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Simulating emergency patient flow during the COVID-19 pandemic

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ABSTRACT

The work presented in this paper is based on two projects that were conducted at St. Olavs Hospital (Norway) when preparing for the COVID-19 pandemic. Three discrete event simulation models are provided to evaluate the resource requirements during the peak of the pandemic. First, we estimate the number of beds needed in the emergency department (ED). In the second model, we estimate the number of ambulances required to maintain prepandemic response times for emergency patients. The third model is a coupling of the two former models, and it is used to study the effects of ED boarding time for COVID-19 patients. The resource needs are analysed under different COVID-19 testing policies. A strict testing policy increases the bed requirements in the ED, while it has the opposite effect for ambulances. Two distinct mechanisms causing boarding time are found. The effects from boarding time are most prominent during night and weekends.

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COVID-19; discrete event simulation; emergency department; boarding time; ambulances

1. Introduction

The COVID-19 pandemic has put the health care sector in many countries under pressure. In Norway, societal restrictions, such as closing down public institutions and instructing social distancing, were imposed on the 12th of March 2020. Moreover, the hospitals reduced the elective patient activity to free resource capacity, resulting in a decrease in the number of inpatient stays in March and April by 39% compared with the same period in 2019. Furthermore, presumably due to less accidents and the fact that people are reluctant towards seeking medical assistance in danger of becoming infected, the activity related to emergency patients decreased by 19% in the same period compared with 2019 (The Norwegian Directorate of Health, 2020).

The main contribution of this paper is to demonstrate how discrete event simulation (DES) can be used to provide decision support for the hospital management when preparing for the pandemic. The second contribution is a novel approach to model boarding time in the emergency department (ED). Boarding occurs when downstream units are not able to serve patients at the rate at which the patients are ready to leave the ED, causing additional demands for beds in the ED. Boarding time is defined as the time between the decision made by a physician to admit a patient and the time the patient leaves the ED to an inpatient unit (Tang et al., 2015).

St. Olavs Hospital is a university hospital located in Trondheim, Norway, treating about 60,000 inpatients each year. The work presented in this paper is based on two projects that were conducted at St. Olavs Hospital between the 17th of March and the 29th of March 2020. The first project was conducted for the ED, and the second for the ambulance services. In each project, one DES model was developed, and eventually these were implicitly combined into a third model. During this period of time, the hospital management proposed that all COVID-19 suspected patients that enter the hospital should be tested for COVID-19 in the emergency department (ED). Furthermore, these patients must be transported by ambulance when going to the hospital, and this also applies to patients that are not confirmed to be COVID-19 negative upon departure from the hospital. To evaluate these proposals, the hospital management required to estimate the need for both additional beds in the ED, and additional ambulances during the peak of the pandemic.

On the 12th of March 2020, the Norwegian Institute of Public Health (NIPH) released a "recommended planning scenario" for the evolvement of the COVID-19 pandemic in Norway, which aimed to provide the Norwegian hospitals with support when preparing for the pandemic. On the 24th of March 2020, the recommended planning scenario was updated with a higher number of COVID-19 patients hospitalised at peak of the pandemic. Both scenarios were used as input for our three models.

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The rest of the paper is outlined as follows. In Section 2, relevant literature is presented to provide a context for our contribution. Then, in Section 3 we present the objectives of the study, the basic assumptions, the logic of the models and the data used to perform the studies. The scenarios considered for analysis are presented in Section 4, while the simulation results are provided in Section 5. Finally, in Section 6 we discuss the main implications of our findings and conclude the paper.

2. Literature

ED crowding, a consequence of a simultaneous increase in the demand for health care and a deficit in available hospital and ED beds, has become a significant public health problem (Bair, Song, Chen, Morris et al., 2010a). A growing body of evidence suggests that ED crowding is linked to adverse quality of care, such as medication errors, patient dissatisfaction and staff burnout (Valipoor et al., 2021). One cause of ED crowding is boarding patients that experience a delay in transfer to hospital wards (Tang et al., 2015). Only 7% of the papers reviewed by Vanbrabant et al. (2019) include boarding time as a key performance indicator, but they were all published in the last 10 years. This confirms the growing interest in ED boarding as a research topic within operations research.

To model ED boarding time, downstream units should be regarded. However, this adds modelling complexity, and some authors sample boarding times to omit this complexity (Bair, Song, Chen, Morris et al., 2010b; De Boeck et al., 2019; Carmen et al., 2014). Other contributions, like Kolb et al. (2007); Kolb et al. (2008) explicitly include the inpatient unit to obtain realistic boarding patterns. Kolb et al. (2007) investigate the effect of the inpatient unit utilisation on ED crowding, while Kolb et al. (2008) evaluate the effect of different buffer concepts. Wood and Murch (2020) develop a continuous Markov chain to model a stroke pathway with different units. Unit capacities are part of the model formulation, and capacity shortage induces delays in patient transfer.

In this paper, we model ED boarding through an implicit coupling of two models, where output data from one model is used as input for the other. This data is used to model the downstream ward capacity through simple counting rules, allowing us to obtain realistic boarding patterns in the ED, and maintain a low model complexity.

DES has also been used to evaluate ambulance systems. Aboueljinane et al. (2013) review the literature on simulation models applied to such systems and find that most simulation studies focus on medium-term decisions such as the deployment problem and long-term decisions such as dimensioning of resources. Lam et al. (2014) use DES to evaluate different strategies for reducing ambulance response times, defined as the time it takes for a dispatched ambulance to arrive on scene. Lutter et al. (2016) use DES to compare different strategies for ambulance location planning. They compare five optimisation models that are used to facilitate ambulance location, and use simulation to compare the solutions in terms of the proportion of calls that are served within the time threshold.

Currie et al. (2020) address how simulation modelling can help reduce the impact of COVID-19. The authors present different problems where simulation can be used as decision support. One of the problems they highlight is related to capacity of inpatient hospital beds and critical care.

Several authors apply DES to provide decision support in relation to the COVID-19 pandemic. Wood (2020), and Melman et al. (2021) both consider the trade-offs related to decreasing the activity for nonCOVID-19 patients during the pandemic. Mallor et al. (2020) aim to predict the number of beds needed by COVID-19 patients both in the Intensive Care Unit and in the rest of the hospital for the coming weeks. In addition to estimating the bed requirements imposed by the COVID-19 patients, Le Lay et al. (2020) also evaluate different policies for managing the increased demand for beds. Wood et al. (2020) aim to predict the number of deaths, which they divide into capacity-dependent and capacity-independent deaths, caused by the COVID-19 pandemic. They analyse different scenarios with regards to both the loading of COVID-19 positive patients and the number of intensive care beds available. Finally, Asgary et al. (2020)apply DES to evaluate different settings related to a drive-through facility for mass vaccination.

This paper adds to the literature on how DES can be a viable tool for decision support when preparing for a state of pandemic. In addition, we extend on the literature on ED boarding by proposing a new method for modelling a downstream ward and the ambulance waiting time experienced by inpatients leaving this ward. In this specific problem, two sources of ED boarding are identified and quantified, but we believe that similar methods can be applied to identify and quantify mechanisms that cause boarding in other systems.

3. Materials and methods

Three cases are considered in this paper; the ED, the ambulance and the combined case, and one DES model is developed for each case. These are referred to as the *ED model*, the *ambulance model* and the *combined model*. Before describing the models, the objectives of the study and a set of basic assumptions are presented. To describe the three DES models, the STRESS guidelines proposed by Monks et al. (2019) are used.

