# A decision support service for hospital bed assignment

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**Abstract**: In recent years, there has been a growing interest in problems related to health facilities. Many authors proposed decision-support approaches to increase efficiency within hospital departments. An efficient use of healthcare resources reduces medical costs and provides better service to users. In this paper, we address patient admission scheduling problems, that consist in deciding which patient to admit, at what time and which room is assigned. Rooms have several characteristics and a limited capacity. These problems are very similar to those addressed in manufacturing process environments. Patients are similar to jobs with a processing time (length of stay), a start date, a due date, and they have to be assigned to an equipped machine (room) in a well-defined planning horizon. Overcrowded rooms are not allowed. Taking into account that a constraint on the maximum number of patients accommodated in every room is imposed, the authors propose an optimization model to make best use of the available resources. The proposed model is based on the initial assumption that the information is available in advance (offline approach). It is tested on a set of instances. Results are represented and discussed.

**Keywords**: Scheduling, Healthcare Management, Combinatorial Optimization

## 1.Introduction

In recent years, interest in problems related to health facilities has increased. In this paper, we discuss about hospital bed assignment problems, in which some patients needing a period of hospitalization have to be assigned to appropriate hospital beds. Currently, they are often solved manually and as a result the available resources are inefficiently used. Then, our main aim is to propose a decision support service for bed managers, based on the use of an optimization model. We mainly refer to the Italian healthcare context.

Patient hospitalization can usually fall into one of the following cases (Azienda Ospedaliera della provincia di Lecco, 2013):

- Elective admissions in ordinary regime
- Elective admissions in day hospital regime
- Complex ambulatory macro-activity
- Low complexity surgery
- Admissions in emergency-urgency
- Admissions for compulsory medical treatment

In this paper, we only refer to elective admissions in ordinary regime. Planned or elective hospitalization is defined as the clinical case, in which a patient chooses to be admitted in hospital and agrees to carry out the hospitalization on a date that is determined by means of the use of a waiting list (Azienda Ospedaliera della provincia di Lecco, 2013). The time spent by every patient in the waiting list is defined as access time and should be controlled to guarantee quality of care (Yeung et al., 2004). Waiting lists should be managed to promote the principles of transparency and equity. The hospitalization is usually the output of a process, shown in Figure 1 (Azienda Ospedaliera della provincia di Pavia, 2012).

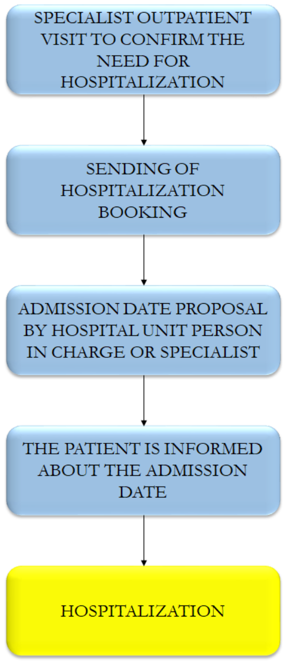


**Figure 1: from specialist visit to hospitalization**

First of all, a specialist visit is necessary to confirm the need for hospitalization. It can be performed by a specialist in hospital or in private practice. After the visit, an admission date is proposed to the patient, based on the length of a waiting list. Nowadays, bad management of waiting lists often causes very long waiting times.

The choice of the hospitalization period should be strongly conditioned by the clinical priority. In Italy, four priority classes are usually considered, as shown in Table 1 (Azienda Ospedaliera della provincia di Lecco, 2013):

**Table 1: priority classes description**

| Priority class | Admission period | Description |
|---|---|---|
| A | Within 30 days | Clinical cases that could potentially worsen and become urgent |
| B | Within 60 days | Clinical cases characterized by intense pain, or severe dysfunction or disability |
| C | Within 180 days | Clinical cases that present minimal pain and/or dysfunction or disability and do not show a tendency to aggravate |
| D | Within 12 months | Clinical cases that do not present symptoms and do not show a tendency to aggravate |

In a health context, three decision-making levels can usually be considered: strategic, tactical, operational (Zeltyn et al., 2011), (Rais and Viana, 2010). Strategic planning involves the long-term decision making, based on aggregate information; operational planning refers to a short-term decision making and concerns the healthcare delivery process; tactical decisions link strategic and operational decisions (Hulshof et al., 2012). In this paper, we refer to the operational level because the decisions to be taken have an impact in the short-term.

