Building Surgical Team with High Affinities
A Bicriteria Mixed-integer Programming Approach

Christine Di Martinelly[1] and Nadine Meskens[2]
[1] *IESEG School of Management, (LEM-CNRS and HEMO), 3 rue de la Digue, 59000 Lille, France*
[2] *Catholic University of Louvain (UCL), Louvain School of Management, Campus Mons, Chaussée de Binche, 151, 7000 Mons, Belgium*

Keywords: Health Care Management, Operating Theatre, OR in Health, Multiobjective Mixed Integer Program.

Abstract: Assuming a task-based approach to model the demand for the nurses in the operating rooms, the paper proposes a bicriteria mixed-integer approach to build surgical teams with high affinities while minimizing the nurses' waiting time. The suggested model builds nurse rosters considering their availabilities, legal constraints and affinities with the operating surgeons. The model is solved using an ε-constraint approach and is tested on instances of a Belgian hospital. From the experiments, it appeared that the 2 objectives considered are conflicting. Relaxing the criterion of the affinities has an impact on the waiting time.

In the document, the terms used to designate persons are taken in a generic sense and refer to males and females without distinction.

1 INTRODUCTION

The operating rooms are one of the cornerstones of hospital activity. It represents one of the highest budget expenses. Managing the operating rooms is a complex task that deals with human and material management: on one side, there is the planning and scheduling of the surgical interventions while minimizing the operating costs of the operating rooms and managing the specific materials; on the other side, there is the planning and rostering of human resources considering legal and personal constraints and preferences of the various staff members (surgeons, anaesthesiologists, nurses) while satisfying the patients. Also, the managed resources are in limited supply.

The objective of this research paper is to help the operating room manager to put together surgical teams to improve the planning and scheduling. Traditional approaches developed to plan and schedule the surgical interventions are made of 2 steps. The time horizon considered is usually one week. First, the surgical interventions are planned taking into account the availabilities of rooms and surgeons. A surgical intervention is assigned to a day and a room. Then, the surgical interventions are scheduled daily under the constraints on the availabilities of personnel and materials.

Numerous papers studied the complexity of planning and scheduling the operating rooms (Cardoen et al., 2010). The various problems studied differentiate on basis of the constraints, decision variables, objectives and solution methods. The composition of the surgical team has been of little interest so far in operations management.

Yet, an increasing number of studies (Mazzocco et al., 2009); (Weaver et al., 2010); (Kurmann et al., 2012) demonstrated that cooperation, coordination and communication between the members of a surgical team have a positive impact on the patient surgical outcome. To the best of our knowledge, only Meskens et al., (2012) took into account the affinities of the surgical team while scheduling the surgeries. While considering the affinities of the personnel, no author considered the nurses' working conditions (maximum number of work per week, days-off, breaks,…).

Those elements are usually considered in the literature of 'nurse rostering' or 'nurse scheduling'. Burke et al., (2004) and, more recently, Van den Bergh et al., (2013) provided detailed reviews on the subject. It is worth noting that none of the papers mentioned considered the specific case of the operating rooms.

Indeed, in most of the hospital departments, the

Di Martinelly C. and Meskens N..
Building Surgical Team with High Affinities - A Bicriteria Mixed-integer Programming Approach.
DOI: 10.5220/0004831804170424
In *Proceedings of the 3rd International Conference on Operations Research and Enterprise Systems* (ICORES-2014), pages 417-424
ISBN: 978-989-758-017-8

demand for nurses is modeled based on shift. The number of staff required is determined to meet a service measure such as for instance a ratio nurse/patient (Ernst et al., 2004). In the operating rooms, on the contrary, the demand for staff is based on a list of tasks. Each task is a surgical intervention characterized by a starting time and duration, to be scheduled and performed.

The objectives considered when building the nursing roster are usually the minimization of the salary costs and the maximization of the nurses' preferences. The nurses' preferences are measured in terms of requests to work at specific time periods (shifts, day-offs, etc.) (Jaumard et al., 1998); (Bard and Purnomo, 2005). However, the models were not taking into account preferences in terms of co-workers or affinities between the surgical team members.

The objective of this paper is to form surgical teams (surgeon, nurses) with a high affinity degree while taking into account the availaibilities of nurses and the legal constraints on working conditions (days-off, breaks,…). We also want to minimize the waiting time of nurses in the operating rooms so that we minimize idle time and limit overtime payments.

