Rapid diagnoses at the breast center of Jeroen Bosch Hospital: a case study invoking queueing theory and discrete event simulation

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Abstract

When suspected tissue is discovered in a patient's breast, swiftly available diagnostic test results are essential for medical and psychological reasons. The breast center of the Jeroen Bosch hospital aims comply with new Dutch standards to provide 90% of the patients an appointment within three working days, and to communicate the test results to 90% of the patients within a week. This case study reports on interventions based on a discrete time queueing model and discrete event simulation. The implemented interventions concern a new patient appointment schedule and an additional multi-disciplinary meeting, which significantly improve in both the appointment and diagnostics delay. Additionally, we propose a promising new patient schedule to further reduce patient waiting times and staff overtime and provide guidelines for how to achieve implementation of Operations Research methods in practice.

Keywords: Breast cancer, Outpatient clinic, Intervention study, Queueing theory, Discrete event simulation

1. Introduction

Breast cancer is the most prevalent cancer type for Dutch women, with incidence rate doubling over the last two decades (Netherlands Cancer Registry (IKNL), 2014). At an early stage, most breast cancer cases can be treated successfully. When suspected tissue is discovered in a patient's breast, swiftly available diagnostic test results are essential for medical and even more for psychological reasons: waiting for diagnostics is demanding for the patient and her family and friends.

In the Netherlands, patients with suspected breast cancer are referred by their General Practitioner (GP) or the Dutch national screening program. Upon referral, patients may choose to go to one of the (academic) hospitals or specialized breast cancer clinics. The Jeroen Bosch hospital (JBH) is a large teaching hospital. It's breast center is an outpatient clinic in which 10 specialties are represented during office hours (or on call). At the center a patient undergoes diagnostic tests, receives their outcome, and if necessary receives treatment and follow-up care. This case study reports on improvements in the diagnosis-phase of the process, as depicted in Figure 1.

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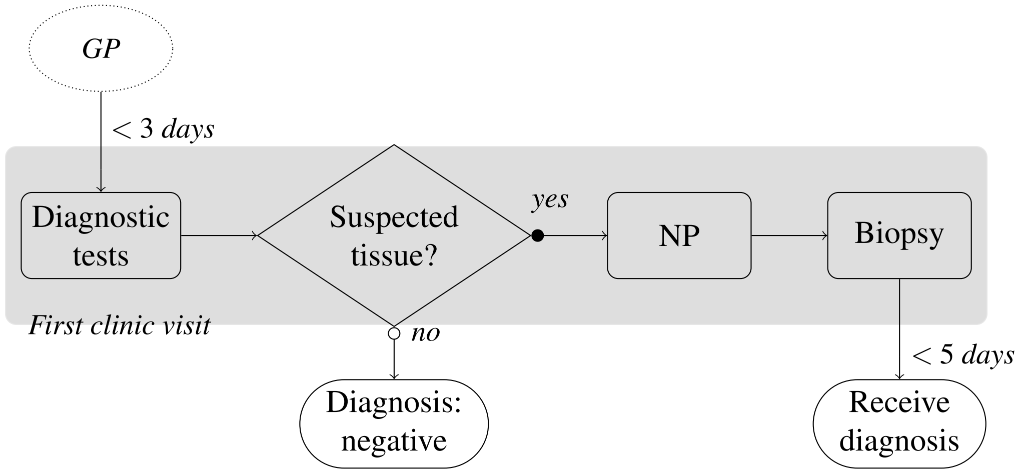

Figure 1: Process description for a patient in the diagnostic phase, 'NP' is a consult with the nurse practitioner.

Dutch breast cancer centers have recently increased their efforts to reduce the time from patients' referrals to their first appointments (access time). In accordance with the recent national standards, the JBH aims for 90% of patients to receive an appointment within three working days. National guidelines require that the access time is at most five working days for 90% of the patients (Nationaal Borstkanker Overleg Nederland, 2008). If a patient's preliminary diagnosis is negative (no cancer), she immediately receives the diagnosis and goes home. Otherwise, the patient consults a nurse practitioner and a biopsy is taken. All patients that got a biopsy must be discussed in a Multidisciplinary Meeting (MDM) after the laboratory results are available, and the patient receives an appointment at the center at a later day to discuss the test results. National guidelines require that 90% of the patients that got a biopsy receive their diagnosis within a week (Nationaal Borstkanker Overleg Nederland, 2008).

Accurately measuring the access time is in most hospitals impossible without additional (manual) data collection, as hospitals often only register the appointment time and not the time the appointment was requested. At the JBH, the data system of the Radiology department does register the time at which an appointment is made. However, the data system only discriminates between new and returning patients accurately for patients originating from the national screening program (hereafter: screening patients). Before the interventions reported in this case study only 54% of the new screening patients were seen within three working days, which is lower than the 90% the JBH aims for. The time from biopsy to the appointment at the center was registered for all new patients; before the interventions 89% of the patients got their diagnosis within five working days, which is close to the 90% target of the JBH.

For designing and implementing interventions, the JBH formed a steering group consisting of all stakeholders in the diagnostic part of the breast cancer care pathway: a Radiologist, an Oncologist, a Surgeon, the capacity coordinator (who managed the entire breast cancer care pathway), and two OR-specialists that were part-time at the JBH. One of the interventions focused on the most effective time for an extra MDM such that the requirements for the time to diagnosis could be met. Based on the results of a discrete time queueing model, a new patient schedule was implemented at the center. After these interventions 84% of new screening patients were seen within three working days (was 54% before the intervention), and 92% of the diagnoses of all new patients were delivered in time. Currently, the JBH is investigating other possibilities to further reduce the access time. As a follow up on the reported interventions, JHB aims to minimize patients' waiting time (the accumulated time a patient waits on the day of their radiological examinations). In this paper we propose a promising new patient schedule based on the results of a Discrete Event Simulation (DES).

In this case study we present a business re-engineering approach based on Operations Research (OR) that is carried out in a hospital and has resulted in considerable improvements of the performance. This is a clear advertisement for the power of OR for process improvements and for real implementation in practice and a guideline for how to achieve implementation of OR in practice. The remainder of this paper is organized as follows. We first review the related literature in section 2. In sections 3 and 4 the interventions for the access time and time to diagnosis are discussed respectively. Section 5 considers optimizing the waiting time, and the last section contains our conclusions.

2. Related literature

At the breast center patients require a series of appointments with multiple resources, of which some are unscheduled before the patient arrives at the center. There are multiple patient types and each type may have its own access time norm. In this section we first discuss literature that is related to the tactical appointment scheduling problems, c.f. Hulshof et al. (2012), of minimizing access and waiting times. Thereafter, we highlight literature that encompasses implementation results of OR models in practice.

