On the design, implementation, and feasibility of hospital admission services: The admission lounge case

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**A R T I C L E   I N F O**

Article history:
Received 20 December 2019
Accepted 10 July 2020
Available online xxx

Keywords:
Healthcare facility planning
Erlang loss model
Decision support system
Capacity analysis
Case mix optimisation

**A B S T R A C T**

An admission lounge is an emerging type of hospital facility that potentially improves the efficiency and efficacy of the perioperative process. We propose a five-step approach for the design, suitability assessment, and optimisation of an admission lounge. The approach uses a case mix optimisation method to select patients for the admission lounge, clinical ward, or both. Also, it determines the required admission lounge and clinical ward capacities using an Erlang loss model combined with a novel analytical model. The approach is integrated into a decision support system, which helps hospitals to identify the suitability of the admission lounge concept, optimise its configuration, and identify the potential bed reduction in the clinical ward. The decision support system is validated and tested in a case study of a Dutch hospital using their historical data.

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1. Introduction

The pressure on healthcare systems rises as both the demand for healthcare and expenditures are increasing [1]. It is possible to significantly reduce healthcare costs through increased efficiency and efficacy of hospital processes [2]. Within hospitals, a promising development termed admissions without beds addresses efficiency and efficacy of the perioperative process. The new admission procedure separates preoperative and postoperative patients by admitting elective patients to a new type of ward: the Admission Lounge (AL). For a potentially large group of elective patients, this replaces the conventional admission procedure to the Clinical Ward (CW), which mostly situates postoperative patients.

Fig. 1A depicts the traditional patient admission process. With the introduction of the AL, this admission process is adapted to the process of Fig. 1B. The dark colored process arrows depict process steps where a patient has an assigned bed. As a result of the introduction of the AL, bed usage is reduced, which improves productivity, reduces bed blocking, and optimises patient flow. Moreover, the separation of preoperative and postoperative patients enables hospitals to assign skilled staff to relevant wards more efficiently.

The increasing shift to day-surgery, the focus on effective bed management, and trend to accommodate admissions without a bed, has led to the introduction of ALs. A dedicated unit for elective surgery admissions reduces the pre-surgery length of stay [3], and the number of cancellations due to insufficient preparation [3], without impacting surgery outcomes [4]. From an efficiency perspective, the AL is associated with earlier starting of the operating theatre [5], and increased bed availability for emergency admissions [3]. Furthermore, the implementation of an AL is associated with increased patient satisfaction [5].

In a preliminary field study [6], we conducted semi-structured interviews with three hospitals to identify their expected effects of the AL, and their strategic decisions. Two hospitals were about to start an AL pilot, and the third hospital has already been using the AL for approximately one year. Each of the hospitals noted that there are three main desired effects of the AL:

- lower workload for the CW staff through separation of preoperative and postoperative elective patients;
- lower staffing costs through the reduction of bed reservations and separation of the aforementioned processes;
- increased patient friendliness through a more comfortable admission environment.

Strategic decisions regarding the (i) case mix selection, (ii) care unit partitioning, (iii) capacity dimensioning, and (iv) facility layout

Please cite this article as: W. Veneklaas, A.G. Leeftink and P.H.C.M. van Boekel et al., On the design, implementation, and feasibility of hospital admission services: The admission lounge case, Omega, https://doi.org/10.1016/j.omega.2020.102308
for the AL are likely to affect the extent in which these desired effects occur [1]. Below, we clarify these decisions in the context of the AL and the CW.

(i) **Case mix selection** refers to the types and volumes of patients that the AL serves (and the patient types and volumes that are admitted to the CW accordingly);

(ii) **Care unit partitioning** addresses both the creation of the AL and CW, and determines which patient groups to consolidate in either the AL or CW. These affect the decisions on how to designate staff, equipment, and beds to each unit;

(iii) **Capacity dimensioning** occurs in conjunction with (ii), and considers the size of the AL and CW expressed in staffed beds, equipment, and staff;

(iv) **Facility layout** concerns the physical positioning of the AL and the CW, based on which facilities should be close to each of the units and the availability of sufficient space.

There is a lack of insight into the relations between the expected performance of the AL and the CW, and the four aforementioned strategic decisions [6]. This leads to an imbalance in workload amongst the two facilities and capacity waste in terms of space, staff, and logistics. To prevent these issues, and to enable decision makers to analyse the relations between strategic decision making and expected performance, we develop a decision support system (DSS). This DSS is designed to work with the hospital information system (HIS) HiX, delivered by a Dutch HIS developer. Our DSS follows a five step strategic decision making approach:

Step 1: **Specify inclusion and exclusion criteria for the AL**. The inclusion and exclusion criteria are specified by hospital management and the effects of the assignments are visualised per criterion using data visualisation techniques.

Step 2: **Determine the appropriate staff, equipment, and supporting processes for the AL and CW**. Hospital management derives the required staff skill mix, appropriate nurse-to-patient ratios, and special equipment requirements as a result of the specified criteria in Step 1.

Step 3: **Analysis of potential bed reductions for the CW and required capacity for the AL**. Following from the inclusion and exclusion criteria of Step 1, the required capacities for the AL and CW can be assessed. The DSS shows the potential bed reductions for the CW given a desired blocking probability, and the required number of beds for the AL with its expected performance.