We face a multiobjective problem with two criteria : to minimize the waiting time of nurses and to maximize the affinities of the surgical teams.

A lexicographic optimization was considered to solve this problem in Di Martinelly and Meskens (2013). It means that an order of importance was set between the objectives: the first objective is optimized; then the second one is optimized under the constraint that the first one stays optimal. There are 2 main limitations to this approach: the decision maker has to determine which objective is the most important to him and none of the solutions generated is a compromise between the objectives; the solution is optimal regarding one of the objectives. For instance, the operating room manager (the decision maker) will have to settle for a nurse schedule that is either optimum for the waiting time or optimum for the affinities of the surgical teams; he won't be provided with a compromise schedule that would probably best suit him.

The approach considered in this paper is different. There is no order of importance between the objectives and both objectives are optimized. We build the set of Pareto optimal solutions (or part of it). The main advantage of this method is the possibility to provide the operating room manager with the set of compromise solutions (meaning the non-dominated solutions in the Pareto sense). The manager can thus choose among them the solution he prefers and estimates the trade-offs between the possible solutions.

The originality of the research is the integration of personnel affinities in the rostering while keeping the personnel costs under control. The problem is modeled as a multiobjective mixed-integer program. It is solved using an ε-constraint approach. The approach is then tested on real data of a Belgian hospital. The rest of the paper is organized as follows: in section 2, we present the context of the paper. In section 3, we propose a mixed-integer program to build the surgical teams and nurse rosters. The model is then tested on real data and the results are discussed in section 4. We finish with conclusion and future work.

2 THE GENERAL FRAMEWORK

The objective of the framework is to provide the decision maker with a tool to obtain a surgical schedule that both satisfy human and managerial constraints. It uses a holistic view of the problem.

The first part consisted in a model developed by Di Martinelly et al., (2011). It considered the planning and scheduling of surgical interventions over 5 days. Each surgical intervention is done by a surgeon, which has availabilities over the week. It requires a number of resources (rooms, anesthesiologists, nurses) to be available. At every time period, the suggested planning must satisfy the constraints on the number of nurses available. The results of this model indicate the starting time of each surgical intervention in a specific room, on a specific day.

The detailed surgical schedule over the week is the workload pattern used to build the nurse rosters and the surgical teams while taking into account the working rules.

The remainder of this paper focuses on the second part of the framework: a multiobjective mixed-integer program that establishes surgical teams maximizing the affinities between the nurses and the surgeons while making the schedule efficient for nurses. We then suggest a solving multiobjective approach based on the ε-constraint method.

3 METHODOLOGY

3.1 Problem Description

Each surgical intervention k requires a number of nurses (n_k), which are present during the entire surgical time (l_k). A surgical intervention is done by one specific surgeon. Each operating surgeon has a degree of preferences to work with each nurse.

The affinity between surgeons and nurses is expressed through an affinity matrix. Based on the preferences expressed by a surgeon to work with a nurse, a score that varies between 0 and 9 is assigned; a score of 0 represents a total incompatibility while a 9 is a strong preference.

A pretreatment is realized: based on the affinity matrix and knowing that a surgery is assigned to one surgeon, we can deduce the degree of affinity between the surgery k and the nurse i (s_{ki}).

The availability of nurse i is defined in a matrix for each day and time period (p_{itd}). If (p_{itd}) = 1, it means that a nurse can be assigned to a surgical intervention; 0 otherwise. The nurses' availabilities are checked for the whole surgical intervention time. Nurses can start working at different time periods (r_{id}), with $r_{id} = \min_t p_{idt}\ \forall i, \forall d$. Each nurse i can work up to a certain number of periods per day d (t_{id}) and per week (z_i). The values are based on the working contract and work regulations. This modeling technique enables us to take into account nurses' requirement (half-day working, 35 hours or 40 hours, etc.).

We determine which nurse i is assigned to the surgical intervention k (y_{ik}). A nurse is assumed to attend the whole assigned surgery k.

As aforementioned, the surgical planning is a data of our problem and is done for a 5-day period. It is obtained by solving the model proposed by Di Martinelly et al. (2011) as mentioned in point 2. The surgical planning is done assuming a number of nurses available and paid and it may require a certain amount of overtime work.