Literature on minimizing access time for patients that require multiple appointments is sparse. In a general hospital setting, Hulshof et al. (2013) optimize the number of elective patients of each type that can be admitted to the hospital on a certain day invoking a mixed integer program. Objectives are access time norm compliance and achieving the hospital's predefined targets on the number of patients to treat. Upon arrival patients appear to require a certain (deterministic) care pathway, and therefore a patient's admission can be viewed as an appointment. Matta and Patterson (2007) use DES to evaluate many possible interventions at an Oncological outpatient clinic, of which two interventions consider rules for scheduling patients. This work mainly focuses on patients requiring a single appointment, in accordance with the general outpatient clinic literature (Cayirli and Veral, 2003; Berg and Denton, 2012). A different related field of literature is on patients who receive Radiotherapy treatment. These patients also require multiple appointments at multiple resources, c.f. Bikker et al. (2015), Pérez et al. (2011), but these are all scheduled in advance. Additionally, there are many papers on tactical scheduling of a single appointment on a single resource for multiple patient types with the objective to minimize access times, c.f. Ayvaz and Huh (2010), Creemers et al. (2012), Holte and Mannino (2013), Klassen and Rohleder (2004), Lee et al. (2013), van Lent et al. (2012a), van Sambeek et al. (2011).

The literature on minimizing patients' waiting time while minimizing the doctors' idle and over time is also sparse for systems in which patients require multiple appointments on multiple resources. In a clinic where patients require multiple appointments, Wu et al. (2014) use DES to determine the best appointment scheduling rules with respect to these objectives. Griffin et al. (2012)

simulate different scenarios for a obstetric clinic, in which each patient is randomly assigned to one of the possible care pathways, but in obstetric clinics most patients are urgent and not scheduled in advance. For a family practice where patients require an appointment with both a nurse and doctor, Oh et al. (2013) invoke a stochastic integer program combined with heuristics to optimize the schedule. Stochasticity is present in the service time durations, but not the care pathways of the patients. The setting studied in Wu et al. (2014) is most related to our case study setting since part of the care pathway is stochastic. There are many papers on scheduling a single appointment on one resource that balance waiting, idle, and overtime, c.f. Klassen and Rohleder (2004), Denton and Gupta (2003), Koeleman and Koole (2012), Qu et al. (2013).

For additional outpatient clinic literature for both the tactical and operational level, the reader is referred to reviews Cayirli and Veral (2003), Berg and Denton (2012). For general appointment scheduling literature in healthcare see the reviews Hulshof et al. (2012), Patrick and Aubin (2013), Gupta and Denton (2008), Gupta and Wang (2012).

Many recent reviews concluded that the literature on Operations Research in healthcare that reports on (the results of) actual implementation of the findings is sparse Cayirli and Veral (2003), Gupta and Denton (2008), Brailsford (2005), Brailsford and Vissers (2011), van Lent et al. (2012b), Mahdavi et al. (2013), van Sambeek et al. (2010). For different types of simulation applications specifically, van Lent et al. (2012b) conclude that only three papers (partially) report on the effects of the implementation in real life. Mahdavi et al. (2013) have found 10 papers reporting on implementation results, of which two are related to our paper as they focus on an outpatient clinic Zonderland et al. (2009), Albin et al. (1990). Both papers use the Queueing Network Analyzer (QNA) of Whitt Whitt (1983) to evaluate different alterations to the process at the clinic, but only consider unscheduled arrivals. Matta and Patterson (2007) also report on implementation of some of their recommendations.

Concluding, the literature on scheduling multiple appointments on multiple resources is sparse, just like the papers mentioning implementation of their results in practice. Our case study reports on an OR-model developed for the multi-disciplinary breast center of the JBH, it's implementation results, and the lessons learned from the cooperation between OR-specialists and healthcare practitioners.

3. Access time

At the breast center of the JBH, new patients originate from two sources: the national screening program and the GP. In the Netherlands all women aged 50-75 are invited every two years by a screening organization for preventive diagnostic tests National Institute for Public Health and the Environment (RIVM) (2012). Patients referred by their GP usually have palpable abnormalities or a heredity risk. In accordance with national guidelines Nationaal Borstkanker Overleg Nederland (2008), new patients aged 30+ are scheduled for a mammography and an ultrasound, and younger patients only for an ultrasound. Younger patients can also be scheduled for an MRI examination, but as the MRI center of the JBH currently meets all its access time requirements, these patients are not considered in this project. We distinguish three types of new patients: patients referred by the screening program (always age ≥ 50), young patients (age < 30) and 'regular' patients referred by their GP. The JBH aims for the access time to be less than three working days for 90% of the patients, but according to national guidelines it should at least be within five working days for 90% of the patients Nationaal Borstkanker Overleg Nederland (2008).

3.1. *Before intervention*

The available JBH data only allows to accurately distinguish new screening patients as new patients. Together with the Radiology department, we determined an inclusion criterion to estimate the fraction of new patients for the other patient types. We determined the rate at which each new patient type arrives for each day, see Figure 2, where the upper and lower edge of each box represent the 75% and 25% percentiles, respectively, and the whiskers extend to the minimum and maximum number of arrivals per day. We define the capacity of the Radiology department by the