Step 4: **Analysis of feasibility of the AL and CW within the facility layout**. With the required capacities for the AL and CW, hospital management can derive whether the new configuration fits within the existing hospital layout.

Step 5: **Optimisation of the inclusion and exclusion criteria for the AL**. The assignment to the AL and the CW, which followed from Step 1, can be optimised in order to attain optimal service levels and occupancy rates in both facilities.

Our proposed five-step approach consecutively addresses a variety of planning decisions. Having the model integrated into a DSS allows managers and planners to quickly access a range of options for the planning issue at hand, and to test how performance may be affected by interventions in the planning process [7]. Fig. 2 is an overview of the inputs and actions for the user, and the working order of the DSS following the five steps of our approach.

The remainder of this paper is structured as follows. **Section 2** reviews the literature on each of the five steps of our DSS, and presents our selection of models that we developed to analyse the relation between strategic decisions and the system’s expected performance. In **Section 3**, we formulate these models, and **Section 4** presents how the models are integrated into the DSS. **Section 5** presents the results of a case study with our DSS in a Dutch hospital. Finally, in **Section 6** we present our conclusions.

2. Literature based model selection

We review the literature related to the five steps of our proposed approach, in **Sections 2.1–2.5** respectively. Section 2.6 concludes with the scientific contribution of the proposed five-step approach.

2.1. Step 1: specify inclusion and exclusion criteria for the AL

The inclusion and exclusion criteria determine the patient grouping of the AL and CW. In patient grouping systems, patients are generally grouped based on various types of data. This may include clinical data (e.g., diagnosis, procedures, ASA classification) [8], demographic data (e.g., age), and resource consumption data (e.g., costs, LOS) [9,10]. Pooled wards are typically organised according to patients’ length of stay [11–14] or to patients’ needs [10,15,16]. In the first case, multi-speciality wards are created for patients of similar lengths of stay. In the second case, wards could be organised on the basis of patient needs [15].

Grouping patients on the basis of LOS is efficient and a main indicator for both postoperative outcome and satisfaction of the patient [10]. To address both efficiency of the AL and patient satisfaction, we require a mix of clinical data and demographic data, which serve as inputs to determine resource consumption levels. The most relevant attributes for elective patient selection for the AL or CW are: ASA score, age, and the (sub)speciality the patient belongs to. The relevance of the attributes is based on their applicability to a wide variety of hospitals and their ability to indicate the patient’s expected length of stay (LOS) [6]. Based on these characteristics, patients can be assigned to the AL or the CW. Patients fall within a ‘grey area’ when they could be assigned to both, or when management cannot decide what assignment is most appropriate. This grey area for patient grouping is, to our knowledge, unique in the literature. In Step 5 (Section 2.5), we optimise the assignment of patients from the grey area to the AL and CW. With the use of data visualisation, we demonstrate the effects of inclusion and ex-
clusion criteria for the AL on the volume and complexity of the AL’s patient population.

2.2. Step 2: determine the appropriate staff and equipment

Appropriate staff and equipment for the AL and CW optimise the quality and cost of care. Workload is a determinant for the appropriate staff level [17], in conjunction with the available equipment [18]. Moreover, the use of better equipment is found to lead to a potential reduction of the staff level [19]. Contrarily, investments in human resources are argued to be more efficient than in newer (better) equipment [17]. To determine the appropriate mix of staff skills and required equipment, the best indicators are diagnosis related groups, case mix groups, and medical speciality indicators [20].

A combination of patient characteristics (including patient acuity) and organisational factors results in the best model for explaining the use of hospital care services [20]. The characteristics found in the review by van Oostven [20] can be used as predictors if they are known prior to a patient’s admission, or as explanatory factors if they occur during admission, for example, to monitor trends in time regarding the demand for care. For the AL, the required staff can be derived from the inclusion and exclusion criteria specified in Step 1 and their effects on the case mix division.

2.3. Step 3: analysis of capacity requirements

Capacity dimensioning determines the appropriate number of beds to admit patients to the AL and CW. The underlying logistical system of the admission and discharge process can be regarded as a job shop system with strong precedence constraints. A job shop allows the processing of various classes of products (patients) with capacity limitations inherent to the control and handling of the products and the preparation times of the machines (in our case the admission facilities: AL and CW). The determination of capacity requirements for the CW and AL is twofold: we want to determine the potential bed reduction for the CW, as well as the required beds for the AL. The required capacities depend on the population volumes and complexity of both facilities, determined in Step 1.

2.3.1. Potential bed reduction for the CW

Various papers study the determination of the number of required beds for a specific clinical department such that almost all patients can be admitted [11,14,21–24]. The Erlang loss model is one of the most widely used queueing-based methods, which was first introduced for the assessment of queues in telecommunication, and was later applied to industry and healthcare settings [25–28].

The Erlang loss model assumes that patient arrivals are Poisson distributed. Many authors have shown that arrival processes, especially unscheduled, can be approximated by a Poisson process [11,13,23,28]. For practical purposes, it is not required that the number of admissions follows the laws of a Poisson distribution exactly. The key point for practical modelling purposes is that the variability in the number of admissions is generally well captured by the Poisson distribution, making this also a reasonable assumption for the arrival distributions that do not follow the Poisson distribution very well [22,23]. Several studies have shown that unscheduled arrivals perform better under the Poisson distribution than scheduled arrivals [11,29]. However, even scheduled arrivals can be modelled under the Poisson assumption [11,21,30], especially if the results are solely required for strategic and tactical decision making [11]. For decisions on the operational level, more accurate approximations may be required [22,31,32]. As the CW has a similar structure as the wards considered in [11], we will apply the Erlang loss model to determine the potential bed reduction for the CW, as presented in Section 3.1.1.

