# Appendices

## A BRIDGING TIMES

Figure 3 illustrates a care trajectory of four stages: *preliminary tests*, *consultation*, *treatment* and *post-treatment appointment*. For example, the preliminary test might be a blood test, followed by the consultation at the outpatient clinic and some type of treatment such as a chemotherapy infusion in case of an oncology clinic. The care trajectory does not include a post-treatment appointment. We will refer to the time between two consecutive appointments, for example the time between preliminary tests and the consultation and the time between the consultation and the treatment, as *bridging time*. Typically, a minimum duration applies for these bridging times, for example to cover the time to analyse the blood draw in the laboratory. Only after the test results are available, the next appointment can take place. This means, for example, that if an oncology patient finishes preliminary tests at 9:15AM and the minimum bridging time equals 45 minutes, this patient's consultation cannot start before 10AM. Similarly, if the consultation of this patient starts at 10AM and finishes at 10:30AM and preparation of chemotherapy drugs in the pharmacy takes one hour, the treatment cannot start before 11:30AM. Patients who start their visit at the hospital with a consultation or treatment do not bridge the time between a preliminary test and this consultation or treatment, but arrive to the waiting area directly from home some time before the planned start of their first consultation or treatment, referred to as *early arrival time*. Besides early arrival and bridging times, patients also experience *waiting times* before their scheduled appointments that occur as a consequence of randomness in arrival, consultation and treatment times.

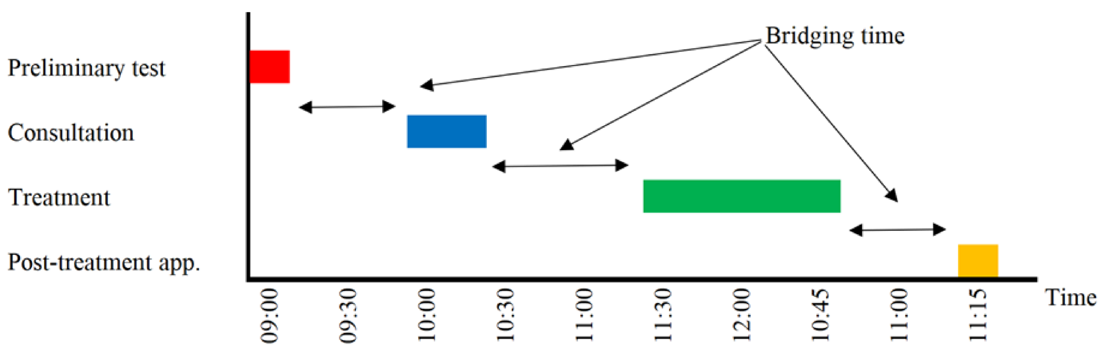



Figure 3: Schematic depiction of a patient trajectory and timeline, derived from [16].

## B MERGING OF PATIENT TRAJECTORIES

Consider the following four care trajectories: *A: blood test - follow-up consultation including electrocardiogram*; *B: blood test - follow-up consultation*; *C: follow-up consultation - treatment 60 min.*; *D: follow-up consultation - treatment 120 min.* Furthermore, assume we gathered 200 days of data let the number of appearances in the gathered data set be: *A:* 80; *B:* 120; *C:* 200; *D:* 80. Since the treatment of care trajectory *C* differs in duration from the treatment of trajectory $D$, these two trajectories differ from a logistical/scheduling point of view and cannot be merged into a single care trajectory. The same applies to $A$ and $B$ if the follow-up consultation including electrocardiogram differs in duration from its counterpart without. However, if the duration does not alter because of the electrocardiogram, this additive is useful from a medical point of view but not from a logistical/scheduling one. Thus, from the latter perspective, we may decide to merge $A$ and $B$ into a single care trajectory. Often, such decision goes hand in hand with the frequency measure. We propose to only include care trajectories that occurred, on average, at least once a day in the data set. Hence, $A$ and $B$ would not be included individually, but the merged trajectory would be. For this merged care trajectory we would reserve one slot a day. Similarly, for $C$ we would also reserve one slot a day and $D$ would, based on the frequency measure, not be included in the blueprint schedule. As may be concluded from this example, the decision on which care trajectories should be included is not unambiguous and should be made in close collaboration clinical staff, managers, and planners and supported by the data analysis.

