5 | 28.00 | 0.88 | 5 | 1.22 | 12 | 5 | 28.00 | 0.88 | 5 | 1.22 | 4 | 13 | 28.00 | 0.88 | 5 | 0.66 | 0 |
| 7 | 3 | 20.00 | 0.92 | 6 | 0.42 | 14 | 3 | 20.00 | 0.92 | 6 | 1.63 | 6 | 19 | 20.00 | 0.89 | 7 | 1.66 | 6 |
| 8 | 2 | 29.41 | 0.95 | 5 | 0.36 | 12 | 2 | 29.41 | 0.95 | 5 | 3.03 | 12 | 4 | 29.41 | 0.95 | 5 | 2.56 | 8 |
| 9 | 0 | 10.00 | 1.06 | 5 | 0.44 | 16 | 0 | 10.00 | 1.06 | 5 | 3.36 | 12 | 2 | 10.00 | 0.97 | 5 | 3.59 | 14 |
| 10 | 0 | 5.26 | 1.09 | 5 | 0.33 | 18 | 0 | 5.26 | 1.09 | 5 | 1.80 | 8 | 6 | 20.00 | 0.92 | 5 | 1.81 | 8 |
| 11 | 1 | 18.18 | 0.97 | 5 | 0.78 | 14 | 1 | 18.18 | 0.97 | 5 | 1.58 | 10 | 5 | 18.18 | 0.95 | 5 | 1.27 | 4 |
| 12 | 1 | 15.29 | 0.99 | 5 | 0.63 | 4 | 1 | 15.29 | 0.99 | 5 | 0.80 | 0 | 13 | 23.40 | 0.86 | 5 | 0.52 | 0 |
| *Average* | *1.25* | *15.78* | *0.99* | *5.17* | *0.60* | *14.36* | *1.25* | *15.78* | *0.99* | *5.17* | *1.62* | *6.36* | *13.17* | *23.05* | *0.88* | *5.25* | *1.39* | *4.55* |

## 6 Conclusions

In this paper we deal with the problem of managing chemotherapy treatments in a shared outpatient cancer centre. We concentrate on the tactical planning level using a pathology-based approach with the aim of maximising the number of treatments performed for each cancer pathology while determining the cyclic weekly assignment of consultation rooms to the cancer pathologies macro groups. We jointly solve the clinician rostering over a mid-term (monthly) planning horizon to cover the exam room blocks accounting for

Table 10: Number of blocks assigned to each cancer Macro Group

| Instance | RH with (26) ($\varepsilon$=0.1) | | | | | | RH without (26) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | cMG 1 | cMG 2 | cMG 3 | cMG 4 | cMG 5 | cMG 6 | cMG 1 | cMG 2 | cMG 3 | cMG 4 | cMG 5 | cMG 6 |
| 1 | 2 | 2 | 1 | 5 | 2 | 3 | 2 | 2 | 1 | 5 | 2 | 3 |
| 2 | 2 | 2 | 1 | 5 | 2 | 3 | 2 | 2 | 1 | 5 | 3 | 2 |
| 3 | 2 | 1 | 1 | 5 | 3 | 3 | 2 | 2 | 1 | 5 | 2 | 3 |
| 4 | 2 | 1 | 1 | 5 | 3 | 3 | 2 | 2 | 1 | 5 | 2 | 3 |
| 5 | 2 | 1 | 1 | 5 | 3 | 3 | 2 | 2 | 1 | 6 | 2 | 2 |
| 6 | 2 | 1 | 1 | 5 | 3 | 3 | 2 | 2 | 1 | 6 | 2 | 2 |
| 7 | 2 | 1 | 1 | 5 | 3 | 3 | 2 | 1 | 1 | 6 | 3 | 2 |
| 8 | 2 | 2 | 1 | 5 | 2 | 3 | 3 | 1 | 2 | 5 | 2 | 2 |
| 9 | 2 | 1 | 1 | 5 | 3 | 3 | 3 | 1 | 1 | 5 | 2 | 3 |
| 10 | 2 | 1 | 1 | 5 | 3 | 3 | 3 | 1 | 1 | 5 | 2 | 3 |
| 11 | 2 | 1 | 1 | 5 | 3 | 3 | 3 | 1 | 1 | 5 | 2 | 3 |
| 12 | 2 | 2 | 1 | 5 | 3 | 2 | 3 | 2 | 1 | 5 | 2 | 2 |

the clinician availability and skills. Different criteria and perspective are considered, such as providing treatment to all the patients with the minimum overtime, minimize the highest workload over all clinicians and minimize the unmet demand of the different pathologies. The problem is thus formulated as a multiobjective problem. However, such goals have not the same importance. We tackle the problem over a several months planning horizon with a rolling horizon approach, where each month is solved separately by using a sequence of MIP models that optmise different criteria. The number of changes in the weekly pattern with respect to the previous month is kept as small as possible. The models have been applied to a real case study of a medium-size Italian public hospital that recently set up an outpatient shared cancer centre to reorganize the chemotherapy activities of the whole hospital. The models and lexicographic approach have been proved able to achieve good values for all the considered objectives in negligible time. The rolling horizon approach provides solutions combining good quality metrics and a small number of weekly pattern variations.