3.1. The objectives of the study

The purpose of the study is to provide decision support for the hospital management when preparing for a state of pandemic. The first objective is to estimate the number of beds that must be present in the ED to host COVID-19 suspected patients that wait for a COVID-19 test result (the ED model). The second objective is to estimate the number of ambulances required to obtain similar response times for the most urgent patients as in a prepandemic state (the ambulance model). We here define response time as the time it takes from the transport request emerges to an ambulance is assigned the mission. The third objective is to estimate the additional number of (boarding) beds required in the ED when considering the delayed transfer of patients from the ED to the COVID-19 ward, due to the lack of available beds in the COVID-19 ward (the combined model). All estimates should reflect the demand during the peak of the pandemic, and different COVID-19 testing policies.

3.2. Basic assumptions

In this section, we specify the assumptions that were made at the time when the two projects were performed.

3.2.1. Patient groups

In all three cases, the emergency patients are considered. We define that the patients are divided into two groups: those that require a stay at the hospital due to their COVID-19 disease, and the rest. In Figure 1, the groups are labelled as the COVID-19 positive and the nonCOVID-19 population, respectively.

As we cannot know to what group a patient belongs before receiving the test results, the patients arriving at the hospital are divided into two categories: those with a COVID-19 suspicion and those without. All patients that are labelled as COVID-19 suspects must be treated as if they belong to the COVID-19 positive population until they are potentially clarified as belonging to the nonCOVID-19 population. We assume that all patients in the COVID-19 positive population have symptoms that place them in the COVID-19 suspicion category. In addition, we assume that a share of the patients that belong to the nonCOVID-19 patient population have symptoms that qualify for placing them in the COVID-19 suspicion category. The testing policy is decided on by the hospital management, and a strict testing policy implies that the threshold for testing is low and that a large share of patients are labelled as COVID-19 suspects. The red dashed line in Figure 1 illustrates how the nonCOVID-19 patient population is separated into either COVID-19 suspects or nonsuspects.

3.2.2. The development of the pandemic

When regarding the development of the pandemic over time, initially, the number of COVID-19 positive admissions increases. At a point in time, a peak period of activity is reached, followed by a period of decreasing incidence. At the time when the projects were conducted, we did not know for how long the peak period would last. To obtain a conservative estimate of the resource requirements, we assumed a peak period lasting longer than the average patient LOS. This implies that there is a stationary period when the number of COVID-19 admissions is equal to the number of COVID-19 patients leaving the hospital, and this period represents the peak of COVID-19 positive patients present in the hospital simultaneously. In comparison to the arrival peak, this peak is delayed by the time equal to the average patient LOS, and we refer to it as the *delayed peak period*.

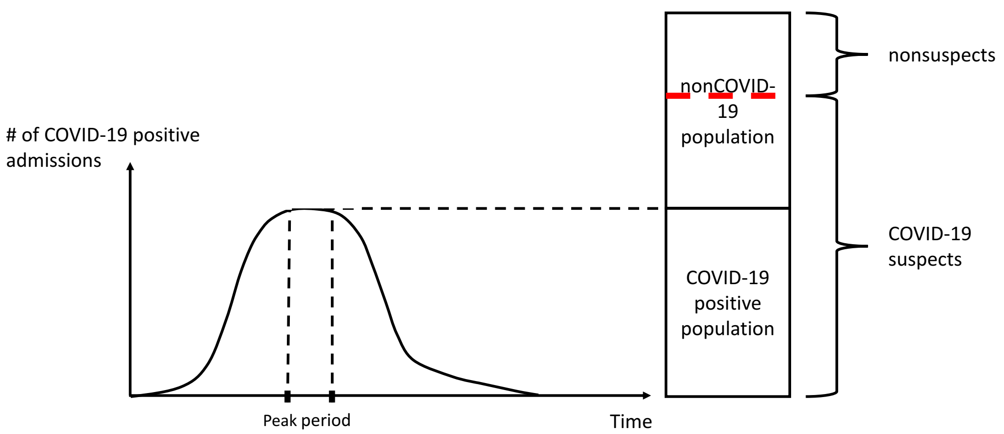

Figure 1. The two patient populations considered, and how they are divided into COVID-19 suspects and nonsuspects. All COVID-19 positive patients are COVID-19 suspects when arriving at the hospital, so is a share of the patients from the nonCOVID-19 patient population.

In addition to the two "recommended planning scenarios", NIPH provided estimates of the average LOS of the COVID-19 positive patients. Based on this information, and since we assume a stationary system (with days as the time resolution) during the delayed peak period, Little's formula (Little, 1961) is used to derive the daily arrival rate of COVID-19 positive patients entering the hospital.

3.2.3. The flow of patients through the hospital

All COVID-19 suspects are admitted to the *COVID-19 area* upon arrival at the ED, where testing is performed. If the test results indicate a COVID-19 disease, the patient is transferred to a hospital ward for treatment. If no beds are available in the downstream ward, patients remain in the ED until a bed becomes vacant. This additional waiting time is referred to as the boarding time, and patients require a bed while waiting to be admitted in the downstream ward. As a simplification, we aggregate the total bed capacity devoted for the COVID-19 positive patients to a common resource, referred to as the COVID-19 ward. The COVID-19 positive patients stay in the COVID-19 ward until they leave the hospital by ambulance. Furthermore, each patient that is not confirmed to be COVID-19 negative in the ED requires an ambulance upon departure, also those that were labelled as nonsuspects upon arrival at the ED.

At the time when the projects were conducted, it was decided by the hospital management to assume that the bed capacity for treating COVID-19 patients is sufficient during the peak period. The total bed capacity at St. Olavs Hospital is approximately 1000 beds, and elective patient activity will be adjusted to provide beds for the COVID-19 positive patients. We therefore assume that the bed capacity in the COVID-19 ward is sufficient and constant during the delayed peak period.

3.2.4. The arrival process of COVID-19 positive patients

Even though the number of COVID-19 patients resting in the COVID-19 ward is assumed to be stationary during the delayed peak period (on a daily basis), the number of COVID-19 patients present in the ED is non-stationary (on a hourly basis). We assume that patients arrive independently of each other and with varying intensity, and we therefore model the patient arrival processes as nonhomogeneous Poisson processes. We assume that the arrival process of COVID-19 positive patients to the ED is similar to the arrival process of semi-urgent patients, who mainly arrive at the ED during daytime. This is based on the assumption that the progression of symptoms is gradually increasing, which makes it possible to avoid travelling during night.

The arrival processes of requests in the ambulance model are also modelled as nonhomogeneous Poisson processes. We assume that all patients that will prove to be COVID-19 positive are transported with an ambulance to the ED. Together with the assumption that the time between a request for ambulance and the arrival at the ED is generally small, this justifies the choice to model the arrival process of patients belonging to the COVID-19 positive population with the same process as we used to generate the arrival of these in the ED model. The patients that are not confirmed to be COVID-19 negative upon departure are assumed to be discharged mainly during daytime, and the the same process is used again to model the discharge process. Even though the processes are the same, the intensities are adjusted to fit the associated expected arrival/ discharge rates.

3.3. The logic of the models

In this section, the logic of the three models are presented.

3.3.1. The ED model

In the ED model, we consider the flow of emergency patients with a COVID-19 suspicion entering the ED. These patients must be isolated from the nonsuspects, and enter an area referred to as the COVID-19 area.

In Figure 2, the system considered in the ED model is illustrated. There is a number of beds available in the COVID-19 area, and each patient is assigned a room and a bed upon arrival. A COVID-19 test is performed just after the arrival, and the patients must remain in the COVID-19 area until their test results are ready. If a patient enters the ED, and no beds are available in the COVID-19 area, the patient is escorted to a buffer area, referred to as the *tent area*, with additional beds. Tests are also performed in the tent area, and the process is not delayed for patients that stay in these beds. We assume that patients who are placed in the tent area are not transferred to the COVID-19 area if beds become vacant there.