# C ITERATIVE APPROACH

The parameter updating of the iterative approach has two elements: (1) the waiting area capacity, and (2) the frequency of care trajectories to be scheduled in the blueprint schedule. In the first run of the ILP, the waiting area capacity parameter is set to the maximum available waiting area capacity of the considered instance and the ILP is solved with the desired case-mix of appointments. Either this results in a feasible solution, in which part of appointments must be performed as telephone or video consultation, or no feasible blueprint schedule could be found (then the waiting area restriction cannot be satisfied) and the number of appointments must be reduced. If a feasible blueprint schedule is found, this blueprint schedule is used in our MCS model to evaluate the impact of variability on the number of patients simultaneously present in the waiting area. If the MCS model shows that the ILP schedule is also feasible under randomness, then this ILP schedule will be used as blueprint schedule. Otherwise, we reduce the capacity of the waiting area and start a new iteration. If this does not have the desired effect, the case-mix is adjusted as described above. We continue this iterative optimisation approach until we obtain a feasible blueprint schedule.

The iterative approach described above reduces the capacity of the waiting area in the ILP to ensure the maximum capacity levels of the waiting are are not exceeded when facing patient and provider unpunctuality. We may reduce the capacity in a static or a dynamic way. With *static reduction*, the reduction is equal for all time slots, if possible equal to the largest difference between the waiting area occupancy in the MCS and the deterministic ILP for any time slot. With *dynamic reduction*, we reduce the waiting area per time slot. This dynamic reduction then forces the ILP to allocate more appointments in time slots that are less occupied in the MCS.

# D ILP

The following ILP is used to develop a blueprint schedule that does not violate the waiting area restrictions while maximising the number of in-person scheduled appointments. An overview of the used notation is provided in Table D1.

The ILP is implemented in Python version 3.9 and solved using Gurobi version 9.1.0.

$$
\begin{aligned}
\max_{x_s(i_s,j_s,t)} \quad & \sum_{t=1}\sum_{s=2}\sum_{i_s=1}\sum_{j_s=1} r(j_s)x_s(i_s,j_s,t) && \text{(D1a)}\\
\text{s.t.} \quad & x_s(i_s,j_s,t)+y_s(i_s,j_s,t)=u_s(i_s,j_s,t) && \forall t,i_s,j_s,s, \quad \text{(D1b)}\\
& \sum_{t=1}^{T}\sum_{i_s=1}^{I_s} u_s(i_s,j_s,t)=c(j_s), && \forall j_s,s, \quad \text{(D1c)}\\
& \sum_{j_s=1}^{J_s} u_s(i_s,j_s,t)\le 1, && \forall t,i_s,s=2,\ldots,S-1, \quad \text{(D1d)}\\
& u_s(i_s,j_s,t)=0, && \forall t\ge T-d(j_s),i_s,j_s,s, \quad \text{(D1e)}\\
& \sum_{j_s^*\ne j_s}\sum_{n=t+1}^{t+d(j_s)} u_s(i_s,j_s^*,n)\le\left(1-u_s(i_s,j_s,t)\right)M, && \forall t,i_s,j_s,s, \quad \text{(D1f)}\\
& \sum_{n=1}^{t}\sum_{i_{s+1}=1}^{I_{s+1}} u_{s+1}(i_{s+1},j_{s+1},n)\le \sum_{n=1}^{t-b(j_s,j_{s+1})}\sum_{i_s=1}^{I_s} u_s(i_s,j_s,n), \forall (j_s,j_{s+1})\in\mathcal{P},s,t, && \text{(D1g)}\\
& \sum_{t=1}^{T}\sum_{i_s=1}^{I_s} x_s(i_s,j_s,t)=\sum_{t=1}^{T}\sum_{i_{s+1}=1}^{I_{s+1}} x_{s+1}(i_{s+1},j_{s+1},t), && \forall (j_s,j_{s+1})\in\mathcal{P},s, \quad \text{(D1h)}\\
& z(t)\le w_{a,t}, && \forall t,a,, \quad \text{(D1i)}\\
& x(i_s,j_s,t),y(i_s,j_s,t),u(i_s,j_s,t)\in\{0,1\} \qquad \forall t,i_s,j_s,s, && \text{(D1j)}
\end{aligned}
$$