The objective of the present model is, based on this demand for nurses, to obtain the best allocation of nurses to the surgeries.

The quality of the nurse roster is evaluated either by the total waiting time of nurses or by the affinities of the surgical team ($\sum_i y_{ik} * s_{ki}$).

3.2 Mathematical Model

Sets

- d set of operating days , $d = 1, .., D$
- t set of time periods per day , $t = 1, .., T$
- k set of surgical interventions over the period , $k = 1, .., K$
- i set of nurses , $i = 1, .., I$

Parameters

- s_{ki} : degree of affinity between the surgeon (related to surgery k) and the nurse i
- p_{itd} : availability of nurse i in period t on day d {0,1}
- r_{id}: time period at which nurse i starts working on day d
- n_k : number of nurses required to perform surgical intervention k
- x_{ktd} : starting time of surgical intervention k in period t on day d {0,1}
- l_k : duration of surgical intervention k in time periods
- t_{id} : available working time in time periods for nurse i on day d
- z_i : available working time in time periods for nurse i over the horizon

Variables

- y_{ik} : a binary variable that represents the assignment of nurse i to surgical intervention k
- m_{id}: the time period at which nurse i finishes her surgical interventions for day d
- w_{id}: the waiting time in periods of nurse i over day d

Model

$$MIN\ f_1 = \sum_i \sum_d \left(m_{id} - r_{id} - \sum_k \sum_t (y_{ik} * l_k * x_{ktd}) \right) \quad (1)$$

$$MAX\ f_2 = \sum_k \sum_i y_{ik} * s_{ki} \quad (2)$$

s.t.

$$\sum_k (y_{ik} \sum_{\tau=t-l_k+1}^{t} x_{ktd}) \le p_{itd} \quad \forall i, \forall t, \forall d \quad (3)$$

$$\sum_i y_{ik} = n_k \ \forall k \quad (4)$$

$$\sum_k (y_{ik} * l_k) \le z_i \ \ \forall i \quad (5)$$

$$\sum_k \sum_t (y_{ik} * l_k * x_{ktd}) \le t_{id} \ \ \forall i, \forall d \quad (6)$$

$$\sum_t (y_{ik} * (l_k + t) * x_{ktd}) \le m_{id} \forall i, \forall d, \forall k \quad (7)$$

$$m_{id}, w_{id} \geq 0, \forall i, \forall d \quad (8)$$

$$y_{ik} \in \{0,1\}, \forall i, \forall k \quad (9)$$

Objective (1) is intended to give the nurses a schedule that minimizes the total waiting times. Objective (2) maximizes the affinities between the surgeons leading the intervention and the nurses.

Equations (3) ensure that a nurse will be assigned to a surgical intervention only if he is available; it also ensures that a nurse can only attend a surgical intervention at a time. Equations (4) ensure that there is the required number of nurses to perform the surgery. Equations (5) ensure that a nurse doesn't work more than the authorized time over the week. Equally, equations (6) ensure that the daily working time of a nurse is respected.

Equations (7) determine when the last surgical intervention of a nurse finishes each day (Makespan of a nurse *i* activity on day *d*). Equations (8) define the variables as positive. Finally, equations (9) define the assignment of a nurse to a surgery as a binary variable.

3.3 ε-Constraint based Approach

The multiobjective mixed-integer linear program described in point 3.2 provides each week the nurse rosters. Our objective is not to provide the decision-maker with all the non-dominated solutions but with a set of them. In a formal way x^* is a non-dominated solution if and only if, in the case of a maximization of all objective functions, there is not any $x \in X$ (where X is the feasible set of variables that satisfies the constraints) such that $f_i(x^*) \leq f_j(x)$ for all i, and $f_j(x^*) < f_j(x)$ for at least one j (Hwang et al., 1979).

The most widely used technique to solve a multiobjective linear problem is the weighting method. However, this technique has some disadvantages, which make it difficult to apply in our problem: the scaling of the objective function, the choice of the weights, and the number of runs needed to generate several alternative solutions (Mavrotas, 2009).

As a result, we used the second more popular approach, the ε-constraint method (Haimes et al., 1971, Chankong and Haimes, 1983). This method has in addition the advantage of being independent of the decision space (Ehrgott and Ruzika, 2008).

