Design of an Acute Medical Unit

Case study at Diakonessenhuis Utrecht

G.G.B. Wilbers$^{*\alpha}$

$^{\alpha}$IEM Master, University of Twente

Under supervision of
A.G. Leeftink - *University of Twente*[2] , H. Bos - *Diakonessenhuis and University of Twente*[3] , S. Rachuba - *University of Twente*[4] , and S. Nagesser - *Diakonessenhuis*

Abstract

An Acute Medical Unit (AMU) is a specialized hospital ward that admits patients with acute medical conditions from Emergency Departments. The main goal of the AMU is to diagnose and stabilize patients. Hospitals face the challenge of increasing patient numbers without being able to expand physically, leading to a need for improved efficiency. This involves reducing the Length of Stay (LoS) and treatment time for patients. Implementing an AMU has the potential to enhance efficiency in both the Emergency Department and Medical Wards.

We propose a four-step approach for designing an effective AMU in hospitals. This approach involves determining patient eligibility, identifying necessary facilities, optimizing the layout, and allocating appropriate bed capacities and designated periods. The admission criteria for the AMU are derived from a thorough review of existing literature and the hospital's expertise. Similarly, the identification of required facilities is based on relevant literature and the hospital's knowledge. To determine the dimensions of the AMU, we utilize Discrete Event Simulation (DES), integrating the admission criteria into the simulation model. Although the literature discusses the fourth step, the case study conducted in this research provides limited information on it.

We validate and test the four-step approach using historical data from a medium-sized Dutch hospital. The case study results confirm the practical value of the step-wise approach. However, further attention is needed to address specific aspects within each step, such as the anticipated reduction in Length of Stay for patients in different wards and the development of an efficient layout.

---

[*]e-mail: g.g.b.wilbers@student.utwente.nl
[2]e-mail: a.g.leeftink@utwente.nl
[3]e-mail: h.bos-1@utwente.nl
[4]e-mail: s.rachuba@utwente.nl

1. Introduction

Emergency Departments (EDs) are continuously overcrowded which negatively affects quality of care [19]. According to Schneider et al. [21] an increase of hospitalisations leads to a decrease in the number of available ED beds in hospitals. Because of space limitations, a hospital is not always able to expand their wards to overcome the overcrowding. This leads to an increase of emergency patients waiting for admission, referred to as *boarders*. According to Doudareva et al. [7] and Schneider et al. [21] boarders have a significantly longer Length of Stay (LoS) at the ED, experience lower quality of care, and are less satisfied about their treatment experience. Optimizing the patient flow of the ED is therefore important. Gualandi et al. [8] reviewed the literature on possible improvements of patient flow. A distinction is made between structure and process optimisations. Structure optimisation entails for example changing the facility's physical layout. An example of process optimisation is changing the admission process, or improving the forecast regarding the arrival rate of patients. Measuring the performance for process and structural optimisation is divided by four indicators: efficiency (e.g., waiting times, access time, etc.), quality of care (e.g., ED mortality rate), financial aspects (e.g., number of nurses before and after optimisation intervention), and perceived quality of care (e.g., patient satisfaction).

To improve patient flow at the ED, an Acute Medical Unit (AMU) could be considered [17]. Literature also refers to an AMU as Acute Medical Assessment Unit, Acute Assessment Unit or Acute Planning Unit [17]. An AMU is a designated hospital ward specifically staffed and equipped for in-patients with acute medical illness from EDs. At the AMU the patient receives multidisciplinary and medical assessment, care, and treatment for a designated period (typically between 24 and 48 hours). Hereafter, the patient will be discharged or transferred to a Medical Ward (MW) [15, 16, 17]. An AMU improves patient satisfaction, decreases the LoS, reduces unnecessary admission, and reduces patients' mortality [5, 17]. Because the flow of patients changes (e.g., instead of going to an MW from the ED, the patient will go to the AMU), as well as the physical layout (in this case adding a new ward), introducing an AMU is both structure and process optimization. Figure 1 illustrates the movement of a patient within a hospital setting, the arrival at the Emergency Department (ED) is denoted by the yellow arrow. Following the initial treatment provided in the ED, the patient is subsequently directed towards one of three destinations: home, the Acute Medical Unit (AMU), or the Medical Ward (MW). The black arrows symbolize the diverse pathways available to patients based on their initial location within the hospital.

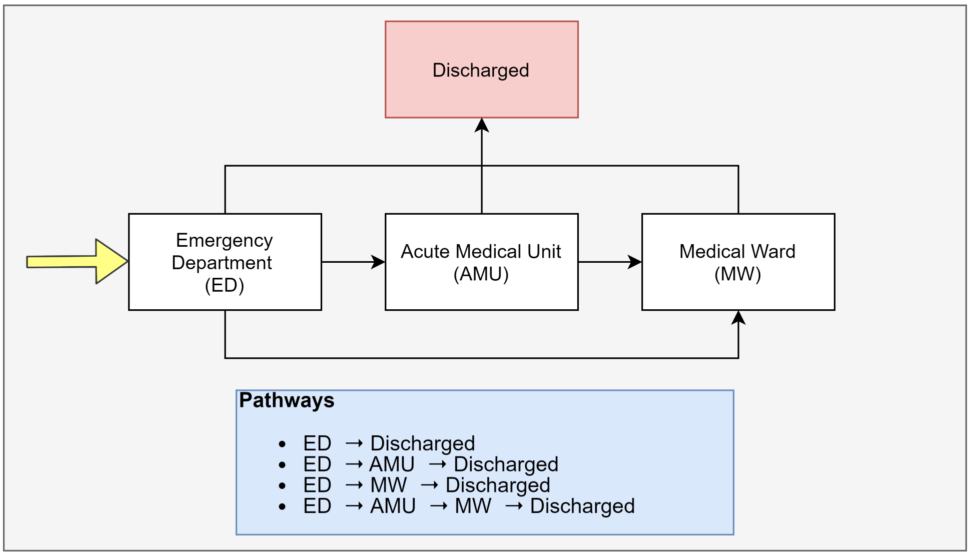

Figure 1: Pathways for a patient when an AMU is introduced to a hospital.

Scott et al. [17] describes different types of AMUs which are distinguished based on the admission criteria, staffing, and designated period. For example, AMUs in the Netherlands handle a broader range of patients, compared t other countries [23]. It is common that, besides ED patients, also surgery, trauma, orthopaedics and urology are admitted to an AMU [23]. The review of Reid et al. [15] compared 33 AMUs, based on entry source, admission criteria, staffing, the operational policies, and the designated period of the AMU. This review showed that every AMU created an improvement regarding the LoS and the percentage of readmitted patients.

The introduction of an AMU in a hospital requires many decisions. According to [23] introducing an AMU can only be done with pre-implementation decisions: the location of the AMU, the number of beds required, the facilities it should have, the amount and type of staffing, a training plan for the staff, the types of protocols required, the type of patients allowed on the AMU, and which logistical responsibilities the AMU has. Thus far, existing literature does not provide a method on how to approach these decisions, in what order, which models to use, and how to validate certain decisions for an AMU.

In this study we propose a 4-step approach for designing an AMU. Besides, we perform a case study for a medium-sized Dutch hospital to validate this method. By using a systematic approach for the design of an AMU we can provide prospective information of how beneficial an AMU is for this specific hospital, before actual implementation in practice, and how to efficiently organize such an AMU.

In Veneklaas et al. [24] the design of an Admission Lounge (AL) was studied, to improve the patient flow within the hospital. The authors designed the AL based on a step-wise Decision Support System (DSS). Comparing the steps from Veneklaas et al. [24] to the the decisions from Reid et al.[15] and van Galen et al.[23] we observe a lot of similarities. For example, the admission criteria, number of beds needed, type of staffing, and operational policies. Because of these similarities we can easily adapt the DSS of Veneklaas et al.[24] to our situation. Even though the steps are sequential, iteration between steps is required.

1. *Specify the admission criteria for the AMU.* This step addresses which patient types are eligible for admission to the AMU.

2. *Determine the facilities, staff and supporting processes for the AMU.* This step indicates which facilities, staff-to-patient ratio, and other special equipment is needed for the AMU based on the decisions of Step 1.

3. *Analyze the total beds required for the AMU, and the possible reduction of the MW.* This step addresses the number of beds required for the AMU, including the reduction at the MW using a model. The input values for this model, among other things, is Step 1.

4. *Analyze how the determined AMU fits within the facility layout.* This step indicates where the location of the AMU is placed within the current facility, including a possible layout.

Using this step-wise approach, we create an overview for designing an AMU. Furthermore, we create insight for the hospital management on how performance can be affected by interventions in the process. In Figure 2 the steps are visualized.

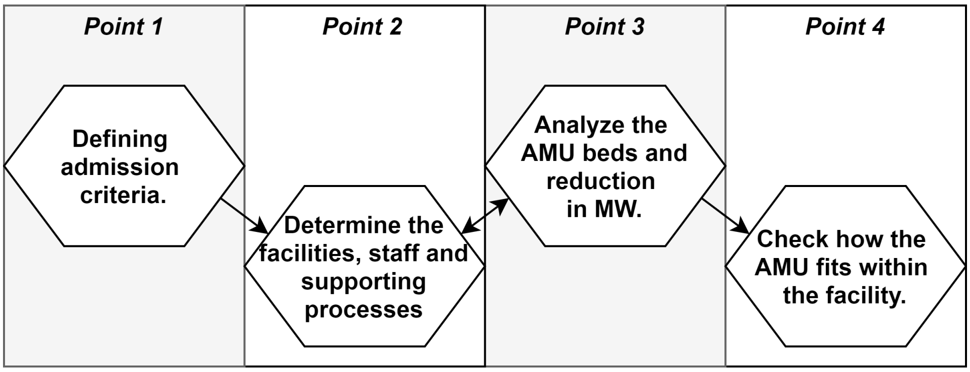

Figure 2: Approach of designing an AMU based on [24].

Our contribution is to provide insight in what decisions and how they should be taken when designing an AMU. We demonstrate the application and efficacy of our proposed approach through a case study conducted within the context of a Dutch hospital. Current literature is mostly focused on the performance and contribution of an AMU. The Key Performance Indicators (KPIs) are compared before and after the introduction of an AMU, where most research conclude that an AMU is beneficial for a hospital. However, existing literature does not describe how to design an AMU.

The subsequent sections of this paper are structured as follows. Section 2 offers a comprehensive literature review pertaining to the implementation of an Acute Medical Unit (AMU), employing the previously discussed methodology as its basis. In Section 3, we introduce a model that establishes the optimal number of beds with the designated period, employing the admission criteria outlined in step 1. In Section 4, a detailed case study conducted at a Dutch hospital is presented, extensively examining steps 1 to 3, while step 4 is due to limitations briefly discussed. Finally, in Section 5, our discussion and conclusions are presented.

2. Literature

The literature review follows the four step approach presented in Figure 2 and Section 1. First, the admission criteria are discussed, Second, the facilities (e.g., type of staff) are analyzed. After that, the effect of an AMU regarding MW beds, but also determining the number of beds for an AMU itself is discussed. At last, information about the facility layout is presented.

2.1. Admission criteria

Admission criteria are rules regarding which patients are eligible for admission on a ward. An AMU can accept almost every inpatient that comes from the ED [3, 13, 17]. However, patients who need intensive care and/or continuous monitoring are not suitable for AMU admission [13, 15, 17, 20].

Clear and effective communication between the ED and the AMU is important to prevent the AMU from becoming a Dumping Area [5]. In order to avoid the AMU becoming a "Dumping Area," Early Warning Scores (EWS) are employed as a preventive measure [17]. EWS scores are specifically designed to categorize patients according to their level of illness [22]. By establishing in advance the acceptable level of illness for admission to the AMU, we can effectively determine which patients are suitable for the AMU. This approach ensures that not all patients are admitted to the AMU, thus preventing it from becoming an Dumping Area. Examples of EWS systems are, the Australasian Triage Scale [17] and the Manchester Triage System (MTS) [9].