where

$$
z(t)=\sum_{s=1}^{S}\left(\sum_{i_s=1}^{I_s}\sum_{n=t+1}^{t+\tilde{b}(j_s)} x_s(i_s,j_s,n)+\sum_{i_s=1}^{I_s}\sum_{n=1}^{t-d(j_s)} x_1(i_s,j_s,n)- \sum_{i_{s+1}=1}^{I_{s+1}}\sum_{j_{s+1}\in\mathcal{P}_{s+1}}\sum_{n=1}^{t} x_{s+1}(i_{s+1},j_{s+1},n)\right). \qquad \text{(D2)}
$$

The demand $d(j_s)\equiv 0$ for all appointment types $j_s$ in stages $s=1,S$ and the auxiliary variable $u$ is introduced in constraint (D1b) for notational convenience.

Table D1: Sets, parameters and variables.

| | |
|---|---|
| **Sets** | |
| $\mathcal{S} = \{1, \dots, S\}$, indexed by $s$ | stages |
| $\mathcal{I}_s = \{1, \dots, I_s\}$, indexed by $i_s$ | available resources at stage $s$ |
| $\mathcal{J}_s = \{1, \dots, J_s\}$, indexed by $j_s$ | appointment types at stage $s$ |
| $\mathcal{J}'_s \subseteq \mathcal{J}_s$ | appointment types at stage $s$ that can take place in-person or digitally |
| $\tilde{\mathcal{J}}_s = \mathcal{J}_s \backslash \mathcal{J}'_s$ | appointment types at stage $s$ that can only take place in-person |
| $\mathcal{P} \subseteq \mathcal{J}_1 \times \dots \times \mathcal{J}_S$, indexed by $(j_1, \dots, j_S)$ | patient trajectories consisting of an appointment of type $j_s$ at stage $s$, $s = 1, \dots, S$ |
| $\mathcal{P}_s \subseteq \mathcal{J}_s$ | patient trajectory consisting only of a single appointment of type $j_s$ at stage $s$ |
| $\mathcal{T} = \{1, \dots, T\}$, indexed by $t$ | time slots |
| $\mathcal{A} = \{1, \dots, A\}$, indexed by $a$ | shared waiting areas |
| $\mathcal{S}_a \subseteq \mathcal{S}$ | stages of which patients wait in shared waiting area $a$ before their appointment |
| **Parameters** | |
| $c(j_s)$ | demand of appointment type $j_s$ |
| $d(j_s)$ | duration of appointment $j_s$, expressed in number of time slots |
| $b(j_{s-1}, j'_s)$ | minimum bridging time between appointment $j_{s-1}$ at Stage 1 and $j'_s$ at stage 2 |
| $\tilde{b}(j_s)$ | early arrival time for appointment $j_s \in \mathcal{P}_s$, i.e., the time a patient coming from home spends in the waiting area of stage $s$ to have appointment $j_s$ |
| $w_{s,t}$ | maximum number of patients allowed in the waiting area of Stage $s$ in time slot $t$ |
| $w_{a,t}$ | maximum number of patients allowed in the shared waiting area $a$ in time slot $t$ |
| $r(j_s)$ | reward for planning appointment $j_s$ |
| $M$ | big-$M$ |
| **Variables** | |
| $x_s(i_s, j_s, t) \in \{0,1\}$ | $x_s(i_s, j_s, t) = 1$ if, at stage $s$, appointment $j_s$ is scheduled in-person at the start of time slot $t$ using resource $i_s$, $x_s(i_s, j_s, t) = 0$ otherwise |
| $y_s(i_s, j_s, t) \in \{0,1\}$ | $y_s(i_s, j_s, t) = 1$ if, at stage $s$, appointment $j_s$ is scheduled digitally at the start of time slot $t$ using resource $i_s$, $y_s(i_s, j_s, t) = 0$ otherwise |