## 2. A relevant literature review

In the literature, the study of hospital bed assignment is quite recent. Demeester et al., (2010) introduced the patient bed assignment problem (PBAP), in which the period of hospitalization of the patients is well defined and main decisions are about beds to be assigned. In this context, the main aim is to maximize the overall patient comfort, considering some important factors: gender, age, preferred or mandatory equipment, room category preference, specialty, etc. Each patient should be assigned to the most suitable room, compatibly with several constraints (e.g., room capacity). The problem introduced by Demesteer et al., (2010) is NP-Hard, as demonstrated by Vancroonenburg et al., (2014). In fact, Demesteer et al., (2010), generated a set of six instances for the problem and proposed a hybrid tabu-search method to solve them in a reasonable computational time. Further seven instances were introduced by Bilgin et al., (2012). Ceschia and Schaerf, (2011) propose a new mathematical formulation for the PBAP, reducing the overall number of decision variables. They solve the problem using a simulated annealing approach and compute some new lower bounds and upper bounds values. Range et al., (2014) present a column generation approach and improve some of the best upper bound values known in the literature. Guido et al., (2018) propose an efficient matheuristic, named FiNeMath, for the PBAP and improve all the best value of bounds of the current state of the art.

Ceschia and Schaerf, (2012) introduced the patient admission scheduling problem under uncertainty (PASU). It consists in deciding which patient to admit, at what time and which room is assigned. The best patient-to-room assignments in terms of quality of care, have to be found. Note that in the PASU, compared to the PBAP, also an admission date and a discharge date have to be decided for every patient. They propose an optimization model and solve the problem in the online manner by a simulated annealing approach. Furthermore, they generate a set of 450 instances characterized by different size (small, med, large) and complexity. In this context, the uncertainty regards the possibility that some patients extend their period of hospitalization. The results about the PASU, were improved by Lusby et al., (2016) using an adaptive large neighbourhood search. Guido et al., (2017) propose a model formulation for the offline version of the PASU and find an optimal solution for the first 50 instances of the small family.

In the literature, some authors use clinical priority as a factor to select a set of patients from a waiting list. Conforti et al., (2011) propose three values of clinical priority in their model for supporting week hospital management. About the radiotherapy patient scheduling problem, Conforti et al., (2010) consider some priority values based on different scenarios. While, Legrain et al., (2014) consider high-priority and low-priority patients to control access to a radiotherapy center.

In this paper, we propose and test an optimization model to support the bed management within hospitals. It is more general than many other approaches proposed in the literature, in order to extend the number of possible applications as much as possible. The decisions are the same addressed by the PASU because for each patient in waiting list, a bed and an admission date have to be determined. However, it also takes into account clinical priority and number of waiting days, to select in the best way patients from a waiting list. A centralized hospital management is proposed.

## 3. Problem statement

In this section, we describe the fundamental aspects of the problem. First of all, we refer to a generic hospital. There is a waiting list, i.e. a set of patients to be admitted. Their main attributes are reported and explained in Table 2.

**Table 2: main characteristics of the patients**

| Attribute | Details |
|---|---|
| Gender | Male or female |
| Registration date | Date at which the patient becomes known to the hospital system |
| Latest admission date | Latest possible date to admit the patient in the hospital, considering a certain planning horizon |
| Clinical priority | There are four priority classes for admissions, based on the severity of the disease |
| Length of stay (LOS) | Number of consecutive nights to be spent in hospital |
| Medical specialty | Needed medical specialty, due to the pathology |

Furthermore, in hospital there is a set of departments, containing one or more rooms. The main room attributes are reported and explained in Table 3.

The problem is defined on a certain planning horizon (e.g., 14 days). Note that patient's latest admission date is computed as the difference between the last day of the planning horizon and the LOS but is updated in the next planning if the patient has not already been hospitalized. In fact we impose that, if a patient is admitted, he/she has to be also discharged in the same planning horizon. Furthermore, we suppose that all the patients are available on the first day of the planning horizon because they were previously included in the waiting list. Note that each patient has to spend his period of hospitalization in not more than one room; transfers are not allowed.

Considering that room capacity is a scarce resource, the objective is to maximize the number of admitted patients on the planning horizon. Two important criteria are used to select patients from waiting list: number of waiting days and clinical priority. An offline scheduling problem is solved (Pinedo, 2012).