The COVID-19 test samples are batched together, and analysed in a machine. Only one machine is available, and only one batch can be analysed at a time. This means that patients that enter just after a batch is initiated must wait to have their tests analysed until this batch is done.

We assume that all ED activities required by the patients are undertaken while the patients wait for the test results. When the test results are ready, the patients leave the ED. After a patient leaves, the room must be sterilised independently of the test result.

The entities of the simulation model are the COVID-19 suspected patients entering the ED, while the resources are the beds in the COVID-19 and the

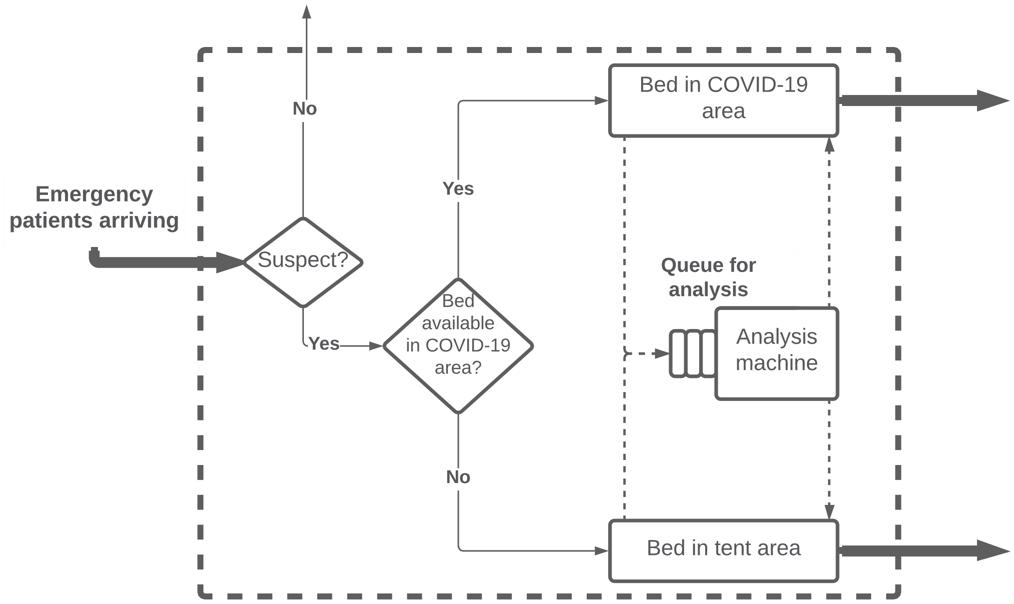

Figure 2. The system modelled in the ED case. The dashed arrows illustrate the flow of tests that are taken immediately after the patient is assigned a bed. The tests queue up in front of the analysis machine, and patients cannot leave the ED before receiving the outcome of the test analysis.

tent area, and the machine for analysing the COVID-19 tests. The state of the system is given by the number of patients in the COVID-19 and the tent area. The events in the simulation model are patients arriving at the COVID-19 area, patients being assigned to a bed either in the COVID-19 or the tent area, starting the analysis of a COVID-19 test batch, ending the analysis of a COVID-19 test batch, patients leaving the COVID-19 or the tent area, starting the cleaning of a room after a patient has left and finishing the cleaning of a room.

3.3.2. The ambulance model

The system modelled in the ambulance case is presented in Figure 3. There are two categories of patient transports considered: the normal and the *COVID-19 transports*. All patients that are either COVID-19 suspects when going to the hospital or that are not confirmed to be COVID-19 negative upon departure, require a COVID-19 transport. Patients that are not confirmed to be COVID-19 negative constitute of those that were confirmed to be COVID-19 positive, and those that were not tested for COVID-19 in the ED (the nonsuspects). The remaining transports are normal transports.

A COVID-19 transport requires additional transportation time, because the ambulance workers must wear an anti-infection coat, and the ambulance must be cleaned after the delivery of the patient. All transports are characterised by an urgency level and a required service time. If two patients request an ambulance at the same time, and only one ambulance is vacant, the most urgent patient is served first. We do not consider the position of the ambulances or the pick-up destinations in the model, but the service times are stochastic to reflect a variation in driving distances.

There is a number of ambulance cars available for patient transportation. Each car can only transport one patient at a time, and a car is unavailable for new missions during the entire service time of the patient that it is carrying. The ambulance personnel are not explicitly considered in the model, but the number of ambulances available through

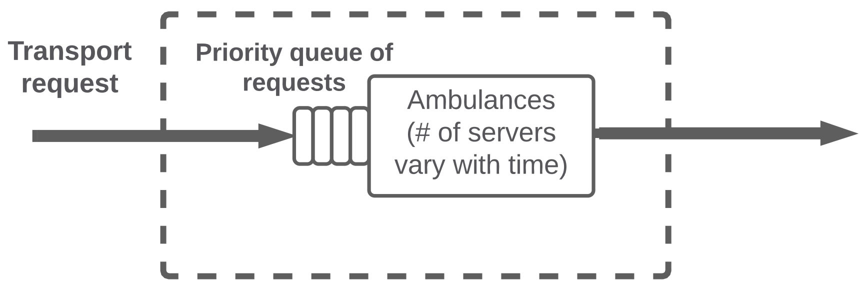

Figure 3. The system modelled in the ambulance case.

the day depends on the number of ambulance personnel on duty at different times during the week.

The entities of the simulation model are the transport requests, and the resources are the ambulances. The state of the system is given by the number of patients in transportation and the number of patients waiting to be assigned an ambulance (number of patients in queue). The events are a new transport request, an ambulance being assigned a patient, a patient leaving the ambulance, starting the cleaning of an ambulance after a COVID-19 transport and finishing the cleaning of an ambulance.

3.3.3. The combined model

This model extends the ED model, and the system under consideration is illustrated in Figure 4. After initial testing in the ED, all COVID-19 positive patients are transferred to the COVID-19 ward to receive treatment, while the COVID-19 negative patients leave the system. If no beds are available in the COVID-19 ward, the COVID-19 positive patients must wait in a boarding bed in the ED until a bed becomes vacant.

Under the assumption that a stay in a boarding bed does not extend the LOS of a patient, we do not have to model the individual patients stay in the COVID-19 ward. However, it is sufficient to know the number of beds available at a given point in time, and keep track of the relative difference from this point as patients enter and leave the COVID-19 ward. This saves computational effort, as the length of stay of COVID-19 patients is typically in the range of days and weeks, while the stay in the ED is in terms of hours.

Both the number of patients present in the boarding beds and the COVID-19 ward beds are handled via counting. At the beginning of the simulated time, a given number of beds are available in the COVID-19 ward. This is represented with a counter that is set to equal the number of available beds. If a patient is transferred from the ED to the COVID-19 ward, the counter is decreased by 1 as one less bed becomes vacant. There is also a counter for the boarding beds, representing the number of patients resting in a boarding bed. If the counter representing the COVID-19 ward is 0 (no beds available), and yet another patient should be transferred to the COVID-19 ward, the boarding bed counter is increased by 1.

When a COVID-19 positive patient is no longer in need of hospital services, an ambulance is requested to transport the patient out. Then, following a delay, an ambulance arrives to transport the patient home. When a patient leaves the COVID-19 ward, the corresponding counter is increased by 1, as one more bed becomes vacant. If there are patients resting in the boarding beds when a patient leaves the COVID-19 ward, one patient is transferred from a boarding bed to the vacant bed in the COVID-19 ward. The net change of patients in this process is −1 in the boarding beds, and 0 in the COVID-19 ward. At the same time, the boarding time of the patient who has stayed in a boarding bed the longest is recorded.