In case of 2 objective functions, the ideal and nadir points can easily be determined (Ehrgott, 2005). Those points are used to build the payoff table without weakly efficient points.

Algorithm to find the ideal and nadir points.

1. Solve the single objective problems $min\ f_1$ and $max\ f_2$. Denote the optimal objective values by w^I and a^I
2. Solve $max\ f_2$ with the additional constraint $f_1 \leq w^I$
3. Solve $min\ f_1$ with the additional constraint $f_2 \geq a^I$
4. Denote the optimal objective values obtained in steps 2 and 3 by a^N and w^N, respectively
5. The nadir point is $N = (w^N, a^N)$ and the ideal point is $I = (w^I, a^I)$

The payoff table, based on the nadir and ideal points, is expressed in table 1. The ideal point $I = (w^I, a^I)$ corresponds in our case to a non-existent point.

Table 1: Payoff table.

	f_1	f_2
$min\ f_1$	w^I	w^N
$max\ f_2$	a^N	a^I

Any value outside the ranges determined by the nadir and ideal points will be discarded. The ranges are then explored starting from the values obtained from the ideal point until we reach the nadir point.

We run in parallel two ε-constraint methods and we start building the Pareto set at the extreme points. The first ε-constraint method maximizes the affinities with the additional constraint (the ε-constraint) on the waiting time (ε_w). The first value obtained is one of the extreme points, $(w^I, f_{2|w^I})$.

The second ε-constraint method minimizes the total waiting time with the additional constraint on the affinities (ε_a). The other extreme point obtained is $(f_{1|a^I}, a^I)$. The ε-constraints are relaxed at each iteration. We iterate as long as the values obtained are better than the nadir point.

Algorithm for the ε-constraint method.

1. Set ε_w to w^I and the number of iterations n_w to 1
2. Set ε_a to a^I and the number of iterations n_a to 1
3. Set the Pareto optimal set to $\mathcal{P} = \emptyset$
4. While $(f_{1|\varepsilon_a} \leq w^N)$ and $(f_{2|\varepsilon_w} \geq a^N)$ do
   Solve $max\ f_2$ with the additional constraint $f_1 \leq \varepsilon_w$; the solution is $f_{2|\varepsilon_w}$
   Set $\varepsilon_w = w^I * 1.05^{n_w}$ and $n_w = n_w + 1$
   Solve $min\ f_1$ with the additional constraint $f_2 \geq \varepsilon_a$; the solution is $f_{1|\varepsilon_a}$

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    Set $\varepsilon_a = a^I * 0.95^{n_a}$ and $n_a = n_a + 1$
    Add the points $(\varepsilon_w, f_{2|\varepsilon_w})$ and
    $(f_{1|\varepsilon_a}, \varepsilon_a)$ to $\mathcal{P}$
  End.
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4 RESULTS AND DISCUSSION

4.1 Test Instances

We tested our model on a data set obtained from a Belgian hospital. The surgical interventions take place between 8 AM and 6 PM at the latest. Each hour is divided in quarter (for a total of 40 quarters a day). There are 8 instances in the set (8 weeks). Each week, the number of surgeries varies between 49 and 90, the number of operating surgeons between 22 and 38 and there are 7 operating rooms.

The model described by Di Martinelly et al., (2011) was run on those data to get the detailed planning and scheduling of the surgical interventions (day and time of the surgical interventions). It was run with the restriction that there were 12 nurses available at every time period of every day. A pool of 14 nurses is available; some of them are working the entire day, others are working only in the mornings or only in the afternoons.

The affinity matrix is built by asking each surgeon to assess his affinity with each nurse using a scale between 0 and 9 (9 being the highest affinity) and is built for the entire period.

4.2 Results and Discussion

The model was developed and solved using FICO Xpress-Optimizer. It was tested on a computer with 2.2 GHz CPU and 8 GB of RAM.

Table 2 displays the payoff table for each instance.

From this table, we can note that both objectives are conflicting: minimizing the waiting time generates surgical teams with affinities lower by 14% on average; while maximizing the affinities creates teams that have to wait up-to 50 times more!

The points (47; 821) and (338; 1091) correspond to the maximization of the affinities under the constraint on the waiting time and the minimization of the waiting time under the constraint on the affinities, respectively.