# E Blueprint schedule outcomes

*Pre-COVID-19 blueprint schedule performance*

Pre-COVID-19 the rheumatology clinic of SMK deployed a blueprint schedule based on appointment types for nurses as well as for physicians and PAs. Consequently, trajectories with the same type of appointment were indistinguishable, e.g., trajectories C – G could be scheduled in the same slots for physicians and C-PA – G-PA could be scheduled in the same slots for PAs.

Figure 4(a) presents the allocation of slots to patient trajectories under the restrictions of the pre-COVID-19 blueprint schedule in the worst possible realisation that results in maximum waiting area occupancy as shown in Figure 4(b), where the waiting area consisting of 18 seats is overcrowded by 22 seats. Figure 4(c) presents the best possible realisation that minimises the waiting area occupancy as shown in Figure 4(d), where the waiting area is overcrowded by 8 seats due to patient and provider unpunctuality. The pre-COVID-19 blueprint includes a few digital consultations (trajectory E – PA) at the end of both the morning and afternoon session of the PAs, that were included in the clinic's pre-COVID-19 blueprint.

Pre-COVID-19, the medical oncology & haematology outpatient clinic of UMCU deployed a blueprint schedule based on appointment types for physicians and PAs at the outpatient clinic, but the day-care department did not use a blueprint schedule. Consequently, the outpatient clinic did not distinguish between trajectories that only differ in Stage 3, such as D-60 – D-210. In addition, the outpatient clinic's pre-COVID-19 blueprint schedule did not discriminate between trajectories with the same patient type in Stage 2, i.e., B – D as well as F – I were indistinguishable, and thus, for example, trajectories B and C could be scheduled in the same slots. The colour coding in Figures 5(a) and (c) uses the first colour for trajectories with the same Stage 2 consultation, i.e., F and G both use colour F. Trajectories B, C, and D have identical Stage 2 consultations, but D is distinguished in our pre-COVID-19 blueprint, because patients that have a day-care treatment must be scheduled at the beginning of each session to enable completion of their day-care appointments on-time, and likewise for trajectories H, and I.

Figures 5(a) and (b) present the worst-case pre-COVID-19 blueprint schedule and corresponding waiting room occupancy that reveals that the capacity of 19 seats may face a shortage of 11 seats in the worst-case. Figures 5(c) and (d) present the best-case pre-COVID-19 blueprint schedule and corresponding waiting room occupancy revealing a shortage of 3 seats.

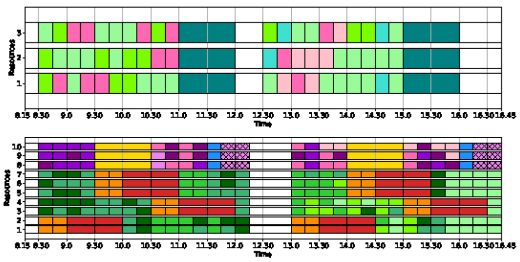
*COVID-19 blueprint schedule performance*