Two mechanisms that cause boarding are identified. First, having many patients ready to leave the ED at the same time (following a test batch) may cause prolonged boarding time if not enough beds are vacant in the COVID-19 ward. We refer to this as *excessive-flow-induced boarding*. Second, additional boarding time might occur when patients that are ready to leave the COVID-19 ward cannot leave because no ambulance is available. This is referred to as *ambulance-induced boarding*.

3.4. Data and experimentation

In the following we present the input data and specify the number of replications used to conduct the studies. The outcome variables that we want to study are referred to as the dependent variables, while the input variables that affect the dependant variables and that we alter through the sensitivity analysis are called the

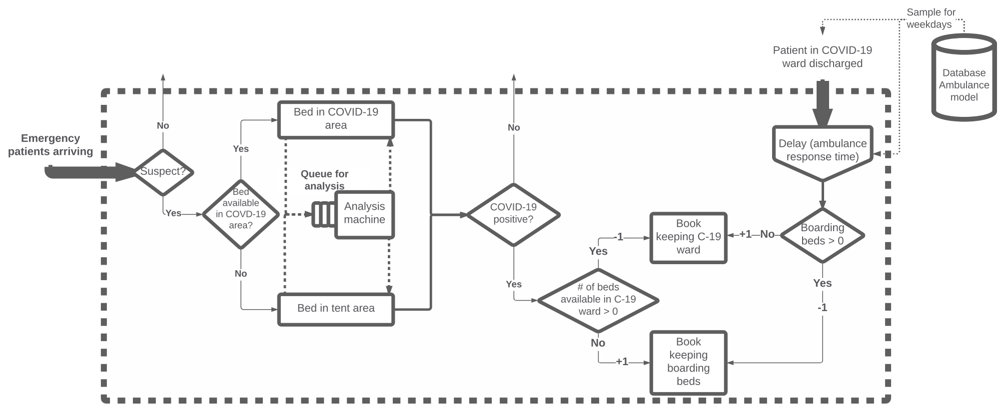

Figure 4. The system modelled in the combined case. The discharge time from the COVID-19 ward and the the ambulance response time are both sampled from the ambulance model output database.

independent variables. Before performing the simulation study, preliminary testing is performed to decide on the length of warm-up necessary to avoid transient effects, and the number of replications needed to ensure accurate results (Law, 2015).

3.4.1. The ED model

The expected arrival rate of the nonCOVID-19 patients at different hours of the week is calculated based on historical data from St. Olav's Hospital, 2019. The weeks 37–47 were chosen by the ED management to represent normal weeks. As stated in Section 3.2, the arrival process of semi-urgent emergencies is used to model the arrival process of COVID-19 positive patients. The intensity is however altered to make sure that the weekly number of arrivals equals the estimates provided by the NIPH scenarios.

There are 27 beds available in the COVID-19 area. Since we want to estimate the need for additional beds required in the ED, the tent area is treated as having infinite capacity. The analysis machine is used for evaluating tests taken both in the ED and in other locations in the region. Each batch has a capacity of approximately 100 test samples, and the tests performed in the ED are prioritised. Even during the peak period, the test intensity in the ED will not require the entire batch capacity. We therefore assume that a test batch has infinite capacity with regards to the tests performed in the ED. Each batch is analysed for 4 hours before receiving the results. The cleaning of a room after a patient has left the ED takes 30 minutes.

For each scenario presented in Section 4, 200 replications of one simulated week are performed, and one week warm-up is applied. In each replication, the output data is aggregated to an hourly resolution, implying that we calculate the average number of beds used during each hour of the simulated week. Based on the 200 samples, we calculate the hourly mean and hourly 90th percentile bed loading during a week. The independent variable is the arrival intensity of COVID-19 suspects, while the dependent variable is the number of beds used in the tent area.

3.4.2. The ambulance model

Six subgroups of transport requests are considered in the model, and each subgroup is associated with an urgency level. Sorted by decreasing urgency, the levels are red, yellow, green and planned transports. For the nonCOVID-19 patient population, we consider red (37%), yellow (36%), green (9%) and planned transports (18%) going to the hospital. The fifth subgroup are patients that will prove to be COVID-19 positive when tested in the ED. These patients request a transport to the ED due to experiencing COVID-19 related symptoms, and they are categorised as yellow transports. The last subgroup are patients that are not confirmed to be COVID-19 negative when leaving the hospital, and these are categorised as planned transports. In Figure 5, the subgroups are displayed, and we include whether they require a normal or a COVID-19 transport.

The expected arrival rate of requests generated by the nonCOVID-19 population at different hours of the week is calculated based on historical data from St. Olav's Hospital, 2019. The weeks covering January to March were chosen by the management at the ambulance services to represent a normal period. As stated in Section 3.2, to generate requests from subgroups five and six, the arrival process of semi-urgent (green) emergencies to the ED is used. The intensity is however altered to fit the scenarios of the sensitivity analysis.

To obtain realistic transport durations, the time spent for each transportation is sampled from the set of historical transport durations from 2019. For COVID-19 transports, 45 minutes are added to the sampled duration to include the cleaning of the ambulance. The number of ambulances available during the week is identical to the ambulance schedule that was present when the project was conducted.

For each scenario presented in Section 4, 300 replications of one simulated week are performed, and one week warm-up is applied. For each patient request, the response time is recorded. The records are used to calculate the mean response times for patients within each urgency category. The independent variables are the arrival intensity of transport requests and the number of ambulances available, while the dependent variable is the ambulance response time.

3.4.3. The combined model

All input data used for the ED model is also applied in the combined model. In addition, two input parameters are used to model the discharge process of patients leaving the COVID-19 ward: the desired discharge time of patients and the corresponding ambulance response time. This data is collected from running the ambulance model for one week (following one week warm-up) with the number of ambulances necessary to obtain prepandemic waiting times for red and yellow emergency patients. The ambulance model is run 500 times, producing a data set containing 500 replications of both the desired discharge times and the corresponding ambulance response times through the week. The data is stored according to the simulated replication (1 to 500) and weekday (1 to 7). For example, on Tuesday in replication 30 there may be 18 COVID-19 positive patients leaving the COVID-19 ward. Patient 13 is discharged at 15:00 and gets an ambulance at 15:20, yielding an ambulance response time of 20 minutes for this patient.