Besides scoring a patient on their level of illness, they can also be admitted based on their expected LoS. This method is typically used for Short Stay Units (SSU) [25]. However, unlike an AMU, an SSU does not provide diagnostics and is just a buffer before the discharge of a patient [12, 25]. Important factors for predicting the LoS are age, cognition, number of medications during admission, and previous hospital admissions [25]. An SSU uses the LoS because it has a dedicated period, typically around 72 hours. The SSU uses the LoS because allocating the patient to an MW after the patient went to a SSU takes more time than placing the patient directly to an MW [25]. Given that the AMU also has a dedicated period, using the LoS as an criteria for an AMU could be beneficial, it is however not mentioned in literature. In the remainder of this work, we combine fixed exclusion (specific patients groups that are not allowed at the AMU), EWS threshold, and the LoS threshold. This way, we define tailored criteria for AMU admission.

2.2. Facilities and staff

The focus of an AMU is diagnosing and stabilizing patients. This does not include invasive monitoring and/or using critical care facilities [13, 17]. Reid et al. [16] interviewed nurses regarding necessary equipment around an AMU bed. They concluded that bedside monitoring and the use of telemetry is important for doctors/nurses. According to [1], lab research, MRI, CT, and ultrasound are the most frequent diagnostics facilities that should be nearby an AMU. We suggest that the facilities of an AMU should be similair to the facilities of a standard MW, given that, as soon as more complex equipment is needed, this is available at the nearby ED.

Another decision for the AMU is the amount and type of staffing. Alferink et al. [1] defined a staffing policy, a so called senior nurse formation, two AMU nurses with specific focus next to the AMU nurses without specific area of interest. However, no information is provided regarding the size of AMU. Reid et al. [15] conducted a literature review where different AMUs are compared. In Reid et al. [15] the staffing policy varied in number of staff members and corresponding staff speciality. These differences are also mentioned in Keshtkar et al. [9]. However, no relation is given regarding the number of staff compared to the number of AMU beds.

The amount of staff needed can be determined with the use of the San Joaquin patient classification system [18]. This system classifies patients (EWS classification for example) and assign the amount of nursing staff needed [18]. The result of this system is a nurse-to-bed ratio determined by their respective classifications.

2.3. Bed allocation

The bed allocation of the AMU significantly impacts the bed allocation in the MW. The introduction of the AMU reduces the number of patients who are sent to the MW, thus affecting the required number of beds in the MW. Depending on the designated period of the AMU, we must carefully balance the number of beds needed. For instance, if the AMU has a short designated period (e.g., 24 hours), it will result in fewer beds being occupied in the AMU. However, due to the shorter designated period, the likelihood of patients being sent home from the AMU will also decrease. As a consequence, there will be a higher demand for beds in the MW [3] compared to a situation where the AMU has a longer designated period. Therefore, it becomes evident that the AMU settings significantly influence downstream bed requirements in the MW.

Ravaghi et al. [14] reviewed recent literature on methods that approximate the number of beds necessary at a hospital ward. A total of sixteen different methods are mentioned with all their own advantages and challenges. Examples of methods are, the ratio method (calculating the number of beds based on the ratio of the total LoS), formula method (based on the target occupancy rates), and simulation (based on distributions). Furthermore, De bruin et al. [6] approximates the number of beds using the Erlang Loss Models (M/G/c/c queuing model).

The first two methods, the ratio, and formula method, are traditional approaches used to determine the number of beds. The ratio method calculates the beds based on average Length of Stay (LoS) and admission rates, without considering age groups and clinical specialties. As a result, it is frequently combined with more recent models, like simulations, to enhance accuracy. The formula method, on the other hand, estimates the number of beds by multiplying the average LoS, admission rate, and projected population size, then dividing by the period duration and target bed occupancy rate. These methods offer simplicity and efficiency, making them popular for hospital-level planning. However, they have limitations, assuming steady state supply and demand, and not accounting for factors such as demographic changes and patient migration.

The simulation method relies on distributions and is frequently used independently or in conjunction with other approaches, such as the ratio method. It aims to closely mimic the hospital's functioning by employing accurate data distributions. While this method offers high accuracy and the ability to handle discrete and random arrival rates [3, 14, 21], it requires precise and extensive data, which can make it expensive and time-consuming.

Queuing models typically assume a random arrival process for all patients. De Bruin et al. [6] does not account for the complexity of patients' treatment in their queuing model. In contrast, Chang et al. [4] also employs the Erlang Loss Model but incorporates the Case Mix Index (CMI), considering both the arrival rate and the complexity of care needed by patients. A higher CMI indicates a greater arrival rate and, consequently, a greater need for beds. While queuing provides an accurate method to calculate the number of beds, it relies on the assumption that all patient arrivals are random, which is not the case for all patients. In hospitals with an AMU, the MW experiences two arrival processes. The first process is deterministic, given the AMU's fixed discharge time, making the arrival process to the MW also deterministic. The second arrival process is from the ED to the MW, which is not deterministic due to the unpredictable nature of the ED discharge process. Having both deterministic and random arrival processes makes it challenging to use queuing theory to determine the bed reduction effectively.

From this, we will determine the number of beds for the AMU and MW using a simulation model.

2.4. Location and Layout

The layout decisions have two key aspects: determining the optimal location of the AMU within the hospital and defining the internal layout of the AMU itself. According to [1, 5, 23], the AMU must be close to the ED department, and the diagnostic facilities. If the AMU is not close by the ED or diagnostics, the positive effect of having an AMU is negligible.

Anjos et al. [2] explains the Facility Layout Problem (FLP) as: "FLPs are a general class of operations research problems concerned with finding the optimal arrangement of a given number of nonoverlapping indivisible departments within a given facility." There are three FLP classes: row FLPs, unequal-areas FLPs, and multi floor FLPs. In general these FLPs are NP-hard [2]. The key factor for the layout are the distances. A generic algorithm, as proposed by [2], finds solutions to most of the FLP problems. Limited research is done regarding a layout in a hospital, however in the design it is important to minimize the distance between patient care rooms and nursing units and to facilitate patient movements in the vertical directions to different floors in order to increase the productivity and efficiency [1].

In our study we do not propose a layout for the designed AMU. This because the hospital does not know where to locate the AMU yet.

3. Model

In the previous section we explored the current literature regarding all the steps in the step-wise approach. From this, we conclude that step 3 must be provided with a DES model, this to compute the optimal number of beds and designated period for the AMU.

This chapter introduces a DES model. This DES model takes the admission criteria from step 1 and uses this criteria to make decisions within the model. The model helps us understand how well the hospital is doing based on the number of AMU beds and the designated period of the AMU. We explain how the ED process is connected to the MW process, and we describe how we're going to simulate this process with an AMU.

3.1. ED process

The ED process in our hospital is as follows. An acute patient arrives at the hospital either on his own or by ambulance. The patient will then be triaged in the triage room. After triage, the patient is placed in an ED room for treatment. Depending on the age, triage score, and treatment type, the patient can be placed in a children, standard, crash, plaster, or lock room. If no ED room is available, the patient will be placed in the ED waiting room. After treatment at the ED, the patient will either go home or transferred to an MW. When a patient is allocated to the MW, they are required to wait in the ED room until two nurses from the respective MW come to collect them. The patient will then finish the treatment at the MW.

If a very urgent patient arrives at the ED ($triagescore \leq 1$) the patient will be placed at a crash room (if available). If such a room is unavailable, and all other rooms are occupied, the least urgent patient from a standard room will be placed back into the waiting room, so the urgent patient can be treated in this standard room.

3.2. DES model

The DES model simulates the ED process given in Section 3.1 including an AMU. We describe how patients move through the model, what the resources are, and how the queuing systems are working. The including departments for this process are the ED, AMU, and MW. The treatment of a patient is simulated as a black box, meaning, a patient enters a room, occupies this room with a given treatment time, and then leaves the room.

The data that is used for the model comes from the Integral Capacity Management (ICM) department. The data consist of patient information through the years 2018-2021. A total of 101973 patients arrived at the ED during this period. The data-set includes patient information such as ID, Age, and Triage score. Additionally, each patient is associated with an ED arrival time and the duration they spend in an ED room. To account for the uncertainty in actual service times within the ED, supplementary measurements were conducted. Over a span of approximately two weeks, observations were gathered from around 700 patients, providing data on both their actual service times and waiting duration within the ED. This extra data contains a more accurate service time regarding the ED treatment and ED waiting time, more information regarding this can be found in Section 3.2.3.

3.2.1. Model description

We do not simulate the triage room. According to nurses, triaging a patient is not a time consuming process in the ED. Furthermore, there is almost no data about triage duration. A detailed overview of the model is presented in Figure 3. The flowchart presents how a patient moves though the model including the decisions that are made.

The flowchart initiates from the left-hand side with a green box, symbolizing the arrival of a patient at the hospital. The initial assessment involves determining whether the patient's condition is urgent; if affirmative, immediate assistance is provided. In the absence of urgency, the availability of a treatment room is assessed. Should no rooms be available, the patient is accommodated in the waiting room until an ED room becomes free, ensuring they receive care at the earliest opportunity.

After receiving treatment in the ED, patients have the option of being discharged or transferred to either the AMU or MW (second green box from the left-hand side). The decision regarding discharge or transfer is determined by a uniform distribution probability model. The likelihood of discharge is influenced by the patient's medical specialty, and these probabilities are outlined in Appendix A, Table 15.

If a patient meets the admission criteria for the AMU and there are available spaces, they are directly assigned to the AMU. Otherwise, they are transferred to the MW. Notably, when a patient is directed to the AMU, they are spared the wait time in the ED to be picked up by an MW nurse. Once the patient completes their stay in the AMU, they can either be discharged or moved to the MW. Subsequently, after receiving treatment in the MW, the patient is discharged.

When a patient arrives at the hospital it has the following attributes, specialty, age, triage score, and arrival time. A total of 28 specialties were observed from 101973 patients retrieved from historical data. We distinguish the outliers based on a minimum number of data points. A patient specialty must occur at least 100 times at the ED over the last 4 years. This reduces the total number of specialties to 14 and number of patients to 100960. The specialties that are included in the model can be seen in Table 1. The age and triage score are based on the percentage of occurrence per specialty. This data can be found in Appendix A, Table 16 and 17.

General Surgery	(CHI)
Internal medicine	(INT)
Pediatrics	(KIN)
Plastic surgery	(PLA)
Neurology	(NEU)
Lung diseases	(LON)
Gastrointestinal and liver diseases	(MDL)
Urology	(URO)
ENT	(KNO)
Cardiology	(CAR)
Allergology	(ALL)
Geriatrics	(GER)
Eye diseases	(EYE)

Table 1: Specialties used in the simulation model, on the right hand side (in brackets) is the Dutch abbreviation.