For SMK, the COVID-19 blueprint schedule resulting from our iterative approach is presented in Figure 4(e) with corresponding waiting area occupancy in Figure 4(f). From Figure 4(f), observe that the blueprint schedule adheres to the waiting area capacity restriction of 18 seats. The optimal blueprint includes a number of digital consultations. For nurses, only trajectory I may be replaced by a digital consultation. In the COVID-19 blueprint schedule 50% of these trajectories are scheduled digitally. For rheumatologists and PAs, respectively, patient trajectories B, B – PA and E, E – PA may be replaced by a digital consultation. In the COVID-19 blueprint schedule, respectively, 21%, 17%, 54%, and 57% of these trajectories are scheduled digitally. In total, of all appointment types, 88% of the consultations are scheduled in-person. Under our proposed COVID-19 blueprint schedule, the rheumatology clinic of SMK can continue to deliver 100% of their required daily appointments.

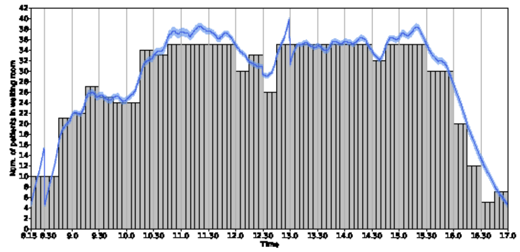
For UMCU, the COVID-19 blueprint schedule is presented in Figure 5(e) with corresponding waiting area occupancy in Figure 5(f). The blueprint schedule adheres to the waiting area capacity restriction of 19 seats. In the blueprint schedule in Figure 5(e), 58% of trajectory B and 57% of trajectory F consultations are scheduled digitally. In total, this corresponds to 81% of the medical oncology appointments and 87% of the haematology appointments to be scheduled in-person, which means that 83% of all appointments can take place in-person. The medical oncology & haematology outpatient clinic of UMCU can continue to deliver 100% of their required daily appointments.

The multidisciplinary intervention team requested the joint design of the UMCU's outpatient clinic and day-care department. Figure 6 presents the corresponding COVID-19 blueprint schedules for both the outpatient clinic (a) and the day-care department (c), with waiting area occupancy in Figures 6(b) and 3(d), respectively.

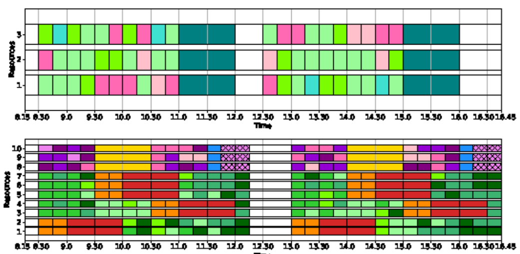
For medical reasons 100% of the day-care appointments take place in-person. Comparing Figure 6(a) and Figure 5(e) shows that including full information on patient trajectories allows for more flexibility in the outpatient clinic's blueprint, as patients with a day-care treatment may now be scheduled after 10:30h in the morning session or 15:00h in the afternoon session. The schedule of Figure 6(a) includes 2 trajectory B and 6 trajectory F consultations that are scheduled in-person when compared to Figure 5(e). We observe an improvement in the outpatient clinic blueprint schedule, resulting in 53% of trajectory B and 29% of trajectory F consultations scheduled digitally (58% and 57% in Figure 5(e), respectively). In total, this means that 87% of all outpatient appointments can take place in-person.



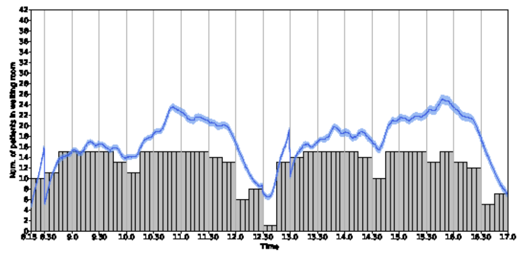
(a) Worst-case pre-COVID-19 blueprint schedule.