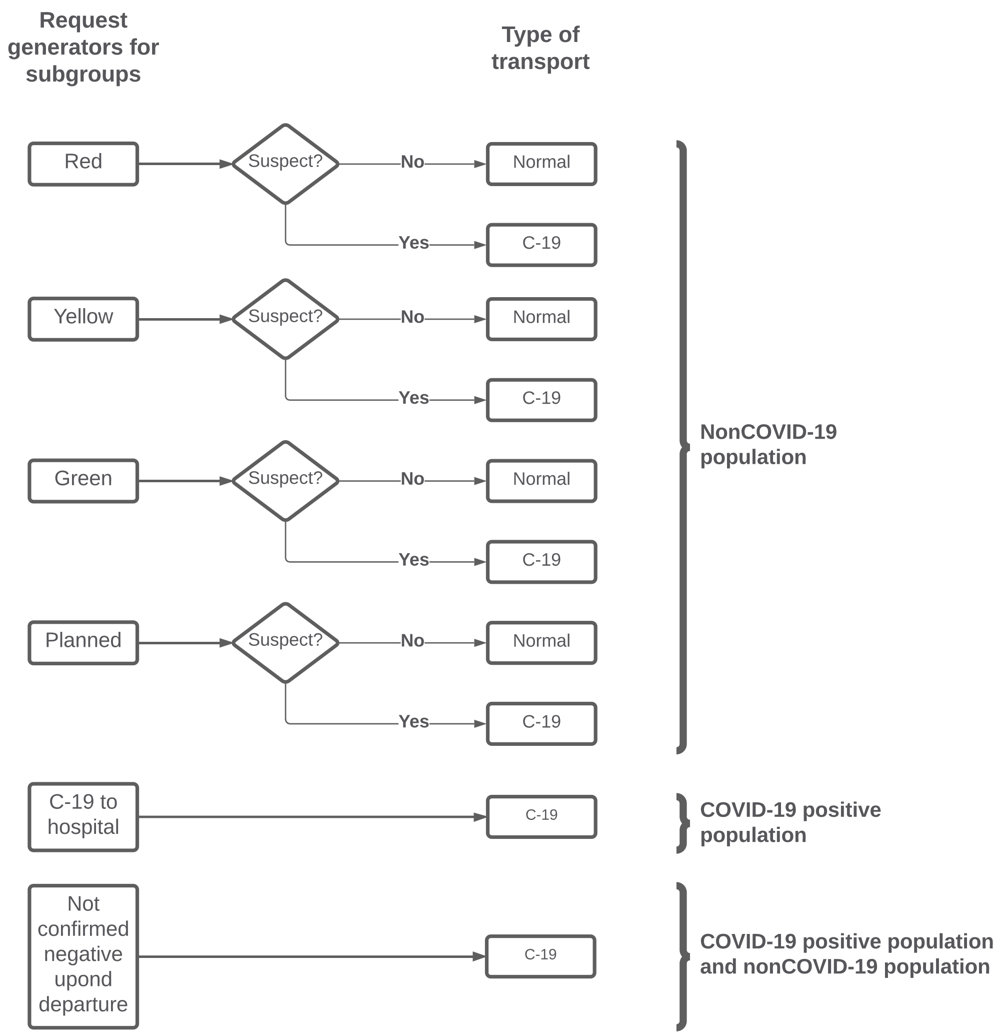

Figure 5. The six patient subgroups and what transport they require.

For each simulated day in the combined model, one replication is sampled, and the data from the corresponding weekday in the sampled replication is used to generate the discharge time of patients in the COVID-19 ward, and the corresponding ambulance waiting time.

One adjustment is made to the input data of the ambulance model when producing the data base. Recall that the last subgroup of patients introduced in Section 3.4.2 contains both the COVID-19 positive patients resting in the COVID-19 ward, and patients that were not tested for COVID-19 in the ED. In the combined model, we are not interested in the latter group of patients. To exclusively model the requests coming from the COVID-19 ward, the last subgroup of patients introduced in Section 3.4.2 is therefore split in two when collecting and storing data from the ambulance model. Furthermore, since we model the delayed peak period, identical distributions are used to generate COVID-19 positive patients entering the ED and COVID-19 positive patients that are discharged from the COVID-19 ward. As we want to estimate the need for boarding beds during the peak of the pandemic, we model the boarding bed capacity as unlimited and evaluate the usage of these.

For each scenario presented in Section 4, 200 replications of one simulated week are performed with the combined model. The independent variables are the arrival intensity of COVID-19 suspects, the departure intensity from the COVID-19 ward and the ambulance response time, while the dependent variable is the boarding bed requirement. In contrast to previous simulations, we are here interested in the transient period starting with the delayed peak, so warm-up is not applied. Furthermore, each simulated replication is initiated at 0 in the night with no patients in the COVID-19 area and 3 vacant beds in the COVID-19 ward. The experiment is run for two modes. In the first mode, the ambulance response time is set to zero, implying that we only observe excessive-flow-induced boarding time. In the second mode, ambulance response time is added.

4. Implementation and the setup of the sensitivity analysis

An Intel(R) Core(TM) i7-8550 U CPU @ 1.80 GHz, 16 GB RAM computer is used when performing the simulations. The simulation models are written in

Python 3.7 and the package SimPy. To perform the random sampling, the algorithms included in Python is used. To reduce output variance, common random numbers are applied when performing sensitivity analysis. In the first replication, a seed is set, and it is then increased by one for each subsequent replication.

A scenario tree is constructed to guide the sensitivity analysis. The tree contains three parameters that represent aspects of uncertainty that are common for the cases:

- The number of COVID-19 positive patients arriving for the ED each day
- The size of the nonCOVID-19 population
- The testing policy, defining the share of nonCOVID-19 patients that will be labelled as suspects

In the first branching, the daily arrival rate of COVID-19 positive patients to the hospital during the peak period is represented. In the second branching, the loading intensity of patients that belong to the nonCOVID-19 patient population, in relation to the reference loading, is represented. The reference loading is the expected number of emergency patients that entered the ED or required an ambulance each day in a normal prepandemic week. The third branching represents the testing policy, describing the threshold of categorising patients as COVID-19 suspects. In reality, the threshold can be related to what symptoms that should trigger a test. The policy levels are given as the percentage of individuals from the nonCOVID-19 patient population that are labelled as COVID-19 suspects when entering the ED or requesting an ambulance to the hospital.

One split is applied in the first and the second branch, while we have four levels of testing policies in the third branch. The split in the first branch reflects the two scenarios provided by NIPH, with 12 and 21 COVID-19 positive patients entering each day respectively. The split in the second branch was discussed with the hospital management, and set to be 80% and 100%. Also the last split was discussed with the hospital management, and the values 33%, 50%, 67% and 100% were applied to cover a wide range of testing policies. In total this yields 16 scenarios. The scenarios are listed in Table 1. For each scenario we obtain the expected number of both COVID-19 suspects arriving for the ED, and transport requests each day. Note that there are intra-day variations in the expectations, but these are not shown in the table. For more information on how the the expected number of both COVID-19 suspects arriving for the ED and transport requests are calculated, see Appendix B.

5. Results

In this section, the results from all three models are presented. The hospital management was mostly interested in the scenarios with the high COVID-19 positive patient loading, which are represented by scenarios 9 to 16. These are therefore emphasised in the following. The main results for all scenarios are presented in Table A1 in Appendix A.

5.1. Results for the ED case

Figure 6 provides results for the ED bed loading in scenarios 9 to 12, which differ in the testing policy. The light shaded area represents the beds in the COVID-19 area, while the dark shaded area is the beds in the tent area. The borders of the shaded areas indicate the mean and the 90th percentile measures for each hour of the week. The mean represents the mean bed requirement over the 200 replications, while the 90th percentile indicates a threshold where only 20 out of 200 measured bed requirements for a given hour of the week equal or exceed the threshold.

Note how the testing policy impacts the number of beds that must be established in the tent area. In scenario 12, all patients are tested upon arrival to the ED. In this case, the tent capacity should be similar to the capacity of the COVID-19 area. Furthermore, the need for additional beds is much less during the weekends. In all scenarios, the use of a tent area emerges at

Table 1. The 16 scenarios applied in the models.