The resources included in the model are the ED, AMU, and MW rooms. The ED consists of a fixed number of rooms/beds with different disciplines (e.g., child room or emergency room). In an official

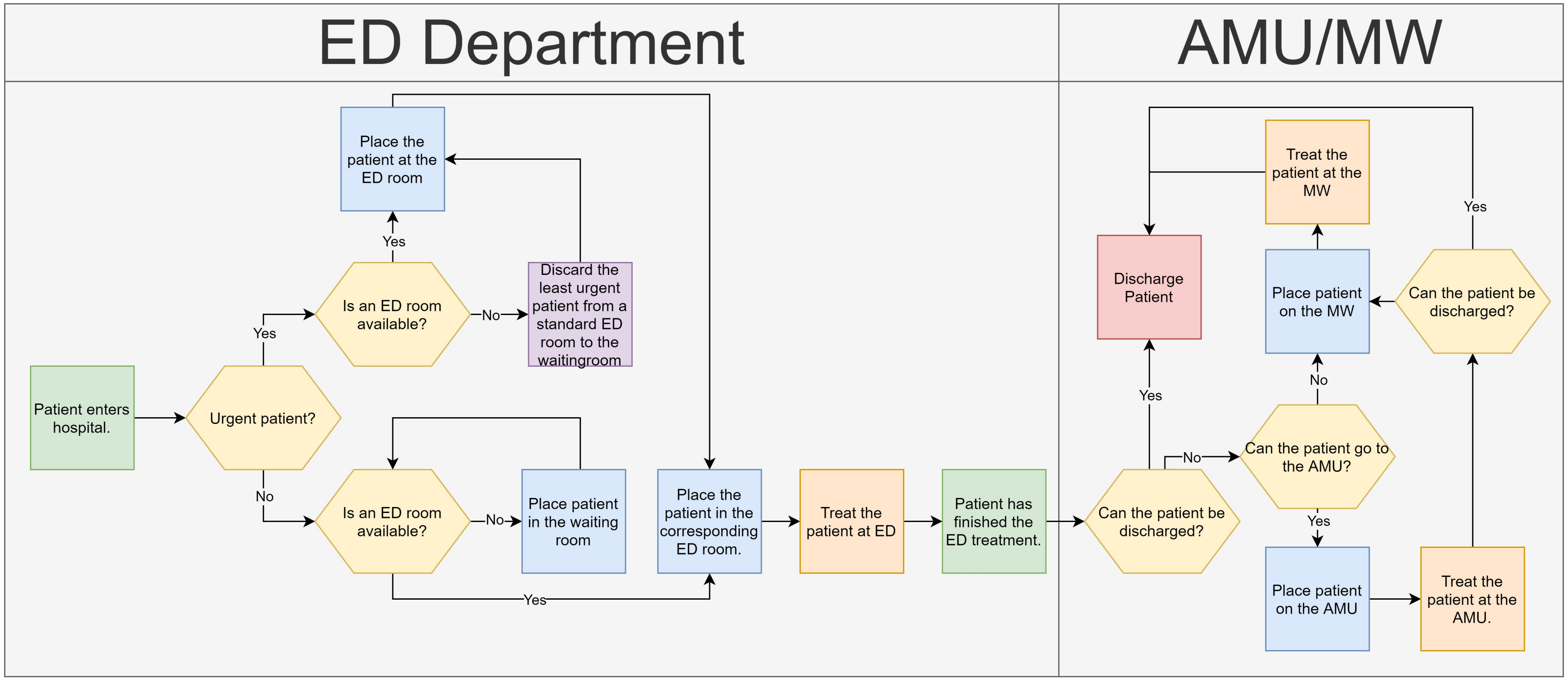

Figure 3: Flowchart of the DES model including all the decisions.

capacity, the Emergency Department (ED) includes designated areas for both plaster treatments and quarantine purposes (for patients with contagious viruses). Regrettably, the data does not encompass any details pertinent to these specific rooms. Furthermore, according to interviews, the rooms are also rarely used. Because of that, we did not include these rooms in the DES model. The AMU has a fixed number of beds where the MW is simulated with an infinite capacity, meaning, we have an infinite number of beds, see Table 2. An infinite number of beds is based on the policy of the hospital. If a patient comes from the ED he or she will always be placed on a bed and never be transported to another hospital, thus an infinite capacity.

Department	**RoomName**	**Capacity**	**DischargeTime**
ED	RoomChild	2	na
ED	RoomCrash	2	na
ED	RoomStand	10	na
AMU	amu	t.b.d.	13:00
MW	na	∞	na

Table 2: Capacity stands for the number of rooms or beds available at that department. The discharge time is the time patients may leave the resource.

Only one waiting room (or queue) is contained in the model, the ED waiting room. When a patient arrives at the ED all rooms could be fully occupied. A patients will then wait in the waiting room. Once an ED room becomes available a patient will be picked from the waiting room and placed in the ED room. The queuing order in the waiting room is based on the triage score of patients. The lower the score the earlier a patient gets treated. If a patient arrives with a triage score of 0 or 1 direct help is needed. Normally these type of patients will be placed on the crash room. But, if all the rooms are occupied in the ED, the least urgent patient that is currently treated will be placed back into the waiting room and the urgent patient will be placed in this ED room. The patient that is placed back in the waiting room has already some part of the treatment finished, so, when this patient enters the ED again his ED treatment time is shorter.

In Figure 4 we show the discharge moments at the AMU compared to the current time. The current time represents the time a patient arrives at the AMU. In general, the time a patient spends in the AMU is equal to the time a patient would have spend at the MW. However, when the designated period is lower than the MW time, the patients treatment time is equal to the designated period.

Algorithm 1 outlines the methodology employed to determine the treatment duration for a patient at the AMU. The initial period a patient occupies within the AMU (P_{time}) is set to the smallest time unit, which is contingent on both the MW treatment time and the designated duration of the AMU.

Subsequently, the algorithm iterates through all possible discharge instances ($D \in DM$), which, in our scenario, occur daily at 13:00. The algorithm then computes the time difference between the discharge moment (d) and the projected discharge time ($C_t + P_{time}$). If this computed value is lesser than the optimal value identified thus far, and if the expected discharge moment surpasses $d + D_t$, the current discharge moment is selected as the most favorable choice. Here, the formula $d + D_t$ signifies a temporal window (in our context, spanning 5 hours). When a patient's departure is anticipated within this window, preference is given to discharge them at $D_m - 1$ instead of D_m. Subsequently, the effective duration a patient spends within the AMU is expressed as $AMU_t = D_{mopt} - C_t$. A visual representation of the algorithm's parameters is provided in Figure 4.

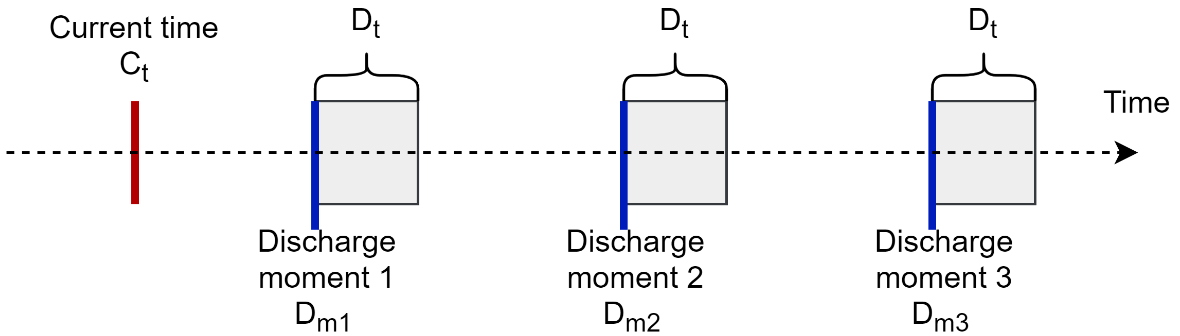

Figure 4: A patient has, depending on the Designated Period, a maximum number of discharge moments, $DM \in D_{m1}, D_{m2}, D_{m3}, ...$ In our model the discharge moment is every day at 13:00.

Algorithm 1: AMU Length of Stay

initialization;
$CurSol = \infty$;
$BestSol = CurSol$;
$P_{time} = min(MW_t, D_p)$;
for $d \in DM$ **do**
    $CurSol = |C_t + P_{time} - d|$;
    if $(CurSol < BestSol)$ AND $(d + D_t \geq P_{time} + C_t)$ **then**
        $CurSol = BestSol$;
        $D_{mopt} = d$
    end
end
$AMU_t = D_{mopt} - C_t$

3.2.2. Modelling patients arrival

As stated in the literature review (Section 2) the arrival of acute patients at the ED can assumed to be Poisson distributed. This is validated for our case study, as can be seen in Figure 5. This gives that the interarrival times are exponential distributed at a certain hour.

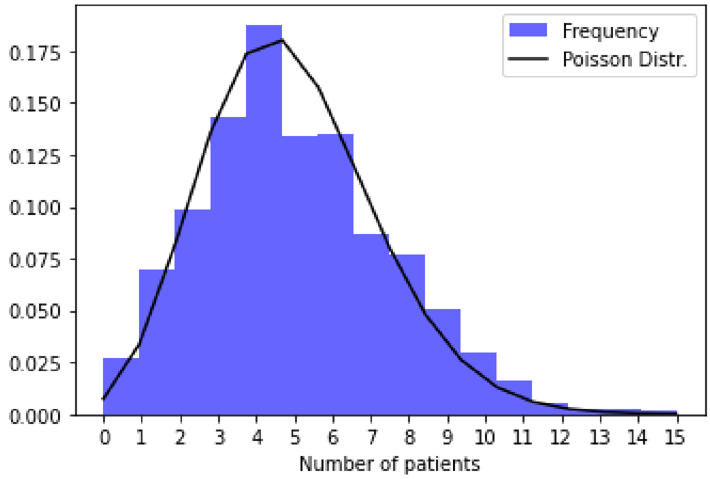

Figure 5: Frequency of arrival rate in number of arrivals between 16:00h and 17:00h, with fitted Poisson distribution with lambda = 4.91. The data comes from the case study hospital where a total of 7081 patients arrived between 16:00 and 17:00 during the period 2018-2021.

The poisson process is not time homogeneous which means that the rate varies over time. To this end, we use a thinning procedure [11]. By this we can simulate the patients arrivals over time, as can be seen in Figure 6. The arrival of a patient depends on an interarrival time at the busiest hour of the day. The interarrival time of the busiest hour is exponential distributed with a lambda equal to 739.19. Depending on the hour we accept or discard this patient, the change of accepting a patient is stated in Appendix B, Table 18. The model does not include any daily or monthly trends.

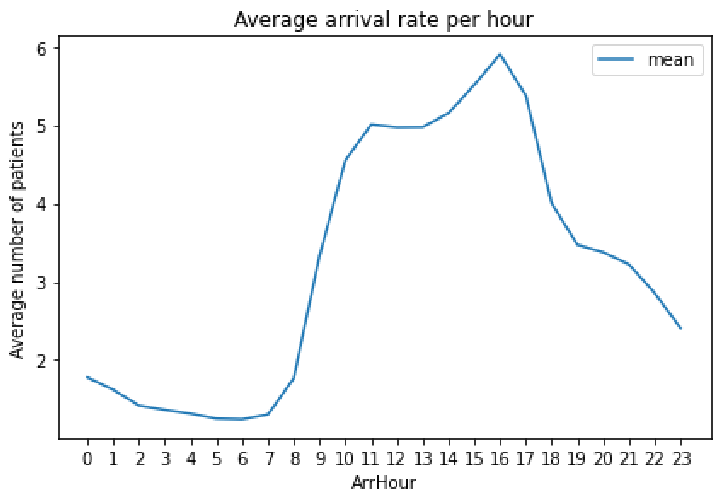

Figure 6: The arrival rate per hour from the case study hospital, also called a whale curve.

3.2.3. Modelling Service Times

The treatment times are divided in three categories, ED treatment time, ED waiting time, and MW treatment time. We assume that the treatment time of the MW is equal to the treatment time of the AMU. Because, a patient that would go the MW is now going to the AMU therefore the treatment time is assumed to be equal. The treatment times are depending on the patient specialty. We check for correlations between the Length of Stay (LoS), triage score, and age of a patient. From the matrix in Figure 7 we can conclude that there is no correlation, therefore we only distinguished on patient specialty.