The proposed approach can be used to analyse the impact of changing the resource capacity, such as increasing the number of exam rooms or the number of time blocks in each day. Future research will be directed to solve the operational multi-appointment scheduling phase using the feasible planning schedule obtained with this approach. A joint optimisation of the two problems can also be considered.

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## References

1. M. White, D. M. Holman, J. E. Boehm, L. A. Peipins, M. Grossman, S. Henley, Age and cancer risk. a potentially modifiable relationship, American Journal of Preventive Medicine 46 (3 Suppl. 1) (2014) S7–S15.
2. WHO report on cancer: setting priorities, investing wisely and providing care for all, World Health Organization, Geneva(CH), Licence: CC BY-NC-SA 3.0 IGO (2020).
3. A. C. Society, Cancer treatment & survivorship facts & figures 2019–2021, American Cancer Society, Atlanta (USA) (2019).
4. B. E. Hillner, T. J. Smith, C. E. Desch, Hospital and physician volume or specialization and outcomes in cancer treatment: Importance in quality of cancer care, Journal of Clinical Oncology 18 (11) (2000) 2327–2340.
5. B. E. Wilson, S. Jacob, M. L. Yap, J. Ferlay, F. Bray, M. B. Barton, Estimates of global chemotherapy demands and corresponding physician workforce requirements for 2018 and 2040: a population-based study, The Lancet Oncology 20 (6) (2019) 769 – 780.
6. W. H. van Harten, Comprehensive cancer centres based on a network: the OECI point of view, eCancer 8 (43) (2014).
7. C. D. Oliveira, R. Pataky, K. Bremner, J. Rangrej, K. Chan, W. Cheung, J. Hoch, S. Peacock, M. Krahn, Estimating the cost of cancer care in British Columbia and Ontario: A Canadian inter-provincial comparison, Healthcare Policy 12 (3) (2017) 95–108.
8. J. Marynissen, E. Demeulemeester, Literature review on multi-appointment scheduling problems in hospital settings, European Journal of Operational Research 272 (2020) 407–419.
9. A. R. Andersen, W. Vancroonenburg, G. V. Berghe, Strategic room type allocation for nursing wards through markov chain modelling, Artificial intelligence in Medicine 99 (101705) (2019).
10. G. Lamé, O. Jouini, J. Stat-Le-Cardinal, Outpatient chemotherapy planning: A literature review with insight from a case study, IIE Transactions on Healthcare System Engineering 6 (3) (2016) 127–139.
11. C. Saville, H. Smith, K. Bijak, Operational research techniques applied throughout cancer care services: a review, Health Systems 8 (1) (2019) 52–73.
12. M. Benzaid, N. Lahrichi, L. Rousseau, Chemotherapy appointment scheduling and daily outpatient-nurse assignment, Health Care Management Science 23 (4) (2020) 34–50.
13. T. Garaix, T. Rostami, X. Xie, Daily outpatient chemotherapy appointment scheduling with random deferrals, Flexible Services and Manufacturing Journal 32 (1) (2020) 129–153.
14. A. Hesaraki, N. Dellaert, T. de Kok, Integrating nurse assignment in outpatient chemotherapy appointment scheduling, OR Spectrum 42 (4) (2020) 935–963.
15. B. Liang, A. Turkcan, Acuity-based nurse assignment and patient scheduling in oncology clinics, Health Care Management Science 19 (3) (2016) 207–226.
16. M. Hesmat, A. Eltawil, Solving operational problems in outpatient chemotherapy clinics using mathematical programming and simulation, Annals of Operations Research (2019) 1–18.
17. Y. Huang, A. Bryce, T. Culbertson, S. Connor, S. Looker, K. Altman, J. Collins, W. Stellner, R. McWilliams, A. Moreno-Aspitia, S. Ailawadhi, R. Mesa, Alternative outpatient chemotherapy scheduling method to improve patient service quality and nurse satisfaction, Journal of Oncology Practice 14 (2) (2018) e82–e91.
18. S. Hahn-Goldberg, M. Carter, J. Beck, M. Trudeau, P. Sousa, K. Beattie, Dynamic optimization of chemotherapy outpatient scheduling with uncertainty, Health Care Management Science 17 (4) (2014) 379–392.

19. A. Sadki, X. Xie, F. Chauvin, Planning oncologists of ambulatory care units, Decision Support Systems 55 (2) (2013) 640–649.
20. M. Alvarado, T. Cotton, L. Ntaimo, E. Pérez, W. Carpentier, Modelling and simulation of oncology clinic operations in discrete event system specification, Simulation 94 (2) (2017) 105–121.
21. M. Amin, S. Edge, F. L. Greene, D. R. Byrd, R. K. Brookland, M. K. Washington, J. E. Gershenwald, C. C. Compton, K. R. Hess, D. C. Sullivan, J. M. Jessup, J. D. Brierley, L. E. Gaspar, R. L. Schilsky, C. M. Balch, D. P. Winchester, E. A. Asare, M. Madera, D. M. Gress, L. R. Meyer, American Joint Committee on Cancer (AJCC) Cancer Staging Manual, Eighth edition, Springer, New York, 2017.