Scenario	# of COVID-19 positive (μ^{C19})	nonCOVID-19 relative to normal (α)	Share of suspects from nonCOVID-19 pop. (β)	$E[suspects]$	$E[transports]$
1	12	80%	33%	31	96
2	12	80%	50%	41	88
3	12	80%	67%	51	81
4	12	80%	100%	70	67
5	12	100%	33%	36	114
6	12	100%	50%	48	105
7	12	100%	67%	60	96
8	12	100%	100%	84	78
9	21	80%	33%	40	114
10	21	80%	50%	50	106
11	21	80%	67%	59	99
12	21	80%	100%	79	85
13	21	100%	33%	45	132
14	21	100%	50%	57	123
15	21	100%	67%	69	114
16	21	100%	100%	93	96

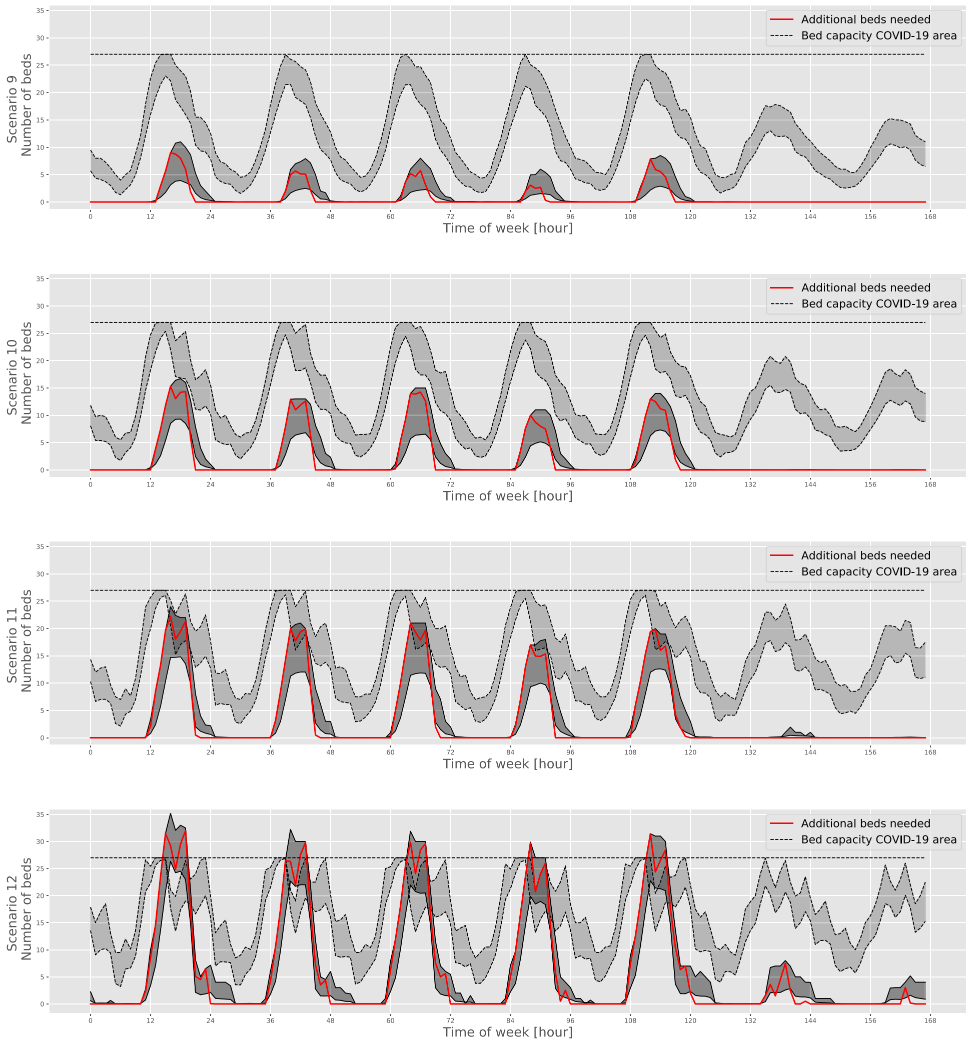

Figure 6. Results from the ED model: The bed loading in the COVID-19 area (dashed lines) and the tent area (solid black lines) through the week for scenarios 9 to 12. The bands cover the area between the mean and the 90th percentile. The solid red line indicate the 90th percentile bed requirement in the tent area if patients can be transferred from the tent area to the COVID-19 area. The horizontal dashed line indicates the planned bed capacity in the COVID-19 area.

around 12:00 (noon) and the peak number of patients in the tent area is observed between 16:00–19:00. The number of patients in the COVID-19 area falls towards the evening, implying that the patients resting in the tent area can be moved inside (although this is not done in the simulation model). The total number of additional beds needed, if we allow for patients to transfer from the tent area to the COVID-19 area, can be derived from the simulated results. This is done by adding the beds used in the COVID-19 area and the tent area, and subtract the capacity of 27 beds (if this becomes negative, the value is set to zero). The resulting number of additional beds in the 90th percentile level can be seen as the solid red line in Figure 6. Depending on the testing policy and the size of the nonCOVID-19 population at the peak of the pandemic, there is a need for between 0 to 41 additional beds during the weekdays, and 0 to 13 additional beds in the weekend.

5.2. Results for the ambulance case

For each scenario, we estimate the minimum number of additional ambulances required to ensure mean response times for red and yellow emergency patients that are equal to or shorter than those of the prepandemic state. To represent the prepandemic situation, the model is first run for a base case. That is, we only include requests from the nonCOVID-19 patient population and apply the ambulance capacity available in a prepandemic situation.

Figure 7 illustrates the mean utilisation of ambulances and the mean response time for different patient categories during the week from simulating the base case. During the weekdays, except from Friday, the ambulance capacity is satisfying yielding short response times. On Friday, the combination of more requests and less capacity available during the evening causes significant waiting times. The waiting times are also prolonged during the weekend because less ambulances are available.

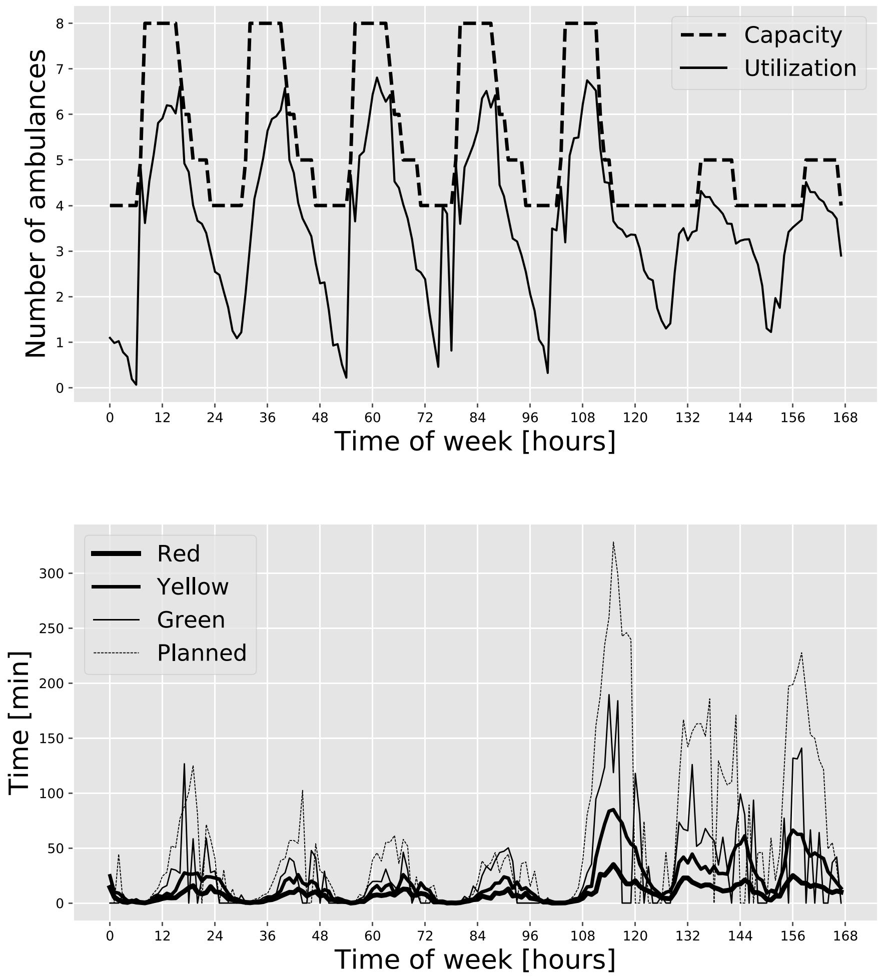

Figure 7. Results from the ambulance model: The base case. Top: Mean utilisation of the ambulance capacity. Bottom: Mean response time during the week.