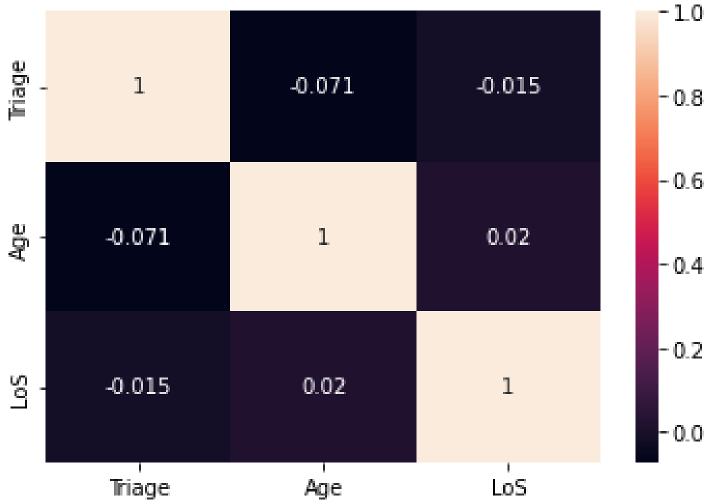

Figure 7: Correlation matrix LoS (treatment duration) with age and triage score.

A patient has an ED treatment time and an ED waiting time. The ED treatment time is the actual time doctors and nurses are helping the patient. The ED waiting time is the time a patient needs to wait before a MW nurse transports the patient to the MW. Determining the ED treatment and ED waiting time is difficult, given that only the total ED LoS is known. Hence, we conducted observations pertaining to the completion of ED treatment and the actual departure of patients from the ED. These observations were carried out over a span of approximately two weeks.

We determined the distribution for the ED waiting time fraction, ED waiting time fraction is the ED waiting time divided by the total ED LoS. We use an ED waiting time fraction instead of actual ED waiting time because the total ED LoS is still used in the model. Therefore, we cannot subtract the ED waiting time because this could result into a negative ED LoS due to randomness. The ED waiting time fraction is not correlated to specialty, age, or triage. In Figure 3 we see that a Lognormal distribution is the most suitable fit over the histogram of the fraction of the ED waiting time. The maximum value of the fraction is the maximum found value within the data set, which is 95 percent. The data for this distribution can be seen in Table 4. When a patient is discharged or is assigned to the AMU, the patient has zero ED waiting time because the patient is assumed to be directly transported to the AMU. Therefore, the ED LoS will be shorter.

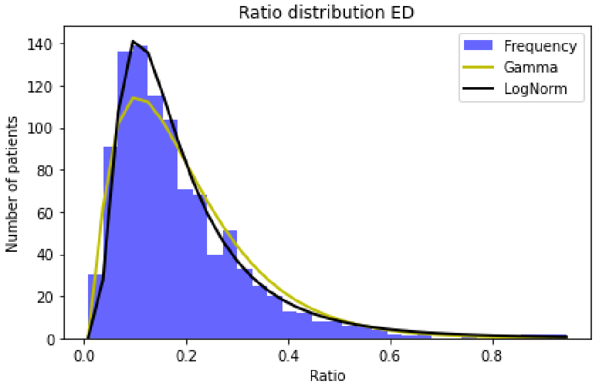

Table 3: The frequency represent the fraction. The yellow and black line present the Gamma and Lognormal distribution plotted over the histogram.

Specialty	Mean	Sigma	Variance	Distribution
ALL	-1.923	0.714	0.0177	LogNormal

Table 4: ED WT information

Regarding the total LoS for the ED and the MW we created a histogram and plotted a Lognormal and Gamma distribution. In both departments we visually observe that the gamma distribution is the most suitable distribution, see Figure 8. The service times presented in numerical terms are stated in Table 5.

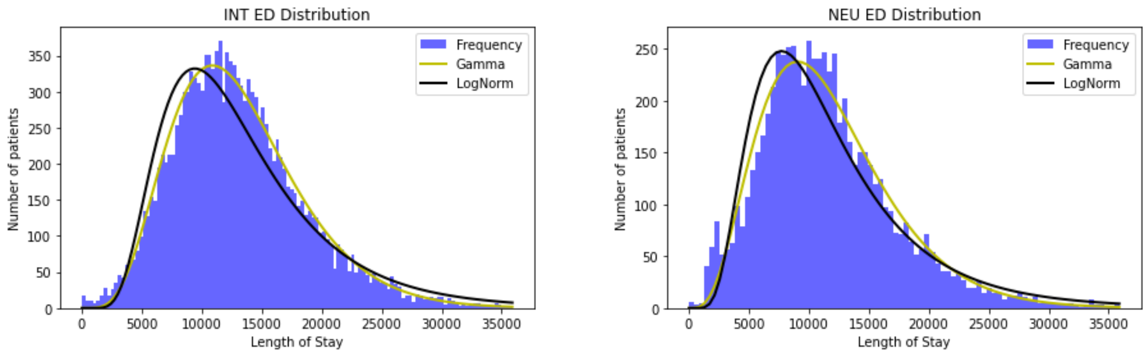

Figure 8: The frequency represents the histogram regarding the LoS at the Emergency Department. The yellow and black line are the Gamma and Lognormal distribution plotted over the histogram.

Specialty	ED Total LoS		MW Total LoS	
	Mean (sec)	**Sigma (sec)**	**Mean (sec)**	**Sigma (sec)**
CHI	8449.86	4929.89	206152.05	383440.39
INT	13058.06	5482.83	411460.08	552804.89
KIN	8220.79	3736.91	411404.14	594310.94
PLA	7225.88	4410.79	383279.45	499845.00
NEU	11530.63	5530.73	250207.20	475045.50
LON	13018.91	5017.50	525926.56	608172.23
MDL	12045.12	5074.97	551645.27	563577.43
URO	9145.95	5194.35	451690.80	610997.42
KNO	6718.94	4443.65	770310.78	660657.73
ORT	10789.78	5362.44	144319.44	343518.48
CAR	13102.21	5713.48	268156.32	299600.10
ALL	6611.32	2651.03	175005.45	177151.94
GER	15113.04	5334.03	14477.14	5241.81
OOG	5222.67	3985.79	41022.86	65515.12

Table 5: The mean, sigma (standard deviation), and variance for the distribution regarding the total LoS per department.

3.3. Key Performance Indicators

The KPIs need to encompass all the different wards; ED, AMU) and MW. Beginning with the ED, we have incorporated the blocking probability and occupancy rate as crucial metrics. Additionally, we've integrated the percentage of patients exceeding a 3-hour LoS threshold, alongside the average waiting time post-treatment in the ED area. It's essential for these time-related metrics and percentages to decrease upon the implementation of an AMU. It's important to note that the choice of ED KPIs is based on the priorities identified by the case study hospital.

Moving on to the AMU, we have opted to employ the same set of KPIs as utilized in the ED. This decision stems from the absence of the AMU as of now, rendering it impossible to gather additional information from a ward that is yet to be established.

Lastly, in the context of the MW, our hospital has assumed an unlimited capacity for the MW. Consequently, there isn't a blocking probability metric applicable here. Instead, we are able to measure the average bed occupancy by acute patients transferred from either the ED or the AMU.

3.4. Model verification and validation

This section comprises two integral components. The initial segment encompasses verification, elucidating the warm-up period and the requisite number of runs for the DES model. The subsequent segment entails validation, assessing the model's performance relative to real-world observations.

3.4.1. Warm-up period and number of runs

The simulation is a non-terminating steady state simulation, given that the model needs a warm-up period and can run indefinitely. The warm-up period is determined using the Welch's approach [10]. The KPI that is used for the warm-up period is the average number of occupied beds at the MW, this because it is the most downstream KPI in the hospital process. We used the average occupied MW beds as KPI for the warm-up period because it is the most downstream ward and will therefore stabilises as last. Figure 9 presents the average number of occupied beds per observation. One observation is equal to half hour in the simulation, so observation one is 1800 seconds, observation two 3600 seconds etc.

From the figure we see that we not only have a warm-up period but also 'cool-down' period at the end of the simulation. The data of a patients is only saved in the model after the treatment is 100 percent finished. Thus, when the simulation stops some patients are still in the system. This results in a drop at the end of the data, as can be seen in Figure 9. The rule of thumb is that the simulation time is 10 times the warm-up period, this would be 300 days. But, because we have a 'cool-down' period, we also delete the last 30 days, this period can be observed by Figure 9. Therefore, we have a total simulation time of 330 days per run.

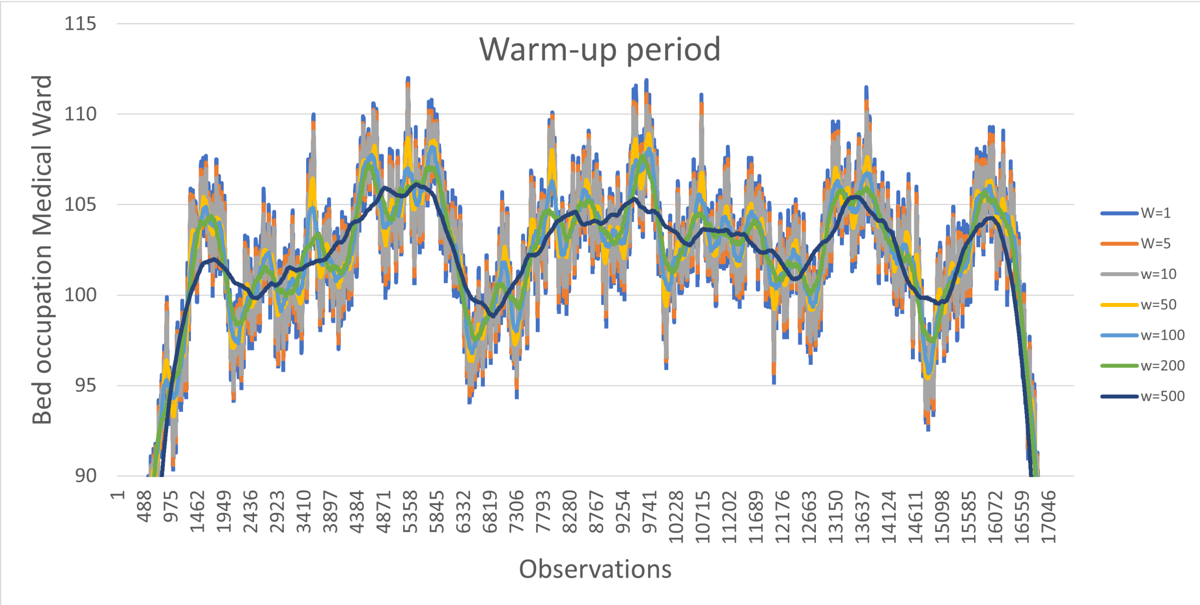

Figure 9: Warm-up period. Observation 1400 represents the start of the steady state. One observation is equal to 1800 seconds, which means a warm-up period of approximately 30 days is necessary to reach steady state. The cool-down period is the approximately the last 30 days of the graph starting at point 16000 until finish.

Subsequently, we determined the necessary number of simulation runs based on the average bed occupancy within the MW. This choice of KPI is rooted in its position as the most downstream metric. Each entry in Table 6 is built upon previous values; for instance, the mean value of the third run corresponds to the average MW beds from runs 1 to 3.

To calculate the error for each run, we divide the Confidence Interval Half-Width (CIHW, $tvalue * \sqrt{Run/variance}$) by the mean. If this error is below the designated threshold (in our situation 95 percent CI), it is deemed acceptable and signifies the required number of runs. Our analysis of Table 6 indicates that the number of runs becomes sufficient after 2 runs.

However, it is worth noting that according to Law et al. [10], a simulation model typically requires a minimum of 5 runs to achieve validation. Consequently, we opt to employ 5 runs per simulation to ensure the model's reliability.