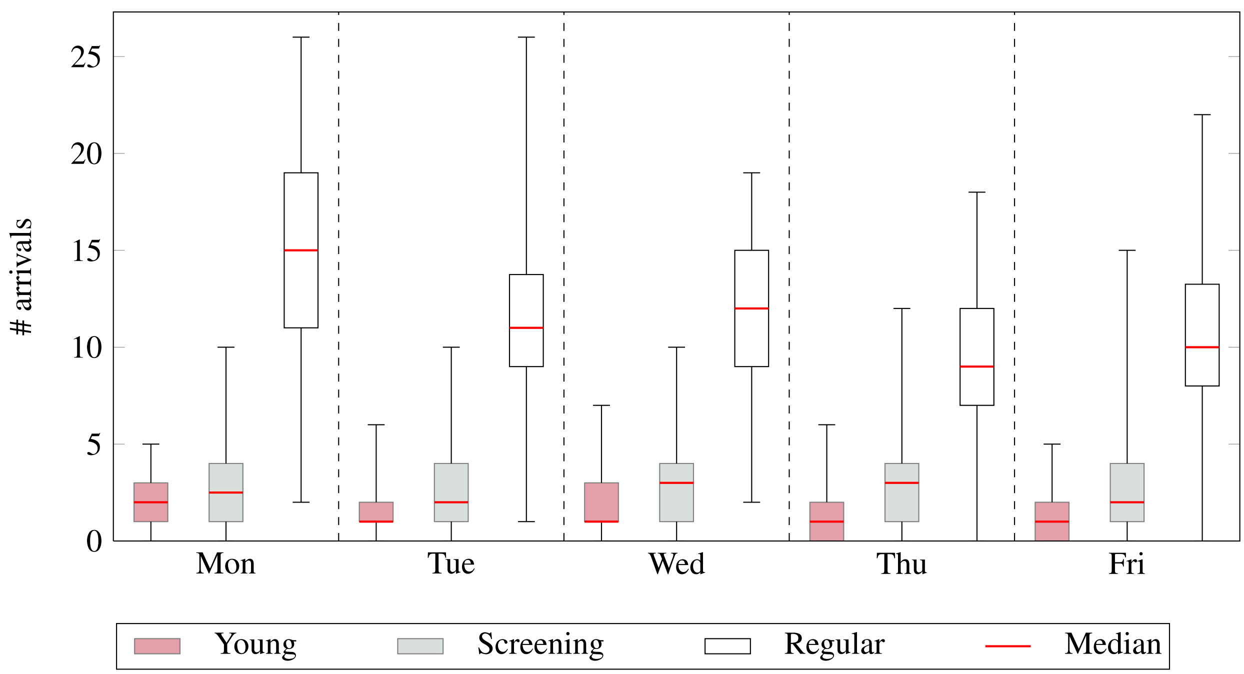

Figure 2: Boxplot of the arrivals per type for each day of the week, data of January 2013-July 2014.

number of appointment slots available for each patient type. This capacity is the same for each day and equals: 4 young, 5 screening and 18 regular patients. From Figure 2 it is clear that the demand is not constant over the weekdays. On average there seems to be enough capacity to cope with the current demand of new patients.

At the JBH only for 34% of the young patients, 31% of the regular patients, and 54% of the screening patients the access time was less than three working days. Only for the screening patients the national guideline was met, while 33% of the young patients and 28% of the regular patients had access times longer than five working days. As the inclusion criterion provided an estimate of the fraction of new young and regular patients, the criterion may result in an overestimation of the access times for these patients.

3.2. *Intervention*

Each day a random number of patients arrives at the clinic, and a certain number of patients receives an appointment. The patients all receive the first appointment available for their type, but are generally not scheduled for the same day as their appointment request. Patients may not be deferred to other clinics, so all arriving patients must receive an appointment. We are interested in determining the daily capacity such that the clinic complies with the access time norms.

We developed a discrete time queueing model similar to the one presented in Kortbeek et al. (2014) to evaluate the access time distribution of new patients, measured in number of days. A queueing model is preferred over optimization or simulation models since queueing models reveal the access time distribution.

The state of the queueing model is the size of the backlog of a specific patient type, so the number of patients that did not have their tests yet. Every day a number of patients (at most equal to the capacity for this type on this day) is removed from the backlog, and a random number of new patients is added to the backlog. We incorporate that patients cannot be scheduled for their first appointment on the day of their arrival. We obtained a discrete, empirical probability distribution for the number of arrivals for each weekday from the hospital data, and used a cyclic schedule with a period of five days. All details of the model can be found in Appendix A.

By means of our queueing model we derived the minimal capacity required to meet the JBH guidelines, see Table 1. The performance of the schedule with minimal capacity and the current

Table 1: Minimal capacity required at the JBZ.

	Young	Screening	Other
Mon	3	5	15
Tue	3	5	14
Wed	3	5	16
Thu	2	5	16
Fri	3	6	14

schedule can be found in Figure 3. Note that the minimal capacity for young and regular patients is less than the current capacity, which seems to contradict the fact that the guidelines were not met with the current capacity. After we presented the results, the Radiology department reconsidered the available capacity, and became aware that the realized capacity for regular patients was usually less than 18 (as scheduled) and often less than 15 (average minimal capacity); each day several slots were closed because one or two patients needed to be prepared for surgery and one Radiologist had to prepare the MDMs.

Discussions of the results with the Radiology staff resulted in two additional interventions. First, data-analysis indicated that the time to take a mammography and ultrasound for returning patients was shorter than the appointment length. The Radiology assistants confirmed that returning patients require less examination time. Therefore, in our intervention all returning patients are scheduled for 15 minute appointments instead of 20 minutes for both mammography and ultrasound tests, thereby increasing the number of daily appointment slots by three. Second, the Radiology

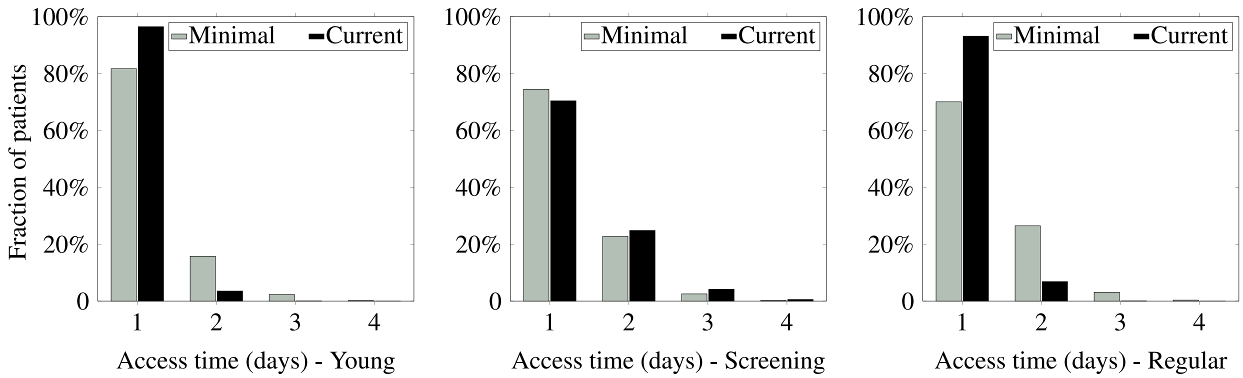

Figure 3: Access time distribution obtained from queueing model.

assistants felt that almost all screening patients required a tomography, which was confirmed by the data. Combining a mammography with a tomography for the new screening patients reduces the processing time of the latter and saves the time that patients (un)dress and change rooms.