Not all patient-to-room assignments are feasible, some constraints have to be taken into account. In fact, if you consider a generic patient $p_1$, a generic room $r_1$ and a day $d_1$, the assignment of $p_1$ to $r_1$ on day $d_1$ is not always possible for some reasons listed below:

- There aren't available beds in room $r_1$ on day $d_1$.
- Department medical staff, to which room $r_1$ belongs, can't treat the specialty required by patient $p_1$.
- Inconsistency between patient's gender and room gender policy.

Therefore, the assignment of patients to hospital rooms is quite complex.

**Table 3: main characteristics of the rooms**

| Attribute | Details |
|---|---|
| Capacity | Number of available beds (single, double, etc.) |
| Medical specialty | It refers to the pathology, which can be treated |
| Gender policy | Male or female |

## 4. Model description and discussion

In this section, the proposed integer linear optimization model is described.

### 4.1 General sets

In this subsection, we report two general sets:

- $D = \{1, 2, \ldots, |D|\}$ is the set of days. $|D|$ is the length of the planning horizon.
- $S = \{1, 2. \ldots, |S|\}$ is the set of medical specialties. $|S|$ is the number of medical specialties, treatable in hospital.

### 4.2 Sets and parameters about patients

In this subsection, we report and describe the information about patients, in terms of sets and parameters:

- $P = \{1, 2, \ldots, |P|\}$ set of patients. $|P|$ is the number of patients in the waiting list, in the current planning horizon.
- $wd_p$ : waiting days of the patient $p \in P$. $wd_p$ is computed as the difference between the first day

of the current planning horizon and the registration date.

- $gen_p$: gender of patient $p \in P$.
- $los_p$: length of stay of patient $p \in P$.
- $lad_p$: latest possible admission date of patient $p \in P$.
- $spec_p$: medical specialty required from patient $p \in P$.
- $pr_p$: clinical priority for patient $p \in P$; $pr_p$ can have four different values: 1, 10, 100, 1000. A high value indicates a high clinical priority.
- $AD_p = \{1, \dots, lad_p\}$ range of possible admission dates for patient $p \in P$.

### 4.3 Sets and parameters about rooms

In this subsection, we introduce all the sets and the parameters related to rooms:

- $cap_r$: number of beds in room $r \in R$.
- $rgen_r$: gender policy of room $r \in R$.
- $NS_r$: set of medical specialties $s \in S$ not treated in room $r \in R$.

### 4.4 Decision variables

In this subsection, we report the meaning of the binary decision variables of the optimization model:

- $ad_{p,d} \in \{0,1\} \, \forall \, p \in P, d \in AD_p$ : 1 if patient $p \in P$ is admitted on day $d \in AD_p$. 0 otherwise.
- $x_{p,r,d} \in \{0,1\} \, \forall \, p \in P, r \in R, \, d \in D$ : : 1 if patient $p \in P$ is assigned to room $r \in R$ on day $d \in D$. 0 otherwise.

### 4.5 Objective function

In this subsection, the objective function is introduced and explained. It is the maximization of the number of admitted patients in the defined planning horizon, considering two important factors: clinical priority and waiting days:

Maximization of the number of admitted patients, weighted by the clinical priority:

$$\sum_{p \in P} \sum_{d \in AD_p} pr_p * ad_{p,d} \quad (1)$$

Maximization of the number of admitted patients, weighted by the waiting days:

$$\sum_{p \in P} \sum_{d \in AD_p} wd_p * ad_{p,d} \quad (2)$$

Substantially, for each patient $p \in P$ an overall weight $(pr_p + wd_p)$ can be defined. A high weight indicates a corresponding high probability for patient $p$, to be selected from the waiting list in the current planning horizon.

### 4.6 Constraints

In this subsection, we introduce the constraints of the model.

Each patient can be admitted in hospital not more than once during the planning horizon:

$$\sum_{d \in AD_p} ad_{p,d} \leq 1 \; \forall \; \mathrm{p} \in \mathrm{P} \quad (3)$$

Assignments in rooms, which do not treat the required specialty are not allowed:

$$x_{p,r,d} = 0 \; \forall \; r \in R, p \in P \mid spec_p \in NS_r, d \in D \quad (4)$$

Consistency between patient's gender and room gender policy:

$$x_{p,r,d} = 0 \; \forall \; r \in R, p \in P \mid gen_p \neq rgen_r, d \in D \quad (5)$$

Each patient, on each day, cannot be assigned in more than one room:

$$\sum_{r \in R} x_{p,r,d} \leq 1 \;\; \forall \; \mathrm{p} \in \mathrm{P}, \; \mathrm{d} \in \mathrm{D} \quad (6)$$