Run	Average MW beds	Mean	Var	t-val	CIHW	Delta	Gamma'	Valid?
1	103.777	*na*	*na*	*na*	*na*	*na*	*na*	*na*
2	104.144	103.960	0.067	12.706	2.329	0.022	0.048	OK
3	104.539	104.153	0.145	4.303	0.947	0.009	0.048	OK
4	98.890	102.838	7.021	3.182	4.216	0.043	0.048	OK
5	103.688	103.008	5.411	2.776	2.888	0.028	0.048	OK
6	100.548	102.598	5.337	2.571	2.424	0.024	0.048	OK
7	102.485	102.582	4.449	2.447	1.951	0.019	0.048	OK
8	100.626	102.337	4.292	2.365	1.732	0.017	0.048	OK
9	106.377	102.786	5.569	2.306	1.814	0.017	0.048	OK
10	102.881	102.795	4.951	2.262	1.592	0.015	0.048	OK

Table 6: Number of runs necessary, using the mean and variance we compute Delta. When the Delta value is below Gamma prime (95 percent confidence) we accept the number of runs.

3.4.2. Validation

Validating DES can be done by comparing the outcomes to the real world to the outcomes from our model [7]. We used the average number of occupied beds at the MW as KPI to compare the real world with the simulation model. The model gives an average of 103.26 occupied MW beds, where the values for our case study is equal to 100.12 MW beds over 1 year. This is a difference of 2.01%. From this we accept that the model is a good representation of the real world.

4. Case study

In the preceding section, we introduced a DES model. We provided relevant data from our case study hospital to elucidate the setup of this DES model. In the present section, we embark on executing each step of the step-wise approach. This comprehensive analysis aims to offer valuable insights and recommendations to the case study hospital. Specifically, the hospital seeks to evaluate the potential impact of implementing an AMU. Throughout this section, we will systematically assess each step of the approach, including an in-depth analysis of the model results presented in Chapter 3.

4.1. Step 1

As indicated in Section 2.1, the establishment of admission criteria can be informed by factors such as patient specialty, age, and expected LoS. However, it is important to note that the EWS score cannot be utilized in this context due to the unavailability of this information within the hospital's data-set. The hospital has the following admission criteria exclusions for the AMU, no patients under 18 and we disallow the following specialties: Allergolocy, Cardiology, Pediatrics, Ear Nose Throat (ENT), and Eye disease.

Using the fixed exclusion from the hospital and adding a maximum expected LoS of 48 hours, we have an initial fixed admission criteria, see Table 7. This criterion allows, using the historical data, 83.5% of the inpatient to the AMU. As an additional setup the hospital wants to know the results without having a 48 hour maximum expected LoS.

Criteria	Allowed on the AMU
Specialty	CHI, GER, INT, LON, MDL, NEU, ORT, URO
Min Age	18
MaxExpectLoS	48h & ∞

Table 7: Initial admission criteria

4.2. Step 2

This step focuses on the necessary equipment, staff en supporting processes that are necessary for the AMU. Obtained by interviewing subject matter experts, the nurse-to-bed-ratio should be 1 to 3. For this ratio, it is assumed that the abilities of the nurses are equivalent to those of the ED nurses. The hospital indicates that the equipment should be similar to the equipment of their current MW. Because the AMU is not dedicated to one patient specialty, the nurses must have the qualities of an ED nurse, and the nurse-to-bed ratio must be 1 over 3. Supporting processes should be the similar to those of an ED. Therefore, the AMU should be placed close to the ED.

4.2.1. Step 3

This stage evaluates the optimal bed requirement and designated duration for the AMU utilizing the DES model outlined in Section 3. In pursuit of identifying the most effective AMU setup (number of AMU beds and AMU designated period), we undertake a series of experiments. Each experiment encompasses a distinct setup. Through a comprehensive analysis of outcomes across various setups, we aim to provide informed guidance on the optimal configuration for the AMU.

First, an experiment is done without the AMU, this to create a baseline. Next, 15 experiments are done without the admission criteria, MaxExpectLoS. For each designated period (24, 48, and 72 hours) we do 5 experiments each with a different number of beds going from 8 to 40 with stepsize 8. The same approach is done including the admission criteria maximum LoS. Finally, we do an experiment where the AMU has an opening and closing time with a maximum of 4 beds, the admission criteria is without the MaxExpectLoS.

In Table 8 the first experiment setup is presented. Here the ED occupation and blocking rate are given, the percentage of patients that has a longer treatment time than 3 hours (LoS>3h), the waiting time to be retrieved from the ED room after treatment (ED in room waiting time), and the average bed occupation in the MW from acute patients coming from the ED (MW bed occupation). The number of beds in the AMU depends on the admission criteria of the AMU. Using the fixed admission criteria (Table 7) we defined the appropriate number of beds and designated period, including the performance of the AMU (occupation percentage and blocking probability).

Experiment	ED occupation percentage		ED blocking percentage		AMU occupation percentage		AMU blocking percentage		LoS>3h ED percentage		ED in room waiting time		MW bed occupation	
	mean	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*
No AMU	0.5316	[0.5266, 0.5366]	0.1742	[0.1653, 0.1832]	0	0	0	0	0.2921	[0.2890, 0.2953]	675.04	[669.70, 680.37]	103.00	[100.97, 105,05]
24x8	0.518*	[0.514,0.523]	0.150	[0.146,0.155]	0.936	[0.936,0.938]	0.9130	[0.912,0.915]	0.276	[0.274,0.278]	533.59	[525.2,541.99]	94.83	[92.92,96.76]
24x16	0.515	[0.512,0.519]	0.150	[0.147,0.154]	0.897	[0.894,0.901]	0.8339	[0.833,0.836]	0.268	[0.266,0.271]	415.83	[412.8,418.88]	90.84	[89.79,91.91]
24x24	0.507	[0.505,0.51]	0.142	[0.139,0.145]	0.851	[0.847,0.857]	0.7656	[0.764,0.769]	0.261	[0.257,0.265]	303.60	[297.15,310.06]	85.94	[84.66,87.23]
24x32	0.503	[0.502,0.504]	0.138	[0.131,0.147]	0.798	[0.794,0.802]	0.7104	[0.71,0.712]	0.256	[0.255,0.259]	215.24	[209.87,220.63]	84.02	[82.1,85.95]
24x40	0.497	[0.495,0.499]	0.140	[0.135,0.146]	0.723	[0.72,0.728]	0.6731	[0.671,0.676]	0.251	[0.25,0.253]	158.58	[153.84,163.33]	79.98	[78.39,81.58]
48x8	0.525*	[0.52,0.531]	0.162	[0.155,0.17]	0.960	[0.959,0.963]	0.9362	[0.936,0.937]	0.282	[0.279,0.285]	571.71	[561.74,581.7]	95.33	[93.75,96.92]
48x16	0.520	[0.517,0.524]	0.156	[0.153,0.16]	0.937	[0.937,0.938]	0.8746	[0.874,0.876]	0.275	[0.272,0.279]	478.44	[470.47,486.43]	92.40	[90.66,94.16]
48x24	0.510	[0.507,0.514]	0.142	[0.14,0.146]	0.910	[0.907,0.914]	0.8161	[0.815,0.818]	0.266	[0.263,0.27]	382.25	[371.29,393.23]	83.98	[81.98,85.99]
48x32	0.505	[0.505,0.506]	0.140	[0.134,0.146]	0.880	[0.878,0.884]	0.7659	[0.765,0.768]	0.262	[0.26,0.264]	306.83	[302.3,311.36]	80.57	[78.45,82.71]
48x40	0.502	[0.499,0.507]	0.141	[0.137,0.145]	0.846	[0.843,0.849]	0.7192	[0.717,0.722]	0.257	[0.256,0.26]	230.67	[226.99,234.36]	75.04	[74.06,76.04]
72x8	0.527*	[0.524,0.531]	0.162	[0.156,0.169]	0.972	[0.971,0.973]	0.9476	[0.947,0.949]	0.283	[0.281,0.286]	590.04	[580.28,599.81]	96.38	[94.88,97.89]
72x16	0.523	[0.521,0.526]	0.157	[0.155,0.16]	0.955	[0.953,0.957]	0.8958	[0.896,0.897]	0.278	[0.277,0.281]	507.46	[500.82,514.11]	90.97	[88.71,93.23]
72x24	0.518	[0.514,0.522]	0.146	[0.137,0.155]	0.936	[0.935,0.939]	0.8462	[0.845,0.849]	0.274	[0.273,0.276]	437.44	[430.34,444.55]	86.27	[84.51,88.04]
72x32	0.509	[0.507,0.513]	0.143	[0.138,0.149]	0.919	[0.919,0.921]	0.7993	[0.799,0.801]	0.265	[0.264,0.267]	356.45	[352.04,360.87]	77.65	[76.86,78.46]
72x40	0.507	[0.503,0.513]	0.140	[0.137,0.144]	0.897	[0.894,0.9]	0.7572	[0.756,0.76]	0.262	[0.26,0.266]	291.65	[278.76,304.56]	74.21	[72.21,76.21]

Table 8: Results without the admission criteria, MaxExpectLoS. The experiment column provides the experiment setup (Designated Period x Number of AMU beds). KPIs including an asterisk are not significantly better compared to the current situation (no AMU).

From the results we see that almost every KPI has a significant improvement compared to the current situation. Furthermore, we see (from Table 8) that increasing the number of beds or designated period has an significant improvement (using a 95% confidence interval) on the KPIs. Noticeable is, the total number of beds necessary in the hospital increases. Using the confidence interval we see whether or not an experiment is significant better based on one KPI. The results from Table 8 are plotted in a graph (see Figures 10 and 11, and Appendix C.1). Most KPIs are significantly different however, from Figure 10 we see that for 8, 16 and 24 beds the designated period has no significant influences on the MW bed occupancy. Having 32 or 40 beds does make a small difference for a designated period of 24 hours, however no significant difference can be found between 48 and 72 hours. Increasing the number of beds does however have a significant difference per designated period. In Figure 11 we see no significant difference between 48 and 72 hours. Furthermore, having 24 beds or more does not differ in any situation.

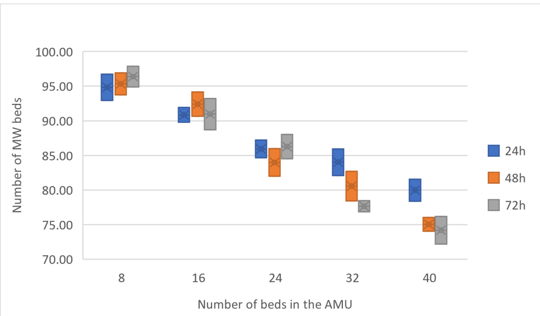

Figure 10: Medical Ward bed occupancy per scenario

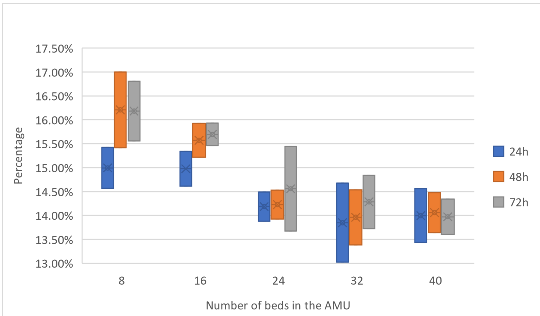

Figure 11: Emergency Department blocking probability per scenario

The second experiment setup includes the admission criteria, maximum expected LoS. Considering that we only allow patients with a LoS below 48 hours it is insufficient to simulate an AMU with a designated period of 72 hours. Therefore, we excluded the designated period of 72 hours. The results are shown in Table 9.