Each of those points represents the weekly roster for all nurses obtained by using as input the planning and scheduling of surgical interventions of week 5, taking into account the nurses' availabilities (day-offs), maximum working time per day and per week (full time/part time) and the operating surgeons' affinities with the nurses.

Table 2: Payoff table of the test instances.

week	w^I	w^N	a^I	a^N
1	0	263	653	592
2	40	257	1152	1021
3	4	208	1093	1007
4	50	295	794	600
5	47	338	1091	821
6	71	378	899	840
7	75	376	776	707
8	64	357	976	745

Figures 1 and 2 display illustrations of the rosters obtained for a particular day of week 5, either minimizing the waiting time with a constraint on the affinities (Figure 1) or maximizing the affinities with a constraint on the waiting time (Figure 2). The horizontal axis represents the hours (expressed in quarter; 1 is 8 AM while 40 is 6 PM); the vertical axis represents the nurse's ID. The roster of a particular nurse is represented on several lines. Each line corresponds to a surgical intervention. For instance, on figure 1, nurse no. 1 is assigned to 3 surgical interventions; nurse no. 14, which starts working in the afternoon (data of the problem), is assigned to 2 surgical interventions.

We can note several differences between the two figures: the nurses are different (nurses 3, 8 and 13 are working in the second schedule, not in the first one), they are not working at the same time periods (and thus the surgical teams are different), and the number of nurses who are working is different. On figure 1, it can be noted that only 10 nurses are required to do the surgical planning; on figure 2, 13 of them are needed. It can be considered that the assignment of figure 1 gives additional flexibility. Indeed, if an emergency occurs or one of the nurses calls in sick, one of the 4 remaining nurses can be used. On figure 2, some nurses have rather long waiting times between the surgical interventions. For instance, nurse no. 10 has to wait 18 quarters between jobs. The objective pursued was to maximize affinities with a constraint on the total waiting time, which may results in differences for the nurses.

Figures 1 and 2 are the extreme solutions of the Pareto set. The other compromise rosters are built by degrading the optimal value obtained on each objective function and by using it as a constraint to optimize the other objective function.

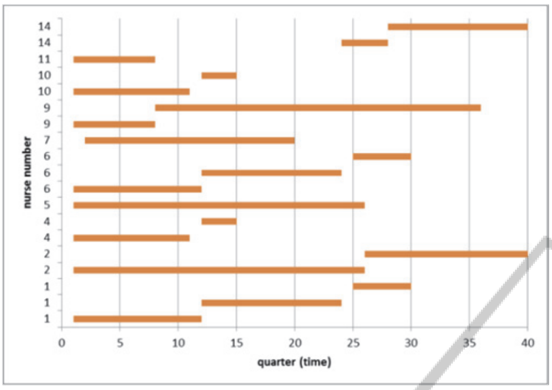

Figure 1: Tuesday roster for week 5 obtained by minimizing the waiting time under the constraint on the affinities.

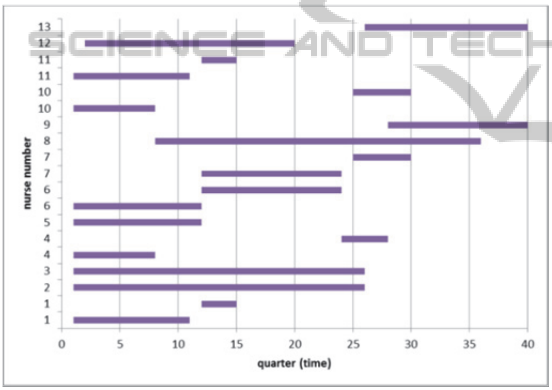

Figure 2: Tuesday roster for week 5 obtained by maximizing the affinities under the constraint on the waiting time.

Figure 3 displays the Pareto frontier built for each instance by degrading the values by 5%. Starting from the extreme points of the Pareto curves, the waiting time criterion is degraded by 5%. The affinity level is increased by 8.5% on average. By degrading the affinity level by 5%, the waiting time of nurses is improved by an average of 380%. However, there are differences between the instances. It seems that the differences are more related to the characteristics of the planning rather than to the surgical loads (average number of nurses per surgery, total operating time for nurses or number of surgery over the week).