2.3.2. Required AL capacity

Contrary to the CW, the AL will not reach a steady state on most working days, as the AL is filled with patients in the morning and is empty by the time the regular operating room (OR)
time has passed. Therefore, we cannot apply the Erlang loss model for the dimensioning of the AL. Other characteristics of the AL are that the patient arrival process is subjected to the surgical appointment planning and that patients require a bed for a short period of time. This is similar to a hospital’s day care department, but contrarily, the patient does not return to the AL after surgery. We were not able to find literature about capacity dimensioning for an AL or similar facilities that do not reach a steady state. Therefore, we developed our own model to determine the required capacity, based on historical arrival intensities. This model is presented in Section 3.2.2.

2.4. Step 4: analysis of feasibility of the AL and CW within the facility layout

Some choices or restrictions within the existing facility layout may have a limiting effect on all preceding decisions. Long distances increase transportation and travel times between facilities, which lead to an increase in indirect care activities. The literature contains a wide range of methods to solve the facility layout problem, in which the multitude of trips from and to facilities is minimised and penalised with the distance travelled. We refer to [25] and [26] for examples of such models.

2.5. Step 5: optimisation of the inclusion and exclusion criteria for the AL

Step 5 optimises the assignment of patients. In Step 1, patients are assigned to admission to either the AL or the CW. Patients that can be admitted to both units are assigned to a grey area. The patients from the grey area should be assigned to either the AL or the CW. To the best of our knowledge, methods to optimise the case mix for the AL or comparable job shop elements do not exist. Our method aims to assist in choosing the most effective and efficient assignments for the AL and the CW. Efficacy is represented by the population size of the patients assigned to the AL. Patient friendliness and reduced workload on the CW staff are induced by a larger AL population size. Efficiency is represented by the bed reduction for the CW versus the bed requirements for the AL. A potential bed reduction indicates increased efficiency. The underlying model is presented in Section 3.3.

2.6. Scientific contribution of the proposed five-step approach

We found several literature gaps that we aim to fill with this research. For our patient selection methodology in Step 1 we require a grey area, which is new to the literature, to our knowledge. In Step 3, we need to determine the expected performance of the AL. Because very little is written about the AL, we need to define a new model for our analysis. Step 5 aims to optimise the case mix within the bounds set by the inclusion and exclusion criteria set in Step 1, a method we did not come across in the literature. Section 3 provides the models for Steps 1, 3 and 5. The integration of the five-step approach into a DSS is discussed in Section 4.

3. Methods and models

This section describes the case mix division methods of Step 1 (Section 3.1), and gives the model formulation for the capacity dimensioning of Step 3 (Section 3.2) and the grey area optimisation of Step 5 (Section 3.3). Steps 2 and 4 predominantly consist of qualitative decisions supported by basic data visualisation techniques, and are therefore not described in this section. All steps are integrated in Section 4.

3.1. Methods for step 1

In Step 1, the user gives input for the case mix division. We use data visualisation techniques to indicate the effects of the patient selection in two ways: the case mix division, and the admission rate to the CW both with and without the AL.

3.1.1. Case mix division

The inclusion and exclusion criteria for the attributes elective status, age, ASA score, and the (sub)specialty lead to a division into the categories AL, CW, and grey area patients. For each attribute, the size of the patient population for each category is presented in a stacked bar chart. The total case mix is also presented. The patient selection method is based on the patient’s attributes: a patient is marked a CW patient if one or more attributes fall in the CW category. A patient is an AL patient if all attributes of the patient fall in the AL category. In other cases, when the patient’s attributes are a combination of grey area and AL, the patient is considered a grey area patient.

3.1.2. Admission rate

The current admission rate represents the admission rate of the CW without the AL. The average number of admissions to the CW per hour is determined. With an AL, the moment that AL patients arrive to the CW is postponed on the day, resulting in a better distribution of the admissions over the course of the day. The admission rates are presented in the DSS with a bar chart.

3.2. Models for step 3

Step 3 focusses on capacity dimensioning of the CW (Section 3.2.1) and the AL (Section 3.2.2).

3.2.1. CW bed reduction model

For the capacity dimensioning of the CW we use the Erlang loss model, also known as the $M/G/c$ queueing model, as it incorporates sufficient detail for strategic and tactical decision making. We follow the notation of [11]. Patients arrive according to a Poisson process with parameter $\lambda$. The LOS of an arriving patient is independent and identically distributed with expectation $1/\mu$, and can follow a general distribution [11]. The term $\lambda/\mu$ is often referred to as the offered load ($\rho$) to the system. The number of operational (occupied) beds equals $c$. The model assumes that there is no waiting area, which means that an arriving patient who finds complete occupancy at the CW is blocked. The blocking probability is given by:

$$P_b = \frac{(\rho)^c}{c!} \sum_{k=0}^c \frac{(\rho)^k}{k!}$$

(1)

The occupancy rate is now defined as:

$$\text{Occupancy rate} = \frac{1 - P_b}{c} \rho$$

(2)

which is equivalent to:

$$\text{Occupancy} = \frac{\text{Average number of occupied beds}}{\text{Number of operational beds}}$$

(3)

With Eq. (1) we are able to assess the blocking probability for a given number of beds to avoid high rejection rates.