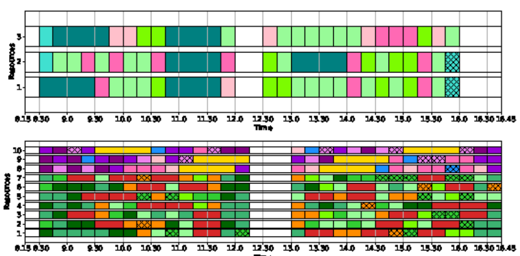
(b) Waiting area occupancy corresponding to (a).



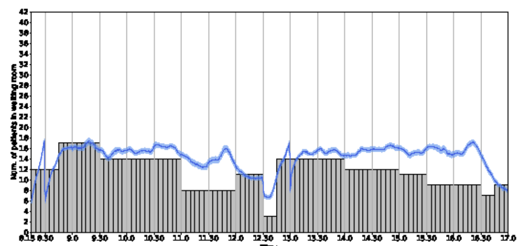
(c) Best-case pre-COVID-19 blueprint schedule.



(d) Waiting area occupancy corresponding to (c).

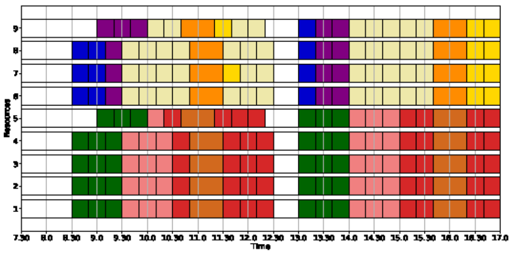


(e) COVID-19 blueprint schedule.

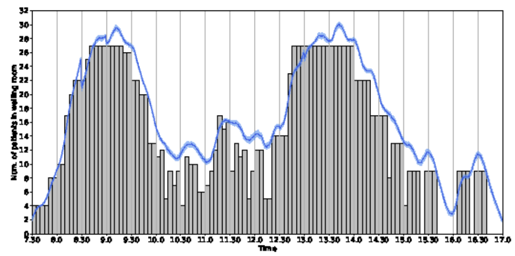


(f) Waiting area occupancy corresponding to (e).

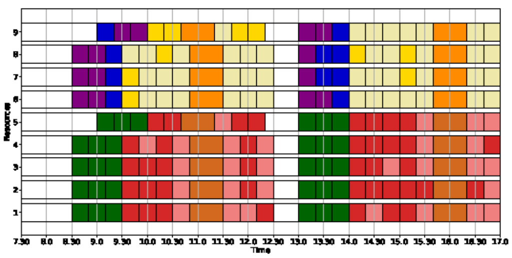
Figure 4: Worst- and best-case realisations of the pre-COVID-19 blueprint schedule and the recommended COVID-19 blueprint schedule for the rheumatology clinic in SMK and the corresponding waiting area occupancy. Each 15 minutes block in the blueprint schedule is colour coded, where the colours refer to the patient trajectories in Table 1 allocated to that block. Hatched (x) blocks correspond to digital consultations of the colour matching the patient trajectory. In (a), (c), and (e), the top-part (resources 1 – 3) considers the three nurses, and in the bottom part resources 1 – 7 correspond to physicians and 8 – 10 to PAs. In (b), (d) and (f), the grey bars represent the waiting area occupancy (number of patients in the waiting room) per 15 minutes block taking into account bridging and mean early arrival times. The blue line, together with its 95%-CI as the shaded area, depicts the waiting area occupancy including randomness in early arrival and consultation times.



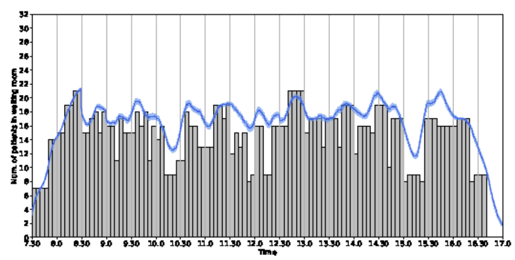
(a) Worst-case pre-COVID-19 blueprint schedule.