Room capacity cannot be exceeded:

$$\sum_{p \in P} x_{p,r,d} \leq cap_r \; \forall \; r \in R, \; d \in D \quad (7)$$

The period of hospitalization of each patient consists of consecutive nights:

$$\sum_{r \in R} \sum_{k=d}^{d+los_p-1} x_{p,r,k} \geq los_p * ad_{p,d} \; \forall \; p \in P,$$

$$d \in AD_p \quad (8)$$

Each admitted patient spends in hospital a number of days equal to his/her LOS:

$$\sum_{r \in R} \sum_{d \in D} x_{p,r,d} = los_p * \sum_{d \in AD_p} ad_{p,d}$$

$$\forall \; p \in P \quad (9)$$

Transfers from a room to another one are not allowed:

$$x_{p,r,d} - x_{p,r,(d-1)} - ad_{p,d} \leq 0 \; \forall \; p \in P, r \in R,$$

$$d \in AD_p \setminus \{1\}, \quad (10)$$

$$x_{p,r,d} - x_{p,r,(d-1)} \leq 0 \; \forall \; p \in P, r \in R,$$

$$d \in D \mid d \geq lad_p + 1, d \leq lad_p + los_p - 1 \quad (11)$$

### 5. Computational experiments

In this section, we describe the validation of the proposed optimization model (1) - (11). It is quite general and could be used to support the decision-making in many healthcare facilities. It was tested on a set of instances, derived from those generated in (Ceschia and Schaerf, 2012) and characterized by real-world features. In order to use them to validate our model, we adequately changed some values and introduced new parameters. In the original families of instances (Ceschia and Schaerf, 2012), the rooms are characterized by two further gender policies, in addition to the male and female gender policies: dependent gender policy (room gender policy is not previously defined but depends on the gender of patients present in it) and no gender policy; we have randomly associated to these rooms a male or female gender policy to guarantee a consistency with the Italian healthcare context. Furthermore, we randomly added a clinical priority to each patient. Moreover, compared to the instances proposed by Ceschia and Schaerf, (2012), in this paper the demand is in general greater than the overall resource because of the hard constraints (5); then, in general, it is not possible to completely empty the waiting list time by time, as shown in Figure 2. At the beginning of the planning horizon 1 (iteration 1), there is a set of patients in the waiting list. Some of them, based on the available resources, are admitted in hospital. Then, the waiting list is powered by new arrivals (orange figures) and a new scheduling problem is solved on the second planning horizon (iteration 2). The overall number of iterations depends on the needs of each healthcare facility.

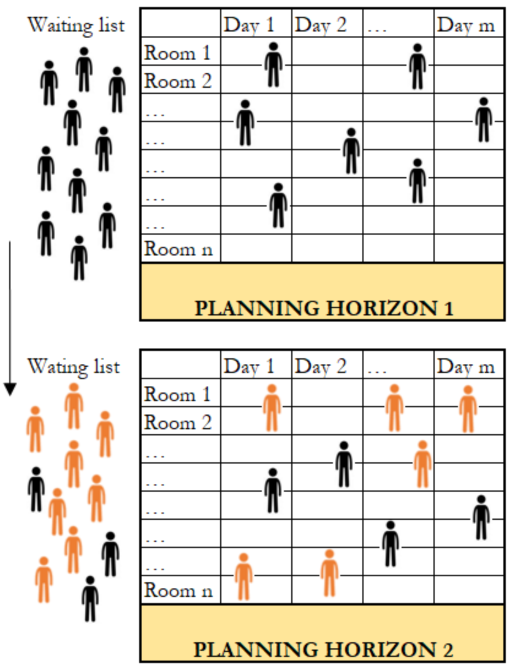


**Figure 2: waiting list management**

## 5.1 Illustrative example

In this subsection, we discuss our computational results. We conducted the computational experiments on a Server running Windows server R2 2012 with Intel Xeon E5-2695v3 14 CORE/64GB. We used CPLEX 12.7.1, Academic License.

We tested the model on a new version of the instances originally proposed in (Ceschia and Schaerf, 2012). In particular, we solved some instances, belonging to the small family (short, mid, long). Their main characteristics are reported in Table 4. |De| is defined as the overall number of departments.