Fig. 3 shows how the LOS in the CW is calculated for CW and AL patients. The LOS for a CW patient $i$ ($LOS^{W,i}$) is measured from the start of the admission to the CW prior to surgery until the discharge from the CW. The LOS for an AL patient $j$ at the CW ($LOS^{W,j}$) starts when the AL patient arrives at the CW after surgery.

Please cite this article as: W. Veneklaas, A.G. Leeftink and P.H.C.M. van Boekel et al., On the design, implementation, and feasibility of hospital admission services: The admission lounge case, Omega, https://doi.org/10.1016/j.omega.2020.102308
The average LOS (ALOS) for the joint sets of AL patients ($s_{AL}$) and CW patients ($s_{CW}$) is given by:

$$ALOS = \frac{1}{|s_{AL}|} \sum_{a \in s_{AL}} LOS^{AL} + \frac{1}{|s_{CW}|} \sum_{c \in s_{CW}} LOS^{CW} \quad (4)$$

This characteristic helps to estimate the potential bed reduction, as the LOS without an AL is expected to be larger than the LOS with an AL. Consequently, a similar service level for the CW can be achieved with fewer CW beds.

### 3.2.2. AL capacity model

AL arrivals will occur according to the appointment schedule of the operating theatre, and are therefore strongly related to the Master Surgery Schedule (MSS). The MSS determines how much OR time is to be assigned to the variety of surgery groups – on the highest level represented by specialties – on each weekday [33]. Because capacity dimensioning decisions mainly focus on assigning OR time to disciplines, resulting in the MSS [34], the MSS is leading in the arrivals approximation for the AL.

We relate the arrivals of the AL patients to the daily total planned OR time for the specialties within the AL case mix. The daily total planned OR time for a specialty is the total planned duration of sessions within the MSS dedicated to the surgeries scheduled for that specialty. We call days on which common amounts of OR time are allocated to a specialty representative days and use those days as a benchmark for the AL performance assessment.

To estimate the patients’ LOS in the AL before the AL has actually been introduced in the hospital, we develop assumptions about the LOS in consultation with the hospital. This allows us to determine the offered load of the AL. The general consensus of our hospital was to have the patient arrive at the AL two hours prior to the scheduled start of surgery. Based on the arrival rate to the OR for each hour the operating theatre is opened, we calculate the offered load during working hours.

For each day representative day $n \in N$, we define time buckets $t_n \in T_n$ with duration $d$ (in minutes) in which arrivals may occur at the AL. The expected admission duration of $D$ is a multiple of $d$ and represents the total time that a patient spends at the AL. The opening time of the AL is at the beginning of $t_n = 0$, the opening time of the operating theatre (OT) $start_{OT} \in T_n$ is in time bucket $t_n$ and marks the moment that patients can leave the AL for transfer to the holding. Fig. 4 gives a graphical representation of $t, d, D, and start_{OT}$ on a timeline, omitting $n$ for simplicity.

Before $start_{OT}$, the arrivals $\lambda_{tn}$ during $t_n \in \{0, 1, 2, \ldots, start_{OT}\}$ remain in the AL. If the patient has spent $\frac{d}{2}$ time buckets in the AL and the OT is open ($start_{OT} \leq t_n$), the patient leaves the AL. The offered AL load $\rho_n$ during time bucket $t_n$ on a given day $n$ is determined by:

$$\rho_n = \begin{cases} \sum_{t_n} \lambda_{tn}, & 0 \leq t_n < start_{OT} \\ \sum_{t_n=max\{t_n-(\frac{d}{2}), 0\}} \lambda_{tn}, & start_{OT} \leq t_n \leq T \end{cases} \quad (5)$$

The average load per time bucket $\overline{\rho_n}$ for a set of $n$ representative days $n$ is obtained through:

$$\sum_{n \in N} \rho_n \overline{\rho_n} \quad \forall t_n \quad (6)$$

The average number of required beds to accommodate all AL arrivals on a certain day amounts max $|\overline{\rho_n}|$. However, assuming that this would suffice as the required number of operational beds would most certainly lead to an underestimation due to variability of the load.

We assess the performance of the proposed AL capacity to determine how the AL would have performed on representative days. To do so, we compare the historical load on the AL by patients that would be assigned to the AL based on their characteristics and the AL inclusion criteria. Whenever the load $\rho_n$ exceeds the set number of beds, a patient would have been rejected and admitted to the CW instead. We define the percentage of the opening hours of the AL on which rejections took place, for all representative days, as the rejected hours rate. We also measure the fraction of days on which at least one rejection took place, termed the rejected days rate. Both indicators incorporate variability and therefore assess the validity of dimensioning the AL according to max $|\overline{\rho_n}|$.

### 3.3. Model for step 5

A grey area of patient selection is defined, based on the inclusion and exclusion criteria for the AL and CW as determined in Step 1. No model is available in the literature to optimise the case mix for the AL or comparable job shop elements. Therefore, in this section, we develop a model to choose the most effective and efficient assignments for the AL and the CW.