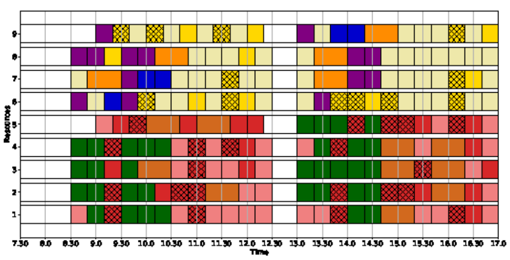
(b) Waiting area occupancy corresponding to (a).



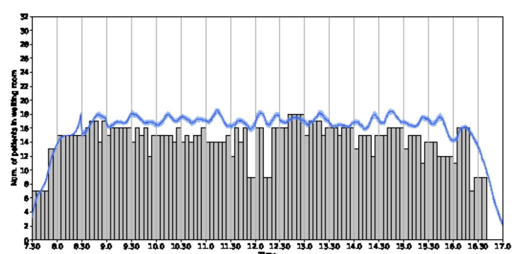
(c) Best-case pre-COVID-19 blueprint schedule.



(d) Waiting area occupancy corresponding to (b).

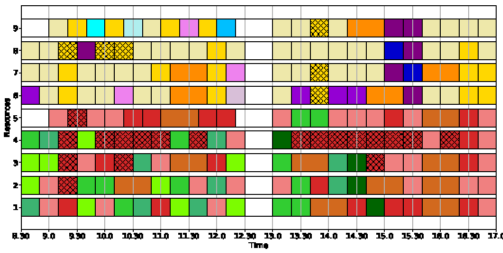


(e) COVID-19 blueprint schedule.

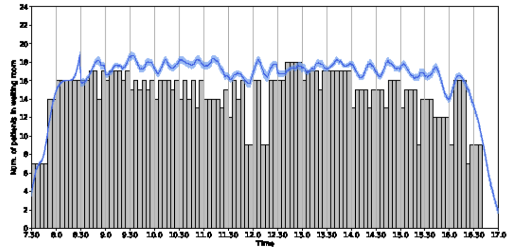


(f) Waiting area occupancy corresponding to (e).

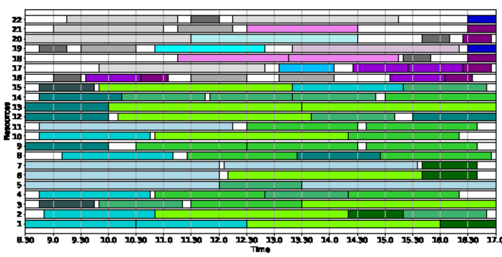
Figure 5: Worst- and best-case realisations of the pre-COVID-19 blueprint schedule and the recommended COVID-19 blueprint schedule for the medical oncology & haematology outpatient clinic in UMCU and the corresponding waiting area occupancy. Details on the figures are provided in the caption of Figure 4.



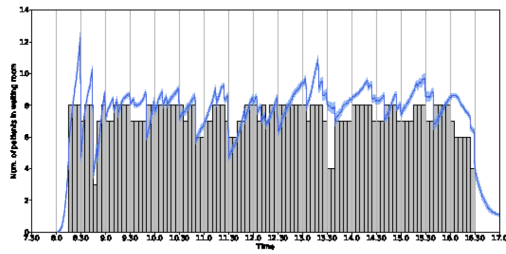
(a) COVID-19 blueprint schedule outpatient clinic.



(b) Waiting area occupancy corresponding to (a).



(c) COVID-19 blueprint schedule day-care department.



(d) Waiting area occupancy corresponding to (c).

Figure 6: COVID-19 blueprint schedule of the outpatient clinic (a) and day-care department (c) for the medical oncology & haematology outpatient clinic in UMCU and the corresponding waiting area occupancies. Details on the figures are provided in the caption of Figure 4.