**Table 4: main characteristics of the benchmark instances**

| Family of instances | \|De\| | \|R\| | \|P\| | \|S\| | \|D\| |
|---|---|---|---|---|---|
| Small short | 4 | 8 | 50 | 3 | 14 |
| Small mid | 4 | 8 | 100 | 3 | 28 |
| Small long | 4 | 8 | 200 | 3 | 56 |

However, we only show and discuss the solution of one instance (named small-short 18), as illustrative example. Room characteristics are shown in Table 5, while the information about the waiting list is in Appendix A, in Table A1.

**Table 5: rooms characteristics of the illustrative example**

| ID | Specialism | Capacity | Gender policy |
|---|---|---|---|
| 1 | Rheumatology | 6 | Male |
| 2 | Cardiology | 6 | Male |
| 3 | Nephrology | 4 | Female |
| 4 | Cardiology | 1 | Female |
| 5 | Rheumatology | 1 | Female |
| 6 | Nephrology | 4 | Male |
| 7 | Cardiology | 1 | Male |
| 8 | Nephrology | 6 | Male |

There are 8 rooms, which treat three medical specialties: nephrology, rheumatology, cardiology. 50 patients are in the waiting list and are characterized by a pathology, a clinical priority, a certain number of waiting days. We have to determine patient-to-room assignments, which allow the best use of available resources, in order to increase hospital productivity. The waiting list should be quickly emptied and the rooms should be as filled as possible. The proposed optimization model is able to find the patient-to-room assignments in a computational time of 4 seconds.

In Figure 3 and Figure 4, the solution of the illustrative example is represented. For each cross room-day, a list of hospitalized patients is shown. E.g., in room 6 on day 8, there are the patients with ID 1, 24 and 35 respectively.

Note that 45 out of the 50 patients are admitted in hospital during the defined planning horizon.

| | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 | Day 6 | Day 7 |
|---|---|---|---|---|---|---|---|
| **Nephrology** | | | | | | | |
| Room 3 | | P8 | P8, P46 | P8, P17, P46 | P8, P46 | P6, P8, P23, P46 | P6, P8, P23, P46 |
| Room 6 | | | | | | | P1, P35 |
| Room 8 | | | | | | | |
| **Rheumatology** | | | | | | | |
| Room 1 | P20, P45, P47, P50 | P20, P50 | P20 | P20 | | P29 | P29 |
| Room 5 | | P44 | P40 | P40 | P19 | P19 | P28 |
| **Cardiology** | | | | | | | |
| Room 2 | | P13 | P13 | | P22, P26 | P2, P22, P26, P37, P49 | P11, P22, P27, |
| Room 4 | P48 | | P39 | P39 | P25 | P25 | P25 |
| Room 7 | | P14 | P14 | P14 | | | |

**Figure 3: illustrative example solution (days 1-7)**

| | Day 8 | Day 9 | Day 10 | Day 11 | Day 12 | Day 13 | Day 14 |
|---|---|---|---|---|---|---|---|
| **Nephrology** | | | | | | | |
| Room 3 | P8, P23, P43 | P8, P36, P43 | P3, P8, P36 | P3, P8 | | P41 | |
| Room 6 | P1, P24, P35 | P1, P24, P35 | P1, P24, P35 | P1, P24 | P24 | P24 | |
| Room 8 | P21 | P21 | P21 | P12, P31 | P12, P31 | P42 | |
| **Rheumatology** | | | | | | | |
| Room 1 | P29 | P29 | P29 | P29 | P29 | | |
| Room 5 | P28 | P7 | P7 | P7 | P32 | P32 | P32 |
| **Cardiology** | | | | | | | |
| Room 2 | P11, P22, P27, | P11, P22, P27, P30 | P10, P11, P30 | P9, P11, P30 | P9 | | |
| Room 4 | | | | | | P38 | P16 |
| Room 7 | | | | | P15 | P15 | |

**Figure 4: illustrative example solution (days 8-14)**

The non-admitted patients have the following ID: 4, 5, 18, 33, 34. Among them, only the patient with ID 4 has a high level of clinical priority. She could be admitted only in room with ID 5, which has a very limited capacity.

## 6. Conclusions

Recently, the diffusion of operational research in health context has increased the possibility of solving better many typical hospital problems.

In this paper, we formulated and validated an optimization model to support the decision-making about hospital bed assignment problem. Today, in many Italian hospitals, this problem is still solved manually and often no criteria are used to select patients from waiting lists. In this way, some patients may have to wait too long, without respect for the principles of equity and transparency. Therefore, in this paper we propose a framework to solve this problem in an automated and fast way.