We assign patients within the grey area to either the AL or CW by enumerating the assignment possibilities in the grey area. The AL and CW selection criteria serve as bounds for the optimisation method. The selection criteria for the dimensions age, speciality, and ASA can be up to discussion in the context of a general hospital. The case mix optimisation has a dual objective: optimal use of the AL in terms of occupancy and rejection rates, and a maximal bed reduction for the CW. This optimisation can be formulated as a MILP, which is able to solve large solution spaces and outputs a
single optimal result. Given the relatively small solution space (explained in the next paragraph) and the desire to let the end-user consider multiple sub-optimal options, we choose to use complete enumeration.

The age category is an interval category, and should thus be divided in subcategories. We propose to use buckets of 5 years (e.g., 20–25, 25–30, etc.), as a result of a trade-off between computational complexity and outcome precision. The ordinal category ASA consists of the three relevant ASA classifications (I, II, III) for the AL. If a hospital has a wide variety of specialties, or the model is refined towards subspecialties, the solution space increases exponentially, by a factor of $2^k$, with $k$ being the number of specialties within the grey area.

After the enumeration we compare the overall performance of all assignment rule sets. Because there is a wide variety of available performance indicators, we apply a scoring method to assess each configuration’s performance, based on the hospital’s individual goals. Hence, we can direct DSS users towards personalised effective and efficient outcomes, and enable them to make comparisons relatively easy.

The scoring method encompasses efficiency and service levels. Efficiency is represented by the occupancy ratios and the required numbers of beds for the AL and the CW. Service levels are represented by the blocking probability for the CW and the hourly acceptance rate for the AL. From an economic point of view, in the analysis we are particularly interested in configurations that may lead to a reduction in the total number of required beds. In these configurations, the bed reduction for the CW exceeds the number of beds required for the AL. We propose the following objective function to allow balancing service level and efficiency of the solution:

$$\text{Performance} = \alpha (\text{bed reduction CW} \times \text{occupancy CW})$$

$$- \beta \left( \text{beds AL} + \frac{(1 - \text{rejected hours rate}) \times \text{occupancy AL}}{2} \right)$$

To personalise this approach, weights $\alpha$ and $\beta$ are assigned to each component of Eq. (7). This allows the user to emphasise on a variety of performance measures: the effectiveness and efficiency of both units, or for a single unit. Furthermore, by setting $\alpha > \beta$, the performance of the CW is emphasised over the AL, and vice versa. As there is a linear relationship between $\alpha$ and $\beta$, increasing either $\alpha$ or $\beta$ will lead to a larger differentiation between preferred solutions. In the remainder of this paper we value the performance of both units equally, and therefore use $\alpha = \beta = 1$.

4. Decision support solution design

Various authors point to capacity problems in healthcare and implement the solution into a DSS [7,10,35–37]. Our five step approach is integrated in a DSS, as shown in Fig. 2, to allow managers and planners to easily use our model. The following subsections discuss the DSS design for each of the five steps. To systematically design the DSS, we incorporate the constructs of the technology acceptance model (TAM) [38].

To setup the DSS, the user first has to specify which historical data is used. The required input parameters are the admission type (day patients and/or clinical patients), the relevant CWs, and the period to use for the analysis. After the data is loaded, the user can use the three tabs in the DSS GUI to go through all the five steps of AL design decision making.

4.1. DSS step 1

The first tab in the DSS (Fig. 5A) shows the decision variables considering the case mix. These variables are presented as a matrix, with the criteria for inclusion and exclusion shown vertically and the assignment to the AL, CW or grey area horizontally. Below the matrix, the population sizes for the assignment of each criteria are visualised. In addition, the total case mix fractions assigned to the AL, CW and grey area are shown.

4.2. DSS step 2

In Step 2, qualitative decision variables are introduced for specifying the appropriate staff, equipment, and supporting processes. These variables are not directly incorporated in the DSS, but can be derived from the qualitative patient selection criteria in Table 1.

4.3. DSS step 3

Tab 2 in the DSS (Fig. 5B) shows how the AL and CW assignments affect the required beds for the CW and AL, for a chosen rejection rate. The table shows the number of beds needed in the CW and the potential bed reductions after the AL is introduced. In addition, the second table shows the hourly and daily rejection rates given the number of beds in the AL. Along with the occupancy rate, these numbers indicate the number of beds required at the AL. Colour codes show how the indicators perform.

4.4. DSS step 4

The performance of the AL and the CW, for a specified number of beds, is also presented in Table 2. From this, the user can derive the required number of AL beds and potential bed reduction for the CW. The number of required AL beds also implies the need for a waiting area (the lounge aspect of the AL) that is sufficiently

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**Table 1**

| Category | Status   | Age     | ASA | Specialties |
|----------|----------|---------|-----|-------------|
| CW       | Non-elective | ≥ 86   | IV, V | –           |
| Grey     |          | 76–85   | III | BAR         |
| AL       | Elective | 18–75   | I, II | CHI, KAA, NCH, ORT, PLA, URO |

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Table 2
Inputs for the Erlang loss models and the corresponding required beds and corresponding occupancy (occ.) ratios (case hospital data, 2015–2017, n = 7565).