Experiment	ED occupation percentage		ED blocking percentage		AMU occupation percentage		AMU blocking percentage		LoS>3h ED percentage		ED in room waiting time		MW bed occupation	
	mean	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*
No AMU	0.5316	[0.5266, 0.5366]	0.1742	[0.1653, 0.1832]	0	0	0	0	0.2921	[0.2890, 0.2953]	675.04	[669.70, 680.37]	103.00	[100.97, 105,05]
24x8	0.521	[0.518,0.526]	0.163*	[0.159,0.169]	0.830	[0.826,0.835]	0.8103	[0.809,0.812]	0.279	[0.277,0.282]	545.11	[538.34,551.89]	100.28*	[99.01,101.55]
24x16	0.518	[0.516,0.522]	0.163	[0.158,0.17]	0.675	[0.671,0.68]	0.6977	[0.696,0.701]	0.276	[0.274,0.278]	467.84	[457.5,478.2]	97.00	[95.72,98.3]
24x24	0.515	[0.512,0.518]	0.160	[0.154,0.166]	0.492	[0.478,0.507]	0.6672	[0.665,0.671]	0.274	[0.273,0.276]	442.98	[435.26,450.72]	98.15	[96.35,99.96]
24x32	0.514	[0.512,0.518]	0.161	[0.156,0.167]	0.370	[0.359,0.381]	0.6661	[0.663,0.671]	0.274	[0.273,0.276]	444.19	[435.3,453.09]	98.59	[97.1,100.08]
24x40	0.514	[0.512,0.518]	0.161	[0.155,0.168]	0.296	[0.288,0.305]	0.6650	[0.662,0.669]	0.274	[0.272,0.276]	442.56	[434.74,450.38]	98.59	[97.1,100.08]
48x8	0.523	[0.52,0.526]	0.164*	[0.16,0.17]	0.855	[0.854,0.857]	0.8265	[0.825,0.829]	0.281	[0.28,0.283]	560.47	[548.61,572.34]	100.10*	[98.23,101.98]
48x16	0.515	[0.514,0.517]	0.155	[0.151,0.159]	0.716	[0.711,0.722]	0.7101	[0.709,0.712]	0.274	[0.272,0.278]	472.19	[468.01,476.38]	96.83	[96.03,97.65]
48x24	0.516	[0.512,0.521]	0.163	[0.159,0.168]	0.539	[0.53,0.548]	0.6736	[0.668,0.68]	0.273	[0.272,0.275]	451.61	[441.64,461.6]	98.99	[97.4,100.59]
48x32	0.514	[0.512,0.518]	0.160	[0.155,0.166]	0.410	[0.398,0.423]	0.6692	[0.666,0.673]	0.274	[0.272,0.276]	446.23	[437.85,454.61]	98.56	[97.07,100.05]
48x40	0.514	[0.512,0.518]	0.160	[0.155,0.167]	0.328	[0.318,0.339]	0.6683	[0.665,0.672]	0.274	[0.273,0.276]	443.70	[434.74,452.67]	98.56	[97.07,100.05]

Table 9: Experiment (Designated Period x Number of AMU beds) is presented including the admission criteria, maximum LoS. KPIs including an asterisk are not significantly better compared to the current situation (no AMU)

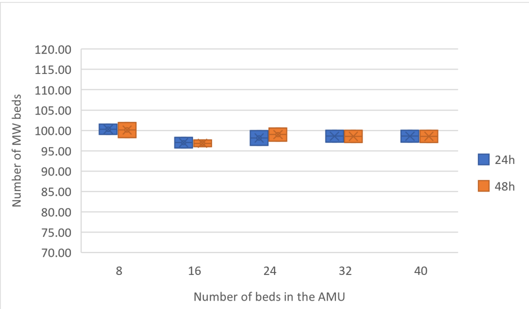

Figure 12: Medical Ward bed occupancy per scenario including a the admission criteria maximum LoS.

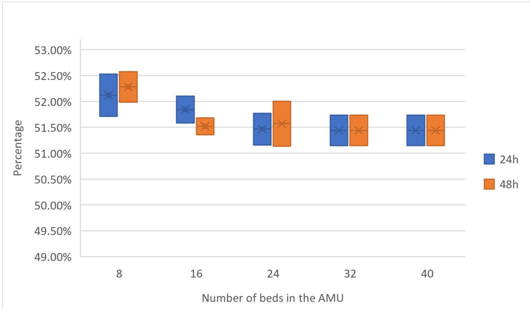

Figure 13: ED occupancy rate per scenario including the admission criteria maximum LoS.

From the results in Table 9 we can see that the KPIs do significantly improve compared to having no AMU. However, the improvement is very minimal and also stabilizing when we increase the number of beds. This can also be seen in Figures 12 and 13, and in Appendix C.2.

At last, instead of creating a new ward we use an existing ward that is not used from 20:00 till 8:00. The AMU only operates between these hours where the rest of the hours patients can only go to the MW. This ward has a capacity of 4 beds and a designated period of 12 hours. Furthermore, patients are only allowed if they can stay in the AMU for at least 5 hours (so assigning a patient to the AMU can only be done before 3:00). The results for this situation are stated in Table 10.

Experiment	ED occupation percentage		ED blocking percentage		AMU occupation percentage		AMU blocking percentage		LoS>3h ED percentage		ED in room waiting time		MW bed occupation	
	mean	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*
No AMU	0.5316	[0.5266, 0.5366]	0.1742	[0.1653, 0.1832]	0	0	0	0	0.2921	[0.2890, 0.2953]	675.04	[669.70, 680.37]	103.00	[100.97, 105,05]
Special AMU	0.524	[0.522,0.526]	0.164	[0.158,0.172]	0.779	[0.777,0.782]	0.9096	[0.909,0.911]	0.282	[0.28,0.285]	594.22	[589.16,599.29]	99.10	[97.6,100.61]

Table 10: Score with 4 beds and a open and closing time of the AMU (20:00-8:00), without the maximum expected LoS as criteria.

Comparing the results to the data without an AMU we see a significant difference between KPIs *LoS>3h ED percentage* and *ED in room waiting time*. The rest of the KPIs are not significantly different.

4.2.2. Step 4

The first option is creating a new ward. The location of this ward in the hospital is still unclear. Because of that, we cannot say what the total layout of the AMU should look like. According to a subject matter expert the layout of an AMU room is more similar to an MW room than to an ED room, because patients that enter the AMU are stable. The differences between an AMU and MW are that patients at the AMU still need diagnostics, and the AMU handles a broader range of patient specialties. The layout is therefore similar to a standard MW layout, where you should consider turning points for the beds, the width of the door for the beds, and the size of the room so the equipment fits within the space (e.g., cabinets, monitor equipment, a nightstand, etc.).

The second option is upgrading an existing ward that is close to the ED and only used from 8:00 till 20:00. We use this facility as AMU with a fixed dedicated period of 12 hours, and a fixed number of beds (4 beds).

4.3. Advise

From the results we conclude that an AMU with an opening time from 20:00 till 8:00 does not work properly. It only improves two KPIs, *LoS>3h ED percentage* improves by 0.1 percent, and the *ED in room waiting time* improves by 80.82 seconds. These difference are almost negligible and therefore this AMU setup is not sufficient.

An AMU that is 24/7 open, including a maximum LoS as admission criteria does show more improvements compared to AMU with an open and closing time. However, every KPI reaches his optimum with 16 beds, except for the *AMU occupation percentage* which keeps decreasing. This can be seen from Figures 10 and 11 and the figures located in Appendix C.2. This gives that 16 beds is optimal for this situation. With 16 beds all KPIs are significantly improving, however there is no significant difference in the designated period of 24 or 48 hours. We therefore compared the situation of 16 beds with a 24 hour designated period, as can be seen in Table 11.

	ED occupation percentage	**ED blocking percentage**	**LoS>3h ED percentage**	**ED in room waiting time**	**MW bed occupation**
Difference	-1.01%	-1.11%	-1.62%	-207.2 sec	-6

Table 11: Mean difference between simulation without an AMU and the simulation model including an AMU with 16 beds, a designated period of 24 hours, and the admission criteria does include a maximum expected LoS of 48 hours.

For a 24/7 open AMU without a maximum expected LoS in the admission criteria, we see that almost every KPI is continuously improving or deteriorating when increasing the number of AMU beds. Only one KPI, the *ED blocking probability*, is stabilizing after 24 or more beds in the AMU. Comparing the designated periods with each other, we see that a 72 hour designated period is the worst scoring setup on every KPI compared to a 24 or a 48 hour designated period. We would expect an improvement at the KPI *MW bed occupancy* however, the KPI scores are not significantly different compared to the KPI scores from 24 or 48 hour designated period. Because of that, we would not advise to use a designated period of 72 hours. Because the KPI *ED blocking probability* is stabilizing after 24 beds (for a 24 and 48 designated period), we advise to use at least 24 beds. The most promising designated period is 24 hours. Because, the KPIs *ED blocking probability* and *Occupancy rate ED* are not significantly different compared to the 48 hour designated period however, having a 24 hour designated period is improving the *ED room avg waiting time*, *AMU blocking probability* and *LoS>3h MW*. Because of that, our advise is to have a 24 hour designated period with either 24, 32, or 40 beds. The improvements per scenario are given in Table 12.

Nr beds	ED occupation percentage	ED blocking percentage	AMU occupation percentage	AMU blocking probability	LoS>3h ED percentage	ED in room waiting time	MW bed occupation
24	-2.47%	-3.23%	0.85	0.77	-3.13%	-371.44	-17.06
32	-2.87%	-3.57%	-5.35%	-5.52%	-3.57%	-459.79	-18.99
40	-3.48%	-3.42%	-12.77%	-9.26%	-4.10%	-516.46	-23.03

Table 12: Mean difference between simulation without an AMU and the simulation model including an AMU with 24, 32, and 40 beds, and a designated period of 24 hours. Because the current situation has no AMU we compare the KPIs AMU occupation percentage and AMU blocking probability with 24 beds as base.

An AMU will decrease the total LoS of patient in the hospital [3, 15]. However, no rule of thumb is given on how much the LoS will improve. Bokhorst et al. [3] does mention improvements between 10 to 30 percent. Therefore, we give an indication on how much an AMU could improve when there is a shorter LoS. We reduce the LoS after treatment at the ED by ten percent if a patient is assigned to the AMU. The results are presented for a 24 hours designated period with 24, 32 and 40 beds, see Tables 13 and 14. The KPIs *ED blocking percentage* and *ED occupancy rate* show no significant difference. For the KPI *LoS>3h* there is only a significant difference between 24 and 40 beds. All the other KPIs are in every situation significantly different. The AMU shows however no improvement regarding the total number of hospital beds. With 40 AMU beds the total number of hospital beds increases by 11. This could be less, if the reduced LoS is more than 10 percent. Despite this downfall we would either go with 24 or 40 beds given that 32 beds does not always shows a significant difference compared to 24 beds.

Experiment	ED occupation percentage		ED blocking percentage		AMU occupation percentage		AMU blocking percentage		LoS>3h ED percentage		ED in room waiting time		MW bed occupation	
	mean	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*	*mean*	*95% CI*
24x24	0.509	[0.507,0.512]	0.140	[0.133,0.148]	0.852	[0.849,0.856]	0.7645	[0.764,0.766]	0.261	[0.258,0.265]	302.11	[296.88,307.36]	82.44	[81.79,83.09]
24x32	0.505	[0.502,0.51]	0.147	[0.146,0.15]	0.796	[0.793,0.801]	0.7129	[0.71,0.716]	0.255	[0.253,0.258]	219.58	[217.79,221.39]	75.82	[74.53,77.11]
24x40	0.499	[0.497,0.502]	0.138	[0.133,0.144]	0.726	[0.722,0.731]	0.6723	[0.67,0.675]	0.252	[0.251,0.254]	157.27	[154.28,160.28]	73.09	[71.61,74.58]

Table 13: KPIs with an improved LoS

Nr Beds	EDoccPerc	EDblockPerc	AMUoccPerc	AMUBlockPerc	LoSPerc	ED_WTLoS	MW_Bed_Occ
24	-2.30%	-3.42%	0.85	0.76	-3.12%	-372.92	-20.57
32	-2.63%	-2.70%	-5.53%	-5.15%	-3.69%	-455.45	-27.19
40	-3.25%	-3.62%	-12.56%	-9.22%	-4.02%	-517.77	-29.91

Table 14: Mean difference between simulation without an AMU and the simulation model including an AMU with 24, 32, and 40 beds, and a designated period of 24 hours. Where we assume a 10 percent improvement regarding the patients LoS.