The use of our model allows to achieve multiple results:

- Increase in efficiency and productivity, due to the saturation of rooms as much as possible. Underutilization is reduced.
- Increase in patient satisfaction; he/she should not remain on the waiting list for too long.
- Protection of the principles of transparency and equity. Patients to be admitted are chosen only by the decision support tool and not by health professionals. Two important criteria are used: waiting days and clinical priority.
- Satisfaction of the local demand. Patients do not move to other healthcare facilities because waiting days are not many. Congestion is avoided.

The proposed model is very general, in order to extend the number of possible applications.

About future works, the transfers from a room to another one could be allowed. Other criteria could be proposed to select the patients from the waiting list. Furthermore, in the objective function we could also consider some quantities closely related to economic aspects, such as costs and revenues.

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## Appendix A. FIRST APPENDIX

**Table A1: waiting list of the illustrative example**

| ID | Gender | Waiting days | LOS | Clinical priority | Specialism |
|---|---|---|---|---|---|
| 1 | Male | 14 | 5 | 1 | Nephrology |
| 2 | Male | 14 | 1 | 10 | Cardiology |
| 3 | Female | 14 | 2 | 100 | Nephrology |
| 4 | Female | 14 | 7 | 1000 | Rheumatology |
| 5 | Female | 14 | 8 | 1 | Rheumatology |
| 6 | Female | 10 | 2 | 10 | Nephrology |
| 7 | Female | 5 | 3 | 100 | Rheumatology |
| 8 | Female | 14 | 10 | 1000 | Nephrology |
| 9 | Male | 11 | 2 | 1 | Cardiology |
| 10 | Male | 5 | 4 | 10 | Cardiology |
| 11 | Male | 10 | 5 | 100 | Cardiology |
| 12 | Male | 5 | 2 | 1000 | Nephrology |
| 13 | Male | 11 | 2 | 1 | Cardiology |
| 14 | Male | 14 | 3 | 10 | Cardiology |
| 15 | Male | 12 | 2 | 100 | Cardiology |
| 16 | Female | 7 | 1 | 1000 | Cardiology |
| 17 | Female | 10 | 1 | 1 | Nephrology |
| 18 | Female | 14 | 2 | 10 | Rheumatology |
| 19 | Female | 3 | 2 | 100 | Rheumatology |
| 20 | Male | 14 | 4 | 1000 | Rheumatology |
| 21 | Male | 13 | 3 | 1 | Nephrology |
| 22 | Male | 14 | 5 | 10 | Cardiology |
| 23 | Female | 14 | 3 | 100 | Nephrology |
| 24 | Male | 12 | 6 | 1000 | Nephrology |
| 25 | Female | 8 | 3 | 1 | Cardiology |
| 26 | Male | 14 | 2 | 10 | Cardiology |
| 27 | Male | 13 | 3 | 100 | Cardiology |
| 28 | Female | 13 | 2 | 1000 | Rheumatology |
| 29 | Male | 13 | 7 | 1 | Rheumatology |
| 30 | Male | 14 | 3 | 10 | Cardiology |
| 31 | Male | 14 | 2 | 100 | Nephrology |
| 32 | Female | 14 | 3 | 1000 | Rheumatology |
| 33 | Female | 5 | 5 | 1 | Rheumatology |
| 34 | Female | 14 | 8 | 10 | Rheumatology |
| 35 | Male | 14 | 4 | 100 | Nephrology |
| 36 | Female | 10 | 2 | 1000 | Nephrology |
| 37 | Male | 12 | 3 | 1 | Cardiology |
| 38 | Female | 11 | 1 | 10 | Cardiology |
| 39 | Female | 14 | 2 | 100 | Cardiology |
| 40 | Female | 13 | 2 | 1000 | Rheumatology |
| 41 | Female | 14 | 1 | 1 | Nephrology |
| 42 | Male | 3 | 1 | 10 | Nephrology |
| 43 | Female | 12 | 2 | 100 | Nephrology |
| 44 | Female | 12 | 1 | 1000 | Rheumatology |
| 45 | Male | 11 | 1 | 1 | Rheumatology |
| 46 | Female | 6 | 5 | 10 | Nephrology |
| 47 | Male | 7 | 1 | 100 | Rheumatology |
| 48 | Female | 11 | 1 | 1000 | Cardiology |
| 49 | Male | 14 | 3 | 1 | Cardiology |
| 50 | Male | 6 | 2 | 10 | Rheumatology |