| Speciality | Current situation | With the admission lounge |
|------------|-------------------|---------------------------|
|            | Current situation | With admission lounge     |
|            | \( \rho_b = 0.05 \) | \( \rho_b = 0.01 \) | \( \rho_b = 0.05 \) | \( \rho_b = 0.01 \) |
| \( \lambda \) | \( \mu \) | Beds | Occ. | \( \mu \) | Beds | Occ. | \( \mu \) | Beds | Occ. | \( \mu \) | Beds | Occ. |
| BAR        | 1.38 | 1.87 | 6 | 42% | 3 | 8 | 32% | - | - | - | - | - |
| CHI        | 3.36 | 4.57 | 21 | 70% | 19 | 25 | 61% | 4.49 | 20 | 72% | 24 | 62% |
| KAA        | 0.07 | 1.19 | 2 | 4% | 2 | 4% | - | - | - | - | - |
| NCH        | 0.29 | 1.17 | 2 | 16% | 3 | 11% | - | - | - | - | - |
| ORT        | 1.97 | 3.03 | 10 | 57% | 9 | 13 | 46% | 2.94 | 10 | 56% | 12 | 48% |
| PLA        | 1.66 | 2.14 | 6 | 49% | 5 | 9 | 39% | 1.92 | 7 | 44% | 9 | 35% |
| URO        | 1.12 | 2.21 | 6 | 40% | 7 | 35% | 2.14 | 7 | 39% | 7 | 34% |
| Pooled     | 0.86 | 3.17 | 37 | 80% | 27 | 53% | - | - | - | - | - |

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### Large.

Management can decide upon the feasibility of the solution within the hospital layout on the basis of the required capacities.

#### 4.5. DSS step 5

**Table 3** of the DSS ([Fig. 5C](#)) shows optimisation possibilities for assigning the patients in the grey area to the AL or CW. Here, the top five outcomes are presented in a table, including the initial assignment. Note that when a different assignment is chosen, the outputs of Tables 1 and 2 will be adjusted accordingly.

## 5. Case study

This section provides the computational and practical results of the introduced DSS. The case study was carried out in collaboration with an average size general hospital in The Netherlands. The hospital is planning to expand, and simultaneously considers to implement an AL. At the time of research they already had a ward dedicated to mainly the admission of elective patients, but not a fully dedicated AL. In Section 5.1 we describe the data input derived from the hospital data. Section 5.2 then discusses the use of the DSS.

### 5.1. Data inputs

For the data preparation we select admissions of clinical patients, during weekdays, from a surgical ward. These admissions took place from 2015 to 2017. This ward admits all adult, elective, surgical patients and had a capacity of 39 beds on average. Irregularities are removed from the dataset by applying a threshold of 0.5% of all admissions per specialty. This leaves us with seven surgical specialties in the dataset (with their Dutch abbreviations mentioned within brackets):

- Bariatrics
- General surgery
- Jaw surgery
- Neuro-surgery
- Orthopaedics
- Plastic surgery
- Urology

We apply our DSS methodology to the case hospital. Recall the five steps:

1. Specify inclusion and exclusion criteria for the AL;
2. Determine the appropriate staff, equipment, and supporting processes for the AL and CW;
3. Analysis of potential bed reductions for the CW and required capacity for the AL;
4. Analysis of feasibility within the facility layout;
5. Optimisation: assignment of the grey area patients.

### 5.2. Use of the DSS

#### 5.2.1. Step 1 case study results

The hospital indicates that patients that are allowed access to the AL are elective patients, aged between 18 and 75, with ASA classification I or II, and from every speciality of the surgical ward, except BAR patients. Patients that are not allowed access are non-elective, 86 years or older, or belong to ASA class IV or V. All other patients are considered to be in the grey area. BAR patients are generally overweight and diabetic, meaning that special equipment is required during the admission process. Because the hospital is interested in the difference in performance of the AL with or without the BAR patients, the specialty is initially assigned to the grey area. Table 1 summarises all inclusion and exclusion criteria.

The patient mix decisions classify the patients into 44% AL patients, 35% grey area patients, and 23% CW patients. Fig. 6 shows that only adult patients are admitted to the AL, and that a small portion of the patients is non-elective. The attribute ASA has the largest grey area. The size of the grey area defines the room for optimisation in Step 5. The lower bound for the number of AL patients is 44% and the upper bound is 77% of all patients.

#### 5.2.2. Step 2 case study results

Step 2 focuses on the selection of the appropriate staff, equipment, and supporting processes for the AL. The hospital indicates that all available staff is qualified to admit higher-complex patients.
with, e.g., an ASA III classification. Clinicians indicated that an appropriate nurse-to-patient ratio for the admission process is 2 to 1 if the admissions have to take place over a short period of time. With a lower nurse-to-patient ratio the nurses’ workload becomes too high, and the patient friendliness decreases.

The hospital has special equipment (larger beds and heavier mattresses) and facilities (wider doors and standing toilets) for the BAR patients. For the other patients there is no indication of special requirements. Currently, a nurse transfers the patient to the holding. Because the CW is one floor level beneath the OT, the nurse has to use an elevator to transfer the patient to the holding, which is found to be time consuming.

5.2.3. Step 3 case study results

In Step 3, we first analyse the plot of the admission and discharge moments at the CW, with and without the AL (Figure 7). We observe that the case hospital experiences a prominent peak load in the CW in the morning, caused by new patient admissions. An AL can strongly reduce that peak load and spread the admission of patients more evenly across the day (Figs. 7A and 7B).