5. Discussion and conclusion

The AMU has a lot of benefits regarding patient satisfaction, reducing the LoS, and reduce unnecessary admission. We introduced a four-step approach for the design of an AMU. This four-step approach creates a clear overview on which decisions should be taken. Step 1 indicates which patients are allowed on the AMU, which creates three patients streams, going from ED to the AMU to home, going from the ED to the MW to home, and going from the ED to the AMU to the MW and finally home. In the case study the admission criteria are based on specialty, age, and expected LoS. With step 2 we indicate the necessary equipment, staff, and supporting processes for the AMU. For the case study having a nurse-to-bed ratio of 1 over 3, where the AMU nurses have capabilities of an ED nurse. In step 3, the bed reduction for the MW and necessary number of beds for the AMU are calculating using DES. In the case study we advise to have 24, 32 or 40 AMU beds with a designated period of 24 hours. During step 4, we indicate where the hospital can implement the AMU to their hospital, this is for our case study however not yet determined. This proposed method determines the dimensions of an AMU. Note that, all dimensions and boundaries can be personalized for each hospital. We validated and tested the four step approach in a case study in a medium sized hospital in the Netherlands. The case study was used to analyze the feasibility of an AMU in the hospital and test the effect of the 4 step approach in the design of an AMU. The hospital self has not (yet) implemented the AMU in the hospital.

The first two steps are determined by the hospital itself. The admission criteria is an input for the DES model. We could argue if a different admission criteria will change the performance of the model. This, because we only considered two different admission criteria setups. However, Reid et al. [15] reviewed multiple papers with different admission criteria where all papers showed improvement to the hospitals performance. No optimal setup can therefore be given because the criteria differ in every situation. Therefore, it could be beneficial to try different admission criteria setups and look at performance differences. The second step considers the facilities an AMU should have. The hospital decides which facilities are necessary in an AMU where some indications are presented by literature. Such as, no intensive monitoring, the AMU must be nearby the diagnostic department, and the use of telemetry is important. It is also dependant on the admission criteria, allowing more critical patients to the AMU obligates more advanced equipment at the AMU. An extension to this step can be a summery, or table, of equipment/facilities that are necessary respective to the patients allowed on the AMU.

In step 3 the KPI results where not as promising as we hoped. Having 40 beds and a designated period of 24 hours is only improving the ED blocking and occupation percentage by $\approx 3.5\%$, this including the assumption that the patients LoS will improve by ten percent. However, according to Bonkhorst et al. [3] this improvement is in line with the (limited) evidence that suggest an AMU will improve the KPIs of the ED. Another factor is the increase of the total number of beds necessary in the hospital despite the assumed ten percent improvement of the patients LoS. For 40 AMU beds the total number of beds in the hospital will increase by 11, however, an AMU should improve efficiency [5, 15, 17]. Bokhorst et al. [3] does mention a possible LoS improvement more than 10 percent (between 10-30 percent). However, we do not know if this goes for all patients or just the patients that enter the AMU. Our assumption is that the improvement is only for patients entering the AMU. But we could also made the assumption that, due to less disturbance from the ED at the MW, the treatment time at the MW could also decrease, which can reduce the LoS of a patient at the MW. This hypothesis was made by an expert to the corresponding field, however not yet investigated. Also, the designated period of the AMU could be correlated to the expected LoS reduction [3]. For example, will a longer designated period reduce the LoS even more of patients, because they have a longer treatment time within the AMU?

The last step indicates how the layout of an AMU should look like. In the case study we did not constructed a model to determine the optimal layout. The main reason is that the hospital does not know where to locate the AMU and therefore this step is difficult to execute. From Anjos et al. [2] a Facility Layout Problem (FLP) is well known, however, not much research is done regarding a hospital layout. Therefore, a new research could be beneficial to show how an optimal layout can be created including the ED, AMU, and MW.

The DES model is used to determine the number of beds. The model is only an approximation of the reality. Where we assume there is no weekly or monthly seasonality. Not every hospital is the same, where a hospital could have seasonality. Because of that we recommend to include seasonality into the model.

The model determines the LoS in the ED based on historical data of the hospital. However, having an AMU decreases this time given that patients do not have to wait for a transfer to the MW. The model therefore first runs the actual treatment time of the patient, then decides whether or not the patient can go to the AMU, if the patient goes to the AMU the patient will be discarded from the ED room and placed at the AMU, if not the patient executes the waiting time within the ED room and is then placed at the MW. This treatment time is determined by subtracting the waiting time from the total time. This waiting time is a random value based on two weeks of historical data, which is inaccurate. A proposed action is to determine the treatment time distribution and the waiting time distribution as narrow as possible and use these two values instead of a subtracting mechanism.

This approach can be used for every hospital, however an interesting extension can be the financial aspects. Building a new AMU, or upgrading an existing ward to an AMU has financial consequences. This is not considered in the model. At last to make the model more accessible, an interface could be created. In here we can change parameters, admission criteria, arrival rate parameters etc. In this way non-technical users can also understand the program.

The step wise approach can be used to design an AMU. In here it partly depends on the decisions a hospital makes, regarding the admission criteria and facilities. Modelling the dimensions of the AMU is still missing some essential information to see the full potential of an AMU. For example, the LoS reduction cannot be determined beforehand and is essential to the performance of the system. Concluding from the results is that the AMU shows improvement to the ED and MW regarding blocking probability and bed occupancy. However, there is still a total increase in the number of beds at the hospital. A next research can show what the LoS improvement will be in the hospital and if a bed reduction, and therefore treatment efficiency, will improve.

References

[1] K M Alferink. *The quantitative and qualitative differences between the locations of an Acute Medical Unit*. PhD thesis, University of Twente, 2017.

[2] Miguel F. Anjos and Manuel V.C. Vieira. Mathematical optimization approaches for facility layout problems: The state-of-the-art and future research directions. *European Journal of Operational Research*, 261(1):1–16, 2017.

[3] Jos A.C. Bokhorst and Taco van der Vaart. Acute medical unit design The impact of rearranged patient flows. *Socio-Economic Planning Sciences*, 62:75–83, 2017.

[4] Jian Chang and Lingjuan Zhang. Case Mix Index weighted multi-objective optimization of inpatient bed allocation in general hospital. *Journal of Combinatorial Optimization*, 37(1):1–19, 2019.

[5] M. W. Cooke, J. Higgins, and P. Kidd. Use of emergency observation and assessment wards: A systematic literature review. *Emergency Medicine Journal*, 20(2):138–142, 2003.

[6] A. M. de Bruin, R. Bekker, L. van Zanten, and G. M. Koole. Dimensioning hospital wards using the Erlang loss model. *Annals of Operations Research*, 178(1):23–43, 2010.

[7] Evgueniia Doudareva and Michael Carter. Discrete event simulation for emergency department modelling: A systematic review of validation methods. *Operations Research for Health Care*, 33:100340, 2022.

[8] Raffaella Gualandi, Cristina Masella, and Daniela Tartaglini. Improving hospital patient flow: a systematic review. *Business Process Management Journal*, 26(6):1541–1575, 2020.

[9] Leila Keshtkar, Wael Rashwan, Waleed Abo-Hamad, and Amr Arisha. A hybrid system dynamics, discrete event simulation and data envelopment analysis to investigate boarding patients in acute hospitals. *Operations Research for Health Care*, 26:100266, 2020.

[10] Averill M Law. *Simulation Modeling and Analysis, FIFTH EDITION*. 2015.

[11] PAW LEWIS and GS SHEDLER. Simulation of nonhomogeneous poisson processes by thinning. *NAVAL RESEARCH LOGISTICS*, 26(3):403–413, 1979.

[12] Benjamin Probert Ashwin Dhanda Louise Powter, Amanda Beale. Development and validation of a tool to select patients for admission to medical short stay units. *Royal College of Physicians*, 14(4):371–375, 2014.

[13] Jung Hun Ohn, Nak Hyun Kim, Eun Sun Kim, Seon Ha Baek, Yejee Lim, Jaehyung Hur, Yun Jong Lee, Eu Suk Kim, and Hak Chul Jang. An Acute Medical Unit in a Korean Tertiary Care Hospital Reduces the Length of Stay and Waiting Time in the Emergency Department. *Journal of Korean Medical Science*, 32(12):1–4, 2017.

[14] Hamid Ravaghi, Saeide Alidoost, Russell Mannion, and Victoria D. Bélorgeot. Models and methods for determining the optimal number of beds in hospitals and regions: A systematic scoping review. *BMC Health Services Research*, 20(1):1–13, 2020.

[15] Lindsay E.M. Reid, Lotte C. Dinesen, Michael C. Jones, Zoe J. Morrison, Christopher J. Weir, and Nazir I. Lone. The effectiveness and variation of acute medical units: a systematic review. *International Journal for Quality in Health Care*, pages 1–14, 2016.

[16] Lindsay E.M. Reid, Ursula Pretsch, Michael C. Jones, Nazir I. Lone, Christopher J. Weir, and Zoe Morrison. The acute medical unit model: A characterisation based upon the National Health Service in Scotland. *PLoS ONE*, 13(10):1–12, 2018.

[17] Ian Scott, Louella Vaughan, and Derek Bell. Effectiveness of acute medical units in hospitals: A systematic review. *International Journal for Quality in Health Care*, 21(6):397–407, 2009.

[18] Walter Sermeus, Luc Delesie, Koen Van den Heede, Luwis Diya, and Emmanuel Lesaffre. Measuring the intensity of nursing care: Making use of the Belgian Nursing Minimum Data Set. *International Journal of Nursing Studies*, 45(7):1011–1021, 2008.

[19] Vivek Soni. Predicting Length of Stay of Emergency Department Patients Using Tree-Based Machine Learning Models. *ProQuest*, 2019.

[20] Belinda Suthers, Robert Pickles, Michael Boyle, Kichu Nair, Justyn Cook, and John Attia. The effect of context on performance of an acute medical unit: Experience from an Australian tertiary hospital. *Australian Health Review*, 36(3):320–324, 2012.

[21] A. J. Thomas Schneider, P. Luuk Besselink, Maartje E. Zonderland, Richard J. Boucherie, Wilbert B. Van Den Hout, Job Kievit, Paul Bilars, A. Jaap Fogteloo, and Ton J. Rabelink. Allocating emergency beds improves the emergency admission flow. *Interfaces*, 48(4):384–394, 2018.

[22] Triagenet. Manchester Triage System, 2022.

[23] L. S. van Galen, E. M.J. Lammers, L. J. Schoonmade, N. Alam, M. H.H. Kramer, and P. W.B. Nanayakkara. Acute medical units: The way to go? A literature review. *European Journal of Internal Medicine*, 39:24–31, 2017.

[24] W Veneklaas, A G Leeftink, P H C M Van Boekel, and E W Hans. On the design , implementation , and feasibility of hospital admission services : The admission lounge case . *Omega*, 100:102308, 2021.

[25] Tuck Y Yong, Jordan Y Z Li, and Susan Roberts. The selection of acute medical admissions for a short-stay unit. *Intern Emerg Med*, pages 321–327, 2011.