The resulting intervention was: to assign slots for the preparations, and schedule on average 1.6 slots per day for young patients, 5 slots per day for screening patients, 15.4 slots per day for regular patients, and 2 flexible slots each day. Additionally, young patients were preferably scheduled for a 3D-ultrasound to both improve diagnostics and alleviate the utilization of the regular ultrasound rooms. By these interventions, the total capacity for new patients theoretically decreased from 27 to 24 slots per day, but in reality it increased since in the process after the intervention it is no longer allowed to close slots that were meant for new patients. The interventions were implemented in July 2014.

3.3. Result

Comparing data from January 2013 to October 2014, we conclude that for all patient types the access time decreased, see Figure 4. From the data it appeared that especially young patients, who require only an ultrasound, were often scheduled for same-day appointments after the intervention. For the screening patients the access time improved the most. However, still for none of the patient

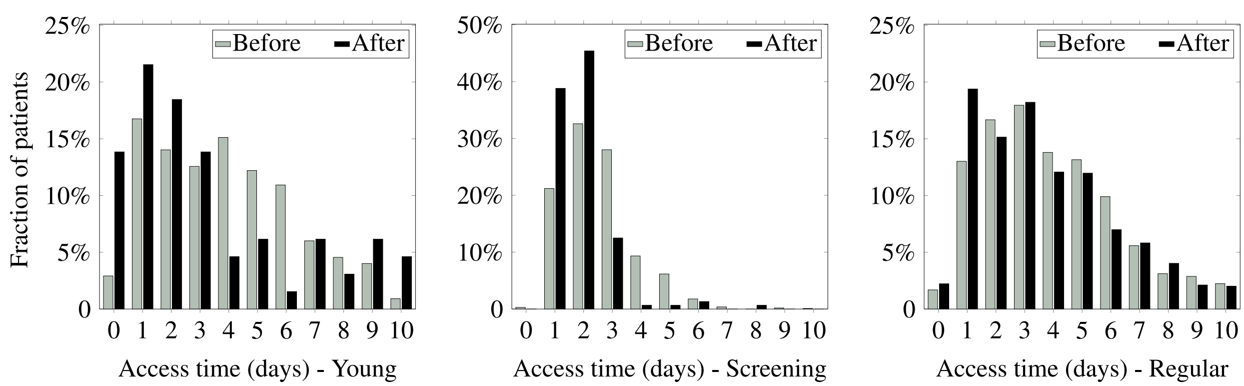

Figure 4: Access time distribution before (Jan 13-Jul 14) and after (Jul 14-Oct 14) interventions.

types the target of 90% within three days is met. Recall that for young and regular patients these results underestimate the real performance, which is confirmed by the fact that patient surveys indicate that 85% of the patients have an access time of five working days or less. The steering group is currently aiming for more improvements, which will be discussed in section 6.

4. Time to diagnosis

For the time to diagnosis, two groups of patients may be distinguished. Patients that do not require a biopsy receive their diagnosis immediately after their last radiologic examination. If a patient does require a biopsy, the extracted tissue is processed by the laboratory on the same day. This process, immunostaining, takes two to five days, where five days rarely occurs. In the Netherlands, the results of a biopsy have to be discussed in an MDM before they can be communicated to the patient. Patients receive a follow-up appointment at the breast center to discuss their test results. The time between the biopsy and the follow-up appointment should be less than or equal to five working days for 90% of the patients Nationaal Borstkanker Overleg Nederland (2008).

4.1. Before intervention

The time between the biopsy and the follow-up appointment at the center was influenced both by the processing time at the laboratory and the frequency of the MDMs. The processing time at the laboratory depended on the time the biopsy was taken: if it was taken before noon, the results were available at the end of the next day, and otherwise at the end of the second day. MDMs were scheduled on Wednesday and Friday afternoon each week. The lab results that were ready on Wednesdays and Fridays could not be discussed in the MDM on the same day, since the results were available too late to prepare for the MDM. Before the interventions, 89% of the diagnoses were given within five working days.

A process description of the steps from biopsy to the availability of the diagnosis revealed a structural problem at the JBZ. For each morning and afternoon of each day, we determined the earliest time that each process step could be finished if a biopsy was taken on that day, see Table 2. From this table it appears that biopsies taken on Thursday morning and in the afternoon of Monday, Wednesday and Thursday, could never be communicated to the patients within five working days because of the way the MDMs were scheduled. Moreover, the number of patients who finished their biopsy before noon was limited; due to the lengths of the tests and the availability of the Radiologists, only the patients with appointments before 9.20h could have their biopsy finished before noon.

4.2. Interventions

We proposed three possible interventions: an extra MDM, shorten the processing times at the laboratory, and only schedule returning patients (and no new patients) on Thursdays. The latter option was very attractive to the Radiology department because fewer additional tests were required on such days, increasing the number of patients that could be seen on one day. The department organized two trial days on which only returning patients were scheduled. From these days, it appeared that the follow-up appointments with the surgeons could not be scheduled with this number of patients seen on one day. Therefore, this solution was not taken into account.

Table 2: Process from biopsy to diagnosis before the interventions.

Biopsy taken on		Lab finished	MDM	Follow-up app.
Monday	Morning	Tue	Wed	Thu
	Afternoon	Wed	Fri	Mon
Tuesday	Morning	Wed	Fri	Mon
	Afternoon	Thu	Fri	Mon
Wednesday	Morning	Thu	Fri	Mon
	Afternoon	Fri	Wed	Thu
Thursday	Morning	Fri	Wed	Thu
	Afternoon	Mon	Wed	Thu
Friday	Morning	Mon	Wed	Thu
	Afternoon	Mon	Wed	Thu

Both the first and second solution were implemented in April 2014 at the JBH; each Monday at lunch break an additional short MDM was scheduled, and the laboratory bought faster machines so the result of all (both morning and afternoon) biopsies are available the next day. This resulted in the 'earliest finish times' of the process reported in Table 3. Note that, since the MDM on

Table 3: Process description with additional MDM on Monday and faster laboratory.

Biopsy taken on	Lab finished	MDM	Follow-up app.
Monday	Tue	Wed	Thu
Tuesday	Wed	Fri	Mon
Wednesday	Thu	Fri	Mon
Thursday	Fri	Mon*	Mon
Friday	Mon	Wed	Thu

Monday (indicated with *) is in the lunch break, the diagnoses of the discussed patients can be communicated on the same day. From Table 3 it is clear that all diagnoses could in principle be communicated to the patients within five working days.