The relation between the two objectives is not linear; degrading the affinities has a more impact on the waiting time than the impact of the degradation of the waiting time on the affinities.

5 CONCLUSIONS

The approach used in this paper considered a task-based approach to model the demand for nurses in the operating room. The present paper focused on the building of surgical teams (surgeon, nurses) with a high affinity degree while taking into account availaibilities of nurses and the legal constraints on working conditions (days-off, maximum working time per week,…). The waiting time of nurses is also minimized in order to limit idle time and overtime payments.

The problem was modeled as a multiobjective mixed-integer problem and solved using an ε-constraint approach. This approach was chosen because it allows the generation of non-dominated nurse rosters. The decision maker can choose the one he prefers and estimates the trade-offs between alternative solutions.

The model was tested on real data from a hospital. From those experiments, we could conclude that the objectives are conflicting and that degrading the affinities has a more impact on the waiting time than the impact of the degradation of the waiting time on the affinities.

From the analysis of the results, it appears that there is an imbalance in the waiting time of the nurses. A third objective could be added to minimize the maximum waiting time of the nurses.

Currently, the authors are working on an extension of the model that takes into account break time periods for nurses.

Future work deals with assessing how those conclusions are robust to variations in the work availabilities of nurses and to the affinity matrix. Affinities between the nurses could easily be integrated. The affinity matrix could also be adapted to take into account the nurses specialty.

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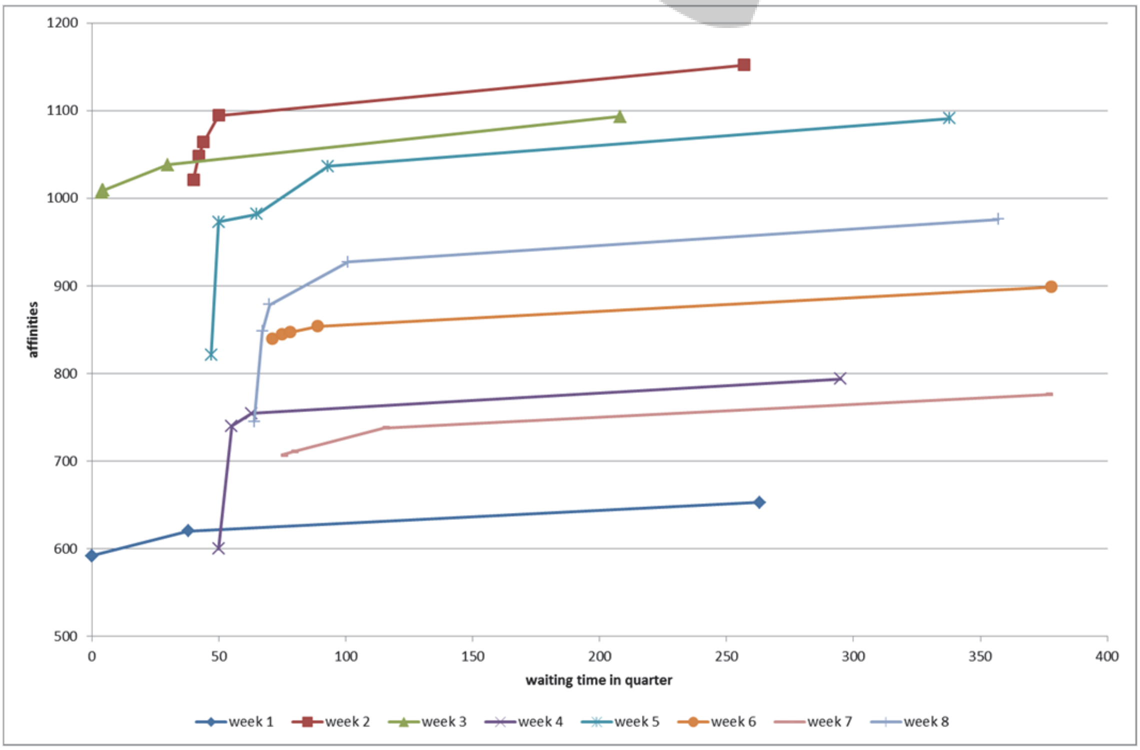

Figure 3: Efficiency frontier built for the different weeks tested.