To obtain the preferred response times in the 16 scenarios, the ambulance resources are added flat. That is, for each additional ambulance, the resource is available through the entire week. When the number of ambulances is increased, the response time decreases towards the base level. The resulting number of additional ambulances needed in scenarios 9 to 16 is presented in Table 2. In general, because of the queue prioritisation rules, the base level response times for the most urgent patient groups are easier obtained compared with the less urgent patients. Adding more ambulances than what is suggested from just regarding the response times for red and yellow requests should be considered, as it dramatically decreases the expected response time for the planned requests. If we consider Scenario 13, going from 6 to 12 additional ambulances yields a decrease in mean response time for planned patients from 585 to 63 minutes. The corresponding values for red and yellow patients are 11 to 3, and 21 to 4 minutes respectively.

Table 2. Results from the ambulance model: The number of ambulances added in scenarios 9 to 16 to obtain similar mean response times as in the base case.

Scenario	Red	Yellow	Green	Planned
9	5	5	6	10
10	5	5	6	10
11	5	5	6	9
12	5	5	6	7
13	6	6	7	12
14	6	6	7	12
15	6	6	7	11
16	6	6	7	9

As for the ED case, the results in the ambulance case are sensitive to the testing policy. The planned patient category is most sensitive to the policy level. A strict testing policy yields fewer COVID-19 transports leaving the hospital, causing relatively short response times for planned patients in these scenarios since the demand for planned transports is reduced. Conversely, in the ED case, a strict testing policy yields a high demand for additional beds in the ED, making those scenarios more demanding.

5.3. Results for the combined case

When generating the ambulance waiting time data, 5 and 6 additional ambulances were added to scenarios 9 to 12 and 13 to 16 respectively. Furthermore, we assume that the boarding beds are located in the ED.

Figure 8 illustrates, for scenarios 9 and 12, the 90th percentile number of additional beds needed in the ED when considering ED boarding and compares it with

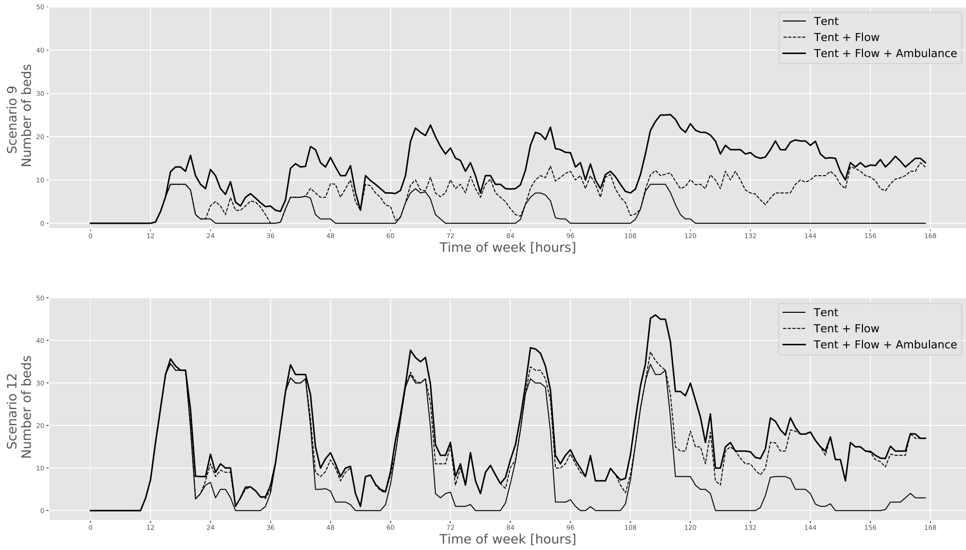

Figure 8. Results from the combined model: 90th percentile number of additional beds when considering boarding for scenarios 9 and 12. The label Tent represents the number of beds needed in the tent area. Tent + Flow is the number of additional beds when adding the excessive-flow-induced boarding. Tent + Flow + Ambulance represents the number of additional beds when also adding the ambulance-induced boarding.

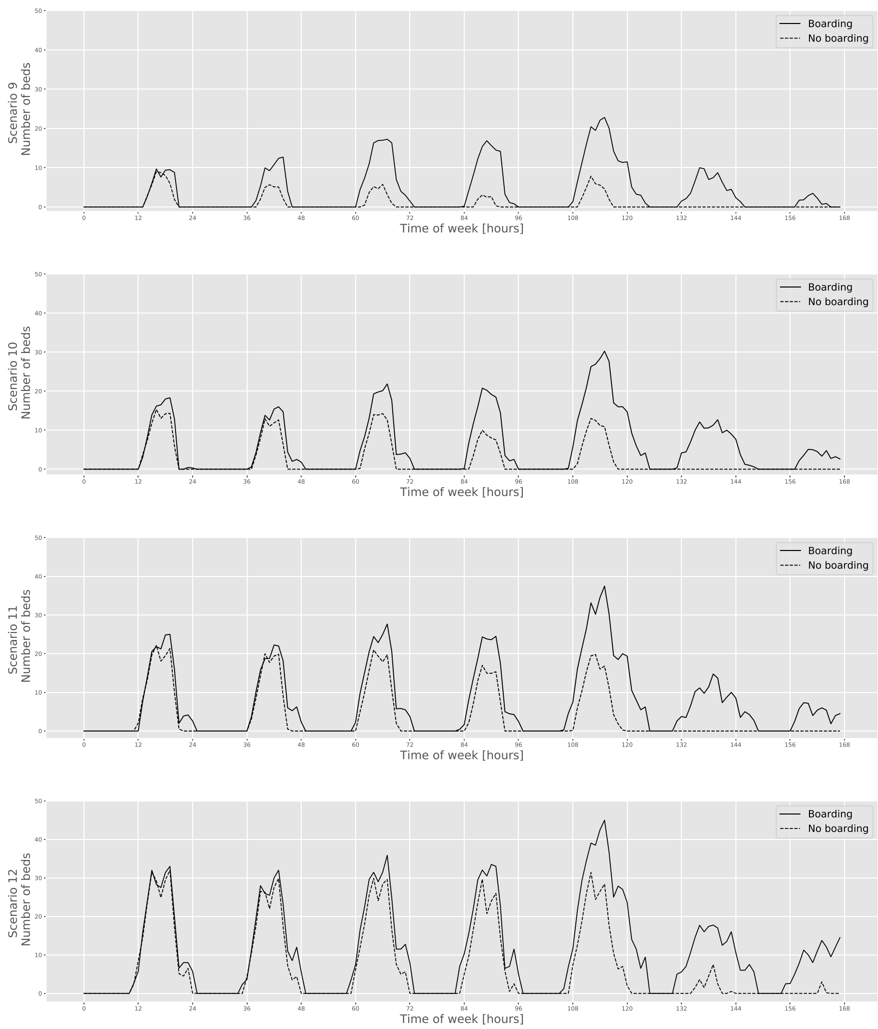

Figure 9. Results from the ED model and the combined model: Comparison of bed usage when boarding is considered and not for scenarios 9–12. The results illustrate the 90th percentile number of additional beds required in the ED when allowing for patients to transfer from the tent area and the buffer beds to the COVID-19 area.

the result when boarding is disregarded. The results clearly indicate the need for excessive bed capacity in the ED when entering the peak period. The excessive-flow-induced boarding results in an increased bed loading primarily during night, as the patients must wait until the next morning for beds to become vacant in the COVID-19 ward. When adding ambulance waiting time, the problems related to boarding starts earlier in the day because patients leaving the COVID-19 ward during the day are delayed. During night, the ambulance waiting time is short and the effect of ambulance-induced boarding is less prominent. Note that because Friday is a busy day for the ambulance service (see Figure 7), the ambulance-induced boarding is most prominent on this day. Finally, the effect of ambulance-induced boarding is less in scenario 12, caused by shorter ambulance waiting times due to the strict testing policy.