4.3. Results

From data from April 2014 until October 2014 it appeared that after the interventions 92% of the patients received their diagnosis within five working days. Although this is only a minor improvement, it resulted in meeting the guideline. In practise it will not be possible to achieve 100% within five working days, because sometimes an additional test needs to be performed to ascertain the diagnosis.

5. Waiting time

Although arrivals to the center are scheduled, the patients' pathways through the center are not deterministic. All young patients receive an appointment for an ultrasound, whereas screening, regular and returning patients receive appointments for both a mammography and an ultrasound. After the mammography is completed, it may appear that the ultrasound is not necessary any more, or that the patient requires additional tests (e.g. 3D-ultrasound, tomography or biopsy). All screening patients and patients that require a biopsy (which are not necessarily disjunct sets) visit a nurse practitioner to receive additional information about their diagnosis and/or the biopsy.

Almost all additional tests are performed on the same day, only MRI's and stereotactic (mammography based) biopsies are scheduled for later days. The tomographies and biopsies are performed on the same resources as the mammographies and ultrasounds, respectively. Since both resources are fully booked in advance, this induces waiting time.

The waiting time for additional tests is distressing patients, since they know that the results of the first tests indicated that additional tests were necessary, implying that they might have breast cancer. Before this project started, the radiology assistants were always assigned to one patient throughout her stay at the Radiology department. Therefore, when their patient was waiting, they were waiting too. This varying pressure of work resulted in reduced work satisfaction of the staff. There are no (national) guidelines for the waiting time for patients, but the JBH aims to minimize waiting time while maintaining the same working hours.

5.1. Approach

For most hospitals it is hard to measure the waiting time from data as the start and end time of an appointment is usually not registered, and the JBH is no exception. Instead of taking measurements manually, we decided to build a proof of concept DES model to advise the Radiology department on possible improvements. Input for the DES is a patient appointment schedule, a Radiologists schedule, and for each patient type the probability of requiring a certain series of tests. For more details on the DES, see Appendix B.

From literature sequencing models, stochastic integer programming models, and dynamic programming models appear promising approaches for optimizing the patient schedule. However, these methods cannot incorporate that patients have to return to a resource with a different service time. Additionally, the state space will explode since we schedule 40 patients, each following one of the 11 possible pathways with a probability depending on her type. A simulation model can incorporate all necessary details of the patients' pathways and can be used to quickly evaluate many schedules. Therefore, we constructed many possible patient schedules manually, all based on the constraints and preferences proposed by the practitioners, and used the DES to identify the best schedule and fine-tune this schedule iteratively.

5.2. Simulation results

We evaluated both the patient appointment schedule used before the project started and after the interventions were implemented. From the DES it appears that the variability of the process is large; even with 520 simulated days the relative precision is not below 20%, and for young patients even around 70%. This confirms the feeling of the staff about strongly varying workloads. Invoking common random numbers Law (2007), the results for the different schedules may be compaired, and the variability of the differences between scenarios is reduced.

In Figure 5 we depicted boxplots of the waiting time per patient accumulated for all tests, for all simulated working days for the schedule before July 2014 (Before), after July 2014 (Current), and the improved schedule. It appears that the interventions of July significantly decreased the waiting time, especially for regular patients.

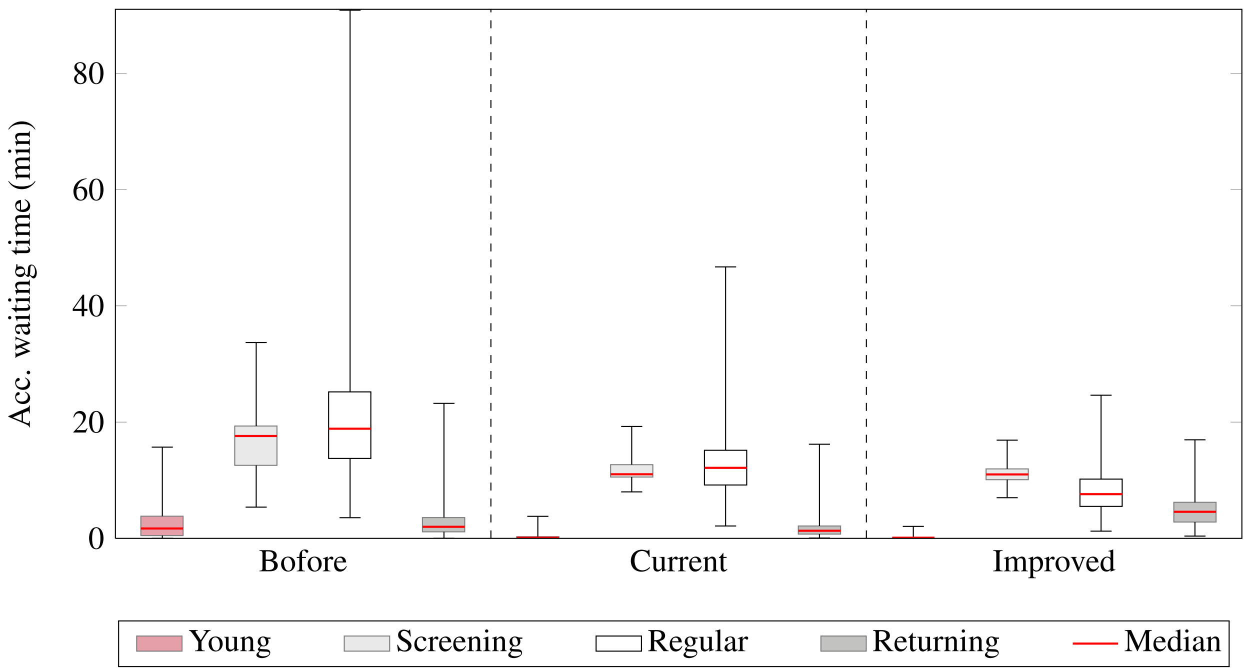

Figure 5: Simulation results for the accumulated waiting time per patient.

The improvements we made to the schedule were scheduling 5 minutes idle time between appointments for screening patients (to allow for the Radiologist to check the test results), add two slots for (unscheduled) biopsies, and distribute the returning patient slots evenly over the entire day (opposed to only new patients in the morning and returning patients in the afternoon). Additionally, we distributed the empty slots already present in the schedule more evenly over the day to be able to provide additional tests. The best distribution of this idle time was obtained through several iterations of simulation and alterations to the schedule. This schedule reduces the waiting time for all patient types, except the average waiting time of returning patients (compared to the schedule currently used), see Figure 5.