Next, we dimension the CW with and without the AL. Table 2 shows that the CW can reduce the required number of beds by 2 for a blocking probability of both 5% and 1% in the pooled situation. The hospital posed that a pooled capacity of 37 beds could be an accurate estimation for the assessed period. Because all surgical specialties are situated in one CW, it is not rel-

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event to compare the results for the individual specialties. However, it is relevant to study the behaviour of the individual specialties: in general, the occupancy rates are relatively low given a blocking probability of 5%. The occupancy further decreases by approximately 8–10 percent points for the larger specialties when the blocking probability of 1% is selected compared to 5%.

We also plot the blocking probability and occupancy ratio (Figs. 8 and 9) as a function of the number of CW beds. The plots are available for the situation without the AL (as presented in this paper) and with the AL. The curves show the same behaviour for both situations, except with a faster convergence for the situation without the AL. The hospital indicated that the additional information given by hoovering over the lines (not shown in the figures) is a helpful extension of the plots because it increases the readability of the plots.

With the current patient selection criteria, the performance of the AL will be as shown in Table 3 (on representative days), with opening hours from 6:30 AM to 11:00 AM. These opening hours may span a short period of time, but few patients assigned to the AL are admitted after 11:00 AM. With the current criteria we recommend to open the AL with 3 or 4 beds. When the hospitals choose to assign four beds to the AL, they may have to close beds during periods with lower demand, because the expected occupancy ratio of 41% is relatively low. With three beds, the occupancy ratio is more than 10% higher (51.8%), and the rejected hours rate increases by only 2.2%.

Table 3 shows that the occupancy ratio is relatively low for a relatively high rejection rate, compared to the performance of the CW. This can be explained by the peak load on the AL early in the morning, seen in Fig. 10. After 8:00 AM, the load on the AL quickly decreases, which is a result of the planning and scheduling methods of the case hospital. AL patients are typically scheduled for surgery early in the morning and arrive accordingly.

5.2.4. Step 4 and 5 case results
The hospital plans on an expansion in the next year, as we mentioned in this section’s introduction. It is still unclear where the AL will be situated, and therefore there are no limits to the size of the AL for our analysis. We enumerate the patient selection criteria to find improvements on the current solution.

Together with the initial case mix selection there are 12 selection options to assess (Table 4). We use the goal function introduced in Section 3.2 to determine the top five performing configurations.

The goal function (see Section 3.2) highlights the top five performing assignment options: 1, 2, 4, 6, and 12 respectively, as shown in Table 5. The number of CW beds is the number of beds that first leads to a rejected hours rate less than 10%. The assignment we considered in the previous steps, assignment 7, is not part of the top 5 performing assignment options. The top three assignments give similar performance results. Assignment 1, the best performing configuration, has the lowest patient complexity profile, lowest rejection rate, and the lowest occupancy rate for the AL. We remark that assignment 6, ranked fourth, causes the largest bed reduction for the CW, with a reduction of 3 beds. Here, the AL requires 4 beds, which is 1 more than the other top five assignments. This higher number of AL beds also comes at the price of the second lowest occupancy ratio for the AL. Given the nurse to patient ratio of 2:1, we believe that assignment 4 has the most potential for the hospital. If inclusion of BAR patients is not desired, we recommend using assignment 1.

6. Conclusions and discussion
An AL has many advantages for the hospital admission process, such as operational and logistical efficiency, cost-efficiency, and increased patient friendliness. We have introduced a five-step approach for the design, critical analysis, and optimisation of an AL. This framework was implemented into a DSS, and validated and tested in a case study to obtain computational and practical results.

The DSS enables hospital management to make strategic decisions regarding the selection of patients and both the partitioning and dimensioning of the AL and the CWs. The DSS follows five steps. In Step 1, hospital management and clinicians specify inclusion and exclusion criteria for the AL, which divides elective patient population in three groups: AL patients, CW patients, and grey area patients. Within our case study the inclusion and exclusion criteria were based on the patient’s age, ASA classification, and speciality. The effects of the inclusion criteria on assignment to either the AL or the CW are visualised by the DSS. During Step 2, the required materials, staff skill mix and supporting processes for the AL can be derived from the selected patients. In Step 3, the potential bed reductions for the CW are calculated using the Erlang loss model, in conjunction with the calculation of the required number of AL beds. During Step 4, hospital management assesses the feasibility of the proposed dimensioning of both the AL and the CW within the facility layout. In Step 5, the case mix for the AL and CW can be optimised by the assignment of grey area patients to either the AL or the CW. Using a goal function, the results of all possible assignments are compared in terms of efficiency (largest bed reduction) and efficacy (largest AL patient population and highest AL occupancy), weighing cost reductions against patient friendliness and workload reductions.

The DSS supports users to systematically make decisions about the implementation of the AL. After the AL is implemented, the DSS can be used for tactical planning purposes by resetting inputs
Fig. 8. Blocking probability (top) and occupancy ratio (bottom) as a function of the number of beds for the individual specialties, without the AL (case hospital data, 2015–2017, n = 7565).