A. Appendix A

Discharged	ALL	CAR	CHI	GER	INT	KIN	KNO	LON	MDL	NEU	OOG	ORT	PLA	URO
Discharged	0.981	0.492	0.817	0.184	0.479	0.586	0.796	0.383	0.370	0.486	0.978	0.607	0.787	0.554
Admission	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 15: Change of discharge per specialty. Based on a uniform distribution a patient will either be discharged or moved further downstream the hospital.

Age	ALL	CAR	CHI	GER	INT	KIN	KNO	LON	MDL	NEU	OOG	ORT	PLA	URO
0	0.000	0.000	0.002	0.000	0.000	0.394	0.004	0.000	0.000	0.000	0.006	0.001	0.003	0.000
5	0.000	0.000	0.052	0.000	0.000	0.802	0.087	0.000	0.000	0.000	0.000	0.002	0.115	0.004
10	0.000	0.000	0.118	0.000	0.000	0.895	0.116	0.000	0.000	0.000	0.000	0.008	0.154	0.019
15	0.000	0.000	0.196	0.000	0.001	1.000	0.141	0.001	0.001	0.001	0.000	0.022	0.000	0.047
20	0.094	0.015	0.274	0.000	0.033	0.000	0.214	0.024	0.026	0.031	0.111	0.050	0.238	0.081
25	0.296	0.041	0.357	0.000	0.090	0.000	0.286	0.062	0.082	0.076	0.172	0.073	0.311	0.122
30	0.478	0.067	0.428	0.000	0.144	0.000	0.374	0.108	0.139	0.118	0.256	0.091	0.350	0.170
35	0.579	0.096	0.484	0.000	0.192	0.000	0.446	0.153	0.198	0.161	0.322	0.116	0.426	0.221
40	0.648	0.126	0.530	0.000	0.236	0.000	0.496	0.191	0.245	0.200	0.372	0.135	0.465	0.256
45	0.711	0.165	0.572	0.000	0.282	0.000	0.541	0.233	0.295	0.245	0.428	0.158	0.535	0.299
50	0.780	0.215	0.619	0.026	0.339	0.000	0.578	0.290	0.365	0.299	0.500	0.199	0.613	0.348
55	0.843	0.276	0.672	0.000	0.398	0.000	0.614	0.360	0.442	0.361	0.556	0.250	0.709	0.402
60	0.899	0.361	0.724	0.000	0.465	0.000	0.654	0.450	0.510	0.427	0.672	0.317	0.779	0.470
65	0.943	0.444	0.770	0.044	0.539	0.000	0.704	0.556	0.591	0.506	0.811	0.415	0.866	0.535
70	0.000	0.537	0.815	0.000	0.619	0.000	0.760	0.667	0.677	0.590	0.883	0.519	0.913	0.630
75	0.000	0.645	0.862	0.114	0.713	0.000	0.824	0.775	0.774	0.692	0.933	0.654	0.933	0.725
80	0.000	0.765	0.903	0.281	0.810	0.000	0.879	0.874	0.853	0.795	0.000	0.764	0.969	0.826
85	1.000	0.887	0.942	0.579	0.904	0.000	0.924	0.950	0.930	0.892	0.989	0.883	0.992	0.924
90	0.000	0.962	0.977	0.860	0.967	0.000	0.980	0.984	0.975	0.969	1.000	0.970	0.997	0.979
95	0.000	1.000	0.995	0.982	0.996	0.000	0.994	0.997	0.998	0.995	0.000	0.996	1.000	0.994
100	0.000	0.000	1.000	1.000	1.000	0.000	1.000	1.000	1.000	1.000	0.000	1.000	0.000	1.000
105	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000

Table 16: Percentage of occurrence age per specialty. Based on a uniform distribution the patient will receive the age at the start of the model.

Triage	ALL	CAR	CHI	GER	INT	KIN	KNO	LON	MDL	NEU	OOG	ORT	PLA	URO
0	0.000	0.008	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.113	0.116	0.092	0.096	0.060	0.034	0.056	0.044	0.016	0.075	0.433	0.030	0.053	0.032
2	0.635	0.513	0.165	0.289	0.283	0.250	0.146	0.352	0.199	0.400	0.544	0.145	0.176	0.184
3	0.881	0.918	0.584	0.754	0.770	0.751	0.511	0.846	0.720	0.840	0.817	0.622	0.583	0.643
4	0.994	0.995	0.962	1.000	0.983	0.985	0.933	0.989	0.990	0.989	0.983	0.958	0.927	0.980
5	1.000	1.000	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 17: Percentage of occurrence triage per specialty. Based on a uniform distribution the patient will receive the triage score at the start of the model.

B. Appendix B

ArrHour	Factor
0	0.304
1	0.276
2	0.242
3	0.233
4	0.224
5	0.213
6	0.212
7	0.223
8	0.301
9	0.565
10	0.771
11	0.849
12	0.842
13	0.844
14	0.872
15	0.936
16	1.000
17	0.914
18	0.679
19	0.590
20	0.575
21	0.548
22	0.485
23	0.409

Table 18: Thinning procedure, change of accepting a patient per hour

C. Appendix C

C.1. No maximum LoS Admission criteria

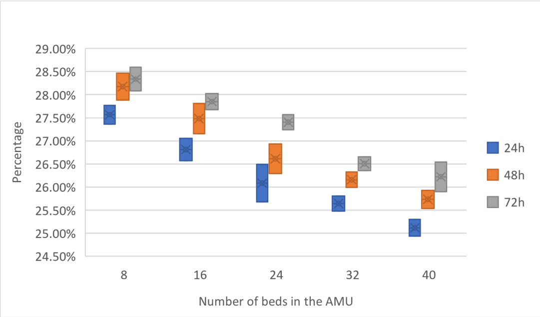

Figure 14: Percentage of patient with a LoS longer than 3 hours per scenario.

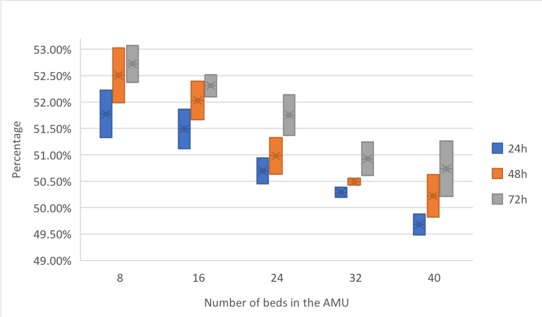

Figure 15: Occupancy rate in the ED per scenario.

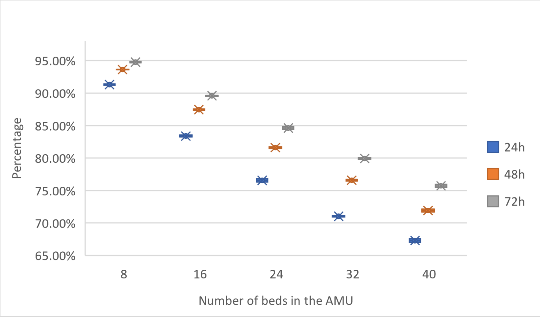

Figure 16: The AMU blocking probability per scenario.

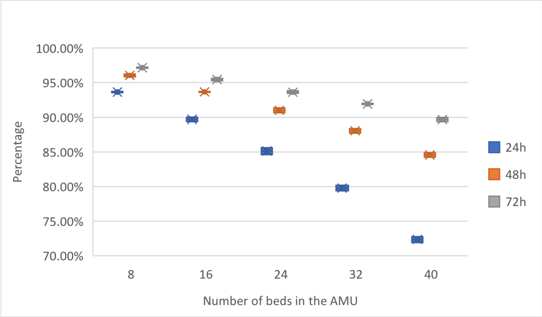

Figure 17: AMU occupancy percentage per scenario.

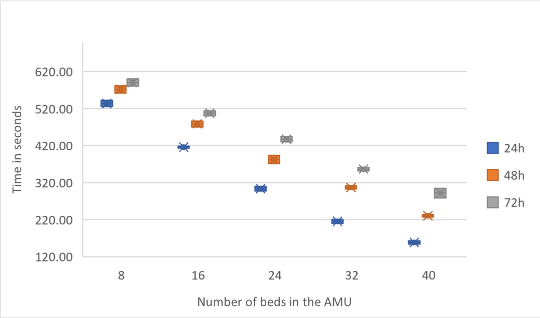

Figure 18: Average in ED waiting time per scenario.

C.2. Including Maximum LoS

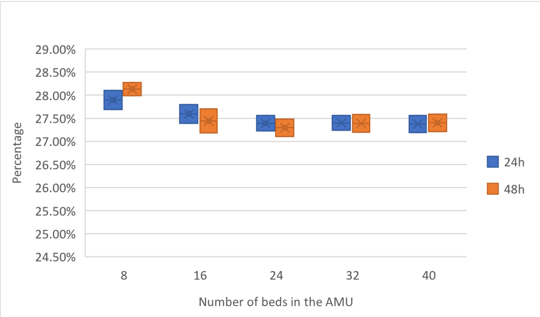

Figure 19: Percentage of patient with a LoS longer than 3 hours per scenario.

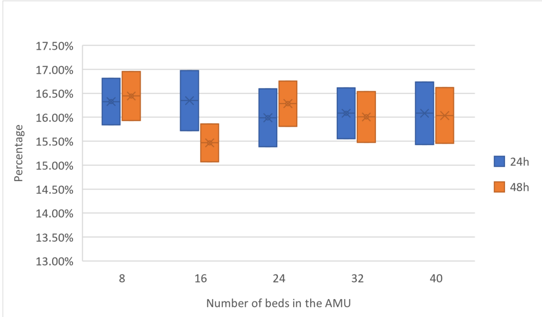

Figure 20: The ED blocking probability per scenario.

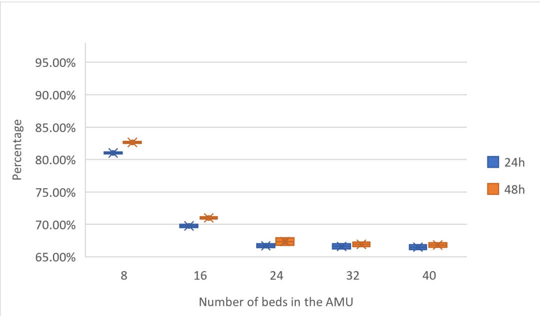

Figure 21: The AMU blocking probability per scenario.

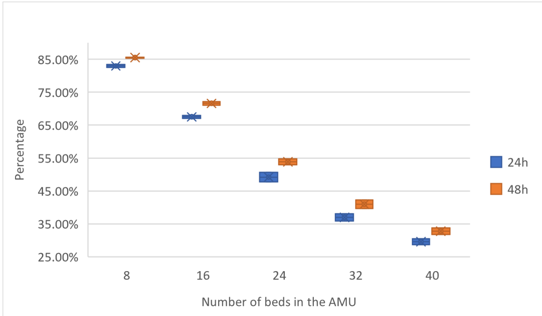

Figure 22: The AMU occupancy percentage per scenario.

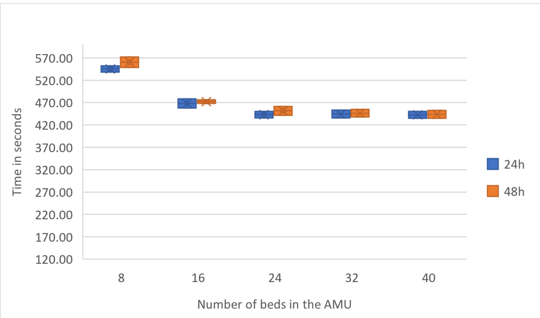

Figure 23: Average in ED waiting time per scenario.