The middle graph of Figure 6 shows that the current schedule results in many days with overtime for both the ultrasound rooms and the nurse practitioner, and the improved schedule induces fewer days with overtime. Both mammography rooms and the 3D-ultrasound room finished within office hours on most of the days. Figure 6 additionally displays the accumulated waiting time of all patients scheduled on a room, and the accumulated idle time (including breaks) before the last patient of the day leaves. For both mammography rooms and the 3D ultrasound room, patients do not wait long for their tests in the current and improved schedule. The percentage of overtime days

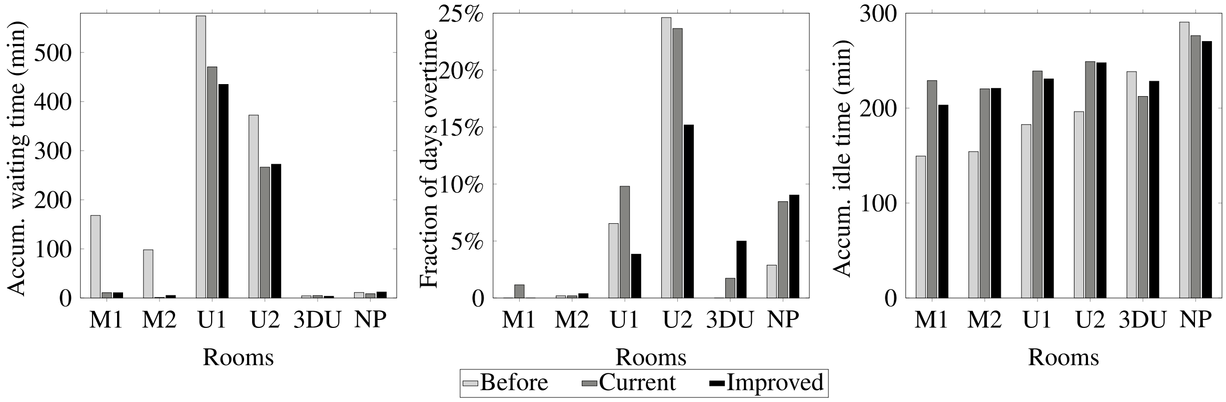

Figure 6: Simulation results for the treatment rooms (f.l.t.r): two Mammography rooms, two ultrasound rooms, a 3D ultrasound room and the Nurse Practitioner.

for ultrasound room 1 is acceptable, but 9% for the nurse practitioner and 15% for ultrasound room 2 are too high. Attempts to decrease the number of overtime days resulted in unacceptable higher waiting time for patients. Therefore, the breast center is currently investigating other possibilities to reduce the waiting time, for example by altering the order of the current process steps such as letting the patient go first to the nurse practitioner in order to take the biopsy directly after the ultrasound. This would reduce the time required for a biopsy significantly.

Regarding the robustness of the results, we performed several tests with the DES. When we assume that the service time durations are not a constant S but uniformly distributed on the interval $[0.9S, 1.1S]$, the results of the DES are similar for the improved schedule, but with higher variation between simulated days and some exceptional days with high waiting times. We also investigated the effect of non-punctual patients, by assuming that patients arrive a random time from their appointment time. We used a Normal distribution with $\sigma = 10$ minutes and three different means: -10, 0, and 10 minutes. It appears that when patients arrive early, the performance of the schedule improves slightly. For patients that arrive in time on average (mean 0), the performance of the schedule is similar to the schedule in the original DES. Only when patients on average arrive 10 minutes late, the number of days working in overtime increases significantly, but there is a slight decrease in the waiting time for patients as well. For the patients the performance is still quite similar to the performance in the original DES, but there are some exceptional days in the DES with relatively high accumulated waiting times. See Appendix B for the exact results of the robustness analysis.

The assumption of punctual patients is not entirely realistic, but the JBH staff confirms that most patients arrive early for their appointments. Both the data and the JBH staff indicate that the assumption of deterministic service times is close to reality, but the tested perturbation is relatively low. Therefore, there probably will be days with exceptional high waiting times in reality.

5.3. Intervention

Although the proposed appointment schedule is not yet implemented, the process at the center has improved during this project. At our suggestion, the laboratory assistants worked in one room the entire day, instead of following patients throughout their stay at the Radiology department.

The assistants were worried that this intervention would decrease patient-friendliness, but after two trail days all were convinced that this intervention reduced the assistant's waiting time significantly and did not affect the patient-friendliness too much. The next appointment schedule that will be implemented at the clinic will be updated with the insights gained through this simulation study.

6. Conclusion

In this case study we present a business re-engineering approach based on OR methods that is carried out in a hospital and has resulted in considerable improvements of the performance. This paper reports on a case study with successful cooperation between JBH healthcare practitioners and OR-specialists. In this project, the steering group and stakeholders secured the proposed OR-approach, and were the key to the successful implementation of the interventions. The OR approach provided a rigorous analysis of the performance of the system, which made the stakeholders aware of additional hidden capacity problems. Our interventions have improved the use of the available capacity, by both making additional capacity available via adapting the length of appointment slots, and rearranging the patient appointment planning. As a consequence, at the breast center of the JBH both the access time and time to diagnosis improved evidently. In addition, we obtained promising results for reducing patients' waiting times. The cooperation had additional positive side-effects that further improved the process at the center. This case study is a clear advertisement for the power of Operations Research for process improvements and for real implementation in practice and a guideline for how to achieve implementation of OR in practice.

It appeared from this project that the resources at the center are not sufficient to both meet the access time guidelines and work within office hours for a high percentage of days. In accordance with national trends, the steering group is currently investigating the possibility of offering 24h-diagnostics, requiring daily MDMs and possibly larger opening hours. The DES built in this project will be extended to investigate the requirements for offering the 24h-diagnostics. Future research will also focus on the care pathway after diagnosis, i.e. the operating theater and radiation therapy schedules. The JBH, like most other hospitals, has a continuous urge to improve the processes for their patients (and thus actually improving efficiency). Therefore, the cooperation between healthcare practitioners and OR-specialists will be continued in future projects.