Figure 9 illustrates the requirement for additional beds if we allow for a transfer of patients from the tent area and the buffer beds to the COVID-19 area in scenarios 9–12, and compares it with the results when boarding is disregarded. As the simulations with boarding are run without a warm-up period and starting from an empty system, the results cannot be directly compared. However, they illustrate some important aspects, like the fact that excessive ED boarding will cause an additional need for beds both during the late evening and in the weekends. Furthermore, we see that the difference between the results when regarding boarding and not is larger for scenario 9 compared with scenario 12, reflecting the shorter ambulance response times in scenario 12.

5.4. Managerial implications

The results from the ED and the ambulance model were used to inform the hospital management, partly through presentations for the hospital pandemic committee and partly as input for a managerial report on how to perform the ambulance planning through the pandemic. Based on these results, the following decisions were made when preparing for a state of pandemic:

- Outpatient clinic examination rooms close to the ED were used to provide additional bed capacity for COVID-19 suspects that required testing in the ED.
- Additional resources for transporting patients to and from the hospital were established, including Red Cross ambulances, and military ambulances operated by the Home Guard.

In August 2020, some months after the first peak in Norway, the management requested updated analysis on the bed requirements in the the ED. At this point in time, new testing regimes had become available, including the option to buy tests that could provide answers within 90 minutes instead of 4 hours. The management wanted to know how the bed requirements would change given different levels of available 90-minutes-tests. To provide decision support, the ED model were extended and new results were presented for the hospital management.

6. Discussion

In this paper we have shown how a set of DES models can be applied to provide decision support for the hospital management when time is limited. Even if the models presented are rather simple, the analyses performed proved to be of great value to the hospital management. The results are highly sensitive to the NIPH planning scenarios, and the relative loading of emergency patients compared with the prepandemic situation. In contrast to the testing policy, these cannot be controlled by the hospital management.

When regarding the number of beds needed in the ED, the results are very sensitive to the testing policy. A strict testing policy increases the need for additional beds in the ED considerably, and consequently the number of nurses required. As a consequence, resources must be reallocated from elective activity, or the capacity must be increased. When regarding the ambulance response times of red and yellow transports, these decrease with a strict testing policy. However, the differences are small and the number of ambulances required to obtain prepandemic response times are not affected by the testing policy. Based on these observations, a less strict testing policy seems reasonable. However, the consequences of admitting a COVID-19 positive patient into a non COVID-19 ward can be fatal, and the costs related to increased resource capacity must be weighted against the potential of ignoring a COVID-19 positive patient in the ED.

When boarding is considered, the bed requirement increases, especially during night and in the weekends. If a less strict testing policy is implemented, the boarding time is to a large extent affected by the ambulance response times of patients discharged from the COVID-19 ward, that are categorised as planned transports. Based on this observation, increasing the ambulance capacity further to decrease the waiting times for planned transports seems reasonable. This will have less effect if a strict testing policy is implemented.

We have demonstrated how boarding can be modelled with simple counting rules. This saves computational effort, as we can omit the explicit modelling of patient stay in the downstream ward. Furthermore, initiating the model is very simple, as the vacant bed capacity is set by a single number. We assumed that the rate of patients leaving the COVID-19 ward was equal to the rate of patients entering the ward. This assumption implies that a stay in a boarding bed does not affect the LOS, meaning that we regard the boarding beds as a server and not as a queue, and consider an infinite server system. In the opposite case, where a stay in the boarding bed delays the healing process, the boarding beds should be considered as a queue for service at the ward. Then, the rate of patients leaving the COVID-19 ward depends on the bed capacity and we may have rates that are unequal.

The counting approach is not appropriate if extended boarding affects the LOS of patients. Extended boarding can sometimes cause misplacement of patients and delay the treatment process. However, boarding time is often measured in the range of minutes and hours, while the LOS is typically several days. In many cases it should therefore a fair assumption that the LOS is not affected by extended boarding time.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A Main results for the three cases

Table A1. Main results for the three cases, scenarios 1 to 16. For the ED and the combined case, the maximum 90th percentile number of additional beds both during the week and the weekend is presented. For the ambulance case, the number of additional ambulances required to maintain base case response times are included. In the combined case, the analysis is performed with the number of additional ambulances as given in the table.

Scen.	Max beds **week**	Max beds **weekend**	Additional **ambulances**	Max beds **week (boarding)**	Max beds **weekend (boarding)**
1	0	0	4	5	0
2	7	0	4	16	3
3	15	0	4	26	6
4	28	2	3	37	13
5	5	0	5	13	2
6	15	0	5	26	8
7	23	0	5	33	11
8	38	9	4	46	18
9	9	0	5	23	10
10	16	0	5	31	13
11	23	0	5	38	15
12	32	8	5	45	18
13	12	0	6	31	18
14	22	0	6	39	19
15	29	3	6	41	21
16	41	13	6	51	23

Appendix B. Calculating the expected number of suspects and transports

Here, we describe how we calculate the expected number of both COVID-19 suspects arriving for the ED and transport requests each day.

B.1. Scenarios for the ED and the combined case

The ED and the combined cases share the same scenario tree, and the expected number of COVID-19 suspects that enter the ED each day in each scenario is calculated by the following formula:

$$E[suspects] = \mu^{C19} + \mu^{Non} \cdot \alpha \cdot \beta \tag{B1}$$

Here, μ^{C19} is the expected number of COVID-19 positive patients entering the ED each day at the peak of the pandemic, and μ^{Non} is the expected number of emergency patients belonging to the nonCOVID-19 patient population that enter the ED each day. This number depends on the weekday. The parameter α is used to adjust the expected patient activity (the second branching), while β represents the share of patients belonging to the nonCOVID-19 patient population that are categorised as COVID-19 suspects (the third branching). Note that since μ^{Non} depends on the weekday, the expected number of suspects given here represents the average day, but the number varies between weekdays.

B.2. Scenarios for the ambulance case

To calculate the daily total number of ambulance transports in each scenario, the following equation is used:

$$\begin{aligned} E[transports] &= (\mu^{Non,A} \cdot \alpha \cdot \beta) + (\mu^{Non,A} \cdot \alpha \cdot (1-\beta)) \\ &+2\mu^{C19} + (\mu^{Non,A} \cdot \alpha \cdot (1-\beta)) \\ &= 2\mu^{Non,A} \cdot \alpha\left(1 - \frac{\beta}{2}\right) + 2\mu^{C19,A} \end{aligned} \tag{B2}$$

Here, $\mu^{Non,A}$ is the expected number of patient transports to the hospital generated by the nonCOVID-19 patient population, and its value depends on the weekday. The parameters α, β and μ^{C19} have the same interpretation as in the ED case. The first term represents the expected number of COVID-19 transports to the hospital generated by the nonCOVID-19 patient population, while the second term is the number of normal transports generated by the same population. The COVID-19 positive patients require a Covid transport both to and from the hospital, which is ensured by the third term. The final term represents the transportation of COVID-19 suspects from the nonCOVID-19 patient population that require an ambulance when leaving the hospital. Note that this equals the second term and represents the fact that all patients that are not tested for COVID-19 in the ED require an ambulance when leaving the hospital.