Table 5
Top 5 performing assignment options for the AL’s patient assignment enumeration (case hospital data, 2015–2017, n = 7565).

| Rank | Option | Beds CW with AL | Reduction CW | Occupancy CW (%) | Beds AL | Rejected hours AL (%) | Occupancy AL (%) |
|------|--------|-----------------|-------------|-----------------|---------|-----------------------|-----------------|
| 1    | 1      | 35              | 2           | 79.6            | 3       | 6.9                   | 56.0            |
| 2    | 2      | 35              | 2           | 79.3            | 3       | 9.1                   | 59.8            |
| 3    | 4      | 35              | 2           | 79.3            | 3       | 9.7                   | 60.1            |
| 4    | 6      | 34              | 3           | 80.1            | 4       | 7.5                   | 56.2            |
| 5    | 12     | 35              | 2           | 79.8            | 3       | 7.9                   | 57.0            |
such as the wards for analysis, the analysis period, or the patient selection criteria.

The proposed systematic implementation of the AL uses novel OM/OR models to determine the AL load and optimise the case mix. The introduced grey area for patient allocation decisions sets boundaries for the solution space and enables hospitals to optimise the AL and CW within their strategic scope. The case mix optimisation is particularly useful in situations where management is hesitant about the qualitative impacts of the assignment of a patient, and needs quantitative support to justify complex decisions. Note that the case mix optimisation can be personalised for each hospital by considering additional relevant case mix variables in the inclusion criteria, or for example by considering other age group buckets.

We validated and tested our DSS in a case study in a relatively small general hospital. The case study was used to obtain computational and practical results that are required before implementing an AL. Note that, as these decision support steps precede the actual implementation of the AL, the case study hospital has not (yet) implemented an AL. This hospital indicated that the DSS was easy to interpret and use. Applying the DSS to a larger or another type of hospital will result in more knowledge about the usability of the DSS. We expect that the DSS can especially be valuable for larger hospitals where the decisions for patient selection and ward selection are more complex than the context we studied. In a specialised hospital, the patient selection decisions might focus on other attributes than in our study. In that case, attributes such as treatment type might be added to the inclusion and exclusion criteria, or the age groups might be defined differently.

The Erlang loss model is used to quantify the potential CW bed reduction. This model is known to lead to an overestimation of the required number of beds. We used the Erlang loss model formulation to determine the potential bed reduction for the CW. To account for the variability in arrivals at the CW, we recommend expanding the model with the time-dependant Erlang loss model [22]. The impact of the AL could also be quantified if the time-dependent arrivals at the CW are based on the visualised admission patterns we incorporated in our DSS. In addition to the quan-

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titative effects of the AL. There is also a wide variety of qualitative benefits that may occur. The main driver for hospitals is expected to be the improved logistics and patient friendliness, while the bed reductions might be of marginal interest.

In our model, we assumed Poisson patient arrivals. However, in practice a Poisson distribution might not give a perfect fit to the data, as is also the case for some of the specialties in our case study. However, when considering the arrivals to the AL, all selected specialties are combined, and for the joint arrival rate the Poisson assumption is valid. Furthermore, the literature suggests that a Poisson distribution is a good assumption in general, but depending on the planning rules of a hospital, the arrival distribution might be different. For general and university hospitals, the Poisson assumption is most likely to give a good fit, especially for larger hospitals. But for example in a highly regulated small sized specialised hospital, arrivals might be uniformly distributed. Including various distributions in the model is an area of future research.

We use representative days to determine the AL load. With this method we automatically exclude outliers from the analysis of the AL. This means that we potentially over- or underestimate the number of days or hours on which patients are rejected. A more accurate AL load could be modelled with a convolution model, based on the expected inflow for a given MSS. To gain more insights about the operational performance of the AL and the CW combined, a simulation study may be required. Another remark on the use of representative days for the analysis of the AL is that they might be non-existent when the MSS changes drastically.

Enumeration of the case mix was done for a relatively small solution space. The solution space increases exponentially with the number of (sub)specialties assigned to the grey area for AL admission inclusion/exclusion. We determined, under the assumption of linear runtime behaviour, that the runtime of the model amounts 91 h with 15 (sub)specialties assigned to the grey area, which is acceptable for strategic decision making. A MILP will most likely be more efficient in terms of computing time and is therefore more useful if only one optimal solution is desired.

The DSS can be used for the implementation of an AL in an existing hospital, or for the design of a new building. In this light, an interesting extension is to add financial considerations to the model, as financial aspects for example highly affect decision making in the design of a new building. In the design of a new building, we also advise to decide on the design of the AL in conjunction with the clustering and assignment of specialties to wards (e.g., those of [14]). In future research, our model should be integrated with clustering and assignment models of specialties to wards. One of the key topics in operations management for healthcare is to balance the care burden across wards [20]. The AL provides such a balance; the preoperative patients are no longer amongst the postoperative patients and therefore the care burden at both the AL and CW is more balanced than it would be without the AL. To further reduce the unbalanced care burden, research should analyse assigning patients to the AL or CW on the basis of their diagnosis.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interest

None.

CRediT authorship contribution statement

W. Veneklaas: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. A.G. Leeflink: Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration. P.H.C.M. van Boekel: Conceptualization, Investigation, Resources, Data curation, Writing - original draft, Supervision. E.W. Hans: Conceptualization, Methodology, Resources, Writing - original draft, Supervision.

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