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Appendix A. Discrete time queueing model

We assume arrivals for day d occur according to a discrete distribution A^d, with $P(A^d = i)$ obtained from hospital data. Each day d a maximum number of patients c^d can be seen. The schedule is cyclic, so $d \in \{0, 1, \dots, D-1\}$ and days are counted modulo D. At the beginning of each day d, we have a backlog of patients B^d. We assume that patients cannot be seen on the same day, for example because they need to make arrangements at their work or some time is required for the GP to send in the results of the screening program. Therefore, following Kortbeek et al. (2014) the transition probabilities for the backlog are given by:

$$P\left(B^{d+1} = j \middle| B^d = i\right) = \begin{cases} P(A^d = j) & \text{if } i - c^d \le 0, \\ P(A^d = j - i + c^d) & \text{if } i - c^d > 0. \end{cases}$$

We fill transition probability matrix $\mathbf{P}$ with the transition probabilities and the distribution of A^d, and obtain the steady state distribution $\pi = [\pi^0 \ \pi^1 \ \cdots \ \pi^{D-1}]$ solving $\pi\mathbf{P} = \pi$ and $\sum \pi = 1$. Then, the conditional probability distribution of the access time is Kortbeek et al. (2014):

$$P\left(W^d > y \middle| B^d = b\right) = \begin{cases} 1 & \text{if } y = 0, \forall b, \\ 1 & \text{if } y > 0 \text{ and } b \ge \sum_{i=0}^{y} c^{d+i}, \\ \frac{\sum_{j=s+1}^{\infty} (j-s) \cdot P(A^d = j)}{\mathbf{E}[A^d]} & \text{otherwise,} \end{cases}$$

with

$$s = \min\left\{ \sum_{i=1}^{y} c^{d+i}, \sum_{i=0}^{y} c^{d+i} - b \right\}.$$

Therefore,

$$P\left(W^d > y\right) = \sum_{b=0}^{\infty} P\left(W^d > y | B^d = b\right) \cdot P\left(B^d = b\right).$$

Moreover, the fraction of arriving jobs for which the access time does not exceed y, $S(y)$, is given by (Kortbeek et al. (2014)):

$$S(y) = \sum_{d=0}^{D-1} \left\{ 1 - P\left(W^d > y\right) \right\} \frac{\mathbf{E}[A^d]}{\sum_{q=0}^{D-1} \mathbf{E}[A^q]}.$$

Note that patient types are independent, so for each type we may evaluate the access time distribution separately.

Appendix B. Discrete event simulation model

We built a DES that takes into account all model assumptions, with input a schedule with patient types. For each patient type, probabilities that a patient of this type has to take a certain combination of tests are obtained from hospital data, see Table B.4, in which we used the following abbreviations: MG for mammography; CR indicates that the Radiologist should check the test results (this time is also used for cleaning the machines and for patients to get (un)dressed); US for ultrasound; NP for nurse practitioner; BI for biopsy; 3D for 3D ultrasound; and TG for tomography.

Table B.4: 'Care pathways' of patients at the breast center.

							Young	Regular	Screening	Returning
1	MG	CR						27.0%		47.0%
2	MG	CR	US	CR				50.3%		26.3%
3	MG	CR	US	NP	BI	CR		3.6%	12.3%	2.2%
4	MG	CR	US	3D	CR			3.4%		
5	MG	CR	3D	CR				5.6%		1.3%
6	MG	CR	US	NP					87.7%	
7	US	CR					93.4%	6.2%		18.6%
8	US	NP	BI	CR			3.6%			
9	US	MG	CR				3.0%			
10	MG	CR	TG	CR				3.9%		2.3%
11	MG	CR	TG	CR	US	CR				2.3%

For each patient type, resource and test it is specified whether this test can take place on the resource and how much time this takes for the given patient type. All service times except for biopsies are deterministic, which is in correspondence with both the data and practitioners' opinions. A biopsy takes a uniformly distributed time between 30 and 45 minutes. A consult with the nurse practitioner is 10 minutes for screening patients that tested negative (no cancer), and 30 minutes otherwise. For each test it is specified whether the Radiologist should be present.

Patients arrive punctually according to the appointment schedule and get assigned a care pathway according to Table B.4. If their first resource is available, they will commence service immediately, otherwise they will join a queue. Every test type has its own queue, and there is a priority rule among the queues. At service completion at a certain resource, the highest priority queue containing a test type that is compatible with the resource, is checked for non-emptiness. The priority rule for emptying the queues is (high to low priority): CR, biopsy, 3D-ultrasound, nurse practitioner, ultrasound, tomography, mammography. We keep an eventlist of all upcoming arrivals and departures, and store an eventlog to obtain patient and system specific performance measures after the DES run.

We implemented the DES graphically in Microsoft Excel; software that is commonly available in most Dutch hospitals, and allows for practitioners at the JBH to use and alter the program. A screenshot of the program is depicted in Figure B.7. In this figure, the squares denote rooms, the white persons are Radiologists, the colored persons are patients. Other practitioners are not incorporated in the DES. The rooms are from left to right: the nurse practitioner, two mammography

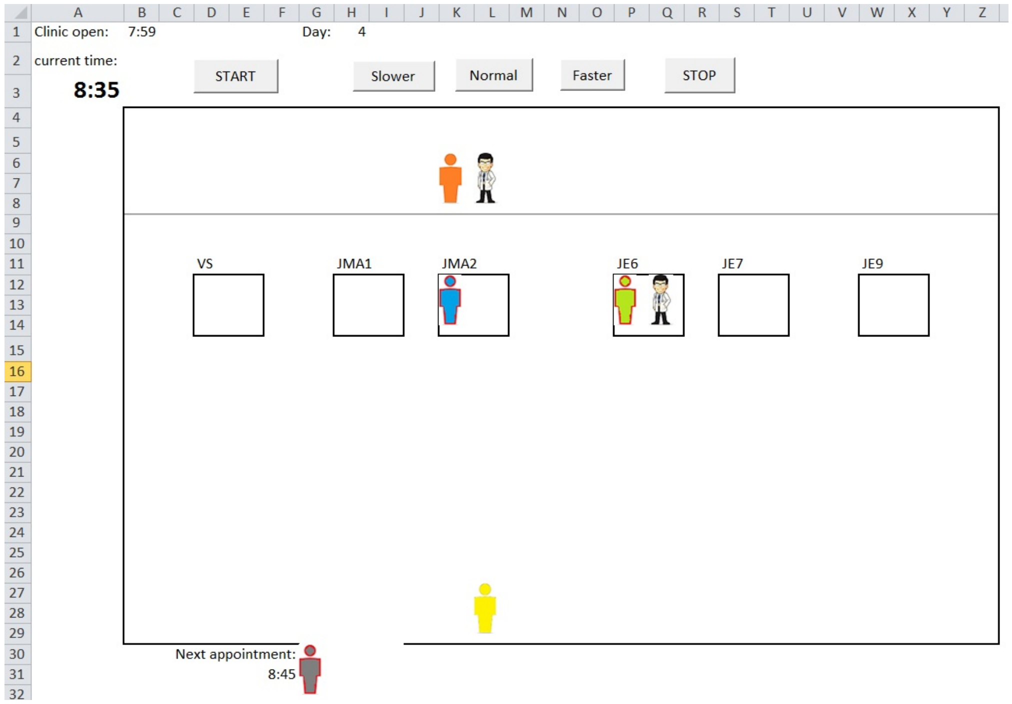

Figure B.7: Screenshot of graphical DES program.

rooms, two ultrasound rooms, and the 3D ultrasound room. The layout of the clinic is similar to the layout of the DES, which provides graphical support in discussing obtained results with practitioners. We additionally implemented a C++ DES for improved random number generation (we used Mersenne Twister Matsumoto and Nishimura (1998)) and faster calculations. With the faster calculations we could obtain adequate confidence intervals within acceptable time.

We use common random numbers in order to compare the schedules Law (2007). Our DES returns the accumulated waiting for all patients, and for each resource the number of tests performed, the accumulated waiting and idle time between tests performed on this resource, and the last departure time.

We validated the DES program by letting practitioners observe the graphical simulation and discussing the results of different DES settings with many practitioners. With the graphical DES, the staff was able to validate the movements of patients and Radiologists through the center, and provided feedback to make the model more realistic.

Regarding the robustness of the results, we performed several tests with the DES. First, we assumed that the service time durations are not a constant S but uniformly distributed on the interval $[0.9S, 1.1S]$. Second, we investigated the effect of non-punctual patients, by assuming that patients arrive a random time from their appointment time. We used a Normal distribution with $\sigma = 10$ minutes and three different means: -10, 0, and 10 minutes.

The results of the scenarios with early and late arrivals, and with stochastic service durations are displayed in Figures B.8 and B.9.

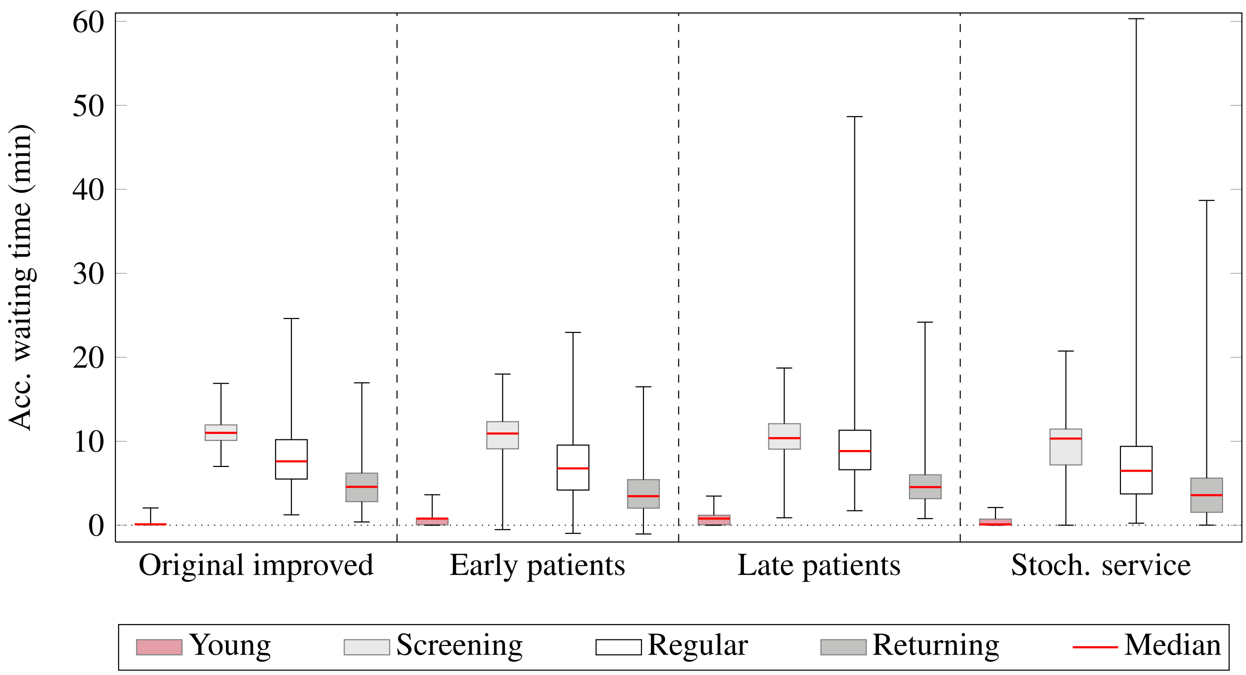

Figure B.8: The accumulated waiting time per patient for the improved schedule in different scenarios.

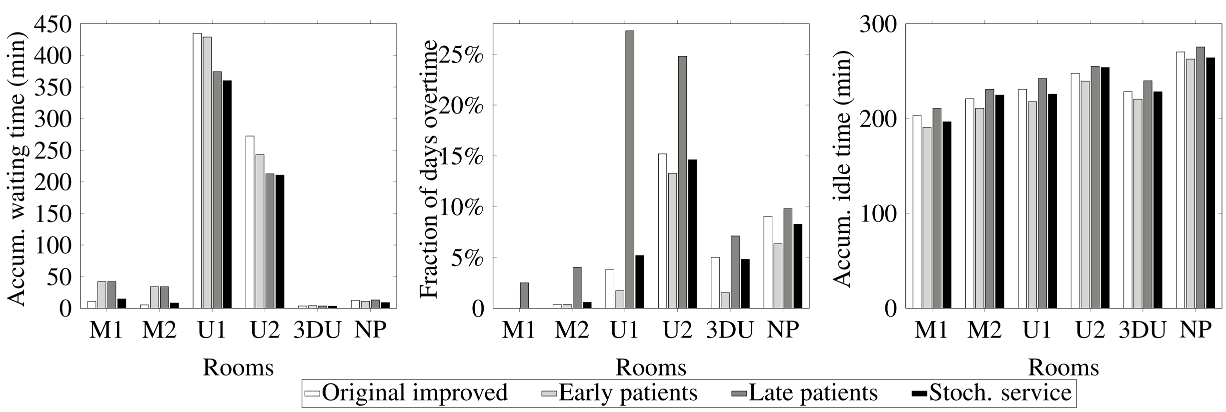

Figure B.9: Results for the improved schedule in different scenarios for the treatment rooms (f.l.t.r): two Mammography rooms, two ultrasound rooms, a 3D ultrasound room and the Nurse Practitioner.

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